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Fault Diagnosis Method for Charging Pile Based on Improved BP Neural Network#

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ABSTRACT

In order to ensure the safe and stable operation of electric vehicle (EV) charging stations and improve the accuracy of fault diagnosis, a fault diagnosis method based on an improved Backpropagation Neural Network (BP) is proposed. This method first preprocesses the operational dataset of the charging stations. Then, the preprocessed dataset is input into the BP model for training to learn the correlation between the normal and faulty states of the charging stations. Finally, an improved optimization technique is introduced to optimize the weights and thresholds of the BP model. This technique combines the Firefly Algorithm (FA) and the Northern Goshawk Optimization Algorithm (NGO) to obtain the optimal model by optimizing the BP model. Simulation results demonstrate that the proposed improved BP method has good computational advantages in terms of precision and recall rates. Compared to the traditional BP algorithm, the improved BP method achieves a 10.83% increase in diagnostic accuracy and can accurately diagnose the status of the charging stations.

Keywords: charging pile, fault diagnosis, neural network, firefly algorithm, northern goshawk optimization.

1. INTRODUCTION

In recent years, there has been a significant growth in the number of electric vehicle charging stations in China, driven by strong government support and the increasing adoption of electric vehicles [1]. However, this rapid expansion has also brought about certain challenges. The charging stations are often numerous and widely dispersed, making them difficult to manage effectively. Moreover, many charging stations operate with limited staff or are unattended, which adds complexity to their maintenance and daily operations [2]. Therefore, there is a pressing need to enhance the fault diagnosis technology for charging stations in order[1] to ensure their efficient maintenance, safe operation, and facilitate the continued growth of the electric vehicle industry [3-5].

In terms of fault diagnosis, three main paradigms are commonly used, including the model-based approaches, signal-based approaches, and knowledge-based approaches [6], which have their advantages and disadvantages over various applications [7]. First, model-based approaches require constructing a diagnosis model in advance and a diagnosis algorithm is also designed to monitor the consistency between the outputs of practical systems and the model-predicted outputs [8]. The prominent advantage of model-based approaches is that only a small amount of data is needed to accomplish the fault diagnosis. However the diagnostic accuracy depends highly on the precision of the constructed model, which is usually difficult to obtain in practical scenarios. Also, the constructed diagnosis model is usually designed to detect faults of specific devices, which has narrow applicability to other diagnostic scenarios [9]. Second, the signal-based approaches extract the features of faults from the measured signals, based on which a diagnostic decision is then made via symptom analysis with prior knowledge of symptoms such as in healthy systems [10]. In particular, the signal-based approaches require no modeling in advance. It is worth noting that the signal-based approaches may demonstrate poor performance when dealing with unknown input disturbances or unbalanced conditions. Third, the knowledge-based approaches use various technologies of artificial intelligence with available historical data to extract implicit dependencies between faults and variables, which are also called the data-driven fault diagnosis. Compared with the model-based approaches and signal-based approaches, the knowledge-based approaches perform better in some aspects, including the system

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portability and anti-interference capability, which thus draw great attention within both academia and industry.

Backpropagation neural networks have advantages such as strong learning ability and wide applicability. However, they are sensitive to initial weights and thresholds, and optimizing these parameters can improve the performance of the BP model [11-12]. Further research is needed to explore how to optimize the weights and thresholds of the BP model to improve its training performance and enhance the accuracy of fault diagnosis.

To address the afore mentioned issues, the author proposes an improved fault diagnosis method for backpropagation neural networks using a combination of Firefly Algorithm (FA) and Northern Goshawk Optimization Algorithm (NGO). By leveraging the advantages of both FA and NGO, the proposed method is called Firefly Algorithm Improves Northern Goshawk Optimization Algorithm (FA-NGO). FA-NGO is utilized to optimize the parameters of the backpropagation model, leading to the attainment of an optimal model. Finally, based on this model, accurate diagnosis of fault states in DC charging stations is performed.

2. EXPERIMENTAL RELATED WORK

2.1 Northern Goshawk Optimization

The hunting strategy of the Northern Goshawk can be divided into two phases: In the first phase, the Northern Goshawk rapidly approaches its prey once it identifies it. In the second phase, the Northern Eagle hunts its prey within a small range. The Northern Goshawk Optimization (NGO) algorithm is proposed based on the aforementioned hunting behavior [13].

In NGO, each individual in the population represents a feasible solution. The algorithm begins by randomly initializing the population within the search space. This population X is defined as:

$$X=\begin{bmatrix} X_1 \\ \vdots \\ X_k \\ \vdots \\ X_N \end{bmatrix}=\begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,D} \\ \vdots & & \vdots & \cdots & \vdots \\ x_{k,1} & \cdots & x_{k,d} & \cdots & x_{k,D} \\ \vdots & \cdots & \vdots & & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,D} \end{bmatrix} \tag{1}$$

where, X_k represents the k Northern Goshawk individual; $x_{k,d}$ represents the value of the d variable of the k feasible solution; N represents the number of individuals in the population; D represents the dimension of variables.

NGO is based on the mathematical model of Northern Goshawk's hunting behavior, and its iteration process can be divided into two phases: the first phase is the identification and attack phase; the second phase is the escape and pursuit phase.

In the first phase, the Northern Goshawk randomly selects a prey G and quickly attacks it. This phase increases NGO's global search ability and can quickly approach the target region of the optimal solution. The mathematical model for this phase is:

$$G=X_s \tag{2}$$

$$X_{k,1}=\begin{cases} X_k+\alpha\left(G-IX_k\right), F_G<F_k \\ X_k+\alpha\left(X_k-G\right), F_G\geq F_k \end{cases} \tag{3}$$

$$X_k=\begin{cases} X, F_{k,1}\geq F_k \\ X_{k,1}, F_{k,1}<F_k \end{cases} \tag{4}$$

where, X_k represents the k feasible solution; $X_{k,1}$ represents the new position of the k feasible solution in the first phase; α is a random number within $[0,1]$; F is the fitness function; s is a positive random number within $[1,N]$; I takes a value of 1 or 2.

In the second phase, after attacking the prey, the Northern Goshawk will try to escape, and the Northern Goshawk will continue to pursue the prey. Because the Northern Goshawk is very fast, it can catch up with the prey in any situation and complete the hunt. This phase enhances NGO's local search ability and can quickly approach the optimal solution. In NGO, assuming the hunting radius of the Northern Goshawk is R , the mathematical model for this phase is:

$$R=\omega\left(1-it/T_{\max}\right) \tag{5}$$

$$X_{k,2}=X_k+R\left(2\alpha-1\right)X_k \tag{6}$$

$$X_k=\begin{cases} X_k, F_{k,2}\geq F_k \\ X_{k,2}, F_{k,2}<F_k \end{cases} \tag{7}$$

where, it represents the current iteration number; $T_{\max}$ represents the maximum number of iterations; ω represents the step size; $X_{k,2}$ represents the new position of k .

Compared to previous intelligent algorithms, the NGO algorithm has a stronger ability to search for optimal parameters and is less prone to getting trapped in local optima.

2.2 Firefly Algorithm

The FA is inspired by the behavior of fireflies, which move based on their relative brightness. It is characterized by the following settings: the movement of fireflies is directly linked to their brightness; the relative brightness is inversely proportional to the distance between fireflies, and directly proportional to their attraction; under normal circumstances, individuals freely move until a brighter firefly appears in their vicinity[14].

In the Firefly Algorithm, Relative Fluorescent Intensity can be defined as:

$$I = I_0 \bullet e^{-\gamma r_{i,j}^2} \tag{8}$$

where, I_0 represents the maximum fluorescent intensity, which is positively correlated with the fitness value. γ is the light absorption coefficient, which is associated with the degree of light absorption by the medium through which light propagates in the air. $r_{i,j}$ represents the relative distance between individual i and j.

The equation for the mutual attraction between fireflies is:

$$\beta = \beta_0 \bullet e^{-Ir_{i,j}^2} \tag{9}$$

where, β_0 represents the maximum attraction when $r = 0$.

The equation for the movement of low-brightness fireflies towards brighter fireflies:

$$x_i^{t+1} = x_i^t + \beta_0 \bullet e^{-\gamma r_{i,j}^2} \left(x_j^t - x_i^t\right) + \alpha\left(rand - 1/2\right) \tag{10}$$

where, t represents the iteration number. x_i^{t+1} represents the coordinate variable of the i firefly in the $t+1$. x_i^t and x_j^t represent the coordinate variables of the i and j fireflies, respectively. α is the algorithmic movement distance, with a range of $\alpha \in [0,1]$.rand is a random value scattered in the range $[0,1]$.

During each iteration, the position of each firefly is updated based on the relative fluorescent intensity and visibility, aiming to search for the optimal solution. The Firefly Algorithm (FA) is characterized by its simplicity, ease of operation, and fast convergence speed.

3. FAULT DIAGNOSIS MODEL BASED ON FA-NGO-BP

3.1 FA Optimizing NGO

Due to the possibility of getting trapped in local optima during the process of finding optimal weights and thresholds, NGO may face limitations. By incorporating FA to optimize NGO, it is possible to enhance the algorithm's global search capability and reduce the likelihood of getting stuck in local optima. This improvement can lead to better exploration of the global optimal solution, thereby enhancing the performance and accuracy of the algorithm.

After the completion of the NGO search process, individuals in the population are subjected to firefly fluorescence disturbances based on the magnitude of their fitness values. This means that the positions of individuals are perturbed according to their fitness values. If a better fitness value is obtained after the perturbation, the position of the Northern Goshawk is updated according to the best fitness value, and the corresponding iteration count is also updated. This approach helps the algorithm escape from local optima and improves its search capability for optimization.

3.2 FA-NGO-BP Prediction Model

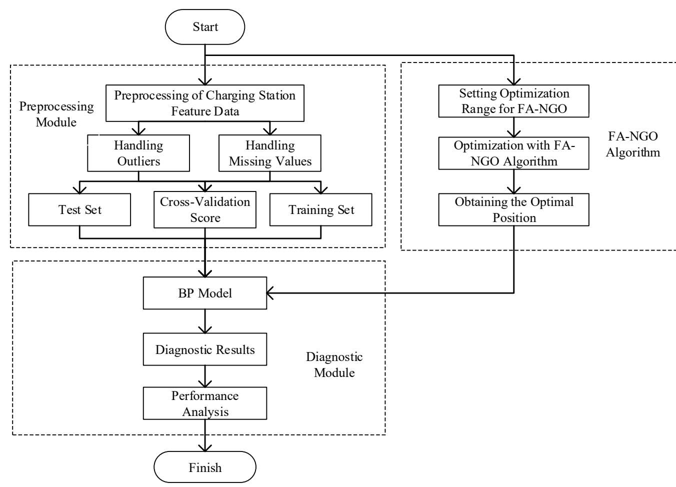

Fig. 1 FA-NGO-BP algorithm flowchart

1) Data preprocessing, including filling missing values, partitioning training and testing sets, normalizing sample data, and shuffling sample data.
2) The fitness function is chosen as the mean squared error (MSE), which is formulated as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\varepsilon_i)^2 \tag{11}$$

3) Set the population size, upper and lower bounds of positions for the Northern Goshawk Optimization Algorithm and Firefly Algorithm, as well as the number of input layers, output layers, hidden layers, and activation functions for the BP neural network.
4) Train the preprocessed data using the backpropagation neural network, searching for the current optimal solution and its corresponding fitness value, to obtain the optimal position of the Northern Eagle.

5) Use the optimized position of the Northern Eagle obtained through the NGO search as the initial firefly positions for the Firefly Algorithm. Calculate the initial fitness of the FA, and then compute the firefly brightness and attractiveness. Finally, update the firefly positions and the optimal fitness based on the motion equation of the fireflies.
6) Assign the obtained optimal position values of the fireflies to the weights and thresholds of the backpropagation algorithm. BP obtains the optimal parameters of this algorithm and undergoes training, resulting in diagnostic output.

4. SIMULATION EXPERIMENT

4.1 Data preprocessing

This study randomly selected 600 sets of data from the 2019 Baidu Novice Competition charging pile fault dataset for the experiment. A total of 480 sets were designated as the training set, while the remaining data was allocated as the test set. The fault dataset consists of 6 features, namely, S1 for K1K2 drive signal, S2 for electronic lock drive signal, S3 for instant stop signal, S4 for access control signal, S5 for voltage total harmonic distortion, and S6 for current total harmonic distortion. In the dataset, '1' represents normal operating status, while '2' represents the fault status.

4.1.1 Data normalization

The normalization approach is used to map the values of different features or data to a unified standard range, in order to eliminate the dimensional differences and improve the accuracy of weight and threshold optimization. The normalization expression is as follows:

$$X_s = \frac{X_{in} - \mu}{\sigma} \tag{12}$$

where, X_{in} is the input, μ is the mean, and σ is the standard deviation. The normalized results are shown in Figure 2.

4.1.2 Data interpolation

Data loss is a common problem during the data collection process. In the operation of charging equipment, there may be situations where some sensor measurement points fail to function properly, resulting in partial loss of collected operational state information. This article uses the mean method to fill in missing data.

$$Y = \frac{\sum_{i=1}^{n} \eta X_i}{m_i} \tag{13}$$

where, X_i represents the data value, m_i is the number of data points, and η determines the need for data filling.

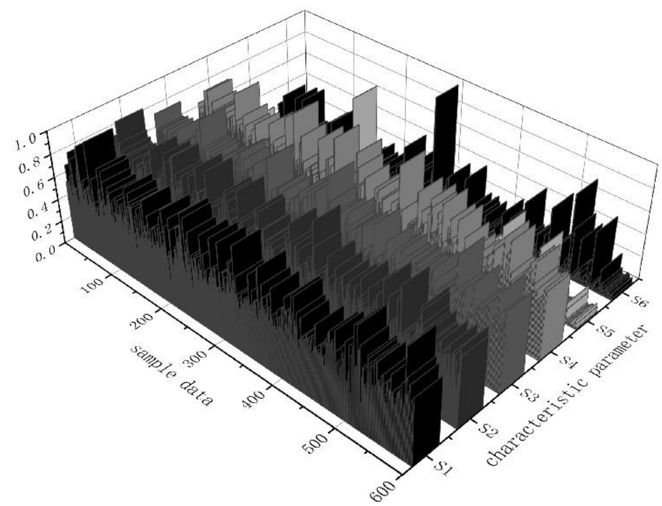

Fig. 2 Normalized data

4.2 Result analysis

To demonstrate the algorithm's good diagnostic accuracy, the dataset was divided into a training set and a test set. The training set was used to train the traditional BP model, NGO-BP model, and FA-NGO-BP model. Then, the trained models were used to predict the test set. Figures 3 to 5 depict the comparison of the four models on the test set, where yellow squares represent the comparison for operating state 1, and green squares represent the comparison for operating state 2. Accuracy rates were determined by dividing the count of correctly predicted values by the total number of predictions. The accuracy rates for the three models are as follows: 81.67% for the BP model, 86.67% for the NGO-BP model, indicating higher prediction accuracy.

4.3 Diagnostic performance analysis

Figures 6, 7, and 8 represent the confusion matrices for the BP, NGO-BP, and FA-NGO-BP algorithms, respectively. The four values in the figures represent the number of instances where the predicted and actual values are both 1, the number of instances where they are both 2, the number of instances where the predicted value is 1 and the actual value is 2, and the number of instances where the predicted value is 2 and the actual value is 1. Based on these figures, we calculated the precision, recall, and F1 score for each algorithm, as shown in Table Ⅱ. Further comparisons of performance metrics revealed that the FA-NGO-BP algorithm exhibits significant advantages in terms of precision and F1 score when compared to the BP algorithm, with performance improvements of 19.28% and 8.28% respectively. Compared to the NGO-BP algorithm, the FA-NGO-BP algorithm shows an improvement of 6.59% in precision, 4.84% in recall, and 5.35% in F1 score. Therefore, the classification prediction model constructed by the FA-NGO-BP algorithm demonstrates better classification prediction effectiveness.

4.4 Error analysis

As shown in Figure 10. Firstly, in the FA-NGO-BP model, the Mean Absolute Percentage Error (MAPE) is

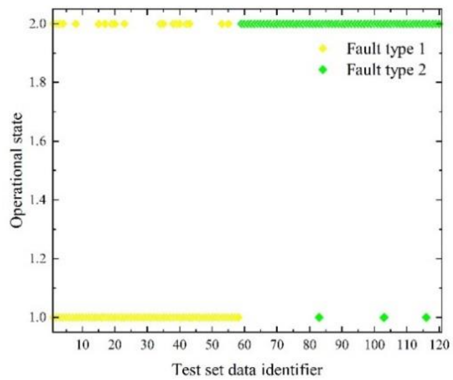

Fig. 3 BP prediction results

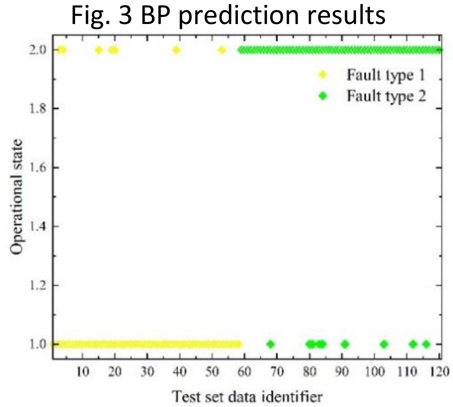

Fig. 4 NGO-BP prediction results

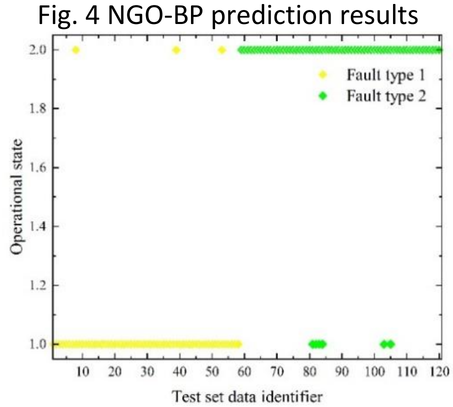

Fig. 5 FA-NGO-BP prediction results

60% of the BP model. This indicates a significant improvement in reducing prediction errors and bringing the model closer to the actual values. Secondly, the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) further measure the differences between predicted and actual values. The MSE and RMSE are reduced by approximately 50.08% and 36.03% respectively compared to the BP model, and by approximately 43.75% and 25.11% respectively compared to the NGO-BP model. This signifies that the FA-NGO-BP model exhibits significant improvement in

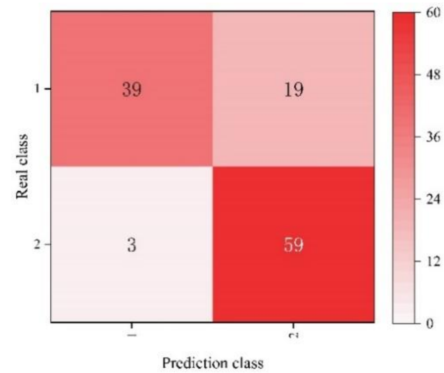

Fig. 6 BP Confusion Matrix

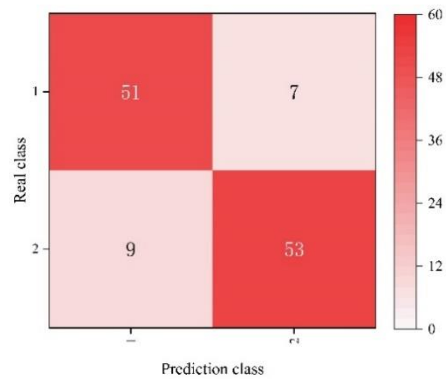

Fig. 7 NGO-BP Confusion Matrix

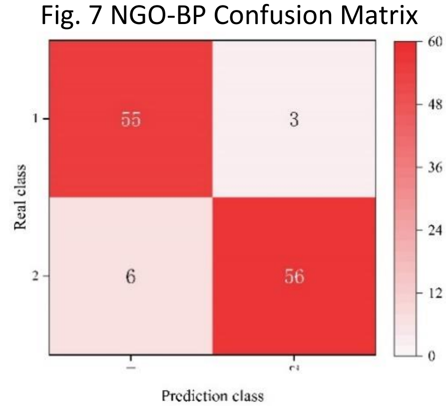

Fig. 8 FA-NGO-BP Confusion Matrix

handling larger errors. Lastly, the coefficient of determination (R2) evaluates the quality of the regression model's fit to the data. In the FA-NGO-BP model, the R2 value is 2.6 times higher compared to before optimization. Therefore, the FA-NGO-BP model demonstrates better performance.

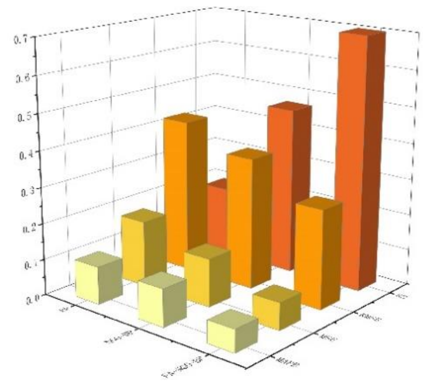

Fig. 9 Error analysis chart

5. CONCLUSIONS

This paper proposes a diagnostic algorithm based on FA-NGO-BP for electric vehicle charging station faults. Leveraging the global search capability of FA, it helps NGO escape local optima, thereby enabling the BP algorithm to obtain optimal weights and thresholds. Experimental results using real charging station data are presented, comparing the traditional BP model with the NGO-optimized BP model. The FA-NGO-BP model achieves higher diagnostic accuracy, reaching 92.5%. Precision and F1 score are improved by 7% to 25%. Additionally, metrics such as mean absolute error, mean percentage error, and root mean square error are significantly reduced. In conclusion, the proposed charging station diagnostic algorithm demonstrates clear advantages in terms of diagnostic accuracy and holds promising application prospects.

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