# Study on transformation method of numerically-controlled machine tool

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**Abstract.**In the research of the transformation method of numerically-controlled machine tool (NC machine), due to the current methods exist the problem of that for solving process is complex and the optimization process is easy to fall into local optimal solution, a transformation method of NC machine based on improved particle swarm optimization algorithm is presented. Firstly, particle swarm algorithm and the training parameters of support vector machine (SVM) are fused, to set up the prediction model of transformation state based optimization SVM for NC machine. And then the genetic algorithm is introduced, in addition, real number coding rules and improved genetic operators are applied to optimize the design of NC machine's spindle, to accurately complete the transformation of NC machine. Simulation results show that the accuracy of the transformation method of NC machine, based on improved particle swarm algorithm proposed in this paper is high, and practicability is strong which can meet the application requirements of the transformation of NC machine.

## Introduction

Many China's units have introduced high-end NC machine from abroad, the service period of some of them is to the deadline, some cannot work normally, in the idle state [1], and it not only caused a great waste of resources, but also cannot meet the needs of normal production and modern high precision, high speed and high reliability requirements of processing. Therefore, the transformation of the NC machine has become the focus subject of many experts, and has been widespread concerned [2].

In literature [3], artificial visual neural algorithm is used to establish the transformation model of the NC machine, to complete the transformation of NC machine. The method has strong adaptability, but has the problems of slow convergence speed, more time-consuming problem. The literature [4] uses a transformation method of NC machine based on support vector machine algorithm. The method can effectively solve the small sample and nonlinear problem, but the solution process is complex and the optimization process is easy to fall into a local optimal solution. The literature [5] focuses on the study of the transformation of NC machine based on ant colony algorithm. Although this method is accurate, problems of easily falling into local minimum, slow convergence rate etc. are existed in it.

In view of the above questions, a transformation method of NC machine based on improved particle swarm optimization algorithm is proposed in this paper. Firstly, particle swarm algorithm and the training parameters of support vector machine (SVM) are fused, to set up the prediction model of transformation state based optimization SVM for NC machine. And then the genetic algorithm is introduced, in addition, real number coding rules and improved genetic operators are applied to optimize the design of NC machine spindle, to accurately complete the transformation of NC machine. Simulation results show that the accuracy of the transformation method of NC machine, based on improved particle swarm algorithm proposed in this paper is high, and practicability is strong which can meet the application requirements of the transformation of NC machine.

## The transformation theory of CNC machine

The principle of NC machine transformation can be detailed by the following formulas:

Taking diameter $d$, outer diameter $D$ and the segments span length $L$ of spindle as design

 

variables $X_i(i=1,2,\ldots n),n$ is the number of design variables of the model, spindle's optimization design variables is expressed as follows:

$$x=\left[d,\sum D_i,\sum L_i\right] \quad (1)$$

$f_1(x)$ is the stiffness target function of spindle, $f_2(x)$ is the volume target function of spindle, then the optimization objective function is shown in formula (2):

$$f(x)=\varpi_1 f_1(x)+\varpi_1 f_1(x)= \varpi_1\frac{1}{\frac{Fa^3}{3EI}\left[\frac{l}{a}+1\right]+\frac{F}{kA}\left[1+\frac{kA}{kB}\right]\frac{a^2}{L^2}+\frac{2_A}{l}} +\varpi_2\sum\frac{\pi}{4}\left[D_I^2-d^2\right]L^1 \quad (2)$$

In the formula, $\varpi_1$ and $\varpi_2$ are weighting factors, reflecting the importance of each objective function, $F$ is the cutting force, $K_A$ is the front supporting stiffness, $K_B$ is the later support stiffness.

## The proposition and implementation of transformation method for NC machine based on improved particle swarm algorithm

### The establishment of prediction model of NC machine's transformation state based on the optimized SVM

In the process of reforming of NC machine, it needs to make fusion of the particle swarm algorithm and the training parameters of support vector machine (SVM), to set up the prediction model of NC machine's transformation state based on optimization SVM. The specific steps are detailed:

Given training sample set $T=\{x_i,y_i\}(i=1,2,\ldots,n)$, wherein: $n$ is the number of training samples, $i$ is the training sample, $x_i$ is the input vector, $y_i$ is the corresponding target value. The basic idea of SVM regression is using nonlinear function $\varphi(x)$ and input it into space data, $x$ is mapped to a high dimensional feature space, and in the space, use the function of $f(x)=\left[w\varphi(x)\right]+b$ for linear regression, of which, $w$ is the weight vector, $b$ is deviation.

By minimizing regularized risk function $R(C)$, the parameters $w$ and $b$ is obtained:

$$R(C)=c\frac{1}{n}\sum_{i=1}^{n}L\varepsilon(y)+\frac{1}{2}\|w\|^2 \quad (3)$$

$$l\varepsilon(y)=\begin{cases}\left|f(x)-y\right|-\varepsilon\\ 0\end{cases} \quad (4)$$

In the formula: $\|w\|^2$ is the structural risk, $l\varepsilon(y)$ is insensitive loss function, $\varepsilon$ is insensitive loss error, the value size of $\varepsilon$ can affect the number of support vectors, $c$ is the penalty parameter, to control the punishment degree to samples which is beyond error.

The introduction of non-negative slack variables $\xi$ and $\xi^*$ are used to measure the sample deviation error, that is the level of insensitive loss error $\varepsilon$, $\xi$ is the top deviation, $\xi^*$ is the bottom deviation, then the optimization problem of formula (3) is :

$$\min\left[\frac{1}{2}\|w\|^2+\sum_{i=1}^{n}\left(\xi_i+\xi^*{}_i\right)\right] \quad (5)$$

$$s\cdot t\begin{cases}y_i-\left[w\varphi(x)\right]-b\le\varepsilon+\xi_i\\ \left[w\varphi(x)\right]+b-y_i\le\varepsilon+\xi\end{cases} \quad (6)$$

The optimization problem in formula (5) is converted into a dual problem:

$$\max\left[\sum_{i=1}^{n}y_i\left(a_i-a_i^*\right)-\varepsilon\sum_{i=1}^{n}\left(a_i+a_i^*\right)\right] \quad (7)$$

$$\frac{1}{2}\sum_{i,j=1}^{n}\left(a_i-a_i^*\right)\left(a_j-a_j^*\right)=0 \quad (8)$$

In the formula: $a_i$ and $a_j^*$ are the Lagrange multiplier, $a_i^*$ $a_j^*$ are the Lagrange multipliers for optimization, $K(x_i, y_i) = \varphi(x_i)\varphi(x_j)$ is kernel function, $i, j$ are respectively as the $i$-th sample and the $j$-th sample.

The introduction of kernel function makes inner product operation can be realized by a function of the input space in the high dimension space, to avoid the dimension disaster. Kernel functions, polynomial kernel function are commonly used radial basis function kernel. As the radial basis kernel function with only one variable to be determined, compared to other kernel function, it is easy to identify, so this paper choose the RBF kernel function. The RBF kernel function is described as:

$$k(x, x_i) = \exp\left(-\frac{\|x - x_i\|}{2\sigma^2}\right) \qquad (9)$$

In the formula, $\sigma$ is the radial basis kernel parameter. Radial base kernel $\sigma$ parameters, the penalty parameter $c$ and the insensitive loss error $\varepsilon$ will be the training parameters of SVM.

Due to the value of the radial basis kernel parameter $\sigma$, the penalty parameter $c$ and the insensitive loss error $\varepsilon$ has great influence on the SVM performance prediction, in order to obtain higher prediction ability, the use of particle algorithm with powerful ability of global search, make the particle algorithm (SVM) combining the training parameters, to obtain the prediction model of NC machine based on the SVM optimization. The specific steps are detailed:

Step 1: initialization. the parameters $\sigma$, $c$ and $\varepsilon$ are composed of a particle, and randomly generate a group of the particle's initial position and velocity.

Step 2: fitness evaluation. Using leave one out cross validation method evaluate the degree of adaptation. Fitness function $f$ is :

$$f = -\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \qquad (10)$$

In the formula, $y_i$ and $\hat{y}_i$ respectively is the actual value and the predicted value.

Step 3: check the end condition, if satisfied, then finish the optimization; otherwise, go to step s.

**Implementation of the transformation of NC machine based on improved particle swarm optimization algorithm**

The optimization design process of genetic algorithm can be divided into determining the coding scheme, setting the initial population, determining the fitness function, genetic operator, and selecting operating parameters and other steps. The specific steps are detailed:

To establish the evaluation function evaluate (), for the individual price criteria is: the greater of fitness value is, the more excellent of design variables $X_i$ are. Evaluating individual is the problem to compute the minimal value of objective function $f(x)$ when the function values $e(j)$ of each individual function evaluate evaluate () is to satisfy in the constraint conditions $g_i(x) \le 0 (i = 1, 2\ldots, m)$ in the feasible region. The penalty function method is used, to realize the constrained optimization problems to transform to the non-constrained optimization problems, and then fitness evaluation function is:

$$evaluate(x) = f(x) + p(x) = \varpi_1 \frac{1}{\frac{ta^3}{3fI}\left[\frac{l}{a}+1\right] + \frac{g}{kA}\left[1+\frac{kA}{kB}\right]\frac{f^2}{g^2} + \frac{2_A}{l}} \qquad (11)$$

Among them: $t$ is the evolving algebra, usually $c = 0.5, \alpha = 2$.

The spindle's optimization design variables can be obtained by the above formula:

$$X = \{d, D1, D2, D3, D4, D5, L1, L2, L3, L4, L5\}^t \qquad (12)$$

Through the following formula, the objective function of spindle's optimization design can be obtained.

$$F(X)=\varpi_1\frac{1}{\frac{ta^3}{3fI}\left[\frac{l}{a}+1\right]+\frac{g}{kB}\left[1+\frac{kL}{kB}\right]\frac{f^2}{g^2}+\frac{2_A}{l}+1}+\varpi_2\sum_{I=1}^{5}\frac{\pi}{4}\left[D_I^2-d^2\right]L^1 \quad (13)$$

In formula (13)， $L$ is the volume of this principal axis, $l=l_4+l_5, a=l_1+l_2+l_3$ 。

Using the following equation can obtain the constructed fitness function:

$$evaluate(x)=f(x)+p(x)=$$

$$\varpi_1\frac{1}{\frac{ta^3}{3fI}\left[\frac{l}{a}+1\right]+\frac{D^g}{kB}\left[1+\frac{kL}{kB}\right]\frac{f^2}{D^2}+\frac{2_A}{l}+1}+\varpi_2\sum_{I=1}^{5}\frac{\pi}{4}\left[D_I^2-d^2\right]L^1+\varpi_2\sum_{I=1}^{5}\frac{\pi}{4}\left[D_I^2-d^2\right]L^1+(Ct)_a \quad (14)$$

In the formula， $g_i(x)$ is constraint function.

In conclusion, it can explain that the transformation method of NC machine based on improved particle swarm optimization algorithm has high accuracy and strong practicability.

## Experiment and simulation Analysis

In order to prove the authenticity of the proposed transformation method of NC machine based on improved particle swarm optimization algorithm, it needed to make an experiment. The lens of the LC0156A/T with IC piezoelectric acceleration sensor is used in the test, and installed on the tool holder. the voltage signal sensors are preprocessed using a signal conditioning module (SCM5B48 acceleration input module, Dataforth company, United States), and then transmitted to the data acquisition card, data acquisition card (high speed data acquisition card PCI-6259, NI company, United States) converts the analog signal to digital signal which can be analyzed and processed by computer, the test data are shown in table 1.

Using the traditional algorithm and improved algorithm respectively make the comparative analysis of prediction accuracy of the NC machine. The prediction curves of NC machine status of improved algorithm and traditional algorithm are as shown in Figure 1, the prediction accuracy is as shown in table 2. From the comparison of prediction results can be seen, in the prediction of NC machine' state, the accuracy of improved algorithm is better than the traditional method.

Table 1 experimental data

| NO. | vibration value | NO. | vibration value |
|---|---|---|---|
| 1 | 0.141 | 18 | 0.159 |
| 2 | 0.144 | 19 | 0.150 |
| 3 | 0.158 | 20 | 0.150 |
| 4 | 0.157 | 21 | 0.142 |
| 5 | 0.153 | 22 | 0.149 |
| 6 | 0.157 | 23 | 0.160 |
| 7 | 0.161 | 24 | 0.161 |
| 8 | 0.157 | 25 | 0.157 |
| 9 | 0.152 | 26 | 0.153 |
| 10 | 0.153 | 27 | 0.159 |
| 11 | 0.159 | 28 | 0.140 |
| 12 | 0.153 | 29 | 0.145 |
| 13 | 0.148 | 30 | 0.157 |
| 14 | 0.156 | 31 | 0.151 |
| 15 | 0.157 | 32 | 0.140 |
| 16 | 0.155 | 33 | 0.153 |
| 17 | 0.148 | 34 | 0.159 |

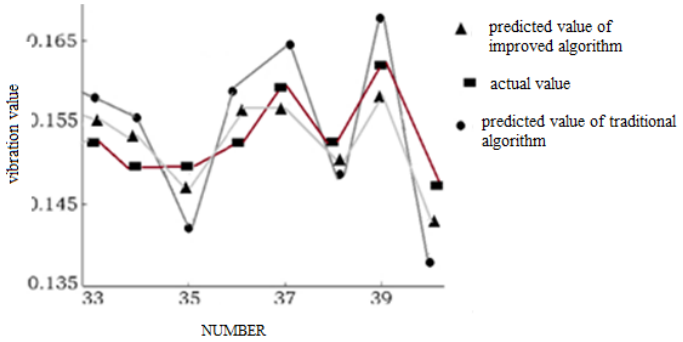


Figure 1 accuracy prediction map of machine's state transformation by using traditional algorithm and improved algorithm

Table 2 Comparison of accuracy of traditional algorithm and improved algorithm

| NO. | actual value / $(m \cdot s^{-2})$ | predicted value | Error of traditional algorithm | *MAPE* | predicted value | Error of improved algorithm | *MAPE* |
|---|---|---|---|---|---|---|---|
| 33 | 0.156 | 0.1582 | 0.0346 | | 0.1532 | 0.0149 | |
| 34 | 0.151 | 0.1553 | 0.0359 | | 0.1533 | 0.0276 | |
| 35 | 0.150 | 0.1418 | 0.0476 | | 0.1460 | 0.0158 | |
| 36 | 0.152 | 0.1585 | 0.0365 | | 0.1564 | 0.0228 | |
| 37 | 0.158 | 0.1644 | 0.0345 | | 0.1570 | 0.0118 | |
| 38 | 0.153 | 0.1486 | 0.0216 | | 0.1497 | 0.0144 | |
| 39 | 0.163 | 0.1685 | 0.0406 | | 0.1584 | 0.0264 | |
| 40 | 0.148 | 0.1376 | 0.0632 | 0.0392 | 0.1430 | 0.0264 | 0.0192 |

The above experiment results can show that the proposed method for transformation of CNC machine based on improved particle swarm optimization algorithm has high precision and efficiency, it is able to meet the requirements of the transformation of NC machine.

## Conclusions

Aiming at the problem of that using the current methods exist the problem of that for solving process is complex and the optimization process is easy to fall into local optimal solution, a transformation method of NC machine based on improved particle swarm optimization algorithm is presented in this paper. Firstly, particle swarm algorithm and the training parameters of support vector machine (SVM) are fused, to set up the prediction model of transformation state based optimization SVM for NC machine. And then the genetic algorithm is introduced, in addition, real number coding rules and improved genetic operators are applied to optimize the design of NC machine spindle, to accurately complete the transformation of NC machine. Simulation results show that the accuracy of the transformation method of NC machine, based on improved particle swarm

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