An adaptive system for decision support of electricity markets negotiations

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Abstract

The increasing penetration of renewable energy sources is bringing a higher sustainability to power systems and to societies as a whole. However, making use of renewable sources in a way to enable taking full advantage from their potential and dealing with the associated variability and uncertainty, is an arduous task. One of the many challenges arise in the energy trading process. This paper presents AiD-EM (Adaptive Decision Support for Electricity Markets Negotiations). AiD-EM is a multi-agent-based decision support system that provides decision support to market players by incorporating multiple sub-(agent-based) systems, directed to the decision support of specific problems. These sub-systems make use of different artificial intelligence methodologies, such as machine learning and evolutionary computing, to enable players adaptation capabilities in the planning phase and in actual negotiations in auction-based markets and bilateral negotiations. AiD-EM is connected to the market simulator MASCEM (Multi-Agent Simulator of Competitive Electricity Markets), which enables the testing and validation of the decision support system.

1 Introduction

The current state of worldwide electricity markets is strongly affected by the increasing use of renewable energy sources. 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 [Odeh *et al.*, 2018].

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 [Ringler *et al.*, 2016].

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 [Niu, *et al.*, 2018].

This gap motivates the development of Adaptive Decision Support for Electricity Markets Negotiations (AiD-EM), which arises with the purpose of providing solutions that enable electricity market players to take the best possible outcomes out of each market context. AiD-EM is an enhanced multi-agent based decision support system developed in JADE. 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) [Pinto *et al*., 2014]. 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.

In summary, AiD-EM enables supporting the decision-making of players that negotiate in electricity markets, thus providing a relevant tool to enable players profiting from the use of new and emerging energy technologies such as renewable energy sources, electric vehicles with vehicle-to-grid capabilities, and demand response programs. In this way, AiD-EM is ultimately contributing to the social good of societies all around the world, by making use of many of the latest advances in the field of artificial intelligence.

2 AiD-EM system

Fig. 1 shows the global structure of the AiD-EM multi-agent decision support system, including the representation of its main components.

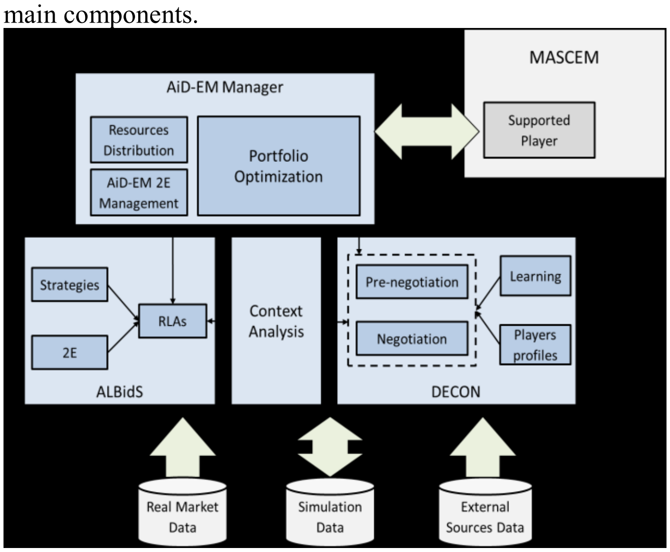

Fig. 1. AiD-EM overview

The AiD-EM system includes the AiD-EM Manager agent, as illustrated in Fig. 1, which acts as the central entity of the system, providing the connection with the MASCEM electricity market simulator [Santos *et al*. 2016].

2.1 Portfolio optimization

The AiD-EM Manager agent executes a Portfolio Optimization, 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 several forecasting methods, such as artificial neural networks, support vector machines and hybrid neuro-fuzzy inference systems [Pang *et al*., 2018]. Once the expected prices in each market are reached, an optimization process maximizes the potential revenue of the supported player by distributing the investment of the available energy among the potential market opportunities. The participation risk in each market is also considered by a multi-objective optimization model (maximizing revenue and minimizing risk) [Faia *et al.*, 2018]. The participation risk in each market is assessed by considering the variability of the prices in each market, and by the difficulty of each forecasting algorithm in reaching good forecasts (forecasting error). There ae several optimization methods available to solve the optimization problem, depending on the needs and characteristics of each problem. Exact mathematical methods are used when the execution time is not a constraint; while meta-heuristic methods (namely particle swarm optimization, simulated annealing, genetic algorithms, differential evolution [Kumar *et al.*, 2010]) are used when faster response times are needed. The choice on which method and respective parameterization to apply in each case is performed through a case-based reasoning approach [Faia *et al.*, 2017]. Indeed, 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.

2.2 ALBidS

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 [Pinto *et al*., 2014] 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 [Chan and Ortiz, 2018], artificial neural networks, reinforcement learning, to the combination of different algorithms using the metalearning concept [Grau-Moya *et al*., 2018] 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' results.

2.3 DECON

The decision support for bilateral contract negotiations is assured by DECON, which considers two main components: *(i)* decision support for the pre-negotiation stage, and *(ii)* decision support for the actual negotiation process. 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. Two alternative approaches are considered in the pre-negotiation phase: the first is based on game-theoretical principles, in which the mini-max approach is used to reach the action that maximizes the potential gain for the player, while considering the safer potential scenario; the second approach considers a multi-objective optimization methodology, in which the potential revenue of the supported is maximized and the potential risk minimized. The risk is modelled my assessing the reputation of the opponent players.

The actual negotiations are supported by a set of different tactics that follow different negotiation 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. This learning process is based on a learning network, in which each node represents a different learning result based on the analysis of different types of information: analysis of data observed directly by the system (from current and previous negotiations); learning from negotiations with similar players; learning based on negotiations in similar contexts. The propagation of the weights between the nodes uses collaborative reinforcement learning and the Bayesian theorem.

2.4 Context awareness

The context awareness of the system is provided by a context analysis mechanism [Pinto *et al.*, 2015]. 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 relevant factors that influence players' negotiation environment considered by the context analysis mechanism are: the electricity market price the transacted amount of power in each market session, the wind velocity, solar intensity and 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).

These characteristics are used by clustering algorithms, namely K-Means and KML, which group hours and days that present similar characteristics concerning the negotiation environment, so that these groups can represent different contexts.

2.5 MASCEM

MASCEM (Multi-Agent Simulator of Competitive Electricity Markets) facilitates the study of complex electricity markets. It considers the most important entities and their decision support features, allowing the definition of bids and strategies, granting them a competitive advantage in the market. MASCEM agents include: market operator, independent system operator, buyers, sellers and aggregators.

MASCEM allows the simulation of the main market models: day-ahead pool (asymmetric or symmetric), bilateral contracts, balancing market, forward markets and ancillary services. Hybrid simulations are also possible by combining the different market models. Defining different specifications for the market mechanisms, such as multiple offers per period per agent, block offers, flexible offers, or complex conditions, as part of some countries' market models, is also available. Some of the most relevant market models that are fully supported by MASCEM are those of the Iberian electricity market – MIBEL, central European market – EPEX, and northern European market – Nord Pool. Some other market types can be provided by different external systems, by using a ontologies, which define the main concepts that must be understood by agents that participate in power systems and electricity markets' related simulations.

The significance of the decision support methodologies provided by AiD-EM 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) [Silva *et al.*, 2016], which uses real electricity market data, extracted in real time from the websites of several market operators, it is possible to recreate the electricity markets' reality in a controlled simulation environment in MASCEM. Realistic simulation scenarios of several European electricity markets are used to test and validate the proposed methodologies.

3 Conclusions

This paper presents AiD-EM, a multi-agent decision support system that helps electricity market players in their negotiation process. AiD-EM is composed by several independent systems, directed to the decision support of specific problems, namely for portfolio optimization, negotiation in auction-based markets, negotiation through bilateral negotiations, and analysis and definition of negotiation contexts. The AiD-EM decision support system is connected to the MASCEM simulator, enabling the testing and validation of the decision support system under realistic conditions, i.e. using real data in decision support and simulation processes.

The contributions brought by AiD-EM support the decision-making process of electricity market players, thus providing an essential framework to enable players profiting from the use of new and emerging energy technologies such as renewable energy sources, electric vehicles with vehicle-to-grid capabilities, and demand response programs. In this way, AiD-EM is ultimately contributing to the social good of societies all around the world, by making use of many of the latest advances in the field of artificial intelligence.

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