Universidade de Trás-os-Montes e Alto Douro

Decision Support for the Strategic Behaviour of Electricity Market Players

Doctorate degree in Computer Science

Tiago Manuel Campelos Ferreira Pinto

Supervisor: Professor Dr. Zita Vale – ISEP/IPP

Co-Supervisor: Professor Dr. Eduardo Solteiro Pires – UTAD

Vila Real, March, 2016

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ABSTRACT

This thesis provides its contribution to the complementary fields of artificial intelligence and power systems by proposing innovative solutions for the intelligent and adaptive decision support of electricity market players, considering their participation in multiple alternative and complementary market opportunities.

The current state of worldwide electricity markets is strongly affected by the increasing use of renewable energy sources during the last years. This increase has been stimulated by new energy policies that result from the growing concerns regarding the scarcity of fossil fuels and their impact in the environment. As consequence of the policies and incentives that have been put in place, huge investments have been made in the power and energy sector. However, the large scale integration of fluctuating renewable sources in the power system, such as wind and sun, poses several constraints that limit not only the production reliability but also its use.

The large scale integration of renewable based energy resources has led to an unavoidable restructuring of the power and energy sector, which was forced to adapt to the new paradigm. This restructuring process resulted in a deep change in the operation of competitive electricity markets all around the world. These markets aim at ensuring increased and fair competition giving electricity buyers more options and pushing power players to increase their efficiency, thus enabling electricity prices decrease. The electricity markets' restructuring process brought out, however, several challenges itself, demanding the transformation of the conceptual models that have previously dominated this sector. The restructuring made the market more competitive, but also more complex, placing new challenges to the participants. The growing complexity and unpredictability of the markets' evolution consequently increases the difficulty of decision making, which is exacerbated by the increasing number of new market types that are continuously being implemented to deal with the new challenges that keep on emerging. Therefore, the intervenient entities are relentlessly forced to rethink their behaviour and market strategies in order to cope with such a constantly changing environment.

So that these entities can deal with the new challenges, the use of decision support tools becomes crucial. The need for understanding the market mechanisms and how the involved

players' interaction affects the outcomes of markets has contributed to the emergence of a large number of simulation tools. Multi-agent based software is the most widely adopted solution as this paradigm is particularly suitable to analyse dynamic and adaptive systems with complex interactions among its elements, such as electricity markets. Current software tools allow studying different electricity market mechanisms and analysing the relationships between market entities; however, they are not prepared to provide suitable decision support to the negotiation process of electricity market players.

This gap motivates the development of this PhD research work, which arises with the purpose of providing solutions that enable electricity market players to take the best possible outcomes out of each market context. The aggregation of the many contributions of this work ultimately results in an enhanced multi-agent based decision support system: Adaptive Decision Support for Electricity Markets Negotiations (AiD-EM). AiD-EM includes a Portfolio Optimization methodology, which decides in which market opportunities should market players negotiate at each moment. The actual negotiation process in each market is supported by specific decision support systems, directed to different types of negotiation. The participation in auction based markets is supported by the Adaptive Learning strategic Bidding System (ALBidS). This decision support system includes a large number of distinct market participation strategies, and learns which should be used in each context in order to provide the best expected response. Negotiations by means of bilateral contracts are assisted by the Decision Support for Energy Contracts Negotiation (DECON) system, which includes methodologies to analyse competitor players' negotiation profiles enabling the adaptation of the adopted negotiation strategies and tactics. All methodologies are supported by a context analysis methodology, which allows analysing and identifying different contexts of negotiation, thus enabling a contextual adaptation of the diverse learning processes.

The developed decision support methodologies have been tested and validated under realistic simulation scenarios using real data from several electricity market operators. The promising results achieved under realistic negotiation conditions support the thesis that the appropriate analysis and learning from historic data can, in fact, improve players' outcomes from their participation in electricity markets.

Keywords: Adaptive Learning; Artificial Intelligence; Automated Negotiation; Decision Support Systems; Electricity Markets; Multi-Agent Simulation.

RESUMO

O contributo desta tese é dado nas áreas complementares da inteligência artificial e dos sistemas de energia, através da proposta de soluções inovadoras para o apoio à decisão, de forma inteligente e adaptativa, dos agentes participantes nos mercados de energia elétrica, considerando a sua participação em múltiplas oportunidades de mercado.

O estado atual dos mercados de energia elétrica deve-se em grande parte ao uso crescente de fontes de energia renovável. Este aumento tem sido estimulado por novas políticas energéticas que resultam das preocupações geradas pela escassez dos combustíveis fósseis e pelo seu impacto no ambiente. Estes incentivos têm dado origem a grandes investimentos no sector energético. No entanto, a penetração em larga escala de fontes de energia renovável de natureza intermitente, como o vento e o sol, tem a si associado um grande número de limitações que restringem, não só a fiabilidade da produção, como também o seu uso

O crescente aumento da integração de recursos energéticos provenientes de fontes renováveis conduziu a uma inevitável reestruturação do sector energético. Este processo de reestruturação resultou em mudanças significativas na operação dos mercados de energia elétrica por todo o mundo. Estes mercados têm como objetivo assegurar uma competição mais acentuada e justa, desta forma potenciando o decréscimo dos preços da energia elétrica. No entanto, a reestruturação dos mercados de energia elétrica criou também vários desafios, pois exigiu a transformação dos modelos conceptuais que dominavam o sector. A reestruturação trouxe, portanto, um mercado mais competitivo, mas também mais complexo e com maiores desafios para os seus participantes. O aumento da complexidade e da imprevisibilidade destes mercados amplifica a dificuldade na tomada de decisão, que é ainda agravada pela crescente introdução de novos mecanismos de mercado. Por estes motivos as entidades participantes têm constantemente de repensar o seu comportamento e estratégias de mercado.

A utilização de ferramentas de apoio à decisão torna-se fundamental para que estas entidades consigam lidar com os novos desafios. A necessidade de perceber o funcionamento dos mercados e de que forma as interações entre as entidades envolvidas afetam os resultados de mercado motivou o desenvolvimento de várias ferramentas de simulação. Os sistemas multi-

agente têm sido a solução mais adotada, uma vez que são especialmente adequados à análise de sistemas dinâmicos com interações complexas entre os seus constituintes. Apesar das soluções existentes permitirem o estudo de diferentes mecanismos de mercado e a análise das relações entre os intervenientes, estas ferramentas não estão, no entanto, preparadas para fornecer um apoio à decisão adequado a estes agentes num contexto de negociação em mercado.

O trabalho de investigação deste doutoramento é motivado pela lacuna identificada, e surge com o objetivo de propor soluções que permitam aos agentes participantes nos mercados de energia elétrica obterem os melhores resultados possíveis em cada contexto de mercado. A agregação das várias contribuições deste trabalho resulta num sistema multi-agente de apoio à decisão: AiD-EM (*Adaptive Decision Support for Electricity Markets Negotiations* – apoio à decisão adaptativo para negociações em mercados de energia elétrica). Este sistema inclui uma metodologia que permite aos agentes de mercado identificar as oportunidades de mercado em devem apostar em cada momento. O apoio à decisão para a negociação efetiva em cada mercado é dado por sistemas de apoio à decisão específicos, dirigidos aos diferentes tipos de negociação. O apoio à participação em mercados com funcionamento por leilão é dado pelo sistema ALBidS (*Adaptive Learning strategic Bidding System* – sistema de aprendizagem adaptativa para licitações estratégicas). Este sistema inclui diversas estratégias de participação em mercado, e tem a capacidade de aprender quais as abordagens que dão maiores garantias de sucesso em cada contexto. Para as negociações de contratos bilaterais foi desenvolvido o sistema DECON (*Decision Support for Energy Contracts Negotiation* – apoio à decisão para a negociação de contratos de energia), que inclui metodologias para analisar os perfis de negociação dos competidores, permitindo assim a adaptação das estratégias de negociação. Por fim, é proposto um método de análise contextual, que analisa e identifica diferentes contextos de negociação, permitindo assim uma adaptação contextualizada dos diversos processos de aprendizagem.

As metodologias desenvolvidas foram testadas e validadas através da simulação de cenários realistas, utilizando dados reais provenientes de diferentes operadores de mercado. Os resultados promissores que foram obtidos em condições realistas de negociação sustêm a tese de que uma análise e aprendizagem adequadas utilizando dados históricos pode, de facto, melhorar os resultados da participação dos agentes em mercados de energia elétrica.

Palavras-chave: Aprendizagem Adaptativa; Inteligência Artificial; Mercados de Energia Elétrica; Negociação Automática; Simulação Multi-Agente; Sistemas de Apoio à Decisão.

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ACRONYMS

2E	Efficiency/Effectiveness
AiD-EM	Adaptive Decision Support for Electricity Markets Negotiations
ALBidS	Adaptive Learning strategic Bidding System
AMES	Agent-based Modelling of Electricity Systems
ANN	Artificial Neural Network
DECON	Decision Support for Energy Contracts Negotiation
EMCAS	Electricity Market Complex Adaptive System
EPEX	European Power Exchange
EPSO	Evolutionary Particle Swarm Optimization
EU	European Union
FAPSO	Fuzzy Adaptive Particle Swarm Optimization
FCT	*Fundação para a Ciência e a Tecnologia* (Science and Technology Foundation)
GA	Genetic Algorithm
GAPEX	Genoa Artificial Power Exchange
GECAD	Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development
IF	Impact Factor
MASCEM	Multi-Agent Simulator of Competitive Electricity Markets
MIBEL	Iberian Electricity Market
MRC	Multi-Regional Coupling
PCR	Price Coupling of Regions

PSO	Particle Swarm Optimization
RealScen	Realistic Scenario Generator
RLA	Reinforcement Learning Algorithm
SCI	Science Citation Index
SEPIA	Simulator for Electric Power Industry Agents
SFLA	Shuffled Frog Leaping Algorithm
SREMS	Short–medium Run Electricity Market Simulator
STH	Six Thinking Hats
SVM	Support Vector Machines
US	United States of America

Chapter 1

Introduction

1 INTRODUCTION

This chapter exposes the motivation that has led to the development of the work done in the scope of this thesis. The background overview presented in section 1.1 leads to the set of research questions and objectives that are presented in section 1.2 and that were the drivers for this PhD research work. A brief outline of the main contributions of this work is provided in section 1.3. Finally, section 1.4 presents the organization of the thesis document.

1.1 MOTIVATION

Nowadays societies are highly dependent on electricity use to ensure safe, reliable, and comfortable living. The increase of electricity demand is expected to continue in the future and it is considered a crucial requirement for economic development. Concerns about the impact of electricity use in the environment and about the eventual fuel based primary source shortage are presently taken as very serious at scientific, economic and politic levels [Lund, 2014]. These concerns have led to intensive research and to new energy policies envisaging the increased use of renewable energy sources for electricity production and increased energy use efficiency.

The European Union (EU) has assumed a pioneer and leading role in energy matters, namely in what concerns the increase of renewable energy sources. EU as a whole has committed to reach its 20% renewable energy target for 2020. This target considers Member States' different starting points and potential for increasing renewables production, which range from 10% in Malta to 49% in Sweden [EC, 2009b]. Moreover, in 23 October 2014, EU leaders agreed on setting a revised target for increasing the share of renewable based energy to at least 27% of the EU's energy consumption by 2030 [EC, 2014]. The EU presents even more ambitious targets for 2050, with the commitment to reduce emissions to 80-95% below 1990 levels [EC, 2011]. As a consequence of these policies and of the subsequent incentives that have been put in place, huge investments have been made in renewable based electricity generation plants and equipment. However, increased renewable based generation capacity

does not directly ensure a corresponding increase in renewable based energy use as several constraints limit not only the production but also its use. Wind and solar-based generation are dependent from natural sources and are not as dispatchable as fuel based thermal plants. Power systems face new challenges to deal with the integration of intermittent renewable sources [Lund, 2014]. Significant research work has already been done around these issues, producing valuable results but also evidencing the limitations of the approaches that are being used.

The electricity sector restructuring [Sioshansi, 2013] aimed at obtaining public benefits, increasing the efficiency of the sector by providing consumers with reliable high quality service at fair costs. This should be achieved by introducing a competitive market-based approach to replace the centralized, monopolistic and/or state owned paradigm that traditionally ruled the sector. The changes were particularly difficult for a sector in which old and new big players want to take the lead, technical and economic factors are more closely interrelated than in most sectors, and for which storage capacity is still at a very low level due to the high cost solutions that are currently available. Prices that, in many cases, do not reflect the costs and the lack of experience in a field for which the sector particularities make prices behaviour significantly different from already existing markets transacting other commodities and products marked the reform departing point and its subsequent evolution [Biggar, 2014].

This restructuring process has been made of successes and failures, some of the later with serious consequences, such as the so called California's electricity crisis of 2000-2001, the 14th August 2003 blackout in the United States of America (US) and the 4th November 2006 quasi-blackout affecting nine European countries and some African nations as well [Sioshansi, 2013]. Such experiences are leading to successive model and rule changes. Ultimately wholesale electricity markets are finally proving to be able to accomplish their goals even if only partially, and the reforms made at local and/or national level are being extended giving place to larger markets at the regional/international level, rapidly evolving to a coupling trend at the continental level. A relevant example is the case of the EU, whose policy aims at establishing the internal electricity market in Europe [EC, 2009a]. Significant steps have been undertaken in this direction with the day-ahead wholesale electricity markets of 19 EU countries presently price coupled allowing the simultaneous calculation of electricity prices and cross-border flows across a region accounting for 85% of European power consumption [APX, 2015]. That achievement has been enabled by the Multi-Regional Coupling (MRC), a pan-European initiative dedicated to the integration of power spot markets in Europe.

In such a dynamic, complex, and competitive environment as the power and energy sector, simulation and decision support tools are of crucial importance. Market players and regulators are very interested in foreseeing market behaviour: regulators to test rules before they are implemented and to detect market inefficiencies; market players to understand market's behaviour and act in order to maximize their results from market participation. The need for understanding those mechanisms and how the involved players' interaction affects the outcomes of the markets contributed to the growth of usage of simulation tools. Multi-agent based software is particularly well fitted to analyse dynamic systems with a large amount of complex interactions among its constituents, such as the electricity markets. Several modelling tools directed to the study of restructured wholesale power markets have emerged. Some relevant tools in this domain are: the Electricity Market Complex Adaptive System (EMCAS) [Koritarov, 2004], the Agent-based Modelling of Electricity Systems (AMES) [Li, 2011] and the Multi-Agent Simulator for Competitive Electricity Markets (MASCEM) [Praça, 2003]. Although some of these works confirm the applicability and the value of simulation tools to the study of electricity markets, particularly by using multi-agent systems, they present a common limitation: the lack of adaptive machine learning capabilities that allow these tools to effectively provide measurable support to market entities. Current tools are directed to the study of different electricity market mechanisms and to the analysis of the relationships between market entities, but they are not fitted to provide support to market negotiating players in what concerns the achievement of the best possible outcomes from power transactions.

These limitations point out the need for the development of adaptive tools, able to provide effective support to market negotiating players. Such tools should provide the means for an actual improvement in players' market results. By using intelligent tools, capable of adapting to different market circumstances and negotiating contexts, players can change their behaviour in a real market environment, and therefore pursuit the achievement of the best possible outcomes. The data generated during simulations and by real electricity markets operation can be analysed by knowledge discovery and machine learning techniques to enable the assessment of each current context and to dynamically and consistently learn over time, in face of the alternative tools and solutions, what are the best ones to be used in each context. Some electricity market simulators have machine learning abilities; however, significant improvements are required so that they can be a real added value for real electricity market players. Enhanced simulation tools are thereby crucial for these players to overcome the limited experience they have in the constantly changing electricity markets operation.

1.2 OBJECTIVES

The identified limitations in the current state of the art refer to the lack of adequate decision support models for electricity market players' actions. The research challenges that arise from this gap bring out the need for the development of enhanced software solutions to support players' decisions, so that these players become able to undertake behaviours that allow them reaching the required advantages from the electricity market negotiating environment. Thus, it is essential to consider players' participation in multiple electricity markets, the context of each particular negotiation and the specific needs of each supported player. For this, the use of all available data is essential, as different pieces of complementary information provide valuable lessons that can be learned in order to improve future actions. Hence, the employment of learning abilities in this scope becomes fundamental. The significant breakthroughs that are necessary in this domain establish the main research question of this PhD thesis:

Can an adequate use of the available data improve the performance of electricity market negotiating players?

Reaching an answer to this question requires dividing the problem into smaller and more focused research topics, which leads to several specific research questions, as follows:

- *How can electricity market players optimize their decisions on which alternative/complementary markets to participate at each moment?*
- *How can players' participation in auction based electricity markets be improved?*
- *How can players' bilateral contracting negotiation capabilities be enhanced?*
- *Does context awareness bring advantages for electricity market players' negotiation process?*
- *Can decision support abilities be tested and validated in a realistic electricity market environment?*

The research work undertaken in the scope of this PhD focuses on achieving answers to these specific questions, as the way to attest the thesis that electricity market players' outcomes from market negotiations can, in fact, be improved from using the available data in an intelligent, adaptive and contextualized way.

The main expected output of this work is a decision support system that is capable of learning the best acting approaches, depending on each situation and context. The learning

process must take into account the system's historic log, taking advantage of all the available information, including data collected during the use of the decision support system itself. In order to achieve this purpose, several algorithms and learning methodologies must be proposed and evaluated, so that together they can contribute to the best decision making in each moment. It is expected that the proposal of new algorithms provides important contributions, including the combination of algorithms and knowledge collecting regarding their criterious usage depending on the context, using the concept of context awareness.

The conception, development and implementation of decision support methodologies shall be directed to the different specific approached problems, *e.g.* negotiation in auction based markets, bilateral contacts' negotiation and participation portfolio optimization. The diversity of methodologies shall be integrated in a multi-agent framework in order to facilitate the simultaneous execution of multiple algorithms, including the distribution of the system's processing over different available machines.

Since the conclusions to be taken from this PhD work should be supported by experimentation based on real or almost real cases, the work to be developed must be integrated with the MASCEM simulator. This simulator allows the study of electricity markets, enabling the construction of scenarios based on information from real electricity markets. In this way, the achieved results can be corroborated under realistic conditions, thus assuring the validation of the achieved solutions.

Taking into account the referred specifications, which guarantee the response to the identified research questions, the following objectives are considered, underlying the essential contributions:

1. <u>Development of a decision support methodology to optimize agents' market participation portfolio</u>. This objective considers:
    a. Analysis of the characteristics and particularities of different alternative and complementary electricity markets, namely auction based markets and negotiation by means of bilateral contracts;
    b. Inclusion of forecasted prices in each market at each time, under different contexts, and for distinct amounts of negotiating power.
2. <u>Development of a multi-agent decision support system directed to the strategic negotiations of market players</u>, including:

a. Proposal and testing of several learning and data analysis algorithms and methodologies, so that together they can contribute to the best decision making of the supported market players, including the development of algorithms directed to specific situations, as well as exploring the relevance of the combination of different types of algorithms;

b. Implementation of learning mechanisms with the capability of choosing the most appropriate strategies at each moment, based on the methodologies performance statistics and probabilities of success in each context, considering the system's log and the historic of competitor agents' past actions;

c. Inclusion of different types of market negotiations, namely auction based markets and bilateral contract negotiations.

3. Development of negotiation context analysis methodology, consisting in:

   a. Analysis of the characteristics and specificities of different market negotiation periods in the scope of each distinct market;

   b. Inclusion of different data types, such as weather information and log of previous market results.

4. Development of multi-agent decision support system for electricity market participating players, considering:

   a. Integration of the three previous objectives outputs in a single multi-agent platform directed to the strategic decision support of electricity market players;

   b. Integration of the developed multi-agent decision support system with the MASCEM electricity market simulator.

5. Simulation of the intelligent participation of players in electricity markets, concerning the following:

   a. Simulation of scenarios based on real electricity markets' data;

   b. Analysis of the realistic scenarios simulation results using the developed system to support market players' actions.

1.3 OUTLINE AND MAIN CONTRIBUTIONS

The fulfilment of the defined objectives and the consequent achievement of responses to the specified research questions fully cover the objectives defined in the PhD scholarship (reference SFRH/BD/81848/2011) in the scope of the "*Doutoramento e Pós-Doutoramento 2011*" (PhD and post-doctoral 2011) programme of FCT (*Fundação para a Ciência e a Tecnologia* - Science and Technology Foundation*)*. Additionally, the work developed in the scope of this thesis also partially covers the objectives and results of several national and international R&D projects in which the Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) participates. The regarded projects are:

- DREAM-GO – Enabling Demand Response for short and real-time Efficient And Market Based smart Grid Operation – An intelligent and real-time simulation approach. This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement number 641794;
- IMaDER – Intelligent Short Term Management of Distributed Energy Resources in a Multi-Player Competitive Environment (PTDC/SEN-ENR/122174/2010), funded by FCT;
- MAN-REM – Multi-Agent Negotiation and Risk Management in Electricity Markets (PTDC/EEA-EEI/122988/2010), funded by FCT;
- SASGER-MeC – Simulation and analysis of smart grids with renewable energy sources in the scope of competitive markets (NORTE-07-0162-FEDER-000101), co-funded by COMPETE under FEDER Programme;
- SEAS – Smart Energy Aware Systems, project number 12004, funded by European Union's EUREKA – ITEA2.

The findings that have been achieved during the development of this work have resulted in the publication of a total of thirty six scientific papers. From these, eighteen have been presented and published in the proceedings of top-level conferences in the fields of artificial intelligence, multi-agent systems and power systems; eleven book chapters have been published

in books dedicated to the related areas; and seven papers have been published in SCI[1] indexed journals with high impact factors. These seven journal papers compose the core of this PhD thesis by covering the proposed objectives and providing response to the research questions. The seven papers are provided in Annex A – Core Papers, and their essential contributions towards the fulfilment of this PhD thesis' objectives are presented in chapter 3. The seven core papers of this PhD work are the following:

I. Tiago Pinto, Isabel Praça, Zita Vale, Hugo Morais and Tiago M. Sousa, "Strategic Bidding in Electricity Markets: An agent-based simulator with game theory for scenario analysis", Integrated Computer-Aided Engineering, IOS Press, vol. 20, no. 4, pp. 335-346, September 2013, Impact Factor (IF) 2013: 4.667 [Pinto, 2013c];

II. Tiago Pinto, Zita Vale, Tiago M. Sousa, Isabel Praça, Gabriel Santos and Hugo Morais, "Adaptive Learning in Agents Behaviour: A Framework for Electricity Markets Simulation", Integrated Computer-Aided Engineering, IOS Press, vol. 21, no. 4, pp. 399-415, September 2014, IF 2014: 4.698 [Pinto, 2014c];

III. Tiago Pinto, Zita Vale, Tiago M. Sousa and Isabel Praça, "Negotiation Context Analysis in Electricity Markets", Energy, Elsevier, vol. 85, pp. 78-93, June 2015, IF 2014: 4.844 [Pinto, 2015b];

IV. Tiago Pinto, Tiago M. Sousa, Isabel Praça, Zita Vale and Hugo Morais, "Support Vector Machines for Decision Support in Electricity Markets' Strategic Bidding", Neurocomputing, Elsevier, in press, August 2015, IF 2014: 2.083 [Pinto, 2015d];

V. Tiago Pinto, Hugo Morais, Tiago M. Sousa, Tiago Sousa, Zita Vale, Isabel Praça, Ricardo Faia and E. J. Solteiro Pires, "Adaptive Portfolio Optimization for Multiple Electricity Markets Participation", Transactions on Neural Networks and Learning Systems, IEEE, in press, August 2015, IF 2014: 4.291 [Pinto, 2015e];

VI. Tiago Pinto, João Barreto, Isabel Praça, Tiago M. Sousa, Zita Vale and E. J. Solteiro Pires, "Six Thinking Hats: A novel Metalearner for Intelligent Decision Support in Electricity Markets", Decision Support Systems, Elsevier, vol. 79, pp. 1-11 November, 2015, IF 2014: 2.313 [Pinto, 2015f];

[1] *Science Citation Index® (SCI®);* http://thomsonreuters.com/products_services/science/science_products/a-z/science_citation_index/

VII. Tiago Pinto, Zita Vale, Isabel Praça, E. J. Solteiro Pires, Fernando Lopes, "Decision Support for Energy Contracts Negotiation with Game Theory and Adaptive Learning", Energies, MDPI, in press, August, 2015, IF 2014: 2.072 [Pinto, 2015g].

The combined contributions provided by the work developed in the scope of this PhD ultimately result in an enhanced multi-agent decision support system – Adaptive Decision Support for Electricity Markets Negotiations (AiD-EM). AiD-EM is presented in paper V [Pinto, 2015e] and in paper VII [Pinto, 2015g], and integrates the decision support features that enable: *(i)* the optimization of players participation portfolio in multiple electricity markets (presented in paper V [Pinto, 2015e]); *(ii)* the strategic participation in auction based electricity markets, using the Adaptive Learning strategic Bidding System (ALBidS), which is the primary focus of paper I [Pinto, 2013c] paper II [Pinto, 2014c], and paper VI [Pinto, 2015f]; *(iii)* the automated negotiation of bilateral contracts, using the Decision Support for Energy Contracts Negotiation (DECON), which has been introduced in paper VII [Pinto, 2015g]; *(iv)* the use of context awareness capabilities (described in paper III [Pinto, 2015b]); and *(v)* the participation in realistic electricity market simulations using the connection to MASCEM (addressed in several papers, such as paper II [Pinto, 2014c], paper III [Pinto, 2015b] and paper V [Pinto, 2015e]). Figure 1.1 shows the global structure of the AiD-EM decision support system, including the representation of its main components.

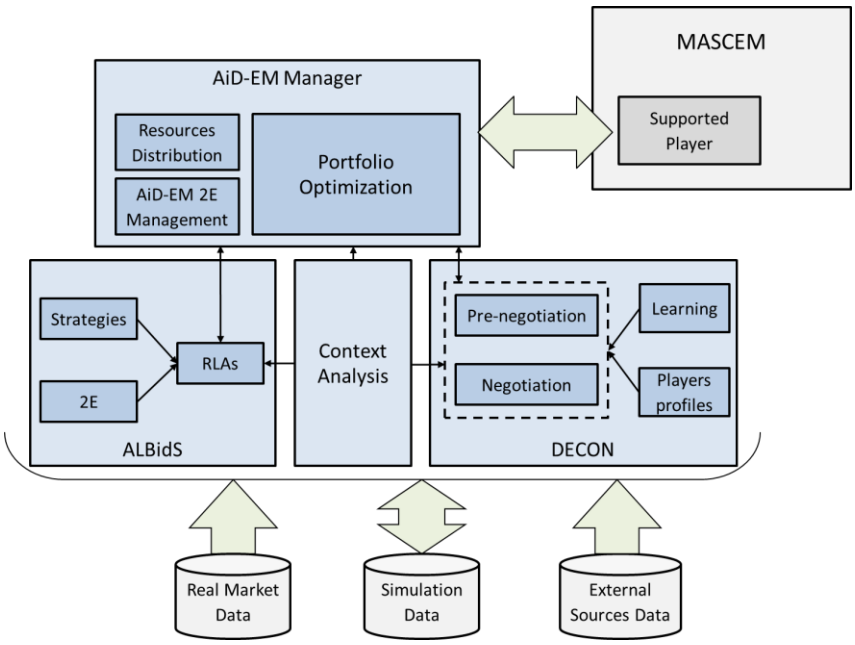

Figure 1.1. AiD-EM components interaction, adapted from paper V [Pinto, 2015e]

The AiD-EM system includes the AiD-EM Manager agent, as illustrated in Figure 1.1, which acts as the central entity of the proposed system, providing the connection with the

MASCEM electricity market simulator. The AiD-EM Manager agent executes the Portfolio Optimization methodology (presented in paper V [Pinto, 2015e] and described in further detail in section 3.2), which defines the amount of power that the supported player should buy or sell in each available market opportunity at each time and according to each context. The expected prices in each market are obtained from forecasting methods (see paper IV [Pinto, 2015d]). The AiD-EM Manager agent also optimizes the performance of the system by distributing the AiD-EM agents by the available machines, and by executing the Efficiency/Effectiveness (2E) balance management mechanism, which defines the amount of time that each of the integrated decision support systems is allowed to use in its execution, depending on the purpose of each simulation and on the user's requirements regarding the expected balance between the achieved quality of results and the execution time of the simulation.

Considering the defined amount of power to be transacted in each market, specific decision support systems are used to provide action suggestions for the supported player to perform in each distinct market type. ALBidS (see paper II [Pinto, 2014c] and section 3.3) is directed to the decision support for negotiations in auction based markets and includes several different methodologies to provide alternative action suggestions. The used approaches range from game theory (see paper I [Pinto, 2013c]) to the combination of different algorithms using the metalearning concept (see paper VI [Pinto, 2015f]), among many others. The approach chosen as the players' actual action is selected by the employment of Reinforcement Learning Algorithms (RLA), which for each different situation, simulation circumstances and context, decide which proposed action is the one with higher possibility of achieving the most success. ALBidS is equipped with its own 2E balance management mechanism, which defines which strategies should be executed at each time, considering the requirements of the AiD-EM 2E management, the execution time of each strategy and the quality of strategies' results.

The decision support for bilateral contract negotiations is assured by DECON (see paper VII [Pinto, 2015g] and section 3.4), which considers two main components: *(i)* decision support for the pre-negotiation stage, and *(ii)* decision support for the actual negotiation process (see paper VII [Pinto, 2015g]). The pre-negotiation step aims at identifying the ideal competitor(s) that should be approached so that the undertaken negotiations can provide as much benefit as possible for the supported player. The expected limits and target prices of each envisaged competitor are also predicted with the purpose of enhancing the decision support for the negotiations. The actual negotiations are supported by a set of different tactics that follow

different strategies. Different combinations of tactics are supported, allowing the supported player to change its tactic strategically in response to the behaviour of the opponent(s) and to the current context. The initial choice and dynamic change of the most appropriate strategies and tactics to use against each opponent is based on a learning approach, considering the analysis and definition of competitor players' profiles.

The context awareness of the system is provided by a context analysis mechanism, which has been presented in paper III [Pinto, 2015b] and that is described in section 3.5. The context analysis considers several relevant factors that influence players' negotiating environment, thus allowing market participation strategies to be adapted and used accordingly to each different negotiation context.

The significance of the introduced decision support methodologies can only be assessed by means of realistic electricity market simulations. The connection with MASCEM plays an essential role in this context. Using the Realistic Scenario Generator (RealScen) [Teixeira, 2014], which uses real electricity market data, extracted in real time from the websites of several market operators [Pereira, 2014], it is possible to recreate the electricity markets' reality in a controlled simulation environment in MASCEM. Realistic simulation scenarios of several European electricity markets have been used to test and validate the proposed methodologies (see section 3.6, section 3.7 and *e.g.* paper III [Pinto, 2015b] and paper V [Pinto, 2015e]).

1.4 DOCUMENT STRUCTURE

This thesis' document consists of four chapters. After this introductory chapter, chapter 2 presents a background overview of the most important topics related to this PhD work, essentially focusing on electricity market simulation and on decision support for electricity market players' negotiations in different types of markets.

Chapter 3 presents the most relevant contributions of this PhD work. The research questions of this PhD are described, and a discussion is provided on how each core paper of this thesis addresses these questions and how the papers fulfil the defined objectives. The organization of chapter 3 is defined by the key contributions of this work, therefore each section deals with the specific research topic that is related to a specific research question.

Finally, chapter 4 presents the most relevant conclusions that have resulted from the developed work. Some perspectives of future work are also presented.

Chapter 2

Background

2 BACKGROUND

This chapter presents a brief overview of the current state of the art of the fields of electricity markets' simulation and participating players' decision support. The discussion presented in this chapter aims at complementing the related work reviews on the specific topics that are included in each core paper of this PhD thesis. The presentation of the background overview as a whole allows reaching important conclusions on the current limitations in the field and on future challenges that are expected. This discussion results in the identification of the critical research themes that are addressed by this PhD work.

2.1 INTRODUCTION

The use of renewable energy sources has increased significantly, stimulated by policies and incentive programs aiming at decreasing the dependency on fossil fuels and avoiding environmental damages. The EU has defined the well-known "20-20-20" as targets [EC, 2009b], which will enable the EU as a whole to reach 20% energy consumption from renewable energy sources in 2020, more than doubling the 9.8% level from 2010. These targets also aim to increase EU's energy efficiency by 20% and to reduce emissions of greenhouse gases by 20% by 2020, taking 1990 emissions as the reference. Furthermore, in October 2014, a commitment has been achieved to reduce EU's greenhouse gas emissions by at least 40% below the 1990 level by 2030 [EC, 2014]. Renewable energy sources such as wind and solar variable and intermittent nature poses new challenges to the power sector and subsequently to electricity markets. Many different market approaches have been experimented all around the world, and all have been subject to multiple revisions. The primary focus is on adapting electricity markets to deliver their intended economic efficiency and reliability outcomes under the new paradigm of growing share of renewable energy sources [Sioshansi, 2013]. One of the main EU priorities concerns the formation of a Pan-European Energy Market. The majority of European countries have already joined together into common electricity markets, resulting in joint regional

markets composed of several countries. Relevant examples are the Iberian electricity market operator – MIBEL [MIBEL, 2015], the central European market – EPEX (European Power Exchange) [EPEX, 2015] and the northern European electricity market – Nord Pool [Nord Pool, 2015]. Additionally, in early 2015, several of these regional European electricity markets have been coupled in a common market platform, operating on a day-ahead basis using the Euphemia market clearing platform [APX, 2013]. The common market platform resulted from the Price Coupling of Regions (PCR) initiative [PCR, 2014], a joint effort of seven European Power Exchanges to develop a single price coupling solution for Europe. This is a crucial step to achieve the overall EU target of a harmonized European electricity market.

This type of initiatives is largely supported by the European Commission, which has created the basis for a significant number of European projects that have been giving substantial contributions to deal with some of the most prominent issues in the field. The Optimate (Open simulation Platform to Test Integration in MArkeT design of massive intermittent Energy) project had a simulation platform as output, which accommodates the simulation of the Pan-European electricity market [Optimate, 2015]. In the scope of CASSANDRA (A multivariate platform for assessing the impact of strategic decisions in electrical power systems), the participation of small consumers in the electricity market has been modelled, including the assessment of their strategic decisions [CASSANDRA, 2015]. eBADGE (Development of Novel ICT tools for integrated Balancing Market Enabling Aggregated Demand Response and Distributed Generation Capacity) is developing a simulation and modelling tool for integrated Balancing and Reserve Markets [eBADGE, 2015]. EMELIE (electricity market liberalisation in Europe) [EMELIE, 2015] focused on the liberalisation of the European electricity market and its potential impacts on market developments. E-PRICE (Price-based Control of Electrical Power Systems) approached the issue of errors in the prediction of both production and demand, and their impact on ancillary services and reserve capacity [E-PRICE, 2015].

These initiatives are, however, strongly directed to the perspective of market operators and regulators, which results in valuable advances in market mechanisms and market operation and validation, but, apart from a few exceptions, almost entirely disregard the decision support of market participant players, and the impact that the interactions between these entities has on the market. This decision support is, however, essential, since the complexity and the constantly changing nature of electricity markets makes the decision making process of the involved entities a very difficult task.

2.2 ELECTRICITY MARKET SIMULATION

The support of players' decisions in the electricity market has been handled by means of simulation tools. The main goal of these tools is to cope with the evolving complex dynamic reality of electricity markets and to provide electricity market players with adequate solutions to adapt themselves to the new reality, gaining experience to act in the frame of a changing economic, financial, and regulatory environment. Operators and regulators need to foresee market developments, and experiment and test new market rules and mechanisms. Market players need to understand how and when they should participate in each electricity market. Addressing these needs has led to the development of several electricity market simulators during the last years. Simulator for Electric Power Industry Agents (SEPIA) [Harp, 2000] is a Microsoft Windows oriented platform, based on a p*lug* and *play* architecture, allowing users to easily create simulations involving several machines in a network, or in a single machine, using various processing units. Power Web [Zimmermann, 2004] is a web-based market simulator that allows participants to interact from everywhere in the globe, supporting simulations with a large set of scenarios and rules. The Short–Medium run Electricity Market Simulator (SREMS) [Migliavacca, 2007] is based on game theory and is able to support scenario analysis in the short-medium term and to evaluate market power. SREMS is especially focused on the study of the Italian electricity market. These simulators present a common limitation, as they have been created with rather rigid architectures and thus lack flexibility to deal with dynamic environments with complex interactions between the involved entities [Praça, 2003].

Multi-agent systems are computer systems composed of autonomous agents that interact to solve problems beyond the individual capabilities of each agent [Woodridge, 1995]. In the past years, a number of multi-agent electricity market simulators has emerged, supporting the claim that multi-agent simulation combined with other artificial intelligence techniques may result in sophisticated tools, namely in what concerns players modelling and simulation, strategic bidding and decision support. EMCAS [Koritarov, 2004] uses an agent based approach with agents' strategies based on learning and adaptation. In EMCAS, different agents are used to capture the restructured markets heterogeneity, including generation, demand, transmission, and distribution companies, independent system operators, consumers and regulators. It allows undertaking electricity market simulations in a time continuum ranging from hours to decades, including several pool and bilateral contract markets. AMES [Li, 2011] is an open-source computational laboratory for the experimental study of wholesale restructured power markets

in accordance with US Federal Energy Regulatory Commission's market design. The Genoa Artificial Power Exchange (GAPEX) [Cincotti, 2013] is an agent-based framework to model and simulate power exchanges. GAPEX is implemented in MATLAB and allows the simulation of artificial power exchanges reproducing exact market clearing procedures of the most important European power-exchanges. Finally, MASCEM [Praça, 2003] is able to recreate a large diversity of market clearing models, based on the mechanisms used in different countries around the world. Negotiating players in MASCEM use several decision support strategies to pursue the best possible outcomes from market participation [Pinto, 2015b]. Moreover, the use of ontologies allows this simulator to interact with different multi-agent systems, resulting in an enhanced platform to simulate complex and dynamic environments [Santos, 2015].

These are valuable but still limited solutions, as they are usually directed to specific market environments and present limitations in coping with the interaction with external systems. This hardens the possibility for co-simulation of distinct and complementary environments, such as the coexistence of multiple electricity markets and the interaction of electricity markets with the upcoming reality of smart grids [Lund, 2014]. Players' simultaneous participation in such complementary negotiation opportunities is, therefore, hardened, as there are no suitable simulation tools that are able to provide them with the required decision support features to enable them to take the most advantages out of the quickly evolving environment of electricity markets.

Such limitations should not be overlooked, and effective solutions should rapidly emerge, so that current and alternative market models can be easily simulated and assessed using realistic models regarding not only electricity markets, but also the present and future penetration of diverse types of energy resources. The main problems of the field such as the massive integration of renewable energy sources in electricity markets, the inadequate models to support the active participation of consumers, the consequent need for accommodating new types of players, and the lack of decision support solutions that enable the participating players to take full advantage from the constantly evolving market opportunities, thus, remain weakly addressed.

2.3 DECISION SUPPORT IN ELECTRICITY MARKETS

The simulation and study potential provided by the large number of electricity market simulators is crucial for market players. For market operators and regulators, in particular, this type of platforms enables the experimentation of alternative market solutions, which could not be tested directed in a real market environment due to the severe implications that such experiments could imply. From the perspective of market negotiating players, electricity market simulators, in their current state, are not yet prepared to provide the required competitive advantages. Suitable decision support methodologies are essential, so that players can be able to take full advantage out of market participation considering the different types of negotiations and the number of alternative and complementary market opportunities that are available.

2.3.1 Portfolio Optimization

Acting in a constantly changing environment, characterized by multiple market types and negotiating opportunities, forces market players to rethink their behaviour and decide whether to and how to participate in each market opportunity in order to maximize the potential gain from market participation. Optimizing players' electricity market participation portfolio becomes essential in this context.

The typical portfolio optimization problem consists in finding the optimum way of investing a particular amount of money in a given set of securities or assets [Fernández, 2007]. Traditionally, the optimal management of a portfolio of assets is solved by minimizing the investment risk while guaranteeing a given level of returns. Markowitz [Markowitz, 1952] introduced this concept and formulated the fundamental theorem of a mean-variance portfolio framework, which explains the trade-off between mean and variance, representing the expected returns and risk of a portfolio, respectively. Risk refers to the possibility of suffering harm or loss, as result from uncertainty. However, there is a difference between risk and uncertainty: risk is something that usually can be controlled while uncertainty is beyond players' control [Conejo, 2014]. The results of players in electricity markets are influenced by many uncertain factors, *e.g.* other players' bidding strategy, penetration of renewable energy sources and change of demand. These uncertainties bring along risks in electricity pricing. The main reason for this may be attributed to the particular characteristic of non-mass storage of electricity [Liu, 2007]. Four different risk measures for the portfolio optimization problem in electricity markets are presented in [Chang, 2009]. These risk measures, all based on mean-variance, are used by

a Genetic Algorithm (GA) to solve the portfolio optimization problem; this paper concludes that GA is an effective method for solving the portfolio optimization problem with different risk measures. Particle Swarm Optimization (PSO) is used in [Cura, 2009] and [Zhu, 2011] as an alternative method to solve the portfolio optimization problem; the used risk measures are also derived from the Markowitz mean-variance model. Meta-heuristic techniques are, in fact, a common choice for the resolution of this optimization problem, as detailed in [Ponsich, 2013], where a rather complete survey on the use of evolutionary algorithms to handle the portfolio optimization problem is presented. Additionally, variations using methods such as fuzzy logic also present promising solutions, *e.g.* [Liu, 2015].

In most approaches the portfolio optimization is formulated as a multi-objective problem with two different objective functions: minimization of the risk and maximization of the return [Babaei, 2015]. The most common approach is the transformation of the two objective functions into a single one using an aggregate function (single-criterion objectives) [Zhu, 2011]. When the transformation into a single objective function is performed it is necessary to consider a trade-off coefficient, so that the investor (player) can choose the portfolio depending on specific risk/return requirements. When solving the problem considering a set of alternative trade-offs it is possible to estimate the efficient frontier, as presented in [di Tollo, 2008].

Most approaches that can be found in the literature present a very economical and financial nature. The resolution of this problem from an electricity market perspective is rather uncommon, and the existing approaches, such as [Liu, 2007] and [Conejo, 2014] make very limitative simplifying assumptions. The influence of the available information (often private) and of the counterparty risk in the outcomes of the portfolio optimization problem (as studied in [Hillairet, 2015]) is often disregarded. The credibility of the risk and return measures [Vercher, 2015] is another important, yet, frequently marginalized aspect. Most importantly, specific characteristics that make electricity markets such complex and dynamic environments are completely overlooked, such as: the possibility for players to sell and buy electricity in the same period in different markets; the influence of market prices' forecasting error in the risk formulation; the real-time adaptation to the most recent events (*e.g.* real-time market data); the adaptability to different market scenarios and to different time ranges of optimization; and the dependency of the return price on the negotiated amount, especially in bilateral contract negotiations, where the settled prices are largely dependent on the envisaged trading amount. Such limitations make the current solutions unusable in a real electricity market environment.

2.3.2 Electricity Markets Participation

The problematic of optimal bidding in electricity market negotiations has been the focus of a wide range of research works during the last years. Most of these works address the problem from the producers' perspective, as can be seen in [David, 2000], which provides a rather complete survey on this subject. The first approaches in this field address the problem using game theory and operational research techniques in order to deal with the considerable data uncertainty that affects agents' decisions in the electricity market, especially when facing multiple market opportunities [Martello, 2014]. The problem of multiple electricity markets participation is approached in [Boomsma, 2014] by formulating the market bidding problem as a multi-stage stochastic programming model considering sequential electricity markets.

Meta-heuristic techniques have been increasingly used during the last years to deal with the problem of electricity market players' strategic behaviour. This type of approach allows considering a larger number of involved players in larger time horizons, as well as considering the need for players' strategies dynamism through evolution over time; thus making it possible to represent a more realistic modelling of the problem. The evolution of appropriate bidding strategies for each current market conditions, using GA is proposed in [Richter, 1999]. Bid prices and quantities in a competitive electricity market context are determined in [Yucekayaa, 2009] using two algorithms based on PSO. Probabilistic estimation is used to model opponents' bidding behaviour. The experimental findings show that for nonlinear cost functions, PSO solutions provide higher expected profits than marginal cost-based bidding. This allows following the frequently changing conditions in the successive trading sessions of a real electricity market. Fuzzy Adaptive Particle Swarm Optimization (FAPSO) is used in [Bajpai, 2007] to determine the optimal bidding strategy for a thermal generator for each trading period in a day-ahead market. The inertia weight of the algorithm is dynamically adjusted by a fuzzy evaluation. A novel approach based on the Shuffled Frog Leaping Algorithm (SFLA) is proposed in [Kumar, 2014] to solve the optimal bidding strategy problem. The proposed memetic meta-heuristic is designed to seek a global optimal solution by performing a heuristic search. It combines the benefits of the genetic-based memetic algorithm and the social behaviour of PSO.

Machine learning approaches have also been used in a few works as a way to adapt agents' behaviour as time progresses. A market participation strategic approach based on the application of the Q-Learning reinforcement learning algorithm has been presented in [Trigo,

2010]. In [Vandael, 2015], the electricity market participation problem is addressed by defining a day-ahead consumption plan for charging a fleet of electric vehicles and following this plan during market operation. The charging process is controlled during market operation by a heuristic scheme, and the resulting charging behaviour of the fleet is learned by using batch mode reinforcement learning. Based on the learned behaviour, a cost-effective day-ahead consumption plan is defined.

The literature offers several methodologies directed to players' decision support in electricity market negotiations. However, most of the proposed approaches target specific negotiation scenarios and market mechanisms of particular countries. Moreover, there is practically no work done in the contextualization of the decision making process. This hardens the process of choosing the most appropriate approaches for each market situation and context, given that the existing methods are suitable for very specific situations. An accurate contextualization of each negotiation process is required, so that the existing models can be adapted and chosen according to the circumstances in which they can bring the most added value. Proper machine learning approaches that make use of this type of contextualization to enhance the learning process are also urgently needed.

2.3.3 Bilateral Negotiations

Automated negotiation plays a crucial role in the decision support for energy transactions due to the constant need for players to engage in bilateral or even multilateral negotiations. The field of automated negotiation has been a constant focus of artificial intelligence research [Fujita, 2015]. A relevant review on automated negotiation for computational agents with a particular focus on artificial intelligence applications has been presented in [Lopes, 2008]. According to this study, automated negotiation is generally composed of four phases: *(i)* preliminaries (the nature of negotiation); *(ii)* pre-negotiation (preparing and planning for negotiation); *(iii)* actual negotiation (moving toward agreement); and *(iv)* renegotiation (analysing and improving the final agreement). According to [Raiffa, 1982] and [Lewicki, 2003] the most important pieces of information that must be considered are: *(i)* the intended limits and targets of the opponent(s); *(ii)* the negotiating history of the opponent(s); and *(iii)* the intended strategies of the opponent(s). Some works consider models that use information about the opposing negotiators, typically encoded into probabilistic distributions, to negotiate more effectively, such as [Li, 2006]. Despite the efforts of these works, there is no relevant work on explicitly modelling the pre-negotiation step of gathering

information either directly or indirectly about the opponent(s). In fact, artificial intelligence researchers have traditionally neglected the pre-negotiation step of gathering information about opposing negotiators [Lopes, 2008].

This tendency is being counteracted by recent works in the emerging field of e-commerce. In this scope, the need for perceiving and predicting competitors' behaviours has direct impact on the economic outcomes of the negotiators, thus some effort is being put into the development of automated negotiation methods. The work presented in [Cao, 2015] results in a multi-strategy negotiating system, based on the integration of both time-dependent and behaviour-dependent tactics. A multi-strategy selection theoretical model is proposed to support the choice of the most appropriate from the available tactics. In [Nguyen, 2005], a methodology for dealing with multiple concurrent negotiations in an e-commerce context is presented. The simultaneous negotiation among agents is also handled by [Tsuruhashi, 2015], which presents a framework to facilitate the implementation and analysis of simultaneous negotiations, including dynamic utility space changes and corresponding strategy changes. The work presented in [Chen, 2015] deals with automated bilateral multi-issue negotiation in complex environments. The proposed approach enables an agent to efficiently model opponents in real-time through discrete wavelet transformation and non-linear regression with Gaussian processes. The prediction of opponents' actions is also the focus of [Zhang, 2015]. This paper proposes an approach that employs Bayesian theory to analyse the opponent's historical offers and to approximately predict the opponent's preference over negotiation issues.

In summary, although some relevant advances have been made, several problems are yet far from being adequately addressed. The definition of adequate models to choose the most appropriate parties to negotiate with is a critical need. Another urgent progress that is required refers to how relevant information regarding competitors' history of previous negotiations can be used to improve the decision making process. In specific regarding the choice of the most suitable negotiation strategies and tactics to be used and the adaptation of the adopted strategies to the different competitors and negotiation contexts. Moreover, and although recent progresses in the field of e-commerce and e-business start providing some solutions to this problem, the modelling of competitor players' behaviours and profiles is still in a very embryonic state. Finally, the conception, development, evaluation and application of automated negotiation models to the specific scope of electricity market players' negotiations is practically completely absent from the literature.

2.4 SUMMARY

The need for much deeper research work regarding the evolution of electricity markets considering the many identified gaps in the field is evident, in order to enable the development of realistic simulation studies of the electricity market environment at diverse levels. Such studies should consider advanced and innovative models, able to cope with the current and future needs of the power sector. Adequate decision support features are also needed in order to enable all the involved entities to take full advantage out of such a dynamic and complex environment. These are crucial steps for the success and increased efficiency of the energy sector in general, and for Europe in particular, given the pioneer position that EU has been assuming in this field, and the significant implications of the several mistakes that can be made.

Current decision support solutions, namely the existing electricity market simulators, are strong tools to study and analyse market mechanisms and market operation from market operators and regulators' perspectives. The decision support of market participant players is, however, being neglected. The literature offers a variety of strategic approaches that aim at providing decision support to market players; however, none of the proposed strategies has shown to be clearly better than the others. Case studies show that different strategies perform better in distinct environments and contexts, as most of the proposed approaches are directed to specific negotiation scenarios and market mechanisms of particular countries. For this reason it is essential that suitable methodologies emerge to provide intelligent, adaptive, and dynamic ways to combine a large number of different market strategies, with different natures and perspectives, enabling the advantageous use of each of these strategies whenever they show to be more adequate and present the highest chance for success. For this, the contextualization of the decision making process should have a prominent role.

The lack of decision support solutions that enable the participating players to take full advantage from the multiple market opportunities is also notorious. The use of real-time market data, the possibility for players to sell and buy electricity in the same period in different markets and the dependency of the return price on the negotiated amount are just a few of the concerns that require an immediate exploration.

The absence of automated negotiation models directed to negotiations between electricity market players also brings out several relevant challenges that must be addressed promptly in order to provide market players with adequate decision support solutions. Some of

the most relevant problems concern the choice of the most suitable negotiation strategies and tactics to be used and the dynamic adaptation of the adopted strategies throughout the negotiation process considering the different competitors and negotiation contexts. The research on modelling competitor players' behaviours and profiles also requires significant advances, so that the developed models can be applied in real market negotiation conditions.

The work developed in the scope of this PhD tackles some of the most urgent and relevant issues in the field, which have been identified by the presented literature review. This review is complemented by the discussion of the work related to each specific subject, which is presented in each paper resulting from this PhD work. The contributions of this work focus on the development and proposal of innovative decision support methodologies that allow electricity market players to take the most advantage out of market participation, considering the participation in multiple complementary and alternative market opportunities.

The adaptation of existing market participation strategies and the proposal of novel approaches is complemented by their combination, using the metalearning concept. The intelligent choice and use of the most appropriate strategies in each context is performed by machine learning algorithms that are supported by a context analysis methodology, which analyses the characteristics and particularities of different negotiation contexts.

The limitations in the automated negotiation field are addressed by the development of decision support methodologies that allow players to analyse competitors' past actions and improve their own actions according to the expected negotiation outcomes. The largely overlooked pre-negotiation step is also tackled by a game theory based methodology, which provides the supported players with suggestions on which competitors should be chosen to undertake the actual negotiation process.

All the proposed methodologies are tested and validated in simulation scenarios based on real electricity markets data. This allows, not only to demonstrate that the developed models are suitable for their specific purposes, but also to identify other issues related to electricity markets effective participation that cannot be recognized by the commonly adopted purely academic research approaches. The applicability and benefit of the proposed methodologies in real market conditions is, hence, assured, which ultimately results in a joint contribution to the multidisciplinary fields of artificial intelligence and power systems.

Chapter 3

Contributions

3 CONTRIBUTIONS

This chapter presents the main contributions of the developed work and discusses how each of the core papers of this PhD thesis addresses the related research questions of the PhD research work. The accomplishment of this work's objectives as result of the several key contributions is also described.

3.1 INTRODUCTION

An adequate decision support is essential to provide electricity market negotiating players with competitive advantage in the market, enabling a contextual adaptation to the competitors' actions and reactions. Using such decision support solutions, players are capable of dealing with the continuous market changes. The current gap in the literature regarding this type of decision support for electricity market negotiating players has led to the research questions presented in the introductory section and to the consequent definition of the objectives for this PhD work.

The development of the AiD-EM decision support system, as result from this PhD research work, provides the crucial breakthrough that is required to overcome the existing limitations in the field. The achieved findings contribute to the advance in the current state of the art by providing answers to the research questions that have been identified as protuberant to enable such advance.

Table 3.1 presents the relationship between each paper that has resulted from this PhD work and the main contributions of this thesis. The key contributions are also associated to the related objectives. Publications I to VII represent the core papers of this PhD work, which have been introduced in section 1.3. The other publications refer to additional papers that have also been published in the scope of this research and that cover complementary parts of the work.

Table 3.1. Contributions and publications

Key contribution	Related Objective	Publications							
		I	***II***	***III***	***IV***	***V***	***VI***	***VII***	***Other***
Portfolio Optimization	1 (see section 3.2)			X	X	X			[Pinto, 2012a] [Pinto, 2014a] [Faia, 2015a] [Faia, 2015b]
Participation in Auction based Markets	2 (see section 3.3)	X	X	X	X		X		[Pinto, 2012a] [Pinto, 2012b] [Sousa, 2012] [Pinto, 2013a] [Pinto, 2013b] [Sousa, 2014b]
Bilateral Contract Negotiations	2 (see section 3.4)			X	X	X		X	[Pinto, 2012a] [Pinto, 2013a] [Ghazvini, 2014] [Lopes, 2014] [Faia, 2015a]
Context Analysis	3 (see section 3.5)		X	X	X	X			[Pinto, 2012a] [Pinto, 2012c] [Marques, 2014] [Pinto, 2014e] [Pinto, 2015a]
Decision Support System	4 (see section 3.6)					X		X	[Faia,2015b] [Pinto, 2015c]
Realistic Simulation Studies	5 (see section 3.7)	X	X	X	X	X	X	X	[Pereira, 2014] [Pinto, 2014b] [Pinto, 2014d] [Teixeira, 2014]

As presented in Table 3.1 all key contributions are addressed by several core papers. In addition, some other publications resulting from this PhD research work help complementing the particular research topics by providing contributions focused on specific subjects of the related topic. Each key contribution is related to the answer of one research question and to the complete or partial fulfilment of one objective of the PhD work. This chapter describes each research question, its relevance to the work done and briefs on how it has been answered by the papers produced as part of this PhD work.

3.2 PORTFOLIO OPTIMIZATION

How can electricity market players optimize their decisions on which alternative/complementary markets to participate at each moment?

The electricity market restructuring has been the catalyser of a continuous process of changes in electricity markets operation rules [Sioshansi, 2013]. Nowadays, the implemented market types are numerous, *e.g.* day-ahead spot markets, balancing markets, intraday markets, bilateral contracts, forward and future contracts' negotiations, among others. The constant change of the existing market mechanisms and the introduction of new solutions requires players to take suitable decisions on whether to and how to participate in each market type.

Paper V [Pinto, 2015e] proposes a portfolio optimization model for multiple electricity market participation. The amount of power that each supported player should negotiate in each available market type in order to maximize its results takes into account the prices that are expected to be achieved in each market, in different contexts. Figure 3.1 illustrates the proposed Portfolio Optimization methodology.

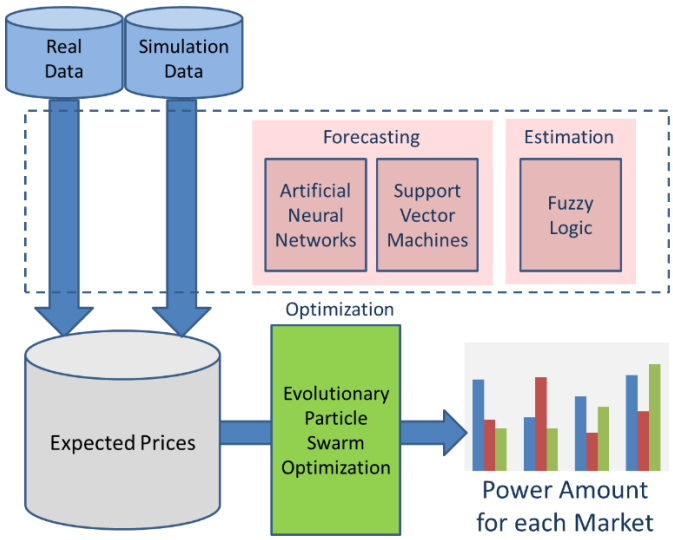

Figure 3.1. Portfolio Optimization methodology, adapted from paper V [Pinto, 2015e]

As shown in Figure 3.1, price forecasts are used to build a database of expected electricity market prices for each market, for each time period of each considered day. The price forecasts are performed considering different ranges of negotiated power amount; *i.e.* the forecasting process takes into account the price that is expected when the expected negotiation

amount is higher or lower. These ranges of power amount are determined by a fuzzy logic process. Using the market prices forecast database, an optimization based on the Evolutionary Particle Swarm Optimization (EPSO) meta-heuristic [Miranda, 2002] is executed to optimize the participation portfolio in a multi-market environment. The EPSO approach comes as an improvement of the previous implementation of the standard PSO meta-heuristic to simplified versions of the problem (see [Pinto, 2014a], [Faia, 2015a] and [Faia, 2015b]). Finally, a risk management approach is used, which allows the decision support process to be subjected to different levels of risk, depending on *(i)* the objectives and characteristics of the supported player, *(ii)* the quality of the price forecasts, and *(iii)* the decision support execution time restrictions.

Paper IV [Pinto, 2015d] presents an electricity market prices' forecasting methodology based on Support Vector Machines (SVM) that provides the forecasting results required by the portfolio optimization methodology. The results from this forecasting process are complemented by those resulting from the application of the Artificial Neural Network (ANN) that has been proposed in [Pinto, 2012a]. Objective 1.b (see section 1.2) is fulfilled by the market prices' forecasting process combined with the fuzzy logic based price estimation for different negotiation power amounts [Faia, 2015a].

The contextualization of the process is provided by the methodology proposed in paper III [Pinto, 2015b]. This paper presents a context analysis and definition method that allows analysing different types of data that present considerable relevance over the evolution of electricity market prices. This analysis results in the characterization of different negotiation contexts, which are used to support the selection of the data that is used for each forecast.

The contribution of this part of the PhD work is a methodology that provides market players with the optimal power amount to negotiate in each distinct market at each time, in each context. The specificities of different types of electricity markets are considered, as well as the supported players' propensity to risk, thus achieving objective 1.a. This contribution provides the answer to the research question considered in this section and fully accomplishes the first objective of this PhD work.

3.3 PARTICIPATION IN AUCTION BASED MARKETS

How can players' participation in auction based electricity markets be improved?

The literature offers a large variety of strategic approaches that aim at providing decision support in auction-based electricity market negotiations (see *e.g.* [David, 2000], which presents a rather complete survey about this topic). However, none of the proposed strategies has shown to be clearly better than the others. Case studies show that there is no strategy that presents the best performance in all environments and contexts, *i.e.* strategies that have performed well in one situation may have mediocre performances in different circumstances.

Paper II [Pinto, 2014c] presents the ALBidS decision support system. The main goal of ALBidS is to take the most advantage out of the alternative market strategies that have been introduced in the literature. With this purpose, the general concept behind ALBidS is the integration of as many distinct market strategies as possible, whose performance is evaluated under different contexts of negotiation. This evaluation is used by the system to learn which strategies are the most adequate and present the highest chance of success in each different context. Figure 3.2 presents ALBidS' multi-agent model.

Figure 3.2. ALBidS conceptual design [Pinto, 2013b]

As illustrated by Figure 3.2, the learning process is undertaken by means of reinforcement learning algorithms, namely the Roth-Erev algorithm [Roth, 1995] and an algorithm based on the Bayesian theorem of probability that has been proposed in [Sousa, 2014b] in the scope of this PhD work. Additionally, a 2E balance management mechanism has

been developed to enable controlling the efficiency and effectiveness of the large variety of algorithms that are executed simultaneously. This method allows ALBidS to adapt the execution time of the system to the purpose of each simulation, *e.g.* if the expected results from ALBidS are as best as it is able to achieve, or if the main requirement is for the system to be executed rapidly to analyse issues other than player's optimal performance in the electricity market. The 2E balance management mechanism manipulates the strategies both externally and internally. From the system's perspective, this mechanism contributes by deciding which tools are used at each moment for each circumstance depending on their observed performance in terms of efficiency and effectiveness. This way this mechanism can choose to exclude certain strategies when they are not fulfilling the ALBidS' requirements for the case in matter. The strategies chosen to be executed are also manipulated internally, so that they can adapt their individual results quality/execution time balance to the needs of each current simulation.

ALBidS incorporates a large variety of market decision support strategies with different natures and perspectives, such as data mining techniques, forecasting methods, artificial intelligence methodologies, application of electricity market directed strategies, mathematic approaches, economic theory based models, and the adaptation of physics theories. This way, the system is able to take advantage of the best characteristics of each approach whenever they show to be advantageous. The system is, thus, prepared to deal with different contexts and scenario situations, guaranteeing a large scope of approaches, which offer a greater chance of having appropriate responses even in very distinct situations. Besides the integration of several methodologies that have been proposed by distinct authors, a number of novel approaches have also been proposed and integrated in ALBidS in the scope of this PhD work. Paper I [Pinto, 2013c] presents a game theoretic based scenario analysis approach, which uses the historic analysis of the market and of competitors' actions to define a set of possible alternative negotiation scenarios. Several possibilities of actions to perform in the market are also defined, so that the expected outcome of each alternative action-scenario combination can be evaluated by a game theoretic decision method. The competitors' actions analysis is performed by the methodology proposed in [Pinto, 2013a]. A strategy that uses the simulated annealing meta-heuristic to accelerate the convergence process of the Q-Learning algorithm in choosing the most appropriate from a set of different possible bids has been proposed in [Pinto, 2012b].

The combination of different strategies, so that they can contribute towards a better outcome by cooperation, alternatively to the general competitive approach of ALBidS, is

proposed by using the metalearning concept, *i.e.* learning about the process of learning itself. Paper VI [Pinto, 2015f] provides its contribution in this scope, by proposing an innovative metalearner based on the principles of the Six Thinking Hats (STH) group decision technique [de Bono, 1985], which associates a hat with a distinct colour for each different direction of thinking. Using the principles of the STH method, a new metalearner is proposed, which combines the different outputs from ALBidS strategies to support the choice of the best possible action for the supported market players. This is performed by using a set of different agents reasoning in a distinct STH point of view. Individual answers are then combined using GA with the purpose of providing a better and evolutionary overall combination of all the answers. The metalearning concept has also been explored in the scope of this PhD work in [Pinto, 2013b]. This work proposes the use of an ANN to combine the outputs of ALBidS' strategies by learning from their past performance. The large variety of strategic approaches that have been considered and their combination using the metalearning concept accomplish objective 2.a.

Electricity market price forecasting methodologies also play an essential role in ALBidS. Paper IV [Pinto, 2015d] introduces a SVM based approach to forecast market prices, which comes to improve the results achieved by previous methodologies also proposed in the scope of this work, namely the ANN presented in [Pinto, 2012a] and a methodology that uses a forecasting error analysis to adapt the ANN predictions, proposed in [Sousa, 2012].

The context awareness capabilities of ALBidS are provided by the context analysis methodology proposed in paper III [Pinto, 2015b]. Different characteristics of each negotiation period and day are analysed so that different negotiation contexts are identified and defined. This methodology enables the learning process of ALBidS to be dependent on the negotiation context by adapting the responses to each current context. Strategies can, in this way, be evaluated and chosen depending on their performance in each specific context. The contextual awareness provided by the implemented machine learning algorithms accomplish objective 2.b.

The contribution of ALBidS to this PhD work is the provision of intelligent, adaptive and dynamic ways to combine a high number of different market strategies, with different natures and perspectives. This enables the advantageous use of each of these strategies whenever they show to be more adequate and present the highest chance for success. This allows taking the most advantage out of the market participation strategies, thus providing the answer to the research question approached in this section, and partially fulfilling objective 2, regarding the participation in auction based electricity markets.

3.4 BILATERAL CONTRACT NEGOTIATIONS

How can players' bilateral contracting negotiation capabilities be enhanced?

The constant need for electricity market players to engage in bilateral or even multilateral negotiations brings out the need for enhanced automated negotiation methods that can provide suitable decision support for energy transactions. Artificial intelligence research has invested considerably in the field of automated negotiation, from which have resulted some relevant advances [Fu, 2015]. However, essential steps have been neglected, such as the gathering of information about the opponent(s) [Lopes, 2008]. This limits the advances that are urgently required in the field, such as the definition of adequate models to choose the most appropriate parties to negotiate with, and how relevant information regarding competitors' history of previous negotiations can be used to improve the decision process. The dynamic choice of the most suitable negotiation strategies and tactics to be used against each opponent is, thereby, yet far from being adequately addressed.

Paper VII [Pinto, 2015g] presents DECON: a multi-agent decision support system for electricity market players' bilateral contract negotiations. DECON considers the pre-negotiation stage, and also the actual negotiation process. The decision support for the pre-negotiation stage (Figure 3.3) identifies the ideal competitor(s) that should be approached so that the undertaken negotiations can provide as much benefit as possible for the supported player. Moreover, the expected limits and target prices of each targeted competitor are predicted, so that they can be used to enhance the decision support for the actual negotiations.

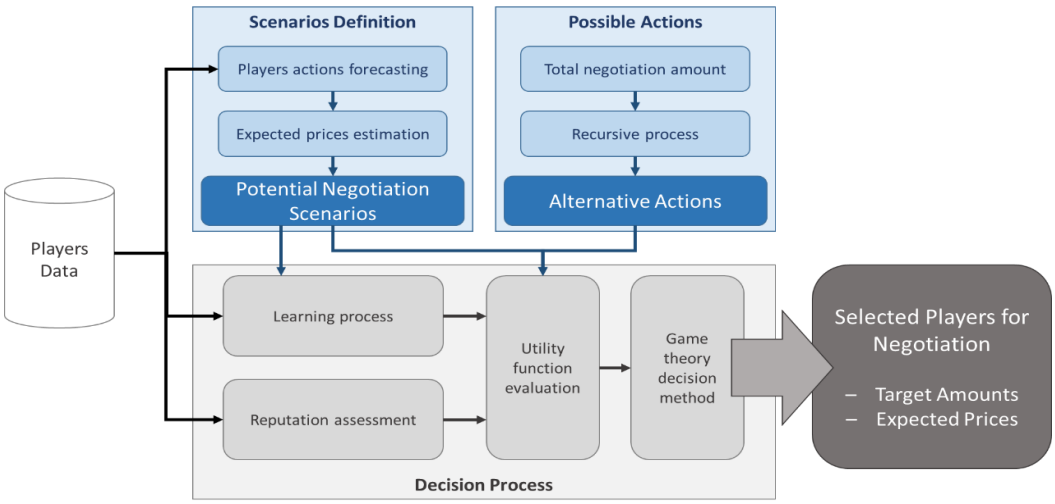

Figure 3.3. Decision process for the pre-negotiation stage (paper VII [Pinto, 2015g])

As presented in Figure 3.3, the decision support for pre-negotiation applies the game theory concept to enable the analysis of several distinct potential scenarios that the supported player is most likely to face when assuming negotiations. The alternative scenarios are created based on the historic analysis of the opponents' past actions. For this, forecasting methods are used, namely ANN [Pinto, 2012a] and SVM (paper IV [Pinto, 2015d]), among others. The forecasting results are then used by a fuzzy logic process, which has been presented in [Faia, 2015a], to estimate the expected limit price values of the opponents when negotiating different amounts of power. A reputation model is also used so that the decision takes into account, not only the expected negotiation prices, but also the benefit that establishing a contract with one or several players should represent to the supported player. Finally, several decision methods are included to allow adaptation depending on the risk that the supported player is willing to take regarding the outcomes of the negotiation process. For this, the Q-Learning reinforcement learning algorithm is used, allowing the proposed model to learn which of the potential scenarios are most likely to represent a reliable approximation of the negotiation environment that the player will face.

The decision support for the actual negotiations consists in a set of different tactics that follow different strategies. Among the considered tactics some are time-dependent, considering an evolution of the proposed prices throughout the time. This evolution is dependent on the nature of the tactics themselves. Some of the included time-dependent tactics have been presented in [Ghazvini, 2014], in the scope of this work. In addition to the considered time-dependent approaches, some behaviour-dependent tactics are included as well. These determine the changes in prices from one proposal to the following as direct response to the proposals of the competitors. The response to the opponent's proposals is determined by the level of desired aggressiveness of the supported player and of the opponent itself. The application of some of these tactics has also been demonstrated in [Lopes, 2014]. Finally, different tactic combinations are also supported by DECON. This allows the supported player to choose and change its tactic strategically. The choice of the most appropriate strategies and tactics to use against each opponent is based on a learning approach, which allows, not only choosing the initial strategy, but also to change it dynamically according to observed events. The learning process considers the analysis and definition of competitor players' profiles that has been presented in [Pinto, 2013a], so that decisions can be taken depending on past events of the same opponent and also of similar opponent players. This process is undertaken after each counter-proposal, so that the negotiation profile of the current competitor player is always re-evaluated and matched with

the most similar player profiles, considering all the most recent observations; thus allowing the adopted tactics and strategies to be dynamically adjusted in each iteration of the negotiation.

The theme of bilateral contracts' negotiation is also handled by paper V [Pinto, 2015e], which addresses the forecast and estimation of the expected bilateral contract prices depending on the opponent player(s), on the amount of desired negotiation power and on the negotiation context. The outcomes from participating in alternative electricity market opportunities, including bilateral contract negotiations are also evaluated in this paper. Paper III [Pinto, 2015b] also contributes to this part of the PhD work by examining, through realistic simulation studies, the outcomes of participating in different electricity market types, including bilateral negotiations, in different contexts of participation.

The DECON system focuses on providing solutions for the current limitations that characterize the decision support for automated negotiation. DECON addresses the research question presented in this section, and, together with the ALBidS system, which has been presented in section 3.3, completes objective 2.c of this PhD work, which consequently accomplishes objective 2.

3.5 CONTEXT ANALYSIS

Does context awareness bring advantages for electricity market players' negotiation process?

Contextualization is critical in every decision making process. Adequate responses to problems depend not only on the variables with direct influence on the outcomes, but also on a correct contextualization of the problem regarding the surrounding environment. While context is critical to information processing in all kinds of situations, it is almost fully absent from the modern information technology infrastructure. Especially in complex and highly dynamic environments, such as the electricity markets, an accurate contextualisation is essential so that the existing models can be adapted and chosen according to the circumstances. The use of proper machine learning approaches equipped with context awareness capabilities to enhance the learning process is urgently needed for this purpose.

In order to endow electricity market negotiation players with context awareness abilities, paper III [Pinto, 2015b] proposes a negotiation context analysis mechanism, which analyses

different characteristics or conditionings that allow characterizing different negotiation periods of different days. This characterization groups periods and days that present similar characteristics concerning the negotiation environment, so that these groups can represent different contexts. The grouping process is executed by using the K-Means clustering algorithm. Being able to recognize different negotiation contexts allows players to adapt their behaviour to best suit the acting requirements at each time. The proposed context analysis mechanism considers several relevant factors that influence players' negotiation environment. The electricity market price is forecasted using the SVM proposed in paper IV [Pinto, 2015d] and the ANN presented in [Pinto, 2012a]. The transacted amount of power in each market session is also considered. The wind velocity is another significant variable, since it affects the generated amount of power; wind speed forecast is approached by means of an ANN in [Pinto, 2012c] and using a SVM based approach in [Pinto, 2014e]. Solar intensity is equally important, and its forecast is the subject of the work in [Marques, 2014] and [Pinto, 2015a]. Finally, the last considered variable is the identification of the type of the day (whether it is a business day or weekend; if it is a holiday, or a special situation day, *e.g.* a day of an important event, which affects the energy consumption). Objective 3.a is achieved through the analysis of data referring to different markets, while the combination of the different types of data for analysis and definition of negotiation contexts satisfies objective 3.b.

Both paper II [Pinto, 2014c] and paper V [Pinto, 2015e] contribute to this theme by using the proposed context analysis to adapt electricity market players' decisions. Paper V [Pinto, 2015e] uses the results of the context analysis to improve players' portfolio optimization process, while paper II [Pinto, 2014c] analyses the influence of contextualization in the decision support process of players participating in auction-based electricity markets by comparing the performance of several market strategies when applied in different contexts of negotiation.

This part of the research work studies the influence of context awareness in the decision making process of agents acting in electricity markets. The proposed context analysis mechanism enables negotiating agents to adapt their acting strategies to different contexts, by considering important characteristics of each negotiation period. The main conclusion is that context-dependant responses do improve the decision making process. Suiting actions to different contexts allows adapting the behaviour of negotiating entities to different circumstances, resulting in profitable outcomes. The achieved response to the research question of this section also accomplishes the third objective defined in the scope of this PhD work.

3.6 DECISION SUPPORT SYSTEM

Can an adequate use of the available data improve the performance of electricity market negotiating players?

A significant amount of data related to electricity markets operation is available in the web. However, it is humanly impossible to analyse and extract much relevant information and knowledge from the immense amount of available data without the aid of software solutions. The potential of a suitable analysis and learning from the past lessons to improve players' performance in the market is, nevertheless, enormous.

The AiD-EM multi-agent decision support system is the ultimate result from this PhD work, and has been presented in paper V [Pinto, 2015e] and in paper VII [Pinto, 2015g]. AiD-EM integrates all the decision support features presented in the previous sections in a unique, enhanced system, thus enabling electricity market players to use the available data in an intelligent and adaptive way in order to cope with the multiple challenges that arise from electricity markets' participation. The integration of all methodologies in a single decision support system fulfils objective 4.a.

AiD-EM uses real market data, data derived from past and current simulations, and external sources data (*e.g.* weather conditions such as wind speed, solar intensity and temperature; or raw materials prices, among other) to support the decision making process. Decisions are modelled specifically for each different market negotiation type, namely the negotiation of bilateral and forward contracts, and participation in auction based markets, such as the day-ahead spot market and balancing markets. The multi-agent approach of AiD-EM facilitates the interactions between the different components and also the communication with external agents, such as the market players themselves, which make use of the decision support. The connection to MASCEM enables testing and validating the developed decision support methodologies under realistic simulation conditions, taking advantage on the enhanced simulation capabilities of MASCEM and on the interactions between the involved players. The connection of AiD-EM to MASCEM, which accomplishes objective 4.b, is depicted in Figure 3.4, along with the interaction between the main AiD-EM components.

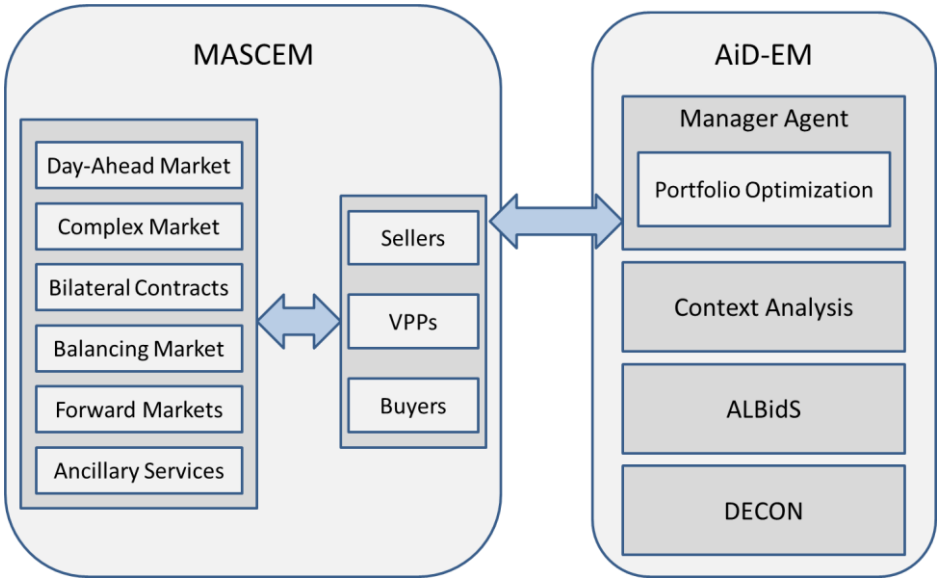

Figure 3.4. AiD-EM connection to MASCEM

As shown by Figure 3.4, the AiD-EM Manager agent is the main entity of the system, detaining the responsibility of providing the connection with the MASCEM electricity market simulator through the direct interaction with the supported market player(s). When several market players require the decision support of AiD-EM simultaneously, multiple AiD-EM Manager agent instances are created, so that each supported market player has its own Manager agent, with the sole responsibility of handling the player's decision making process. For this, the AiD-EM Manager agent executes the Portfolio Optimization methodology, presented in section 3.2, in order to decide whether and when the supported market player should participate in each market type. The introduction of the Portfolio Optimization in AiD-EM is approached in paper V [Pinto, 2015e] and in [Faia, 2015b]. Once the objectives for each market participation are defined, ALBidS is used to support the negotiations in auction based markets, *e.g.* spot, balancing and intraday markets. The integration of ALBidS in AiD-EM is detailed in [Pinto, 2015c]. Complementarily, when the negotiation by means of bilateral negotiations is also envisaged, the DECON system is used. Paper VII [Pinto, 2015g] shows the incorporation of this decision support system in AiD-EM.

The AiD-EM system, resulting from the integration of all the decision support methodologies developed in the scope of this PhD work, allows market players to make use of the available data regarding each distinct specific problem, in order to produce adaptive and intelligent behaviours that allow them achieving better outcomes from market participation. This part of the work provides the answer to the main research question of this PhD, and completes objective 4 of this work, as defined in the introductory chapter.

3.7 REALISTIC SIMULATION STUDIES

Can decision support abilities be tested and validated in a realistic electricity market environment?

The conception, development and implementation of decision support methodologies for electricity market players must be tested and validated under real or almost real conditions, so that reliable conclusions can be taken from the applicability and potential advantage of using the proposed methods. Realizing that experiments in real electricity market negotiations could result in catastrophic results for the subject player(s), the solution is to test the models using realistic electricity market simulations.

The AiD-EM interaction with the MASCEM electricity market simulator provides the means for experimenting the developed decision support methods under realistic simulation conditions. MASCEM makes use of the RealScen scenarios generator, which has been presented in [Teixeira, 2014], to create simulation scenarios that are the representation of real markets of a specific region; or even consider different configurations to test the operation of the same players under changed, thoroughly defined scenarios. RealScen uses real data that is available online, usually in market operators' websites. Data is gathered in real time, as soon as it is made available by each different source, using an automatic data extraction tool that has been presented in [Pereira, 2014]. The considered data concerns market proposals, including quantities and prices; accepted proposals and established market prices; proposals details; execution of physical bilateral contracts; statement outages, accumulated by unit type and technology; among others. The study presented in [Pinto, 2014d] shows that simulations performed in MASCEM using scenarios created by RealScen are able to represent the electricity markets reality in a very similar way, even when considering a reduced number of market agents. The use of real data based simulation scenarios fulfils objective 5.a.

The generated simulation scenarios are used to test and validate the methodologies developed in the scope of this PhD work. Paper V [Pinto, 2015e] presents simulation results of the application of the Portfolio Optimization methodology in a scenario based on the several market types of the Iberian electricity market operator – MIBEL [MIBEL, 2015]. These simulations include the day-ahead spot market, the balancing market, the negotiation of bilateral

contracts, the forwards market and a smart grid based market, which has been based on data resulting from previous simulation studies.

The case studies of paper II [Pinto, 2014c] and paper IV [Pinto, 2015d] include simulations based on realistic scenarios that represent the day-ahead spot market of MIBEL. Results show that the proposed decision support methodologies are able to provide the supported market players with improved outcomes out of market participation. In paper VII [Pinto, 2015g] MIBEL data is also used as basis to assess the performance of the DECON decision support features. A unified European electricity market simulation using real data from several European market operators has been presented in [Pinto, 2014b], demonstrating the simulation capabilities of MASCEM, taking advantage from the simulation scenarios generated by RealScen, and showing the possibility of experimenting different decision support methodologies under different realistic simulation scenarios.

Paper III [Pinto, 2015b] presents a set of simulation studies including not only different electricity market operators, namely MIBEL [MIBEL, 2015], EPEX [EPEX, 2015] and Nord Pool [Nord Pool, 2015], but also the representation of specific situations in the past with special relevance for studying purposes, *e.g.* real cases where an unexpected high and low amount of wind based generation has been verified, occurrences of large variations of the market price, and days that have been characterized by special events (in specific, a football game with significant influence over the energy consumption during several hours of the considered day). The achieved results show that the context awareness capabilities of AiD-EM allow players to adapt their behaviours to different contexts, thus improving their market results.

Table 3.2 summarizes the electricity market operators and respective market types that each paper has used as basis for the creation of realistic simulation scenarios in order to test and validate the developed decision support methodologies. The considered market types are represented in the table as follows:

- Day-Ahead Spot Market: DAS;
- Balancing Market: BM;
- Intra-Day Market: IDM;
- Bilateral Contracts: BC;
- Forward Contracts: FC.

Table 3.2. Summary of the performed case studies

Paper	Market Type		
	MIBEL	***EPEX***	***Nord Pool***
Paper I [Pinto, 2013c]	DAS		
Paper II [Pinto, 2014c]	DAS		
Paper III [Pinto, 2015b]	DAS, BM, BC, FC	DAS, IDM, BC	DAS, IDM, BC
Paper IV [Pinto, 2015d]	DAS		
Paper V [Pinto, 2015e]	DAS, BM, BC, FC		
Paper VI [Pinto, 2015f]	DAS		
Paper VII [Pinto, 2015g]	BC		
[Pinto, 2014b]	DAS	DAS	DAS
[Pinto, 2014d]	DAS		

Table 3.2 provides a clearer picture on the market types that have been considered in the case studies of each paper. MIBEL is understandably the most approached market, since this PhD work has been developed in Portugal, which is a member of MIBEL, thus the study of this market has a bigger priority than the others. Nevertheless, other important market operators have been used as basis for the simulation scenarios in some of the performed studies. Nord Pool is especially relevant due to its status as the bigger electricity market in Europe (*i.e.* the electricity market that supports the larger amount of transacted power). EPEX has been chosen due to its central position in Europe, which plays a crucial role in the interaction with the other European electricity markets, thus being fundamental to the process of the European electricity market unification. The use of different market environments to test and validate the proposed methodologies enhance the applicability and potential of AiD-EM.

The improvement of market players' outcomes using the proposed decision support methodologies is confirmed by the test and validation of the proposed methodologies in realistic electricity market simulation scenarios using the MASCEM electricity market simulator, thus achieving objective 5.b of this work. These simulation studies and the evaluation of their results provides the answer to the final research question of this PhD work, and complete objective 5, the final objective specified for this PhD thesis.

3.8 CONCLUSIONS

The main contribution of this work is the response to the core research question of this PhD, namely: *Can an adequate use of the available data improve the performance of electricity market negotiating players?*

The work developed in the scope of this PhD, in pursuit of the answers to the specific research questions, has ultimately resulted in the development of the AiD-EM decision support system. This system provides the answer to the main research question by integrating a variety of different decision support solutions, directed to different purposes, which together contribute to the improvement of electricity market players' performance in market negotiations. The soundness of the decision support methodologies developed in the scope of this PhD work has been assessed through the test and validation of the proposed methods in realistic simulation scenarios. The encouraging results achieved under realistic negotiation conditions support the thesis that the proper analysis and learning from historic data can, in fact, generate profitable outcomes from players' market participation.

The improvement of market results is largely owed to the context awareness capabilities of AiD-EM. The aptitude to analyse and define different contexts provides AiD-EM with contextual adaptive learning capabilities. In this way, the diverse decision support methodologies that compose AiD-EM can adapt themselves to each context. Depending on the context, the Portfolio Optimization methodology decides *when* and *where* should the supported players negotiate their required amount of power, *i.e*. the participation in the different available electricity market opportunities is optimized. The responsibility of deciding *how* the negotiation in each market should be conducted is allocated to specific decision support systems, targeting different types of negotiation. Negotiations by means of bilateral contracts are aided by DECON, which considers both the phases of pre-negotiation and of actual negotiations. The participation in auction based markets is supported by ALBidS. This decision support system includes a large number of distinct market participation strategies, and learns which should be used in each context in order to provide the best expected response.

The contributions of the work developed in the scope of this PhD provide the answers to all the specific research questions, which together result in the answer to the main research question. The research work leading to the achievement of such responses also allows fulfilling all the defined objectives for this PhD work.

Chapter 4

Conclusions and future work

4 CONCLUSIONS AND FUTURE WORK

This chapter concludes the thesis manuscript by presenting the most relevant conclusions derived from this work and by giving directions for possible future work in continuation of the current research.

4.1 MAIN CONCLUSIONS AND CONTRIBUTIONS

The electricity market restructuring process placed several challenges to the field, demanding the transformation of the conceptual models that have previously dominated the sector. The restructuring not only made the market more competitive, but also more complex, placing new challenges to the participants. The growing complexity and unpredictability of the market's evolution consequently increases the decision making difficulty. Therefore, the intervenient entities are forced to rethink their behaviour and market strategies.

So that these players are able to face the new challenges, the use of decision support tools becomes crucial. Multi-agent based solutions for electricity markets' simulation are particularly successful in this domain, as they are well fitted to analyse dynamic and adaptive systems with complex interactions among its constituents, such as electricity markets. Current solutions present, however, the common limitation of lacking decision support features for electricity market players' negotiation process. This gap has led to the definition of several research questions, which were the basis for the specification of this PhD work objectives.

This thesis presents AiD-EM, a multi-agent decision support system that enables surpassing the identified limitations in the field by integrating a large variety of different decision support methodologies, which deal with the specific identified problems that compose the main topic addressed in this work.

The Portfolio Optimization methodology addresses the problem of planning the participation in multiple electricity market opportunities depending on the expected prices in each market in each context. DECON and ALBidS approach the subject of negotiation in

specific market types, namely in negotiations by means of bilateral contracts, and participation in auction based markets, respectively. These decision support systems make use of the context awareness capabilities provided by the Context Analysis methodology to adapt their responses according to each different negotiation context.

The integration of AiD-EM with MASCEM provides the means to perform market simulations based on real data. Taking advantage on the developed case studies based on real data, it was possible to validate the developed methodologies, guaranteeing the adequate coordination between the several mechanisms of this system and the competence of the system in achieving its purpose in realistic scenarios.

The achieved results show that the AiD-EM methodologies accomplished considerably better results than all the other methods to which they were compared. From the achieved results, this system demonstrated its ability to learn, showing evidence of a clear improvement in its performance throughout the time, due to learning and adaptation according to the change of the circumstances, by using the available resources. These resources are the distinct approaches that the system has at its reach, namely the distinct decision support systems and the corresponding negotiation strategies and learning and data analysis algorithms, which allow the system to choose at each time and in each context the best decisions to perform. This allows AiD-EM to learn what to perform, so that it can continually improve the best way of achieving its objectives. The decisions are performed so that the system can achieve the best outcomes by learning with its errors and adapting itself by observing the behaviour of others.

The findings resulting from the development of AiD-EM, from the achievement of responses to the research questions, and from the consequent accomplishment of all the defined objectives, have contributed to relevant advances in the state of the art of the multidisciplinary fields of artificial intelligence and power systems. The main contributions to the artificial intelligence area were mainly given in the fields of machine learning and data analysis; while in the power systems' field they were specifically related to the electricity markets domain. The thirty six scientific papers that have been published as result of this PhD work, and the contribution of this work towards the achievement of several national and international projects' objectives are clear indications of the relevance of the achieved findings.

4.2 PERSPECTIVES OF FUTURE WORK

Departing from the results of this PhD work, the dynamism and learning and adaptation capabilities of this and other tools should be enlarged in order to ensure an adequate response to future changes in the electricity markets' field. Suitable decision support solutions are fundamental to enable players an advantageous participation in new market realities, such as: *(i)* the introduction of novel electricity market mechanisms and the adaptation of the current ones in order to accommodate the large scale integration of renewable based generation and the active participation from the consumers' side; *(ii)* the unification of European electricity markets; and *(iii)* the implementation of new markets at the smart grids' level as well as the interaction between these new market environments with the wholesale market.

The contributions of this PhD work to the artificial intelligence area, and more specifically to the machine learning field, have been provided with concern to the combination of different machine learning techniques, taking advantage on their complementarities and on the application contexts in which they bring the most advantages. Additionally, several novel techniques and methodologies have been introduced to improve the intelligent and automatic resolution of several problems. The achieved advances in the scope of this work will be the foundation to new proposals for improvement of diverse methodologies aiming at a more effective and efficient automatic learning, with a deeper context awareness and dynamism concerning the circumstances of application. Among the many future developments that this work potentiates, some of the most relevant are listed as follows:

- Expansion of the decision support solutions towards a multi-level negotiation environment, concerning the introduction of market-based smart grid models. The multi-level negotiation environment considers: *(i)* negotiation between members of smart grids, considering the specific characteristics, objectives and restraints of these small players; *(ii)* negotiation among neighbour smart grids and between smart grid operators and other large layers and aggregators; and *(iii)* negotiations of aggregators, including smart grid operators, in wholesale electricity markets (at regional and continental scales);
- Improvement of the Portfolio Optimization methodology, considering the new market prospects that are arising (including smart grids) as alternative and/or complementary negotiation opportunities for market players;

- Adaptation of the Portfolio Optimization methodology in order to include the minimization of market participation risk as a complementary objective, thus defining a multi-objective problem;
- Integration of different metaheuristic approaches to solve the Portfolio Optimization problem both for single and multi-objective formulations, including different evolutions of *e.g.* PSO [Soares, 2013], GA and simulated annealing [Sousa, 2014a];
- Implementation of a case-based learning approach [Bianchi, 2015] to support the decision of which alternative optimization solution to use in each context and simulation circumstance (considering AiD-EM's 2E requirements);
- Expansion of DECON's decision support features to cope with negotiations of aggregation contracts and diverse types of services' provision;
- Enhancement of the learning process of DECON regarding the dynamic selection and adaptation of the tactics and strategies to use at each moment and in each context, by developing specific learning algorithms using the developments in the cooperative learning field [Xu, 2015];
- Implementation of alternative forecasting methodologies for the different approached problems (*e.g.* market price, wind speed, solar intensity and consumption forecast), using the advances in the field of big data, namely: incremental learning, deep learning and other hybrid approaches such as fuzzy inference systems [Luo, 2015].

The majority of these future work suggestions has been considered, not only as future development of this PhD work, but also as a relevant part of the core of some ongoing international research projects, which guarantee the continuity of the research undertaken in the scope of this PhD, namely the following:

- DREAM-GO – Enabling Demand Response for short and real-time Efficient And Market Based smart Grid Operation – An intelligent and real-time simulation approach. This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement number 641794;
- SEAS – Smart Energy Aware Systems, project number 12004, funded by European Union's EUREKA – ITEA2.

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Annexes

Annex A. Core Papers

Paper I [Pinto, 2013c]:

Tiago Pinto, Isabel Praça, Zita Vale, Hugo Morais and Tiago M. Sousa, “Strategic Bidding in Electricity Markets: An agent-based simulator with game theory for scenario analysis”, Integrated Computer-Aided Engineering, IOS Press, vol. 20, no. 4, pp. 335-346, September 2013, Impact Factor 2013: 4.667

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Strategic bidding in electricity markets: An agent-based simulator with game theory for scenario analysis

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Abstract. Electricity markets are complex environments, involving a large number of different entities, with specific characteristics and objectives, making their decisions and interacting in a dynamic scene. Game-theory has been widely used to support decisions in competitive environments; therefore its application in electricity markets can prove to be a high potential tool. This paper proposes a new scenario analysis algorithm, which includes the application of game-theory, to evaluate and preview different scenarios and provide players with the ability to strategically react in order to exhibit the behavior that better fits their objectives. This model includes forecasts of competitor players' actions, to build models of their behavior, in order to define the most probable expected scenarios. Once the scenarios are defined, game theory is applied to support the choice of the action to be performed. Our use of game theory is intended for supporting one specific agent and not for achieving the equilibrium in the market. MASCEM (Multi-Agent System for Competitive Electricity Markets) is a multi-agent electricity market simulator that models market players and simulates their operation in the market. The scenario analysis algorithm has been tested within MASCEM and our experimental findings with a case study based on real data from the Iberian Electricity Market are presented and discussed.

Keywords: Decision making, electricity markets, intelligent agents, game theory, multiagent systems, scenario analysis

1. Introduction

All over the world electricity restructuring placed several challenges to governments and to the companies that are involved in generation, transmission and distribution of electrical energy. Potential benefits, however, depend on the efficient operation of the market. The definition of the market structure implies a set of complex rules and regulations that should prevent strategic behaviors [31]. Several market models exists, with different rules and performances creating the need to foresee market behavior, regulators want to test the rules before they are implemented and market players need to understand the market so they may reap the benefits of a well-planned action [3,21].

Usually, electricity market players use rather simple strategic behaviors. Most entities keep their biddings constant along the time, while others base their proposed prices in the generation costs of their installations. The most elaborated strategic behaviors go no further than performing simple averages or regressions of the historic market prices. This matter, a highly unexplored and unimplemented issue, of huge importance for the maximization of players profits, supports the need for the development of proper market acting strategies.

The main contribution of this work is to complement the Multi-Agent Simulator for Electricity Markets (MASCEM) [26,33] simulator. MASCEM is a modeling and simulation tool that has been developed

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by this team for the purpose of studying complex restructured electricity markets operation. MASCEM's ability to model the most relevant market players and negotiation mechanisms provides the means for an adequate development and study of models and techniques to support market players' actions in the best possible way. It provides market players with simulation and decision-support resources, being able to give them competitive advantage in the market.

The contribution is provided through the development of a new computational model, implemented to support the development of dynamic pricing strategies, taking advantage of the interactive environment between market agents and on the gathered knowledge during market participation. The methodology is characterized as a scenario analysis algorithm able to support players' strategic behavior. The proposed model includes four innovative components which arise as separate, however, complementary contributions: (i) scenarios definition, concerning the automatic creation of distinct market scenarios based on different perspectives and potential states of the electricity market evolution along the time; (ii) players profiles definition, which is an independent computational model directed to the creation of competitor players' models, in what concerns their characteristics and expected behavior, performing analysis and forecasts of their current and past observed actions and continuously gathered information; (iii) possible actions definition, aiming at establishing a set of coherent and realistic possibilities of actions for the supported player to take on an electricity market environment, taking into account each current context (concerning market and competitor players' states at each point in time); (iv) adaptation of the game-theory concept [6,23] to the electricity market negotiation environment, both concerning bi-lateral and multi-lateral negotiations, which is a major contribution by itself, in a sense that this adaptation concerns such a dynamic and specific context, with so many particularities and constraints. Notice however, that the use of game theory is to support the decisions of the agents and not to reach equilibrium in the market.

After this introductory section, Section 2 introduces the theme of multi-agent simulation in electricity markets, outlining the main features of MASCEM, providing an essential insight of this simulator, contributing to an adequate understanding of the simulated multi-agent environment, in order to properly expose the advantages of the proposed work; Section 3 explores the proposed computational model, including the game theory approach for scenario analysis; Section 4 presents a case study based on real electricity market data, testing the proposed models and comparing its results with the results for the same scenario using other two well established methodologies for decision support of players acting in electricity markets. Finally Section 5 presents the most relevant conclusions and contributions of this paper.

2. Multi-agent simulation of competitive electricity markets

Simulation tools are very suitable to find market inefficiencies or to provide support for market players' decision. Multi-agent based simulation is particularly well fitted to analyze dynamic and adaptive systems with complex interactions among constituents [2,7,8, 15,22,27,29]. With multi-agent simulation tools the individual behaviors may be studied, as well as the system behavior and how the individual behaviors may affect its performance. Another very relevant issue is that the multi-agent model may be dynamically enlarged to accomplish new rules or participants.

Indeed several multi-agent tools have been fruitfully applied to the study of restructured wholesale power markets [2,8,19,20,26,27]. Some of the most relevant tools in this domain are the Electricity Market Complex Adaptive System (EMCAS) [19] and Agent-based Modelling of Electricity Systems (AMES) [20].

Within EMCAS software agents have negotiation competences and use strategies based on machine-learning and adaptation to simulate Electricity Markets. AMES is an open-source computational laboratory for studying wholesale power markets, restructured in accordance with U.S. Federal Energy Regulatory Commission (FERC). It uses an agent-base test bed with strategically learning electric power traders to experimentally test the extent to which commonly used seller market power and market efficiency measures are informative for restructured wholesale power markets.

MASCEM was presented to the scientific community in 2003 [26], combining agent based-modeling and simulation. In its initial form MASCEM provided the modeling of the most relevant entities that participate in electricity markets, as well as some of the most common market mechanism found worldwide. One of MASCEM's objectives is to be able to simulate as many market models and players types as possible so it can reproduce in a realistic way the operation of real electricity markets. This enables it to be used as a simu-

lation and decision-support tool for short/medium term purposes but also as a tool to support long-term decisions, such as the ones taken by regulators. MASCEM includes several negotiation mechanisms usually found in electricity markets [30]. It can simulate several types of markets, namely: day-ahead markets, bilateral contracts, balancing markets and forward markets. This implies that each agent must decide whether to, and how to, participate in each market type.

In 2011 a new enhanced version of MASCEM arose [33], where agents use several distinct strategies when negotiating in the market and learning mechanisms in order to best fulfill their objectives. Although MASCEM's purpose is not to explicitly search for equilibrium points, but to help understand the complex and aggregate system behaviors that emerge from the interactions of heterogeneous individuals, agents learn and adapt their strategies during a simulation, thus possibly converging toward equilibrium.

There are also several entities involved in the negotiations in the scope of electricity markets; MASCEM multi-agent model represents all the involved entities and their relationships. MASCEM model includes: a Market Facilitator Agent, Seller Agents, Buyer Agents, Virtual Power Producer (VPP) [34] Agents, VPP Facilitator Agents, a Market Operator Agent and a System Operator Agent.

2.1. *MASCEM strategies for competitor players profiles definition*

In order to build suitable profiles of competitor agents, it is essential to provide players with strategies capable of dealing with the constant changes in competitors' behavior, allowing adaptation to their actions and reactions. For that, it is necessary to have adequate forecasting techniques to analyze the data properly, namely the historic of other agents past actions. The way each agent bid is predicted can be approached in several ways, namely through the use of statistical methods, data mining techniques [9,28,32], neural networks (NN) [1,14], support vector machines (SVM) [35], or several other methods [5,13,16,17]. But since the other agents can be gifted with intelligent behavior as well, and able to adapt to the circumstances, there is no method that can be said to be the best for every situation, only the best for one or other particular case.

To take advantage of the best characteristics of each technique, we decided to create a method that integrates several distinct technologies and approaches. The method consists of the use of several forecasting algorithms, all providing their predictions, and, on top of that, a reinforcement learning algorithm that chooses the one that is most likely to present the best answer. This choice is done according to the past experience of their responses and also to the present characteristics of each situation, such as the week day, the period, and the particular market context in which the players are acting.

The main reinforcement algorithm presents a distinct set of statistics for each acting agent, for their actions to be predicted independently from each other, and also for each period. This means that an algorithm that may be presenting good results for a certain agent in a given period, with its output chosen more often when bidding for this period, may possibly never be chosen as the answer for another period. The tendencies observed when looking at the historic of negotiation periods independently from each other show that they vary much from each other, what suggests that distinct algorithms can present distinct levels of results when dealing with such different tendencies.

All forecasting algorithms may be weighted to define its importance to the system. This means that a strategy that has a higher weight value will detach faster from the rest in case of either success or failure.

The way the statistics are updated, and consequently the best answer chosen, can be defined by the user. MASCEM provides three alternative reinforcement learning algorithms, all having in common the starting point. All the algorithms start with the same value of confidence, and then, according to their particular performance, that value is updated.

The three algorithms are: a simple reinforcement learning algorithm; the revised Roth-Erev reinforcement learning algorithm; and a learning algorithm based on the Bayes theorem of probability. These three algorithms are detailed in [33].

Concerning the simple reinforcement learning algorithm, the updating of the values is done through a direct decrement of the confidence value C in the time t, according to the absolute value of the difference between the prediction P and the real value R. The updating of the values is expressed by Eq. (1).

$$C_{t+1} = C_t - |(R - P)| \tag{1}$$

The revised Roth-Erev reinforcement learning algorithm [17], besides the features of the previous algorithm, also includes a weight value W, ranging from 0 to 1, for the definition of the importance of past experiences. This version is expressed as in Eq. (2).

$$C_{t+1} = C_t \times W - |(R - P)| \times (1 - W) \quad (2)$$

In the learning algorithm based on the Bayes theorem of probability [10], the updating of the values is done through the propagation of the probability of each algorithm being successful given the facts of its past performance. The expected utility, or expected success of each algorithm is given by Eq. (3), being E the available evidences, A an action with possible outcomes O_i, $U(O_i|A)$ the utility of each of the outcome states given that action A is taken, $P(O_i|E, A)$ the conditional probability distribution over the possible outcome states, given that evidence E is observed and action A taken.

$$EU\,(A|E) = \sum_i P(O_i|E, A) \times U(O_i|A) \quad (3)$$

The algorithms used for the predictions are based on neural networks, several statistical approaches, pattern analysis, history matching, second-guessing and self model predictions.

One of the algorithms is based on a feed-forward neural network trained with the historic market prices, with an input layer of eight units, regarding the prices and powers of the same period of the previous day, and the same week days of the previous three weeks. The intermediate hidden layer has four units and the output has one unit – the predicted bid price of the analyzed agent for the period in question.

There are five forecasting strategies based on statistical approaches, using average values or regressions from previous days. Even though this type of strategies, especially those based on averages, may seem too simple, they present good results when forecasting players' behaviors, taking only a small amount of time for their execution. These strategies consider different time horizons, such as:

- Average of prices and powers from the agents' past actions database, using the data from the 30 days prior to the current simulation day, considering only the same period as the current case, of the same week day;
- Average of the agent's bid prices considering the data from one week prior to the current simulation day, considering only business days, and only the same period as the current case. This strategy is only performed when the simulation is at a business day. This approach, considering only the most recent days and ignoring the distant past, gives us a proposal that can very quickly adapt to the most recent changes in this agent's behavior. It is also a good strategy for agents that tend to perform similar actions along the week;
- Average of the data from the four months prior to the current simulation day, considering only the same period as the current case. This offers an approach based on a longer term analysis;
- Regression on the data from the four months prior to the current simulation day, considering only the same period of the day;
- Regression on the data of the last week, considering only business days. This strategy is only performed when the simulation is at a business day.

About pattern analysis there are three algorithms concerning: the most repeated sequence along the historic of actions of the player; the most recent sequence among all the found ones; sequences in the past matching the last few actions. In the latter approach the sequences of at least 3 actions found along the historic of actions of the player are considered. The sequences are treated depending on their size. The longer matches to the recent history are attributed a higher importance.

There is also an algorithm based on history matching, regarding not only the player actions, but also the results obtained. This algorithm finds the previous time that the last result happened, i.e., what the player did, or how he reacted, the last time he performed the same action and got the same result.

Another simple but efficient method for players that tend to perform recurrent actions, is an algorithm returning the most repeated action of the player.

Finally, we have second-Guessing the predictions. Assuming that the players whose actions we are predicting are gifted with intelligent behavior, it is essential to shield this system, avoiding being predictable as well. So this method aims to be prepared to situations when the competitors are expecting the actions that the system is performing. We consider second and third-guesses.

Second-Guess, if the prediction on a player action is P, and it is expecting the system to perform an action $P1$ that will overcome its expected action, so in fact the player will perform an action $P2$ that overcomes the system's expected $P1$. This algorithm prediction is the $P2$ action, in order for the system to expect the player's prediction.

Third-Guess is one step above the previous algorithm. If a player already understood the system's second guess and is expecting the system to perform an action that overcomes the $P2$ action, than it will perform an action $P3$ that overcomes the system prediction, and so, this strategy returns $P3$ as the predicted player action.

Concerning Self Model prediction, once again if a player is gifted with intelligent behavior, it can perform the same historical analysis on the system's behavior as the system performs on the others. This strategy performs an analysis on its own historic of actions, to predict what itself is expected to do next. From that the system can change its predicted action, to overcome the players that may be expecting it to perform that same predicted action.

In the Second-Guess/Self Model prediction, the same logic is applied as before, this time considering the expected play resulting from the Self Model prediction.

3. Game theory based scenario analysis

The scenario analysis algorithm supports strategic behavior with the aim of providing complex support to develop and implement dynamic pricing strategies.

Each agent develops a strategic bid, taking into account not only its previous results but also other players' bids and results and expected future reactions. This is particularly suitable for markets based on a pool or for hybrid markets, to support Sellers and Buyers decisions for proposing bids to the pool and accepting or not a bilateral agreement. The algorithm is based on the analysis of several bids under different scenarios. The analysis results are used to build a matrix which supports the application of a decision method to select the bid to propose. Each agent has historical information about market behavior and about other agents' characteristics and past actions. This algorithm's organization is presented in Fig. 1.

To get warrantable data, agents using this method perform an analysis of the historical data. With the gathered information, agents can build a profile of other agents including information about their expected proposed prices, limit prices, and capacities. With these profiles, and based on the agent own objectives, several scenarios, and the possible advantageous bids for each one, are defined.

Seller and Buyer agents interact with each other, in MASCEM environment, taking into account that their results are influenced by competitor's decisions. Game theory is well suited for analyzing these kinds of situations [6,23].

3.1. Scenario definition

MASCEM is implemented as a Decision Support tool, so the user should have the flexibility to decide

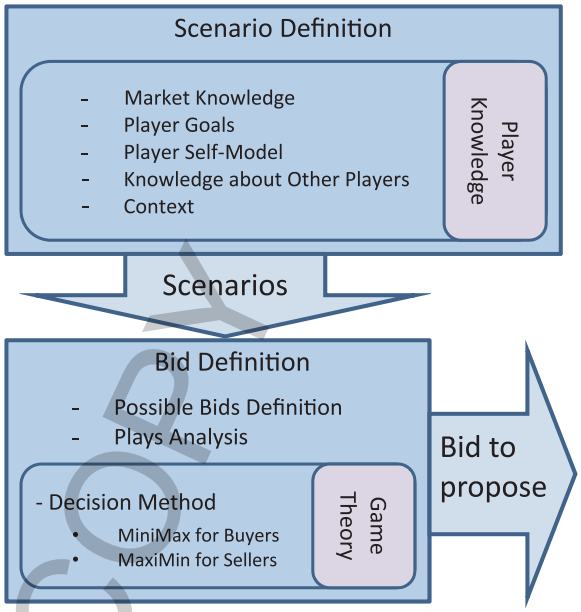

Fig. 1. Scenario analysis algorithm. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/ICA-130438)

how many and which scenarios should be analyzed. To do so, the user must define the scenarios to be simulated by specifying the price that competitor agents will propose Eq. (4):

$$Price_i = \lambda \times Probable\_Price_i + \varphi \times Limit\_Price_{i,},$$
$$\lambda \text{ and } \varphi >= 0, \lambda + \varphi = 1 \quad (4)$$

where λ and φ are scaling factors that can be different for each agent and for each scenario.

The *Probable_Price* is a predicted value concerning the expected bidding price of each competitor player. This prediction is reached by using the players' profiles definition mechanism, presented in section 2. This prediction allows the proposed method to use adequate and realistic values when considering other players' actions.

The *Limit_Price* corresponds to maximum price that can be bided by a seller agent, or the minimum price that can be bided by a buyer agent.

Equation (4) is used to provide the definition of alternative scenarios, concerning agents may define bids between their limit and probable prices.

Let us suppose that the user selects $\lambda = 0$ and $\varphi = 1$ for every Seller and $\lambda = 1$ and $\varphi = 0$ for every Buyer; this means an analysis of a pessimistic scenario. If the user selects $\lambda = 1$ and $\varphi = 0$ for every agent, then the most probable scenario will be analyzed. Using this formula the user can define for each agent the proposed prices for every scenario that it desires to consider.

Each scenario considers a fixed number of players, each with constant amounts of power. Only the bidding prices for each player vary from scenario to scenario.

3.2. Bid definition

An agent should analyze the income that results from bidding its limit, desired, and competitive prices – those that are just slightly lower (or higher, in the buyers' case) than its competitors' prices.

A play is defined as a pair of bid – scenario, so, the total number of plays to analyze for each player is Eq. (5):

$$n = number\_of\_bids \times number\_of\_scenarios \quad (5)$$

and the maximum value it can achieve is Eq. (6):

$$(2 \times n + 2) \times 2^n \quad (6)$$

considering that agents only bid their limit or expected prices. However, an agent may bid prices between its limit and expected prices, or even above that limit price. If we consider each agent may bid numprices prices, the number of scenarios becomes equal to npn, and the number of plays to analyze is Eq. (7).

$$(numprices \times n + 2) \times numprices^n \quad (7)$$

The user is also allowed to choose the number of bids that will be considered as possibilities for the final bid. In this case, the value of the bids is calculated depending on an interval of values that can also be defined by the user. That interval is always centered on a trusted value, the value of the market price of the same period of the previous day. In this way the considered possible bids are always around that reference value, and their range of variance depends on the bigger or smaller value of the user defined interval.

So, being *nb* the number of bids defined by the user, *int* the value defining the interval to be considered, and *mp* the market price from the same period of the previous day, the possible bids *b1...nb* are defined as Eqs (8) and (9):

$$\mathrm{b}_1 = mp - \frac{int}{2} \quad (8)$$

$$b_m = b_{m-1} + \left(\frac{int}{nb-1}\right), m \in [2, nb] \quad (9)$$

After defining all the scenarios and bids, market simulation is applied to build a matrix with the expected results for each play.

The matrix analysis with the simulated plays' results is inspired on the game theory concepts for a pure-strategy two-player game, assuming each player seeks to minimize the maximum possible loss or maximize the minimum possible gain.

After each negotiation period, an agent may increase, decrease or maintain its bid, increasing the number of scenarios to analyze. So, after k periods, considering only three possible bid updates, the number of plays to analyze becomes Eq. (10):

$$(np \times n + 2) \times np^n \times 3^{(k-1)\times n} \quad (10)$$

3.3. Game theory for scenario analysis

A seller, like an offensive player, will try to maximize the minimum possible gain by using the MaxiMin decision method. A buyer, like a defensive player, will select the strategy with the smallest maximum payoff by using the MiniMax decision method.

Buyers' matrix analysis leads to the selection of only those situations in which all the consumption needs are fulfilled. This avoids situations in which agents have reduced expenses but cannot satisfy their consumption needs completely.

The state space to be searched is related to the possible plays of other agents, regarding possible bids from one agent. Figure 2 illustrates this procedure.

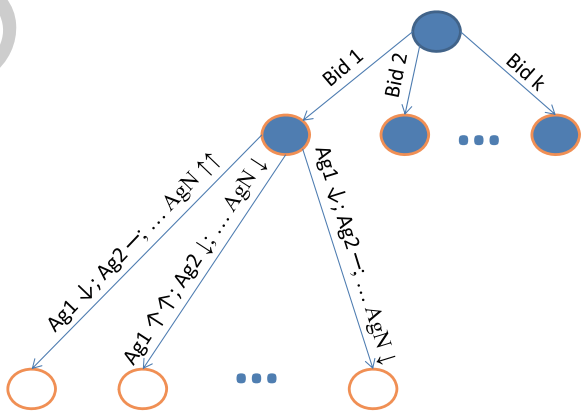

Fig. 2. Game theory for scenario-space search. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/ICA-130438)

Each bid of a specific agent (e.g. Ag_i) is analyzed by considering several possible scenarios, in order to support the decision of this agent. The scenarios are evaluated by considering the prices other agents may propose, regarding the previous proposed prices. It is also considered that each agent may change its price: increasing a lot (↑↑), increasing a little (↑), maintaining (-), decreasing a little (↓), or decreasing a lot (↓↓) its

bid price (A little means from 0 to 10% and a lot from 10% to 30%). Here the concepts of little and lot will consider the historic data of agents' bids and will be converted to variations in cents. It is important to observe that it is impossible to consider all kind of variations, due to the complexity of the problem, as we have seen before. The required time for solving the problem with a large set of combinations would be impractical since a complete market simulation is required for each scenario.

Each leaf node of the tree in Fig. 2 corresponds to a possible scenario. The idea is to evaluate each one of these scenarios and apply a MiniMax or MaxiMin based algorithm to select the safest bid to be offered by agent Ag_i.

Notice that our use of game theory is intended for supporting one specific agent and not for achieving the equilibrium in the market. The idea of the methodology proposed in this paper is to provide a specific agent with decision support.

For each simulated scenario (leaf of Fig. 2) we will calculate the price P_{market} for each MW.h (Megawatt hour), defined as the result of the simulated market. For the support of seller agents the evaluation of the scenario (in profits, F) is made by the product of the energy sold by the supported agent *Agi*, $Energy\_Sold_i$, by the profit, obtained from the difference between P_{market} and the cost associated to each MW.h sold by *Agi*, $Cost_i$, according to Eq. (11):

$$F = Energy\_sold_i \cdot (P_{market} - Cost_i) \tag{11}$$

Notice that the part of this formula that demands the higher processing cost is the calculation of the value P_{market}, since it implies to run the simulation of the scenario in order to determine the market clearing price.

Additionally, there are two methods for solving problems of equality in the evaluation of scenarios. In case of a seller, the MaxiMin algorithm chooses the bid that offers the maximum gain, from the worst possible scenario. In case of more than one scenario being evaluated with equal value as worst scenario, the options for choosing among them are:

- a greedy approach, choosing the scenario, among the equally worst ones, that presents the bid that allows the higher payoff from all the possible bids;
- an average of the results of all possible bids for these scenarios, choosing the one that gets the worst average as the worst possible scenario.

The user is able to choose among these two methods for solving the problems of equality. He can also choose a third option that is a mechanism that chooses automatically among these two options, accordingly to the success that each of them is presenting. This mechanism uses a reinforcement learning algorithm, with initial equal values of confidence for the two options. As the time evolves, the values of success of each option are updated, and the one that presents the best confidence in each run, is the one chosen.

The updating of these confidence values is performed by running the two options and saving the answer proposed by each one. Later, after the bid is chosen as the agent's action for the actual market, this method analyzes the market values and checks which of the outputs proposed by each method would have led to the best results.

This procedure is similar to the one used for updating the values of the players' profile definition methodology, by comparing the values proposed by each of the algorithms used for forecasting with the actual actions the each player performed in the market.

The scenario analysis algorithm is implemented in JAVA,[1] for a smoother integration with MASCEM simulator. However, for efficiency issues, the majority of data analysis methods, namely the pattern analysis and history matching algorithms for players' profiles definition, are implemented in LPA Prolog.[2] The neural network was developed in MatLab.[3]

4. Experimental findings

This section presents a case study with two main objectives: (i) understand how to use the proposed approach, by comparing the performance of different parameterizations; (ii) compare the results that can be achieved with the proposed approach and with other reference decision support strategies.

The results are evaluated by comparing the incomes that are achieved in an electricity market simulation, using the different approaches and parameterizations.

4.1. Case study characterization

This case study concerns three simulations undertaken using MASCEM, referring to the same 16 con-

[1] http://www.java.com/.
[2] http://www.lpa.co.uk/.
[3] http://www.mathworks.com/products/matlab.

secutive days, starting from Friday, 15th October, 2010. The data used in this case study has been based on real data extracted from the Iberian market – Iberial Electricity Market – MIBEL [24].

These simulations involve 7 buyers and 5 sellers (3 regular sellers and 2 VPPs). This group of agents was created with the intention of representing the Iberian reality, reduced to a smaller group, containing the essential aspects of different parts of the market, allowing a better individual analysis and study of the interactions and potentiality of each of those actors. This group of agents results from the studies presented in [33].

4.1.1. Simulated agents strategic behavior

For these simulations we will consider different biddings for each agent. Seller 2, which will be our test reference, will use the proposed method with different parameters in each of the three simulations. This allows comparing the performance of this method when using distinct parameterizations and taking conclusions on its suitability and the influence of the different parameters presented in Section 3. This section additionally presents the comparison between the results obtained by each of the three considered parameterizations and the results obtained by using two other strategies which are well established and with verified performance and results, in order to determine in what degree the proposed game theory based strategy is best or worst suited for providing decision support to market players. These strategies are: (i) the AMES strategy [20]; (ii) the SA-QL strategy [32].

The AMES strategy is used by the AMES electricity markets simulator [20] to provide support to the modelled players when bidding in the market. This strategy is based on a study of the efficiency and reliability of the Wholesale Power Market Platform (WPMP), a market design proposed by the U.S. Federal Energy Regulatory Commission for common adoption by all U.S. wholesale power markets [11,12]. The AMES strategy was adapted by the authors of this paper in a previous work [25], to suit it to the purposes of asymmetrical and symmetrical pool markets, such as the Iberian Electricity market – MIBEL [24]. This strategy uses a reinforcement learning algorithm – the Roth-Erev algorithm [17] to choose from a set of the possible actions (or Action Domain) which is based on the companies' production costs analysis. Additionally, the Simulated Annealing heuristic [4] is implemented to accelerate the convergence process.

The SA-QL strategy [32] is similar to the AMES strategy in its fundamentals: the use of a reinforcement learning algorithm to choose the best from a set of possible actions. The differences concern two main aspects: the used reinforcement learning algorithm is the Q-Learning [18] algorithm; and the set of different possible bids to be used by the market negotiating agent is determined by a focus on the most probable points of success (in the area surrounding the expected market price). This strategy also uses the Simulated Annealing heuristic to accelerate the process of convergence.

The other simulated players' bids are defined as follows:

- Buyer 1 – This buyer buys power independently of the market price. The offer price is 18.30 c€/kWh (this value is much higher than average market price).
- Buyer 2 – This buyer bid price varies between two fixed prices, depending on the periods when it really needs to buy, and the ones in which the need is lower. The two variations are 10.00 and 8.00 c€/kWh.
- Buyer 3 – This buyer bid price is fixed at 4.90 c€/kWh.
- Buyer 4 – This buyer bid considers the average prices of the last 4 Wednesdays.
- Buyer 5 – This buyer bid considers the average prices of the last 4 months.
- Buyer 6 – This buyer bid considers the average prices of the last week (considering only business days).
- Buyer 7 – This buyer only buys power if market prices are lower than average market price.
- Seller 1 – This seller needs to sell all the power that he produces. The offer price is 0.00 c€/kWh.
- Seller 3 – This seller bid considers the average prices of the last 4 months with an increment of 0.5 c€/kWh.
- VPP 1 – Includes 4 wind farms and offers a fixed value along the day. The offer price is 3.50 c€/kWh.
- VPP 2 – Includes 1 photovoltaic, 1 co-generation and 1 mini-hydro plants; the offer price is based on the costs of co-generation and the total forecasted production.

4.1.2. Parameterization

The common parameters in all the simulations using the game theory strategy are: the selection of the automatic mechanism for solving the problems of equality among scenarios; for all seller agents the limit price is fixed as 0 c€/kWh, for it does not make sense to bid

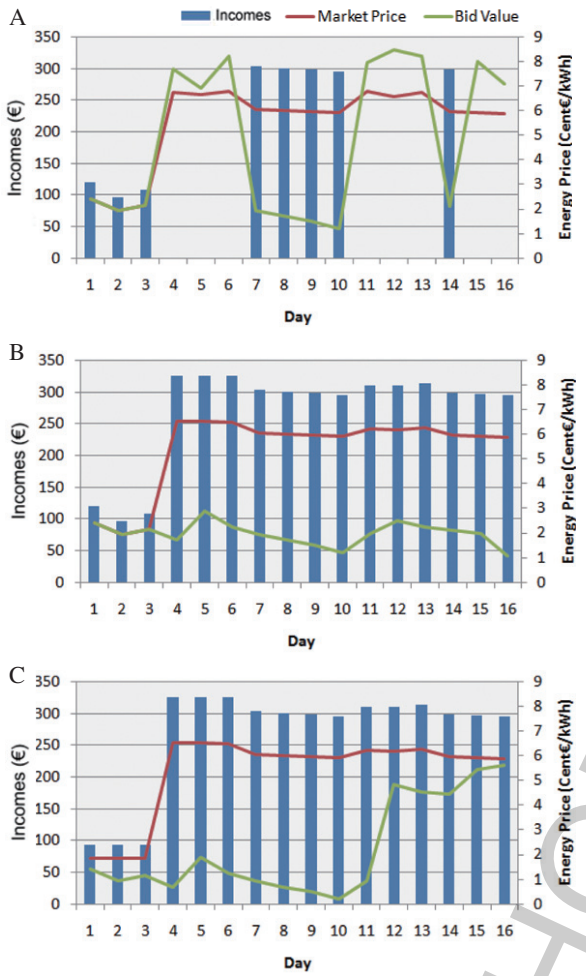

Fig. 3. Incomes obtained by Seller 2 in the first period of the considered 16 days, using: A) the first parameterization, B) the second parameterization, C) the third parameterization. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/ICA-130438)

negative values; for all buyer agents the limit price is 20 c€/kWh, a high value for allowing the players to consider a good margin of prices. Also, the selected reinforcement learning algorithm for the players' profiles definition has been the revised Roth-Erev, with equal value of the algorithms weight. The past experience weight W value is set to 0.4, a small value to grant higher influence to the most recent results, so that it can quickly learn and catch new tendencies in players' actions. For each scenario the scaling factors for competitors' probable price λ and limit price φ, will be equal for every competitor agent, in order to give the same importance to the price forecast of each agent. These scaling factors will only vary from scenario to scenario, but always maintaining the equality among agents.

The variations introduced in each simulation are as follows.

In the first simulation Seller 2 will use the scenario analysis method with a small number of considered scenarios and possible bids. This test will allow us to perceive if a restrict group of scenarios, and consequent advantage in processing speed, will be reflected on a big difference in the results quality. For this simulation the number of considered scenarios is 3, the number of considered bids is 5, and the interval for the possible bids definition is 8. Considering the 3 scenarios, the first will attribute to all agents $\lambda = 1$ and $\varphi = 0$; the second $\lambda = 0{,}95$ and $\varphi = 0{,}05$; and the third $\lambda = 0{,}9$ and $\varphi = 0{,}1$. These values give higher importance to the most probable prices, in order to consider the most realistic scenarios.

In the second simulation Seller 2 will use the scenario analysis method with an intermediate number of considered scenarios and possible bids. The number of considered scenarios is 5, the number of considered bids is 7, and the interval for the possible bids definition is 8. Considering the 5 scenarios, the first will attribute to all agents $\lambda = 1$ and $\varphi = 0$; the second $\lambda = 0{,}95$ and $\varphi = 0{,}05$; the third $\lambda = 0{,}9$ and $\varphi = 0{,}1$; the fourth $\lambda = 0{,}8$ and $\varphi = 0{,}2$; and the fifth $\lambda = 0{,}7$ and $\varphi = 0{,}3$.

Finally, in the third simulation Seller 2 will use the method with a higher number of considered scenarios and possible bids, in order to obtain a more detailed analysis. The number of considered scenarios is 7, the number of considered bids is 10, and the interval for the possible bids definition is 10, granting also a bigger interval for considered bids. Considering the 7 scenarios, the first will attribute to all agents $\lambda = 1$ and $\varphi = 0$; the second $\lambda = 0{,}95$ and $\varphi = 0{,}05$; the third $\lambda = 0{,}9$ and $\varphi = 0{,}1$; the fourth $\lambda = 0{,}8$ and $\varphi = 0{,}2$; the fifth $\lambda = 0{,}7$ and $\varphi = 0{,}3$; the sixth $\lambda = 0{,}5$ and $\varphi = 0{,}5$; and the seventh $\lambda = 0{,}2$ and $\varphi = 0{,}8$.

After the simulations, the incomes obtained by Seller 2 using the proposed method with each of the three combinations of parameters can be compared. This agent's power production to be negotiated in the market will remain constant at 50 MW for each period throughout the simulations. Regarding the costs of all players, they are defined as null, for facilitating the comparison of the results.

4.2. Results

Since the reinforcement learning algorithm for the players' profiles definition treats each period of the day

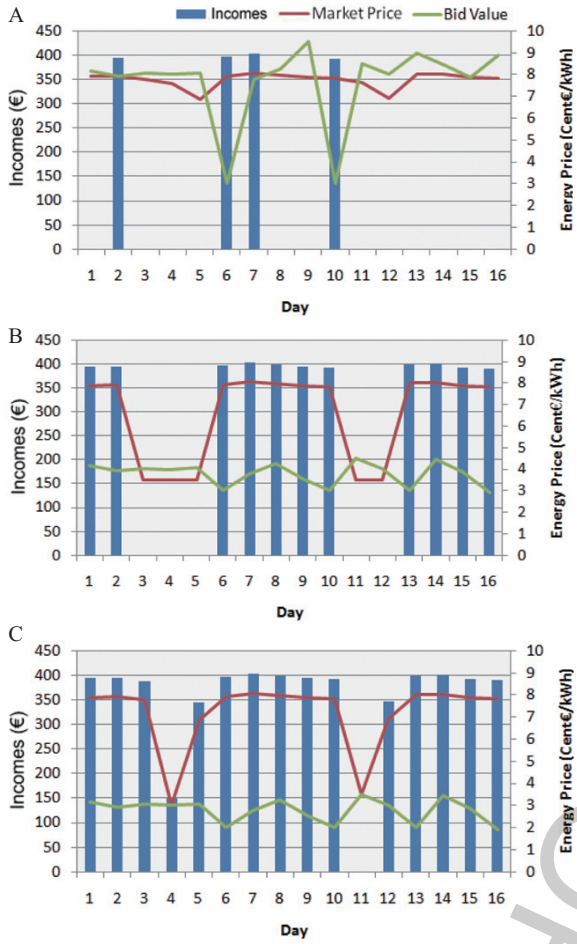

Fig. 4. Incomes obtained by Seller 2 in the twelfth period of the considered 16 days, using: A) the first parameterization, B) the second parameterization, C) the third parameterization. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/ICA-130438)

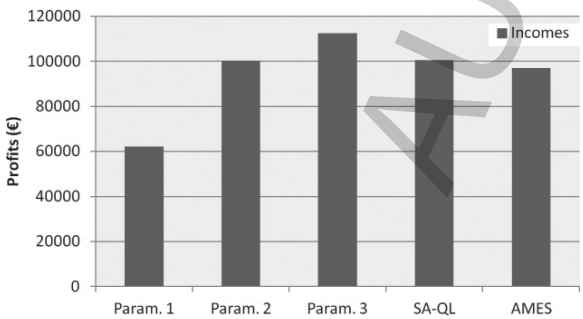

Fig. 5. Total incomes obtained by Seller 2 for the considered 16 days.

as a distinct case, the analysis of the development of the performance must be done for each period individually. Figure 3 presents the evolution of Seller 2 incomes in the first period of each considered day, along the 16 days, using each of the three considered combinations of parameters.

Figure 4 Presents the results of Seller 2 in the twelfth period of each considered day.

Figure 5 presents the comparison between the three parameterizations of the game theory strategy and the other two strategies' performance: The AMES strategy, and the SA-QL.

4.3. Discussion of the results

Comparing the graphs presented in Fig. 3, it can be concluded that the first simulation was clearly the most disadvantageous for Seller 2 for this period. The second and third simulations present very similar results in what concerns the incomes obtained by this agent in the first period.

The results of the twelfth period (Fig. 4) show the first parameterization worst results when compared with the other two. However, in this case, the third parameterization clearly obtained better results than the second one. The global results for all periods of the considered 16 days, presented in Fig. 5, support this tendency.

From Fig. 5 it is visible that the first parameterization presents a large difference from the other two, and a smaller difference between the results achieved by the second and third parameterizations can be clearly seen. The comparison of the different parameterizations' performances allows taking an important conclusion: when it is required for the simulations to improve the processing times, a criterious reduction of the search space may not represent a significant decrease of the method's effectiveness. As proven by simulation 2, which even though considering fewer scenarios and possible bids than the parameterization of simulation 3, its results were still acceptable for situations for which the method's processing time is crucial.

Regarding the comparison between the use of the game theory strategy and the other two comparing strategies, it is visible that the first parameterization of the proposed strategy achieves lower results than the two reference strategies. This was expected and it is easily justified by the low number of scenarios and possible bids that this parameterization concerned. The second parameterization achieves very similar results to the ones obtained by the two reference strategies. This means that, even using an intermediate number of scenarios and bids, the proposed game theory strategy is capable of achieving levels of performance that are

similar to the results of reference and well established strategies. In what concerns to the third parameterization, it is capable of achieving best results than any of the other strategies, for the considered days. This is a motivating result, suggesting that the proposed method is able to provide better results to a market negotiating player's actions, when the parameters are suitably defined.

5. Conclusions and future work

This paper proposed a computational model for bid definition in electricity markets. The proposed model comprises the definition of markets scenarios, concerning different perspectives and the electricity markets evolution; other players profiles definitions, based on the analysis of the gathered information through prediction algorithms; the establishment of a set of possible actions taking into account each current context and the adaptation of the game theory concept to the electricity market negotiation environment, intended for supporting one specific agent and not for achieving the equilibrium in the market. The proposed method was integrated in MASCEM, an electricity market simulator developed by the authors' research centre.

The model proves to be adequate for providing decision support to electricity markets players, allowing an analysis of different scenarios, taking into account the predictions of competitor players' actions.

The results presented in the experimental findings section show that it can achieve good results when using suitable parameterizations, as in simulation 3. These good results are also shown not to be directly proportional to the scenarios search space, which is a relevant aspect when dealing with timely exigent simulations. This conclusion facilitates the adaptability of the decision making process regarding the method's efficiency and effectiveness.

Additionally, when comparing the results of the proposed game theory strategy with the performance of two other well documented and reference strategies, it was found that this strategy is capable of achieving best results when the parameters are defined correctly. In fact, even when opting by a faster but less broad approach (parameterization with less considered scenarios and a smaller action domain), the game theory strategy was still able to achieve results in the same range as the reference strategies.

Considering the improvement of this method, further work will be done in what concerns a detailed analysis in the neighborhood of the scenario selected by the algorithm. To achieve this, an evolutionary approach will be included and combined with the game theory.

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Adaptive learning in agents behaviour: A framework for electricity markets simulation

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Abstract. Electricity markets are complex environments, involving a large number of different entities, playing in a dynamic scene to obtain the best advantages and profits. MASCEM (Multi-Agent System for Competitive Electricity Markets) is a multi-agent electricity market simulator that models market players and simulates their operation in the market. Market players are entities with specific characteristics and objectives, making their decisions and interacting with other players. This paper presents a methodology to provide decision support to electricity market negotiating players. This model allows integrating different strategic approaches for electricity market negotiations, and choosing the most appropriate one at each time, for each different negotiation context. This methodology is integrated in ALBidS (Adaptive Learning strategic Bidding System) – a multiagent system that provides decision support to MASCEM's negotiating agents so that they can properly achieve their goals. ALBidS uses artificial intelligence methodologies and data analysis algorithms to provide effective adaptive learning capabilities to such negotiating entities. The main contribution is provided by a methodology that combines several distinct strategies to build actions proposals, so that the best can be chosen at each time, depending on the context and simulation circumstances. The choosing process includes reinforcement learning algorithms, a mechanism for negotiating contexts analysis, a mechanism for the management of the efficiency/effectiveness balance of the system, and a mechanism for competitor players' profiles definition.

Keywords: Adaptive learning, artificial intelligence, electricity markets, machine learning, multiagent simulation

1. Introduction

Electricity markets are complex environments with very particular characteristics. A critical issue regarding these specific characteristics concerns the constant changes they are subject to. This is a result of the electricity markets' restructuring, which was performed so that the competitiveness could be increased and consequently instigate a decrease in electricity prices, however, it also had exponential implications in the increase of the complexity and unpredictability in these markets scope [35].

The constant growth in markets unpredictability resulted in an amplified need for market intervenient entities in foreseeing market behavior. The need for understanding the market mechanisms and how the involved players' interaction affects the outcomes of the markets, contributed to the growth of usage of simulation tools [7,57]. Multi-agent based software is particularly well fitted to analyze dynamic and adaptive systems with complex interactions among its constituents, such as electricity markets [20,23,55].

This paper presents a model that allows integrating different strategic approaches for electricity market negotiations, and choosing the most appropriate one at each time, depending on the past performance that each strategic approach has presented for each different negotiation context. This adaptive learning methodology is the core of ALBidS – Adaptive Learning strategic Bidding System, a multiagent system that has been created to provide decision support to market negotiating players. This system is integrated with an electricity markets simulator – MASCEM (Multi-Agent Simula-

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tor of Competitive Electricity Markets) [43,48], so that ALBidS' benefit in supporting market players' actions can be tested and validates using realistic scenarios, based on real markets' data.

The main contribution brought by ALBidS is the integration and combination of several different methodologies based on very distinct approaches (artificial intelligence approaches [58], data mining techniques [19], forecasting algorithms [1,3,59], among many others [2,26,34]), in order to provide alternative suggestions of which are the best actions for the supported player to perform. The approach chosen as the market players' actual action is selected by the employment of reinforcement learning algorithms [27], which, for each different situation, simulation circumstances and context, decide which proposed action is the one with higher possibility of achieving the most success. The evaluation of the results has to be done by comparing the profits that the supported market player is able to achieve when participating in the electricity market.

Some of the considered approaches are supported by a mechanism that defines profiles of competitor players. These profiles are built accordingly to the observed past actions and reactions of competitor players, when faced with specific situations, such as success, failure, or acting in different negotiation contexts.

The system's context awareness is provided by a context analysis mechanism, which analyses the characteristics and particularities of the negotiation environment in each moment, and defines different contexts, under which the circumstances are similar.

ALBidS is also equipped with adaptation and learning capabilities in what concerns the balance between results performance and execution time. Considering each comprised algorithm's quality of results, and the time taken to achieve such results, a fuzzy logic [53] process is used to determine in what amount each strategy should reduce its execution time, by adapting itself internally, or if any is taking too long to provide not so good results, and so, be excluded from the decision making process. This process makes sure that the decision making process does not take longer than absolutely necessary, depending on the time requirements of each situation.

After this introductory section, Section 2 provides a brief review of the state of the art regarding the related work. Section 3 presents the proposed methodology of ALBidS, and Section 4 demonstrates the advantage of using the strategies' combination provided by ALBidS, by comparing the performance of this system with the performance of two individual bidding strategies. Finally, Section 5 discusses the most relevant conclusions and future work.

2. Related work

The optimal bidding strategies' problematic has been the focus of a wide range of research works during the last years. Most of these works address the problem from the producers' perspective, as can be seen by [16], which provides a rather complete survey on this subject. The first approaches in this field address the problem using game theory and operational research techniques. The authors in [60] have presented a market participation strategic approach based on the application of the Q-Learning reinforcement learning algorithm.

The evolution of appropriate bidding strategies for each current market conditions, using genetic algorithms (GA) is proposed in [52]. Heuristic optimization, as well as other artificial intelligence based methods, has been increasingly used during the last years to deal with the problem of electricity market players' strategic behavior. This type of approach allows considering a larger number of involved players in larger time horizons, as well as considering the need for players' strategies dynamism through evolution over time; thus making it possible to represent a more realistic modeling of the problem.

Bid prices and quantities in a competitive electricity market context are determined in [65] using two algorithms based on particle swarm optimization (PSO). Probabilistic estimation is used to model opponents' bidding behavior. The experimental findings show that for nonlinear cost functions, PSO solutions provide higher expected profits than marginal cost-based bidding. This allows following the frequently changing conditions in the successive trading sessions of a real electricity market.

Fuzzy adaptive particle swarm optimization (FAPSO) is used in [8] to determine the optimal bidding strategy for a thermal generator for each trading period in a day-ahead market. The inertia weight of the PSO algorithm is dynamically adjusted by a fuzzy evaluation. Methods for supporting players' portfolio decisions using PSO and GA, are respectively presented in [5,6,18].

Electricity market price forecasting is essential to support market players in their decisions, enabling adequate risk management. This is, however, a rather difficult task, as electricity prices are dependent from a wide set of factors and evidence unusually high spikes even when compared to other commodities markets, mainly due to the electric energy non-storability in large quantities [61]. Due to their capacity to perform

almost every complex function [12,29], artificial neural networks (ANN) have been extensively used in price forecast, e.g. the authors in [54] use a combination of ANN and fuzzy logic. A method to forecast day-ahead electricity prices based on Self-Organizing Map (SOM) ANN and Support Vector Machine (SVM) models is presented in [64]. SOM is used to automatically cluster the data according to their similarity and SVM models for regression are built on the categories clustered by SOM separately. Parameters of the SVM models are chosen by a PSO based algorithm. A hybrid method based on wavelet transform, Auto-Regressive Integrated Moving Average (ARIMA) models and Radial Basis Function Neural Networks (RBFN) to forecast day-ahead market price is presented in [39]. This method uses PSO to optimize the network structure which adapts the RBFN to the specified training set, reducing computation complexity and avoiding overfitting. A SVM based approach is proposed in [4] to forecast the electricity market price for hourly negotiating periods of the following day. A test period of three years is used in the presented case study, concerning the market price of the Ontario electricity market.

The large range of developed decision support models reaches its highest peak of utility when combined appropriately. For this reason, several modeling and simulation tools have been developed during the last years, facilitating the integration of different models that can fruitfully come in aid of professionals that are involved in the electricity market sector [24,38].

Multiagent technology is being increasingly used to represent, model and simulate complex and dynamic environments [15,31,36]. The possibility of representing different entities as independent software agents with their own particular behavior and objectives; and the opportunity for easily enlarging the represented models, are some of the main reasons why multiagent technology is widely chosen as the best option for developing complex simulation tools for constantly evolving environments such as the electricity markets.

Among the most relevant multiagent based simulators of electricity markets the following can be referred: EMCAS (Electricity Market Complex Adaptive System) [31]; AMES (Agent-based Modeling of Electricity Systems) [33]; GAPEX (Genoa Artificial Power Exchange) [15], and MASCEM (Multi-Agent Simulator for Competitive Electricity Markets) [48,62].

However, some other simulators that are not based on a multiagent architecture also present a special relevance: SEPIA (Simulator for Electric Power Industry Agents) [24]; Power Web [67]; and SREMS (Short – Medium run Electricity Market Simulator) [38].

MASCEM (Multi-Agent Simulator for Competitive Electricity Markets) [48,62] has been firstly introduced to the scientific community in 2003 [48]. MASCEM is able to recreate a high diversity of market clearing models, based on the mechanisms used in different countries all around the world. Negotiating players in MASCEM use several decision support strategies to pursue the best possible outcomes from the market participation. The application of game theory has been proposed in [42]; a methodology based on the Q-Learning reinforcement learning algorithm, which uses the Simulated Annealing meta-heuristic to accelerate the convergence process is presented in [45]; and the application of the metalearning concept has been approached in [44].

Substantial work has already been done in the field of decision support to electricity market participating players. A reference platform for comparing the performance of different strategies is PowerTAC (Power Trading Agent Competition) [47]. PowerTAC provides a simulation server where different approaches can compete with each other. As referred in this section, many strategic approaches that aim to provide decision support to market players have been developed. However, none of the proposed biding strategies has shown to be clearly better than the other. Case studies show that different strategies perform better in distinct environments and contexts. This is the reason why the work that is proposed in this paper is essential, as it provides an intelligent, adaptive, and dynamic methodology for combining a high number of different market biding strategies, from different natures and perspectives, enabling the advantageous use of each of these strategies whenever they show to be more adequate and present the higher chance for success for the supported player.

3. ALBidS

Electricity market players require strategies capable of dealing with the constant market changes, allowing adaptation to the competitors' actions and reactions, in order to achieve competitive advantage in the market negotiations. For that, adequate forecast techniques are necessary to analyze the market data, namely the historic market prices. The way prices are predicted can be approached in several ways, namely through the use of statistical methods, data mining techniques [19], artificial neural networks (ANN) [1,3,59], support vector machines (SVM) [32], or several other methods [14, 17,25]. There is no method that can be said to be the

best for every situation, only the best for one or other particular case.

To take advantage of the best characteristics of each technique, a new system that integrates several distinct technologies and approaches has been proposed. The ALBidS decision support system is implemented as a multiagent system, and its goal is to provide decision support to an electricity market player. Although several players can use it at the same time; in this case a different instance of ALBidS is created for each different player. There is one agent performing each distinct algorithm, detaining the exclusive knowledge of its execution, this way the system can be executing all the algorithms in parallel, preventing as possible the degradation of the method's efficiency. As each agent gets its answer, resulting from its individual strategy, it sends this result to the Main Agent, which is responsible for choosing the most appropriate answer among all that it receives. This way, strategic approaches can be seen as tools that are available to the main system, and that can be used, or adapted, depending on the circumstances and the negotiation context at each time.

Strategy agents are implemented using the *factory* and *interface* software patterns [21]. These patterns allow all the different strategies to present a single interface to the Main Agent, which highly facilitates the process of launching a new agent, and also the integration of further strategy agents. The creation, initialization, responses, and update, of all strategies follow the same interaction format, through the same interface. I.e. the requests, responses, and interactions are the same between the Main Agent and all the strategy agents; only the values and parameters differ, depending on what the strategy of each agent requires. This way, in order to include a new strategy, it is only required to respect this interface (containing the format of the interactions for the creation, initialization, responses, and update processes), and the new strategy is automatically recognized by the whole system. ALBidS' conceptual model is presented in Fig. 1.

From Fig. 1 it is visible how the different modules and methodologies that are part of ALBidS interact. The different strategies/methodologies for market actions' definition are executed, using their own independent inputs. These methodologies are adapted in order to cope with the requirements from the Efficiency/Effectiveness (2E) balance mechanism. These adaptations refer to the reduction of each strategies' execution time, or even the exclusion of some, in case of the need being more demanding. The outputs of each methodology (action proposals for the supported

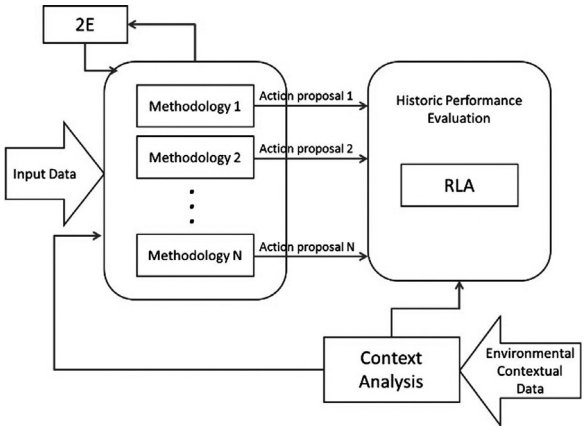

Fig. 1. ALBidS conceptual design.

market player to perform in the electricity market) are sent to the Main Agent. The Main Agent evaluates the historic performance of each strategy when acting in each different context (defined by the context analysis mechanism), and chooses the action suggestion of the strategy that shows the best confidence for being the most successful one. The choosing process is performed using Reinforcement Learning Algorithms (RLA).

ALBidS is connected to the MASCEM electricity markets simulator [43,48], providing decision support to players negotiating in this environment. This integration also provides the means for ALBidS' performance to be tested in realistic simulation scenarios. MASCEM is equipped with a data-extraction tool [49] that gathers real electricity markets data from the websites of several market operators, and feeds a realistic scenarios generator [56], which allow MASCEM simulation scenarios to be as representative of the reality as possible. This way, the performance of ALBidS when supporting decisions of market players can be extrapolated to the reality, being possible to analyze the impact of the decisions in a real environment.

3.1. Main agent

The Main Agent interfaces the MASCEM and ALBidS systems. It receives requests from the market negotiating players of MASCEM when they require decision support, and provides them the corresponding answers. These answers are achieved after managing the ALBidS internal mechanism, including the interactions with the strategy agents – the agents responsible for executing the different strategies.

The choice of the most appropriate strategy to be used at each moment is based on the application of

reinforcement learning algorithms [27]. The approach that presents the best results for a given context of the current scenario is chosen as the final response. So, given as many answers to each problem as there are algorithms, the reinforcement learning algorithm will choose the one that is most likely to present the best answer according to the past experience of the responses and to the present characteristics of each situation, such as the considered day, the period, and the particular market context that the algorithms are being asked to forecast.

The main reinforcement algorithm presents a distinct set of statistics for each context, which means that an algorithm that may be presenting good results for a certain period, with its output chosen more often when bidding for this context, may possibly never be chosen as the answer for another period, since they are completely independent from each other. The tendencies observed when looking at the historic of negotiation periods independently from each other show that they vary much from each other, what suggests that distinct algorithms can present distinct levels of results when dealing with such different tendencies, dependant on the context.

The way the statistics are updated, and consequently the best answer chosen, can be defined by the user. ALBidS provides three reinforcement learning algorithms, all having in common the starting point. All the algorithms start with the same value of confidence, and then according to their particular performance that value will be updated. All algorithms also have the option of being attributed a weight value that defines its importance to the system. This means that a strategy that has a higher weight value will detach faster from the rest in case of either success or failure. The three versions are:

- A simple reinforcement learning algorithm, in which the updating of the values is done through a direct decrement of the confidence value C in the time t, according to the absolute value of the difference between the prediction P and the real value R. The update of the values is expressed by Eq. (1).

$$C_{t+1} = C_t - |(R - P)| \quad (1)$$

- The revised Roth-Erev reinforcement learning algorithm [27] that, besides the features of the previous algorithm, also includes a weight value W for the definition of the importance of past experience, which can be defined by the user. This version is expressed as in Eq. (2).

$$C_{t+1} = C_t \times W - |(R - P)| \times (1 - W) \quad (2)$$

- A learning algorithm based on the Bayes theorem of probability [30,51], in which the updating of the values is done through the propagation of the probability of each algorithm being successful given the facts of its past performance. The expected utility, or expected success of each algorithm is given by Eq. (3), being E the available evidences, A an action with possible outcomes *Oi*, *U(Oi|A)* the utility of each of the outcome states given that action A is taken, *P(Oi|E,A)* the conditional probability distribution over the possible outcome states, given that evidence E is observed and action A taken.

$$EU(A|E) = \sum_i P(O_i|E, A) \times U(O_i|A) \quad (3)$$

3.1.1. Context analysis

Contexts are an important factor in what concerns the adaptation of the approaches to be chosen as the final action to be performed in the market by the supported player. A mechanism to analyze and define different market negotiating contexts is executed by the Main Agent, hence providing the means for the chosen actions to be adapted and chosen depending of the different circumstances that are encountered at each moment.

The context definition process takes into consideration some influential conditionings or characteristics that affect the prices [41], such as:

- The market price for the period and day in matter;
- The amount of transacted power in the market;
- The wind intensity verified in that period of the day (this is important because it affects the production of wind plants, and therefore the total negotiated amount of power);
- The type of the day (whether it is a working day or weekend; if it is a holiday, or a special situation day, e.g. a day of an important event, such as an important game in a certain sport, which affects the energy consumption in that day, both because of the consumption in the stadium, and for increasing the number of people with the TV on to watch it).

The grouping of a day's periods depending on their context is performed through the application of a clustering mechanism. The clustering mechanism analyses the characteristics of each period throughout the days, and attributes each period to the cluster that presents the most similar characteristics. The number of contexts/number of clusters, can be defined by the user. It

is also adapted by the Efficiency/Effectiveness balance management, so that a higher number of contexts is used when the available execution time is higher, and less contexts when the simulations have to be executed faster.

3.1.2. Efficiency/effectiveness balance management

The diversity of algorithms and approaches that are used by ALBidS bring out the need for the development of a mechanism that is able to manage the balance between the Efficiency and Effectiveness (2E) of the system. This mechanism provides the means for the system to adapt its execution time to the purpose of the simulation, i.e., if the expected results from ALBidS are as best as it is able to achieve, or, on the other hand, if the main requirement is for the system to be executed rapidly, since the purpose of the considered simulation is to analyze issues other than player's optimal performance in the electricity market. For that the user can define a percentage value for preference of efficiency or effectiveness of the system. The 2E management mechanism manipulates the strategies both externally and internally. From the system's perspective this mechanism contributes by deciding which tools are used at each moment for each circumstance; depending on their observed performance in terms of efficiency and effectiveness. This way this mechanism can choose to exclude certain strategies when they are not fulfilling the ALBidS' requirements for the case in matter. The strategies chosen to be executed are also manipulated internally, so that they can adapt their individual results quality/execution time balance to the needs of each on-going simulation.

The adaptation process is performed by means of a fuzzy process [53,63,66]. Two dynamic fuzzy variables characterize the efficiency and the effectiveness of each strategy. The characterization is what concerns the efficiency of each strategy comprises the difference between each strategy's execution time, and the reference execution time of the simulation without the use of decision support. This means that the higher the difference is, i.e. the longer a strategy takes to achieve results, when compared to the reference simulation time, a worse classification is attributed to the strategy. Regarding the characterization of the efficiency of each strategy, the quality of the forecasts is analyzed, comparing the forecasted value, and the actual market price that was verified. The confusion matrix that combines the two fuzzy variables, plus the preference value of the user for a faster or better decision support, determines which strategies must be excluded from the system, for taking too long to achieve not so good results, or which must adapt their execution times, reducing them in by a certain amount. The internal adaptation of each strategy concerning the execution time is dependent on the characteristics of each strategy (e.g. a neural network can reduce the training data, to achieve faster, yet worse, results; the game theory strategy can reduce the number of considered scenarios; the optimization based strategies can use heuristic processes rather than deterministic approaches, in order to achieve faster results, even if only near-optimal).

3.2. Strategy agents

A highly dynamic environment such as the electricity market forces players to be equipped with tools that allow them to react to diverse negotiation circumstances. The existence of a variety of different strategies grants ALBidS the capability of always being prepared for the diversity of situations that a market negotiation player can encounter in the market. The very different natures of the considered strategies offer coverage over a diversity of areas, guaranteeing a high probability that is always one strategy suited for each different context, even if its applicability to other contexts is not as advantageous. The considered strategies are:

- Based on statistical approaches:
  - Average market prices of the same weekday for the last month;
  - Average market prices of the last week considering only business days;
  - Average market prices of the last four months;
  - Regression on the market prices of the last four months;
  - Regression on the market prices of the last five business days.

These are simple, yet very fast approaches, which are especially useful for cases when the execution time is critical.

- Dynamic Feed Forward Neural Network (NN) [43,59] trained with the historic market prices, with an input layer of eight units, regarding the prices and powers of the same period of the previous day, and the same week days of the previous three weeks. The intermediate hidden layer has four units and the output has one unit – the predicted market price for the period in question. This NN is retrained in each iteration so that the data observed at each moment is considered for the next forecasts, this way constantly adapting the NN forecasting results [43].

- Adaptation of the AMES bidding strategy. This strategy uses the Roth-Erev [27] reinforcement learning algorithm to choose the best among a set of possible bids that are calculated based on the relation cost/profit that the player presents when producing electricity. The various possible bids differ from each other due to the distinct combination of the input parameters. The most combinations we set, the best chances there are of getting a good result. However, the number of combinations affects the processing time and the number of runs required for a satisfactory convergence. Complete details concerning the methodology of this strategy can be found in [33].
- The Composed Goal Directed strategy is based on two consecutive objectives, the first one may be increasing the profit, and the second one reducing the greenhouse effect emissions. This strategy will try to obtain the highest profit, decreasing the price if in the same period of the previous day the first objective was not completely satisfied, and then try to fulfil the second goal, while maintaining the first satisfied.
- The Adapted Derivative-Following strategy is based on a Derivative Following strategy proposed by Greenwald [22]. The Adapted Derivative-Following strategy adjusts its price by looking at the amount of revenue earned in the same period of the previous day, as a result of that period's price change. If that period's price change produced more revenue per good than the same period of two days before, then the strategy makes a similar change in price. If the previous change produced less revenue per good, then the strategy makes a different price change.
- The Market Price Following strategy, as the name suggests, follows the market price of the same period of the previous day. It is a very simple strategy, but it presents good results when prices show a tendency to stabilize in a certain period, for some consecutive days.
- The SA-QL strategy [45] uses the Simulated Annealing heuristic [9] to accelerate the process of convergence of the Q-Learning [28] algorithm in choosing the most appropriate from a set of different possible bids to be used by the market negotiating agent whose behaviour is being supported by ALBidS.
- The Game Theory strategy is characterized as a scenario analysis algorithm able to support strategic behaviour, based on the application of the game theory [40,42]. This strategy creates several scenarios that represent different possibilities of the reality, concerning competitor players' actions and market environment itself. By analysing these scenarios and the possible actions that the supported player can perform, a decision method applied to choose the best, or the most safe, action to take, given the expected environment.
- The Economic Analysis strategy implements an analysis based on the two most commonly used approaches of forecasting in a company's scope. These approaches are the internal data analysis of the company, and the external, or sectorial, data analysis [46]. These two analyses, plus the risk associated to the player's action, determine the action that should be performed.
- The Determinism Theory strategy executes a strategy based on the principles of the Determinism Theory [10]. This theory states that due to the laws of cause and effect, which apply to the material universe, all future events are predetermined.
- The Error Theory strategy's goal is to analyse the forecasting errors' evolution of a certain forecasting method [50], to try finding patterns in that error sequence and provide a prediction on the next error, which will be used to adequate the initial forecast.
- A Support Vector Machine (SVM) [32] based strategy is used to forecast the electricity market prices, providing results with a similar quality to the NN, but requiring only half of the resources and execution time.
- The Metalearner strategies use the results of the learning process from all the other strategies presented before, as inputs to apply their own learning [44], and therefore create new outputs. ALBidS includes three versions of metalearners:
  - The Simple Metalearner performs a simple ensemble average of the output values of all ALBidS' strategies, to create its output;
  - The Weighted Metalearner includes a methodology in which the way the other strategies' outputs are considered for building the metalearner's output depends on their confidence weight to the Main Agent. This means that the better a strategy is performing, the higher its influence on this method's results will be. This is done through the application of a weighted average of the outputs of all strategies, using their confidence values in each context as weights;

* The ANN based Metalearner uses a dynamic ANN to combine the outputs of the strategies, using their associated confidence values as importance weights;
* The Six Thinking Hats [11] Metalearner performs an adaptation of a strategy for conflict resolution in a meeting environment. The Six Thinking Hats methodology suggests attributing different roles (ways of thinking) for each intervenient, which are then used by a central entity (blue hat) to determine the solution to the problem. The representation of this method in ALBidS is performed by using different strategies as intervenient players, whose actions are combined by applying genetic algorithms [25].

All strategies allow the definition of their particular parameters, or can alternatively be executed with their default inputs (a combination of parameters for each strategy that has achieved good results for different simulations).

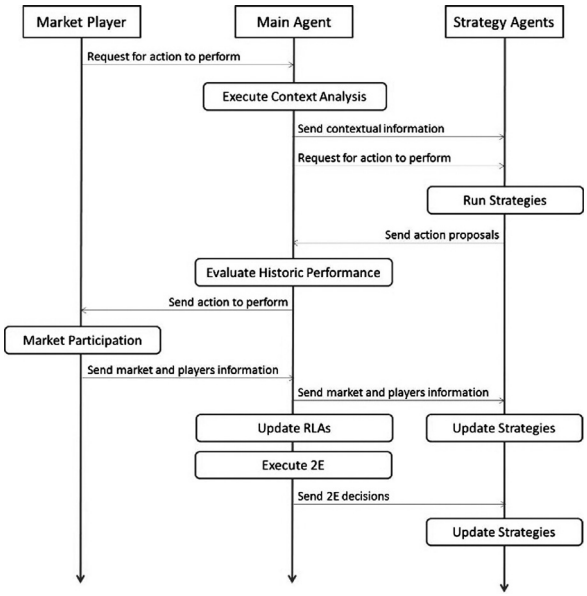

Fig. 2. Interactions between the involved agents.

3.3. Player profile definition

In order to build suitable profiles of competitor agents, it is essential to provide players with strategies capable of dealing with the possible changes in competitors' behavior, allowing adaptation to their actions and reactions. For that, it is necessary to have adequate techniques to analyze the data properly, namely the historic of competitor agents past actions. Analogously to the definition of market operation strategies, the way each agent's bid is predicted can be approached in several ways. So, the way to deal with this issue was to follow the same idea as for the main system's methodology. There are several algorithms for defining the players' profiles, all providing their predictions, and on top of that a reinforcement learning algorithm that chooses the one that is more likely to present the best answer according to the past experience of their responses for each particular market context.

The used reinforcement algorithm is the Roth-Erev algorithm [46]. It presents a distinct set of statistics for each acting agent, for their actions to be predicted independently from each other, and also for each market context. This means that an algorithm that may be presenting good results for a certain agent in a certain context, with its output chosen more often when bidding in this context, may possibly never be chosen as the output for another context or another player.

The update of the stats is done accordingly to the difference between the predictions and the action each player actually performed. The best rewards are attributed to the profile definition algorithms that present the smaller difference. This way, all algorithms' confidence values are updated in every prediction, whether a prediction is chosen as the final answer or not.

The strategies that are used to predict an agent's behavior depend on the efficiency/effectiveness balance which is defined. If the preference is fully attributed to the efficiency of the method, only the faster strategies are used, allowing a huge reduction of the execution time. Otherwise, all strategies are used. However, the NN is adapted for each circumstance. The higher the preference for effectiveness, the bigger the amount of data considered for training the NN. This allows reducing the execution time when required, even if just for a small amount, or increasing the quality of the predictions, when that is the main goal.

Figure 2 presents a sequence diagram, which shows the timings of the interactions between the involved agents, and how these interactions influence the execution of the several methodologies. This figure refers to a single iteration (process for the decision support of a market player in a single participation in the electricity market).

From Fig. 2 it is visible that the decision support process starts with a request from the market participant player, asking for the action it should perform in the market. When the Main Agent receives this request, the context analysis mechanism is executed, and the respective contextual information is sent to each strategy

agent. A request for each Strategy Agent is also sent, so that each provides its action suggestion for the current context.

After receiving the request from the Main Agent, all Strategy Agents execute their respective methodologies, and send their individual action suggestion for the Main Agent. After receiving all proposals from the Strategy Agents, the Main Agent evaluates the historic performance of all strategies in the current context, and chooses the suggestion of the strategy that presents the higher confidence values for the current context as the final proposal for the supported market player. This final action proposal is sent to the market player.

The supported market player participates in the electricity market using the proposed action, and after the market negotiations are terminated, the player sends the feedback to the Main Agent, providing all the information concerning the market environment that it has encountered, including the information regarding the actions of the competitor players that have participated in the same market session. The Main Agent forwards this information to all Strategy Agents, so that they can update their individual strategies according to facts that have been observed in the market. While the Strategy Agents perform the update of their strategies, the Main Agent updates the RLAs, by comparing the suggestions that each Strategy Agent has provided with the actual market development. A new confidence value for each strategy for the current context is stored. The Main Agent also executes the 2E balance management mechanism, using the performance evaluation of each strategy, and the execution time that each Strategy Agent has needed to send its action proposal. The results of the 2E mechanism are sent to the Strategy Agents, and these perform once again their updating process, which, this time, refers to the reduction of the execution time, or to the finalization of the agent, in case its execution time is found to be irremediably high for the quality of results it is originating.

This process is performed once per iteration, i.e. every time the supported market player wishes to participate in the electricity market.

4. Case study

4.1. Market negotiations' specification

The spot or day-ahead market is a daily basis functioning market [36], where players negotiate electric power for each hour, or half hour of the following day. Such markets are structured to consider production fluctuations as well as differences in production costs of distinct units.

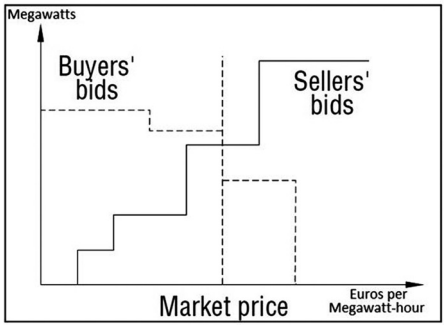

Fig. 3. Symmetric market price establishment.

In this market, each participating entity must present their selling or buying proposals for each of the 24 hourly periods of a day. These proposals or bids are typically composed by a tuple (power, price), with different meanings, whether they come from buyers or sellers, respectively: power stands for amount of power to be bought or sold, and price is the maximum accepted price or minimum selling price.

When the negotiation is finished, an economic dispatch for each period is set by the market operator. At the end of each period the market operator uses a market-clearing tool establishing the market price – a unique price that will be applied to all transactions of this period.

In market pools, the most common type of negotiation is a standard uniform auction. MIBEL day-ahead spot market works as a symmetric market, where both suppliers and consumers submit bids. The market operator orders the selling and demand offers: selling bids start with the lowest price and move up, and demand bids start with the highest price and move down. Then, the proposed bids form the supply and demand step curves, and the point at which both curves intersect determines the market price, paid to all accepted supplier and consumers. The bids of every supplier offering prices lower than the established market price and every consumer offering prices higher than the market price will be accepted. Figure 3 shows the symmetric market prices definition.

The profits can be improved by submitting bids that are advantageous for the player in the bidding process; i.e. for a seller player, a bid price below the established market price, but still as high as possible, in order to assist in increasing the market price (origination of higher profits, through a higher market price). In the

case of a buyer agent, the bid price should be above the established market price, but as low as possible, in order to reduce the cost that is paid for the bought energy.

4.2. Specifications

This section presents the results of a set of simulations undertaken using MASCEM, with the objective of assessing the performance of ALBidS, by comparing its performance to that of all the individual strategies that have been mentioned in this paper.

The metric for comparing the performance of the methods is the profits that each is able to originate for an electricity market participant player – a seller; since the goal of ALBidS and of all strategies is to maximize the profits of a market player. The costs of production are kept constant throughout all hours of all considered days, in order to facilitate the comparison of the achieved profits.

In order to provide a suitable comparison, the same market scenario, with the exact same players, under the same circumstances, is executed repeatedly. The only variation is the behavior of the test subject player, Seller 2. In each simulation Seller 2 uses the decision support of each of the 20 mentioned strategies, and finally of ALBidS, in order to compare the performance of all.

The simulations refer to the same 62 consecutive days (two months), starting from Saturday, 1st December, 2012, until Thursday, 31st January, 2013. The data used in this case study has been based on real data extracted from the Iberian market operator – MIBEL [37], using an automatic data extraction that has been presented in [49].

This scenario was created with the intention of representing the Iberian reality, reduced to a smaller summarized group, containing the essential aspects of different parts of the market, in order to allow a better individual analysis and study of the interactions and potentiality of each of those actors. Further details on the test scenario and on the specifications for this case study can be consulted in [13].

All comparisons are performed for three distinct cases: (i) 100% preference for the effectiveness of the strategies, i.e. all strategies, and consequently ALBidS, perform at their full potential; (ii) 50% preference for effectiveness, i.e. the execution times of the most demanding strategies are reduced, which means a reduction in their quality of results; (iii) 0% preference for the effectiveness, i.e., most of the strategies are excluded from the system, while only the faster to execute are maintained.

For all three cases, the context analysis mechanism receives the input of 4, as the number of alternative contexts to be used, so that it is possible to compare the performance of the strategies when acting in different contexts. For the considered scenario, the four different contexts are easy to understand: separation between business days and weekends plus holidays; and separation from peak and off-peak consumption hours of the day. From the 62 considered days, 42 are business days and 20 are not (9 weekends, which equals 18 days, plus two holidays verified in both countries of MIBEL (Portugal and Spain): 25th December, and 1st January). From the 24 hours of the day, 5 are grouped as peak hours of consumption: from 19 h to 23 h; and the remaining 19 are clustered as off-peak. Therefore, the four different contexts are as follows:

- Context 1: Peak hours of business days (total of 210 periods during the 62 days);
- Context 2: Off-peak hours of business days (total of 798 hourly periods);
- Context 3: Peak hours of non-business days (total of 100 periods);
- Context 4: Off-peak hours of non-business days (total of 380 periods).

Besides the comparison of the profits that each strategy originates in each context, the strategies' confidence weights evolution throughout the time is also compared, as well as the rate each strategy is chosen as the final output of ALBidS. The choice process is undertaken using the Roth-Erev RLA (Eq. (2)), with a weight value W for past events of 0,4; a low value to allow a faster adaptation to new observed events.

4.3. Results for 100% preference for effectiveness

Figure 4 presents the comparison of the confidence weights of the Main Agent on each of the strategies, throughout the simulation time, for each of the four contexts.

From Fig. 4 it is visible that, by starting with the same confidence weights and with no previous learning process, strategies take a number of iterations between a significant separation can be observed. During the first iterations the same strategies have presented higher confidence weights in all contexts: the simpler strategies, with reduced or null learning capabilities, such as the strategies based on averages and regressions, and the simple metalearner. After a few iterations, the SVM starts increasing its confidence values, as this methodology requires a reduced amount

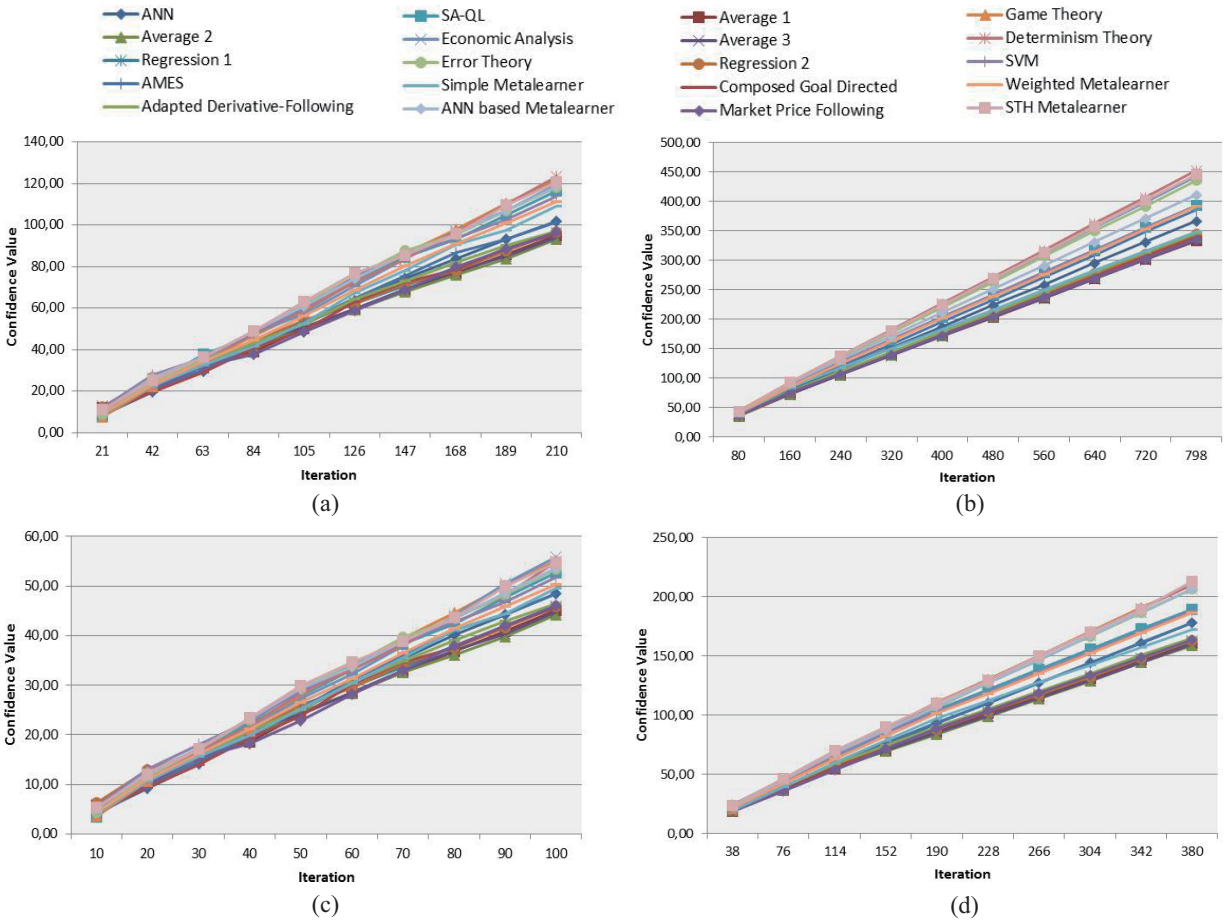

Fig. 4. Confidence weights of each of the strategies in: (a) Context 1, (b) Context 2, (c) Context 3, (d) Context 4.

of training data. As the time progresses, the strategies with more complex learning processes start improving their performance, due to the experience that they start gathering, and their learning process starts becoming more effective. In the final iterations of Context 3, in Fig. 4(c), which maximum number of iterations is 100, it is visible that the more complete strategies start detaching from the simpler ones. This detachment is more evident from Fig. 4(a), in Context 1, which, with its 210 iterations allows the learning process of the most complete strategies to show better performances, therefore increasing their confidence values. From the Contexts with the higher number of iterations, namely Context 2 and Context 4, in Figs 4(b) and (d) respectively, not only is this detachment even more clear, as one can additionally see some intermediate sub-groups, of medium complexity strategies, such as the SA-QL, the ANN-based metalearner, and the AMES strategy. In these contexts the simpler strategies show that their best confidence values during the first iterations are long gone, and they show the worst confidence values in the end. The group of strategies that achieves the higher confidence values in the bigger number of iterations is composed by the Game Theory strategy, the Determinism Theory, The Economic Analysis, and the STH Metalearner.

Figure 5 presents the rate in which each strategy has been chosen by the Main Agent as the final output of ALBidS, in each context.

From Fig. 5 it is visible that the simpler strategies, such as the ones based on averages and regressions of the market prices, have been chosen a number of times in all 4 contexts. They have been chosen during the first iterations, while the other, more complex strategies do not reach an adequate learning maturity which enables them to achieve the most advantage results. The SVM has also been chosen a considerable amount of times in all four contexts (The most evident is in Context 3 – Fig. 5(c), which by presenting a smaller number of iterations, does not provide enough time for the most com-

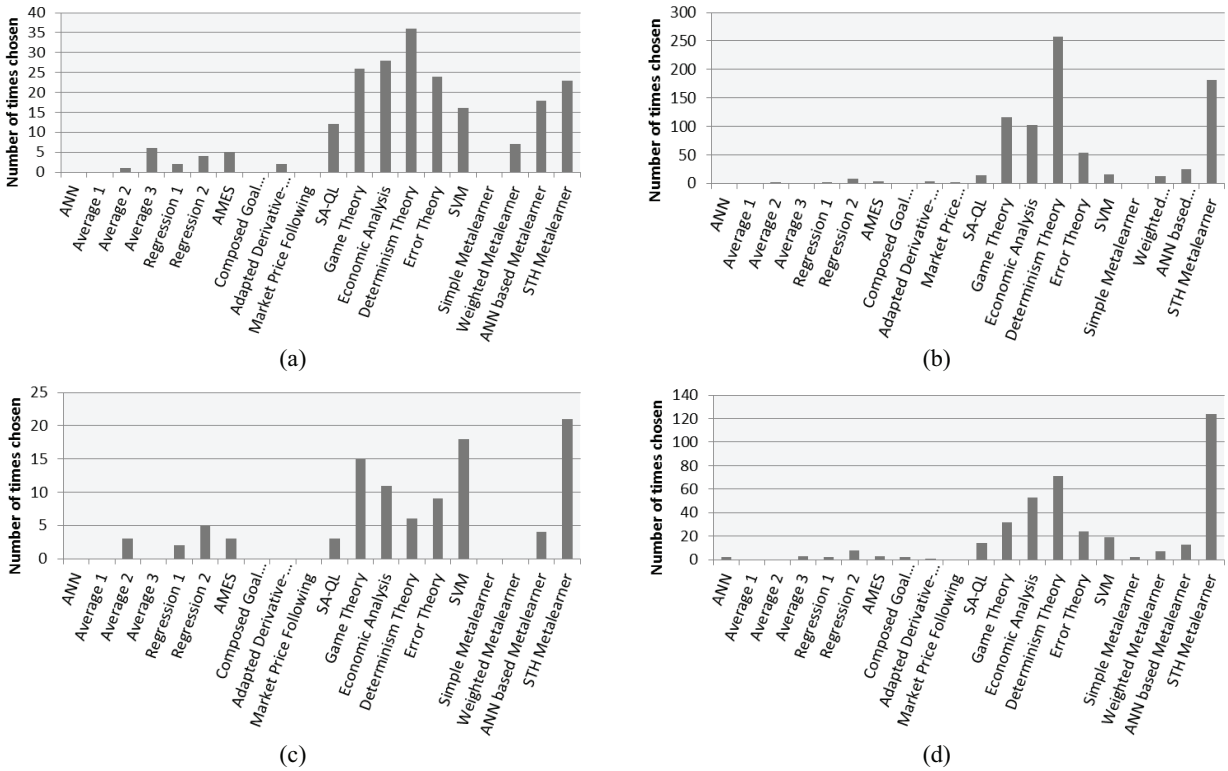

Fig. 5. Strategies choice rate for: (a) Context 1, (b) Context 2, (c) Context 3, (d) Context 4.

plex strategies to evidence themselves, therefore the SVM still manages to end up as the second more chosen strategy). This is due to the low amount of training data that this approach requires, which enables it to achieve good results from an early point. Intermediate complexity strategies such as the SA-QL, AMES, and the Weighted Metalearner, also present some amount of selections. However, it is evident that the strategies with the more complex learning capabilities, such as the Determinism Theory, the STH Metalearner, Game Theory, Economic Analysis, are the ones that end up being chosen more often, mainly in the contexts with the higher number of iterations, due to the best performance that is achieved after the learning process matures.

Figure 6 presents the comparison of the profits that each strategy has provided for the supported market player in the total of the iterations of each context.

From Fig. 6 it is visible that ALBidS is able to achieve higher profits than all strategies, in all four contexts. The difference between ALBidS and the individual strategies is more visible in the contexts with larger number of iterations, namely Context 2 and 4, Figs 6(b) and (d) respectively. The larger number of iterations gives more time for all strategies to refine their independent learning process, and ALBidS benefits from that, as the quality of choices improves. The contexts with the least number of iterations, namely Context 3, Fig. 6(c) represent a more balanced outcome between all strategies, although the difference between the quality of the strategies can still be noticed. Nevertheless, ALBidS is able to achieve higher profits than all. The good response of ALBidS in all contexts is supported by Fig. 7, which shows the total profits that have been achieved by each strategy in the total of the 24 periods of the 62 considered days (total of the four contexts).

From Fig. 7 it is visible that ALBidS has been able to provide higher profits for the supported player than all the other strategies, in the total of the 62 considered days. The simpler strategies show that their capability of outperforming the more complex strategies in the first iterations is not nearly enough to compete with those, as the differences are evident in the total profits. The strategies that show the best performances, and that obtain the higher profits are the Determinism Theory, followed very closely by the STH Metalearner, and by the Game Theory, Economic Analysis, and Error Theory.

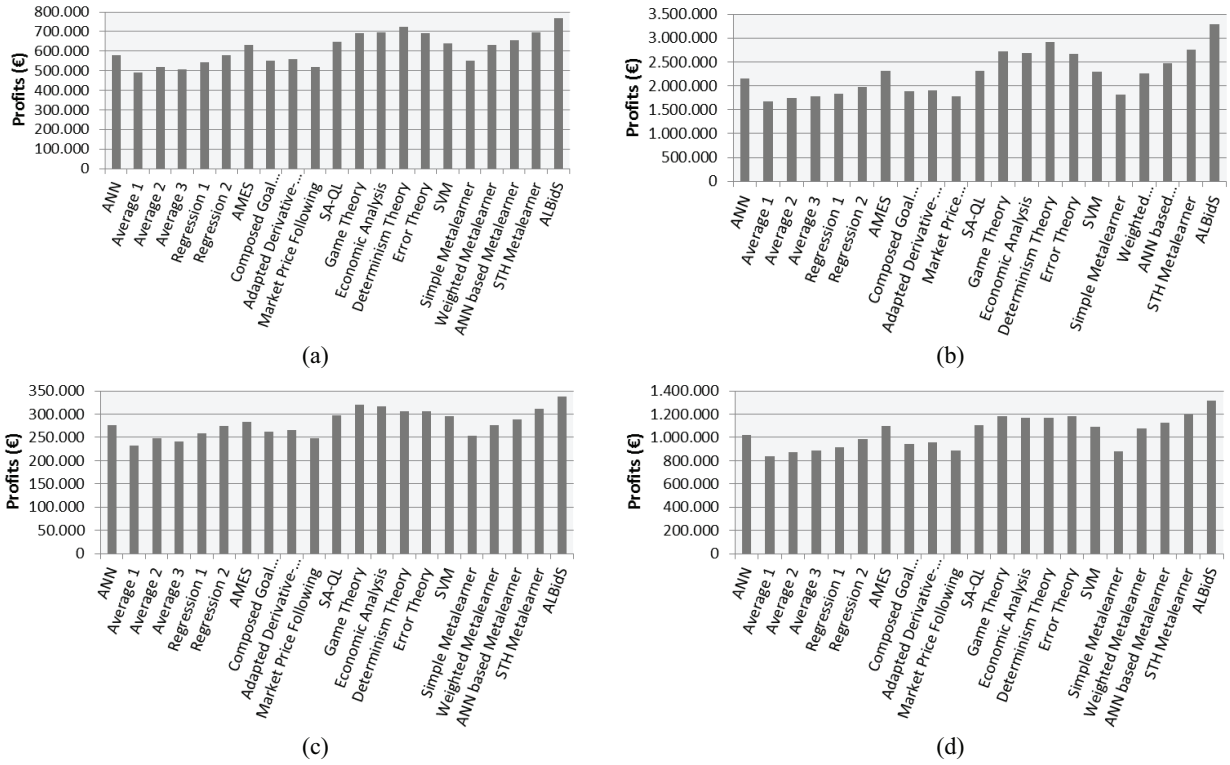

Fig. 6. Profits provided by all strategies, and by ALBidS, in: (a) Context 1, (b) Context 2, (c) Context 3, (d) Context 4.

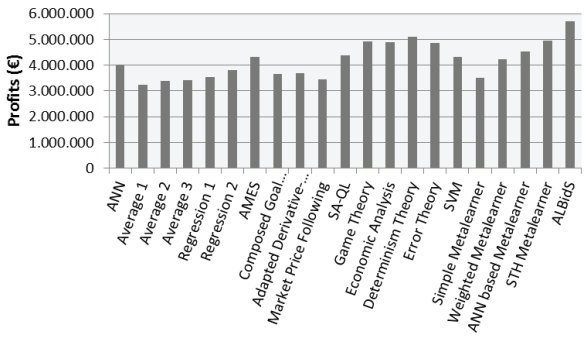

Fig. 7. Profits provided by all strategies, and by ALBidS in the total of the 62 considered days.

4.4. Results for 50% preference for effectiveness

The execution with 50% preference for effectiveness results in the reduction of the execution time of the most time demanding strategies. The ones that suffer the most from this reduction, which is verified by their decrease in quality of results, are the Game Theory strategy, the Determinism Theory, STH Metalearner. From the strategies that have achieved the best results in the case with 100% preference for effectiveness, the one that is required to reduce the execution time by a smaller amount, due to its relatively faster execution time when compared to the other more complex strategies, is the Economic Analysis. Table 1 presents a summary of the results that have been verified in this case.

From Table 1 it is visible that, despite the decrease in execution time, and consequent degradation in execution time, the Determinism Theory strategy has still been able to be the strategy with the higher confidence value and the most chosen strategy in Context 1. In the other contexts, the Economic Analysis has been the strategy that achieves the best results. It is also visible that, while the simpler strategies maintain their performance, the most complex ones, present a decrease in their confidence values, when compared to the case with 100% preference for effectiveness. Figure 8 presents the profits that each strategy, and ALBidS have achieved in this case, in the total of the 62 days, for the four contexts.

From Fig. 8 it is visible that the strategies that presented the best results in the case with 100% preference for effectiveness have decreased their achieved profits. The exception is the Economic Analysis strategy, which is now the strategy that achieves the higher profits. ALBidS is once again able to achieve higher prof-

Table 1
Summary of the case with 50% for effectiveness

	Chosen rate				Final confidence value			
Context	1	2	3	4	1	2	3	4
ANN	0	0	0	2	101.92	367.56	48.44	178.01
Average 1	0	0	0	0	94.98	333.49	45.15	161.10
Average 2	1	2	3	0	93.45	340.48	44.27	159.05
Average 3	6	0	0	3	94.27	333.95	44.74	160.46
Regression 1	2	2	2	2	96.27	339.91	45.92	163.18
Regression 2	4	8	5	8	96.85	343.86	45.88	162.82
AMES	5	4	3	3	101.65	385.64	48.50	177.80
Composed goal directed	0	0	0	2	96.00	339.66	45.62	165.08
Adapted derivative-following	2	3	0	1	97.31	346.03	46.46	164.86
Market price following	0	1	0	0	96.70	335.27	46.02	164.02
SA-QL	22	14	6	14	116.57	393.19	52.70	189.52
Game theory	12	48	8	18	112.26	409.26	50.75	193.49
Economic analysis	36	375	28	168	119.53	443.14	55.91	206.88
Determinism theory	51	102	6	31	121.06	430.19	52.16	199.77
Error theory	24	53	9	24	108.63	400.91	49.24	189.97
SVM	16	26	18	38	113.91	393.21	51.84	187.75
Simple metalearner	0	0	0	0	97.43	340.72	46.95	165.02
Weighted metalearner	7	12	0	7	103.58	363.65	47.80	173.17
ANN based metalearner	6	25	4	13	110.34	383.25	49.91	192.18
STH metalearner	16	123	8	46	112.45	414.25	50.94	198.05

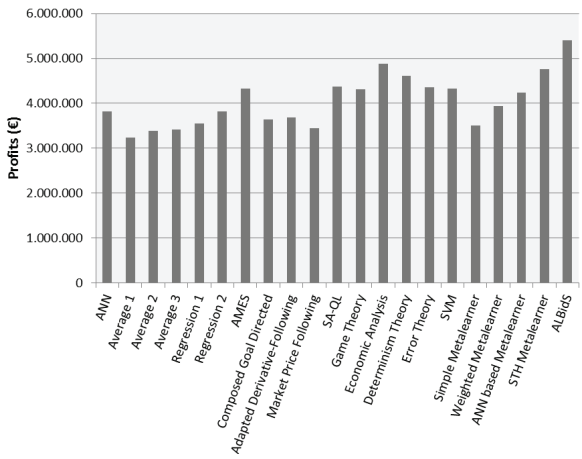

Fig. 8. Profits provided by all strategies, and by ALBidS in the total of the 62 considered days.

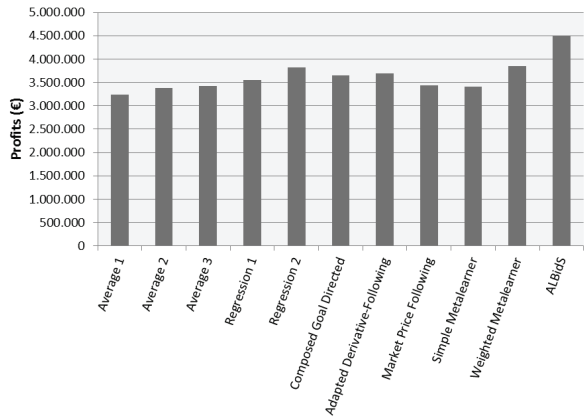

Fig. 9. Profits provided by all strategies, and by ALBidS in the total of the 62 considered days.

its than all strategies, by choosing the most appropriate strategy as the time progresses.

4.5. Results for 0% preference for effectiveness

Using 0% preference for the effectiveness of ALBidS means that all strategies that need more time than the execution time of MASCEM for running the market simulation, are excluded. This results in the utilization of a reduced number of strategies, i.e. only the faster to execute. Table 2 shows the summary of the results for the case with 0% preference for effectiveness.

From Table 2 it is visible that using a reduced number of strategies leads to higher competitiveness between them. The faster response time and minor learning capabilities from the strategies supports this fact. In the first two contexts, the strategy that was chosen more often was the Weighted Metalearner. In Context 3 the most chosen strategy was a regression approach, and in Context 4, the Composed Goal Directed strategy. However, the Weighted Metalearner was the strategy that achieved the best confidence weight in the final of all iterations in all contexts except for one. Note that finishing the simulation with the higher confidence values does not necessarily mean that the strategy is chosen more often than others. It means that it is the

Table 2
Summary of the case with 0% for effectiveness

	Chosen rate				Final confidence value			
Context	1	2	3	4	1	2	3	4
Average 1	0	4	0	6	94.98	333.49	45.15	161.10
Average 2	1	34	8	0	93.45	340.48	44.27	159.05
Average 3	6	8	0	3	94.27	333.95	44.74	160.46
Regression 1	14	29	6	6	96.27	339.91	45.92	163.18
Regression 2	31	82	34	8	96.85	343.86	45.88	162.82
Composed goal directed	36	24	11	195	96.00	339.66	45.62	165.08
Adapted derivative-following	18	286	14	39	97.31	346.03	46.46	164.86
Market price following	11	8	4	6	96.70	335.27	46.02	164.02
Simple metalearner	0	0	0	0	94.99	337.09	44.92	159.49
Weighted metalearner	93	323	23	117	99.25	348.20	46.29	168.55

one being chosen in the final iterations, but it may be chosen much less often during previous iterations where its confidence value was not still as high. Figure 9 presents the comparison of the achieved profits from the used strategies in the case with 0% preference for effectiveness.

From Fig. 9 it is visible that ALBidS has achieved higher profits than all the strategies, even when using a limited number of approaches. The Weighted Metalearner was the strategy that achieved the higher profits, followed by Regression 2.

5. Conclusions

This paper presented a model that enables choosing the most appropriate from a set of decision support strategies. This model takes into account the context in which strategies are being used, and uses reinforcement learning algorithms to update confidence values on each strategy, which facilitate the choice on the best strategy to be applied according to the previous performance that each has shown in each different context.

This methodology is the core of ALBidS, a multiagent system that provides decision support to electricity market negotiating players. ALBidS is integrated with the MASCEM simulator, which provides the means for testing and suiting ALBidS' implemented tools and mechanisms.

ALBidS' design, architecture, and integration with MASCEM proved to be adequately implemented, as showed by tests presented in Section 4. These experimental findings have shown that ALBidS is able to achieve higher profits for the supported market player than all of the implemented strategies. This has been verified for different contexts, and for cases where the used strategies are limited. The demonstration of results for different contexts has also shown that different strategies do, in fact, perform differently under different contexts. Although the best strategies tend to outperform the others in all cases, they still show that the best strategy varies from context to context. The learning capabilities of ALBidS are able to deal with that, showing an highly advantageous means of taking the best of the available assets (strategies) by understanding when and how they perform at their best.

The wide range of approaches that provide action proposals for the Main Agent to choose from (from mathematics to physics, from power systems' applications to artificial intelligence techniques) guarantees that at each moment responses based different views are suggested, offering a high variety of possible actions for the ALBidS system to consider. This provides the means for the system to increase its chances of always be provided with at least one adequate answer, even when the majority of the approaches fail in the accomplishment of its purposes.

This fact is extended to the other mechanisms which complement the system, i.e. the Context Analysis mechanism, the Player Profile Definition mechanism, and the Efficiency/Effectiveness Management mechanism.

Finally, regarding the main entity in the ALBidS system – the Main Agent, it also proved to efficiently accomplish its purposes, showing its ability to choose the most appropriate actions for the supported player to take, by using the reinforcement learning algorithms at its disposal, and taking advantage on the complementary mechanisms that aim to enlarge ALBidS' capabilities of adaptation and providing of intelligent decision support.

Among the many developments that ALBidS creation potentiated, allowing many future works and scientific findings, the continuous improvement of ALBidS considers the complementation of ALBidS with a new mechanism directed to the optimization

of market players' investments in alternative markets. This can be done by analysing the characteristics and particularities of the several existing markets, including complementary markets such as derivatives market. This way, adequate predictions of the expected incomes resulting from the investments in each of those markets can be achieved, depending on each circumstance and context.

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Negotiation context analysis in electricity markets

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ABSTRACT

Contextualization is critical in every decision making process. Adequate responses to problems depend not only on the variables with direct influence on the outcomes, but also on a correct contextualization of the problem regarding the surrounding environment. Electricity markets are dynamic environments with increasing complexity, potentiated by the last decades' restructuring process. Dealing with the growing complexity and competitiveness in this sector brought the need for using decision support tools. A solid example is MASCEM (Multi-Agent Simulator of Competitive Electricity Markets), whose players' decisions are supported by another multiagent system – ALBidS (Adaptive Learning strategic Bidding System). ALBidS uses artificial intelligence techniques to endow market players with adaptive learning capabilities that allow them to achieve the best possible results in market negotiations. This paper studies the influence of context awareness in the decision making process of agents acting in electricity markets. A context analysis mechanism is proposed, considering important characteristics of each negotiation period, so that negotiating agents can adapt their acting strategies to different contexts. The main conclusion is that context-dependant responses improve the decision making process. Suiting actions to different contexts allows adapting the behaviour of negotiating entities to different circumstances, resulting in profitable outcomes.

1. Introduction

The EM (electricity markets) restructuring has been changing the EM paradigm over the last two decades. The privatization of previously state owned companies, the deregulation of privately owned systems, and the internationalization of companies, are some examples of the transformations that have been applied [1]. Nowadays EM operate in more complex and reliable models. However, EM are still restricted to the participation of large players. Thus, the increased use of DG (distributed generation), mainly based on RES (renewable energy sources) of intermittent nature, hardly contributes to the efficiency of the system. Moreover, they are still supported by governmental stimulus [2].

The reduction of fossil fuels' environmental impact, risk and high prices, potentiates the investment of the power industry in renewable based power generation and EM organization. These two key fronts of investment have the additional objective of making the sector more efficient through competitiveness [3]. Despite the favourable scenario for DG growth, there are important aspects to consider of both economic and technical nature. To take advantage of an intensive use of DG, issues such as the dispatch ability, the participation of small producers in the markets and the high cost of maintenance must be solved [2,3].

The problem of DG growth and integration into EM is being addressed by a wide range of different approaches all around the world; however, during the last years some common solutions are globally being adopted. EM are evolving to RM (regional markets) and some to continental scale, supporting transactions of huge amounts of electrical energy and enabling the efficient use of renewable based generation in places where it exceeds the local needs. A reference case of this evolution is the European EM. The majority of European countries have joined together into common market operators, resulting in joint regional EM composed of several countries. The types of markets in which players can participate differs in each region, under each operator, however, the market mechanisms are evolving towards a uniform architecture, in order to accommodate a Continental level EM – the Pan-European EM [4].

Since February 2006, seven regional markets were launched: Central-West (EPEXSPOT [5]), Northern (Nord Pool [6]), UK and

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Ireland, Central-South (GME [7]), South-West (Iberian Market Operator - MIBEL [8]), Central East and Baltic. The merging process between these operators is the ultimate goal, and is currently being prepared [4]. The transformation of National EM into Regional and Continental EM is evidenced by other examples, such as the U.S. EM [9–11], and the Brazilian EM [12]. These markets, although not representing a Continent as a whole, can be considered as Continental EM due to these countries' size. The management and operation of these markets is an important example for the emerging ones. EM put a new emphasis on the economic dimension of the problem. However, the basic infrastructure, namely the power system network has a real physical nature, with specific limitations [5–12]. The introduction of EM has shown the fragility of power systems infrastructures to operate in a competitive context. Several severe incidents, including blackouts, occurred (e.g. the 14th August 2003 Blackout in the US, and the 4th October 2006 quasi-blackout affecting nine European countries and some African nations as well).

A globally adopted solution is approaching the electricity network as a series of subsystems [13], giving birth to the concept of microgrid [14,15]. Experimental implementations of microgrids are arising all around the world [14,16], considering the management of local generation, loads, and storage systems, as independent from the main system, although connected with the main grid through a connection bus, or even working as an isolated system (in islanded mode). The intelligent management of these smaller electricity grids has been evolving and potentiating the implementation of SG (Smart Grids) as an upcoming reality [13,16,17]. There are several approaches regarding SG management and practical implementations [14–17], and the results are promising, ensuring that it is just a matter of time until this reality is implemented in a global scale as a core part of the electrical grids all around the world.

Due to the constant evolution of the EM environment, and the change in the operation and participation in EM, it becomes essential for professionals in the area to completely understand the markets' principles, and how to evaluate their investments in such a competitive environment. The usage of simulation tools, with the purpose of taking the best possible results out of each market context for each participating entity, has grown with the need for understanding those mechanisms and how the involved players' interaction affects the outcomes of the markets. To analyse complex interactions in dynamic and adaptive systems, multi-agent based systems are particularly well suitable. AMES (Agent-based Modelling of Electricity Systems) [18], EMCAS (Electricity Market Complex Adaptive System) [19], and MASCEM (Multi-Agent Simulator of Competitive Electricity Markets) [20–24] are examples of some of the relevant tools that have emerged to study restructured wholesale power markets.

EM simulators must be able to cope with the dynamic reality of the rapid evolution of EM and adapt to the new models and rules of the market, in order to provide players adequate tools to adapt themselves to the changing environment. This brings an increasing need to consider the concept of context awareness. Taking into account the influence that the characteristics of each negotiation moment has on the negotiation process itself, players can adapt their actions in order to best fulfil their needs.

This paper proposes a new context analysis mechanism, with the aim of providing adaptive capabilities to decision support systems directed to the enhancement of EM negotiating players. The proposed context analysis mechanism considers several relevant factors that influence players' negotiation environment. The correct understanding of each market characteristics [5–12], such as the negotiation mechanisms; the usual market prices that are practiced in each market in different situations; the influence of different players' participation in the negotiation process; the external environmental factors, such as wind surplus or shortage [25,26]; and the perception regarding different types of days, which lead to different market negotiating results, e.g. the difference between business days and weekends; are variables that have huge importance for players to be able to adapt their actions. Hence, the proposed methodology has the goal of analysing the negotiation context in order to distinguish days and periods with similar characteristics, so that market participation strategies can be adapted and used accordingly to each context; i.e. the proposed methodology is not a market strategy itself, it is rather a model that enables complementing existing market strategies so that their use can be optimized by deciding when and how to employ different market strategies, depending on each different context that each day and period fits in.

After this introductory section, section 2 presents an overview of simulation tools in the scope of EM, including a brief state of the art regarding the most relevant EM simulators that can be found in the literature, and a description of MASCEM and ALBidS (Adaptive Learning strategic Bidding System) [21,24,27], the two systems in which the proposed context analysis mechanism is integrated, and which support the testing and validation of the proposed methodology. Section 3 presents the description of the proposed context analysis mechanism, and section 4 depicts some simulation results regarding the participation of EM players in the MIBEL, EPEX and Nord Pool, using the support of ALBidS equipped with the proposed context analysis features. Finally, section 5 presents the most relevant conclusions and future work.

2. Electricity markets simulation

Electricity Markets are not only a new reality but an evolving one as the involved players and rules change at a relatively high rate [3]. The emergence of a diversity of new players (e.g. aggregators) and new ways of participating in the market (distributed energy resources and demand side are gaining a more active role) are signs of this [3,28]. Restructured electricity markets are sequential open-ended games with multiple participants trading electric power. Market players and regulators are very interested in foreseeing market behaviour: regulators to test rules before they are implemented and to detect market inefficiencies; market players to understand market's behaviour and operate in order to maximize their profits. These necessities turned electricity markets into an attractive domain for developers of software tools. Simulation and artificial intelligence techniques may be very helpful under this context.

2.1. Electricity market simulators

Electricity market simulators must be able to cope with this evolving complex dynamic reality and provide electricity market players with adequate tools to adapt themselves to the new reality, gaining experience to act in the frame of a changing economic, financial, and regulatory environment. With a multiagent simulation tool the model may be easily enlarged and future evolution of markets may be accomplished. Multiagent simulation combined with other artificial intelligence techniques may result in sophisticated tools, namely in what concerns players modelling and simulation, strategic bidding and decision-support [21,24,29,30]. For example, consumers' role has significantly changed in this competitive context, making load analysis, consumer profiling and consumer classification very important [31]. The data generated during simulations and by real electricity markets operation can be used for knowledge discovery and machine learning, using data mining techniques [21,31], in order to provide electricity markets

players with simulation tools able to overcome the little experience they have in electricity markets operation. Some of the existent electricity markets simulators have machine learning abilities [18,19,21,24], but huge advances are required so they can be a real added value for real electricity markets players.

Each player acting in an electricity market has its own goals and should use adequate strategies in order to pursuit those goals, its strategic behaviour being determinant for its success. Player behaviour exhibits changes in response to new information and knowledge; this may refer to its self knowledge, to knowledge coming from the exterior and from the dynamic complex interactions of the heterogeneous individual entities. Each agent has only partial knowledge of other agents and makes his own decisions based on his partial knowledge of the system. Methodologies for strategic bidding in electricity markets [18,19,21,24,29,30] can help players making more successful decisions but they must be combined together with dynamic behaviour strategies able to take advantage from the knowledge concerning past experience and other players.

There are several experiences that sustain that a multiagent system with adequate simulation abilities is suitable to simulate electricity markets [18–24,32–35], considering the complex interactions between the involved players. It is important to note that a multiagent system is not necessarily a simulation platform but simulation may be of crucial importance for electricity markets study, namely concerning scenarios comparison, future evolution study and sensitive analysis. Some relevant examples of multiagent electricity market simulators are: the EMCAS (Electricity Market Complex Adaptive System) [19], which uses an agent based approach with agents' strategies based on learning and adaptation; the AMES (Agent-based Modelling of Electricity Systems) [18], an open-source computational laboratory for the experimental study of wholesale restructured power markets in accordance with U.S. FERC (Federal Energy Regulatory Commission)'s market design. In AMES, each generation company agent uses stochastic reinforcement learning to update the action choice probabilities; the GAPEX (Genoa Artificial Power Exchange) [35], which is an agent-based framework for modelling and simulating the most important European power exchanges; and the MASCEM (Multi-Agent Simulator for Competitive Electricity Markets) [20–24], which is presented in section 2.2. However, some non-agent-based electricity market simulators are also significant, such as the SEPIA (Simulator for Electric Power Industry Agents) [32], which is a Microsoft Windows oriented platform; Power Web [33], a Web-based market simulator that allows participants to interact from very distinct zones of the globe; and The SREMS (Short – Medium run Electricity Market Simulator) [34], which is based on game theory and is able to support scenario analysis in the short-medium term and to evaluate market power.

2.2. MASCEM and ALBidS

MASCEM (Multi-Agent Simulator of Competitive Electricity Markets) [20–24] aims to facilitate the study of complex electricity markets. It represents the entities that typically participate in electricity markets as software agents, namely: market operator agent, independent system operator agent (ISO), market facilitator agent, buyer agents, seller agents, VPP (Virtual Power Player) agents [22,23], and VPP facilitators. In the scope of MASCEM, these agents detain the following roles:

- The market operator regulates pool negotiations by validating and analysing buyer and seller agents' bids depending on the type of negotiation, and determines the market price, the accepted and refused bids, and the economical dispatch which is then sent to the system operator;
- The ISO examines the technical feasibility from the power system's point of view and solves congestion problems that may arise after being informed of all negotiations to be held. The ISO is responsible for the system's security as well as to assure that all conditions are met within the system;
- The market facilitator regulates all existing negotiations, coordinating and assuring the proper operation of the market. It knows all the market players, their roles and services;
- Buyer and seller agents are the key elements of the market. Buyers represent consumers and distribution companies, and sellers represent the electricity producers or other entities able to sell energy in the market. Seller agents compete with each other trying to maximize their profits, and cooperate with buyers to establish agreements that are gainful for both parties;
- In order to be able to compete in the market on equal footing with the big companies, small independent producers, mainly based on distributed generation and renewable sources, or consumers, need to make alliances between them. VPPs [22,23] represent these alliances, managing their aggregates' information, and are seen as common seller or buyer agents from the market's standpoint. They are modelled as a coalition of agents, maintaining high performance by allowing agents to be installed on separate machines.

MASCEM allows the simulation of the main market models: day-ahead pool (asymmetric or symmetric, with or without complex conditions), bilateral contracts, balancing market, forward markets and ancillary services. Hybrid simulations are also possible by combining the market models mentioned above. Also, the possibility of defining different specifications for the market mechanisms, such as multiple offers per period per agent, block offers and flexible offers, as part of some countries' market models, is also offered.

To allow players to automatically adapt their strategic behaviour according to their current situation, a new MAS (Multi-Agent System) has been integrated with MASCEM. This platform is ALBidS (Adaptive Learning Strategic Bidding System) [21,24,27], and provides agents with the capability of analysing contexts of negotiation, allowing players to automatically adapt their strategic behaviour according to their current situation. To choose the most adequate technique, ALBidS uses reinforcement learning algorithms [18] and the Bayes theorem. ALBidS techniques include: ANN (Artificial Neural Networks) [30], data-mining [31], statistical approaches, machine learning algorithms [21,24,27], the application of game theory, competitor players' actions prediction, and approaches based on strategies used by other simulators for market analysis and forecast [18]. Fig. 1 illustrates the integration of ALBidS with MASCEM.

ALBidS is implemented as a MAS itself, in which each agent is responsible for an algorithm, allowing the execution of various algorithms simultaneously, increasing the performance of the platform. It was also necessary to build a suitable mechanism to manage the algorithms efficiency in order to guarantee the minimum degradation of MASCEM's execution time. For this purpose, a methodology to manage the efficiency/effectiveness (2E) balance of ALBidS has been developed [27]. The 2E balance management methodology analyses the quality of results that each algorithm of ALBidS is achieving at each moment, and the time needed to achieve such results. Algorithms that are taking too long to achieve not so good results, given the requirements of each simulation, can be excluded from the system, or asked to reduce their execution time by adapting themselves internally.

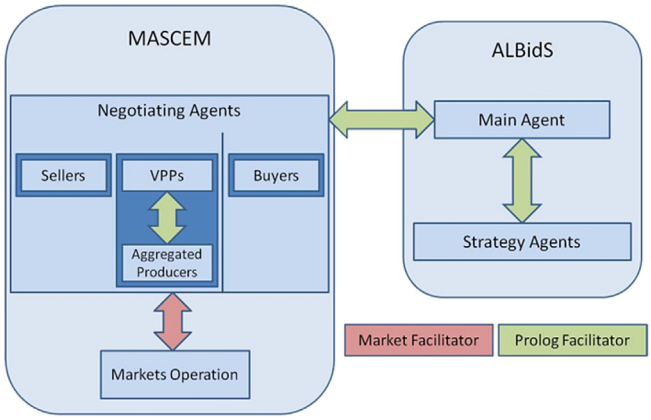

Fig. 1. Integration of MASCEM and ALBidS.

Additionally, ALBidS is equipped with a portfolio optimization methodology, which enables players to decide the participation investment that should be made in each available type of market, in order to optimize the potential profits from selling their power, or minimize the costs of buying the required amounts of power [36,37]. The portfolio optimization methodology considers the forecasted market prices that are expected to be found in each alternative market or market session that the supported player is allowed to participate in (e.g. day-ahead spot market, each session of the intraday market, bilateral contracts, forward markets).

3. Context analysis

Regardless the scope of where it is acting, when a certain subject desires or needs to take the maximum advantage on its surrounding environment, a full understanding of that environment's characteristics and particularities is a critical issue. These characteristics' particularities and conditions define the circumstances in which a certain event exists or occurs inside the considered environment. This is called context.

Context is present everywhere, and unquestionably influences the way information is processed in every situation [38,39]. While context is critical to information processing in all kinds of situations, it is almost fully absent from the modern information technology infrastructure. There is some work done in providing computer systems with context awareness [40], namely in multi-agent simulation [41]. However, the concept of context awareness is very far from being widely used in the computer system's area. The fact that this is an important issue to consider and its lack of consideration in decision support systems made it essential to include context analysis in this work. The analysis and definition of different contexts of negotiation in electricity markets are performed to support an adequate acting of negotiating players, adapting their actions to best suit the context they are encountering at each moment.

The first step when analysing context in the electricity market environment is to consider its most basic conditionings, i.e. on what these negotiations depend: days and periods. These are the two main factors to consider when bidding in the market, since transactions are made for each negotiation period of each day.

Valuable information regarding the functioning of liberalized markets over the last years is most of the times available to the community through market operators' websites. Indeed, market operators such as the Iberian Market Operator - MIBEL [8], Nord Pool [6], EPEXSPOT (European Power Exchange) [5], MISO [10] and GME (Gestore Mercati Energetici – Italian Energy Market Operator) [7] provide on their web sites information regarding market proposals and transactions, usually after a period of confidentiality. The available information depends on each different market operator, however, essential information such as market proposals, with quantity and price; accepted proposals and established market prices are usually available. This information grows up in a very dynamic way, as it is put available in the various websites.

Fig. 2 a presents the typical market price curve along the twenty-four hourly periods of one day (in this case, Monday, September 1st, 2014). Fig. 2 b presents the price curve along the thirty days of September 2014, considering always the same period – period twelve. These values have been taken from the website of the Iberian electricity market – MIBEL [8].

When analysing the typical market price throughout the periods of one day - Fig. 2 a, it is visible that the market prices' variation is much higher than throughout the days for a certain period. In the first case, for the presented example, the market prices vary from 35.5 €/MWh in period 5, to 65.65 €/MWh in period 22; a variation of 30.15 €/MWh throughout the day. On the other way, in Fig. 2 b, considering the same negotiation period throughout the days, market prices only vary from 55.3 €/MWh in day 7–72.2 €/MWh in day 29; a variation of only 16.9 €/MWh, nearly half the variation of the tendency throughout the considered day. Moreover, this variation only assumes the value of 16.9 €/MWh due to the prices of weekends (particularly Sundays, as can be seen by Fig. 2 b in days 7, 14, 21 and 28, which present lower market prices than the business days); this means that if excluding the weekends, or even only Sundays, the variation would decrease to approximately only

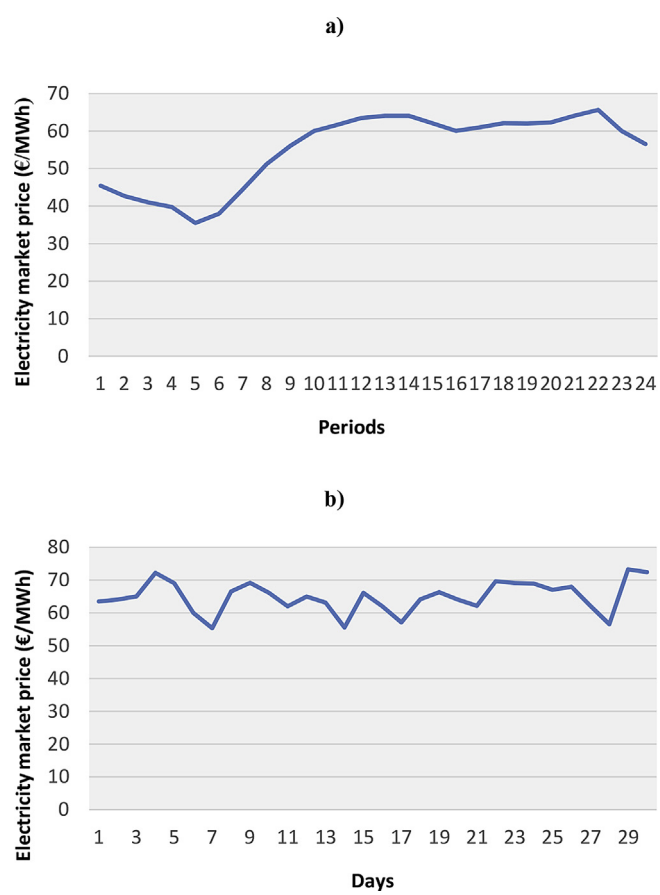

Fig. 2. Evolution of the market price throughout: a) the hourly periods of one day – September 1st 2014, b) the 30 days of September 2014, concerning only one period – period twelve. Adapted from Ref. [8].

10 €/MWh. The difference in these tendencies is behind the first approach of this work when dealing with data analysis. This first approach in considering contexts concerned a data analysis throughout the days, for each period independently, taking advantage on the prices much lower variation, and so facilitating the prices forecast process.

The developed context definition process takes into consideration the analysis of the situations concerning both perspectives, evolution throughout the days and throughout day periods. To perform this analysis, some conditionings that affect the prices in both cases were considered. The considered conditionings, or characteristics of a day and period are:

- the market price for the period and day in matter;
- the amount of transacted power in the market;
- the wind intensity verified in that period of the day (this is important because it affects the production of wind plants, and therefore the total negotiated amount of power);
- the solar intensity;
- the type of the day (whether it is a working day or weekend; if it is a holiday, or a special situation day, e.g. a day of an important event, such as an important game in a certain sport, which affects the energy consumption in that day, both because of the consumption in the stadium, and for increasing the number of people with the TV on to watch it).

The market price is the most important aspect of all, since it defines the revenues or expenses that each market player will have in each negotiation period. However, this price is influenced by a number of factors. The most influential is doubtless the amount of transacted power at each moment, since the power consumption and generation that are verified at each moment are the aspects that present the higher impact over the achieved market prices.

The variation of the consumption and generation throughout the time is itself dependable on several factors. The generation based on renewable, intermittent sources, such as wind and solar plants, brings a certain uncertainty to the amount of produced generation at each moment and consequently to the outcomes of the market sessions. Studies show the influence that the wind intensity variation has on the electricity market prices [42,43], concluding that the lack of wind generation power can lead to the increase of prices, while the surplus of wind generated power can lead to a significant decrease of the prices, in some cases even reaching the value of 0 cent€/MWh. Two examples of the correlation between market prices and wind speed variation are shown by Fig. 3, which shows the wind based generated power variation throughout two days in the Iberian Peninsula, as reported by the Portuguese National Electricity Network management entity [44], and by Fig. 4, which shows the variation of the electricity market prices in MIBEL [8] during the same two days.

By comparing the wind based generation during the two presented days, by Fig. 3, it is possible to see that in April, 15th 2012, the values are very high during almost the entire day. This has led to market prices with a value of zero in Spain during most of the day (as shown by Fig. 4 a). The market prices are only stabilized in the last hours of the day, which coincides with the hours in which the wind based generation starts decreasing.

By analysing Fig. 4 b it is possible to see that the market price in MIBEL has presented two peaks of high prices during the day of October, 17th 2012 – the first around hours 7 to 9, and the second during hours 21 to 23. From Fig. 3b one can see that these hours are coincident with the two off-peaks of wind based generation. The opposite correlation is also observable during the initial hours of the same day: the wind based generation is very high, and consequently the electricity market prices during the first hours of the day assume low values.

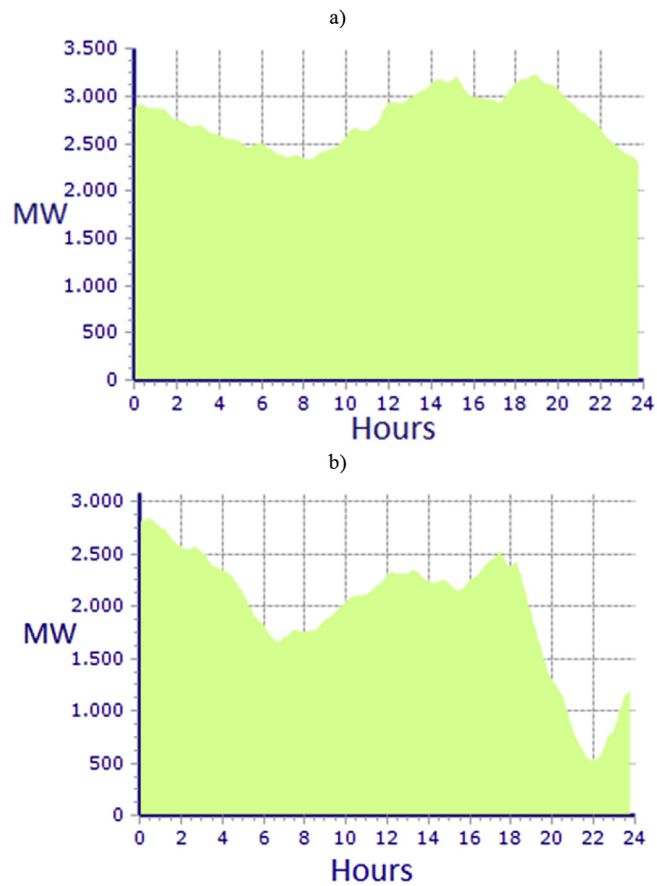

Fig. 3. Wind power generation in the Iberian Peninsula during the 24 h of: a) April, 15th 2012, b) October, 17th 2012. Adapted from Ref. [44].

The variations of energy consumption throughout each day are usually evident, mainly when comparing peak and off-peak periods of the day. The consumption tendency during each day is rather stable, only presenting variations along the seasons of the year and also in the comparison between business days and weekends. Additionally, on some special types of days the consumption diagram varies as well. These are the aspects that have been considered as the most important to be taken into consideration by the context analysis mechanism.

The core approach of the context analysis mechanism is the grouping of a set of different periods of different days in the recent history of the considered market, taking into account their specific characteristics, and bringing together the ones that are more similar concerning these characteristics, defining each group as a different context. This way, for each new negotiation period of each day, it is possible to compare its expected characteristics with those of the achieved groups, and realize which is the negotiation context in which this period fits the most. This allows adapting the actions of the supported player, taking into account the information regarding the past actions that were taken when acting in the same context, facilitating the learning process of the player, and allowing a contextualization of the past performances in order to retrieve the most relevant information for the new situation. The detection of wind speed variations and other variables is performed by the use of supporting forecasting techniques that have been developed in previous work, such as ANN [25,26] and SVM (Support Vector Machines) for wind speed forecasting [45], and hybrid approaches

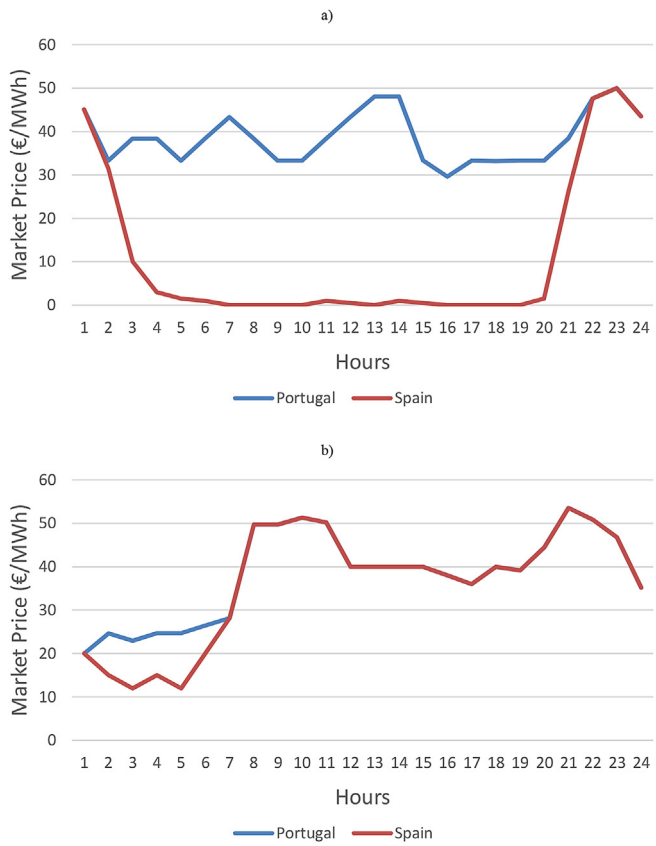

Fig. 4. Variation of the market price in Portugal and Spain throughout the 24 hourly of: a) April, 15th 2012, b) October, 17th 2012. Adapted from Ref. [8].

to forecast solar intensity [46]. These approaches are used with the purpose of achieving acceptable reference values that help classifying different periods of the day under different contexts.

The grouping of each day's periods depending on their context is performed through the application of a clustering mechanism [47]. The clustering mechanism analyses the characteristics of each period throughout the days, and assigns each period of each day to the cluster that presents the most similar characteristics. The clustering is performed using the K-Means clustering algorithm [48], which is implemented in MATLAB [49]. The K-Means clustering methodology considers a set of observations ($x_1, x_2, \ldots, x_n$), where each observation is a d-dimensional real vector, and n is the number of considered observations. The clustering process aims at partitioning the n observations into k ($\leq n$) clusters $C = \{C_1, C_2, \ldots, C_k\}$ so that the WCSS (Within-Cluster Sum of Squares) is minimized (1).

$$\min \sum_{i=1}^{k} \sum_{x \in C_i} \left|\left| x - \mu_i \right|\right|^2 \tag{1}$$

where μ_i is the mean of points in C_i, i.e. the cluster *centroid*.

The dimension of the vector that characterizes each observation $x_p, p \in \{1, \ldots, n\}$ is equal to the sum of five vectors of equal size, each containing the observable information regarding each of the five characteristics presented before in this section (in the bullet points); i.e. $x_p = \{mp_p, pw_p, ws_p, si_p, sp_p\}$, where mp_p represents the set of market price values associated to each hour of each day that compose each observation, pw_p represents the amounts of transacted power, ws_p represents the wind speeds that have been verified, si_p, the solar intensities, and sp_p is the indication of special cases, where the value of 0 indicates a business day, 1 signifies a weekend day, 2 represents a holyday, and 3 a special situation day, e.g. days in which relevant events occur during certain hours of a day. The length of each of the five vectors that compose x_p are dependent on the amount of data that is considered as part of each observation, e.g. taking as example the test presented in Table 1, where the objective is to group each of the 24 hourly periods into different clusters, the number of observations is 24, one per each hourly period; and each of these observations is composed by the market price, power amount, wind speed, solar intensity, and special situation indication in the corresponding period, along 7, 14 or 30 days.

With the objective of minimizing equation (1), the clustering process executes an iterative process between two steps: (i) the assignment step, where each observation x_p is assigned to the cluster $C^{(t)}$ whose mean value yields the minimum WCSS in iteration t, as presented in (2); and (ii) the update step, where the new means of each cluster are calculated, considering the newly assigned observations, determining the new centroid μ_i of each cluster, as in (3).

$$C_i^{(t)} = \left\{ x_p \; : \left|\left| x_p - \mu_i^{(t)} \right|\right|^2 \leq \left|\left| x_p - \mu_j^{(t)} \right|\right|^2 \; \forall j, \; 1 \leq j \leq k \right\} \tag{2}$$

$$\mu_i^{(t+1)} = \frac{1}{\left| C_i^{(t)} \right|} \sum_{x_j \in C_i^{(t)}} x_j \tag{3}$$

The execution of the algorithm stops when the convergence process is completed, i.e. when the assignments of observations to different clusters no longer change. By minimizing the WCSS objective, in equation (1), the K-Means clustering methodology assigns observations to the nearest cluster by distance. This means that each subject will be grouped in the same cluster as the ones that are more similar.

Table 1 presents the results of the tests performed to three distinct data sets taken from MIBEL [8]. The first data set refers to the period from Monday, March, 28th to Tuesday, April, 26th, 2011; the second data set starts on Monday, May 2nd and ends on Tuesday, May 31st, 2011; and the third data set ranges from Monday, May 30th to Tuesday, June 28th 2011. For each data set the clustering algorithm is applied, using a matrix where the rows represent the periods, and the columns represent days. For each day, the information regarding the characteristics presented previously in this section (in the bullet points) is used. The considered number of days for analysing the periods, and the number of clusters are variable, depending on the preference for efficiency/effectiveness balance of ALBidS [27]. For this case, the tests are performed for two and three clusters, and for seven (one week), fourteen (two weeks) and thirty (one month) days. Table 1 presents a number in each cell, which represents a different cluster.

From Table 1 it is visible that, considering two clusters, the tendency is the grouping of from ten to twenty three periods in one cluster, and the rest in another. This separation reflects the peak and off-peak periods of the day in what concerns electrical energy consumption. This tendency is more evident and subject to less misclassified cases, when the considered number of days for analysis is increased. Regarding the tests using three clusters, the same tendency is verified, with the additional cluster being used for grouping the transition periods between peak and off-peak.

The same type of tests is performed to analyse the similarity of the days (see Table 2). In this case the matrix rows represent the days of the month, and the columns represent the periods. The same five characteristics that have been presented previously in

Table 1
Clustering results for grouping periods with similar characteristics.

Days	7						14						30					
Clusters	2			3			2			3			2			3		
Period / Data Set	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
1	1	1	1	3	3	1	1	1	1	3	3	1	1	1	1	3	3	3
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
7	1	1	1	1	1	3	1	1	1	1	1	3	1	1	1	1	1	1
8	1	1	2	3	3	3	1	1	2	3	3	3	1	1	1	3	3	3
9	1	1	2	3	3	3	1	1	2	3	3	3	1	1	1	3	3	3
10	2	2	2	2	2	3	2	1	2	2	2	2	2	2	2	2	2	2
11	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
12	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
13	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
14	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
15	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
16	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
17	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
18	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
19	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
20	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
21	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
22	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
23	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
24	1	1	2	3	1	2	1	1	1	3	3	3	1	1	1	3	3	3

this section (in the bullet points) are considered for the analysis of each period. The considered number of periods to analyse the days is twelve (2 h periods) and twenty four (1 h periods), as displayed in the first row of Table 2. The different number of considered periods is used to compare the performance of the clustering process when using different amounts of information, and also to verify the applicability of the methodology to electricity markets that consider a different number of daily negotiation periods. Note that the thirty considered days of the three used data sets always start on a Monday, to ease the interpretation of the results.

For the cases concerning two clusters, Table 2 shows a clear tendency in separating the work days from the weekend days. That tendency is clearer when the considered number of periods for analysing the days is increased. Concerning the cases with three clusters, the grouping additionally considers the separation between Sundays and Saturdays. A special regard for day twenty six, which, for the first data set is always placed on the same cluster as the weekends, for the cases of two and three clusters. This fact is due to this day being a special situation day (a holiday – April 22nd 2011, which refers to the Good Friday, a national holiday in both Spain and Portugal, the members of MIBEL). This day's characteristics were found to be more similar to weekends than to working days.

Regarding the cases with five clusters, the tendencies are not very clear. It is visible that Mondays and Fridays are placed in cluster 4 in the majority of the cases, but that is not a constantly observed event. Therefore, until further studies are performed, allowing the understanding of the reasons behind the clustering results for these cases, the consideration of a high number of clusters is discouraged.

The actual context definition is performed through an overlapping of the two result matrixes, concerning the analysis of the days and the analysis of the periods. The result matrixes concern only one option in what regards the number of clusters and the number of days or periods for analysis. Table 3 presents an excerpt of the results of the overlapping of the results matrixes, concerning only two clusters, for an easier understanding of the results, and considering 24 periods in the analysis of the days, and 30 days in the analysis of the periods.

This excerpt considers the necessary days and periods to demonstrate the adequacy of the Context Analysis mechanism. Regarding the days, using two clusters and twenty four periods for the analysis, an evident separation between working days and weekends was found. Regarding the periods, when using two clusters and thirty days for their analysis it was clear a separation between periods from ten to twenty three from the rest. The defined contexts result from the combination of both result matrixes. D1 represents the days that were grouped in the first cluster, D2 the days that were grouped in the second cluster, P1 the periods grouped in the first cluster of the period analysis, and finally, the periods grouped in the second cluster are represented by P2. The cells of Table 3 represent the different combinations of days and periods' clusters, hence representing the different contexts.

Analysing Table 3, D1P1 represents the first context: off-peak periods of working days. D1P2 represents the second context: peak periods of working days. D2P1 represents the third context: off-peak periods during weekend days. Finally, D2P2 represents the fourth context: peak consumption periods of the weekend days.

These contexts are defined in order to support the adaptation of the action approaches on behalf of a market negotiation agent,

Table 2
Clustering results for grouping days with similar characteristics.

	Periods				12									24					
	Clusters		2			3			5			2			3			5	
Day	Data Set	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
1		1	1	1	1	1	1	4	4	4	1	1	1	1	1	1	4	**4**	**4**
2		**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
3		**1**	**1**	**1**	**1**	**1**	**1**	**5**	**5**	**5**	**1**	**1**	**1**	**1**	**1**	**1**	**5**	**5**	**5**
4		1	1	2	1	1	2	5	1	2	1	1	1	1	1	1	1	1	1
5		1	1	1	1	1	1	4	4	4	1	1	1	1	1	1	4	4	4
6		2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
7		2	2	2	3	3	3	3	3	3	2	2	2	3	3	3	3	3	3
8		1	1	1	1	1	1	4	4	4	1	1	1	1	1	1	4	4	4
9		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
10		1	1	1	1	1	1	5	5	5	1	1	1	1	1	1	5	5	5
11		1	1	1	1	1	1	1	4	1	1	1	1	1	1	1	1	4	1
12		1	1	1	1	1	1	4	4	4	1	1	1	1	1	1	4	4	4
13		2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
14		2	2	2	3	3	3	3	3	3	2	2	2	3	3	3	3	3	3
15		1	1	1	1	1	3	4	4	4	1	1	1	1	1	1	4	4	4
16		1	1	1	1	1	1	5	4	4	1	1	1	1	1	1	4	4	4
17		1	1	1	1	1	1	5	5	5	1	1	1	1	1	1	5	5	5
18		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
19		1	2	1	1	2	1	4	4	4	1	1	1	1	1	1	4	4	4
20		2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
21		2	2	2	3	3	3	3	3	3	2	2	2	3	3	3	3	3	3
22		1	1	1	1	1	1	4	4	4	1	1	1	1	1	1	4	4	4
23		1	1	1	1	1	1	5	5	5	1	1	1	1	1	1	5	5	5
24		1	1	1	1	1	1	5	5	5	1	1	1	1	1	1	5	5	5
25		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
26		2	1	1	2	1	1	4	4	4	2	1	1	2	1	1	4	4	4
27		2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
28		2	2	2	3	3	3	3	3	3	2	2	2	3	3	3	3	3	3
29		1	1	1	1	1	1	4	4	4	1	1	1	1	1	1	4	4	4
30		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

depending on the different contexts this agent will act on during a market simulation.

The context definition mechanism proved to efficiently recognize and group distinct market contexts. This mechanism's applicability and influence in supporting the ALBidS system for providing adequate support to a market negotiation player is demonstrated in the case studies presented in section 4.

4. Experimental findings

The case studies presented in this section have the goal of demonstrating the importance of the proposed context analysis methodology for the performance of market players. With this objective, five case studies are presented, which aim at comparing the influence of the several factors that are used to determine different contexts in the proposed solution. Additionally, tests are performed in the scope of three different electricity markets: MIBEL, EPEX and Nord Pool. Real data concerning each of the three markets is used to generate simulated agents that perform as representation of the real players that participate in the scope of each market. Also, the market mechanisms of the three electricity markets are modelled by MASCEM, generating highly realistic simulation scenarios. The ALBidS system is used as decision support of the subject player (the electricity market player that will be equipped with decision support capabilities, with and without the use of the proposed context analysis mechanism, so that comparisons of the outcomes that result from the used of the proposed methodology can be made).

Table 3
Context definition results.

		Period					
		7	8	9	10	11	12
Day	*1*	D1 P1	D1 P1	D1 P1	D1 P2	D1 P2	D1 P2
	2	D1 P1	D1 P1	D1 P1	D1 P2	D1 P2	D1 P2
	3	D1 P1	D1 P1	D1 P1	D1 P2	D1 P2	D1 P2
	4	D1 P1	D1 P1	D1 P1	D1 P2	D1 P2	D1 P2
	5	D1 P1	D1 P1	D1 P1	D1 P2	D1 P2	D1 P2
	6	D2 P1	D2 P1	D2 P1	D2 P2	D2 P2	D2 P2
	7	D2 P1	D2 P1	D2 P1	D2 P2	D2 P2	D2 P2
	8	D1 P1	D1 P1	D1 P1	D1 P2	D1 P2	D1 P2

4.1. MIBEL – business days vs. weekends and influence of the 2E balance mechanism

In this case study three simulations using MASCEM are presented. These simulations are performed in a realistic scenario based on real data from the Iberian electricity market operator – MIBEL [8]. This scenario represents the Iberian reality in a summarized way, using software agents to transpose real market participating players into the simulation scenario.

In all three simulations the participating players behave exactly the same, except from Seller 2, which is the test subject for this case. In the first simulation, Seller 2 uses ALBidS without considering the proposed context definition mechanism, and using a 100% preference for effectiveness (i.e. all ALBidS strategies are used at their full potential). In the second simulation, the preference for effectiveness is maintained at its maximum, but this time using the proposed context definition mechanism. To ease the understanding of the results, the contexts are defined using only two clusters for the day analysis. This way the only separation of contexts is between week days and weekends. Finally, in the third simulation, the context definition is used once more, but this time the preference goes 100% for efficiency (in order to test the influence of the context analysis mechanism in cases when ALBidS strategies do not behave at their full potential).

Fig. 5 presents the incomes obtained in each of the three simulations, along 61 simulated days, for the twelfth period of the day. The starting day for these simulations is Monday October 4th, to facilitate the spotting of both, working days, and weekend days, in the graphs.

Analysing the chart presented in Fig. 5 a, the pattern concerning the weekend days results is clearly visible. The achieved incomes are always much lower on weekends than during working days. This tendency is softened slowly over the days, but never completely. This is due to the consideration of all days in the same way, not taking into account the different characteristics that weekend days present.

This is visible by analysing Fig. 5 b, which by considering weekend days as a different context, and consequently treating these days independently from the rest, manages to get better results on weekends, with no degradation of the results of the business days. Looking closely at this graph, it is visible that the results improvement on weekends starts on the second weekend and continues improving until the end of the simulation days. Regarding the first weekend (days 6 and 7), the results are still weak, since the strategies for this context are still in an initial point, i.e., as initialized. This is easily visible by Fig. 6, which presents the comparison of the incomes of Seller 2 in the first and second simulations.

Concerning the third simulation, since the full preference is given to the efficiency of the method and not to its effectiveness, the results are much more unstable. However, it is still possible to see in Fig. 5, the weekends' worst results pattern in the beginning of the simulation, which is softened throughout the days, to the point that at the end it is almost imperceptible. This is due to the context definition influence, which is highly advantageous, even the used strategies themselves are not achieving their best results (using with a low preference for effectiveness).

4.2. MIBEL – peak vs. off-peak periods and influence of special cases

This case study has the objective of showing the importance of considering different hours of the day as different contexts of negotiation, when these hours show different patterns of energy consumption and market prices. During a day, the variance of market price and energy consumption is usually significant, particularly during peak and off-peak consumption hours of the day; for this reason, the applied strategic behaviour of market participant players should be dependable on these different contexts, rather than be constant regardless of the different circumstances that are found during the day.

Another main objective of this case study is analysing the performance of the proposed context analysis methodology when dealing with special cases that occur in certain days, and that have influence on the energy consumption of that day, or at least in some hours of the day. In order to show this influence, a specific special day has been chosen for this study. The chosen day is Saturday, May, 24th 2014, the day when the football's UEFA Champions League final has been played. The UEFA Champions League is probably the most important football competition besides the FIFA World Cup, and the final is always an event with millions of viewers. In 2014 the UEFA Champions League final has been played in Lisbon (Portugal), and the two participating teams were Atlético de Madrid and Real Madrid, two Spanish teams. Besides the millions of spectators all around the globe, this event had special visibility in Spain and Portugal – the two countries that compose the MIBEL electricity market. Given the logistics that surround the event itself, and the huge number of people watching the event, not only at the stadium but also watching in the TV at home or in public spaces, it is only expected that the event should have influence on the electricity market price during the hours of the match, and consequently on the electricity market price. Fig. 7 presents the comparison between the total energy consumption and the electricity market price during the day of the event: Saturday, May, 24th 2014, and the previous and following Saturdays: 17th and 31st May, 2014.

From Fig. 7 a it is visible that in May, 24th the energy consumption is above the normal values (verified in the immediately previous and following Saturdays) throughout all day. Nevertheless, the peak from hour 18 to 24 is the most evident – the special event has taken place from 19h45 to approximately 22h30. Although the most visible evidence occurs during the evening, it is also visible from Fig. 7 a that the electricity demand in 24th May is higher than the preceding and following Saturdays during all day. There is no evidence on significant variation of other factors that justifies the increase of consumption throughout the rest of the day [50]. The only justification is that the football match has influenced the demand throughout all day, due to the particular characteristics of this day and the importance and large scale interest of the global public in this event (in both Spain and Portugal, in this case). Regarding the market price, from Fig. 7 b, a peak is also visible during the same hours, showing the influence of the event on both the amount of energy consumption and the market price, which has a direct influence on the outcomes of players participating in the electricity market.

Fig. 8 presents the incomes achieved by the subject market player when participating in the MIBEL electricity market when using and when not using the proposed context analysis methodology to support the decision support provided by ALBidS, during the day of 24th May 2014. The outcomes result from simulations undertaken using MASCEM, where the subject player participates in the market to sell a fix amount of 50 MW per hour, in order to facilitate the interpretation of results.

From Fig. 8 it is visible that using the context analysis methodology, the player is able to achieve extra incomes in some hours of the day. These hours correspond to different contexts, namely the periods of lower consumption of the day and the peak hours of consumption. The extra incomes were possible due to the adaptation of the player's strategic behaviour when acting under different contexts, in contrast to the constant strategic behaviour throughout

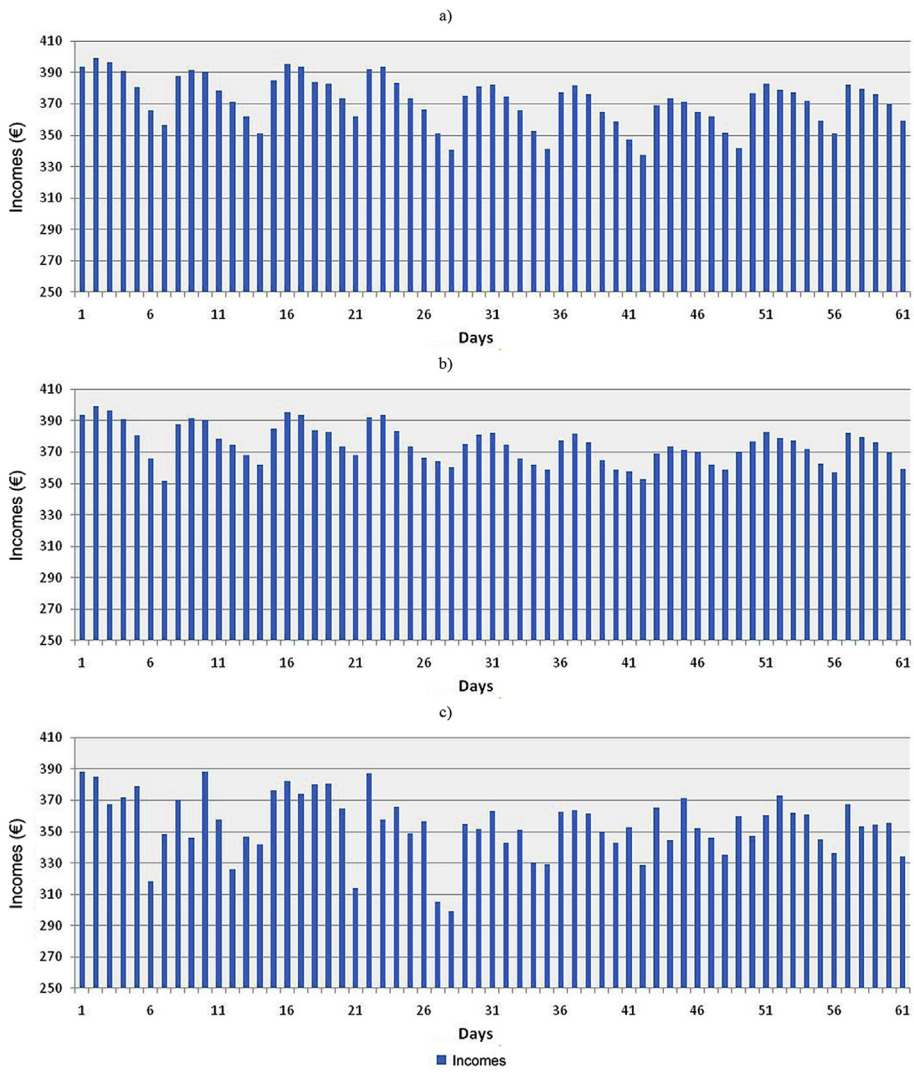

Fig. 5. Incomes obtained by Seller 2 in the twelfth period of the considered 61 days, in: a) the first simulation, b) the second simulation, c) the third simulation.

all hours of the day. The higher incomes were achieved as a result of the adaptation of the portfolio optimization mechanism of ALBidS, depending on each different context, as can be seen in Fig. 9.

From Fig. 9 it is visible that, interpreting different times of the day as different negotiation contexts, the portfolio optimization mechanism of ALBidS suggested the subject player to perform differently throughout the different times of the day. During the off-peak hours, in which the market price is usually lower, the player sold some of its power via bilateral contracts, instead of selling the full amount on the day-ahead spot market. This led to the achievement of some advantageous deals, at higher prices than the ones found in the day-ahead market. During the peak hours of consumption, particularly being this a special event day, the player was able to sell extra amounts of power in the day-ahead market, taking advantage on the high prices during the hours of the football event, by buying extra power in advance in bilateral contracts at lower prices.

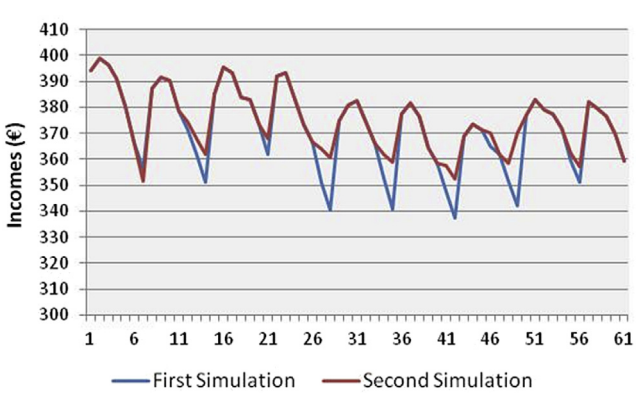

Fig. 6. Incomes obtained by Seller 2 in the first and second simulations, for the twelfth period of the considered 61 days.

This adaptation of the behaviour depending on the context is, however, not exclusive to special cases. Fig. 10 presents the incomes of the subject player during the day of 17th May, 2014 (the Saturday before the considered special event).

From Fig. 10 it is visible that the subject player was also able to achieve some extra incomes during this day, by considering peak and off-peak hours of the day as different negotiation contexts. The extra incomes were achieved by selling some amount of power in bilateral contracts during the hours of lower prices in the day-ahead spot market, as can be seen by Fig. 11.

From Fig. 11 one can see that a percentage of the total amount of available power has been sold in bilateral contracts, taking

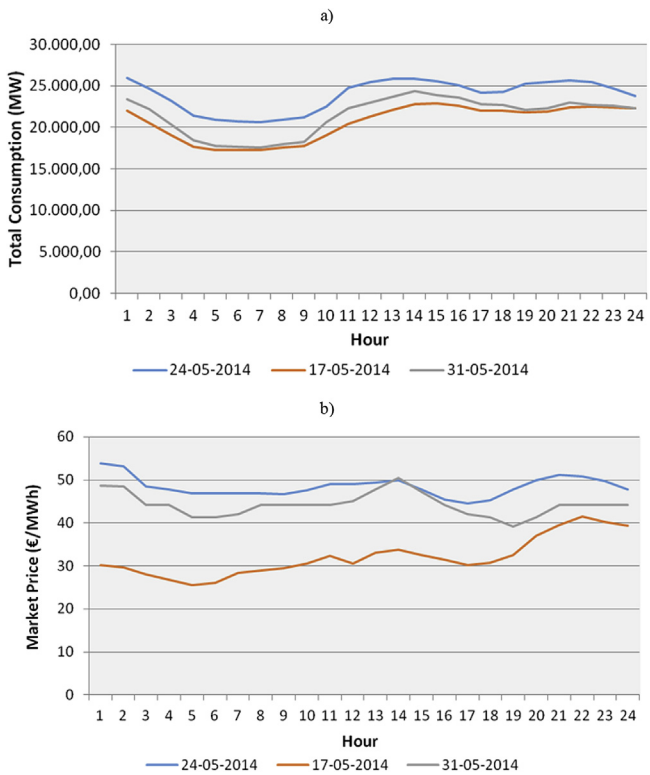

Fig. 7. Comparison between the a) total consumption, and b) electricity market price, that has been verified in MIBEL in 17th, 24th and 31st May, 2014 (based on data extracted from the MIBEL Website [8]).

advantage on the possibility of achieving deals with higher prices than the ones found in the day-ahead spot market, during the hours of off-peak consumption and price.

Table 4 presents a summary of the results of this case study, including the total incomes achieved by the subject player when acting in each of the different defined contexts, resulting from the proposed context analysis methodology.

From Table 4 it is visible that, in both cases, one context is defined during hours 3 to 9, representing the context of off-peak of consumption. In 17th May the remaining hours are grouped as a distinct context; however, in 24th May, due to the special event, an extra context is verified, from hours 19 to 23. From Table 4 it is also visible that in Context 2 the use of the context analysis methodology does not bring additional incomes. This occurs because the

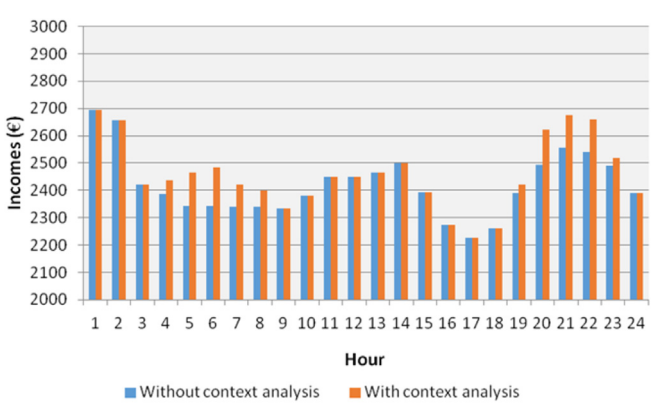

Fig. 8. Incomes achieved by the subject player throughout the 24 hourly periods of 24th May 2014.

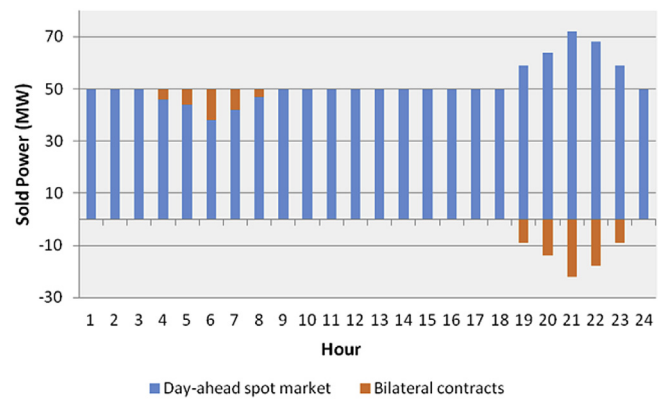

Fig. 9. Subject player's sold power in different markets throughout the 24 hourly periods of 24th May 2014.

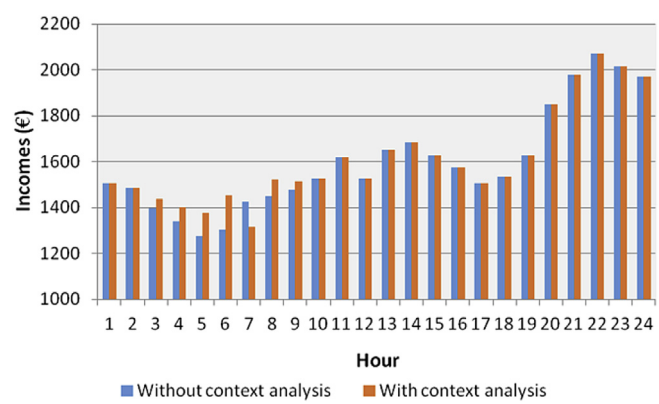

Fig. 10. Incomes achieved by the subject player throughout the 24 hourly periods of 17th May 2014.

decision support provided by ALBidS during these hours is equal with and without the use of context analysis, i.e. the used strategy is considered by the decision support system as the best that can be applied. However, in Contexts 1 and 3, the decision support is able to provide higher incomes by adapting the strategic behaviour to meet the different circumstances of the different contexts.

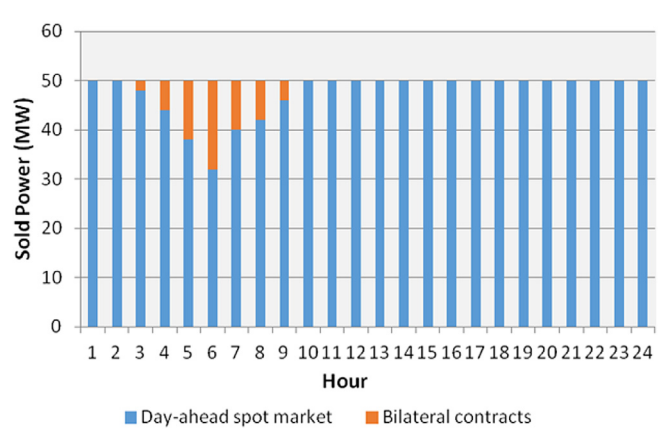

Fig. 11. Subject player's sold power in different markets throughout the 24 hourly periods of 17th May 2014.

Table 4
Total incomes of the subject player in each different context during the two analysed days.

	17 May, 2014			24 May, 2014		
	Hours	Without context analysis	With context analysis	Hours	Without context analysis	With context analysis
Context 1	3 to 9	9668	10 018	3 to 9	16 510	16 960
Context 2	1, 2, 10 to 24	28 740,5	28 740,5	1, 2, 10 to 18, 24	29 142	29 142
Context 3	–	–	–	19 to 23	12 470,5	12 900,5
Total	–	38 408,5	38 758,5	–	58 122,5	59 002,5

4.3. MIBEL – excessive wind based generation and null market prices

As discussed in section 3, the high volatility of the wind speed presents a big influence on the variation of electricity market prices [42,43], mainly in electricity markets where the penetration of wind based generation is huge, such as the case of MIBEL, since Portugal and Spain present approximately 20% of the total production based on wind generation. The wind speed is, therefore, closely related to the variation of electricity market prices. In cases where the wind based generation is excessive, the market prices tend to decrease drastically, as studied in Ref. [43]. In some cases the price even decreases to values of zero, or near. Fig. 12 presents a summary of the times in which the electricity market price of MIBEL has reached values below 2€/MWh, during the year of 2012.

From Fig. 12 it is visible that during the year of 2012 there have been 47 occurrences of market prices below the value of 2€/MWh in MIBEL. In most of these cases a high correlation with high values of wind speed can be found. It is also visible that in most of these cases, the market price is different in the two areas of MIBEL, which means that a market splitting has occurred. The variation of the wind speed, for its influence on the variation of the market prices is, therefore, an extremely important factor to define the context of negotiation. Null market price values, or even very low values, near zero, are a market context that must be addressed by participant players, and that cannot be approached as any other market situation. In this scope, the proposed context definition methodology brings an important contribution. Fig. 13 presents the incomes achieved by the subject player, offering a fix amount of 50 MW per hour, when participating in the MIBEL market throughout the 47 cases of the excessive wind context, with and without the use of the proposed context analysis methodology. For the purposes of this experiment, the subject player is located in Spain.

From Fig. 13 it is visible that, without using the context analysis methodology, the subject player assumes these cases as any other, maintaining its normal behaviour, which leads to the achievement of very low incomes, even null in most of the cases, due to the market prices that are verified in the Spanish area of MIBEL. Using the context analysis methodology, the decision support provided to the subject player takes into account that the occurrence of very high wind speed leads to a context defined by the decrease of the market price to very low values. Also, taking into account that, in most of these cases, a market splitting occurs, dividing Portugal and Spain into two different zones, with different market prices, and that the market prices in the Portuguese zone are not so severely affected; the subject player specifically chooses Portuguese players to negotiate bilateral contracts, which leads to the achievement of deals with higher prices.

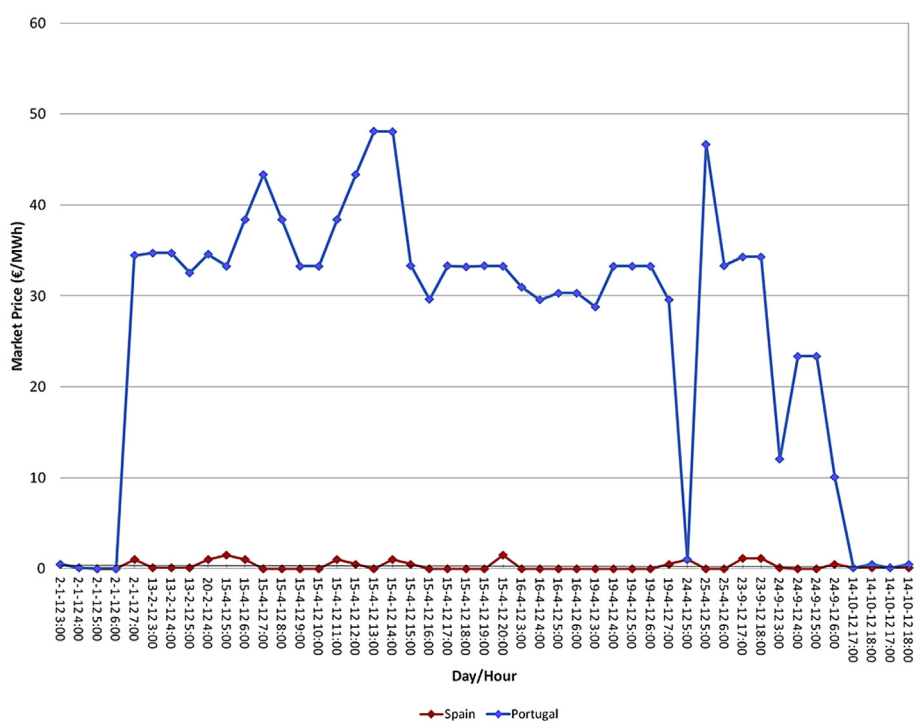

Fig. 12. Occurrences of market prices below 2€/MWh in MIBEL, during the year of 2012 (based on data extracted from the MIBEL Website [8]).

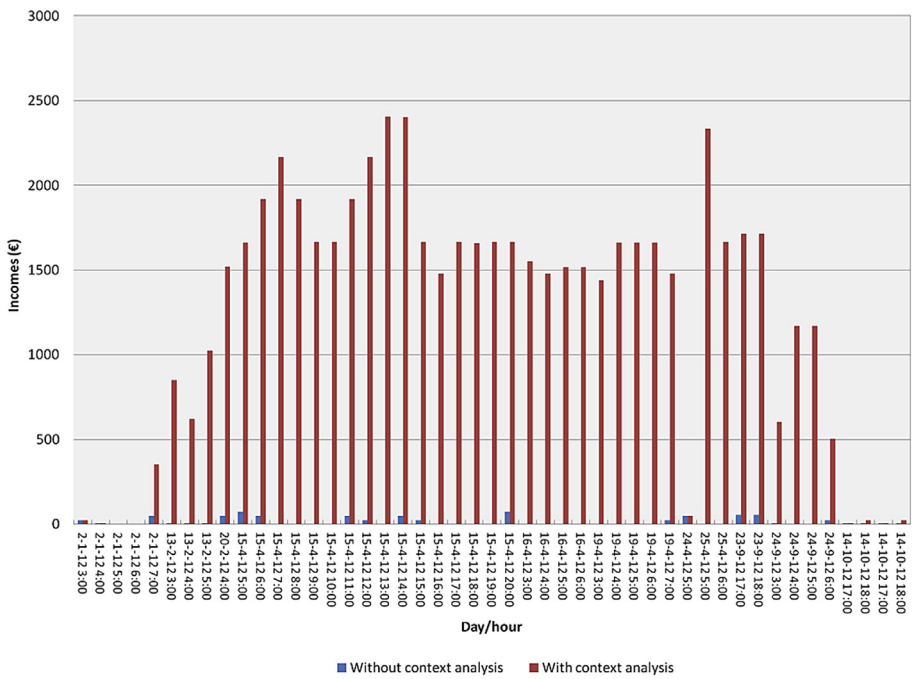

Fig. 13. Incomes achieved by the subject player during the 47 cases of market price values below 2€/MWh in MIBEL, during the year of 2012.

4.4. Nord Pool – negative market prices

During several periods of 26th December, 2011, electricity market prices assumed negative values in Nord Pool [6]. Negative prices occur when the supply of electricity temporarily exceeds the demand; this usually occurs during the night, when the demand is low and wind and hydro production reach high levels of production. Fig. 14 presents a comparison between the market price of Nord Pool during the 24 hourly periods of 26th December, 2011, and the annual average price of 2011 in Nord Pool.

The electricity market price tendency during the 26th December, 2011 is clearly below the annual average values, as can be seen by Fig. 14. The peak negative value is verified in hour 4, where the market price reaches a value of −150 €/MWh. Similarly to the previous case study, presented in section 4.3, the excessive value of wind speed leads to a huge decrease of the market price; in this case the situation is even more critical, since the market price is negative in several hours of the day.

The use of the context analysis methodology is simulated using MASCEM, considering the execution of the Nord Pool electricity market for the day of 26th December, 2011, and the participation of a player which intends to sell a fix amount of 50 MW during the 24 hourly periods of the day, using ALBidS as decision support for its actions in the market. Once again, as in the previous cases, the outcomes of the participation of the subject player using ALBidS with and without the use of the context analysis methodology, is compared. Fig. 15 presents the incomes achieved by the subject player in the Nord Pool market during the day of 26th December, 2011.

From Fig. 15 one can see that the subject player was able to achieve some more incomes using the proposed contexts analysis methodology. The incomes are not high, but still better than the prejudice that came from the selling of power at negative prices, which led to a global negative income during that day of 6020 €.

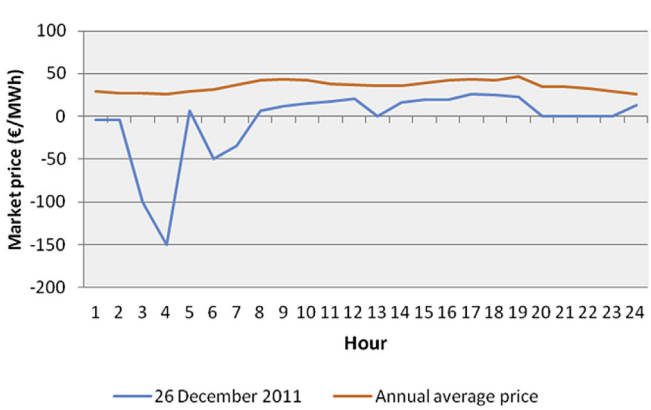

Fig. 14. Electricity market prices of Nord Pool in 26th December, 2011 and annual average price during the year 2011.

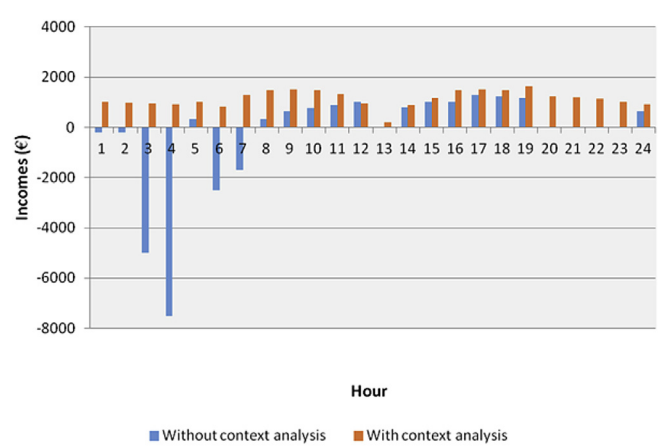

Fig. 15. Incomes achieved by the subject player in the Nord Pool market during the day of 26th December, 2011 with and without the use of the proposed context analysis methodology.

The incomes achieved by the subject player using ALBidS with the context analysis methodology came from the large participation in bilateral contracts in this context of high wind speed and low demand, particularly during the evening hours, as detailed in Fig. 16.

Fig. 16 shows that the sold power of the subject player occurred mainly through bilateral contracts during the evening hours. The participation in the day-ahead spot market increased during the day, which nevertheless led to a decrease of incomes compared to what could be achieved if completely abstracted from this market. However, the incomes are still positive throughout all day.

4.5. MIBEL, EPEX and Nord Pool – comparative study

This case study aims at comparing the performance of the proposed context analysis methodology when applied to three different electricity markets: MIBEL, EPEX and Nord Pool, during a whole year of simulation. For that, the three electricity markets are simulated in MASCEM, referring to the year of 2013. In each market a subject player participates to sell a fix amount of 50 MW. The outcome of the subject player when using the proposed context analysis methodology, and when not using it, is compared, to support the decision process of ALBidS.

For all three markets the specifications of the context analysis mechanism is similar: periods of the day are divided into five clusters, and days are divided into four. This leads to twenty different contexts, as result of the combination between the grouping of days and periods, as depicted in Table 5. In Table 5, the special cases are the same as special situations. In the case of the analysis by periods they represent special situations that affect only a few periods, while in the analysis of days they represent events that affect the whole day.

The values that define exceptionally high or low wind speeds are defined by the clustering process, i.e. when a new day is analysed, the expected values of each characteristic (wind speed, consumption, etc.) are fed to the proposed methodology, and then this new event is classified as belonging to one of the groups that have resulted from the clustering process. Each of these groups contains events with higher wind speeds, other with lower, and so on. Therefore, what is considered high or low wind speed depends on the similarity between the observed events; e.g. in a case where the wind speed variation along the time is very high, the separation between events considered as presenting high or low wind speeds is more evident, and the group (or cluster) of periods/days containing events with low wind speeds will only contain really low values. While in a case where the variation throughout the time is minimal, higher values, which are only slightly below the average value, will be considered as low, or even no events are clustered as low, and they are all placed in the same cluster (normal wind speed). It always depends on the observed events.

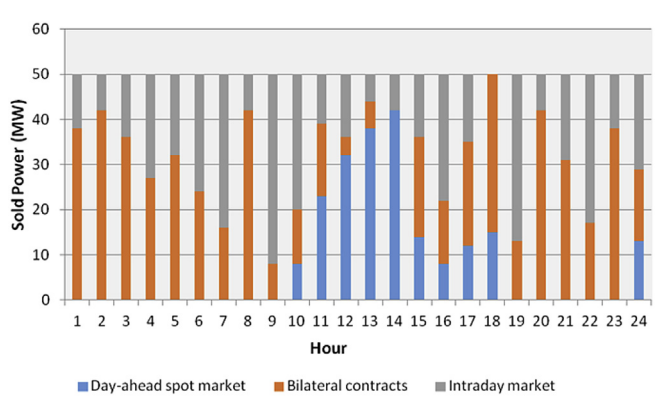

Fig. 16. Subject player's sold power in different markets throughout the 24 hourly periods of 26th December, 2011 in Nord Pool.

From Table 5 it is visible that days and periods of the day are combined into twenty different contexts. P1 to P5 represent the period clusters, and D1 to D4 represent the four clusters that group the days by their characteristics' similarity. The combination of the two groups of clusters results in contexts C1.1 to C5.4. Table 6 presents the summary of the global incomes achieved by the subject player in each of three markets, during the entire year of simulation, for each different context.

From Table 6 it is visible that, in all three markets, the overall incomes considering the whole year of simulation are superior when using the proposed context analysis methodology. This is also visible for the generality of different contexts, for all three electricity markets. Although the strategies used by ALBidS as decision support of the subject player are exactly the same when using and when not using the proposed context analysis methodology, the consideration of distinct contexts allowed to use the most adequate strategies whenever they are most advantageous. Additionally, ALBidS is able to separate the learning process, so that it becomes independent for each context, meaning that the process of suiting strategies to the best context of use becomes facilitated. The use of the proposed context analysis methodology has originated an increase of 7.55% in the total incomes of the player in the MIBEL market for the year 2013. In EPEX the total increase was 2.95%, while in Nord Pool the total increase in incomes was approximately 5.76%. The proposed context analysis methodology has shown to be advantageous when applied to the three electricity markets, although the increase of incomes assumes different dimensions when applied to the different markets. The lower incomes achieved in Nord Pool, regardless of the use of the context analysis methodology are due to the lower prices' tendency verified during the year of 2013, as can be seen by Fig. 17.

5. Conclusions

Electricity markets are complex environments, with dynamic, constantly evolving characteristics. These changes have been potentiated by the electricity markets restructuring and by the need to accommodate the increasing penetration of distributed energy resources, and consequent necessity of facilitating the participation of small players in the market.

Players' participation in such a dynamic scene brings the need for these entities to be prepared to deal with different environments, in order to take the most advantage of the negotiations at all times. For this, players must be aware of the different contexts they are faced with, so that they can adapt their behaviour according to the distinct circumstances.

In order to provide a sense of context awareness for electricity market negotiation players, this paper proposed a context analysis mechanism, which analyses different characteristics or conditionings, that allow characterizing different negotiation periods of different days. This characterization groups periods and days that present similar characteristics in what concerns the negotiation environment, so that these groups can assume the representation of different contexts. Being able to recognize different negotiation contexts allows players to adapt their behaviour to best suit the acting requirements at each time.

The proposed context analysis mechanism is used by the ALBidS decision support system to provide adaptation capabilities to market negotiation players, by differentiating players' actions depending on each context, in a way that these actions can originate the best outcomes for the supported player.

The integration of ALBidS with the MASCEM electricity markets simulator gives the chance for the proposed mechanism to be

Table 5
Contexts definition for the year-long case study.

	P1	P2	P3	P4	P5
	Peak consumption hours	Off-peak consumption hours	Special cases	Exceptional high wind speed	Exceptional low wind speed
D1 Business days	C1.1	C2.1	C3.1	C4.1	C5.1
D2 Weekends	C1.2	C2.2	C3.2	C4.2	C5.2
D3 Holidays	C1.3	C2.3	C3.3	C4.3	C5.3
D4 Special situations	C1.4	C2.4	C3.4	C4.4	C5.4

Table 6
Incomes, in €, achieved by the subject player when acting in each context, for each of the three considered electricity markets, during the entire year of 2013.

	MIBEL		EPEX		Nord pool	
	Without context analysis	With context analysis	Without context analysis	With context analysis	Without context analysis	With context analysis
C1.1	5.073.828,65	5.479.734,94	4.291.809,62	4.356.186,76	3.407.220,10	3.529.880,03
C1.2	1.908.158,85	2.007.383,11	1.611.227,38	1.627.339,66	1.249.302,59	1.299.274,69
C1.3	377.907,89	405.495,17	337.274,38	377.747,31	240.390,32	262.025,45
C1.4	215.020,48	247.273,55	195.711,32	227.025,13	140.541,92	158.812,37
C2.1	9.334.737,06	9.894.821,28	8.518.192,98	8.560.783,95	6.192.680,85	6.477.544,17
C2.2	3.464.988,87	3.652.098,27	3.190.942,01	3.210.087,66	2.186.730,48	2.280.759,89
C2.3	734.793,21	756.837,01	586.587,11	591.279,81	439.308,83	452.488,10
C2.4	384.143,56	430.240,79	343.394,26	374.299,74	246.070,03	270.677,03
C3.1	335.504,92	375.765,51	277.525,88	310.828,98	205.368,02	230.012,19
C3.2	126.068,76	146.239,76	110.181,72	127.810,80	77.118,82	89.457,83
C3.3	23.880,88	26.627,18	20.870,33	23.270,42	15.557,07	17.346,13
C3.4	13.776,77	16.807,66	12.135,80	14.805,68	8.180,68	9.980,44
C4.1	988.074,66	1.215.331,83	881.458,90	1.084.194,44	638.396,61	785.227,83
C4.2	356.574,20	449.283,49	322.017,13	405.741,59	237.160,33	298.822,02
C4.3	71.744,38	84.658,37	63.952,96	75.464,49	46.969,20	55.423,66
C4.4	39.660,15	51.954,80	35.489,01	46.490,61	26.680,36	34.951,28
C5.1	253.247,65	255.780,13	218.123,08	224.666,77	158.662,17	159.931,47
C5.2	98.038,12	100.979,26	82.505,34	83.247,89	62.125,49	63.430,12
C5.3	19.634,64	20.518,20	16.521,62	16.587,70	12.888,65	13.533,09
C5.4	10.921,60	11.587,82	9.468,64	10.046,23	7.026,31	7.307,36
Total	23.830.705,29	25.629.418,11	21.125.389,46	21.747.905,60	15.598.378,83	16.496.885,11

tested and validated in realistic simulation scenarios. The results of the simulations presented in the case study section shown that the proposed context analysis mechanism is, in fact, suitable for its purposes, being able to grant the supported market player with higher incomes, when compared to situations when the context analysis mechanism is not used. This increase in incomes is verified by a positive difference in certain specific contexts that before were considered as similar situations as any others. The presented case studies considered the influence of several factors that determine the definition of contexts, such as: business days vs. weekends, peak vs. off-peak consumption hours, special events and high wind generation. Additionally, a comparative study has been performed to the application of the proposed methodology to three different electricity markets, MIBEl, EPEX and NordPool, which offered promising results, with visible improvements in incomes in all three considered markets.

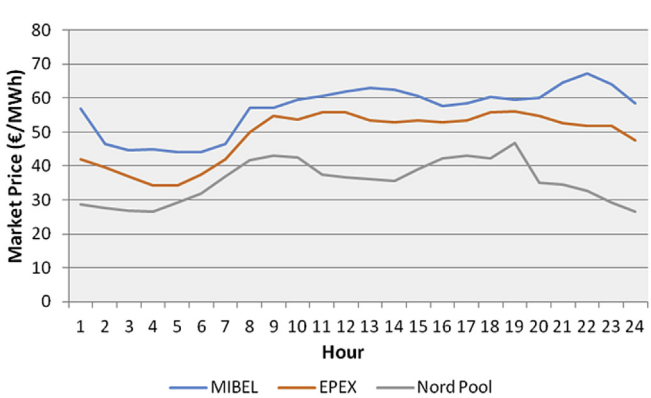

Fig. 17. Comparison of the average hourly market price during the year of 2013 in MIBEL, EPEX and Nord Pool.

As future work, the potentialities of the proposed methodology are huge. The inclusion of rainfall information in the context definition process can be important to better suit the case of markets with large hydro based production penetration. The application of the proposed methodology to the energy resources' management is an important perspective, as well as the application to several issues in the smart grid paradigm perspective. The utilization of the proposed methodology in the buildings' consumption management problem, including demand response is also an interesting application.

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Support Vector Machines for decision support in electricity markets' strategic bidding

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ABSTRACT

Energy systems worldwide are complex and challenging environments. Multi-agent based simulation platforms are increasing at a high rate, as they show to be a good option to study many issues related to these systems, as well as the involved players at act in this domain. In this scope the authors' research group has developed a multi-agent system: Multi-Agent System for Competitive Electricity Markets (MASCEM), which simulates the electricity markets environment. MASCEM is integrated with Adaptive Learning Strategic Bidding System (ALBidS) that works as a decision support system for market players. The ALBidS system allows MASCEM market negotiating players to take the best possible advantages from the market context. This paper presents the application of a Support Vector Machines (SVM) based approach to provide decision support to electricity market players. This strategy is tested and validated by being included in ALBidS and then compared with the application of an Artificial Neural Network (ANN), originating promising results: an effective electricity market price forecast in a fast execution time. The proposed approach is tested and validated using real electricity markets data from MIBEL – Iberian market operator.

1. Introduction

The study of the operation of electricity markets has become increasingly important in recent years as a result of the challenges that the restructuring of these markets originated, this restructuring has increased the competitiveness of the market, but also its complexity. The increasing complexity and unpredictability, consequently, increase the difficulty in decision making. The bodies involved are then forced to rethink their behavior and market strategies [1], which makes it essential to use tools that allow the study and different market mechanisms and the relationships between the participating entities [2].

Regulators and players have an interest in predicting market behavior; regulators to test regulations before they are implemented, and detect market inefficiencies, the market players to realize market behavior in order to optimize their profits. The need to understand these mechanisms and how the interactions between the players affect the market has contributed to the increased use of simulation tools. Multi-agent software is particularly directed to the analysis of dynamic and adaptive systems with complex interactions among stakeholders. Several modeling tools for the study of electricity markets have emerged. Some relevant examples are Electricity Market Complex Adaptive System (EMCAS) [3], Agent-based Modeling of Electricity Systems (AMES) [4], Genoa Artificial Power Exchange (GAPEX) [5], and Multi-Agent System for Competitive Electricity Markets (MASCEM) [6,7].

Although some studies have emerged, confirming the applicability of simulation tools to study these markets, particularly using multi-agent systems, these tools present a common limitation: the lack of adaptive learning capabilities that enable them to provide effective support to the decisions of market entities. Current tools are directed to the study of market mechanisms and interactions among participants, but are not suitable for supporting the decision of the players' negotiators in obtaining higher profits in energy transactions.

These limitations highlight the need to develop adaptive tools, which enable strong support for market players. These tools will enhance the improvement of the results of these players. Being adaptable to different market circumstances and contexts of negotiation, intelligent tools can get realistic and appropriate suggestions for players' actions so that they can direct their behavior in search of the best possible results.

With a view to eliminating this gap, the Adaptive Learning strategic Bidding System (ALBidS) [7,8] has been developed. ALBidS is based on multi-agent technology, assembling several

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different strategic approaches to act in the electricity market. The ALBidS system is integrated with the MASCEM simulator, a system that models the environment of electricity market and the interactions between the major participating organizations, both in negotiation and management.

The competitive nature of electricity markets, which translates to constant and rapid changes in this environment, also require an endless search for new methods of artificial intelligence, adaptive learning and decision support, enabling systems like ALBidS adequate adaptation at all times. The nature of these new approaches should reflect an increasing effectiveness in forecasts in the shortest time possible execution.

Support Vector Machines (SVM) [9] is a technique for classification and data forecasting (closely related to Artificial Neural Networks (ANN) [10]), which, by its characteristics, offers some guarantees to grant ALBidS with the required specifications: good predictive power in short execution time. SVMs have been used in many areas, such as pattern recognition, image recognition, classification and regression analysis, text categorization, medical science, weather forecast, energy prices, and many other applications [11,12].

This paper presents the development of an SVM based methodology for electricity markets' participation and its integration in the ALBidS system [8]. The main goal of the proposed SVM approach is to provide a bid suggestion for market participation, based on the electricity market price forecast. The forecasted price is used as a basis for an operational strategy of agents participating in the electricity market. The strategic action proposal provided by the SVM approach can be used by ALBidS as a suggestion for the action that should be performed by the supported electricity market negotiating player. The integration of the proposed SVM methodology with the MAS model of ALBidS provides an innovative approach, taking full advantage on the complementarily of the several artificial intelligence (AI) approaches that compose ALBidS with the best features of SVM: high quality results in a very short execution time. The interconnection with ALBidS and MASCEM [6] allows the testing and validation of the proposed strategy in a realistic electricity market simulation environment, using real data from the Iberian power market – MIBEL [13].

After this introductory section, Section 2 presents an overview of the MASCEM simulator and of ALBidS decision support system. Section 3 presents the proposed SVM based approach for decision support in an electricity market environment. Section 4 shows the experimental results of the proposed methodology, comparing them to the performance of other forecasting methodologies, under three distinct perspectives: (i) comparison of forecasting capabilities; (ii) execution times; (iii) results when used as decision support for electricity markets participation. Finally, Section 5 presents the most relevant conclusions of this work.

2. MASCEM and ALBidS overview

MASCEM [6,7] is a multi-agent system that models the most important players that take part in electricity markets, collecting data in the medium and long term to support the decisions of these agents according to their characteristics and objectives, thus allowing better understanding of the mechanisms and behaviors that are common to this type of markets. The MASCEM simulator uses several approaches and learning techniques for modeling and supporting market actors in their decisions. Fig. 1 shows the main features of the MASCEM simulator.

The simulator is directed to the study of various types of markets, including the day-ahead spot market, balancing markets, forwards markets, and bilateral contracts. MASCEM allows defining the simulation settings and market scenarios to simulate, including the definition of the characteristics of buyers and sellers

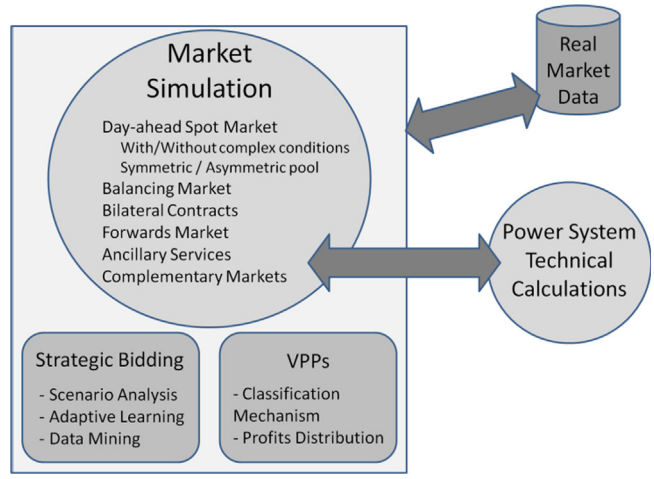

Fig. 1. Key features of MASCEM [14].

and their number. These scenarios are supported by real data from several electricity market operators [13], which provides a realistic representation of such markets.

After the simulations it is possible to analyze the amounts of energy transacted by each agent, the respective market prices, and the obtained profits/costs in each period.

One advantage of MASCEM, being a simulator of electricity markets, is to allow the study of multiple models for different market types, and to be able to achieve results with high accuracy, facilitating the drawing of conclusions on the future uncertain environment of power systems.

The user can perform several simulations, such as studying the same exact market or the same scenario negotiations as often as needed to draw the necessary conclusions, or using several different scenarios for testing. It is also possible to change the settings for each buyer or seller agent, and create the trading scenarios, and analyse their results under different circumstances.

To help in the analysis of results, MASCEM comes accompanied with a series of graphs that are generated during each negotiation process, so that the results of the agents, whether sellers or buyers, can be tracked. Configuration files are generated for each agent and simulation; these files can also be used to repeat the simulations or to execute close variations in order to compare results.

Adaptive Learning strategic Bidding System (ALBidS) [7,8] is a multi-agent system, which integrated with MASCEM. ALBidS uses adaptive learning to make MASCEM agents capable of analyzing negotiation contexts, such as the types of markets in which they are inserted, economic and weather conditions, the type of day (e.g. business, weekend, or holiday) and the trading period (e.g. peak or off-peak).

Thus, agents can adapt to any market automatically, being prepared for unexpected changes in electricity markets, managing to change their strategy of buying or selling through this system. For this, ALBidS uses Reinforcement Learning Algorithms (RLA) to choose the strategy that best fits each specific context. Fig. 2 shows the interconnection between MASCEM and ALBidS.

From Fig. 2 it is visible that interactions between MASCEM and ALBidS are performed through the Main Agent. Electricity market negotiating agents, such as buyers and sellers, which request the decision support of ALBidS, ask the Main Agent for action suggestions. The Main Agent, which is the top entity in ALBidS, sends the requests to the Strategy Agents, which are responsible for executing the different strategies based on different approaches and techniques. Once all Strategy Agents finish the execution of their action strategies, they send their specific action suggestions to the

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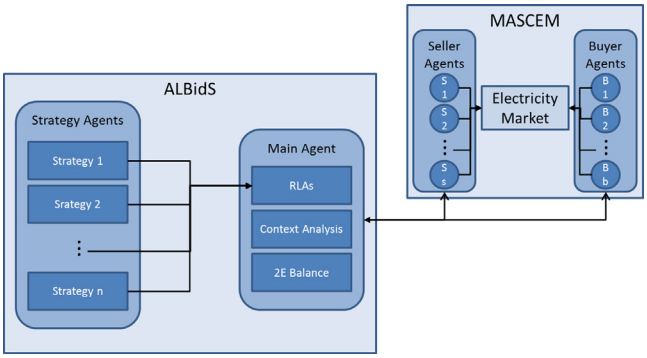

Fig. 2. Main interactions between MASCEM and ALBidS.

Main Agent, which is responsible for executing the RLAs; allowing ALBidS to choose the best strategy that most suits each specific situation. This is done by suiting the confidence values on each strategy to each different context, and simulation circumstances. For this, the Main Agent runs the Context Analysis mechanism and the Efficiency/Effectiveness (2E) balance management, which is used to suit the balance between the execution time and the quality of results to the purpose of each simulation. Further details on the model, execution, and specifications of ALBidS can be consulted in [8].

3. Strategic bidding based on Support Vector Machines

In 1936, Fisher [9] created the first algorithm for pattern recognition. Subsequently, Vapnik and Lerner [15] created an algorithm called Generalized Portrait (SVM algorithm is implemented by a generalization of the nonlinear algorithm Generalized Portrait). This was the first running kernel of SVM, only for classification and linear problems.

The SVM concept can be tracked to when statistical learning theory was developed further with Vapnik, in 1979. However, the SVM approach in the current form was first introduced with a paper at the COLT conference, in 1992 [16]. Statistical bounds on the generalization of soft margin algorithms and for the regression case were given by Shawe-Taylor and Cristianini in 2000 [17].

During the last decades several applications of SVM can be found, both for classification and for regression problems. Some examples are: pattern recognition, image recognition, classification and regression analysis, text categorization, medical science, classification of proteins, weather forecast, wind speed prediction, energy prices forecast, among other practical applications [11,12,18–21].

A wine preferences' modeling approach using SVM has been proposed in [11]. The problem of wind speed forecasting using SVM is presented in [12]. A least squares SVM for classification and regression, considering the existence of noise in data has been proposed in [19]. Also for classification, in [20] a Laplacian least squares SVM is proposed.

A new incremental learning approach to endow a Takagi-Sugeno-type fuzzy classification model with high generalization ability is presented in [22]. The proposed fuzzy model is learned through incremental SVM. The prediction of earthquake occurrence using a combination of singular value decomposition (SVD)-based technique for feature extraction and SVM classifier is presented in [23]. An iterative active learning technique based on self-organizing map (SOM) ANN and SVM classifier is presented in [24]. The proposed method exploits the properties of the SVM classifier and of the SOM ANN to identify uncertain and diverse samples to be included in the training set.

A fuzzy-based SVM classification algorithm is proposed in [25] with the goals of determining the controllable bound from the real data, of reducing feature from extensive candidate inputs, and of training the SVM model parameters. In [26] a new learning algorithm called extreme learning machine (ELM) for single-hidden layer feedforward neural networks is proposed. ELM chooses hidden nodes randomly and analytically determines the output weights. In theory, this algorithm tends to provide good generalization performance at extremely fast learning speed. The problem of feature selection in the context of Semi-Supervised SVM is studied in [27].

SVM application using kernels got popular for reasons such as

- often concentrating on convex problems,
- allowing many linear algebra techniques to be used in a non-linear way,
- have showed robustness in many application domains,
- spend fewer resources and half the time of Artificial Neural Networks.

The information to use in an SVM must follow the format suggested in (1):

$$(y_i, X_i), \ldots (y_i, X_i), \quad x \in R^n, \quad y \in R, \tag{1}$$

where each example x_i is a space vector example; y_i has a corresponding value; n is the size of training data. For classification y_i assumes finite values; in binary classifications: $y_i \in \{+1, -1\}$; in digit recognition: $y_i \in \{1,2,3,4,5,6,7,8,9,0\}$; and for regression purposes, y_i is a real number ($y_i \in \mathrm{R}$).

The implementation of SVM requires considering some important aspects, namely

- *Feature space* is the method that can be used to construct a mapping into a high dimensional feature space by the use of reproducing kernels. The idea of the kernel function is to enable operations to be performed in the input space rather than the potentially high dimensional feature space. Hence the inner product does not need to be evaluated in the feature space. This provides a way of addressing the curse of dimensionality. However, the computation is still highly dependent on the number of training patterns, and a good data distribution for a high dimensional problem generally requires large training sets.
- *Loss functions*. In statistics, the decision theory and machine learning, the loss function is a function that maps an event to a real number, representing some "costs" associated with the difference between the estimated and the actual data for an occasion. The purpose of this function is to modulate the input data, when applied to a training set, and then forecasting the values (or sorting). The loss function uses the forecast values and compares how much they deviate from the actual values, quantifying the deviation.
- *Kernel functions*. The kernel functions, in general, are a set of algorithms for pattern examination. The main task is to find patterns and study the type of associations, in a particular pattern (e.g., groups, classifications, major components, correlations, classifications) for general types of data (such as sequences, text documents, sets of points vectors, images, etc.). The kernel function approach the problem by mapping the data to a dimensional space, where each coordinate corresponds to a characteristic of each input value transforming the data into a set of points in Euclidean space. Some examples of kernels are [28] Polynomial, Gaussian Radial Basis Function, Exponential Radial Basis Function, Multi-Layer Perceptron, Splines, B splines.

- *Non-linear regression*. Likewise to classification problems, a non-linear model is typically required to effectively model data. In the same method as the non-linear Support Vector Classification (SVC) approach, a nonlinear mapping can be used to map the data into a high dimensional feature space where linear regression is executed. The kernel approach is again employed to address the curse of dimensionality.

After exhaustive preliminary testing, it has been found that the most applicable kernels for the specific problem approached in this paper (forecast of electricity market prices as basis for the decision support in an electricity market negotiation process) are the Radial Basis Function (RBF) and the Exponential Radial Basis Function (eRBF). Although these two kernels can be applied to both classification and regression problems, they show their best potential when directed to regression in time series data. RBF have received significant attention by the scientific community, most commonly with a Gaussian of the form (2).

$$K(x,y) = \exp\left\{\frac{(x,y)^2}{2\sigma^2}\right\} \tag{2}$$

Classical techniques utilizing radial basis functions employ some method of determining a subset of centers. Typically a method of clustering is first employed to select a subset of centers. A smart feature of the SVM is that this selection is implicit, with each support vectors contributing one local Gaussian function, centered at that data point. By further thoughts it is possible to select the global basis function width, or angle (σ) using the structural risk minimization (SRM principle) [16].

The development of the SVM approach was performed in MATLAB, which is a framework highly directed to mathematical calculations, such as required by this problem. The SVM approach for regression of the electricity market prices, takes as parameters as follows:

- *Training limit* – limit number of training days;
- *kernel* – kernel function that will be used in the regression process;
- *e_Val* – value of ε-insensitive (sensitiveness to error);
- *C* – limit of kernel function;
- *p1* – angle of the kernel function (σ);
- *p2* – offset of the kernel function.

In order to run the SVM, given the day and period for which the SVM will predict the market price, the application automatically creates a MS Excel file with all the data necessary for training, which is gathered from the database of historic market prices. The file contains a worksheet, which contains a column with the number of lines that were set as the limit for training. Then, the SVM approach is ran with the specified parameters, and the forecasted price is returned to the application to be used by ALBidS.

4. Case study

This section demonstrates some results of the tests that were performed to the implemented SVM approach. The performance of the SVM is compared to some other strategies that are already integrated in ALBidS, with the same purpose as the proposed SVM approach – forecasting electricity market prices to provide decision support to electricity market negotiating players. These strategies include an ANN [29], the market price following strategy, some time series regression approaches, and some simple (but fast) market price forecasting averages [30]. The comparison of results is performed in three different dimensions: (i) comparison of the forecasting error using the Mean Absolute Percentage Error (MAPE); (ii) comparison of the execution times of the different approaches; (iii) comparison of the incomes originated to an electricity market player, when used as decision support in market negotiations.

4.1. Market negotiations' specification

The spot or day-ahead market is a daily basis functioning market [13], where players negotiate electric power for each hour, or half hour of the following day. Such markets are structured to consider production fluctuations as well as differences in production costs of distinct units.

In this market, each participating entity must present their selling or buying proposals for each of the 24 hourly periods of a day. These proposals or bids are typically composed by a tuple (power, price), with different meanings, whether they come from buyers or sellers, respectively: power stands for amount of power to be bought or sold, and price is the maximum accepted price or minimum selling price.

When the negotiation is finished, an economic dispatch for each period is set by the market operator. At the end of each period the market operator uses a market-clearing tool establishing the market price – a unique price that will be applied to all transactions of this period.

In market pools, the most common type of negotiation is a standard uniform auction. MIBEL day-ahead spot market works as a symmetric market, where both suppliers and consumers both submit bids. The market operator orders the selling and demand offers: selling bids start with the lowest price and move up, and demand bids start with the highest price and move down. Then, the proposed bids form the supply and demand step curves, and the point at which both curves intersect determines the market price, paid to all accepted supplier and consumers. The bids of every supplier offering prices lower than the established market price and every consumer offering prices higher than the market price will be accepted. Fig. 3 shows the symmetric market prices definition.

The profits can be improved by submitting bids that are advantageous for the player in the bidding process; i.e. for a seller player, a bid price below the established market price, but still as high as possible, in order to assist in increasing the market price (origination of higher profits, through a higher market price). In the case of a buyer agent, the bid price should be above the established market price, but as low as possible, in order to reduce the cost that is paid for the bought energy.

4.2. Test scenario

The test scenario involves 7 buyers and 5 sellers (3 regular sellers and 2 VPPs). This group of agents has been created with the intention of representing the Spanish reality, reduced to a smaller group,

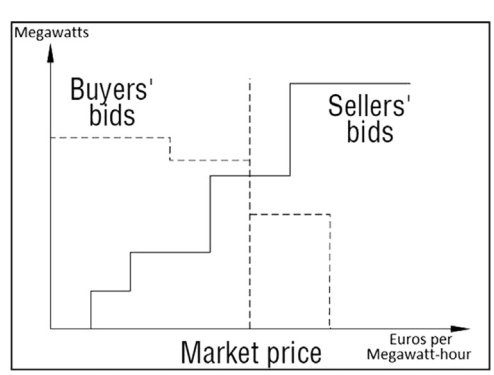

Fig. 3. Symmetric market price establishment, adapted from [6].

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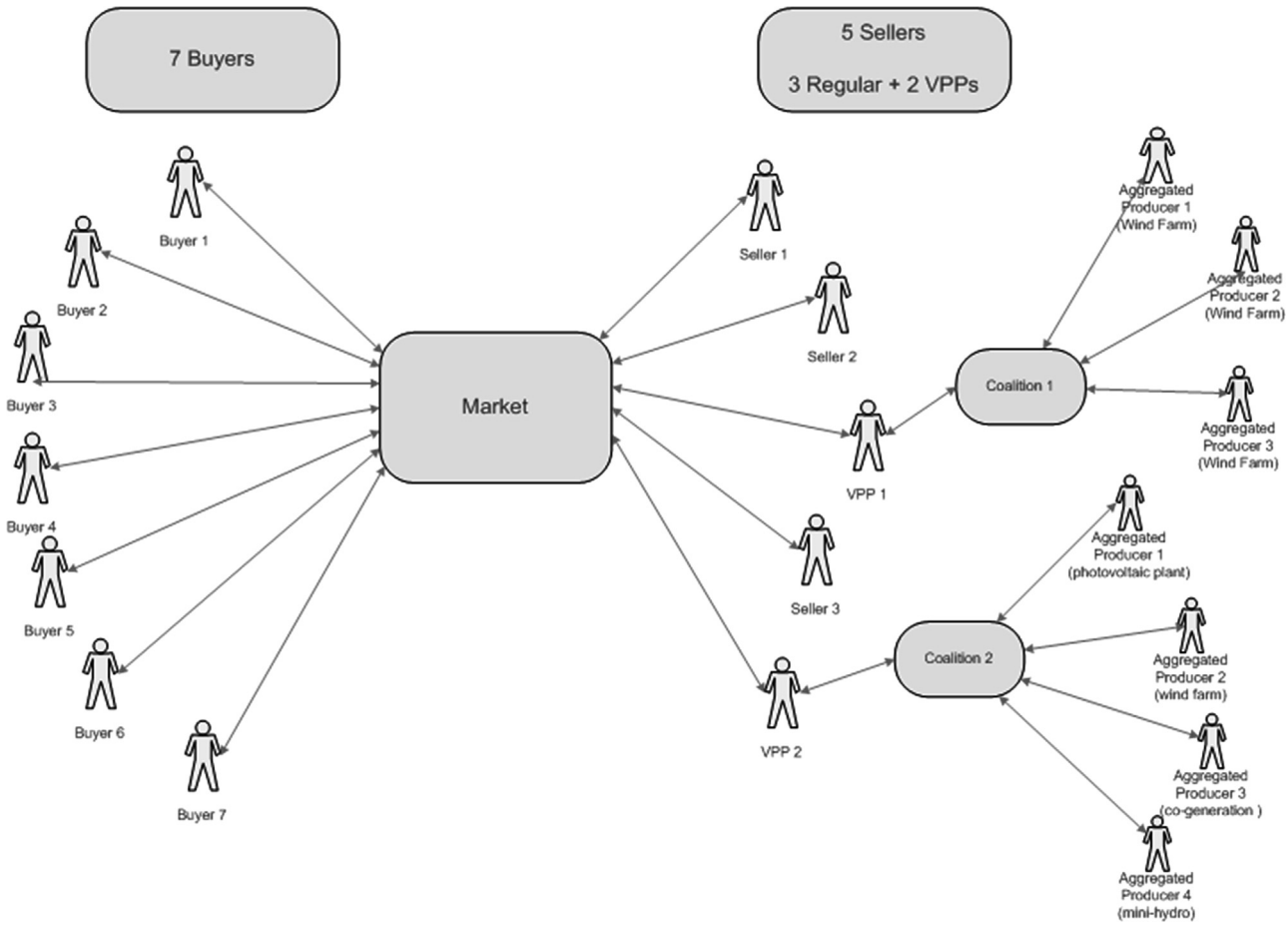

Fig. 4. Test scenario structure, adapted from [14].

containing the essential aspects of different parts of the market, allowing a better individual analysis and study of the interactions and potentiality of each of those actors [13]. The data used in this case study has been based on real data extracted from the Iberian market operator – MIBEL [31], using an automatic data extraction that has been presented in [32]. The forecasting process is executed using the extracted data concerning 24, hourly electricity market prices per day. Fig. 4 presents the test scenario structure.

The simulations consider different biddings for each agent. Seller 2, which is used as the test reference, will use each presented strategy with different parameters, depending on what it is important to be shown. Its bid power is kept constant at 50 MW for all periods of all simulated days, in order to make it easier to compare the results.

The competitor players' bids are defined as follows:

- Buyer 1 – this buyer buys power independently of the market price. The offer price is 18.30 c€/kWh (this value is much higher than average market price).
- Buyer 2 – this buyer bid price varies between two fixed prices, depending on the periods when it really needs to buy, and the ones in which the need is lower. The two variations are 10.00 and 8.00 c€/kWh.
- Buyer 3 – this buyer bid price is fixed at 4.90 c€/kWh.
- Buyer 4 – this buyer bid considers the average prices of the last four Wednesdays.
- Buyer 5 – this buyer bid considers the average prices of the last four months.
- Buyer 6 – this buyer bid considers the average prices of the last week (considering only business days).
- Buyer 7 – this buyer only buys power if market prices are lower than the usually verified market price (around 4.0–8.0 c €/kWh), by bidding a much lower value: 2.0 or 3.0 c€/kWh, depending on whether the current negotiation period is at a peak time of the day.
- Seller 1 – this seller needs to sell all the power that he produces. The offer price is 0.00 c€/kWh.
- Seller 2 – this seller bid considers the average prices of the last four months with an increment of 0.5 c€/kWh.
- VPP 1 – includes four wind farms and offers a fixed value along the day. The offer price is 3.50 c€/kWh.
- VPP 2 – includes one photovoltaic, one co-generation and one mini-hydro plants; the offer price is based on the costs of co-generation and the amount to sell is based on the total forecasted production.

In order to facilitate the understanding of the results, all the considered market negotiating entities will be attributed a constant total cost. This way, this value will not affect the results in the analysis of each test.

All tests were performed on a computer with two Intel® Xeon® X5450 3.0 GHz processors, each one with 2 cores, 4 GB of random-access-memory and Windows Server 2008 32 bits operating system.

4.3. Specifications

The electricity market negotiations are simulated in MASCEM, using the defined test scenario. The simulations, as well as all the tests concern 61 consecutive days (2 months) starting on September 1st, 2009.

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All results are analyzed by period independently, since in the scope of ALBidS, periods are considered as different, independent contexts [8]. Regarding the SVM parameterization, two kernels are considered: RBF and eRBF. After exhaustive sensibility analysis, the parameterizations that achieved the best results, and the ones used in this case study, are

- kernel RBF: *training limit*=20, $p1(\sigma)=6$, ε-*insensitive*=0, $C=\infty$, $p2=0$ and
- kernel eRBF: *training limit*=20, $p1(\sigma)=18$, ε-*insensitive*=0, $C=\infty$, $p2=0$

The performance of the proposed SVM approach is compared to several alternative market price forecasting strategies, namely

- An ANN based approach that has been presented in [29]. It is characterized as a feed-forward ANN, with a variable number of hidden nodes in the intermediate layer. The training process of this approach is updated in all iterations so that the most recent available data is always considered as input for the training.
- The market price following (MPF) approach [8]. As the name suggests, this strategy follows the market price of the same period of the previous day. It is a very simple strategy, but it presents good results when prices show a tendency to stabilize in a certain period, for some consecutive days.
- Average Agent 1 (AA1) – This agent performs an average of the prices from the market historic database. It uses the data from the 30 days prior to the current simulation day, considering only the same period as the current case, of the same week day. This allows having a strategy based on the tendencies per week day and per period.
- Average Agent 2 (AA2) – This agent performs an average of the market prices considering the data from one week prior to the current simulation day, considering only working days, and only the same period as the current case. This strategy is only performed when the simulation is at a business day. This approach, considering only the most recent days and ignoring the distant past, provides a proposal that can very quickly adapt itself to the most recent changes in the market.
- Average Agent 3 (AA3) – This agent uses an average of the data from the four months prior to the current simulation day, considering only the same period as the current case. This offers an approach based on a longer term analysis.
- Regression Agent 1 (RA1) – This agent performs a regression on the data from the four months prior to the current simulation day, considering only the same period of the day, similarly to the method used by Average 3 Agent.
- Regression Agent 2 (RA2) – This agent performs a regression on the data of the last week, considering only business days. This strategy is only performed when the simulation is at a business day.

Further details on the Average and Regression Agents have been presented in [30].

4.4. Results

Table 1 presents the average MAPE values of forecast of the SVM approach using each of two kernels (RBF, and eRBF) and the ANN, for the 61 considered days.

From Table 1 it is visible that the error values using the proposed SVM approach are always located below 1%. Comparing the performance of the SVM with the ANN one can see that the forecast results are very similar for all cases. In the total of all error values for the four considered periods of the 61 days, the SVM approach using the RBF kernel achieved a higher error than the ANN, while the SVM approach using the eRBF kernel was able to achieve lower error values than the ANN. However, the error values are so similar, that conclusions on what is the best approach for forecasting electricity market prices cannot be taken. Comparing the forecasting error between the SVM and the remaining forecasting methodologies, it is visible that the error achieved with the proposed methodology is always lower.

Table 1
MAPE forecast error values (%).

Strategies	Period				
	1	6	12	18	Average
SVM (RBF)	0.297	0.044	0.788	0.033	0.342
SVM (eRBF)	0.262	0.107	0.385	0.099	0.261
ANN	0.326	0.027	0.579	0.003	0.284
MPF	0.514	0.043	0.913	0.090	0.490
AA1	0.376	1.154	0.952	0.142	0.560
AA2	0.614	0.170	1.607	0.256	0.837
AA3	0.426	0.064	1.127	0.088	0.416
RA1	0.468	0.070	1.241	0.053	0.458
RA2	0.467	0.039	0.829	0.080	0.354

Table 2
Average execution times of the SVM approach (ms).

Training limit	Execution times (ms)		
	Minimum	Average	Maximum
5	4776	5022	9501
10	4730	4984	5830
15	4721	5107	7437
20	4789	5092	10,136
35	4793	4942	23,595

Table 2 presents the average execution times of the SVM approach with different amounts of training data, after 1000 run trials.

Table 2 shows that the SVM approach, using either of the two considered kernels, takes an average of 5 s to execute. From Table 2 it is also visible that the increase in considered days for training does not represent a considerable degradation in execution time. Table 3 presents the average execution times of the ANN approach, for different amounts of training data.

Table 3 shows the average execution time of the ANN. It is visible that, even with parallel programming for a faster access to data, the minimum average value is of 11 s (more than twice the average execution time of the SVM). Note that the amount of data that the ANN requires for its training is enormous when comparing to the SVM (ANN: 60–730 days to achieve acceptable results; SVM: 5–35 days).

Finally, Table 4 presents the comparison of the incomes that were achieved in the simulated electricity market, by a player using the SVM and the ANN as decision support for market negotiations.

From Table 4 it is visible that both the SVM, using each kernel, achieved higher incomes than the ANN approach. Given the similarity in the SVM and ANN forecasting capabilities for this problem, as shown in Table 1, these results are explained by the fact that the SVM forecasting errors are often by defect (below the real value), which originates that the player is always able to sell, even if at a bit smaller price; while when bidding above the market price (as happens more often with the ANN) means not selling at all, as explained in Section 4.1. Regarding the performance of the other strategies, it is visible that all have presented

Table 3
Average execution times of the ANN approach (ms).

Training limit (days)	Execution time (ms)	
	Without parallelism	With parallelism
60	15,000	11,000
120	18,000	13,000
200	22,000	14,000
365	30,000	17,000
730	49,000	20,000

Table 4
Incomes achieved in the simulated electricity market, using the both *kernels* of the SVM and the ANN (€).

Strategies	Total incomes
SVM (RBF)	48,287.37
SVM (eRBF)	55,378.33
ANN	31,918.13
MPF	26,051.47
AA1	23,194.85
AA2	21,007.16
AA3	27,216.02
RA1	26,895.50
RA2	28,629.41

lower incomes than the SVM and ANN approaches, due to their weaker forecasting capability.

5. Conclusions

This paper has presented a methodology for electricity market negotiation, based on the concept of Support Vector Machine. SVMs have been widely used in the last decades, and can be applied to classification and regression problems. The main advantages are the good forecasting capabilities, and the small amount data required for the training process, which leads to very low execution times.

The proposed approach was integrated with ALBidS, a decision support system for electricity market players, which is connected to the MASCEM electricity market simulator. This integration provided the means for the testing of the proposed approach under a realistic simulation scenario based on the Iberian electricity market – MIBEL. The results achieved with the SVM approach are encouraging, in a sense that, for both considered kernels, the forecasting achieved very good results (always below 1% error), which are very similar to the performance of the ANN, and superior to the results achieved with other alternative electricity market forecasting methods. However, in what concerns the execution time, the SVM approach showed all of its advantage, by taking less than half the time of the ANN to provide results, by using only the data of a few days for training, while the ANN requires several months. When supporting a market player's decisions the electricity market, the SVM approach was able to provide higher incomes than the other strategies, hence proving its applicability for the considered problem of decision support in electricity market negotiation.

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Paper V [Pinto, 2015e]:

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Adaptive Portfolio Optimization for Multiple Electricity Markets Participation

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***Abstract*—The increase of distributed energy resources, mainly based on renewable sources, requires new solutions, able to deal with this type of resources' particular characteristics (namely, the renewable energy sources intermittent nature). The smart grid concept is increasing its consensus as the most suitable solution to facilitate small players' participation in electric power negotiations, while improving energy efficiency. The opportunity for players' participation in multiple energy negotiation environments (smart grid negotiation in addition to the already implemented market types, such as day-ahead spot markets, balancing markets, intraday negotiations, bilateral contracts, forwards and futures negotiations, among other) requires players to take suitable decisions on whether to, and how to participate in each market type. This paper proposes a portfolio optimization methodology, which provides the best investment profile for a market player, considering different market opportunities. The amount of power that each supported player should negotiate in each available market type in order to maximize its profits, takes into account the prices that are expected to be achieved in each market, in different contexts. The price forecasts are performed using artificial neural networks, providing a specific database with the expected prices in the different market types, at each time. This database is then used as input by an evolutionary particle swarm optimization process, which originates the most advantage participation portfolio for the market player. The proposed approach is tested and validated with simulations performed in MASCEM (Multi-Agent Simulator of Competitive Electricity Markets), using real electricity markets data from the Iberian operator – MIBEL.**

***Index Terms* — Adaptive Learning, Artificial Neural Network, Electricity Markets, Multi-Agent Simulation, Portfolio Optimization, Swarm Intelligence.**

I. Introduction

ELECTRICITY markets worldwide are complex and challenging environments, involving a considerable number of participating entities, operating dynamically trying to obtain the best possible advantages and profits [1]. The restructuring of these markets increased the competitiveness of this sector, leading to relevant changes and new problems to be addressed, namely physical constraints, market operation rules and financial issues [1, 2]. Potential benefits depend on the efficient operation of the market [1].

The large scale integration of distributed generation, mainly based on renewable energy sources, is probably the biggest challenge that must be overcome in the present panorama of power systems. A globally adopted solution is approaching the electricity network as a series of subsystems, giving birth to the concept of smart grid [3-5]. Experimental implementations of smart grids are arising all around the world [3, 4], considering the management of local generation, loads, and storage systems, as independent from the main system, although connected with the main grid through a connection bus, or even working as an isolated system (in islanded mode). The intelligent management of these smaller electricity grids has been evolving and potentiating the implementation of smart grids as an upcoming reality [3, 5].

The introduction of smart grids, along with the emergence of new paradigms and approaches that deal with the challenges that are constantly arising in the power system's sector, generate a complex and dynamic environment, for which the involved entities must always be prepared. Market players and regulators are very interested in foreseeing market behavior, as it is essential for them to fully understand the market's principles and learn how to evaluate their investments in such a competitive environment [2].

The development of simulation platforms based in multi-agent systems is increasing as a good option to simulate real systems in which stakeholders have different and often conflicting objectives. These systems allow simulating scenarios and strategies, providing users with decision making according to their profile of activity. Several modeling tools can be fruitfully applied to study and explore restructured power markets, such as "AMES Wholesale Power Market Test Bed" [6] and "EMCAS - Electricity Market Complex Adaptive System" [7].

MASCEM - Multi-Agent Simulator for Electricity Markets [8, 9] is also a modeling tool to study and explore restructured electricity markets. Its purpose is to be able to simulate as many market models and player types as possible, enabling it to be used as a simulation and decision-support tool for short/medium term purposes but also as a tool to support long-

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term decisions, such as the ones taken by regulators. Agents in MASCEM use several distinct strategies when negotiating in the market and learning mechanisms in order to best fulfill their objectives. The learning process is undertaken using MASCEM's connection with another multi-agent system: AiD-EM (Adaptive Decision Support for Electricity Markets Negotiations). AiD-EM provides decision support to electricity markets' negotiating players, allowing them to analyze different contexts of negotiation, such as the week day, the period, the particular market in which the player is negotiating, the economic situation and weather conditions, and automatically adapt their strategic behavior according to the current situation. This system implements several negotiation mechanisms and data analysis algorithms, enhancing the strategic behavior of the players.

Despite the continuous development of multiagent software, the ability of learning and adaptation to provide the best possible results for electricity market players is yet very far from adequately addressed [10, 11]. In particular, the automatic and intelligent use of multiple market opportunities as they arise is yet a relatively unexplored issue, and should be properly addressed in order to provide players with the capability of optimizing their participation in several simultaneous electricity markets.

This paper proposes a portfolio optimization model for multiple electricity market participation. The proposed model considers real-time adaptation to the most recent perceived events, and it is different from other existing methodologies [12, 13] because it is not centered in a specific single scenario; it offers the possibility of buying and selling in the same period, in different markets, while usually approaches consider only the selling or buying perspective; it is adaptive to different time ranges of optimization; and it is based on real markets data. With this model, players are able to change their participation profiles (participating or not in each market type, and with what amount) as the time progresses. Additionally, real data is used, referring to each point in time for when the optimization is required, making the optimization adaptive to the evolution of negotiation contexts throughout the time. Firstly, a database is created, filled with the prices expected for each market session of the several electricity markets in which the player is registered over the various negotiation periods of each day. This database is filled using price forecasts made by artificial neural networks [14, 15] trained with historical data of real electricity markets [16]. The database is used to execute an optimization based on the Evolutionary Particle Swarm Optimization (EPSO) [17-19] meta-heuristic, in order to optimize participation investments in a multi-market environment. The proposed methodology also considers a fuzzy logic process [20] to deal with different power amount ranges. Additionally, a risk management approach is used, which allows the decision support process to be subjected to different levels of risk, depending on (i) the objectives and characteristics of the supported player, (ii) the quality of the price forecasts, (iii) the decision support execution time restrictions. The optimal power amount to negotiate in each distinct market is used as basis for the decision support capabilities provided by MASCEM and AiD-EM, with the goal of providing the best possible profits for the supported player when acting in several electricity markets simultaneously. The integration of the proposed methodology in AiD-EM, and consequently in MASCEM, provides the means for the test and validation using realistic simulations based on data extracted from real electricity markets [16].

After this introductory section, section II presents the decision support capabilities provided by MASCEM and AiD-EM, which allow electricity market players to take full advantage of the participation in a single market. Section III presents the proposed methodology, including the electricity market price forecast using artificial neural networks, for the creation of the necessary database of expected prices for distinct situations; and also the optimization problem that uses the forecasted prices as input to achieve optimal participation amounts for each market. The proposed methodology is tested in a realistic environment using the simulation capabilities of MASCEM, and the results are depicted in section IV. Finally, the most relevant conclusions are presented in section V.

II. Decision Support for Electricity Markets Participation

MASCEM [8, 9] is a simulation platform developed to study the electricity markets' restructuring. It creates agents dynamically, including their interactions, information and experience acquirement in long term so it can support players' decisions, according to their own characteristics and goals. The purpose of MASCEM is to simulate a diversity of market models and agent types so that it can realistically represent the electrical markets environment. This allows MASCEM to be used as a simulation and decision-support tool for players.

MASCEM can represent the most important entities involved in electrical markets' negotiations and their relations. The market operator agent controls the pool and validates offers to set the price market. The system operator agent ensures that all conditions are according to regulations and is responsible for the system security. Buyer and seller agents are the key players in the market. Buyers represent consumers and distribution companies. Sellers represent electricity producers, competing among themselves to get the highest profit. Moreover, buyers and sellers can cooperate with each other so they can achieve their goals.

MASCEM includes the negotiation mechanisms normally found in electricity markets, such as the day-ahead pool (asymmetric or symmetric, with or without complex conditions), bilateral contracts, balancing markets, forward markets and ancillary services. MASCEM is also capable of simulating energy negotiations at a smart grid level.

The different trading types implemented in MASCEM and the interactions between the participating entities in different situations create the necessity for the use of adaptive learning. A new system - AiD-EM - has been integrated with MASCEM with the purpose of providing decision support for electricity market participants. This multi-agent system provides decision support to market players for different types of negotiations. ALBidS (Adaptive Learning strategic Bidding

System) [9] is a specific decision support system directed to negotiations in auction based markets. ALBidS includes an agent responsible for performing each distinct strategy to support the bidding process; thus preventing the degradation of the system's performance. As each agent gets his answer, it sends the response to the main agent. The main agent uses the distinct acting proposals, provided by each algorithm, and chooses the most appropriate from them through the use of reinforcement learning algorithms (RLA). These RLA are dependent on the context, so that different algorithms can be considered for distinct negotiating contexts.

The diversity of algorithms and approaches that are used by AiD-EM bring out the need for the development of a mechanism that is able to manage the balance between the Efficiency and Effectiveness (2E) of the system. This mechanism provides the means for the system to adapt its execution time to the purpose of the simulation, i.e., if the expected results from AiD-EM are as best as it is able to achieve, or, on the other hand, if the main requirement is for the system to be executed rapidly, since the purpose of the considered simulation is to analyze issues other than player's optimal performance in the electricity market. The 2E Management mechanism manipulates the strategies both externally and internally. From the system's perspective this mechanism contributes by deciding which tools are used at each moment for each circumstance; depending on their observed performance in terms of efficiency and effectiveness. This way this mechanism can choose to exclude certain strategies when they are not fulfilling the requirements for the case in matter. The strategies are also manipulated internally, so that they can adapt their individual results quality/execution time balance to the needs of each simulation.

A highly dynamic environment such as the electricity market forces players to be equipped with tools that allow them to react to diverse negotiation circumstances. The variety of different strategies grants AiD-EM the capability of being prepared for the diversity of situations that a market negotiation player faces. The very different natures of the considered strategies offer coverage over a diversity of areas, guaranteeing a high probability that at least one strategy is always suited for each different context, even if its application to other contexts does not bring as much benefits.

The decision support provided by AiD-EM is directed to the actual market negotiations, *i.e.* AiD-EM decision support systems are prepared to optimize the outcomes in a certain market type, when negotiating a given power amount. However, when a player is faced with the participation in multiple simultaneous markets, the total amount of power that a player needs to buy or sell must be divided by each market type, as best suits the objectives of the player. The methodology proposed in this paper has this exact purpose. Figure 1 presents the architecture of AiD-EM. From Figure 1 it is visible that the proposed methodology, represented in the figure by the *Investment Management* module, determines the amount of power that the supported player should negotiate in each available market type, before the decision support for the actual market negotiations is provided by AiD-EM.

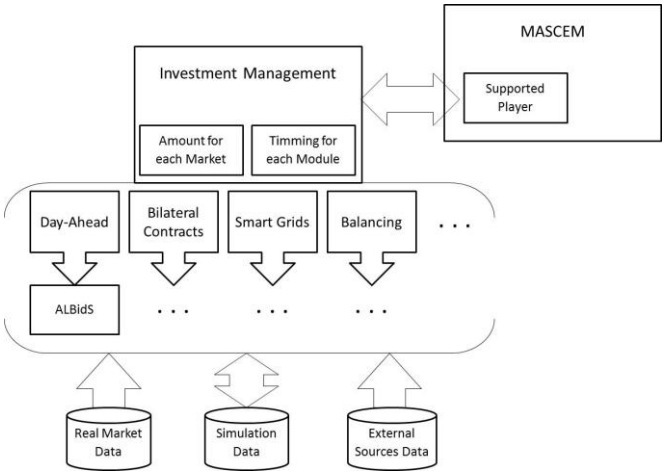

Fig. 1. AiD-EM system architecture

III. Market Portfolio Optimization

The objective of the proposed methodology is the analysis of the specific characteristics of electricity markets' historical data. This provides the ability to intelligently manage the investments to be made, *i.e.*, based on different markets' prices forecast, the amount of power that should be negotiated in each market, in each context, can be optimized. The process of the proposed methodology is presented in Figure 2.

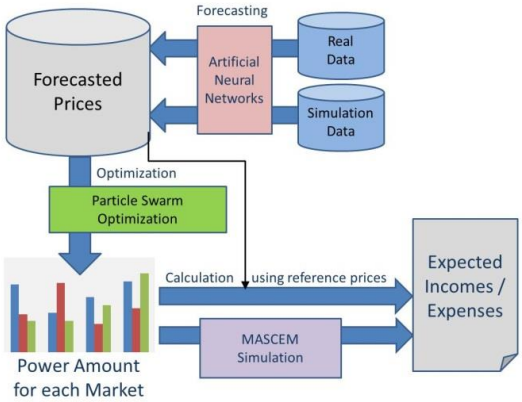

Fig. 2. Proposed methodology diagram

The first step of the methodology concerns a forecast process, using the historic market prices from all the considered markets and market sessions. These forecasts, using the artificial neural network that is presented in sub-section III.*A.3*., are used to build a database of expected market prices for each market, for each time period of each considered day. The different market prices' forecasts are referent to each period of each considered day, for each considered market types. Additionally, for each period, the forecasts are performed for different range of negotiated power amount; *i.e.* the forecasting process takes into account the price that is expected when the negotiation amount is higher or lower. These ranges of power amount are determined by a fuzzy logic process, which is presented in sub-section III.*A.2*.

Using the market prices forecast database, filled with the forecasting values achieved by the artificial neural networks forecasts for each power amount, an optimization process is

executed in order to achieve the optimal amount of power that should be negotiated by the supported player in each market type, at each time period (given the total amount the player desired to sell or buy). This optimization process originates a reference value of incomes that should be expected by investing the suggested amounts of power in each market. Finally, realistic market simulations using real data from different electricity markets are used to validate the results, and analyze if the outcomes of the optimization process are in accordance to what can be expected in the reality.

A. Data Preparation

The first step of the proposed methodology is the creation of a database containing the forecasts of different market prices under different contexts. The database is generated dynamically, and it considers five distinct dimensions:

- Market types in which the player is able to participate;
- The number of days considered for the market participation portfolio optimization;
- The number of negotiation periods in each market type;
- Minimum, average, and maximum expected prices in each market, in each context. These different forecast values are used to support the risk management, as detailed next, in sub-section *A.1.*;
- Power amount ranges, which are dynamic, depending on the maximum power capacity and on the execution time restrictions, as detailed in sub-section *A.2*.

A different price forecast is required for every combination of values of the five dimensions.

1) Risk Management

The price forecast values used to fill the database, as any forecast, are always subjected to some prediction error. The higher the forecast error is, the lower is the confidence in such predicted vale, and therefore the risk associated to the participation of the player in the market considering such reference value increases.

The implemented risk management procedure takes into consideration, not only the quality of the forecasts (associated prediction error), but also the objectives and characteristics of the supported player, which determine the player's propensity for risk taking; and the restrictions of execution time, demanded by the Efficiency/Effectiveness (2E) balance management mechanism (see section II).

When a seller player has a low predisposition for assuming a risk position, a lower price reference value is assumed, in order to play more safely, avoiding risk as much as possible. The higher the forecasting error is, the faster the reference prices should decrease in this case, escaping quicker from riskier price ranges. The opposite is applied to situations when the propensity for risk is high, where higher prices are used as reference, in order to aim for higher profit possibilities.

Besides the player's predisposition for risk taking, and the forecasting error, the 2E mechanism has also influence on the risk management procedure. When a low execution time is required for the decision support process, the quality of the decision support naturally tends to decrease. In this case the risk propensity is automatically decreased, in order to achieve safe results even with a low level decision support. The opposite occurs when the requirement of the 2E mechanism is the best possible quality of results, ignoring the execution time. In this case the risk can be increased, since the decision support tools that are able to deal with riskier environments are at their best behavior.

In order to achieve lower and higher price reference values, three forecast values are always considered: minimum, medium and maximum. These three values represent predictions of: the minimum value that the market price can achieve; the average expected market price; and the maximum value that can be attained in a given period of one day. This risk management approach has been based on the methodology presented in [21].

2) Power Range

The result achieved by players in some markets depends on the amount of negotiated power. Bilateral contracts, forward markets, and smart grid internal markets are examples of this. This means that even though the optimal participation solution would be to allocate everything in the market with the higher expectation, the negotiated amount is by itself restrictive, and obligates the solution to disperse the allocation by other markets, depending on the expected prices and power amount.

Power amount ranges (e.g. from 0 to 50MW, 51 to 100 MW, etc.) are used to take this into account. This way, price forecasts are performed for each amount range independently, representing the expected price that can be achieved when negotiating different amounts of power.

Fuzzy logic [20] is used to smooth the ranges' transition values. E.g. when negotiating 50 MW in a certain market, part of one power range, the expected price is *X*; when negotiating 51 MW in the same market, amount of a different power range, the expected price is *Y*. However, the difference from 50 to 51 MW is minimal, and not enough to represent a large difference in the expected price. The fuzzy process allows these transition values between different ranges to be smoother, avoiding abrupt price changes. Figure 3 shows the fuzzy variable that represents the different ranges' transition.

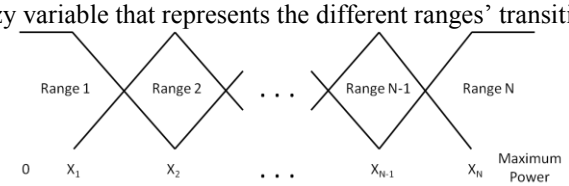

Fig. 3. Fuzzy variable representing the power ranges

The fuzzy intervals are defined dynamically, depending on the number of power ranges determined by the 2E mechanism. The more restricted the available execution time is, the smaller the number of power ranges (less power ranges means less price forecasts, which means less execution time in running the neural networks). The power ranges are defined by a clustering mechanism, which groups the ranges of amounts that present similar prices in each market.

The 2E mechanism defines the number of fuzzy intervals. The number of fuzzy intervals corresponds to the number of clusters that is set by the clustering process. From the clustering process results the grouping of power amounts considering their similarity. I.e., for a case where the

supported player has 50MW available to negotiate, and the 2E mechanism defines the number of power ranges as 2, the clustering mechanism will separate the historic cases in which transactions of the specific market, in the current context (e.g. same negotiation period, same day of the week, same season of the year) have been established with values from 0 to 50MW, into two different groups, considering the price at which transactions have been established. Each cluster has a centroid, which represents the value in which this group is most represented by. E.g. transactions from 0 to 20MW are grouped in the first cluster, and transactions from 20 to 50MW are assembled in the second cluster. The first cluster has a centroid of 10, and the second cluster has a centroid of 35. These values, 10 and 35, are the representative values of each cluster, and represent the points where each corresponding fuzzy membership function assumes the maximum value.

The fuzzy membership functions are defined dynamically. All membership functions, except from the first and last, are triangular, each with the maximum value equal to one of the cluster centroids, and the lower and upper limits equal to the previous, and following centroid values, respectively. The first and the last membership functions, which do not have a previous or subsequent centroid, are trapezoidal functions, assuming a lower limit of zero, in the case of the first membership function, and an upper limit equal to the maximum power, for the last membership function, as seen from figure 3, where each $X_{1...N}$ represents a cluster centroid. Assuming a case where the player negotiates 50MW, the number of fuzzy intervals/clusters is equal to 3, and the clustering process defines the three clusters with the centroids equal to 10, 25 and 40; the first membership function will have its maximum value equal to 10, lower limit equal to 0 and upper limit of 25; the second membership function has its maximum value at 25, lower limit equal to 10 and upper limit equal to 40; the third fuzzy membership function has its maximum value equal to 40, lower limit equal to 25 and upper limit of 50. This process is similar regardless of the number of considered intervals, and it is executed dynamically.

3) Artificial Neural Network

The considered artificial neural network (NN) [14, 15] is characterized as a feedforward neural network, receiving as inputs the market prices and total amount of negotiated energy in the market, referring to: the day before the desired forecasted day, one week before, two weeks before, and three weeks before. The NN considers four nodes in the intermediate layer, and one output – the forecasted market price. This topology has been presented in [22], and has been defined after some analysis and experiences, as presented in [23]. The structure of this NN is presented in Figure 4.

Backpropagation using the gradient descent method [24] has been used as training algorithm for the NN. This requires calculating the derivative of the squared error function with respect to the weights of the network. The squared error function E for the single output neuron is defined as in (1).

$$E = \frac{1}{2}(t - y)^2 \tag{1}$$

where t is the target output for a training sample, and y is the actual output of the output neuron.

For each neuron j, its output o_j is defined by feedforward calculation, as in (2).

$$o_j = f\left(\sum_{k=1}^{n} w_{kj} x_k\right) \tag{2}$$

where n is the number of input units to neuron j, and w_{kj} is the weight between neurons k and j. Hence, the input for the activation function f of a neuron is the weighted sum of outputs o_k of the previous neurons. The used activation function f is the logistic function, a log-sigmoid function, which can be defined as in (3).

$$f(z) = \frac{1}{1 + e^{-z}} \tag{3}$$

The backpropagation algorithm is used as the training method of the designed artificial neural network. The backpropagation algorithm includes the following steps [24]:

1. Initialize weights as small random numbers;
2. Introduce training data to the NN and calculate the output by propagating the input forward through the network using (2);
3. Calculate the error using (1)
4. Propagate the sensitivities backward through the network by simply taking the derivative of the activation function (3) with respect to the network parameters;
5. Calculate w_{kj} updates;
6. Update the values of w_{kj};
7. Repeat steps 2 to 6 until all examples are classified correctly.

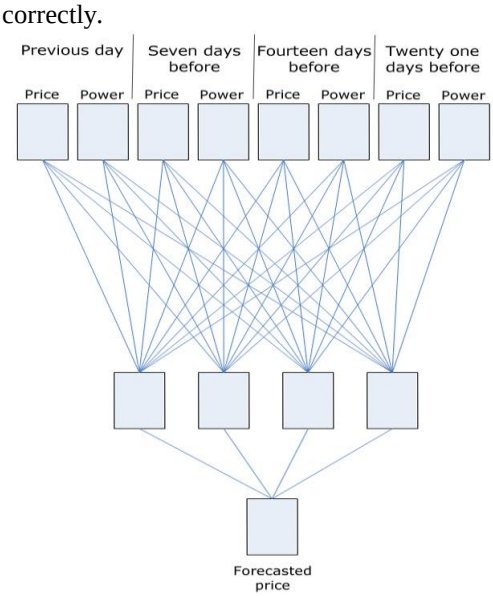

Fig. 4. Artificial Neural Network topology

The number of previous days considered for the training is dependent on the restrictions of the 2E mechanism, in terms of execution time. This indicates if the NN will use more or less values for training, meaning a faster but worse forecast, or a slower but more effective forecast. Note that considering an exaggerated amount of data may lead to over-training, making the NN memorize the examples instead of learning the relationship between the data. Also, it may lead to the consideration of inadequate data, from a long time before, which possibly has no added value to the learning of the most recent tendencies of the data. As the necessary amount of data increases, so does the required time to retrieve the data from the database, due to the necessary number of consults. In order to smooth this time's increase, parallel programming was used, dividing each data matrix into various, and creating a different thread to fill each of these smaller matrixes.

The proposed NN is executed several times for each forecast (100 times as default), using different initialization weights for the neurons. The maximum, minimum and average forecast values are extracted from the different results that are achieved. The average forecast value is simply the average of all achieved forecasts; the maximum forecast value *maxf* is calculated as in (4); and the minimum forecast *minf* value is calculated as in (5).

$$maxf = \max(fv_t) + 2\sigma, \qquad t \in [1, NT] \tag{4}$$

$$minf = \min(fv_t) - 2\sigma, \qquad t \in [1, NT] \tag{5}$$

where NT is the number of executed forecasts, fv_t is the actual forecasted value of forecast execution t, and σ is the standard deviation of all performed forecasts.

After experimentation the result is that when a larger amount of training data is used, the results of the forecasts tend to uniform, leading to a σ of nearly zero. When less data is used for training, the dispersion of the forecast results is higher, due to the larger influence of the initialization weights, which makes the minimum and maximum forecast values become more distant from the average forecast value.

Taking into account that the NN is used for real time forecasting purposes, using real data that is made available at all moments, in order to provide further dynamism and adaptation capabilities to the forecasting process, the used NN is re-trained in every iteration, so that it always considers the most recent available data in the training process. This way the NN becomes more prepared to deal with every recent event. Also, every negotiation period is forecasted independently from the other, i.e. the NN only considers data concerning each period separately, so that distinct information does not degrade the quality of forecasting results for different contexts. For this reason, forecasting market prices for the 24 hourly periods of one day, in a single market, requires executing 24 distinct forecasts, each with the respective re-training process.

B. Problem Formulation

Considering the expected production of a market player for each period of each day, the amount of power to be negotiated in each market is optimized to get the maximum income that can be achieved.

The inputs are:

- the weekday, referred as d in equation (6);
- the number of days, *Nday*;
- the negotiation period, referred as p;
- the number of periods, *Nper*;
- a boolean variable for each distinct market or negotiation platform, indicating if this player can enter it to sell: $Asell_{M1\ldots NumM}$;
- a boolean variable for each session of the balancing market, indicating if this player is allowed to buy in each of them: $Abuy_{S1\ldots NumS}$;
- *M1, M2, …, NumM* are the considered markets;
- *S1, S2, …, NumS* are the considered balancing market sessions;

The outputs are:

- $Spow_{M1\ldots NumM}$ representing the amount of power to sell in each market;
- $Bpow_{S1\ldots NumS}$ representing the amount of power to buy in each session of the balancing market;

In this formulation $ps_{M,d,p}$ is the expected price for the selling of power, and $pb_{S,d,p}$ the expected price for buying. A simplified version of this problem formulation has been partially presented in reference [9]. The complete problem formulation is presented in (6).

$$\begin{aligned} & f(Spow_{M1\ldots NumM}, \mathrm{Bpow}_{S1\ldots NumS}) = \\ & Max\left[\begin{array}{l} \sum_{M=M1}^{NumM}\left(Spow_{M,d,p} \times ps_{M,d,p} \times Asell_M\right) - \\ \sum_{S=S1}^{NumS}\left(Bpow_S \times pb_{S,d,p} \times Abuy_S\right) \end{array}\right], \\ & \forall d \in Nday, \forall p \in Nper, Asell_M \in \{0,1\}, Abuy \in \{0,1\} \\ & ps_{M,d,p} = \mathrm{Value}(d, p, Spow_M, \mathrm{M}) \\ & pb_{S,d,p} = \mathrm{Value}(d, p, Bpow_S, \mathrm{S}) \end{aligned} \tag{6}$$

The *Value* function returns the expected value of the power for each particular period of each day, and for each market. That also depends on the power amount to trade. When a player tries to establish a bilateral contract, the deals may be highly dependent on the amount of power that is being negotiated. The same fact is verified in other markets, even if not in such a clear way. So, this prediction takes that in consideration too, by applying fuzzy logic on the absolute amount of the power, to classify it in one of the categories defined by a clustering mechanism, which groups the ranges of amounts that present similar prices in each market. The correspondent price is obtained through the Data matrix which stores all the prices. The value function is expressed in (7).

$$Value(day, per, Pow, Market) = Data(fuzzy(Pow), day, per, Market) \tag{7}$$

This formulation has some constraints that are dependent on the individual characteristics and requirements of each particular market. Other constraints that must be taken into

consideration are the ones imposed by the complex conditions that each player can present. These constraints are formulated depending on the set of conditions that the player presents, that also depend on each market that it enters.

The main constraint, which is applied to every situation, is expressed in (8), to impose that the total power reserved to be sold in the set of all markets is never higher than the total expected production (TEP) of the player, plus the bought power along all sessions of the balancing market.

$$\sum_{M=M1}^{NumM} Spow_M \leq TEP + \sum_{S=S1}^{NumS} Bpow_S \tag{8}$$

Variables *Abuy* and *Asell* are Boolean variables that indicate if the player is "allowed to buy or sell" in each session of each market, i.e. if the participation as a seller or as a buyer is permitted. A reference example is the balancing market, where a player that is registered as seller, is able to buy, and vice-versa; also, in bilateral contracts, and in smart grid negotiations, there is no restriction, meaning that any player is able to buy or sell power. However, there is no restriction that obligates a player to do so; it just indicates if the player is able to do it if he desires to.

The definition of *Abuy* and *Asell* results from the rules of each market, i.e. since the proposed methodology is integrated in the decision support system for multi-markets simultaneous participation, which is, in turn, connected to the MASCEM simulator, depending on the rules of the specific electricity market in which the supported market player is participating, *Abuy* and *Asell* are automatically defined.

This formulation is defined in the perspective of a seller, which means that in order to maximize the profits, the tendency is to sell and achieve incomes, and not to buy, and reduce the incomes. A seller player will only buy when this purchase will originate higher incomes by selling the purchased power at higher prices in other market.

By restriction (8), the increase of the bought power (*Bpow*), which comes from the purchase of power in the positive Abuy sessions, makes the *Bsell* value increase, i.e., it allows the player to sell larger amounts of power at higher prices. Since the objective function is maximized, *Bpow*, and consequently the use of positive *Abuy* sessions, will only increase when there are *ps* (sale prices) in any market, that are higher than *pb* (bought price) in the same period, i.e., prices that will increase incomes by selling larger amounts of power in markets with higher prices, by purchasing power in markets with lower prices in the same period. Once again, since this is a maximization, and since there is no restriction that obligates players to sell the full amount of their power, the output, in the worst case scenario, is 0, when the player does not buy anything and does not sell anything as well. The player will achieve no incomes, but he will achieve no prejudice (negative incomes) as well. However, this will only occur when all sale prices of all markets, in all periods, are equal to zero. It takes only one market with the market price higher than zero to make the player have positive incomes with the sale of some power. In fact, even in cases where the market price is negative in all markets, the player will achieve positive incomes nevertheless, by not selling anything and buying at negative values, which lead to positive incomes.

Summarizing, this optimization process allows us to:

- Play with the possibility to negotiate with different players in the bilateral contracts, and so having the chance to get higher or lower prices, depending on the circumstances. By using power ranges to separate prices that are expected from negotiating different power amounts in the same market, as in (7), where the expected price is dependent on the negotiated power amount in each context, players are able to deliberately negotiate more or less power in each market, depending on the expected price for each amount of power.
- Play with the chance to wait for the later sessions of the balancing market to sell higher amounts of energy, if it is expected for the price to go up. Although balancing market sessions are sequential in their timing, they are referent to the same negotiation periods, giving player the chance to negotiate several times the amount of power for the same time period. Taking advantage on the *Asell* and *Abuy* specifications, the player is able to choose in which sessions to invest the larger amount of power, even if it means waiting for the latest sessions in time, when they are expected to provide higher returns.
- Play with the possibility for sellers to buy and buyers to sell in the balancing market, to get good business opportunities: using arbitrage opportunities, buying extra energy when the prices are expected to be lower, and then selling it later when the prices go up; or if the prices show the opposite tendency, offer more energy than the player actually expects to produce, to get greater profit, and then buy that difference in the expected lower prices opportunities. From (8), the power that can be sold (*Spow*) increases when the bought power (*Bpow*) in the same period is higher. This means that depending on the *Asell* and *Abuy* values, players are able to sell and buy power referring to the same negotiation period, and with that buy extra amounts of power in sessions where *pb* is lower, and sell larger amounts of power in the same period, in sessions where *ps* is higher.

C. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an evolutionary technique developed by James Kennedy and Russell Eberhart [17], which intends to simulate a simplified social system. Initially, the basic idea was to demonstrate the behavior that flocks of birds or shoals of fish take in their local random flight, but globally determined. In a computational way, PSO algorithms appear as an abstraction of natural biological behavior where demand for a better spot is the search for an optimal solution, and the set of particle positions the search space or space of possible solutions. The behavior of each particle is based on its previous experience, and the other particles with which it relates. As in genetic algorithms where the fittest individuals are preserved, the PSO also safeguards the best positions found, which theoretically means the solution found, with the highest quality.

This method is different from other evolutionary techniques, showing encouraging developments. PSO considers N particles, and each particle adjusts its direction

based on its experience of flight and the experience of the general population (group of particles). These particles are inserted in the solution space, and are based on deterministic procedures to make the search for the optimal location. Each movement of each particle is based on three parameters: the sociability factor, the factor of individuality, and the maximum speed. PSO combines these parameters together with a random generated value (between 0 and 1), and calculates the next position of the particle, the parameters are:

Global Attraction Factor (*C2*): determines the attraction (convergence) of the particles to the best solution discovered by a member of the group;

Local Attraction Factor (*C1*): determines the attraction of the particle with the best position;

Speed Factor (*W*): delimits the movement, since this is directional and determined.

In addition to the mentioned factors, it is necessary to specify a few parameters such as the number of particles, their size, and stopping criteria. Each particle is treated as a point in a multidimensional space, so it is necessary to specify the value for that dimension. Each particle stores the positions of their size into data structures. This position is decisive for the calculation of fitness. Typically, in the statement of PSO several notations are used for the representation of variables central to its operation:

Current position of the particle. Stores the current position of the particles via $Xi = Xi1, Xi2, ..., XiD$, where X represents the position of particle i in dimension D. The position values are changed depending on the change of speed;

Best local positions. The best positions for found by each particle, i.e. positions which achieved the best calculated fitness to date: $Pi = Pi1, Pi2, ..., PiD$;

Best overall position: to store the best position, for which the calculation of the fitness reaches the best overall value. At the end of the search space of solutions, the solution found by the algorithm is given by Gd;

Rate of change of velocity: this value is decisive for the change of position on each particle $Vi = Vi1, Vi2, ..., Vid$. The values for each velocity of the particle i, are calculated using expression (9).

$$Vidt+1 = Wt * Vidt + C1 * R1t * (Pid - Xidt) + C2 * R2t * (Gd – Xidt) \quad (9)$$

where *R1* and *R2* are random variables, ranging from 0 to 1.

The hybridization of PSO with evolutionary algorithms has been presented in [18]. The Evolutionary Particle Swarm Optimization (EPSO) relies on the basic idea of using simultaneously the power of evolution strategies and the exploring capacity of particle swarms. EPSO delivers a self-adapting model, not requiring extensive tuning of parameters by the user to solve specific problems, but able to self-tune in an intelligent way to respond to the characteristics of each problem [19]. The evolutionary features of EPSO are provided by the self-adaptation of the traditional PSO parameters, namely *C1, C2,* and *W*. The self-evolution of the parameters is performed through a mutation of the parameters. Hence, *C1, C2* and *W*, become $C1^*$, $C2^*$ and W^* respectively, by equations (10), (11) and (12).

$$C1^* = C1\ [logN(0,1)]^{\sigma} \quad (10)$$

$$C2^* = C2\ [logN(0,1)]^{\sigma} \quad (11)$$

$$W^* = W\ [logN(0,1)]^{\sigma} \quad (12)$$

where σ is a learning parameter that must be defined externally. The rate of velocity update becomes, therefore (13), replacing the traditional PSO velocity equation (7).

$$Vidt+1 = W^*t\ Vidt + C1^*\ (Pid - Xidt) + C2^*\ (Gd – Xidt) \quad (13)$$

The new velocity equation (13) does not require the inclusion of the random variables *R1* and *R2*. With this evolution, all the parameters are self-evolving; the need for exhaustive parameter combination experimentation is no longer required, being that the only need for parameters specification is now the learning rate σ, the number of particles, and the iteration stopping criterion.

As claimed in [18] and [19], besides the facilitation of use of EPSO, when compared to traditional PSO approaches, the obtained results are superior to traditional and similar approaches. For this reason, the implementation of the PSO process for this specific problem assumes the process of EPSO, as described in this sub-section.

IV. Case Study

A. Specifications

This section presents a case study with the goal of demonstrating the performance of the proposed methodology for portfolios optimization. For this case study, five different types of markets are considered: day-ahead spot market, balancing market, bilateral contracts, forwards market, and a smart grid market [5]. The historic of real electricity market prices and amounts of transacted power from the Iberian Market – MIBEL [16] is used, concerning the time range from January, 2002 to October, 2012. The used data is extracted from the MIBEL website [16]. The data used to model the smart grid market, including the historic log of negotiations, is based on previous works from the authors [5]. The used data set is characterized as follows:

- Day-ahead spot market prices and transacted power amount for each hourly period or each day of the considered 11 historic years, from MIBEL [16];
- Balancing market prices and transacted power amount for each period or each of the six daily sessions of the considered 11 historic years, from MIBEL [16];
- Bilateral contracts' established prices and power amounts, concerning deals established during the considered 11 years, from MIBEL [16];
- Forward market contracts' established prices and power amounts, concerning deals established during the considered 11 years, from MIBEL [16];
- Smart grid contracted market prices and transacted power amounts referring to simulated negotiations established in previous works [5].

These data is used to train the NN, providing the forecasts

of the price for each market for each circumstance. With the database built from these predictions, the EPSO approach is ran, for four different cases, concerning four different amounts of days: 1 day, 7 days, 30 days and 60 days; always starting from September, 1st 2012. The subject player is a seller player negotiating a fix amount of 50MWh for each period of the considered days. The optimization process concerns the portfolio planning performed one day before the first day of simulation; *i.e.* the forecast values are executed concerning data prior to this day, meaning that larger time ranges require many days-ahead forecasting. The parameterization of the EPSO approach is set as:

- $\sigma = 0{,}1$, as recommended in [18, 19];
- The number of particles is set as 20 for the 1 day case, 30 for the 7 days case, 50 for the 30 days case, and 100 for the 60 days case;
- The stopping criterion is set as 15 consecutive iterations without improvement of the global best value of the objective function.

For each time-horizon, the portfolio optimization approach is executed for three different cases, considering the supported player's propensity for risk:

- Assuming a very low risk (using the minimum expected prices as reference values);
- Assuming a medium risk (using the average expected prices as reference values);
- Assuming a very high risk (using the maximum expected prices as reference values);

From these three optimization processes result the respective optimal negotiation amounts of power in each market, for each case. Additionally, the objective function represents the total amount of expected incomes of the player.

Finally, in order to validate the optimization results, a simulation using MASCEM is performed considering the participation in all five considered market types. This simulation is performed for the same periods of the days considered in the optimization process, using a realistic scenario, representing the MIBEL electricity market.

The amounts of power that the subject seller player tries to negotiate in each market type are the optimal amounts resulting from the optimization process considering the medium expected prices (the ones with smaller forecast error). From these simulations result the incomes that the player achieves in a realistic and most reliable scenario, which projects the MIBEL market reality. The achieved incomes can then be compared to those resulting from the optimization processes, in order to realize if the optimization expected results are, in fact, reliable or not. Additionally, these results are compared to the reference incomes that the player would achieve if participating exclusively in the day-ahead spot market (as is the most common case in the reality, being the electricity market in which the high majority of the power is transacted every day). The spot market results are attained by considering the total sale of the player's 50MWh at the real market price that was verified in MIBEL during the 24 hourly periods of the considered days.

All simulations have been performed on a computer with two Intel® Xeon® X5450 3.0GHz processors, each one with 2 cores, 4GB of random-access-memory and Windows Server 2008 32 bits operating system.

B. Results

Table I presents the average Mean Absolute Percentage Error (MAPE) values, concerning the forecasts for the five market types, for each alternative time-horizon of portfolio optimization.

TABLE I. MAPE forecast error values (%)

Days		Day-ahead Spot	Balancing	Bilateral Contracts	Forwards	Smart Grid
1	Min	2,03	3,86	2,62	4,07	3,2
	Avg	5,62	7,92	8,37	16,32	8,84
	Max	8,31	12,25	18,1	26,02	23,15
7	Min	2,59	4,69	2,97	4,30	3,94
	Avg	7,00	8,87	10,40	17,19	11,24
	Max	9,87	14,58	21,71	28,81	26,02
30	Min	3,91	7,82	4,95	6,78	6,38
	Avg	10,96	14,41	14,77	19,46	17,91
	Max	15,95	23,40	26,88	33,85	31,48
60	Min	4,69	9,39	5,94	8,14	7,65
	Avg	13,15	17,29	14,73	21,35	19,49
	Max	19,14	25,08	29,26	36,62	34,78

From Table I it is visible that the error values vary from 2% to 26% for the 1 day optimization case. The worst forecasting accuracy values are referent to the most volatile markets, namely the Forwards market, and the Smart Grid market. The forecasting error values are higher as the time horizon increases. This is due to the anticipation of the forecasts in the cases considering a larger number of days. Note that a higher error value is not restrictive in using such predictions, since the purpose of these forecasts is to provide a basis price that is expected for a certain market, for a certain period of the day. The actual incomes achieved by the player in the market depend on its actual actions in the market after realizing which markets are most adequate to invest in at each time.

Figure 5 presents a graphic comparison between the real electricity market values of the day-ahead spot market during the day of September, 1st 2012, and the correspondent forecasted values (minimum, average, and maximum, as explained in sub-section *3.A.1 – Risk Management*)

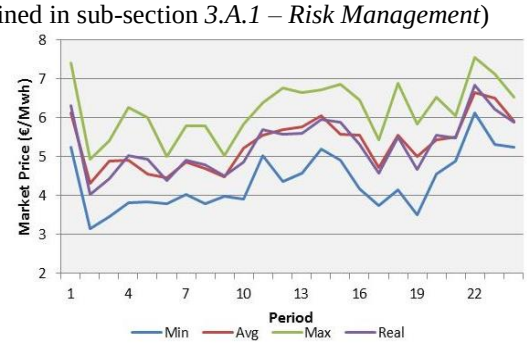

Fig. 5. Real and forecasted prices during one day in the day-ahead spot market

From figure 5 it is visible that the average forecasted price is very close to the real market price during all day, while the minimum price is always located below the real price, and the

maximum always above, however, still always being able to trail the real market price tendency.

Figure 6 presents the comparison of the objective function value (incomes in €) resulting from the optimization process considering the participation of the subject player for the three risk cases, the MASCEM simulation results, and the reference day-ahead spot market results, with the time horizon of 1 day.

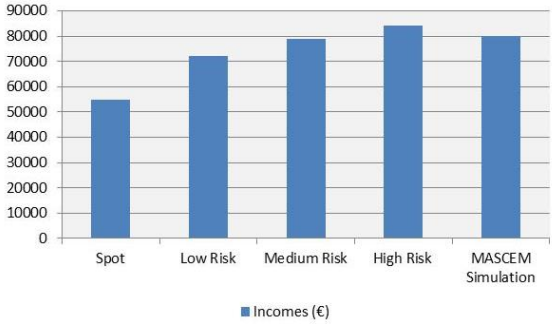

Fig. 6. Incomes of the subject player in the case of 1 day optimization

Figure 6 shows that, using the proposed portfolio optimization approach, the supported player is able to achieve higher incomes, when compared to the exclusive participation in the day-ahead spot market, regardless of the risk that the player is willing to assume. Even when considering a very low risk, the player achieves nearly 20.000 € of extra incomes, in the total of the considered day. The incomes when assuming a high risk are potentially the highest (however, the actual achieved results by the player always depend on the player's negotiation capabilities in each market type). Considering the MASCEM simulation, where the supported player acts in a realistic environment, representing the MIBEL market, interacting with agents that represent the actual players that participate in this market, it is visible that the achieved results are very close to the optimization results when using a moderate risk. In fact the difference is smaller than 2.000 € in the total of the seven days, when the player achieves nearly 80.000 € (1,45% difference). This means that the optimization results are very well representative of the reality, providing a high confidence for its use in real cases. Figure 7 presents the outputs of the optimization process for one negotiation day, using a moderate risk, regarding the optimal participation of the supported player in the considered simultaneous markets.

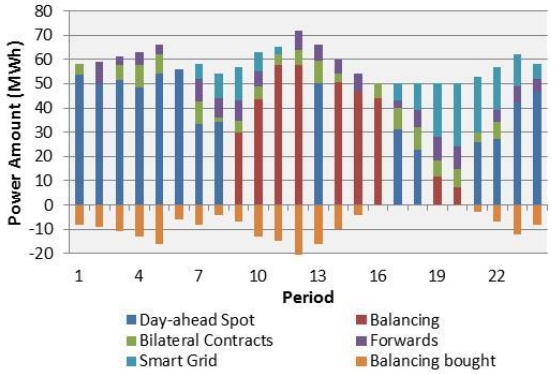

Fig. 7. Supported player participation in the several markets during one day

Figure 7 shows that the majority of the available power amount is allocated to the main market types, the day-ahead spot market in most periods of day, and the balancing market in the other. The player is, however, able to take advantage of the lower prices in some balancing market sessions to buy some extra amount of power, which is sold at higher prices in other market opportunities that present higher prices. The simultaneous selling and buying of power in the same period, in different markets, proves to be one of the main sources of advantage for the supported player. Additionally, bilateral contracts are also used for establishing favorable deals, at best prices than the ones achieved in other market types. However, these deals are, most of the times, referent to small amounts of power. Finally, the sale of power at a smart grid level is also done depending on the advantage of the deals. This means that the sales done at this level are also usually referent to smaller amounts of power. From the graph of figure 7 one can see that most of these sales are done in periods of peak consumption (periods 7 to 10, and from 17 to 23). The reason is that when the needs for consumption (of small consumers, mainly residential) increase, the opportunities for achieving some advantageous sale deals also increase.

Figure 8, figure 9, and figure 10 present the results of the optimization process for the case considering the time horizon of 7 days, 30 days and 60 days, respectively.

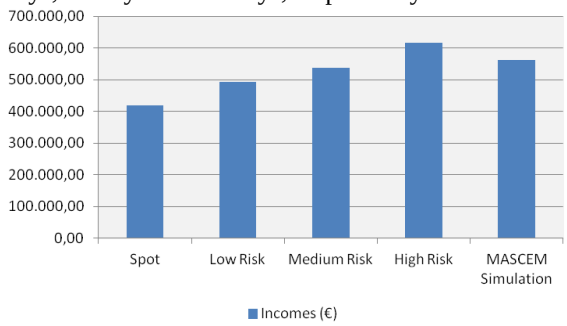

Fig. 8. Incomes of the subject player in the case of 7 days optimization

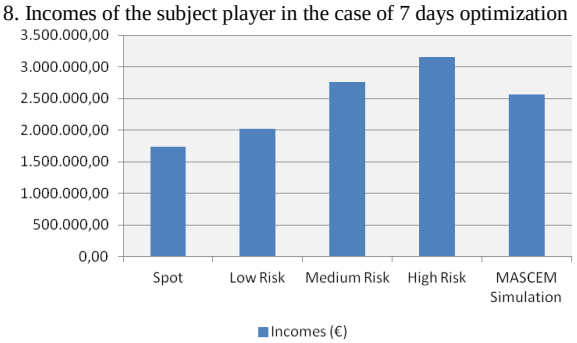

Fig. 9. Incomes of the subject player in the case of 30 days optimization

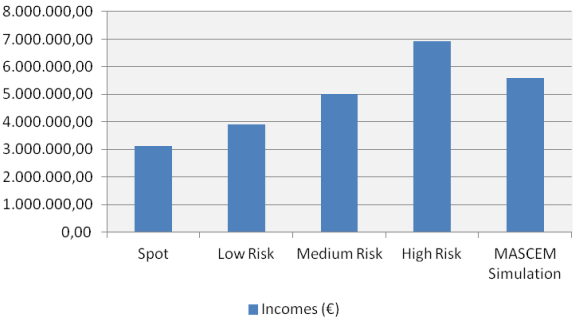

Fig. 10. Incomes of the subject player in the case of 60 days optimization

From figures 8, 9 and 10, one can see that the incomes achieved by the optimization process, regardless of the propensity to risk, are always superior to the incomes that the

player would achieve by participating exclusively in the day-ahead spot market. Additionally, for the three time horizons: 7 days, 30 days, and 60 days, the difference between the day-ahead spot market results and the results achieved by the optimization process, and by the MASCEM simulation, increase when the time horizon is larger. This is due to the continuous utilization of the alternative opportunities throughout the days; which brings a global achievement of incomes that is much higher than the simple participation in the day-ahead spot market. However, the difference between the results of the medium risk optimization approach and the MASCEM simulation also increases in larger time horizons. The variation between these two values is nearly 4% in the 7 days case; close to 8% in the 30 days case; and almost 11% on the 60 days case. The forecasting error that is associated to large time-ahead forecasts brings less reliability to the portfolio planning process, which suggests that the portfolio optimization should be performed for smaller time horizons in order to achieve near optimal results. The months-ahead planning is associated to a huge volatility of many necessary factors; which means that it can be used as reference for long term planning, when re-adapted as days go by, taking into account the new forecasting values that can be achieved with much higher accuracy in closer time-ranges. However, it cannot be looked at as strict decision support in such a long time frame, since it is impossible to reach sufficiently good forecasts to create precise decision support two-months ahead.

The execution time of the proposed portfolio optimization methodology has significant influence on the decision support process. As referred in sub-section *III.A.3)* the execution time is dependent on the requirements of ALBidS' 2E balance management. The NN forecasting process, in particular, is adaptive depending on the 2E requirements, which influence the amount of training data that is used for training. The amount of training data, has itself, a large influence on the execution time of the forecasting process. Taking into account the 2E requirements, the amount of training data is decreased when the demand for faster results increases, leading to a much faster training process, which still results in fairly good forecasts, achieved much more quickly than when aiming at the best possible forecast result. Table II shows the comparison of the execution time of the NN training process when using different amounts of training data.

TABLE II
NN'S AVERAGE EXECUTION TIME, WITH AND WITHOUT PARALLEL COMPUTING (IN SECONDS)

Training data amount (number of days)	Without parallelism	With parallelism
60	*15,36*	*11,43*
120	*18,21*	*13,19*
200	*22,54*	*14,47*
365	*30,26*	*17,20*
730	*49,18*	*20,34*

The increase in execution time as the amount of training data increases is visible by Table II. The use of a faster, yet less effective forecast, or a great forecast with the adjacent time demand, is decided by the 2E balance management mechanism. Another important aspect to be taken from Table II is the huge decrease in execution time when using parallelism in the access to data, as discussed in sub-section *III.A.3)*. Although a multiagent system, such as MASCEM and ALBidS, is by definition a parallel execution framework, where all agents are executed at the same time, there are still situations in which extra parallelism can be essential. The access to data, when it is done in a large scale, is a reference example, as can be seen by Table II.

Table III presents a summary of the average execution time of the proposed PSO approach (over 1000 executions), considering 120 days for training of the NN and the same five market types that have been used in this case study, each with 24 hourly periods. Table III also provides the comparison of the execution time of each of the processes that compose the proposed methodology, namely: the forecasting process, the creation of the dynamic fuzzy variables, and the PSO optimization approach.

TABLE III. Average execution time of the PSO approach (in seconds)

Optimization time horizon (days)	NN Forecasting	Creation of Fuzzy Variables	PSO optimization process	Total
1	*1565,30*	*3,12*	*22,97*	*1591,39*
7	*10922,30*	*22,08*	*192,95*	*11137,33*
30	*45881,40*	*89,32*	*1740,38*	*47711,10*
60	*94602,60*	*180,26*	*6261,52*	*101044,38*

From Table III it is visible that the most time-consuming process of the proposed methodology is the forecasting process. The retraining of the NN in each iteration, considering independent training processes for each of the 24 periods, and the multiple market types for which forecasts are necessary, are the main reasons. The execution time of the NN is, however, proportional to the number of considered days for the optimization process. The same is verified regarding the creation of fuzzy variables, since the creation of each fuzzy variable is independent from the other. For this reason, the time demand for the creation of the fuzzy variables is proportional to the number of considered simulation days. On the other hand, the increase of the optimization process' execution time, using the proposed PSO methodology, does not present the same proportionality. As the number of considered days increases, the number of considered variables increases as well, which has a direct influence on the difficulty of the optimization resolution. For this reason the execution time increase is more evident for larger number of days.

The total execution time for 1 day optimization is more than 25 minutes. Taking into account that the proposed methodology is integrated with ALBidS, for decision support purposes, acceptable execution times are essential. Considering that ALBidS includes many other decision support methodologies, which are time consuming as well, it becomes important for all methodologies to be as fast as possible in their execution, so that the decision support can be provided in due time. Additionally, and considering a 1 day time frame, for a day-ahead planning, the proposed

methodology is executed several times during one day (every time a market runs, the planning is re-executed taking only into account the remaining markets). For this reason, the acceleration of the optimization process execution time that the proposed PSO approach provides is indispensable.

C. Summary

The conjugation of different market opportunities throughout the time allows the proposed methodology to allocate the player's negotiating power amounts accordingly, in the pursuit for the highest incomes. Table IV presents the summary of results achieved in each of the four time-horizons.

TABLE IV. Summary of results - objective function value (incomes in €)

Days	Case	Day-ahead Spot	Balancing	Bilateral Contracts	Forwards	Smart Grid	Total
1	Spot	54804,03	-	-	-	-	54804,03
	Low Risk	33995,77	14483,81	6356,45	7266,87	10107,36	72210,26
	Medium Risk	35550,47	19761,31	6942,06	7147,72	9461,27	78862,83
	High Risk	32071,22	21104,49	7413,91	11002,48	12631,05	84223,16
	MASCEM Simulation	35272,54	20051,63	7044,04	7252,73	10400,49	80021,43
7	Spot	419399,04	-	-	-	-	419399,04
	Low Risk	222259,08	123546,36	43401,26	44687,04	59151,23	493044,96
	Medium Risk	253192,30	130623,77	45536,22	46885,26	61060,96	537298,52
	High Risk	277528,43	154268,74	54193,88	55799,40	73860,41	615650,87
	MASCEM Simulation	253074,51	140675,62	49418,69	50882,74	67352,34	561403,90
30	Spot	1736452,57	-	-	-	-	1736452,57
	Low Risk	911288,03	506554,42	177950,19	183222,05	242526,90	2021541,61
	Medium Risk	1247345,05	693357,24	243573,15	250789,12	331963,90	2767028,45
	High Risk	1423796,40	791440,62	278029,38	286266,13	378924,03	3158456,56
	MASCEM Simulation	1144890,15	636406,00	223566,44	230189,70	324696,92	2559749,22
60	Spot	3117856,39	-	-	-	-	3117856,39
	Low Risk	1767111,21	982277,79	345069,58	355292,43	470292,59	3920043,61
	Medium Risk	2259965,52	1256238,96	441310,86	454384,90	601459,05	5013359,29
	High Risk	3127577,03	1738515,07	610732,20	628825,43	832362,04	6938011,77
	MASCEM Simulation	2428192,80	1466370,89	484870,16	518049,65	696309,99	5593793,49

From Table IV it is visible that, for all time horizons, the medium-risk approach is the one that achieves the closer values to the ones achieved in MASCEM simulations. The difference between the incomes achieved using the proposed portfolio optimization approach are significantly higher than the incomes achieved by the exclusive participation in the day-ahead spot market. The advantage of the proposed method is, therefore, evident, by allowing market participant players to achieve higher incomes in market negotiations, even when their propensity to risk is low.

V. Conclusions

This paper proposes a methodology for optimizing an electricity market player participation in several simultaneous market types. The objective of the proposed portfolio optimization methodology is to provide market players the capability of using the different market opportunities to their best advantage, considering the evolution of expected prices in each market throughout the time.

The electricity market restructuring, characterized by the inclusion of several market types, along with the constant evolution of power systems, which leads to the introduction of concepts such as the smart grids, create the need for participant players to be able to choose how to, and whether to, participate in each market opportunity that arises.

The proposed methodology includes the forecasting of the different market prices, under different circumstances. Artificial neural networks are used for this purpose. Using these expected market prices, an optimization process suing an evolutionary particle swarm approach is executed in order to provide the best participation portfolio in the different simultaneous markets in which the supported player is able to participate, along several participation days.

The results show that the proposed methodology is capable of providing adequate participation profiles for market players, being the achieved incomes much higher than the exclusive participation in the day-ahead spot market, as occurs in the majority of real cases. The possibility of buying and selling power in the same negotiating period, in parallel markets, along with the capability to perceive advantageous negotiation opportunities as they arise are the most influential aspects. The risk management features allow the supported player to adapt its risk aversion, depending on the quality of the forecasts, and on the execution time of the decision making process. The diverse time scales of portfolio planning, supported by the proposed approach, give player the opportunity to plan their investments in different time horizons. As demonstrated by the presented case study, even for cases where the time-range of the planning is larger, the results are still satisfactory, providing players with suggestions on what can be expected from their future participation in several alternative markets.

Simulations using MASCEM, a real data based electricity market simulator, contribute to the validation of the proposed methodology in a realistic market environment.

As future work, the risk management process is a critical issue that must be addressed, namely by considering the risk minimization as an additional objective to the problem formulation. Also, the calculation of the minimum and maximum forecast values, which are essential for the risk management procedure, should be improved, namely by applying different forecasting methodologies, such as support vector machines, and different variations of NN with different parameterizations and topologies, so that the dispersion of the achieved forecast values increases. Additionally, the consideration of different PSO based approaches, as well as other meta-heuristic processes, such as genetic algorithms, or simulated annealing methodologies, can be implemented, so that alternatives can be tested and compared.

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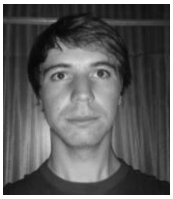

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Six thinking hats: A novel metalearner for intelligent decision support in electricity markets

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ABSTRACT

The energy sector has suffered a significant restructuring that has increased the complexity in electricity market players' interactions. The complexity that these changes brought requires the creation of decision support tools to facilitate the study and understanding of these markets. The Multiagent Simulator of Competitive Electricity Markets (MASCEM) arose in this context, providing a simulation framework for deregulated electricity markets. The Adaptive Learning strategic Bidding System (ALBidS) is a multiagent system created to provide decision support to market negotiating players. Fully integrated with MASCEM, ALBidS considers several different strategic methodologies based on highly distinct approaches. Six Thinking Hats (STH) is a powerful technique used to look at decisions from different perspectives, forcing the thinker to move outside its usual way of thinking. This paper aims to complement the ALBidS strategies by combining them and taking advantage of their different perspectives through the use of the STH group decision technique. The combination of ALBidS' strategies is performed through the application of a genetic algorithm, resulting in an evolutionary learning approach.

1. Introduction

The electricity industry has been facing an important challenge since the 1980s—a market environment is replacing the traditional centralised-operation approach, thereby creating a more competitive and complex environment [1]. This deregulation, often accompanied by privatisation processes, has brought many changes. For example, presently the industry is organised in a horizontal way, replacing the previous vertical organisation. Many electricity companies used to be responsible for the complete business chain; now, they are split into several companies, with each one focusing exclusively on one business area: generation, transmission, distribution, and retail. The changes also aim to give consumers a more active role in the market, ensuring their ability to choose their energy supplier [2]. The new electricity market environment is more complex and unpredictable, forcing interveners to rethink their strategies and behaviour. Several market models exist, with different rules and constraints, creating the need to foresee market behaviour. Regulators need to test the rules before they are implemented, and market players need to understand the market so that they can reap the benefits of well-planned actions. The employment of simulation tools is an adequate way to find market inefficiencies and to provide support for players' decisions. The multiagent paradigm is useful for the job because it can represent several constituents with their own individual features, interacting in a dynamic system. Relevant tools in this domain are the Electricity Market Complex Adaptive System (EMCAS) [3] and Agent-based Modelling of Electricity Systems (AMES) [4].

The Multi-Agent Simulator of Competitive Electricity Markets (MASCEM) [5,6] is another simulator, which has been developed by the authors' research team to address the constant changes in the electricity market operation all around the world. With this purpose, MASCEM is always under improvement, updating the existent market mechanisms and integrating new ones to reflect different countries' approaches and realities [7,8]. The different market opportunities, together with the necessity to address the increasing complexity in the electricity market environment, force players to adapt and act strategically to take the most advantage from their negotiations.

To complement the MASCEM simulator with new strategies, learning, and adaptability, a new system was developed in [6]: ALBidS—Adaptive Learning strategic Bidding System. This system implements several new strategies and behaviours along with those originally implemented in MASCEM. The purpose of ALBidS is to provide market players with the capability to act and react accordingly to the different contexts they encounter in the market, which is achieved using several different strategies and adaptive learning techniques to choose the most appropriate way to use each of them, according to the context [9]. The approach generally adopted by ALBidS is to take advantage of the differences and particularities of each strategy, considering them as different options that are most

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suitable for different contexts. However, the different natures of the strategies can provide complementary aspects, which, when combined, can prove to be much more powerful than the simple "sum of the parts." It is in the understanding of these complementarities, and how to combine different approaches, that this paper gives its contribution.

The main goal of a metalearner is to use meta-data to improve the performance of existing learning algorithms [10]. By using meta-data derived from other learning algorithms, a metalearner creates flexibility in solving different types of learning problems [11]. Metalearners are especially useful when dealing with dynamic environments, with a high level of associated uncertainty, as is the case of the electricity market environment. The combination of the meta-data derived from the different existing learning algorithms must be performed appropriately to obtain a valuable output. Six Thinking Hats (STH) is a parallel thinking method built to change the way meetings are run and the way stakeholders work and interact [12]. For each direction of thinking, STH associates a hat with a distinct colour. Using this method, participants discard any conflict that emerges in the meeting. Taking advantage of stakeholders' capabilities should result in better decisions.

Using the principles of the STH method, this paper proposes a new metalearner that combines the different outputs from ALBidS strategies to support the choice of the best possible action for market players. This is performed using a set of different agents reasoning in a distinct STH point of view. Individual answers are then combined using genetic algorithms (GA) [13,14] with the purpose of providing a better and evolutionary overall combination of all the answers. The proposed method, acting as a metalearner, offers the possibility of combining different strategic bidding approaches so that through cooperation they can contribute to an overall better response than individually. The best potential result that can be achieved from the use of different methodologies in parallel is equal to the result of the best individual approach. On the other hand, taking advantage of the cooperation and combination of the individual methodologies, the final result is not limited to the threshold of the best strategy; it is open to the accomplishment of better results, achieved by taking advantage of the best assets of each individual approach. These results are demonstrated by the case study that is presented in Section 4, which shows that the proposed STH-based metalearner is able to achieve better results than the individual strategies by themselves. GA has been applied in diverse fields, such as machine learning [15,16], optimisation [17], scheduling [13], and many others [14]. However, the use of an evolutionary approach as a metalearner, combining the learning processes of different learning algorithms, has not been presented in the literature. Moreover, approaching the different meta-data resulting from the distinct learning processes in a way that each approach is considered dependently of its nature (or way of thinking) by using methods that result from fields that specifically study the interaction of different entities—sociology (such as the STH) is a novelty that complements the development of a GA-based metalearner.

After this introductory section, Section 2 examines the electricity markets simulation thematic, including an overview of the main electricity market models found worldwide and an outline of the main features of MASCEM and ALBidS. The characteristics and particularities of the STH method are addressed in Section 3, including its adaption to decision support by means of metalearning through integration in ALBidS and MASCEM. The results of the proposed method are presented in Section 4, using case studies based on real data from the Iberian Market—MIBEL [18], from which the performance of the STH-based metalearner is compared to other approaches. Finally, Section 5 presents the most relevant conclusions and contributions of this work.

2. Electricity markets simulation

The electricity industry has experienced major changes in the structure of its markets and in its regulation around the world. This transformation is often called the deregulation of the electricity market. The industry is becoming more competitive, as a market environment is replacing the traditional centralised-operation approach; this change allows market forces to drive electricity prices [2]. The liberalised market environment typically consists of a day-ahead spot market, based on a pool, as well as a floor for bilateral contracts. Most electricity markets also include intraday or balancing markets. Additionally, forward negotiations are also often implemented, as well as ancillary services [1]. These markets' operation usually involves a market operator and a system operator. The market operator is responsible for the correct functioning of the market; it manages the pool using a market-clearing tool to establish the market price and the set of accepted bids for each negotiation period. The system operator is responsible for the management of the transmission grid and also analyses the technical feasibility (from the power system point of view) of the trades.

The increasing complexity brought by the conception of such a diversity of market types has resulted in major changes concerning the relationship between the electricity sector entities. The complexity has also resulted in the emergence of new entities, mostly dedicated to the electricity sector and electricity energy trading management [19, 20], such as virtual power players (VPP), traders, and brokers. These entities introduce new behaviours, e.g., aggregation of smaller size players and participation in alternative market mechanisms. The new roles of market operators, regulators, and system operators also signify an important change.

In most electricity markets, namely, all seven regional European markets, such as MIBEL—the Iberian electricity market, which is used as a case study in this paper—the regulator does not interfere in the electricity market price establishment [18]. The market price is obtained through a clean auction between the sellers and buyers of energy. This means that only the negotiating entities influence the market prices. However, players' bids are based on several highly volatile factors, such as raw materials' prices, other players' actions, the wind speed, and solar intensity. The variability of the factors that affect the outcomes of the market makes the results non-deterministic; therefore, the market environment cannot be approached as deterministic.

In addition to the dependency of the market price on the variations of raw materials' prices, including those based on renewable sources, such as wind, sun, or water, this volatility results in a greater difficulty in managing the energy resources [21,22]. This may originate due to deficient management of operators and a huge waste of produced power, especially in the case of wind power generation. The excess of production above forecasted values brings the market prices to values of zero, or very near this value, which results in huge losses for the generation units, not only taking into account the inability to cover production costs but also to justify the high investments that are necessary to implement such generation facilities. Complete and realistic electricity market simulators offer the possibility of testing different management alternatives, so that such wastes can be drastically reduced, and the investments made by countries in green energy sources can be monetised [23]. Most importantly, these studies are an extremely important asset for green energy to be harnessed and become an added value to the global population. An example of experiences that can be made is the analysis of scenarios in which high variations occur between the forecasted and real wind speed and solar intensity. When such situations are expected, opportunities should be given to consumers so that they can purchase power at very low prices, or even for free in extreme cases, as long as they "shift" some of their consumption, so that they can take advantage of such moments. This would offer great business opportunities for aggregated consumers and drastically reduce the waste of power.

Realistic electricity market simulators, capable of providing scenarios based on real data are an enormous asset for the study of electricity markets. Market operators and regulators are able to experiment and test new market rules and mechanisms, which could not be tested directly in reality due to the impact that such experiments could have for the global population and to obtain valuable insights regarding the

consequences of such changes, both in what affects the market itself and also in the way it influences the market players [24].

Electricity market simulators also provide the means for supporting electricity market players in their decisions, so that they are able to take advantage of the market environment by testing different strategic behaviours and analysing their results. Real market players are able to thoroughly study competitor players' actions, coming to an understanding of how they behave, act, and react in different circumstances and contexts, providing a valuable tool for adapting their own behaviours to the expected actions of competitors. This ultimately leads to the achievement of higher profits from sellers and decreases the purchase costs of buyers.

In addition to the advantages for market players, regulators, and operators, students, researchers, and ultimately end energy consumers can benefit from electricity market simulators. The MASCEM simulator is a solid example of a system that provides the necessary simulation features.

2.1. MASCEM simulator

MASCEM [5,6,19,20] is a modelling and simulation tool that has been developed with the purpose of studying complex restructured electricity market operation. MASCEM models the complex dynamic market players, including their interactions and medium-/long-term gathering of data and experiences to support players' decisions according to their own characteristics and objectives. MASCEM's most important features are presented in Fig. 1.

MASCEM's goal is to simulate as many market models and player types as possible, so it can reproduce, in a realistic way, the operation of real electricity markets. This enables it to be used as a simulation and decision support tool for short-/medium-term purposes but also as a tool to support long-term decisions, such as those taken by regulators. Unlike traditional tools, MASCEM does not postulate a single decision maker with a single objective for the entire system. Rather, it allows agents representing the different independent entities in electricity markets to establish their own objectives and decision rules. Moreover, as the simulation progresses, agents can adapt their strategies based on previous successes or failures. MASCEM's key players reflect actual entities from real markets and provide a means for aggregating consumers and producers. Presently, there are agents representing independent entities, such as the system operator, which is another simulator that obtains the economical dispatch and undertakes power-flow analysis to assure economical agreements can be implemented without disturbing power-grid stability and technical constraints.

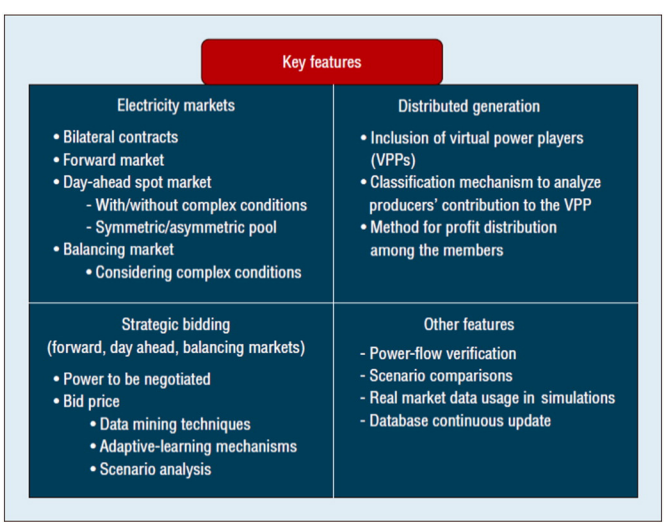

Fig. 1. MASCEM's key features [19].

MASCEM includes several negotiation mechanisms usually found in electricity markets, being able to simulate, namely, pool markets, bilateral contracts, balancing markets, forward markets, and ancillary services. The different market types offer players the chance to approach market negotiations strategically, taking advantage of the several opportunities that arise at each time. Based on the previously obtained results, buyer and seller agents review their strategies for the future. With the purpose of providing decision support to the strategic behaviour of negotiating market players, ALBidS (Adaptive Learning strategic Bidding System) was developed and integrated with MASCEM [25].

2.2. ALBidS decision support system

Electricity market players require strategies capable of dealing with constant market changes and allowing adaptation to the competitors' actions and reactions to achieve competitive advantage in market negotiations. The way prices are predicted, to create suitable decision support, can be approached in several ways, namely, using statistical methods, data-mining techniques [26,27], artificial neural networks (ANN) [28], support vector machines (SVM), or several other methods [29–31]. There is no method that can be said to be the best for every situation, only the best for particular cases.

To take advantage of the best characteristics of each technique, a new system that integrates several distinct technologies and approaches was developed. ALBidS is implemented as a multiagent system, where each agent performs a distinct algorithm, detaining the exclusive knowledge of its execution; in this way, the system can execute all of the algorithms in parallel, preventing the degradation of the method's efficiency. As each agent gets its answer, resulting from its individual strategy, it sends its result to the main agent, which is responsible for choosing the most appropriate answer among all of the answers that it receives.

2.2.1. Main agent

The main agent interfaces the MASCEM and ALBidS systems. It receives requests from market negotiating players when they require decision support and provides them with the corresponding answers. These answers are achieved by managing the ALBidS internal mechanism, including the interactions with the strategy agents.

The choice of the most appropriate strategy for each moment is based on the application of reinforcement learning algorithms [32]. The approach that presents the best results for a given context of the current scenario is chosen as the final response. Therefore, based on the results of each algorithm, the reinforcement learning algorithm chooses the one that is most likely to present the best answer according to the past experiences and to the characteristics of the actual scenario, such as the considered day, the period, and the particular market context that the algorithms are being asked to forecast [6].

2.2.2. Strategy agents

A highly dynamic environment, such as the electricity market, forces players to be equipped with tools that allow them to react to diverse negotiation circumstances. The existence of a variety of different strategies grants ALBidS the capability of always being prepared for the diversity of situations that a market negotiation player can encounter in the market. The very different natures of the considered strategies offer coverage of diverse areas, guaranteeing a high probability that there is always one strategy suited for each context, even if its applicability to other contexts is not as advantageous. The considered strategies are as follows [25]:

- Based on statistical approaches, through the application of simple averages and regressions.
- Dynamic feed forward neural network (ANN) trained with the historic market prices.

This NN [19] is retrained in each iteration so that the data observed at each moment are considered for the next forecasts, constantly adapting the NN forecasting results.

- Adaptation of the AMES bidding strategy. This strategy uses the Roth–Erev [32] reinforcement learning algorithm to choose the best among a set of possible bids that are calculated based on the relation cost/profit of the player. The various possible bids differ from each other due to the distinct combination of the input parameters. The more combinations that are tested, the better the chances of obtaining a good result. However, the number of combinations affects the processing time and the number of runs required for satisfactory convergence. Complete details concerning the methodology of this strategy can be found in [4].
- The Composed Goal Directed strategy is based on two consecutive objectives. It attempts to accomplish the first goal and then tries to fulfil the second while keeping the first satisfied.
- The Adapted Derivative-Following strategy, proposed by Greenwald [33], adjusts the price by looking at the amount of revenue earned in the same period of the previous day as a result of that period's price change. If that period's price change produced more revenue per good than the same period of 2 days before, then the strategy makes a similar change in price. If the previous change produced less revenue, then the strategy makes a different price change.
- The Market Price Following strategy, as the name suggests, follows the market price of the same period of the previous day. It is a simple strategy, but it presents good results when prices show a tendency to stabilise in a certain period for some consecutive days.
- The SA-QL strategy uses the simulated annealing heuristic [34] to accelerate the process of convergence of the Q-Learning [35] algorithm in choosing the most appropriate from a set of different possible bids to be used by the market negotiating agent.
- The Game Theory strategy is characterised as a scenario analysis algorithm able to support strategic behaviour based on the application of game theory [31,36].
- The Economic Analysis strategy implements an analysis based on two of the most commonly used approaches of forecasting in a company's scope. These approaches are the internal data analysis of the company, and the external, or sectorial, data analysis [37].
- The Determinism Theory strategy executes a strategy based on the principles of determinism theory [38]. This theory states that due to the laws of cause and effect, which apply to the material universe, all future events are predetermined.
- The Error Theory strategy's goal is to analyse the forecasting errors' evolution of a certain forecasting method [39] to find patterns in that error sequence and to provide a prediction of the next error, which is then be used to adjust the initial forecast.
- The Metalearner strategies use the results of the learning process from the other strategies as inputs to apply their own learning [10,11] and to create new outputs. In addition to the proposed STH metalearner, ALBidS includes two basic metalearners: the Simple Metalearner, which performs an ensemble average of the output values of all ALBidS strategies to create its output; and the Weighted Metalearner, which considers the strategies' confidence weights to the main agent as weights to adapt the influence each strategy will have on the metalearner's output. [40].

The interaction between the strategy agents and the main agent creates the basis of the ALBidS decision support process. The ALBidS agent structure is presented in Fig. 2. Fig. 2 shows that the main agent receives the suggestions of all strategy agents. These are used by the main agent to generate the final output, which is sent to MASCEM's supported market player.

Fig. 2 also shows the integration of the proposed STH metalearner. The STH metalearner allocates different thinking hats to the different strategies, representing different ways of approaching the problem. The outputs of the strategy agents are then used by the blue agent to generate a combined output, resulting from the metalearning process, as presented in Section 3. The final result of the STH metalearner is finally sent to the main agent, so that it can be considered as an alternative suggestion.

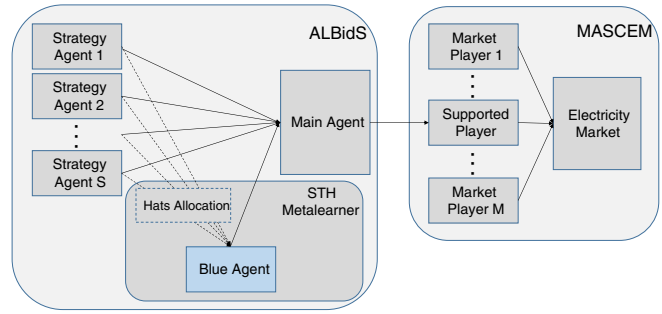

Fig. 2. ALBidS agent architecture.

3. Six Thinking Hats

STH is a parallel thinking method built to change the way meetings are run and the way stakeholders work and interact [12]. This method proposes to, among other results, increase the speed at which decisions are made without hastening the process. The method also "promises" to harness and take full advantage of the intelligence, information, and experience of each party present in the meeting. By using this method, participants are invited to discard, almost entirely, any emerging conflict in the meeting. Taking full advantage of stakeholders' capabilities should also result in better decisions.

3.1. The method and its advantages

The Six Thinking Hats method offers itself as the "exact opposite of argument, adversarial, confrontational thinking." Using this method, each participant is asked to take one direction of thinking at a time, always avoiding confrontation and non-constructive criticism. This allows full exploration of the discussed subject [12]. Should it come to choosing between two opposite goals or options, this step must be taken down the road—one of the key concepts is that a meeting is a way forward while fully exploring the subject [12]. STH associates a hat with a distinct colour for each thinking direction. The following sections present a summary of each hat's role. STH also assumes the existence of a moderator, responsible for picking the direction to take and enforcing rules.

3.1.1. White hat

White is neutral and objective. The white hat is concerned with objective facts [12]. Using this hat, participants are asked to supply any information on the subject they have or are aware of; no judging or opinions are allowed. Each detail, each piece of information given in this step is similar to the piece of a puzzle; each one enriching and completing the global map. Once the map is finished, the route becomes more or less obvious to everyone. It is the moderator's job not to allow any ready-made idea, feeling, opinion, or anything that is not neutral information, to creep into the discussion. In fact, in the practice of this hat, the moderator should establish a two-tier system: believed facts and checked facts, i.e., it is important to be able to classify all given facts during this stage. STH acknowledges the impossibility of having each fact scrutinised with the rigour of scientific testing.

3.1.2. Red hat

In a normal business discussion, you are not supposed to allow your emotions to enter in. They enter anyway—you merely disguise them as logic. The red hat provides a unique and special opportunity for feelings,

emotions, and intuition to be put forward [12]. This hat gives the thinker a channel to express any simple feeling (fear, like/dislike, suspicion, mistrust) or more complex ones, such as hunches and intuition, on the subject under debate, or even at the conduct of the meeting itself. No justification or details about the feeling are required; emotions do not have to be logical or consistent. The red hat makes feelings visible so that they can become part of the thinking map.

3.1.3. Black hat

The most used and perhaps the most important of all hats, the black hat is the hat of caution. The black hat is all about carefulness, awareness, and survival. The black hat notes how something does not fit the resources, policy, strategy, ethics, and values [12]. Black hat thinking brings experience onto the playing board; under this hat, we look for patterns that do not match our own experience.

Although caution is a good thing, constant destructive criticism is very bad for the discussion, which is why time framing of this step is essential. A warning must be issued: black hat thinking is not a permit to go back to argumentative discussion. Procedural errors can be noted; parallel statements that express a different point of view can be laid down. In the end, there should be a clear map of possible problems or obstacles to be clarified and elaborated.

3.1.4. Yellow hat

The exact opposite of the black, the yellow hat, has the role of bringing positive thoughts to our thinking map. At this stage of the discussion, one is expected to bring only constructive and positive thoughts. The nature of optimistic thinking allows it to cover a very broad spectrum of ideas, ranging from the logical and practical at one end, to dreams, visions, and hopes at the other. This also includes foolish thoughts, thoughts that are too impractical or truly over-optimistic; therefore, an effort should be made to stand somewhere on the middle of the spectrum, keeping away from the edges. Whereas the edge where all is sound and safe will result in minimal progress, over-optimistic ideas may be hazardous to the decision. A thinker wearing this hat is expected to make an active effort to seek the value of the ideas; however, it is important that this value is logically based.

3.1.5. Green hat

The green hat is the creative hat [12]. Under the green hat, we propose new ideas, options, and alternatives. These include both the obvious alternatives and fresh ones that seek to modify and improve suggested ideas. Under the green hat, you are permitted to propose "possibilities," which play a much bigger role in thinking than most people believe. Without possibilities, you cannot make progress. Creativity involves provocation, exploration, and risk taking. In STH [12], there is mention of the term "lateral thinking," which is about cutting across patterns instead of just following them. When cutting across to a new pattern is perceived to make sense, we have the "eureka" effect [12]. "Normal" thinking uses judgement—"how does this idea compare to what I know?"—which relates very closely to black hat thinking. What is asked in green hat thinking is that we use an idiom de Bono coined: movement. Movement stands for using an idea for its forward effect; we use an idea to see where it will lead us. Lateral thinking is an active process, so there is a need to set off these provocations intentionally, i.e., the green hat is asked to put some "crazy" ideas into discussion. De Bono even suggests the usage of random words at meetings, drawn right out of a dictionary to sprout some new paths of thinking.

3.1.6. Blue hat

The blue hat is for thinking about thinking, i.e., process control. It is under the initial blue hat that the agenda or sequence of use of the other hats is laid out. The blue hat sets the thinking "strategy." During the session, the blue hat keeps the discipline and ensures that entities keep to the relevant hat. The blue hat also announces a change of hats. Typically, the blue hat is worn by the facilitator, chairperson, or leader of the session. This is a permanent role. Any participant can be asked to, or voluntarily use the blue hat to, for example, examine if the building of our "thinking map" is going the right way. At the end of a session, the blue hat asks for the outcome. This may be in the form of a summary, a conclusion, a decision, or a solution. The blue hat may even acknowledge that little progress has been made. Under the final blue hat, the next steps are laid out. These might be action steps or further thinking on some points.

3.1.7. Summary

Fig. 3 illustrates a summary of the STH methodology. The blue hat is not in the centre of the figure, although it plays a crucial role in the meeting, because any participant besides the moderator can intervene in a blue-hat way.

The STH method was designed to shift thought from the habitual argumentative style to a cartographic style. This is achieved by a two-stage process: first, the map development; second, the choice of the route. If the map is sufficiently good, a better route is usually obvious. The greater value of the hats is its own artificiality. It offers a formality and convention to require a certain type of thought from every participant. STH lays down the rules of the thought game. Whoever plays the game has to know these rules (people are generally good at following rules and playing games).

3.2. ALBidS methodology based on STH

The focus of this work is the creation of a metalearner based on the STH method. For this, ALBidS agent strategies are adapted to each different "hat way of thinking." This means that a smooth combination of the different ALBidS approaches takes place in a quick, cooperative, and complementary way. This approach uses information regarding a first level of learning: about the problem (ALBidS strategies), as input for a methodology that moulds this information, creating its own knowledge and answer to the problem—metalearning, or learning about learning [11].

To adapt the STH methodology to this problem, it was necessary to relate MASCEM and ALBidS' internal working to that of a common STH method-driven meeting, mainly concerning (i) a moderator entity,

Fig. 3. STH overview [41].

leading different interveners in the decision—the blue hat or the moderator sets the agenda for the meeting, determines its closing and final decision; (ii) different ways of thinking about the problem to solve; and (iii) no arguing or debating, no confrontation.

The STH metalearner has been built as an ALBidS strategy agent. Enacting the STH's blue hat role as moderator, this agent is responsible for controlling the process and determining the final decision to be sent to ALBidS. Each intervenient acts out a role, which is played by an ALBidS strategy agent. For this purpose, we mapped a relation between each Hat's behaviour and the existing ALBidS strategy agents. The reasons that led to the hat–agent relation are as follows:

- White agent—this hat is responsible for bringing data, figures, and numbers into discussion, as such, little or no treatment should be performed on the data; it was clear that we could use an average approach for this role.
- Red agent—we decided to examine emotions as related to the recent past. Though not a true emotional decision, it is reasonable to assume a human intervenient could say something such as "due to our recent past, I've got a hunch that we should not raise prices"; a regression approach using exclusively the recent past has been chosen for this role.
- Black agent—this role is for caution, to avoid danger. It is fair to think of it as knowing our position in the market, and knowing what we can or cannot do; this is why we chose to fill this role with an economic analysis agent with little or no propensity for risk.
- Yellow agent—optimism without foolishness is the best way to describe the yellow hat thinker; also, as the opposite of the black view, we saw this agent as a logical analyser with some appetite for risk. Therefore, once again, the economic analysis agent is selected, this time with medium to high risk tolerance.
- Green agent—the evolutionary traits of Particle Swarm Optimization used in the determinism theory agent made this strategy a suitable candidate for the creative thinking part. We are looking for logical and adjusted decisions that are somehow different from the normal.
- Blue agent—the one responsible for the development of the process and the final decision. This is the STH agent, which gathers all of the other agent decisions, combines them, and delivers a final answer to ALBidS. This agent's capabilities and structure are addressed in Section 3.3.

Table 1 shows the final version of this relation.

Each of these agents are, henceforth and in the STH context, referred to by the colour of its respective hat, i.e., red hat agent will refer to regression 1 agent, or collectively as STH agents.

3.3. STH agent—a new strategy/metalearner agent

In the STH method, all decisions pass, ultimately, through the moderator. For this reason, the communications process of our blue agent are similar to the already-existent ALBidS metalearners, although with different inputs. Our goal for this work is to provide a decision that reflects the combined efforts of several different points of view working together. The blue agent's output is a set of ordered bids to the market, corresponding to each of the 24 periods of the day. In our first tests for a single period, the STH agent's answers varied between 3.68 and 8.65; for such precision, and considering prices with two decimals, we would have (8.65–3.68) * 100 + 1 = 498 possible prices (n), which means that the cardinality of our solution space, Pr, for 24 daily periods, d, is (1):

$$Pr_n^d = n^d = 498^{24} \tag{1}$$

The result, in decimal notation, is a 65-digit number. In addition to the fact that finding the optimal solution in such a large space would be computationally impractical, the electricity market results are not deterministic due to the volatility of the factors that influence market prices, as discussed in Section 2. Therefore, the use of a deterministic method is not credible, and for this reason, a heuristic evolutionary approach has been chosen [42]. Our choice was to use a genetic algorithm [15,43], which allows a combination of answers to create a strong solution, but never an optimal solution, which does not exist in this context. A swarm approach could be applicable as well; however, GA has been chosen because it achieves robust responses in a shorter time than other heuristics.

3.3.1. Genetic algorithm in STH

Genetic algorithms (GA) represent a class of algorithms based on a simplified computational model of the biological evolution process. They represent a class of general purpose adaptive search techniques that have the properties of parallel search and an enhanced ability to avoid local optima [13].

The purpose of the use of a genetic algorithm is to find the individual from the search space with the best "genetic material." The quality of an individual is measured with an evaluation function, called fitness. The part of the search space to be examined is called the population [43].

3.3.1.1. Population definition. Generally, the first step of GA is to initialise the population either randomly or by using seeds. In this work, our population results from the execution of the other strategies. The individuals composing the population are the ordered sets of bid values that each agent submitted to the blue agent, i.e., the chromosome of every individual is composed of a set of 24 bids for each period of the following day. To introduce some variation to our genetic pool, in addition the outputs of the several STH agents, the following individuals are added to the population:

- GAI_{minima}—an individual with the minima of bids for each period of the STH agents' results;
- GAI_{maxima}—an individual with the maxima of bids for each period of the STH agents' results;
- $GAI_{average}$—an individual with the averages of the STH agents' results;
- GAI_{D1} and GAI_{D2}—two individuals with R random values in the interval expressed by (2)

$$\begin{cases} \vartheta = |S_{max} - S_{min}| * p,\ S_{max} \geq S_{min},\ 0 \leq p < 1 \\ R \in [S_{min} - \vartheta, S_{max} + \vartheta] \end{cases} \tag{2}$$

  where S_{min} and S_{max} are, respectively, the minimum and the maximum of all values provided by the STH agents, and p is user-defined;
- GAI_{R1} and GAI_{R2}—two individuals with random values between 0 and 10—we chose the top value after analysis of historic data in the database—bids do not usually go above 10 cents of euro; it also does not make sense to bid a negative value.

Although it was possible to tackle this problem by dividing the population into several smaller populations, applying different GAs to each of them [13] and then breeding across populations, we have chosen to use a single population in this study.

Table 1
Relation between STH's roles and existing ALBidS entities.

STH's role	ALBidS' existing agent
White	Average 1 agent
Red	Regression 1 agent
Black	Economic analysis agent—with low risk
Yellow	Economic analysis agent—with medium-high risk
Green	Determinism theory agent—using PSO
Blue	None

3.3.1.2. GA process. Once the initial population is generated, three operations (*selection*, *crossover*, and *mutation*) are used to generate the following generation [15].

Selection is the stage of GA in which individual genomes are chosen from a population for later breeding. The roulette wheel selection procedure is implemented by evaluating the fitness function of each individual, providing fitness values that are then normalised (normalisation means dividing the fitness value of each individual by the sum of all fitness values, so that the sum of all resulting fitness values equals 1). Once normalised, the population is sorted by descending order of fitness value. The accumulated normalised fitness values are computed (the accumulated fitness value of an individual is the sum of its own fitness value plus the fitness values of all previous individuals). A random number R between 0 and 1 is then chosen, and the selected individual is the first whose accumulated normalised value is greater than R.

Crossover is the exchange of a portion of each individual's (involved in the reproduction) genetic material. The crossover is a genetic operator used to exchange genetic material/information between two chromosomes. It is analogous to reproduction and biological crossover, upon which GA is based. Crossover is a process of taking more than one parent's solutions and producing a child solution from them. A two-point crossover approach has been used, where the two points are selected on the parent strings. Everything between the two points is swapped between the parent organisms, rendering two child organisms. The two crossover points can be defined by the user; however, these should represent points that significantly separate information contained in the genes. For this reason, the default crossover points of 10 and 23 are defined, as a result of the contextual analysis performed in [25]. From this analysis, it is concluded that these two points represent a significant separation between hours of the day, taking into account different aspects, such as the historic market price and energy consumption. In this way, the information that is contained between genes 10 and 23 represents the hours of the day, where higher prices and consumption are verified, whereas the remaining genes represent the hours of the night. Fig. 4 illustrates a sample individual and the detail of its chromosomes; the crossover points (used to "cut" chromosomes when individuals are reproducing) are also depicted.

Finally, *mutation* represents a low-probability random modification of a chromosome of an individual. Mutation is used to promote genetic diversity over generations. It is analogous to biological mutation observed during meiosis or DNA replication [42]. Mutation may alter one or more gene values in a chromosome. Hence, GA can reach better solutions using mutation. Mutation occurs during evolution according to a user-definable mutation probability. This probability is normally set to a low value. If it is set too high, the search process will turn into a primitive random search. Nevertheless, this parameter is set by the user in the implemented approach. After a period of time (number of iterations, also user-defined), the most suitable individuals will dominate the population, providing an optimal (or near-optimal) solution.

3.3.1.3. Fitness evaluation. For our fitness function, we run a simplified simulation of the electricity market mechanism (as presented in subsection 4.1.1—Market Negotiations' Specification), using predictions of the bidding values of all other competing agents; in this way, we have an approximation of the market price, providing us with an accurate evaluation of the potential of our solution. This simulation is implemented in LPA-Prolog [44], for performance reasons; hence, we also chose to develop the GA algorithm in the same logic programming language. The objective is to maximise the profit P of market player i in each negotiation period p of each day d, where P is defined as (3):

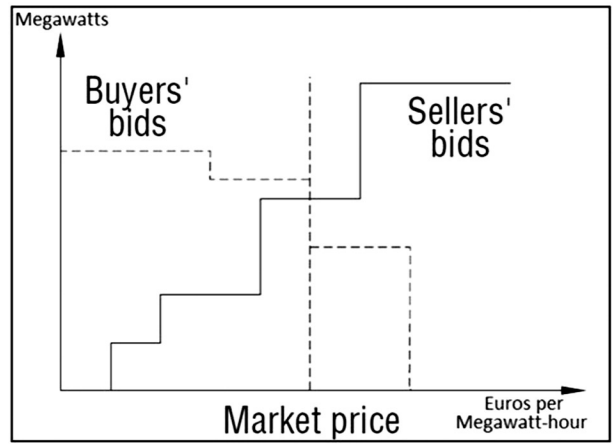

Fig. 5. Symmetric market price establishment.

$$P_{idp} = A_{idp} * MP_{dp} \tag{3}$$

In (3), A_{idp} is the amount of power that is sold in the market by player i, and MP_{dp} is the market price at which the power of agent i is sold. Both MP_{dp} and A_{idp} result from the market execution, as described in subsection 4.1.1—Market Negotiations' Specification. These values depend on all market players' submitted bids, defined as the tuple power Pow_{idp}, price Pri_{idp}, which represent each player's desired amount of power to sell or buy in the market and the maximum accepted price for power purchase (for buyers) or minimum accepted price for sale (for sellers). The main restrictions of the market process are (4), (5), and (6).

$$TSA_{dp} = TBA_{dp} \tag{4}$$

where TSA_{dp} represents the total amount sold in the market, and TBA_{dp} symbolises the total amount of power bought by all participant players. Only sale bids that respect (5) are actually sold, and only purchase bids that fulfil (6) are accepted.

$$Pri_{idp} \leq MP_{dp} \tag{5}$$

$$Pri_{idp} \geq MP_{dp} \tag{6}$$

Eqs. (5) and (6) mean that sellers must submit bids that are lower or equal to the market price; otherwise, they will not sell the desired power in the market. On the other hand, they should bid a value as high as possible to contribute to the increase of the market price, hence increasing P_{idp}. The opposite is valid for buyers, as observed in (6). Further details on the market negotiation mechanism are presented in sub-section 4.1.1.

3.3.2. Integration with ALBidS

The STH agent is seen by ALBidS as any other strategy agent, using the already-existing system architecture and communication structure.

Period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
W.A. Bids	1.67	2.93	4.94	1.38	1.59	2.8	4.03	4.1	4.57	3.85	3.74	1.16	0.98	3.99	3.07	4.01	2.45	4.33	1.29	2.29	2.15	2.9	1.71	3.22

Crossover point 1 Crossover point 2

Fig. 4. White agent bids sample.

Table 2
GA sensibility test parameterisations.

	Strategies weights	Generations	Deviation	Crossover points	Mutation prob.
1	Same	100	0.10	10 and 23	0.025
2	RLA	100	0.10	10 and 23	0.025
3	Same	200	0.10	10 and 23	0.025
4	Same	100	0.20	10 and 23	0.025
5	Same	100	0.10	8 and 21	0.025
6	Same	100	0.10	10 and 23	0.5

During operation, the STH agent creates instances of the other strategy agents using a factory method pattern and invokes the appropriate methods to obtain each agent's response. The STH method operates at the day-ahead level, i.e., its output is a set of bids for all periods of the following day. The results from the case study—Section 4—show the advantage of considering each set of hourly offers as the genetic material of each individual of the population.

4. Case study

The case studies presented in this section illustrate some of the advantages of using the proposed metalearner to complement the previous ALBidS strategies.

Two different case studies are presented after the specifications subsection, in which the market negotiation mechanism (which is used for both the simulations and also as a fitness function of the GA approach) is described, and the parameterisations of the used methods are depicted. The first case study, in Section 4.2, presents a simulation study undertaken using MASCEM to analyse STH's behaviour. This is a realistic case study, based on previous simulation studies [19,20,36] based on data from the Iberian market extracted from MIBEL [18]. Section 4.3 shows the results of several strategies when applied in the same simulation scenario. From these results, it is possible to compare the performance of the proposed STH-based metalearner against other well-established decision support strategies that are included in ALBidS.

4.1. Specifications

4.1.1. Market negotiations' specification

The spot or day-ahead market is a daily basis functioning market [18] where players negotiate electric power for each hour or half hour of the following day. Such markets are structured to consider production fluctuations as well as differences in the production costs of distinct units. In this market, each participating entity must present their selling or buying proposals for each period of the day. These proposals or bids are typically composed by a tuple (power, price), where power stands for the amount of power to be bought or sold, and price is the maximum accepted price to buy or the minimum selling price. When the negotiation is finished, an economic dispatch for each period is set by the market operator. At the end of each period, the market operator uses a market-clearing tool to establish the market price—a unique price applied to all the transactions of the same period.

In market pools, the most common type of negotiation is a standard uniform auction. The MIBEL day-ahead spot market works as a symmetric market, where both suppliers and consumers submit bids. The market operator orders the selling and demand offers: selling bids in ascending order and demand bids in descending. Then, the proposed bids form the supply and demand step curves, and the point at which both curves intersect defines the market price. The bids of every supplier whose prices are lower than the established market price and the consumer bid prices that are higher than the market price are accepted. Fig. 5 shows the symmetric market prices definition. Profits can be improved by submitting bids that are advantageous for the player in the bidding process, i.e., for a seller player, a bid price below the established market price, but still as high as possible to assist in increasing the market price (resulting in higher profits through a higher market price). In the case of a buyer agent, the bid price should be above the established market price, but as low as possible to reduce the cost that is paid for the energy.

4.1.2. Parameterisation

Given that the STH strategy uses several other strategies, these studies use the same parameterisation. The default values are the same as used in [25], as follows:

- All ALBidS' strategies receive as parameters the date and the period for the simulation;
- Average 1 (white) and Regression 2 (red) strategies take no additional parameters;
- Economic analysis (black with low risk, yellow with medium–high risk) strategy's parameter is the risk factor that the agent should take in the decision. These values are set respectively as 0.2 for black and 0.8 for yellow agents;
- Determinism Theory Agent using PSO (green), we set the efficiency/effectiveness to 50 so that it would use a heuristic, which is, by implication, the PSO;
- The GA parameters, used directly by the STH agent (or blue agent), are analysed by means of a sensibility test in the following sub-section (4.2).

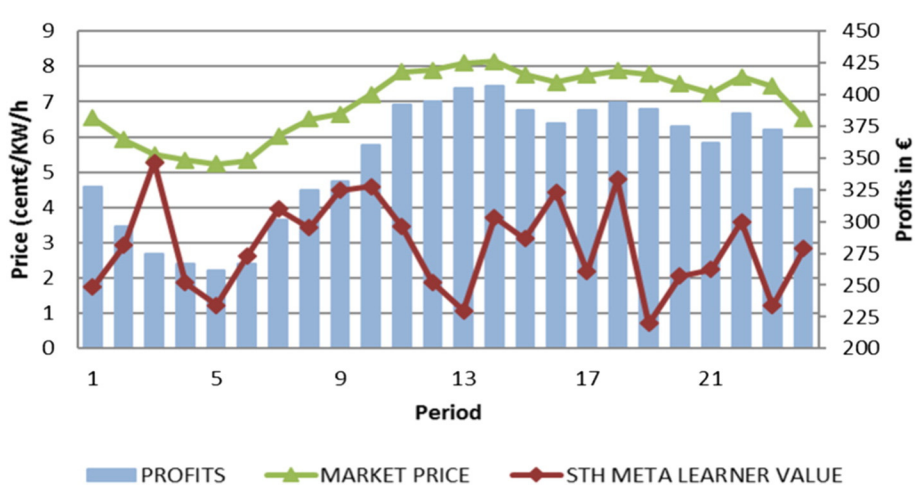

Fig. 6. STH strategy results in the electricity market.

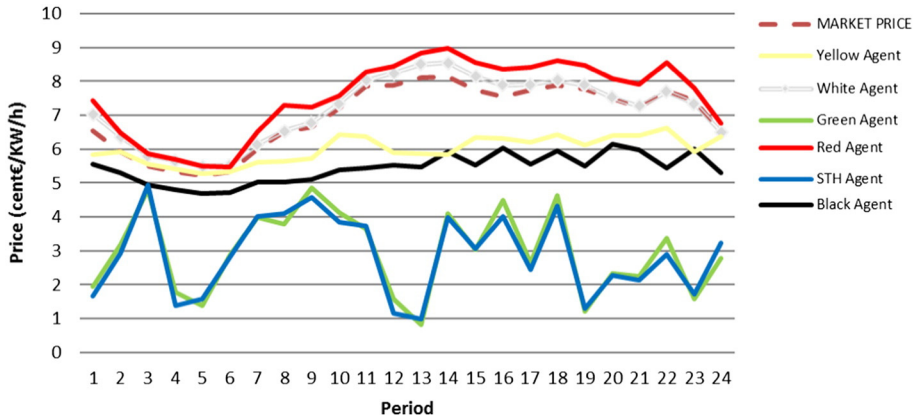

Fig. 7. Individual hat agent's answers and STH final answer for the default settings.

4.2. STH performance in the market

In this case study, the STH's performance in the market is evaluated. Six simulations were made, each for September 1st, 2008. Table 2 presents the parameters used for the GA sensibility test.

The reason the default crossover points 10 and 23 was explained previously; it is based on an analysis made by k-means clustering in [25]. The values 8 and 21 are based on sunrise and sunset information for Madrid on September 1, 2008, taken from TimeAndDate.com [45].

For the default number of generations, we opt for a number high enough so that there will be a chance of mutation occurring. We found 10% to be a reasonable value for the deviation.

None of the different parameterisations detached from the others, and all had good results for selling all energy in all periods of the day. For this reason, we decided to do some additional testing to determine if STH would behave differently with some not so reasonable parameters—we found no significant differences for 10,000 iterations or a mutation probability of 0.9. Fig. 6 presents the performance of the STH strategy in the market.

The results from Fig. 6 are typical outcomes for the STH performance in the market for the 61 considered days. The main reason for the behaviour being similar despite the parameterisation difference is that generally, as shown in Fig. 7, STH's answers are strongly influenced by the answers given by the green agent, even with the same weights for every strategy.

Similar profits are achieved with each parameterisation. The execution times are approximately 0.6 milliseconds (ms) per generation. This means that all of the considered parameterisations required approximately 60 ms to go through 100 generations, except from parameterisation 3, which required nearly 120 ms.

The simulations show that the fitness function will often opt for the lowest values in the genetic pool—allowing their survival and reproduction—because of the way the market price is chosen because with the current mechanism, bids lower than the established market price will be accepted.

Further testing showed that the low values of the green agent's answers have almost fourfold weight in the algorithm because they contribute solely to the genes of the individual GAI_{minima} and strongly contribute to the genes of the individuals GAI_{D1} and GAI_{D2}.

4.3. Strategies' comparison

To validate the STH strategy results, it is essential to compare the performance of the proposed strategy with the outcomes of other reference strategies. Hence, the performance of the STH metalearner is compared to that of all other strategies that are implemented by ALBidS.

The simulations concern the 24 hourly periods of 61 consecutive days, starting from October 1st, 2012. For these simulations, the STH metalearner uses parameterisation 1 (as presented in Table 2) because none of the tested sets outperforms the others. All other strategies use their standard parameterisations, which can be found in [25]. Fig. 8 presents the profits that are achieved by a market negotiation agent using each strategy for the same simulation scenario, in the 61 simulated days, for the first period of the day.

From Fig. 8, it is visible that the proposed STH metalearner achieves similar profits to those attained by the Determinism Theory strategy (which is used as the green hat agent by the STH metalearner). This similarity of results occurs due to the tendency of the GA mechanism of the blue hat agent to follow the green hat answers because of this agent's high-quality expected results, as concluded in Section 4.2. The STH

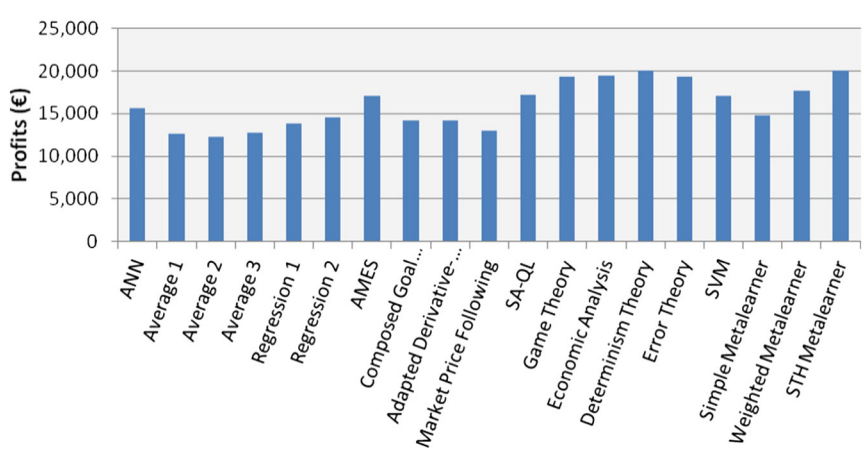

Fig. 8. Total profits achieved by each strategy in the first period of the 61 simulated days.

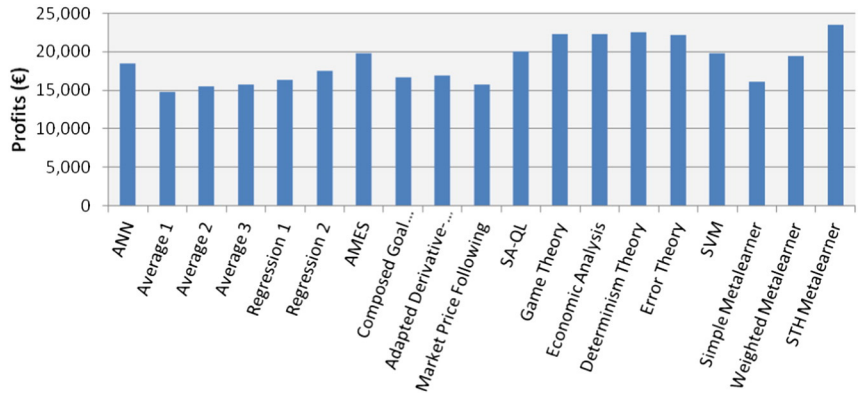

Fig. 9. Total profits achieved by each strategy in the twelfth period of the 61 simulated days.

metalearner and the Determinism Theory strategy are, in fact, the two most successful strategies in the first period of the simulated days. Fig. 9 presents the results for the twelfth period of the 61 simulated days.

In the twelfth period, the STH metalearner outperforms all considered strategies, including the Determinism Theory, as seen from Fig. 9. Comparing these results to those of the first period (Fig. 8), the overcoming of the Determinism Theory results is due to the GA optimisation process, which, although following the green hat tendency, is able to improve these results by taking advantage of the mutations that occur and of the breeding with other individuals. The enhancement of the STH metalearner's results is supported by Fig. 10, which presents the total profits achieved by each strategy in all 24 periods of the 61 considered days.

Fig. 10 shows that in the global analysis of the 61 simulated days, the proposed STH-based metalearner achieves higher profits than all other strategies. By using the other strategies' outputs as meta-data to create a new, improved solution, the STH metalearner outperforms the other strategies that are included in the decision making process, or in the worst case scenario, matches the results of the best strategy by using it as a possible solution to optimise its performance.

5. Conclusions

This paper presented a new path for research in agent-based decisions by converting a decision driven method into a metalearner with auspicious results in the fields of artificial intelligence and power systems, namely, through electricity market study (by using MASCEM and ALBidS).

ALBidS combines several different strategic approaches, perceived as tools by the main agent; this work extended ALBidS by presenting a new strategy combining previously existing strategies in a way so that they can cooperate rather than being perceived as mutually exclusive.

The proposed STH method is a different way to assemble information about the decisions at hand. It treats several agents as if they were different persons in a meeting addressing a single decision and then applies the natural concept of the survival of the fittest over the aggregate of all of the ideas and routes to pick one final decision. Unlike ALBidS' main concept, where all strategies' answers are independent, concurrent and mutually exclusive, STH attempts to combine the best of each "idea."

The results show that the proposed STH metalearner provides better results than the individual strategies. The higher incomes when compared to the other strategies in the same scenario demonstrate the benefit of using the proposed method for decision support. In fact, using a strategy that effectively combines the best of the others proves to be a great asset in the decisions made by ALBidS and for other systems in related fields.

As future work, the use of all ALBidS strategies as additional hats or the use of more than one strategy to create the output of each hat is proposed. Another important development is the analysis of the genetic algorithm behaviour with different crossover points, using, for instance, the sunrise–sunset data to take full advantage of the difference between these events each day of the year.

Acknowledgments

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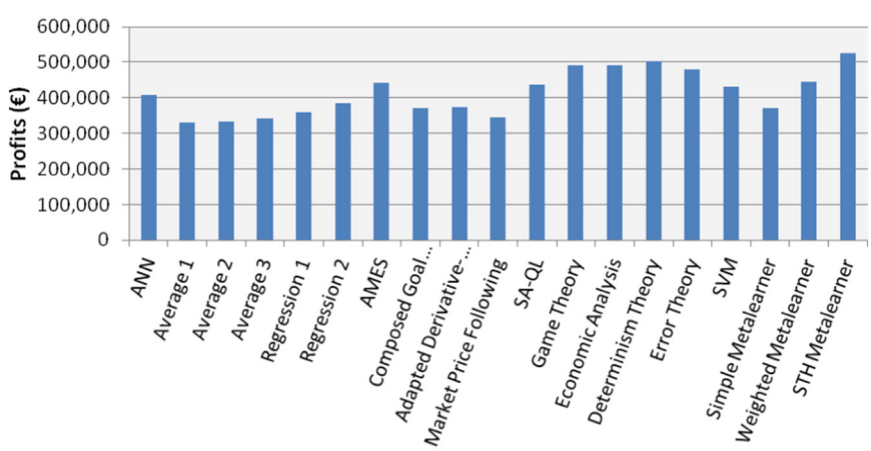

Fig. 10. Total profits achieved by each strategy in the 24 periods of the 61 simulated days.

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Article

Decision Support for Energy Contracts Negotiation with Game Theory and Adaptive Learning

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Abstract: This paper presents a decision support methodology for electricity market players' bilateral contract negotiations (DECON). The proposed model is based on the application of game theory, using artificial intelligence to enhance decision support method's adaptive features. This model is integrated in AiD-EM (Adaptive Decision Support for Electricity Markets Negotiations), a multi-agent system that provides electricity market players with strategic behavior capabilities that enable them competitive advantage when engaging negotiations for electrical energy transactions. Although a diversity of tools that enable the study and simulation of electricity markets has emerged during the past few years, these are mostly directed to the analysis of market models and power systems' technical constraints, making them suitable tools to support decisions of market operators and regulators. However, the equally important support of market negotiating players' decisions is being highly neglected. The proposed model contributes to overcome the existing gap concerning effective and realistic decision support for electricity market negotiating entities. The proposed method is validated by realistic electricity market simulations using real data from the Iberian market operator – MIBEL. Results show that the proposed adaptive decision

support features enable electricity market players to improve their outcomes from bilateral contracts' negotiations.

Keywords: adaptive learning; bilateral contracts; decision support; electricity markets; game theory; multi-agent simulation

1. Introduction

The last few decades have been characterized by an intensive electricity markets (EM) restructuring process, which has been completely changing the EM paradigm. The privatization, liberalization and international integration of previously nationally owned systems are some examples of the transformations that have been applied [1]. Nowadays EM operate using more reliable and complex models. However, EMs are still restricted to the participation of large players [2], which hardens the massive integration of renewable energy sources in the power system. This problem is being addressed in different ways in different parts of the globe [3]. However, during the last years some common solutions are being globally adopted. Worldwide EMs are evolving into regional markets and some into continental scales, supporting transactions of huge amounts of electrical energy and enabling the efficient use of renewable based generation in places where it exceeds the local needs.

A reference case of this evolution is the European EM where the majority of European countries have joined together into common market operators, resulting in joint regional EM composed of several countries [4]. Additionally, in early 2015, several of these regional European EM have been coupled in a common market platform, performing in a day-ahead basis [5]. The transformation of National EM into regional and continental EM is evidenced by other examples, such as the U.S. EM, which operates using several regional markets, e.g. California Independent System Operator (CAISO) [6] and Midcontinent Independent System Operator (MISO) [7]. In Latin-American, Brazil has also integrated all the regions in a joint EM [8]. These markets, although not representing a Continent as a whole, can be considered as continental EM due to these countries' size.

Each EM has its own rules and clearing price mechanisms, taking into account the power systems reality and the available energy mix. Some markets have the clearing mechanism based on the optimization of offers, such as most EM in the U.S. [7]; and other based on symmetric or asymmetric auctions, as is the case of most European countries. In essentially all energy markets worldwide, energy trade by means of bilateral contracts is also supported [9]. Despite the differences, market mechanisms are tending to become more and more alike in order to ease the transition towards markets unification.

Due to the constant evolution of the EM environment, including the introduction of new players [10] and changes in EM operation, it becomes essential for professionals in this area to completely understand the markets' principles and how to evaluate their investments under such a competitive environment [11]. The use of simulation tools has grown with the need for understanding those mechanisms and how the involved players' interaction affects the outcomes of the markets [12]. Artificial Intelligence (AI) plays an important role in this field, as multi-agent based simulation is particularly well fitted to analyze dynamic and adaptive systems with complex interactions among constituents, such as the EM [13]. This is supported by the several multi-agent modeling tools that can be fruitfully applied to the study of

restructured wholesale power markets. Some relevant tools in this domain are AMES (Agent-based Modelling of Electricity Systems) [14], EMCAS (Electricity Market Complex Adaptive System) [15], GAPEX (Genoa Artificial Power Exchange) [16], and MASCEM (Multi-Agent Simulator of Competitive Electricity Markets) [13, 17]. EM simulation platforms provide good solutions to test, validate and experiment new alternatives for market operation and players' interactions. However, these tools are usually focused on the market perspective, being valuable for market operators and regulators, while almost completely disregarding the market negotiation players' side. In fact, the decision support for electricity market negotiating players is a rather unexplored area, which should be properly addressed in order to provide the means for market players to adapt to the constantly changing EM environment, and learn how to take the most advantages out of market participation.

This paper approaches the problem of lack of decision support solutions for EM players, by proposing an innovative model, based on game theory [18], to support EM players' actions when participating in bilateral contract negotiations. The problematic of bilateral negotiation is a recurrent theme in the literature of several fields, e.g. social psychology [19], economics and management science [20], international relations [21], and AI [22, 23]. A relevant review on automated negotiation for computational agents with a particular focus on AI has been presented in [24]. According to this study, automated negotiation is generally composed of four phases: (i) preliminaries (the nature of negotiation); (ii) pre-negotiation (preparing and planning for negotiation); (iii) actual negotiation (moving toward agreement); and (iv) renegotiation (analyzing and improving the final agreement). However, several models consider the first two phases as a single initialization phase where all the necessary requirements, protocols and decisions that are essential before the actual negotiation process, are defined [24].

The initialization phase includes the selection of an appropriate initial strategy. The dual concern model for strategic choice in bilateral negotiation is proposed in [25]. This model stresses that negotiation strategies result from the combination of self-concern (own outcomes) and other-concern (other party's outcomes). A similar model of strategic choice is proposed in [26], and states that negotiation strategies result from the interplay of concern about own outcomes and concern about the relationship with the other party. According to [27] and [28] the most important pieces of data that must be considered in this phase are: (i) the intended limits and targets of the opponent(s); (ii) the negotiating history of the opponent(s); and (iii) the intended strategies of the opponent(s). Negotiators may speculate about the limits of the other parties and think stereotypically. However, they can also gather this data directly from them through the exchange of information prior or during the actual negotiation. Negotiators should also gather information about the past behavior of the other parties. Some works consider models that use information about the opposing negotiators (typically encoded into probabilistic distributions) to negotiate more effectively, such as [29] and [30]. Despite the efforts of these works, the authors are aware of no work on explicitly modeling the pre-negotiation step of gathering information either directly or indirectly about the opponent(s). In fact, AI researchers have traditionally neglected the pre-negotiation step of gathering information about opposing negotiators [24]. In summary, although some advances have been made regarding the pre-negotiation phase, several problems are yet far from being adequately addressed, such as the definition of models to choose the most appropriate parties to negotiate with, and how relevant information regarding competitors' history of previous negotiations can be used to improve the decision making process, namely regarding the choice of the most suitable negotiation strategies and tactics [24].

Given the identified limitations in the field, this paper gives its contribution by proposing a novel methodology to support the decisions of bilateral contract negotiating players. The proposed model applies the game theory concept to enable the analysis of several distinct potential scenarios that the supported player is most likely to face when assuming negotiations. The alternative scenarios are created based on the historic analysis of the opponents' past actions. For this, forecasting methods are used, namely Artificial Neural Networks (ANN) [31] and Support Vector Machines (SVM) [32], among others. The forecasting results are then used by a fuzzy logic process to estimate the expected limit price values of the opponents when negotiating different amounts of power. A reputation model is also used [33], so that the decision takes into account, not only the expected negotiation prices, but also the benefit that establishing a contract with one or several players should represent to the supported player. Finally, several alternative decision methods are included to allow adaptation depending on the risk that the supported player is willing to face regarding the outcomes of the negotiation process. For this, a reinforcement learning algorithm is used, allowing the proposed model to learn which of the potential scenarios are most likely to represent a reliable approximation of the real negotiation environment that the player will face. The development of the proposed game theoretic based model aims at fulfilling an important gap in the field of bilateral contract negotiation, taking into account the advances that have been accomplished in parallel fields, such as AI and microeconomics.

The study presented in [34] reviews several models that game theory/microeconomics provide to study the problem of negotiation and bargaining. According to [34] there are two main approaches, which both model the preferences of the agents over the possible agreements by using the utility functions of von Neumann and Morgenstern [18]. The first approach is called cooperative, while the second is called non–cooperative or strategic. The bargaining problem was indeterminate by economics until the works by Nash [35, 36] where the formal theory of bargaining, usually called axiomatic bargaining, was introduced. During the years several studies have extended and perfected this work; some relevant advances are the introduction of multilateral bargaining [37, 38], and the modelling of the bargaining problem as an alternating–offers game [39], which approximates the mathematical models to the actual molds of most negotiations. Developments in game theoretic models have also potentiated their application to several research fields, such as energy (e.g. [40] presents an energy management model based on game theoretic assumptions, in [41] the optimization of the distribution system planning is performed using game theory, and [42] proposes a game theory based strategy for electricity market participation).

After this introductory section, section 2 presents an overview of AiD-EM (Adaptive Decision Support for Electricity Markets Negotiations), the decision support system in which the proposed model is integrated, and that provides the means for real data-based experimentation through the complementarity with other specific decision support models, such as DECON (Decision support for Energy Contracts Negotiation) and ALBidS (Adaptive Learning strategic Bidding System). Section 3 presents the proposed method, including the forecast based scenarios generation and the adaptive decision methods. The proposed methodology is tested and validated using realistic simulation scenarios, and the achieved results are depicted in section 4. Finally, section 5 provides the most relevant conclusions and contributions of this work.

2. AiD-EM Decision Support System

The AiD-EM system has been developed with the purpose of providing decision support to electricity market negotiating players. This system is composed by several distinct and independent decision support systems, each directed to the resolution of different specific problems. RealScen (Realistic Scenarios Generator) [43] is directed to the creation of realistic simulation scenarios based on real data extracted from multiple sources in real-time. ALBidS (Adaptive Learning Strategic Bidding System) [17] focuses on the support of market players' decisions when participating in auction-based markets. The participation in bilateral contract negotiation is supported by DECON (Decision Support for Energy Contracts Negotiation), which is presented in this paper. The multi-agent approach of AiD-EM facilitates the interactions between the different components and also the communication with external agents, such as the market players themselves, which make use of the decision support. Figure 1 presents the global picture of the interaction between the several systems that compose AiD-EM, including the interface with the MASCEM electricity market simulator.

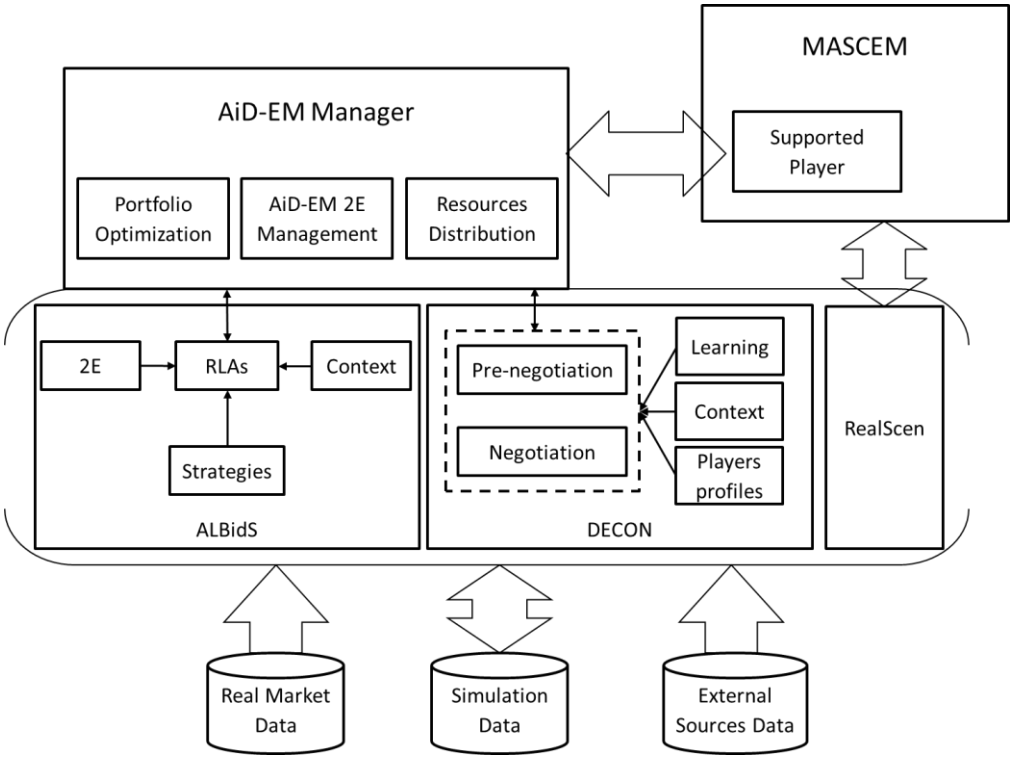

Figure 1. Overview of AiD-EM's main components

As presented in Figure 1 AiD-EM uses real market data, data derived from past and current simulations, and external sources data (e.g. weather conditions such as wind speed, solar intensity and temperature; or raw materials prices, among other) to support the decision making process and to generate realistic simulation scenarios. Decisions are modeled specifically for each different market negotiation type, such as the negotiation of bilateral contracts, balancing market participation, negotiation of forward contracts, or participation in the day-ahead spot market. The connection to MASCEM enables testing and validating the developed decision support methodologies under realistic simulation conditions, taking advantage on the enhanced simulation capabilities of MASCEM and on the interactions between the involved players.

MASCEM [13, 17] aims to facilitate the study of complex electricity markets. It considers the most important players that are usually part of the electricity markets' environment, and models them as software agents. MASCEM players include: a market operator agent, an independent system operator agent (ISO), a market facilitator agent, buyer agents, seller agents, and Virtual Power Player (VPP) agents. MASCEM allows the simulation of several market models, namely: day-ahead pool (asymmetric or symmetric, with or without complex conditions), bilateral contracts, balancing market, forward markets and ancillary services. Hybrid simulations are also possible by combining the market models mentioned above. Also, the possibility of defining different specifications for the market mechanisms, such as multiple offers per period per agent, block offers and flexible offers, or complex conditions, as part of some countries' market models, is also offered. Simulation scenarios in MASCEM are generated automatically using RealScen.

2.1. RealScen

RealScen uses real data that is available online, usually in market operators' websites. The gathered data concerns market proposals, including quantities and prices; accepted proposals and established market prices; proposals details; execution of physical bilateral contracts; statement outages, accumulated by unit type and technology; among others. By combining real extracted data with the data resulting from simulations, RealScen offers the possibility of generating scenarios for different types of electricity markets. Taking advantage on MASCEM's ability to simulate a broad range of different market mechanisms, this framework enables users to consider scenarios that are the representation of real markets of a specific region; or even consider different configurations, to test the operation of the same players under changed, thoroughly defined scenarios [43]. When summarized, yet still realistic scenarios are desired (in order to decrease simulations' execution time or facilitate the interpretation of results), data mining techniques are applied to define the players that act in each market. Real players are grouped according to their characteristics' similarity, resulting in a diversity of agent types that represent real market participants.

2.2. AiD-EM Manager Agent

The several alternative/complementary market opportunities that electricity market players face require that these players are endowed with suitable means to analyze the diverse opportunities in order to decide whether to, when to and how to participate in each market type. With this purpose AiD-EM is equipped with a portfolio optimization module, which, taking into account the different market types that each player can participate in, optimizes players' market participation portfolio in order to maximize the potential gain of investing different amounts of power in each market type considering the expected prices at each time depending on each different context [44]. Additionally, the instants each module should be executed are defined, taking into account the occurrence timings of each market. Moreover, the execution time that each module/system is allowed to spend is also defined, accordingly to the user specifications; i.e. faster execution time but with some degradation of results; or a slower, yet more robust decision support. Finally, the use of computational resources is also optimized by distributing the execution resources (agents and computational modules) among the available machines, taking into account the machines' processing power and installed software, which conditions what can be executed

in each machine. Once decisions are taken regarding the computational resources scheduling, the execution timings requirements, and the amount of power that should be sold or bought in each market opportunity at each time and in each context, specific decision support systems for each market negotiation type are used, such as ALBidS and DECON, so that the supported player can take the most advantage out of each market negotiation.

2.3. ALBidS

ALBidS [17, 42] is a decision support system that integrates several distinct technologies and approaches directed to auction-based negotiations, such as the day-ahead spot markets and balancing markets of most European electricity markets. ALBidS techniques include: artificial neural networks, data mining approaches, statistical approaches, machine learning algorithms, game theory techniques, competitor players' actions prediction, and approaches based on strategies used by other simulators for market analysis and costs forecasts. The set of algorithms is placed below a main reinforcement learning algorithm (RLA), which allows that in each moment and in each circumstance the technique that presents the best results for every actual scenario is chosen as the actual response. So, given as many answers to each problem as there are algorithms, the RLA will choose the one that is most likely to present the best answer according to the past experience of their responses and to the present context of each situation. The RLA presents a distinct set of statistics for each context. This means that an algorithm that may be presenting good results for a certain context, with its output chosen more often when bidding for this context, may possibly never be chosen as the answer for another context, since they are seen as independent from each other. ALBidS is implemented as a multi-agent system itself, in which each agent is responsible for an algorithm, allowing the execution of various algorithms simultaneously, increasing the performance of the platform. It was also necessary to build a suitable mechanism to manage the algorithms efficiency in order to guarantee the minimum degradation of the decision support execution time. For this purpose, a methodology to manage the efficiency/effectiveness (2E) balance of ALBidS has been developed [17].

2.4. DECON

The negotiation of bilateral contracts is a central process in any electricity market around the globe. Forward and Futures markets usually adopt this type of negotiation to establish power transaction agreements that can have different time horizons. In the scope of AiD-EM, the decision support for market player negotiations through bilateral contracts is provided by the DECON system. This decision support considers two main components, as presented in the following sub-sections: (i) decision support for the pre-negotiation stage, and (ii) decision support for the actual negotiation process.

2.4.1. Pre-negotiation

The pre-negotiation step is the main focus of this paper, and is presented in detail in section 3. The decision support for this stage aims at identifying the ideal competitor(s) that should be approached, so that the undertaken negotiations can provide as much benefit as possible for the supported player.

Moreover, the expected limits and target prices of each targeted competitor are predicted, so that they can be used to enhance the decision support for the actual negotiations.

With this objective, the decision support for the pre-negotiation stage considers the analysis of the past actions of competitor(s) so that the expected prices of each player can be used to create different potential negotiation scenarios. These scenarios also include the evaluation of each competitor player's reputation. A set of possible actions that the supported player is able to perform is defined, and game theory is applied to assess each combination action-scenario through the application of a utility function. Depending on the user's preferences regarding the aversion to risk, the optimal distribution of the amount of power that is intended to be transacted among the potential competitor players is defined. Details are presented in section 3.

2.4.2. Actual negotiations

Once the target competitors are defined, as well as the supported player's objectives (amount of power to be negotiated with each competitor), and the expected limits and target prices, it is time to undertake the actual negotiations. For this, a set of different tactics that follow different strategies, has been developed. Among the considered tactics, some are time-dependent [24], considering an evolution of the proposed prices throughout the time. This evolution is dependent on the nature of the tactics themselves. Four main types of time-dependent tactics are included: (i) Determined - prices remain constant throughout the period of negotiation; (ii) Anxious - high changes to the price are made after a small amount of trading time; (iii) Moderated - small changes to the price are made in an intermediate stage of negotiation period; (iv) Gluttonous - the price is significantly changed, but only in late trading. In addition to the considered time-dependent approaches, some behavior-dependent [24] tactics are included as well. These determine the changes in prices from one period of negotiation to the following as direct response to the proposals of the target competitors. The response to the opponent's proposals is determined by the level of desired aggressiveness of the supported player and of the opponent itself; i.e. the proposal to be sent by the supported player takes into account the degree in which the opponent has conceded in the last iterations, and the level of aggression that is intended to be applied in response. Finally, different tactic combinations are also supported by the decision support system. This allows the supported player to start using a certain approach, and as time progresses, change its tactic strategically; e.g. the supported player can start using a rigid tactic, conceding very slowly, in order to evaluate the profile of the competitor in a first phase, and assess if the limits and target prices of the opponent are as expected; then change to a faster conceding tactic in order to get closer to an agreement; and finally, near the end of the negotiation, change once more to a firmer approach in order to get as much benefit as possible from the negotiation without jeopardizing the agreement.

The choice of the most appropriate strategies and tactics to use against each opponent is based on a learning approach, which allows, not only choosing the initial strategy, but also to change it dynamically according to observed events. The learning process considers the analysis and definition of competitor players' profiles, so that decisions can be taken depending on past events of the same opponent and also of similar players. For this purpose, a knowledge base is kept updated, including the outcomes that each adopted strategy and tactic originated against each opponent. This allows selecting the most suitable approach against each negotiation profile. In order to overcome gaps in the history log concerning past

negotiations of the actual target opponent, all past opponents are stereotypically grouped into different clusters, according to the similarity of their negotiation profiles. This is achieved by using a clustering approach, namely the K-Means algorithm [45]. When a new negotiation is taking place, the evolution of the current iterations (proposals and counter-proposals) of the opponent is classified into one of the stereotypical clusters according to their similarity, i.e. the opponent is classified as belonging to the group that contains the players with most alike negotiation profiles. The classification process is undertaken using support vector machines [32] and artificial neural networks [31]. Finally, the knowledge base returns the strategy and tactic that has been most successful in the past against players of that group, and this is the approach that is used. This process is repeated after each counter-proposal, so that the negotiation profile of the current competitor player is always re-evaluated and matched with the most similar player profiles, considering all the most recent observations; thus allowing the adopted tactics and strategies to be dynamically adjusted in each iteration of the negotiation process.

3. Proposed Methodology

The presented work concerns the decision support to electricity market negotiating players (both sellers and buyers when participating in bilateral negotiations. Bilateral negotiations can be undertaken with a single competitor, or by facing multiple competitor players. A seller player wishes to maximize its incomes, by choosing to negotiate against the competitor or competitors that offer the best expectations of return. On the other hand, buyer agents desire to achieve as low contract prices as possible, thus the intention is to choose to negotiate against the competitor seller players that offer the lower expected contract prices. Besides the economic return of the established contracts, players should, when choosing the opponents, take also into account the expectation of opponents' ability to accomplish the contracted terms of the contract, i.e. an opponent that allows achieving a very good contract price but that after the agreement is done, is not able to deliver the committed amount of power, may not be the most advantageous option.

The proposed game theory based scenario analysis method has the objective of supporting the decisions of bilateral contracts' negotiating players, namely concerning the pre-negotiation stage. The outputs of the proposed method are: (i) the selection of the most appropriate competitor players to negotiate with, aiming at optimizing the gain of the supported player in its transactions; (ii) the suggested amount of power that should be negotiated with each of the selected competitors in order to maximize the outcomes of the supported player; and (iii) the expected target price of each selected competitor player. These outputs are essential to enhance the results of the negotiation process, and are achieved through the application of a game theoretic based scenario analysis decision method, which evaluates the potential results of assuming different actions under distinct negotiation scenarios. The general process of the proposed methodology is illustrated by the diagram of Figure 2.

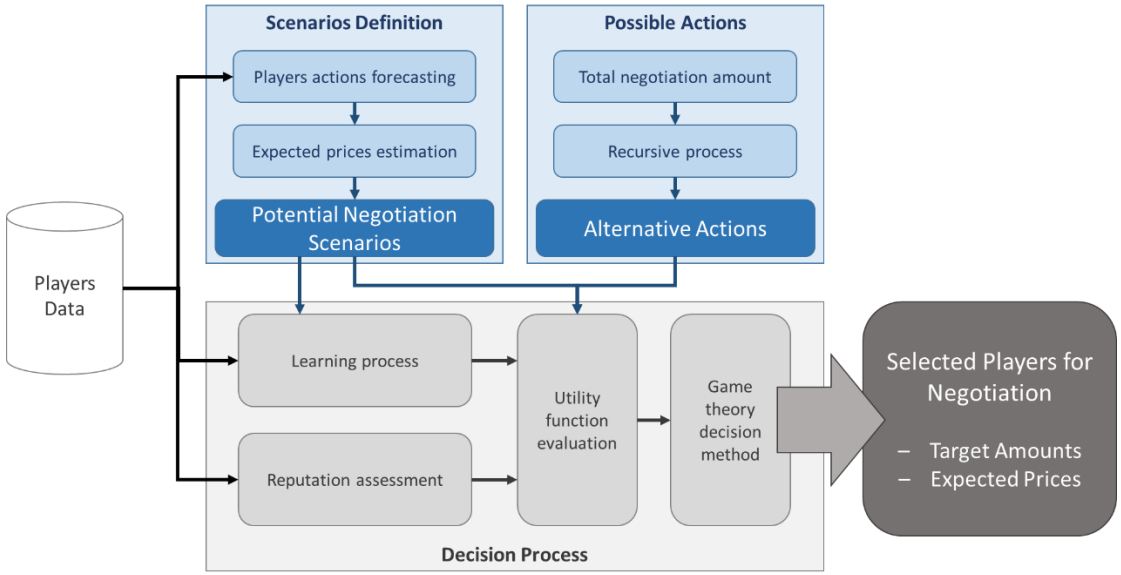

Figure 2. Decision process of the proposed methodology

Figure 2 shows that the proposed methodology is composed by three main parts, as follows:

- Scenarios definition. Is detailed in sub-section 3.1 and considers the specification of different potential negotiation scenarios that the supported player may face when engaging the negotiation process. These alternative scenarios are created based on the analysis of the past results of the potential competitor players. Several forecasting methodologies are applied to predict the expected established contract price for each player, for different transacted amounts. Since the history log is often reduced, an estimation process is also required, to achieve the expected prices when negating amounts that are not possible to predict by the forecasting process;
- Possible actions definition. As presented in sub-section 3.2, this process refers to the stipulation of the set of alternative actions that the supported player can undertake. The total amount of power that is intended to be negotiated is distributed among the potential competitor players by a recursive process, covering all the possible combinations;
- Decision process. The selected competitor players to negotiate with and the respective target amounts of negotiating power and expected prices result from the application of a game theoretic decision method, which uses an utility function to evaluate the potential outcome of each pair action-scenario. Hence, the result of assuming each alternative action under each scenario is calculated, using the reputation of the competitor players as the means to complement the assessment of the benefit for the supported player. Three distinct decision methods can be used: (i) a *Pessimistic* approach, (ii) an *Optimistic* approach, or (iii) the *Most probable* case. Reinforcement Learning Algorithms (RLA) [17] are used to provide the proposed method with learning capabilities, in order to perceive, throughout the time, which are the scenarios that present the higher probability of occurrence in each current context. The decision methods are presented in sub-section 3.3.

A detailed description of the proposed pre-negotiation model is provided in the following sub-sections. As mentioned above, the pre-negotiation stage will be followed by an actual negotiation phase. This phase can involve a simple bilateral negotiation between two players or alternatively a set of concurrent bilateral negotiations, i.e., the supported player can negotiate simultaneously with several competitor players. Each negotiation will involve mainly an iterative exchange of proposals and counter-proposals regarding the prices for the energy.

3.1. Scenarios definition

The alternative negotiation scenarios represent the alternative situations that the supported player can face when participating in bilateral contract negotiations. Scenarios are composed by the prices that are expected to be achieved from the negotiation with each of the potential competitor players, when negotiating different amounts of power. The amount is closely related to the expected price, since it is usual that a player agrees with different prices when negotiating distinct amounts of power. The expected prices from each player are calculated by several forecasting methodologies (as presented in sub-section 3.1.1.). However, predictions of expected prices for different amounts of power than those contained in the historic log are often required. Hence, an adequate estimative to is essential to reach the values that are not attainable via forecasting (as presented in sub-section 3.1.2). Each estimative, based on the predicted prices resulting from each forecasting methodology, results in an alternative scenario.

3.1.1. Contract price forecasting

The prediction of competitor players' expected negotiation prices requires adequate forecasting techniques, able to provide adequate data analysis; namely of the historic of competitor players' past contracts, the amount of power that each price is associated to, and also the context to which the contract settlement refers to. The way each contract price is predicted can be approached in several ways, namely through the use of statistical methods, data mining techniques [45], neural networks (NN) [31], support vector machines (SVM) [32], or several other methods [17]. However, no method presents a better performance than all others in every situation, only in particular cases and contexts [17]. For this reason, and given that all forecasting methods are subject to some error degree, a set of different approaches is used, and the outcomes of each alternative are considered as basis to create a distinct scenario. In this way, the proposed methodology considers as many alternative scenarios as the number of different forecasting approaches.

All algorithms used for the predictions are endowed with context awareness. The context analysis and definition methodology presented in [46] is used to separate the historic data into different groups, which represent different negotiation contexts. This way, the forecasting processes consider only the data that refers to the same context as the one the decision support is intended to (e.g. negotiation of bilateral contracts for business days or weekends; directed to peak or off-peak hours of consumption, etc.). Thus, the contextualization of the forecasting process is enabled, resulting in forecasts that most reflect each current circumstances and context. The used algorithms are listed as follows:

- A feed-forward ANN, trained with backpropagation using the historic contract prices of each subject player, for the amounts of power available in the history log.
- SVM using the exponential radial basis function (eRBF) as training kernel.

- Based on Statistical approaches. There are two strategies in this category:
    - Average of prices from the players' past actions database;
    - Regression on the contract prices historic data.
- Algorithms based on pattern analysis:
    - Sequences in the past matching the last few actions of the competitor player. In this approach are considered the sequences of at least 3 actions found along the historic of actions of this player. The sequences are treated depending on their size. The longer matches to the recent history are attributed a higher importance.
    - Most repeated sequence along the historic of actions of the target player.
    - Most recent sequence among all the found ones.
- Algorithm based on history matching. Regarding not only the player actions, but also the result they obtained. This algorithm finds the previous time that the last result happened, i.e., what the player did, or how he reacted, the last time he performed the same action and got the same result.
- Algorithm returning the most repeated action of the target player. This is an efficient method for players that tend to perform recurrent actions.

The methods that are used in each decision support process depend on the requirements of the AiD-EM 2E balance management mechanism. When the requirement is the achievement of the best possible decision support results, all approaches are used, resulting in a large number of alternative scenarios to be analyzed by the decision method of the proposed methodology. On the other hand, when the execution time restraints are significant, only a few approaches are used (the faster ones to execute), so that the time demand of the decision support method is reduced.

The results of the forecasting process consider the expected contract prices for each competitor player, for the power amounts that are available in the history log. However, as explained before, the decision making process requires the expected prices of each player for each amount of negotiated power. For this reason, the estimation of the missing values is essential.

3.1.2. Contract price estimation

The decision making process requires the expected return prices for each possible amount of power, for each competitor player. This, however, is impracticable due to the number of possible amounts (which tends to infinite when increasing the number of decimal places of the power amount value). For this reason, a dynamic *fuzzy* variable that approximates the values of contract prices for different negotiated power amounts has been proposed in [47] and is used in the scope of this work. This methodology allows estimating the large number of historic contract prices by means of a single fuzzy variable, hence reducing drastically the execution time of the proposed methodology.

Historic contract information is limited, i.e. the information concerns only prices for certain values of contracted power amounts. When it is necessary to achieve expected prices for contracts based on amounts of power that have never been negotiated before, these value has to be estimated. Using *fuzzy* logic, the estimative is done by defining power intervals, for which the expected price is similar. The fuzzy process allows smoothing the interval transition values. E.g. when negotiating 50 MW with a

certain player (part of one power interval) the expected price is *X*; when negotiating 51 MW with the same player, amount of a different power interval, the expected price is *Y*. However, the difference from 50 to 51 MW is minimal, and not enough to represent a large difference in the expected price. The *fuzzy* process allows these transition values between different intervals to be smoother, avoiding abrupt price changes. Figure 3 shows the *fuzzy* variable that represents the different intervals.

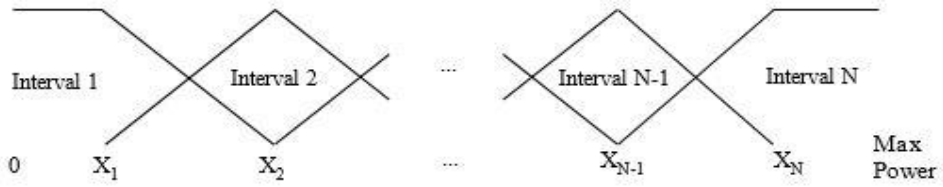

Figure 3. Dynamic *fuzzy* variable [47]

The lower limit of the function variable is zero and the upper limit is the maximum power in the input data. Intervals are constructed according to the forecasted prices resulting from the algorithms presented in sub-section 3.1.1. Each forecasted price defines the maximum membership value of each *fuzzy* function, *i.e.* X_1 to X_N of Figure 3 are the power amounts for which a forecast has been performed. The limits of each function assume the value of the preceding and following price forecast, which assume membership values of zero. All membership functions are triangular, except from the first and last. The *fuzzy* variable is, therefore, dynamic, since its definition in done at runtime, depending on the number of performed forecasts, since these vary with the available historic data.

A distinct *fuzzy* variable is created to estimate the missing values that result from the forecasts of each alternative forecasting approach, for each competitor player. Each negotiation scenario is composed by the estimates of the expected contract prices of all competitor players, resulting from the values returned by each forecasting methodology.

3.2. Possible actions definition

Once the alternative negotiation scenarios are defined, it is necessary to identify the set of possible actions that the supported player is able to perform. The alternative actions consist in the amount of power that will be allocated to the negotiation with each competitor player. The most advantageous from these alternatives will be chosen by the decision method (presented in sub-section 3.3.) as the action that presents the most potential for the success of the supported player, by optimizing its benefit.

The definition of the alternative actions is done by distributing the total amount of desired negotiation power among the potential competitor players. Each alternative action comprehends a different distribution of the total amount among the competitor players, in a way that all combinations are represented by the different possible actions. This is achieved through the use of a recursive process that guarantees that the total amount is always fully distributed among the players in each alternative action, and that all combinations are considered. The combinations range from allocating the total amount of power to the negotiation with a single competitor player, to the equal distribution of the desired negotiation amount among all competitor players.

The enlarged range of possible actions enables the decision method to consider the evaluation of a great number of alternative action-scenario combinations, thus facilitating the achievement of the most advantageous action for the supported player to perform, with the aim of increasing the quality of the outcomes of the negotiation process.

3.3. Decision method

The decision method has the role of assessing the combinations action-scenario and choosing the action that presents the greatest potential benefit for the supported player. Figure 4 presents an illustration of the decision making process.

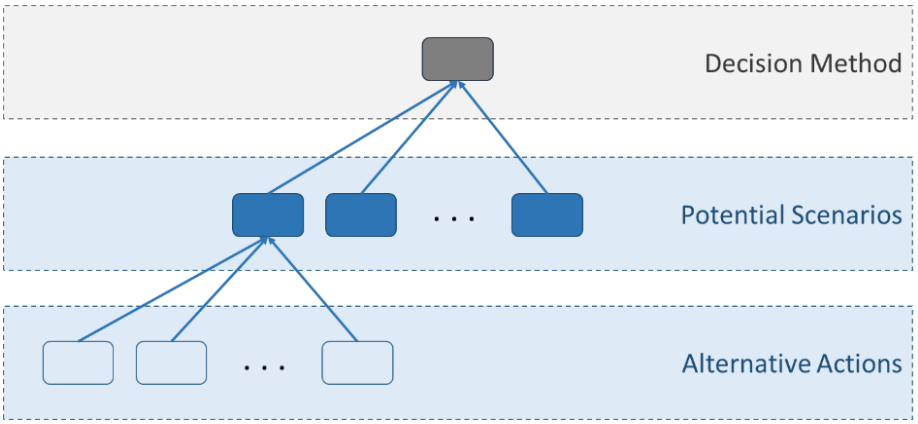

Figure 4. Decision making based on the evaluation of each action-scenario combination.

The evaluation of the action-scenario combinations is performed using a risk-based utility function, which adapts the evaluation of the potential benefit of the supported player to the player's propensity to risk; the utility function is presented in sub-section 3.3.1. The risk management is considered by including the reputation of each competitor player in the utility function evaluation; this way the supported player may choose to undertake negotiations with players that present a slightly lower potential profit, but compensate the gain by ensuring safer deals with players that present better reputations, which provide a different level of security, especially regarding the prospect of complying with the terms of the established contract. The used reputation model is presented in sub-section 3.3.2. Finally, using the evaluation results of the performance of each action in each scenario, a decision method based on game theoretic concepts is used to make the final decision of what should be the best action for the player to perform. The decision method is also dependent on the player's propensity to risk, and can assume one of three approaches: (i) *Pessimistic* or safe; (ii) *Optimistic*; or (iii) the *Most probable* case. The latter uses a learning process based on RLA in order to perceive which, from all the alternative scenarios, is the most likely to occur in the current context. This way, the suggested action for the supported player is the best potential action under the scenario with the larger probability of occurrence. The decision method is presented in sub-section 3.3.3.

3.3.1. Utility function

The benefit for the supported player of adopting each action under each scenario is evaluated using a utility function. The utility function U_{as}, which is presented in equation (1), allows assessing the outcome of action a in scenario s.

$$U_{as} = rE'_{as} + (1 - r)R_a \tag{1}$$

where r represents the supported player's propensity to risk, and ranges from 0 to 1. E'_{as} is the normalized economic gain (income when selling or cost when buying) of performing action a under scenario s, and R_a is the reputation component that results from negotiating the amounts defined in a with each of the corresponding competitor players.

U_{as} is defined so that a high propensity to risk considers almost exclusively the potential economic gain of the player, while neglecting the reputation of the players with whom contracts will be negotiated. On the other hand, a low value of propensity to risk means a larger weight to the reputation component, providing a larger influence to the reputation of competitor players and a lower importance to the economic gains, which results in safer and more reliable contract deals.

Both the reputation and the economic components range from 0 to 1, so that both components present a similar influence on U_{as}, depending only on the risk. The reputation component R_a is defined as in equation (2).

$$R_a = \sum_{p=1}^{np} R_p \frac{A_{ap}}{TP} \tag{2}$$

where p represents each competitor player from the total set of potential competitor players np. R_p is the reputation of player p, as defined in sub-section 3.3.2. A_{ap} is the amount of power that is allocated by action a to be negotiated with player p, and TP is the total amount of power that the supported player needs to negotiate with all competitors. R_a thus represents the accumulated reputation of the players with whom negotiations will occur by undertaking action a. Each of the competitor players' reputations is relative to the percentage from the total power that is allocated to that player, i.e. if the total amount of needed power is allocated to the negotiation with a single player, R_a is equal to R_p; contrarily, if the total amount is divided equally among two competitor players, the reputation of both will also contribute equally to the value of R_a.

The economic component E'_{as} defines the level of income or cost, in a scale from 0 to 1, by normalizing the actual income/cost values E_{as}, as presented in equation (3).

$$E'_{as} = \begin{cases} \dfrac{E_{as} - E_{min}}{E_{max} - E_{min}}, & \textit{when the supported player is selling} \\ \\ \dfrac{E_{max} - E_{as}}{E_{max} - E_{min}}, & \textit{when the supported player is buying} \end{cases} \tag{3}$$

where E_{min} is the minimum value of E_{as} that results from all combinations action-scenario, and E_{max} is the maximum value of E_{as} from all combinations. By using (3) when a player is selling, E'_{as} will assume the maximum value of 1 when the return of E_{as} is maximum, while when a player is buying, E'_{as} will assume the maximum value of 1 when the return of E_{as} is minimum (minimum buying cost). E_{as}

represents the absolute value of income/cost that results from transacting the amounts of power with the competitor players defined in action *a* under the expected prices from each player that result from scenario *s*, as defined in equation (4).

$$E_{as} = \sum_{p=1}^{np} A_{ap} EP_{spA_{ap}} \tag{4}$$

where $EP_{spA_{ap}}$ is the expected price of player *p* in scenario *s*, for the amount of power A_{ap}.

E_{as} thus represents the total income/cost of the supported player when negotiating the amounts of power defined in action *a* with the competitor players defined in same action, and achieving the expected prices defined in scenario s.

The risk management capability provided by the utility function enables further adaptation to the decision making process, by not limiting the supported player to exclusively pursue the maximum possible economic gain, but also taking into account the potential benefit of the established contracts depending on the reputation of the competitor players with whom negotiations will take place.

3.3.2. Reputation model

The reputation is included in the model in order to endow the proposed decision support methodology with the capability of considering, not only the potential economic gain of the supported player in the undertaken negotiations, but also the benefit from a contract reliability standpoint. The reputation component represents the level of confidence that the supported player can have on the opponent's service, i.e. in this case, the level of assurance that the opponent will fulfil the conditions established in the contract. Several works regarding the computational modeling of reputation and trust can be found in the literature, as discussed in [33], which provides an interesting review on the subject. The most recognized and globally accepted models are those resulting from the work of Sabater and Sierra [48]; the REGRET system, developed by these authors, accommodates several models for representing and assessing the reputation, trust, and credibility of different types of actors and players. The present work considers such proposed models to model the reputation of bilateral contract negotiating players.

The reputation R_p of the competitor player *p* is assessed from the perspective of the supported player *sp*. Two components are considered: the individual component $R_{sp,p}$, which represents the direct observations and experience of the supported player in regard to the subject competitor player; and the social component R_s, considering the perspective of the group in which each player is inserted, and also the prejudice regarding the player type. Group and player type, in the scope of this work, refer to the generation type of seller players (e.g. players that represent wind farms will tend to have a similar reputation, as they will have the same type of difficulty in fulfilling the agreed amount of power, as they are equally dependent on the wind speed), and consumer types, in case of buyer players (e.g. large industry, medium commerce, small players). The prejudice refers to the a-priori idea regarding the reliability of each player type. R_p is, therefore, defined in equation (5).

$$R_p = w_i R_{sp,p} + w_s R_s \tag{5}$$

where w_i and w_s are weights that are attributed to the individual and social component, respectively. The sum of both weights should be equal to 1, and these should reflect the confidence that the supported player has on its own experience and on the experience of others.

$R_{sp,p}$ is updated whenever a new observation is available. A positive or negative experience of the supported player regarding the subject competitor affects the new value of $R_{sp,p}$ as defined in (6).

$$R_{sp,p} = \frac{NPE}{TNE} \tag{6}$$

where *NPE* represents the number of positive experiences and *TNE* the total number of experiences that the supported player has had with the subject competitor player.

The social component R_s allows, not only to include the opinion of others, but also to surpass the difficulties that arise from the usually very limited number of experiences that two players have directly with each other (it is unusual that players establish a large number of different contracts with the same player). Thus, the social component allows using information on similar players, and also to make use of the experience of other players regarding their personal experiences with the subject player. R_s is defined as in equation (7).

$$R_s = w_{gp}R_{sp,Gp} + w_{gsp}R_{Gsp,p} + w_g R_{Gsp,Gp} + w_p P_s \tag{7}$$

where $R_{sp,Gp}$ represents the reputation of the subject competitor player's group form the perspective of the supported player, $R_{Gsp,p}$ represents the reputation that the subject competitor player has from the perspective of the supported player's group, $R_{Gsp,Gp}$ represents the reputation that the competitor player's group has from the eyes of the supported player's group, and P_s is the prejudice component.

$R_{sp,Gp}$ is defined by considering the individual reputation of all members that are part of the subject competitor player's group, as described in equation (8).

$$R_{sp,Gp} = \sum_{p_i \in Gp} w_{sp,p_i} R_{sp,pi} \tag{8}$$

where $\sum_{p_i \in Gp} w_{sp,p_i} = 1$. $R_{sp,pi}$ is the reputation of member *i* of the subject competitor player's group from the standpoint of the supported player *sp*; and $w_{sp,pi}$ represents the weight that is given to each of these individual reputations of the group members. These weights can be defined according to the similarity of each group member with the subject player.

$R_{Gsp,p}$ is defined ty taking into account the opinion of each player that is part of the supported player's group in regard to the reputation of the subject competitor player, and is defined as in equation (9).

$$R_{Gsp,p} = \sum_{gsp_i \in Gsp} w_{gsp_i,p} R_{gsp_i,p} \tag{9}$$

where $\sum_{gsp_i \in Gsp} w_{gsp_i,p} = 1$. $R_{gspi,p}$ is the reputation of the subject competitor player from the perspective of each member *i* of the supported player's group; and $w_{gspi,p}$ represents the weight that is given to each of these individual reputations of the group members. These weights can be defined according to the credibility of each group member from the perspective of the supported player.

$R_{Gsp,Gp}$ is defined ty taking into account the opinion of each player that is part of the supported player's group in regard to the reputation of each member of the subject competitor player's group, and is defined as in equation (10).

$$R_{Gsp,Gp} = \sum_{gsp_i \in Gsp} w_{gsp_i,Gp} R_{gsp_i,Gp} \tag{10}$$

where $\sum_{gsp_i \in Gsp} w_{gsp_i,Gp} = 1$. $R_{gspi,Gp}$ is the reputation of the subject competitor player's group from the perspective of each member *i* of the supported player's group; this reputation value is achieved by applying equation (8) from the perspective of each player of the supported player's group. $w_{gspi,Gp}$ represents the weight that is given to each of these individual reputations of the group members. These weights can be defined according to the credibility of each group member from the supported player's perspective.

Considering the credibility of the opinions of other players to define the weights that will be attributed to their responses, requires analyzing the responses that are given from each player, and comparing them to the actual experience of the subject player; e.g. if a certain player attributes a large reputation value to the subject competitor player, and when the supported player establishes a contract with this opponent verifies that this player is not able to fulfill the contracted conditions, the supported player will not only update the reputation of the competitor player taking into account the bad experience, but will also update the credibility on the responses of the player that provided the misleading evaluation of the competitor player's reputation. The credibility update is performed by using equation (6), however, in this case, the good or bad experience is not assessed by the player's ability in fulfilling the contracted terms, but by comparing its provided opinion regarding the opponent's reputation with the actual verified experience with the same opponent.

3.3.3. Decision methods

The reputation model provides its input for the utility function, so that each pair action-scenario can be evaluated. The utility values that result from the evaluation of all combinations are used by the decisions methods to choose the suggested action for the supported player to perform. Three alternative decision methods are proposed, which consider different perspectives for assessing the utility values and making the selection of the final action for the supported player. The three alternatives are:

- *Pessimistic* approach. This decision method considers the usual mini-max game theoretic approach [34, 42]. This method evaluates the global utility of each scenario individually, and chooses the action that presents the maximum utility (max) for the scenario with the minimum global utility (min). The global utility *GU* of scenario *j* is calculated as in equation (11).

$$GU_{s_j} = \sum_{a \in A} U_{a_k s_j} \tag{11}$$

  where *a* is each action from the set of all possible actions *A*. Hence, the global utility of scenario *j* is the sum of the utilities of applying each possible action under scenario *j*. The scenario with the lowest *GU* is chosen, and the action that presents the higher utility under this scenario is selected as the final action to be used by the supported player. This decision

method allows the supported player to prepare for the worst case scenario it can find, and perform the safer action, which provides the best outcomes for the worst possible scenario.

- *Optimistic* approach. This approach uses the utility function evaluation of equation (1) to find the action-scenario combination that presents the best gain among all combinations. The action that presents the higher possible gain is the one chosen as the final suggestion for the supported player to perform. This optimistic approach enables the supported player to risk, and perform the action that is able to provide the best possible gain under all scenarios.
- *Most probable* scenario. The third decision method uses a learning process to assess the probability of occurrence of each alternative scenario. The final chosen action is the one that presents the higher expected utility value for the most probable scenario. This approach allows the supported player to be prepared for the scenario that is the most likely to occur, and perform the action that should provide the best outcomes under this scenario. An adaptation of the Q-Learning algorithm [49] is proposed to undertake the learning process. Q-Learning is a very popular reinforcement learning method. It is an algorithm that allows the autonomous establishment of an interactive action policy. It is demonstrated that the Q-Learning algorithm converges to the optimal proceeding when the learning state-action pairs Q is represented in a table containing the full information of each pair value [50]. The proposed approach includes the contextualization of the learning process in order to avoid the over-generalization of the learning process, hence adapting the learning to each context. The basic concept behind the proposed Q-Learning adaption is that the learning algorithm is able to learn a function of optimal evaluation over the whole space of context-scenario pairs c x s. This evaluation thus defines the confidence value Q that each scenario is able to represent the actual encountered negotiation scenario s in context c. The Q function performs the mapping as in equation (12).

$$Q: c\ x\ s\ \rightarrow U \tag{12}$$

where U is the expected utility value when selecting scenario s in context c. As long as the context and scenario states do not omit relevant information, nor introduce new information, once the optimal function Q is learned, the decision method will know precisely which scenario results on the higher future reward under each context. The reward r is attributed to each pair scenario-context in each iteration, representing the quality of this pair (how well does the scenario represent the real negotiation scenario under context c), and allows the confidence value Q to be updated after each observation. r is defined as in (13).

$$r_{s,c,t} = 1 - norm\left|RP_{c,t,a,p} - EP_{s,c,t,a,p}\right| \tag{13}$$

where $RP_{c,t,a,p}$ represents the real price that has been established in a contract with an opponent p, in context c, in time t, referring to an amount of power a; and $EP_{s,c,t,a,p}$ is the estimation price of scenario that corresponds to the same player, amount of power and context in time t. All r values are normalized in a scale from 0 to 1, in order to allow the $Q(c, s)$ function to remain under these values, so that the confidence values Q can be easily assumed as probabilities of scenario occurrence under a context. $Q(c, s)$ is learned through by try an error, being updated every time a new observation (new contract establishment) becomes available, following equation (14).

$$Q_{t+1}(c_t, s_t) = Q_t(c_t, s_t) + \alpha\left[r_{s,c,t} + \gamma U_t(c_{t+1}) - Q_t(c_t, s_t)\right] \quad (14)$$

where α is the learning rate; γ is the discount factor; and U_t (15) is the utility resulting from scenario *s* under context *c*, obtained using the Q function learned so far.

$$U_t(c_{t+1}) = \max_s Q(c_{t+1}, s) \quad (15)$$

The Q learning algorithm is executes as follows:

- For each *c* and *s*, initialize *Q(c,s)* = 0;
- Observe new event;
- Repeat until the stopping criterion is satisfied:
  - Select the scenario that presents the higher *Q* for the current context;
  - Receive reward $r_{s,c,t}$;
  - Update *Q(c,s)*;
  - Observe new context *c'*;
  - $c \leftarrow c'$.

As the visiting of all scenario-context pairs tends to infinite, the method guarantees a generation of an estimative of Q_t which converges to the value of *Q*. In fact, the actions policy converges to the optimal policy in a finite time, however slowly. In order to accelerate the convergence process, not only the *Q* value of the chosen scenario is updated, but also that of all scenarios, since the *r* regarding all alternative scenarios can be computed by comparing the estimated prices by each scenario and the actual values that have been verified in a new contract agreement. After each updating process, all *Q* values are normalized, as in equation (16), so that they are always kept in a scale from 0 to 1, thus facilitating the interpretation as the probability of each scenario in correctly representing the negotiation reality.

$$Q'(c, s) = \frac{Q(c, s)}{\max[Q(c, s)]} \quad (16)$$

In all three decision methods ties may occur when choosing the action with the higher utility value. In order to surpass this problem, the following tie-breaking conditions have been defined:

- When the supported player's propensity to risk is ≤ 0.5, the selected action is the one with the higher reputation component from all that present the same utility value;
- Otherwise, if the propensity to risk is > 0.5, the selected action is the one with the higher economic gain component;
- If after the tie-break some action remain tied, the inverse condition is applied, i.e. from the actions with the higher reputation component when the propensity to risk is ≤ 0.5, the one with the higher economic gain component is selected; the opposite is applied to the actions tied in economic gain when the propensity to risk is > 0.5.

The decision method to be applied in any case can be selected directly by the supported player as input, or it can be defined dynamically depending on the risk aversion value. In this case, the *Pessimistic* decision method is used when the risk is ≤ 0.3; the *Optimistic* method is applied when the risk is ≥ 0.7, and the *Most probable* scenario is used otherwise.

4. Experimental Findings

This section presents a case study that demonstrates the advantages of using the proposed methodology. For this purpose, real data from the Iberian electricity market – MIBEL [51] has been used to assemble a historic database concerning the past log of established contracts of 37 electricity market participating players. This database is used to apply the proposed methodology and assess its performance, namely by comparing the achieved results (assignment of the negotiation amount among the set of potential competitor players) to the outcomes of allocating the total negotiation amount to a single player, which is the common approach in the pre-negotiation stage of bilateral contract negotiations.

All the simulations presented in this case study have been executed in a machine with one Intel® Xeon® E5-2620v2 - 2.10 GHz processor, with 12 cores, 16GB of Random-Access-Memory (RAM) and Windows 8.1 Professional.

The first part of this case study considers a set of 5 electricity market players as potential opponents, in order to facilitate the demonstration of the proposed methodology's decision support process and to allow a detailed description of results. The total negotiation amount to be allocated to be sold to the competitor players is of 10 MW. Figure 5 presents the price estimation error, using the Mean Absolute Percentage Error (MAPE) that results from the application of each of the 9 forecasting algorithms that have been presented in sub-section 3.1.1.

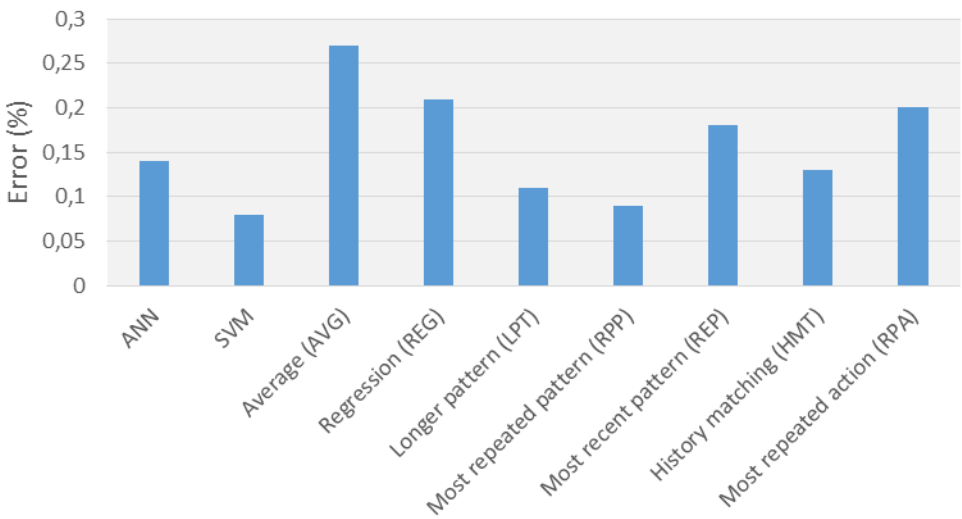

Figure 5. MAPE estimation error using each of the considered forecasting algorithms.

From Figure 5 it is visible that algorithm that is able to achieve the best results for this case is the SVM, closely followed by the Most repeated pattern search and by the Longer pattern search. The worst estimations come from the application of the average and regression of the historic contracted prices.

In order to determine the *Most probable* scenario the Q-Learning based algorithm is applied, using $\alpha = 0.8$ and $\gamma = 0.2$, in order to provide the learning algorithm with a quick learning rate, with the aim at facilitating the fast adaptation to the most recent perceived events. The confidence value Q in each of the scenarios created using the forecasts resulting from each of the 9 algorithms throughout 25 observations (newly established contracts) is presented in Table 1.

Table 1. *Q* values of each scenario throughout 25 iterations

Iteration	ANN	SVM	AVG	REG	LPT	RPP	REP	HMT	RPA
5	0.23	0.74	1	0.86	0.31	0.3	0.68	0.42	0.93
10	0.37	0.84	0.97	0.91	0.38	0.52	0.73	0.65	1
15	0.53	1	0.84	0.85	0.47	0.78	0.88	0.71	0.97
20	0.78	1	0.79	0.81	0.76	0.85	0.93	0.89	0.91
25	0.91	1	0.72	0.78	0.97	0.98	0.89	0.93	0.83

Table 1 shows that after 25 iterations the scenario that presents the higher *Q* value is the one based on the estimation from the forecasting results of the SVM, which corresponds to the strategy that also presents best MAPE results. During the first iterations, with very few data to train the most advanced algorithms, the approaches that have achieved the best results are the simpler ones, namely the average, regression and most repeated player's action. With the increase of the number of iterations, one can see the significant increase of the confidence value in the most complex algorithms, and a relative decrease of the *Q* value of the simpler strategies. Figure 6 presents the price estimation and forecasting results that compose the *Most probable* scenario (based on SVM).

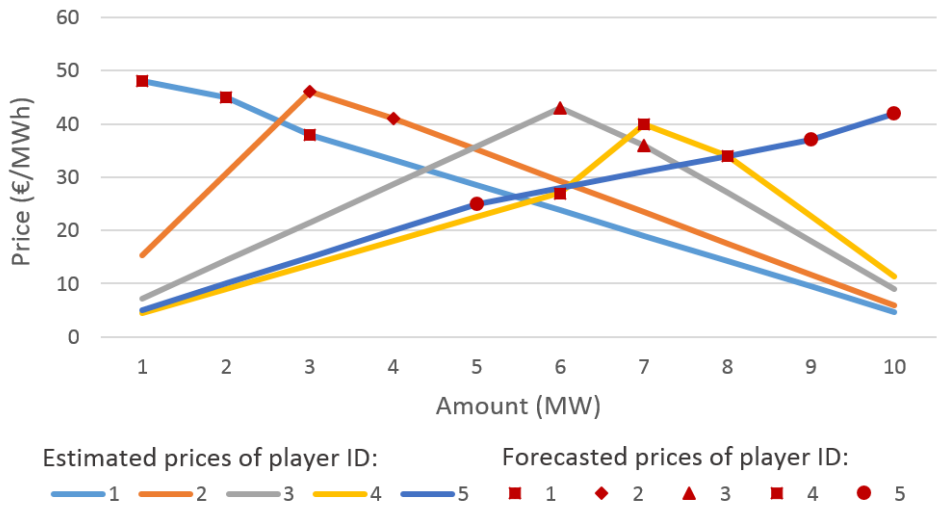

Figure 6. *Most probable* scenario estimation values.

Figure 6 shows that the forecasted (marked up) expected prices for each competitor player are very few. The reduced contract history of each player only enables the forecasting of a very strict amount of prices. This requires that the expected prices for the remaining amounts of power are estimated using the fuzzy process introduced in sub-section 3.1.2. It is important to notice that the estimation of prices for amounts that are not available in the historic log have a decreasing tendency towards the value of 0. Since no information is available regarding past contract settlements of a player for such amounts of power, it cannot be assumed that the player would be willing to negotiate at higher price values, thus the expectation is that these prices present a decreasing tendency. E.g. regarding opponent player ID 1, only

three prices could be forecasting, concerning the amounts of 1MW, 2MW and 3MW. The prices that refer to these amounts present a decreasing tendency, therefore this tendency is maintained throughout the remaining power amounts.

Executing the utility function that is necessary for the decision making process requires the use of reputation values referent to each competitor player. Since no real information regarding this aspect can be found, and using realistic values would require a sociologic study, which is out of the scope of this work, default reputation values have been attributed to each competitor player, in order to allow the test of the complete model. The reputation values that have been assigned to each competitor player are presented in Table 2.

Table 2. Reputation of the competitor players

Player ID	**1**	**2**	**3**	**4**	**5**
Reputation	0.9	0.7	0.5	0.3	0.1

Table 2 shows that the reputation values assigned to the competitor players are all distinct and ranging from 0.1 to 0.9. This enables an easier verification of the influence of the reputation component on the proposed decision support model. Table 3 shows the utility values that result from the application of the proposed methodology to the present case, for different levels of risk propensity, considering the three decision methods, and the allocation of the total 10 MW to each of the 5 players.

Table 3. Utility function values for different risk propensity values

	Risk propensity				
Decision Method	**1**	**0.8**	**0.5**	**0.2**	**0**
Pessimistic	0.86	0.74	0.70	0.68	0.90
Optimistic	1.00	0.91	0.83	0.78	0.90
Most Probable	0.91	0.82	0.77	0.72	0.90
All Player 1	0.00	0.18	0.45	0.72	0.90
All Player 2	0.08	0.20	0.39	0.58	0.70
All Player 3	0.13	0.20	0.32	0.43	0.50
All Player 4	0.18	0.20	0.24	0.28	0.30
All Player 5	0.72	0.59	0.41	0.22	0.10

From Table 3 it is visible that, for a risk value of 1, which means that only the economic component is considered by the utility function, the *Optimistic* decision method is able to achieve the maximum utility value of 1. This occurs because the *Optimistic* method selects the action that presents the best possible outcome from all scenarios, thus the selected action-scenario combination is the one that

achieves the maximum possible income. From equation (3), the maximum income corresponds to a value of 1 in the economic component of the utility function evaluation. On the other hand, negotiating the total amount of 10MW with Player 1 results in an utility value of 0, since this is the worst possible action that can be performed; as can be seen by Figure 6, the expected negotiation price for Player 1 for the amount of 10MW corresponds to the lowest possible price among all that are estimated. In fact, negotiating the total 10MW with a single player, considering only the economic component, always leads to very bad incomes, with the exception of Player 5. This player (as presented in Figure 6) presents a relatively good expected price for the amount of 10MW, hence resulting a fairly good utility value for a risk value of 1.

Looking at the other extreme, considering a risk value of 0 means that only the reputation component is considered by the utility function. When negotiating the total amount with a single player, by equation (2), the reputation component is equal to the reputation of that player, therefore the utility value when negotiating the total amount with each player, for a risk value of 0, is equal to the reputation value presented in Table 2. All three decision methods have reached a utility value equal to the negotiation of the total amount with player 1. This occurs due to the exclusion of the economic component when risk is equal to 0, which means that the chosen scenario is irrelevant in this case, and only the choice of the opponent player(s), considering their reputation, is important. For this reason, regardless of the chosen scenario, the best action is always to negotiate the full amount with the player that presents the higher reputation, in this case Player 1.

For all intermediate risk values, the same tendency is always observed: the higher utility value is achieved by the *Optimistic* method, followed by the *Most probable* method, and with the *Pessimistic* method in third place. The negotiation of the whole amount with each player individually results in lower utility function values, for all players and for all intermediate risk propensity values.

Figure 7 presents the allocation results (amount to be negotiated with each competitor player) of the *Most probable* decision method, for the 5 considered risk propensity values.

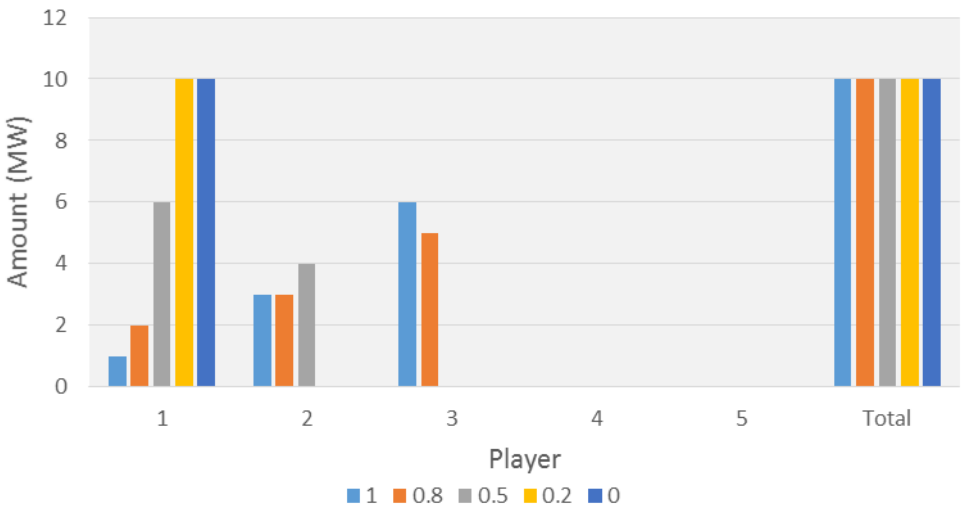

Figure 7. Actions resulting from the *Most probable* decision method for different risks.

By matching the results presented in Figure 7 to the estimation results of the *Most probable* scenario, depicted in Figure 6, it is possible to interpret the reasons why these actions have been chosen by the

Most probable decision method. Considering a risk value of 1, where only the economic component is assessed, from the 10MW, 6MW are allocated to the negotiation with Player 3, 2MW to Player 2, and 1MW to Player 1. From Figure 6 one can see that these amounts correspond to the peak expected prices from these 3 players, thus representing the higher possible economic gain considering the expected prices in the scope of this scenario (the most probable scenario). With a risk value of 0.8, the reputation component is already taken into account, even if just slightly. This is, however, enough to make the amount allocated to Player 3 decrease by 1MW, which is now allocated to Player 1, which presents a much higher reputation value, and whose expected price for the negotiation of 2MW is just slightly lower than the expected price for the negotiation of 1MW. The gain in the reputation component compensates the slight decrease in the economic component. A risk value of 0.5 represents an equal consideration of both the economic and the reputation component. In this case, the negotiation with Player 3 no longer pays off due to the relatively poor reputation value of this player, and the 10MW are negotiated between Player 1 and Player 2, which are the players with the higher reputation, and whose expected prices for the negotiation of respectively, 6MW and 4MW are still very reasonable. The cases where the risk value is set to 0.2 and to 0, which represent a prominence of the reputation component, result in the allocation of the total 10MW to the negotiation with Player 1 – the player with the higher reputation.

Figure 8 presents the execution time of the proposed methodology for different amounts of negotiation power, and for different numbers of potential competitor players.

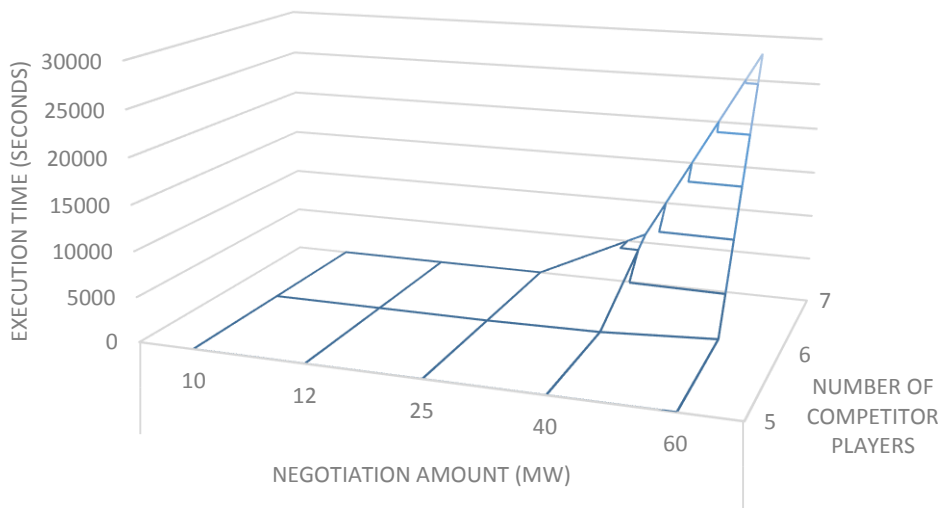

Figure 8. Execution time of the proposed methodology.

From Figure 8 it is visible that the execution of the proposed methodology for a relatively small amount of power (up to 25MW) and for a reduced number of players takes only a few seconds to run. However, when both the negotiation amount and the number of alternative players increase, the required execution time also increases significantly. This increase is verified to the enlarged number of alternative actions that result from the negotiation of a large amount of power among a large number of players, which require an extensive number of alternative action-scenario evaluations. Moreover, the increase of

the number of players also has a large implication of the time required to perform the forecast and estimation process for each player, for each distinct amount.

Table 4 presents the utility function results for the application of the proposed methodology to the negotiation of 10MW among the complete set of 37 considered potential competitor players, for different values of risk propensity, and comparing the different decision methods with the negotiation of the total amount with a single player (the best one for each risk value). The reputation values for all players have been assigned randomly, and all parameterizations are kept equal to those of the previous case.

Table 4. Utility function values for different risk propensity values, considering 37 competitor players

	Risk propensity				
Decision Method	**1**	**0.8**	**0.5**	**0.2**	**0**
Pessimistic	0.89	0.83	0.80	0.84	0.98
Optimistic	1.00	0.98	0.92	0.93	0.98
Most Probable	0.96	0.92	0.87	0.89	0.98
Best Player	0.82	0.73	0.78	0.84	0.98

Table 4 shows that, as before, for a risk value of 0, all decision method reach the same utility value as the best player, since the total amount of negotiation is allocated to the player with the higher reputation (in this case the player with the higher reputation has a value of 0.98). For a risk value of 1, the *Optimistic* method is once again able to reach a utility function value of 1, by allocating the negotiation of the required 10MW among the players that present the best possible economic gain in the scenario that presents the most advantageous price expectations. The negotiation of the total amount with a single player (the best player for each value of risk) always results in smaller utility function values than all three decision methods of the proposed methodology. From the three decision methods, the *Optimistic* is always the one that achieves the best expected outcomes, the *Pessimistic* is the method that presents the worst expected outcomes from the three (although assuming the safer option is still above the negotiation with a single player), and the *Most probable* decision method reaches intermediary utility function results, while representing the best action to take in the *Most probable* case scenario.

5. Conclusions

This paper proposed a methodology to provide decision support to electricity market negotiating players, when participating in bilateral contract negotiations. The proposed methodology allows the supported player to decide the amounts of power that should be negotiated with its competitors in order to optimize its expected outcomes. For this, a game theoretic decision method is used and refined with a reinforcement learning approach that enables identifying the *Most probable* scenarios to occur in each context. The decision methods make use of a utility function that considers the reputation of the competitors in addition to the expected economic gain, to evaluate the outcomes of each combination

action-scenario. Alternative scenarios are built from the expected price forecasts, using the competitor players' historic contract settlements, complemented by the estimative of missing expected price values.

Results show that the proposed methodology is able to achieve higher utility function values, using any of the three decision methods, than the utility that results from negotiating the total amount of desired price with any single player. As previously identified in the introductory section, the pre-negotiation stage of negotiations as been largely neglected, as well as the proper use of historic data to model opponents' behaviors and act accordingly, which is recognized by the authors themselves [24]. For this reason, there are no significant pieces of work to which the proposed methodology can be compared; therefore the only way to assess its advantage is by comparing the results of the proposed methodology with the expected outcome of negotiating the total amount with a single (the best) competitor player rather than distributing the negotiation amount among the possible opponents taking into account their expected performance. The outcomes of all three decision methods are always superior to those of negotiating the total amount with a single player, even for the *Pessimistic* decision method, which considers only the best actions to perform under the worst possible negotiation scenario that may occur. Thus, in this case, even if everything goes as bad as possible, the proposed method is always able to provide a suggested action that is most advantageous for the supported player then the negotiation with a single player.

Regarding the execution time of the proposed method, the conclusion to be taken is that the proposed methodology is perfectly suitable to deal with a moderate negotiation amount of power and number of competitor players; but its application to larger problems is only possible as planning decision support (which is its main objective) to be taken some hours before the actual negotiations, or even during the previous days. The execution time can also be adapted by changing the 2E balance requirements of the AiD-EM decision support system, resulting in the use of less forecasting methods (using only the faster ones), and thus considering a reduced number of alternative scenarios. The result is the possible decrease of the achieved utility values, as result of the limited alternatives, but an important increase in execution time performance.

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Conflicts of Interest

The authors declare no conflict of interest.

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