Surface roughness prediction of end milling process based on IPSO-LSSVM

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Abstract
Surface roughness is a significant index in evaluating workpiece quality. So research about predicting surface roughness precisely prior to machining is necessary in order to save cost and attain high productivity levels. In this paper, a method called improved particle swarm optimization-least square support vector machine (IPSO-LSSVM) is proposed to predict the surface roughness of end milling. Firstly, an improved particle swarm optimization(IPSO) algorithm is used to optimize the parameters of LSSVM method which have significant influence on the accuracy of LSSVM model. Secondly, a surface roughness prediction model is established through LSSVM method with the optimized parameters. Then prediction accuracy of the established model can be attained through test data. Finally, the prediction accuracy of IPSO-LSSVM method is compared with the accuracy of other methods, and the results show that IPSO-LSSVM method is competent in fields of surface roughness prediction.

Key words: End milling, Surface roughness, Prediction, Improved particle swarm optimization(IPSO), Least square support square vector machine(LSSVM)

1. Introduction

Surface roughness is not only an important technical requirement in designing products but also a principal index in evaluating workpiece quality in manufacturing industry. The quality of surface roughness has significant influence on the functional characters of workpieces such as friction and wear, contact stiffness and corrosion resistance etc. Surface roughness prediction before machining can reduce the follow-up labor intensity, also achieve a set of optimal machining parameters which can improve the quality of workpiece surface roughness. In recent years, the idea of predicting surface roughness prior to machining has attracted much attention and become a hot spot in machining quality research.

The common way to predict surface roughness is as follows. Firstly, establishing the surface roughness prediction model by different methods, then conducting a number of experiments to test the accuracy and generalization of the established model. In summary, from the literatures, the methods of surface roughness prediction can be divided into theoretical modelling method and data analysis method. And also the data analysis method also can be divided into in-process analysis method and artificial intelligence method.

Theoretical modelling method aims to predict surface roughness through analyzing the machining theory such as process kinematics, chip formation mechanism or influence of machining parameters. Antoniadis et al., (2003) proposed a Milling Software Needle(MSN) program to predict the surface roughness of ball-end milling. Gao et al., (2006) simulated the surface topography of end and ball-end milling by considering the trajectory equations of the cutting edge relative to the workpiece. Based on Z-map method, Liu et al., (2006) developed a comprehensive simulation system to predict the surface roughness in finish milling process. However, the machining process is complex and full of uncertainty, and the models based on theoretical method are commonly simplified and can not consider the influence of all machining factors. So the theoretical models are generally not accurate and have a large error between the actual surface roughness values and the predicted results.

Through collecting and analyzing the signals in machining process, in-processing analysis method can be used to establish the relationship between surface roughness and influence factors such as collected signals and tool geometry etc. Considering the influence of machining parameters and the relative displacement between tool and workpiece, Chang et al., (2007) established the surface roughness prediction model of cutting operation based on linear regression...
algorithm. Huang and Chen (2003) measured the cutting force by a three-component dynamometer and developed an in-process neural network-based surface roughness prediction (INN-SRP) system of end milling. Lou and Chen (1999) collected the vibration signals of machining process and built an in-process surface roughness recognition (ISRR) system to predict the surface roughness in end milling. These methods can get a good accuracy in predicting surface roughness through combining sensor technology with mathematical analysis, but the redundant signals, measurement errors and high cost of sensors limit the wide application of these methods.

Artificial intelligence method is commonly used to predict the surface roughness by analyzing the data using the artificial intelligent algorithms such as neural network (NN), fuzzy algorithm and particle swarm optimization et al. Based on Taguchi method, Davim (2001), Feng and Wang (2002), Ozcelic and Bayramoglu (2006) achieved the influence rules of the machining parameters on surface roughness. Muñoz-Escalona and Maropoulos (2010) predicted the surface roughness of turning AL7075-T7351 based on three kinds of artificial neural networks. Lo (2003) used the adaptive-network based fuzzy inference system (ANFIS) to predict the surface roughness of end milling. Based on particle swarm optimization neural network, Razfar et al. (2010) built the surface roughness prediction model of face milling. Through processing the experiment data using a certain kinds of mathematical algorithms, this method can obtain a good relationship between surface roughness and machining factors. Currently, the artificial intelligent method is becoming a most widely used method in surface roughness prediction.

Support vector machine (SVM) is one of artificial intelligent algorithms which is based on statistical learning theory and structural risk minimization principle. It has been successfully applied in pattern recognition and function estimation problems (Lu and Wu, 2010; Cayda and Ekici, 2012; Prakasvudhisarn, et al., 2009). Least square support vector machine (LSSVM) is an extension of the standard SVM. It is computationally more efficient than the standard SVM method and can solve the small sample and nonlinear problems perfectly (Ma, et al., 2011), which make the LSSVM method suitable for the surface roughness prediction. So, in this paper, the LSSVM method is introduced in the fields of surface roughness prediction. But when predicting through LSSVM method, there are some parameters of LSSVM that have a large influence on the prediction accuracy. Currently, the common method to select these parameters is grid search, which is heavy workload and time consuming. In this paper, a method called improved particle swarm optimization least square support vector machine (IPSO-LSSVM) which combines the IPSO algorithm with LSSVM method is proposed to predict the surface roughness in end milling process.

Three milling parameters are selected as input parameters to predict the surface roughness, the parameters and their meanings are listed in Table 1. Based on the three milling parameters, how to use the IPSO-LSSVM method to precisely predict the surface roughness of end milling is investigated.

Table 1 Parameters used in IPSO-LSSVM

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sp</td>
<td>Spindle speed (r.p.min.)</td>
</tr>
<tr>
<td>F e</td>
<td>Feed rate (mm.p.min.)</td>
</tr>
<tr>
<td>D ep</td>
<td>Depth of cut (mm.)</td>
</tr>
<tr>
<td>Ra</td>
<td>Roughness (μm.)</td>
</tr>
</tbody>
</table>

2. Theoretical foundation
2.1 Least Squares Support Vector Machines (LSSVM)

Considering a given training set of N samples \( \{(x_i, y_i), i = 1,2,\ldots, n\} \), where \( x_i \in \mathbb{R}^d \) is a \( d \)-dimensional input vector and represents the input values, \( y_i \in \mathbb{R} \) is a scalar data and represents the output value. According to LSSVM theory, the unknown nonlinear function between input and output values can be estimated in a high dimensional feature space as follows (Suykens and Vandewalle, 2000):

\[
f(x) = w^T \phi(x) + b
\]

where \( \phi(x) \) is nonlinear transform function which transforms the input space into a high-dimensional space, \( w \) is the weight vector of high dimensional feature space, \( b \) is the corresponding bias term. Then the regression issue can be transformed into the following optimization problem as follows:
\[
\begin{align*}
\min_{w,\xi} Q(w,\xi) &= \frac{1}{2} \|w\|^2 + \frac{\rho}{2} \sum_{i=1}^{n} \xi_i^2 \\
\text{subject to} &:\; y_i = w \cdot \phi(x_i) + b + \xi_i, i = 1, 2, \ldots, n
\end{align*}
\]

where \(\xi\) denotes the random error, \(\rho > 0\) denotes the regularization parameter which determines the balance between training errors and model complexity. According to the Lagrange multiplier and KKT theorem, the formula (2) can be solved and the corresponding LSSVM model can be expressed as follows:

\[
f(x) = \sum_{i=1}^{n} a_i \phi(x_i, x) + b
\]

In this paper, radial basis function (RBF) is chosen as the kernel function because of its high solving ability for non-linear regression problems. The RBF kernel function is written as:

\[
\phi(x, x_i) = \exp\left(-\frac{\|x - x_i\|^2}{\sigma^2}\right)
\]

where \(\sigma\) is the kernel parameter of RBF kernel function.

### 2.2 Improved Particle Swarm Optimization (IPSO)

Particle Swarm Optimization (PSO) algorithm is inspired by a social behavior of bird flock and is widely used to solve the optimization problem (Kennedy and Eberhart, 1995). In PSO algorithm, each single solution is a ‘particle’, and every ‘particle’ can ‘fly’ to a better solution according the experience of their own and other ‘particles’. After a certain number of iteratively updating, the optimal solution can be obtained.

Standard particle swarm optimization supposes that a swarm consists of \(n\) particles which fly in a \(d\)-dimensional search space. The \(i\)th particle at the \(k\)th iteration has the position \(X_i(k) = (x_{i1}(k), x_{i2}(k), \ldots, x_{in}(k))\) and velocity \(V_i(k) = (v_{i1}(k), v_{i2}(k), \ldots, v_{in}(k))\), then by calculating the fitness values of each particle, the best position of each particle \(p_{\text{best}i}(k) = (p_{\text{besti}1}(k), p_{\text{besti}2}(k)\ldots, p_{\text{besti}n}(k))\) and the best global position of all particles \(g_{\text{best}}(k)\) at \(k\)th iteration can be determined. Therefore, the particles can update its velocity and position according to the following formulas:

\[
v_i(k+1) = w \cdot v_i(k) + c_1 \cdot \text{rand} \cdot (p_{\text{best}i}(k) - x_i(k)) + c_2 \cdot \text{rand} \cdot (g_{\text{best}}(k) - x_i(k))
\]

\[
X_i(k+1) = X_i(k) + V_i(k+1)
\]

Where \(V_i(k)\), \(V_i(k+1)\), \(X_i(k)\), \(X_i(k+1)\) represent the velocity and position of the \(k\)th iteration and \((k+1)\)th iteration respectively, \(\text{rand}\) is a random number between 0 and 1, \(c_1, c_2\) are learning factors, \(w\) is inertia weight factor.

The research has shown that the inertia weight factor \(w\) is a key parameter of PSO algorithm (Zheng, et al., 2003). The larger \(w\) has a strong ability of global convergence, while the smaller \(w\) has a strong ability of local convergence. Therefore, with the increase of iterations, the value of \(w\) should be gradually decreased to make the PSO algorithm performance better. In this paper, an improved particle swarm optimization (IPSO) algorithm is introduced to obtain a high performance optimizer for the selection of the optimal parameters of LSSVM. In this method, the value of \(w\) gradually diminishes as follows:

\[
w = w_{\text{max}} + (\text{iter}_{\text{max}} - \text{iter}) \cdot (w_{\text{max}} - w_{\text{min}}) / \text{iter}_{\text{max}}
\]

Where \(w_{\text{max}}\) and \(w_{\text{min}}\) are the maximal and minimal values of \(w\), \(\text{iter}\) is the number of current iteration and \(\text{iter}_{\text{max}}\) is the largest iteration number.

Through gradually reducing the value of \(w\), IPSO algorithm not only can hold the advantages of standard PSO such as simple structure and fast running speed but also enhance the convergence rate and accuracy effectively.

### 2.3 IPSO-LSSVM

When modelling through LSSVM method, the regularization parameter \(\rho\) and kernel parameters \(\sigma\) of RBF kernel function have significant impact on prediction accuracy of LSSVM model. Therefore, in order to obtain the optimal parameters, the IPSO algorithm is used to search for the optimal parameters of LSSVM automatically. The calculating steps of IPSO-LSSVM are as follows:
(a) Set the initial parameters and so randomly initialize the positions $X(0)$ and velocities $V(0)$ of particles.

(b) Calculate the fitness value of current particle $fit(x_i)$ according to the following formula.

$$fit_i(x_i) = \frac{1}{n} \sum_{i=1}^{n} \left( \sum_{j=1}^{\Lambda} y_i - y_i \right)^2$$

In the equation $fit_i$ denotes the fitness value of $ith$ partial, $y_i$ denotes the prediction value through LSSVM method, $y_i$ denotes the real value, $n$ represents the number of samples.

(c) Compare the fitness value of $p_{best}$ and $g_{best}$ with $fit(x_i)$, if $fit(x_i)$ is better than the fitness value of $p_{best}$, then set $p_{best}$ to the current position $X(i)$; if $fit(x_i)$ is better than the fitness value of $g_{best}$, then set $g_{best}$ to the current particle $X(i)$.

(d) Update the velocities $V_i$ and positions $X_i$ according the formulas (5) (6). If $V_i > V_{\max}$ then $V_i = V_{\max}$. If $V_i < V_{\min}$ then $V_i = V_{\min}$. If $X_i > X_{\max}$, then $X_i = X_{\max}$. If $X_i < X_{\min}$ then $X_i = X_{\min}$.

(e) Judge if the stopping criteria is satisfied, if it fulfills the need, finish the calculating and set the corresponding number of the particle as the optimal parameters of LSSVM, else go back to step (c).

(f) Establish LSSVM model with the optimized parameters and test the prediction accuracy of the established model.

The flowchart of IPSO-LSSVM method is shown in Fig.1.

3. Experiment design

In order to investigate the feasibility of the proposed IPSO-LSSVM method, a total of 72 sets data (Lo, 2003; Prakasvudhisarn, et al., 2009) were chosen to establish the surface roughness prediction model and to test the accuracy of the established model.
The end milling experiments were conducted under dry cutting condition by using Fadal CNC vertical machining center. A four-flute end milling cutter made of high-speed steel (HSS) with a diameter of 19.05 mm was used to machine one 6061 aluminium block (25.4mm × 25.4mm × 25.4mm) in the experiments. The various feed rates, spindle speeds and axial depths of cut, based on the limitations of the machine, were tested. The cutting parameters (spindle speed, feed rate and axial depth of cut) were changed according to different cutting conditions for each run. Also, after every specimen was cut, the cutting tools were cleaned to avoid built-up edge (BUE) which may affect the surface roughness of the following cutting experiments. The tools were also checked to make sure that they are sharp properly. The surface roughness was measured off-line with a stylus-based Hommel profilometer on the machined surface of workpiece and the profile arithmetic average deviation (Ra) is used to evaluate surface roughness in this paper. When measuring the surface roughness, three different random points along the direction perpendicular to the feed direction were selected to measure the surface roughness value of the selected points. The average surface roughness of the three points are considered as the corresponding surface roughness of milling parameters. The detail experiment parameters are shown in Table 2. Firstly, 48 sets of training data are used to search for the optimal parameters of LSSVM and to establish the prediction model with the optimal parameters, and then another 24 sets of testing data are used to verify the precision of the predicted values after the training completes.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sp (r.p.min)</td>
<td>750, 1000, 1250, 1500, 750, 1000, 1250, 1500</td>
</tr>
<tr>
<td>Fe (mm.p.min)</td>
<td>152.4, 304.8, 457.2, 609.6, 228.6, 381, 533.4</td>
</tr>
<tr>
<td>Dep (mm)</td>
<td>0.254, 0.762, 1.27, 0.254, 0.762, 1.27</td>
</tr>
</tbody>
</table>

4. Results and discussion

Section 4.1 elaborates on the parameters selection of LSSVM using training data through the IPSO algorithm. The flowchart of optimization procedure through IPSO-LSSVM is shown in Fig. 2. Section 4.2 aims to predict the surface roughness using LSSVM method with the obtained optimized parameters and test the prediction accuracy of the established model. Figure 3 shows the flowchart of predicting surface roughness via LSSVM method.

4.1 Parameter optimization

48 sets of training data are used to search for the optimal parameters of LSSVM in this section. Before optimization procedure processing, in order to eliminate the effect of variable dimensions of the machining parameters the training data are normalized between 0 and 1. The normalized values can be obtained according to the following formula:
\[ \bar{x} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \]  

where \(x\) and \(x'\) are the data before and after normalization, \(x_{\text{min}}\) and \(x_{\text{max}}\) are the minimum and maximum data of the corresponding variables. RBF is selected as the kernel function of LSSVM method in this paper. As to IPSO algorithm, the population size of IPSO is set as 20; the learning factors \(c_1 = c_2 = 2\); the iteration maximum \(\text{iter}_{\text{max}} = 100\); the maximum velocity \(v_{\text{max}} = 20\) and the minimum velocity \(v_{\text{min}} = -20\); the maximum and minimum value of inertia weight factors \(w_{\text{max}} = 0.9\) and \(w_{\text{min}} = 0.4\). Searching intervals of regularization parameter \(\Gamma\) and kernel parameter \(\sigma\) are respectively set as \([0, 1000]\) and \([0, 2]\). Then the fitness values of each iterations are calculated by Eq. (8) and the \(p_{\text{best}}\) and \(g_{\text{best}}\) of the particles are updated by iterations. When the iterations are over, the fitness value turns to its minimum value and the optimal values of parameter \(\sigma\) and \(\Gamma\) can be obtained when \(X = (0.1378, 520.6806)\). The evolution process of the fitness values of IPSO-LSSVM along with the change of iterations is shown in Fig. 4.

![Fig. 4 Evolution process of the fitness values](image)

4.2 Modeling with optimal parameters

According to the optimization process in section 4.1, it can be seen that the kernel parameter \(\sigma\) and the regularization parameter \(\Gamma\) are equal to 0.1378 and 520.6806 respectively. Then the prediction model is established based on LSSVM method with these two optimal parameters and the prediction results of training data are obtained. The comparisons between the prediction values and experiment values of training data are shown in Fig.5.

![Fig. 5 Comparison between prediction values and experiment value of training data](image)
From Fig. 5, it can be seen that the prediction values of training data are very close to the real values of surface roughness. Actually, the accuracy reaches to 99.4% as high as by calculating the detail values, which means that the LSSVM model established with the optimal parameters can reflect the complex relationship between machining conditions and surface roughness of training data precisely.

In order to verify the prediction and generalization ability of the established surface roughness prediction model, the other 24 sets of machining parameters, which are not used in the training data, are used as input values to predict the corresponding surface roughness. After normalizing, the test data are introduced into the established LSSVM model and the prediction values are obtained. The prediction results are shown in Table 3. From Table 3, it can be seen that the prediction errors are almost within 10%, which means that most prediction values of the test data are close to the real values and the predicted surface roughness values can be trusted.

Table 3 Surface roughness prediction results of test data

<table>
<thead>
<tr>
<th>Test number</th>
<th>Parameters</th>
<th>Ra(μm)</th>
<th>Error(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sp(r.p.min)</td>
<td>Fe(mm.p.min)</td>
<td>Dep(mm)</td>
</tr>
<tr>
<td>1</td>
<td>750</td>
<td>228.6</td>
<td>0.254</td>
</tr>
<tr>
<td>2</td>
<td>750</td>
<td>228.6</td>
<td>1.27</td>
</tr>
<tr>
<td>3</td>
<td>750</td>
<td>381</td>
<td>0.762</td>
</tr>
<tr>
<td>4</td>
<td>750</td>
<td>381</td>
<td>1.27</td>
</tr>
<tr>
<td>5</td>
<td>750</td>
<td>533.4</td>
<td>0.254</td>
</tr>
<tr>
<td>6</td>
<td>750</td>
<td>533.4</td>
<td>0.762</td>
</tr>
<tr>
<td>7</td>
<td>750</td>
<td>533.4</td>
<td>1.27</td>
</tr>
<tr>
<td>8</td>
<td>1000</td>
<td>228.6</td>
<td>0.254</td>
</tr>
<tr>
<td>9</td>
<td>1000</td>
<td>381</td>
<td>0.762</td>
</tr>
<tr>
<td>10</td>
<td>1000</td>
<td>533.4</td>
<td>0.254</td>
</tr>
<tr>
<td>11</td>
<td>1000</td>
<td>533.4</td>
<td>0.762</td>
</tr>
<tr>
<td>12</td>
<td>1000</td>
<td>533.4</td>
<td>1.27</td>
</tr>
<tr>
<td>13</td>
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<td>381</td>
<td>0.254</td>
</tr>
<tr>
<td>14</td>
<td>1250</td>
<td>381</td>
<td>0.762</td>
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<tr>
<td>15</td>
<td>1250</td>
<td>533.4</td>
<td>0.254</td>
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<tr>
<td>16</td>
<td>1250</td>
<td>533.4</td>
<td>0.762</td>
</tr>
<tr>
<td>17</td>
<td>1250</td>
<td>533.4</td>
<td>1.27</td>
</tr>
<tr>
<td>18</td>
<td>1500</td>
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<td>0.762</td>
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<tr>
<td>19</td>
<td>1500</td>
<td>381</td>
<td>0.254</td>
</tr>
<tr>
<td>20</td>
<td>1500</td>
<td>381</td>
<td>0.762</td>
</tr>
<tr>
<td>21</td>
<td>1500</td>
<td>381</td>
<td>1.27</td>
</tr>
<tr>
<td>22</td>
<td>1500</td>
<td>533.4</td>
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<td>0.762</td>
</tr>
<tr>
<td>24</td>
<td>1500</td>
<td>533.4</td>
<td>1.27</td>
</tr>
</tbody>
</table>

Average error 3.26

Figure 6 shows the scatter diagram of predicted surface roughness values and measured values of test data. In Fig. 6, there is a 45° line, if the values of prediction surface roughness are laid on the line, this means that the prediction values are equal to the real surface roughness values which is a ideal situation. From Fig. 6, it can be seen that the predicted surface roughness values are all following the 45° line very closely, which means that the predicted values are close to the real values and the prediction precision is very high. Figure 7 shows the comparison between the predicted values and measured values of the surface roughness of test data and the phenomenon is identical with that shown in Fig. 6. From Figs 6, 7, it can be seen that the predicted surface roughness values of test data are quite close to experimental.
surface roughness, these comparison results indicate that the prediction model based on IPSO-LSSVM can predict and generalize the surface roughness well for the other machining parameters which are not listed in training data.

![Prediction values](image1)

Fig. 6 Scatter diagrams of the predicted values and measured values of test data

![Real values, Prediction values](image2)

Fig. 7 Comparison between prediction values and experiment value of test data

4.3 Analysis and comparison of different methods

In order to prove the good performance of IPSO-LSSVM method in surface roughness prediction, the prediction accuracy of IPSO-LSSVM is first compared with the accuracy of theoretical modelling method.

In milling process, surface roughness is influenced by milling parameters such as milling speed, feed rate and milling depth. So the theoretical surface roughness, Ra, for end milling can be estimated using the following equation (Juneja and Sekhon, 2003):

$$Ra = cv_c^k f^l a_p^m$$

(10)

Where $c, k, l, m$ are the modelling coefficients, $v_c$ is the milling speed, $f$ is the feed rate, $a_p$ is the milling depth.

So, the theoretical surface roughness prediction model can be established through using the training data as follows.
Where $s_p$ is the spindle speed, $f$ is the feed rate, $a_p$ is the milling depth.

According to Eq. (11), the surface roughness prediction values of testing data can be obtained and the comparison of the prediction values between the theoretical model and IPSO-LSSVM is shown in Fig.8.

$$Ra = 10^{0.3908 s_p^{-0.4985} f^{0.5962} a_p^{-0.0698}} \quad (11)$$

From Fig.8, it can be seen that the deviation of the prediction values of theoretical method from the real values is bigger distinctly than that of IPSO-LSSVM method. Actually, the biggest prediction error can reach as high as 19.16%, this means that the theoretical method is difficult to meet the requirements of high accuracy for surface roughness prediction.

The IPSO-LSSVM method is one of artificial intelligent methods, so the prediction accuracy of IPSO-LSSVM is also compared with the predicted accuracy of other artificial intelligent methods such as NN, ANFIS and SVM used in the previously published references to prove the good performance of IPSO-LSSVM method in surface roughness prediction. The comparison results are shown in Fig.9 and Table 4. The values of the training and test columns in Table 4 are average percentage accuracy which can be calculated as follows:

$$\text{average percent accuracy} = \frac{\sum_{i=1}^{n} \frac{\hat{R}_i}{R_i} \times 100}{n} \quad (12)$$

where $\hat{R}_i$ denotes the prediction values of surface roughness, $R_i$ denotes the measured value and $n$ is the number of testing data.

From Fig.9, it can be seen that the prediction values of IPSO-LSSVM are closer to the real values compared with those of other methods. And from Table 4, it can be seen that the maximum average accuracy of SVR method is 95.86% in training data prediction and 95.45% in testing data prediction respectively, the maximum average accuracy of ANFIS method is 95.35% in testing data prediction, and the maximum average accuracy of NN method is 91.54% in testing data prediction. However, the training average accuracy of IPSO-LSSVM method can reach 99.4% as high as and the testing average accuracy also get to 96.74%, which is higher than the other methods. Therefore, compared with other methods, the IPSO-LSSVM method can reflect the complex relationship between machining condition and surface roughness well, also can predict the surface roughness precisely before machining. The high prediction accuracy and generalization of IPSO-LSSVM method make it to become a powerful tool for industrial applications especially in the surface roughness research field and also lay a solid foundation for the machining parameters optimization to improve the surface roughness.
Fig. 9 Comparison of real values and predicted value of IPSO-LSSVM and other artificial intelligent methods

Table 4 Comparison of prediction accuracy between different methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy of training data</th>
<th>Accuracy of test data</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPSO-LSSVM(GRBF Kernel)</td>
<td>99.4%</td>
<td>96.74%</td>
</tr>
<tr>
<td>SVR+GRBF Kernel (Prakasvudhisarn, et al. 2009)</td>
<td>95.86%</td>
<td>95.45%</td>
</tr>
<tr>
<td>SVR+Poly Kernel (Prakasvudhisarn, et al. 2009)</td>
<td>90.00%</td>
<td>93.91%</td>
</tr>
<tr>
<td>ANFIS(Triangular MF) (Lo, 2003)</td>
<td>N/A</td>
<td>95.35%</td>
</tr>
<tr>
<td>ANFIS(Trapezoidal MF) (Lo, 2003)</td>
<td>N/A</td>
<td>92.69%</td>
</tr>
<tr>
<td>NN (Prakasvudhisarn, et al. 2009)</td>
<td>91.19%</td>
<td>91.54%</td>
</tr>
</tbody>
</table>

This paper aimed to verify that the IPSO-LSSVM method proposed is suitable for surface roughness prediction compared with other common prediction methods, so the machining parameters used to establish the model in this paper have to be same with the parameters other methods used, so that to make the comparison reliable. In manufacturing industry, the surface roughness is influenced by a lot of factors such as machining condition, tool geometry and material properties etc, if these factors are considered in the machining experiments, the IPSO-LSSVM method is also available to build a high accurate prediction model about the more machining parameters by using the experiment data.

5. Conclusions

This paper proposes an IPSO-LSSVM method to precisely predict the surface roughness in end milling process. The spindle speed, the feed rate and the depth of cut are selected as model variables in IPSO-LSSVM method. In the predicting process, the IPSO algorithm is used to tune the most suitable parameters of LSSVM firstly. Then the LSSVM model is established by using the optimal parameters. After the prediction model is established, other 24 sets machining parameters are used to validate the performance of model. The following conclusions can be drawn:

1. The IPSO algorithm can convergence to the global optimal value fast which makes the optimization of the parameters $\gamma$ and $\sigma$ more effective. And the LSSVM can solve the small sample and non-linear problems preferably which usually occur in surface roughness prediction. Therefore, the IPSO-LSSVM method combines the advantages of both LSSVM and IPSO, it is competent for surface roughness prediction.

2. The predicting accuracy of the proposed IPSO-LSSVM method is found to be 96.74% which is higher than that
of other prediction methods. Therefore, the IPSO-LSSVM method can predict the surface roughness precisely. Once the spindle speed, the feed rate and the depth of cut are given, the surface roughness can be easily and precisely predicted.

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