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Short-term Photovoltaic Power Prediction Method based on ISABO-DELM

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Abstract: To address the issue of inaccurate precision due to the randomness and instability of photovoltaic power generation, this paper proposes a short-term photovoltaic power prediction model based on an Improved Subtraction Average Based Optimizer (ISABO) and Deep Extreme Learning Machine (DELM). First, the k-means algorithm is used to classify weather types, and then Variational Mode Decomposition (VMD) is employed to decompose the original signal, fully extracting input factor information from the dataset to improve data quality. Next, an improved ISABO algorithm is proposed to optimize the parameters of the input layer and thresholds of the DELM model. Tent chaotic reverse learning is utilized to initialize the SABO population, enhancing population quality. The ISABO algorithm incorporates a Lévy flight mutation strategy to avoid local optima. Finally, the predicted values of different sequences are superimposed to obtain the final prediction result. Simulation results indicate that the proposed ISABO-DELM model has a smaller prediction error.

Keywords: Variational Mode Decomposition; Improved Subtraction Average Based Optimizer; Levy Flight Mutation; Deep Extreme Learning Machine.

1. Introduction

Under the strategic backdrop of the "14th Five-Year Plan", the goal of carbon peaking by 2030, and carbon neutrality by 2060, China is increasingly emphasizing the importance of renewable energy. Photovoltaic power generation, as a form of renewable energy, plays a crucial role in reducing greenhouse gas emissions and accelerating the transformation of the energy structure. However, PV power generation is highly inaccurate and unpredictable within the grid power system, mainly due to the instability of solar radiation and the variability of environmental conditions. Therefore, accurate PV power forecasting is key to ensuring stable grid operation and efficient energy dispatch.

Currently, research on PV power forecasting, both domestically and internationally, has made some breakthroughs. Generally, PV power forecasting methods are divided into two main categories: one involves using physical models or indirect forecasting methods through irradiance prediction, while the other is based on direct forecasting models constructed from historical power data and meteorological information. Although indirect forecasting methods theoretically have certain advantages, their complex practical application and high computational demands limit their widespread use. In contrast, direct forecasting methods based on artificial intelligence technology are favored by many scholars and researchers for their relatively simple visualization and efficient computational performance. These direct methods utilize neural networks and machine learning algorithms to process large amounts of data quickly, providing more accurate forecasting results. Traditional direct forecasting methods include deep belief networks, neural networks , and support vector machines . Reference uses the Empirical Mode Decomposition (EMD) algorithm to decompose time series data to reduce noise and data volatility, but EMD tends to cause mode mixing problems, and most parameters need to be manually set. Reference points out that Variational Mode Decomposition (VMD), compared to EMD, suppresses mode mixing to a certain extent, yielding more stable and consistent decomposition results. Reference utilizes VMD-decomposed subsequences and inputs them into an optimized Elman neural network for PV power forecasting, but the Elman neural network is prone to gradient vanishing and explosion issues, making training difficult. The Extreme Learning Machine (ELM), proposed by Guang-Bin Huang and others, is a neural network forecasting algorithm with high learning speed and excellent generalization performance. ELM improves learning efficiency by randomly initializing weights and biases from the input layer to the hidden layer, enhancing training speed and avoiding local convergence issues. Inspired by deep neural networks, researchers began exploring deep ELM (DELM) by stacking multiple ELM layers as autoencoders and introducing regularization. References mention that the DELM model integrates the advantages of machine learning and deep learning, offering efficient training speed and precise fitting of complex nonlinear relationships. DELM not only leverages the quick training speed of ELM but also incorporates the multi-layer structure of deep learning, overcoming the limitations of traditional ELM in handling high-dimensional and nonlinear data. This results in excellent performance on large-scale datasets, accelerating model training speed and improving prediction accuracy and generalization capability. Despite the many advantages demonstrated by DELM in PV power forecasting, its effectiveness heavily depends on the initial setup of network structure and parameters.

Based on the above analysis, this paper proposes a short-term PV power forecasting model based on the Improved Subtractive Averaging-based Optimization (ISABO) algorithm and DELM. Firstly, the k-means clustering algorithm is used to classify historical PV power data into three categories according to weather conditions: sunny, cloudy, and rainy. VMD is then used to decompose the original signal, fully extracting input factor information to improve data quality. Subsequently, an improved SABO algorithm is proposed to optimize the input layer and threshold parameters of the DELM model. The Tent chaos reverse learning initializes the SABO population, enhancing population quality, and the Lévy flight mutation strategy is introduced in the ISABO algorithm to avoid local optima. Finally, different sequence forecasts are aggregated to obtain the final forecast result. Simulation results show that the proposed ISABO-DELM model has smaller prediction errors.

2. Data Processing Methodology

(1) K-means Clustering Analysis

K-means clustering analysis is a widely used unsupervised learning algorithm for grouping data points into a predetermined number of clusters. The algorithm minimizes the distance between points within a cluster and the cluster center to find natural groupings in the data. For PV power generation, the most significant weather conditions are sunny, cloudy, and rainy days, so k=3 is chosen for weather clustering. This classification method reflects the impact of different weather conditions on power generation, aiding in processing and analyzing weather data to improve the accuracy of power forecasting models under various weather conditions.

Steps of K-means Clustering Analysis:

1) Initialization: Choose K as the number of clusters to form. Randomly select 3 samples from the dataset as initial cluster centers (also known as centroids).

2) Assign samples to the nearest cluster center: Calculate the Euclidean distance between each point in the dataset and each cluster center, then assign each point to the cluster represented by the nearest cluster center.

3) Update cluster centers: For each cluster, calculate the mean of all points in the cluster and set this mean as the new cluster center.

4) Iterate until convergence: Repeat steps 2 and 3 until convergence criteria are met (e.g., changes in cluster centers are less than a preset threshold, or a maximum number of iterations is reached), at which point the clustering process ends.

(2) Variational Mode Decomposition

VMD is an adaptive signal processing method used to analyze non-stationary signals by decomposing a complex non-stationary signal into several intrinsic mode functions (IMFs). Each IMF has local stability within a specific frequency band, allowing the network to more accurately capture the signal's variation characteristics. The constrained variational model is:

$$\begin{cases} \min_{(a_i);(w_k)} \left\{ \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{\mathrm{j}}{\pi t} \right) u_k(t) \right] \mathrm{e}^{-j\omega k'} \right\|_2^2 \right\} \\ \text{s.t. } \sum_{k=1}^{K} u_k = f, k = 1, 2, \cdots, K \end{cases} \quad (1)$$

Where: {uk}={u1,u2,...,uk} represents k IMF components obtained from VMD decomposition; ωk is the center frequency of the KTH mode component; K total for decomposition; δ(t) is a Dirac function.

By introducing a penalty factor α and Lagrange multiplier λ, the constrained variational optimization model is transformed into an unconstrained optimization problem. Subsequently, the Alternating Direction Method of Multipliers (ADMM) is employed for iterative updates until k modal components are solved.

$$\begin{aligned} L\left(\{u_k\},\{\omega_k\},\lambda\right) &= \alpha \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{\mathrm{j}}{\pi t} \right) u_k(t) \right] \mathrm{e}^{-jk^k} \right\|_2^2 \\ &+ \left\| x(t) - \sum_{k=1}^{K} u_k(t) \right\|_2^2 + \left[\lambda(t), f(t) - \sum_{k=1}^{K} u_k(t) \right] \end{aligned} \quad (2)$$

3. Prediction Model and Principle

(1) Subtractive Average-Based Optimization Algorithm

The Subtractive Average-Based Optimization (SABO) algorithm, proposed by Trojovský Pavel and Dehghani Mohammad in 2023, is a mathematically-inspired intelligent optimization algorithm. This algorithm features strong optimization capabilities and fast convergence speed.

Random Initialization of the Population:

$$x_{i,j} = lb_j + r_{i,j} \cdot (ub_j - lb_j) \quad (3)$$

Where xi,j represents an individual, ri,j is a random number between [0,1], and lbj and ubj are the lower and upper bounds of the decision variables, respectively.

The basic inspiration for SABO comes from mathematical concepts such as averages, differences in search agent positions, and the difference in the signs of two objective function values. Instead of merely using the best or worst search agent's position to update all search agents' positions (i.e., constructing all population members for the t+1t+1t+1-th iteration), SABO calculates the arithmetic mean position of all search agents (i.e., population members of the iteration). This idea is not novel, but SABO's method of computing the arithmetic mean isunique because it is based on a special operation"-v", Search agent B from search agent A subtracted by v, definedas follows:

$$A - \mathrm{v}B = \mathrm{sign}(F(A) - F(B))(A - \vec{v} * B) \quad (4)$$

where v is a vector from the set {1,2}, F(A) and F(B) are the fitness values of corresponding individuals A and B.

$$X_i^{\text{new}} = X_i + \vec{r}_i * \frac{1}{N} \sum_{j=1}^{N} \left(X_i - \mathrm{v} X_j \right), i = 1, 2, \ldots, N \quad (5)$$

Where X_i^{new} is the new location of the i search agent X, NIs the total number of individuals, $\vec{r}_i$ Is a vector of dimension m, The values of each component are normally distributed in the interval [0,1]. If the fitness value of the new position increases, the new position is accepted, otherwise it remains unchanged.

$$X_i = \begin{cases} X_i^{\text{new}}, & F_i^{\text{new}} < F_i \\ X_i, & \text{else}, \end{cases} \quad (6)$$

(2) Improved Subtractive Average-Based Optimization Algorithm

1) Tent Chaos Mapping for Initializing the Population

Chaos mapping is a method that uses chaotic sequences to generate initial solutions, characterized by ergodicity, randomness, and determinism. These features give it strong advantages in population initialization. By introducing chaos mapping, the algorithm effectively avoids local optima, thereby enhancing global search capability and convergence speed.

Tent mapping improves the error parameter initialization by generating high-quality initial parameter individuals. Reverse learning seeks corresponding reverse solutions to the current solutions, optimizing population parameter candidates to approach global optima. Thus, initializing the population using Tent chaotic reverse learning can enhance SABO's efficiency in finding optimal solutions, allowing rapid and accurate global search. Tent chaotic sequence is generated by equation (7) :

$$x_{n+1} = \begin{cases} \mu x_n & \text{if } x_n < 0.5 \\ \mu(1-x_n) & \text{if } x_n \geq 0.5 \end{cases} \tag{7}$$

Where a is a random value, 0<a<1, X≠a, This generates the chaotic sequence Xn(i=1,2,3..., N). Consequently, the individuals in the reverse population X^* are:

$$X_{nm}^{*} = X_{ub\ m} + X_{lb\ m} - X_{nm} \tag{8}$$

Where $X_{ub\ m}$ and $X_{lb\ m}$ are the boundaries of the search space for error parameters. A new population $\{X \cup X^*\}$ is formed and sorted based on the objective function values, selecting the top N optimal initial error parameters to form the initial population X.

$$\begin{aligned} & X_{\min} \leq X_{n,m} \leq X_{\max}, m \in [1,9] \\ & 25X_{\min} \leq X_{n,m} \leq 25X_{\max}, m \in [10,12] \end{aligned} \tag{9}$$

Here, X_{min} and X_{max} represent the minimum and maximum search boundaries for population parameters, respectively, with values of -2 and 2.

2) Lévy Flight Mutation Strategy

Lévy Flight, proposed by the French mathematician Paul Lévy, is a random walk model where step lengths follow a specific probability distribution. Introducing Lévy Flight allows for longer jumps and multiple changes in direction, balancing short-distance local search with long-distance global jumps. This method enhances neighborhood search near the optimal solution while also exploring far-reaching solutions in the algorithm space.

The random step length of Lévy Flight is:

$$s_i = \frac{\mu}{|v|^{\frac{1}{\varphi}}} \tag{10}$$

where μ and ν are normally distributed random numbers:

$$\begin{cases} \mu \sim N(0,\sigma_v^2) \\ v \sim N(0,\sigma_\mu^2) \end{cases} \tag{11}$$

and σ_μ and σ_v are defined as:

$$\begin{cases} \sigma_\mu = \left(\dfrac{\Gamma(1+\varphi)\sin\left(\dfrac{\pi\varphi}{2}\right)}{\Gamma\left(\dfrac{(1+\varphi)}{2}\right) 2^{\frac{(\varphi-1)}{2}} \varphi} \right)^{\frac{1}{\varphi}} \\ \sigma_v = 1 \end{cases} \tag{12}$$

In the equation, the typical range for φ is 1<φ<=3. In this paper, φ is set to 1.5; Γ denotes the gamma function.

$$X_i^{new} = \omega_1 X_i + \omega_2 x_{best+} \alpha \oplus Levy(\lambda) \tag{13}$$

The random step lengths generated by Levy(λ) provide long-distance jumps, which help explore uncovered areas. α is the step length scaling factor, typically chosen from α ∈ {0,1] for point-to-point multiplication.

3) Deep Extreme Learning Machine

The Deep Extreme Learning Machine (DELM) is a deep learning network composed of multiple Extreme Learning Machine Autoencoders (ELM-AEs) stacked together. ELM-AE serves as the basic unit of DELM, and by stacking multiple ELM-AEs, a deep learning network with multiple hidden layers is formed. ELM-AE is the result of adding a regularization term to ELM. An Autoencoder (AE) is trained through unsupervised learning to keep the input and output consistent. By minimizing the reconstruction error, the output is made to closely resemble the original input. Through layer-by-layer training, it can learn high-level features and complex patterns of the original data. DELM can achieve precise and efficient predictions and classifications in various applications, effectively enhancing the computational and generalization capabilities of the model. For specific DELM principles and steps, refer to reference.

4. Short-term Photovoltaic Power Prediction Model

(1) VMD-ISABO-DELM

Based on the above, the specific steps to construct the VMD-ISABO-DELM photovoltaic power prediction model are as follows:

1) Preprocess historical photovoltaic power data and meteorological data. Use the k-means algorithm to divide historical data into three weather types: sunny, cloudy, and rainy, based on the size of the influencing factors.

2) Decompose different weather types into original power using the VMD algorithm. This decomposes the non-stationary signal into several modal components, making the signal stationary and better capturing its changing characteristics.

3) Divide the dataset into training and testing sets. Train the ISABO-DELM model using the training set. Then, input the testing set into the trained ISABO-DELM model to obtain the model's predicted values for each component. Sum these values to get the final prediction result.

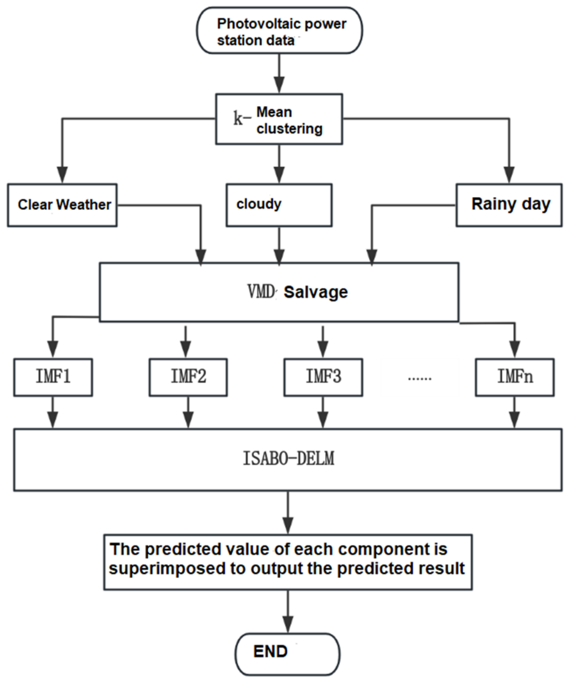


Fig 1. Flowchart of VMD-ISABO-DELM prediction

4) When evaluating the model's performance, test it on various prediction evaluation metrics, and compare the

prediction results of different models through comparative experiments.

The flowchart of the VMD-ISABO-DELM model prediction process is shown in Figure 1.

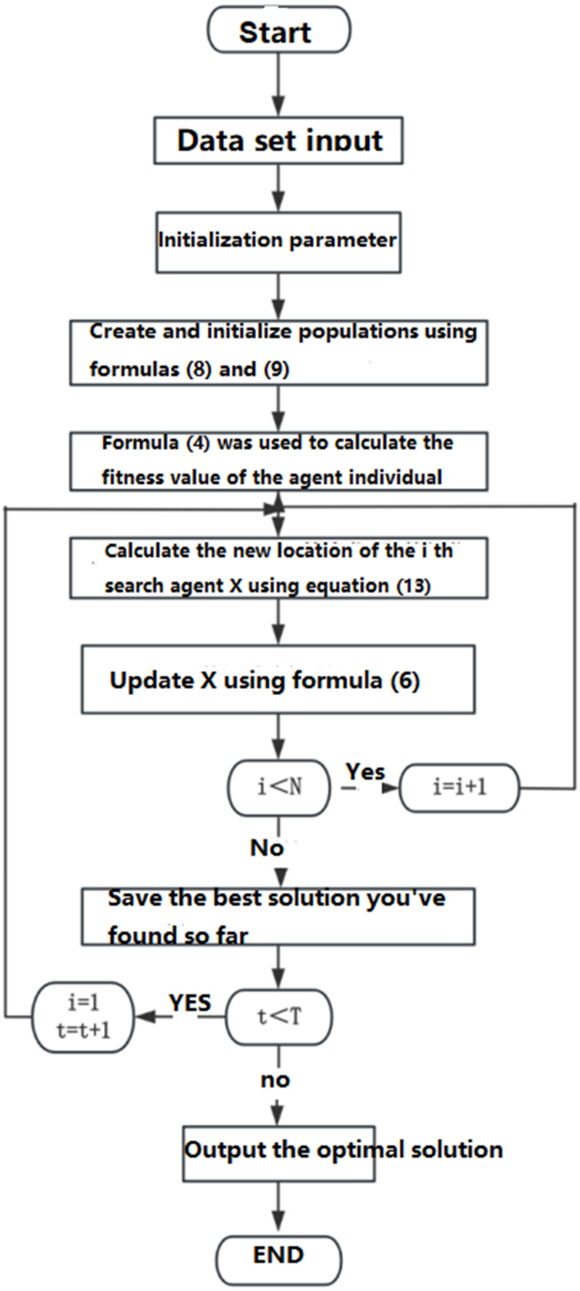


Fig 2. Flowchart of ISABO-DELM overall optimization

(2) ISABO-DELM Optimization Process

DELM is composed of multiple ELM-AEs stacked together. The weights and outputs of ELM-AEs determine their initialization settings. However, the input weights and thresholds of the hidden layers in DELM are randomly generated, which can lead to unstable prediction effects. To improve prediction stability, a multi-strategy improved Subtraction-Averaging-Based Optimization (ISABO) algorithm is used to optimize multiple hyperparameters in DELM. The specific steps are as follows:

1) Preprocess the data and divide it into datasets.

2) Set the optimization range for the bias c and weights w of the input layer of DELM, and determine the population size and maximum number of iterations.

3) Build the ISABO-DELM prediction model, determine the algorithm parameters, and randomly initialize the population.

4) Calculate the initial fitness of the proxy individuals.

5) Update the new position of the search agents according to Equation (13), using subtraction and averaging rules to simulate interactions between individuals, and generate new hyperparameter solutions.

6) Calculate the fitness of the search agents at the new positions.

7) If the fitness of the search agents at the new positions is high, accept the new positions; otherwise, keep them unchanged.

8) Repeat steps 5 to 7 until the termination criterion is met, and determine the optimal parameter combination.

9) End of the algorithm.

5. Case Study Analysis

(1) Evaluation Metrics

Three evaluation metrics are used in this study: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics comprehensively reflect the prediction accuracy of the model and can evaluate the performance of the model from different perspectives.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{p}_i - p_i\right)^2} \tag{14}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{p}_i - p_i\right| \tag{15}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|\hat{p}_i - p_i\right|}{p_i}\times 100\% \tag{16}$$

In the equations, p_i represents the actual photovoltaic power, and $\hat{p}_i$ represents the predicted photovoltaic power.

(2) Data Selection and Processing

Taking the dynamic data of a 100MW photovoltaic power station in Jiangsu Province in 2021 as an example, the data records the photovoltaic power and meteorological characteristics of the power station every day, including total radiation, direct radiation, diffuse radiation, module temperature, ambient temperature, air pressure, and relative humidity, totaling seven dimensions. These data are collected every 15 minutes. Since photovoltaic power generation is mainly affected by solar radiation, data for the time period 7:00-18:45 were selected, with a total of 48 sampling points per day. To make more accurate predictions, the annual data were divided according to the differences in power variation curves for different weather types, and predictions were made for each category separately. First, Pearson correlation coefficient analysis was used to analyze the correlation between photovoltaic power and meteorological factors, and the results are shown in Table 1.

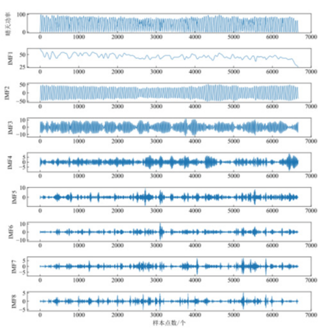
From Table 1, it can be seen that the total radiation, direct radiation, scattered radiation, module temperature, and ambient temperature are strongly correlated with photovoltaic power, while air pressure and relative humidity are weakly correlated. Therefore, in the following model training, the data for air pressure and relative humidity will be excluded, and only the data for total radiation, direct radiation, scattered radiation, module temperature, and ambient temperature will be retained as input features.

Table 1. PCC between photovoltaic power and meteorological factors

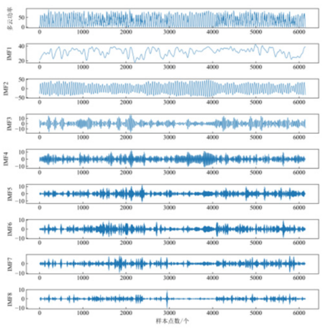
Factors	Total radiation	direct radiation	diffuse radiation
PCC	0.91	0.68	0.65
module temperature	ambient temperature	Air pressure	relative humidity
0.38	0.22	0.14	0.09

(3) VMD Decomposition Results

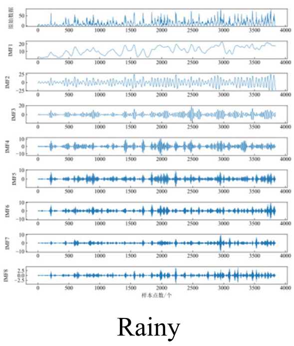
There are two parameters to be set in the VMD decomposition, namely the number of modes k and the penalty factor α. Choosing the appropriate value for k is crucial: if k is too small, the decomposition will be insufficient; if k is too large, the modes will repeat severely or introduce additional noise. The penalty factor α also affects the decomposition results and speed. With k determined, a smaller α will result in a slight overlap of modes, while a larger α will narrow the frequency band boundaries, increasing reconstruction error. Therefore, choosing the appropriate k and α is essential for achieving the best decomposition results. Figure 3 shows the power components obtained by using the VMD algorithm to decompose the three types of weather, sorted from low to high frequency. These power components will serve as the output sequence for the prediction model, with the corresponding weather data as the input sequence. After predicting each sequence separately and summing them, the final prediction result is obtained.



Sunny



Cloudy



Rainy

Fig 3. Decomposition results of power data for three weather types

(4) Overall Prediction Results Analysis

To verify the effectiveness of the proposed method in power prediction, comparative experiments between single models and combined models were conducted.

Figures 4 to 6 show the prediction curves of each single model under three weather types: sunny, cloudy, and rainy. It can be seen that as the complexity of the weather increases, the prediction curves fluctuate more around the actual values. Among these, the DELM model's prediction results are closer to the actual power values.

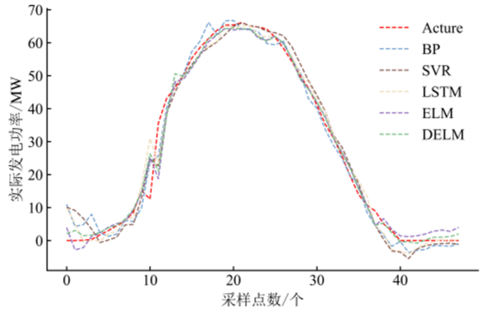


Fig 4. Prediction comparison curve of a single model under sunny conditions

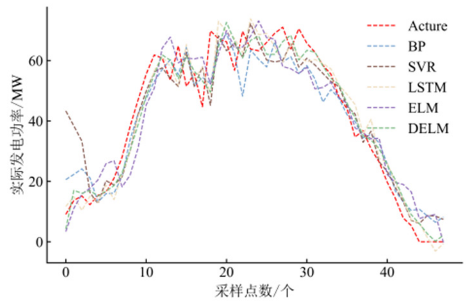


Fig 5. Prediction comparison curve of a single model under cloudy conditions

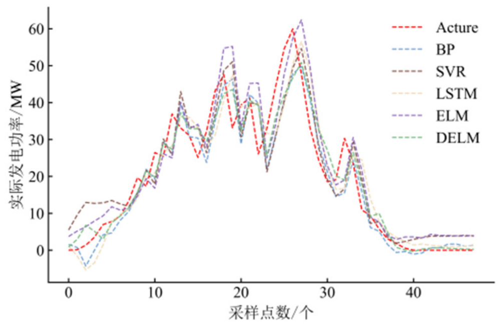


Fig 6. Prediction comparison curve of a single model under rainy conditions

The comparison of prediction error metrics for different single models under various weather types is shown in Table 2. The smaller the error metrics, the better the model's performance. From the results, it can be seen that under sunny, cloudy, and rainy weather conditions, the error metrics for the DELM model are all at their minimum values. This indicates that the DELM deep learning structure performs excellently in handling complex time series data, being able to fully extract information from the data.

To visually demonstrate the improvement in prediction accuracy of the proposed model in this paper, five combined prediction models were set up: SABO-DELM, EEMD-SABO-DELM, VMD-WOA-DELM, VMD-PSO-DELM, and VMD-ISABO-DELM. Comparative experiments were conducted under the same parameters to verify the effectiveness of the proposed model. Figures 7 to 9 show the comparison curves of the predicted values and the original power data of each prediction model under different weather conditions.

Table 2. Comparison of forecast indexes of each single model under different weather types

Single model	Error index	Clear Weather	cloudy	Rainy day
SVR	RMSE	4.34	9.77	7.53
	MAE	3.24	7.19	6.23
	MAPE	10.34	19.87	25.53
BP	RMSE	3.82	8.03	6.52
	MAE	2.82	6.74	4.87
	MAPE	9.67	17.06	23.27
LSTM	RMSE	4.19	7.00	6.98
	MAE	2.62	5.59	5.20
	MAPE	11.97	14.74	25.84
ELM	RMSE	3.66	8.56	7.54
	MAE	2.25	7.19	5.88
	MAPE	8.56	17.70	27.28
DELM	RMSE	3.43	6.13	5.82
	MAE	2.23	4.88	4.34
	MAPE	9.65	12.26	22.41

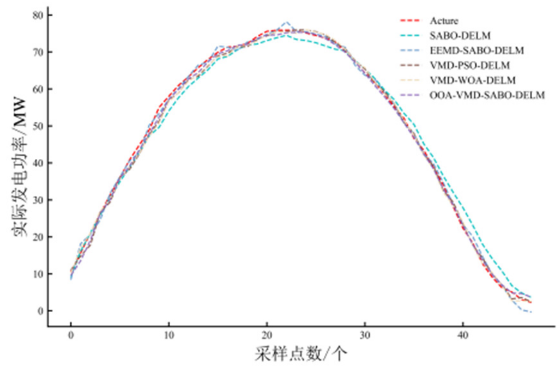


Fig 7. Prediction comparison curves of various combined models under sunny conditions

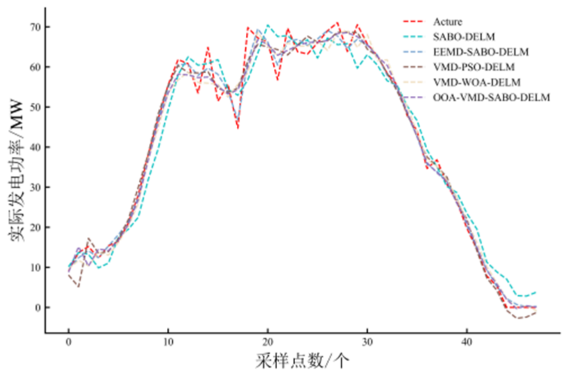


Fig 8. Prediction comparison curves of various combined models under cloudy conditions

As shown in Figure 7, due to the high and stable radiation intensity on sunny days, the photovoltaic power is relatively high and stable. The prediction curves of each model in the figure are very close to the actual power generation curves, indicating that the models can effectively capture the power output characteristics on sunny days. In this environment, the high-precision predictions of each model provide favorable data support for grid scheduling and improve energy utilization.

As shown in Figure 8, under cloudy conditions, the instability of radiation caused by constantly changing cloud cover leads to significant power output fluctuations. The performance of prediction models slightly declines in such complex weather, but the model proposed in this paper still shows good adaptability and accuracy compared to other models. This improved prediction accuracy is crucial for accurately predicting power changes during peak electricity demand, ensuring grid stability, and is vital for actual grid scheduling.

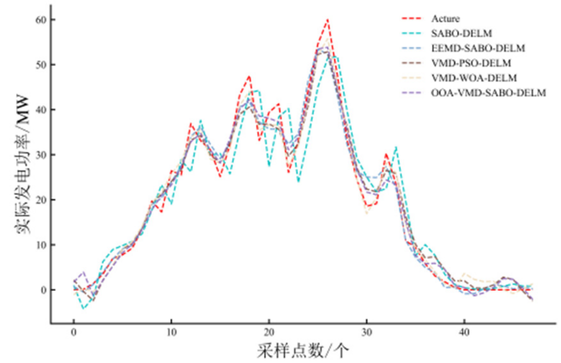


Fig 9. Prediction comparison curves of various combined models under rainy condition

As shown in Figure 9, rainy days exhibit the lowest overall power output with the most significant fluctuations, posing a greater challenge to the models. However, the proposed model in this paper can still accurately predict the trend of changes during sudden shifts, performing better than other models.

Table 3 presents the evaluation results of the prediction models under different weather conditions using three evaluation metrics. First, comparing SABO-DELM, EEMD-SABO-DELM, and the proposed method shows that using decomposition methods yields higher prediction accuracy than not using decomposition methods. Additionally, using the VMD method compared to the EEMD method under sunny, cloudy, and rainy conditions decreases RMSE by 58.08%, 62.11%, and 65.94%, respectively; MAE by 62.54%, 60.66%, and 63.17%, respectively; and MAPE by 63.22%, 31.42%, and 71.04%, respectively. This demonstrates that compared to EEMD, VMD effectively overcomes the mode mixing phenomenon by decomposing the original time series into several stationary subsequences, thereby reducing prediction difficulty and improving accuracy.

Finally, comparing the VMD-WOA-DELM, VMD-PSO-DELM, and the proposed method models shows that using the ISABO algorithm reduces RMSE by 48.74% and 46.15%, MAE by 52.65% and 51.45%, and MAPE by 49.10% and 48.04% under sunny conditions compared to using the WOA and PSO algorithms, respectively. Under cloudy and rainy conditions, although the power errors of the models vary, overall, the prediction accuracy of the proposed method is superior to other methods with the same data.

Table 3. Comparison of forecast indexes of various combined models under different weather types

Combination model	Error index	Clear Weather	cloudy	Rainy day
SABO-DELM	RMSE	2.684	5.254	5.892
	MAE	2.259	4.039	4.619
	MAPE	5.882	10.929	23.373
EEMD-SABO-DELM	RMSE	1.269	2.415	2.845
	MAE	1.025	1.586	2.050
	MAPE	2.841	3.701	9.973
VMD-WOA-DELM	RMSE	1.038	1.588	1.746
	MAE	0.811	1.278	1.437
	MAPE	2.053	3.959	4.995
VMD-PSO-DELM	RMSE	0.988	1.661	1.880
	MAE	0.791	1.157	1.526
	MAPE	2.011	4.010	5.646
Textual method	RMSE	0.532	0.915	0.969
	MAE	0.384	0.624	0.755
	MAPE	1.045	2.538	2.871

6. Conclusion

This paper proposes a method for photovoltaic power prediction based on an improved subtraction-average optimization algorithm to optimize the DELM model. Firstly, the variational mode decomposition (VMD) is used to decompose the original data, reducing data instability and improving prediction accuracy by decomposing the output power. Experiments demonstrate the effectiveness of this approach. The subtraction-average optimization algorithm is used to optimize the DELM, reducing the impact of randomly initialized parameters on the DELM model. Comparative experimental analysis shows that the proposed VMD-ISABO-DELM model improves prediction accuracy. However, the decomposition and optimization process of the combined model increases training time, indicating a need for further efficiency improvements. Additionally, considering the limited experimental data, increasing the dataset can effectively enhance the model's generalization capability.

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