Decision Support System for Opponents Selection in Electricity Markets Bilateral Negotiations

Demonstration

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ABSTRACT

This paper presents a new multi-agent decision support system with the purpose of aiding bilateral contract negotiators in the pre-negotiation phase, through the analysis of their possible opponents. The application area of this system is the electricity market, in which players trade a certain volume of energy at a specified price. Consequently, the main output of this system is the recommendation of the best opponent(s) to trade with and the target energy volume to trade with each of the opponents. These recommendations are achieved through the analysis of the possible opponents' past behavior, namely by learning on their past actions. The result is the forecasting of the expected prices against each opponent depending on the volume to trade. The expected prices are then used by a game-theory based model, to reach the final decision on the best opponents to negotiate with and the ideal target volume to be negotiated with each of them.

KEYWORDS

Decision support systems; bilateral negotiations; ma-chine learning; power and energy systems

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1 INTRODUCTION

Nowadays, there is an increased awareness of the need to protect the planet. The reduction of gas emissions would have a great contribution to this mission. The European Union (EU) has been addressing this need and has the ambitious objective to reduce gas emissions in 2050 to 30% of the 1990's level [1]. For this purpose, the EU has been increasing the share of renewable energy from 8:5% in 2004 to 17% in 2016, with the targets of 20% in 2020 and 27% in 2030. Electricity Markets (EMs) have been updating their operation mode to deal with the increased use of renewable energy. The sector has been liberalized and some national systems are integrated [2]. As result, EMs models were frequently improved but at cost of added complexity. The participating entities needed auxiliary tools to study the EM operation, rules, entities' interaction, and to be able to improve their results.

Several tools arose with the aim of simulating EMs but are mainly focused in auction-based models. Bilateral contracts model still lacks further exploration. EMCAS (Electric Market Complex Adaptive System) [3], GENIUS (An Integrated Environment for Supporting the Design of Generic Automated Negotiators) [4] and MAN-REM (Multi-Agent Negotiation and Risk Management in Electricity Markets) [5] present in the literature a contribution to study this model, however they lack a further exploration of the pre-negotiation phase, one of the main phases of automated negotiation, as reviewed in [6]. An important feature that is missing in current tools, is the possible opponents' analysis, which helps the supported player to increase its knowledge about its possible opponents and make a better selection, regarding its objectives.

This paper presents the demonstration of a Decision Support System (DSS) for the pre-negotiation of bilateral contracts, which has the aim of providing bilateral negotiators with a detailed opponents' analysis. For this purpose, the tool is capable to help the supported player to select the best opponent(s) to trade with, and how much to trade with each, to maximize the negotiation outcomes. Demonstration video available: https://youtu.be/KD_F4gBpcWM.

2 MAIN PURPOSE

This paper presents a new DSS with the purpose of aiding bilateral contracts negotiators in the pre-negotiation phase [7], through the analysis of their possible opponents, resulting in the recommendation of the best opponent(s) to trade with and how much to trade with each. To reach this objective, the tool follows the process presented in Figure 1.

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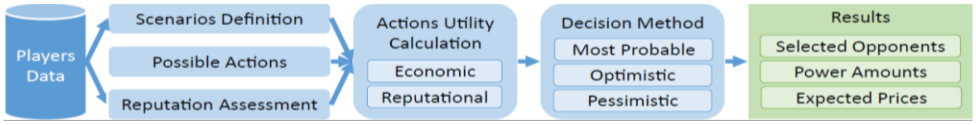

Figure 1: General process of the DSS

As observed in Figure 1, the DSS starts with three simultaneous tasks, which support the game-theory decision model: Scenarios Definition, Possible Actions and Reputation Assessment. In the Scenarios Definition, several different scenarios are generated through the analysis of the player's data (historical contracts). Each scenario is a set of expected prices for each opponent for each power amount, from 1 to the desired amount to trade. The prices are obtained through forecasts and, for quantities with missing data, estimations are applied [8]. The Possible Actions is the task of generating every possible action that the supported player can take. An action is a certain distribution of the power to trade among the possible opponents. At last, in this first phase, the reputation of each opponent is assessed (considering the personal and social dimensions). Then, the utility of every possible action is calculated through the weighted sum of the economic and reputational components. The economic component represents how economically advantageous the action is and the reputation is the weighted average reputation of the opponents. The impact of each component depends on the risk desired by the supported player. The minimum risk only considers the reputational dimension and maximum risk only considers the economic perspective.

After determining the utility of each action, the tool offers three decision methods which dictates the recommended action. The Most Probable is a decision method that uses the Q-Learning reinforcement learning algorithm [9] to identify the scenario that is most probable to occur in reality. This is archived by comparing the generated scenarios with the real scenarios, once available. The Optimistic decision method selects the action with the highest utility among all the scenarios. The third and last decision method is the Pessimistic which, by applying the mini-max game theory approach [10], selects the action with the highest utility of the scenario with the lowest global utility (actions' utility sum).

With the DSS' execution, the supported player is provided with the opponent(s) to trade with, how much to trade with each, and the expected price that each will offer.

3 DEMONSTRATION

Figure 2 shows the graphical interface of the DSS with focus on the Results tab. The tool contains seven tabs that guide the supported player through the process to obtain decision support. In the tabs Negotiation Details, Opponents, Reputation and Decision, the supported player fills the configuration that better suits its interests. In the Negotiation Details, the user indicates the power amount to trade, if it is buying or selling and select the negotiation context. The Opponents tab allows the user to select a list of possible opponents. Then, in the Reputation tab, the user can choose the weights of each component that is used for the opponents' reputation calculation. The decision method can be selected in the Decision tab as well as the level of risk that the user is willing to take. After these steps, the Overview tab presents the summary of the given input and allows the user to execute the main process of the DSS, which can be followed in the Execution tab. At the end of the main process, the Results tab is presented, where the user obtains recommendation of the opponent(s) to trade with, how much with each, the expected price for each, and the total price. There is also information about the utility of the selected action with the contribution of each component. For further details, the user can click in the More Details button to obtain information about the opponent's reputation and expected prices per scenario.

4 CONCLUSIONS

This paper presents a new DSS that supports EM players in the pre-negotiation phase of bilateral contracts negotiation. For this purpose, the tool provides an analysis of the possible opponents, recommending the opponent(s) that may guarantee the best negotiation outcomes. The negotiation risk is also considered, allowing the supported player to weight the economical and reputational components as desired.

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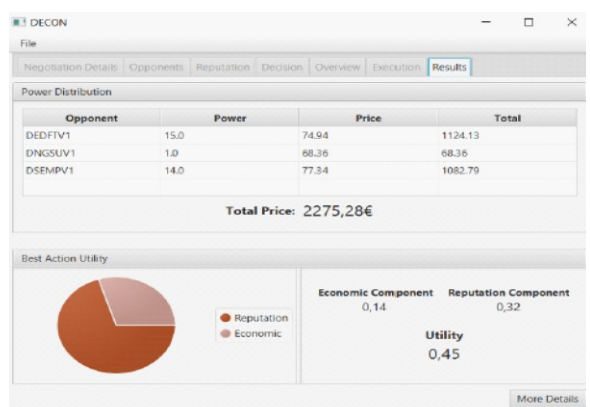

Figure 2: Results presentation

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