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Analysis and Accurate Prediction of User's Response Behavior in Incentive-Based Demand Response

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ABSTRACT Incentive-based demand response can fully mobilize a variety of demand-side resources to participate in the electricity market, but the uncertainty of user response behavior greatly limits the development of demand response services. This paper first constructed an implementation framework for incentive-based demand response and clarified how load-serving entity aggregates demand-side resources to participate in the power market business. Then, the characteristics of the user's response behavior were analyzed; it is found that the user's response behavior is variable, and it has a strong correlation on the timeline. Based on this, a prediction method of user response behavior based on long short-term memory (LSTM) is proposed after the analysis of the characteristics of the LSTM algorithm. The proposed prediction method was verified by simulation under the simulation environment setup by TensorFlow. The simulation results showed that, compared with the traditional linear or nonlinear regression methods, the proposed method can significantly improve the accuracy of the prediction. At the same time, it is verified by further experiments that the proposed algorithm has good performance in various environments and has strong robustness.

INDEX TERMS Artificial neural networks, machine learning algorithms, state estimation, power demand, activity recognition, consumer behavior.

I. INTRODUCTION

As one of the important means for resource scheduling on the demand side, the demand response can fully invoke the resources on the demand side so as to alleviate the problem of decreased flexibility of power system caused by large-scale penetration of renewable energy resource [1]–[3]. Incentive-based demand response can integrate demand side resources flexibly and extensively, and then participate in the business of the electricity market [4]–[7]. Load Serving Entity(LSE) can deliver appropriate incentives for target users based on user's response flexibility, which is obtained by analyzing the user's historical data, so that the profit of LSE can be maximized on the premise of completing the response goal [8], [9].

In its 2016 report [10], the International Energy Agency proposed to integrate home users and participate in the electricity market. Coincidentally, in the long-term planning of the PJM power market, it also proposed the need to further expand the scope of demand response to participate in the power market business [7]. Demand response can significantly improve the efficiency and economy of grid operation [11]. Demand response potential typically amounts to around 15% of peak demand. The International Energy Agency (IEA) assessed that the potential could exceed 150 gigawatts (GW) by 2050 in the European Union [10]. Demand response programs could also be an alternative to investment in network capacity upgrades to address congestion. In the case of the United Kingdom, it has been estimated that the cost of network reinforcement could be around one-third less in a system with optimal demand response combined with 100% penetration of electric vehicles and heat pump space heating [13]. In PJM, over 2 million end use customers across almost every segment (residential, commercial, industrial, government, education, agricultural, etc.) participate as Load Management resources [6]. A large number of distributed residential users have a huge demand response potential. It is able to form a large-scale demand response capacity through the aggregation of a large number of small resident users, and then participate in the demand response business of the electricity market [14], [15]. However, the distributed residents' electricity consumption and response behavior are diversified and distributed, which makes LSE face great uncertainty in implementing demand response services, and it is difficult for LSE to accurately estimate the actual effect of demand response [16], which greatly limits the ability of demand-side aggregated resources to participate in the power market business. With the development of intelligent information collection technology [17] and the development of user information analysis technology [18], it is possible to analyze and predict user behavior.

Based on this, the recognition and prediction of the response behavior of users under different incentives have become the primary conditions for LSE to successfully aggregate demand side resources and participate in Electricity market.

A. LITERATURE REVIEW

There has been a lot of research on the prediction and optimization of user behavior. Gao *et al.* [19] propose a novel cross-domain recommendation model for the information processing and computing in CPS(Cyber-physical systems), alleviated the sparsity problems in individual domain and improved across recommendation accuracy. Qiao *et al.* [20] studied domain-independent prediction algorithms and spatio-temporal based prediction method, searching for low cost and simple location/place prediction methods that can be implemented on mobile device. Xie *et al.* [21] proposed a combined model STL-ENN-ARIMA (SEA), based on the combination of the Elman neural network (ENN) and the autoregressive integrated moving average (ARIMA) model, improved the performance of heat demand prediction. Zeng *et al.* [22] propose a new methodological framework to assess the potential reliability value of DR in smart grids, to deal with the the uncertainty on the demand side. Liu *et al.* [23] optimized the incentive function of the traditional Elman neural network model, introduced the influence factors of demand response, and improved the accuracy of short-term power load forecasting. Zhang *et al.* [24] proposed an effective model predictive control method that can minimize the operating cost of residential microgrid and is robust to the uncertainty of the prediction. Garulli *et al.* [25] compared the prediction performance of several linear and nonlinear load forecasting models, including the black box model that does not require preprocessing of the original data, and the gray box model that is applied after a certain preprocessing of the original input signal. Li *et al.* [26] abstracted the user's response cost into a quadratic function and uses a least-squares method to train the user's cost function. Fei *et al.* [27] proposed a synchronous pattern matching principle based residential customer baseline load estimation approach without historical data requirement. Campos and Wei [28] formed a mixed-integer linear programming model for short-term decisions of power retailers and solved the model to maximize profits, the user's response under different incentives is reported by the user beforehand. Jindal *et al.* [29] proposed a novel data analytical demand response management scheme for residential load with an aim to reduce the peak load demand after analyzing the smart user's home load data. Yu *et al.* [5] viewed DR as a multi-interest game process and used game theory to analyze the coordination among decision makers. The user's response cost function was abstracted to a quadratic function. Dadkhah and Vahidi [30] provided demand-side flexibility by using an optimal real-time pricing scheme. Different levels of rationality are given by extending demand-price elasticity matrices for different types of consumers. Paterakis *et al.* [31] predicted the load curve of residential load under the price signal based on artificial neural network and wavelet transform methods.

From the analysis of the above literatures, it can be seen that most of the behavioral analysis of users in demand response focuses on the prediction of user load, and lack of analysis and prediction of the user's response behavior under different environments and incentive signals. Therefore, this paper analyzed this issue.

B. CONTRIBUTION OF THIS PAPER

The main contributions of this paper are summarized as follows:

Firstly, the architecture of the incentive-based demand response is constructed and analyzed, providing a reference for the implementation of incentive-based demand response business.

Secondly, the user's response behavior is analyzed economically. Based on the existing user's response cost abstract formula, the user's response elasticity is analyzed to provide support for the user's response behavior identification.

Finally, the characteristics of the Long Short-Term Memory (LSTM) algorithm are analyzed, and the LSTM-based user's response behavior identification method is proposed. Through simulation experiments, it is verified that the method can accurately predict the user's response behavior. At the same time, it has good performance in different environments and has strong robustness.

The remainder of this paper is organized as follows: In Section II, the implementation framework and method of the refined demand response are described. And the user's economic characteristics when participating in the demand response are analyzed in depth at the same time. In Section III, the characteristics and basic flow of the LSTM algorithm are analyzed. Based on this, an accurate identification method of user's response behavior based on LSTM is proposed. In Section IV, the accuracy of the proposed algorithm for predicting the user's response behavior is verified by simulation experiments, and the performance of the algorithm is analyzed from multiple perspectives. Section V concludes the paper.

II. IMPLEMENTATION ANALYSIS OF INCENTIVE-BASED DEMAND RESPONSE

The implementation process of incentive-based demand response is shown in Figure 1. LSE can integrate the resources on the demand side to participate in the electricity market as an independent entity. LSE obtains the target quantity of demand response and corresponding subsidies from the electricity market through bidding or other means. At the moment of implementation of demand response, different incentives are sent to users according to their status in order to achieve the target response.

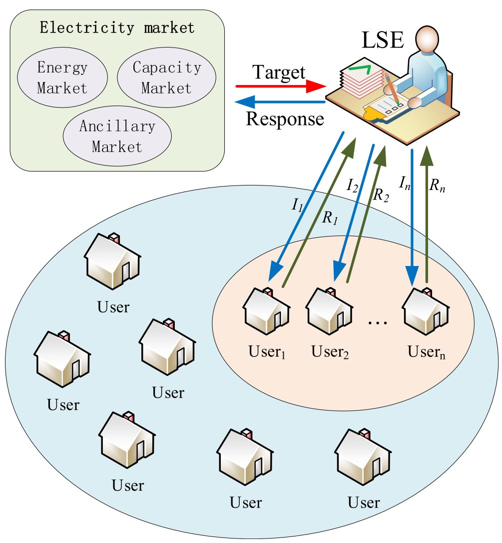

FIGURE 1. Incentive-based demand response implementation diagram.

The conventional services in the power market all have requirements for deviations. Take PJM as an example, in energy market, LSE need to participate real-time electricity trading or purchase ancillary services to make up for the deviations between electricity obtained from day-ahead market and the real electricity. Also, in ancillary market and capacity market, LSE can provide load reduce through demand response. In accordance with the provisions of the PJM power market, all the load involved in load management (Contains 4 types of demand response: Limited DR, Extended Summer DR, Annual DR, and Capacity Performance DR) that is not dispatched during its availability period must perform a mandatory test to demonstrate it can meet its capacity commitment or receive a penalty. If the load capacity reported by the LSE is too small, the profit will be reduced. On the contrary, it may be punished for failing to achieve the goal. Therefore, when the LSE integrates the demand side resources to participate in the regular business of the power market, it needs to have a precise prediction of the user's response behavior. LSE delivers different demand incentives I to the target users according to response requirement in each demand response service. Different from TOU, RTP and other load adjustment methods, the incentive-based demand response can make the adjustment of the LSE more flexible and help to improve the precision of its business development. For each user, the received incentive value I from LSE may be the same or different, so that highly flexible users can participate more in the demand response business, which can further improve the overall efficiency, the user responds according to the incentive value, and transmits the response R back to the LSE.

In the entire business process of incentive-based demand response, the user's response to different incentives is affected by many factors. The response characteristics of different users can be described using price elasticity. For different users, the price elasticity may be different, for the same user, the price elasticity may also change under different external environments [32]. In general, the user's response elasticity is mainly affected by the following factors [16], [33]:

① Availability of similar alternatives. For example, the gas stove can easily replace the role of the induction cooker when the electric price is high if the home is equipped with both of these, the gas water heater can also replace the electric water heater to reduce the whole cost. In this case, the user's response flexibility may be high.

② The current load status of the user. If the current load is high and the interruptible or transferable load is relatively large, the user will be more likely to respond to the incentive, and the response elasticity will be high.

③ The proportion of electricity consumption expenditure in households' total expenditure. In general, when the user's economic status is better, the proportion of electricity expenses in its total expenditure is smaller, and the user may be less sensitive to incentives. Conversely, users may be more sensitive to incentives.

④ External environment. For example, at high temperatures during the summer noon, the user's demand elasticity may be low, so if the LSE wants to encourage the user to change or shut down the temperature control device to reduce the load through incentives, the higher cost is required, and in the evening, as the external environment temperature decreases, the user's demand elasticity may increase. At this time, the user may be more willing to respond to the load-reducing demand at a lower price.

In economics, demand elasticity is used to characterize the user's sensitivity to a commodity price change. Similarly, response sensitivity can also be used to characterize the user's responsiveness to incentive prices. The user's response elasticity formula is as follows:

$$E_R = \frac{\Delta R/R}{\Delta I/I} = \frac{\Delta R}{\Delta I} \cdot \frac{I}{R} \tag{1}$$

where E is the elasticity of demand, R is the response amount of the user in the demand response, and I is the amount of incentive received by the user.

The participation of users in the demand response service will be accompanied by a certain degree of loss of comfort. Therefore, the user's response is costly. Since the user's comfort cost is a very abstract quantity, it is difficult to express it in terms of physical models. According to the current research, the user's comfort loss will increase at a faster rate as the response volume increases and the change curve is similar to a quadratic function and can be approximated by a quadratic function. Therefore, the cost function that the user participates in the demand response can be expressed as [5], [26]:

$$U(R) = \frac{1}{2}\beta_{\cos t}R^2 + \alpha_{\cos t}R \tag{2}$$

Formula (2) can reflect the response characteristics of different users with different parameters (α_{cost} and β_{cost}). In general, the user is willing to respond when the incentive received by the user can compensate for the loss of comfort, if LSE wants the user's response to be R, the incentive I sent to the user should be greater than or equal to the user's response cost. In this paper, it is assumed that the user is willing to respond when the amount of incentive received by the user is higher than or equal to the cost of the response. Maybe not all the users want to respond when the incentive received is equal to the comfort loss(they may respond when the incentive received higher than the comfort loss), but we can find the critical point that the user is willing to respond by adjusting the parameters α and β. It should be noted that the actual maximum response of the user should not exceed the current load. Therefore, it is necessary to add a constraint on the amount of the user's response. In this case, the relationship between the user's response and the incentive can be expressed as:

$$\begin{aligned} &U_{ad}(R) = \frac{1}{2}\beta_{ad}(R+\varepsilon)^2 + \alpha_{ad}(R+\varepsilon) \\ &s.t.\ R \le L \end{aligned} \tag{3}$$

where U_{ad} is the user's response cost, L is the user's current load, ε is the noise of the user response, α_{ad} and β_{ad} are undetermined parameters, and their values depending on the user's response characteristics. Actually, the user's participation in the demand response can be seen as the LSE purchase response from the end user, that is, the user can be regarded as the supplier and provide the "goods" to the LSE. In economics, the price elasticity of supply is expressed as the ratio of the percentage change in supply to the percentage change in price. According to formula (3), the user's supply elasticity can be calculated, Since the noise of the user response is low-order and random, we ignore the noise when analyzing the user's supply elasticity. The user's response elasticity is as follows:

$$E_R = \frac{dR}{dU_{ad}} \cdot \frac{U_{ad}}{R} = \frac{\beta_{ad}R + 2\alpha_{ad}}{2\beta_{ad}R + 2\alpha_{ad}} \tag{4}$$

where E_R is the supply elasticity coefficient of user, reflects the sensitivity of the user's response to changes in incentives. Different users have different response characteristics [34], and these differences can be reflected by different α and β values. Relationship between incentive and response of user and the elasticity coefficient curve are shown in Figure 2:

As can be seen from the above figure, the user's response flexibility will gradually decrease, and the incentive cost will increase rapidly with the increase of user's response. It also can be seen that the user's response curve shows different rising speeds for different user with different α and β values. Under the same incentive, user1's response is significantly greater than user2's response. In the incentive-based demand response business model, the LSE can achieve the goal of minimizing the incentive cost when the total response is constant by providing different incentives for each user based on incentive-based prediction of user's response. Therefore, it is very important to accurately predict the response of users under different incentives.

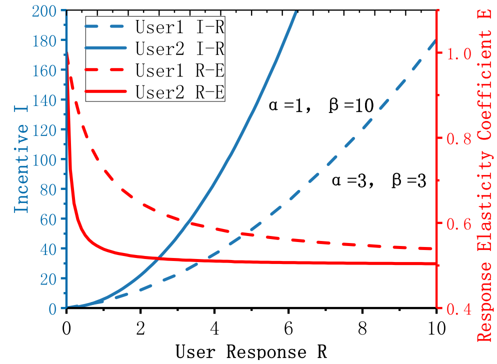

FIGURE 2. User's response cost curve and its elasticity curve.

The above description is only an approximation of the user's response behavior in an ideal environment. However, in actual situations, the user's response behavior (α and β values) may fluctuate [32]. Therefore, using a simple quadratic function obviously cannot accurately describe the user's response behavior, and a more accurate method is needed to predict the user's response behavior.

III. PREDICTION METHOD OF USER RESPONSE BEHAVIOR BASED ON LSTM

The response characteristics for the same user at different times of a day may be different because the user's response characteristics are affected by the external environment and the user's response characteristics have a strong context on the timeline because its electricity behavior has periodic characteristics. Existing methods for predicting user behavior, whether it is an approximate abstract function or a linear or nonlinear approximation, are difficult to describe the relationship in time series, so it is difficult to accurately predict the user's response behavior. The LSTM network has a powerful processing capability for time-series related data. It stores historical response status through the cell, and removes less relevant data through forget gates so the user's response behavior can be accurately predicted by using the LSTM network [35], [36].

According to formula (3), the incentives received by the user directly determines the response of the user, and different external factors affect the parameters α_{ad} and β_{ad} of the user response in formula (3).

For the incentives the user receives, in each demand response business process, LSE will determine the amount of incentives to be sent to each user based on the different total target response and the response status of each user, with the goal of benefit maximization. If LSE knows the user's response state, that is the α and β values in formula (3), LSE can optimize the amount of incentives sent to each user using the Lagrangian multiplier method under the total target response in each demand response business. But LSE don't know the relationship between external factors and user response status.

There are many external factors (Such as temperature, humidity, wind speed, sunshine conditions, etc.) that affect the user's response behavior. For LSTM networks, the more relevant factors they input, the more accurate the training results may be. However, in actual situations, some data is difficult to collect or it is difficult to form continuous structured data (such as real-time temperature, humidity, wind speed, etc.) or its acquisition cost is high (such as real-time power consumption data of a user's individual electrical equipment including air conditioners, electric water heaters, lighting equipment, etc. , the collection of this data requires the user's authorization and requires the installation of electrical data acquisition and transmission devices). Although external factors affecting user response behavior are diverse, in similar days, all the external influence factors of user response behavior will be similar. Considering that the user's load behavior has periodic characteristics, that is, users have similar response behaviors in similar time periods in similar day. In order to enable the algorithm to identify historical similar days, we select the daily maximum and minimum load(these data can be acquired from load prediction [37], [38]) as one of the inputs. Similarly, in order to enable the algorithm to identify similar time periods, we choose time as one of the inputs. The user's current load status determines the user's maximum response potential, so select the user's current load as one of the inputs, too. In summary, the inputs selected for the LSTM network is as follows: daily maximum load, daily minimum load, current load, time, and incentives received.

The structure of a typical LSTM is shown in the following figure [35], [36], [39]:

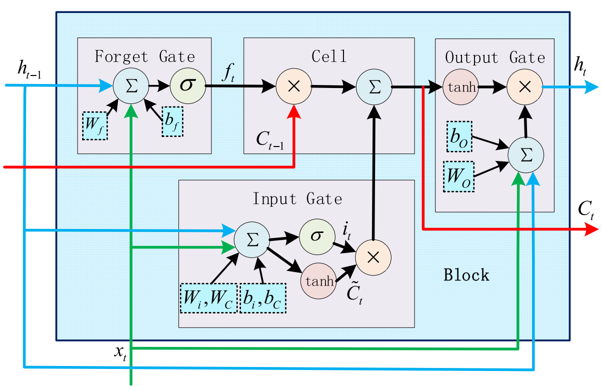

FIGURE 3. LSTM structure diagram.

In the LSTM structure, what kind of information is discarded is determined by the Forget Gate. The Forget Gate reads the status information h_{t-1} at the last moment and the input information x_t at the current moment, and then outputs a 0 to 1 digit f_t to the Cell. The information stored in the Cell is the state information of the previous time, and the useful information is retained and the useless information is discarded according to the input f_t of the Forget Gate. During the execution of the program, external environmental information and incentives that are far apart from the current status are discarded, and similar external environmental information and incentives are retained. The Forget Gate update formula is as follows:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{5}$$

where, σ is the sigmoid function, W_f is the weight of the Forget Gate, b_f is the offset of the Forget Gate, h_{t-1} is the output of the last moment, and x_t is the input of the current moment.

The Input Gate decides what kind of value will be used to update the status of the Cell, replace non-similar day information with similar day information. The input vector is processed by the activation function sigmoid to generate i_t, and the candidate value vector $\tilde{C}_t$ is generated using the tanh function at the same time. The Input Gate update formula is as follows:

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{6}$$
$$\tilde{C}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \tag{7}$$

where, W_i, b_i is the weight and offset of input, respectively. W_C, b_C is the weight and offset of the candidate vector, respectively. $\tilde{C}_t$ is a candidate value vector.

The status data of the previous time is recorded in the Cell. After reading of the current input data, the status information in the cell needs to be updated. The content to be discarded is selected using the data input from the Forget Gate, and the content to be updated is selected using the data input from the Input Gate. The update formula for the Cell is as follows:

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{8}$$

After updating the Cell state, it is necessary to determine the content to be output according to the Cell state content and the current input, that is, the user's expected response amount. The output gate update formula is as follows:

$$o_t = \sigma\left(W_o\,[h_{t-1}, x_t] + b_o\right) \tag{9}$$
$$h_t = o_t \times \tanh\left(C_t\right) \tag{10}$$

where, W_O, b_O is the weight and offset of the Output Gate, respectively.

This paper simulates the LSTM network based on TensorFlow. The algorithm flow is shown in Figure 4.

Step 1: read data. Input data include daily maximum load, daily minimum load, daily average load, time and received incentive, tag data is user response. Since the units of different

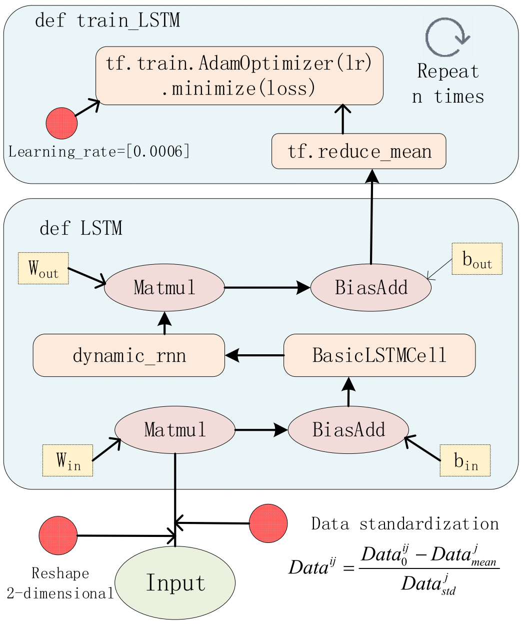

FIGURE 4. TensorFlow-based LSTM algorithm flow chart.

input data are different, they need to be standardized. The standardized formula is as follows:

$$Data^{ij} = \frac{Data_0^{ij} - Data_{mean}^{j}}{Data_{std}^{j}} \tag{11}$$

where, $Data^{ij}$ is the data after processing, $Data_0^{ij}$ is the original data, $Data_{mean}^{j}$ is the average value of the jth column data, and $Data_{std}^{j}$ is the standard deviation of the jth column data. Due to the requirements of the TensorFlow function, the format of the input data needs to be converted into 2 dimensions, which can be implemented by calling the reshape function of TensorFlow. After the above processing, the input data x_t shown in Fig. 3 is formed.

Step 2: Building LSTM network graph. The algorithmic logic of TensorFlow determines that the graph of the LSTM network needs to be built first, that is, establish the LSTM network shown in Figure 3. Calls "BasicLSTMCell" to define Cell, the number of hidden layers is set to 10.

Step 3: Initialization parameters. After building graph, all the variables (include all the weights and biases) involved in Figure 3 need to be initialized. Initialize weights using normal distribution with 0 as the mean and 1 as the standard deviation, all initial biases are set to 0.1.

Step 4: Training LSTM model. When training the model, the gradient descent algorithm can be used to train the parameters. If θ is used to represent the parameters (weights and biases) of the neural network, $LOSS(\theta)$ represents the loss function of the whole network. The optimization process is to find a parameter θ such that $LOSS(\theta)$ is the smallest. The gradient descent method updates the parameter θ in an iterative manner along the opposite direction of the gradient (that is, the direction in which the parameter is made smaller toward the total loss):

$$\theta_{n+1} = \theta_n - \alpha \frac{\partial LOSS(\theta_n)}{\partial \theta_n} \tag{12}$$

where, α is the learning rate, LOSS is the mean square error between the predicted and actual values. In order to speed up the training, a random gradient descent method can be used: in each iteration, the loss function of the training sample is randomly selected for optimization, thereby speeding up the update speed of each iteration. However, the minimum loss obtained by the stochastic gradient descent method may not represent the minimum loss of all data. Therefore, combined with the advantages of gradient descent and random gradient descent, a small portion of the loss function of the training data is calculated each time. We call this part of the data batch. The use of batch makes the parameters optimized in each iteration not too small, and it can reduce the number of iterations to reach convergence, and make the convergence result closer to the gradient. In TensorFlow, we can call the function "tf.train.AdamOptimizer(α).minimize(LOSS)" to implement this process. Where learning rate α is set to 0.0006, batch size is set to 60.

Step 5: Predict the user's response behavior. After n times training on the LSTM network, the loss function will reduce to a lower level. At this point, the training process is completed and then save the model. Use the method in step 1 to standardize the input data, and then call the trained model to predict the user's response.

IV. SIMULATION RESULTS

As described in Section 2, a user's response behavior can be approximated by a quadratic function. The response elasticity of the same user at different times of the day may be different [40], therefore, the user may have different values of α and β at different time periods. Generate historical response data of users according to [5], [26], and [41]. In order to reflect the random noise ε in the user's response behavior, the α and β values are generated using a Gaussian distribution. The Parameter settings are shown in the following table:

TABLE 1. User's response behavior parameters.

Time	0-6	7-12	13-18	19-24
The mean of α	1.5	3	1	1.7
The mean of β	6	5	6	4.2
Standard deviation	0.2	0.2	0.2	0.2

In the simulation, 20 sets of data are set as the test group. These 20 sets of data are actually 20 demand response events, so the number of times is used to represent each test group. The incentives received by the test group are shown in Figure 5:

Existing literature often uses linear or nonlinear regression methods to fit the user's response, Li *et al.* [26] use the least square method, its assumption is that the user's α and β values are the same in each period. But in reality, the response

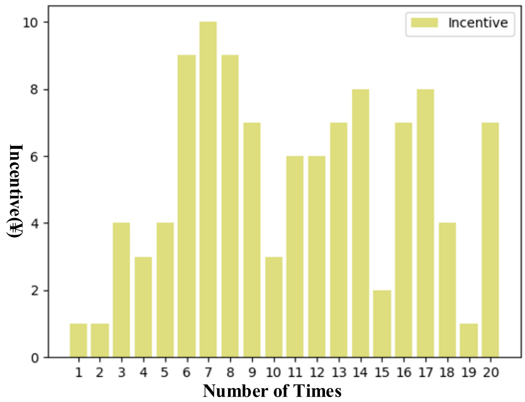

FIGURE 5. Incentives received by the test group.

flexibility of the user at different time periods may change, under the condition of changing α and β, the least square method may produce a large error.

At present, there are many prediction methods, mainly including least squares method, k-nearest neighbors(KNN), support vector regression(SVR), Neural Network and Random Forest, etc.. In order to compare the accuracy of these methods in prediction, take 1000 sets of data to train and predict the user's response behavior using the LSTM method and other methods mentioned above. The first 980 groups were used as the training set, and the last 20 groups were used as the test set. The average error of each prediction method is shown in Table 2 and the prediction results are shown in Figure 6:

TABLE 2. Average errors of prediction results by different prediction methods.

Prediction Methods	Average Errors
Least Squares	50.85%
Neural Network	25.50%
SVR	19.82%
KNN	27.60%
Random Forest	17.35%
LSTM	12.81%

From Table 2 we can see that the average error (|*predicted value* - *actual value*| / *actual value*) of different prediction methods has a big difference. The least squares method has the largest average error, reaching more than 50%, while the LSTM average error is 12.81%. From Figure 6, we can see that for all prediction methods, the largest error appears in the first two test groups with the smallest response. This may because the similar scenes in the training group appear less. Among them, the maximum error of Least Squares, Neural Network, SVR and KNN all reach or exceed 100%. According to the average error, the performance gap between random forest and LSTM is not very large, but the maximum error of random forest exceeds 60%, while the maximum error of LSTM is about 30%, indicating that the prediction result given by LSTM has better stability.

Although LSTM has a large advantage in prediction accuracy compared to other methods, its prediction accuracy

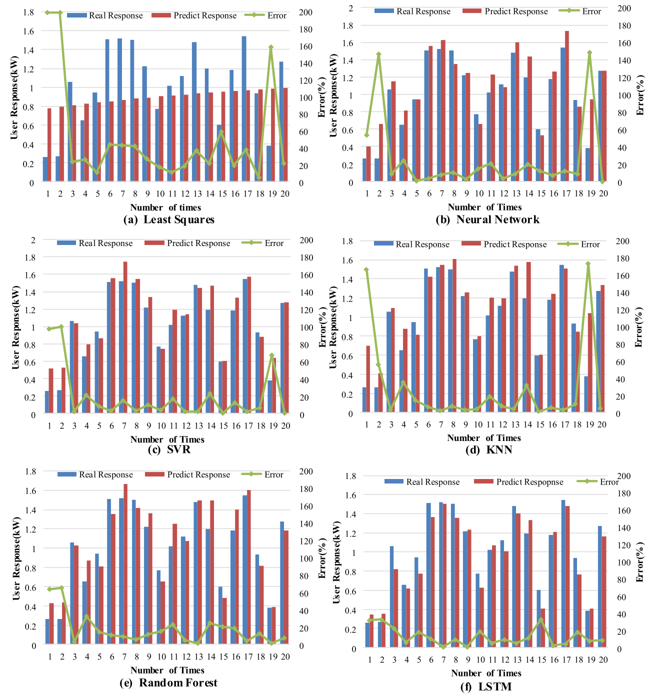

FIGURE 6. Comparison of prediction results of different prediction methods.

needs to be further improved. So further analysis of the influencing factors of the algorithm is needed to improve the accuracy of the proposed algorithm and to make it perform well in any scenario.

The number of LSTM training times may have a greater impact on the accuracy of the prediction. Too many training times will occupy too many computing resources, and will greatly increase the calculation time, while fewer training times may make prediction errors increase significantly. Therefore, this paper compared the prediction results under different training times. Select 200 sets of historical data for analysis, the result is shown in Figure 7:

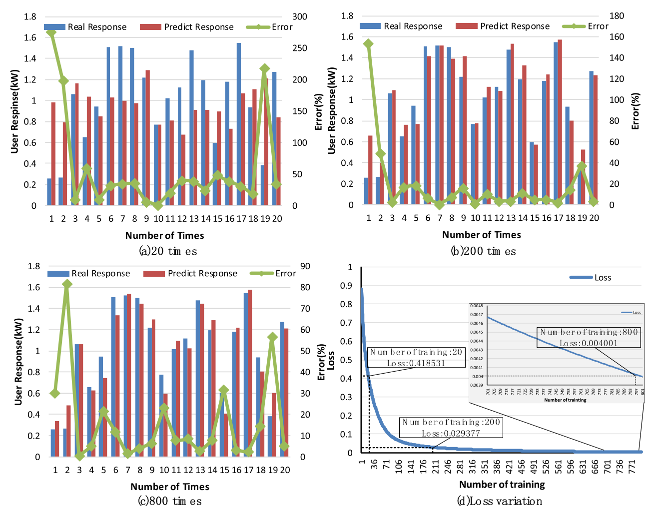

FIGURE 7. Comparison of prediction results of different training times.

As can be seen from Figure 7, training loss decreased significantly with the increase in the number of training and the prediction error of the user response behavior also decreased. When the number of trainings is 20, the maximum prediction error reaches nearly 300%, and the average error of 20 tests is 58.55%. As the number of training increases, the average training error decreases to 18.29% and 16.11%, respectively, at training times of 200 and 800. Training loss has the same trend as prediction error. At the early stage of training, the error decreases rapidly. With the increase of the number of trainings, the error tends to be stable. However, the training error is still large, and unstable conditions may occur. For example, in the case of 800 trainings, although the average error is 16.11%, the error of the second test group still exceeds 80%. Therefore, further analysis of factors affecting prediction accuracy is needed.

The number of user history data may also affect the accuracy of LSTM prediction, especially if the user history data is too small, the prediction accuracy of the LSTM method may decrease significantly. However, in some cases, especially in the early stage of demand response implementation, it is difficult to collect a large amount of user historical data, so the user response behavior can only be predicted using limited historical data. Considering this reason, this paper analyzed the impact of the number of historical data on the prediction accuracy, as shown in Figure 8:

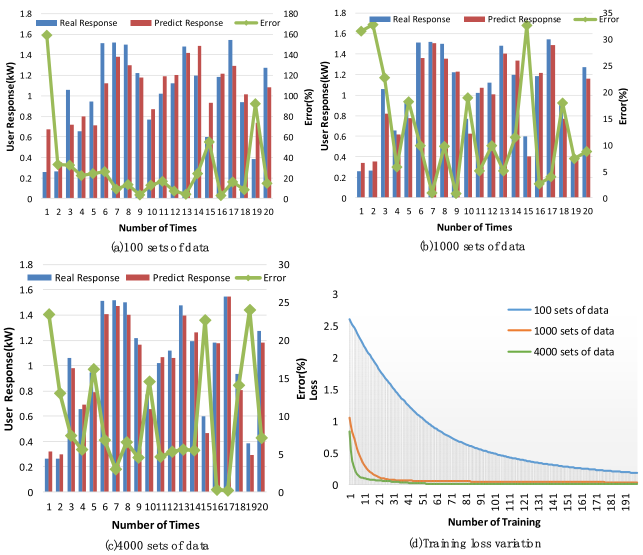

FIGURE 8. The effect of historical data quantity on prediction accuracy.

It can be seen from Figure 8 that under the same number of training times, the loss of 100 sets of data is larger, while the training error of 1000 sets of data and 4000 sets of data are similar. The average prediction errors in the three cases were 28.93%, 12.81%, and 9.53%, respectively. Although the average error is acceptable, the volatility of the single prediction error is still large, even in the case of sufficient historical data, the maximum error still reaches 23.99%. The error is mainly caused by the random fluctuation of the user. Therefore, it is necessary to analyze the influence of the user's random fluctuation on the prediction error.

Increase the value of α and β from 0.2 to 2, take 1000 sets of historical data and train 800 times, the prediction result is shown in Figure 9:

FIGURE 9. Prediction results of high volatility users.

Figure 9 shows the result of 800 training times for 1000 sets of user data. As can be seen from the figure, compared with Figure 8(b), the predicted error has increased significantly, the maximum error has risen from below 35% to nearly 90%, and the average error has increased from 12.81% to 29.25%. We can conclude that the user's random volatility has a large impact on the accuracy of the prediction.

In fact, from the previous simulation experiments, it can be seen that there are positive and negative errors in the prediction of user response behavior. Therefore, when the LSE integrates the overall response behavior of the user group, the positive and negative errors between different users cancel each other, and the overall response error of the user group will decrease. From formula (3), the response of a single user can be solved, and then the expected response of the user group is as follows:

$$\begin{aligned} E\left(\sum_{i=1}^{n} R_i\right) &= E\left(\sum_{i=1}^{n}\left(\frac{-\alpha_i+\sqrt{\alpha_i^2-2\cdot\beta_i\cdot I_i}}{\beta_i}+\varepsilon_i\right)\right) \\ &= E\sum_{i=1}^{n}\left(\frac{-\alpha_i+\sqrt{\alpha_i^2-2\cdot\beta_i\cdot I_i}}{\beta_i}\right)+E\left(\sum_{i=1}^{n}\varepsilon_i\right) \end{aligned} \tag{13}$$

Since the user's error is random (approximate to Gaussian distribution), when the number n of users is large enough, $E\left(\sum_{i=1}^{n}\varepsilon_i\right)$ approaches 0, so that the response of the user group can theoretically be predicted unbiased [26]. In order to verify this conclusion, we use 100 users to form a user group to verify the accuracy of the algorithm proposed in this paper(2000 sets of historical data, training 200 times). The α and β values for each time period of each user are randomly generated. First, in the range of [0.2, 20], the desired centers of α and β values are randomly generated, and then the Gaussian distribution is used to generate the final α and β values to simulate the random fluctuation of the user. The Parameter settings are shown in the following table:

TABLE 3. **User's response behavior parameters.**

Time	0-6	7-12	13-18	19-24
The mean of α	[0.2,20]	[0.2,20]	[0.2,20]	[0.2,20]
The mean of β	[0.2,20]	[0.2,20]	[0.2,20]	[0.2,20]
Standard deviation	0.2	0.2	0.2	0.2

The simulation results are as follows:

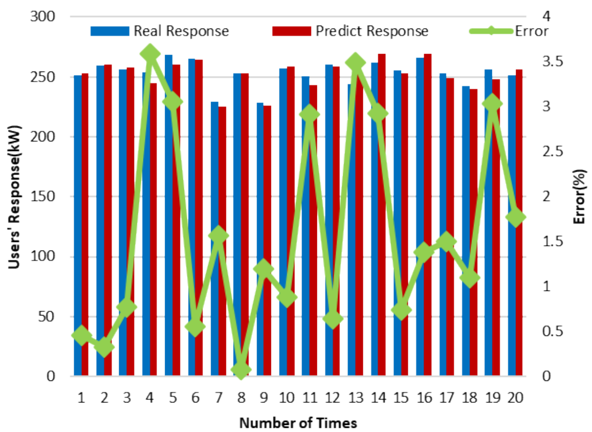

FIGURE 10. **Comparison of user group prediction results and error analysis (100 users, standard deviation 0.2).**

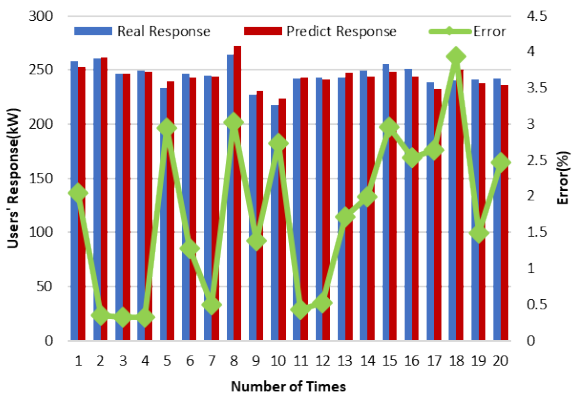

FIGURE 11. **Comparison of user group prediction results and error analysis (100 users, standard deviation 2).**

As can be seen from Figure 10 and Figure 11, whether it is a high-volatility user or a low-volatility user, the error can be kept at a low level. For a user group with a standard deviation of 0.2, the error can be kept below 4%. For a user group with a standard deviation of 2, the error can also be maintained below 4.5%. The average error of the experimental results of the two groups of users was 1.60% and 1.78%, respectively, compared with the prediction results of single users, the accuracy has been greatly improved. Therefore, when the number of users is large enough, the prediction result can control the error within a small range.

V. CONCLUSION

In the incentive-based demand response, the current research lacks accurate prediction of user response behavior, and it is difficult for LSE to aggregate the demand-side users into the regular business of the electricity market.

In this study, the user demand response characteristics and influencing factors are deeply analyzed, and the applicability of the LSTM algorithm is analyzed theoretically. Then the user response behavior prediction method based on LSTM network is designed and tested by TensorFlow. Through simulation experiments, it can be seen that compared with the linear regression method, the proposed algorithm in this paper can improve the prediction accuracy of the response behavior of a single user, and can accurately predict the response behavior of user group. Also, the proposed algorithm in this paper has a strong adaptability, even if the user group behavior is volatile, it can also accurately predict its behavior. The work of this paper can advance the precise process of demand response and provide support for LSE to aggregate the demand-side resources to participate in the regular business of the electricity market.

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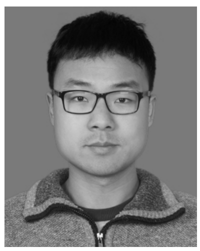

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