Clustering-based negotiation profiles definition for local energy transactions

Ângelo Pinto[1], Tiago Pinto[2], Isabel Praça[1], Zita Vale[3], Pedro Faria[1]
[1]GECAD Research Center, Polytechnic of Porto, Porto, Portugal
{icp, pnfar}@isep.ipp.pt
[2]BISITE Research Centre, University of Salamanca , Salamanca, Spain
tpinto@usal.es
[3] Polytechnic of Porto, Porto, Portugal
zav@isep.ipp.pt

***Abstract*—Electricity markets are complex and dynamic environments, mostly due to the large scale integration of renewable energy sources in the system. Negotiation in these markets is a significant challenge, especially when considering negotiations at the local level (e.g. between buildings and distributed energy resources). It is essential for a negotiator to be able to identify the negotiation profile of the players with whom he is negotiating. If a negotiator knows these profiles, it is possible to adapt the negotiation strategy and get better results in a negotiation. In order to identify and define such negotiation profiles, a clustering process is proposed in this paper. The clustering process is performed using the *kml-k-means* algorithm, in which several negotiation approaches are evaluated in order to identify and define players' negotiation profiles. A case study is presented, using as input data, information from proposals made during a set of negotiations. Results show that the proposed approach is able to identify players' negotiation profiles used in bilateral negotiations in electricity markets.**

***Index Terms*— Clustering, Local energy markets, Profile modelling, k-means algorithm**

I. Introduction

The massive introduction of renewable energy sources in power and energy systems has brought about significant changes in this sector [1]. The variability associated to natural resources these generators depend on, brings relevant challenges for centralized management and operation of the system. In this way, energy management and operation are evolving towards a distributed, and local, paradigm [2]. Renewable energy needs to be addressed locally, and therefore, so does consumption. This local and distributed paradigm brings the additional requirement of transactions being also conducted locally, established between the generator and the consumer (building), directly [3].

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Due to the many changes that have occurred in the last years, electricity markets are also becoming very complex, not only evolving towards local market structures but also towards the unification of different regional markets. E.g. in Europe several markets are being unified, following the tendency to create continental markets [4]. In Latin America, some countries have also joined in a common electricity market. In addition, there are different types of markets, so it is not easy to understand these markets and predict fluctuations in the markets [5].

The evolution of the power and energy system, and, in specific, the changes in electricity markets, support the need for decision support for negotiation in these markets, especially when considering local transactions. Some models have been introduced in this domain, e.g. in [6] an agent technology for automatic bargains between buyers and sellers in e-markets is presented; in [7] reciprocity in trade negotiations and welfare is explored; and [8] discusses the role of information in negotiations under uncertainty. However, current works neglect the importance of players' negotiation profiling as support for strategic negotiations. In order to overcome this gap, this paper addresses the topic of decision support for players' negotiations by introducing a clusteringbased approach [9] that enables identifying and defining competitor players' negotiation profiles. The *k-means* algorithm [10] is used to find correlations among previous negotiations (proposals and counter-proposal in bilateral negotiations) in order to group players according to the similarity of their past behavior. In this way, it is possible to reach groups of similar players, in which each group differs from the others in what regards the typical negotiation profile. Using these players negotiation profiles, it is possible to employ specific negotiation strategies depending on the types of player that are being faced in the negotiation.

After this introductory section, section II presents a brief overview of related work. Section III presents the method proposed in this work, and section IV presents the experimental results and respective discussion. Finally, section V presents the most relevant conclusions of this work.

II. RELATED WORK

To model an opponent player there are 3 main factors to consider and 3 questions that need to be answered [11]:

- 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 [12].

- 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 – meaning the time when a player must reach an agreement.
- 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.

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"* [13]. 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.

III. MATERIAL AND METHODS

In the current work, clustering is used to identify typical negotiation profiles from players negotiating bilateral contracts. Clustering is applied considering the data of 9 bidding strategies, which include many approaches that are used in these negotiations. Knowing these profiles, it is possible to classify the opponents into one of them and negotiate in a way that brings the best expected outcomes.

Clustering is one the most used Data Mining techniques for finding similarities/patterns in data. In this study, clustering was used through *k-means* algorithm to easily group developed strategies into players' profiles and also enable an easier classification of data. Thus, it was possible to identify which is the profile group of an opposite player to then negotiate using different strategies for each group, trying to use the best approach to deal with the different groups found. Clustering has the capability of congregating players into stereotype groups, so in a future negotiation an opponent is not put in a very restrict group, which could jeopardize the negotiation in case it was put in the wrong group.

In order to obtain input data for clustering, simulations were made considering a maximum of 8 proposals (N=8) before ending the negotiation. The minimum price was 33 euros/MW and maximum of 55 euros/MW, as these were trading average prices in MIBEL market [14] in March, 2015. For clustering analysis, nine time-dependent strategies were considered. Some of the strategies have parameters (an increase or decrease factor) which can be used to vary their behaviour. Three examples have been used for each strategy that has an increase/decrease factor. It was used the factor standard value plus more two with a higher and lower value to include cases where prices are increased (for a buyer) or decreased (for a seller) faster.

Data has been scaled, so that all values were put in a 0 to 1 scale using feature-scaling method. This method allows to scale data using price range's maximum and minimum value, so after scaling all minimum values are set to 0 and maximum values to 1. As the final goal is to classify proposals into a certain group and to correctly classify them, scaling data is essential. Feature-scaling formula is presented next in (1), where z' is the obtained scaled value, z is the value to be scaled and MinN and MaxN are the minimum and maximum values used during the negotiation.

$$\boldsymbol{z'} = \frac{\boldsymbol{z} - MinN}{MaxN - MinN} \quad (1)$$

Clustering has been performed using kml library of R software, this library is an implementation of k-means algorithm and it was specially developed to analyze longitudinal data, which is the current case. K-means is a hillclimbing algorithm capable of clustering. The used K-means method follows the following steps:

1. User defines a k number of clusters to find.
2. The algorithm finds central points for each cluster found.
3. Each data point calculates the distance to the nearest central point, forming different groups of data points with a common nearest center.
4. Each center searches for the centroid of its group and takes that position.
5. First 4 steps are repeated until none center can change to another group.

After choosing a number of *k* clusters to find, *km*l has 7 different methods to assign points to clusters being the default one *k-means++*. Kml library can calculate distance between points using different methods including Manhattan, Euclidean, Minkowski and others. Default method is the Euclidean Distance with Gower Adjustment (capable of dealing with missing values). To calculate the distance between 2 points $\boldsymbol{yi}$ and $\boldsymbol{yj}$, if $\boldsymbol{yi}$,$\boldsymbol{yj}$ or both are missing variable $\boldsymbol{wijl}$ is 0, if none is missing $\boldsymbol{wijl}$ is 1. The distance is calculated as in (2).

$$Dist_{NA}^{E}(y_i, y_j) = \sqrt{\frac{t}{\sum_{l=1}^{t} w_{ijl}} \sum_{l=1}^{t} (y_{il} - y_{jl})^2 . w_{ijl}} \quad (2)$$

Clustering results show then a quality criteria for a number of k clusters chosen. This criterion ranges from 0 to 1 and is used to understand if a certain number of clusters is better than another. Quality criteria is measured using 5 different criteria [15], namely Calinski & Harabasz, Calinski & Harabasz Kryszczuk variant, Ray & Turi and Davies & Bouldin criterion. This is very helpful, as it is possible to make a decision based on different criteria. In the current case, all criteria pointed to the same number of clusters. Clustering process using *kml* library follows the next 3 phases:

1. **Data preparation -** First, data is read from an excel file and a clusterLongData object is built that gets as parameter data for clustering, names of the strategies for each group of values, number of values that each strategy has and name of the variable to analyze, in this case it's the price.
2. **Build optimal partition** - KML library was used for data partitioning, considering between 2 to 9 strategies, as there were 9 usable strategies and the algorithm was executed 3 times.
3. **Export results -** Results were exported into excel files, and function "plotAllCriterion" was used to check which was the best number of clusters. Function "choice" was used to open a graphical window that helps to understand obtained results and to choose which results to export.

The analysis of charts and excel files exported using this library was very helpful, allowing to understand which clusters had a better evaluation, as kml library evaluates the number of clusters considering different criteria. The exported files have detailed information about which strategies belong to which cluster found, each clusters' trajectories and centroids. Clustering results are detailed in section III.

IV. RESULTS AND DISCUSSION

The clustering process has been used to identify the profile of players negotiating bilateral contracts. This section details the obtained results for both buyers and sellers. In order to determine the main profiles that could be found, a total of 15 strategies have been used. Nine basic strategies plus 6 strategies with different parameters for widening the quantity of strategies and improving the range of possible results. Tables 1 and 2 show input data used in the clustering process. Table 1 represents data from proposals made by buyers and was used to profile buyers, whereas Table 2 represents data from proposals made by sellers and was used to profile sellers. Both cases consider a maximum of 8 proposals during the negotiation. Prices shown were scaled using feature scaling, values 0 and 1 correspond to minimum and maximum prices used during the negotiation, respectively.

TABLE I. Clustering input values for all negotiation strategies used by buyers (inc. – increase; fac. – factor)

No. of proposal **Strategy**	1	2	3	4	5	6	7	8
Anxious inc. fac.=0,6	0	0,464	0,675	0,796	0,874	0,929	0,969	1
Gluttonous inc. fac.=0,9	0	0,02	0,048	0,086	0,143	0,238	0,429	1
Moderated	0	0,143	0,286	0,426	0,571	0,714	0,857	1
Determined	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
Percentage inc. 4%	0	0,127	0,258	0,395	0,538	0,686	0,84	1
Gluttonous + Anxious	0	0,022	0,052	0,093	0,575	0,794	0,919	1
Gluttonous + Anxious + Gluttonous	0	0,024	0,056	0,595	0,841	0,981	0,989	1
Anxious + Gluttonous + Anxious	0	0,464	0,676	0,685	0,697	0,712	0,911	1
Gluttonous + Anxious + Gluttonous + Anxious + Gluttonous	0	0,022	0,524	0,752	0,762	0,775	0,994	1
Anxious inc. fac.=1	0	0,571	0,762	0,857	0,914	0,952	0,98	1
Gluttonous inc. fac.=1	0	0,020	0,048	0,086	0,143	0,238	0,429	1
Percentage inc. 5%	0	0,123	0,252	0,387	0,53	0,679	0,835	1
Anxious inc. fac.=0,8	0	0,524	0,725	0,832	0,898	0,943	0,975	1
Gluttonous inc. fac.=0,8	0	0,020	0,047	0,086	0,143	0,238	0,429	1
Percentage inc. 3%	0	0,130	0,265	0,403	0,546	0,693	0,844	1

TABLE II. Clustering input values for all negotiation strategies used by sellers (inc. – increase; fac. – factor)

No. of proposal **Strategy**	1	2	3	4	5	6	7	8
Anxious dec. fac.=0,6	1	0,536	0,325	0,204	0,126	0,071	0,031	0
Gluttonous dec. fac.=0,9	1	0,98	0,952	0,914	0,857	0,762	0,571	0
Moderated	1	0,857	0,714	0,571	0,429	0,286	0,143	0
Determined	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
Anxious dec. fac =0,8	1	0,476	0,275	0,168	0,102	0,057	0,025	0
Anxious dec. fac =1	1	0,429	0,238	0,143	0,086	0,048	0,02	0
Gluttonous dec. fac =0,8	1	0,98	0,952	0,914	0,857	0,762	0,571	0
Gluttonous dec. fac =1	1	0,98	0,952	0,914	0,857	0,762	0,571	0
Percentage dec. 4%	1	0,839	0,685	0,536	0,394	0,257	0,126	0
Percentage dec. 3%	1	0,844	0,692	0,545	0,403	0,264	0,13	0
Percentage dec. 5%	1	0,834	0,677	0,527	0,385	0,25	0,122	0
Gluttonous + Anxious	1	0,978	0,948	0,907	0,425	0,206	0,081	0
Gluttonous + Anxious + Gluttonous	1	0,976	0,944	0,405	0,159	0,019	0,011	0
Anxious + Gluttonous + Anxious	1	0,536	0,324	0,315	0,303	0,286	0,089	0
Gluttonous + Anxious + Gluttonous + Anxious + Gluttonous	1	0,978	0,476	0,248	0,238	0,225	0,006	0

Fig. 1 shows a chart with clustering results for buyers. In ***x*** axis the number of clusters is presented, the ***y*** axis shows the quality criteria for each number of clusters. Nine basic strategies were used for the clustering process, so choosing more than 5 clusters would not be reasonable, because it would not sufficiently group the strategies. Considering from 2 to 5 clusters, the best results are with 4 and 5 clusters. The difference between quality of results from 4 to 5 clusters is not significant, which supports the choice of 4 clusters as the best value of *k* (the smaller the *k*, with the best quality of results, the better the outcome). Analyzing clusters' trajectories it was noticeable that if 5 clusters were chosen, two of them would have too much similar trajectories, so 4 was chosen as the best number of clusters, as all of the 4 clusters have distinct trajectories. Fig. 2 represents the trajectories for each of the 4 clusters for buyers and the percentage of strategies (players) that each cluster covers.

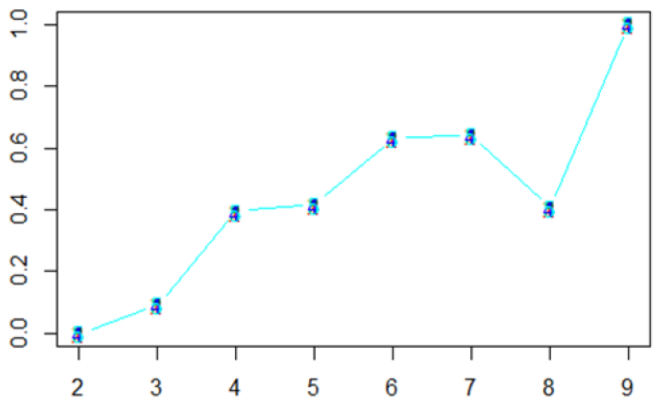

Figure 1 - Clustering results using buyer strategies as input

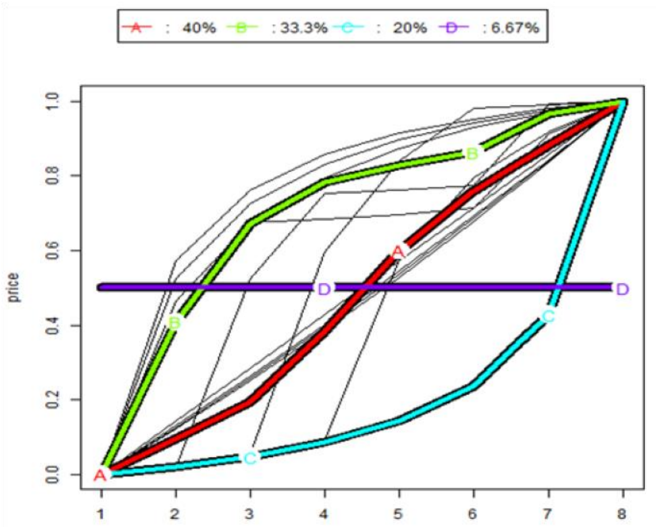

Figure 2 - Trajectories for all the 4 profiles that buyers have, resulting from clustering process

Table 3 details the cluster/profile where each of the strategies considered for buyers have been classified. The same process has been used for sellers. Fig. 3 is similar to Fig. 1, but it shows clustering results for sellers. These results were more inconclusive than the ones from Fig. 1. It was not reasonable to choose 8 or 9 as the number of clusters because there would be many clusters with only one strategy, but considering from 2 to 7 clusters the quality criteria is almost equal, so conclusions could not be taken. The problem was only solved when analyzing the trajectories individually considering from 2 to 7 clusters. Doing this it was clear that 4 is also the best number of clusters, because each of the clusters has a distinct trajectory. Fig. 4 represents the trajectories for each of the 4 clusters for sellers and the percentage of strategies that each cluster covers.

Table III - Buyers strategies and their respective cluster

Strategy used by buyer	**Cluster**
Anxious inc. fac.=0,6	2
Gluttonous inc. fac.=0,9	3
Moderated	1

Determined	4
Percentage inc. 4%	1
Gluttonous + Anxious	1
Gluttonous + Anxious + Gluttonous	1
Anxious + Gluttonous + Anxious	2
Gluttonous + Anxious + Gluttonous + Anxious + Gluttonous	2
Anxious inc. fac.=1	2
Gluttonous inc. fac.=1	3
Percentage inc. 5%	1
Anxious inc. fac.=0,8	2
Gluttonous inc. fac.=0,8	3
Percentage inc. 3%	1

Table IV - Sellers strategies and their respective cluster

Strategy used by seller	**Cluster**
Anxious dec. fac.=0,6	2
Gluttonous dec. fac.=0,9	3
Moderated	1
Determined	4
Percentage dec. 4%	1
Gluttonous + Anxious	1
Gluttonous + Anxious + Gluttonous	1
Anxious + Gluttonous + Anxious	2
Gluttonous + Anxious + Gluttonous + Anxious + Gluttonous	1
Anxious dec. fac.=1	2
Gluttonous dec. fac.==1	3
Percentage dec. 5%	1
Anxious dec. fac.==0,8	2
Gluttonous dec. fac.==0,8	3
Percentage dec. 3%	1

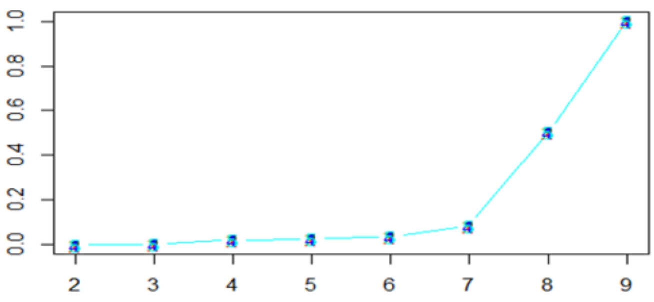

Figure 3 - Clustering results using seller strategies as input

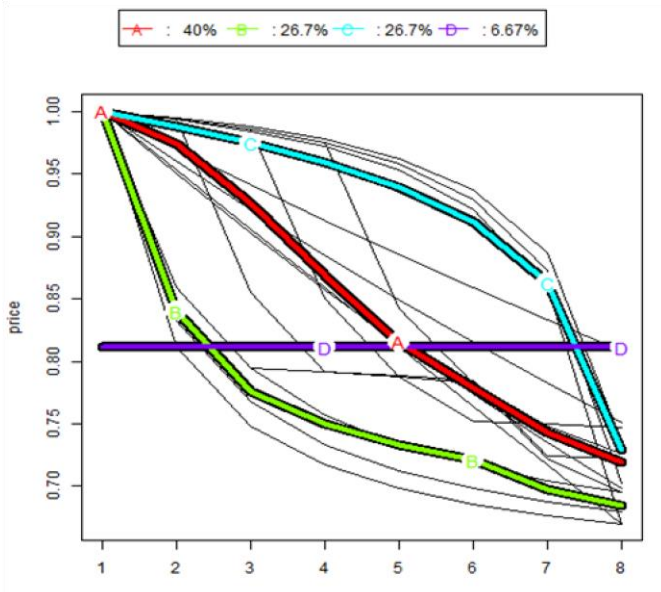

Figure 4 - Trajectories for all the 4 profiles that sellers have, resulting from clustering process.

V. CONCLUSION

With the current changes in power system paradigm, negotiating in electricity markets is not an easy task without any kind of support. A relevant problem to overcome in order to address this challenge is to be able to identify and define the opponent players' profile. This can be achieved through a clustering process that analyses usual negotiation strategies and gathers them into general groups, which can be considered general players profiles.

This paper explores this issue by identifying and defining electricity markets players' profiles through a clustering process. The clustering process has been performed using the *k-means* algorithm and the complete process has been detailed. A case study has also been presented, based on several players that behave based on 9 usual strategies. The results show that the proposed method is able to group players according to their similarity and thus identify and define negotiation profiles accordingly.

As future work, a classification approach based on ANN and SVM will be proposed, in order to enable classifying new players as belonging to one of the previously identified negotiation profiles (when presenting a similar negotiation profile to other players).

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