GMDH-type Neural Network Based Short-term Load Forecasting Method in Power System

Yin-Yin Bao, Yu Liu*, Jie-Sheng Wang, Ming-Wei Wang

Abstract—In modern electric power systems, operational planning procedures matter considerably in ensuring whether technical and economic performance standards are met while also meeting the power load requirements. A short-term load prediction method based on the Group Method of Data Handling (GMDH)-type neural network was proposed to address this. Combining the GMDH-type neural network could achieve accurate short-term load prediction in power systems. The neural network analyzed historical load data and other relevant factors to learn patterns and predict the near future. Besides, simulation experiments were also conducted to validate the effectiveness of the proposed algorithm, which fully demonstrated its capability to accurately predict short-term load in power systems, thus contributing to improving the operational planning and decision-making and enhancing the technical and economic performance of power systems. Overall, utilizing the GMDH-type neural networks in short-term load forecasting was found to be efficient in enhancing the operational efficiency and reliability of modern power systems.

Index Terms—power system, load forecasting, GMDH neural network, performance comparison

I. Introduction

THE operational planning procedure is essential for the operation of modern power systems. Short-term load forecasting (STLF) plays a crucial role in predicting the power load within an hour to a week. Sulf has been successfully applied in various fields, including wind and photovoltaic power [1-2].

The commonly used intelligent forecasting methods include fuzzy theory, artificial neural network (ANN), support vector machine (SVM), etc. Artificial neural networks (ANNs) are mathematical models that utilize distributed parallel algorithms for information processing. These networks rely on interconnected nodes for information processing based on the system's complexity. An ANN model based on the back-propagation algorithm was proposed in the context of temporary load forecasting for microgrid power systems [3].

Various single-variable methods based on neural networks, such as multi-layer perceptron, radial basis function (RBF) neural network, generalized regression neural network, and autonomous mapping neural network, were applied to realize short-term power load forecasting [4]. An effective short-term load forecasting model based on the generalized regression neural network and the stepper fly optimization algorithm was finally proposed [5]. Ref. [6] introduced an interval decomposition reconstruction ensemble learning method for predicting the interval-valued loads. Empirical results demonstrated this learning method's significantly better prediction accuracy compared to single models and unreconstructed decomposition-ensemble models. Ref. [7] proposed a time-series convolutional network with multiple attention mechanisms for ultra-short-term load forecasting. By incorporating a threshold structure in the temporal convolutional network, this model could extract the multidimensional information from the input features using multiple hidden convolutional kernels at different scales without deep stacking layers. An online learning scheme specifically designed for edge computing implementation was presented in Ref. [8], which updated the prediction model without requiring large-scale computation. The proposed method was evaluated using real-world residential load data, with both computational cost and accuracy considered.

In recent years, soft computing and artificial intelligence techniques have been extensively applied to estimate complex phenomena, including pattern recognition, hydrology, and mechanics. Among these techniques, the Group Method of Data Handling (GMDH) stands out as a self-organizing system capable of solving complex nonlinear problems [9]. GMDH has found applications in various fields, such as education test construction optimization, control, and geological engineering, inorganic chemical materials, cancer diagnosis, hydraulic structure scour prediction, and shear wave velocity estimation [10-13]. The paper also introduces the structure and algorithm of the GMDH-type neural network. Its effectiveness was verified through simulation experiments in the context of the short-term load forecasting for electric power systems. In addition to GMDH, neural networks have been extensively adopted in numerous other domains. For instance, Kevin et al. employed a Convolutional Neural Network (CNN) approach with MobileNetV2 transfer learning to recommend vegetarian recipes based on vegetable image data [14]. The dataset, consisting of labeled and preprocessed vegetable images, was trained on CNN models and implemented on a website-based system, resulting in the significant accuracy improvement.

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Helene et al. conducted a study on the aging coefficients of a new polymer B and the second aging of A-150 and A-185 polymer systems [15]. A sustainability prediction model was also developed using artificial neural networks, and experimental issues and theoretical aspects related to Bayesian regularization and BFGS algorithms were explored.

Herein, we present a short-term load forecasting method for power systems utilizing a GMDH-type neural network.The researchers further validated the effectiveness of the proposed method through simulation experiments. Section 2 introduces the principle of the Group Method of Data Handling. Section 3 describes the design of the GMDH neural network. The simulation experiments and detailed results analysis are presented in Section 4. Finally, the conclusion summarizes the key findings of the study.

II. Group Method of Data Handling (GMDH)

Group method of data handling (GMDH) is a kind of induction method of the multiple parameter data set based on computer mathematical modeling with a fully automatic structure and parameter optimization model, which is a new heuristic self-organization and complicated nonlinear system modeling method based on the principle of multi-layer neural network and K-G polynomial. It constantly deletes some combinations to identify the nonlinear system model and effectively realizes the high-order nonlinear system identification.

GMDH is mainly used in knowledge discovery, data mining, complex system modeling, forecasting, and related research fields. The related research results show that the GMDH neural network has better prediction performance than classical prediction algorithms, such as the single exponential smoothing, the double exponential smoothing, ARIMA, and the back-propagation neural network. The induction process characterizes the GMDH algorithm, and utilizing the so-called external criterion, the hierarchical polynomial model is sorted, and the optimal solution is selected. The choice of the GMDH algorithm depends on the accuracy and completeness of the information presented in the experimental data samples. It depends on the type of problem to be solved.

A. *Polynomial Support Function*

The method involves sorting continuously and testing the selected model from a set of candidate models according to the specified criteria. Almost all known GMDH algorithms use the polynomial support functions. The general connection between input variables and output variables can be found in the form of a function Volterra series, whose discrete analogs are named Kolmogorov-Gabor polynomials, which is defined in Eq. (1).

$$y = a_0 + \sum_{i=1}^{M} a_i x_i + \sum_{i=1}^{M}\sum_{j=1}^{M} a_{ij} x_i x_j + \sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{k=1}^{M} a_{ijk} x_i x_j x_k \tag{1}$$

where, $X(x_1, x_2, \ldots, x_M)$ is the vector of the input variable, $A(a_1, a_2, \ldots, a_M)$ is the sum coefficient vector. Other support functions are also used, such as the logistic function:

$$y = a_0 + \frac{\sum_{i=1}^{M} a_i}{1+\exp(-x_i)} \tag{2}$$

The number of polynomial terms estimates the complexity of the model structure. The sorting process is calculated as the structure of the model changes gradually. GMDH, as an iterative method, closely approximates the optimal regression method. However, the difference lies in its effectiveness in organizing the search for the optimal model structure. In addition, it also uses the internal and particular external sort criteria. The model sorts by group or equal structure complexity sequence and finds the optimal model for each sequence according to the criterion.

Theoretically, the minimum mathematical expectation of external criterion is unique for noise data and a small sample. If we calculate the entire data sample, we call it an internal criterion. External criteria are calculated using new information that is not employed to estimate model coefficients. For instance, to compute regular standards, we sort the sample points according to variance and include every third point in a test sub-sample used for estimating the model structure. The remaining points in the sample set are used to estimate the model coefficients.

B. *Interpretation and Induction of GMDH Algorithm*

The self-organization of the model can be defined as minimizing the structure of prior information. In particular, the number of external instructions for the modeler is minimized. In the GMDH deductive method, the internal precision criterion is applied to the model sorting, and the calculation results are only used to select the best model of the iterative sequence. An expert or modeler specifies the number of this series. The amount of prior information required is relatively small, so the self-organization of the model is realized by induction and deduction of the GMDH algorithm.

In contrast, the model sorts the inductive GMDH algorithm according to the external accuracy criterion, uses two standard calculation results to select the best model in each sequence, and objectively realizes the selection based on the number of iterations series. The most accurate optimal nonphysical model meets the minimum of external standards. The law of differential equations is recognized as difference analogs, that is, in the form of algebraic polynomials, including delayed parameters.

1) Combined GMDH Algorithm

The combinatorial GMDH algorithm has a muti-layer and iteration structure. It is characterized by the fact that the iteration rule does not remain unchanged but expands with each new sequence. In the first series, all models have the simplest form of structure.

$$y = a_0 + a_1 x_i \tag{3}$$

where, i=1,2…, M.

These models are sorted and based on selected criteria to obtain the optimal model value F. The model with the more complex structure was ordered in the second sequence. We construct these models using the output variables of the best model for the first sequence.

$$y = a_0 + a_1 x_i + a_2 x_j \tag{4}$$

where, i=1,2…, F; j=1,2…, F.

In the third sequence, the sorting involves a more complex structure:

$$y = a_0 + a_1x_i + a_2x_j + a_3x_k \tag{5}$$

where, i=1,2..., F; j=1,2..., F; k=1,2..., M.

And so on, if the standard minimum is reduced, the construction of this sequence will continue. For the degree of freedom of choice F=M, this algorithm guarantees the complete sorting of all models with the polynomial form.

2) Iteration Muti-layer GMDH Algorithm

In the multi-layer GMDH algorithm, all sequences' iteration rule remains unchanged. For example, a specific description of the first series is described as:

$$y = a_0 + a_1x_i + a_2x_j + a_3x_ix_j \tag{6}$$

A specific description of the second sequence is described as:

$$z = b_0 + b_1y_i + b_2y_j + b_3y_iy_j \tag{7}$$

A specific description of the third sequence is described as:

$$w = c_0 + c_1z_i + c_2z_j + c_3z_iz_j \tag{8}$$

In other words, the previous sequence's output value is the following sequence's parameter. With this iterative approach, some models may be ignored, leading to multi-level errors. The convergence of the self-organizing process of the model needs to be studied, and the same criteria are used for the regression analysis.

3) Object System Analysis (OSA) Algorithm

The algorithm consists of sorting the equations rather than the individual equations. The set is obtained through implicit difference templates.

$$\text{M=1:} \quad x_{i(k)} = f_1(x_{i(k-1)}, x_{i(k-2)}) \tag{9}$$

$$\text{M=2:} \quad \begin{aligned} x_{i(k)} &= f_1(x_{i(k-1)}, x_{i(k-2)}, x_{j(k)}, x_{j(k-1)}, x_{j(k-2)}) \\ x_{j(k)} &= f_2(x_{j(k-1)}, x_{j(k-2)}, x_{i(k)}, x_{i(k-1)}, x_{i(k-2)}) \end{aligned} \tag{10}$$

Each change of the template requires the solution of a set of linear equations, whose result is an estimate based on the convolution of the criteria calculated by a single equation.

C. Flowchart of GMDH Algorithm

Step 1: Training set A and testing set B have the adopted samples, and prediction set C has the predicted samples. The number of data points in set A is $N1$, the number of data points in set B is $N2$, and the number of data points in set C is $N2$.

Step 2: The maximum possible time delay can be calculated by:

$$m = \sqrt{N1 + N2} \tag{11}$$

Step 3: The model reference function is defined as:

$$Y_t = a_0 + a_1 * Y_{t-1} + a_2 * Y_{t-2} + ... + a_m * Y_{t-m} \tag{12}$$

Step 4:

(1) Regard the non-coefficient part of each addition unit in the reference function as a new independent variable. The number of new independent variables is m. The m new independent variables are used as the first layer's input and are combined in pairs, so the number of generated local functions is $M = C_m^2$.

(2) The coefficients of these local functions are obtained by fitting the set A and W respectively by using the least square method, and the obvious intermediate model is obtained.

(3) By adopting these models, the estimation of the corresponding set A, W, and C is calculated as $Z_{k-1,i}$, $Y2_t$ and $Z_{k-1,i}$.

(4) Each absolute anti-interference criterion value of intermediate models is obtained by adopting Eq. (13).

$$\Delta^2(A) = \sum_{t \in A} (y_t^m(A) - y_t^m(W))^2 \tag{13}$$

(5) Found the minimum value of this layer. Judgment: IF it is not the first layer, it will be the minimum value, then stop the cycle and go to Step (7).

(6) Eliminate M-m intermediate models with large external criteria values, and the estimated values $Y1_t$, $Y2_t$ and $Y3_t$ of the m intermediate models are entered into the next layer, and they are combined in pairs to generate new m local functions and then conduct Step (2)-(5).

(7) The intermediate model corresponding to the minimum external criterion value is the optimal complexity model, and the estimated value $Y3_t$ is the sample value to be predicted.

III. GMDH Neural Network

A. Basic Principle of GMDH Neural Network

The neural network with GMDH organizational structure is named the GMDH neural network. It belongs to the feed-forward neural network. On the other hand, it is a new multi-layer neural network with no fixed network structure and is often used as a practical neural network prediction model. The data processing method is a heuristic self-organizing modeling method for complex and variable nonlinear systems.

GMDH has the basis for continuous self-organizing screening to identify nonlinear systems to effectively identify K-G polynomials of higher-order nonlinear systems. In the GMDH network structure shown in Fig. 1, the neuron acts as a node and is only responsible for passing the input signal to the intermediate hidden layer node in the input layer. Apart from the input layer, all other layers in the network are identical. As each node and output node in the hidden layer has only two inputs, the previous layer must have only two hidden layer nodes if the network output is a single output.

In addition to the input layer nodes, the relationship between each input node and each output node of the hidden layer in the GMDH neural network is described as follows:

$$\begin{aligned} Z_{k,l} &= a_{k,l}(z_{k-1,i}, i)^2 + b_{k,l}z_{k-1,i}z_{k-1,j} \\ &+ c_{k,l}(z_{k-1,j})^2 + d_{k,l}z_{k-1,i} + e_{k,l}z_{k-1,j} + f_{k,l} \end{aligned} \tag{14}$$

Eq. (14) is also known as the Ivakhnenko polynomial. In Eq. (14), $Z_{k,l}$ is the output of the l-th node of the k-th layer in the network, $Z_{k-1,i}$ is the output of the i-th node of the

(k-1)-th layer in the network. $Z_{k-1,j}$ is the output of the j-th node of the (k-1)-th layer in the network. The coefficient of the polynomial in the formula is the value of $Z_{0,i}$, $a_{k,l}$, $b_{k,l}$, $c_{k,l}$, $d_{k,l}$, $e_{k,l}$ and $f_{k,l}$.

Therefore, the output of each node in the GMDH neural network has a quadratic polynomial relationship with the input. At the same time, whenever one layer is added to the network, the number of polynomials is also increased by two orders.

B. Implementation Steps of GMDH Neural Network

The schematic diagram of producing the optimal model based on the GMDH method is shown in Fig. 2. The implementation steps of the GMDH neural network prediction model are described as follows.

Step 1: Divide the data sample set (N data samples) into training set A and testing on set B ($N_\omega = N_A + N_B, \omega = \mathrm{A} \cup \mathrm{B}$). If a prediction model is established, the data sample set is divided into learning set A, testing set B, and checking set C ($N_\omega = N_A + N_B + N_C$, $\omega = \mathrm{A} \cup \mathrm{B} \cup \mathrm{C}$).

Step 2: Establish a general relationship between the dependent variables (output) and the independent variables (input) as a "reference function ," generally using the K-G polynomial. For example, for a three-input single-output system, a second K-G polynomial can be described as:

$$f(x_1,x_2,x_3) = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + a_4x_1^2 + \\ + a_5x_2^2 + a_6x_3^2 + a_7x_1x_2 + a_8x_1x_3 + a_9x_3x_2 \quad (15)$$

As the reference function, its sub-items are used to produce the m initial models in the modeled network structure.

$$v_1 = a_0, v_2 = a_1x_1, v_3 = a_2x_2, \ldots, v_{10} = a_9x_3x_2 \quad (16)$$

Step 3: Select one (or several) criteria with the external supplemental properties as the objective function, also named the outer criterion.

Step 4: Generate an intermediate model in the first layer. The transfer function $y_k = f_k(v_i, v_j)(k = 1,2,\ldots,10)$ is the intermediate model in the first layer, which is adaptively generated by the self-organizing process, and the number of variables and the function structure are different from each other. Then, the parameters of y_k on training set A are estimated at the same time.

Step 5: Select the intermediate model of the first layer. According to the external criteria, the intermediate model in the first layer is selected on the testing set B, so the selected intermediate model $w_k(k = 2,3,6,7,9)$ will be the input variables in the second layer of the network.

Step 6: Form an optimal complexity model network structure. Repeating Step 4 and Step can sequentially generate the following intermediate models and finally form an explicit optimal complexity model that can be used for analysis.

Here, the state after the third layer is taken as an example. In the model y^*, the number of variables v_i is less than or equal to 4, and the number of network initial variables is 5, so the initial variable v_2 is automatically eliminated in the selection process.

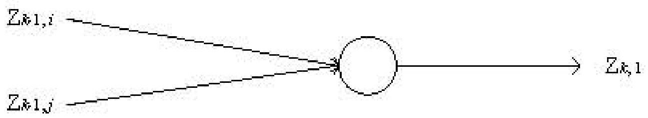


Fig. 1 Processing unit of GMDH neural network.

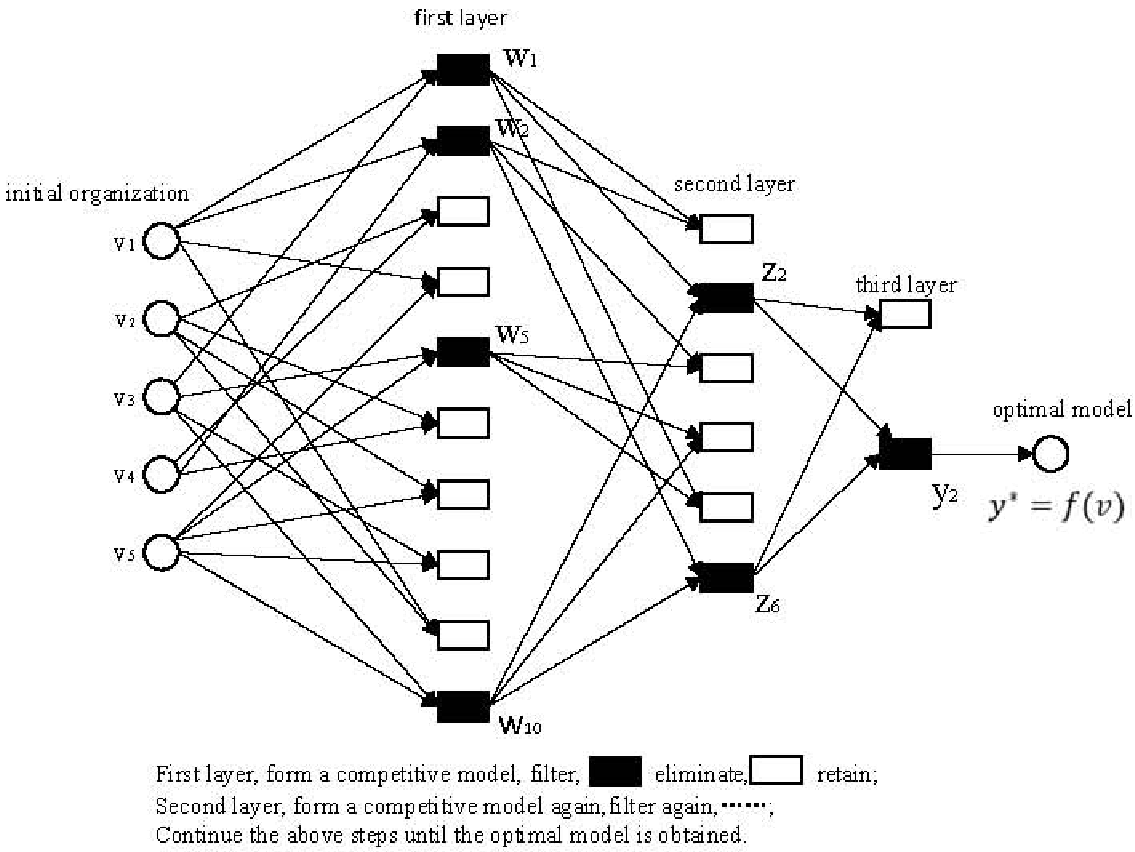


Fig. 2 Schematic diagram of producing the optimal model based on GMDH method.

C. Prediction Flowchart Based on GMDH Neural Network

The forecasting procedure by adopting the GMDH neural network is described as follows.

Step 1: Preprocess the sampled data, including normalizing the acquired data. When dealing with the data to train the GMDH neural network, it is first necessary to uniformly simplify it. We preprocess the collected electrical load data to create the input and output data by adopting Eq. (17).

$$\left.\begin{aligned} u_1^* &= \frac{u_i - u_{\min}}{u_{\max} - u_{\min}} \times 2 - 1 \\ y_1^* &= \frac{y_i - y_{\min}}{y_{\max} - y_{\min}} \times 2 - 1 \end{aligned}\right\} \quad (17)$$

where, $u_{\min}$, $u_{\max}$, $y_{\min}$ and $y_{\max}$ are the minimum and maximum values of u_i and y_i, respectively. When the input and output are the *i*-th group, the input and output experimental data pairs are u_i and y_i.

Step 2: Determine the number of input signals to decide the number of output signals. For predictions, it is necessary to use n known observed output values.

Step 3: The observed experimental data samples must be organized into training and output samples. The sample data is subdivided into two categories: training set *A* and testing set *B*. Many models to be selected are generated on the learning set *A*, and the data in the testing set *B* will be used to test and select the obtained models.

Step 4: Establish an input neuron layer. The number of neurons is related to the number of input signals. Relative to each input number, there is a corresponding neuron, so the corresponding number of neurons can be obtained as C_i^2.

Step 5: The initial weights in the input neuron layer established in Step 4 should be assumed as zero.

Step 6: The training data set composed of the observed electrical load data is fed into each neuron in the input layer. At time *k*, extract $y_{k-1} (k = 1,2, \ldots)$ as the input signal, y_k is the expected output, calculate the error between the expected y_k and the actual observed value, and constantly update its weights to minimize the root mean squared error (RMSE). When RMSE exceeds the calculated value of the previous cycle, the data training is stopped.

Step 7: Check the trained network performance by using the checking data set, which may be a combination of the above sample data and test data or a new set of data used to check the performance of the network. In the training GMDH neural network termination rule, the calculation can be terminated when the prediction evaluation satisfies the following two termination conditions.

(1) If the simulation result using the predictive evaluation criteria reaches the preset standard determined based on the sampling error, stop the training process and output the predictive results.

(2) If the simulation calculation is carried out, there is no significant change in the calculation results on the electric load forecasting.

IV. Simulation Experiment and Result Analysis

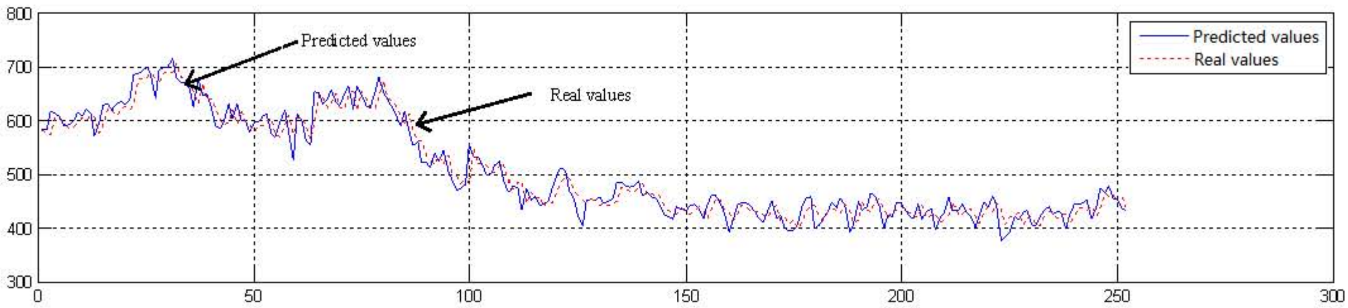
Accurate forecasting of power loads is crucial for the power supply of a city or even a country. Correct load forecasting can ensure the smooth operation of the country's economy and, at the same time, satisfy the people's demand for electricity. Therefore, power load forecasting is the basis for the sustainable development of the power industry. Many factors influence power load forecasting, some visible while others cannot be described in words, such as climate and statutory holidays. These factors produce cyclical variations in power load. For the power load forecasting study, we have collected a region's power load usage data for a year. These data covered 365 days of the year and were recorded every half hour. From these, 365 data of a particular moment were selected as the prediction object, and simulation experiments were conducted by using the GMDH neural network in the MATLAB environment.

The data were divided into the training set and the testing set. The simulation results on the training set, testing set, and all data are shown in Fig. (3)-(5), where sub-graph (a) shows the prediction results corresponding to the electric load forecast data, sub-graph (b) shows the prediction error corresponding to the power load forecast data, and sub-graph (c) shows the prediction error mean and variance corresponding to the power load prediction data. The state distribution of the power load prediction results is shown in Fig. (6), and the statistical results of forecasting performance indicators on the power short-term load are listed in Table I.

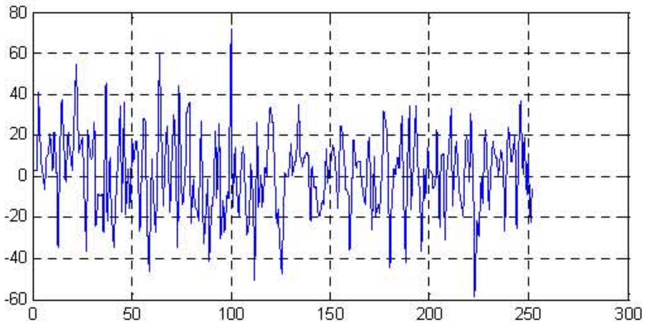
According to the simulation results shown in Fig. 3-6, we can see that the power load prediction based on the GMDH neural network shows excellent accuracy in the experiments with three sets of data. The predicted values are very close to the actual values, indicating that the method accurately predicts power load. In addition, by looking at the histogram of the power load prediction error, we can see that it performs excellently. The prediction errors are distributed within a small range, with no significant deviations or outliers. This further proves the reliability of the GMDH neural network-based prediction method in dealing with short-term load forecasting for electricity.

Further combining the data in Table I, we can conclude that the short-term power load forecasting method based on the GMDH neural network shows excellent results in several performance indicators. First, in terms of prediction accuracy, the method demonstrates a high degree of accuracy and can accurately predict the trend of power load changes. Secondly, in terms of stability, the method can maintain more stable prediction results under different environmental conditions without interference from external factors. In addition, in terms of adaptability, the method can automatically adjust and optimize according to the actual changes in the power system and adapt to various complex operating conditions. These excellent performances indicate that the short-term power load forecasting method based on the GMDH neural network has exceptionally high reliability and practicability in practical applications. It can effectively support the operation and planning of the power system and provide powerful support for relevant decisions.

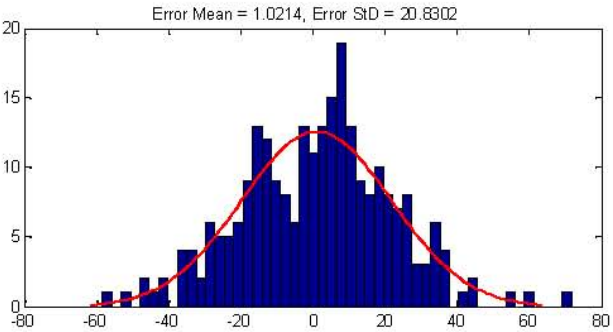
In summary, through the comprehensive analysis of the experimental simulation results, the short-term power load forecasting method based on the GMDH neural network shows excellent accuracy, stability, and adaptability in various performance indicators. This lays a solid foundation for applying the method in power systems and provides an essential reference for further research and improvement. Therefore, the short-term load forecasting method for electric power based on the GMDH neural network is an efficient and reliable method with potential for broad application.



(a) Forecasting results on power load

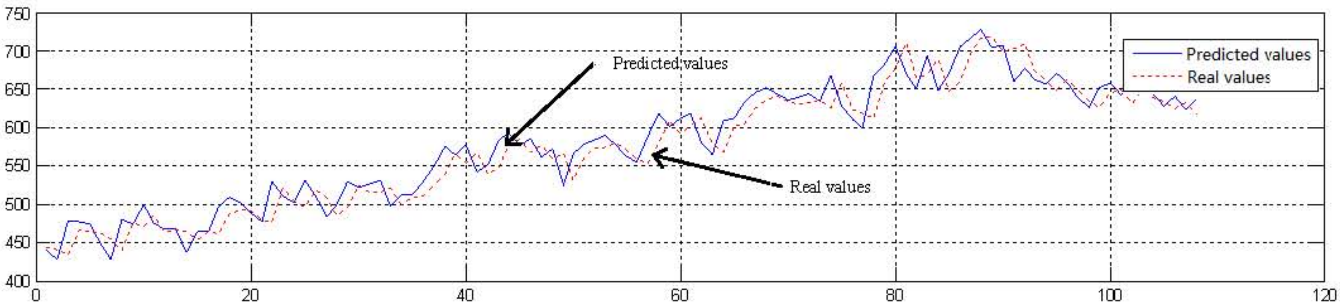


(b) Forecasting error on power load

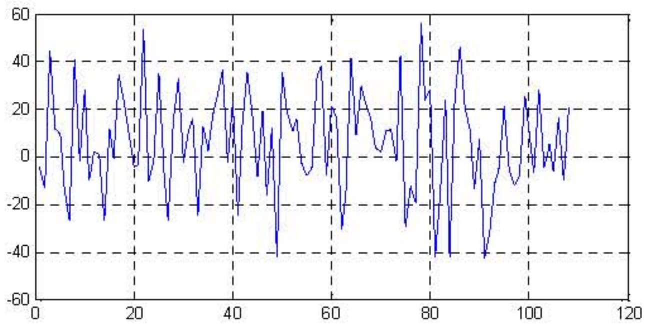


(c) Mean and variance diagram of power load prediction results

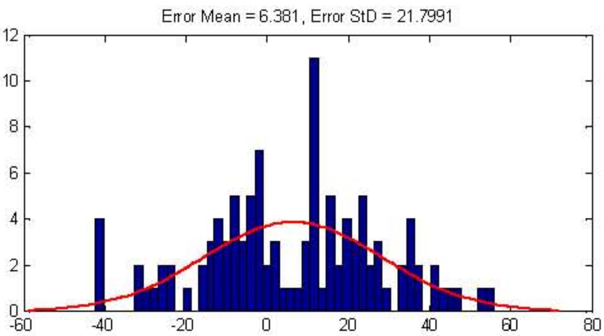
Fig. 3 Power load prediction results on training data.



(a) Forecasting results on power load

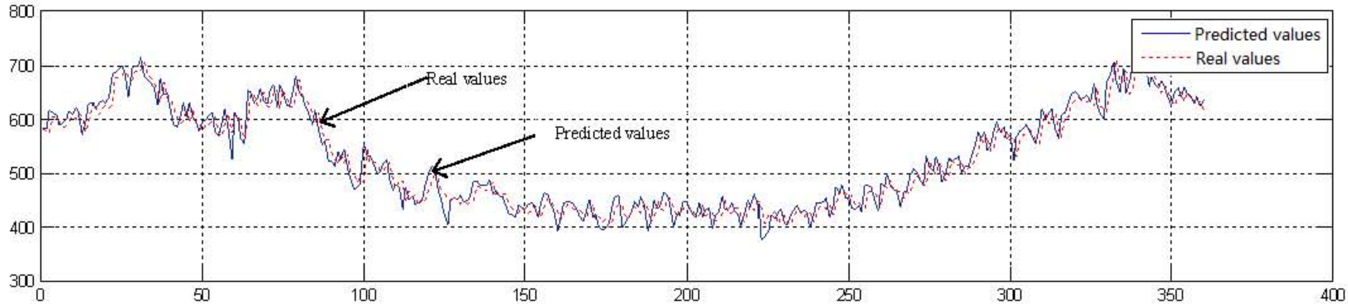


(b) Forecasting error on power load

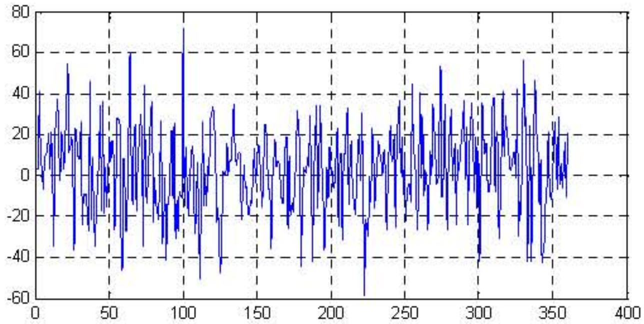


(c) Mean and variance diagram of power load prediction results

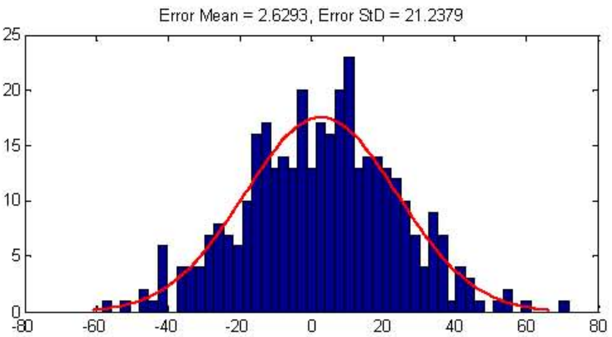
Fig. 4 Power load prediction results on testing data.



(a) Forecasting results on power load

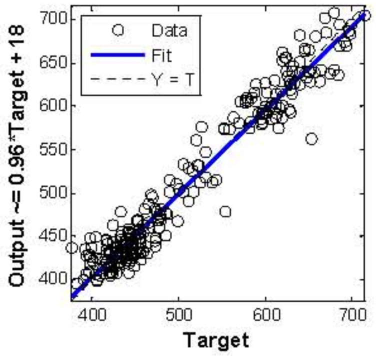


(b) Forecasting error on power load

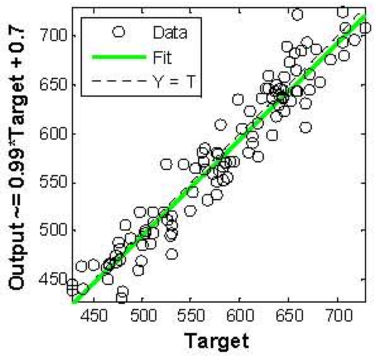


(c) Mean and variance diagram of power load prediction results

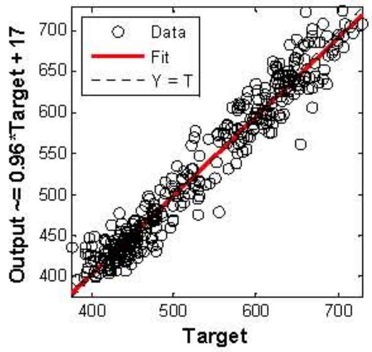
Fig. 5 Power load prediction results on all data.



(a) Training data



(b) Testing data



(c) All data

Fig. 6 Status distribution of the predicted results.

TABLE. I PERFORMANCE INDICATORS OF PREDICTED RESULTS

Performance indicators	Training data	Testing data	All data
Mean square error (MSE)	433.2189	511.5161	456.708
Root mean square error (RMSE)	20.8139	22.6167	22.6167
Mean of error	1.0214	6.381	2.6293
Error standard deviation	20.8302	21.7991	21.2379

V. CONCLUSION

The present study proposes a novel method for short-term power load prediction based on an analytical investigation of the GMDH neural network-based modeling approach and its training process. As a prediction method for highly nonlinear time-dynamic systems, the GMDH neural network, with its excellent fault tolerance and robustness, demonstrates high accuracy in many complex nonlinear system prediction results. Through simulation experiments, we verify the excellent performance of the method in predicting nonlinear time series systems. The experimental results show that the method is highly adaptable and accurate for predicting nonlinear time series systems. The advantages of the GMDH neural network are thoroughly demonstrated in short-term power load time series prediction. Its fault tolerance and robustness enable it to deal with the noise and disturbance in the system, thus improving the stability of the prediction. At the same time, the high-precision prediction results of the GMDH neural network provide a reliable reference basis for the operation and planning of the power system. The time series forecasting modeling method based on the GMDH neural network provides a reliable and efficient short-term power load forecasting solution. The method has significant advantages in predicting nonlinear time series systems and provides strong support for power system operation and planning. Future research can further explore the method's potential for application in other fields and optimize and improve it.

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