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In-process prediction of corner wear in drilling operations

H.S. Liu[a], B.Y. Lee[a], Y.S. Tarng[b,*]

[a]Department of Mechanical Manufacture Engineering, National Huwei Institute of Technology, Yunlin 632, Taiwan, ROC
[b]Department of Mechanical Engineering, National Taiwan University of Science and Technology, Taipei 106, Taiwan, ROC

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Abstract

The paper presents an in-process prediction of corner wear in drilling operations by means of a polynomial network. The polynomial network is composed of a number of functional nodes and well organized to form an optimal network architecture using an algorithm for synthesis of polynomial networks (ASPNs). Thrust force or torque in drilling operations has been correlated with corner wear in this study. It has been shown that the thrust force is better than the torque as the sensing signal for the in-process prediction of corner wear. Experimental results have shown that the corner wear over a wide range of drilling conditions can be predicted with a reasonable accuracy if the cutting speed, feed rate, drill diameter, and thrust force are given.

Keywords: Corner wear; Drilling; Prediction; Polynomial networks

1. Introduction

It has been reported that one third operation of material removal processes performed in industry is drilling operations [1]. Therefore, drilling is a very important and commonly used material-removal process. However, tool failure may occur in drilling operations as a result of tool-wear. Hence, in-process prediction of tool wear in drilling operations should be developed. In the literature, a number of tool wear prediction techniques have been reported for drilling operations [2–6]. These techniques involve the correlation of tool wear with process variables such as force, surface finish, vibration, torque, and acoustic emission. However, there are difficulties involved concerning the reliability, calibration, and cost in the use of these detection techniques. Continued progress is being made to improve these prediction techniques for achieving commercial success.

Basically, there are two main regions of tool wear in a cutting tool, i.e., flank wear on the tool flank face and crater wear on the tool rake face. However, in this paper, corner wear instead of flank wear or crater wear is used to predict the tool wear in drilling operations. This is because not only is corner wear on the drill easy to measure but also drill life is characterized strongly by corner wear on the drill [7]. To improve the reliability of the tool-wear prediction model, a polynomial network [8] is constructed to predict the corner wear in drilling operations. The polynomial network is a self-organizing adaptive modeling tool with an ability to construct the relationships between input variables and output feature spaces [9]. A comparison between the polynomial network and the back-propagation network has shown that the polynomial network has a greater prediction accuracy and fewer internal network connections [10–12]. The best network structure, number of layers, and functional node types can be determined by using an ASPN [13]. Experimental results have shown in this paper that thrust force is better than torque as the sensing signal for the prediction of corner wear. Under a variation of drill diameters, cutting speeds, and feed rates, corner wear can be predicted reasonably by the network if the thrust force in the drilling process is given.

In what follows, polynomial networks are introduced first. An experimental set-up for measuring corner wear in drilling operations is described next. A polynomial network for predicting corner wear is then developed. Finally, experimental verification of the developed network is shown.

2. Polynomial networks

The polynomial networks proposed by Ivakhnenko [14] are group method of data handling (GMDH) techniques

* Corresponding author. Tel.: +886-2-2737-6456; fax: +886-2-2737-6460.
E-mail address: ystarng@mail.ntust.edu.tw (Y.S. Tarng)

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[15]. In a polynomial network, complex systems are decomposed into smaller, simpler sub-systems and grouped into several layers using polynomial functional nodes. The inputs of the network are sub-divided into groups, then transmitted into individual functional nodes. These nodes evaluate the limited number of inputs by a polynomial function and generate an output to serve as an input to subsequent nodes of the next layer. The general methodology of dealing with a limited number of inputs at a time, then summarizing the input information, and then passing the summarized information to a higher reasoning level, is related directly to human behavior as observed by Miller [16]. Therefore, polynomial networks can be recognized as a special class of biologically inspired networks with machine intelligence and can be used effectively as a predictor for estimating the outputs of complex systems.

2.1. Polynomial functional nodes

The general polynomial function known as the Ivakhnenko polynomial in a polynomial functional node can be expressed as

$$y_0 = w_0 + \sum_{i=1}^{m} w_i x_i + \sum_{i=1}^{m}\sum_{j=1}^{n} w_{ij} x_i x_j + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} w_{ijk} x_i x_j x_k + \cdots \quad (1)$$

where x_i, x_j, x_k are the inputs, y_0 is the output, and w_0, w_i, w_{ij}, w_{ijk} are the coefficients of the polynomial functional node.

In the present study, several specific types of polynomial functional nodes (Fig. 1) are used in the polynomial network for predicting corner wear in drilling. An explanation of these polynomial functional nodes is given as follows:

1. *Normalizer.* A normalizer transforms the original input into a normalized input, where the corresponding polynomial function can be expressed as

$$y_1 = w_0 + w_1 x_1 \quad (2)$$

in which x_1 is the original input, y_1 the normalized input, and w_0 and w_1 are the coefficients of the normalizer.

During this normalization process, the normalized input y_1 is adjusted to have a mean value of zero and a variance of unity.

2. *Unitizer.* On the other hand, a unitizer converts the output of the network to the real output. The polynomial equation of the unitizer can be expressed as

$$y_1 = w_0 + w_1 x_1, \quad (3)$$

where x_1 is the output of the network, y_1 the real output, and w_0 and w_1 are the coefficients of the unitizer.

The mean and variance of the real output must be equal to those of the output used to synthesize the network.

3. *Single node*. The single node only has one input and the polynomial equation is limited to the third degree, i.e.,

$$y_1 = w_0 + w_1 x_1 + w_2 x_1^2 + w_3 x_1^3, \quad (4)$$

where x_1 is the input to the node, y_1 the output of the node, and w_0, w_1, w_2, and w_3 are the coefficients of the single node.

4. *Double node*. The double node takes two inputs at a time and the third-degree polynomial equation has the cross-

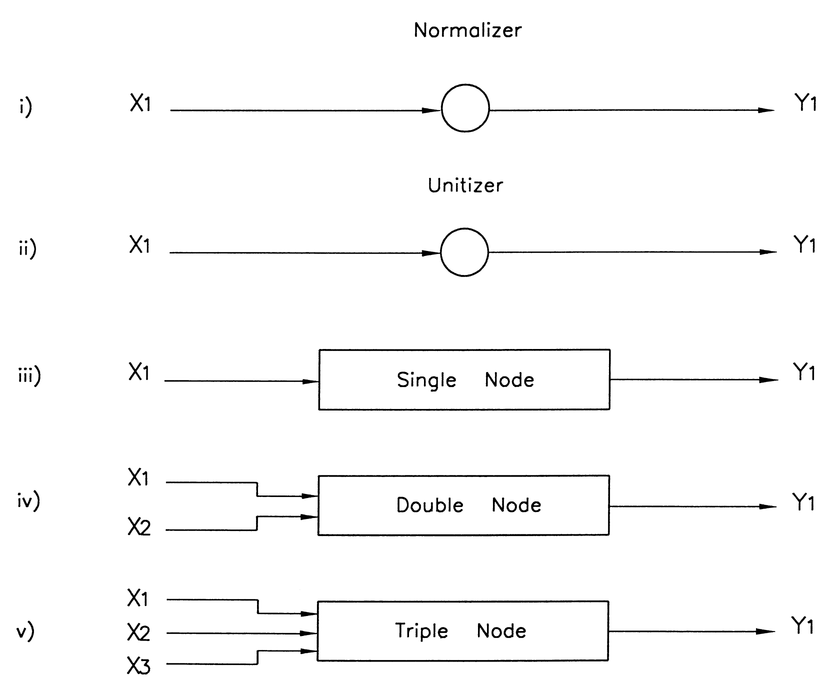

Fig. 1. Various polynomial functional nodes.

term so as to consider the interaction between the two inputs, i.e.,

$$y_1=w_0+w_1x_1+w_2x_2+w_3x_1^2+w_4x_2^2+w_5x_1x_2+w_6x_1^3+w_7x_2^3, \quad (5)$$

where x_1, x_2 are the inputs to the node, y_1 the output of the node, and w_0, w_1, $w_2, \ldots, w_7$ are the coefficients of the double node.

5. *Triple node*. Similar to the single- and double-nodes, the triple node with three inputs has a more complicated polynomial equation allowing the interaction amongst these inputs, i.e.,

$$y_1=w_0+w_1x_1+w_2x_2+w_3x_3+w_4x_1^2+w_5x_2^2+w_6x_3^2+w_7x_1x_2 +w_8x_1x_3+w_9x_2x_3+w_{10}x_1x_2x_3+w_{11}x_1^3 +w_{12}x_2^3+w_{13}x_3^3, \quad (6)$$

where x_1, x_2, x_3 are the inputs to the node, y_1 the output of the node, and w_0, w_1, $w_2, \ldots, w_{13}$ are the coefficients of the triple node.

2.2. Synthesis of polynomial networks

To build a polynomial network, a training database with the information of inputs and outputs is required first. Then, an algorithm for synthesis of the polynomial networks (ASPNs), called the predicted-squared-error (PSE) criterion [13], is used to determine an optimal network structure. The principle of the PSE criterion is to select as accurate but less complex network as possible. To accomplish this, the PSE is composed of two terms, i.e.,

$$\mathrm{PSE} = \mathrm{FSE} + \mathrm{KP}, \quad (7)$$

where FSE is the average-squared-error of the network for fitting the training data and KP is the complex penalty of the network.

The average-squared-error of the network FSE can be expressed as

$$\mathrm{FSE} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2, \quad (8)$$

where N is the number of training data, $\hat{y}_i$ the desired value in the training set, and y_i is the predicted value from the network.

The complex penalty of the network KP can be expressed as

$$\mathrm{KP} = \mathrm{CPM}\frac{2\sigma_\mathrm{P}^2 K}{N}, \quad (9)$$

where CPM is the complex penalty multiplier, K the number of coefficients in the network, and σ_P^2 is a prior estimate of the model error variance, also equal to a prior estimate of FSE.

Usually, a complex network has a high fitting accuracy. Hence, FSE (Eq. (8)) decreases with the increase of the complexity of the network. However, the more complex the network is, the larger will be the value of KP (Eq. (9)). Therefore, the PSE criterion (Eq. (7)) performs a trade-off between model accuracy and complexity. In addition, it has to be pointed out that CPM (Eq. (9)) can be used to adjust the trade-off. A complex network will be penalized more in the PSE criterion as CPM is increased. On the contrary, a complex network will be selected if CPM is decreased.

3. Experimental set-up and training database

To build a polynomial network for predicting corner wear under a variation of cutting conditions, a training database with regard to different cutting parameters and corner wear needs to be established. A number of drilling experiments were carried out on a CNC machining center (First MCV-641) using HSS twist drills for the machining of S45C steel plates. The drilling cutting parameters were selected by varying the cutting speed in the range 16–36 m/min, the feed rate in the range 0.06–0.30 mm/rev, the drill diameter in the range 6–10 mm, and the average corner wear in the range 0.1–0.65 mm. The drill geometry with corner wear is shown in Fig. 2. The corner wear land was measured by both cutting edges of the drill (w_a and w_b) using an optical tool microscope. The average corner wear land w is calculated by averaging w_a and w_b on the cutting edges. Each of these cutting parameters was set at the three levels that are listed in Table 1. In the experiments, 27 drilling experiments were designed based on the cutting parameter combinations.

The thrust force and torque signals were measured using a dynamometer (Kistler 9271A) under the workpiece. The thrust force and torque corresponding to corner wear, cutting speed, feed rate, and drill diameter are summarized and also listed in Table 1. Based on the developed training database, a three-layer polynomial network for predicting corner wear is synthesized using the PSE criterion. Figs. 3 and 4 show the developed polynomial networks for predicting corner wear using torque and thrust force, respectively. All of the polynomial equations used in the networks (Figs. 3 and 4) are

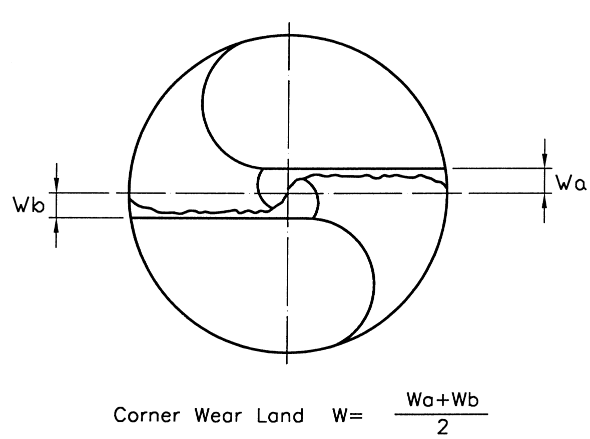

Fig. 2. Features of the corner wear land on the drill.

Table 1
Experimental drilling cutting parameters, torque, thrust force, and corner wear land for the training database

Test no.	Cutting speed (m/min)	Feed rate (mm/rev)	Drill diameter (mm)	Torque (N cm)	Thrust force (N)	Corner wear (mm)
1	16	0.06	6	31	224	0.100
2	16	0.18	8	117	414	0.100
3	16	0.30	10	269	818	0.100
4	26	0.06	8	54	244	0.100
5	26	0.18	10	181	621	0.100
6	26	0.30	6	103	469	0.100
7	36	0.06	10	80	351	0.100
8	36	0.18	6	71	347	0.100
9	36	0.30	8	167	558	0.100
10	16	0.06	6	37	321	0.375
11	16	0.18	8	133	970	0.375
12	16	0.30	10	295	1614	0.375
13	26	0.06	8	58	630	0.375
14	26	0.18	10	215	1214	0.375
15	26	0.30	6	113	773	0.375
16	36	0.06	10	98	548	0.375
17	36	0.18	6	72	543	0.375
18	36	0.30	8	191	1168	0.375
19	16	0.06	6	49	468	0.650
20	16	0.18	8	173	1091	0.650
21	16	0.30	10	361	2107	0.650
22	26	0.06	8	119	760	0.650
23	26	0.18	10	265	1813	0.650
24	26	0.30	6	154	1119	0.650
25	36	0.06	10	135	935	0.650
26	36	0.18	6	100	896	0.650
27	36	0.30	8	252	1250	0.650

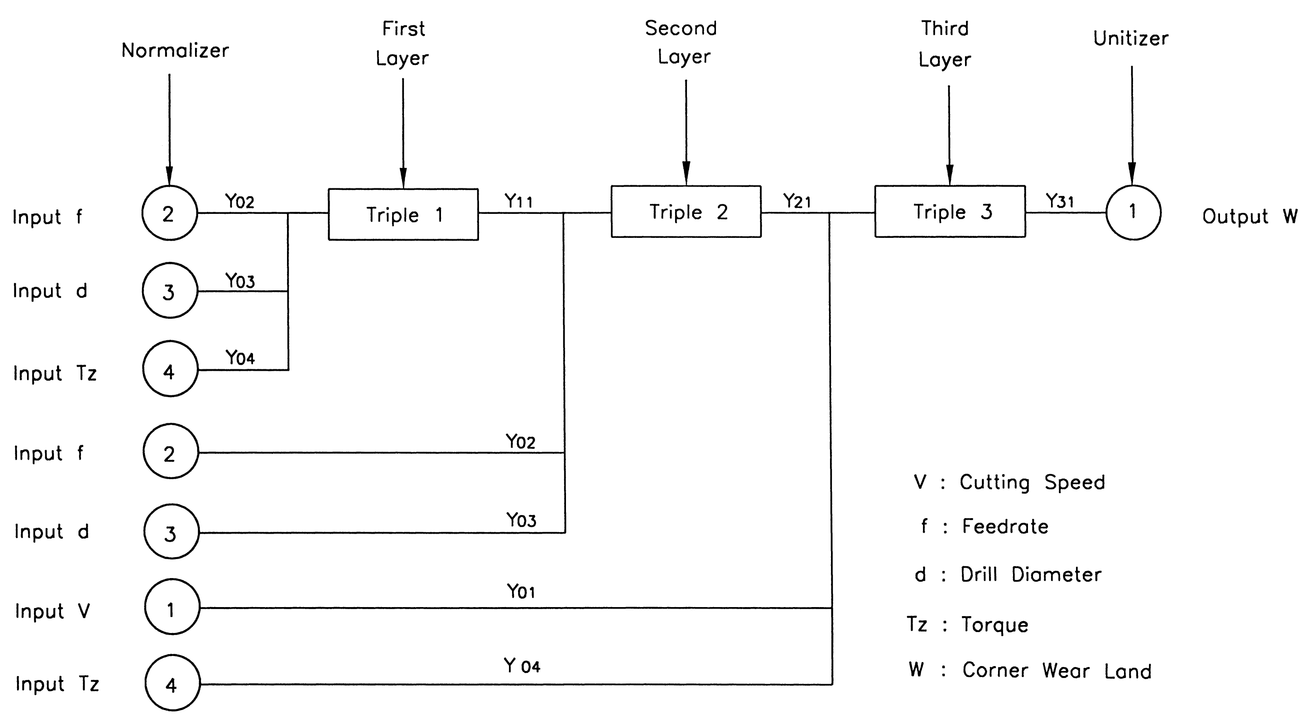

Fig. 3. Polynomial network for predicting corner wear using the torque as the sensing signal.

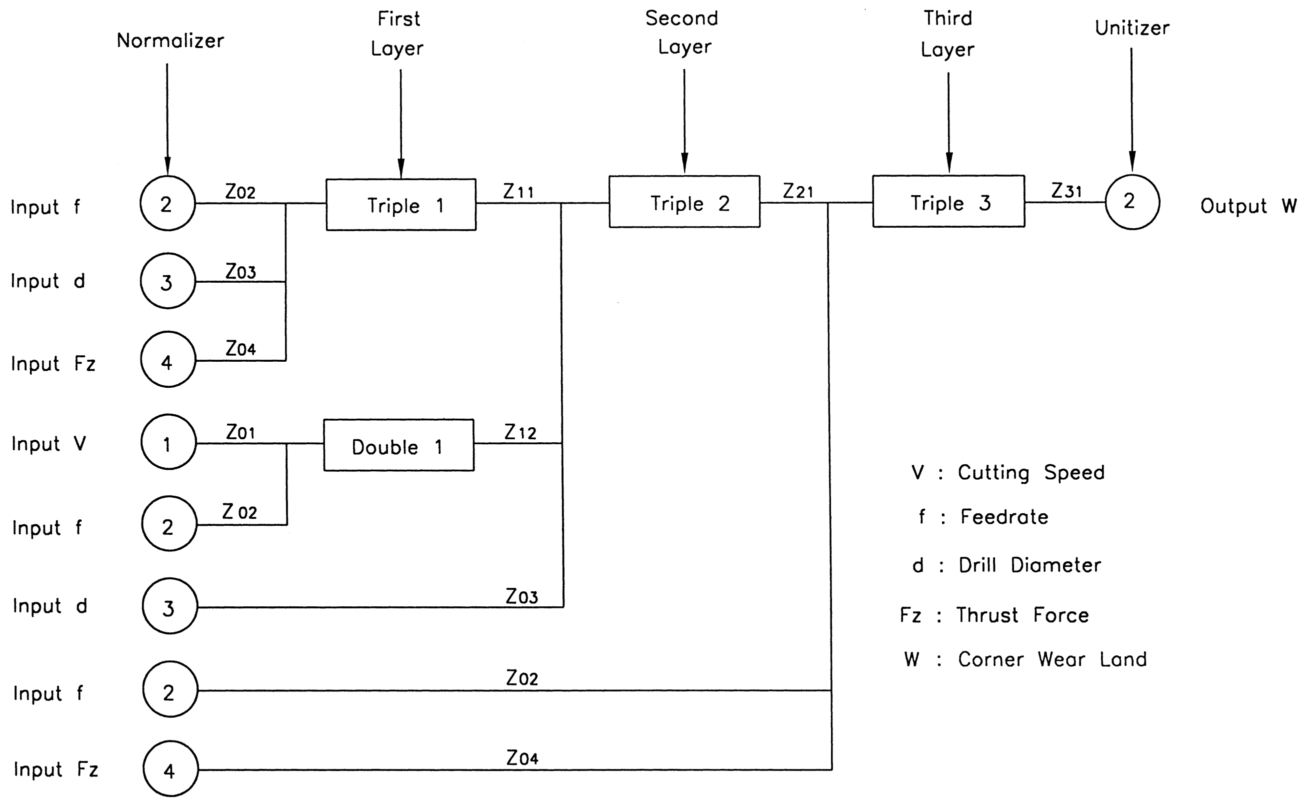

Fig. 4. Polynomial network for predicting corner wear using the thrust force as the sensing signal.

listed in Appendices A and B. A schematic diagram of the experimental set-up for predicting corner wear by the polynomial network is shown in Fig. 5.

4. Experimental verification and discussion

To evaluate the developed networks for predicting corner wear, eight drilling tests using different cutting parameters were performed (Table 2). Once the cutting speed, feed rate, drill diameter, and torque or thrust force are fed into the polynomial network, the predicted corner wear can be calculated quickly using the polynomial functions listed in Appendices A and B. A comparison of measured corner wear and predicted corner wear using the two polynomial networks (Figs. 3 and 4) is presented in Table 3. The average absolute error between the measured corner wear and the predicted corner wear using the polynomial network with torque is 25.8% and the maximum absolute error is 72.4%. However, the average absolute error between the measured corner wear and the predicted corner wear using the polynomial network with thrust force is 7.0% and the maximum absolute error is 13.8%. It is shown clearly that the thrust force is better than the torque as the sensing signal for the in-process prediction of corner wear in drilling operations.

5. Conclusions

A polynomial network for predicting corner wear in drilling operations has been reported in this paper. The

Table 2
Experimental drilling cutting parameters, torque, thrust force, and corner wear land for the tool-wear verification

Test no.	Cutting speed (m/min)	Feed rate (mm/rev)	Drill diameter (mm)	Torque (N cm)	Thrust force (N)	Corner wear (mm)
1	21	0.12	6	52	382	0.169
2	31	0.24	8	146	717	0.172
3	31	0.24	6	95	595	0.210
4	31	0.24	10	245	1058	0.240
5	31	0.24	10	280	1215	0.290
6	21	0.24	6	142	1138	0.650
7	31	0.12	10	185	1189	0.650
8	36	0.18	6	100	896	0.650

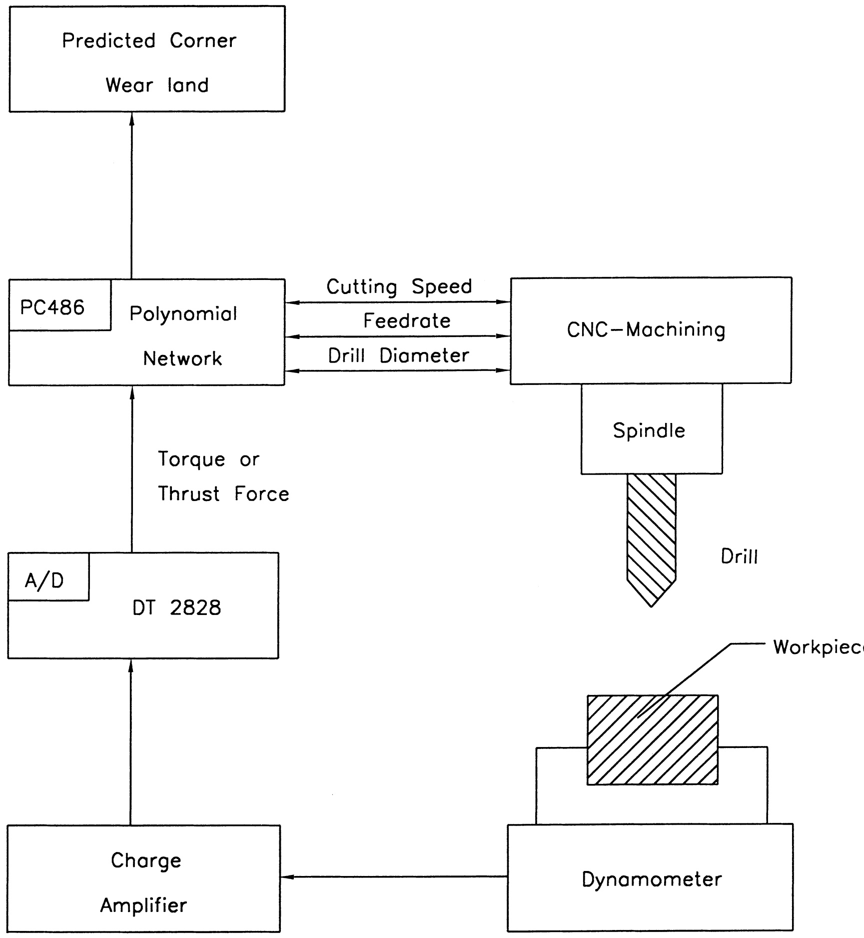

Fig. 5. Schematic illustration for the prediction of corner wear.

polynomial network uses a self-organized method for modeling the relationships amongst the cutting parameters (cutting speed, feed rate, drill diameter), the process parameters (torque, thrust force), and the corner wear. Several verification tests have shown that the thrust force is better than the torque as the sensing signal for the in-process prediction of corner wear in drilling operations. The average absolute error between the measured corner wear and the predicted

Table 3
Comparison of measured corner wear and predicted corner wear using different polynomial networks

Test no.	Corner wear land (mm)			Error (%)	
	Measurement	Prediction		From Fig. 3: polynomial network	From Fig. 4: polynomial network
		From Fig. 3: polynomial network	From Fig. 4: polynomial network		
1	0.169	0.120	0.180	+29.0	−6.5
2	0.172	0.140	0.172	+18.6	+0.0
3	0.210	0.300	0.188	−42.8	+10.5
4	0.240	0.290	0.207	−20.8	+13.8
5	0.290	0.500	0.255	−72.4	+12.0
6	0.650	0.560	0.669	+13.8	−2.9
7	0.650	0.590	0.598	+9.2	+8.0
8	0.650	0.650	0.636	+0	+2.2
MAE[a] (%)				72.4	13.8
AAE[b] (%)				25.8	7.0

[a] Maximum absolute error.
[b] Average absolute error.

corner wear using the thrust force as the sensing signal is less than 10%. In other words, polynomial networks can be used effectively to predict the corner wear over a wide range of cutting conditions in drilling.

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Appendix A.

1. Normalizer:
   1.1. $Y_{01}=-1.67+0.0116\,V$,
   1.2. $Y_{02}=-1.8+10f$,
   1.3. $Y_{03}=-4.81+0.601d$,
   1.4. $Y_{04}=-1.07+0.0116\mathrm{Tz}$.
2. Unitizer:
   2.4. $W=0.368+0.233Y_{31}$.
3. Triple node:
   3.4. $Y_{11}=0.293-1.98Y_{02}-1.83Y_{03}+2.93Y_{04}-0.182Y_{02}^2-0.119Y_{03}^2-1.45Y_{04}^2-0.958Y_{02}Y_{03}+1.32Y_{02}Y_{04}+0.654Y_{03}Y_{04}-0.207Y_{02}Y_{03}Y_{04}+0.208Y_{04}^3$,
   3.5. $Y_{21}=0.349+1.57Y_{11}-0.0287Y_{03}-0.324Y_{11}^2+0.168Y_{02}^2-0.148Y_{03}^2-0.119Y_{11}Y_{02}-0.115Y_{11}Y_{03}-0.0531Y_{02}Y_{03}+0.133Y_{11}Y_{02}Y_{03}-0.219Y_{11}^3$,
   3.6. $Y_{31}=0.0446+0.905Y_{21}+0.0827Y_{01}-0.0228Y_{04}-0.0631Y_{21}^2-0.016Y_{01}^2+0.0732Y_{04}^2-0.0622Y_{21}Y_{01}-0.0591Y_{21}Y_{04}-0.0253Y_{01}Y_{04}+0.0333Y_{21}Y_{01}Y_{04}+0.0901Y_{21}^3$.

Appendix B.

1. Normalizer:
   1.1. $Z_{01}=-3.12+0.12V$,
   1.2. $Z_{02}=-1.8+10f$,
   1.3. $Z_{03}=-4.81+0.601d$,
   1.4. $Z_{04}=-1.68+0.00205\mathrm{Fz}$.
2. Unitizer:
   2.4. $W=0.360+0.233Z_{31}$.
3. Double node:
   3.4. $Z_{12}=-6.5e-1.7Z_{02}^2-0.0198Z_{01}Z_{02}$.
4. Triple node:
   4.4. $Z_{11}=0.0845-0.795Z_{02}-0.632Z_{03}+1.52Z_{04}+0.283Z_{02}^2+0.0415Z_{03}^2-0.229Z_{04}^2+0.106Z_{02}Z_{02}-0.152Z_{02}Z_{04}-0.377Z_{03}Z_{04}-0.0501Z_{02}Z_{03}Z_{04}-0.0871Z_{04}^3$,
   4.5. $Z_{21}=0.171-0.946Z_{11}+38.8Z_{12}-0.0168Z_{03}+0.099Z_{11}^2+261Z_{12}^2-5.28Z_{11}^2+9.48Z_{11}Z_{12}Z_{03}-4.92e^4Z_{12}^3$,
   4.6. $Z_{31}=0.0643+0.558Z_{21}-0.115Z_{02}+0.4Z_{04}-0.086Z_{21}^2-0.158Z_{02}^2-0.156Z_{04}^2-0.229Z_{21}Z_{02}+0.446Z_{21}Z_{04}+0.276Z_{02}Z_{04}+0.184Z_{21}Z_{02}Z_{04}+0.293Z_{21}^3-0.155Z_{04}^3$.

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