Demonstration of Decision Support System for Opponents Selection in Electricity Markets Bilateral Negotiations

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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 20% of the 1990's level (Commission 2018). 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.

The Electricity Markets (EMs) has been updating their operation mode to deal with the increased use of energy from renewable sources. The sector were privatized, liberated and some national systems were integrated (Meeus, Purchala, and Belmans 2005). As result, the EMs models were frequently improved but at cost of added complexity. The participating entities needed auxiliary tools to study the EMs operation, the rules, the 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. The bilateral contracts model still lacks further exploration. The tools EM-CAS (Veselka and others 2002), GENIUS (Lin and others 2014) and MAN-REM (Lopes, Rodrigues, and Sousa 2012) present in the literature a contribution to study this model, however they lack a further exploration of the prenegotiation phase, one of the main phases of automated negotiation, as reviewed in (Lopes, Wooldridge, and Novais 2008).

A 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 a Decision Support System (DSS) for the pre-negotiation of bilateral contracts (Silva and others 2017), 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, regarding its objectives.

Main Purpose

This paper presents a new DSS (Silva and others 2017) with the purpose of aiding bilateral contracts negotiators in the pre-negotiation phase, 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.



Figure 1: Main process of the DSS

As observed in Figure 1, the DSS starts with three simultaneous tasks: 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. 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 (weighted sum of personal opinion and social opinion). 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 involved opponents. The impact of each component depends on the risk desired by the supported player. The minimum risk only considers the reputational and maximum risk only considers the economic.

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 Q-Learning, a reinforcement learning algorithm, to identify the scenario that is most probable to occur in reality. This is

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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, selects the action with the highest utility of the scenario with the lowest global utility (actions' utility sum).

At the end of 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.

Demonstration

The 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.

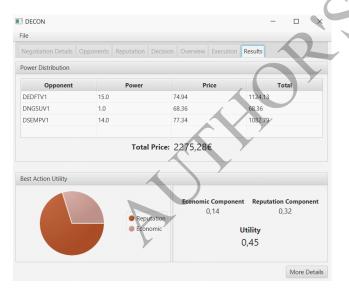


Figure 2: Results presentation of the DSS

At the end of the main process, the Results tab is presented where the user obtain the 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.

Conclusions

The evolution of the EMs created the need of proper tools to aid the participating entities. Several tools arose for this purpose but the bilateral contracts model remains quite unexplored. Although the negotiation process itself is widely explored in the literature, most solutions overlook the prenegotiation phase. This is also verified in the current solutions for EM bilateral contracts negotiations. However, the impact of this phase in the overall negotiation should not be underestimated, specially regarding one of its key features, the opponents analysis, which can have a great impact in the negotiation outcome.

This paper presents a new DSS with the aim of supporting EMs players in the pre-negotiation phase of their 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. All the possible actions of several different scenarios are considered, allowing an increased preparation for the negotiation to come. The generated scenarios depends on the negotiation context as the opponents' may act differently in different contexts. The supported player can prepare itself for the worst scenario, or attempt to maximize its negotiation outcome, or just focus on the most probable scenario. The negotiation risk is also considered, allowing the supported player to weight the economical and reputational components as desired. By the end of the DSS' main process, the user knows exactly how much power to trade with each opponent, as well as the expected price that they will offer.

References

Commission, E. 2018. Renewable energy statistics. http://ec.europa.eu/eurostat/ statistics-explained/index.php/

Renewable_energy_statistics. [Online; accessed 20-September-2018].

Lin, R., et al. 2014. GENIUS: An Integrated Environment for Supporting the Design of Generic Automated Negotiators. *Computational Intelligence* 30(1):48–70.

Lopes, F.; Rodrigues, T.; and Sousa, J. 2012. Negotiating Bilateral Contracts in a Multi-agent Electricity Market: A Case Study. In 2012 23rd International Workshop on Database and Expert Systems Applications, 326–330.

Lopes, F.; Wooldridge, M.; and Novais, A. Q. 2008. Negotiation among autonomous computational agents: principles, analysis and challenges. *Artificial Intelligence Review* 29(1):1–44.

Meeus, L.; Purchala, K.; and Belmans, R. 2005. Development of the internal electricity market in europe. *The Electricity Journal* 18(6):25 – 35.

Silva, F., et al. 2017. Decision support system for the negotiation of bilateral contracts in electricity markets. In 8th International Symposium on Ambient Intelligence (ISAmI 2017), 159–166. Springer International Publishing.

Veselka, T., et al. 2002. Simulating the Behavior of Electricity Markets with an Agent-based Methodology: the Electric Market Complex Adaptive Systems (emcas) Model.