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Research article

Optimization strategy of power purchase and sale for electricity retailers in a two-tier market

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ABSTRACT

Against the backdrop of the gradual advancement of China's electricity market reform, the number of Power Trading Companies in China has been increasing year by year, and as of October 2022, the number has reached more than 10,000. As an important hub connecting the electricity market and users, electricity retailers face double risks from downstream user load fluctuations and electricity market price fluctuations. Therefore, a reasonable power purchase and sale strategy is very important for an electricity retailer. In this study, a block bidding mechanism is adopted to optimize the clearing of the medium-to long-term market and a DA-RBF neural network is established for spot electricity price forecasting model based on numerical feature similarity to improve the accuracy of electricity price forecasting. Furthermore, the model considers the differences in user demand responses and investigates the optimal power purchase and sale strategy, guided by differentiated time-of-use electricity pricing. The case study analysis demonstrated that the proposed power purchase and sale optimization strategy yields favorable results, improving profitability and enhancing the stability of the power system.

1. Introduction

Power system reform has been an important issue in China in recent years, and the release of Several Opinions on Further Deepening the Reform of the Electricity System in March 2015 has opened a new round of power system reform in China [1]. The purpose of the reform is to "control the middle and liberalize the two ends", and the orderly liberalization of the power sales side of the market has become a major highlight of the reform. In recent years, the development of electricity marketization has taken its initial shape, and as an important hub connecting the electricity market and users, electricity retailers face double risks from downstream user load fluctuations and electricity market price fluctuations [2,3]. Therefore, how to determine reasonable power purchase and sale strategies and reduce the risks has become an urgent issue [4]. Many experts and scholars around the world have conducted in-depth research on such issue, which is mainly divided into two aspects: power purchase strategy and power sale strategy.

The power purchase strategy focuses on how to allocate power purchases from various channels to reduce the risks and increase the benefits of power purchases for electricity retailers [5]. Electricity retailers mainly purchase power through the medium to long-term market by signing medium to long-term contracts with power generators with a longer period, and they can also purchase electricity in the spot market.

The bidding mechanism in the medium to long-term market has a direct impact on the price and type of medium to long-term

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contract. Therefore, a scientific and reasonable bidding mechanism can ensure fair competition among competitors in the market. At present, countries around the world basically use the hourly bidding mechanism for electricity bidding and market clearing [6]. Ma et al. [7] proposed a block-of-use (BOU) electricity retail pricing addresses fairness and cross subsidy issues by varying prices within blocks instead of time periods in TOU pricing. Experts have proposed a block bidding mechanism [8] to address the issue of disregarding the physical characteristics of continuous electricity production and consumption in the traditional hourly bidding mechanism, which often results in increased generator start-ups and shutdowns [9]. This mechanism assigns different prices to different load segments according to their power quality, which has higher fairness and cost-effectiveness, and is more suitable for medium to long-term market transactions. While long-term contracts provide a reliable purchasing source, retailers still engage in the spot market to balance real-time load. To make optimal retail decisions, retailers must optimize their portfolio of forward contracts and spot market transactions [10].

Accurate spot electricity price forecasting is crucial for optimizing bidding strategies and maximizing profits in the spot market [11], which includes the day-ahead and real-time markets and is characterized by greater randomness and volatility [12]. Tan et al. [13] introduced a comprehensive bidding framework for a renewable energy aggregator, encompassing the day-ahead, intra-day, and balancing markets, utilizing a hybrid data-driven IGDT-RO scheme to effectively manage uncertainties. In addition to utilizing uncertainty models to handle the uncertainty of spot electricity prices, researchers have employed various approaches for spot electricity price forecasting, including traditional mathematical modeling methods [14,15] and artificial intelligence techniques [16,17]. Among them, Abdellatif et al. [18] proposed a hybrid deep learning model combining bidirectional LSTM and a CNN for short-term electricity price forecasting, and used linear bypass to solve the scale insensitivity problem. Pourdaryaei et al. [19] first used a combination of mutual information (MI) and a neural network (NN) to select input variables, and then built a hybrid forecasting model by combining an ANN and ACS. Tan et al. [20] utilized an improved complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) method to decompose complex data sequences, thereby enhancing the performance of a hybrid deep learning model.

From the above literatures, it can be observed that the focus of improving predictive model performance lies in the research of ensemble algorithms and data processing. In the same way, Sai et al. [21] proposed a methodology that leveraged numerical feature similarity to optimize the dataset, which was then integrated with the DA-RBF neural network for accurate spot electricity price forecasting. However, retailers procured a minimal amount of electricity from the real-time market, and the forecasting accuracy in this market was significantly lower compared to the day-ahead market. Therefore, this study focused solely on the day-ahead market when referring to the spot market.

On the other hand, the power sale strategies mainly aim to develop innovative sales methods or demand response mechanisms [22,23] to enhance the profitability of retailers and the benefits of users by guiding downstream customers to use electricity in a rational manner. This, in turn, improves the market competitiveness of electricity retailers.

Many scholars have conducted researches on price-based demand responses, most of which focused on time-of-use pricing (TOU) and real-time pricing (RTP). Kaur et al. [24] introduced a method for calculating time-of-use (TOU) electricity prices based on peak and off-peak contribution coefficients of electric vehicles (EVs), encouraging efficient demand response. Kong et al. [25] enhanced the accuracy of user demand response assessment by combining GRU, AM, and NTM, and proposed a Real-Time Pricing (RTP) scheme using DDPG algorithm with PER to optimize electricity pricing based on user reactions. Furthermore, there are a few studies focusing on improving demand response. Cortez et al. [26] proposed the Intraday Block Pricing (IBP) scheme, incentivizing demand response by considering consumption-blocks in shorter time-slots, aiming to minimize peak-to-average ratio. However, the above literature does not consider the differences of user behavior with different levels of rationality when facing the same demand response service. To simulate load variation accurately, Zhang et al. [27] introduced real-time elasticity and proposes a two-stage customized retail pricing design based on personalized demand response incentives for different residential users. Nevertheless, implementing individual pricing can lead to a complex optimization problem and face scalability challenges in practical scenarios [28]. Therefore, this study proposed a differentiated time-of-use (TOU) pricing approach, where users with similar consumption behavior were subject to the same TOU pricing, while users with different consumption behavior were subject to different TOU pricing. Moreover, based on the load change predictions for different demand response scenarios as outlined in Ref. [29], a sales optimization model was developed for the retailer, aiming to optimize the purchase and sale electricity strategies based on differentiated TOU pricing.

To summarize, the existing market trading mechanism ignores the continuous production characteristics of electricity. Electricity retailers face significant price fluctuation risks when designing power purchase and sale strategies. Additionally, time-of-use electricity pricing lacks differentiation for users with different electricity consumption behaviors. Taking these points into consideration, the main contributions of this paper can be summarized as follows.

(1) A two-tier market power purchase model is constructed, and the electricity retailer can take into account the allocation of power purchases in the medium to long-term market and the spot market, and improve the profit while ensuring the stability of revenue.
(2) In the spot electricity price prediction model, the numerical feature similarity method is introduced to optimize the dataset, which effectively improves the problem of low prediction accuracy of the algorithm due to the large amount of redundant data.
(3) The optimization strategy of power purchase and sale for the electricity retailer based on differentiated time-of-use pricing sets different electricity prices for different user groups, which can make the load curve smoother and the peak-to-valley difference smaller, thus improving the profit of power purchase and sale and increasing power system stability.

The reminder of the rest of the paper is as follows. Section 2 investigates the power purchase price forecasting method in the two-tier market, and establishes the medium to long-term market clearing model and a power price forecasting model for the spot market.

Section 3 considers differentiated TOU pricing and establishes an optimization model for power purchases and sales by electricity retailers. Section 4 validates the applicability of the block bidding mechanism, the superiority of the DA-RBF neural network spot electricity price forecasting model based on numerical feature similarity, and the effectiveness of the power purchase and sale optimization strategy based on differentiated TOU pricing through arithmetic examples. Section 5 concludes the whole paper.

2. Forecasting electricity purchase prices for electricity sold in the two-tier market

2.1. Medium to long-term market clearing price

2.1.1. Block bidding

The hourly bidding mechanism clears in a chronological order, allowing loads at the same time to have the same clearing price. China mainly focuses on thermal power generation, and thermal power unit generation requires high continuity, and the number of startups and shutdowns has a great impact on the operating costs of generating units. Secondly, the generation cost of the standby unit is higher, and it contributes more to the stable operation of the power system, and according to the principle of market fairness, the electricity of the standby unit should have a higher price. The block bidding mechanism divides the different load segments according to the different durations and then assigns different prices to different load segments according to their power quality. The more load segments there are, the fairer the price of electricity will be.

In unilateral block bidding, both generators and retailers need to bid and declare for each load segment. The generator needs to declare the offer step curve, i.e., different combinations of prices and capacities, for the bidding load segment. The electricity retailers need to declare the purchased capacity, i.e., the amount of electricity to be purchased, for each load segment. A large number of studies have been conducted by experts and scholars on the load segmentation approach, which shows that the medium to long-term market power purchase needs to be carried out in advance, as it is only necessary to simply divide the load into several segments, reflecting the differences in the load segments. Therefore, this study simply divided the load into five duration load segments: 24, 12, 8, 4, and 2h; according to the different starting times, the medium to long-term market has a total of 24 kinds of load segments to choose from, and the specific load segments are shown in Table 1. Such segmentation can better meet the needs of market participants and improve the efficiency and fairness of the market.

2.1.2. Medium to long-term market clearing methods

In block bidding, the medium to long-term market trading center uses the lowest cost of power purchase as the objective function to clear the market sequentially, and the mathematical model of the medium to long-term market clearing algorithm is as (1):

$$\min \sum_{l=1}^{N_l} T_l \sum_{gr=1}^{N_G} \sum_{r=1}^{N_r} \left(\beta_{r,l}^{ok} \cdot q_{gr,r,l} \right) \tag{1}$$

where T denotes duration; N_L denotes the total number of load segments; N_r denotes the total number of offer steps in the generator's bid curve; gr denotes the generator's serial number; β^{ok} denotes the market clearing price; and q denotes the winning capacity.

The clearing process is also subject to constraints on the functioning of the market. The specific constraints are.

① The load balance constraint is as (2):

$$\sum_{gr=1}^{N_G} \sum_{r=1}^{N_r} q_{gr,r,l} = q_{R,l} \quad l = 1, 2, \cdots, N_L \tag{2}$$

② The operating power constraint is as (3):

Table 1
The load segments within the block bidding mechanism.

Number	Load segment	Start and end time	Number	Load segment	Start and end time
1	24h_a	00:00–24:00	13	2h_a	00:00–02:00
2	12h_a	06:00–18:00	14	2h_b	02:00–04:00
3	12h_b	18:00–06:00 (next day)	15	2h_c	04:00–06:00
4	8h_a	00:00–08:00	16	2h_d	06:00–08:00
5	8h_b	08:00–16:00	17	2h_e	08:00–10:00
6	8h_c	16:00–24:00	18	2h_f	10:00–12:00
7	4h_a	00:00–04:00	19	2h_g	12:00–14:00
8	4h_b	04:00–08:00	20	2h_h	14:00–16:00
9	4h_c	08:00–12:00	21	2h_i	16:00–18:00
10	4h_d	12:00–16:00	22	2h_j	18:00–20:00
11	4h_e	16:00–20:00	23	2h_k	20:00–22:00
12	4h_f	20:00–24:00	24	2h_l	22:00–24:00

$$0 \le q_{gr,r,l} \le q_{gr,r,l}^{bid} \quad \mathrm{r} = 1, 2, \cdots, N_r \tag{3}$$

③ Climbing constraints is as (4):

$$\triangle q_{gr,l} \le \triangle q_{gr}^{\max} \tag{4}$$

Where q^{bid} denotes the bid capacity; $\triangle q$ denotes the climb increment; and superscript max denotes the maximum value.

The algorithmic flow of the medium to long-term market clearing based on block bidding is shown in Fig. 1.

The specific steps are as follows.

I. The electricity retailers divide the downstream customer loads into 24 load segments according to 1.1.1 in the order of the load segment serial number.
II. In load segment 1, a combination of all generators is made such that the total declared capacity of the combined generators needs to be greater than or equal to the capacity required for the Load Segment No., and the total declared capacity of the combined generators minus the declared capacity of the generator with the smallest declared price in the combination needs to be less than the capacity required for Load Segment No. 1.
III. The bids from power generators participating in each group are arranged in ascending order from lowest to highest.
IV. The medium to long-term market trading center clears the 24-h load segments sequentially.
V. The clearing price and the awarded capacity of the generators are output.

2.2. Spot electricity price forecasts

In order to reduce the influence of redundant data on the accuracy of electricity price forecasting, firstly, the similarity between the load curves in the test data and the load curves in the learning data is analyzed using combinatorial fuzzy closeness and the learning data are screened from high to low similarity. The filtered load-price learning data are used as the training set to train the DA-RBF neural network, and finally, the trained DA-RBF neural network is used to predict the spot electricity price of the test data.

2.2.1. Numerical feature similarity

A cloud model is a kind of uncertainty transformation model which represents the transformation relationship between qualitative and quantitative data based on the concept of a "cloud", which is proposed in Ref. [30]. As an uncertainty transformation model, the cloud model can not only generate quantitative cloud droplets from qualitative *Ex*, *En* and He numerical features of clouds, but it can also describe clouds qualitatively from quantitative cloud droplets through *Ex*, *En* and *He*. The models that accomplish both transformations are the forward and inverse cloud generators, respectively [31].

The forward generator generates more cloud droplets distributed in that cloud through the *Ex* , *En* and He numerical features of the cloud and the mathematical model of the forward generator is as (5)–(6):

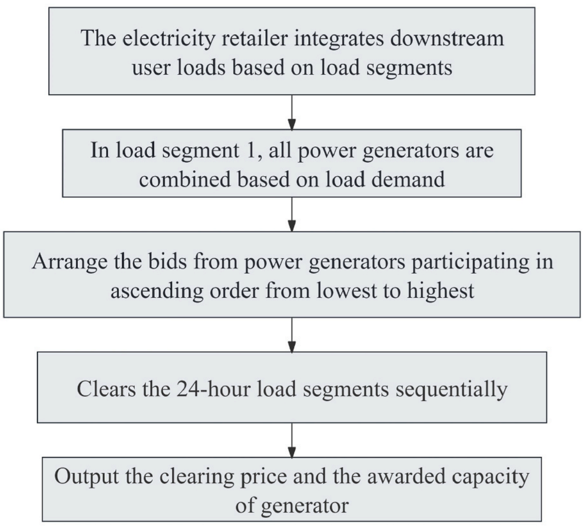

Fig. 1. The algorithmic flow of the medium to long-term market clearing based on block bidding.

$$f_{xi}(x) = \frac{1}{\sqrt{2\pi}|En|}\exp\left(-\frac{(x-Ex)^2}{2En^2}\right) \tag{5}$$

$$f_{En}(x) = \frac{1}{\sqrt{2\pi}|He|}\exp\left(-\frac{(x-En)^2}{2He^2}\right) \tag{6}$$

The inverse generator calculates the Ex, En and He numerical features of the cloud based on all the cloud droplets and the mathematical model of the inverse generator is as (7)–(10):

$$Ex = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{7}$$

$$En = \sqrt{\frac{\pi}{2}} \times \frac{1}{n}\sum_{i=1}^{n} |x_i - Ex| \tag{8}$$

$$He = \sqrt{S^2 - En^2} \tag{9}$$

$$S^2 = \frac{1}{n-1}\sum_{i=1}^{n} |x_i - Ex|^2 \tag{10}$$

In this study, the combined fuzzy closeness method was used to calculate the similarity between the load data in the learning data and the load curves in the test data based on the numerical features of *Ex*, *En* and He of all daily load curves [32], where the numerical features of the historical daily load curves are $\mathrm{Y_u}(Ex_u\ ,\ En_u\ ,\ He_u)$, the numerical features of the predicted load curves are Y_{P_r} $(Ex_{\mathrm{Pr}}\ ,\ En_{\mathrm{Pr}}\ ,\ He_{\mathrm{Pr}})$, and the specific formula for the similarity of their cloud droplet distribution $\delta(Y_u, Y_{\mathrm{Pr}})$ is as (11)–(12):

$$\delta(Y_u, Y_{\mathrm{Pr}}) = \frac{1}{2} + \frac{1}{2\varphi\left(\frac{\sqrt{2}|Ex_{\mathrm{Pr}} - Ex_u|}{\sqrt{En_u^2 + He_u^2} + \sqrt{En_{\mathrm{Pr}}^2 + He_{\mathrm{Pr}}^2}}\right)} - \varphi\left(\frac{\sqrt{2}|Ex_{\mathrm{Pr}} - Ex_u|}{\sqrt{En_u^2 + He_u^2} + \sqrt{En_{\mathrm{Pr}}^2 + He_{\mathrm{Pr}}^2}}\right),\ u = 1, 2, \cdots N_u \tag{11}$$

$$\varphi(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt \tag{12}$$

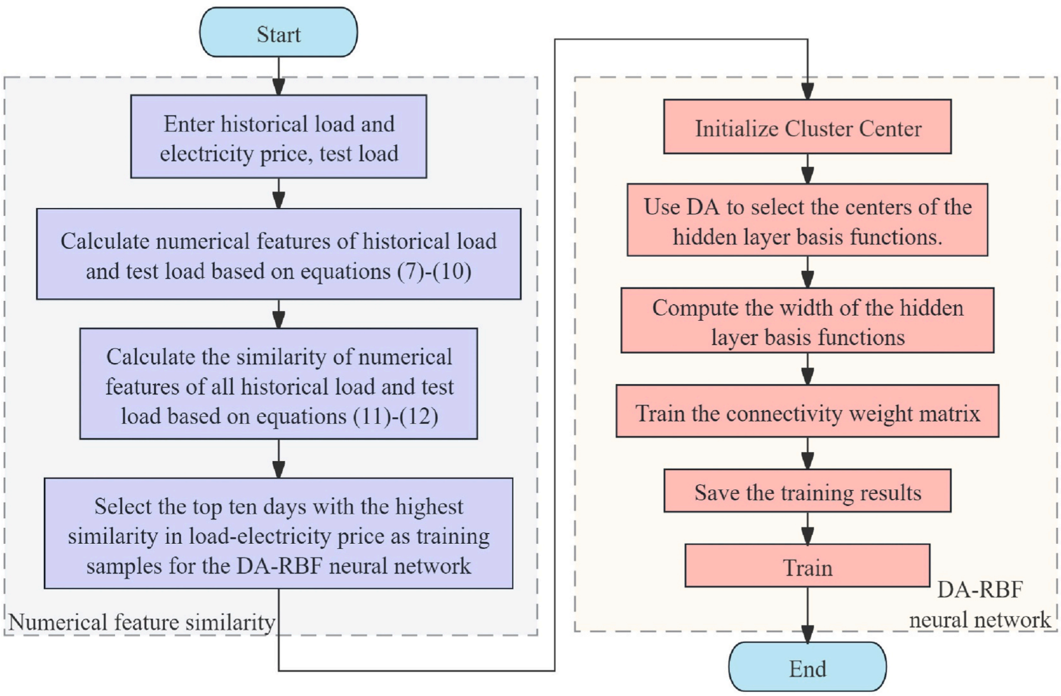

Fig. 2. Algorithm flow of spot electricity price forecasting by DA-RBF based on NFS.

In the formula, the subscript u denotes the serial number of the historical daily load curve; N_u denotes the number of the historical daily load curve; and the subscript P_r denotes the code of the forecast load curve.

2.2.2. Spot electricity price forecasting models

A radial basis function neural network (RBF) trained with optimization algorithms based on biogeography can fit any nonlinear function, and it exhibits a faster convergence speed and higher forecasting accuracy [33]. Hence, it is suitable for spot market electricity price forecasting. Therefore, in this study, the dragonfly algorithm (DA) was adopted to train the RBF neural network for forecasting spot electricity prices. The algorithm flow for spot electricity price prediction using the DA-RBF neural network based on numerical feature similarity (NFS) is illustrated in Fig. 2.

Inputs: All historical sample load values and their spot electricity price and forecast day load values.

Output: Spot electricity price on the forecast date.

Step 1. Calculate the numerical features of all input load profiles. The numerical features of the historical sample load profiles are ordered by natural numbers, i.e., Y1 (Ex1, En1, He1), N2 (Ex2, En2, He2), …, YNu (ExNu, EnNu, HeNu). The predicted daily load cloud model is YPr (ExPr, EnPr, HePr).

Step 2. Calculate the similarity between each historical sample load cloud model and the predicted daily cloud model $\delta(Y_u, Y_{\mathrm{Pr}})$.

Step 3. The loads and their spot prices for the ten days with the largest similarity $\delta(Y_u, Y_{\mathrm{Pr}})$ are selected as training samples to be input into the DA-RBF neural network.

Step 4. Train the DA-RBF neural network using the filtered learning data until the error is within the specified range.

Step 5. Input the forecast day load profile to the trained DA-RBF neural network to output the spot electricity price on the forecast day.

3. Optimization strategy for power purchases and sales for electricity retailers

In this study, taking into account the differences in users' electricity behavior, the K-means algorithm was used to cluster the users and divide the TOU pricing periods according to the typical daily load curves of different user groups; then, the TOU pricing of different user groups are used as the optimization variables, and the optimization model of electricity purchase and sale strategies for the electricity retailer is established with the maximization of the profit of the electricity retailer as the objective function.

3.1. K-means algorithm

In this study, the K-means algorithm was used to realize the clustering of users with different electricity usage behaviors; this algorithm has a faster convergence speed, better clustering effect, fewer parameters that need to be adjusted and stronger interpretability [34]. After clustering, the clusters of users with similar electricity consumption patterns can be guided to adjust the electricity behavior through the same TOU pricing, and the different clusters show the differentiated pattern of electricity consumption between the different clusters.

The Euclidean distance, i.e., the distance between the user curve $x_z = (x_{z1}, x_{z2}\ , \cdots x_{zN_m})$ and the clustering center $\mu_s\ =\ (\mu_{s1}, \mu_{s2}, \cdots, \mu_{sN_m})$, $d(x_z, \mu_s)\ \ (z = 1, 2, \cdots, N_I)$ is calculated publicly as (13):

$$d(x_z, \mu_s) = \sqrt{\sum_{m=1}^{N_m} (x_{zm} - \mu_{sm})^2} \tag{13}$$

In this study, five commonly used daily load characteristic indexes were selected to characterize the daily load curve for dimensionality reduction, and the individual clustering features and their significance are shown in Table 2.

3.2. Method of dividing time-of-use pricing periods

Peak and valley TOU pricing is a price incentive method in demand response, through setting high prices in peak hours and low prices in valley hours to incentivize users to adjust their electricity consumption behavior and realize peak shaving and valley filling.

Table 2
Clustering characteristics and their significance for classifying user electricity consumption behavior.

Characteristic	Formulas	Significance
Daily load factor	$q^{av}/q^{\max}$	Reflects load profile changes throughout the day
Peak-to-valley ratio	$(q^{\max} - q^{\min})/q^{\max}$	Reflects the difference between the maximum and minimum loads
Peak load factor	q^{peak}/q^{all}	Reflects the tendency of users to load during peak hours
Valley load factor	q^{val}/q^{all}	Reflects the tendency of users to load during the trough
Usual load factor	q^{flat}/q^{all}	Reflects the tendency of users to load during peak hours

Reasonable division of peak and valley time and TOU price is of great significance to demand response [35].

The half trapezoidal affiliation function is used to calculate the affiliation of each point on the load curve for the peak hours and for the valley hours with the following (14)–(15):

$$PK_{b_0}^{t}=\frac{q_{b_0}^{t}-q_{b_0}^{\min}}{q_{b_0}^{\max}-q_{b_0}^{\min}} \tag{14}$$

$$VL_{b_0}^{t}=\frac{q_{b_0}^{\max}-q_{b_0}^{t}}{q_{b_0}^{\max}-q_{b_0}^{\min}} \tag{15}$$

where $PK_{b_0}^{t}$ and $VL_{b_0}^{t}$ denote the peak affiliation and valley affiliation of user group b0 at time t, respectively; $q_{b_0}^{t}$, $q_{b_0}^{\min}$ and $q_{b_0}^{\max}$ denote the load value, minimum value and maximum value of the typical load profile of user group b0 at time t, respectively.

The peak and valley affiliations are used to cluster the points of the load curve to determine the peak and valley hours of the time-of-use pricing; the clustering method is the same as in Section 2.1, and the distance is calculated as (16):

$$\min d_{b_0}=\sqrt{\left(PK_{b_0}^{t_1}-PK_{b_0}^{t_2}\right)^2+\left(VL_{b_0}^{t_1}-VL_{b_0}^{t_2}\right)^2} \tag{16}$$

In the formula, d_{b_0} denotes the Euclidean distance between the loads at the moment of t_1 and the loads at the moment of t_2; t_2 denotes the moment of the center of clustering; $PK_{b_0}^{t_1}$ and $VL_{b_0}^{t_1}$ denote the affiliation of the loads at the moment of t_1 to the peak and the valley periods, respectively; $PK_{b_0}^{t_2}$ and $VL_{b_0}^{t_2}$ denote the affiliations of the center of clustering to the peak and the valley periods, respectively.

3.3. Power purchase and sale strategies based on differentiated TOU pricing

When users' actual electricity consumption exceeds the load purchased by power retailers in the medium to long-term market, retailers must procure additional electricity from the spot market to reduce the deviation power. The spot market consists of the day-ahead and real-time markets, with this study focusing solely on the day-ahead market due to the limited amount of electricity purchased from the real-time market and its high price volatility and unpredictability. The daily spot market power purchase is divided into 48 intervals, while the contracted power corresponds to load segments with varying start and end times and durations. Consequently, the contracted power must be decomposed into 48 intervals to calculate the deviation power at each moment of the day, representing the spot market power purchase. The decomposition of medium to long-term market power purchase at moment t is as (17):

$$q_L^t=\sum_{l=1}^{N_l}\eta_{l,L}^{t}\cdot q_{l,L} \tag{17}$$

Where $\eta_{l,L}^{t}$ denotes the decomposition ratio of the electricity of contract l at moment t.

Since segmented bidding contracts are cleared for load segments of different durations, the contracted power is the total power for that load segment, which needs to be distributed equally to each moment within the load segment. Within the starting and ending time period of each contract, the power decomposition ratio of each contract is the inverse of the duration of the contract, and the duration interval is calculated according to 30 min. When moment t does not fall within the starting and ending time of the contract, the contract power breakdown ratio is 0. The contract power breakdown ratio is as (18):

$$\eta_{l,L}^{t}=\begin{cases}\dfrac{1}{T_{l,L}},\mathrm{t}\in U_{l,L}\\ 0,\mathrm{t}\notin U_{l,L}\end{cases} \tag{18}$$

Where $T_{l,L}$ denotes the duration of contract l; $U_{l,L}$ denotes the set of all moments within the starting and ending time points of contract l.

3.3.1. Objective function

The maximum profit of one day of the electricity retailer is the optimization objective, and TOU electricity price is the optimization variable. The objective function is the one-day profit of electricity purchases and sales of the electricity retailer as (19):

$$\begin{aligned}&\max C=C_{IN}-C_L-C_{RT}-C_{dev}\\ &=\sum_{t=1}^{T}\sum_{b_0=1}^{N_b}p_{b_0}^{t}\cdot q_{b_0}^{t}-\sum_{l=1}^{N_l}p_{l,L}\cdot q_{l,L}-\sum_{t=1}^{T}p_{RT}^{t}\cdot q_{RT}^{t}-\sum_{\mathrm{t}=1}^{T}\left(p_{dev}^{+}\cdot q_{dev}^{t,+}+p_{dev}^{-}\cdot q_{dev}^{t,-}\right)\end{aligned} \tag{19}$$

where max denotes the function to obtain the maximum value; $p_{b_0}^{t}$ denotes the price of electricity sold by the electricity retailer to the user group b_0, $q_{b_0}^{t}$ denotes the electricity consumption of the user group b0; L and N_l denote the number of the medium to long-term market and contract, respectively; l denotes the number of the contract; p_{RT}^{t} denotes the spot price of electricity at the moment of t; q_{RT}^{t} denotes the amount of electricity purchased in the spot market at the moment of t; p_{dev}^{+} and p_{dev}^{-} denote the unit penalty cost of positive and negative deviations of the power quantity; $q_{dev}^{t,+}$ and $q_{dev}^{t,-}$ denote the amount of positive and negative deviations of the power quantity. Positive deviation means that the actual electricity consumption of the user is greater than the amount of electricity purchased, and negative deviation means that the actual electricity consumption of the user is less than the amount of electricity purchased, both of which are mutually exclusive. Positive deviation means that the actual power consumption of the user is greater than the purchased power of the electricity retailer, and negative deviation means that the actual power consumption of the user is less than the purchased power of the electricity retailer, which are mutually exclusive and cannot occur at the same time.

3.3.2. Constraints

① User participation in demand response capability constraint is as (20):

$$\Delta q_{DT,i}^{t,\max,-} \leq \Delta q_{DT,i}^{t} \leq \Delta q_{DT,i}^{t,\max,+} \tag{20}$$

In the formula, $\Delta q_{DT,i}^{t,\max,+}$ and $\Delta q_{DT,i}^{t,\max,-}$ denote the maximum value of positive and negative adjustments, respectively.

② Power balance constraint is as (21):

$$q_{RT}^{t} + q_{L}^{t} + \Delta q_{dev}^{t} = \sum_{b_0=1}^{N_b} q_{b_0}^{t} \tag{21}$$

③ Peak-to-valley pricing ratio constraints are as (22)–(23):

$$3P_{val,b_0} \leq P_{peak,b_0} \leq 5P_{val,b_0} \tag{22}$$

$$P_{val,b_0} < P_{flat,b_0} < P_{peak,b_0} \tag{23}$$

Where $P_{peak}, P_{val}, P_{flat}$ denote the price of electricity at peak, valley and flat moments, respectively.

④ Time-of-use pricing constraints are as (24)–(26):

$$P_{peak}^{\min} \leq P_{peak,b_0} \leq P_{peak}^{\max} \tag{24}$$

$$P_{flat}^{\min} \leq P_{flat,b_0} \leq P_{flat}^{\max} \tag{25}$$

$$P_{val}^{\min} \leq P_{val,b_0} \leq P_{val}^{\max} \tag{26}$$

where $P_{peak}^{\min}$ and $P_{peak}^{\max}$ denote the minimum and maximum values of peak hour price set by the government, $P_{flat}^{\min}$ and $P_{flat}^{\max}$ denote the minimum and maximum values of normal hour price set by the government, and $P_{val}^{\min}$ and $P_{val}^{\max}$ denote the minimum and maximum values of valley hour price set by the government.

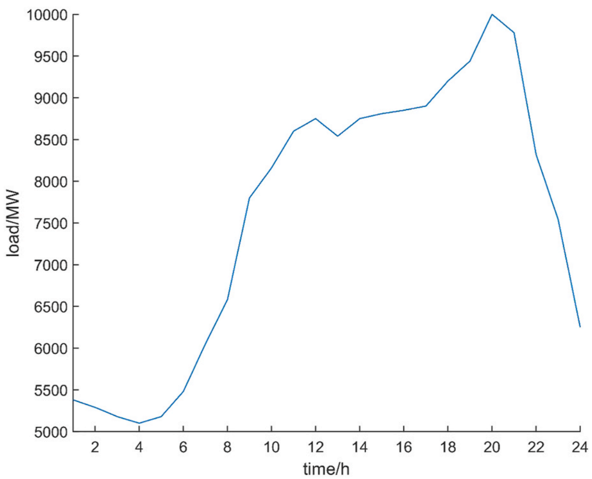

Fig. 3. Daily load curve.

4. Simulation

4.1. Analysis of the results of the price forecasts for power purchases by retailers in the two-tier market

4.1.1. Medium to long-term market clearing results based on the block bidding mechanism

4.1.1.1. Data Preparation. In this study, the daily load profile of a place with a time step of 1 h (as shown in Fig. 3) is used, which translates into the purchased power capacity required by the electricity retailer per hour as shown in Table 3. According to the 24 load segments proposed in 2.1.1 to divide the load of electricity retailers (the division results are shown in Table 4). Since segmented bidding is most favorable for the continuous working characteristics of thermal power units, this study assumed that the generation side is bidding for thermal power generators. Assuming that there are five generators (referred to as generators A, B, C, D and E) with a ramp-up constraint of 800 MW/h, the generator offer parameters are shown in Table 5.

4.1.1.2. Results and discussion. The clearing prices for each load segment in the medium to long-term market based on the block bidding mechanism are shown in Table 6, with a positive deviation penalty of 10 EUR/MWh for the medium to long-term market (p_{dev}^{+}) and a negative deviation penalty of 5 EUR/MWh (p_{dev}^{-}).

From Tables 6 and it can be seen that the clearing price according to the order of the load number shows an upward trend where the longer the duration of the load section, the lower the clearing price is; this result is in line with the idea of homogeneous and equal price of electricity proposed in this paper. The duration of load sections 4, 5 and 6 are all 8 h, but the starting time is different and the clearing price also shows an upward trend; this is because the starting time of the previous load section and the closer connection to the previous load section leads to a lower production cost, and thus, the results of the load was expected. In addition, as can be seen from Table 6, the longer the duration of the load segment, the lower the power purchase price; under this power price, the electricity retailer can integrate the downstream power user load curve, guide the user to lower the peak usage and increase usage in the valley, increase the purchase volume of the long-time load segment, and reduce the purchase volume of the short-time segment load segment, so as to reduce the cost of the electricity retailers' power purchases, and to increase the profit of the power purchases and sales.

4.1.2. Spot electricity price forecasting results based on numerical feature similarity

4.1.2.1. Data Preparation. The spot electricity price forecasting model was trained using load and spot electricity price data from January to December 2006 in Australia, and it was tested using data specifically from January 1, 2007.

4.1.2.2. Results and discussion. In order to analyze the forecasting performance of the DA-RBF neural network spot electricity price forecasting method based on numerical feature similarity proposed in this paper, the DA-RBF neural network, BP neural network [36] and SVM model [37] were compared to the forecasting method of this paper, firstly from the curve of the predicted value and the real value; the comparison of forecasting result curves is shown in Fig. 4.

As can be seen in Fig. 4, the overall trend of the forecasting results obtained by the four forecasting methods is consistent with the true value. The predicted electricity prices obtained by the DA-RBF neural network are significantly higher than the true values when the load value is high. Conversely, the SVM model underestimates spot electricity prices when the load is high and significantly underestimates them during low-load hours between 2:30–4:30. Furthermore, at lower load levels, the BP neural network demonstrates a larger deviation from the true electricity prices. Notably, the DA-RBF neural network approach based on the similarity of numerical features proposed in this paper, results in spot electricity price forecasts most closely aligned with the true values, regardless of the high or low load value.

In this study, the mean absolute percentage error (MAPE), root mean square error (RMSE) and the time required for forecasting were used as the evaluation indexes to assess the forecasting results of each algorithm, and each evaluation index of the forecasting results is shown in Table 7. As can be seen from Table 7, the MAPE of the predicted electricity price obtained from the DA-RBF neural

Table 3
Electricity retailers' 24-h power purchase requirements.

Time point (h)	Capacity(MW)	Time point (h)	Capacity(MW)
1	5290	13	8540
2	5290	14	8540
3	5100	15	8810
4	5100	16	8810
5	5180	17	8900
6	5180	18	8900
7	6050	19	9440
8	6050	20	9440
9	7800	21	8320
10	7800	22	8320
11	8600	23	6250
12	8600	24	6250

Table 4
Bidding parameters of electricity purchase by electricity retailers based on 24 segments.

Load segment number	Capacity (MW)	Load segment number	Capacity (MW)
1	5100	13	190
2	950	14	0
3	0	15	80
4	0	16	0
5	1750	17	0
6	1150	18	800
7	0	19	0
8	0	20	270
9	0	21	0
10	740	22	1490
11	1700	23	2070
12	0	24	0

Table 5
Bidding parameters of generators.

Quotation section number	Generator A		Generator B		Generator C		Generator D		Generator E	
	q^{bid}	β^{bid}	q^{bid}	β^{bid}	q^{bid}	β^{bid}	q^{bid}	β^{bid}	q^{bid}	β^{bid}
1	1700	9.92	1200	10.32	1800	9.68	1200	10.56	1200	10.6
2	2200	10.6	1600	12.48	2300	10.96	1650	12.6	1650	12.08
3	2750	13	2200	13.8	2600	14.32	1850	13.92	2150	12.4
4	3200	17.04	2400	16.6	3100	17.52	2100	17.84	2400	16.4

q^{bid} in megawatts (MW), β^{bid} in EUR/MWh.

Table 6
The clearing prices for each load segment in the medium to long-term market.

Load segment number	Clearing price (EUR/MWh)	Load segment number	Clearing price (EUR/MWh)
1	10.6	13	12.08
2	10.6	14	12.08
3	10.6	15	12.08
4	10.6	16	12.08
5	10.6	17	12.08
6	10.96	18	12.4
7	10.96	19	12.4
8	10.96	20	12.4
9	10.96	21	12.4
10	10.96	22	12.48
11	12.08	23	13
12	12.08	24	13

network spot electricity price forecasting method based on numerical feature similarity proposed in this paper was 2.43%, and the RMSE was 1.0582, and both of the error indexes are significantly smaller than those of the other forecasting algorithms.

This shows that DA-RBF based on numerical feature similarity performs better in both the overall evaluation index and the detailed load prediction curve. The main reason is that, although the historical data has complexity and diversity, the method proposed in this paper can filter the data by judging the numerical feature similarity between the learning data and the test data, avoiding the error caused by the interference of the redundant data, and the obtained prediction model has the characteristic of individual customization, which is more suitable for the prediction of spot electricity price, so it has better prediction accuracy.

4.2. Analysis of the optimization results of power purchases and sales based on differentiated TOU pricing

4.2.1. Data Preparation

This study performed clustering analysis on the monthly average load curves of 404 users from the publicly available CER dataset [38]. The complete dataset contains load data, electricity price data, demand response service data, and more for electricity users during the years 2009–2010, with a sampling frequency of every 30 min.

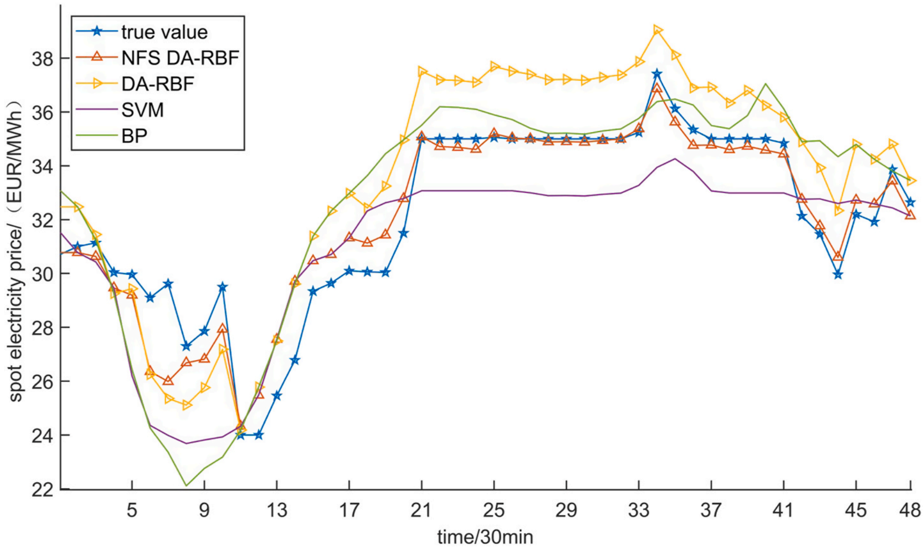

Fig. 4. Comparison of predicted spot pricing curves using four forecasting methods.

Table 7
MAPE and RMSE of different forecasting models.

Evaluation indicators	MAPE (%)	RMSE
NFS DA-RBF	2.43	1.0582
DA-RBF	6.51	2.2130
SVM	6.38	2.3472
BP	6.43	2.5928

4.2.2. Results and discussion

4.2.2.1. Optimization results of differentiated TOU pricing. Based on the silhouette coefficients of the clustering results for different cluster numbers, the optimal number of clusters was determined to be k = 4, and the clustering results are shown in Fig. 5. As illustrated in Fig. 5, the number of load curves belonging to class 1, 2, 3, and 4 are 251, 10, 22, and 121, respectively. Then, based on the half trapezoidal affiliation function and K-means clustering algorithm, the load values on the typical load curves of each user group are clustered to obtain the results of TOU pricing period division for each type of user group.

Since the time period is divided into peak, valley and flat time periods, the center of the clustering is taken to be k = 3. The clustering result was combined with the shape of the load curves to be analyzed, and the following results were obtained. In the time division results of TOU pricing for each type of user group, because user group 2 is a smooth user, the fluctuation of electricity consumption in a day in this group was small, so that the original pricing remains unchanged. For the other user groups, according to the time division results of the implementation of different TOU pricing and the optimization model of the purchases and sales of electricity strategy based on the particle swarm, the differentiated TOU pricing was obtained as shown in Table 8.

4.2.2.2. Comparison of different time-of-use electricity pricing strategies. In order to show that the implementation of differentiated TOU pricing for different user groups has a better effect for reducing the peak usage and increasing the valley usage, a comparative analysis was conducted using a single TOU pricing. The time period was divided based on the total user load curve, and the results of time period division and pricing are presented in Table 9.

A comparison of the customer load curve after differentiated TOU pricing guidance and the customer load curve after single TOU pricing [15] guidance is shown in Fig. 6. In Fig. 6, curve 1 shows the customer load curve after differentiated TOU pricing guidance, curve 2 shows the customer load curve after single TOU pricing guidance, and curve 3 shows the customer load curve under the original fixed pricing of 22 EUR/MWh.

From Fig. 6, it can be seen that the differentiated TOU pricing makes the load curves of customer groups 1, 3 and 4 smoother and with smaller peak-to-valley differences than the load curves under the original fixed pricing. Customer group 2 keeps the fixed pricing unchanged, and its load profile was also smoother than the original load profile. The single time-of-use pricing resulted in a new peak at 22:00 for the load curve of customer group 1, a significant peak and valley for the load curve of customer group 2, and a smaller load value for the load curve of customer group 3 located in the valley from 14:30 to 15:30. The time period division of customer group 4 is similar to the single time-of-use pricing time period division, so only the load curve of customer group 4 had a better peak and valley reducing effect under the single time-of-use pricing. This is because the differentiated time-of-use pricing strategy proposed in this

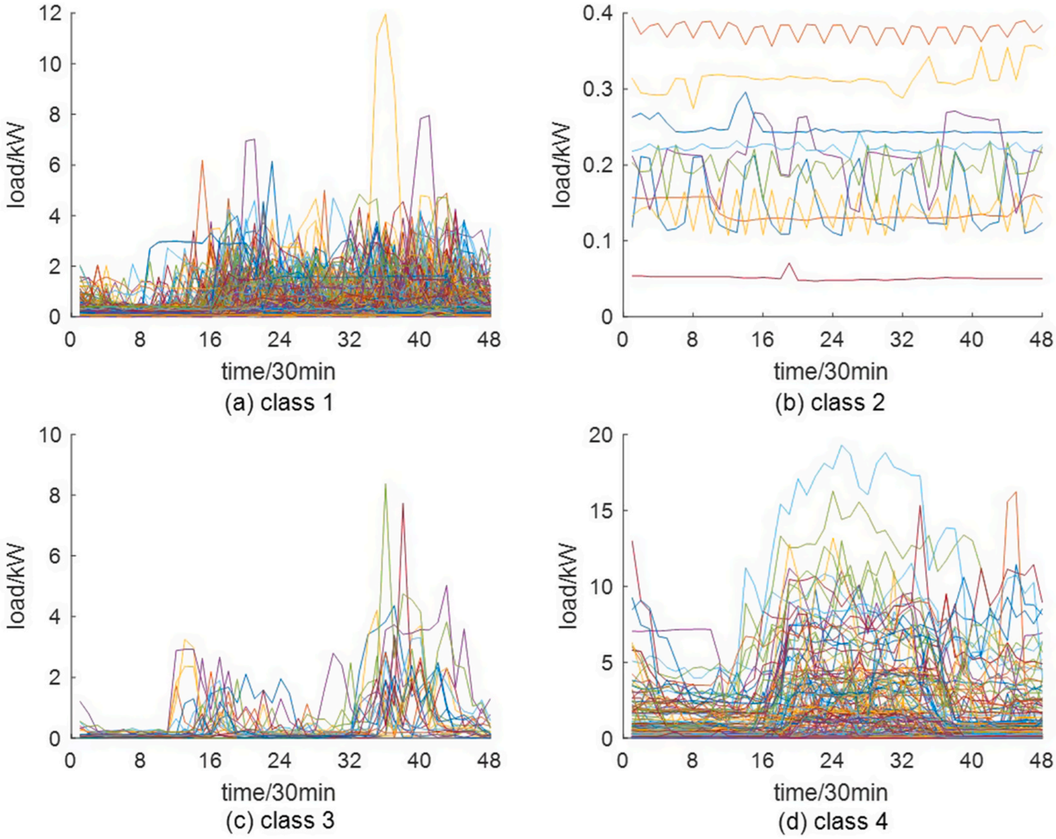

Fig. 5. The clustering results of load curves of 404 users when k = 4.

Table 8
The time period division and pricing results for the differentiated time-of-use (TOU) pricing strategy.

User group	Time slot	Electricity price (EUR/MWh)	Start and end
1	Peak	35.14	10:30–21:00
	Plateau	24.35	Rest of the day
	Valley	17.64	2:30–8:30
2	–	22	–
3	Peak	22.60	9:30–14:00, 16:00–18:00
	Plateau	22.37	Rest of the day
	Valley	16.77	14:30–15:30, 20:30–2:00 The following day
4	Peak	27.82	8:30–21:30
	Valley	17.50	Rest of the day

Table 9
The time period division and pricing results for the single time-of-use (TOU) pricing strategy.

Time slot	Start and end	Electricity price/(EUR/MWh)
Peak	8:30–21:30	38.82
Valley	0:00–8:30; 21:30–24:00	15.90

paper can effectively differentiate between users and implement different time-of-use prices for users with different electricity consumption characteristics, which can more effectively guide various types of users to develop their own peak-shaving potential and improve power system stability.

In addition, as shown in Table 10, the profit of electricity purchased and sold by electricity retailers using differentiated TOU pricing, single TOU pricing and fixed pricing was EUR 2,477,000, 1,793,200 and 1,486,900, respectively. Compared with the single TOU pricing, the differentiated TOU pricing is more effective in increasing the revenue from electricity sales, which is 66.59% higher than that of the profit obtained by the electricity retailers when demand response is not carried out. The strategy of electricity retailers

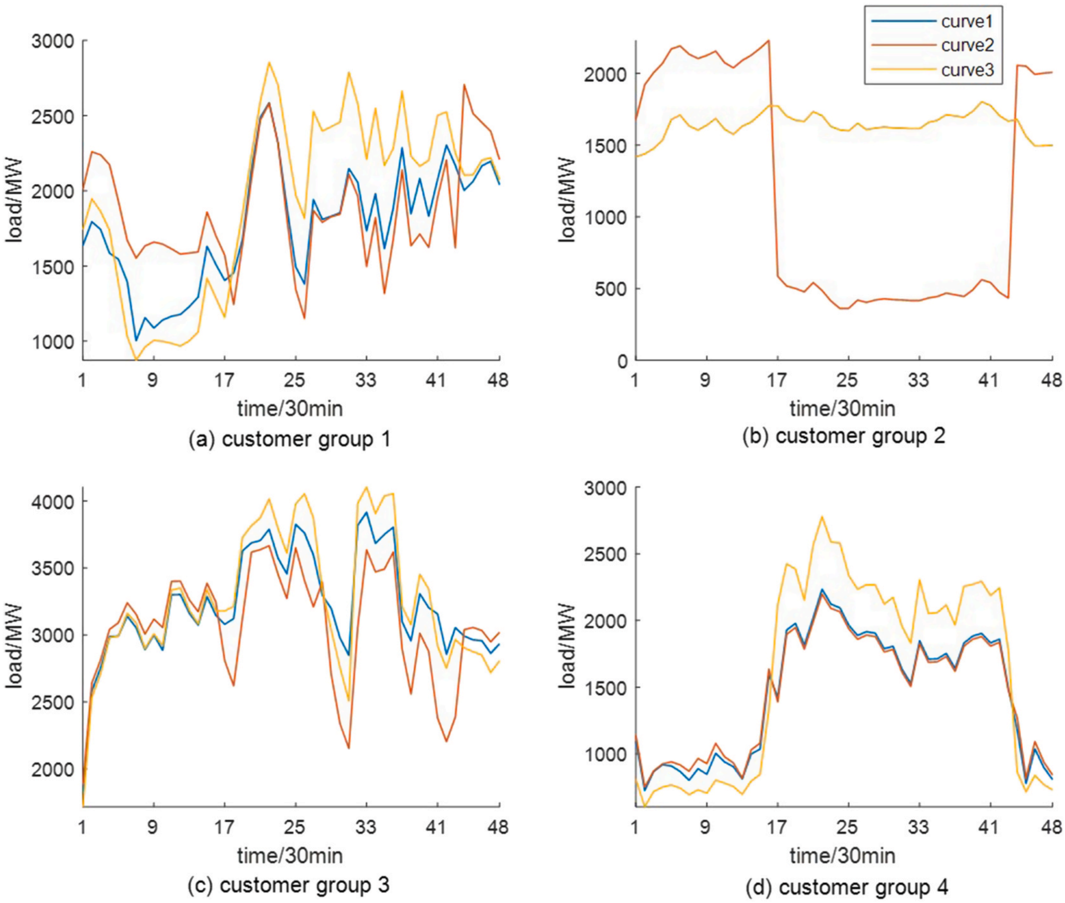

Fig. 6. Comparison of different TOU pricing strategies.

Table 10
Comparison of profitability among different sales strategies employed by electricity retailers.

Various costs/(EURx10^4)	Differentiated TOU pricing	Single TOU pricing	Fixed pricing
Profit of electricity retailers	247.7	182.99	148.69

based on differentiated TOU pricing aims to guide users in adjusting their electricity consumption in a more targeted manner to cope with the peak of spot electricity prices, thereby reducing purchasing costs. Simultaneously, the smoother load curve resulting from TOU pricing helps retailers increase their market share in the long term and reduces purchasing costs. Additionally, the proposed spot electricity price prediction in this study helps mitigate the risks associated with spot market electricity purchases. Therefore, while all three strategies enhance the profit of electricity retailers, the optimized strategy proposed in this study demonstrates greater profitability and risk reduction.

5. Conclusions and future works

In the current study, in terms of electricity procurement, a medium to long-term market clearing model and spot electricity price forecasting model have been established in a two-tier market, laying the foundation for decision-making on electricity procurement plans for electricity retailers. In addition, considering that different users have different levels of demand response sensitivity, a differentiated demand response model has been developed, using time-of-use pricing to optimize the profit of electricity procurement and sales by retailers. The study employs a particle swarm iterative learning method for iterative learning. The study yielded the following conclusions.

(1) The feasibility of the medium- and long-term market clearing methodology using the segmented bidding mechanism has been proven, and the clearing results are in line with the guideline of homogeneous tariffs. This approach effectively balances supply and demand, ensuring fair pricing across different market segments.

(2) The comparison of the proposed DA-RBF spot electricity price prediction method with DA-RBF, SVM, and BP algorithms demonstrates that the predicted electricity prices obtained by this method closely align with the actual values. Furthermore, the MAPE and RMSE metrics are significantly smaller than those of other prediction algorithms. This indicates that the proposed method effectively mitigates errors caused by redundant data interference, leading to higher accuracy and reliability in the prediction results. Therefore, this approach is well-suited for spot electricity price forecasting.
(3) Differentiated time-of-use electricity pricing is implemented to incentivize users to adjust their electricity consumption, resulting in smoother user load curves. This approach has led to a 66.59% increase in profits for electricity retailers, while also reducing the peak-to-valley load differential by 8.82%. Users who participate in demand response programs can benefit from this initiative. For electricity generators, smoother load curves translate to increased demand during longer-duration load periods, leading to fewer start-stop cycles, lower generation costs, and reduced pressure on the power supply during peak periods. This, in turn, saves costs associated with backup generation unit planning and construction. Electricity retailers benefit from the implementation of peak and off-peak pricing, as it guides users to shift their electricity usage away from peak periods and increase their purchases from the mid-to-long-term market, thus lowering procurement costs. In conclusion, the adoption of differential time-of-use pricing strategies by retailers creates a mutually beneficial situation for users, electricity generators, and retailers.

The limitations of DA-RBF based on NFS come from the lack of similarity data or low similarity between similar days, which may lead to poor predictions. Future research will focus on addressing these limitations. In addition, the impact of users' limited rationality on demand response can also be explored in future work.

Data availability statement

Data included in article/referenced in article.

Ethics declarations

Informed consent was not required for this study because the data used in this study came from public databases, and did not involve animal and human experiments, as well as other data related to human privacy.

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CRediT authorship contribution statement

Bowen Zhou: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition. **Yuwei Guo:** Writing – review & editing, Investigation, Data curation. **Xin Liu:** Writing – review & editing, Investigation, Data curation. **Guangdi Li:** Investigation, Funding acquisition. **Peng Gu:** Investigation, Funding acquisition. **Bo Yang:** Supervision, Methodology.

Declaration of competing interest

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