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Artificial neural network approach for revealing market competitors' behaviour

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Abstract: This paper proposes a novel approach for modeling and revealing the competitors' behavior from perspective of an intended player (IP). To this end, from perspective of IP, we define an Equivalent Rival (ER) whose behavior in the electricity market reflects the aggregation of behaviors of all individual competitors. It is assumed that IP and its ER participate in an equivalent market which its outcomes are approximately equal to those of the real market. The revealing procedure is designed as a two-stage Artificial Neural Network-based approach to estimate and predict the bids of ER after each run of the real market. Predicted bids of ER are used for the bidding strategy of IP. The proposed approach has been examined on two different case studies. In the first case study the aggregate supply curve of a market with 12 players has been obtained using the proposed approach and the result has been compared with a Bayesian inference approach. In the second case study a six-player electricity market is considered. The competitors' behavior has been revealed from perspective of an intended player using proposed approach and an optimal bidding strategy based on the proposed approach has been constructed.

Nomenclature

D	index for demand
eqr	index for an equivalent rival
J	index for IP
H	hour in which IP decides about bid offering
MCP_h	market-clearing price at hour h in a real market
MCP'_h	market-clearing price at hour h in an equivalent market
$P_{i,h}$	active power allocated to player i at hour h in a real market
$P'_{i,h}$	active power allocated to player i at hour h in equivalent market
$P_{i\min}$	minimum limit of produced power by player i
$P_{i\max}$	maximum limit of produced power by player i
α_i	slope of marginal cost function of player i
β_i	intercept of marginal cost function of player i
$a_{i,h}$	slope of supply function of player i at hour h
$b_{i,h}$	intercept of supply function of player i at hour h
$\mathrm{SF}_{i,h}$	supply function of player i at hour h

1 Introduction

After the emergence of electricity markets in the 1980s in different countries, the traditional role of power producers changed substantially. In this new competitive environment, power producers attempt to maximise their own profit by optimally offering their bids in the liberalised electricity market. Therefore, the need for new decision-making tools for strategic producers has arisen. The interactions with competitors are a fundamental issue in this regard which is addressed in the literature [1]. Therefore the ability of modelling and prediction of the competitors' behaviour is a great privilege for a market player. In the electricity market, modelling of the competitors' behaviour is an important but complex task due to a large amount of uncertain information. Generally, in the previous literature, the ways to provide additional information for an electricity market player to offer its optimal bid are divided into three major categories: (i) scenario-based approaches, (ii) price and load forecasting and (iii) analysis of the competitors' behaviour. As the examples for the *first* category, [2, 3] could be mentioned. In [2], a multi-stage risk-constrained stochastic complementarity model has been presented for implementation of optimal bidding strategy for a wind generator that participates in both the day-ahead and the balancing markets. In this paper, uncertainties such as rivals' offers, market prices, wind-power productions, and demand's bids have been modelled using a set of scenarios. An optimal bidding strategy has been formulated in [3] as a two-stage stochastic optimisation problem by considering a wind power generator which participates in an electricity market. In this paper, uncertainties related to the amount of wind farm production, the day ahead and real-time price are considered as a number of scenarios. For the *second* category, forecasting techniques have been used for providing additional information to increase players' bidding strategy efficiency. Forecasting techniques help scenario-based methods to generate and to consider more accurate scenarios. Market price prediction [4–7] and system load forecasting [8–12] are some of the most applied techniques in this regard. The literature of the third category mostly has been focused on the estimation of the market players aggregate supply curve based on available data. The importance of providing an accurate estimation of the aggregate supply curve and its significant impact on the improvement the bidding strategy discussed in [1] comprehensively. Crespo [13] proposes a bid function equilibrium model to predicting the supply curves of participants based on their marginal costs. However, this information is not available in real electricity markets. Ruiz *et al.* [14] proposed an inverse optimisation method in order to estimate the market players' historic bids which could be used to estimating the aggregate supply curve. This paper assumed that the market players' technical characteristics and power allocated to them are available. Based on our best researches, in practice, this information is confidential. Mitridati and Pinson [1] proposed a Bayesian inference approach to estimate the net aggregate supply curve based on practically available data. The mentioned paper has modelled the electricity market mechanisms with a hidden Markov model and has considered the net aggregate supply curve as a hidden state and spot prices and the total electricity traded as observed states.

In this paper, we propose a novel approach in order to modelling the competitors' behaviour from the perspective of an

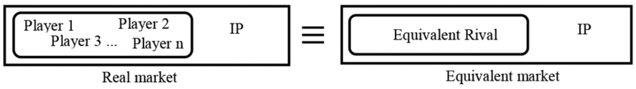

Fig. 1 *Real market and equivalent market*

intended player (IP) and estimating the competitors' aggregate supply function which will result in estimating the net aggregate supply curve. To this end, the paper proposes the novel concept of ER, accompanied by a new modelling procedure for the behaviour revealing of the competitors. We will show that this approach can estimate the net aggregate supply curve more accurately than the proposed method in [1] based on simulation results. Also, the market-clearing price (*MCP*) and the allocated power of IP will be predicted with high accuracy using the proposed approach. Furthermore, we use the obtained model to optimise the bidding strategy of the IP and show the superiority of this method compared with a fuzzy *Q*-learning based approach. The major contributions of this paper are

- Modelling and revealing the behaviour of competitors from the viewpoint of an IP by defining the ER concept.
- Estimate the net aggregate supply curve and compare the result with the Bayesian inference approach proposed in [1].
- Overcoming the information uncertainty regards the competitors' behaviour.
- Predicting *MCP* and allocated power of IP.
- Propose an optimal bidding strategy and compared the results with a fuzzy *Q*-learning-based approach.

The rest of the paper is organised as follows: In Section 2, the concepts of equivalent rival and equivalent market are presented. The two-stage ANN-based bid revealing procedure is provided in Section 3. In Section 4, the effectiveness of the proposed approach is examined in two case studies. Finally, in Section 5, the overall conclusion of the paper is presented.

2 Equivalent rival and equivalent market concepts

The purpose of this paper is to provide an approach to reveal and model the behaviour of market competitors from the perspective of an IP based on practically available data. To this end, we introduce an ER concept. We model the behaviour of the IP and its ER in an equivalent market, as shown in Fig. 1. ER's corresponding actions in the equivalent market reflect the aggregation of all of the competitors' behaviour in the real market. In other words, determining the ER bidding strategy is equal to modelling the competitors' behaviour. From the perspective of IP, this approach models the real market with the unknown number of players to an equivalent market with two completely known players, i.e. IP and its ER.

The actions of ER must be modelled in a way that the results of the equivalent market-clearing are almost equal to those of the real market. In order that the proposed approach is comparable with the approach proposed in [1], we focused on the same electricity market. Therefore, without loss of generality, the proposed approach is applied to an hour-ahead market and we neglect transmission constraints, ramping limits and unit commitment variables. Also considered electricity market is one-sided (i.e. only producers offer their bids) and it is assumed that the players submit their bids based on the total demand ($P_{D,h}$).

Assume n producers (players) participate in the real electricity market. Each player, according to the cost function, offers the bid $(a_{i,h}, b_{i,h})$ in the real market. Afterwards, Independent System Operator (ISO) clears the real market by solving the following conventional optimisation model to maximise social welfare

$$\min_{P_{i,h}} . \sum_{i=1}^{n} a_{i,h}P_{i,h}^2 + b_{i,h}P_{i,h} \tag{1}$$

$$\text{s.t.} \quad \sum_{i=1}^{n} P_{i,h} = P_{D,h} \quad \forall h \tag{2}$$

$$P_{i\min} \le P_{ih} \le P_{i\max} \quad \forall h, \forall i \in \{1, 2, \ldots, n\} \tag{3}$$

Equations (1)–(3) expressed total generation costs, the balance between generated and consumed power, and power generating limits of each player, respectively. The ISO determines the power allocated to each player by solving the optimisation model expanded in (1)–(3) and calculates the *MCP* based on the Lagrange coefficient. In the equivalent market, we consider two players: IP and ER. Market clearing model of the equivalent market is as

$$\min_{P'_{i,h}} . \sum_{i \in \{J, \mathrm{eqr}\}} a_{i,h}P'^2_{i,h} + b_{i,h}P'_{i,h} \tag{4}$$

$$\text{s.t.} \quad \sum_{i \in \{J, \mathrm{eqr}\}} P'_{i,h} = P_{D,h} \quad \forall h \tag{5}$$

$$P_{i\min} \le P'_{i,h} \le P_{i\max} \quad \forall h, \forall i \in \{J, \mathrm{eqr}\} \tag{6}$$

As the equivalent market is the equivalent of the real market, the optimisation problem extended in (4)–(6) is equivalent to the optimisation problem extended in (1)–(3) and the solution of both optimisation problems should be approximately equal. It means that

$$P'_{j,h} \simeq P_{j,h} \quad \forall h \tag{7a}$$

$$\mathrm{MCP}'_h \simeq \mathrm{MCP}_h \quad \forall h \tag{7b}$$

$$P'_{\mathrm{eqr},h} = P_{D,h} - P'_{j,h} \simeq P_{D,h} - P_{j,h} \quad \forall h \tag{7c}$$

The proposed approach should reveal competitors' behaviour based on practically available data for the IP. So we assume that the total electricity traded ($P_{D,h}$), MCP_h and power allocated to the IP ($P_{j,h}$) at each hour are the only available data. As shown in (7c), since there are only two players in the equivalent market, knowing total electricity traded and power allocated to the IP, the power allocated to ER is known too. Since the ER is not a real market player, we determine its characteristics based on our needs. Therefore the limits of power production of ER should set in a confident interval, which ensures that the IP and the ER as the only producers of the equivalent market are able to supply the system demand in any situation. For this purpose, the minimum power production limit of ER could be considered as zero and its maximum power production limit should be considered an arbitrary value larger than the maximum expected demand of the system which could determine based on our pre-knowledge about the power system. Therefore, the characteristics of the equivalent market in comparison to the real market are as follows: In the real market, there are n market players, which IP is not aware of the number of them, their characteristics and power allocated to them. However, in the equivalent market, there are two participants (IP and its ER) which IP is aware of the number of them, their characteristics and power allocated to them for all previous hours. This is the major advantage of ER and equivalent market concepts which make possible revealing the ER's bids from the results of the market-clearing. This is not possible in the real market because of the lake of information. As ER's corresponding actions in the equivalent market reflect the aggregation of all of the competitors' behaviour in the real market, revealing and modelling the ER's bidding strategy is equal to modelling the competitors' behaviour. To this end, we propose a two-stage ANN-based approach for estimation and prediction of ER's bids.

3 Equivalent rival's bid revealing

In this section, a two-stage ANN-based procedure is devised to reveal the ER's bidding strategy. At the first stage, ER's bids of the previous hours are estimated based on corresponding available data of the real market. The data obtained from the first stage (bid

$$[a_{J,h}, b_{J,h}, P_{J,h}, P_{D,h}, MCP_h] \rightarrow \boxed{\text{Bid Estimator}} \rightarrow [a_{eqr,h}, b_{eqr,h}]$$

Fig. 2 *Input–output diagram of the ANN-based bid estimation for h < H (first stage)*

$$[\, P_{D,H} \,] \rightarrow \boxed{\text{Bid Predictor}} \rightarrow [a_{eqr,H}, b_{eqr,H}]$$

Fig. 3 *Input–output diagram of the ANN-based bid predictor for hour H (second stage)*

estimation) is used for training a bid predictor. At the second stage, ER's bids of the next hour are predicted using the bid predictor and equivalent market-clearing results are calculated based on these predicted bids which are a prediction of real market clearing results for the next hour.

3.1 First stage: bid estimation

This stage aims to estimate the bid parameters of ER for the previous hours ($h < H$) in a way that the equivalent market (4)–(6) becomes equivalent to the real market (1)–(3). For this purpose, the bid parameters of the ER should determine in a manner which the equalities in (7) are satisfied. On the other side, as described in Section 2, if the results of equivalent market-clearing are available, estimation of the bid parameters of ER is possible. As the total electricity traded ($P_{D,h}$), MCP_h and power allocated to the IP ($P_{j,h}$) are available for all previous hours, according to (7), the complete results of equivalent market clearing are available for the IP. Therefore the IP could estimate the bid parameters of ER for all previous hours using an ANN which is named bid estimator. Fig. 2 shows the input–output diagram of the devised bid estimator. Enough pairs of inputs and corresponding outputs need to train the bid estimator. To this end, the optimisation model of (4)–(6) is solved for an arbitrary number of random bids and demands ($a_{\mathrm{J},h}, b_{\mathrm{J},h}, a_{\mathrm{eqr},h}, b_{\mathrm{eqr},h}, P_{D,h}$). After obtaining the results of all optimisation runs ($P_{J,h}, P_{\mathrm{eqr},h}, \mathrm{MCP}_h$), the pairs of input–output of the bid estimator are formed and used to train the ANN. Additionally, careful considerations should be given to the topology architecture of the ANN. Note that the simulation of the equivalent market for random bids is possible because the characteristics of equivalent market players are known.

3.2 Second stage: bid prediction

The aim of this stage is to design an ANN to predict the bid parameters of the ER at the current hour and the next hours ($h \geq H$). This ANN is named a bid predictor. To design the bid predictor, we need the historic bids of the ER. Using the bid estimator designed in Section 3.1, we can estimate the bids of ER for all previous hours. In order to predict the ER's bid parameters, we need to find the relationship between the bid parameters as dependent variables and some independent parameters which could have an effect on market players' behaviour. Bids of a player depend on the total demand and behaviour of its competitors. Assuming that each player submits its optimal bid in each load considering bids of its competitors, it can be assumed that the players submit their bids based on the total demand ($P_{D,h}$). In this regard, demand is considered as the input of the devised bid predictor of Fig. 3. As shown in Fig. 3, the output of the bid predictor consists of the slope and intercept of the bid function of the ER. Note that this assumption does not result in any loss of generality in the proposed approach since we can take into account any effective parameter without loss of efficiency of the bid predictor because of the high flexibility of neural networks. The bid predictor will be trained with the total demand of previous hours as training inputs and corresponding estimated bids as training outputs. Careful considerations should be given to the topology architecture of the ANN.

After training of the bid predictor, IP predicts the bids of ERs for hour H using the demand of hour H ($P_{D,H}$) as the input. Therefore, the supply function of the ER will be revealed ($SF_{\mathrm{eqr},H}(P_{\mathrm{eqr},H}) = a_{\mathrm{eqr},H}P_{\mathrm{eqr},H} + b_{\mathrm{eqr},H}$). As ER's actions in the equivalent market reflect the aggregation of all of the competitors' behaviour in the real market, the ER's supply function is an approximation of competitors' aggregate supply function.

After predicting the bid of ER at hour H, the following bi-objective optimisation model is solved to obtain the optimal bid of IP ($a_{J,H}, b_{J,H}$) in the equivalent market:

$$\text{Max} \quad P'_{J,H} \cdot \mathrm{MCP'}_H - C_{J,H}(P'_{J,H}) \tag{8}$$

$$\text{s.t.} \quad (4)-(6) \tag{9}$$

where $C_{J,H}(\, P'_{J,H})$ is the cost of producing energy of IP at hour H. Ass the results of the equivalent market are approximately equal to those of the real market, the optimal bid in the equivalent market will be optimal in the real market too. As the market players' behaviour may change because of several non-predictable reasons, it is necessary to have an adaptation mechanism that detects the change of holistic behaviour of market competitors and renovation the obtained model of competitors' behaviour. For this purpose, at the end of each day (24 h), the IP compares the announced results of the real market with the predicted value of them and calculate the Mean Absolute Percentage Error (MAPE) for predicted parameters. While the MAPE of the announced results and predicted value of them are less than threshold values (in this paper 5% for power allocated to the IP and 2.5% for MCP), it means that the holistic behaviour of competitors is not significantly changed and the obtained model is reliable yet. Otherwise, the process of detecting the ER's bids and training the bid predictor should be repeated using the announced results of the last 24 h. Therefore, the proposed approach is an adaptive approach and it is fully robust against non-predictable changes in market player behaviour. Fig. 4 shows the flowchart diagram of the proposed approach.

4 Tests and results

The effectiveness of the proposed approach has been examined in two different case studies in this section. In the first case study, the aggregate supply curve of a market with 12 players has been obtained using the proposed approach and the result has been compared with the Bayesian inference approach proposed in [1]. In the second case study, a six-players electricity market is considered. The competitors' behaviour has been revealed from the perspective of an IP using the proposed approach and the bidding strategy of the IP has been optimised based on that. The results have been compared with those of the fuzzy *Q*-learning-based optimal bidding strategy proposed in [15]. As the real data on bid parameters and supply functions of market participants' are not available, we use the simulated markets in both case studies.

4.1 First case study: obtaining aggregate supply curve

The first case study is the modified version of the IEEE 24-bus system with 12 thermal generators, and 6 200 MW wind farms, as considered in [1]. The technical characteristics of players, supply function of each, simulation period, load profiles, total wind production, and spot prices (*MCP*) over the simulation period are exactly the same as [1]. The authors in [1] modelled electricity market mechanisms using a hidden Markov model (HMM). They modelled the spot prices and total electricity demand (available data) as the observed states and net aggregate supply curve as the hidden states of the system and presented a Bayesian inference algorithm to approximate the posterior distribution of the aggregate supply curve. Then they obtained the average of estimated aggregate supply curves of several hours, which is an approximation for the average net aggregate supply curve and compared it with the real net aggregate supply curve.

In this subsection, we use the proposed approach to reveal the competitors' behaviour from the perspective of player1 which is named g1 in [1]. Therefore the characteristics of player1, its bid parameters and power allocated to it are available with total electricity traded and *MCP* for all hours of the simulation period. In order to reveal the competitors' behaviour, after organising the

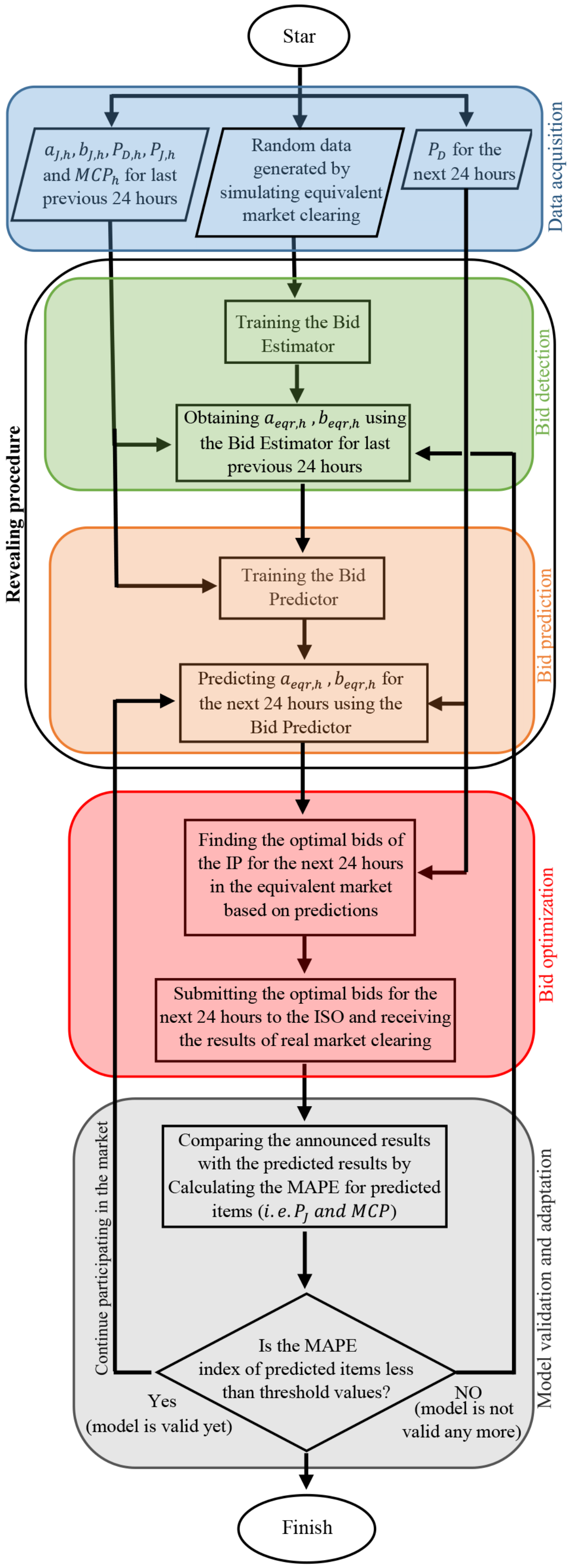

Fig. 4 *Flowchart diagram of the proposed approach*

equivalent market, we have designed a two-layer perceptron with 25 neurons in the hidden layer as the bid estimator and have trained with the Levenberg–Marquardt algorithm as described in Section 3. Using this bid estimator, we estimate the bid parameters of the ER for all hours of the simulation period. In order to evaluate the performance of the bid estimator, we have done the equivalent market-clearing using estimated bids and corresponding demand

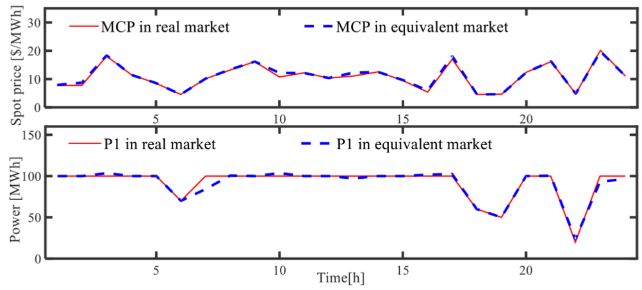

Fig. 5 *Comparison of power allocated to player1 and Spot price (MCP) in the real market and equivalent market*

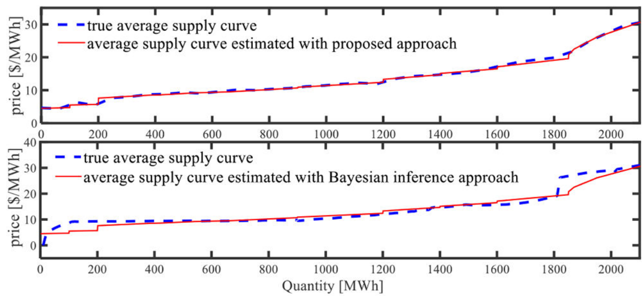

Fig. 6 *Comparison of the true aggregate supply curve and estimated aggregate supply curve with the proposed approach and Bayesian inference algorithm*

and bids of player1 for a 24 h period for example. A comparison of the results of equivalent market clearing with corresponding results of real market clearing shows the precision and performance of the bid estimator. This comparison is shown in Fig. 5. As illustrated in Fig. 5 the results of the equivalent market are approximately equal to the real market, which means that the ER's behaviour is approximately equal to real competitors.

In order to provide a numerical index for measuring the accuracy of the estimation, the MAPE presented in follows is used:

$$MAPE(P_1)[\%] = \frac{1}{24}\sum_{h=1}^{24}\frac{|P_{1,h} - P'_{1,h}|}{P_{1,h}} \tag{10}$$

$$MAPE(MCP)[\%] = \frac{1}{24}\sum_{h=1}^{24}\frac{|MCP_h - MCP'_h|}{MCP_h} \tag{11}$$

Based on the simulation results the *MAPE* value for the power allocated to player1 is 1.8%, and for *MCP* is 1.27%, which confirms the effectiveness of the equivalent market approach to modelling the competitors' behaviour.

Know we are ready to estimate the posterior net aggregate supply curve and compare the result with the result of the Bayesian inference algorithm. We have the estimation of the ER's supply function for all hours of the simulation period (720 h). On the other side, we know the bid parameters' of player1 as the IP too. So we have the supply functions of both players of the equivalent market for all hours of the simulation period, which means that we have the aggregate supply functions of the equivalent market. The net average aggregate supply function is an average of the aggregate supply functions of several hours. Fig. 6 shows the comparison of the true average aggregate supply curve and the estimated average aggregate supply curve using the proposed approach and Bayesian inference algorithm.

As illustrated in Fig. 6, the proposed approach has estimated the average of the net aggregate supply curve with appropriate accuracy which is obviously more accurate than the estimation provided by the Bayesian inference algorithm. Based on the simulation results, the MAPE value for the proposed approach is 1.53%, and for Bayesian inference algorithm is 5.77%.

Table 1 Characteristics of the market players

	β, \$/Mwh	α, \$/Mw^{2}h	P_{max}, Mw	P_{min}, Mw	Bid set, \$/Mwh
player1	20	0.20	800	0	{20,25,30,35,40}
player2	17.5	0.175	800	0	{20,25,30,35,40}
player3	30	0.25	400	0	{30,35,40}
player4	10	0.625	500	0	{10,15,20,25,30,35,40}
player5	30	0.25	300	0	{30,35,40}
player6	32.5	0.0834	550	0	{35,40}

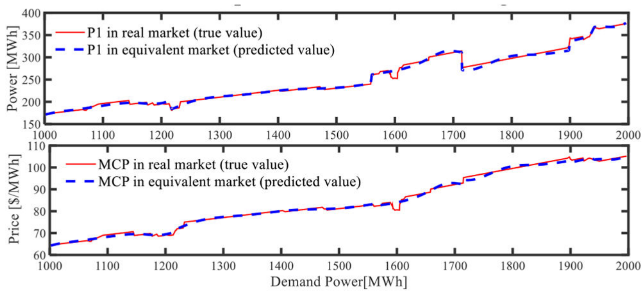

Fig. 7 *Comparison of power allocated to player1 and MCP in the real market (true values) and equivalent market (predicted values)*

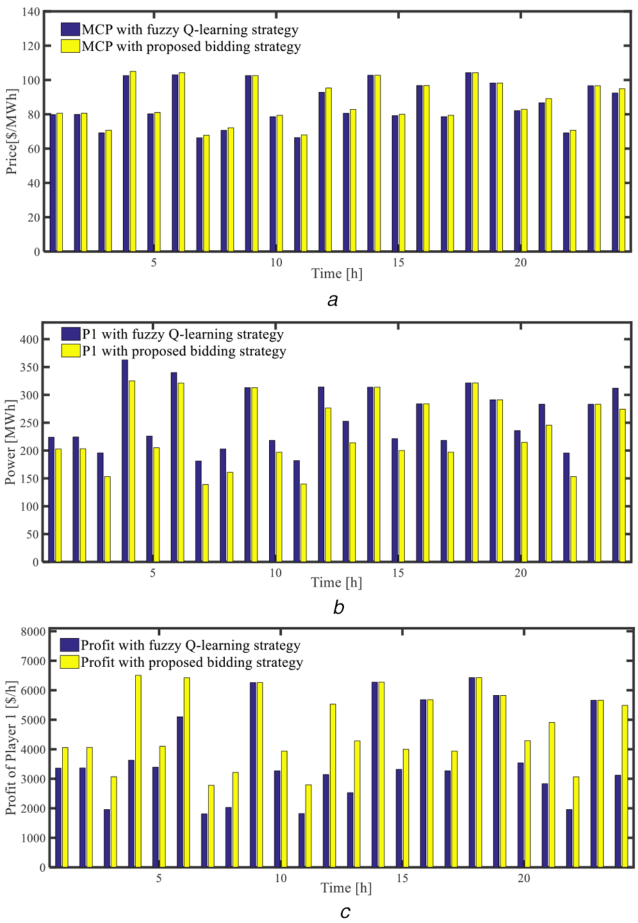

Fig. 8 *Comparison of MCP, power, and profit of player 1 based on fuzzy Q-learning and the proposed approach for a 24-hour period*
(a) MCP, ***(b)*** Power allocated to player 1, ***(c)*** Profit of player 1

4.2 Second case study: obtaining optimal bidding strategy

In the previous case study, the bid parameters of players were stochastic variables; therefore, the prediction of them was not possible. In order to evaluate the performance of the proposed approach in modelling and predicting the competitors' behaviour in this subsection, a market with strategic players is considered. For this purpose, the IEEE 30-bus test system [15] with six 150 MW wind farms and six thermal producers (players) are considered. It is assumed that the wind farms are not strategic players and just thermal producers strategically participate in the market. Table 1 shows the technical characteristics of the market players. Demand power assumed to be variable between 1000 and 2500 MW randomly. Same as the first case study we consider a European market without transmission constraints and use historic wind production factors from Nord Pool witch has shown in [1] for a 30 days period. In order to simulate an hour-ahead competitive electricity market, we use the fuzzy Q-learning approach proposed in [15]. It is assumed that the learning and exploration rate of all competitors is the same and is equal to 0.1. Therefore, each player competes in the market using the optimal bidding strategy learned from fuzzy *Q*-learning. In this case study, player1 is considered as IP which will change its bidding strategy using the proposed approach. Therefore, the characteristics of player1, its bid parameters and power allocated to it are available with total electricity traded and *MCP* for all previous hours. Player1 wants to reveal and model the competitors' behaviour using available data of previous hours and use this model to predict competitors' behaviour and market clearing results for the next hours and optimise its bid based on this additional information. For this purpose, as described in Section 2, in the first step, the equivalent market is organised from player1 perspective. Then, we have designed a two-layer perceptron with 25 neurons in the hidden layer as the bid estimator and a two-layer perceptron with 5 neurons in the hidden layer as the bid predictor and provide training data for them as described in Section 3. Both of the ANNs have trained with the Levenberg–Marquardt algorithm. Now, palayer1 can use the bid predictor to predict the competitors' behaviour which is reflected in ER's bid parameters. As shown in Fig. 3, the bid predictor takes the demand of hour H ($P_{D,H}$) as input and provides the bid parameters' of ER ($a_{\text{eqr},H}, b_{\text{eqr},H}$). Player1 optimise its bid in the equivalent market based on these predicted bids by solving the bi-objective optimisation model proposed in (8) and (9). Ass, the results of the equivalent market, are approximately equal to those of the real market, the optimal bid in the equivalent market will be optimal in the real market too. On the other side, the results of the equivalent market will be a prediction of those of the real market. The results of the clearing of the real market (true values) and clearing of the equivalent market (predicted values) are obtained for 500 different hours and shown in Fig. 7. The comparison of results shows that the equivalent market provides a precise approximation for the real market in this case too.

Also, the MAPE presented in (10) and (11) is used to measure the accuracy of the prediction. By using the simulation results, which have been shown in Fig. 7, the MAPE value for the power allocated to player1 is 3.06%, and for *MCP* is 1.65%, which confirms the effectiveness of the equivalent market modelling.

Fig. 8 compares the *MCP*, power allocated to player1 and its profit while it uses the method proposed in this paper, and when it uses the optimal bidding strategy learned from fuzzy *Q*-learning for a 24 h period. The results show that, in most of the hours, our proposed approach is superior in comparison to the fuzzy *Q*-learning approach. In Table 2, the average values of the power allocated to player1, the *MCP*, and the profit of player1 for these two approaches are brought and compared. The results show a 25.7% of profit increase while player1 uses the proposed approach of this paper.

Note that the fuzzy *Q*-learning based strategy has learned in a learning process with 8000 iterations. Therefore, it expends about one year in an hour ahead market to learn this strategy while the

Table 2 Comparison of market outcomes for a 24-hour period

Applied bidding strategy	Bidding strategy based on fuzzy *Q*-learning	Bidding strategy based on the proposed approach
power allocated to player1, MW	258.16	234.52
MCP, \$/MWh	85.80	86.90
profit of player 1, \$	3731	4690

proposed strategy used the data of a 24 h period to provide training data for the bid predictor. Therefore, it expends just one day in an hour ahead market to learn this strategy, which is an important advantage for the proposed approach especially for players who are just about to enter the market.

5 Conclusion

This paper introduced the concept of ER and the equivalent market from the perspective of an IP. ER competes with IP in the equivalent market. The output of the equivalent market-clearing procedure conforms to those of the real market. The behaviour of ER in the equivalent market is a model of aggregate competitors' behaviour in the real market and is used to predict the result of the real market and to provide the optimal bidding strategy. A two-stage ANN-based procedure for revealing the competitors' behaviour in the electricity market was designed. The proposed approach examined in two different case studies. In the first case study, the aggregate supply curve of a market with 12 participants obtained using the proposed approach and the result compared with the Bayesian inference approach. The simulation results show that the estimation of the net aggregate supply curve provided by the proposed approach is more accurate than those of the Bayesian inference approach. In the second case study, a six-participant electricity market is considered. The competitors' behaviour revealed from the perspective of an intended player using the proposed approach and constructed an optimal bidding strategy based on the proposed approach. The results have been compared with those of the fuzzy Q-learning-based optimal bidding strategy. Simulation results showed the effectiveness of the proposed approach in modelling competitors' behaviour and predicting *MCP*. Also, simulations proved the high efficiency of the proposed method in reaching the optimal bid. The results show 25.7% of profit increase while IP uses the proposed approach. In this paper, we focused on a one side market and neglect transmission constraints, ramping limits and unit commitment variables. In general case, it is possible to extend the proposed approach to a market with transmission constraints, ramping limits and unit commitment variables by expanding the equivalent rival to a market player with several consumption and production units that are located in different buses of the intended power system. In the future works, we develop the approach for the two-sided market in which transmission constraints are included in the market-clearing procedure.

6 References

[1] Mitridati, L., Pinson, P.: 'A Bayesian inference approach to unveil supply curves in electricity markets', *IEEE Trans. Power Syst.*, 2018, **33**, (3), pp. 2610–2620

[2] Baringo, L., Conejo, A.J.: 'Offering strategy of wind-power producer: a multi-stage risk-constrained approach', *IEEE Trans. Power Syst.*, 2016, **31**, (2), pp. 1420–1429

[3] Morales, J.M., Conejo, A.J., PÉrez-Ruiz, J.: 'Short-term trading for a wind power producer', *IEEE Trans. Power Syst.*, 2010, **25**, (1), pp. 554–564

[4] Alanis, A.Y.: 'Electricity prices forecasting using artificial neural networks', *IEEE Latin. Am. Trans.*, 2018, **16**, (1), pp. 105–111

[5] Ji, Y., Thomas, R.J., Tong, L.: 'Probabilistic forecasting of real-time LMP and network congestion', *IEEE Trans. Power Syst.*, 2017, **32**, (2), pp. 831–841

[6] Mosbah, H., El-hawary, M.: 'Hourly electricity price forecasting for the next month using multilayer neural network', *Can. J. Electr. Comput. Eng.*, 2016, **39**, (4), pp. 283–291

[7] Uniejewski, B., Weron, R., Ziel, F.: 'Variance stabilizing transformations for electricity spot price forecasting', *IEEE Trans. Power Syst.*, 2018, **33**, (2), pp. 2219–2229

[8] Ding, N., Benoit, C., Foggia, G., *et al.*: 'Neural network-based model design for short-term load forecast in distribution systems', *IEEE Trans. Power Syst.*, 2016, **31**, (1), pp. 72–81

[9] Li, S., Wang, P., Goel, L.: 'A novel wavelet-based ensemble method for short-term load forecasting with hybrid neural networks and feature selection', *IEEE Trans. Power Syst.*, 2016, **31**, (3), pp. 1788–1798

[10] Lin, W., Tu, C., Yang, R., *et al.*: 'Particle swarm optimisation aided least-square support vector machine for load forecast with spikes', *IET Gener. Transm. Distrib.*, 2016, **10**, (5), pp. 1145–1153

[11] Sun, X., Luh, P.B., Cheung, K.W., *et al.*: 'An efficient approach to short-term load forecasting at the distribution level', *IEEE Trans. Power Syst.*, 2016, **31**, (4), pp. 2526–2537

[12] Zeng, P., Jin, M.: 'Peak load forecasting based on multi-source data and day-to-day topological network', *IET Gener. Transm. Distrib.*, 2018, **12**, (6), pp. 1374–1381

[13] Crespo, J.G.: 'The theory of bid function equilibria and its application to spot markets for electricity'. Ph.D. dissertation, University of North Carolina at Chapel Hill, 2001

[14] Ruiz, C., Conejo, A.J., Bertsimas, D.J.: 'Revealing rival marginal offer prices via inverse optimization', *IEEE Trans. Power Syst.*, 2013, **28**, (3), pp. 3056–3064

[15] Salehizadeh, M.R., Soltaniyan, S.: 'Application of fuzzy Q-learning for electricity market modeling by considering renewable power penetration', *Renew. Sustain. Energy Rev.*, 2016, **56**, pp. 1172–1181