Classification of local energy trading negotiation profiles using artificial neural networks

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***Abstract*—Electricity markets are evolving into a local trading setting, which makes it for unexperienced players to achieve good agreements and obtain profits. One of the solutions to deal with this issue is to provide players with decision support solutions capable of identifying opponents' negotiation profiles, so that negotiation strategies can be adapted to those profiles in order to reach the best possible results from negotiations. This paper presents an approach that classifies opponents' proposals during a negotiation, to determine which is the typical negotiation profile in which the opponent most relates. The classification process is performed using an artificial neural network approach, and it is able to adapt at each new proposal during the negotiation process, by re-classifying the opponents' negotiation profile according to the most recent actions. In this way, effective decision support is provided to market players, enabling them to adapt the negotiation strategy throughout the negotiations.**

***Index Terms*— Artificial neural networks, classification, electricity markets, profile modelling**

I. Introduction

Globalization has a huge impact in many areas, being one of them the electricity markets. The markets have evolved in previous years due to many changes like their liberalization and evolution towards local energy market, which makes them a very complex environment. Around the world there are many electricity market models with distinct rules. In Europe there are markets such as MIBEL – Iberian market [1], the northern Europe market Nord Pool Spot [2] and the EPEX Spot, which works in Germany, France, Austria and Switzerland. With today's globalization, there is a tendency to create continental markets. A good example in Europe is the union of countries like Italy, Belgium, Denmark, Finland, France, Germany, Great Britain, Portugal, Sweden and others in an electricity market for day-ahead negotiations [3]. In other parts of the world, some countries have also joined in a common electricity market.

Electricity sellers and buyers operating in these markets must plan and define the best strategy for negotiating [4]. All these facts support the idea that it is necessary to have some kind of support while negotiating in these markets. This support should help them adapt their negotiation approaches to opponent players, so that they can get the best results out of negotiations and guarantee the agreements are achieved as often as possible. In order to reach a suitable decision support for negotiations, it is essential to be able to identify and define opponent players' profiles and predict their next proposals. In this way it is possible to define and adapt negotiation strategies so that the best outcomes from negotiations can be targeted.

This paper proposes a model for classifying opponent players negotiation profiles when negotiating bilateral contracts in electricity markets. A classification approach based on Artificial Neural Networks (ANN) [5] is proposed to identify the typical negotiation profile in which the opponent negotiation behavior most relates to. The proposed model takes into account the deadline of the negotiation for both players and tries to predict the bidding strategy of the opponent player.

The main contributions from this work, towards surpassing the identified gaps are:

- Classification of proposals made by opponent players during a negotiation;
- Analysis of the best strategy to use as a counter strategy against each opponent at each time, given the opponent's identified negotiation profile;
- Improvement of bilateral negotiations' results.

After this introductory section, section II presents a discussion on related work, focusing on the field of automated negotiation. Section III described the proposed methodology, and section IV presents the case study that enables assessing the performance of the proposed methodology. Finally, section V presents the conclusions of this work

II. Related work

When analyzing an opponent during a negotiation, there are 3 aspects that need to be considered [6]

- Preference estimation - What is the opponent trying to achieve?
- Strategy prediction – Which actions will he/she do, and when?
- Opponent classification - What is the profile of the opponent player and what can we do to counteract that profile?

In a negotiation, this type of knowledge can be used to minimize costs, adapt to the opponent player or reach agreements where both players win. There are 4 main attributes that need to be considered when trying to model another player [7]:

- The acceptance strategy – it refers to whether a player will accept an agreement and can be figured out by public knowledge of that player or estimating a certain probability of acceptance.
- Deadline of the negotiation.
- Preference profile – this attribute is related to the importance of issues/negotiations for a player.
- Bidding strategy – it refers to the actual strategy negotiation of a player, which means if a player concedes more or less, how it negotiates.

A recent study developed new tactics for bilateral negotiations [8]. The tactics are called Conceder, Moderate Conceder, Linear, Moderate Hardheaded and Hardheaded. The approaches from these tactics change, respectively, from conceding a lot in prices in the beginning (Conceder) until conceding just a bit in the end (Hardheaded). In the field of automated negotiation of bilateral contracts, the most used learning methods are Bayesian Learning, Non-linear Regression, Kernel Density Estimation and Artificial Neural Networks [9]. An algorithm for choosing the best strategy among a number of available strategies can be found in [10].

Negotiation approaches vary according to the players' profile. As it is difficult to determine exactly another player's profile, a good solution is to model a player into a group that includes similar negotiation approaches. A way of achieving this is through a clustering process. Clustering is a data mining technique that *"divides data into groups (clusters) that are meaningful, useful or both"* [11]. The analysis is made using information within the available data and the goal is to form groups with similar objects that have the least similarity with objects from other groups as possible. The accuracy of the process is higher when the similarities within a group are higher and the groups are more distinct between them.

Learning in which group, or in this case, negotiation profile, a new player fits, is an arduous task. Data classification enables to classify data in order to evaluate them, extract valuable information and take conclusions. In Data Mining it can be defined as "*the task of assigning objects to one of several predefined categories*" [12].

The development of algorithms that allow the computer to learn and improve its performance based on data (also known as machine learning) is, essential to enable this task. In this sense, the performed models are usualy divided into the following three categories: unsupervised, supervised and reinforcement learning.

Unlike unsupervised learning, supervised learning requires already pre-defined outputs [13]. Nowadays, the development of the field of research has been almost explosive. ANN's are at the forefront of computational systems designed to produce, or at least mimic, intelligent behavior [14]. In computer science, neural networks gained a lot of steam over the last few years in areas such forecasting, data analytics, as well as data mining [15]. There are many types of ANN such as: Feed Forward Neural Network, Self-Organizing Map (SOM), Hopfield Neural Network, Simple Recurrent Network (SRN), Simple Recurrent Network (SRN), Feed forward Radial Basis Function (RBF), among many others.

In this work, the applied classification approach is a feedforward ANN. ANN are based on biological nervous system, like human brains. A large number of deeply connected elements working together, called perceptrons (artificial neurons), form the structure of this type of network [16]. ANN use a learning process to solve specific problems like classification problems, pattern recognition and others. Inside an ANN, neurons are organized in layers.

The main advantages of ANN are:

- Easiness of use, as it works through examples, and ability to deal with complex functions and adapt to new situations.
- Fault tolerance and autonomous learning.

Although there are already some simulators that enable studying specific problems in the power and energy domain, there is a lack of support solutions for the negotiation of bilateral contracts, especially regarding the provision of decision support to the players in the electricity market. The Multi-Agent Simulator for Competitive Electricity Markets (MASCEM) simulator already provides support decision for bilateral markets [17], [18], but it is still possible to improve its performance, namely in the negotiation step and in the choice of the best strategy

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for approaching a negotiation. With the improvement proposed in this paper, it is possible to improve negotiation results when selling and buying electricity [19].

III. MATERIAL AND METHODS

Classification using a feedforward ANN is used in this work to identify the typical negotiation profile in which an opponent's actions most relate to. The typical negotiation profiles are achieved using a clustering approach. By identifying these profiles, it is possible to classify the opponents into one of them and negotiate in a way that brings the best expected outcomes.

The considered ANN is a Multi-Layer Perceptron (MLP) feedforward neural network, which considers the information about the proposals and counter-proposals that are submitted by the opponent. The output is the corresponding cluster, or typical negotiation profile, they are most associated to. Figure 1 depicts an overview of the MLP topology.

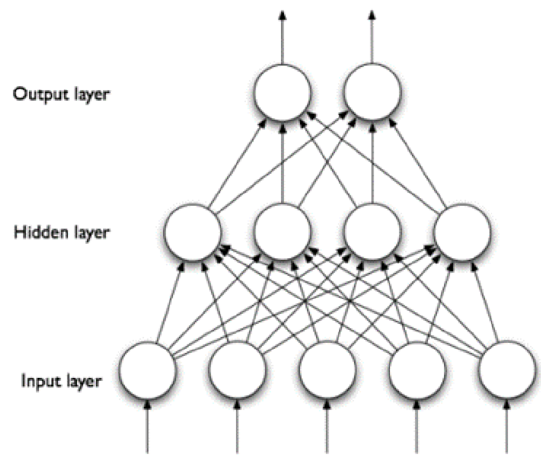

Fig. 1. Artificial Neural Network topology

The considered ANN is composed by 3 layers.

- Input layer – Data is inserted in this layer for analysis.
- Hidden layer – Data processing is done in this layer by the many neurons and there can be more than one hidden layer.
- Output layer – Results of the process are shown in this layer.

The learning process of the ANN follows the next steps:

- The network is trained to perform a specific function adjusting the weights between the perceptrons.
- Training is done so that a specific input produces a specific output.

The applied training algorithm is backpropagation using the gradient descent method [20]. 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. The logistic function is used as activation function f, as in (3).

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

1) Assessment measures

Mean absolute percentage error (MAPE) expresses the accuracy of the model by comparing the real vs. forecast values and can be defined by the equation (4):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{4}$$

where, A_t is the real value, F_t is the forecast value and n is the number of considered samples.

Class error (CE) expresses the accuracy of the forecast model by comparing the number of samples that wrongly predict the number of clusters with the total number of considered samples and can be represented by the equation (5):

$$CE = \frac{n_{error}}{n} \tag{5}$$

where, n_{error} is the number of samples with the wrong class, n is the number of considered samples.

IV. Results and discussion

In this case study it is assumed that the supported market player is a buyer. Therefore the behavior of opponent sellers is assessed. 11 common tactics have been considered for determining the typical negotiation profiles from sellers. These strategies are listed as follows:

- Anxious strategy – players decrease prices in the beginning of the negotiation;
- Gluttonous strategy – price variations are only made near the end of a negotiation;
- Moderated strategy – price variations are made in a steady way;
- Determined strategy – players only make slight changes to the initial price;
- Percentage decrease (3%, 4% and 5%);
- Combination between Gluttonous (in the beginning of the negotiation) and Anxious (near the end of the negotiation);
- Combination between Gluttonous (in the beginning of the negotiation), Anxious (in the middle of the negotiation), and Gluttonous again (near the end of the negotiation);
- Combination between Anxious (in the beginning of the negotiation), Gluttonous (in the middle of the negotiation), and Anxious again (near the end of the negotiation);
- Gluttonous + Anxious + Gluttonous + Anxious + Gluttonous strategy.

Fig. 2 shows the clustering results for seller players, detailing the resulting 4 typical profiles, their trajectories and the percentage of strategies that each cluster covers. Table 1 details for each of the selling strategies the cluster where they were placed.

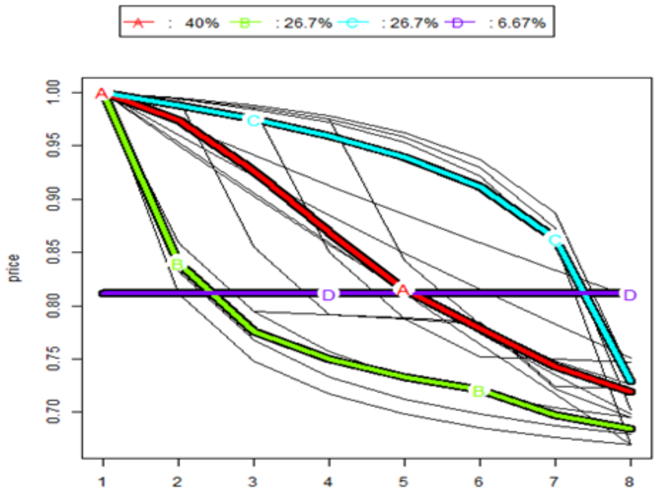

Figure 2 - Trajectories for all the 4 profiles that sellers have, resulted from clustering process.

Table 1 - Sellers strategies and their respective cluster

Strategy used by seller	Cluster
Anxious	B
Gluttonous	C
Moderated	A
Determined	D
Percentage dec. 4%	A
Gluttonous + Anxious	A
Gluttonous + Anxious + Gluttonous	A
Anxious + Gluttonous + Anxious	B
Gluttonous + Anxious + Gluttonous + Anxious + Gluttonous	A
Percentage dec. 3%	A
Percentage dec. 5%	A

Simulations have been made to realize which would be the most effective strategy to be applied by a buyer when negotiating against sellers using each of the players' profiles. Table 3 shows these results.

Table 2 – Players profiles and their counter strategies

Cluster/Profile	Counter strategy to be used
A	Gluttonous
B	Gluttonous
C	Gluttonous + Anxious + Gluttonous
D	Moderated

Through the classification of proposals it is possible to place an opponent player in a class/group of negotiators, in this case one of the clusters found. Hence, it is possible to use the best approach to negotiate against the other players' profile. Classification was performed using the proposed ANN. An opponent player is classified as the negotiation reaches its 3^{rd} proposal (there is not enough information to reach a suitable classification without at least 3 proposals). The seller is then identified as being part of one of the 4 (in this case) typical negotiation profiles which are associated to a different cluster. Every time a new proposal is submitted by the opponent seller, its negotiation profile is reclassified. In this way, the proposed model always has an up-to-date perspective on what the expected behavior of the opponent is.

In this case study, a maximum of 8 proposals is considered, before terminating a negotiation if the agreement has not been reached yet. Hence, the ANN classifies the opponent iteratively starting from the time it places its 3^{rd} proposal until he submits its 8^{th} proposal. The training is performed considering the points from each cluster' trajectories. The minimum considered price was 33 euros/MW and maximum of 53 euros/MW. This process makes it possible to calculate the next proposals that the supported buyer should submit during a negotiation.

Table 3 shows the negotiation process between the supported buyer player and a seller using the Gluttonous+Anxious negotiation tactic. In this table it is possible to see the 8 proposals that are submitted by the opponent and the counter-proposals submitted by the supported buyer player throughout the bilateral negotiation. The evolution of the supported player's proposals is based on the application of the counter-strategy identified as the best against the expected negotiation profile of the opponent (as shown in Table 2). The (re-)classification of the opponent throughout the negotiation is also shown in Table 3.

The classification process using the ANN has showed good results. Considering the full extent of experiments that have been executed (negotiation against a seller using each of the considered negotiation strategies, and the same for classifying buyers as opponents), the ANN had an average classification accuracy of 94,4%.

In the particular negotiation case that is presented in Table 3, the ANN had an accuracy of 66,6%. Although accuracy is not 100% in all cases, misclassification only happens, always when there are less than 5 proposals made. With a minimum of 5 proposals, the ANN has sufficient data to correctly classify a player in a profile. Therefore, when negotiations reached this phase, accuracy was 100% in all cases. The performed simulations proved that the module is capable of adapting the classification during a negotiation. From Table 3 it is possible to see that when the opponent made his 3^{rd} and 4^{th} proposals, ANN classified him in profile C, leading the supported player to apply the "Gluttonous+ Anxious + Gluttonous" counter-strategy, as this is the one identified as the best against players acting as in profile C (Table 2). This classification happened because profiles located in clusters A and C are similar in the beginning of a negotiation, which may lead to misjudgments. Then, from the seller's 5^{th} proposal onwards, the ANN has correctly classified him in cluster A until the end of the negotiation. Hence, the applied counter-strategy from that point onwards is the "Gluttonous" – best counter against players located in cluster A.

Table 3 – Negotiation against Gluttonous+Anxious seller and classification based on opponent proposals

Proposal no.	**Supported player (buyer) proposal**	**Opponent (Gluttonous+Anxious seller) proposal**	**Counter strategy used**	**Cluster where opponent is classified**
1	33	58	Gluttonous	
2	33,321	57,759	Gluttonous	
3	33,743	57,438	Gluttonous+ Anxious + Gluttonous	C
4	40,964	56,988	Gluttonous+ Anxious + Gluttonous	C
5	41,506	51,742	Gluttonous	A
6	42,409	49,358	Gluttonous	A
7	44,214	47,996	Gluttonous	A
8	47,114	47,114	Gluttonous	A

V. Conclusion

Bilateral negotiation of electrical energy is becoming increasingly important, especially due to the evolution of electricity markets towards local energy markets. Small players need to engage in bilateral negotiations to purchase or sell energy, which is a difficult task due to their lack of experience. Decision support solution become, therefore, crucial to enable players reaching advantageous deals.

This paper proposes a solution to improve decision support in the negotiation of bilateral contracts in the electricity market. The main idea is to identify the negotiation profile of an opponent player, to be able to counter their strategy and achieve better results in negotiations. The negotiation tendencies of opponent players are used in a clustering process to discover groups of players with similar negotiation profiles. A classification model using ANN is then applied during the negotiation process with a new player to identify the representative negotiation profile to which the opponent player most relates to. After exhaustive simulation, the best strategy to apply against each representative profile of negotiation is determined. The negotiation strategy is thus adapted throughout the negotiation by applying the best expected negotiation strategy against the identified negotiation profile of the opponent.

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