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# Profit maximization for an electricity retailer using a novel customers' behavior leaning in a smart grid environment

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**Abstract**

With the establishment of the smart grids platform, demand response (DR) programs have improved the operation and reliability of the power grid by increasing the participation of customers. This article investigates the issue of bidding strategy for an electricity retailer, which interacts with a set of residential customers. In this environment, the price-responsive customers react to the announced prices optionally. Thus, the retailer requires to learn the behavior of its customers. The proposed model enlisting the analytic hierarchy process (AHP) and a strength deep learning (DL) algorithm represents a pioneer study of applying a data-driven method into the bidding strategy problem. Herein, the energy usage patterns of customers in response to the dynamic pricing are firstly extracted, and a profit maximization problem of the retailer for the DR management is then developed with the consideration of the market constraints. The numerical results show the good performance of the proposed approach for improving the profitability of the retailer.


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*Keywords:* Analytic hierarchy process; Bidding strategy; Customers' behavior learning; Deep learning; Power market; Smart grids

## 1. Introduction

With the increasing electricity demand and the integration of new technologies in human life, the traditional electricity system is facing many challenges. Demand response (DR), a promising solution to address those challenges, provides an opportunity for consumers to play a significant role in the new smart grids [1]. Dynamic pricing is a kind of DR strategy, where the customers receive the time-variant prices according to the fluctuation of the wholesale market over time.

The models available in the existing literature on dynamic pricing based on DR programs usually take the assumption that customers are equipped with smart meters and there is an optimizer tool, i.e., there is a home energy

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management system (HEMS) that maximizes the comfort of customers or minimizes their energy payments [2–4]. Thus, the retailer has the ability to track the electricity usage behaviors of its customers. In the above references and in some others unlisted here to save the space, the main assumption is that the defined utility functions are maximized by the customers and then the prices are designed by the retailer according to the customers' utility functions. However, some customers may not choose such a scenario for various reasons, such as different lifestyles, economic and technical difficulties, and data privacy issues [5]. Without such HEMS employed, customers using two-way communication infrastructure are informed about the retail prices and subsequently respond to the prices according to their personal lifestyles, knowledge, and experiences which may not always result in the optimal operation. In this case, the retailer must learn the energy consumption patterns of price-responsive customers to maximize the profit [6]. Current publications on learning the energy consumption behavior of customers mostly focus on responsive load models, including linear, logarithmic, exponential, and potential demand functions or demand elasticity-based approaches [7–9]. In our previous work [10], we extracted the reaction of customers to the reported retail prices based on the aggregated load using a customers' behavior learning machine (CBLM) method.

In this paper, as a novel approach, the energy consumption pattern of the customers under the day-ahead prices is investigated by extracting the effective criteria on the reaction of customers based on the historical data. This is something that is missing in the existing approaches. Motivated by the above idea, a hybrid behavior learning model is applied to analyze how the retailer can determine dynamic retail prices while interacting with a set of price-responsive customers, to maximize the profit of the retailer and minimize the costs of customers.

The proposed model takes advantage of the analytic hierarchy process (AHP), one of the most important and comprehensive systems for multi-criteria decision-making, and deep learning (DL) network as a valuable development of artificial neural networks. The main idea of this model is that human knowledge alone, without the use of computer power, cannot extract the hidden relationships between historical patterns and, on the other hand, without considering human knowledge, artificial intelligence decisions reduce the accuracy of the results. To the best of our knowledge, this is the first paper that investigates a bidding strategy of a retailer based on the AHP + DL model to learn the energy consumption pattern of customers. The main contributions of this paper are fourfold:

- Employing a customer behavior learning framework to address dynamic pricing DR algorithm in a smart grid.
- Extracting the energy consumption pattern of price-responsive customers based on a hybrid learning model consisting of AHP and DL to forecast the day-ahead demand of the retailer under relevant market constraints.
- Learning the behaviors of customers and simultaneously forecasting the short-term load of the grid using the proposed model.
- Formulating the profit maximization model for the retailer based on the optimal day-ahead dynamic pricing in such a meaningful electricity market scenario where customers respond to the retail prices optionally.

The manuscript organization is as follows. The problem statement is examined in Section 2. In Section 3, the proposed model is described in detail. Section 4 includes the simulation results. Finally, the paper is concluded with some remarks in Section 5.

## 2. Problem statement

A residential power network based on a retailer and customers is considered. The retailer acts as an intermediary between energy producer companies and customers in the electricity market. It procures electricity from the wholesale market and sells it to the end-users [11]. The retailer can adaptively decide about retail prices with the consideration of both the energy consumption profiles of its customers and the cost of buying electricity from the wholesale market to maximize its profit. It is assumed that there is two-way communication between the retailer and its customers, and each customer can take the advantage of using a smart meter. In addition, it is assumed that the customers are not equipped with HEMS. The retailer announces the 24-h retail prices for the next day and the customers respond to the prices based on their lifestyle, knowledge, and experience, which does not always meet the optimal utilization of energy. As a result, the retailer is not aware of the reaction function of customers and needs to extract the energy consumption patterns of customers and then determines the optimal retail prices according to their behavior analysis. Because of this, a 'right' retail price designed by the retailer and in consequence the 'right' response from the customer can provide a win–win situation for both sides.

## 3. Proposed model

The main aim of this study is to support a retailer that serves a set of residential customers in the price-responsive environment of the smart grid. To this end, the retailer needs to design the optimal retail prices according to the reaction behaviors of its customers to the day-ahead prices. The more accurate forecasts of the consumption pattern of customers, the more suitably designed retail prices and thereby more profit for the retailer.

### 3.1. Customers' behavior learning

Using the historical load data and the effective factors influencing energy consumption, the reaction function of price-responsive customers is forecasted. Fig. 1 shows the proposed model for learning the behavior patterns of the customers to the retail prices. The proposed model consists of three main stages described as follows:

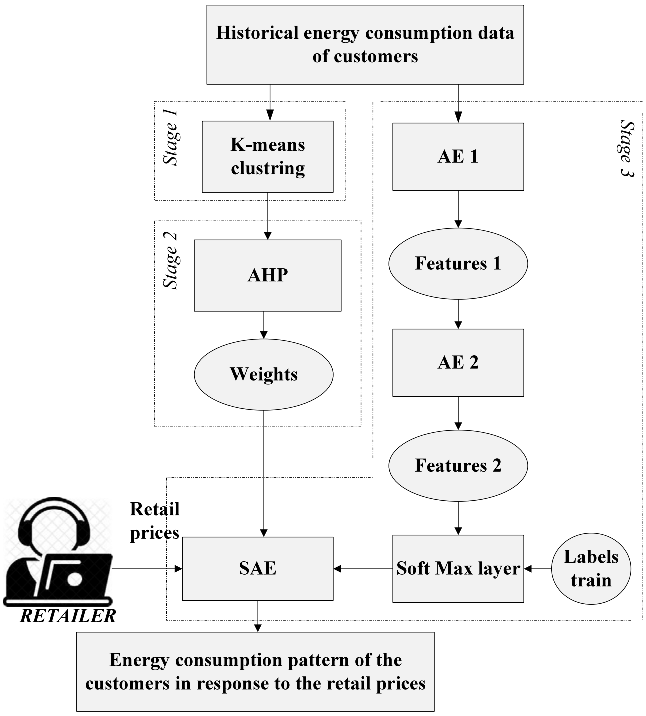


**Fig. 1.** Proposed model.

- **Stage 1.** K-means clustering:

K-means clustering is an effective unsupervised technique to collect similar data points and recognize the underlying patterns. To this aim, K-means seeks a fixed number $k$ of clusters in a dataset in a way that the members of each obtained cluster are as similar as possible to each other. The historical load data of a set of customers are clustered to $k = 5$ groups representing the energy consumption alternatives of a customer to the retail prices in a hierarchical manner.

- **Stage 2.** Analytic Hierarchy Process (AHP):

One of the most complete systems applied for multi-criteria decision making (MCDM) is the AHP, an intuitive technique for formulating decisions, introduced by El Saaty [12]. AHP is a practical way using an eigenvector calculation method widely used in decision-making for dealing with complex problems to select an optimal solution among the Pareto-front, evaluation, preparation, and forecasting issues.

The possibility of formulating the problem in a hierarchical way, the feasibility of considering different quantitative and qualitative criteria in the problem, and the ability to involve different options in decision-making and sensitivity analysis on the criteria are the main benefits of this decision-aiding tool. Besides, this method can facilitate judgment and computation because of its pairwise comparisons feature. The AHP is also able to express the degree of compatibility and incompatibility of the decision, which is a prominent feature of this method in solving MCDM problems. Finally, it is worth mentioning that this method has benefited from a strong theoretical basis and is based on axiom principles.

The hierarchy structure includes three main layers, namely a goal layer, the main criteria layer, and the alternatives layer, as illustrated in Fig. 2. In this paper, the goal is to extract and learn the energy consumption pattern of customers using four effective criteria on energy consumption, including the retail price, temperature, humidity, and time of usage. The four criteria are not dealt with equally; instead, the pairwise comparison matrix (CM) is applied for determining the significance of each criterion. The customers may react to the criteria by five alternatives, i.e., curtail, reduce, normal, increase, or the highest level of energy consumption. In this layer, the priority vector concerning the criteria for achieving the desired goal is computed by multiplying the input data of the alternative by the preference of its corresponding criterion. Finally, the optimal weight of the edges is obtained and the decision compatibility is examined.

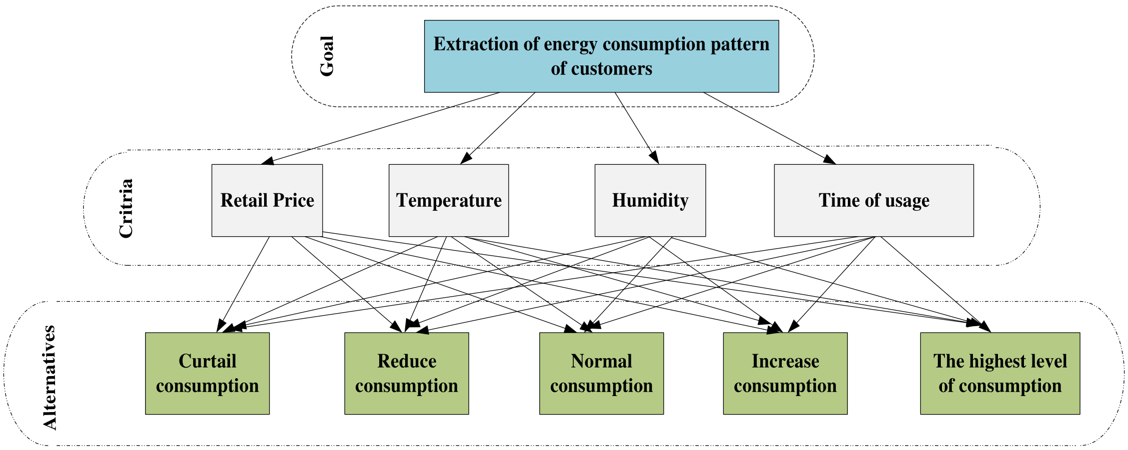


**Fig. 2.** Hierarchy structure.

In AHP, the elements of each level are compared in pairs to their respective higher-level elements and their weights are calculated as local priorities (normalized weights) for the alternatives for each criterion. Then, the final weight of each option is determined by integrating local priorities, which defines the global priorities (normalized weights) for the criteria in terms of their importance. After extracting the important criteria, an expert person (the decision-maker or manager, or a group of experts) examines the importance of each criterion with the other criterion in a pairwise comparison and the final judgment matrix is formed. Pairwise comparison among elements in the hierarchy is conducted with the use of a 1–9 scale explained in [12].

The results obtained by AHP in this step are applied to the DL network as the initial weight inputs. It is worthwhile to note that DL does not require prior knowledge of the problem to perform the learning task, but this method incorporates expert knowledge into the decision-making process in addition to the past information data.

• **Stage 3.** Deep Learning (DL) network:

DL networks are a subset of machine learning methods attempting to learn high-level features in data using structures formed by multiple non-linear transformations. The depth of these complex neural networks leads to better and more efficient training of the network than the traditional ones, e.g., multi-layer perceptron (MLP). While the universal approximation theorem [13] indicates that a single layer neural network can theoretically model any non-linear relationship, in practice, this capability is not always possible to achieve. In this situation, a deep network with more than one hidden layer can model the same relationships with fewer neurons.

In comparison to typical shallow neural networks, DL has more ability to learn non-linear relationships in deeper inner hidden layers of the network. The DL is initialized by an unsupervised Greedy layer-wise training and subsequently tuned by supervised training with labels that can progressively produce more abstract and high-level features layer by layer [14,15]. Among the available deep networks, the stacked auto-encoder (SAE) method is used herein to learn the energy consumption pattern of a set of customers so that the initial weights generated by AHP are considered as inputs of the SAE.

The SAE network stacks multiple auto-encoder (AE) layers together (see the workflow in Fig. 1). In this network, the output of the hidden layer of the first AE is considered as the input to the second AE to generate the optimized weight matrix of the encoder and decoder. It should be noted that the activation and decoding functions considered in the proposed approach are sigmoid and rectified linear units, respectively. Once all the hidden layers are pre-trained, fine-tuning the weights and bias is conducted by involving all the layers together using a supervised backpropagation (BP) algorithm. More information on the fundamental basis for the presented SAE method can be found in our previous work [10].

Eventually, the forecasted reaction function of a set of residential customers to the announced retail prices for the next 24-h is calculated by 24 iterative predictions.

### 3.2. Profit maximization of the retailer

The profit of the retailer is computed as the difference between the revenue of selling energy to the customers (customer cost/payment) and the electricity cost of buying energy from the wholesale market or service costs. The objective of the retailer is to achieve a set of retail prices ($\lambda_t$) at each hour $t \in \mathrm{T} = \{1, 2, \ldots, T\}$, where $T = 24$ is day-ahead dynamic pricing, based on the aggregated load of customers providing the optimal profit. In this paper, the following simple quadratic cost function is used as the cost of providing electricity at each hour $t$ for the retailer:

$$C_t(\tilde{L}_t) = a_t \tilde{L}_t^2 + b_t \tilde{L}_t + c_t \tag{1}$$

where $C_t(\tilde{L}_t)$ is convex and increasing in $\tilde{L}_t$ defined as the aggregated load of customers at each hour $t$ which should be provided by the retailer. Furthermore, $a_t > 0$, $b_t > 0$, and $c_t > 0$ for each hour $t$.

The minimum and maximum prices that the retailer can provide to its customers for each hour are:

$$\lambda_t^{\min} \le \lambda_t \le \lambda_t^{\max} \tag{2}$$

The maximum supply capacity ($S^{\max}$) of the tie-line between the retailer and customers for each hour $t$ should be higher than the reaction of customers to the retail prices. Thus,

$$\tilde{L}_t \le S^{\max} \tag{3}$$

A revenue cap ($R^{\max}$) for the retailer is the other market constraint that should be considered. Accordingly, the following constraint is taken into account:

$$\sum_{t=1}^{H=24} \lambda_t \times \tilde{L}_t \le R^{\max} \tag{4}$$

Finally, the profit maximization problem for the retailer who serves the price-responsive customers can be modeled as below:

$$\begin{aligned} &\max \sum_{t=1}^{T=24} \lambda_t \times \tilde{L}_t - C_t(\tilde{L}_t) \\ &s.t.\,(1)\,to\,(4)\,. \end{aligned} \tag{5}$$

Model (5) is a non-convex and non-linear problem that is not easy to be solved using conventional non-linear programming techniques. Thus, the particle swarm optimization algorithm (PSO) is used here to solve the above profit maximization problem for the retailer.

### 3.3. Solution algorithm

A hybrid approach is proposed to learn the energy consumption pattern of a set of price-responsive customers using a DL network equipped with a decision-making algorithm (e.g., AHP) that prioritizes between network input features and generates its initial weights. The whole process of the solution algorithm is shown in *Algorithm 1* and *Algorithm 2*.

| ***Algorithm 1:*** Profit maximization the retailer | ***Algorithm 2:*** Learning the energy consumption patterns of customers |
|---|---|
| 1. Generate initial population with $\rho$ particles randomly. Each particle represents a strategy of the retailer over the next 24h.<br>**for** $i$=1 to $\rho$ do<br>2. The retailer broadcasts the retail prices to its customers.<br>3. Through two-way communication of the smart grid, the responsive demand of the customers is received based on Algorithm 2.<br>4. Calculate fitness function and satisfy constraints (2) to (4).<br>**end for**<br>5. Create the new generation of particles.<br>6. Repeat steps 2-5 until the stopping condition is reached.<br>7. The retailer announces the retail prices to its customers. | • **AHP:**<br>1. Get the priority vector and get a pairwise CM.<br>2. Calculate AHP weights.<br>• **SAE:**<br>1. Pre-train the first AE with a hidden layer of size 20 and a linear transfer function for the decoder.<br>2. Extract the features in the hidden layer.<br>3. Pre-train a second AE using the features from the first AE.<br>4. Extract the features in the hidden layer.<br>5. Pre-train a softmax layer for classification using the extracted features.<br>6. Stack the encoders and the softmax layer to form a deep network.<br>7. Pre-train the deep network on the wine data and weight AHP.<br>8. Fine-tuning the weights and bias is performed to forecast the energy consumption of customers at hour $t$. |

## 4. Numerical results and analysis

It is assumed that each customer informed about the next 24-h prices in the evening before using a smart meter. In the proposed model, the retailer firstly learns the response of customers to the declared prices based on the historical data. Secondly, it optimizes the 24 h retail prices for the target day (here, 30 August 2019) according to the optimization and learning results on Nordpool market, a typical market structure in Europe, Zone DK2 [16].

To determine the weights of the deep learning network, a questionnaire was completed by a group of experts based on the Likert scale of the necessity and importance of each criterion affecting energy consumption. The numerical results for the factors affecting the energy consumption derived from a hierarchical analysis are retail price = 0.562, temperature = 0.183, time of the day = 0.168, and humidity = 0.0869. It can be concluded that the retail price is the most important criterion. In order to avoid saturation and over-fitting of the neurons in the SAE network, the input variables are normalized between 0 and 1. To evaluate the learning machine, the mean absolute percentage error (MAPE) is used as follow:

$$MAPE = \frac{1}{T}\sum_{t=1}^{T=24}\frac{\left|L_t^a - \tilde{L}_t^f\right|}{L_t^a} \times 100 \tag{6}$$

where $\tilde{L}_t^f$ and $L_t^a$ are the forecasted and actual load of the retailer, respectively.

The forecasted energy consumption on the target day is demonstrated in Fig. 3. It can be seen that the learning model can extract the behavior patterns of the customers and forecast the day-ahead demand of the grid with a low value of $MAPE = 4.21$.

For simplicity, $b_t = 0$, $c_t = 0$, and $a_t = 0.0004$ is considered in the retailer cost function. Fig. 4 also compares the original and optimal prices on the objective day. As can be seen, the optimal prices generated by the proposed model are more reasonable than the original prices according to the behaviors of customers and could achieve a higher profit on the target day. Furthermore, Fig. 5 provides a comparison between the revenue (payment of customers) and the profit of the retailer based in optimized and original prices. Fig. 5 clarifies that the optimal prices lead to a higher profit (2.75% increase) compared with the original prices. It can be concluded that increasing the knowledge of the retailer from its customers will enhance its profitability potential. On the other hand, the high responsiveness and sensitivity of customers to the prices announced by the retailer can minimize their payments. It is worth mentioning that since the optimal retail prices are determined based on the economical behaviors of customers, a lower payment for customers and higher profit for the retailer are expected [10].

By increasing the customers' knowledge and responsibility to the retail prices, the payoff of the customers will decrease, as well. In a similar manner, by increasing the retailer's insight of customers' reaction to the retail prices, the profit of the retailer will increase. Therefore, both the retailer and the customers can benefit from the proposed model.

## 5. Conclusion

The profitability and economic viability of a retailer are highly dependent on how to adopt real-time prices according to the energy usage patterns of customers. Through two-way communication between the retailer and

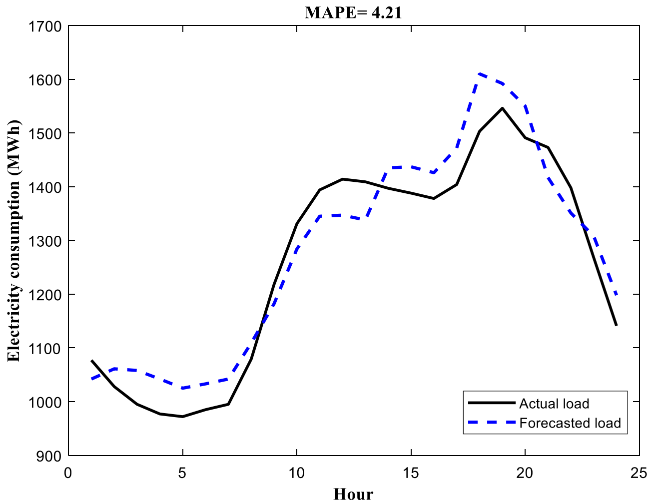


**Fig. 3.** Actual and forecasted load on the target day.

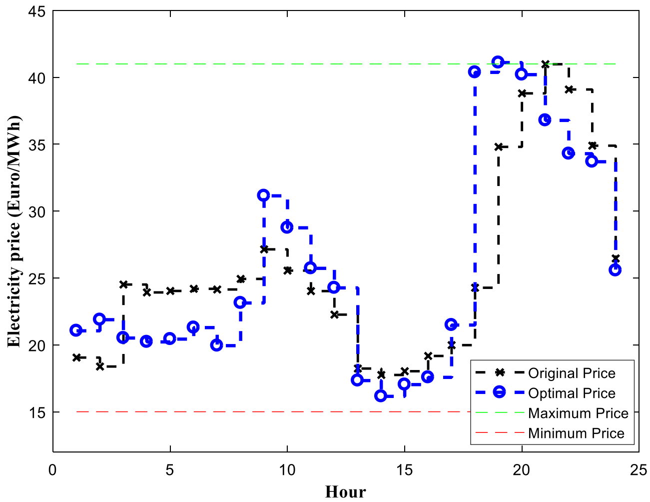


**Fig. 4.** Comparison between the optimized prices and the original prices on the target day.

customers, the customers are informed about retail prices and can adjust and manage their demand in response to the prices. The retailer has to learn their utility functions to maximize profit. In this paper, a new model using a hybrid AHP + DL (a combination of a decision-making approach and machine learning model) is considered. The more improvement in the learning model, the better decision-making ability and more profit achievement. The results show the effectiveness of the presented models and their potential to help the utility companies in market decision-making and pricing model design. The profit maximization of the retailer is performed using a PSO-based pricing optimization, demonstrating the profitability potential of the proposed model.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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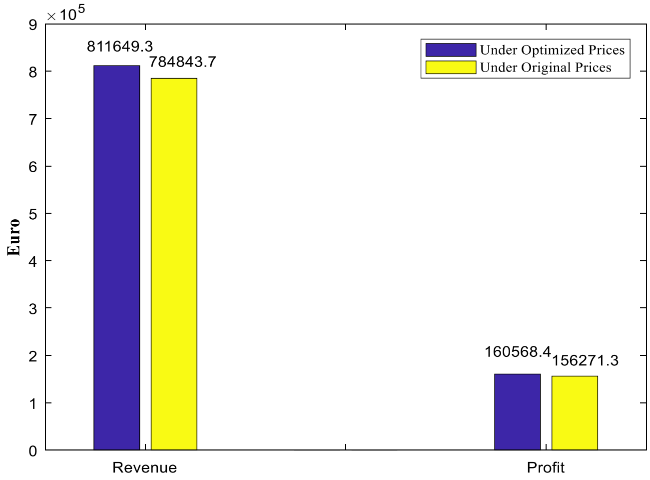


**Fig. 5.** Profit and revenue based on optimized and original prices.

## References


[1] Saeidpour E, Bahrami HR, Choi S. A low complexity and secure demand response technique for peak load reduction. IEEE Trans Smart Grid 2019;10(3):3259–68, 2019.
[2] Latifi M, Khalili A, Rastegarnia A, Sanei S. Fully distributed demand response using the adaptive diffusion–stackelberg. IEEE Trans Ind Inform 2017;13(5):2291–301, 2017.
[3] Chai B, Chen J, Yang Z, Zhang Y. Demand response management with multiple utility companies: A two-level game approach. IEEE Trans Smart Grid 2014;5(2):722–31, 2014.
[4] Mohsenian-Rad AH, Wong VW, Jatskevich J, Schober R, Leon-Garcia A. Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid. IEEE Trans Smart Grid 2010;1(3):320–31, 2010.
[5] Meng F, Zeng X. A profit maximization approach to demand response management with customers behavior learning in smart grid. IEEE Trans Smart Grid 2016;7(3):1516–29, 2016.
[6] Meng F, Zeng X, Zhang Y, Dent Ch J, Gong D. An integrated optimization + learning approach to optimal dynamic pricing for the retailer with multi-type customers in smart grids. Inform Sci 2018;4:215–32, 2018.
[7] Hosking J, Natarajan R, Ghosh S, Subramanian S, Zhang X. Short-term forecasting of the daily load curve for residential electricity usage in the smart grid. Appl Stoch Models Bus Ind 2013;29(6):604–20, 2013.
[8] Thimmapuram PR, Kim J. Consumers' price elasticity of demand modeling with economic effects on electricity markets using an agentbased model. IEEE Trans Smart Grid 2013;4(1):390–7, 2013.
[9] Ma Q, Meng F, Zeng X. Optimal dynamic pricing for smart grid having mixed customers with and without smart meters. J Mod Power Syst Clean Energy 2018;7(6):1244–54, 2018.
[10] Taherian H, Aghaebrahimi MR, Baringo L, Goldani SR. Optimal dynamic pricing for an electricity retailer in the price-responsive environment of smart grid. Int J Electr Power Energy Syst 2021;130:107004, 2021.
[11] Conejo AJ, Morales JM, Baringo L. Real-time demand response model. IEEE Trans Smart Grid 2010;1(3):236–42, 2010.
[12] Saaty LT. Decision-making with the AHP: Why is the principal eigenvector necessary? Eur J Oper Res 2003;145(1):85–91, 2003.
[13] Hornik K, Stinchcombe M, White H. Multilayer feedforward networks are universal approximators. Neural Netw 1989;2(5):359–66, 1989.
[14] Lago J, De Ridder F, De Schutter B. Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms. Appl Energy 2018;221:386–405, 2018.
[15] Zhang C, Patras P, Haddadi H. Deep learning in mobile and wireless networking: A survey. IEEE Commun Surv Tutor 2019;21(3):2224–87, 2019.
[16] Nord Pool market, Available online at: http://www.nordpoolspot.com.