A Predictive Model of Dimensional Deviation Based on Regeneration PSO-SVR with Cutting Feature Weight in Milling

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Abstract. Support vector regression (SVR) optimized by particle swarm optimization (PSO) has low predictive accuracy and premature convergence in milling. To solve this problem, a PSO-SVR model combined with the cutting feature weight was proposed in this paper. Firstly, basing on the SVR, the feature weight was integrated with the kernel function, and added the premature judging to the PSO to improve the global searching ability. Secondly, the mathematical model composed of the cutting force, temperature and cutting vibration was built based on the datasets obtained by experiment. The covariance was calculated to get the characteristic weights of process parameters, which promoted the incremental data in turn. Finally, the predictive model of the dimensional deviation was established based on the promoted PSO-SVR and the result was compared with the general PSO-SVR. The accuracy of the predictive model reached 97.5%. And compared with the predictive model of the general PSO-SVR without feature weighting, the dimensional deviation predictive accuracy and generalization ability of the regeneration PSO-SVR predictive model with feature weighting was improved by 37.75% and 24.5%.

Keyword. Cutting feature weight, milling, premature judging, PSO-SVR.

1. Introduction
With the intelligent manufacturing developing faster and faster, the milling process of complicated components presents the characteristics of fast production-line changing and rapid adjusting. In order to cater to the new trend and meet the demand, the soft computing methods [1] were introduced such as artificial neural networks (ANN), support vector machine (SVM), Gaussian process regression (GPR), particle swarm optimization algorithm (PSO), Long Short-Term Memory (LSTM) etc.

These intelligent algorithms tend to be highly adaptive and robust owing to its data-driven ability [2], which has a great application prospect in properties prediction. H. Hegab et al. established a smart tool wear prediction model in drilling of woven composites by GPR [3]. The literatures [4-7] took LSTM [4], ANN [5], SVR [6] and the other machine learning algorithms [7] as a tool to deal with a large number of practical engineering problems and make a big difference to material property mechanical study. PSO-SVR is one of the machine learning methods with the advantage of excellent convergence dealing with the high dimension problem. Apart from that it can simplify the regression process and maintain the generalization ability because it doesn’t involve the theorem of large numbers and probability measure. However, this algorithm will fall into local convergence easily and lead to be premature, which will decrease the accuracy of the model. In addition, the lack of datasets
with the complete label poses the challenges to the accuracy of the model. According to the previous studies [8-10], feature weight plays a positive role in improving both the reliability of the datasets and the predictive ability of the machine learning model. In the circumstances of the small sample of the datasets, this paper adopted the feature weight into the SVR model, which aimed to predictive accuracy. To calculate the feature weight, Hailin L et al. [11] proposed a feature-weighted clustering method based on two distance measurement methods called dynamic time warping (DTW) and shape-based distance (SDB). Wei et al. [12] established an optimized feature-weight model based on the gray relational analysis method, which gave the calculating equation as a result.

Therefore, in order to improve the predictive accuracy with the limited datasets. Firstly, the regeneration PSO-SVR with cutting feature weight was proposed in this paper. Then the correlation model between the process parameters and the dimensional deviation was established based on the designed milling experiment. The cutting feature weight matrix was obtained by calculating covariance of the process parameters. And the incremental data were supplied based on the correlation model as well. Finally, the predictive result was given and a comparison was done between the general PSO-SVR and the regeneration PSO-SVR with cutting feature weight.

2. Regenerating PSO-SVR Predictive Model Combined with Cutting Feature Weighting

2.1. Support Vector Regression
The predictive model took four process parameters, which are spindle speed, feed rate, number of cutter blade and cutting-in as the inputs respectively and took dimensional deviation as the output. Based on the SVR and the gaussian kernel function fussed with the cutting feature weight, the regression model was built in the form of equation (1).

\[ y \approx f(x) = \alpha x + b = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(Rx_i, Rx) + b \]  

(1)

To decrease the variance we introduced the positive number \( \varepsilon \) as the accuracy of the model and penalty factor C. The training process was completed by finding the best \( \alpha_i \) and b to minimize the objective function (as shown in equation (2)).

\[
\min \frac{1}{2} \| \omega \|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \]

\[
\begin{align*}
& y_i - f(x_i) \leq \xi_i + \varepsilon \\
& s.t. \quad f(x_i) - y_i \leq \xi_i + \varepsilon \\
& \xi_i, \xi_i^* \geq 0
\end{align*}
\]  

(2)

In the equation, \( y \) is the inspection result and \( f(x) \) is the regression result of the inspection result. \( \omega \) is the regressing coefficient. \( b \) is the deviation of the function. \( x \) is the variable determined by process parameters. \( \sigma \) is the coefficient of the kernel function. \( \xi \) is the relaxing factor. \( R \) is the feature weight matrix.

2.2. Regeneration PSO
PSO is a stochastic optimization technique based on population, initially proposed by Kennedy and Eberhart [13]. It was inspired by birds swarm’s foraging. In the algorithm (as shown in the equation (3)), \( V \) is the velocity of the particle, while the \( x \) is the position of the particle. The individual is regarded as zero weight and volume and is regarded as the solution in the target search space. By calculating the fitness of each solution, the optimal solution can be found.

\[ v_{i}(t+1) = v_{i}(t) + c_1 r_1(t)(p_{i}(t) - x_{i}(t)) + c_2 r_2(t)(p_{g}(t) - x_{i}(t)) \]  

(3)

However, in the PSO, the individual population is affected by the optimal particle, which leads to precocity due to the fast convergence. To handle this problem, we presented the regeneration PSO.
Firstly, it will determine whether a particle is premature. When the state of particles appears to be in the local convergence, the algorithm will force it jumping out of local minimum point by substituting the global optimal fitness with the individual fitness. Then the population continues participating in the iteration, until the best fitness is found (as shown in the figure 1).

![Figure 1. Regeneration PSO-SVR principle.](image)

Regeneration PSO still follows the randomness and ergodicity. Compared with simulated annealing particle swarm, it reserves optimal value, disturbs all the particles. With the advantage of particle number, it can effectively increase the possibility of searching the global optimal, which thus improving the ability of global convergence of the algorithm, and lowering requirement to the optimization objective function.

3. Cutting Feature Weight Calculation and Predictive Model Building

3.1. Milling Experiment
The HT300 gray cast iron was used in the experiment. The process parameters have tool blade, spindle speed (n), feed rate (v_f) and cutting depth (a_p). Each parameter had 3 values, which constituted 81 groups of data in total (as shown in table 1).

| Blade | n (r/min) | v_f (mm/min) | a_p (mm) |
|-------|-----------|--------------|----------|
| 1     | 1000      | 200          | 0.1      |
| 3     | 3000      | 250          | 0.15     |
| 4     | 5000      | 300          | 0.2      |
The cutting features containing the cutting force, cutting temperature and cutting vibration were obtained by acceleration transducer (as shown in table 2), which formed the 81 groups of data with integrated label together with the dimensional deviation(ΔS) obtained by vernier caliper.

Table 2. Milling experiment results.

| Number | Force(N) | Temperature(°C) | Vibration(mm) | ΔS(mm) |
|--------|----------|-----------------|---------------|--------|
| 1      | 56       | 75              | 0.013         | 0.039  |
| 2      | 36       | 48.76           | 0.012         | 0      |
| 3      | 18       | 45.08           | 0.011         | 0.07   |
| ......  |          |                 |               |        |
| 40     | 72       | 81.5            | 0.013         | 0.01   |
| 41     | 40       | 49.79           | 0.01          | 0.01   |
| 42     | 30       | 57.46           | 0.009         | 0.09   |
| ......  |          |                 |               |        |
| 79     | 100      | 74.19           | 0.012         | 0.06   |
| 80     | 71       | 69.52           | 0.01          | 0.07   |
| 81     | 58       | 65.52           | 0.009         | 0.07   |

3.2. The Calculation of Cutting Feature Weight and Incremental Data

According to the empirical model as shown in equation, we built the correlation model between the process parameters and the cutting feature (as shown in the equation (4)), based on the datasets which obtained from the milling experiment.

\[ F = 347.4331 \times n^{0.0014} \times a_p^{0.7194} \times v_f^{0.7509} \]
\[ T = 97.7754 \times n^{-0.092} \times v_f^{0.2434} \times a_p^{0.2801} \]
\[ D_s = 0.0252 \times n^{-0.0666} \times v_f^{0.1541} \times a_p^{-0.0916} \]

(4)

In order to polish up the accuracy of the model, we built the correlation model combined the cutting feature with the inspection result based on the surface response function. Basing on the least square method and the datasets, the coefficients were obtained, and the relationship between the ΔS and the cutting feature was established (as shown in the equation (5)).

\[ \Delta S = 0.9823 \cdot F + 0.0235 \cdot T - 89.0548 \cdot D_s + 0.0001 \cdot F \cdot T - 2.1231 \cdot F \cdot D_s \\
+ 4.8625 \cdot T \cdot D_s + 0.00008 \cdot F^2 - 0.00016 \cdot T^2 - 3549.8 \cdot D_s^2 \]

(5)

Integrating the Process parameters-Cutting feature weight model into the Cutting feature-Inspection result model, we obtained the comprehensive model based on the mechanism effect and utilized it to generate more data to expend the datasets (the results are shown in the table 3). The expended datasets has 256 groups of data. The covariance was calculated and used as the feature weight, which was shown as equation (6).

\[ R_s = \begin{bmatrix} 0.5917 & -0.1495 & 0.8317 & 0.8519 \end{bmatrix} \]
### Table 3. ∆S regression results based on the designed process parameters.

| Number | Blade | n (r/min) | v₁ (mm/min) | a₀ (mm) | ∆S (mm) |
|--------|-------|-----------|-------------|---------|---------|
| 1      | 2     | 1000      | 100         | 0.1     | 0.354   |
| 2      | 2     | 1000      | 160         | 0.1     | 0.606   |
| 3      | 2     | 1000      | 230         | 0.1     | 0.878   |
| .......|       |           |             |         |         |
| 137    | 4     | 1000      | 160         | 0.36    | 1.051   |
| 138    | 4     | 1000      | 230         | 0.36    | 1.72    |
| 139    | 4     | 1000      | 300         | 0.36    | 2.57    |
| .......|       |           |             |         |         |
| 254    | 6     | 5000      | 100         | 0.5     | 0.516   |
| 255    | 6     | 5000      | 160         | 0.5     | 0.7405  |
| 256    | 6     | 5000      | 230         | 0.5     | 0.9804  |

### 4. Predictive Result and Analysis

#### 4.1. Model Parameter Initialization

The parameters of gaussian are kernel parameter σ(0.01-10), predictive accuracy ε(0.001), penalty factor C(0.01-100) and k-fold parameter k(k=3). The parameters of PSO are the size of population (popsize=20), the number of iterations (Maxgen=200), the max and min weight (ω_{min}=0.01, ω_{max}=0.9) and the learning factor c₁ and c₂(c₁=c₂=2).

#### 4.2. Predictive Result

Based on the parameters set in the section 4.1, the predictive results of the dimensional deviation were given by regeneration PSO-SVR. As is shown in the figure 2(a), the fitness curve represents the process of optimization and the best parameters of SVR optimized by PSO are C=100, σ=0.99895. In the circumstances of small sample, the environment of experiment makes a great difference to the predictive result.

The results of MSE (mean-square error) are all less than 0.23 within the limits of acceptance and will be lower if the number of datasets increases. The average fitness curve witnesses series of fluctuation because the individual fitness is such close to the optimal fitness that it appears to be premature in the process of iteration. Therefore, the global optimal is used to replace the individual optimal, and the individual optimal results affect the average fitness, resulting in fluctuations, which quickly approach to the optimal fit position after the fluctuation. In the process of iterations, the variation range of the average fitness curve is large, because the particles fall into local convergence. Particle swarm has been close to the direction of the local optimal solution, but the overall optimal fitness change is small. Undergoing series of fluctuations, the CVmse (CVmse=0.17449) with lower value is found. The best fitness curve shows a downward trend and the ability of global searching gets promoted maintaining the randomness.

The figure 2(b) shows the predictive results of general PSO-SVR without feature weight. The holistic trend is basically the same. However, with the lack of regeneration, the particles fall into the local convergence. The overall average fitness and optimal fitness are higher than the regeneration PSO-SVR with feature weight, which means the MSE is higher as well (as is shown in the table 4 as well). In the process of optimization, there is no obvious sign of approaching to the best position, which means that the search ability is poor. The best fitness is 0.221514. Comparing the general PSO-SVR without feature weight, the ability of generalization of the optimized PSO-SVR was increases by 24.5%.
Figure 2. PSO fitness curve of Dimensional deviation.

Table 4. Examples of the comparison between the predictive results and experiment results.

| Serial number | Trial (mm) | Prediction (mm) | Error       |
|---------------|------------|----------------|-------------|
| 1             | 0.039      | 0.0367         | 0.3919%     |
| 7             | 0.04       | 0.0378         | 0.3664%     |
| 13            | 0.01       | 0.0123         | -0.3919%    |
| 19            | 0.038      | 0.0400         | 0.3378%     |

By analyzing the figure 3, the deviation of the predictive result and the experimental result is greater. And by calculating the relative error of the whole result, the accuracy of the regeneration PSO-SVR with cutting feature weight reached 97.5%, while the accuracy of the general PSO-SVR was just about 60%. Thus, the error of the latter one is 37.75% higher than the regeneration PSO-SVR with feature weight, which proved that the regeneration PSO-SVR made a significant difference to improving the accuracy.

Figure 3. The predictive results of general PSO-SVR and the promoted PSO-SVR.

5. Conclusions
In this paper, a promoted PSO-SVR model was proposed by adding the process of judging regeneration. In meanwhile, a model of the dimensional deviation predictive was built based on the regeneration PSO-SVR with cutting feature weight. This improved algorithm can improve the global searching and alleviate the premature phenomenon. Trained by SVR with feature weight and
optimized by regeneration PSO. The accuracy of dimensional deviation model reaches 97.5%. Compared with the general PSO-SVR prediction model without feature weighting, the dimensional deviation predictive accuracy and generalization ability of the regeneration PSO-SVR predictive model with feature weighting improved by 37.75% and 24.5%.

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