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Strategic participation in competitive electricity markets: Internal versus sectorial data analysis

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ABSTRACT

Current approaches for risk management in energy market participation mostly refer to portfolio optimization for long-term planning, and stochastic approaches to deal with uncertainties related to renewable energy generation and market prices variation. Risk assessment and management as integrated part of actual market negotiation strategies is lacking from the current literature. This paper addresses this gap by proposing a novel model for decision support of players' strategic participation in electricity market negotiations, which considers risk management as a core component of the decision-making process. The proposed approach addresses the adaptation of players' behaviour according to the participation risk, by combining the two most commonly used approaches of forecasting in a company's scope: the internal data analysis, and the external, or sectorial, data analysis. The internal data analysis considers the evaluation of the company's evolution in terms of market power and profitability, while the sectorial analysis addresses the assessment of the competing entities in the market sector using a K-Means-based clustering approach. By balancing these two components, the proposed model enables a dynamic adaptation to the market context, using as reference the expected prices from competitor players, and the market price prediction by means of Artificial Neural Networks (ANN). Results under realistic electricity market simulations using real data from the Iberian electricity market operator show that the proposed approach is able to outperform most state-of-the-art market participation strategies, reaching a higher accumulated profit, by adapting players' actions according to the participation risk.

1. Introduction

The electricity sector restructuring [29] aimed at obtaining public benefits, increasing the efficiency of the sector by providing consumers with reliable high quality service at fair costs. This should be achieved by introducing a competitive deregulated market approach to replace the centralized, monopolistic and/or state-owned paradigm that traditionally ruled the sector [31]. Prices that, in many cases, do not reflect the costs and the lack of experience in a field for which the sector particularities make prices behaviour significantly different from already existing markets transacting other commodities and products marked the reform departing point and its subsequent evolution [4]. Market rules, however, should be thoroughly refined, as generating companies increasing market share can prepare the environment for the emergence of (tacit) collusion between these companies; see e.g. [1,14] which may lead to actions preventing effective competition, as has happened in the UK energy market [3].

In such a dynamic, complex, and competitive environment as the power and energy sector, simulation and decision support tools are of crucial importance. Market players and regulators are very interested in foreseeing market behaviour: regulators to test rules before they are implemented and to detect market inefficiencies; market players to understand market's behaviour and act in order to maximize their results from market participation. The need for understanding those mechanisms and how the involved players' interaction affects the outcomes of the markets contributed to the growth of usage of simulation tools. Multi-agent based software is particularly well fitted to analyse dynamic systems with a large amount of complex interactions among its constituents, such as the electricity markets. Several modelling tools directed to the study of restructured wholesale power markets have emerged. Some relevant tools in this domain are: the Electricity Market Complex Adaptive System (EMCAS) [10,30], the Agent-based Modelling of Electricity Systems (AMES) [12,11] and the Multi-Agent Simulator for Competitive Electricity Markets (MASCEM) [32,27]. Although some of these works confirm the applicability and the value of simulation tools to the study of electricity markets, particularly by using

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Nomenclature

P	profits from selling energy (€)
t	time (hour)
I_t	incomes in time t (€)
E_t	expenses in time t (€)
FC	fixed costs (€)
V	volume of power generation (W)
a	generation cost factor
b	generation cost factor
D	decision (to risk or to act towards equilibrium)
FMP	forecasted market price (cent.€/kWh)
Q	ANN error function - squared error
q	target output for a training sample - market price (cent.€/kWh)
y	real value for a training sample - market price (cent.€/kWh)
j	ANN neuron
o_j	output of neuron j
w_{kj}	weight between neurons k and j
f	ANN activation function
n	set of observations in K-Means
x	observation/sample containing the d variables that characterize it
d	number of variables that characterize an observation
k	number of clusters
C	cluster
μ_i	cluster centroid
SRP	sector reference price (cent.€/kWh)
B_j	bid price of player j (cent.€/kWh)
S	supported player
γ	bid decrement [0, 1]
β	risk factor [0, 1]
RP	reference price (cent.€/kWh)
BP	final bid price (cent.€/kWh)
MP	actual market price resulting from the market execution (cent.€/kWh)
Y	real market price values (cent.€/kWh)
F	forecasted market price values (cent.€/kWh)
N	number of forecasted periods
d	distance between each observation assigned to each cluster and the centroid of the corresponding cluster
R	mean point of all observations

multi-agent systems, they present a common limitation: the lack of adaptive machine learning capabilities that allow these tools to effectively provide measurable support to market entities. Current tools are directed to the study of different electricity market mechanisms and to the analysis of the relationships between market entities, but they are not fitted to provide support to market negotiating players in what concerns the achievement of the best possible outcomes from power transactions.

Several studies addressing the strategic behaviour of market players can be found in the literature, e.g. exploring the game theoretic dimension of the market [2], assessing risk management in line with the portfolio theory [6], or by using forecasting approaches to predict prices and optimize the bidding process [16]. However, current models are not capable of adapting to different market circumstances and negotiating contexts, as they are limited to specific market scenarios and are not integrated in actual market simulation or decision support systems. Thereby current approaches are not able to provide market players with the means to change their behaviour in a real market environment, and therefore pursuit the achievement of the best possible outcomes. The data generated during simulations and by real electricity markets operation can be analysed by knowledge discovery and machine learning techniques to enable the assessment of each current context and to dynamically and consistently learn over time, in face of the alternative tools and solutions, what are the best ones to be used in each context. The contextualization of the decision-making process should thereby have a prominent role in order to enable players to adapt their behaviour and risk aversion according to each market context.

This paper addresses this limitation by providing an original contribution towards the adaptability of market players' actions according to the context. An innovative model that dynamically adapts players' decisions according to the evolution of players' participation risk is proposed. A riskier or more conservative exposure to the market is determined based on the combination between the two most commonly used approaches of forecasting in a company's scope. These approaches are the internal data analysis of the company, and the external, or sectorial, data analysis [8]. The internal data analysis considers the assessment of the company's evolution in terms of market power and profitability. The sectorial analysis addresses the assessment of the competing entities in the market sector. This is achieved by grouping the competing companies according to their similarity using a clustering approach, namely the K-Means [10,9] algorithm. In this way, the entities with more market power are identified, and also those with the higher similarity to the subject entity, i.e. the direct competitors. By balancing the two components, a risk aversion factor is revised, which enables adapting the market behaviour of the supported player in real time, using as reference the market price forecast. The forecasting process is performed using a dynamic Artificial Neural Network (ANN) [23].

The proposed methodology is tested and validated in a simulation scenario based on real electricity markets data from the Iberian market – MIBEL [15]. This is enabled by the integration of the proposed model in the Multi-Agent Simulator of Competitive Electricity Markets (MASCEM) [27]. MASCEM is an agent based simulator that has the capability of simulating a diversity of market models used in real electricity markets throughout the world. The integration in MASCEM is achieved through the including of the proposed model in the Adaptive Decision Support for Electricity Market Negotiations (AiD-EM) decision support system [21]. This decision support system includes several benchmark market participation strategies, which enables comparing the performance of the proposed model against several other state of the art approaches, thus demonstrating that the proposed model is able to outperform most current market negotiation strategies, reaching a higher accumulated profit, by dynamically adapting the player's actions according to each context and to the suitable level of risk.

After this introductory section, Section 2 presents the proposed methodology, including the considered market mechanisms and assumptions. Section 3 includes a case study based on real data from the Iberian market, and Section 4 wraps-up the paper with the most relevant conclusions from this work.

2. Data, methodology and limitations

2.1. Data

The data used in this study is based on real data extracted from the Iberian market operator – OMIE website [19], using an automatic data extraction that has been presented in [25]. This data extraction tool enables downloading the market results and players' submitted bids immediately after the market is executed. In this way, it is possible to automatically generate simulation scenarios that represent the reality of the MIBEL market, and execute them a few minutes after the market is closed. Simulation scenarios are generated by the Realistic Scenarios Generator (RealScen), a system presented in [28]. RealScen enables the automatic generation of market simulation scenarios, allowing the representation, through software agents, of the exact reality that has occurred in the market (reflecting all real players' exact actions – resulting in a scenario with thousands of agents), or, alternatively, the generation of reduced simulation scenarios, including a limited number of software agents that represent the reality in a summarized manner, considering different preferences that can be specified (e.g. having only one agent representing all real players of the same generation type; one agent per specific geographic location, etc).

The effective data used to define the simulation scenarios, and thus execute the simulations in this study, refers to (all data can be consulted in [19]):

- all real players characteristics, including generation type, geographic location, etc;
- all players submitted bids for each market, for each period of each day. Bids are defined in Section 2.2;
- all players complex conditions associated to their bids;
- all players market results, including the transaction price and traded volume (accepted/rejected bids);
- the general market results, including the defined market price, total traded volume, imported/exported volume.

2.2. Market mechanism

Double auction markets are, currently, the most used market model [29]. They are used by most market operators in Europe for day-ahead spot markets and intraday markets [15,17,7]. Double auction based markets comprise bids from both sellers and buyers. Sellers are all entities that participate in the market to sell and buyers are all entities that participate in the market to purchase, regardless of whether they are retailers, traders, distribution companies, consumers, prosumers or generators. Such markets are structured to consider production fluctuations as well as differences in production costs of distinct units. In this market, each participating entity must present their selling or buying proposals for each negotiation period (typically 24 hourly periods of a day in day-ahead markets, but also for different numbers of periods in intraday markets). These proposals or bids are typically composed by a tuple (power, price), with different meanings, whether they come from buyers or sellers, respectively: power stands for amount of power to be bought or sold, and price is the maximum accepted price or minimum selling price. When the negotiation is finished, an economic dispatch for each period is set by the market operator. At the end of each period the market operator uses a market-clearing tool establishing the market price – a unique price that is applied to all transactions in the period.

The market mechanism works as a symmetric market, where both suppliers and consumers submit bids. The market operator orders the selling and demand offers: selling bids start with the lowest price and move up, and demand bids start with the highest price and move down. Then, the proposed bids form the supply and demand step curves, and the point at which both curves intersect determines the market price, paid to all accepted supplier and consumers. The bids of every supplier offering prices lower than the established market price and every consumer offering prices higher than the market price are accepted. Fig. 1 shows the symmetric market prices definition.

The profits can be improved by submitting bids that are advantageous for the player in the bidding process; i.e for a seller player, a bid price below the established market price, but still as high as possible, in order to assist in increasing the market price (origination of higher profits, through a higher market price). In the case of a buyer agent, the bid price should be above the established market price, but as low as possible, in order to reduce the cost that is paid for the bought energy.

Distinct variations of this market type are used by different market operators, e.g. MIBEL accommodates the submission of complex offers [15], Nord Pool supports block orders [17], and EPEX includes the possibility for flexible orders [7].

2.3. Proposed methodology

The main principle of the proposed approach is to decide when are the most appropriate moments to opt by a riskier or a safer approach in market negotiations. This decision is based on the combination between the internal data analysis of the supported company and the external/sectorial analysis. Fig. 2 shows a general diagram with the interaction between the main blocks that compose the proposed methodology.

From Fig. 2 it can be seen that the proposed methodology has as main output a final bid, which is provided to the supported player so that it can be submitted to the market. This bid is defined according to a decision method, detailed in Section 2.3.3. This decision is achieved by combining the reference market price, resulting from a market price forecasting using an ANN [24], as presented in Section 2.3.1, and the sectorial reference price, which results from a clustering process using K-Means [10,9], which groups all the companies involved in the market according to their similarity, as presented in Section 2.3.2. ANN is used because of the very good performance in forecasting electricity market prices compared to multiple other reference learning and data mining approaches, as is demonstrated in multiple works [16,18,24]. K-Means is used due to its demonstrated ability to deal with power system problems, including some similar problems that address the grouping of energy characteristics; see e.g. [22] and [13].

The way these two reference prices are used to reach the final bid price is dependent on the decision to risk or play safe, which results from the internal analysis, which is described as follows.

2.3.1. Internal analysis

The internal analysis of the company can be viewed as its economic development, *i.e.*, the increasing or decreasing of the achieved profits. The profits P in time t are calculated according to the total incomes I_t and expenses E_t in t. as defined as in (1). E_t is calculated as in (2), taking into consideration the company's fixed costs FC, such as the personnel expenses, the infrastructures' costs, the overheads, continuous maintenance, etc. Additionally, it also considers the variable costs, which are dependent on the volume of energy generation V, and are usually represented through a quadratic function, considering two variable factors: a and b.

$$P_t = I_t - E_t \tag{1}$$

$$E_t = a.\ V_t^2 + b.\ V_t + FC_t \tag{2}$$

The analysis on the profits evolution is performed through a comparison between the most recent achieved profits, with the immediately previous ones. If the evolution is crescent, *i.e.*, the recent profits are increasing, it is considered that the company is consolidating its

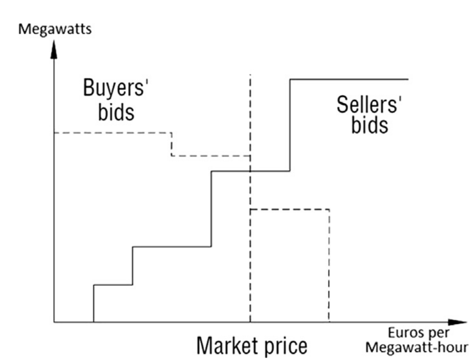

Fig. 1. Symmetric market price establishment [20].

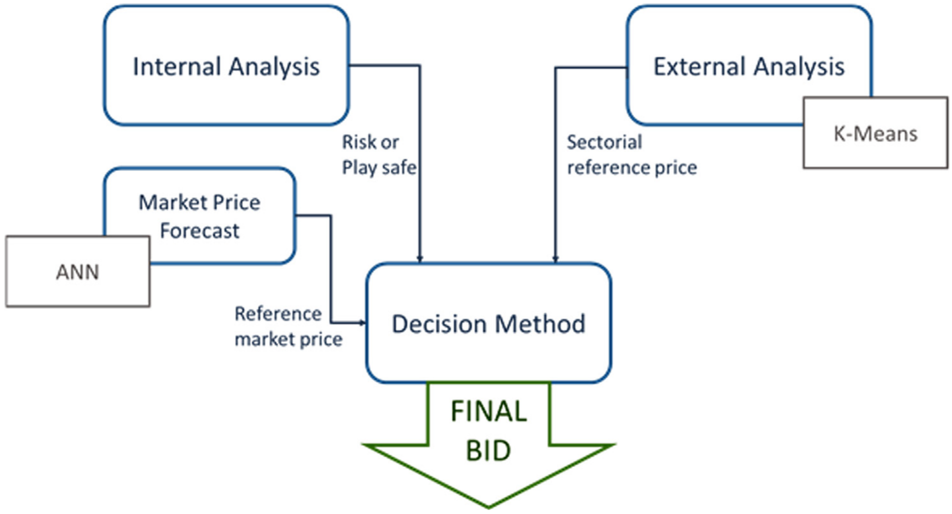

Fig. 2. Proposed methodology overview.

position on the market, and therefore it is in a position where it can afford to take risks, in order to try obtaining higher profits.

On the other hand, if the recent profits tendency is decreasing, the company must play safe, acting towards equilibrium, in a way to assure the continuous achievement of incomes, even if they are not as high as they could be if assuming a riskier position in the market. These strategic models are presented in Section 2.3.3 Decision Method. This decision D is formalized as in (3).

$$\begin{cases} D = risk, & if \quad P\uparrow \\ D = equilibrium, & if \quad P\downarrow \end{cases} \tag{3}$$

When the decision is set for risking, and trying to achieve the higher possible profits, the forecasted market price is used as reference for setting the bid price for market negotiation, as it is the threshold of where a bid should be located, in order to obtain profits (when biding a price higher than the market price the bid will be rejected, assuming a classical double auction market, as in most day-ahead spot markets, especially in Europe [29], including in MIBEL [15], which is considered in the case study presented in Section 3). The market price forecast is performed using an ANN, as described in detail in [23]. The considered ANN is characterized as a feedforward neural network, receiving as inputs the market prices and total amount of negotiated energy in the market, referring to: the day before the desired forecasted day, one week before, two weeks before, and three weeks before. The ANN considers four nodes in the intermediate layer, and one output – the forecasted market price (*FMP*). The topology of this ANN is presented in Fig. 3.

Backpropagation using the gradient descent method [26] has been used as training algorithm for the ANN. This requires calculating the derivative of the squared error function with respect to the weights of the network. The squared error function Q for the single output neuron is defined as in (4).

$$Q = \frac{1}{2}(q - y)^2 \tag{4}$$

where q is the target output for a training sample, i.e. the expected/real value (market price) of training instances; and y is the actual output of the output neuron, i.e. the actual forecasted market price in each iteration of the training process.

For each neuron j, its output o_j is defined by feedforward calculation, as in (5).

$$o_j = f\left(\sum_{k=1}^{n} w_{kj} x_k\right) \tag{5}$$

where n is the number of input units to neuron j, w_{kj} is the weight between neurons k and j, and x_k is the actual training data observation associated to neuron k. Hence, the input for the activation function f of a neuron is the weighted sum of outputs o_k of the previous neurons. The used activation function f is the logistic function, a log-sigmoid function, which can be defined as in (6).

$$f(z) = \frac{1}{1 + e^{-z}} \tag{6}$$

The backpropagation algorithm is used as the training method of the designed artificial neural network. The backpropagation algorithm includes the following steps [24]:

1. Initialize weights as small random numbers;
2. Introduce training data to the ANN and calculate the output by

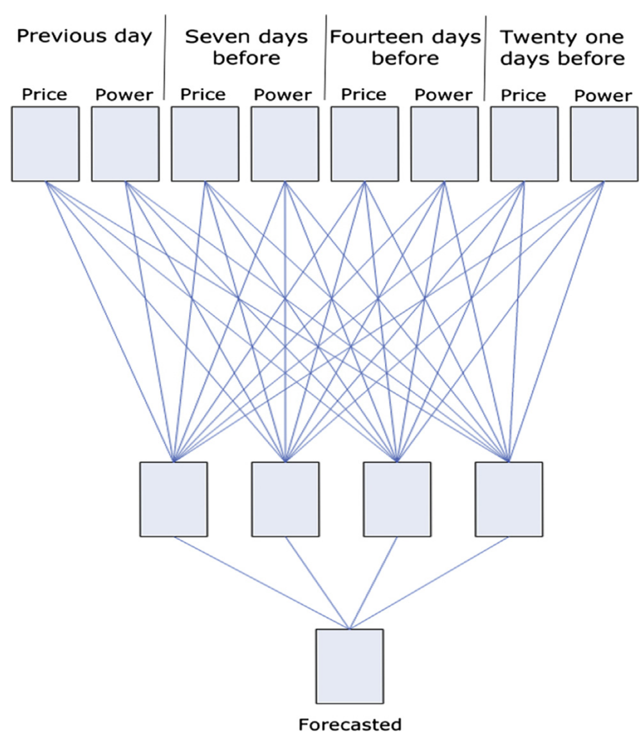

Fig. 3. Artificial neural network topology.

propagating the input forward through the network using (5);
3. Calculate the error using (4)
4. Propagate the sensitivities backward through the network by simply taking the derivative of the error function (4) with respect to the network parameters;
5. Calculate w_{kj} updates through optimization using the gradient descent method [26]; i.e. using the calculated derivative of the error function with respect to the network weights, the ANN optimizes the weights such that the error decreases;
6. Update the values of w_{kj} according to the values calculated in step 5;
7. Repeat steps 2 to 6 until all examples are classified correctly.

2.3.2. External/Sectorial analysis

When the decision from the internal analysis is acting towards equilibrium, and consequently playing safe, safeguarding the achievement of profits, even if they are not optimal, the reference value used for bidding is based on the external or sectorial analysis. The sectorial analysis intends to: firstly, understand how the sector (in this case the electricity sector) is moving inside the global market; secondly, realize in which sub-sector (most influent companies, less powerful ones, etc.) the company that is being supported by this method is located; and thirdly, analyse how each of these sub-sectors is developing, e.g., going towards the unification of several sub-sectors, or otherwise, distance themselves.

In order to define the sub-sectors inside the electricity market sector, a clustering mechanism is used to group the companies that act in the electricity market, in different groups, according to their characteristics. The companies are grouped according to their similarity in what concerns their dimension (amount of produced energy), the prices they are practicing recently (the most recent bid prices), and the average price they presented for the last month and year. The clustering is performed using the K-Means algorithm [10,9]. K-Means is one of the most widely used clustering algorithms, mostly due to its effectiveness in different domains. K-Means contemplates a set of n observations (x_1, x_2, …, x_n), in which each is a d-dimensional real vector. Each dimension represents a different variable that characterizes the observation, e.g. size and prices. The clustering process partitions the n observations into k ($\leq n$) clusters $C = \{C_1, C_2, …, C_k\}$ so that the Within-Cluster Sum of Squares (WCSS) is minimized, as in (7).

$$\min \sum_{i=1}^{k} \sum_{x \in C_i} ||x - \mu_i||^2 \tag{7}$$

where μ_i is the mean of points in C_i, i.e. the cluster *centroid*.

The vector that characterizes each observation x_p, $p \in \{1, …, n\}$ is equal to the sum of the individual dimensions of n vectors. Each n vector comprises the information referring to a different variable. The clustering process undergoes an iterative process aiming at minimizing (7):

- Step 1 - each observation x_p is assigned to cluster $C^{(t)}$ whose mean value yields the minimum WCSS in iteration t, as presented in (8);
- Step 2 - the updated means are calculated for all clusters, considering the newly assigned observations, determining each cluster's new *centroid* μ_i, as shown in (9).

$$C_i^{(t)} = \{x_p: ||x_p - \mu_i^{(t)}||^2 \leq ||x_p - \mu_j^{(t)}||^2 \ \forall j, 1 \leq j \leq k\} \tag{8}$$

$$\mu_i^{(t+1)} = \frac{1}{|C_i^{(t)}|} \sum_{x_j \in C_i^{(t)}} x_j \tag{9}$$

The iterative process finishes when the convergence process is completed, i.e. when the observations assignment to distinct clusters stabilizes. Hence, the K-Means assigns observations to the nearest cluster by distance by minimizing the WCSS objective, in (7).

A value of $k = 3$ is pre-defined, so that the clustering mechanism groups the companies into three different clusters. In most cases, one will be representing the most influential companies, one representing the most similar companies to the one that is being supported by the proposed methodology, and one representing the less influent companies over the market, however, the supported player may also be identified as belonging to the most influential or less influential groups of companies.

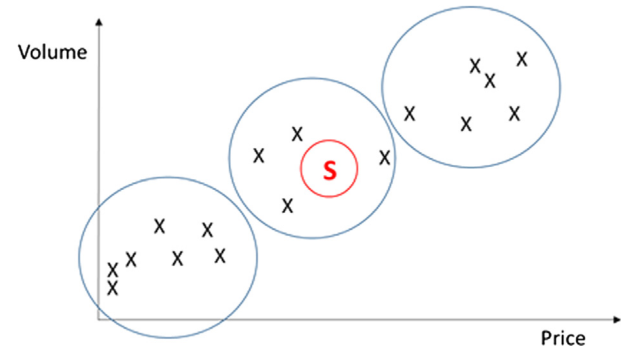

Fig. 4. Clustering process using $K = 3$.

Fig. 4 shows an illustrative example considering a two-dimensional clustering using only the price and volume, in order to facilitate the visualization. Each company, illustrated by a X is allocated to one cluster, according to the similarity between the different companies. S represents the supported player, which is also allocated to one of the 3 clusters.

The average bid price of the companies grouped in the same cluster as the supported one, is determined as the sector reference price (*SRP*), as in (10), and it is used as reference for the situations in which the decision is to act towards equilibrium, as explained in Section 2.3.1.

$$SRP^{(t)} = \frac{1}{|C_i^{(t)}|} \sum_{B_j \in C_i^{(t)}} B_j,\ S \in C_i^{(t)} \tag{10}$$

where B_j is the bid price of player j, which is part of the same cluster as the supported player S.

2.3.3. Decision method

Using the results from the Internal and External data analysis, a decision method is applied to define the final bid. Fig. 5 presents a flowchart that shows the decision process.

From Fig. 5 one can see that from the Internal Analysis results a decision on whether to risk or play safe, as shown in Section 2.3.1. depending on this decision, one of two reference prices will be considered: either the forecasted market price when risking, or the cluster reference price when playing safe. The only situation in which this may not apply is when the supported company is placed in a highly competitive cluster, with high risking prices. In this case, since the objective is still acting safe, the price assumed as reference is the lower value between the cluster reference and the market price forecast. Both reference values (sector reference price in case of equilibrium, or market price in case of risking), are subject to a decrement γ before being defined as the final bid price for the supported player. The calculation of γ is based on a risk factor β (11), user-defined accordingly to the company's intrinsic objectives and goals, with the purpose of guaranteeing that the final bid price is located below the reference, regardless of which; thereby safeguarding the success of the bidding process.

$$\beta \in [0, 1] \tag{11}$$

The higher β is, the smaller is γ, meaning a higher proximity to the used reference values, and therefore increasing the risk to which it is subject. The initial decrement is calculated as in (12).

$$\gamma_t = 1 - \beta,\ t = 0 \tag{12}$$

If the decision in a certain moment is acting towards equilibrium, γ

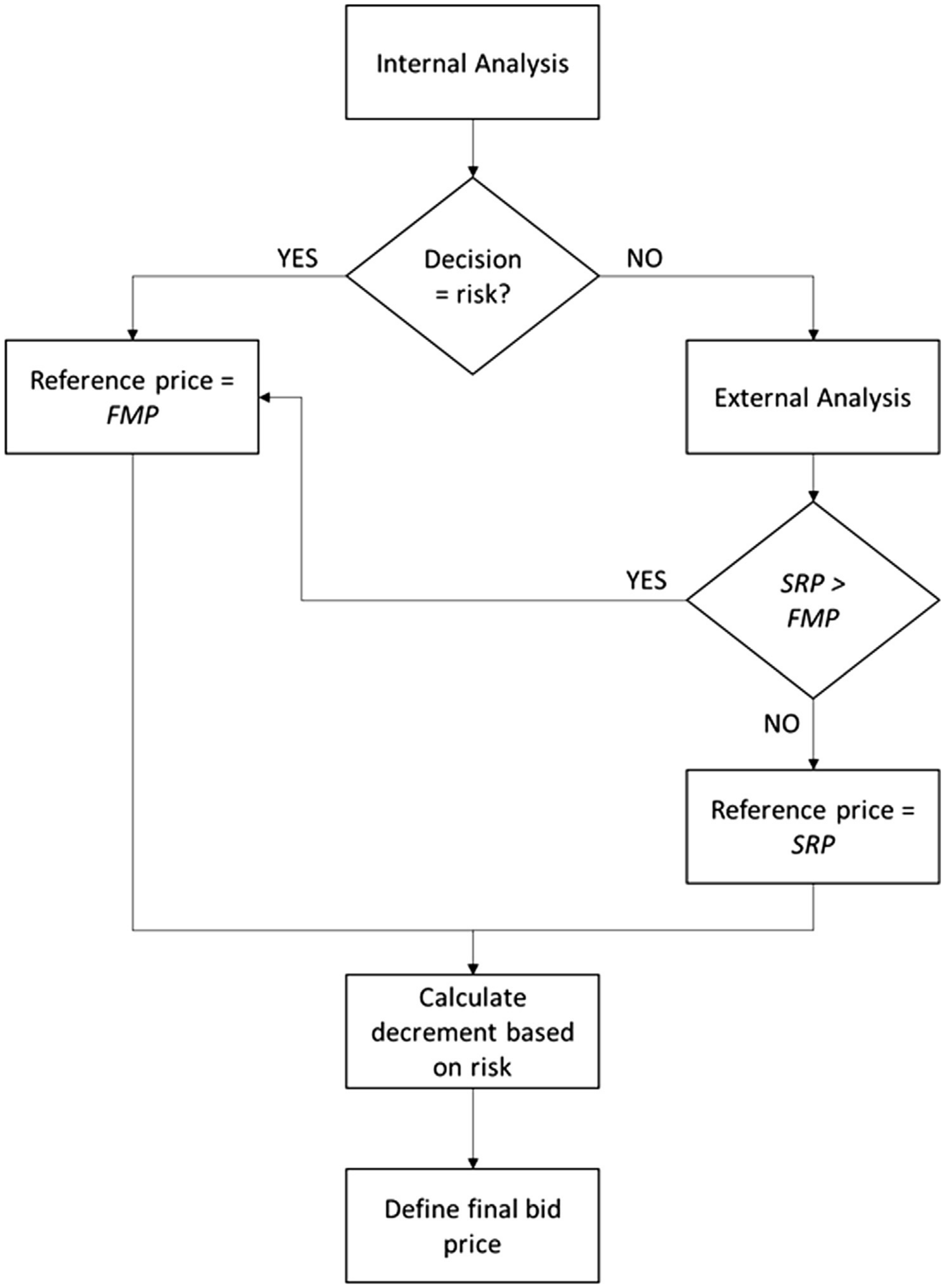

Fig. 5. Decision process flowchart.

stays fixed at this value. On the other hand, if the decision is risking for a continuous number of periods, γ decreases according to (13), slowly increasing the risk, until the bid price is equal to the reference value. If the sequence of risking periods is interrupted (due to a sudden decrease of profits), γ returns to its initial value.

$$\gamma_{t+1} = \gamma_t(1 - \beta) \tag{13}$$

Using this decrement and the reference price (*RP)* (which equals *SRP* or *FMP* according to the decision process) it is now possible to define the final bid price BP_t, as in (14).

$$BP_t^p = \gamma_t RP_t^p \tag{14}$$

The advantage of the defined bid can evaluated by the profits *P* it originates to the supported player. The objective is thereby to maximize the player's profits, as defined in (15).

$$\text{argmax} P_t^p = I_t - E_t \tag{15}$$

where *I* and *E* are the incomes and expenses, as explained in (1). The incomes are a direct result of the market outcomes, as in (16) which are dependent on the bids of the participant players as explained in Section 2.2; hence the importance of defining a bid price that is able to maximize these incomes.

$$I_t = MP_t^p V_t \tag{16}$$

where *MP* is the actual market price resulting from the market execution, and *V* is the volume of traded power of the supported player.

An adequate balance between the decision of taking higher risks, and acting safe, towards equilibrium, is the main goal of this methodology, by constantly adapting the supported player's exposure to risk, and consequently the aggressiveness of the negotiation process, depending on the evolution of the market sector and of the internal evolution of the supported entity. The decision making concerning the adequate times to risk is thereby the essential aim of this strategy, and it is where this approach provides its main contribution.

2.4. Limitations and assumptions

The main limitation of the proposed methodology is that it is designed to consider the market mechanisms used by most EU market operators, as detailed in Section 2.2. Thereby no Locational Marginal Price (LMP) based models, or US based market models are considered in this study.

The studies undertaken in this work assume that all players except for the supported player (the one using the decision support provided by the proposed methodology), behave as they did in reality, i.e. all players submit exactly the same bids as they did in the real Iberian market. In this way it is possible to assess the performance of the supported player if this player had performed different actions in the market.

According to the used market model, although all the involved players have the potential to affect the market price, as the market price is defined based on all players' bids; most smaller player do not have an effective impact on the price, since their bid volume is negligible when compared to larger players, and even more when compared to the total volume placed in the market. For this reason, although the supported player in the considered study may affect the market price in some cases, in most situations this player acts a price-taker.

Market operators and system operators may use this type of simulation systems, and decision support solutions to experiment alternative market models and rules, in order to assess their likely impact before their costly implementation in reality. The studies can be performed to assess possible alternative changes in market regulation to enable the participation of small player, e.g. small consumers (and flexibility trading) and renewable based distributed generation; and also to prevent tacit collusion between generators [1,3,14]. These solutions may also be used to experiment possible interaction models between wholesale markets and local energy markets and smart grids; thus enabling possible regulatory and policy changes to facilitate the integration of small sized resources. Market negotiating players also benefit from these models and systems, as they are the central players in the proposed methodology. They can use decision support approaches, such as the one proposed in this paper, to experiment different alternative market actions, to learn how to take the most advantage out of market participation and therefore improve their market results. This improvement results in a further incentive to the widespread distributed generation.

3. Case study

3.1. Characterization

This section presents the results of a set of simulations undertaken using MASCEM, with the objective of assessing the performance of the proposed methodology. Besides the analysis of the market results of a subject player using the proposed approach, its performance is compared to that of several state of the art negotiation strategies provided by AiD-EM.

3.1.1. Evaluation

The main metric for comparing the performance of the methods is the profits that each is able to originate for an electricity market participant player – a seller; since the goal is to maximize the profits of a market player, as defined in (15). The costs of production are kept constant throughout all hours of all considered days, in order to facilitate the comparison of the achieved profits.

The accuracy of the forecast may be evaluated by several error indices, such as the mean absolute error (MAE), the mean absolute percentage error (MAPE), the symmetric mean absolute percentage error (SMAPE) and the standard deviation (SD). MAE represents the average of the absolute errors (17).

$$MAE = \frac{1}{N}\sum_{h=1}^{N} |Y_h - F_h| \tag{17}$$

where Y_h and F_h are the actual and forecasted values for each h period, while N corresponds to the number of forecasted periods.

In MAPE the average of all the percentage errors is computed, producing a measure of relative overall fit (10).

$$MAPE = \frac{100\%}{N}\sum_{h=1}^{N} \left|\frac{Y_h - F}{Y_h}\right| \tag{18}$$

The Mean Index Adequacy (MIA) and Clustering Dispersion Indicator (CDI) [5] are used to evaluate the quality of the clustering process. These approaches assess the dispersion of the observations among the clusters. MIA uses the Euclidean distance method to determine the value that reflects the quality of a cluster partition. CDI is determined by the association of the distance between elements of the cluster, and the inverse of the distance between the values that represent each cluster.

MIA depends on the average of the mean distances d between each observation assigned to each cluster and the centroid of the corresponding cluster μ_i, as defined in (19).

$$MIA = \sqrt{\frac{1}{K}\sum_{k=1}^{K} d^2(x^{(k)}, \mu^{(k)})} \tag{19}$$

CDI assesses: (i) the distance among the data points clustered in the same group, and (ii) the distance from each data point to all other clusters' centroids, as in (20), where R is the mean point of all observations, and n is the number of observations assigned to each cluster.

$$CDI = \frac{\sqrt{\frac{1}{K}\sum_{k=1}^{K}\left[\frac{1}{2 . n^{(k)}}\sum_{n=1}^{n^{(k)}} d^2(x^{(m)}, \mu^{(k)})\right]}}{\sqrt{\frac{1}{2K}\sum_{k=1}^{K} d^2(x^{(k)}, R)}} \tag{20}$$

The distance between two observations x_i and x_j is calculated as defined in (21).

$$d(xi, xj) = \sqrt{\frac{1}{H} \times \sum_{h=1}^{H} (xi(h) - xj(h))^2} \tag{21}$$

where H is the size of the vector that contains all elements that represent each observation.

The variance assessment provided by MIA and CDI for different numbers of k enables analysing the gain (in variance reduction) of adding an extra cluster. When the variance from k *to* $k + 1$ is no longer significant and starts stabilizing, one has reached the optimal k.

3.1.2. Specifications

In order to provide a suitable comparison, the same market scenario, with the exact same players, under the same circumstances, is executed repeatedly. The only variation is the behaviour of the test subject player, Seller 2. In each simulation Seller 2 acts based on the decision support provided by the proposed approach using different parameters, and also based on the actions suggestion provided by the other AiD-EM strategies. Seller 2 uses the proposed approach with different risk factor values. The first test concerns a risk value of 0.2, a small value, meaning a low risk. In the second, an intermediate value of 0.5, and in the third a higher value, 0.8. The fourth and final test will present Seller 2′s results using the proposed approach exclusively directed to equilibrium, by playing safe and submitting a low bid price. These tests intend to show a comparison of this strategy's performance using different risk factors, and also to demonstrate the advantage of both decisions: risking or playing safe, towards equilibrium. Moreover, the assessment of the results from the internal and external analysis are also provided.

As explained in Section 2.1, the data used in this study is based on real data extracted from the Iberian market operator – OMIE website [19], using an automatic data extraction that has been presented in [25]. The simulations refer to three data sets, namely:

- Data set 1: 62 consecutive days (two months), starting from Saturday, 1st December 2012, until Thursday, 31st January 2013;
- Data set 2: 1st January to 31st December 2016 (one year);
- Data set 3: 1st January to 31st December 2017 (one year);

The first data set is used to evaluate the different specific components of the proposed method (by being smaller it enables an easier interpretation of the results. Data set 2 and Data set 3 enable evaluating the performance of the proposed approach for more recent and longer simulations, thus assessing the generalization of the results. All data sets include the data referred in Section 2.1, namely regarding market players' characteristics and actions and market results.

The simulation scenario was created with the intention of representing the Iberian reality, reduced to a smaller summarized group, containing the essential aspects of different parts of the market, in order to allow a better individual analysis and study of the interactions and potentiality of each of those actors. The scenario is composed by 7 buyers and 5 sellers, from which 2 are aggregators, aggregating several small generators. No network constraints are considered in these simulations, as the focus of the experiments is on the economic component of the market. The subject player, Seller 2, sells a fixed power amount of 50 MW in all periods of each day, and no generation costs are considered, in order to facilitate the interpretation of results. As mentioned in Section 2.4 it is assumed that all other players behave as the corresponding player in the Iberian market (same bid price and sale/purchase amount in each period of each considered simulation day). Since no significant random variables have influence over the results, all simulations are executed only once. All results correspond to MASCEM simulations for each (hourly) period of each considered day. Further details on the test scenario and on the specifications for this case study can be consulted in [20].

3.2. Results

3.2.1. Internal analysis

In order to enable the decision process, the two reference prices must be obtained (forecasted market price and sectorial reference price). Table 1 shows the results of the market price forecasting process, using the ANN presented in Section 2.3.1, for the three considered data sets.

From Table 1 it is visible that the average achieved market price forecasting errors are quite similar in the three Data sets. The STD is also quite low, which means that the forecast consistency is good. Analysing MAPE, the average errors are located below 10%, which is the threshold considered acceptable in forecasting in this domain [18].

3.2.2. External analysis

The sectorial reference price is achieved as result of the clustering process that groups the involved companied according to their similarity. Fig. 6 shows the MIA and CDI dispersion indexes for the clustering process using the 3 considered data sets, for different values of k.

The graphs in Fig. 6 show that, by analysing the evolution of MIA as k increases, the gain in reduction of dispersion is not significant, which means that having more clusters does not result in a significant gain in clustering quality. On the other hand, when comparing the CDI values, it is visible that there is a significant decrease in dispersion from $k = 2$ to $k = 3$, especially when using Data set 1, see Fig. 6 a). This so called "elbow" is also visible in Fig. 6 c). When using Data set 2, this decrease is not so obvious, but smaller "elbows" are still identified when $k = 3$ and $k = 5$.

The analysis of results using the 3 data sets, support the choice of $k = 3$ as the most beneficial number of clusters to be used in the proposed methodology.

3.2.3. Decision process

Fig. 7 presents the incomes obtained for Seller 2 in the simulations using Data set 1, and a comparison between the market price and Seller 2′s bid price, for the twelfth period of each day, for the test scenario. Period 12 is chosen arbitrarily, for demonstration purposes.

From Fig. 7 one can see that Seller 2 was able to obtain incomes in almost all days regarding the first three tests, while in the fourth it could effectively sell at all times. Additionally, in the first three cases, it is visible that following a day of bad results – not selling, or selling a low amount of power – the agent's bid price decreases, lowering the risk, and acting towards equilibrium. When the incomes are higher, the bid price for the following day is much closer to the market price, meaning a higher risk and the possibility to achieve higher profits.

The selling of power in all days in the fourth test is an evident proof of the advantage of using the equilibrium approach, as supported by the incomes in the total of the 24 periods, for the 61 considered days, obtained in each of the four tests, presented in Table 2.

Table 2 shows that the equilibrium approach allowed the player to achieve higher global incomes, even though the tendency of profits evolution when increasing the risk not proving to be increasing. Regarding the three risking approaches, the third, which presents the higher risk, is the one that showed to be the most advantageous. However, although the equilibrium approach presented higher global incomes for this case study, it does not mean that this is the best decision to take in all situations. In fact, when risking in the right moments, a strategy can actually get even higher incomes. In Fig. 7 it is visible that the first three approaches presented some periods in which they could not sell, and consequently not obtain incomes, but when considering the selling periods, the incomes obtained by increasing the risk are higher than the equilibrium approach. This is supported by Table 3, which presents the comparison of the total incomes obtained in the third and fourth tests, starting from day 37 - the following day to the last one in which Seller 2 could not sell using a $\beta = 0.8$.

It is visible in Table 3 that the approach using $\beta = 0.8$ obtained higher incomes than the equilibrium approach when considering the periods in which both approaches were able to sell. This means that risking is advantageous for achieving higher incomes, when this is done in the adequate moments. The simple settling for equilibrium does not provide the best solution when the goal is achieving the highest possible incomes, rather a conjugation of both, done in the right times, and in the adequate amounts.

The way bids are defined in the first three tests, whether risking or going for equilibrium are dependent on the players' recent results. Fig. 8 presents the bid definition in the four tests, in comparison with the two reference values: market price forecast and cluster reference price, which are the basis for the equilibrium and the risk actions.

The graphs in Fig. 8 show that Seller 2′s bid is always located below a reference value, either the forecasted market price, when assuming a higher risk, or the cluster reference value when going for equilibrium. In the fourth test, as the player uses the equilibrium approach at all times, the bid is always closely below the cluster reference value. Regarding the first three tests, it depends on the recent results. When comparing Fig. 8 with Fig. 7 it is visible that the cluster reference value

Table 1
Results of the market price forecasting for the three considered data sets, using the ANN.

Data set	MAE	MAPE (%)	STD
Data set 1	5.36	9.15	5.1
Data set 2	4.32	7.25	3.6
Data set 3	4.86	7.83	3.1

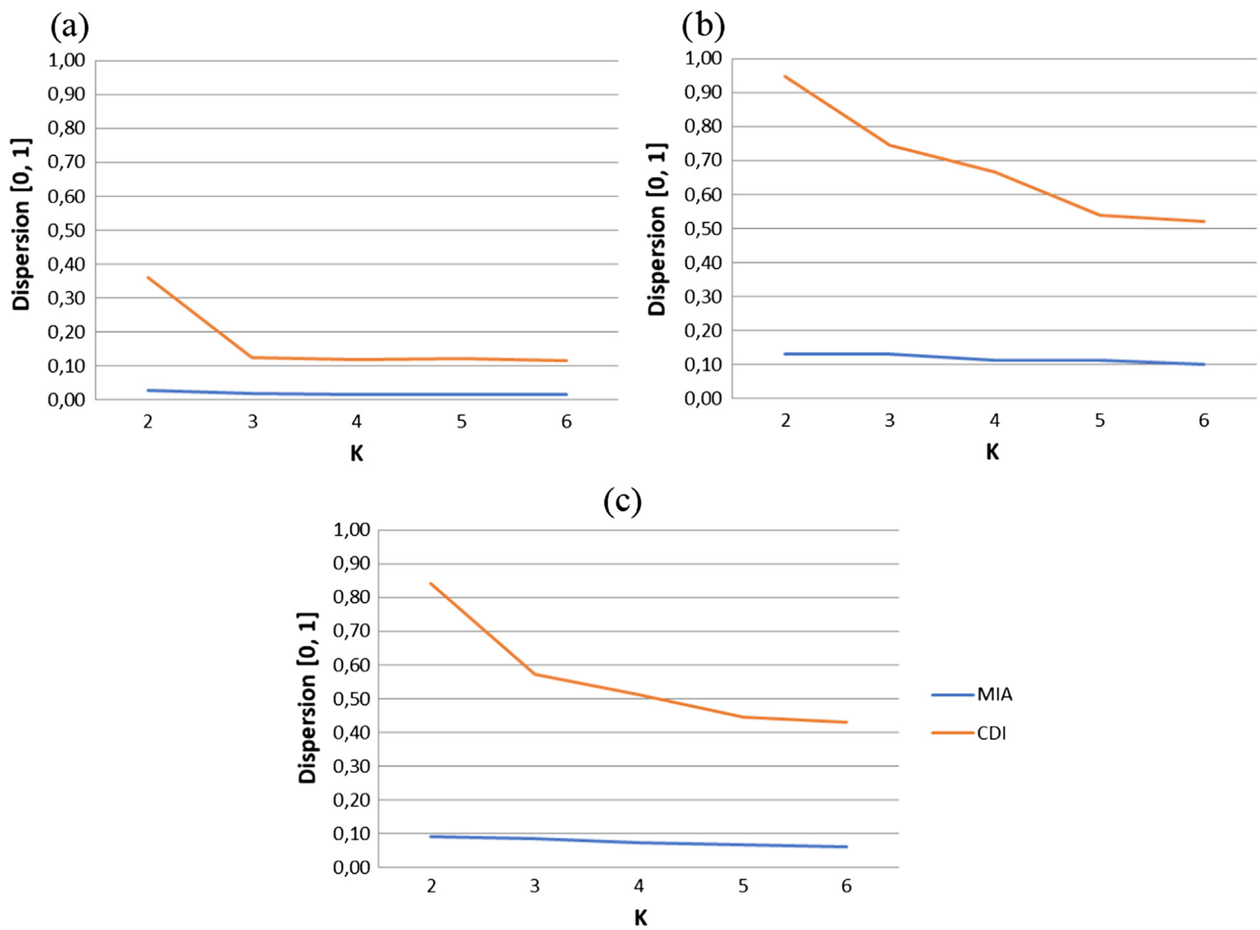

Fig. 6. MIA and CDI dispersion values for different K, for: (a) Data set 1, (b) Data set 2, (c) Data set 3.

is used after the periods in which the player got worst results. Comparing the bids among these first three tests, it is visible that the higher the risk of the approach, the closer the bid value gets to the reference values. Fig. 9 presents the differences of the bids in each case, from the used reference value.

In the first case, using $\beta = 0.2$, the bid value is located much lower than the reference prices, as shown in Fig. 9, presenting an average difference of 0.18 cent.€/kWh. In the second case, the differences are intermediate, with an average of 0.16 cent.€/kWh. Regarding the third case, where the risk factor is defined as 0.8, the bid comes very close the reference values, being the difference average of 0.11 cent.€/kWh. Finally, in what concerns the equilibrium approach, the difference is constant, being maintained at 0.2 cent.€/kWh in all situations.

These simulations demonstrate the adequacy and advantage of using the proposed approach, as it shows being able to provide high incomes to the supported player. This conclusion is supported by the comparison with several other state of the art market negotiation strategies, as shown in Section 3.2.4.

3.2.4. *Comparison with other relevant approaches*

The considered state of the art market negotiation strategies are integrated in the AiD-EM decision support system, and can be consulted in detail in [20]. All simulations have been executed in the same simulation scenario, considering the same days and specifications. Results for Data set 1, Data set 2 and Data set 3 are presented in Fig. 10.

From Fig. 10 it is visible that the total incomes achieved by the proposed approach in the total of the 61 considered simulation days, when using Data set 1 are higher than those achieved by most of the reference strategies, being its values very similar to the maximum values achieved by the best strategies. In fact, only the Game Theory strategy has been able to achieve higher accumulated incomes than the proposed approach (4,916,956 € against 4,878,842 € of the proposed approach, a difference of less than 1%). The third strategy with the best results is the STH Metalearner with an income of 4,863,214 €. Data set 2 and Data set 3 correspond to a full year of simulation each, namely 2016 and 2017. Results from using Data set 2 show that the proposed methodology is the second best from all strategies with a total accumulated income of: 33,529,182 €, being very close to the total accumulated incomes of the best strategy in this simulation, which is the STH Metalearner, achieving 33,854,096 €. Finally, when analysing the results from the simulations using Data set 3, one can see that in this case the proposed approach is the strategy that achieved the highest incomes from all, with an accumulated income of 35,435,188 € against 34,618,988 € and 33,639,292 € achieved by the STH Metalearner and Game Theory strategies, respectively.

3.3. *Discussion*

Results have shown that the proposed methodology is a promising approach for decision support of players' negotiations in auction based electricity markets. The proposed approach has shown a competitive performance against the best state of the art strategic approaches in the literature, reaching similar accumulated incomes to the best strategies in all three Data sets. In fact, the proposed approach has reached the best accumulated incomes from all considered strategies when using Data set 3: data from the whole year of 2017. This result is associated with the best electricity market forecasting results achieved for Data set 3, as shown in Section 3.2.1. A better quality of price forecast means that, when choosing to risk, and use the forecasted market price as reference price to define the bid, the methodology has a better chance

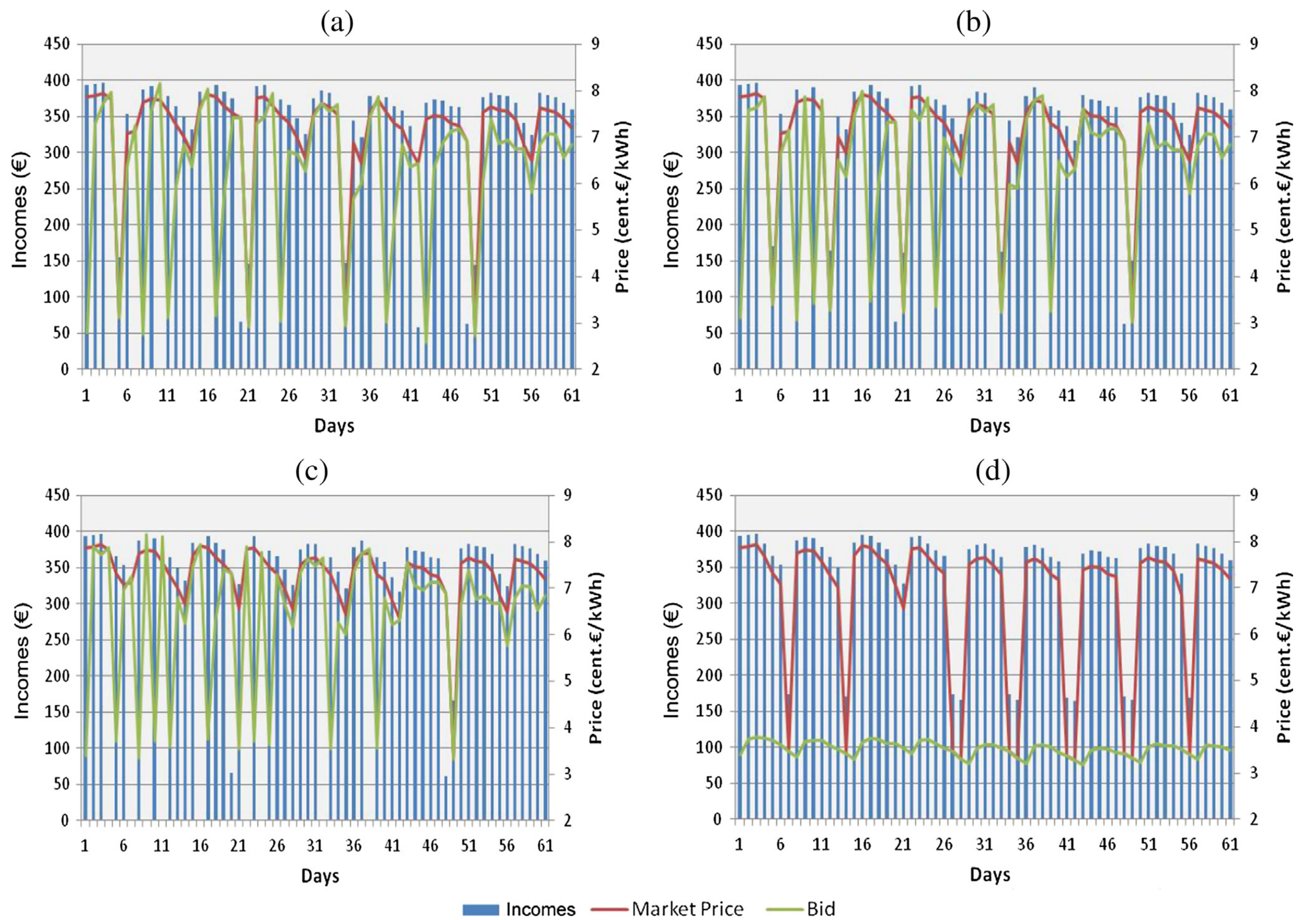

Fig. 7. Incomes obtained by Seller 2 in the twelfth period of the considered 61 days, with: (a) $\beta = 0.2$, (b) $\beta = 0.5$, (c) $\beta = 0.8$, (d) equilibrium.

Table 2
Total incomes obtained in the twelfth period.

	Risk factor			Equilibrium
	0.2	0.5	0.8	
Total Income(€)	435482.16	429537.36	438655.92	494,574

Table 3
Total incomes obtained in the twelfth period starting from day 37.

	Risk factor 0.8	Equilibrium
Total Incomes(€)	7871,75	7497,12

of being successful; while when using lower quality forecasts the chances of defining a bid that does not reflect the actual market price is bigger, e.g. as happens with Data set 1.

The sectorial reference is achieved as result from the clustering process of the most similar companies. Different numbers for K have been experimented, and results show that K = 3 is, in fact the most appropriate number of clusters, as increasing this number does not lead to a significant improvement in the clustering accuracy, as shown in Section 3.2.2.

The decision process using the two reference prices (forecasted market price and sectorial reference price) as basis has demonstrated that proposed methodology is able to effectively decide when to risk and when to play safe. These results show that the combination of risk with equilibrium depending on the internal and external analysis of a company, as performed by the proposed approach, is in fact a promising solution to address market negotiations.

Further alternative models for risk modelling can be promising approaches to improve the results of the proposed model; e.g. Conditional Value-at-Risk (CVaR) [33], which is a valid alternative model for potential application in the addressed problem. However, the proposed methodology considers a constant adaptation and learning of the most recent perceived event, thus becoming a more dynamic strategic for real-time adaptation, while CVaR is more suitable for longer-term planning. The adaptation of such models may nevertheless improve the decision process on the most suitable times to perform riskier actions.

4. Conclusion

This paper proposes a methodology for decision support of electricity market players' actions in market negotiations. The proposed approach is based on the combination between the internal analysis of the company, which refers to the analysis of the company's market power evolution (evaluated through the achieved profits tendency); and the external or sectorial data analysis, which refers to the assessment of the market and sector position of the competing entities. Through the combination of both these analyses, the exposure of the supported player to market risk is dynamically adapted, which results in a constant adaptation to market context.

Results show that the proposed approach is able to achieve a significant quality of results, having achieved better results than most of the considered reference strategies. Results also show that when

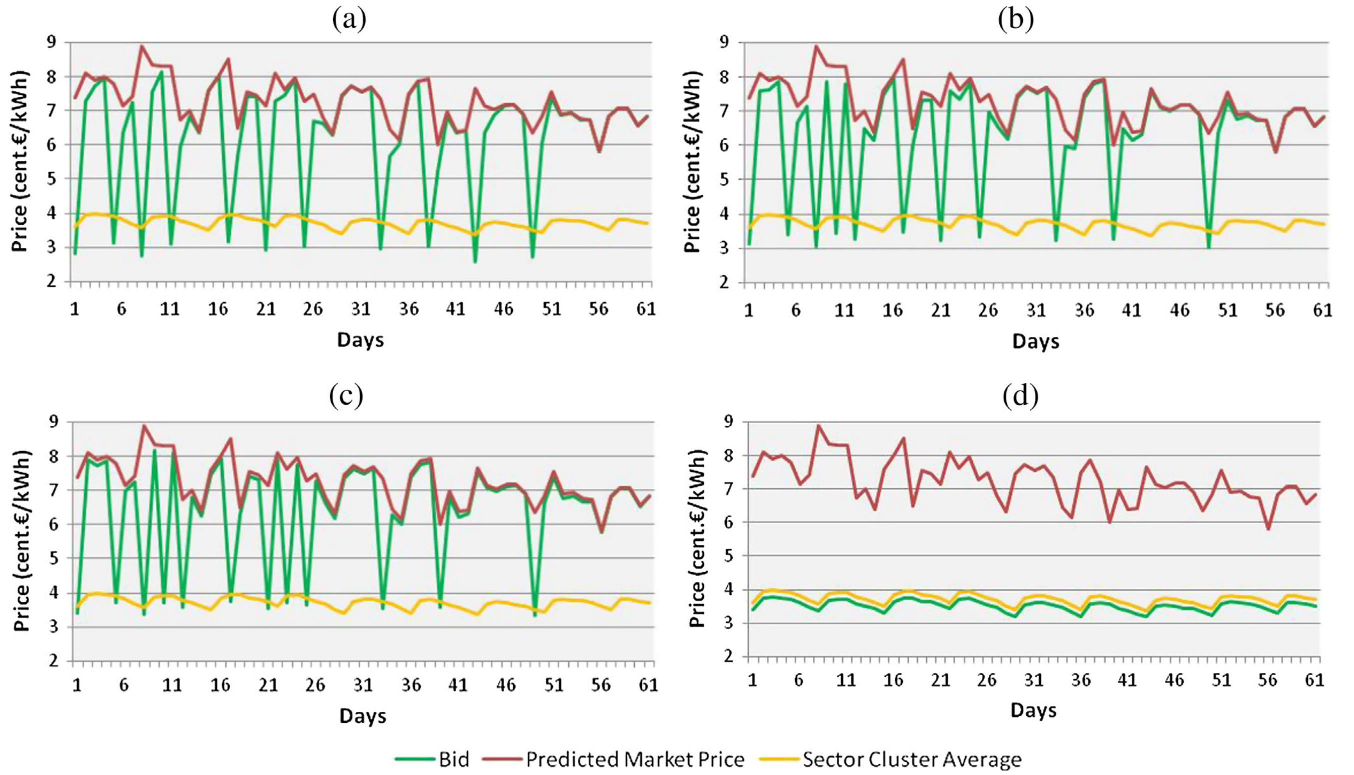

Fig. 8. Seller 2′s bid comparison with the reference values in the twelfth period of the considered 61 days, with: (a) $\beta = 0.2$, (b) $\beta = 0.5$, (c) $\beta = 0.8$, (d) equilibrium.

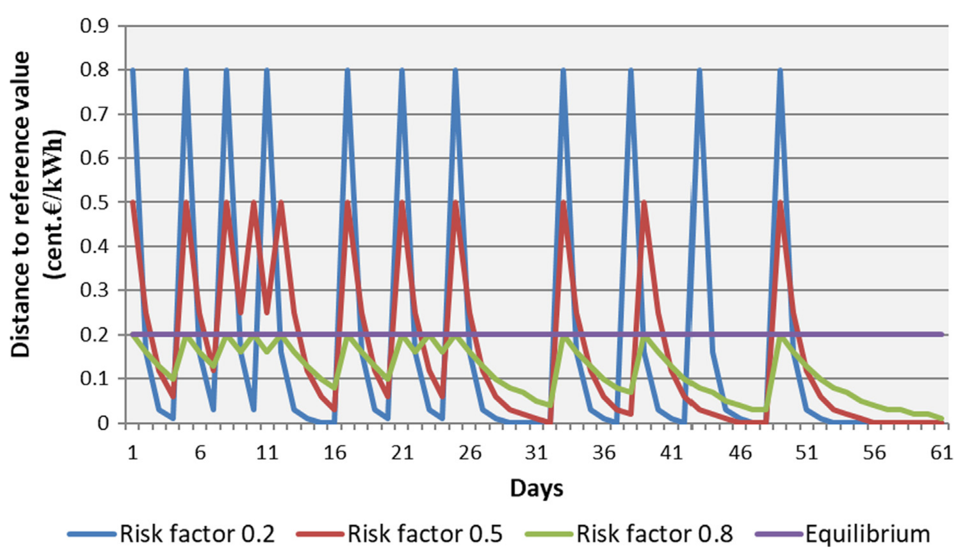

Fig. 9. Difference between the reference value and Seller 2′s bid in the four considered cases.

considering a safe approach, towards market equilibrium, the supported player is always able to sell. On the other hand, although assuming a riskier approach leads to some periods in which the market agreement is not achieved, and thus the player is not able to sell; when assessing the established agreements (all the periods in which the supported player has been able to sell), the achieved incomes are higher when assuming a riskier position.

The consistency of the proposed approach is also assessed through its application to three different data sets, including data from 2016 and 2017. Results show that the proposed approach is able to reach promising results, being even able to reach better outcomes than all other strategies using the 2017 data set, which is associated to a smaller electricity market prices forecasting error. By comparing the achieved results with the reference strategies in the literature, it can be concluded that the proposed approach is in line with the related literature in the field, showing to be a significant contribution in this domain.

Future work considers the improvement of the decision process regarding the changes in the risk approach, with the aim at achieving a more balanced position between risking and playing safe, so that the riskier positions can be assumed in more strategic timings, in order to try and avoid periods in which the transaction is not possible, while still maintaining the higher gains accomplished when assuming riskier positions in selected times. In fact, the study and analysis of correlated uncertainties, and the derivatives and bilateral contracts to hedge against financial risks are suggested for further exploration on the problem. The time frames of the simultaneous markets, e.g. the power

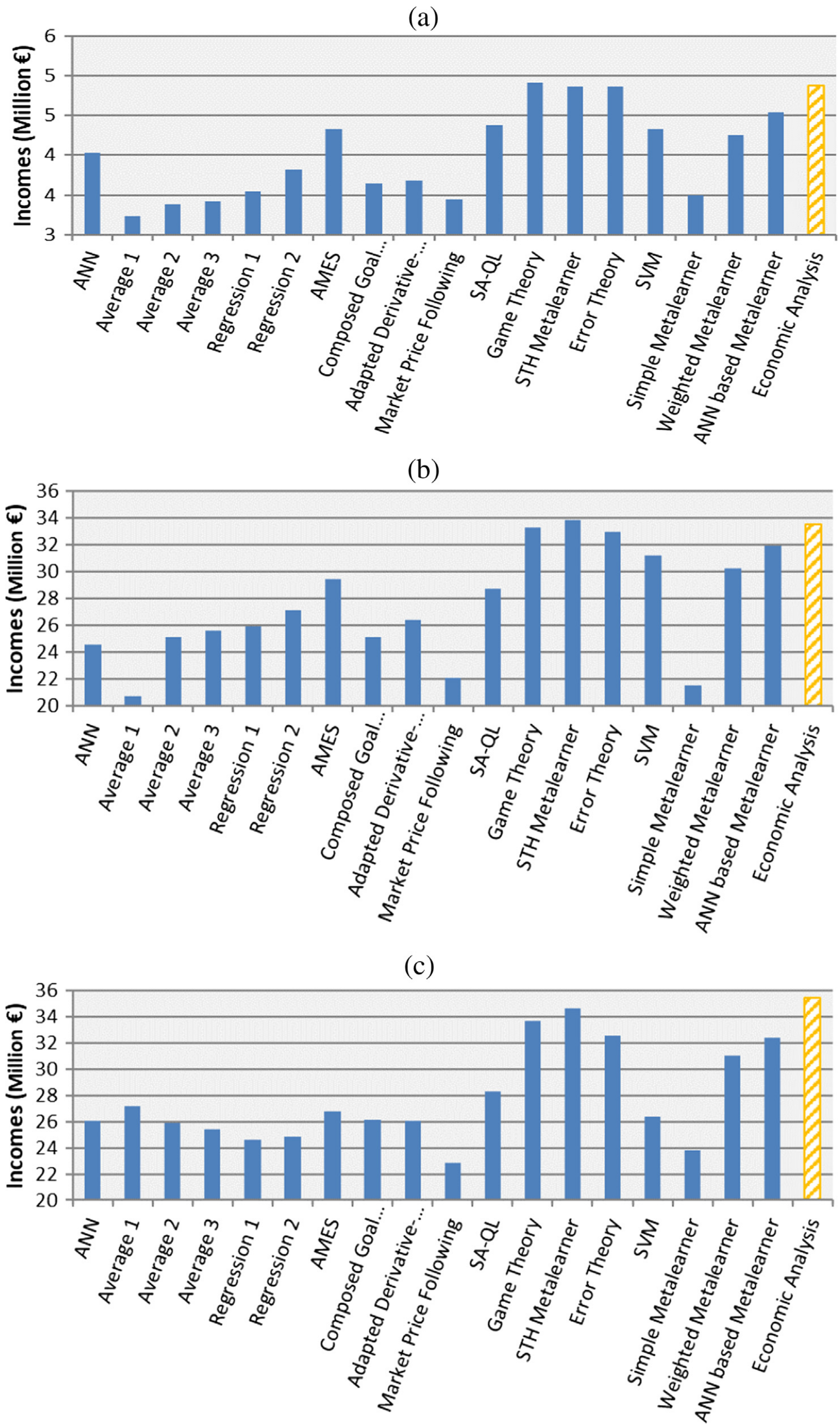

Fig. 10. Incomes achieved by all strategies in the total of the 24 h of the considered simulation days, for: (a) Data set 1, (b) Data set 2, (c) Data set 3.

delivery based on the day-ahead, real-time schedules, and futures contracts, is a research topic that also requires special attention. An alternative model including a CVaR based model to define the basis long term strategy, combined with the proposed method for dynamic adaptation to the most recent events, is also proposed as future work

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