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Prediction of the Supply and Demand Gap of Green Electricity in Industrial Parks Based on Machine Learning Algorithms

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Abstract. In response to the dual carbon goals, industrial parks, as the main force of energy consumption, accelerating the substitution of green electricity is the key to emission reduction. However, the two-way fluctuations in the supply and demand of green electricity make it more difficult to predict the gap. The uncertainty of supply and demand makes it hard for traditional experience-based dispatching to accurately match supply and demand, which may lead to the abandonment of green electricity due to excess or the reliance on thermal power for supplementation. This not only affects the emission reduction effect but also increases energy consumption costs. Therefore, there is an urgent need for high-precision green power supply and demand gap prediction methods to support dispatching decisions. This paper proposes the DE-Transformer-BiLSTM regression algorithm. Firstly, correlation analysis and violin plot analysis are carried out, and then it is compared with various machine learning algorithms such as tree models, neural networks, linear regression, SVR and decision trees. The results show that the algorithm performs better overall in terms of mean square error, root mean square error, mean absolute error, mean absolute percentage error and coefficient of determination, providing effective technical support for industrial parks to precisely schedule the supply and demand of green electricity, improve the utilization efficiency of green electricity, reduce energy costs and promote the implementation of the dual carbon goals.

Keywords: Green electricity substitution, supply and demand gap prediction, Transformer, BiLSTM.

1. Introduction

Under the impetus of the dual carbon goals, industrial parks, as the main force of energy consumption, accelerating the replacement of green electricity has become a key to emission reduction. However, the two-way volatility of green power supply and demand has intensified the difficulty of gap prediction: on the supply side, the output of photovoltaic and wind power is highly random due to meteorological factors such as sunlight and wind speed, with daily output fluctuations reaching over 40%. On the demand side, industrial loads exhibit a superimposed characteristic of periodicity and suddenness with production shifts, equipment start-up and

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shutdown, and process adjustments. For instance, the start-up and shutdown of high-energy-consuming equipment can cause load fluctuations of 20% to 30% within a short period of time [1]. This uncertainty on both the supply and demand sides makes it difficult for traditional experience-based dispatching to precisely match green power supply with industrial demand, easily leading to situations where there is an excess of green power being abandoned or insufficient supply relying on thermal power for supplementation. This not only affects the emission reduction effect but also increases the energy cost of the park. Therefore, there is an urgent need for high-precision green power supply and demand gap prediction methods to support dispatching decisions [2].

Traditional prediction methods such as time series analysis and linear regression are difficult to effectively capture the nonlinear correlations and multi-factor coupling characteristics in the green power supply and demand system. The prediction error often exceeds 15%, which cannot meet the dispatching requirements [3]. Machine learning algorithms, with their powerful data processing and feature mining capabilities, have become the core technology to solve this problem [4]. On the one hand, machine learning can integrate multi-source data such as weather, load, and shift data, and automatically learn the implicit correlations between supply and demand variables through model training. For instance, LSTM can capture the short-term dependencies of time series data, and Transformer can mine the key influencing factors in long sequences [5]. On the other hand, machine learning models can continuously improve prediction accuracy through iterative optimization. Models trained based on historical data can dynamically adapt to changes in supply and demand patterns, keeping prediction errors within 10%. This provides timely and accurate gap warnings for green power dispatching in parks, reduces the rate of green power waste and the frequency of thermal power energy replenishment, and simultaneously lowers the subjectivity of dispatching decisions. Improve the efficiency of green power consumption [6].

Although existing machine learning models have shown potential in predicting the gap between green power supply and demand, there are still shortcomings: LSTM has limited ability to capture long-term time series features and is prone to vanishing gradients; The attention mechanism of Transformer may assign excessive weights to redundant features, leading to overfitting of the model. Moreover, the hyperparameters of both are mostly set based on experience, making it difficult to adapt to the supply and demand characteristics of different parks.

2. Data sources

This dataset contains a total of 685 valid samples, covering 11 input variables and 1 predictor variable. The input variables include external environmental variables such as sunshine duration, wind speed, and ambient temperature, demand-side variables such as the number of high-energy-consuming equipment in operation and the total industrial load, as well as supply-side variables such as photovoltaic output, wind power output, purchased green electricity, and energy storage discharge replenishment. The predictor variable is the gap between the supply and demand of green electricity. Correlation analysis was used to calculate the correlations among various variables, and a correlation heat map was drawn, as shown in Figure 1.

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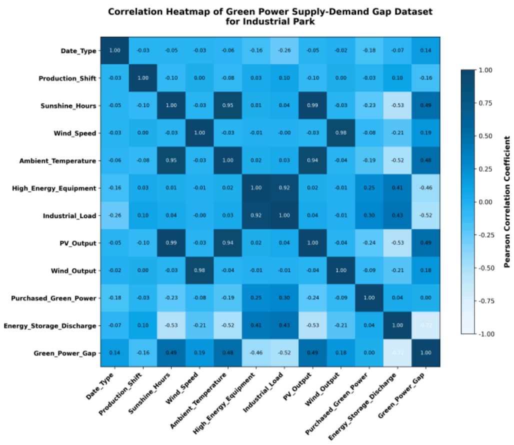

Figure 1. The correlation heat map

The violin plots of each continuous variable are shown in Figure 2. Through the violin plots, the distribution of the data can be observed.

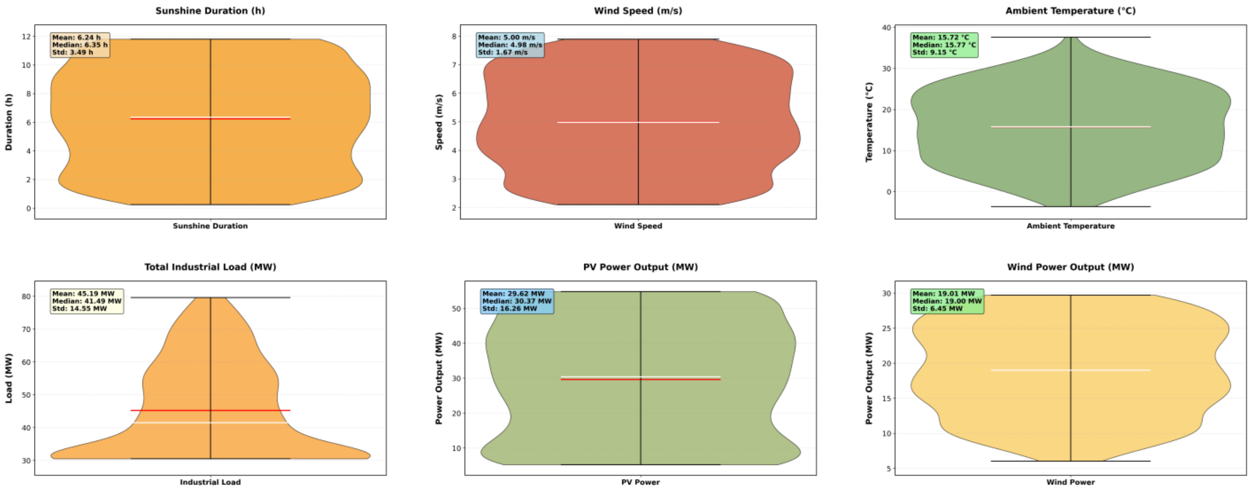

Figure 2. Violin diagrams of each variable

3. Method

3.1. Differential evolution algorithm

Differential evolution algorithm is an evolutionary optimization algorithm based on swarm intelligence, whose core simulates the mutation, crossover and selection processes of biological evolution [7]. This algorithm forms an initial population with a set of randomly generated candidate solutions. It performs differential mutation operations on individuals in the population - by scaling the difference vectors of two individuals and superplacing them on a third individual to generate a mutation solution. Then, it fuses the features of the mutation solution and the parent solution through crossover operations.

3.2. Transformer

The Transformer algorithm is a deep learning model based on the self-attention mechanism. Its core abandons the serial structure of recurrent neural networks and captures the dependency relationships

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at different positions in sequence data through a multi-head self-attention mechanism [8]. The model is composed of encoder and decoder modules. Each module contains a multi-head self-attention layer and a feedforward neural network layer. At the same time, position encoding is introduced to supplement the temporal information of the sequence, solving the defect of no sequential perception in the self-attention mechanism. Multi-head self-attention can efficiently mine the global dependencies of long sequences by parallelly calculating the association weights of each position with all positions in the sequence. The network structure of the Transformer is shown in Figure 3.

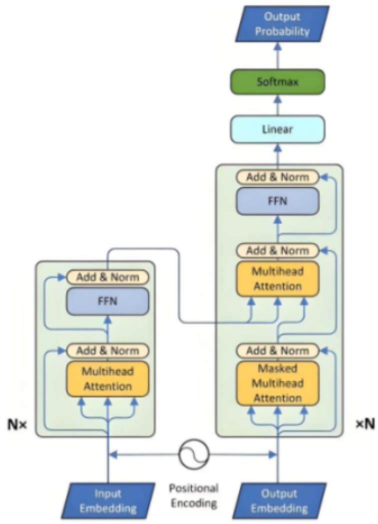

Figure 3. The network structure of the Transformer

3.3. BiLSTM

Bidirectional Long Short-Term Memory Network (BiLSTM) is an extended form of Long Short-Term Memory Network (LSTM). Its core adds a reverse processing layer on the basis of unidirectional LSTM, making full use of the context information of time series data. Unidirectional LSTM controls the input, forgetting and output of information through input gates, forgetting gates and output gates, alleviating the vanishing gradient problem of traditional recurrent neural networks. Meanwhile, BiLSTM builds two LSTM layers, the forward layer captures the dependency of the forward time step of the sequence, and the reverse layer captures the dependency of the backward time step. Finally, concatenate the two layers of output to fuse the context features. This algorithm can fully mine the bidirectional associations of time series data, but it retains the serial processing logic [9]. The network structure of BiLSTM is shown in Figure 4.

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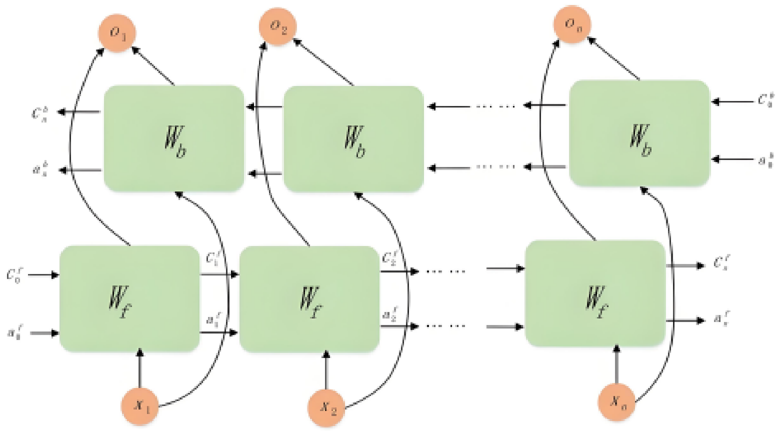

Figure 4. The network structure of BiLSTM

3.4. DE-Transformer-BiLSTM

The DE-Transformer-BiLSTM regression algorithm is a hybrid algorithm that integrates optimization algorithms and deep learning models. Its core is to enhance the performance of time series regression prediction through the complementary advantages of the three [10]. This algorithm first utilizes the DE algorithm to optimize the key hyperparameters of Transformer and BiLSTM, such as the number of attention heads, the number of hidden layer nodes, and the learning rate, to solve the problem of poor adaptability caused by the empirical setting of hyperparameters. Then, the time series data is input into the Transformer module. Long-distance time series dependencies are captured through multi-head self-attention, and the output feature sequence is sent to the BiLSTM module to mine bidirectional context associations. Finally, integrate the two layers of features and output the regression prediction results through the fully connected layer.

4. Result

The parameter Settings of the project are as follows: the number of search agents is 8, the maximum number of iterations is 6, the dimension of the optimization parameters is 3, the lower bounds of the parameters are 1e-3, 10, 1e-4 in sequence, and the upper bounds are 1e-2, 30, 1e-1 in sequence, corresponding to the learning rate, the number of hidden layer nodes, and the regularization coefficient respectively. The ratio of the training set to the dataset is 0.7, the maximum number of training rounds is 1000, the batch size is 256, the learning rate decline factor is 0.1, the decline period is 850, the gradient clipping threshold is 10, the number of self-attention heads is 4, the number of key channels for each head is 128, the maximum position encoding is 512, and the dropout rate is 0.01.

Comparative experiments were conducted using multiple machine learning algorithms, as shown in Table 1.

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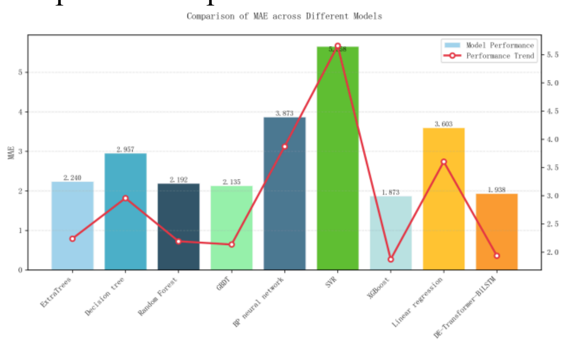
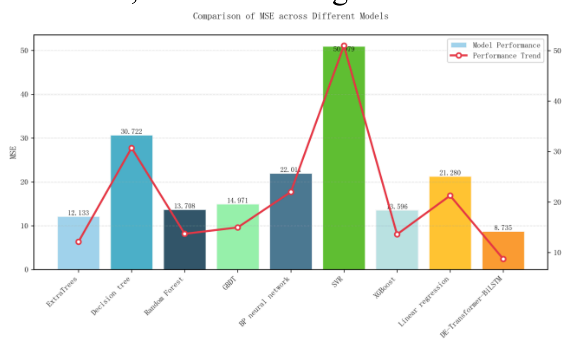
Table 1. The results of the comparative experiment

Model	MSE	RMSE	MAE	MAPE	R^2
ExtraTrees	12.133	3.483	2.24	47.966	0.838
Decision tree	30.722	5.543	2.957	125.122	0.431
Random Forest	13.708	3.702	2.192	32.675	0.75
GBDT	14.971	3.869	2.135	38.137	0.743
BP neural network	22.011	4.692	3.873	65.894	0.704
SVR	50.979	7.14	5.658	88.003	0.344
XGBoost	13.596	3.687	1.873	46.203	0.838
Linear regression	21.28	4.613	3.603	103.023	0.695
DE-Transformer-BiLSTM	8.735	2.956	1.938	34.611	0.859

From the perspective of the prediction performance evaluation indicators of each algorithm, the DE-Transformer-BiLSTM algorithm proposed in this paper shows an overall better performance: Its mean square error (MSE) is 8.735, which is significantly lower than that of tree models such as 12.133 by ExtraTrees, 13.708 by Random Forest, and 13.596 by XGBoost. It is also far lower than 22.011 for BP neural network, 21.28 for linear regression, 50.979 for SVR and 30.722 for decision tree. The root mean square error (RMSE) is 2.956, which is superior to all comparison algorithms. Among them, the performance of SVR at 7.14 and decision tree at 5.543 is the worst. The mean absolute error (MAE) is 1.938, only slightly higher than 1.873 of XGBoost. The rest are all lower than algorithms such as 2.24 of ExtraTrees and 2.192 of Random Forest. And it is far lower than 3.873 of BP neural network, 3.603 of linear regression and 5.658 of SVR; The mean absolute percentage error (MAPE) was 34.611, only higher than 32.675 of Random Forest, lower than 38.137 of GBDT, 46.203 of XGBoost and other algorithms, while 125.122 of Decision tree performed the worst. The coefficient of determination R^2 is 0.859, which is the highest among all algorithms. It has a significant improvement compared to 0.838 of ExtraTrees and XGBoost, and is also significantly higher than algorithms such as 0.75 of Random Forest and 0.743 of GBDT. It far exceeds the 0.344 of SVR and 0.431 of decision tree. Overall, the DE-Transformer-BiLSTM algorithm is only slightly inferior to XGBoost in the MAE metric and slightly inferior to Random Forest in the MAPE metric. In the other core evaluation metrics, it is superior to traditional machine learning algorithms and classic deep learning models. It fully demonstrates the performance advantages of this algorithm in this prediction task.

Output the comparison charts of the indicators of each model, as shown in Figure 5.





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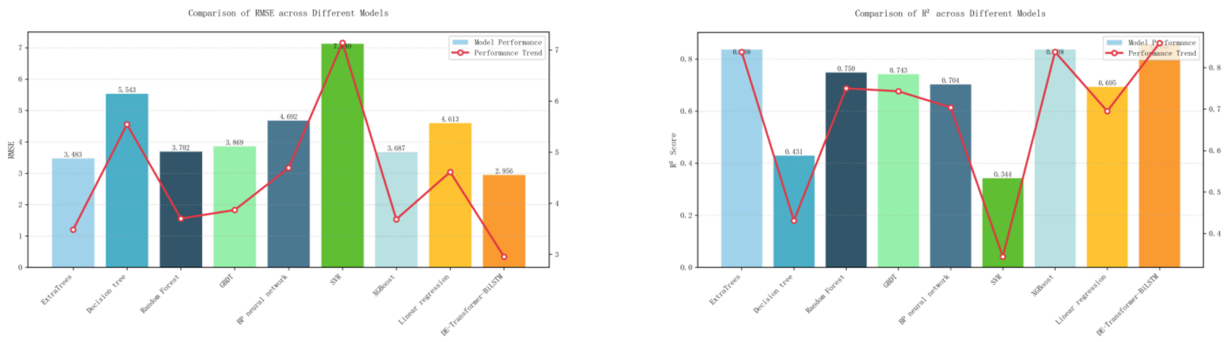

Figure 5. The line graphs comparing the indicators of each model

Output the line graph of the predicted values - actual values of the DE-Transformer-BiLSTM model test set, as shown in Figure 6.

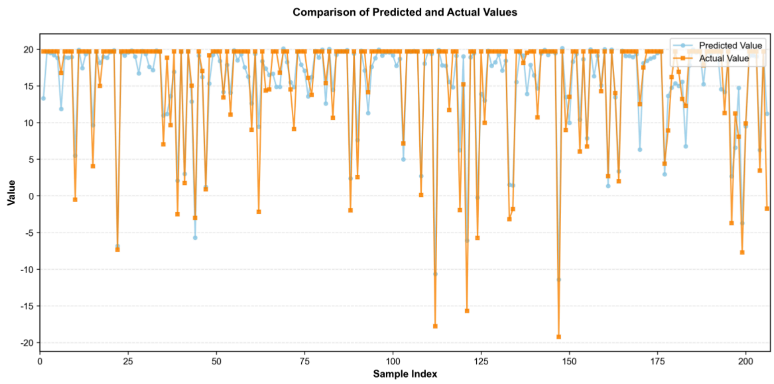

Figure 6. The line graph of the predicted values - actual values

5. Conclusion

Driven by the dual carbon goals, industrial parks, as core energy-consuming scenarios, promoting green electricity substitution has become a key measure to achieve emission reduction targets. However, the volatility on both the supply and demand sides of green electricity has significantly increased the complexity of gap prediction. The uncertainty of supply and demand makes it difficult for traditional empirical dispatching to precisely match green electricity supply with industrial demand. As a result, there is often an excess of green electricity that is abandoned or an insufficient supply that relies on thermal power for supplementation. This not only weakens the effectiveness of emission reduction but also raises the energy cost of industrial parks. This algorithm provides reliable technical support for industrial parks to optimize green power dispatching, reduce energy consumption costs, and promote the implementation of the dual carbon goals, which has significant practical significance.

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