A NOVEL FAULT DIAGNOSIS ALGORITHM FOR COMPUTER
NUMERICALLY CONTROLLED MACHINE TOOL BASED ON
IMPROVED BIOGEOGRAPHY-BASED OPTIMIZATION
ALGORITHM AND RADIAL BASIS FUNCTION NEURAL
NETWORK

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ABSTRACT: This paper aims to develop an accurate and robust method for diagnosing the
faults of computer numerically controlled (CNC) machine tools. For this purpose, a fault
diagnosis algorithm for CNC machine tools was designed based on improved biogeography-

Based optimization (BBO) algorithm and radial basis function neural network (RBFNN). The
local search strategy in migration and mutation of the BBO was adopted to improve the
migration operator and the mutation operator. Then, the improved BBO was employed to train
the RBFNN, aiming to accelerate the convergence and reduce the training time of the latter.
The optimized RBFNN was applied to diagnose the actual faults of a CNC machine tool and
compared with the RBF and the genetic algorithm-optimized RBF (GARBF). The simulation
results show that the proposed algorithm can avoid the local optimum trap of the RBF and
achieve higher diagnosis accuracy than the two contrastive algorithms. The research results
provide valuable insights on fault diagnosis of CNC machine tools.

KEY WORDS: Biogeography-based optimization (BBO), computer numerically controlled
(CNC) machine tools, radial basis function (RBF), algorithm training, fault diagnosis

1 INTRODUCTION

Computer numerically controlled (CNC) machine tools is a mainstream machine that
represents the level of mechanical manufacturing. In recent years, there is a growing trend in the scale,
complexity and sophistication of CNC machine tools, which pushes up the requirements on the
stability of these tools (Shen, 2015; Zhang et al., 2017). The current CNC machine tools are featured
by numerous devices and complex structures. The collaboration between devices is prone to failure,
posing a threat to the life, accuracy and reliability of the tools. To solve the problem, the device failure
should be predicted or treated properly through accurate fault diagnosis of CNC machine tools
(Sheng et al., 2015).

The traditional fault diagnosis methods fall into mathematical modelling and online identification.
The mathematical modelling relies heavily on the structure of the target system. However, the system
structure may change due to some faults. If such a change takes place, it is difficult to establish a
robust mathematical model due to the lack of onsite data. Even more difficulties are expected for
modelling of complex systems that involve multiple faults and coupled variables (Xu, 2011; Deng et al.,
2017). As for online identification, it is too slow to meet the timeliness requirement of fault diagnosis.

One of the latest strategies for fault diagnosis lies in neural network (NN) (Pan, 2016). This diagnosis
technique relies partly on the collected signals, and partly on the logic reasoning, comprehensive
calculation and discrimination of the NN. In this way, reliable diagnosis results can be achieved with
simple detection hardware circuit (Klancnik et al., 2016). At present, the NN has been gradually
applied to diagnose the faults of motors and mechanical devices (Miao et al., 2013).

Many algorithms have been developed for the NN. For instance, Reference (Rekanos, 2016) introduces
the principle of radial basis function (RBF) and implements it in seismic prediction, revealing that it
outperforms the backpropagation (BP) NN in convergence of the learning process. Reference
(Feng et al., 2013) combines the biogeography-based optimization (BBO) and BPNN in two steps:
first, the chaotic motion operator was adopted to
widened the transverse range of chaotic motion, aiming to enhance the search ability of standard BBO; then, the weights and thresholds of the NN were trained by the modified BBO.

In this paper, the migration and mutation operators of the standard BBO were modified; then, the improved BBO was employed to train the RBFNN, with the aim to accelerate the convergence and reduce the time of the training process. Finally, a fault diagnosis algorithm for CNC machine tools was proposed based on the improved BBO and trained RBFNN and validated through simulation.

2 THEORETICAL INTRODUCTION

2.1 BBO

In nature, each habitat has a unique habitat suitability index (HSI) (Simon, 2016). Features that correlate with HSI include rainfall, vegetative diversity, topographic diversity, land area, temperature, and others. The features that determine each habitat suitability index variables (SIVs). All of these are accurately represented by the BBO algorithm in engineering. In fact, the BBO mimics how different species look for the best habitat in a N-dimensional search space (He et al., 2012). The solutions to the optimization problem in the N-dimensional search space can be expressed as:

\[
X_i = (x_{i1}, x_{i2}, \ldots, x_{in}), i = 1, 2, \ldots, n
\]  

(1)

The suitability of each solution can be obtained by the fitness function \(G(x_i)\). The single-habitat species migration model is presented in Figure 1. Note that \(\mu\) is the eviction rate, \(\tilde{\alpha}\) is the migration rate, \(s\) is the number of species in a single habitat, \(I\) is the maximum migration probability, \(E\) is the maximum eviction probability. If \(s\) is zero, \(\mu\) is zero and \(\tilde{\alpha}\) is maximized; if \(s\) is maximized, \(\tilde{\alpha}\) is zero and \(\mu\) is maximized; if \(s = S_0\), \(\mu\) is equal to \(\tilde{\alpha}\).

![Figure 1. Single-habitat species migration model](image)

Assuming that \(S_{\text{max}} = n\), the migration rate and the eviction rate can be obtained as:

\[
\mu(S_i) = ES / S_{\text{max}}
\]  

(2)

\[
\lambda(S_i) = I(1 - S_i / S_{\text{max}})
\]  

(3)

In the BBO, the evolutionary process mainly consists of migration and mutation.

1) Migration

The SIVs in the neighboring habitat \(j\) will migrate to habitat \(i\) when it decides to operate on habitat \(i\). The eviction rate \(\mu\) is a monotonous non-decreasing function of the HSI, which is inversely proportional to the HSI. Then, the suitability \(G(x_i)\), \(i = 1, 2, \ldots, n\) of habitat \(i\) should be recalculated:

\[
G(x_i) = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{n} (y_i^j - y_{i0})^2
\]  

(4)

2) Mutation

In nature, the HSI of a habitat will change under sudden disasters. The variance is simulated as mutation in the BBO by the following equation:

\[
M(S) = M_{\text{max}} \cdot (1 - P_r / P_{\text{max}})
\]  

(5)

where \(M_{\text{max}}\) is maximum mutation rate; \(P_r\) is the probability of accommodating \(s\) species in the habitat; \(P_{\text{max}}\) is the probability of accommodating the maximum number of species in the habitat.

2.2 Improved BBO

With the increase in the number of iterations, the information difference between individuals will continue to decrease in the standard BBO, leading to reduced diversity of the population. In this case, the evolution will stagnate and the algorithm will fall into the local optimal trap. To make up for the defect, the standard BBO was modified in two aspects.

1) Improvement of migration operator

In standard BBO, the migration of feature information is not directly correlated with the HSI of the habitat receiving the feature information. Here, the differential evolution algorithm is employed to improve the migration process, and a two-dimensional migration operator is proposed to mimic the two features \(X_{(i,j1)}\) and \(X_{(i,j2)}\) of the selected migration habitat individual \(X_i\). The migrations in both dimensions share the same mechanism but differ in the method of replacement. When migration occurs in dimension \(j_1\), a local search should be performed around the feature information \(X_{(i,j1)}\) with radius \(X_{(i,j1)} - X_{(i,j1)}\), when the feature information of dimension \(j_2\) moves in, the emigrated habitat is no longer habitat \(X_{i1}\), such that the feature information could communicate efficiently between habitats. The two-dimensional migration operator can be expressed as follows:
3 FAULT DIAGNOSIS ALGORITHM FOR CNC MACHINE TOOLS BASED ON IMPROVED BBO AND RBFNN

3.1 Common faults of CNC machine tools

The faults of CNC machine tools are generally identified according to their locations. The common locations include spindle, feed axis, CNC system, tool magazine, rotary axis, automatic tool changer (ATC), automatic pellet changer (APC), fixture and auxiliary device. The faults of each part can be decomposed based on the structure and function. Table 1 lists the common faults of CNC machine tools.

<table>
<thead>
<tr>
<th>Faults name</th>
<th>Suggest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knife arm clamping</td>
<td>Repair knife bar telescopic</td>
</tr>
<tr>
<td>I/O output voltage is abnormal</td>
<td>Check I/O module</td>
</tr>
<tr>
<td>The magazine does not rotate into place</td>
<td>Repair tool magazine</td>
</tr>
<tr>
<td>Spindle orientation parameter change</td>
<td>Correct spindle orientation</td>
</tr>
<tr>
<td>Spindle encoder failure</td>
<td>Repair spindle encoder</td>
</tr>
<tr>
<td>Spindle position encoder</td>
<td>Replace spindle position encoder</td>
</tr>
<tr>
<td>Spindle position encoder</td>
<td>Replace spindle position encoder</td>
</tr>
<tr>
<td>Three-axis tool change point offset</td>
<td>Replace the three-axis tool</td>
</tr>
</tbody>
</table>

3.2 Proposed fault diagnosis algorithm

Considering the global search features of the improved BBO, the randomly selected samples of the RBF was replaced with the dimensional space of the population in the improved BBO, and all the samples for target parameter optimization in the improved BBO were taken as the centre of each neuron in the RBF. The improved BBO was relied on to adjust the migration rate, mutation rate, migration topology, migration interval and migration strategy, aiming to promote information sharing and compute habitat suitability. The optimal solution was determined when the fitness function reached the maximum number of iterations of the RBF.

In the NN, the hidden layer transforms the nonlinear separable input space into a linear separable feature space, and then the output layer completes the classification through linear partitioning. Therefore, the weight of the output layer and the node parameters of the hidden layer were determined by solving the linear equations. The determination process is as follows:

\[ X_{(k,j1)} = X_{(k,j1)} + \text{Rand}(X_{(k,j1)} - X_{(i1,j1)}) \]
\[ X_{(k,j2)} = X_{(k,j2)} + \text{Rand}(X_{(k,j2)} - X_{(i2,j2)}) \]

where \( k, i1, i2=1,2,...,N \) are not equal; \( j1,j2=1,2,...,D \) are not equal.

The modified migration mechanism expands the search space for information exchange, prevents the drawbacks of direct migration, and corrects the exchanged information. Thus, excellent feature information is more likely to migrate to high-risk habitat. Suffice it to say that the modification improves the HSI of habitats and optimizes population information.

(2) Improvement of mutation operator

Mutation occurs when the habitat is affected by random external events. It has a random adaptive effect on the population. In other words, the mutation may produce good results or bad results. Despite the randomness, mutation is essential to maintaining population diversity and creating new individuals. When evolution is stagnant, the occurrence of mutation helps prevent the algorithm from falling into the local optimum trap. In light of this, the mutation operator of the standard BBO was modified into a two-dimensional mutation operator. The two-dimensional mutation operations were performed on two features \( X_{(k,j1)} \) and \( X_{(k,j2)} \) of the selected individuals \( X_k \) in the habitat. The two-dimensional mutation operator can be expressed as:

\[
\begin{align*}
X_{(k,j1)} &= N_1 X_{(k,j1)} \\
X_{(k,j2)} &= N_2 X_{(k,j2)}
\end{align*}
\]

where \( j1,j2=1,2,...,D \) are not equal, \( N_1 \) and \( N_2 \) are random numbers obeying the standard normal distribution between \([0, 1]\). Compared with the standard BBO, the two-dimensional mutation operator can increase the chance of mutation in the habitat, thereby enriching the population diversity and enhance algorithm convergence.

2.3 RBFNN

The RBFNN (Ahmad and Kumar, 2016) is a popular feedforward NN inspired by the response of human brain cells to external stimuli. Featuring fast computing and strong nonlinear mapping, the RBFNN can enhance the convergence of BPNN learning and improve the prediction effect.
(1) Create a generalized RBFNN model. In the improved BBO, the dimension of each habitat corresponds to the number of input samples. The number of input samples (equation (1)) also determines the number of hidden layer nodes.

(2) Determine the data centre of the RBF, i.e. the optimization result, by the cluster optimization function of the improved BBO. In this process, the only parameters to be considered include expansion constants and the weights of output layer nodes.

(3) Introduce Gaussian function, together with uniform extension constant, to the RBF. The extension constant is positively correlated with the width of the RBF, and negatively with the migration performance of the RBFNN.

(4) Calculate the weights of output layer nodes by least squares method.

The RBFNN was optimized by the improved BBO through the following steps:

(1) Initialize the parameters of the improved BBO.

Let \( n \) be the number of habitats, \( D \) be the dimensions of each habitat, \( S_{\text{max}} \) be the maximum number of species, \( I_{\text{max}} \), be the maximum migration rate, \( E_{\text{max}} \), be the maximum eviction rate, and \( M_{\text{max}} \), be the maximum mutation rate.

Take the learning sample as the initial group \( P \), assuming that:
\[
U = [u_1, u_2, ..., u_D]
\]
\[
L = [l_1, l_2, ..., l_D]
\]
\( U \) and \( L \) are the upper and lower bounds.

(2) Randomly initialize the suitability of each habitat \( G(x_i), i = 1, 2, ..., n \) to calculate the migration rate and eviction rate. Obtain the suitability of each species and determine whether each species should be moved into or out of the habitat according to the migration rate.

(3) If a migration occurs in habitat \( i \), perform roulette selection using the eviction rate of other habitats.

For habitats \( i \), if a shift operation occurs, use the eviction rate of other habitats to perform the roulette selection operation, replace the location of habitat \( i \) with habitat \( j \), and recalculate habitat HSI \( G(x_i), i = 1, 2, ..., n \).

(4) After finding the optimal solution, terminate the RBF clustering process. Then, set the optimal solution as the centre \( \alpha_i \) of the RBF, which is selected as a Gaussian function:
\[
y_i = \sum_{i=1}^{\infty} \alpha_i \exp(-\frac{1}{2\sigma^2}||x_p - c_i||^2), j = 1, 2, ..., n
\]

The variance of the RBF can be expressed as:
\[
\sigma = \frac{1}{p} \sum_{j=1}^{\infty} ||d - y||^2
\]

(11)

Calculate the variance according to equation (12):
\[
\sigma_i = \frac{c_{\text{max}}}{\sqrt{2}h}, i = 1, 2, ..., h
\]

(12)

where \( c_{\text{max}} \) is the maximum distance between the selected centres. Take the maximum distance as the width, and obtain the weight by least squares method:
\[
\omega = \exp\left(\frac{h}{c_{\text{max}}}||x_p - c_i||^2\right)
\]
\( p = 1, 2, ..., p; i = 1, 2, ..., h \)

(13)

(5) Output the prediction results.

4 SIMULATION

Four common faults of CNC machine tools were selected to simulate the proposed diagnosis method, including the spindle encoder fault (fault 1), three-axis shift point offset (fault 2), cutter arm encoder fault (fault 3) and tool bed gearbox fault (fault 4).

According to the flow of the BBO-optimized RBFNN, the simulated fault diagnosis covers the following steps. First, collect the fault data from the sensors in the key parts of CNC machine tools, and pre-process these data into a training set and a diagnosis set. The training set contains 8 data samples (Table 2). Then, import the training set into the BBO-optimized RBFNN for group training. Finally, perform distributed fault diagnosis and analyse the fault data with the BBO-optimized RBFNN. The fault diagnosis model was programmed in Matlab. There are 5 input layers, 6 hidden layers and 5 output layers in the RBFNN. The error threshold, the number of trainings, the output target value, the maximum number of iterations for NN weights and the maximum number of iterations for BBO were empirically set to 0.01, 2,000, 0.004, 300 and 600, respectively. In addition, the nonlinear Sigmoid function was adopted as the excitation functions for the hidden layers and the output layers. The training errors are displayed in Figure 2.
Table 2. Training samples and expected output

<table>
<thead>
<tr>
<th>Sample number</th>
<th>Sample input</th>
<th>Expected output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$I_1$</td>
<td>$I_2$</td>
</tr>
<tr>
<td>1</td>
<td>0.941</td>
<td>0.014</td>
</tr>
<tr>
<td>2</td>
<td>0.975</td>
<td>0.458</td>
</tr>
<tr>
<td>3</td>
<td>0.135</td>
<td>0.957</td>
</tr>
<tr>
<td>4</td>
<td>0.253</td>
<td>0.932</td>
</tr>
<tr>
<td>5</td>
<td>0.027</td>
<td>0.248</td>
</tr>
<tr>
<td>6</td>
<td>0.369</td>
<td>0.021</td>
</tr>
<tr>
<td>7</td>
<td>0.342</td>
<td>0.309</td>
</tr>
<tr>
<td>8</td>
<td>0.089</td>
<td>0.267</td>
</tr>
</tbody>
</table>

Figure 2. Training error of the proposed algorithm

Select 12 faults of the 4 types of faults from Table 1, the training outputs of the proposed algorithm, the RBF algorithm, and the genetic algorithm-optimized RBF (GARBF) (Yu et al., 2017) for spindle encoder fault samples are shown in Table 3. It can be seen that the proposed algorithm had a lower learning frequency and closer-to-expectation results than the two contrastive algorithms. Table 4 gives the diagnosis results of the proposed method or CNC machine tools. It is clear that the faults were diagnosed accurately with limited test error, and the actual outputs were close to the expected values. Thus, the proposed algorithm is applicable to the actual diagnosis of CNC machine tool failures.

Table 3. Training outputs of three algorithms on fault 1 samples

<table>
<thead>
<tr>
<th>Sample number</th>
<th>RBF algorithm</th>
<th>GARBF algorithm</th>
<th>Proposed algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.989</td>
<td>0.992</td>
<td>0.997</td>
</tr>
<tr>
<td>2</td>
<td>0.993</td>
<td>0.994</td>
<td>0.998</td>
</tr>
<tr>
<td>3</td>
<td>0.008</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td>4</td>
<td>0.004</td>
<td>0.005</td>
<td>0.001</td>
</tr>
<tr>
<td>5</td>
<td>0.007</td>
<td>0.010</td>
<td>0.006</td>
</tr>
<tr>
<td>6</td>
<td>0.002</td>
<td>0.009</td>
<td>0.002</td>
</tr>
<tr>
<td>7</td>
<td>0.006</td>
<td>0.008</td>
<td>0.001</td>
</tr>
<tr>
<td>8</td>
<td>0.005</td>
<td>0.006</td>
<td>0.002</td>
</tr>
</tbody>
</table>

Table 4. Fault diagnosis results of the proposed algorithm

<table>
<thead>
<tr>
<th>Sample number</th>
<th>Test sample input</th>
<th>Test sample output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$I_1$</td>
<td>$I_2$</td>
</tr>
<tr>
<td>1</td>
<td>0.971</td>
<td>0.107</td>
</tr>
<tr>
<td>2</td>
<td>0.012</td>
<td>0.943</td>
</tr>
<tr>
<td>3</td>
<td>0.059</td>
<td>0.023</td>
</tr>
<tr>
<td>4</td>
<td>0.094</td>
<td>0.019</td>
</tr>
</tbody>
</table>

The three algorithms were further compared through diagnosis of 12 faults of CNC machine tools under the same parameter settings and simulation environment. The results are shown in Table 5.

As shown in Table 5, the proposed algorithm correctly diagnosed 11 out of the 12 faults, putting the hit rate as 91.7%; the GARBF was correct at 10 faults (83.3%); the RBF correctly identified 8 faults (66.7%). To sum up, the proposed algorithm achieved the best performance, followed by the GARBF and then the RBF.

In addition, the three algorithms were applied to diagnose 12 faults of CNC machine tools and the results are presented in Figure 3.

In Figure 3, the horizontal axis is the samples of the 12 faults, the vertical axis is the actual output value of the corresponding sample whose output value is 1. It can be seen that the outputs of proposed algorithm were closer to the target output than those of the GARBF and the RBF, and the
The prediction curve of the proposed algorithm was the most stable one among the three prediction curves. This means the proposed algorithm can achieve higher diagnose accuracy of CNC machine tools than the other two algorithms.

Next, the three algorithms were run separately 8 times in Matlab to compare their number of iterations and runtime (Table 6).

![Fault diagnosis results of the three algorithms](image)

**Table 5. Fault diagnosis results of the three algorithms**

<table>
<thead>
<tr>
<th>Number</th>
<th>Actual fault</th>
<th>RBF algorithm</th>
<th>GARBF algorithm</th>
<th>Proposed algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Diagnostic faults</td>
<td>Diagnostic result</td>
<td>Diagnostic faults</td>
<td>Diagnostic result</td>
</tr>
<tr>
<td>1</td>
<td>Spindle position encoder failure</td>
<td>Correct</td>
<td>Spindle position encoder failure</td>
<td>Unable to judge</td>
</tr>
<tr>
<td>2</td>
<td>Spindle position encoder failure</td>
<td>Correct</td>
<td>Spindle position encoder failure</td>
<td>Correct</td>
</tr>
<tr>
<td>3</td>
<td>Spindle position encoder failure</td>
<td>Wrong</td>
<td>Three-axis tool change point offset</td>
<td>Wrong</td>
</tr>
<tr>
<td>4</td>
<td>Three-axis tool change point offset</td>
<td>Correct</td>
<td>Three-axis tool change point offset</td>
<td>Correct</td>
</tr>
<tr>
<td>5</td>
<td>Three-axis tool change point offset</td>
<td>Wrong</td>
<td>Arm encoder failure</td>
<td>Correct</td>
</tr>
<tr>
<td>6</td>
<td>Three-axis tool change point offset</td>
<td>Correct</td>
<td>Three-axis tool change point offset</td>
<td>Correct</td>
</tr>
<tr>
<td>7</td>
<td>Arm encoder failure</td>
<td>Unable to judge</td>
<td>Arm encoder failure</td>
<td>Correct</td>
</tr>
<tr>
<td>8</td>
<td>Arm encoder failure</td>
<td>Correct</td>
<td>Three-axis tool change point offset</td>
<td>Wrong</td>
</tr>
<tr>
<td>9</td>
<td>Arm encoder failure</td>
<td>Correct</td>
<td>Arm encoder failure</td>
<td>Correct</td>
</tr>
<tr>
<td>10</td>
<td>Knife bed gearbox failure</td>
<td>Correct</td>
<td>Knife bed gearbox failure</td>
<td>Correct</td>
</tr>
<tr>
<td>11</td>
<td>Knife bed gearbox failure</td>
<td>Correct</td>
<td>Knife bed gearbox failure</td>
<td>Correct</td>
</tr>
<tr>
<td>12</td>
<td>Knife bed gearbox failure</td>
<td>Correct</td>
<td>Three-axis tool change point offset</td>
<td>Wrong</td>
</tr>
</tbody>
</table>

Figure 3.
It can be seen from Table 6 that, when the RBF algorithm was used to train thresholds and weights, the initial values were all selected empirically; there was a huge variation in the initial values, leading to a vast different in the number of iterations. Besides, the RBF was prone to the local optimum trap and the premature convergence. When the GARBF algorithm was implemented, the network convergence was accelerated by the genetic algorithm. Thus, the fault diagnosis effect of the proposed algorithm, the RBFNN was optimized by the GARBF was better than that of the RBF. In the proposed algorithm, the RBFNN was optimized by the BBO. The optimization stabilised the number of iterations and prevented the local optimum trap. Meanwhile, the training error of the proposed algorithm satisfied the requirements on fault diagnosis of CNC machine tool.

5 CONCLUSIONS

This paper designs a fault diagnosis algorithm for CNC machine tool based on improved BBO algorithm and RBFNN. The local search strategy in migration and mutation of the BBO was adopted to improve the migration operator and the mutation operator. Then, the improved BBO was employed to train the RBFNN, aiming to accelerate the convergence and reduce the training time of the latter. The optimized RBFNN was applied to diagnose the actual faults of CNC machine tool and compared with the RBF and the GARBF. The simulation results show that the proposed algorithm can avoid the local optimum trap of the RBF and achieve higher diagnosis accuracy than the two contrastive algorithms.

6 REFERENCES