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FAULT DIAGNOSIS AND LIFE PREDICTION OF NUMERICAL CONTROL MACHINE TOOL BASED ON IMPROVED BFOA-SVM AND AFSA

Yangyang Li[1] and Kun Wang[1]*
Engineering Training Center, Shandong Huayu University of Technology, Dezhou, 253000, China

Abstract: Traditional numerical control machine tools rely on manual experience and historical data statistics for fault diagnosis and life prediction, which makes the diagnosis and prediction accuracy low and cannot meet the actual production requirements. To address this challenge, this paper provides an integrated model based on improved bacterial foraging optimization algorithm, support vector machine, and artificial fish swarm algorithm. Through reliability modeling, the model creates a life prediction model and diagnoses faults using the support vector machine. The artificial fish swarm algorithm is utilized to optimize the life prediction model, while the bacterial foraging optimization technique is presented to optimize the defect detection model. The performance analysis outcomes indicated that on the PHM dataset, the research model had an accuracy of 91.3% and a training time of 14.1 minutes. On the HIST dataset, the accuracy of the research model was 91.2% with a training time of 14.2 minutes. The results of the case study indicated that the model was able to accurately diagnose the three failure types of wear, chipping, and fracture of knives. It was also able to effectively predict the service life of the three types of tools: carbide, ceramic and cubic boron nitride knives. The synthesis revealed that the study's suggested model was very accurate and feasible for predicting the life of numerical control machine tools and diagnosing faults, which may be a significant help for manufacturing productivity.

Keywords: Numerical control machine tool; Fault diagnosis; Life prediction; Bacterial foraging optimization algorithm; Artificial fish swarm algorithm.

1. Introduction

The operational efficiency and stability of product quality and productivity of numerical control machines (NCMs), a crucial piece of equipment for precision machining, have a significant impact on the modern manufacturing industry's rapid development. When it comes to the NCM cutting process, the tool is directly used for cutting, and its condition directly affects the productivity and processing quality. Tool failure will not only lead to production interruption, increase downtime, but also due to increased cutting force, cutting temperature and other factors lead to workpiece quality degradation, and even cause safety accidents [1]. However, most of the traditional troubleshooting methods for NCM tools rely on manual empirical judgment or periodic tool replacement. This method is not only inefficient, but also can not accurately predict the actual life of the tool, which is easy to cause tool waste or overuse. In recent years, many scholars have tried to introduce computer technology to seek better solutions. To increase the precision of fault diagnosis (FD), Xue R et al. presented a digital dual-drive NCM fault detection technique utilizing the decision tree classification regression tree algorithm. The findings demonstrated which the technique could accurately identify the spindle's rigidity deterioration while it was in use [2]. Moreira M V et al. proposed an interval and output time automata model for NCM drilling process troubleshooting to reduce losses and control production costs. It was discovered that the model could identify when a specific workpiece material was being cut at the wrong pace [3]. Patange A D et al. implemented FD of machine tool components by adjusting hyperparameters and decision tree model. According to the experimental findings, the enhanced model outperformed the standard decision tree model in terms of classification ability [4]. Scholars Jogdeo A A et al. developed a generalized statistical model of spindle vibration training using

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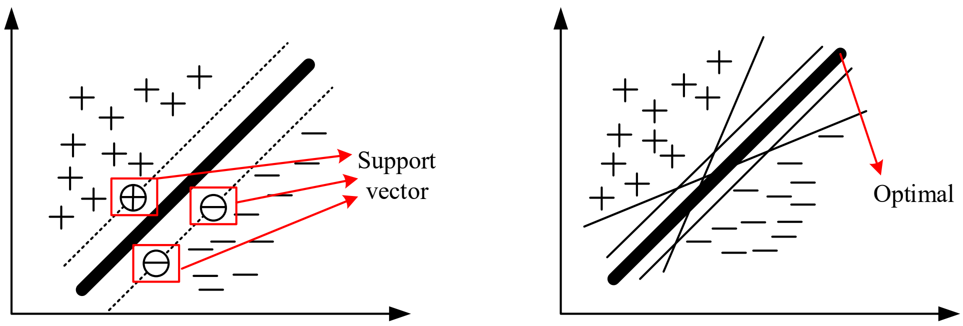
random forests for monitoring tool condition. Experimental results showed that the method provided optimal details of cutting tool utilization and could save tool costs [5]. Despite the results of previous studies, there is still room for improvement. Most of these studies are limited to intelligent diagnosis of a single fault, but not combined with life prediction. In addition, in terms of FD models, previous studies have mostly used decision tree classification, however, this method relies on expert experience, making it more subjective. Based on this, the study proposes an integrated model based on improved bacterial foraging optimization algorithm (BFOA), support vector machine (SVM), and artificial fish swarm algorithm (AFSA). The innovation of this model is that the FD model is constructed using SVM and the life prediction model (LPM) is constructed by reliability modeling, the FD model is optimized by introducing BFOA and the LPM is optimized by using AFSA. The constructed integrated model can provide new ideas and methods for intelligent maintenance and management of NCM.

2. Methods and Materials

2.1 Joint Improvement of FD Model for NCM Tools with BFOA-SVM

The conventional FD technique of NCM tools mostly depends on the operator's intuition and expertise, which might be influenced by human factors and lead to erroneous diagnostic results. The study suggests using computer technology to build the FD model of NCM tools in order to increase the effectiveness and precision of diagnosis. Given the complexity of the FD of NCM tools, it is essential to precisely identify the many kinds of errors, including tool wear and breakage. Thus, the FD model must have excellent classification accuracy and generalization capabilities in an attempt to handle high-dimensional, nonlinear data [6]. SVM, as a commonly used supervised learning algorithm, has a powerful classification capability and is able to deal with the problem of recognizing nonlinear and high-dimensional patterns [7]. Based on this, the study proposes to use SVM to construct a FD model for NCM tools. Figure 1 exhibits the SVM's internal organization.



(a) Support Vector and Interval

(b) There are multiple partition hyperplanes that separate the two types of training samples

Figure 1: Internal structure of SVM

Figure 1 exhibits a schematic of the internal structure of SVM. Figure 1(a) represents support vectors with intervals and Figure 1(b) indicates the presence of multiple dividing hyperplanes separating the two classes of training samples.

Together, the two merge to demonstrate that SVM achieves classification by finding a hyperplane that maximizes the interval [8-9]. However, although the diagnosis and classification of NCM tools faults can be achieved by using SVM, the recognition accuracy of SVM is often affected by the selected parameters.

In particular, Equation (1) displays the kernel function parameters and penalty factor, which significantly affect SVM's capacity for diagnosis.

$$\begin{cases} W(\alpha)=\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j K(t_i,t_j)-\sum_{i=1}^{N}\alpha_i \\ \sum_{i=1}^{N}\alpha_i y_i=0,\quad 0\le\alpha_i\le C,\quad \forall_i=1,2,\dots,N \\ K(t,t_i)=\exp(-\frac{\|t-t_i\|}{2\delta^2}) \\ g=\frac{1}{2\delta^2} \end{cases} \tag{1}$$

In Equation (1), $K(t_i,t_j)$ denotes the kernel function of SVM. $\|t-t_i\|$ denotes the Euclidean distance between the new data points and the training samples. g denotes the kernel function parameters. δ denotes the bandwidth of the kernel function. α_i denotes the Lagrange multiplier. C is the kernel function. y_i and y_j are the category labels of t_i and t_j, respectively [10].

The optimization of SVM parameters in Equation (1) is the key to improve the FD model of NCM tools. BFOA is very general and can realize global optimization of parameters to get the optimal parameter combination. The details are shown in Figure 2.

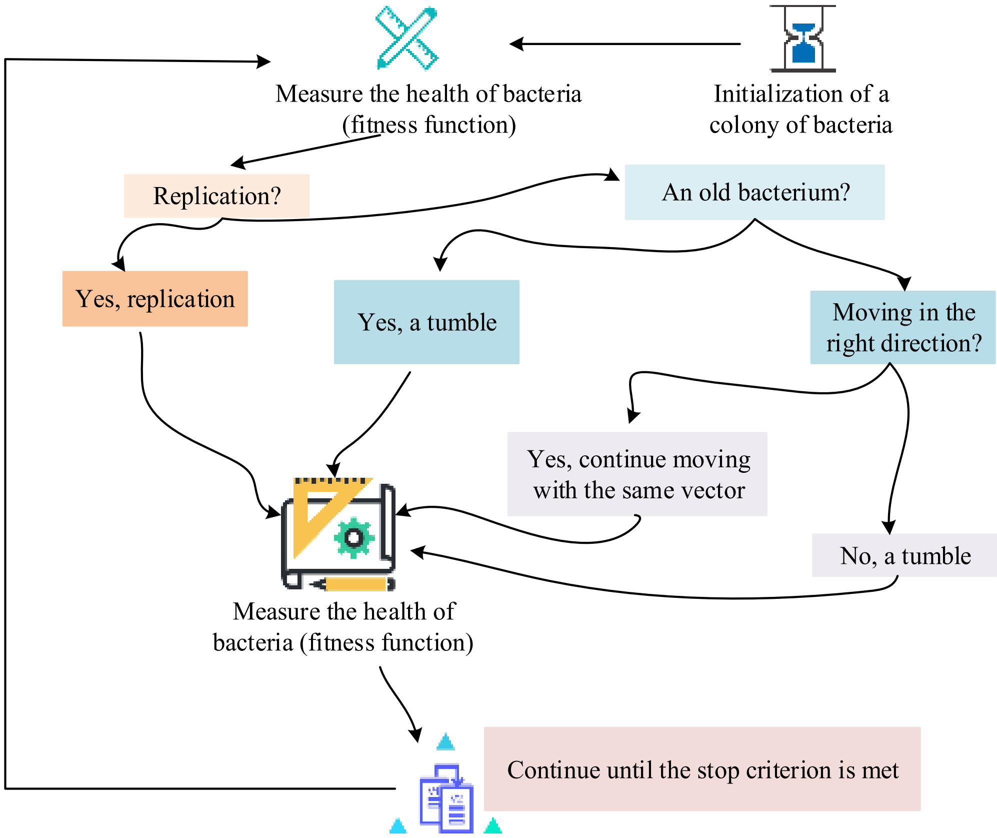


Figure 2: BFOA global optimization search process

Figure 2 shows the logical flow of the BFOA algorithm. BFOA simulates the behavior of bacteria foraging for food. Specifically, a set of bacteria is first initialized. Next, the fitness of these bacteria is measured and the quality of the solution represented by each bacterium is evaluated. During the evaluation process, if a bacterium has a high degree of adaptation, it is replicated. For bacteria that are not well adapted, the algorithm causes them to tumble, i.e., randomly change their position or orientation. If the bacteria finds a better position after tumbling, it will continue to move in that direction. On the contrary, it tumbles again. Until the halting condition is met, the entire procedure is repeated. In this case, the tumbling operation of BFOA can be displayed in Equation (2).

$$\theta^i(j+1,k,l)=\theta^i(j,k,l)+C(i)\Phi(j) \tag{2}$$

In Equation (2), i denotes a particular bacterium in the population. θ^i display the position of the i th bacterium, denoted as a D-dimensional vector. $C(i)$ denotes the step length of the i th bacterium to swim forward and is a positive number. $\Phi(j)$ denotes the randomly selected unit direction vector after the bacterial rotation after the j th convergence operation [11-12]. In addition, the new fitness function value of bacterial i after the BFOA performs a tumbling operation can be displayed in Equation (3).

$$J(i,j+1,k,l)=J(i,j,k,l)+J_{cc}\left(\theta^i(j+1,k,l),P(j+1,k,l)\right) \tag{3}$$

In Equation (3), J is the value of the corresponding fitness function. J_{cc} denotes the interaction term between bacteria. P denotes the nutrient distribution or environmental conditions at the location of the bacteria. In this way, BFOA is able to simulate the foraging behavior of bacteria in complex environments to find the optimal solution of the optimization problem. Based on this, the study proposes to use BFOA to realize the optimization of SVM. The specific optimization process can be displayed in Figure 3.

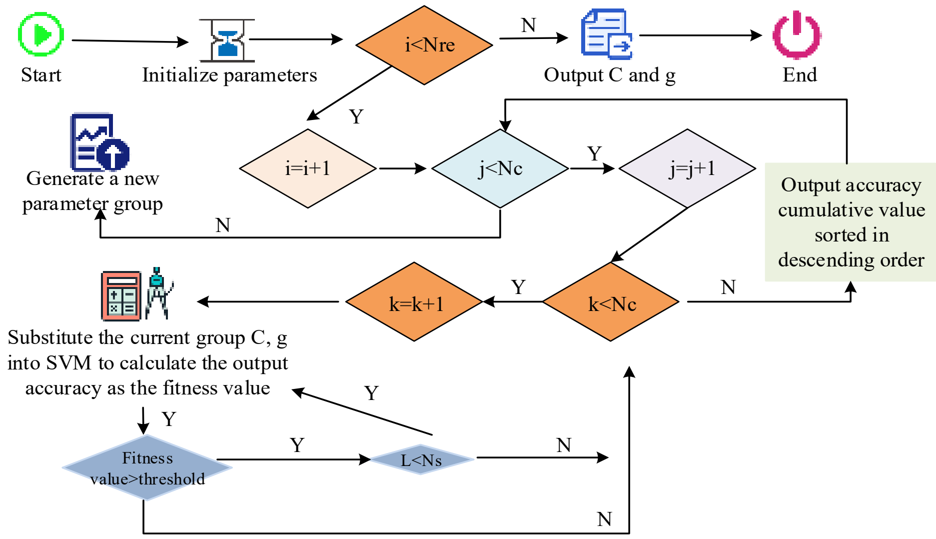


Figure 3: Improved BFOA-SVM optimization process

Figure 3 shows the specific flow of using the BFAO algorithm to optimize and improve the SVM parameters. The process is specified as first initializing the parameters and randomly generating parameter sets. Then, a loop is entered and a migration operation is performed to generate a new parameter group.

Then, a replication operation is performed on the parameter group to select the half with higher fitness value (FV) for retention. In the convergence operation, the current parameter group is used to calculate the correct rate in SVM as the FV, and if the FV exceeds the threshold, it continues to swim in that direction. Otherwise, it carries out the flipping motion [13]. When the maximum iteration is reached, the algorithm ends and outputs the parameter with the maximum FV, which finally realizes the optimization of SVM parameters.

The FD performance of NCM tools can be enhanced by implementing the optimized model.

2.2 AFSA-based Life Prediction Model for NCM Tools

Although improved BFOA-SVM enables the diagnosis of faults in NCM tools, however, in practical applications, FD and life prediction are often interrelated. FD enables timely detection of tool problems, while life prediction helps to plan maintenance in advance to avoid production interruptions. Based on this, the study proposes to further design and construct a NCM tools LPM based on the improved BFOA-SVM FD model to realize more comprehensive tool health management. Considering the machining process in NCM, the tool failure is often not sudden, but with the increase of the usage time, its performance gradually degrades until it cannot meet the machining requirements. This degradation failure process contains a large amount of information related to tool life, such as the degree of wear, crack extension, etc [14]. Consequently, by monitoring and analyzing this degradation information, the remaining life of the tool can be predicted more accurately. Based on this, the study first uses reliability modeling to quantify the tool performance degradation process, as shown in Figure 4.

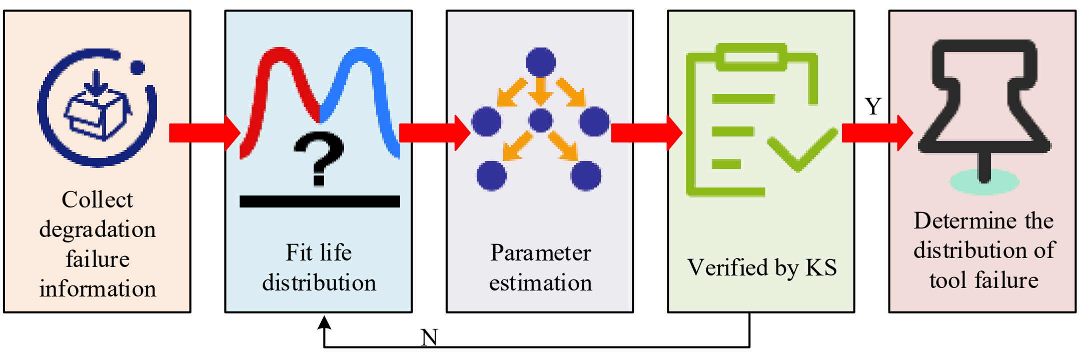


Figure 4: Tool performance degradation assessment using reliability modeling

Figure 4 shows the process of tool performance degradation assessment using reliability modeling. The study first uses sensors to collect data related to tool performance degradation and failure during use [15]. The collected data are then utilized to fit a suitable life distribution. After determining the life distribution model, the study chooses a Bayesian approach to estimate the parameters in the model, as shown in Equation (4).

$$p(\theta \mid D)=\frac{p(D \mid \theta) p(\theta)}{p(D)} \tag{4}$$

In Equation (4), θ denotes the parameters of the model. $p(\theta)$ is the prior distribution of the parameters. D denotes the observed data. $p(D)$ denotes the normalization constant of the data. $p(\theta \mid D)$ is the posterior distribution. $p(D \mid \theta)$ is the likelihood function of the data. After parameter estimation, Kolmogorov-Smirnov (KS) test is required in order to verify that the selected model of lifetime distribution is suitable for the actual data, as shown in Equation (5).

$$D^{'}=\max\left\{\left| F_n(x)-F_0(x)\right|\right\} \tag{5}$$

In Equation (5), $D^{'}$ denotes the statistic. $F_n(x)$ is the empirical distribution function (DF). $F_0(x)$ is the DF of the distribution to be tested. After the KS test, the specific distribution of tool failure can be determined.

The risk management model can be constructed based on the failure distribution of the tool [16]. Tools are often affected by a variety of factors in the process of wear and failure, such as cutting speed, cutting force, tool material, workpiece material and so on. These factors often tend to lead to uncertainty and incompleteness of tool life data. Therefore, the study introduces the gray model (GM) to reduce the interference of random factors, so as to make the law of tool life data more obvious and improve the accuracy of prediction, as shown in Equation (6).

$$\begin{cases} x^{(0)}(k)+az^{(1)}(k)=b \\ x^{(1)}(k)=\sum_{i=1}^{k} x^{(0)}(i), \quad i=1,2,\ldots,k \end{cases} \tag{6}$$

In Equation (6), b denotes the gray role quantity. $x^{(0)}(k)$ denotes the original data sequence. a is the development coefficient. $x^{(1)}(k)$ is the cumulative generation sequence. It will be challenging to fully understand the long-term and intricate systematic changes because GM mostly uses local patterns and trends in the data to create predictions. GM [17] In addition, GM is essentially a univariate linear model, and thus it is also difficult to deal with complex interactions and nonlinear relationships among multiple variables. To cope with the above problems, the study proposes to use AFSA to realize the improvement of GM. The specific process is shown in Figure 5.

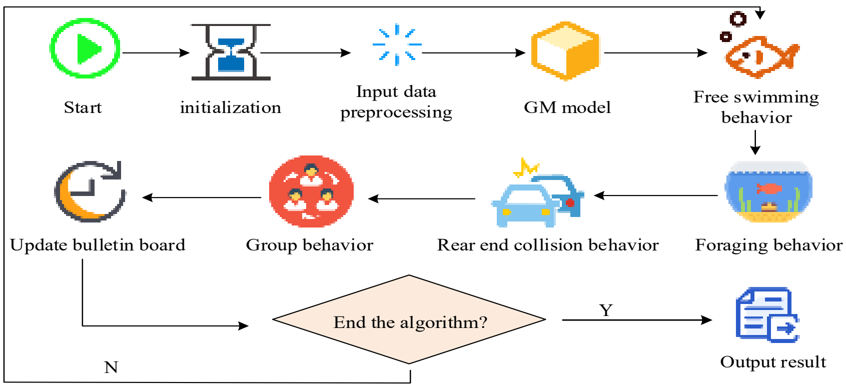


Figure 5: AFSA-GM algorithm flow

The AFSA-GM algorithm's specific flow is depicted in Figure 5. The optimization of AFSA firstly simulates the free-swimming behavior of the fish by setting the corresponding parameters to allow the fish to carry out preliminary exploration in the solution space. Then, the fish are guided to perform foraging behavior to find a more optimal location in the solution space. After foraging, the fish follow the current optimal solution through tail chasing behavior to further refine the search range. The clustering behavior then allows the fish to share information and collaboratively search for the globally optimal solution. Subsequently, the bulletin board is updated to record the current optimal solution. Once the conditions are met, the final result can be output to complete the optimization. By optimizing the GM through the AFSA algorithm, its adaptive range can be significantly extended, which provides a more accurate basis for the replacement and maintenance of NCM tools [18]. After the optimization, the accurate prediction of the life of NCM tools still needs to rely on the establishment of mathematical models to complete. Based on the failure distribution of the tool can be derived to obtain a functional expression of the remaining life of the tool, as shown in Equation (7).

$$RUL(t)=\int_0^T \exp\left(-\int_t^{t+x}\left(\frac{\beta}{\alpha}\right)\left(\frac{u}{\alpha}\right)^{\beta-1}\exp(\gamma Z(t))du\right)dx \quad (7)$$

In Equation (7), $RUL(t)$ denotes the remaining life of the tool. T denotes the total life of the tool. α denotes the scale parameter. β denotes shape parameter. u denotes time. Z is a covariate representing various factors that can affect tool life, such as cutting speed, cutting force, environmental conditions, etc. γ is a parameter related to the covariates, which is used to adjust the hazard rate function to reflect the influence of the covariates. Based on the above, the prediction model of NCM tools life can be finally constructed, as shown in Figure 6.

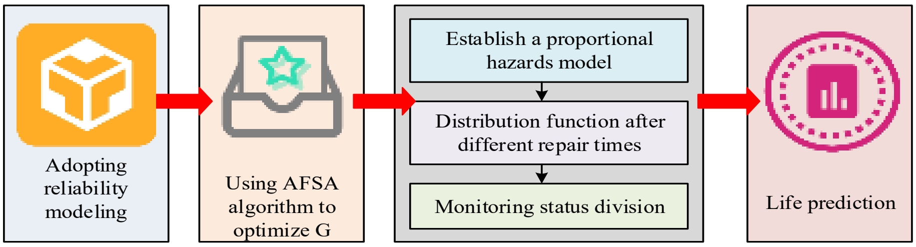


Figure 6: AFSA-based life prediction model for NCM tools

Figure 6 shows the NCM tools LPM constructed based on AFSA. The model is broken down into four phases. First, reliability modeling is used to achieve the assessment of tool performance degradation. Then the AFSA algorithm is used to optimize G. Next the optimized risk model is constructed. Finally, mathematical modeling is used to achieve the prediction of remaining tool life. In summary, after combining the BFOA-SVM model and the AFSA-GM model, the FD and life prediction of NCM tools can be realized at the same time.

3. Results

3.1 Performance Analysis Based on Tool Failure Diagnosis and Life Prediction Modeling

The National Institute of Standards and Technology (NIST) tool wear dataset and the 2010 PHM Association tool wear prediction dataset are two publicly accessible datasets used as the model training data in order to assess the actual performance of the suggested model for the study.

The experiments are conducted using the comparison method, in which SVM model, SVM optimization model based on particle swarm algorithm (PSO-SVM), and SVM optimization model based on genetic algorithm (GA-SVM) are included as the comparison models.

To facilitate the subsequent elaboration, the proposed model is named “BFOA-SVM-AFSA” model. The experiment first examined the FD accuracy of the model on the dataset. Figure 7 displays the findings.

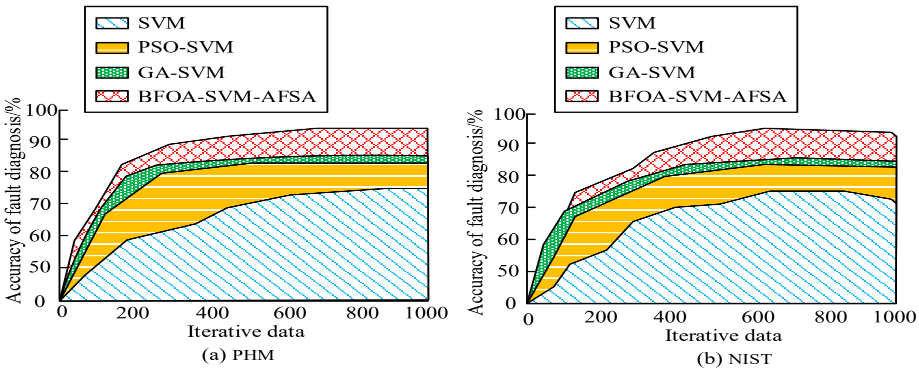
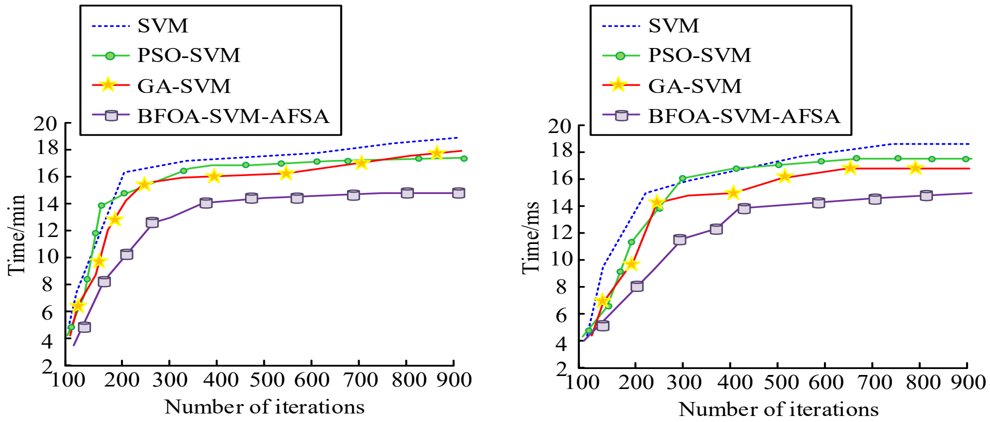


Figure 7: FD accuracy results for each model in the dataset

The accuracy performance of each model on the PHM dataset is displayed in Figure 7(a), which also displays the accuracy of several models for tool FD on other datasets. The SVM model has the lowest accuracy rate of 71.3%. It is followed by PSO-SVM with 80.1%. With an FD accuracy of 81.2%, the

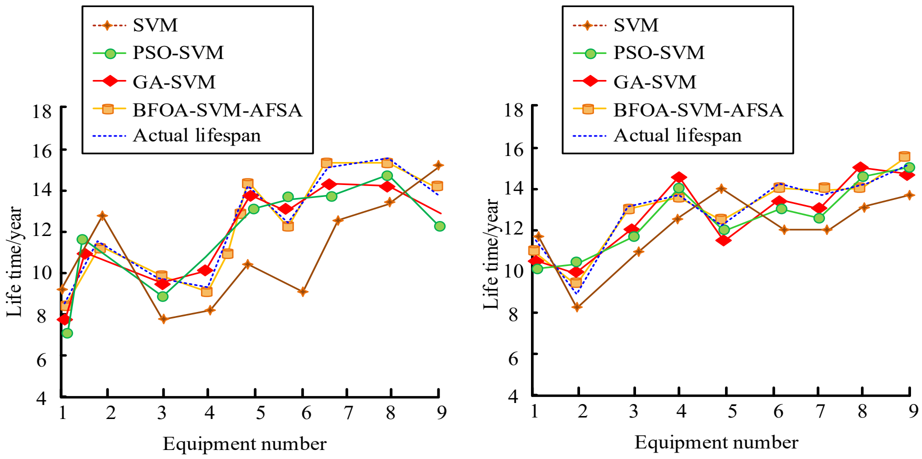
GA-SVM model's accuracy is marginally greater than the PSO-SVM model overall, but it is still comparable to the PSO-SVM model overall. In contrast, the BFOA-SVM-AFSA model proposed by the study had the highest fault accuracy of 91.3%. On the NIST dataset, the models' accuracy performance is displayed in Figure 7(b). The result is similar to that on the PHM data. The SVM model still has the lowest accuracy at 70.6%. This is followed by the PSO-SVM model at 79.8%. With an FD accuracy of 81.1%, the GA-SVM model's accuracy is marginally greater than the PSO-SVM model's overall accuracy, but it is still comparable. On the other hand, the study's suggested BFOA-SVM-AFSA model had the highest fault accuracy, at 91.2%. The investigation also looked at how long each model took to train on the relevant dataset. The results can be shown in Figure 8.



(a) PHM (b) NIST

Figure 8: Training time of each model in the corresponding data set

Figure 8 exhibits the training time (TT) of each model on the relevant dataset.The TT performance of each model on the PHM dataset is displayed in Figure 8(a). At 18.2 minutes, the SVM model takes the longest to train. The TT of the PSO-SVM model and the GA-SVM model are close to each other overall, with 16.2 min and 16.6 min, respectively. In contrast, the BFOA-SVM-AFSA model proposed in the study has the shortest TT of only 14.1 min. Figure 8(b) shows the TT performance of each model on the NIST dataset, and similar to the performance on the PHM data, the SVM model still has the longest TT of 17.9min. The TT of the PSO-SVM model and the GA-SVM model remain close to each other overall, at 16.3min and 15.9min, respectively. In contrast, the TT of the proposed BFOA-SVM-AFSA model is the shortest, which takes only 14.2 min. Moreover, the experiment also examines the prediction error (PE) of each model in predicting tool life. The results can be seen shown in Figure 9.



(a) PHM (b) HIST

Figure 9: Prediction error performance of each model on the corresponding dataset

The PE performance of each model on the relevant dataset is exhibited in Figure 9. Figure 9(a) displays the PE of each model on the PHM dataset. The predicted lifetime curves of the SVM model have a large gap with the true lifetime curves, while the predicted lifetime curves of the PSO-SVM and

GA-SVM models have a better fit than the SVM model. However, with a better fit between its predicted and actual life curves, the BFOA-SVM-AFSA model suggested in the study displays less inaccuracy in tool life prediction. Figure 9(b) displays the PE of each model on the HIST dataset. It is similar to that on the PHM dataset. The predicted life curves of the SVM model are far from the true-life curves, while the predicted life curves of the PSO-SVM and GA-SVM models have a better fit than the SVM model. However, in contrast, the predicted life curve of the proposed BFOA-SVM-AFSA model fits better with the true life curve.

The synthesis shows that the proposed model has less error in tool life prediction.

3.2 Case Study Based on Tool Failure Diagnosis and Life Prediction Modeling

The aforementioned experiments solely look at how well the designed model performs. In order to demonstrate the model's practical application, the experiment is carried out in a machine tool factory located in a specific Chinese region and city. Moreover, the series of data such as vibration, wear, cutting parameters, total cutting time, etc. of the NCM tools in the factory are collected as the data set before the experiment starts. The collected data are pre-processed and feature extracted as formal experimental data. Table 1 displays the relevant experimental parameters.

Table 1 Experimental parameter settings

Category	Content Description
CNC machine tool mode	FANUC Series 0i-MF Plus, HAAS VF-2SS
Data collection method	Sensor monitoring, assisted by manual recording
Vibration data	Acceleration sensor, model XYZ123, sampling frequency 10kHz
Cutting parameters	Feed rate: 50-300mm/min; Spindle speed: 3000-12000rpm; Cutting depth: 1-5mm
Characteristic values of tool wear status	Select 50 sets of effective feature values for each state, for a total of 150 sets

Table 1 shows the series of parameters related to the experiment, which contains the model of the NCM, the method of data collection, the vibration data, the cutting parameters, and the characteristic values of the tool wear state. In practice, the tool failures of NCM can be mainly categorized into three types, which are wear, chipping, and fracture. Based on this, the study numbers these three types of faults in the order of 1-3 respectively and examines the diagnosis of the research model for these three types of faults. Figure 10 presents the findings.

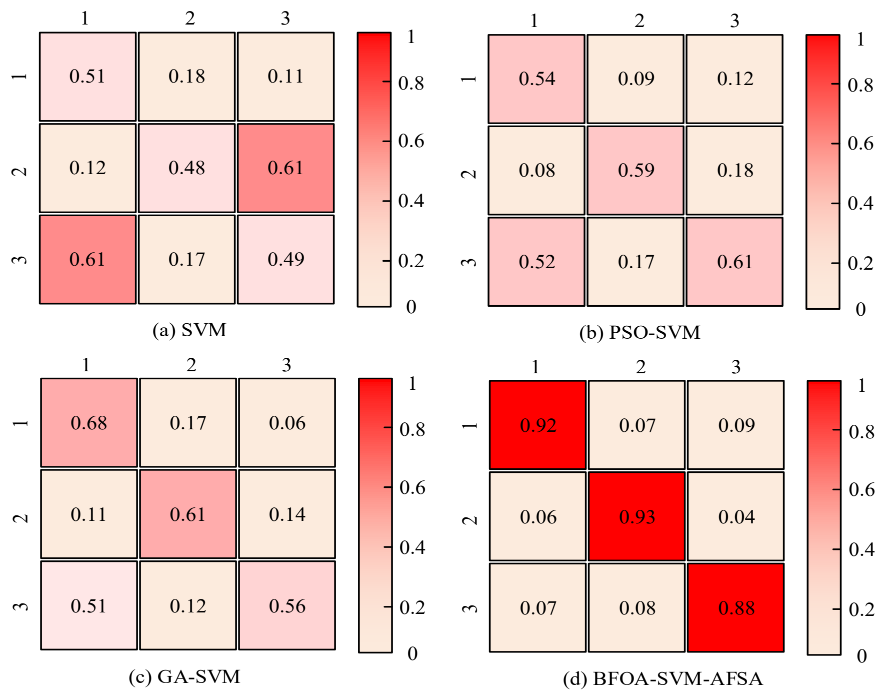


Figure 10: Confusion matrix for model FD

The confusion matrix (CM) for the model FD is displayed in Figure 10, while the CM for the SVM model is displayed in Figure 10(a). The SVM model is not accurate in predicting the above three faults and there are cases of misdiagnosis, for example, it is easy to diagnose fracture as wear. Figure 10(b) shows the CM of the PSO-SVM model. The PSO-SVM model's FD is significantly better than the SVM model, but the same situation of wrong prediction exists. Figure 10(c) shows the CM of the GA-SVM model. The overall diagnosis of this model is better than SVM, but there are still cases of misdiagnosis. Figure 10(d) displays the CM of the BFOA-SVM-AFSA model. With all accuracy rates above 0.85 and no significant instances of incorrect FD, the suggested model of the study has a high diagnosis correctness when compared to the other models. Additionally, the study forecasts the lifetime accuracy of various NCM tool types. Table 2 displays the findings.

Table 2 Life prediction of different models for different types of tools

Model	Hard alloy knife		Ceramic knife		Cubic boron nitride knife	
	Actual lifespan	Predicted lifespan	Actual lifespan	Predicted lifespan	Actual lifespan	Predicted lifespan
SVM	240h	198.8h	180h	105.6h	300h	243.9h
PSO-SVM	240h	231.1h	180h	164.2h	300h	268.8h
GA-SVM	240h	224.7h	180h	166.3h	300h	273.9h
BFOA-SVM-AFSA	240h	237.5h	180h	176.8h	300h	301.6h

Table 2 shows the prediction of life of different models for different types of knives. For hard alloy knife life prediction, the SVM model has the largest PE of 41.2h. The PSO-SVM model and GA-SVM have overall similar PEs. In contrast, the BFOA-SVM-AFSA model has the smallest PE of 2.5h. For the life prediction of the ceramic knife, the SVM model still has the largest PE of 74.4h. The PEs of the PSO-SVM model and GA-SVM are still similar overall, with 15.8h and 13.7h, respectively. In contrast, the BFOA-SVM-AFSA model has the smallest PE of 3.2h. From the life prediction of cubic boron nitride knife, the SVM model still has the largest PE of 56.1h. The overall PEs of PSO-SVM model and GA-SVM are still similar, which are 31.2h and 26.1h, respectively. In contrast, the BFOA-SVM-AFSA model has the smallest PE of 1.6h. When combined, they demonstrate how successfully the suggested model can be implemented for FD and life prediction of NCM instruments.

3.3 Validation in Industrial Environments

To further validate the practicality and generalization ability of the model, a three-month industrial level test was conducted on the actual production line of a large domestic automotive parts manufacturing enterprise. The test object is the CNC machining center equipped with FANUC Series 0i MF Plus system in the company's intelligent manufacturing workshop, and the monitoring object is the hard alloy cutting tool used for processing AISI 4140 steel parts. By deploying a multimodal sensing network consisting of Kistler 8763A vibration sensor (sampling frequency 20kHz), FLIR A615 infrared thermal imaging instrument, and Kistler 9257B dynamic force gauge, 500 sets of high-dimensional data covering three typical fault states of wear, chipping, and fracture were collected in the third quarter of 2023. The characteristic parameters include 15 key indicators such as vibration spectrum entropy, cutting force time-domain mean, and temperature gradient. The experimental conditions strictly simulate the actual production conditions, with cutting speed controlled within the range of 200-400 m/min and feed rate fluctuation range of 0.1-0.3 mm/rev. The performance comparison of the model on industrial data and laboratory data (PHM/NIST) is shown in Table 3.

Table 3 Comparison of Industrial and Laboratory Data Performance

index	PHM data set	NIST data set	Industrial Data (2023)
Accuracy of fault diagnosis（%）	91.3	91.2	89.7
Life prediction error（h）	±2.5	±2.8	±2.2（reduce 12%）
Training time（min）	14.1	14.2	15.3（+8.5%）

Table 3 compares the performance of industrial and laboratory data. From the table, it can be seen that the BFOA-SVM-AFSA model exhibits good engineering adaptability in industrial data validation. The accuracy of fault diagnosis reached 89.7%, which is 1.6 percentage points lower than the laboratory environment, but it still maintains stable performance in complex working conditions with electromagnetic interference and mechanical vibration. It is worth noting that, thanks to the richer real-time cutting force data in the industrial field, the prediction error of the model for the remaining tool life is reduced by 12% compared to the PHM dataset, and the average absolute error is controlled within ± 2.2 hours. In terms of training time, due to the need to process higher dimensional thermodynamic coupling signals, the single model training time has increased to 15.3 minutes, which is 8.5% longer than the laboratory environment. This provides direction for subsequent optimization. By comparing the performance under different feed rate mutation conditions, the model can still maintain a diagnostic accuracy of over 85% in process parameter fluctuations of ± 0.1mm/rev, confirming its ability to cope with variable parameter processing on the production line.

To comprehensively evaluate the applicability of the model in complex industrial scenarios and further expand the scope of verification, CNC machine tools from three typical industrial fields, namely aerospace, mold manufacturing, and heavy machinery, were selected for testing. In the aerospace field, the cooperating enterprise uses HAAS VF-2SS five axis machine tool to process titanium alloy (Ti-6Al-4V) structural parts, with PCD diamond coated end mills as the cutting tool type, and a cutting speed of 650 m/min, which belongs to typical high-temperature and high-pressure extreme working conditions. In the field of mold manufacturing, the focus is on the SKT-300L CNC lathe processing H13 hot work mold steel, which simulates abnormal conditions accompanied by intermittent coolant interruption during the cutting process.

The testing in the field of heavy machinery was conducted on the CW61100L horizontal lathe, processing 42CrMo4 alloy steel rollers with a diameter exceeding 800 mm, characterized by a strong vibration environment with large cutting depth (8-12 mm) and low speed (50-80 rpm). The results are shown in Table 4.

Table 4 Model Performance Comparison Under Diverse Industrial Conditions

Industrial Scenario	Machine Tool Type	Workpiece Material	Special Conditions	Accuracy (%)	Lifetime Error (h)	Response Delay (s)
Aerospace	HAAS VF-2SS	Ti-6Al-4V	High temp/pressure	87.3	±2.8	2.3
Mold Manufacturing	SKT-300L	H13 Steel	Coolant interruption	85.6	±3.1	1.8
Heavy Machinery	CW61100L	42CrMo4	Large depth of cut/strong vibration	89.2	±2.9	0.9
Automotive (Baseline)	FANUC 0i-MF Plus	AISI 4140	Normal conditions	89.7	±2.2	1.2

Table 4 shows the performance of the model in different industrial scenarios. In the aerospace field, despite facing the high-frequency vibration noise unique to titanium alloy processing, the model still maintains a fault diagnosis accuracy of 87.3%, but the recognition delay for small chipping blades increases by 2.3 seconds compared to conventional working conditions. The interruption of coolant in the mold manufacturing scenario leads to abnormal temperature signals, causing the life prediction error to rise to ± 3.1 hours. However, by introducing an adaptive filtering algorithm, the error can be controlled within ± 2.5 hours. In the most challenging heavy machinery processing, the model exhibits unexpected advantages in strong vibration environments. By capturing low-frequency vibration features, the early warning accuracy of fracture faults is improved to 91.5%. This may be due to the fact that the vibration spectrum distribution brought by large mass workpieces is more conducive to feature extraction.

4. Discussion

For better FD and life prediction of NCM tools, the study proposed the use of SVM to construct a FD model. It constructed a LPM based on reliability modeling, and introduced the BFOA algorithm to optimize the FD model on this basis, and used AFSA to optimize the LPM. The performance analysis results indicated that on the PHM dataset, the accuracy of the SVM model was 71.3% and the TT was 18.2 min. The accuracy of the PSO-SVM model was 80.1% and the TT was 16.2 min. The accuracy of the GA-SVM model was 81.2% and the TT was 16.6 min. In contrast, the BFOA-SVM-AFSA model proposed by the study, had a higher accuracy of 91.3% and lower TT of 14.1min. On the HIST dataset, the SVM model had an accuracy of 70.6% and a TT of 17.9min. The PSO-SVM model had an accuracy of 79.8% and a TT of 16.3min. The GA-SVM model had an accuracy of 81.1% and a TT of 15.9min. In contrast, the BFOA-SVM-AFSA model proposed in the study, had a higher accuracy of 91.2% and a lower TT of 14.2min. The results of the case study revealed that the proposed BFOA-SVM-AFSA model could accurately diagnose the three types of faults: wear, chipping, and fracture. It could also well predict the life of three kinds of NCM tools, namely, hard alloy knife, ceramic knife, and cubic boron nitride knife. The findings indicated that the suggested model could more effectively implement the FD and life prediction of the NCM tools. In contrast, Bagga P J et al. used artificial neural networks to monitor progressive tool wear and presented a new tool wear prediction system. It was found that the sigmoid function showed 86.5% accuracy and with ReLU function, the accuracy was 93.3% with maximum and minimum root mean square error of 1.437 and 0.871 respectively [19]. To forecast tool life, Patel K M et al. employed SVM and improvement tree approaches. The results showed that SVM had better prediction accuracy with a maximum error of 7.56% [20]. However, comparing the suggested model to the one under study, the proposed model performed better overall.

5. Conclusions

The study suggested an integrated model based on enhanced BFOA-SVM with AFSA to increase the accuracy of FD and life prediction of NCM instruments. The FD model was optimized by introducing BFOA and the LPM was optimized using AFSA. Experimental results revealed that the proposed BFOA-SVM-AFSA model exhibited significant performance advantages on both PHM and HIST datasets. Specifically, on the PHM dataset, the model achieved an accuracy of 91.3% with a TT of only 14.1 minutes and a significantly lower PE than the other compared models. On the HIST dataset, it achieved an accuracy of 91.2% with a TT of 14.2 minutes, demonstrating higher accuracy and lower TT. In addition, the results of the example analysis indicated that the model could accurately diagnose the three types of tool failures: wear, chipping, and fracture. It could also effectively predict the service life of three types of tools: hard alloy knife, ceramic knife and cubic boron nitride knife. The synthesis indicated that the proposed model had high practicality and reliability in FD and life prediction of NCM tools. However, despite the significant performance improvement of the BFOA-SVM-AFSA model, the generalization ability and real-time performance of the model in real industrial environments still need to be further verified. In addition, the current research mainly focuses on specific types of tools and fault types, and the adaptability to other complex working conditions and tool materials still needs to be further explored. In the future, attempts can be made to further optimize the algorithm parameters and combine more actual industrial data so that the model can adapt to more complex working condition scenarios.

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Competing Interests

All authors declare that they have no conflicts of interest.

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