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An Integrated SVM-LSTM Method for VPP Resource Classification and Load Forecasting in Real-time Market Trading

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The operation of virtual power plants in the electricity market requires handling complex resource scheduling and market trading decision-making problems. The research aims to enhance the participation efficiency and responsiveness of virtual power plants in the electricity market and solve practical operational challenges by improving market trading strategies. Therefore, a resource grading model based on improved support vector machine was developed. The model is optimized using adaptive synthetic sampling, principal component analysis, and deep clustering algorithms. In addition, an improved long short-term memory network is utilized to achieve ultra short-term load forecasting. The results showed that the recall rate and F1 mean of the resource grading model based on the improved support vector machine algorithm were as high as 81.07% and 85.41%, respectively. The average prediction error of the improved long short-term memory neural network algorithm is 0.35%, and the maximum error is only 0.62%. In the basic scenario, the maximum deviation between the declared amount of backup auxiliary services based on load adjustable capacity prediction and the actual amount is only 88.62 kW. The method proposed by the research institute has significant advantages in improving the efficiency and responsiveness of virtual power plant market participation, which is conducive to promoting the overall economic benefits of virtual power plants in the electricity market.

ACM CCS (2012) Classification: Computing methodologies → Machine learning → Machine learning approaches

Keywords: virtual power plant, market trading, machine learning, SVM, LSTM

1. Introduction

With the continuous improvement of new power systems, Virtual Power Plant (VPP) has gradually become a key component of the power system [1]. In recent years, the market that includes spot and ancillary services has gradually become more perfected. Its role in resource allocation has become increasingly prominent. Under this trend, VPP real-time market trading strategies have strategic significance [2−3]. Although VPP can participate in the medium to long term market for electricity purchases, its flexibility is poor. In real-time market trading, VPP demonstration projects mainly focus on meeting demand response and auxiliary services. Some regions encourage VPP to participate in the electricity spot market. However, most of them are unilateral markets on the power generation side, which cannot play a flexible regulatory role. In addition, VPP can manage multiple controllable resources and participate in real-time electricity market trading through aggregation [4]. The demand side resource-based VPP mainly aggregates distributed power sources, user side energy storage, and adjustable loads. The supply side resource oriented VPP mainly aggregates distributed power sources and grid side energy storage. The hybrid type aggregates the output of energy storage resources with the internal power generation consumption of VPP.

Although existing literature has explored how to improve the overall efficiency of VPP by optimizing resource allocation, most of these studies focus on optimizing single resource types or analyzing in existing market environments, without fully considering the hierarchical nature and multi-level optimization of demand side resources [5]. In addition, existing research often lacks a systematic evaluation of VPP market trading strategies, failing to develop more accurate trading strategies based on actual system needs and market dynamics. Therefore, it is necessary to explore the hierarchical resource allocation on the demand side of VPP and develop more reasonable market trading strategies. Firstly, the purpose of this study is to optimize the real-time market trading strategy of VPP by establishing an improved resource grading model. Specifically, by implementing more refined hierarchical management of demand side resources, more efficient market transactions and responses can be achieved. Secondly, the aim is to develop effective trading strategies based on actual system requirements and market dynamics. Finally, by quantitatively evaluating the economic benefits of resources and considering system requirements, enhance the overall value and market performance of VPP. To this end, advanced machine learning models were constructed and optimized, and advanced machine learning algorithms were introduced for load forecasting to address the gaps in existing research. The research innovation lies in the improvement of SVM for VPP resource classification, which has successively introduced Adaptive Synthetic Sampling (ADASYN), Principal Component Analysis (PCA), and Deep Embedded Clustering (DEC). Furthermore, the study introduces an improved Long Short-Term Memory (LSTM) for ultra short-term load forecasting to propose effective real-time market trading strategies. This can enable the formulation of intraday scheduling strategies and capacity declaration during market trading processes. Compared with existing methods, the integrated model proposed in this paper has significant advantages in processing complex data, improving prediction accuracy, and optimizing decision strategies, which are conducive to enhancing the operational and management capabilities of VPP in real-time electricity markets. The research contribution lies in improving the operational efficiency and market competitiveness of VPP in the electricity market through improved machine learning methods. This provides strong support and reference for the intelligence and sustainable development of future power systems.

The main content of the study includes four parts. The first part mainly reviews the operation and market trading strategies of VPP, as well as the impact of electric vehicles on VPP operation. The second part introduces the construction of a load resource classification model and the prediction of ultra short-term load and adjustable capacity. The first section introduces the load resource grading model based on improved SVM, and improves it by introducing ADASYN, PCA, and DEC algorithms to address its shortcomings. In the second section, based on the hierarchical model, an improved machine learning algorithm combining LSTM and adaptive differential evolution algorithm is further proposed to achieve ultra short-term load forecasting, and is jointly applied to adjustable capacity forecasting. The third part conducts experimental analysis on the hierarchical model based on improved SVM in this paper, and verifies the performance of ultra short-term load forecasting based on LSTM SaDE algorithm, exploring the matching degree between the reserve market declaration results obtained from load adjustable capacity prediction and the actual quantity. The fourth part summarizes the research results and proposes future research prospects.

2. Related Works

In the electricity market, the operation and market trading strategy of VPP are related to the overall economic benefits and stability. Chung *et al.* proposed a new smart grid management framework that combined cloud computing-based energy trading and demand response to meet the demand for fast charging services in the power grid. Meanwhile, the interaction between VPP and car owners was modeled as a non-cooperative game. Car owners with electric vehicles and storage devices could effectively reduce charging costs and achieve greater profits [6]. Wu *et al.* found that the high proportion of intermittent renewable energy in VPP led to high transaction costs in the electricity market.

Therefore, they constructed a Stackelberg game model and established corresponding objective functions. This method effectively reduced the purchasing electricity cost and improved the operational and economic benefits of VPP [7]. Dogan *et al.* believed that accurate predictions of load demand, renewable energy generation, and electricity prices were crucial for maximizing the VPP market trading' returns. To this end, the team constructed a maximum likelihood model to predict VPP uncertainty. This method achieved effective uncertainty prediction [8]. Tsaousoglou *et al.* found that it was difficult to obtain flexibility costs in price and quantity quotations in electricity market trading. To this end, the team proposed a universal method that considered future time slot uncertainty and utilized offline simulation to train different machine learning algorithms. These machine learning methods made flexible decisions for balancing energy supply in investment portfolios [9].

Yang *et al.* constructed a charging model to explore how electric vehicles affected VPP operation and introduced the three stages of the electricity market from a trading perspective. Meanwhile, an improved artificial bee colony algorithm was utilized to solve the optimal bidding strategy for VPP. The VPP bidding model had better performance [10]. Wozabal *et al.* proposed a multi-stage stochastic programming method for optimizing the bidding strategy of VPP operating in the electricity spot market. This method set the bidding for a single day operation as a Markov decision process and utilized a stochastic dual dynamic programming algorithm for solution. Compared with deterministic programming algorithms, the optimal strategy obtained by random programs was significantly better [11]. Zhang *et al.* proposed a new stochastic adaptive robust optimization model to determine the optimal scheduling plan for VPP participation in the day ahead reserve market. Meanwhile, fully considering the uncertainty of market clearing prices, they proposed a solution method based on improved Benders dual decomposition. This method improved profitability while achieving real-time operations [12]. Ghasemi-Olanlari *et al.* found that medium to long-term scheduling strategies in the electricity market increased fault risk. A two-stage stochastic model considering risk constraints was constructed for this purpose. Meanwhile, the team adopted LSTM and scenario generation methods to predict uncertain parameters such as electricity load and market prices in the model. This method effectively reduced the occurrence rate of faults in distributed generator sets [13].

To summarize, in the electricity market, many researchers adopt various advanced algorithms and models to optimize the operation and market trading strategies of VPP. This is to address the volatility and market uncertainty of renewable energy. However, VPP may integrate multiple types of distributed energy resources, making it difficult to accurately predict and manage in market trading. To this end, a VPP resource classification model is proposed, and an ultra short-term load forecasting method is proposed. The paper aims to develop intraday scheduling strategies and declare capacity during market trading processes.

3. Methodology

Firstly, a load resource classification model based on improved SVM is constructed. ADASYN, PCA, and DEC are introduced to address its shortcomings. Subsequently, based on the hierarchical model, an improved machine learning algorithm combining LSTM and Self-adaptive Differential Evolution (SaDE) is further proposed. This is to achieve ultra short-term load forecasting and jointly apply it to adjustable capacity forecasting.

3.1 Construction of Load Resource Classification Model Based on Improved SVM

The role of VPP in the electricity trading market includes purchasing and selling electricity. Figure 1 is a schematic diagram of its participation in market trading regulation. VPP not only needs to predict future high and low electricity prices in the external market environment, but also needs to predict load demand. When the external market environment shows high spot electricity prices, VPP mobilizes aggregated resources to increase power generation through internal value transmission mechanisms. When predicting lower future electricity prices, compensation prices decrease. VPP dominated by power supply will reduce power generation and lower declared power generation. User centric VPP will increase electricity consumption and increase declared electricity consumption [14].

VPP mainly guides resource transfer during power generation and consumption periods through its predictive ability. Real-time market trading profits are represented by equation (1).

$$R = Q \cdot (P_1 - P_2) - Q \cdot P_c \tag{1}$$

In equation (1), P_c refers to the compensation price that VPP needs to pay to the regulating resources based on the electricity price, Q represents the transferred electricity, P_1 refers to the period of increasing power generation and reducing electricity consumption and P_2 refers to the period of reducing power generation and increasing electricity consumption. In the electricity market, VPP needs to determine the market generation and consumption situation at different time periods based on load and daily demand side forecasting results to maximize demand side resources' benefits. Therefore, a load resource classification model based on improved SVM is constructed based on historical load data. SVM is suitable for data classification and regression problems, which can assist power companies and energy suppliers in power scheduling and resource management. In order to construct an accurate and effective load resource classification model, relevant data needs to be preprocessed, including data missing value processing and data normalization processing. In the processing of missing values, interpolation is mainly performed on the missing values, using methods such as mean, median, mode imputation, and interpolation for data processing. Next, the data is standardized and transformed into a distribution with a mean of 0 and a standard deviation of 1, eliminating scale differences between features and making the SVM model training process more stable. In addition, in the classification of load resources, there are often problems of imbalanced sample classification and complex resource characteristics that are difficult to classify [15−16]. In response to this issue, this research improves SVM by introducing ADASYN before training to increase the number of class samples. Subsequently, PCA is utilized to reduce the dimensionality of the data sample. DEC is utilized to enhance the sensitivity of the hyperplane. Figure 2 shows the improved SVM process.

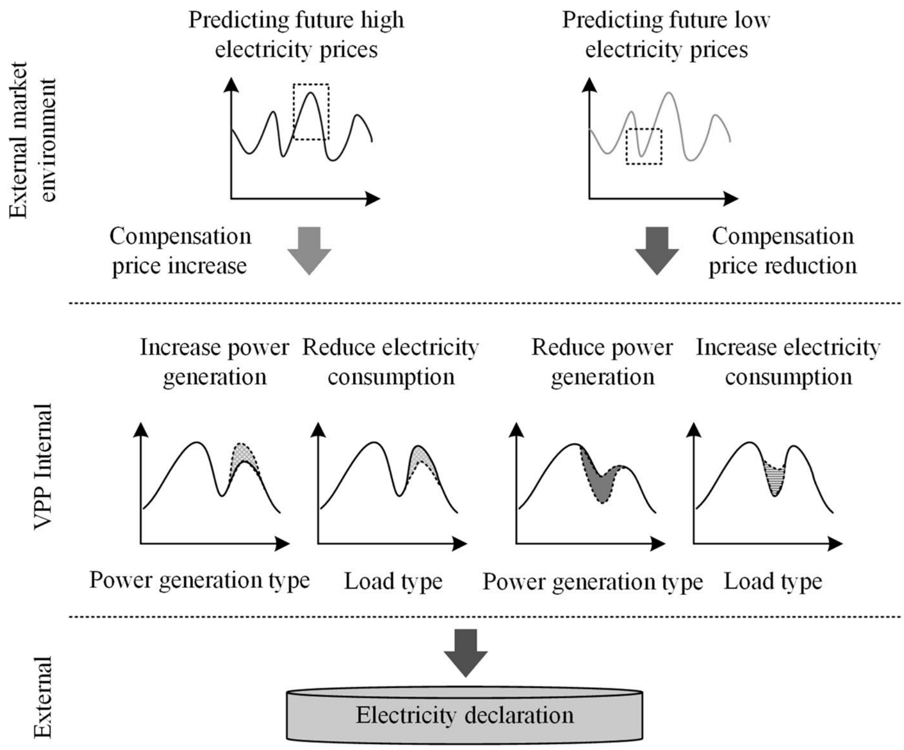


Figure 1. Schematic diagram of VPP participating in market trading regulation.

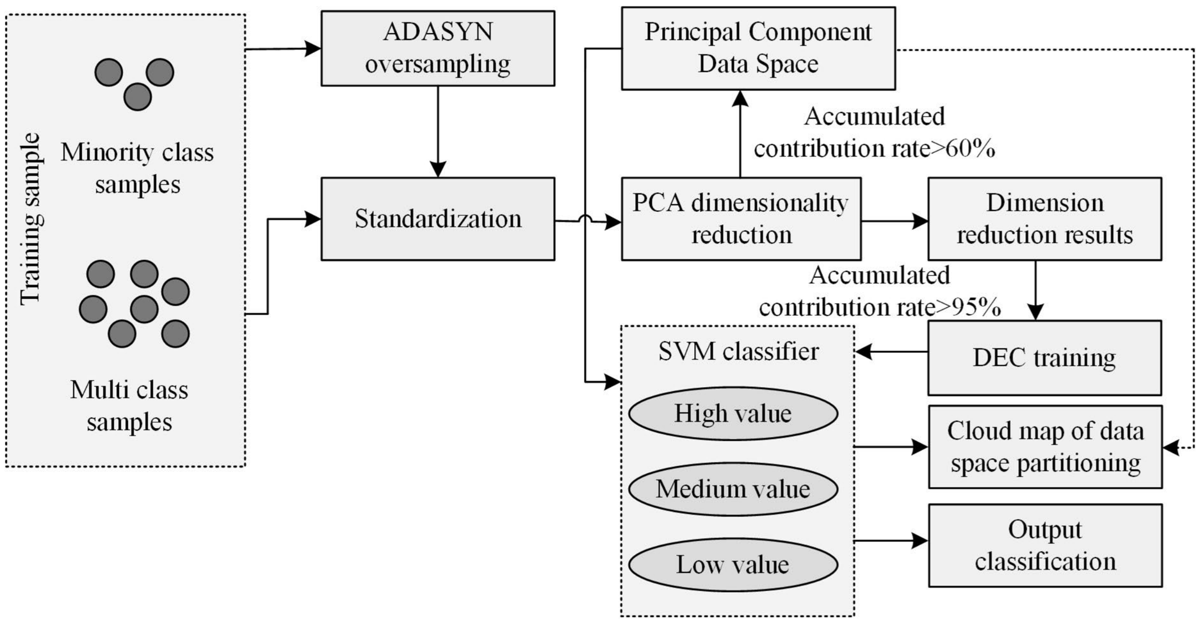


Figure 2. Flow chart of the improved SVM process.

To solve the imbalanced sample classification, the study resamples the training samples. Compared to undersampling, oversampling preserves important samples. For this purpose, oversampling is adopted to increase sample diversity. For this study, oversampling was used to increase sample diversity. Although SMOTE is a classic oversampling method, the new samples it generates are based on linear interpolation of existing samples and do not specifically focus on regions that are difficult to classify, resulting in lower effectiveness than ADASYN. For this purpose, the ADASYN method was chosen in the study, which enables the model to focus on unclassifiable regions and effectively avoids the problem of imbalanced classification. Firstly, the quantity of few class and multi-class samples is corrected, as shown in equation (2).

$$H = \delta \cdot (|S_{\max}| - |S_{\min}|),\ \delta \in (0,\ 1] \tag{2}$$

In equation (2), $S_{\max}$ refers to multi-class samples, namely medium and low value samples. $S_{\min}$ refers to small class samples, *i.e.* high-value samples. Then, the proportion of synthesized samples with few class samples to the total samples is calculated, represented by equation (3).

$$\psi_a = \Delta x_a \cdot \frac{K}{S_{\min}} \tag{3}$$

In equation (3), K refers to the algorithm parameters. Δx_a refers to the quantity of multi-class samples in the K points closest to a few class sample x_a. Subsequently, the quantity of oversampling is determined, represented by equation (4).

$$h_a = \psi_a \cdot H \tag{4}$$

Finally, a sample is randomly selected as a new few class sample, represented by equation (5).

$$x_b = x_a + \phi \cdot (\hat{x}_a - x_a),\ \phi \in [0,1] \tag{5}$$

In equation (5), $\hat{x}_a$ refers to one of the K samples closest to x_a. Due to the complex characteristics of load resources, it is necessary to perform dimensionality reduction, including PCA, local linear embedding, t-distribution random neighborhood embedding, independent component analysis, and other methods. Due to the complexity of load resource data and its dependence on linear relationships, PCA can more effectively extract the main information of the data compared to other methods. Meanwhile, PCA can compress high-dimensional data into fewer principal components while preserving most of the variance in the data. Therefore, the research mainly adopts PCA algorithm to achieve dimensionality reduction of resources, in order to achieve more effective load resource classification. The calculation expression of PCA is shown in the following formula.

$$X_{\text{pca}} = X_{\text{aug}}W \tag{6}$$

In equation (6), X_{aug} represents the data before dimensionality reduction, X_{pca} represents the data after dimensionality reduction, and W represents the dimensionality reduction matrix. Figure 3 shows the feature dimensionality reduction process based on PCA.

In addition, traditional SVM does not consider the issue of data imbalance. Therefore, this study utilizes DEC to improve and enhance the algorithm's learning ability for imbalanced data. Compared with other methods, the DEC algorithm sets two different penalty parameters for positive and negative class samples, respectively. This mechanism allows the model to impose higher penalties on minority class samples, thereby reducing the classifier's bias on imbalanced data and effectively improving the model's performance on imbalanced data. The calculation of DEC algorithm is shown in the following formula.

$$L_{\text{cluster}} = \sum_{a=1}^{N_{\text{aug}}} \sum_{b=1}^{M} u_{ab} \log \frac{u_{ab}}{v_{ab}} \tag{7}$$

In equation (7), u_{ab} represents the probability that sample a belongs to cluster b, and v_{ab} represents the true label probability of cluster b. Figure 4 shows the process of DEC.

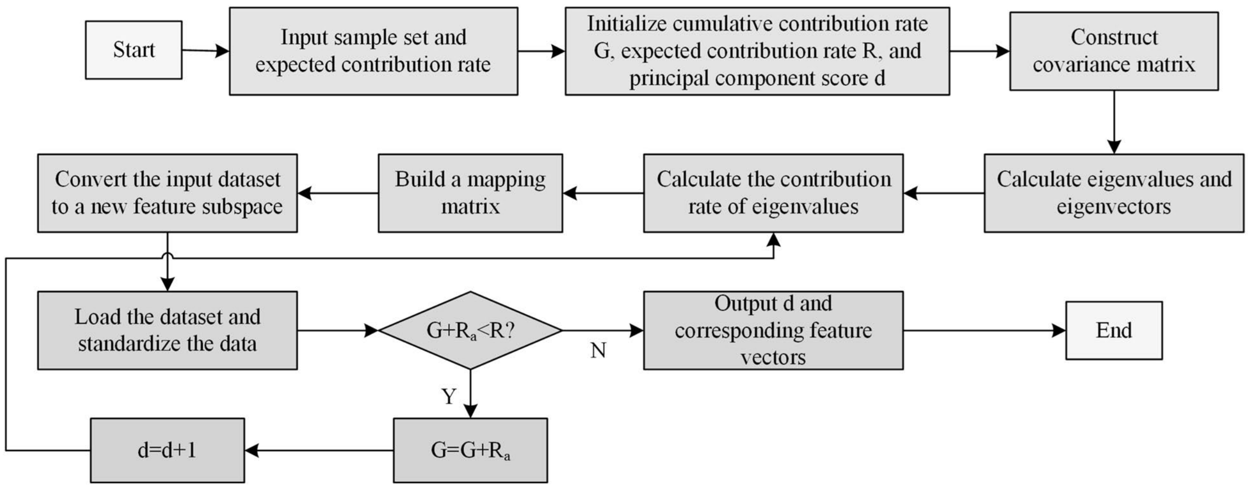


Figure 3. Feature dimensionality reduction process based on PCA.

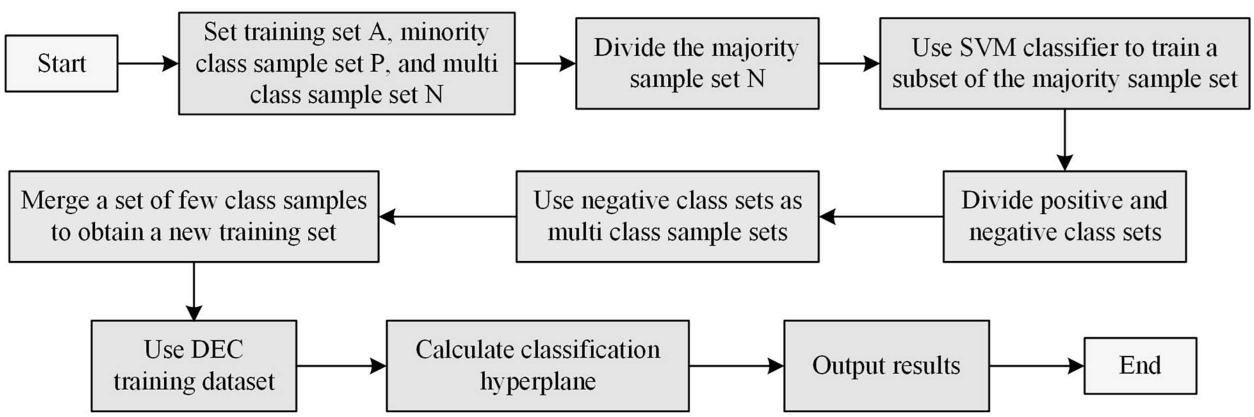


Figure 4. The process of DEC.

3.2. Prediction of Ultra Short-term Load and Adjustable Capacity Based on LSTM-SaDE

Based on the improved SVM classification method, the experiment further selects the trading strategy of medium value resource analysis VPP participating in the real-time electricity market. Firstly, it should predict the ultra short-term load of VPP and analyze how real-time electricity prices affect the load to achieve adjustable capacity prediction. Based on accurate predictive data, VPP can develop power dispatch plans and market declaration volumes in advance. Predicting the adjustable capacity of VPP helps in the formulation of intraday scheduling strategies and capacity declaration in market trading [17-18]. In ultra short-term load forecasting, machine learning has significant advantages over traditional methods in terms of prediction accuracy. An improved method combining LSTM and SaDE is adopted to achieve ultra short-term load forecasting. Before conducting load forecasting, time-series analysis is required. The study adopts the AutoRegressive Integrated Moving Average (ARIMA) model. ARIMA's input feature is a time-series variable, which can be processed by ARIMA to obtain predicted values for the next few days. This model's prediction involves five steps. Firstly, stationarity identification is performed based on time-series scatter plots or function graphs. Then, differential processing is performed on the data sequence to eliminate heteroscedasticity. The third step is to select the corresponding model based on the recognition rules. If the autocorrelation function is truncated and the partial correlation function is trailing, MA is chosen. Otherwise, AR is chosen. If both functions belong to trailing, ARMA is chosen. The fourth step is to test the model. Finally, data prediction is achieved based on the validation model. LSTM mainly controls the information flow through input, forget, and output gates, which is beneficial for processing long sequence information. This method requires manual setting of parameters, making it difficult to obtain the optimal solution [19]. To this end, the study utilizes Differential Evolution (DE) to improve LSTM and introduces adaptive crossover factors, thereby generating LSTM-SaDE. The adaptive cross factor is represented by equation (8).

$$CR = CR_{\max} - \frac{G(CR_{\max} - CR_{\min})}{GenM} \tag{8}$$

In equation (8), $CR_{\max}$ and $CR_{\min}$ correspond to the maximum and minimum values of the cross parameters, G refers to the current iteration, and $GenM$ refers to the maximum iteration. Figure 5 shows the ultra short-term load forecasting process based on LSTM SaaDE.

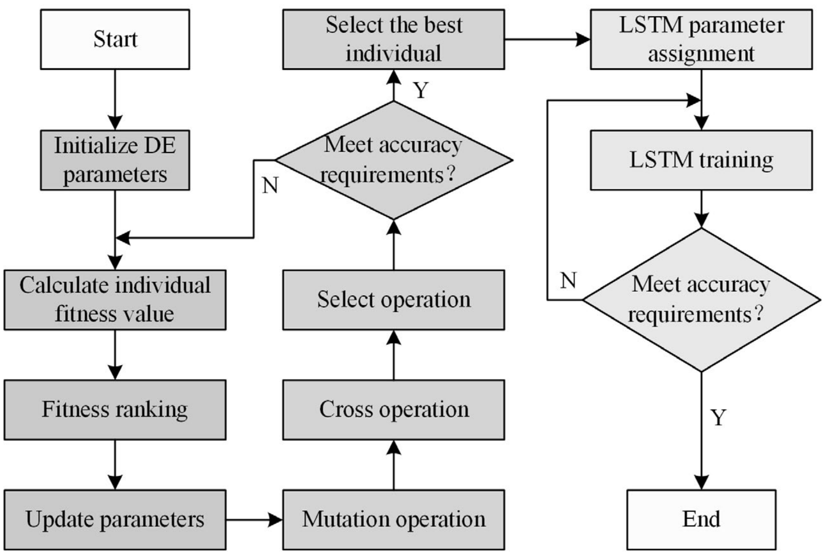


Figure 5. The ultra short-term load forecasting process based on LSTM-SaDE.

The LSTM SaDE model mainly utilizes the adaptive optimization capability of SaDE to optimize hyperparameters in LSTM networks, such as learning rate, number of hidden units, *etc.* This hyperparameter has a significant impact on the performance of LSTM, and SaDE can adjust these parameters more accurately, thereby reducing overfitting and underfitting problems of the model and improving its prediction accuracy. In addition, for load data with high nonlinearity and long-term dependencies, SaDE's optimization capability can help LSTM better capture these complex patterns. Therefore, the LSTM SaDE model has higher prediction accuracy and faster convergence speed compared to traditional LSTM models. Load-based VPP mainly achieves auxiliary services by increasing or decreasing user electricity consumption. For loads, it should reduce electricity consumption as the load increases. When the load increases, the generator set needs to output more power, which belongs to positive standby. Otherwise, it belongs to a negative standby. VPP's reserve declaration volume is mainly achieved through adjustable capacity prediction. Figure 6 shows the specific prediction scheme.

In Figure 6, first, the user's willingness to adjust is calculated based on the corresponding cost and real-time electricity price data. Subsequently, historical data are combined and quantified using the theory of demand elasticity. The elasticity quantification of demand income mainly reflects the impact of compensation prices and adjustment costs on electricity consumption. The changes in electricity prices after marketization can convey electricity price signals and adjust electricity consumption behavior. Subsequently, the standardized coefficient method is utilized to conduct correlation analysis on the willingness to mediate. The willingness to mediate is weighted according to its relative importance. Subsequently, based on LSTM-SaDE-based ultra short-term load forecasting, they are jointly used in load adjustable capacity forecasting. The predicted values are utilized for reserve market declaration. For cost adjustment, within the capacity range, the cost shows a linear upward trend with the increase of the adjustment ratio. The adjustment of proportion can be divided into multiple stages and categories. A lower proportion of adjustments has little impact on users. However, a higher proportion of adjustments will lead to a rapid increase in costs, as it should improve the technical level to enhance backup capacity [20]. From the perspective of real-time electricity prices, under the guidance of marketization, real-time electricity prices will fluctuate with different electricity supply and demand conditions. The willingness to adjust costs and real-time electricity prices is expressed by equation (9).

$$e_{k,t} = \frac{\dfrac{\partial q_t}{q_t^0}}{\dfrac{\partial p_t}{p_t^0}} \tag{9}$$

In equation (9), k refers to the user, t refers to the moment, $e_{k,t}$ refers to willingness elasticity, q_t^0 refers to the electricity load before regulation, and p_t^0 refers to the real-time electricity price or adjustment cost before adjustment. Due to the continuous electricity consumption of users, the study utilizes cross elasticity coefficients to describe the regulation law, represented by equation (10).

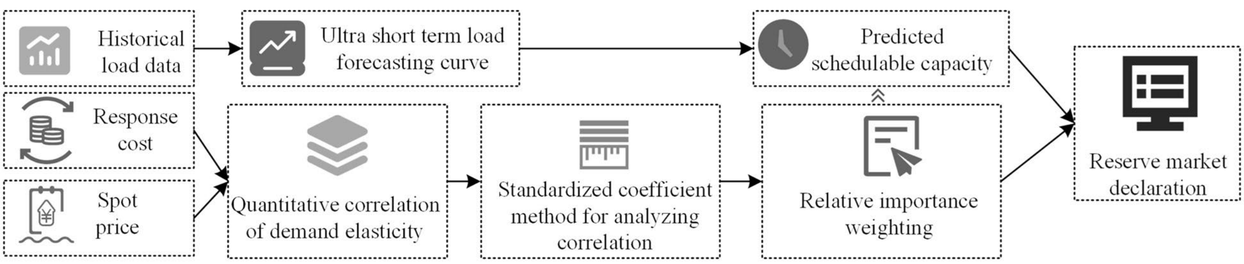


Figure 6. Adjustable capacity prediction scheme.

$$e_{ij} = \frac{\dfrac{\partial q_i}{q_i^0}}{\dfrac{\partial p_i}{p_j^0}} \tag{10}$$

In equation (10), i and j represent different time periods. Next, the standardization coefficient analysis will be conducted. The standardization of panel data will be represented by equation (11).

$$\tilde{y} = \frac{y - \dfrac{\tilde{\beta}}{\tilde{x}}}{s.d.(y)} \tag{11}$$

In equation (11), y refers to a dependent variable, x is an explanatory variable, and $\tilde{\beta}$ represents that for every standard deviation change in the explanatory variable, the dependent variable will change by $\tilde{\beta}$ standard deviations.

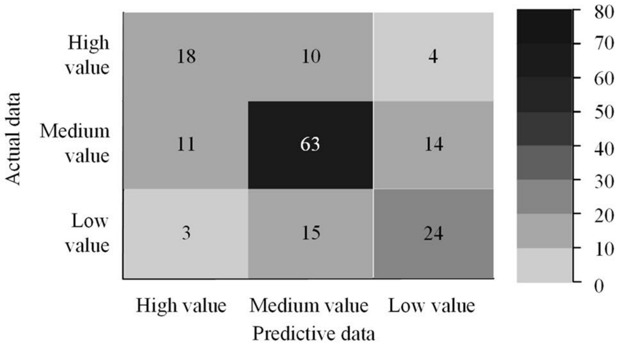
4. Results and Discussion

Firstly, the study validated the proposed classification model based on improved SVM. Different kernel functions' impact on the model's classification performance was analyzed. In addition, ablation experiments were conducted. Subsequently, the ultra short-term load forecasting performance based on LSTM-SaDE was verified. The matching degree between the reserve market declaration results obtained from load adjustable capacity forecasting and the actual volume was explored to confirm its effectiveness.

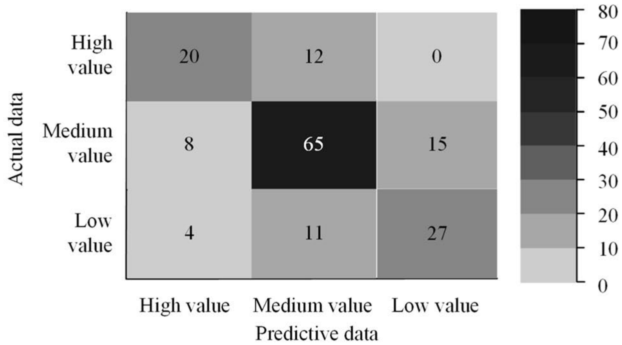
4.1 Experimental Analysis of Classification Model Based on Improved SVM

In the study, an experimental analysis was conducted using the summer operation of a power grid in a certain region to verify the proposed classification model based on improved SVM. There are 20 commercial buildings, 762 residential buildings, and 34 industrial users in the power grid of the region. The study selected 80% of resources as training samples and 20% as testing samples. The testing samples include 42 low value samples, 88 medium value samples, and 32 high value samples. The experiment utilized SVM classifiers with different kernel functions to classify and predict load levels, including linear kernel functions, polynomial kernel functions, and Radial Basis Function Kernel (RBF). Figure 7 shows the classification confusion matrix under different kernel functions. In Figure 7 (a), the SVM classifier with linear kernel function had classification accuracy of only 56.25%, 71.59%, and 57.14% for high, medium, and low value loads, respectively. In Figure 7 (b), the SVM classifier with polynomial kernel function had classification accuracy of 62.5%, 73.86%, and 64.29% for each load level, respectively, which showed a slight improvement when compared to the linear kernel function. In Figure 7 (c), the SVM classifier with RBF had classification accuracy of 84.38%, 92.05%, and 85.71% for different load levels, respectively, which was significantly better than the other two kernel functions. The SVM classifier based on RBF achieved better classification accuracy. By more precise classification of load levels, VPP operators can better optimize resource allocation and market trading strategies, meet users' electricity needs, and improve user satisfaction and service quality.

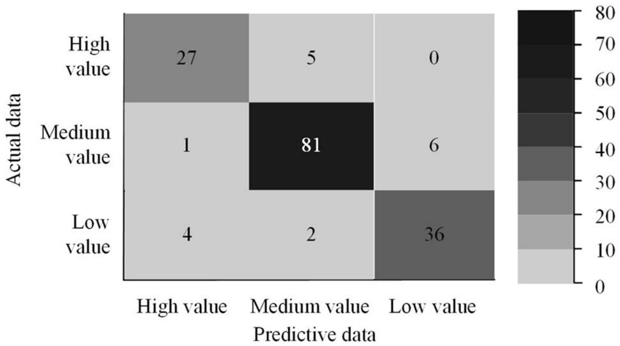
The study continued to utilize recall and F1 value to evaluate confusion moments. Figure 8 shows the classification recall and F1 value of SVM classifiers based on different kernel functions for load levels. In Figure 8 (a), the classification recall of the linear kernel function for high, medium, and low values was 50.13%, 77.68%, and 69.14%, respectively. The polynomial kernel function's recall was 63.58%, 73.46%, and 72.91%, respectively. RBF's classification recall was 82.41%, 90.04%, and 91.36%, respectively, which was significantly higher than for other kernel functions. In Figure 8 (b), the F1 values of the linear kernel function for high, medium, and low values were 60.07%, 68.34%, and 70.05%, respectively. The F1 values of polynomial kernel functions were 70.04%, 84.71%, and 76.81%, respectively. Finally, the F1 values of RBF were 83.14%, 93.85%, and 82.91%, respectively. This indicated that SVM classifiers based on RBF had better classification performance. The reason is that RBF can map the original sample to an infinite dimension, which distinguishes difficult to distinguish key points and, thus, improves classification performance.



(a) Confusion Matrix of Linear Functions.

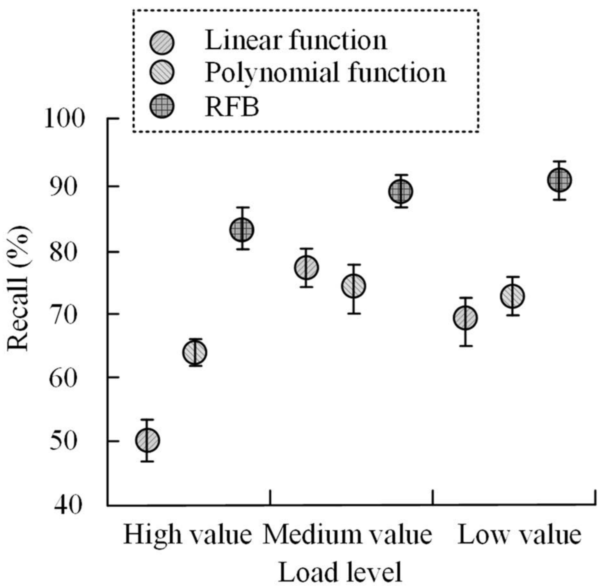


(b) Confusion Matrix of Polynomial Functions.

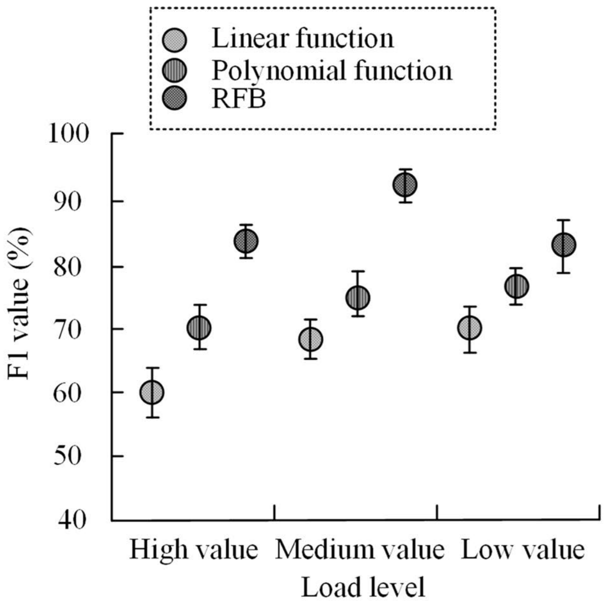


(c) Confusion Matrix of RFB function.

Figure 7. Confusion matrix of SVM classifiers based on different kernel functions.



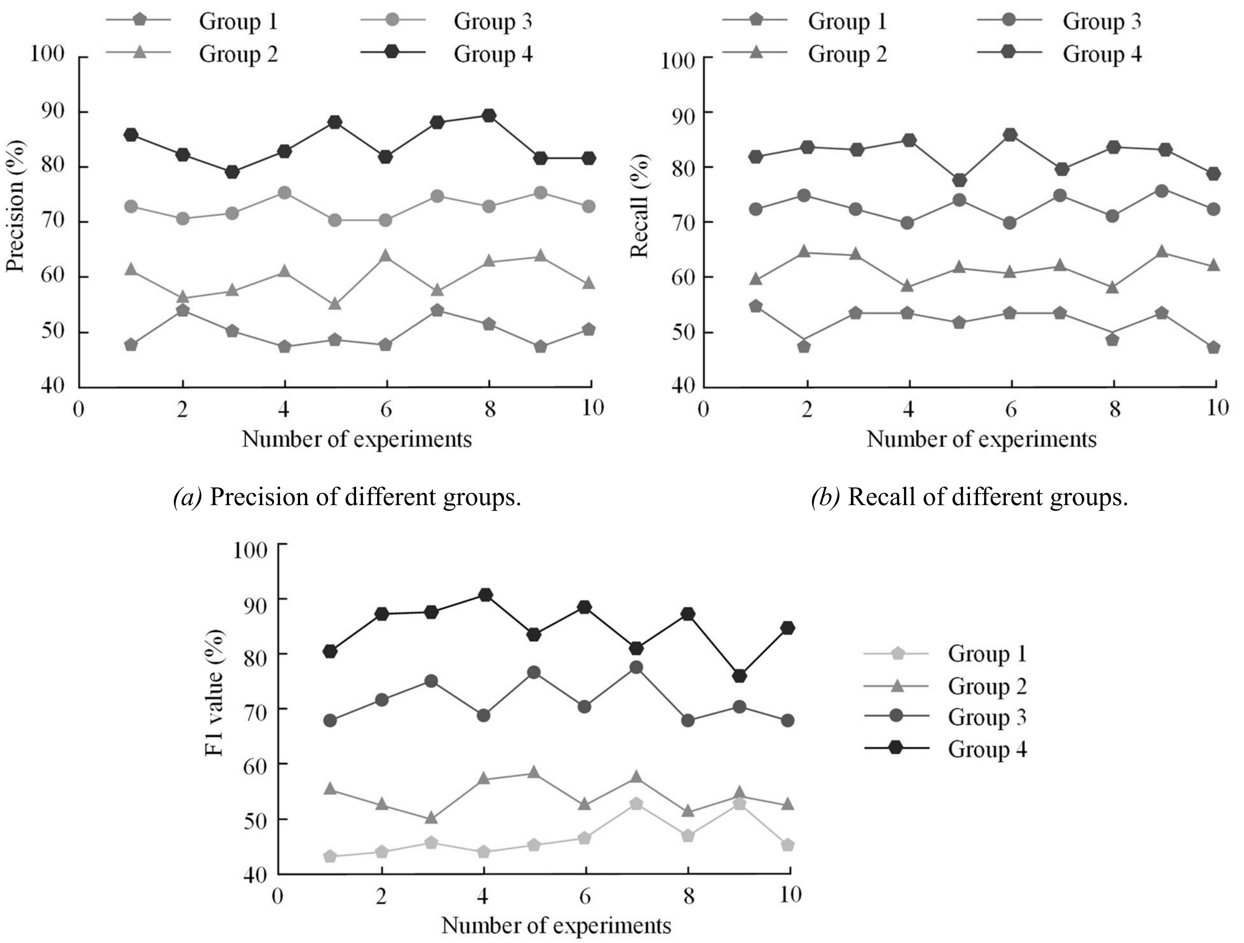
(a) Recall rates of different kernel functions.



(b) F1 value of different kernel functions.

Figure 8. Classification recall and precision of SVM classifiers based on different kernel functions.

To validate the improved SVM's superiority, ablation experiments were conducted. Four groups were set up. Firstly, solely the SVM used. The second group added the ADASYN synthesis step for few class samples to the SVM configuration. The third group added PCA dimensionality reduction processing on the previous configuration. The fourth group further added steps for DEC to enhance the sensitivity of hyperplanes based on the previous configurations. The evaluation indicators were precision, recall, and F1 value. 10 tests were conducted. Figure 9 shows the hierarchical model test results of four algorithms. In Figure 9 (a), the fourth group's precision was significantly better than the other groups, with an average value of 84.12%. Meanwhile, the second group's precision increased by 8.17% compared to the first group. The third group's precision increased by 10.58% compared to the second group. In Figures 9 (b) and 9 (c), the fourth group's recall and F1 value were higher than the other groups, with their mean values reaching 81.07% and 85.41%, respectively. ADASYN, PCA, and DEC all contributed to improving the classification model's classification performance, confirming its effectiveness. The reason is that ADASYN can increase the few class samples by generating composite samples, thereby improving the model's classification ability for minority classes. PCA can preserve the most important feature information by reducing the dimensionality of the data. DEC can effectively learn and extract abstract feature expressions from data through unsupervised learning, combined with autoencoder and clustering methods.



(a) Precision of different groups.

(b) Recall of different groups.

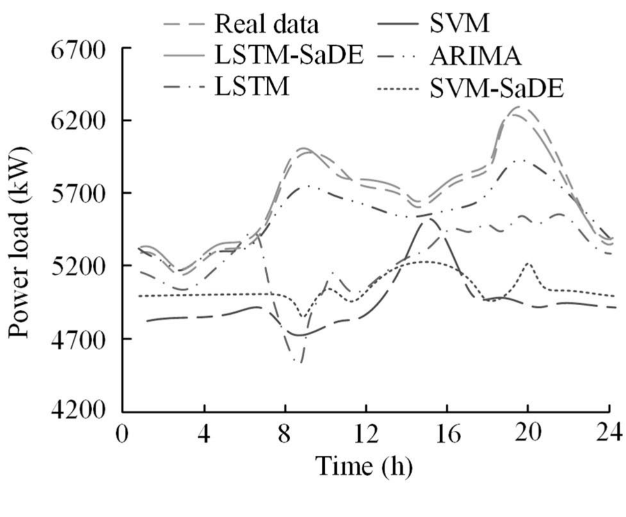
(c) F1 value of different groups.

Figure 9. Performance test results of hierarchical models based on different algorithms.

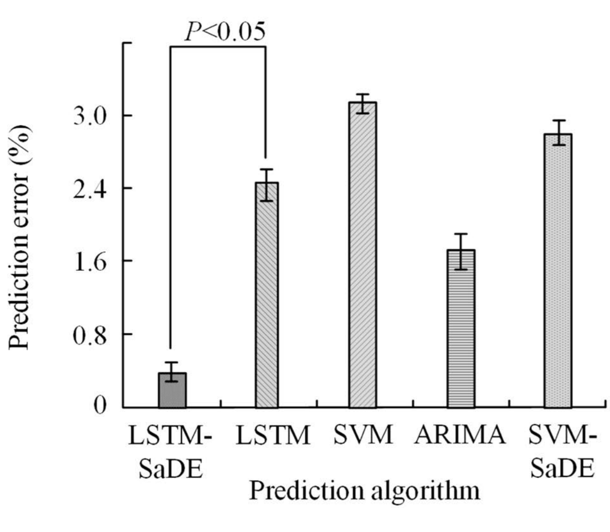
4.2. Load Adjustable Capacity Prediction Analysis

The study utilized the summer daily load curve of 1000 households as the test set to validate the predictive performance based on LSTM-SaDE. LSTM-SaDE, LSTM, SVM, ARIMA, and SVM SaDE were utilized to generate predicted load curves. Figure 10 shows the predicted and actual load curves' fit. In Figure 10 (a), the load forecasting curves of LSTM, SVM, ARIMA, and SVM SaDE differed significantly from the true values. LSTM-SaDE's predicted curve was similar to the true curve, having the best fit. In Figure 10 (b), LSTM-SaDE's average prediction error was 0.35%, and the maximum error was only 0.62%. The individual errors of ARIMA were relatively large, with an average of 1.68%. LSTM-SaDE achieved better prediction accuracy in ultra short-term power load forecasting scenarios. To evaluate the statistical significance of the performance improvement of the LSTM SaDE model proposed in our research compared to the baseline method, paired t-tests were conducted. The results showed a significant difference (P<0.01) between our model and the LSTM model, indicating that the improvement was not accidental but made substantial contributions. Reducing prediction errors can provide more reliable data support for long-term planning and optimization of power grid construction, resource investment, and operation strategies, enabling VPP operators to gain an advantage in the market, optimize trading strategies, and increase their market share.

VPP is only a price taker and does not have the ability to make declaration decisions. Meanwhile, the electricity prices and compensation mechanisms vary in different regions. Therefore, real-time market trading strategies need to adjust operating parameters based on different external conditions. The experiment set up three scenarios based on commercial characteristics and policy environment, including basic, high resource, and high electricity price scenarios. Table 1 shows the model parameter settings for different scenarios. In Table 1, when the power regulation coefficient increases by 10%, the total revenue of the model increases by about 8%, while the regulation cost increases by about 6%. On the contrary, when the coefficient decreases by 10%, the revenue decreases by about 7% and the adjustment cost decreases by about 5%. When the dividend ratio of backup services increases by 10%, the investment in backup resources increases by about 12%, and the total revenue increases by about 9%. When the proportion decreases by 10%, the input of backup resources decreases by about 10%, and the total revenue decreases by about 8%. In case when the cost and adjustment parameters increase by 10%, the total cost increases by about 7% and the adjustment efficiency improves by about 5%. When the parameters are reduced by 10%, the total cost is reduced by about 6% and the



(a) Prediction curves of different algorithms.



(b) Prediction error of different algorithms.

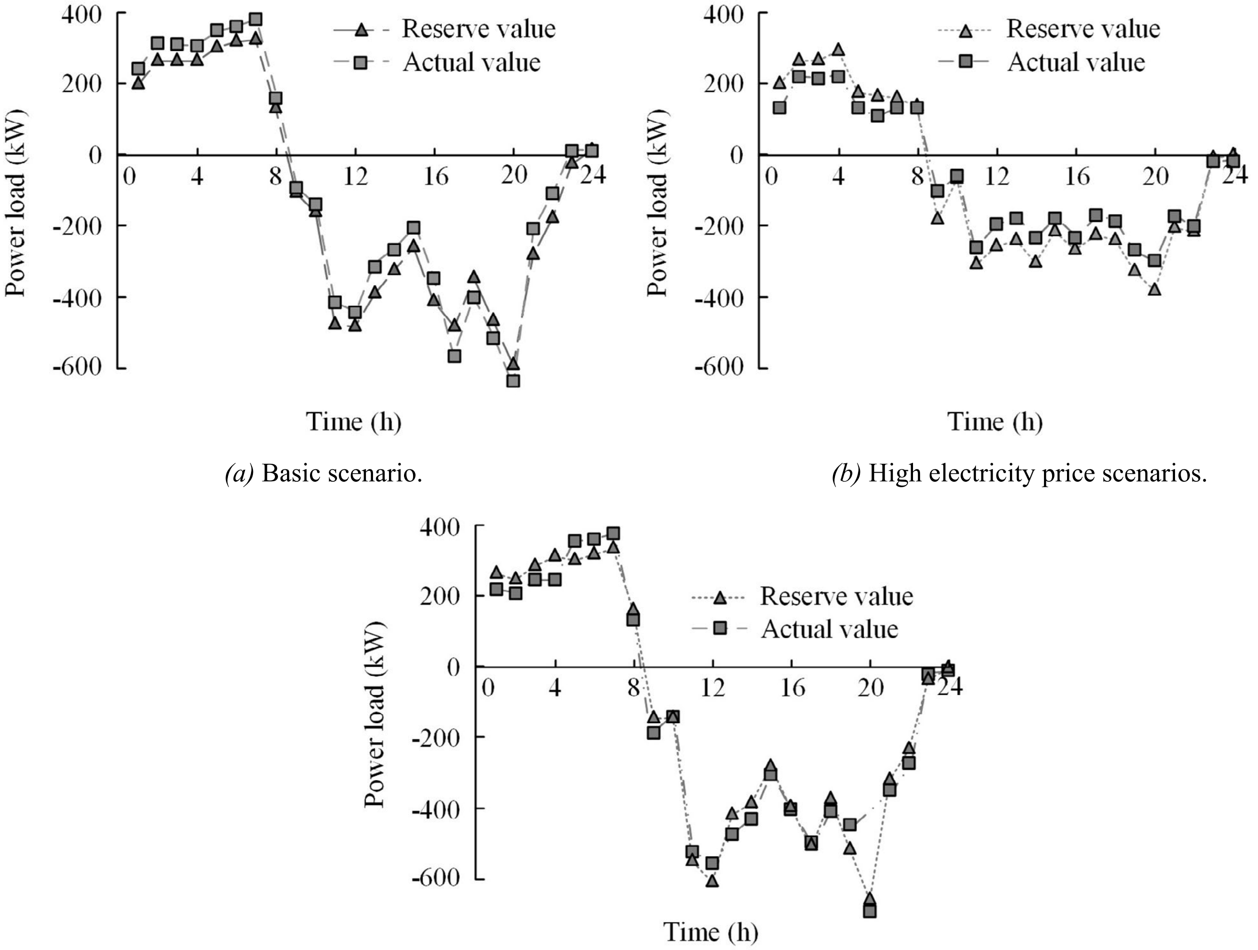
Figure 10. The fit between the predicted curve and the actual load curve.

regulation efficiency is reduced by about 4%. Furthermore, when the price of non water excess consumption vouchers increases by 10%, consumer demand decreases by about 8%, but the income of a single voucher increases by about 9%. When the price decreases by 10%, consumer demand increases by about 9%, but the income from a single coupon decreases by about 8%. When the price parameter increases by 10%, the total revenue increases by about 7%, and the transaction cost increases by about 5%. For the case when the parameter range is reduced by 10%, the total revenue decreases by about 6% and the transaction cost decreases by about 4%. When the total excess consumption voucher price increases by 10%, market demand decreases by about 6% and total returns increase by about 5%. When the price decreases by 10%, market demand increases by about 7% and total revenue decreases by about 6%. When the parameter for evaluating the proportion of new energy consumption increases by 10%, the utilization rate of new energy increases by about 8%, and the total revenue increases by about 6%. When the proportion decreases by 10%, the utilization rate of new energy decreases by about 7%, and the total revenue decreases by about 5%.

The research adopted the ultra short-term load forecasting results based on LSTM-SaDE to jointly use in load adjustable capacity forecasting. The predicted values were utilized for reserve market declaration. The actual load adjustable capacity prediction effect in actual reserve market declaration was analyzed. The backup auxiliary services' declared volume and the actual volume's matching degree in different scenarios was verified. Figure 11 shows the declared and actual quantities of backup auxiliary services in different scenarios. In Figure 11 (a), in the basic scenario, the declared and actual standby auxiliary service quantities based on load adjustable capacity prediction had consistent variation, with a maximum deviation of only 88.62 kW. In Figure 11 (b), in the high electricity price scenario, the maximum deviation between the declared and actual standby auxiliary services obtained by the proposed method was only 87.69 kW. In Figure 11 (c), in a high resource scenario, the maximum difference between the declared and actual amount of backup auxiliary services was only 52.39kW. The reason is that this method effectively enhances the cost and price's sensitivity, thereby improving the reserve declaration prediction accuracy.

Table 1. Model parameter settings for different scenarios.

	Basic scenario	High resource scenarios	High electricity price scenarios
The coefficient of the relationship between electricity regulation	1	0.8	1.5
Reserve auxiliary service dividend ratio	0.2	0.3	0.15
Cost and regulation parameters	0.4	0.3	0.5
Non water excess consumption voucher price (yuan)	53.62	70.14	42.58
Price parameters (%)	70~120	80~120	80~110
Total excess consumption voucher price (yuan)	48.25	38.59	62.68
New energy consumption assessment ratio parameters	0.9	0.8	1.0



(a) Basic scenario. *(b)* High electricity price scenarios.

(c) High resource scenarios.

Figure 11. The declared and actual quantities of backup auxiliary services in different scenarios.

5. Discussion

In order to optimize the real-time market trading strategy of VPP, a resource grading model based on an improved SVM algorithm was constructed and optimized. On this basis, an ultra short term load forecasting and adjustable capacity forecasting method based on an improved LSTM algorithm was proposed. The results showed that the SVM classifier with RBF kernel function achieved classification accuracies of 84.38%, 92.05%, and 85.71% for different load levels, with classification recall rates of 82.41%, 90.04%, and 91.36%, and F1 values of 83.14%, 93.85%, and 82.91%, respectively. Similarly, scholars such as Ali I M S proposed a new data classification model, which uses an optimized multi-core SVM classifier and utilizes hyper heuristic skip group optimization for adjustment. The results show that the classification accuracy of this method is as high as 95.69% [21]. Compared to it, the classification accuracy of the SVM classifier used in the study is slightly lower, because the hyper heuristic skip group optimization algorithm adopted by Ali IMS can explore the parameter space on a larger scale, thereby finding better parameter combinations. In contrast, the SVM classifier used in the study did not employ advanced optimization algorithms, resulting in insufficient parameter tuning and affecting the accuracy of the model, thus requiring further improvement. In load forecasting experiments, the load forecasting curves of LSTM, SVM, ARIMA, and SVM SaDE algorithms differ significantly from the actual values. The predicted curve of LSTM SaDE algorithm is similar to the trend of the real curve, with the highest degree of fit. Among them, the average prediction error of LSTM SaDE algorithm is 0.35%, and the maximum error is only 0.62%. However, ARIMA has relatively large individual errors, with an average of up to 1.68%. Ghasemi Olanlari and other scholars' research used LSTM to predict uncertain parameters of electricity load, DA market price, wind speed, and solar radiation. The results show that the LSTM model has an error of 1.94% in load prediction [13]. This value is significantly higher than the prediction error of the LSTM SaDE model used in the study, indicating that the research has significantly improved the prediction accuracy of the LSTM model after improvement. By using improved SVM and LSTM SaDE models for data classification and ultra short term load and adjustable capacity prediction, VPP operators can improve the accuracy of resource management and market transactions, thereby optimizing operational efficiency, reducing costs, and increasing market revenue. Stakeholders in the electricity market will also benefit from a more stable market environment and fair competition.

Although the improved SVM and LSTM SaDE models proposed in the study perform well in classification and prediction, in the case of sparse data, the models may not be able to effectively learn patterns in the data, resulting in performance degradation. Especially in load forecasting tasks, if historical load data is insufficient or unevenly distributed, the prediction accuracy of the model may be limited. Future research can explore solutions to the problem of data sparsity, such as using generative adversarial networks to generate more training samples, or using transfer learning techniques to improve model performance in situations of insufficient data.

6. Conclusion

With the continuous improvement of new power systems, VPP, as a key component, needs to efficiently schedule and make precise trading decisions while faced with a large number of resources and demands. Currently, there is an urgent need to optimize the technologies in these areas. Therefore, the study proposed an improved SVM for resource allocation. On the basis of the hierarchical model, the LSTM SaDE algorithm is further proposed to achieve ultra short-term load and adjustable capacity prediction.

The results show that the SVM classifier with a linear kernel function has classification accuracies of only 56.25%, 71.59%, and 57.14% for high, medium, and low value load levels, respectively. The classification accuracy of SVM classifier with polynomial kernel function for each load level was 62.5%, 73.86%, and 64.29%, respectively. Finally, the SVM classifier with the RBF kernel function had classification accuracy of 84.38%, 92.05%, and 85.71% for different load levels, respectively, which was significantly better than the other two kernel functions. The SVM classifier based on RBF kernel function achieved better classification accuracy. In the ablation experiment, SVM model improvement based on ADASYN, PCA, and DEC achieved higher precision, recall, and F1 value. In addition, in high electricity price scenarios, the maximum deviation between the declared amount of backup auxiliary services obtained by the proposed method and the actual amount was only 87.69 kW. In high-resource scenarios, the maximum difference between the declared amount of backup auxiliary services and the actual amount was only 52.39 kW.

The comprehensive application of improved SVM and LSTM SaDE models effectively enhances the efficiency of VPP in complex resource scheduling tasks, making resource allocation more precise and market participation more flexible. Meanwhile, this method optimizes market trading decisions and enhances the overall economic benefits of VPP in the electricity market. Subsequent research can explore how to apply generative adversarial networks or transfer learning to generate more high-quality load data samples, in order to alleviate the problem of data sparsity and improve the learning ability and prediction accuracy of the model.

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