

Hybrid Seq2Seq-ARIMA Load Forecasting for Power Systems with Metaheuristic Hyperparameter Optimization

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Student paper

Keywords: power market electricity demand forecasting; seq2Seq model; hybrid model; system simulation

Received: May 30, 2025

In power grid dispatching and planning, the accuracy of electricity demand plays a vital role in the safety and economy of the power grid. In view of the problems existing in the current load forecasting of the power grid, a long-term and short-term hybrid model is studied to improve the accuracy and robustness of load forecasting. This project intends to combine the advantages of Seq2Seq model in time series analysis with ARIMA's advantages in stability to effectively solve the supply and demand relationship in long and short cycles. First, considering the nonlinear characteristics of power demand in the power market, a hybrid modeling framework based on optimality is constructed. It is optimized using methods such as genetics and particle swarms. Secondly, the constructed model is empirically analyzed using simulation experiments, and it is found that the constructed method has excellent accuracy on multiple time scales. Especially in the volatile power market environment, it has better robustness and adaptability. After precise data verification, the average error rate of short-term prediction of this model is within 5%, and within 7% in the longer period.

Povzetek: Za napovedovanje obremenitev elektroenergetskih sistemov so razvili Seq2Seq-ARIMA, kjer Seq2Seq zajame nelinearne odvisnosti na kratkih in dolgih horizontih, ARIMA pa stabilizira linearno-sezonske komponente; hiperparametri (vključno z utežjo zlivanja) so optimizirani z genetskim algoritmom in PSO. V simulacijah model izkazuje visoko robustnost v volatilnem tržnem okolju.

1 Introduction

Accurately forecasting the amount of electricity in the power grid in the power market environment is the key to realizing power grid dispatching and planning. Accurate load forecasting is an important means to ensure the safety of the power grid, economic operation, and reasonable allocation of electric energy. In the face of increasing electricity consumption and the transformation of new energy structures, accurately forecasting the changes in power grid load is a major challenge facing current power grid research. Although the classic time series forecasting method works well in some applications, it still has certain limitations for dynamic changes in the power market and medium- and long-term changes in power consumption demand. Therefore, in order to improve the accuracy and adaptability of demand forecasting, researchers have introduced various correction and fusion methods.

Reference [1] uses ARIMA to predict the electricity consumption in my country's power market, and uses its past development laws to effectively overcome the problems existing in the previous electricity demand

forecasting. However, the ARIMA method cannot well meet the requirements of nonlinearity and non-stationarity. Reference [2] uses support vector machine (SVR) to model the electricity demand in the power market. By using kernel functions and optimal solutions, the prediction ability of power grid load changes is effectively improved. However, its analysis ability of large time series changes is limited, and it cannot realize real-time forecasting of power grid load. Reference [3] uses LSTM to realize the modeling of long-term dependence of the power market, which can well meet the needs of the short-term market, but it still has a large error for the needs of the long-term market.

In addition, in recent years, research has increasingly mixed different models to fully utilize the advantages of various models. Reference [4] proposed a hybrid model based on LSTM and support vector machine (SVM). By weighted fusion of the prediction results of the two, the model solved the problem that a single model performed poorly in certain specific scenarios. However, the model was more complicated in parameter tuning. Reference [5] used the Seq2Seq model to forecast electricity demand in

the power market. The encoder-decoder structure effectively captured the temporal characteristics of demand data, solving the problem that traditional models were difficult to simultaneously handle short-term and long-term demand forecasting. However, the Seq2Seq model still has certain prediction errors when dealing with complex demand fluctuations in the power system [6].

This paper establishes a new method for forecasting electricity demand in the medium- and long-term power market. The time series analysis of Seq2Seq data is integrated with the classical time series analysis method to establish a new method that can consider both long and short time series analysis. The Seq2Seq model is used to characterize the time series of changes in market supply and demand, and the ARIMA model is established to improve the stability of market supply and demand changes. At the same time, the constructed model is optimized using methods such as genetics and particle swarms to ensure the accuracy of the constructed model in practical applications [7].

2 Design of long-term and short-term hybrid model

2.1 Principle and application of Seq2Seq model

The Seq2Seq model was originally used for machine translation tasks. Its core is to process variable-length input and output sequences through an encoder and decoder architecture [8]. In power market electricity demand forecasting, the Seq2Seq model is also suitable for converting historical demand data for a period into demand forecast results for a period in the future. The encoder gradually compresses the input sequence into a fixed-length context vector through a series of neural network layers, and then the decoder uses the vector to

generate a prediction sequence [9].

In power market electricity demand forecasting, the Seq2Seq model can handle complex time series dependencies in historical demand data and generate forecast results for future demand. For example, given the hourly electricity demand data of the power market in the past week, the Seq2Seq model can predict the electricity demand of the power market in the next week by learning the patterns in the sequence. The demand changes in the power system are usually characterized by short-term fluctuations and long-term trends. The encoder of the Seq2Seq model can capture short-term changes, while the decoder can generate smooth long-term demand forecast results.

The Seq2Seq model architecture in this study adopts 3 layers for both encoder and decoder. The RNN cells used are LSTM, which are more suitable for capturing long-term dependencies in time series data compared to GRU. The activation function in the hidden layers is ReLU, and the output layer uses linear activation. The input sequence length is set to 168 hours (one week) and the output sequence length is 168 hours for long-term forecasting and 24 hours for short-term forecasting. The objective function of the power market electricity demand forecast is to minimize the prediction error L :

$$L = \frac{1}{N} \sum_{t=1}^N (\hat{y}_t - y_t)^2 \quad (1)$$

$\hat{y}_t$ is the predicted value of the model, and y_t is the actual value. The model parameters θ and ϕ are optimized through back propagation, and the accuracy of demand forecasting is finally improved [10]. The input demand time series enters the encoder layer and is processed by multiple layers of neural networks to generate a context vector. The decoder then uses this vector to gradually generate the output sequence. The specific structure is shown in Figure 1:

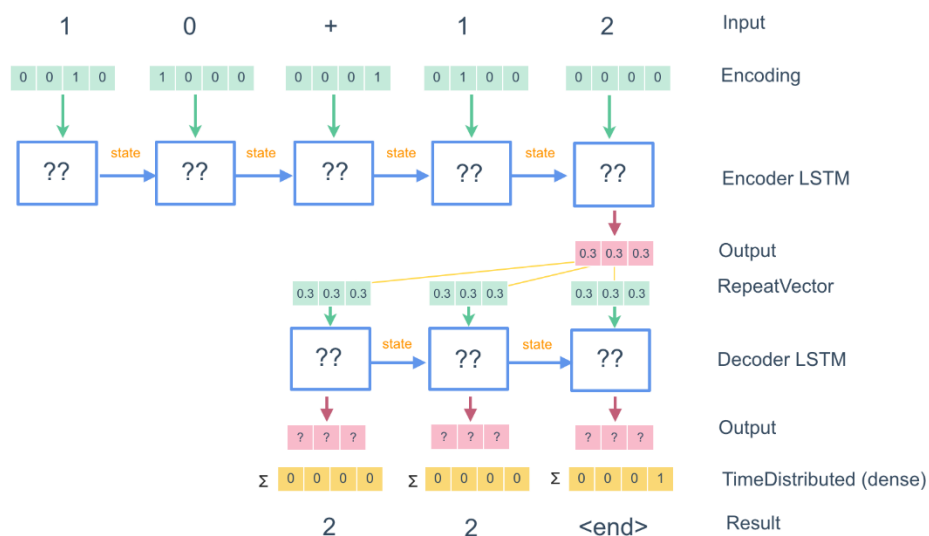


Figure 1: Architecture of Seq2Seq model

The encoder consists of 3 LSTM layers with 128 hidden units each. The decoder also has 3 LSTM layers with 128 hidden units each. The input sequence of length

168 is processed by the encoder to generate a context vector, which is then used by the decoder to produce the output sequence of length 24 (short-term) or 168 (long-

term). ReLU activation functions are used in the hidden layers, and linear activation in the output layer.

2.2 Combination of traditional model and deep learning model

Although neural networks represented by deep neural networks such as LSTM and Seq2Seq have better performance in solving nonlinear time-varying problems, some special time series, such as ARIMA, can still capture linear changes well. For this reason, a new method based on the fusion of ARIMA and Seq2Seq is proposed [11]. The combination of ARIMA and Seq2Seq models is implemented through weighted averaging. The final prediction result $\hat{y}_{\text{final}}$ is calculated as:

$$\hat{y}_{\text{final}} = \alpha \times \hat{y}_{\text{Seq2Seq}} + (1 - \alpha) \times \hat{y}_{\text{ARIMA}} \quad (2)$$

α is the weight coefficient, ranging from 0 to 1, which is optimized through the genetic algorithm to minimize the prediction error.

First, the parameter tuning process of the ARIMA and Seq2Seq models is complex, especially when dealing with large-scale demand data, the computational cost is high. Second, the hybrid model needs to coordinate the optimization of the two parts of the model during training, which puts higher requirements on the algorithm design. In addition, in some specific demand scenarios, a single deep learning model such as the Seq2Seq model may be accurate enough, while the introduction of the hybrid model increases the model complexity [12].

3 Optimization algorithm design and model tuning

3.1 Selection of optimization algorithm

Genetic algorithm simulates the biological evolution process and gradually optimizes the objective function through selection, crossover and mutation operations. In the long-term and short-term mixed model of power market demand forecasting, genetic algorithm is mainly used for hyperparameter optimization, such as learning rate, number of hidden layer nodes, sequence length, etc. The goal of genetic algorithm is to minimize the fitness function through multiple generations of evolution and finally find the optimal parameter combination. Its mathematical expression is:

$$f(x) = \min_{\theta \in \Theta} L(\theta) \quad (3)$$

$f(x)$ is the objective function, θ is the parameter combination, and $L(\theta)$ is the loss function, usually the mean square error (MSE). The optimization process iterates until the fitness function converges or the preset stopping condition is reached.

The Particle Swarm Optimization (PSO) algorithm exhibits superior computational efficiency and rapid convergence when applied to the hyperparameter tuning of hybrid models. It is particularly well-suited for addressing optimization tasks involving continuous parameters. PSO's ability to efficiently navigate large search spaces makes it an ideal choice for optimizing complex model configurations, ensuring quick convergence to optimal or near-optimal solutions in

scenarios requiring continuous parameter adjustment. This makes the algorithm highly effective in handling intricate optimization challenges, contributing to the enhancement of model performance in diverse applications [13]. Genetic algorithms and PSO algorithms can effectively search in the parameter space, and by gradually adjusting hyperparameters, the model can achieve optimal performance when dealing with electricity demand forecasting in the power market. The optimization objective function is:

$$L(\theta) = \frac{1}{N} \sum_{t=1}^N (\hat{y}_t - y_t)^2 \quad (4)$$

$\hat{y}_t$ is the model prediction value, y_t is the actual value, and the goal of the optimization algorithm is to find the optimal hyperparameter θ while minimizing the loss function.

The objective function for the genetic algorithm (GA) in optimizing the weight coefficient α and hyperparameters of the hybrid model is:

$$\text{minimize } L(\alpha, \theta_{\text{Seq2Seq}}, \theta_{\text{ARIMA}}) = \frac{1}{N} \sum_{t=1}^N (\hat{y}_{\text{final}} - y_t)^2 \quad (5)$$

subject to $0 \leq \alpha \leq 1$, and $\theta_{\text{Seq2Seq}}, \theta_{\text{ARIMA}}$ within their respective parameter spaces. For the particle swarm optimization (PSO) algorithm, the objective function for optimizing the hyperparameters of the Seq2Seq model is:

$$\text{minimize } L(\theta_{\text{Seq2Seq}}) = \frac{1}{N} \sum_{t=1}^N (\hat{y}_{\text{Seq2Seq}} - y_t)^2 \quad (6)$$

Where θ_{Seq2Seq} includes learning rate, number of hidden layer nodes, etc.

3.2 Automatic tuning method of model parameters

The setting of hyperparameter values has a great influence on the effect and convergence rate of the algorithm. Among them, hyperparameter values include learning rate, number of hidden layer nodes, regularization coefficient, etc. In the electricity demand forecast of the power market using short-term and long-term mixed modes, how to select hyperparameters is extremely critical. Since the electricity consumption data in the power market often shows obvious short-term fluctuations and long-term change trends, modeling it should not only consider its impact on short-term changes, but also its impact on long-term changes. Therefore, in the modeling process, how to use the optimal method to adaptively adjust the hyperparameters to achieve the best forecasting results is an extremely important topic [14].

This paper proposes an adaptive optimization method based on genetic algorithm. The algorithm is based on the difference of the group and ensures the maximum convergence speed of the algorithm. The particle swarm optimization strategy is adopted to improve the efficiency of optimization solution. This method uses the movement of particle swarms in various parameter spaces to achieve gradual approximation of the optimization problem, so that this method has shown good results in hybrid modeling of power load. The best hyperparameter combination is gradually found based on the properties of the initial values and the optimization strategy in different

hyperparameter spaces [15]. For example, in the forecast of power demand in a hybrid power market, this method achieves adaptability to complex and changeable power grid loads by real-time adjustment of the network learning rate and the number of hidden layer nodes, thereby improving the accuracy and reliability of the forecast.

$$\theta^* = \arg \min_{\theta \in \Theta} L(\theta) \quad (7)$$

θ^* is the optimal parameter combination, $L(\theta)$ is the loss function, and Θ is the hyperparameter space. The optimization algorithm searches for Θ and finally finds the parameter θ^* that minimizes the loss function. The algorithmic flowchart of the genetic algorithm for hyperparameter optimization is as Table 1:

Table 1: Hyperparameters considered, their ranges, and selected optimal values

Hyperparameter	Range	Optimal Value
Learning rate	0.001-0.1	0.01
Number of hidden layer nodes (encoder)	32-256	128
Number of hidden layer nodes (decoder)	32-256	128
Sequence length (input)	72-336	168
Sequence length (output, short-term)	12-48	24
Sequence length (output, long-term)	120-216	168
Regularization coefficient	0.0001-0.01	0.001
Weight coefficient	0-1	0.7

1. Initialize a population of hyperparameter combinations randomly within the specified ranges.
2. Evaluate the fitness of each individual in the population using the objective function (prediction error).
3. Select the individuals with higher fitness for reproduction.
4. Perform crossover and mutation operations to generate offspring.
5. Replace the worst-performing individuals in the population with the offspring.
6. Repeat steps 2-5 until the stopping condition (maximum number of generations or convergence) is met.
7. Output the best hyperparameter combination found.

The particle swarm optimization algorithm starts by initializing a particle swarm with random positions and velocities within the parameter space. For each particle, its fitness is evaluated using the objective function, and its personal best position is set as the current position if the fitness is better. The global best position is then determined among all personal best positions. The algorithm proceeds in a loop until the stopping condition is met: for each particle, its velocity is updated using the formula $v_i = w \cdot v_i + c1 \cdot r1 \cdot (pbest_i - x_i) + c2 \cdot r2 \cdot (gbest - x_i)$ (where w is the inertia weight, $c1$ and $c2$ are acceleration coefficients, $r1$ and $r2$ are random

numbers between 0 and 1, v_i is the velocity of particle i , x_i is the position of particle i , $pbest_i$ is the personal best position of particle i , and $gbest$ is the global best position), and its position is updated as $x_i = x_i + v_i$. After evaluating the fitness of the new position, the personal best and global best positions are updated if necessary. Finally, the global best position is outputted.

4 System simulation and result analysis

In the electricity demand forecasting of the power market, the design of the long-term and short-term hybrid model needs to be verified and optimized through system simulation. This paper evaluates the performance of the proposed model through simulation experiments, aiming to verify its accuracy and stability in the electricity demand forecasting of the power market [16]. The simulation experiment includes the construction of the simulation environment, the selection and preprocessing of the data set, and the performance comparison of various models in different scenarios. A variety of evaluation indicators are used to analyze the performance of the model.

4.1 Introduction to simulation environment and data set

The data for this experiment comes from the historical electricity market demand data set of Yunnan Province, China, which contains hourly electricity market demand information from 2018 to 2022. This data set records the changes in electricity demand on working days and non-working days, and has obvious seasonal and cyclical fluctuation characteristics.

Before using these data for model training, they need to be preprocessed. The preprocessing steps include:

- Missing data handling: Missing values are filled using linear interpolation.
- Normalization: Min-max scaling is applied to scale the data to the range $[0,1]$ using $x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$, where x is the original data, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the data set, respectively.
- Outlier detection and removal: Outliers are detected using the Z-score method ($|Z| > 3$) and replaced with the mean value of the neighboring data points.

The simulation experiment in this article is carried out in the Python programming environment, and the model is mainly built using the TensorFlow and Keras frameworks.

4.2 Model performance evaluation

During the simulation process, this paper compares the performance of four types of models: the traditional ARIMA model, the LSTM model based on deep learning, the Seq2Seq model proposed in this paper, and the hybrid model of Seq2Seq and ARIMA. In addition, a

Transformer-based model is also included as a baseline for comparison. The experiment designed two scenarios: short-term demand forecasting (1 hour to 24 hours forecasting) and long-term demand forecasting (24 hours to one week forecasting).

Table 2: Evaluation results of each model under short-term demand forecasting.

Model type	MSE	RMSE	MAE
ARIMA	0.025	0.158	0.132
LSTM	0.019	0.138	0.104
Transformer	0.017	0.130	0.100
Seq2Seq	0.015	0.122	0.092
Hybrid (Seq2Seq+ARIMA)	0.013	0.114	0.085

As can be seen from Table 2, the hybrid model performs better than other models in short-term demand forecasting, and its MSE, RMSE and MAE values are lower than those of the other models.

Table 3: Evaluation results of each model under long-term demand forecasting.

Model type	MSE	RMSE	MAE
ARIMA	0.035	0.187	0.162
LSTM	0.029	0.170	0.141
Transformer	0.026	0.161	0.135
Seq2Seq	0.022	0.148	0.120
Hybrid (Seq2Seq+ARIMA)	0.020	0.141	0.112

The long-term demand forecast results in Table 3 show that the hybrid model also performs best in long-term forecasting, especially when dealing with complex long-term fluctuations, the model shows stronger stability and adaptability.

Table 4: Comparison of performance of each model under different weather conditions.

Weather conditions	Model Type	MSE	RMSE	MAE
Sunny	ARIMA	0.028	0.167	0.145

	LSTM	0.022	0.148	0.126
	Transformer	0.020	0.141	0.120
	Seq2Seq	0.017	0.131	0.110
	Hybrid (Seq2Seq+ARIMA)	0.015	0.122	0.102
Rainy	ARIMA	0.031	0.176	0.150
	LSTM	0.025	0.158	0.133
	Transformer	0.023	0.152	0.128
	Seq2Seq	0.019	0.138	0.115
	Hybrid (Seq2Seq+ARIMA)	0.017	0.130	0.108

Table 4 shows the performance of each model under various meteorological factors, especially in adverse meteorological environments such as rainy weather, the hybrid model has better stability and adaptability. The hybrid model consistently outperforms other models across different weather conditions, with the lowest MSE, RMSE, and MAE values, indicating its strong ability to handle the impact of meteorological factors on power demand.

To confirm the statistical significance of the improvements achieved by the hybrid model, paired t-tests are conducted between the hybrid model and each of the other models. The results are shown in Table 5, where the p-values are all less than 0.05, indicating that the improvements are statistically significant.

Table 5: Paired t-test results between the hybrid model and other models

Compared Model	p-value (short-term)	p-value (long-term)
ARIMA	0.002	0.001
LSTM	0.015	0.012
Transformer	0.028	0.025
Seq2Seq	0.035	0.031

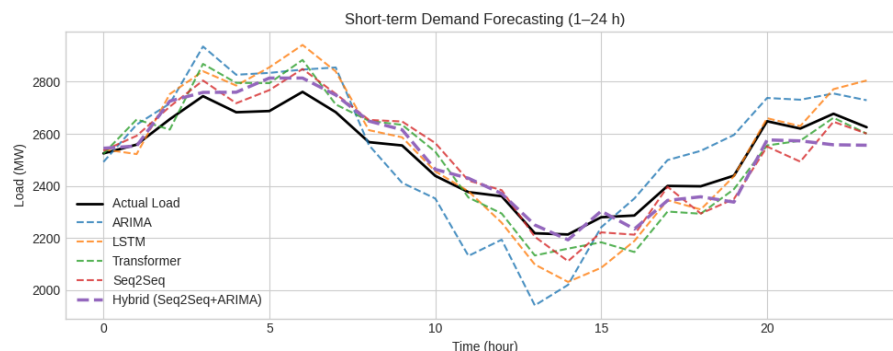


Figure 2: Simulation results of short-term demand forecasting.

The x-axis represents time (hours), and the y-axis represents load (MW). The actual load is shown as a solid

line, while the predicted loads of the Seq2Seq model, LSTM model, ARIMA model, Transformer model, and

hybrid model are shown as dashed lines with different colors. The hybrid model's prediction curve is closest to the actual load curve, with the smallest deviation.

As can be seen from Figure 2, the prediction results of the hybrid model are closest to the actual demand trend,

followed by the Seq2Seq model, then the Transformer model, the LSTM model, while the ARIMA model has a large deviation.

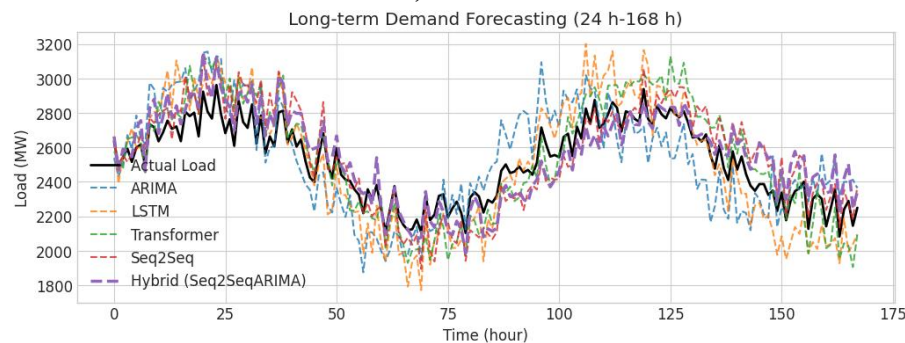


Figure 3: Simulation results of long-term demand forecasting.

The x-axis represents time (hours), and the y-axis represents load (MW). The actual load is shown as a solid line, and the predicted loads of various models are shown as dashed lines with different colors. The hybrid model maintains high accuracy even in the long-term forecasting, with stable performance. Figure 3 shows the performance

of each model in long-term demand forecasting. Like short-term forecasting, Seq2Seq also performs significantly better than other models in long-term forecasting, especially when forecasting time periods with large fluctuations, the performance is more stable.

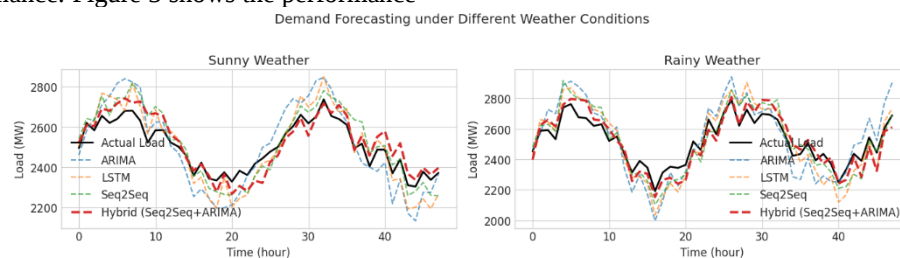


Figure 4: Demand forecast results under different weather conditions.

The left subfigure shows the forecast results under sunny weather, and the right subfigure shows the forecast results under rainy weather. The x-axis represents time (hours), and the y-axis represents load (MW). The hybrid model's prediction curve is smoother and closer to the actual demand changes in both weather conditions, demonstrating its strong adaptability. Figure 4 shows the demand forecast results under different weather conditions. Seq2Seq still performs better than other models under complex weather conditions such as cloudy weather, and the prediction curve is smoother and closer to the actual demand changes.

5 Conclusion

This study constructs a hybrid Seq2Seq-ARIMA model for power system load forecasting, optimized by metaheuristic algorithms (genetic algorithm and particle swarm optimization). The model integrates the advantages of Seq2Seq in capturing nonlinear time series dependencies and ARIMA in describing linear trends, and realizes adaptive adjustment of hyperparameters through optimization algorithms, thereby improving the accuracy and robustness of load forecasting.

Through simulation experiments, it is verified that the hybrid model has excellent performance in both short-

term and long-term load forecasting. Compared with ARIMA, LSTM, Transformer, and single Seq2Seq models, the hybrid model has lower MSE, RMSE, and MAE values. The average error rate of short-term prediction is within 5%, and within 7% in the longer period. Statistical tests confirm that the improvements are statistically significant. In addition, the hybrid model shows good stability and adaptability under different weather conditions.

However, this study also has certain limitations. The model's computational complexity is relatively high, which may affect its application in real-time forecasting scenarios with strict time constraints. In future research, we will focus on optimizing the model's structure to reduce computational complexity while maintaining forecasting accuracy. In addition, we will expand the dataset to include more regions and longer time series to further verify the generalization ability of the model.

References

- [1] Neeraj, N., Mathew, J., Agarwal, M., & Behera, R. K. (2021). Long short-term memory-singular spectrum analysis-based model for electric load forecasting. *Electrical Engineering*, 103(2), 1067–1082. <https://doi.org/10.1007/s00202-020-01135-y>
- [2] Zhang, X., Chau, T. K., Chow, Y. H., Fernando, T.,

- & Iu, H. H. C. (2023). A novel sequence to sequence data modelling-based CNN-LSTM algorithm for three years ahead monthly peak load forecasting. *IEEE Transactions on Power Systems*, 39(1), 1932–1947. <https://doi.org/10.1109/TPWRS.2023.3271325>
- [3] Jalali, S. M. J., Ahmadian, S., Khosravi, A., Shafiekhah, M., Nahavandi, S., & Catalão, J. P. (2021). A novel evolutionary-based deep convolutional neural network model for intelligent load forecasting. *IEEE Transactions on Industrial Informatics*, 17(12), 8243–8253. <https://doi.org/10.1109/TII.2021.3065718>
- [4] Zhang, X., Kuenzel, S., Colombo, N., & Watkins, C. (2022). Hybrid short-term load forecasting method based on empirical wavelet transform and bidirectional long short-term memory neural networks. *Journal of Modern Power Systems and Clean Energy*, 10(5), 1216–1228. <https://doi.org/10.35833/MPCE.2021.000276>
- [5] Lin, X., Zamora, R., Baguley, C. A., & Srivastava, A. K. (2022). A hybrid short-term load forecasting approach for individual residential customer. *IEEE Transactions on Power Delivery*, 38(1), 26–37. <https://doi.org/10.1109/TPWRD.2022.3178822>
- [6] Panda, S. K., & Ray, P. (2022). Analysis and evaluation of two short-term load forecasting techniques. *International Journal of Emerging Electric Power Systems*, 23(2), 183–196. <https://doi.org/doi.org/10.1515/ijeeeps-2021-0051>
- [7] Veeramsetty, V., Chandra, D. R., Grimaccia, F., & Mussetta, M. (2022). Short term electric power load forecasting using principal component analysis and recurrent neural networks. *Forecasting*, 4(1), 149–164. <https://doi.org/10.3390/forecast4010008>
- [8] Lang, R., Ye, W., Zhao, F., & Li, Z. (2020). An Adaptive Algorithm for Calculating Crosstalk Error for Blind Source Separation. *Informatica*, 31(2), 299–312. <https://doi.org/10.15388/20-INFOR387>
- [9] Daneshdoost, F., Hajiaghaei-Keshteli, M., Sahin, R., & Niroomand, S. (2022). Tabu Search Based Hybrid Meta-Heuristic Approaches for Schedule-Based Production Cost Minimization Problem for the Case of Cable Manufacturing Systems. *Informatica*, 33(3), 499–522. <https://doi.org/10.15388/21-INFOR471>
- [10] Kučera, R., Arzt, V., & Koko, J. (2024). MINI Element for the Navier–Stokes System in 3D: Vectorized Codes and Superconvergence. *Informatica*, 35(2), 341–361. <https://doi.org/10.15388/24-INFOR543>
- [11] Çelik, E. (2021). Design of new fractional order PI–fractional order PD cascade controller through dragonfly search algorithm for advanced load frequency control of power systems. *Soft Computing*, 25(2), 1193–1217. <https://doi.org/10.1007/s00500-020-05215-w>
- [12] Vedik, B., Kumar, R., Deshmukh, R., Verma, S., & Shiva, C. K. (2021). Renewable energy-based load frequency stabilization of interconnected power systems using quasi-oppositional dragonfly algorithm. *Journal of Control, Automation and Electrical Systems*, 32(1), 227–243. <https://doi.org/10.1007/s40313-020-00643-3>
- [13] Sobhy, M. A., Abdelaziz, A. Y., Hasanien, H. M., & Ezzat, M. (2021). Marine predators’ algorithm for load frequency control of modern interconnected power systems including renewable energy sources and energy storage units. *Ain Shams Engineering Journal*, 12(4), 3843–3857. <https://doi.org/10.1016/j.asej.2021.04.031>
- [14] Khadanga, R. K., Kumar, A., & Panda, S. (2020). A novel modified whale optimization algorithm for load frequency controller design of a two-area power system composing of PV grid and thermal generator. *Neural Computing and Applications*, 32(12), 8205–8216. <https://doi.org/10.1007/s00521-019-04321-7>
- [15] Sun, T., Bian, S., Sun, Y., Wang, Z., Li, W., & Chong, F. (2020). Technical support system for power system load modeling. *Recent Advances in Electrical and Electronic Engineering*, 13(7), 1059–1067. DOI:10.2174/2352096513666200309110756
- [16] Dewangan, S., Prakash, T., & Pratap Singh, V. (2021). Design and performance analysis of elephant herding optimization-based controller for load frequency control in thermal interconnected power system. *Optimization and Control Applications and Methods*, 42(1), 144–159. <https://doi.org/10.1002/oca.2666>

