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# FAULT DIAGNOSIS OF CNC MACHINE TOOLS BASED ON SUPPORT VECTOR MACHINE OPTIMIZED BY GENETIC ALGORITHM

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**Abstract.** To enhance the accuracy of CNC machine tool fault diagnosis, this study proposes an intelligent optimization method based on the combination of Particle Swarm Optimization (PSO) and Bacterial Foraging Algorithm (BFA), referred to as PSO-BFA. By simulating the local foraging behavior of bacteria, the PSO-BFA algorithm demonstrates characteristics of local convergence, replicability, and migratory properties during parameter selection, effectively improving the local optimization capability and fitness value of the model. This leads to faster convergence to the optimal solution in the fault data training process. The study utilizes a Deep Confidence Network (DCN) model, known for its strong adjustability of model structure, for training the fault feature set. The PSO algorithm is employed to search for the optimal value in the global range. Simulation data indicate that the PSO-BFA intelligent optimization method significantly outperforms traditional swarm intelligence methods in multi-fault diagnosis and classification, achieving the peak fitting value in fewer iterations.

**Key words:** CNC, PSO-BFA; local optimization; migratory properties

**1. Introduction.** Modern manufacturing organizations rely heavily on CNC (Computer Numerical Control) machine tools as their primary equipment due to their advanced capabilities in mechanical manufacturing technology, automatic control technology, signal control technology, and computer science. With increasing demands for precision and processing efficiency in machining products, the automation level of CNC machine tools has risen significantly [1, 2]. However, the structural complexity of these tools also increases the risk of failure, reducing their reliability and potentially leading to significant financial losses and safety hazards for operators. A sudden breakdown during high-speed operations can result in severe consequences, making real-time fault diagnosis and monitoring essential.

Fault diagnosis techniques for CNC machine tools have traditionally relied on detecting and analyzing fault signal characteristics, fuzzy reasoning, and other methods. However, as fault data sets grow larger, noise interference can lead to a decline in diagnostic accuracy, making it difficult to meet online monitoring requirements. To address these challenges, this paper proposes a hybrid intelligent optimization method combining Particle Swarm Optimization (PSO) and Bacterial Foraging Algorithm (BFA), referred to as PSO-BFA [3, 4].

The primary objective of this study is to enhance the accuracy and efficiency of fault diagnosis for CNC machine tools by leveraging the strengths of PSO and BFA algorithms [5, 6]. PSO is known for its global optimization capabilities, but it often struggles with local optimal solutions. BFA, on the other hand, mimics bacterial foraging behavior to achieve local optimization, enhancing the ability to adjust model parameters dynamically. By integrating these two algorithms, the PSO-BFA method aims to improve the local and global optimization capabilities of the fault data training model, leading to higher diagnostic accuracy and faster convergence to optimal solutions.

In this study, a Deep Confidence Network (DCN) model is selected for training the fault feature set due to its strong adjustability and effectiveness in handling large-scale data. The PSO algorithm is used to search for optimal values across the global range, while the BFA algorithm focuses on local optimization to avoid falling into local optima [7, 8]. The hybrid PSO-BFA approach allows for faster and more accurate parameter selection, reducing optimization time and improving the overall fault diagnosis process.

This paper is organized as follows: Section 2 describes the optimization of PSO-BFA swarm intelligence algorithm parameters. Section 3 presents the application of the PSO-BFA algorithm in online problem diagnosis

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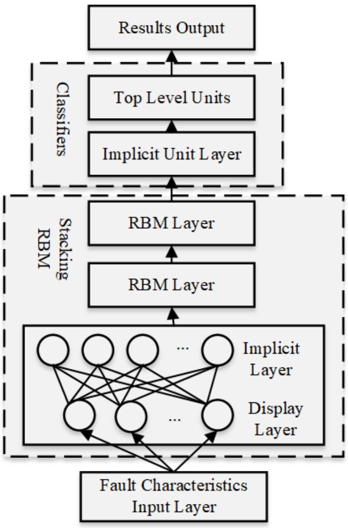


Fig. 2.1: CNC machine tool defect feature set training process.

for CNC machine equipment. Section 4 discusses the types and diagnoses of faults in CNC machine tools, along with an analysis of training samples for fault phenomena and diagnostic convergence effects. Finally, the study's conclusions and future research directions are outlined.

By improving the fault diagnosis techniques for CNC machine tools through the PSO-BFA intelligent optimization method, this research aims to significantly enhance the reliability and efficiency of CNC machine tool operations, ultimately contributing to the advancement of modern manufacturing technologies [9].

**2. Optimizing PSO-BFA swarm intelligence algorithm's parameters.** In this paper, we select the deep confidence network model with stronger adjustability of model structure among existing large-scale fault data training methods, such as production adversarial network model [10, 11, 12, 13], convolutional neural network model [14], and deep confidence network model [15]. The main component of fault feature set training is model parameter optimization and adjustment, which enhances the fault set training model's capacity for both local and global optimization and, eventually, raises the diagnostic accuracy of machine tool failures. By combining the benefits of the BFA and PSO group intelligence algorithms, the PSO-BFA intelligent optimization algorithm selects the model parameters more quickly, accurately, and with a shorter optimization time. There is a reduction in the amount of time needed for optimization, more accuracy, and speedier parameter selection. The structural design of the deep confidence network model is depicted in Fig. 2.1. The deep confidence network is composed of multiple RBMs stacked (restricted Boltzmann machines) that process the bottom layer input data [16]-[17], intermediate hidden layer data training, and top layer unit output training results.

Due to its high global optimization capabilities, the PSO algorithm has an advantage in the parameter optimization and training model selection processes. Assuming that each solution in the D-dimensional space of the defect feature set is a particle, the total number of $n$ , as well as the starting velocity and position of the $i$-th particle, are represented as follows:

$$\left\{ \begin{array}{l} l_i = (l_{i1}, l_{i2}, \cdots, l_{iD}), i = 1, 2, \cdots, n; \\ v_i = (v_{i1}, v_{i2}, \cdots, v_{iD}), i = 1, 2, \cdots, n_{\circ} \end{array} \right. \tag{2.1}$$

The th particle's inertia weight is $\omega$ , and the learning factors are $\kappa_1$ and $\kappa_2$, both in the interval [0, 1]. These factors initialize the population particles' location and velocity, of which the global ideal position is $L_g$ , and the individual optimal position is $L_i$.The particles move in space at a specific speed, and in order to achieve the global optimization in the range, they dynamically adjust their own velocity and the present occupied position based on their own and other people's movement experiences. The following describes the procedure used to update the ith particle's position and velocity at the $k+1$st moment:

$$\left\{\ l_i^{k+1}=l_i^k+v_i^{k+1}\right. \tag{2.2}$$

where the model's random number is represented by rand. According to the particle swarm population size to determine the proper fitness function, calculate the fitness value of the particles in the swarm and compare it with the global optimal extreme point.The BFA algorithm is combined with the traditional PSO algorithm in this paper to optimize and enhance the parameters of the confidence network model. While the PSO algorithm can achieve optimization in the global range, it is prone to settling into the local optimal solution.The foundation of the BFA algorithm is the idea of mimicking the foraging behavior of bacteria in order to accomplish local optimization. The basic idea behind the BFA algorithm is to mimic bacterial foraging in order to accomplish the goal of local optimization. The PSO algorithm's population particles are attributed to the foraging role of bacteria, meaning that they possess the traits of migration, replicability, and convergence.Individual bacteria are capable of local optimization seeking, which allows them to swim to the local enriched zone and modify the fitness value target in real time.In the PSO-BFA algorithm, the jth convergence operation process of particle $i$is represented by$\eta_i\left(j,k,l_j\right)$, the number of replication operations is indicated by$k$ , and particle $i$'s current fitness value is $J_i\left(j,k,l_j\right)$.Assuming that particle$i$'s movement direction and moving step size are represented by the symbols$\varphi(i)$and$c(i)$, we can represent particle $i$'s single convergent operation as follows:

$$\left\{\ \eta_i\left(j+1,k,l_j\right)=\eta_i\left(j,k,l_j\right)+\varphi(i)\times c(i)\right. \tag{2.3}$$

The PSO-BFA algorithm's population particles have bacterial pheromone detecting capabilities, which allows them to detect the nutritional data that other particles near individual $i$ are carrying. One benefit of the PSO-BFA algorithm is its localized sensing capacity. The benefit of local sensing is that it can maintain a healthy spacing between particle people and prevent population members from being very dense in one area. By determining the distance between all nearby particles—that is, all particles in the population—particle $i$ gathers and sends nutritional information to the outside world. This mechanism is explained as follows:

$$\zeta\left(\tau,\eta_i\left(j,k,l_j\right)\right)=\sum_{i=1}^{n}\left[-\zeta_{att}\exp\left(-w_{att}\sum_{k=1}^{m}\tau_m-\tau_m^i\right)^2\right]+\sum_{i=1}^{n}\left[-\zeta_{rep}\exp\left(-w_{rep}\sum_{k=1}^{m}\tau_m-\tau_m^i\right)^2\right] \tag{2.4}$$

where $\tau$ is the composite pheromone of particle transfer information, which comprises the current particle's position, direction, and velocity, among other details; The gravitational depth between particles is represented by $\zeta_{att}$, the repulsive depth by $\zeta_{rep}$, the gravitational width by $w_{att}$, and the repulsive width by $w_{rep}$. The PSO-BFA technique is able to realize the local optimization of the adjustment of the training parameters of the defective dataset of the machine tool of the deep confidence network model by utilizing the group sensing mechanism between particles [18]-[19].

**3. Online problem diagnosis for CNC machine equipment.** The PSO-BFA algorithm is used to locally search all population particles for a certain amount of time. The natural evolutionary law of organisms states that certain individuals are removed if they cannot locate adequate food or are in an unfavorable location [20]. A population's convergent behavior—in which the total individual fitness of the population is used to determine its activity level—must periodically be confirmed, even if healthy individuals will replicate to maintain the number of active individuals in the population. The BFA technique allows for local optimization and prevents parameter selection from falling into local optimal solutions, whereas the standard PSO algorithm excels in global optimization. The formula for the movement speed of the population particles defines the traveling direction of the entire population as well as the optimization process. The moving speed $V$ of the population at the $k+1$-th moment is given as follows:

$$V=\omega v_i^{k+1}\zeta\left(\tau,\eta_i\left(j,k,l_j\right)\right)+\kappa_1 rand()\left(L_i^k-l_i^k\right)+\kappa_2 rand()\left(L_g^k-l_i^k\right) \tag{3.1}$$

Following the implementation of the BFA algorithm for local step update, the most recent position is indicated as follows:

$$L_g^{k+1}=V+L_{g^\circ}^k \tag{3.2}$$

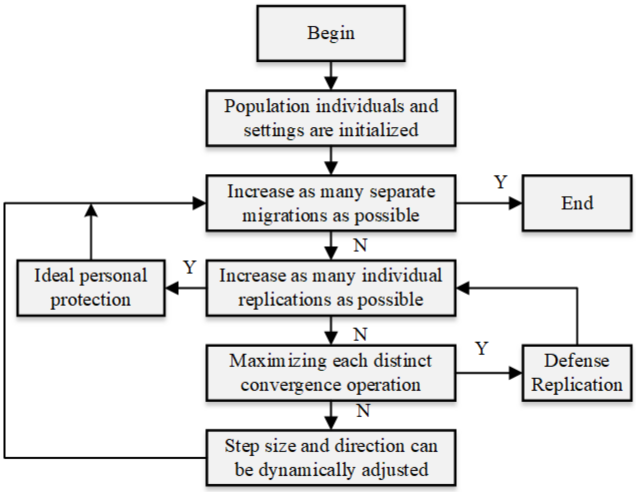


Fig. 3.1: Local parameter optimization of the PSO-BFA algorithm procedure.

Throughout the population migration process, the PSO-BFA algorithm will be assigned a probability value $p_0$. In order to prevent falling into the optimal solution during the local optimization, the migration operation of the population individuals will only be carried out at this point if the probability of the random number selection is lower than $p_0$ during the individual migration.In order to prevent the population from growing as a result of individual elimination and situations involving individual reduction and return, the PSO-BFA algorithm also considers the particle swarm global search optimization problem during local optimization. This ensures both the accuracy of global optimization and the velocity of movement. Fig.3.1 illustrates the specific parameter optimization process[21].

The individual convergence operation's goal is to filter out the best individuals from the current population. The immune replication link is the essential component of the fault data training model's parameter optimization process [22]. In order to determine whether or not the global optimum has been reached, the following steps are taken: first, the fitness value of each individual is calculated; second, the excellent individuals are replicated in order to maintain the population's size; and third, the immunoreplicated population's overall fitness is optimally calculated. The traditional BFA methodology is optimized by the use of immunoreplication. In the standard BFA mode, the individuals are sorted according to their fitness values, and the locations of the reproduced individuals are the same as the original ones, i.e., the placements of the people are not optimized, but only the fitness values of the individuals are improved. In contrast, in the immunological replication mode, the replication of individuals is based on convergence, and the particle population individuals have strong foraging capacity following replication and high-frequency mutation[23]. To fulfill the goal of individual local optimization searching, its place within the population is further optimized. The replication target was selected from among the elite individuals with the highest degree of adaptability[24]; n/2 replicated individuals in total. Here, the individual adaptability values were computed for every member of the population following replication and mutation. Start the cycle processing for individual migration number maximization, replication number maximization, and individual convergence operation maximization. Once the BFA algorithm has been improved to an optimal level, each particle swarm individual is given the ability to search for optimization, which includes both direction and step length control. This means that each particle swarm member will swim towards the local nutrient-rich region until its fitness value stops increasing, at which point its local optimization-seeking will have found the best solution.

$$\left\{ \eta_{\max}\left(j+1, k, l_n\right) = \eta_n\left(j, k, l_n\right) + \varphi(i) \times c(i) \right. \tag{3.3}$$

At this point, the population particles' local convergence operation reaches its peak $\eta_{\max}\left(j+1, k, l_n\right), \varphi(i) \times c(i)$ value and begins to drift toward zero. When the individual convergence operation reaches the optimum,

Table 4.1: A portion of the set related to the failure of CNC machine tools.

| No. | Warning Indications of Failure | No. | Warning Indications of Failure |
|---|---|---|---|
| 1 | Non-functioning spindle motor | 6 | There is no spindle lubricant circulation |
| 2 | Erratic motor speed | 7 | The servo motor is broken |
| 3 | Rotation of the spindle stops | 8 | axis tremor when cutting |
| 4 | Heating of the spindle | 9 | harm to electrical parts |
| 5 | Upon severe cutting force, the spindle stops | 10 | Electrical parts can burn out, smoke and catch fire, or overheat. |

Table 4.2: A portion of the set related to the failure of CNC machine tools.

| No. | Warning Indications of Failure | No. | Warning Indications of Failure |
|---|---|---|---|
| 1 | The enable signal is not connected correctly | 8 | Ball Screw Sub-Gap |
| 2 | The knife frame itself failing | 9 | Overly |
| 3 | faulty connection in the electrical wiring | 10 | Interference |
| 4 | Inadequate motor performance or personal error | 11 | Inadequate lubrication |
| 5 | Zero switch lacks sensitivity | 12 | Connecting wires and the encoder |
| 6 | unreasonable parameter configuration | 13 | Negative |
| 7 | Insecure connections | 14 | Overload |

the local fitness value of the individual is no longer increased on the elite individuals to replicate and mutate to better optimize the population. If the individual convergence operation is not maximized, to continue adjusting the step size and direction of the individual until the local optimum is reached.The optimized population's convergence performance is finally confirmed. Population $A_0$ has $n$ active population members in total. The immune-immune space geometry for any given initial state of the population is $I^*$. There are $N$ optimal solutions in total for the population, and the set of optimal solutions is $B_N^*$. This means that the numerical training parameter search for fault characteristics finds the optimal solution both locally and globally when the following probability distribution conditions are met:

$$\lim P\left[\eta(N)1 \mid \eta(0)=A_0\right]=1 \tag{3.4}$$

The population members in the local and global scope are in a state of quasi-optimality when the algorithm cyclically replicates and adjusts for convergence. At this point, the PSO-BFA algorithm's optimal parameter selection also tends to converge, allowing the depth of the confidence network to be utilized for fault feature recognition and data training.

**4. Types and diagnoses of faults in CNC machine tools.** The machinery industry has made extensive use of CNC machine tools, and as a result, maintenance and repair work on these tools has grown in importance. In order to improve the maintenance efficiency of CNC machine tools, maintenance level and fault diagnosis rate, row of CNC machine tool system failure is one of the important tasks in the occurrence of CNC machine tool failure, the failure of the triggering factors for judgment and assessment, so as to facilitate the accurate determination of the location of the fault occurred in a timely and effective way to take appropriate fault diagnosis measures for fault repair [22]. Table4.1 and 4.2 illustrate frequent failure phenomena and triggers for CNC machine tools.

**4.1. Analysis of training samples for fault phenomena.** The experimental apparatus is a CNC lathe, model number CAK6150. Common fault indications and root causes are categorized, and the likelihood of faults occurring is mined and fed into an SSA-BP neural network. Owing to the wide range in fault frequency, the diagnostic method generates a grade for the fault indications that is classified as high, medium, or low. The particular outcomes are displayed in Fig. 4.1. The cause-and-effect relationship between common faults and machine tool processing repetition should be understood in light of the information presented in Fig. 4.1. As an illustration, consider the spindle frequent defects.

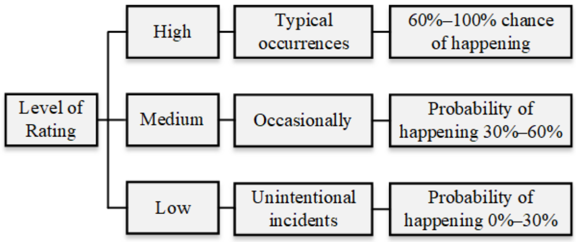


Fig. 4.1: Chance of a fault occurring.

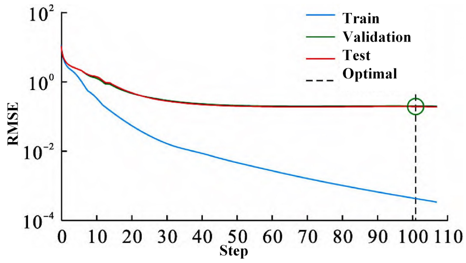


Fig. 4.2: BP Neural Network Convergence.

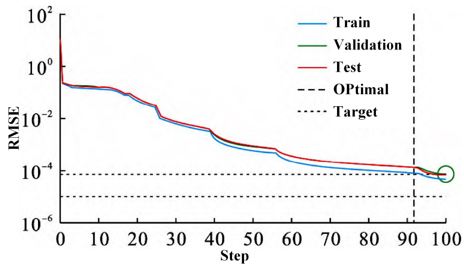


Fig. 4.3: SSA-BP neural network convergence.

**4.2. Diagnostic Convergence Effect Comparison.** The BP neural network's convergence is depicted in Fig. 4.2. The substantial simulation error, poor iterative convergence impact, and large error oscillation phenomenon of the conventional BP network on frequent failures of CNC machine tools.

Fig. 4.3 illustrates the SSA-BP neural network convergence after it was trained using MATLAB software and retested utilizing the CNC machine tool defect data that occurred under real-world operating conditions as the network sample set. How the SSA-BP neural network can achieve a 100 iteration effect. Its convergence speed is faster and its convergence curve is smoother than that of the regular BP neural network.

Fig. 4.4 shows the prediction fault output error of the SSA-BP neural network. The SSA-BP neural network prediction error, which is 2.29%. This is quite near to the theoretical output, which is the expected effect corresponding to the theoretical deviation. In comparison to a typical BP neural network, the prediction fault output error of the SSA-BP neural network is smaller.

**4.3. Defect Recognition.** The moment of occurrence of each transient in the vibration signal is converted into a series of sparse representation coefficients using this approach of sparsely representing the vibration signal. This allows for the identification of transients and the diagnosis of automatic tool change system defects. Fig. 4.5 displays the appropriate ideal dictionary atom.

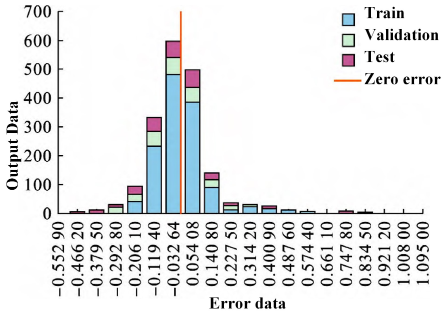


Fig. 4.4: A neural network with SSA-BP predicts fault output error.

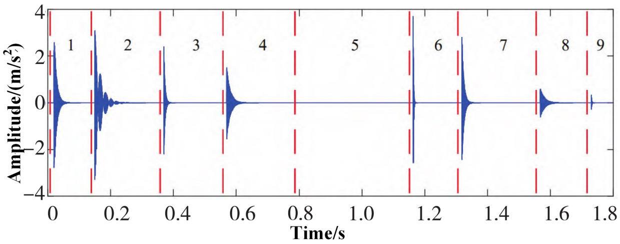


Fig. 4.5: Ideal dictionary atoms.

Fig. 4.6 displays the results of the sparse representation achieved by the proposed method in this chapter. The tool-changing timing diagram's results are largely consistent with the occurrence moments of each transient, which can be obtained from Fig. 4.6. The accuracy of the extracted time intervals of the neighboring transients is very high, as evidenced by the mere 0.7% relative error. Fig.4.6demonstrates how the technique can successfully pinpoint each tool change vibration signal transient's moment of occurrence and extract the properties of nearby transients.

**5. Conclusion.** This research suggests a PSO-BFA-based intelligent optimization technique. In order to enhance the adaption value and the local optimization capability of model parameters, the BFA algorithm is presented to replicate the local foraging behavior of bacteria. The fault data training model chooses a deep confidence network model with customizable scale. The suggested approach performs noticeably better than the conventional technique in terms of multi-fault classification and diagnosis capacity, according to simulation findings.

**Data Availability.** The experimental data used to support the findings of this study are available from the corresponding author upon request.

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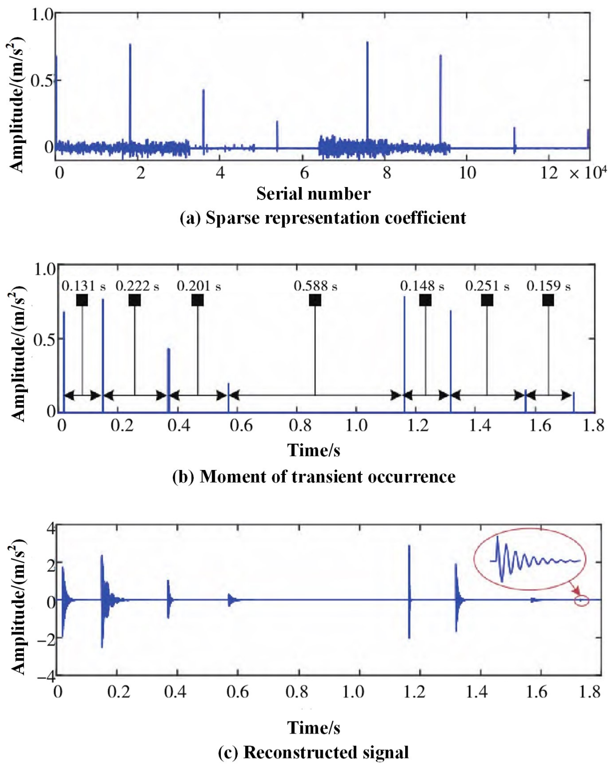


Fig. 4.6: Outcomes of the vibration signal's sparse representation for a typical tool change cycle.


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