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Development of Machine Learning-based Electromechanical Fault Prediction Models

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Abstract In order to fully explore the fault information embedded in electromechanical faults and realize the accurate judgment of electromechanical faults, this paper improves the FOA algorithm with an electromechanical fault prediction model based on IFOA-SVM. The population division process is added, the better subpopulation and the worse subpopulation are updated according to different steps, the balance of the algorithm's search ability in different periods is realized, and the optimal parameters of the support vector machine are obtained by using the improved fruit fly algorithm. It not only realizes the diagnosis of electromechanical faults with higher accuracy, but also solves the defects that the fruit fly algorithm is easy to fall into the local optimum and has low convergence accuracy in the later stage. In the experimental validation, the gun control box component in the fire control system of a certain tank is selected as the research object, and the IFOA algorithm is compared with BP neural network, GA-SVM, GWO-SVM and other algorithms, and the average prediction accuracy of the three experiments reaches 100.00%, and optimal fitness is obtained when the number of iterations reaches 10 times. The research in this paper provides a new effective method for electromechanical fault prediction, which has important theoretical and practical application value.

Index Terms Improved Drosophila algorithm, Support vector machine, Population segmentation, Electromechanical fault diagnosis

I. Introduction

In recent years, with the development and application of machine learning technology, machine learning-based failure prediction and diagnosis methods for electromechanical systems have gradually become a research hotspot [1], [2]. Failure prediction and diagnosis of electromechanical system is a key issue, which can help us to detect system failures in advance and take timely measures to avoid catastrophic consequences such as production line downtime [3]-[5].

Machine learning is a method of automatically discovering patterns and laws in data through learning and mining of large amounts of data, and making predictions and judgments in this way, and supervised learning, unsupervised learning, integrated learning, deep learning, etc. are commonly used methods and techniques [6]-[9]. In electromechanical system fault prediction and diagnosis, machine learning can be applied to the following aspects:

(1) Feature extraction and selection: Electromechanical systems usually have a large amount of sensor data, including temperature, pressure, current, vibration, and many other signals [10], [11]. Machine learning can analyze these signals to extract and select the most relevant features to help us better understand the system state and failure modes [12], [13].

(2) Failure prediction: Based on historical data and features, machine learning can construct prediction models for predicting the probability or time of failure in electromechanical systems [14], [15]. This can help us develop a reasonable maintenance plan and replace components with higher failure risks in time, thus reducing the losses caused by failures [16], [17].

(3) Fault diagnosis: When an electromechanical system fails, machine learning can perform automatic diagnosis by analyzing the failure patterns and characteristics to find out the cause and location of the failure, so as to guide the maintenance and repair work [18]-[21].

Literature [22] describes the application of deep learning techniques in system fault prediction and proposes a new deep learning-based fault diagnosis method for electromechanical systems based on the limitations of deep learning models, which possesses the advantages of ease of use and adaptability and is supported by unsupervised stacked self-encoders and supervised discriminant analysis. Literature [23] describes the application of electromechanical actuators and proposes an automatic motor fault detection and isolation method with long and short-term memory neural networks, pointing out that the algorithm has good fault detection capability and the method can accomplish the fault isolation task. Literature [24] describes the development of intelligent fault diagnosis in electromechanical systems (EMS) and initiates the study of various combinations of electromechanical faults in EMS, introduces the use of wavelet features extracted from current and vibration signals, develops a defect detection system based on Support Vector Machines, and discusses the results of the study. Literature [25] points out the shortcomings of traditional methods of fault diagnosis in electromechanical systems and emphasizes the effectiveness of utilizing predictive maintenance (PM) and deep learning (DL) methods, in order to help the technicians of electromechanical systems to understand the use of PM using the DL methodology for multi-fault diagnosis, work on the DL technique applied to PM in electromechanical systems is discussed, revealing that electric motors are the most selected devices for PM. Literature [26] proposed a deep learning and optimization algorithm based fault diagnosis and predictive maintenance method for electromechanical equipment and verified that the method achieved significant performance improvement with good accuracy and generalization ability, which helps to improve productivity and ensure equipment safety. Literature [27] emphasized the importance of failure prediction of electromechanical equipment and proposed a failure prediction method based on spatio-temporal graph information, which was verified to be feasible and accurate, and could accurately complete the task of long-term and short-term failure prediction. Literature [28] proposed a hierarchical multiscale dense network for fault identification in electromechanical systems, aiming to learn the intrinsic and multiscale feature information necessary for fault identification of mechanical signals under non-stationary conditions, and verified that the method can achieve state-of-the-art performance compared to some competing methods. Literature [29] proposed a scalable and lightweight convolutional neural network framework based on high-dimensional raw condition monitoring data for the automatic detection of multi-electromechanical faults in wind turbine generators, revealing that the fault detection system has a good performance and its classification accuracy is very high. Literature [30] proposed a current-assisted vibration fusion network aimed at diagnosing faults in electromechanical drive systems and designed a current-assisted fusion module to achieve full fusion of cross-modal information, showing that the proposed method has strong robustness and diagnostic performance. Literature [31] constructed a fault diagnosis system and used LSTM neural network to construct a fault diagnosis model for electromechanical equipment, revealing that the model has high accuracy, recall and F1, and the training time and prediction time are very short, which can be used for fault prediction and diagnosis of electromechanical equipment. Literature [32] proposed a rolling bearing fault diagnosis method for electromechanical equipment - weighted prototype network, which effectively solves the shortcomings of the small number of effective samples and the long-tailed distribution of the health monitoring data, enhances the dependence of the samples on the global data, and improves the accuracy of the model classification. Literature [33] proposed an improved deep learning-based fault diagnosis framework for EMAs, which is based on a triple network with coupled clustering loss, and was revealed to improve the performance of traditional deep learning-based methods through experiments on real EMA datasets from NASA. Literature [34] proposed a deep learning based cross-sensor domain adaptive approach for mechanical fault diagnosis and designed different tasks to simulate different cross-sensor domain adaptive problems in fault diagnosis, which demonstrated that the method has a very high detection accuracy in most of the tasks. The above study explores the application of machine learning methods such as deep learning, optimization algorithms, and long and short-term memory neural networks in the prediction, targeting, and detection of electromechanical faults, and by comparing them with the traditional methods, they show excellent fault detection capabilities with very high accuracy rates.

Support Vector Machines, as an efficient classification and regression algorithm, have been widely used in the prediction of electromechanical faults, however, the performance of SVMs is largely dependent on the selection of parameters such as the penalty factor and kernel parameters. Considering that the Drosophila algorithm has improved the optimization performance for support vector machines, but it has the problems of low accuracy and easy to fall into the local optimum, this paper proposes an improved Drosophila algorithm, which realizes the position update of the better subpopulation and the worse subpopulation by dynamically dividing the Drosophila populations and according to the different step-size determination methods. The performance of this paper's algorithm is verified in practical applications, which provides new ideas for the application of intelligent algorithms in the industrial field.

II. Optimized SVM based on Drosophila algorithm for electromechanical fault prediction model

II. A. Data collection and pre-processing

II. A. 1) Data collection

The temperature sensor can accurately determine the temperature of the generator coolant, the vibration sensor can effectively monitor the vibration status of the generator rotor, and the current sensor is specifically designed for real-time detection of changes in generator current. The data collected by these sensors provide timely information feedback on the operating status of the equipment, which helps to detect and recognize potential signs of failure in time.

In model training, the collection of historical fault records is of indispensable importance as they provide valuable training samples for the model. Taking transmission lines as an example, insulator breakdowns, line short circuits and other faults have occurred in the past, and these detailed fault records not only record the time, location and type of faults, but also describe in detail the impact of the fault on the equipment. By deeply analyzing these historical fault records, researchers can discover the unique characteristics of different failure modes, thus providing solid data support for future fault prediction and equipment diagnosis. Its calculation formula is:

$$\rho(X,Y)=\frac{\sum_{i=1}^{n}(x_i-x)(y_i-y)}{\sqrt{\sum_{i=1}^{n}(x_i-x)^2\sum_{i=1}^{n}(y_i-y)^2}} \tag{1}$$

where: X,Y is the variable characteristics. x_i,y_i is the sample value of the variable characteristics. $x_i,\overline{y}$ is the mean value of the variable features, which indicates the degree of linear correlation between the variables. During feature selection, the correlation coefficient can be used to predict the features that are most relevant to the diagnosis.

II. A. 2) Data cleaning and pre-processing

Data cleansing [35] is one of the key steps in ensuring data quality and usability. In this phase, issues such as outliers, missing values and duplicates in the data need to be identified and dealt with.

1) Outliers handling. Outliers in data can be detected and handled through statistical methods such as box-and-line plots or threshold-based methods. For example, the presence of values significantly outside the normal range in the temperature sensor data of an electrical device may imply sensor malfunction or environmental anomalies that need to be dealt with.

2) Missing value processing. Missing values may affect the training and prediction results of the model, so appropriate methods need to be taken to deal with them. Common methods include interpolation, mean padding, or model-based padding methods to ensure data integrity and availability. The formula for this is:

$$\text{Missing value}=\frac{(x_{mewt}\times(t_{misc}-t_{pew})(t_{moxt}-t_{pew})}{x_{rowv}} \tag{2}$$

x_{pov} is the pre-missing value observation. x_{mu} is the post missing value observation. t_{nod} is the timestamp of the observation before the missing value. t_{pev} is the timestamp of the observation after the missing value.

3) Normalization. Scaling the range of values of different features to the same scale helps to eliminate the difference in magnitude between the features. For example, in electrical equipment fault prediction, data of different magnitudes such as temperature and current are scaled uniformly to ensure the accuracy and stability of model training.

4) De-noise. Noise interference may affect the quality of the data and the performance of the model, so de-noising measures are needed. Common methods include filtering techniques such as moving average, median filtering or wavelet transform to reduce the effect of noise in the data.

II. B.Electromechanical fault prediction model based on IFOA-SVM

II. B. 1) Support Vector Machine Algorithm

SVM [36] is a machine learning method based on the principle of statistics, which is often used to deal with classification problems under small samples.The idea of SVM to deal with classification problems is to maximize the distance between the hyperplane and the interface between the hyperplane and the partitions under different samples by constructing the optimal hyperplane, which is expressed as:

$$\begin{cases}\min\left(\frac{1}{2}\|\omega\|^2+C\sum_{i=1}^{n}\varepsilon_i\right)\\ \text{s.t.}\quad y_i\left[(\omega x_i)+b\right]\geq 1-\varepsilon_i\end{cases} \tag{3}$$

where ε_i is the slack variable in the linearly indivisible case, $\varepsilon_i>0$. $i=1,2,\cdots,n$. ω is the hyperplane normal vector. x_i is the sample value. y_i is the label value. b is the set threshold. C is the penalty parameter.

The objective function is transformed by introducing Lagrange multipliers:

$$L(\omega,b,\alpha)=\frac{1}{2}\|\omega\|^2+\sum_{i=1}^{m}\alpha_i\left[1-y_i(\omega^{\mathrm{T}}x_i+b)\right] \tag{4}$$

A partial derivation of ω and b to 0 yields its dual form as:

$$\begin{cases}\max\left(\max\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i,j=1}^{n}y_iy_j\alpha_i\alpha_jx_i^Tx_j\right)\\ \text{s.t. } 0\le\alpha_i\le C;\sum_{i=1}^{n}\alpha_iy_i=0\end{cases} \tag{5}$$

In the nonlinear case, the introduction of a kernel function mapping yields:

$$K(x_i^T,x_j)=\left[\varphi(x_i),\varphi(x_j)\right] \tag{6}$$

This leads to the derivation of the decision function as:

$$f(x)=\operatorname{sgn}\left[\sum_{i=1}^{n}\alpha_iy_iK(x_i,x_j)+b\right] \tag{7}$$

where y_i is the desired output. x_i is the input sample vector. n is the total number of samples. $\varphi(x)$ is the mapping function. $K(x_i,x_j)$ is the kernel function, which is generally a radial basis function. The specific expression for $K(x_i,x_j)$ is:

$$K(x_i,x_j)=\exp(-g\|x_i-x_j\|^2) \tag{8}$$

The parameters that affect the classification performance of SVM are the penalty parameter C and the kernel parameter g.

II. B. 2) Drosophila algorithm for bicluster differential step size

The basic FOA algorithm [37] has six main steps, which are detailed below:

Step 1: Initialize the relevant parameters. It mainly includes the size of the Drosophila population (i.e., the number of individual Drosophila) $Popsize$. Maximum number of iterations (i.e., the condition under which the iteration stops) $Maxiter$. The search step length L of Drosophila individuals. Initial center position of the population (X_axis,Y_axis).

Step 2: Start the search process. Each Drosophila individual F_i conducts a flight search randomly in its own line of sight to the surrounding according to the search step L to find food.

$$\begin{cases}X_i=X\_axis+L\\ Y_i=Y\_axis+L\end{cases} \tag{9}$$

Step 3: Calculate food concentration. Calculate the food concentration determination value S_i, which is the reciprocal of the value of the distance between the location of the individual Drosophila F_i and the origin of the coordinates.

$$\begin{cases}Dist_i=\sqrt{X_i^2+Y_i^2}\\ S_i=1/Dist_i\end{cases} \tag{10}$$

Step 4: Calculate the fitness. Calculate the fitness value $Smell_i$ of the Drosophila individual F_i, which is obtained by substituting S_i into the fitness function.

$$Smell_i=function(S_i) \tag{11}$$

Step 5: Information Recording. Record the fitness value of the Drosophila individual with the largest $Smell_i$ in the current iteration and the coordinates of the location where it is located.

$$\left[bestSmell, X_b, Y_b\right] = \max(Smell_i) \tag{12}$$

Step 6: Population aggregation. Record the largest $bestSmell$ in all iterations, and after that, the fruit fly population aggregates towards the location of the optimal fruit fly individual obtained in the current iteration.

$$\begin{cases} Smellbest = bestSmell \\ X\_axis = X_b \\ Y\_axis = Y_b \end{cases} \tag{13}$$

Step 7: Iterate repeatedly. Repeat the execution of Step 2 Step 6, and after reaching the maximum number of iterations Maxiter, the algorithm stops and outputs the optimal result.

In step 2 of the above FOA calculation, the individual fruit fly searches for food in flight according to the search step length L, which determines the scope and precision of the individual fruit fly search. The value of L needs to be set by human beings, and whether it is set reasonably or not has an important influence on the final optimization result of the algorithm. For example, when the value of L is set to a large value, the step size of Drosophila individuals will become larger, which is easy to miss the potential optimal solution. On the contrary, when it is set too small, although the search of Drosophila individuals is more delicate, it will greatly increase the amount of computation and reduce the search efficiency. Therefore, how to reasonably and efficiently determine the value of L is particularly critical to improve the performance of FOA. To address this problem, this paper proposes the IFOA algorithm on the basis of FOA. Its main idea includes two parts, one is to divide the Drosophila population dynamically. The second is the position update of different populations according to the difference step.

Regarding the dynamic division of the population, it is mainly realized by the following equation.

$$\begin{cases} D_i \geq D_{mean} & \text{Fruit fly } F_i \text{ was classified into the superior subgroup} \\ D_i < D_{mean} & \text{Fruit fly } F_i \text{ was classified into the poor subgroup} \end{cases} \tag{14}$$

where D_i is the distance between the Drosophila individual F_i and the optimal Drosophila individual F_{beu} in the current iteration. D_{mean} is the average of all distances as shown in the following equation.

$$D_i = \| F_i - F_{iest} \| \tag{15}$$

$$D_{mean} = \frac{1}{Popsize} \sum_{i}^{popsize} \| F_i - F_{bost} \| \tag{16}$$

The Drosophila population is then dynamically divided into two subpopulations, i.e., the better subpopulation and the worse subpopulation.

Regarding the position update of different populations according to the difference step, it is mainly realized by the following equation.

$$\begin{cases} L_y = L \times lgt\left(\dfrac{iter}{Maxiter}\right) \\ X_i = X_i + L; Y_i = Y_i + L \end{cases} \tag{17}$$

$$X_i = X_i + L; Y_i = Y_i + L \tag{18}$$

where $iter$ is the current iteration number. $Maxiter$ is the maximum number of iterations. lgt is the logistic transformation function, as shown in the following equation.

$$lgt(x) = \frac{1}{1+e^{20(x-0.5)}} \tag{19}$$

When the Drosophila population completes one iteration, it will be divided into better and worse subpopulations by dividing the Drosophila population into two subpopulations, and then the better subpopulation will complete the position update by calculating the adaptive change of the step size L_y, while the worse subpopulation will complete the position update with the initially set step size L. The step size of the better subpopulation will adaptively decrease according to the increase of the iteration number, which ensures that the population can search in a wide range with a larger step size at the early stage, and search in a small range with a smaller step size at the later stage, realizing the balance of convergence accuracy and speed. The worse subpopulation is positionally updated according to the original fixed step size L, which ensures the global optimization search ability of the population. At the same time, since the population is re-divided after each iteration is completed, i.e., the individuals and the number of individuals contained in the two subpopulations are dynamically changing, this realizes the information exchange between the two subpopulations, which is more helpful to improve the search effect.

II. B. 3) Optimization of SVM parameter selection based on IFOA

When using SVM to deal with nonlinear problems, the selection of the penalty parameter C and kernel parameter g directly affects the final classification results of the model. In order to improve the classification accuracy of SVM, IFOA is utilized to select the optimal SVM parameters based on sample data, and the specific process is as follows.

Step I, set the number of populations M, the maximum number of iterations $T_{iteration}$, and utilize the Tent-logistic chaotic mapping to generate the initial position information (X_0, Y_0) of Drosophila individuals. Since the number of variables to be optimized is 2, the position update formula of the Drosophila individual is:

$$\begin{cases} X(i,1) = X_o + \omega \\ X(i,2) = X_o + \omega \\ Y(i,1) = Y_o + \omega \\ Y(i,2) = Y_o + \omega \end{cases} \tag{20}$$

where i is the current number of iterations. ω is the dynamic adaptive step size parameter.

Step 2, calculate the distance D between the individual position and the origin, and get the flavor concentration determination value P after solving the reciprocal.

$$\begin{cases} D(i,1) = [X(i,1)^2 + Y(i,1)^2]^{1/2} \\ P(i,1) = 1/D(i,1) \\ D(i,2) = [X(i,2)^2 + Y(i,2)^2]^{1/2} \\ P(i,2) = 1/D(i,2) \end{cases} \tag{21}$$

Step 3, set the variable to be optimized penalty parameter C and the kernel parameter g as a function of the flavor concentration determination value P.

$$\begin{cases} C = 10P(i,1) \\ g = P(i,2) \end{cases} \tag{22}$$

In step 4, the fitness function is set to the classification error rate of the SVM. Input the optimization parameters determined by the flavor concentration determination value P into the SVM to obtain the value of the fitness function, i.e., the food flavor concentration $Smell_i$ at the location of the fruit fly individual. The minimum fitness value and the corresponding individual location during each iteration are recorded.

$$\begin{cases} Smell_i = function(p_i) \\ Smell_{best} = Smell_{min} \\ index_{best} = index(Smell_{best}) \end{cases} \tag{23}$$

where $index$ is a location index based on the current food flavor concentration.

Step 5, iterate the FOA population to determine whether $Smell_{i+1}$ is less than $Smelll_i$, and if this condition is satisfied, update the globally optimal food flavor concentration, $Smell_{best}$, and the corresponding globally optimal location; otherwise, continue iterating.

Step 6, iterate until the maximum number of iterations, record the information of Smell and the corresponding individual position at this time, and output the optimal penalty parameter C and kernel parameter g.

II. C. Standard function test of the improved Drosophila algorithm

II. C. 1) Test Functions

In order to verify the effect of the improved FOA algorithm, the standard function is generally used first to test it, this paper uses the Sphere function, Schaffer function, Griewank function and Rastrigin function which are four commonly used intelligent algorithms to test the performance of the function, in order to better highlight the effect of this paper's algorithmic improvements, respectively, with the standard FOA, the decreasing step size FOA, this paper In order to better show the effect of the improvement of this paper's algorithm, the standard FOA, the decreasing step FOA, and the improved FOA of this paper, respectively, are used to carry out simulation experiments on these four standard functions to find the minimal value of the function by matlab, and compare the test results.

II. C. 2) Test results and analysis

The parameters of the improved Drosophila algorithm are set: the population size is 20, the maximum number of iterations is set to 500, the minimum value of weight is 0.01, and the maximum value of weight is 100, because the purpose of the IFOA in this paper is to optimize the RBF kernel function parameter σ of the SVM and the penalty factor C. Therefore, the dimensionality of the test functions are all set to 2, and the annealing coefficient is 1. The parameters of the FOA, DS-FOA, and the IFOA settings are the same. The same, for each test function are individually run 10 times respectively to calculate the optimal value, the worst value, the average value, the standard deviation of the four indicators to reflect the algorithm's performance of the search for excellence, the test results are shown in Table 1.

From the test results, it can be seen that whether it is a complex multi-peak function or a simpler single-peak function, the IFOA algorithm has very good optimization results compared to the other two, the DS-FOA algorithm optimization results than the standard Drosophila algorithm to be higher than the standard Drosophila algorithm by two orders of magnitude, there is a certain degree of improvement, but the ability to improve is limited, and this paper improves the Drosophila algorithm compared to the other two algorithms, optimization effect has greatly improved, for the Sphere function, the IFOA algorithm has a much better performance. Sphere function, the IFOA is improved by nearly more than 170 orders of magnitude, and the standard deviation is zero, indicating that the algorithm has better stability. For the Schaffer function, Griewank function and Rastrigin function, the optimal and worst values of the IFOA solution are 0, which is consistent with their actual values, indicating that the improvement effect is extremely obvious. From the above results, it can be seen that compared with FOA, the index values of IFOA solving test function are closer to the actual values and reach the expected results of this paper. And the indexes of IFOA's optimization search are also much better than DS-FOA, indicating that the improved fruit fly algorithm in this paper helps the algorithm jump out of the local optimal solution very well and improves the convergence speed and accuracy of the algorithm.

Table 1: Comparison of three algorithm test results

Function	Algorithm	Taste value			
		best	worst	mean	sd
Sphere	FOA	1.691E-11	1.732E-11	1.711E-11	1.165E-11
	DS-FOA	6.701E-14	6.938E-14	6.812E-16	6.887E-15
	IFOA	3.995E-185	4.254E-189	6.335E-185	0.000E+00
Schaffer	FOA	1.703E-11	1.74E-11	1.717E-11	9.677E-13
	DS-FOA	6.675E-13	6.901E-13	6.795E-13	6.842E-14
	IFOA	0.000E+00	0.000E+00	0.000E+00	0.000E+00
Griewank	FOA	1.731E-11	1.785E-11	1.755E-11	1.438E-13
	DS-FOA	7.837E-13	8.092E-13	7.971E-14	7.973E-15
	IFOA	0.000E+00	0.000E+00	0.000E+00	0.000E+00
Rastrigin	FOA	1.282E-5	1.321E-5	1.301E-5	1.082E-7
	DS-FOA	5.111E-8	5.246E-8	5.175E-8	4.771E-9
	IFOA	0.000E+00	0.000E+00	0.000E+00	0.000E+00

III. Example validation analysis of electromechanical failure prediction model

III. A. Data pre-processing

The author chose the gun control box component in the fire control system of a certain type of tank as the research object.

In order to avoid the computational imbalance of Bayesian network processing different orders of magnitude of the original data, and at the same time reduce the computational complexity of the algorithm and improve the performance of Bayesian network, the normalized processing results are shown in Figure 1.

The distribution shape of the normalized data is the same as that of the original data, but the data distribution range is reduced to [0.2,0.8], which eliminates the influence of too large data range on data processing and improves the performance of the algorithm.

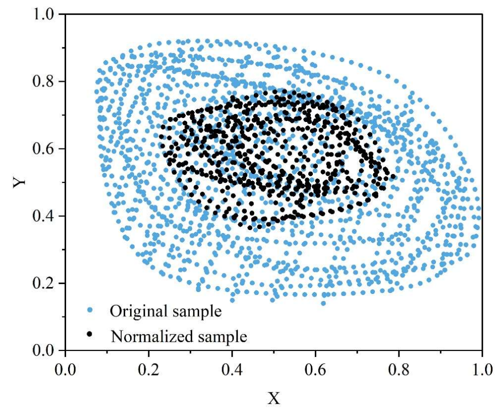
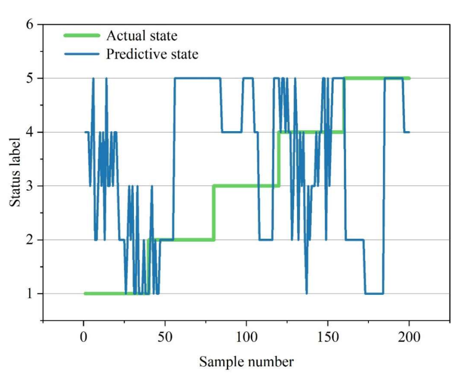


Figure 1: The data of electromechanical equipment is normalized

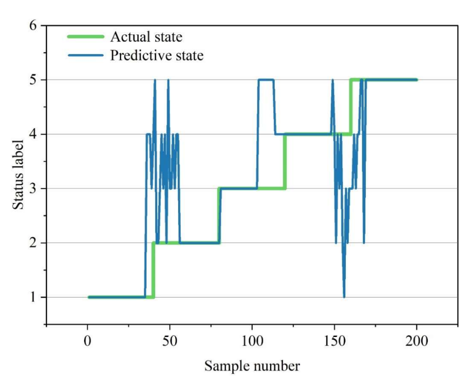
III. B. Experimental results

Four hundred groups of gun control box data were selected for experimental verification. The status of the gun control box was divided into five mode labels: normal, abnormal aiming control module, abnormal image stabilization control module, abnormal signal module from the gyroscope group, and abnormal amplifier module. In order to improve the reliability of the experimental results, three groups of experimental comparative analyses were conducted: In Experiment 1, half of the data sets in each type of state mode were extracted. The extracted 200 sets of data were used as training samples, and the remaining 200 sets of data were used as test samples. In Experiment 2, 40 groups of data were extracted from each type of state pattern, 200 groups of data were extracted as training samples, and the remaining 200 groups of data were used as test samples. In Experiment 3, 20 groups of data are extracted from each type of state model, 100 groups of data are used as training samples, and the remaining 300 groups of data are used as test samples. The sample datasets are fed into GA-SVM, GWO-SVM, IFOA-SVM, and BP neural network to train the samples for prediction. The number of populations in GA-SVM, GWO-SVM and IFOA-SVM is set to be 30, the number of iterations are all taken to be 100, and the nodes of the hidden layer in the BP neural network are 10. Taking the prediction results in Experiment 1 as an example, the prediction results are shown in Fig. 2, and Figs. (a), (b), (c), and (d) are shown in Figs. (a), (b), (c), and (d), respectively, for BP neural network, GA-SVM, GWO-SVM, and IFOA-SVM prediction results.

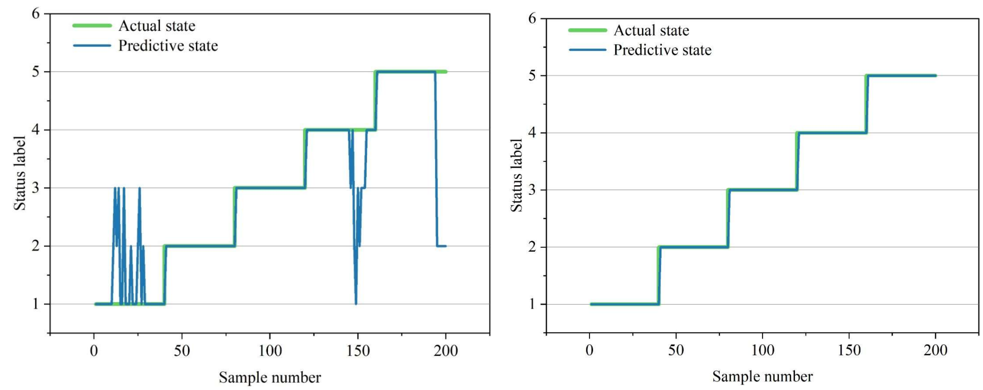
As can be seen from the figure, the prediction result of IFOA-SVM is optimal, and the prediction accuracy reaches 100.00%, while the prediction accuracy of BP neural network is lower, which is only 32.00%.The prediction accuracies of GA-SVM and GWO-SVM are 70.00% and 80.00%, respectively, and the prediction accuracies of this paper's faulty fault prediction model are all improved to a different degree compared with the comparison model. The algorithm in this paper can effectively improve the accuracy of fault prediction of electromechanical equipment of gun control box.



(a)Bp neural network prediction results



(b)GA-SVM prediction results



(c)GWO-SVM prediction results (d)IFOA-SVM prediction results

Figure 2: Different algorithms predict the results

In order to increase the persuasiveness of the experimental results, the author conducted 10 state prediction experiments for each algorithm when conducting experiments 1, 2 and 3, and the comparative analysis of their prediction results is shown in Table 2, where the data in the table are the average values of the 10 states. Through the experimental comparative analysis of the training set and test set with 3 different numbers of groups, it is found that in the state prediction comparison of the 4 algorithms, the average time used for BP neural network prediction is the shortest, and with the increase of the number of groups in the training set, the average time used for IFOA-SVM processing is close to the average time used for GA - SVM processing.The prediction result of BP neural network is very unstable, and the prediction results of GA-SVM are not so stable, GWO-SVM is not so stable, and the prediction result of GWO-SVM is not so stable. BP neural network prediction results are very unstable, GA-SVM prediction results are also not very stable, GWO-SVM and IFOA-SVM prediction results are more stable, and the more the number of training set groups the more accurate prediction of the results, but IFOA-SVM in the state prediction accuracy is obviously better than the other three algorithms, the algorithm prediction accuracy in three experiments are 100.00%, the accuracy of the prediction results of the dependence on the number of training sets is also less than the other three algorithms.

Table 2: Comparative analysis of four algorithms in 1~ 3

Comparison term	Experiment 1		Experiment 2		Experiment 3	
	Accuracy /%	Time/s	Accuracy /%	Time/s	Accuracy /%	Time/s
BP	32.00	1.856	45.00	1.564	29.00	1.455
GA-SVM	70.00	23.451	69.00	31.145	39.00	10.213
GWO-SVM	80.00	12.124	69.00	24.512	25.00	6.124
IFOA-SVM	100.00	13.411	100.00	19.541	100.00	9.214

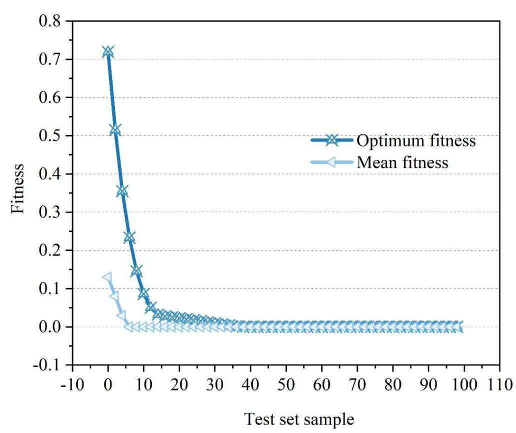


Figure 3: The fitness curve of this algorithm

As an example, the curves of the adaptability of the improved algorithm of this paper and the adaptability of the gray wolf search algorithm in Experiment 1, the comparison results are shown in Fig. 3 and Fig. 4, respectively. From the comparison of fitness curves, it can be seen that the number of iterations used by IFOA-SVM to find the optimal fitness is significantly less than that of GWO-SVM, and the algorithm in this paper finds the optimal fitness when it is 10 iterations, and the fitness value calculated by IFOA-SVM is also significantly better than the fitness value calculated by GWO-SVM, which means that IFOA-SVM can find the best individual with the best fitness faster and better, which improves the prediction accuracy of the support vector machine and has obvious advantages.

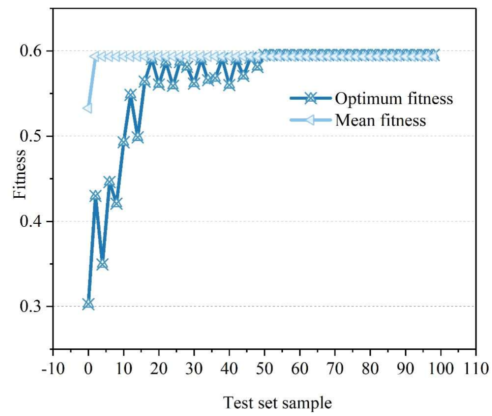


Figure 4: The fitness curve of the GWO-SVM algorithm

IV. Conclusion

In this paper, we propose an electromechanical equipment fault prediction model based on the fruit fly algorithm optimized support vector machine, which improves the optimization search accuracy and convergence speed in traditional machine learning training.

Taking the population division and different step update methods as optimization points, IFOA dynamically divides the Drosophila population and updates the position according to the difference step on the basis of the original Drosophila algorithm, which achieves the balance of information searching ability of different populations and ensures the searching accuracy and efficiency of the algorithm. In the task of predicting the faults of electromechanical equipment in the gun control box, the diagnostic accuracy of IFOA-SVM reaches 100.00%, and the average elapsed time of the three experiments is only 14.055 s. Compared with all the compared algorithms, the diagnostic accuracy of the IFOA-SVM algorithm is the highest, and the operation elapsed time is less than that of most of the methods, which guarantees an extremely high prediction accuracy while ensuring a lower operation time, and verifies the accuracy and efficiency of the IFOA-SVM algorithm. the effectiveness of the IFOA-SVM method.

The optimization prediction model in this paper can accurately predict the failures of electromechanical equipment, provide strong support for the maintenance and overhaul of the equipment, and help to detect the potential failures of the electromechanical equipment in advance, reduce the downtime and maintenance cost of the equipment, and ensure the safe and stable operation of the electromechanical system. Although the model in this paper has achieved more excellent results in the experiment of the gun control box, but in the future, we can still collect data on electromechanical failures of different types and under different working conditions to provide more experimental support for the testing and validation of the model.

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