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Context aware Q-Learning-based model for decision support in the negotiation of energy contracts

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ABSTRACT

Automated negotiation plays a crucial role in the decision support for bilateral energy transactions. In fact, an adequate analysis of past actions of opposing negotiators can improve the decision-making process of market players, allowing them to choose the most appropriate parties to negotiate with in order to increase their outcomes. This paper proposes a new model to estimate the expected prices that can be achieved in bilateral contracts under a specific context, enabling adequate risk management in the negotiation process. The proposed approach is based on an adaptation of the Q-Learning reinforcement learning algorithm to choose the best scenario (set of forecast contract prices) from a set of possible scenarios that are determined using several forecasting and estimation methods. The learning process assesses the probability of occurrence of each scenario, by comparing each expected scenario with the real scenario. The final chosen scenario is the one that presents the higher expected utility value. Besides, the learning method can determine which is the best scenario for each context, since the behaviour of players can change according to the negotiation environment. Consequently, these conditions influence the final contract price of negotiations. This approach allows the supported player to be prepared for the negotiation scenario that is the most probable to represent a reliable approximation of the actual negotiation environment.

1. Introduction

The Electricity Markets (EM) restructuring placed several challenges to governments and to the companies that are involved in generation, transmission, and distribution of electrical energy. 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].

Environmental concerns related to the use of fossil fuels have led to an increase in renewable energy generation sources. The considerable increase of distributed generation units makes EM more competitive, and consequently encourages a decrease in electricity prices [2,3]. However, some recurrent problems that are being addressed all over the world must be considered, such as the dispatch ability, limitations in the power system network, and the integration and large participation of small producers in the EM, among others [3]. Despite these problems, some global solutions are being adopted, some examples are the case of evolution of European EM. The majority of European countries have joined together into common market operators, resulting in joint regional EM composed of several countries, which supports transactions of huge amounts of electrical energy and allows the efficient use of renewable based generation in places where it exceeds the local needs [4].

Nowadays several market models exist, with a set of complex rules and particular regulations, creating the need to anticipate market behaviour. Some implemented market types have the clearing mechanism based on the optimization of offers, such as most electricity markets in the U.S. [5] and other based on symmetric or asymmetric bids, as is the case of most European countries [4]. However, electricity trade worldwide is also supported by means of bilateral contracts negotiation [6], which are the scope of this study.

The common behaviour of market players in contracts negotiation is mainly based on the definition of prices and quantities in energy transactions with each competitor. Hence, relevant information concerning competitors' history of previous negotiations can be used to improve the decision-making process, considering the characteristics of

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the moment of negotiation, namely to improve the forecasting of possible contract prices before the negotiation process [6]. It is essential to consider the concept of context awareness, since it influences the prices and quantities of energy to be negotiated. One example is the new ways of participating in EM, such as renewable resources, which has hardly influenced the players' participation in the negotiation process, due to the dependency of environment factors, such as wind or solar intensity, that influence the final price of electricity. Other examples of contexts are the different types of days such as business days, weekends, holidays, or other days with special situations that affects energy consumption. A unique review of context analysis mechanism of EM negotiating players is presented in [7], which proposed a methodology of analysing the past negotiation context to distinguish days and periods with similar characteristics.

Those introduced aspects have significant implications in the increase of the complexity and unpredictability in EM. Hence, the constant change of the EM environment requires the need to understand market's mechanism and how the interaction between the players affects the markets. It has contributed to the increased use of simulation and decision support tools, in order to achieve the best possible results of each market context for each participating entity [2]. Several modelling tools based in Multi-agent software for the study of electricity markets have emerged [8]. Some relevant examples are Electricity Market Complex Adaptive System (EMCAS) [9], Agent-based Modelling of Electricity Systems (AMES) [10], Genoa Artificial Power Exchange (GAPEX) [11], and Multi-Agent System for Competitive Electricity Markets (MASCEM) [12].

Current tools are directed to the study of market mechanisms and interactions among participants, but are not suitable for supporting the decision of the negotiating players in obtaining higher profits in energy transactions. A new multi-agent adaptive learning system – AiD-EM (Adaptive Decision Support for Electricity Markets Negotiations) – has been integrated with MASCEM market simulator with the purpose of providing effective decision support to electricity markets' negotiating players [8]. This decision support system is modelled for different market negotiation types, namely the participation in auction based markets and the automated negotiation of bilateral contracts. The latter negotiation type is addressed in this paper, namely through the DECON system (Decision Support for Energy Contracts Negotiation). DECON implements several methodologies to analyse competitor players' negotiation profiles, enabling the adjustment of the adopted negotiation strategies and tactics in each step of automated negotiation [13]. Techniques such as adaptive learning and game theory [14], which explores the study of algorithms that can learn from and make predictions or decisions on data, allows the assessment of each current negotiation context[1] and to dynamically learn over time [15,16]. Such concepts should be adopted in order to overcome the current gap in the literature related to the lack of analysis of past information about opponents, and the inadequate exploration of the pre-negotiation stage, as identified in the review on automated negotiation presented in [13].

In the literature, is possible to find some tools that support bilateral contracts negotiation such as EMCAS [17], General Environment for Negotiation with Intelligent Multi-Purpose Usage Simulation (GENIUS) [18] and the Multi-Agent Negotiation and Risk Management in Electricity Markets (MAN-REM) [19]. EMCAS is a multi-agent simulator that is able to simulate electricity market bilateral contracts, established between a demand agent and a generation company agent [17]. The generation agents decides the price of the demand agents' proposals that may or may not be accepted by the proposers. GENIUS is a multi-agent simulator that facilitates and evaluates the strategies of automated negotiators [18]. The tool supports domain-independent bilateral negotiations and considers three negotiation phases: Preparation (negotiation protocol and domain), Negotiation, and Post-negotiation (negotiation analysis). MAN-REM simulates the bilateral contracts negotiation through the combination of small multi-agent simulators. The tool models the buyer, seller, trader (distribution), and market operator (validation) agents. Three negotiation phases are considered: Pre-Negotiation (contract's preferences and response to counter-offers definition), Actual Negotiation, and Post-Negotiation (final agreement) [19]. The analysed tools presents a lack of exploration of the pre-negotiation phase, only focusing the actual negotiation. The GENIUS simulator has the most complete exploration of the pre-negotiation phase, but also lacks opponents analysis. 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. 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 to enable market players to adapt to the constantly changing electricity market environment, and learn how to take the most advantages out of market participation.

In order to overcome these limitations, this paper presents a new learning model which has the aim of supporting the decisions of players in the pre-negotiation of bilateral contracts, achieving an advantageous position that allows to identify the ideal negotiators to trade with, enhancing the outcomes of the negotiation process. This method is based on the application of reinforcement learning algorithm (RLA), namely an adaptation of the Q-Learning algorithm, to learn which is the forecasting method that is able to provide a potential contract price that is closer to reality. The proposed algorithm determines the best method depending on the negotiation context. The forecast scenarios are determined using several different methods, such as data mining techniques [20], artificial neural networks (ANN) [21], support vector machines (SVM) [8], fuzzy logic [22], among other methods [8], where each methods suggests an expected price for each amount of energy. However, no method presents a better performance than all others in every situation, only in particular cases and contexts [8]. Thus, these contract prices forecasting are submitted to some error degree. Because of that, the quality of definition of the best forecast method is essential for supporting the decision process. The proposed model is implemented and integrated in the DECON decision support system to enable its experimentation and validation.

After this introductory section, Section 2 presents a discussion on the need of decision support tools for bilateral negotiation in EM, and an overview of the developed methodology for DECON. Section 3 provides the proposed learning method to estimate bilateral contract prices using a Q-Learning based approach. Section 4 presents a case study that shows the experimental results of the proposed methodology, using the alternative negotiation scenarios furnished by DECON and historic bilateral contracts data. Finally, Section 5 presents the most relevant conclusions of this work.

2. Bilateral contracts negotiation

Bilateral contract is a EM rigid model that enables players to directly negotiate with each other, establishing a fixed price for a quantity of energy for an agreed period. When a player wishes to participate in the bilateral market, it contacts potential players offering his power and price proposal. The target players analyse the proposal and, if interested, they can accept it or try to renegotiate it. Before reaching an agreement, the supplier must be sure that it is feasible to deliver energy in the buyer's location, and for that the system operator's feedback is

[1] Negotiation context refers to characteristics or circumstances under which the negotiation process occurs, *e.g.* if it is a business day or weekend, the season, the current global consumption, the current amount of generation, etc.