Research on Hybrid Model for Short-term Power Load Forecasting Based on Error Compensation

Yuan Qingyun, Li Hengchen, Pan Yu, Wang Zhenyu, Ma Qingyuan, Liu Tan

Abstract: **Due to the susceptibility of short-term load forecasting to multiple influencing factors in short-term, traditional single prediction models often struggle to ensure sufficient accuracy. To address this challenge, this paper proposes a short-term power load modeling approach with error compensation. First, the Northern Goshawk Optimization (NGO) algorithm is used to optimize the hyperparameters in the CNN-BIGRU-AT framework, and an optimized basic model for short-term load forecasting is established. Subsequently, the same NGO-CNN-BIGRU-AT architecture is reapplied to construct an error prediction model, effectively simulating the residual patterns of the basic model. Ultimately, by integrating the outputs of the basic load forecasting model and error compensation model, the final prediction is obtained thereby enhancing the overall prediction accuracy. Comparative experiments with conventional single prediction models have verified the feasibility and superiority of the proposed error compensation model, demonstrating significant improvements in prediction performance.**

Index Terms—**Power load forecasting, convolutional neural network, bidirectional gated recurrent unit, attention mechanism, north grey wolf optimization algorithm, error compensation.**

I. Introduction

SHORT-TERM load forecasting (STLF), as the foundation of power grid planning and construction, not only provides critical references for network framework design, site selection, and capacity determination, but also offers technical support for grid status analysis and saturation load prediction. Consequently, accurate STLF is essential for enhancing the efficiency of power grid planning. STLF typically accounts for meteorological factors and day-type classifications to estimate electricity demand for the next 24 hours, days or weeks. Thus, accurate STLF is vital for power system scheduling and grid stability.

Common short-term load forecasting algorithms include backpropagation neural networks (BPNNs) [1], support vector machines (SVM) [2], deep learning [3], and grey wolf optimization (GWO) [4]. Although these methods achieve rapid convergence through a simplified internal architecture, they fail to adequately capture temporal dependencies between input and output data, resulting in poor prediction accuracy. To address this limitation, researchers utilize the robust temporal processing capabilities of long short-term memory (LSTM) and gated recurrent unit (GRU) networks for power load forecasting. For example, Chen [5] proposes an LSTM-based load modeling method, which improved the prediction accuracy. Similarly, Gong et al. [6] use a GRU model optimized by intelligent algorithms for full-day load forecasting, which enhanced the prediction performance.

Most of the above-mentioned power load prediction models are single models with limited forecasting accuracy. Based on this, Wu et al. [7] used a combination of graph convolutional network (GCN) and gated recurrent unit (GRU) to predict the power load, and verified the feasibility of the GCN-GRU model by comparing it with the model based on distance adjacency matrix. Zhu et al. [8] decomposed the wind power series using VMD, reconstructed and preprocessed the data analysis foe each mode using SSA and finally compensated the error of the model using GPA, thereby improving the prediction accuracy and anti-interference ability of the model, further enhancing the prediction accuracy. Geng et al. [9] used LSTM to predict load, then used GRU to train the error for obtaining error compensation values, and finally used error compensation to obtain a more accurate load prediction value. Li et al. [10] established a stacked reverse double-layer high-low-level gated recurrent unit (SRDHLGRU) network model to predict the short-term power load by improving the underlying structure of BIGRU. Based on the error sequence generated during the model prediction process, the SRDHLGRU model is established again for training and prediction to compensate the error of the first stage results. In conclusion, the prediction accuracy of the model can be improved by combining the model or compensating the error of the model.

Building on the synergistic advantages of hybrid modeling and error compensation, this study integrates these two strategies into power load forecasting to achieve higher precision. First, a CNN-BIGRU-AT hybrid model is constructed by synergistically integrating convolutional neural networks (CNN), bidirectional GRU (BIGRU), and attention mechanisms (AT). Meanwhile, NGO algorithm is used to determine the parameters in the hybrid model, and an NGO-CNN-BIGRU-AT model is established for power

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load forecasting. In addition, to address the problem of difficulty in describing the error of the power load forecasting model, NGO-CNN-BIGRU-AT is once again applied to characterize the model error, achieving the error compensation for the hybrid power load forecasting model and improving the prediction accuracy of the model.

II. Analysis of Influencing Factors of Power Load

There are many factors that affect the power load, such as meteorology, temperature, etc., but considering that if all variables are added to the input of the model, it may lead to the problem that it is difficult to converge or the iteration time is too long in the model training process, so the Pearson correlation coefficient is used to analyze the factors influencing power load, and the actual values of the whole month of August 2018 are selected from the historical data samples for Pearson correlation analysis. The Pearson correlation coefficients between electric load and six critical predictors are shown in Table 1, which are the maximum temperature, minimum temperature, average temperature, relative humidity, historical load, and rainfall, respectively.

TABLE I
PEARSON PHASE RELATION TABLE OF POWER LOAD RELATED FACTORS

	Mat	Mit	Avt	Reh	Rav	Hil	Elp
Mat	1	0.452	0.901	-0.759	-0.342	0.033	0.311
Mit	0.452	1	0.723	-0.501	-0.603	0.179	0.439
Avt	0.901	0.723	1	-0.841	-0.475	0.132	0.496
Reh	-0.759	-0.501	-0.841	1	0.442	-0.061	-0.309
Rav	-0.342	-0.603	-0.475	0.442	1	-0.009	-0.186
Hil	0.033	0.179	0.132	-0.061	-0.009	1	0.432
Elp	0.311	0.439	0.496	-0.309	-0.186	0.432	1

where Mat is the maximum temperature, Mit is the minimum temperature, Avt is the average temperature, Reh is the relative humidity, Rav is the rainfall volume, Hil is the historical load, and Elp is the electrical power load.

The Pearson correlation coefficient ranges from -1 to 1. A value approaching 1 indicates a strong positive linear relationship, while a value approaching -1 signifies a strong negative linear relationship. A value of 0 suggests no linear association between the variables. Table 2 explains the relationship between the absolute value of Pearson correlation coefficient and the correlation strength.

TABLE II
JUDGMENT CRITERIA OF PEARSON CORRELATION COEFFICIENT AND CORRELATION DEGREE

Correlation coefficient	Correlation degree
0.0~0.19	Extremely low correlation
0.20~0.39	Low correlation
0.40~0.69	Moderate correlation
0.70~0.89	High correlation
0.90~1.00	Extremely high correlation

According to Tables 1-2, the correlation between rainfall and power load is extremely low. The correlation between the maximum temperature, relative humidity and power load is relatively low. The correlation between the minimum temperature, average temperature, historical load and power load is moderate. Therefore, the maximum temperature, minimum temperature, average temperature, relative humidity, and historical load are finally selected as input variables for the model.

III. NGO-optimized CNN-BIGRU-AT Process Model

Accurate models are the cornerstone of power load forecasting research. The architecture of hybrid models has demonstrated superior capability in capturing the nonlinear dynamic patterns of power loads. However, such models face challenges in manual parameter adjustment and inherent randomness. Therefore, in order to improve the accuracy of the hybrid model, this study uses NGO to optimize the parameters of CNN-BIGRU-AT model, forming the initial model for subsequent load forecasting error compensation modeling.

A. CNN-BIGRU-AT Model

The structure of CNN-BIGRU-AT prediction model proposed in this paper is shown in Fig. 1.

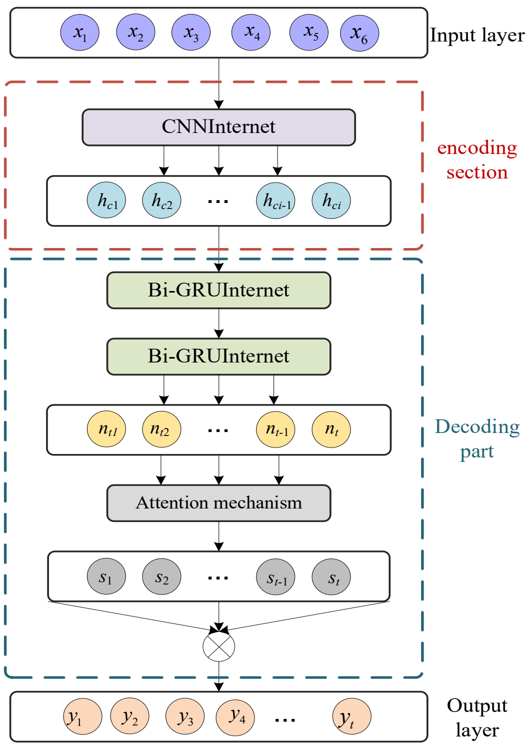

Fig. 1 Structure diagram of CNN-BIGRU-AT model

As can be seen from Fig. 1, the establishment steps of CNN-BIGRU-AT prediction model are as follows:

Step 1 Take the factors that affect changes in power load as model inputs, including the maximum temperature, the minimum temperature, the average temperature, the relative humidity, and the historical load, to constitute the input vector.

Step 2 The CNN layer extracts features from power load sequences, primarily consisting of a one-dimensional convolutional layer, pooling layer, and fully connected layer. The one-dimensional convolutional layer (Conv1D) extracts feature from the power load data input to the CNN network.

Maximizing pooling eliminates irrelevant information to prevent overfitting. The output values of the CNN layer are obtained through the Sigmoid activation function.

Step 3 BIGRU layer [11] is composed of forward GRU layer and reverse GRU layer. It receives new features extracted by CNN for training and captures the internal change rules of the sequence. The AT mechanism takes the output of BIGRU layer as input [12], and iteratively updates the weights to improve the contribution of important information. The fully connected layer calculates the predicted value through the Relu activation function [13].

Step 4 The output layer obtains the prediction result by calculation.

Convolutional neural network (CNN) is used to extract the relevant features from the original data of power load[14], and based on these features, BIGRU composed of forward GRU and backward GRU captures the nonlinear dynamic laws of power load. In order to further strengthen the effective extraction of power load characteristic data, attention mechanism (AT) is introduced to discard useless information and strengthen important information [15]. By combining CNN, BIGRU and AT, a relatively complete framework for power load forecasting model has been constructed, which can effectively capture the spatiotemporal characteristics and nonlinear dynamic relationship of power load data.

B. NGO-Optimized CNN-BIGRU-AT Model

NGO is an intelligent group optimization algorithm. This algorithm simulates the hunting behavior of northern goshawk to find the optimal solution, with good global search ability, high accuracy, and stability. Therefore, this paper proposes an NGO-optimized CNN-BIGRU-AT power load forecasting model, its structure is shown in Fig. 2.

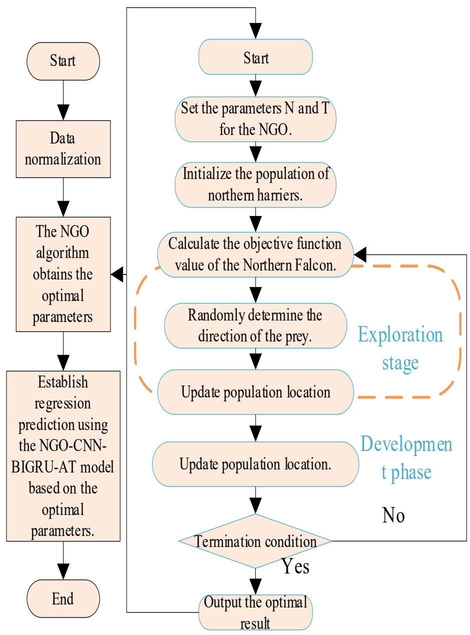

Fig. 2 Structure diagram of NGO-CNN-BIGRU-AT

NGO [16] was used to optimize the number of hidden layer nodes, initial learning rate parameters, and regularization coefficients of BIGRU, in order to establish the optimal NGO-CNN-BIGRU-AT prediction model. The main steps for NGO to optimize BIGRU are as follows:

Step 1: Set basic parameters, such as the population size and the maximum iteration number.

Step 2: Initialize the Northern Goshawk population.

Step 3: Using the root mean square error (RMSE) as the fitness function, and the number of hidden layer nodes, learning rate parameters, and regularization coefficients in BIGRU as the position of the Northern Goshawk to calculate the root mean square error between the actual load and the predicted load.

Step 4: In the exploration stage [17], update the individual position of the northern goshawk, calculate the fitness function value, and compare the fitness function value with the original fitness value. If the fitness function value decreases, the position is regarded as the current optimal position. Otherwise, the original position will be retained as the optimal position.

Step 5: In the development stage [18], when the Northern Goshawk chases its prey, the prey will try to escape, but due to its fast attack speed, it can eventually capture the prey successfully. Update the individual position of the northern goshawk, calculate the fitness function value, and compare it with the original value. If the fitness function value decreases, the position is regarded as the current optimal position. Otherwise, the original position will be retained as the optimal position.

Step 6: Check whether the iteration count meets the termination criterion. If satisfied, the current optimal solution will be adopted as the final parameters. Otherwise, proceed to Step 3 for further optimization.

Step 7: Obtain the BIGRU prediction model with the optimal parameters.

IV. Error Compensation Model

For complex power load forecasting, the model is established by simply using the NGO-CNN-BIGRU-AT algorithm, and the results obtained are often not ideal. In order to reduce the error between the output of the model and the actual value, it is of positive significance to characterizing the error distribution characteristics of the built model. Therefore, based on the initial model constructed by NGO-CNN-BIGRU-AT, the error model is constructed, and then the initial model is compensated. For the modeling method of the error compensation model, this paper still adopts the NGO-CNN-BIGRU-AT algorithm, which takes the initial model input and the predicted value of the model as the input variables of the error compensation model, and the training error as the output variable to form the training sample of the error compensation model. The error compensation model is trained by the NGO-CNN-BIGRU-AT algorithm, so that the model is achieved. That is, the relationship between the initial model and the error compensation model is as follows:

$$Z_x = Z_{xi} + Z_{xl} \tag{1}$$

where Z_x is the predicted value after error compensation, Z_{xi} is the predicted value of the initial model and Z_{xl} is the predicted value of the error model.

To sum up, the structure of the error compensation NGO-CNN-BIGRU-AT model is shown in Fig. 3.

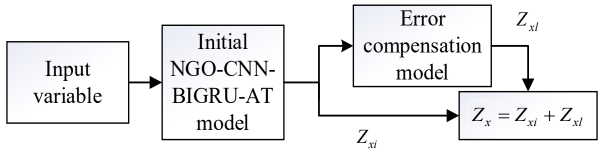

Fig. 3 Flow chart of error compensation model

As shown in Fig. 3, the specific steps are as follows:

Step 1 Determine the input and output variables for the initial NGO-CNN-BIGRU-AT model. The maximum temperature, minimum temperature, average temperature, relative humidity and historical load are taken as input variables of the model, and the power load is taken as the output.

Step 2 Establish the initial NGO-CNN-BIGRU-AT model and obtain the load predicted value Z_{xi} of the initial model.

Step 3 Construct the error compensation model. The input variables of the initial NGO-CNN-BIGRU-AT model are taken as the input variables of the error model, and the error $V = Z - Z_{xi}$ between the predicted value of the initial NGO-CNN-BIGRU-AT model and the actual value is taken as the output variable, and he above data is used to compose of the training samples for the error model. By training the error model, the predicted value of the error compensation model Z_{xl} is obtained.

Step 4 Calculate the final predicted value Z_x of the model by Equation (1).

V. Example Verification and Analysis

To validate the effectiveness of the proposed forecasting model, historical load data spanning three months (July 10 to October 10, 2018) from a southern region was selected for experiment. The dataset comprises 96 daily sampling points at 15-minute intervals and was partitioned into training and testing sets at a 7:3 ratio.

To evaluate the distinctiveness of the proposed model, under identical conditions, NGO-CNN-BIGRU-AT was compared with error-compensated models including E-BIGRU, E-CNN-BIGRU-AT, and E-NGO-CNN-BIGRU-AT. Comparative analysis includes load comparison curves and evaluation metrics, as illustrated in Figs. 4-5. Fig. 4 displays the alignment between the actual values of 288 consecutive data points (3 days) in the testing sample and the predicted values of different models. Fig. 5 presents a comparative visualization of error metrics for the testing set.

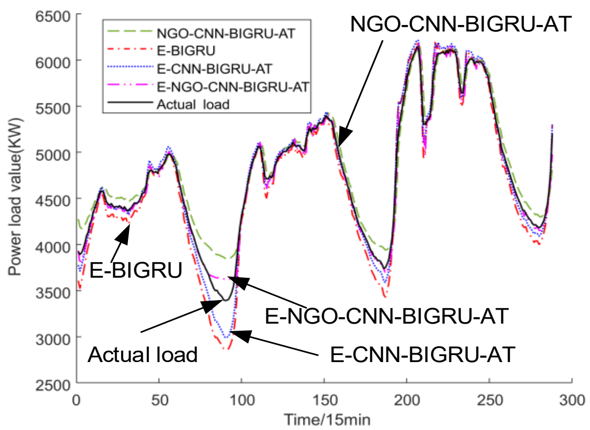

Fig 4. Comparison of power load prediction for three consecutive days.

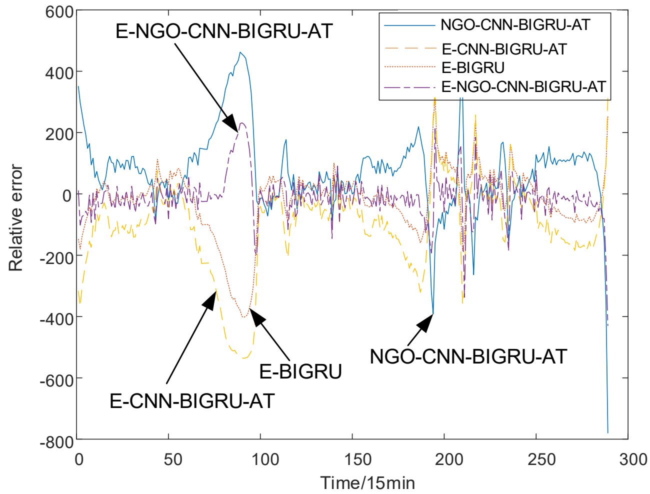

Fig 5. Comparison of power load prediction error results in test set.

The performance evaluation indicators of each model in the test set can be obtained from Figs. 4 -5, as shown in Table 3.

TABLE III

Performance Evaluation Indexes of Each Model in the Test Set

	MAE	RMSE	R^2	MAPE/%
NGO-CNN-BIGRU-AT	171.16	263.824	0.989	2.25
E-BIGRU	153.74	221.18	0.990	2.12
E-CNN-BIGRU-AT	113.95	179.09	0.991	1.5
E-NGO-CNN-BIGRU-AT	87.21	151.97	0.992	1.10

As can be seen from Fig. 4, among the experimental scheme compared by various models, the load prediction curve of the E-NGO-CNN-BIGRU-AT model proposed in this paper is closest to the actual load curve and has the best fit compared to the prediction curves of the other three models. From Table 3 and Fig. 5, it can be seen that the MAE, RMSE, MAPE and R^2 of E-CNN-BIGRU-AT and E-BIGRU have significantly improved compared to the NGO-CNN-BIGRU-AT model, indicating that the error compensation model can effectively improve the prediction accuracy. Compared with E-BIGRU, MAE, RMSE and MAPE of E-CNN-BIGRU-AT decreased by 25.8%, 18.6% and 29.2%, respectively, and R^2 increased by 0.001. This indicates that by extracting the features of influencing factors through CNN network and using attention mechanism (AT) to focus on key information, more information can be taken into account, thereby further improving the prediction performance of the model.

In addition, compared with E-BIGRU, E-NGO-CNN-BIGRU-AT and E-CNN-BIGRU-AT has further improved MAE, RMSE, MAPE and R^2. Compared with other models, the proposed E-NGO-CNN-BIGRU-AT had MAE, RMSE, MAPE and R^2 of 87.21, 151.97, 1.10% and 0.992, respectively, and all indicators are optimal. Compared with the NGO-CNN-BIGRU-AT model, the MAE, RMSE, MAPE and R^2 of the E-NGO-CNN-BIGRU-AT are reduced by 49%, 42.3%, 0.51% and 0.001, respectively. This shows that the construction of error compensation model can effectively improve prediction accuracy. Therefore, the error compensation model can effectively predict the changes in actual load, and its performance is better than other comparative models, making it more suitable for short-term load forecasting.

Fig 6 shows the comparison curve between the actual values of each sampling point and the predicted values of different models on September 29, 2018.

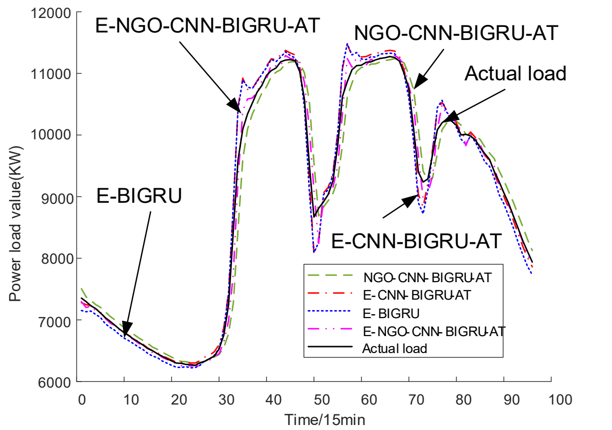

Fig. 6 Comparison of load prediction results on rest days.

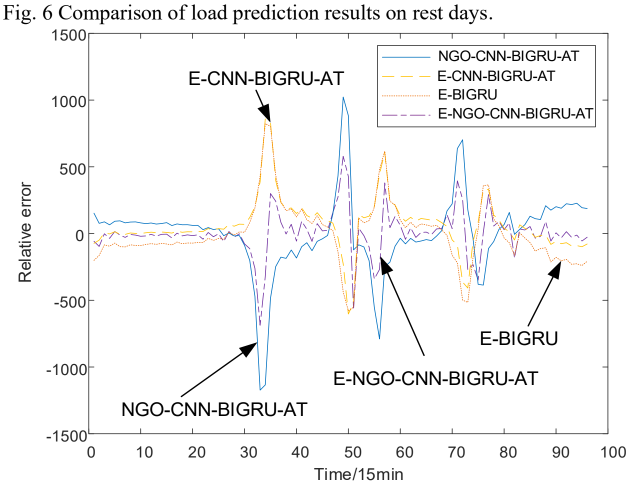

Fig. 7 Comparison of load prediction error results on rest day

The performance evaluation indicators of each model on rest days can be obtained from Figs. 6-7, as shown in Table 4.

TABLE IV

PERFORMANCE EVALUATION INDEXES OF EACH MODEL ON REST DAYS

	MAE	RMSE	R^2	MAPE/%
NGO-CNN-BIGRU-AT	181.83	297.03	0.97	2.00
E-BIGRU	161.81	232.15	0.98	1.78
E-CNN-BIGRU-AT	129.94	210.95	0.99	1.36
E- NGO-CNN-BIGRU-AT	100.42	171.99	0.992	1.08

According to Table 4, compared with E-BIGRU and E-CNN-BIGRU-AT, the MAPE of E-NGO-CNN-BIGRU-AT decreased by 0.22% and 0.64%, respectively. RMSE decreased by 64.88 and 86.08, respectively. MAE decreased by 20.02 and 51.89, while R^2 increased by 0.01 and 0.02, respectively. The prediction accuracy of the model is improved, and proves the validity of the model. Moreover, comparing the prediction results of rest days based on the E-NGO-CNN-BIGRU-AT model with the NGO-CNN-BIGRU-AT model, the weekly average MAPE decreased from 2.00% to 1.08%, a decrease of 0.92%. The weekly average RMSE decreased from 297.03 to 171.99, a decrease of 125.04. These two critical metrics have been significantly optimized, further validating the effectiveness of the E-NGO-CNN-BIGRU-AT model in enhancing prediction accuracy. As can be seen from the load prediction curve of E-NGO-CNN-BIGRU-AT in Fig. 6, the load prediction curve is very close to the actual load curve, achieving the expected effect.

Fig. 8 shows the comparison curve between the actual value of each sampling point and the predicted value of different models on working days.

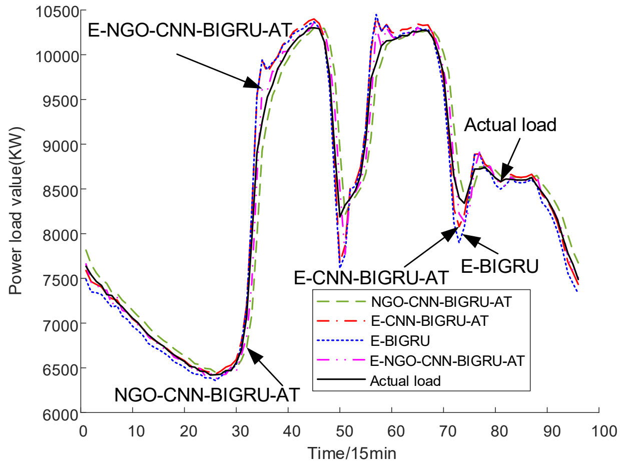

Fig. 8 Comparison of load prediction results on working days.

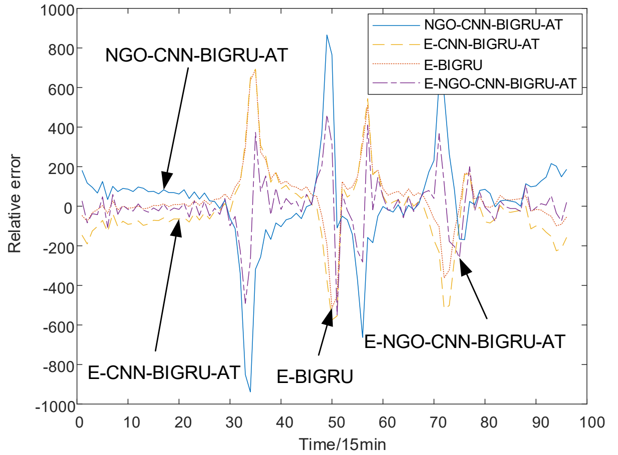

Fig. 9 Comparison of load prediction error results of working days.

The performance evaluation indicators of each model on working days can be obtained from Figs. 8-9, as shown in Table 5.

TABLE V

PERFORMANCE EVALUATION INDEXES OF EACH MODEL IN WORKING DAYS

	MAE	RMSE	R^2	MAPE/%
NGO-CNN-BIGRU-AT	144.35	239.45	0.982	1.71
E-BIGRU	131.06	197.72	0.983	1.55
E-CNN-BIGRU-AT	98.66	166.19	0.985	1.12
E- NGO-CNN-BIGRU-AT	86.77	144.49	0.990	1.01

As can be seen from Table 5, MAE, RMSE, MAPE and R^2 of E-CNN-BIGRU-AT reached 98.66, 166.19, 1.12 and 0.985, respectively. Compared with E-BIGRU, MAE, RMSE and MAPE decreased by 25.7%, 16% and 0.43% respectively. R^2 has been improved by 0.02. which verifies that CNN and attention mechanism can improve the forecasting performance of load forecasting model. Compared with NGO-CNN-BIGRU-AT, MAE, RMSE and MAPE of E-NGO-CNN-BIGRU-AT decreased by 39.8%, 39.6% and 0.7%, respectively, and R^2 increased by 0.08.

Obviously, when dealing with a single model, the load forecasting model incorporating error compensation demonstrates superior forecasting accuracy and strong predictive performance.

Fig.10 shows the comparison curve between the actual value of each sampling point and the predicted value of different models on National Day.

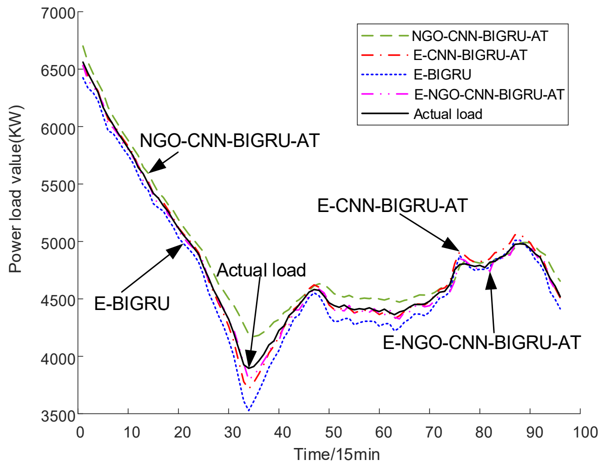

Fig. 10 Comparison of load prediction results on National Day

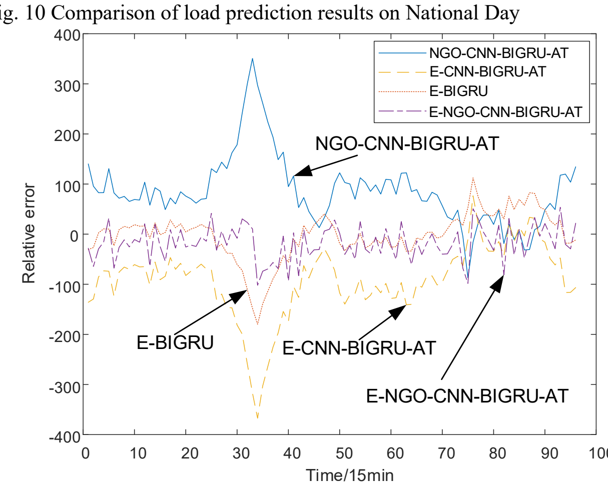

Fig. 11 Comparison of load prediction error results on National Day

According to Figs. 10-11, the performance evaluation indicators of each model on National Day can be obtained, as shown in Table 6.

TABLE VI

PERFORMANCE EVALUATION INDEXES OF EACH MODEL ON NATIONAL DAY

	MAE	RMSE	R^2	MAPE/%
NGO-CNN-BIGRU-AT	90.52	110.86	0.97	11.98
E-BIGRU	83.49	103.24	0.961	2.12
E-CNN-BIGRU-AT	33.87	47.65	0.990	0.75
E- NGO-CNN-BIGRU-AT	30.56	38.22	0.991	0.65

As can be seen from Fig. 10 and Table 6, there is a large deviation between the NGO-CNN-BIGRU-AT model and the actual load value in predicting holidays, in this prediction scenario, the hybrid model NGO-CNN-BIGRU-AT has reached its performance ceiling. After adding the error model, the E-BIGRU prediction results were relatively stable, MAE, RMSE and MAPE decreased by 7.76%, 6.87% and 9.86%, respectively, and R^2 increased by 0.01 compared with the NGO-CNN-BIGRU-AT model. The prediction results of the mixed forecasting model for holidays are relatively more accurate. The MAE, RMSE, MAPE and R^2 of the error model CNN-BIGRU-AT model reached 33.87, 47.65, 0.75% and 0.99. The NG-CNN-BIGRU-AT mixed prediction model with error compensation decreased by 63.3%, 62.8% and 69.3% compared with E-BIGRU's MAE, RMSE and MAPE, and the R^2 increased by 0.03. Compared with E-CNN-BIGRU-AT, the accuracy of MAE, RMSE and MAPE increased by 9.7%, 19.7% and 13.3%, and the R^2 increased by 0.001. In summary, the E-NGO-CNN-BIGRU-AT model has higher accuracy for power load forecasting than other models.

VI. CONCLUSION

The error-compensated NGO-CNN-BIGRU-AT short-term forecasting model proposed in this paper significantly enhances the accuracy of power load forecasting. Experimental results demonstrate that when applied to real-world 2018 datasets encompassing weekends, weekdays, and holidays, the model outperforms non-error-compensated counterparts, exhibiting smaller mean absolute error (MAE) and root mean square error (RMSE) values, as well as higher coefficient of determination (R^2). These findings confirm that the proposed model not only achieves superior prediction precision, but also maintains robustness in fitting degree, laying a theoretical foundation and practical framework for future research and application of short-term load forecasting.

REFERENCES

[1] H. Liu. "Research on electricity load forecasting based on BP neural network". *Light Source and Lighting*, no.12, pp. 65-67, 2021.

[2] X. Y. Zhang, H. C. Lin, B. Huang, et al. "EMD-SVR short-term load forecasting based on optimal intersection similarity day". *Strait Science*, no.7, pp.30-35+41,2023.

[3] H. T. Shen, F. Li, L. Shi, et al. "Short-term power load forecasting based on weather data dimensionality reduction and hybrid deep learning". *Power Construction*, vol.45, no.1, pp.13-21,2024.

[4] J. C. Wang. "Short-term power load forecasting based on CEEMDAN-GGO-BI-GRU". *Automation Application*, vol.65, no.21, pp.148-150, 2024.

[5] X. T. Chen. "Short-term forecasting of multivariate power load based on LSTM". *Modern Information Technology*, vol.6, no.24, pp.155-158, 2022.

[6] T. Gong, H. Li, H. Liu. "Short-term power load forecasting method based on improved GRU". *Communication and Power Supply Technology*, vol.4, no.38, pp. 1-4+7, 2021.

[7] J.Y. Wu, X. Lu, H. Liu, et al. "Ultrashort-term multiregional power load forecasting based on Spearman-GCN-GRU model". *China Electric Power*, vol.57, no.6, pp.131-140,2024.

[8] X. Zhu, J. D. Lin, X. Y. Shi, et al. "Ultra-short-term prediction of wind power based on VMD-SSA and error compensation". *Journal of Fujian University of Technology*, vol.21, no.06, pp. 573-579.2023.

[9] Y. Geng, H. L. Wang, N. Zhang, et al. "Multivariate load forecasting for integrated energy systems based on error-compensated LSTM-GRU". *Journal of Electrical Engineering*, vol.18, no.04, pp.320-330, 2023.

[10] L.B. Li, J. Q. Li, H.M. Liu, et al. "Short-term power load forecasting based on SRDHLGRU neural network and differential error compensation". *China Test*, vol.49, no.06, pp.143-150,2023.

[11] L. Zhang, X. Li. "Fault diagnosis model of wind turbine generator based on improved CNN and BiGRU with dual-channel feature fusion". *Journal of Tianjin University of Science and Technology*, vol.1, no.38, pp. 55-60+69, 2023.

[12] Q. Lian, W. Sun. "Short-term ship traffic flow prediction model based on attention mechanism of stacked LSTM". *Journal of Dalian Maritime University*, pp. 1-10, 2023.

[13] Y. Xie, H. Wang, Y. Yue. "Short-term load forecasting considering VMD residual and optimized BiLSTM". *Complexity Systems and Complexity Science*, pp. 1-9, 2023.

[14] Y. Huang, J. Li, Y. Li. "An improved hybrid CNN-LSTM-Attention model with Kepler optimization algorithm for wind speed prediction".

Engineering Letters, vol. 32, no. 10, pp.1957-1965, 2024.
[15] Y. Hou, W. Gu, K. Yang. “Deep reinforcement learning recommendation system based on GRU and attention mechanism”. *Engineering Letters*, vol. 31, no.2, pp.695-701, 2023.
[16] W. Fu, X. Zhang, H. Zhang. “Research on ultra-short-term wind speed forecast based on INGO-SWGMN hybrid model”. *Journal of Solar Energy*, pp. 1-11, 2023.
[17] Y. Han, H. Zhu, K. Li. “Short-term photovoltaic power forecasting using clustering and stochastic configuration network”. *Journal of Electronic Measurement and Instrumentation*, pp. 1-12, 2023.
[18] J. Song, S. Cui, H. Liu. “Ultra-short-term wind power forecasting based on quadratic decomposition NGO-VMD residual and long short-term memory neural network”. *Science Technology and Engineering*, vol.6, no.23, pp. 2428-2437, 2023.