Comparison of applying static and dynamic features for drill wear prediction

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Abstract
This paper defines static and dynamic component parameters based on the method that converts thrust and torque detected during drilling process into equivalent thrust force and principal force. Features of the parameters are extracted by wavelet packet transform (WPT) and then used to train a back propagation neural network (BPNN) to predict the drill wear. Experiments with different drilling conditions and workpiece materials were conducted and it has been confirmed that both static and dynamic component parameters are affected by the drilling conditions. The features extracted from dynamic components in lower frequency band can predict the drill corner wear better.

Key words: Drill wear prediction, Wavelet packet transform, Back propagation neural network

1. Introduction
This paper is concerned with the prediction of drill wear with features extracted from the static and dynamic components of forces by wavelet packet transform (WPT) using back propagation neural network (BPNN).

All of the literatures in drill wear prediction have taken the thrust and torque as independent physical quantities without taking the information of the relationship between them into account (Jantunen, 2002). Dynamic components of the resultant force of principal force and feed force were used to indicate the adhesion of tool-chip interface and predict the surface finish successfully (Tezuka, et al., 2009). Therefore, a conversion method of thrust and torque is discussed and based on which the static and dynamic components are defined.

The features of the dynamic components are extracted by an n level WPT. Signals of dynamic components are decomposed into 2^n sets of coefficients generating many frequency bands which provides opportunities to find useful signal features (SFs) (Teti, et al., 2010). Then the features along with drilling conditions such as spindle speed, feed rate are used to train a BPNN with drill corner wear as its output.

S.S. Panda et al (Panda, et al., 2008) compared back propagation neural network (BPNN) and radial basis function network (RBFN) in predicting of flank wear of drills using spindle speed, feed rate, drill diameter, thrust force, torque and vibration as input parameters.

In this paper, relations between features, cutting conditions and drill corner wear are discussed.

2. Definition of the static & dynamic component parameters and the features extraction method

Owing to the complexity of the geometry of drill bit, usually, cutting in the chisel region was treated as orthogonal cutting with different cutting speeds while the cutting forces along the cutting lips were represented as a series of oblique sections (Strenkowski, et al., 2004).

In this paper, the thrust (Fz) and torque (Mz) monitored by the dynamometer during the drilling process are conversed to equivalent thrust force (Ft) and principal force (Fp) on two symmetrical points at each cutting lip as shown in Fig. 1.

The equivalent thrust force (Ft) and equivalent principal force (Fp) can be drawn as Eq.(1) and Eq.(2).

\[ \begin{align*}
Ft &= Fz/(2 \times \sin(\varphi/2)) \\
Fp &= 2Mz/d
\end{align*} \]

In which \( \varphi \) means the point angle and \( d \) means the diameter of the drill bit.
Then a rectangular coordinate is applied with the horizontal axis as principal force and vertical axis as thrust force. Therefore, any point in this rectangular coordinate means the resultant force of the equivalent thrust force and principal force. The data sampled and processed from the experiment become a series of the resultant force vectors in time sequences and to be the trajectory of the resultant force.

\[ F_t \quad \text{and} \quad F_p \] are the mean values of the equivalent thrust force and principal force, as shown in Fig. 2, and they comprise the static components together with \( \theta \) and \( \rho \) which can be described as Eq.(3) and Eq.(4).

\[
\theta = \text{atan}(\frac{F_t}{F_p}) \\
\rho = \sqrt{F_t^2 + F_p^2}
\] (3) (4)

\( \Delta F_t \) and \( \Delta F_p \) are the fluctuation ranges of \( F_t \) and \( F_p \) and \( \Delta \theta \) and \( \Delta \rho \) indicate the variation range of the resultant force in polar form as shown in Fig. 3, in combination with 3 other parameters they form the dynamic component parameters. Intuitively, the concentration levels of the trajectories directly indicate the stability of the resultant force. Therefore, “ConvHullArea” is defined as the area of the convex hull (as shown in Fig. 3) of the discretely distributing data points. “STDEV” is defined as the average distance from each trajectory point \( (F_{tj}, F_{pj}) \) to the center point \( (\bar{F}_t, \bar{F}_p) \) by Eq.(5). Another dynamic parameter “TrackLength” is defined as the path length in unit time \( (t_o) \) of the resultant force trajectory by Eq.(6).

\[
\text{STDEV} = \frac{1}{n} \sum_{i=1}^{n} \sqrt{(F_{t1} - \bar{F}_t)^2 + (F_{p1} - \bar{F}_p)^2} \\
\text{TrackLength} = \frac{1}{t_o} \sum_{j=1}^{m} \sqrt{(F_{tj} - \bar{F}_t)^2 + (F_{pj} - \bar{F}_p)^2}
\] (5) (6)

In Eq. (5), \( n \) means the number of data points during the whole sampling period; while in Eq. (6) \( m \) indicates the number of data points in the period of \( t_o \).

For features extraction, the sampled thrust and torque signals are first transferred into equivalent thrust force and principal force, then they are decomposed by a 3 level WPT, after that 8 sub signals of different frequency band are reconstructed according to the 8 sets of coefficients as shown in Fig.4. The original sampling frequency is 20 kHz, so each of the frequency band is 2.5kHz varying from 0-2.5kHz to 17.5-20kHz. At last, the features of each frequency band are calculated by the method discussed before.
3. Experimental set up

The experiments were conducted on a Mitsubishi CNC machining center with a Kistler 9365B dynamometer, a Kistler 5073 charge amplifier (Frequency response 20 kHz) and a Yokogawa DL750 scope corder. The drill bits used were Mitsubishi SDD series standard uncoated HSS drills, and 2 different materials used were S45C and SUS304.

The whole drilling process of a single workpiece can be divided into 3 stages as shown in Fig.5, according to the cutting edges position. When the cutting edges are not entirely inside the work piece, where the drill point depth is around 3 mm (drill point height is about 2.4 mm) under the workpiece surface called entry stage and another near the workpiece thickness named penetration stage, the forces change significantly.

![Fig. 5 The 3 stages of drilling process](image)

To obtain static & dynamic component parameters under a relatively stable condition, data intercepted during the stage between the former two stages named medial stage is used for further analysis.

4. Effect of important process parameters on extracted features

4.1. Effect of feed rate

Table 1 shows the conditions for experiments with different feed rate.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spindle Speed</td>
<td>745 rpm</td>
</tr>
<tr>
<td>Feed Rate</td>
<td>0.05, 0.1, 0.2, 0.3, 0.4 mm/rev.</td>
</tr>
<tr>
<td>Drill Bit Diameter</td>
<td>8 mm</td>
</tr>
<tr>
<td>Workpiece Material</td>
<td>S45C</td>
</tr>
<tr>
<td>Workpiece Thickness</td>
<td>15 mm</td>
</tr>
<tr>
<td>Lubrication</td>
<td>Dry</td>
</tr>
</tbody>
</table>

![Fig. 6 Ft to Fp with different feed rate.](image)
It is a very clear and typical distribution of the resultant force trajectories as plotted in Fig. 6. It shows that along with the increase of feed rate, both the position and distribution of the trajectories change. And it’s also been noticed that the center points of trajectories of the resultant force keep in line, indicating a certain ratio between $F_t$ and $F_p$ (mean values as shown in Fig. 2). The ratio value 0.59 can be calculated by linear fitting as shown in Fig. 6, which means a greater increase of $F_p$ than $F_t$ in average as shown in Fig. 7(a) and results in the reduce of $\bar{\theta}$ in Fig. 7(b). Hence the linear growth of $\bar{\rho}$ is logical as shown in Fig. 7(b).

Feed rate also affects the dynamic component parameters. As shown in Fig. 8 (a), along with the increasing of feed rate, $\Delta F_t$ hovers around 200N while $\Delta F_p$ increases gradually from 300N to 800N, demonstrating that $\Delta F_p$ is much more sensitive comparing with $\Delta F_t$. Swing of the direction of the resultant force ($\Delta \theta$) decreases because of the leap of its magnitude as shown in Fig. 8 (b).

The other three dynamic component parameters all reach their peaks when feed rate is 0.4 mm/rev., which are more than 2 times of the values when feed rate is around 0.1 mm/rev as shown in Fig. 9. When feed rate increases from 0.05-0.1 mm/rev, small changes emerge, but for TrackLength, value when feed rate is 0.05 mm/rev is smaller than that of 0.1 mm/rev, which is different from the other two and this indicates that the trajectory points is more central focused in spite of a longer path distance. When feed rate increases from 0.3-0.4 mm/rev, growth of ConvHullArea is about 100% which is much more than the other two. STDEV is relatively stable in all of the 3 parts due to its statistical average property.

### 4.2 Effect of spindle speed

Table 2 shows the conditions for experiments with different spindle speed.
Table 2  Conditions for experiments with different spindle speed.

<table>
<thead>
<tr>
<th>Spindle Speed</th>
<th>325,415,545,745,980,1300,1800 rpm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feed Rate</td>
<td>0.2 mm/rev.</td>
</tr>
<tr>
<td>Drill Bit Diameter</td>
<td>8 mm</td>
</tr>
<tr>
<td>Workpiece Material</td>
<td>S45C</td>
</tr>
<tr>
<td>Workpiece Thickness</td>
<td>15 mm</td>
</tr>
<tr>
<td>Lubrication</td>
<td>Dry</td>
</tr>
</tbody>
</table>

![Fig. 10](image1)  \( F_t, F_p, \theta, \bar{\rho} \) vs. spindle speed.

Figure 10 shows that as spindle speed increases the cutting forces decrease and, the direction of resultant force has a small shift (about 4° from 41° to 45°) while the magnitude reduces about 25%. Figure 11 shows the variation behaviors of \( \Delta F_t, \Delta F_p, \Delta \theta \) and \( \Delta \rho \). These dynamic components are high when the spindle speed is as low as 300-400rpm, but they get lower when spindle speed increases to around 500rpm. They increase again and reach another peak when spindle speed approaches 1000rpm. For spindle speed above 1000rpm, dynamic component parameters decrease with the increasing of spindle speed.

![Fig. 11](image2)  \( \Delta F_t, \Delta F_p, \Delta \theta \) vs. spindle speed.

![Fig. 12](image3)  \( STDEV, ConvHullArea \& TrackLength \) vs. spindle speed.

Similar changes occur for the other 3 dynamic component parameters as shown in Fig. 12.

Comparing to the effect of feed rate, spindle speed does not have a great influence to both the static and dynamic component parameters.

5. Drill corner wear prediction by back propagation neural network

5.1 Neural network architecture and back propagation training algorithm

A multilayer feed-forward neural network consists of at least three layers. The three layers are input layer, hidden
layer and output layer (Basheer and Hajmeer, 2000). Figure 13 shows the architecture of a back propagation neural network model. The input layer receives information from the external sources and passes this information to the network for processing. The hidden layer, composed by several sigmoid neurons, receives information from the input layer, and does all the information processing. And the output layer, consist of a linear neuron receives processed information from the network, and sends the results out to an external receptor.

Fig. 13 Architecture of a 3 layered feed forward neural network.

There are 3 main learning paradigms for neural networks: supervised, unsupervised and hybrid (Jain and Mohiuddin, 1996). In supervised learning, the network is provided with a correct answer (or answer set, targets), according to which it is trained to produce answer (output) as close as possible to the correct answer. In contrast, unsupervised learning does not require a correct answer and it explores the underlying structure in the data to organize or category them. The hybrid learning, just as its name implies, combines supervised and unsupervised learning. Naturally the prediction of drill wear requires supervised learning with actual drill corner wear as the correct answer.

The back propagation learning algorithm based on error-correction rule within supervised learning is one of the most popular learning methods for multi-layer feed forward neural networks. Functioning of back propagation proceeds in three stages, namely learning or training, testing or inferences and validation(Panda, et al., 2006). The data is commonly divided into 3 sets randomly: training set, validation set and testing set. The training set is used to train the network; the validation set is for avoiding overfitting and the testing set is used to obtain the performance characteristics such as accuracy, sensitivity, specificity and so on of the neural network.

Fig. 14 Back propagation algorithm procedure.

Figure 14 shows the procedure of back propagation algorithm. And The main processes of back propagation algorithm proceeds as follows: first, inputs are presented to the network and errors are calculated; second, sensitivities are propagated from the output layer to the first layer; then, weights and biases are updated (Biron, 1997).
5.2 Data grouping and neural network setup

Spindle speed, feed rate, $\overline{F_t}$, $\overline{F_p}$, $\Delta F_t$, $\Delta F_p$, $\Delta \theta$, $\Delta \rho$, STDEV, ConvHullArea, TrackLength are selected as input parameters of the network, and the drill corner wear is chosen as the only output. For comparison, the inputs are divided into 2 groups differing in the dynamic component parameters: $\Delta F_t$, $\Delta F_p$, $\Delta \theta$, $\Delta \rho$ in group 1 and STDEV, ConvHullArea, TrackLength in group 2. For group 1, a 8-10-1 BPNN is employed, which comprises 8 neurons in the input layer, 10 in hidden layer and 1 in output layer and, for group 2, a 7-10-1 structure is adopted with the same neuron number in the hidden layer.

Table 3. Conditions of experiments for drill wear prediction.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spindle Speed</td>
<td>300, 400, 500, 600, 800, 1000, 1200 rpm</td>
</tr>
<tr>
<td>Feed Rate</td>
<td>0.05, 0.1, 0.2, 0.3, 0.4 mm/rev.</td>
</tr>
<tr>
<td>Drill Bit Diameter</td>
<td>8 mm</td>
</tr>
<tr>
<td>Workpiece Material</td>
<td>S45C/SUS304</td>
</tr>
<tr>
<td>Workpiece Thickness</td>
<td>20 mm</td>
</tr>
<tr>
<td>Lubrication</td>
<td>Dry</td>
</tr>
</tbody>
</table>

Table 3 shows the experimental conditions for acquiring data sets for the inputs and targets of the neural network. Each 64 different data instances with different conditions and drill corner wear are obtained from experiments with S45C and SUS304 as workpiece material. 60% of the data (38 instances) are randomly picked to train the network with Levenberg-Marquardt back propagation algorithm, 15% (10 instances) for checking the validation and the remaining 25% of the data (16 instances) are used to evaluate the testing error.

5.3 Result and discussion

![Fig. 15 BPNN simulation results for S45C with inputs in different groups and frequency bands.](image1)

![Fig. 16 BPNN simulation results for SUS304 with inputs in different groups and frequency bands.](image2)

![Fig. 17 Predicted corner wear vs. real corner wears for S45C.](image3)

![Fig. 18 Predicted corner wear vs. real corner wears for SUS304.](image4)
Pearson's Correlation Coefficient (R) is adopted as the evaluator of the correlation between the real corner wear and those provided by the network. And as R is closer to 1 the approximation is better.

The prediction result using features of the static and dynamic component parameters in 2 groups extracted from different frequency band as inputs of the network with S45C and SUS304 as workpiece materials are shown in Fig. 15 and Fig. 16 respectively. As shown in Fig. 15, results with group 2 as input is better than that with group 1 and, results with features extracted in frequency band 1 is better. For SUS304, in Fig. 16, same results can be obtained.

The feature values in group 1 are defined as the difference between the maximum and the minimum values. However, the maximum and the minimum values are both momentary values which may probably appear with some random disturbance or vibration. Unexpected higher feature values may also exist in the occasion where drill bit has lower corner wear. The effect of these undesired values can be eliminated by the extraction method of group 2 features.

The features in lower frequency band can predict drill corner wear better indicates that the lower frequency components hold more fraction of the variance. Similar result was obtained in turning with motor power signal and cutting forces (Pal, et al., 2009).

Figure 17 shows the errors between the predicted corner wear and measured corner wear when S45C was used as workpiece material, and the inputs to BPNN used were parameters in group 2 and frequency band 1. It demonstrates that most of the errors between outputs of BPNN and real corner wear values are less than 5%. And for SUS304, as shown in Fig. 18, most of the errors between outputs of BPNN and real corner wear values are under 5% when using inputs in group 2 and frequency band 1.

6. Conclusions

It has been observed from the present study that both static and dynamic component parameters are affected by the drilling conditions. And the features extracted from dynamic component parameters in lower frequency band can predict the drill corner better using a back propagation neural network. The newly defined features, STDEV, ConvHullArea, TrackLength, are better than those defined as the differences of dynamic components, as they provide the information of a drilling process with a certain corner wear in a more comprehensive manner. Thus a good prediction result can be obtained using these features with back propagation neural network.

Reference


