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Neural network fusion optimization for photovoltaic power forecasting

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Abstract. This paper aims to establish a comprehensive photovoltaic power generation prediction model. By collecting photovoltaic power generation data and weather data for a year, we analyzed the photovoltaic output characteristics in different seasons and found that the output characteristics in different seasons are also different. This article uses three neural network models, Long Short Term Memory Network, Recurrent Neural Network, and Dense Neural Network, to analyze the output characteristics of different seasons. Training, prediction, and prediction error analysis found that different models have different prediction accuracy in different seasons. Therefore, this paper proposes a weighted ensemble model add weights model based on the Nelder-Mead method to train and predict different seasons respectively. By analyzing the prediction error, the prediction accuracy needs to be better than a single model. We add noise to the data set to simulate unstable lighting conditions such as rainy days, and train and predict the data set after adding noise. The prediction results show that the comprehensive model has higher prediction accuracy than a single model in extreme weather. In order to verify the reliability of the model, this article uses a sliding window to extract the confidence interval of the prediction results, and uses the Bootstrap method to calculate the confidence interval. By analyzing and comparing each model's Average Coverage, Root Mean Squared Length, and Mean Width, the prediction accuracy and reliability of add weights model are better than those of a single model.

Keywords: photovoltaic power forecast, long short term memory, recurrent neural network, dense neural network, Nelder-Mead method

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ЭНЕРГЕТИКА

Научная статья
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Оптимизация объединения нейронных сетей для прогнозирования фотоэлектрической энергии

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Резюме. Целью является проведение исследований в области прогнозирования выработки солнечных электростанций. В качестве объекта исследования предложена ансамблевая нейросетевая прогнозная модель ADWM на основе взвешенных нейронных сетей: сети долгой краткосрочной памяти LSTM, рекуррентной нейронной сети RNN и полносвязной нейронной сети DNN. При этом для поиска оптимальных весов использован метод безусловной оптимизации Нелдера-Мида для получения лучшей предсказательной эффективности прогнозной модели. С целью валидации предложенной прогнозной модели использованы реальные данные о выработке солнечных электростанций на основе фотоэлектрических панелей и метеорологические данные из Австралии за период – один год. Для имитации условий неустойчивой низкой инсоляции использована аугментация данных, добавление шума к набору данных. Анализ прогнозных моделей на реальных временных рядах показал, что в разные сезоны как данные выработки, так и наиболее значимые признаки существенно различаются. Установлено, что точность прогнозирования разных нейросетевых моделей в различные сезоны может существенно варьироваться. Результаты прогнозирования показывают, что предложенная комплексная модель имеет более высокую точность прогнозирования, чем отдельные модели в экстремальных погодных условиях. Для проверки надежности предложенной модели использовано скользящее окно для извлечения доверительного интервала и метод Bootstrap для расчета доверительного интервала. Таким образом, экспериментальным путем установлено, что точность и надежность прогнозирования комплексированной прогнозной нейросетевой модели ADWM выше, чем у традиционных нейросетевых моделей. Проведенные исследования позволят более эффективно использовать углеродно-нейтральные источники фотоэлектрической энергии и планировать работу энергосистем с распределенной генерацией.

Ключевые слова: прогноз мощности фотоэлектрических систем, нейросеть долгой краткосрочной памяти, рекуррентная нейросеть, полносвязная нейросеть, метод Нелдера-Мида

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INTRODUCTION

As the global demand for renewable energy continues to grow, photovoltaic energy has emerged as one of the cleanest and most sustainable energy sources [1]. However, the characteristics of photovoltaic power generation, such as weather changes and day-night cycles, make its output highly unstable and seasonal, posing challenges to the reliable operation and energy management of the power system [2, 3]. Therefore, accurate prediction of photovoltaic power becomes a crucial task aimed at maximizing the efficiency, sustainability, and economy of the power system [4]. In current research on PV power forecasting, the prediction methods can be categorized into three types: based on physical models, based on statistical models, and based on machine learning [5]. The physical model primarily models the irradiance and photovoltaic inverter based on the characteristics of photovoltaic power generation and makes predictions using real-time data. While the physical model can offer a certain level of accuracy, the prediction system is relatively complex [6]. The statistical model is built on historical data and statistical analysis. By observing and analyzing the time series data of the photovoltaic system power output, a statistical model has been developed to predict future changes in power. Compared to physical models, statistical models are less complex, but the prediction results heavily rely on the quality of historical data [7]. Machine learning models train algorithms to identify patterns in data and then utilize those patterns to make predictions. For predicting PV power, machine learning models can utilize various algorithms, including neural networks, support vector machines, and decision trees. These models are capable of adapting to complex nonlinear relationships in order to better capture the intricate changes in photovoltaic system power output [8]. In the field of photovoltaic (PV) power forecasting, neural network models have proven to be a powerful tool capable of capturing complex nonlinear relationships and temporal dependencies, thus performing well in time series forecasting. However, a single neural network model still faces several challenges, such as model complexity, data diversity, overfitting, and other issues. A single model may not effectively adapt to the prediction requirements of various climate types in different regions. In the paper [9], the author utilizes the T-S (Takagi-Sugen) fuzzy model and the deep belief network (DBN) for making predictions. Finally, a genetic algorithm is employed to optimize the model weights, resulting in a much smaller prediction error compared to that of a single model. Paper [10] proposed a prediction method based on long short term memory LSTM-ATTENTION. Compared to a single LSTM, the prediction accuracy has improved, but the model's generalization ability and stability have not been verified. In the paper [11], the author employs a fusion model of DCNN and LSTM neural network, fully leveraging the data mining capabilities of DCNN, and achieves promising results in short-term photovoltaic power prediction. Paper [12] uses backpropagation (BP) neural network to assign weight coefficients to the gray model and improve gray models.

In Paper [13], the author categorized the day-ahead weather into different types by hour. They combined this information with historical weather forecast data, trained separate datasets for each weather type, and divided the yearly data into four seasons based on the seasons. For training and prediction in each season, the author compared the prediction results of four models such as LSTMNN and recurrent neural network (RNN), but did not assess the prediction performance of different models across different seasons.

Although the prediction results of LSTMNN are better than those of other models, the data used for prediction are all from one season, which limits the ability to verify the adaptability of the model. In this paper, we divide the data into four parts by season and use different models to train and predict different seasons.

In the aforementioned papers, single and combined neural networks were utilized to construct models for prediction. This study proposes an integrated model consisting of three neural networks: LSTM (long short-term memory network), RNN, and dense neural network (DNN), to enhance the accuracy and reliability of photovoltaic power prediction [14].

The main objective of this study is to develop an ensemble method that combines multiple neural network models to enhance PV power predictions by fully leveraging the strengths of each model. Specifically, we will explore various types of neural network models, including LSTM, RNN, and DNN. By assigning weights to each model, we will then utilize the Nelder-Mead method to optimize the weights and ultimately achieve the optimal weighted model. In deep learning prediction models, the selection of hyperparameters significantly affects the accuracy of the predictions. In current research, the primary methods for hyperparameter optimization include Bayesian optimization, random search optimization, and other approaches. In the paper [15], the author compared the performance of various hyperparameter optimization methods in neural networks and concluded that the Nelder-Mead method yields better optimization results and is simpler than Bayesian optimization. The significance of this research lies in its potential to assist power system operators, energy companies, and government agencies in enhancing the planning and management of photovoltaic energy usage. This can lead to a reduction in the challenges posed by instability, as well as an improvement in system reliability and sustainability. In addition, the model exhibits good adaptability, allowing for the adjustment of weights based on the model's error to minimize output prediction errors.

INTEGRATED MODEL FRAMEWORK

The structure of the photovoltaic power prediction model in this article is shown Fig.1. The combined model comprises four components: an LSTM photovoltaic power prediction model, an RNN photovoltaic power prediction model, a DNN photovoltaic power prediction model, Nelder-Mead weight optimization, and a combined prediction model.

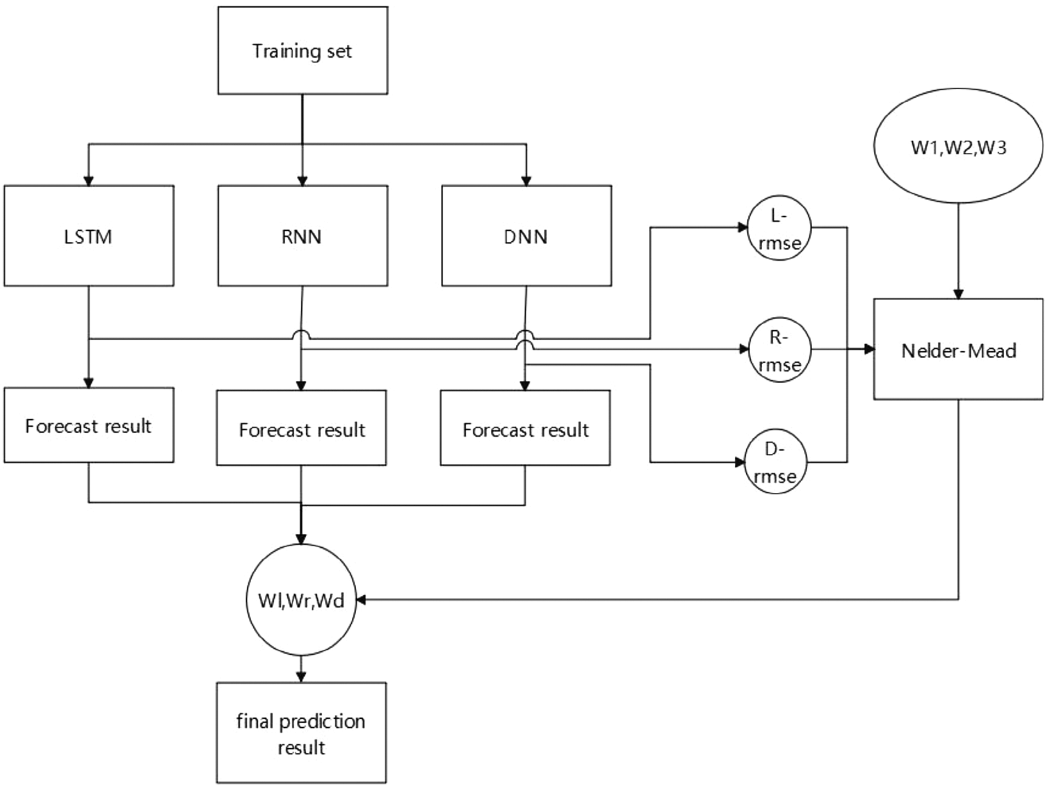

Fig. 1. Framework diagram of the prediction model
Рис. 1. Структурная схема модели прогнозирования

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LONG SHORT TERM MEMORY

LSTM neural network model is an improved RNN [16]. It uses memory cells to save historical information at the previous moment, and selectively remembers or forgets historical information through forgetting gates, solving the gradient explosion and gradient disappearance problems of RNN shortcomings. So it is suitable for long-term series forecasting problems. The computing nodes of the LSTM model include input gate, output gate, forget gate and memory cell. Among them, the input, output, and forgetting gates are the key to controlling information. The forgetting gate is used to filter the information that needs to be remembered, and the Cell is used to update the current state. The x_t of the input gate controls the storage vector in the memory unit after passing through the activation functions σ and $\tanh$,where x_t is the photovoltaic power input vector. The forgetting part of the memory unit is determined by xt and the intermediate output h_{t-1} of the previous moment. The intermediate output h_t is determined by the updated St, the calculation method is as follows:

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f); \quad (1)$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i); \quad (2)$$

$$h_t = o_t \cdot \tanh(C_t); \quad (3)$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o); \quad (4)$$

$$\tilde{C}_t = \tanh(W_C.[h_{t-1}, x_t] + b_C); \quad (5)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}. \quad (6)$$

There: yt is forget gate, ot and $h\ t$ are output gate, it and Ct are input gate, Ct is cell state. The predicted value of the final output layer is: $y_t = \sigma(W_y \cdot h_t + b_y)$.

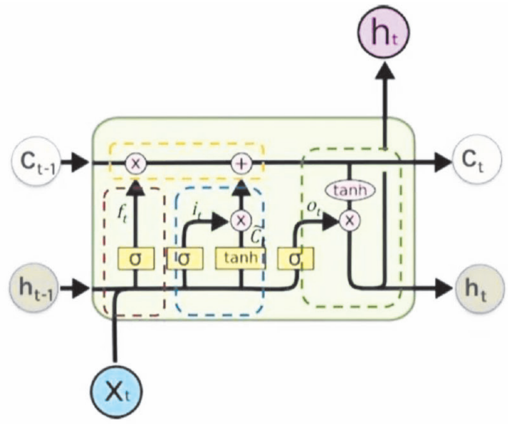

Fig. 2. Long short term memory
Рис. 2. Долгая краткосрочная память

RECURRENT NEURAL NETWORK

Recurrent Neural Network is a type of neural network designed to handle sequential data [17]. The device has memory capabilities and can capture temporal dependencies in sequence data. The core concept of RNN is that when processing the current input sample, the hidden state from the previous time step can be utilized to incorporate historical information into the model. The structure of an RNN is relatively simple and mainly consists of an input layer, a hidden layer, and an output layer. The input year receives sequence data, the hidden layer calculates the current input and the hidden state from the previous moment, and the output layer produces the result. The advantage of RNN is that it can handle variable-length sequences, possesses memory capabilities, and can capture long-term dependencies in sequence data.

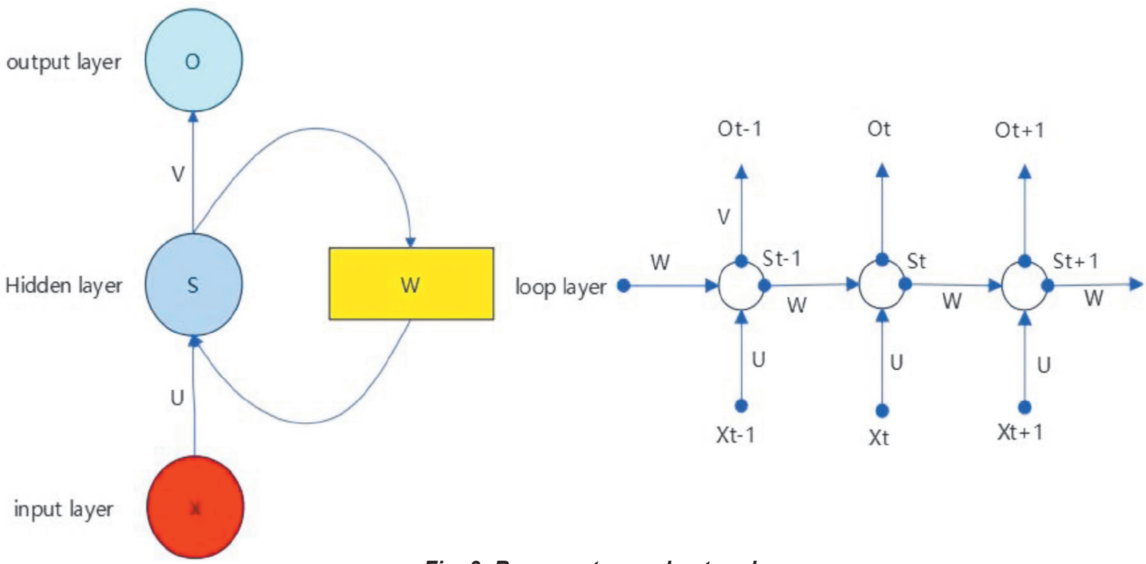

Fig. 3. Recurrent neural network
Рис. 3. Рекуррентная нейронная сеть

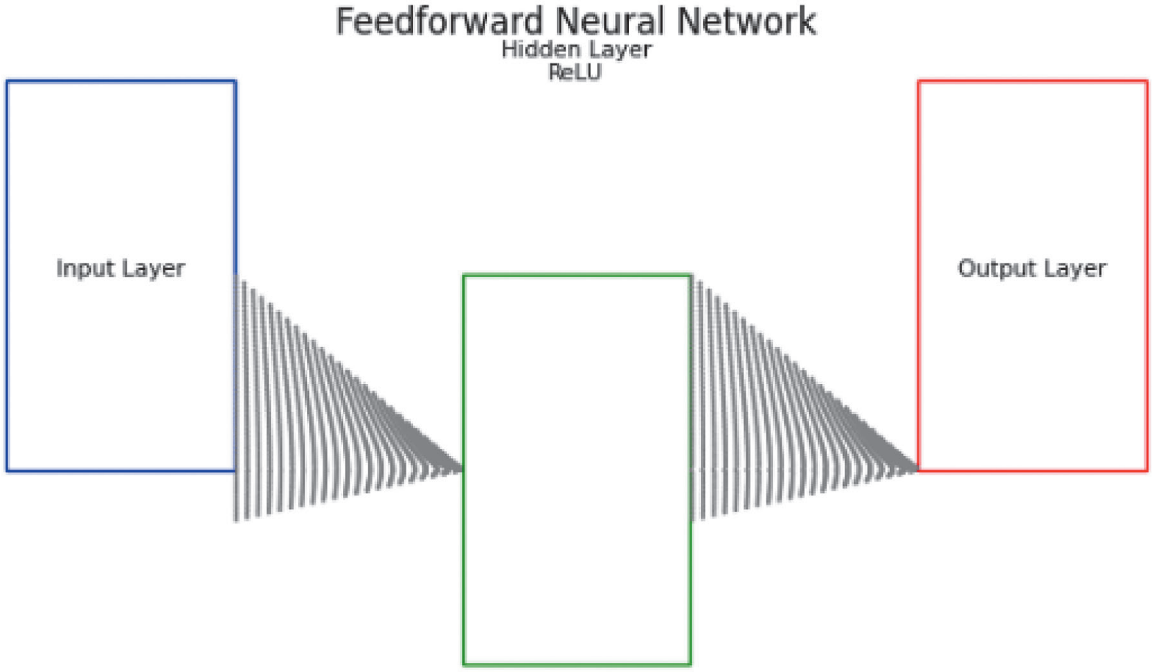

Fig. 4. Dense neural network
Рис. 4. Полносвязная нейронная сеть

Here, X represents the input, which generates S through a weight matrix U, and S generates O through a weight matrix V. The key distinction between RNN and traditional neural networks is that each time the previous output is brought to the next hidden layer and trained together. U represents the weight matrix from the input layer to the hidden layer, O is a vector representing the value of the output layer, and V is the weight matrix from the hidden layer to the output layer.

$$h_t = f(U_{xt} + W_{st-1} + b); \tag{7}$$

$$y_t = softmax(V_{st} + c). \tag{8}$$

DENSE NEURAL NETWORK

In this paper, we constructed a basic feedforward neural network [18]. The model includes a hidden layer with 64 neurons and a ReLU activation function, as well as an output layer without an activation function. The model uses the Adam optimizer with a learning rate of 0,001 and the mean square error as the loss function. The model is trained with 64 samples per batch for 50 training epochs.

ADD WEIGHTS MODEL

In this paper, we employ the Nelder-Mead method to optimize the weight of each model based on the prediction error of a single model, and subsequently integrate the weighted prediction results into a single prediction outcome. The process is as follows. First, we input the processed dataset into three models for training and prediction. We obtain the prediction error of each model, randomly set a weight combination W, and tune the model group based on the error to obtain the best weight combination, W1. This weight combination is then added to the prediction result to obtain the best overall prediction result. The Nelder-Mead method is a gradient-free optimization algorithm that is appropriate for situations where the objective function is not smooth or differentiable. It finds the minimum of a function by conducting a local search on simplices in the search space.

The specific process is depicted in Fig. 5.

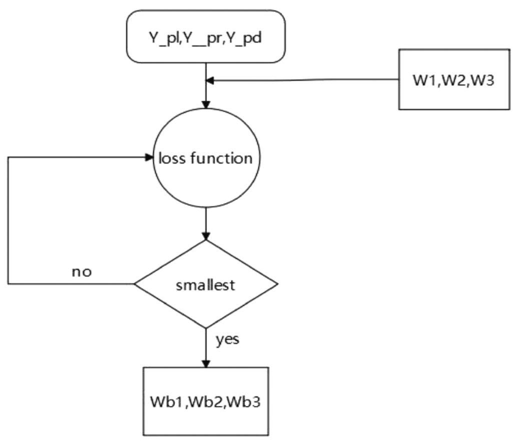

Fig. 5. Nelder-Mead
Рис. 5. Нельдер-Мид

$$Loss = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \omega_1 \times y_{pli} - \right.$$
$$\left. - \omega_2 \times y_{pri} - \omega_3 \times y_{pdi}\right). \quad (9)$$

Here y_i are the true values, ω_1, ω_2, ω_3 are the initial weight of each model, y_{pli}, y_{pri}, y_{pdi} are the predicted values of each model.

RESEARCH METHODS

This paper analyzes the photovoltaic power generation data from a power station in Australia over the course of one year. Data is collected every 5 minutes, including actual power, wind speed, horizontal irradiance, diffuse irradiance, temperature, and other environmental factors. First, we preprocess the data by addressing data outliers and missing values. We analyze the data using a box plot and observe that the output power is not 0 during non-sunrise hours (22-6 o'clock), and there is a very small output. Ideally, we set these nonzero values to 0. Since there are still missing values in the data, this article employs spline interpolation to fill in the missing values. After completing the above operations, we normalize and standardize the data to make it suitable for model training, therefore, the power in the prediction result graphs in this paper is the normalized power. Given the multitude of meteorological features, it is necessary to engage in feature engineering in order to perform correlation analysis on the features, identify those with high correlation, and analyze the heat map based on the correlation analysis of the data. As shown in Fig. 6. It can be observed that the correlation between radiance and output power is 0,98, the correlation of temperature is 0,46, and the correlation of wind speed is 0,16.

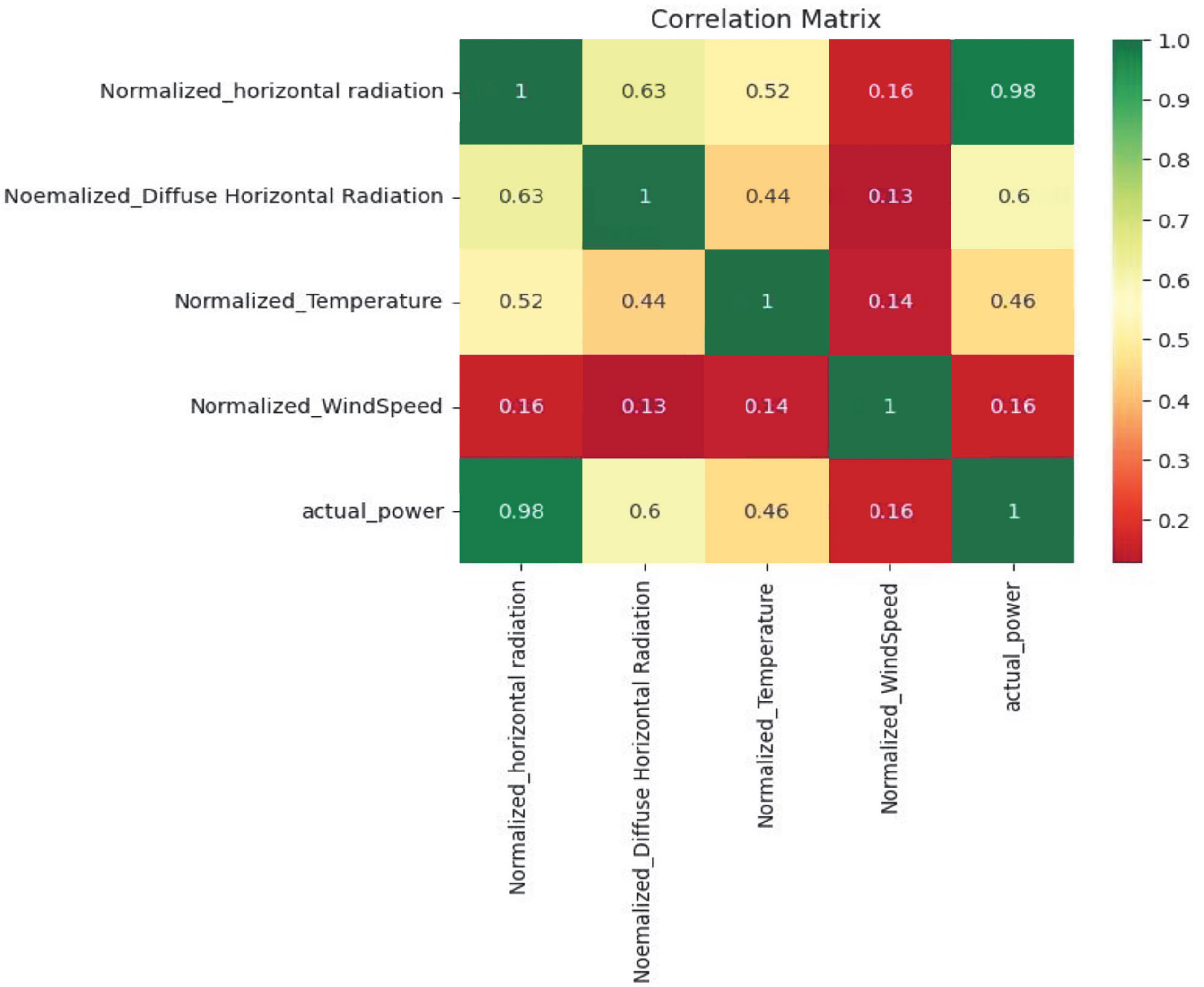

Fig. 6. Correlation heat map
Рис. 6. Корреляционная тепловая карта

In this paper, the two characteristics selected for analysis are radiance and temperature. To assess the performance of each model across different seasons, we segmented the data into four seasons–spring, summer, autumn, and winter–based on the seasonal dates in Australia. Subsequently, we conducted separate training and testing for each model. This study aimed to analyze the climate characteristics and output power variations across different seasons. The data for one year was divided into four seasons, and output power curves and box plots were created for each season. We can observe from Fig. 7 that power fluctuates in different seasons. The Fig. 7 shows that fluctuations are more frequent in winter and summer, and relatively stable in spring and autumn. Therefore, the prediction accuracy of a single model will vary for each season. This paper uses three common neural network models as the base model, which improves the adaptability of the model and can play their best advantages in response to different seasons.

Since each model exhibits varying prediction performance across different seasons, we train predictions for each season separately using each model. We train the data of each season separately, and use the last day of each season as the test set, 80% of the remaining data as the training set, and 20% as the validation set. By analyzing the output power characteristics of each season, we can observe that the fluctuations in output power vary across seasons due to distinct seasonal characteristics. Therefore, if only a single model is used for power prediction, this will reduce the accuracy of the model's predictions.

HYPERPARAMETER OPTIMIZATION

In this paper, we use the random search method to optimize the hyperparameters of the three neural networks used in this paper. The search space sets the learning rate to 0, 001.0, 01. 0,1. Batch size is 32, 64, 128. Epochs are 50, 100, and 200. During the random search process, we evaluate and compare the performance of each set of hyperparameters based on the cross-validation evaluation index RMSE, and finally select the hyperparameter combination with the best performance. This method can more efficiently find the optimal solution in a large number of hyperparameter combinations, and has a certain degree of randomness, which helps avoid falling into a local optimal solution.

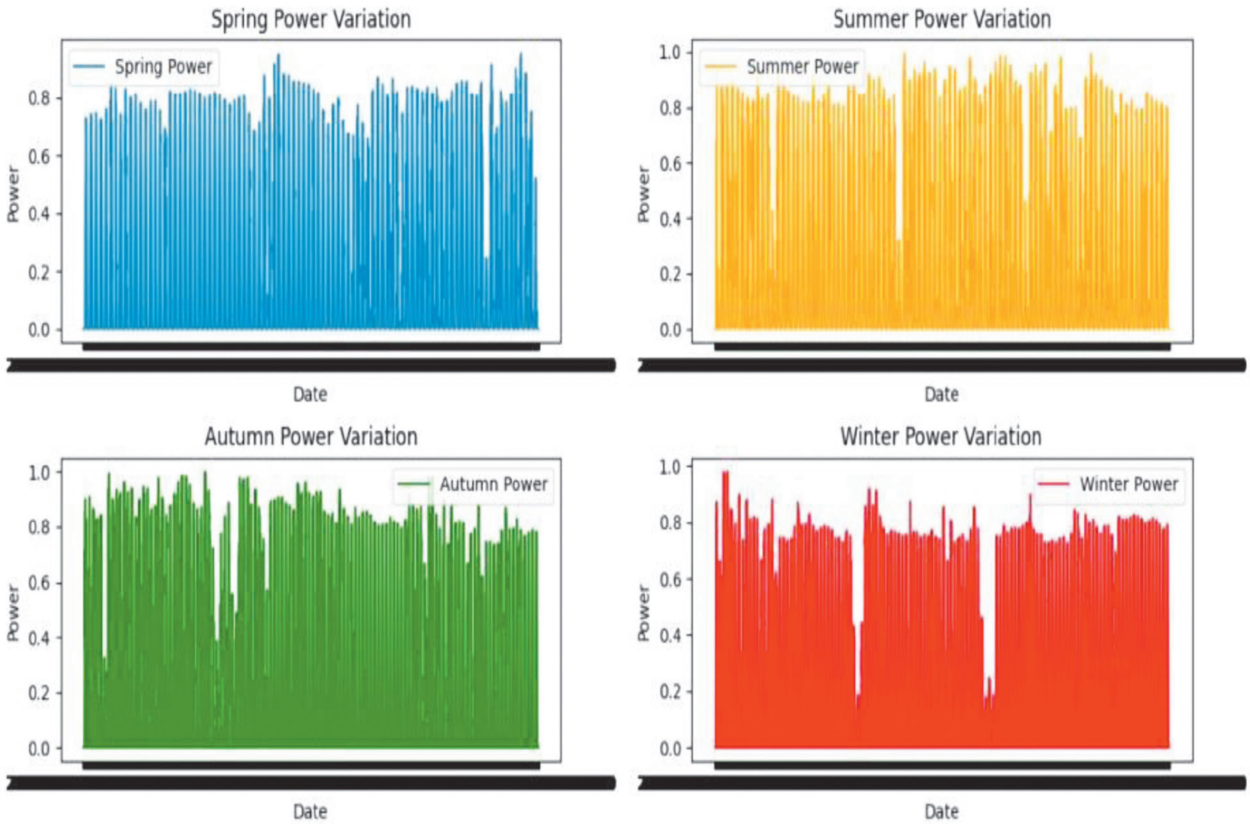

Fig. 7. Power fluctuations in different seasons
Рис. 7. Колебания мощности в разные времена года

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MODEL EVALUATION AND RESULT ANALYSIS

When evaluating and estimating prediction error, the mean absolute error (MAE) and root mean square error (RMSE) are used. Additionally, the coefficient of determination (R-squared, R2) is used to assess the accuracy of the model's predictions [19]. The calculation formula for each evaluation index is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y_i} - y_i|; \quad (10)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y_i} - y_i)^2}; \quad (11)$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y_i}-y_i}{y_i}\right|. \quad (12)$$

By weighting the model's prediction results, we obtain the evaluation criteria and prediction map for each model. We select the preprocessed summer data set for training and prediction. The time point interval of the data set is 5 minutes. From the final prediction result, as shown in Fig. 8, it can be observed that the prediction accuracy of the model improved after optimization was added, surpassing that of the single model. This study achieved improved prediction results by incorporating weights from three simple models, surpassing the performance of a single model. The main advantage of this integrated model is its ability to adjust the weights as the region and environment change, resulting in higher prediction accuracy. Compared with a single model, it demonstrates better adaptability. Through the prediction results, as shown in Table 1, we observed that the LSTM model has the best predictive accuracy among the single models. After analyzing the weighted output prediction results, as shown in Table 2, we found that all error indicators decreased. This indicates that the model has advantages over a single model.

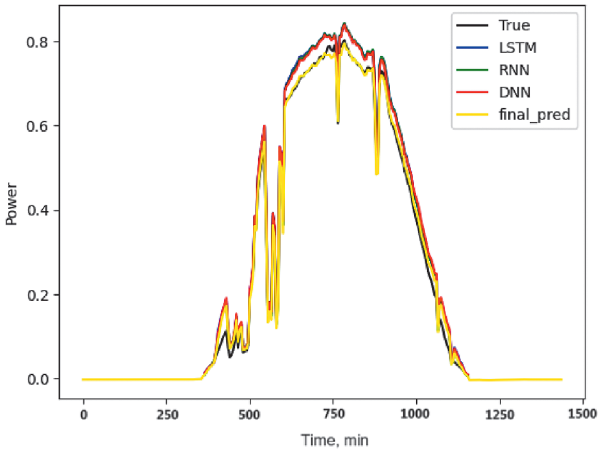

Fig. 8. Forecast results
Рис. 8. Результаты прогноза

CONFIDENCE INTERVAL COMPARISON

In this paper, we calculated three confidence interval indicators using the Bootstrap method: average coverage, Root Mean Squared Length (RMSL), and Mean Width [20]. Use a sliding time window with a window size of 15 to calculate the confidence intervals for various time periods. By iterating through the sliding window, data within each window is intercepted for prediction and confidence interval calculation. And plotted the confidence interval for each model, as shown in Fig. 9–12.

$$Coverage = \frac{1}{n}\sum_{i=1}^{n} Indicator(L_i \le y_i \le U_i); \quad (13)$$

$$MeanWidth = \frac{1}{n}\sum_{i=1}^{n}(U_i - L_i); \quad (14)$$

$$RMSL = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(U_i - L_i)^2}. \quad (15)$$

Table 1. Forecast errors of various models in different seasons
Таблица 1. Ошибки прогноза различных моделей в разные времена года

RMSE	RNN	LSTM	DNN
spring	0.030859	0.032103	0.031261
summer	0.022935	0.020825	0.021334
autumn	0.020222	0.022085	0.021396
winter	0.019157	0.021151	0.019446

Table 2. Forecast results
Таблица 2. Результаты прогноза

Modal	MAE	RMSE	MAPE
LSTM'	0.01591	0.02549	11.18%
RNN	0.01859	0.03074	12.55%
DNN	0.02036	0.03423	13.88%
ADWM	0.00786	0.02307	8.38%

There: U_i is the upper bound of the i-th sample, L_i is the lower bound of the i-th sample, y_i is the actual observed value.

From Fig. 9–12, we can see the confidence intervals for each model. We assessed the accuracy of the confidence intervals for each model by calculating the average coverage. The average coverage reflects the frequency with which the actual observations fall within their respective confidence intervals. A higher average coverage indicates that the model's uncertainty estimation is more accurate and reliable. From the calculation results, it is found that the average coverage of the integrated model (ADWM) is 60% higher than that of other models, which confirms that the prediction accuracy of the integrated model is superior to that of a single model. By calculating the Root Mean Squared Length, we can assess the length of the confidence interval, which represents the level of uncertainty surrounding the predicted results. The root mean square length of ADWM is 0.157346, which is smaller than that of a single model. This indicates that the confidence interval of the ADWM model is relatively compact, reflecting a more accurate estimate of the predicted value. Through the Mean Width measure, we analyze the average uncertainty of the model across the entire forecast horizon. The average width of ADWM is 0.148075, which is smaller than that of a single model. A model with a larger average width may indicate higher prediction uncertainty during certain periods or conditions. The reliability of the model in this paper is confirmed by the accuracy of the prediction results. The prediction accuracy of the mixed model is higher. The prediction results after adding weights (refer to Table 3) show that all indicators outperform those of the single model.

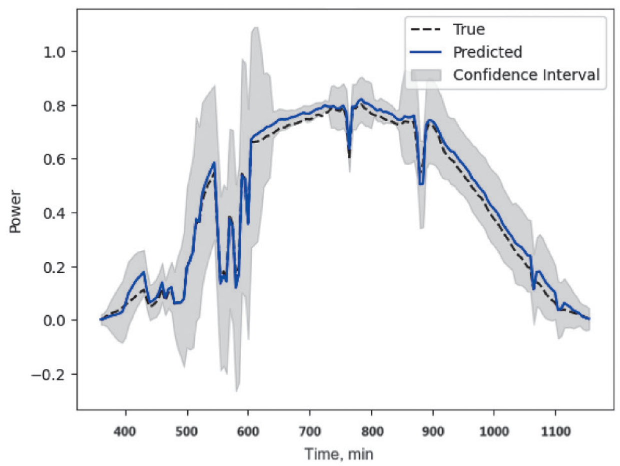

Fig. 9. Results for long short term memory
Рис. 9. Результаты применения ИНС долгой краткосрочной памяти

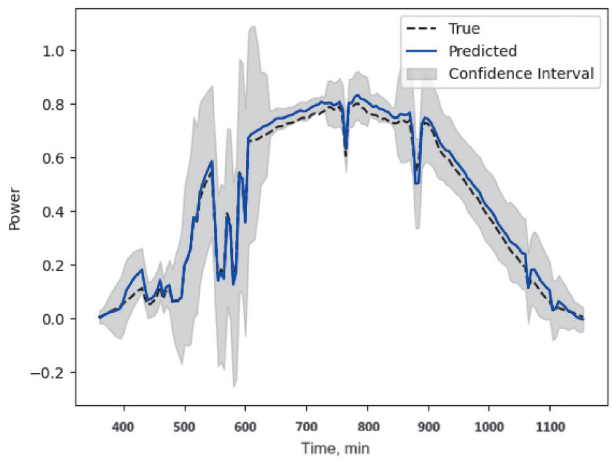

Fig. 10. Dense neural network
Рис. 10. Результаты применения полносвязной нейронной сети

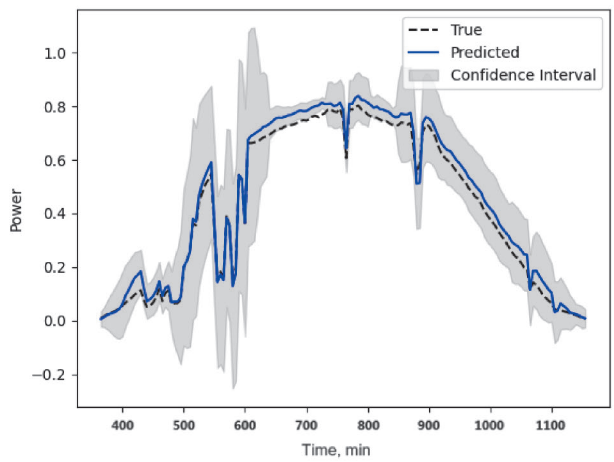

Fig. 11. Recurrent neural network
Рис. 11. Рекуррентная нейронная сеть

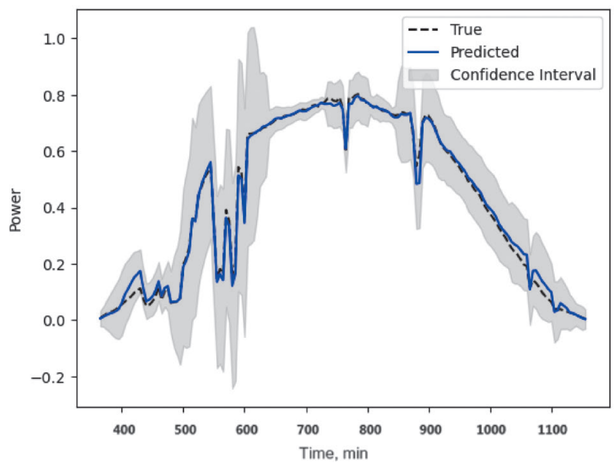

Fig. 12. Add weights model
Рис. 12. Модель добавления весов

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Table 3. Confidence interval
Таблица 3. Доверительный интервал

	LSTM	DNN	RNN	ADWM
Average Coverage	0.57986	0.59375	0.55556	0.600694
Average Root Mean Squared Length	0.16396	0.16417	0.16513	0.157346
Average Mean Width	0.15408	0.15432	0.15533	0.148075

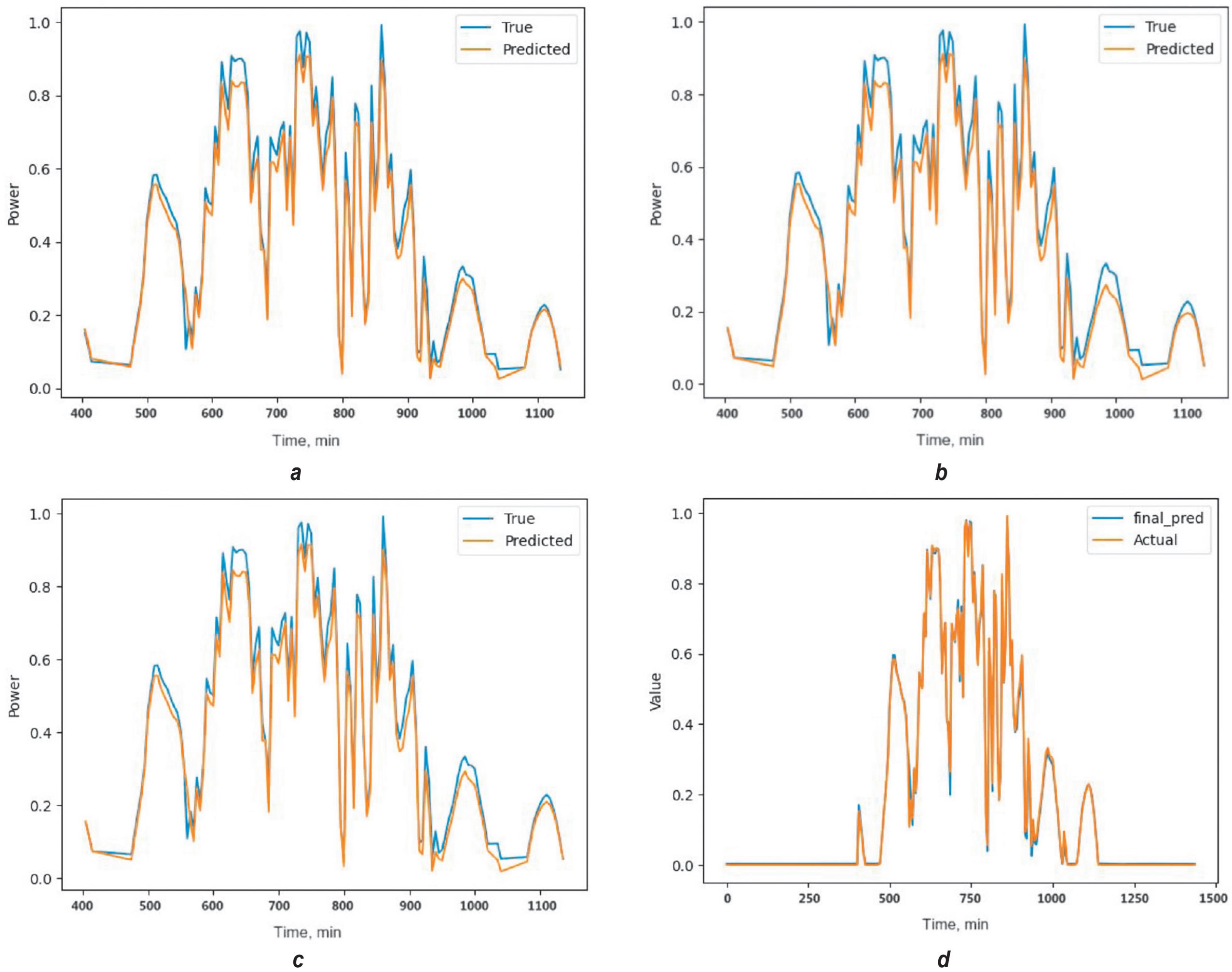

Fig. 13. Rainy day forecast results: a – DNN-R; b – RNN-R; c – LSTM-R; d – ADWM-R
Рис. 13. Результаты прогноза дождливого дня: a – DNN-R; b – RNN-R; c – LSTM-R; d – ADWM-R

MODEL VALIDATION

To assess the model's stability in extreme rainy weather, we utilized a dataset specifically focused on rainy weather conditions for training and testing. The prediction results are shown in Fig. 13. From the prediction results (Table 4), we can observe that in rainy weather, the prediction error is larger. However, the model proposed in this article demonstrates better prediction results than a single model.

Table 4. Rainy weather forecast results
Таблица 4. Результаты прогноза дождливой погоды

Modal	MAE	RMSE	MAPE
LSTM	0.01836	0.02923	12.43%
RNN	0.02085	0.03188	13.40%
DNN	0.01801	0.02784	10.11%
ADWM	0.00771	0.02294	6.81%

CONCLUSION

This paper proposes a neural network based on three types of recurrent neural networks: LSTM, RNN, and DNN. It performs weighted optimization on the prediction results, utilizes the Nelder-Mead method to optimize its weights, and outputs the optimized prediction results. According to the experimental data, we can conclude that the integrated model proposed in this paper exhibits higher prediction accuracy and better stability compared to a single model. Due to the variability of the weights, it adapts to the forecasting needs of different regions in different seasons. This article has confirmed that optimizing weights using the Nelder-Mead method can improve the prediction accuracy of the model and enhance its stability. However, it does not delve into the hyperparameter tuning method for a single model, so the output results will be more accurate after hyperparameter tuning.

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Denis N. Sidorov has been a member of the editorial board of the iPolytech Journal since 2021, but she did not take part in making decision about publishing the article under consideration. The article was reviewed following the Journal's review procedure. The authors did not report any other conflicts of interest.

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