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Drilling Projects by Tool Condition Monitoring System (TCMS)

Justo GARCÍA-SANZ-CALCEDO[1]), David R. SALGADO[2])
Alfonso G. GONZÁLEZ[2])

[1]) *University of Extremadura*
Graphical Expression Department
Avda. Elvas s/n (06070) Badajoz, Spain
e-mail: jgsanz@unex.es

[2]) *University of Extremadura*
Mechanical, Energetic and Materials Engineering Department
Avda. Elvas s/n (06070) Badajoz, Spain

In this paper, an online tool condition monitoring system (TCMS) for drilling is presented. The method is based on monitoring the spindle and feed motor currents. Root mean square (RMS) values of the spindle and feed motor currents, drill diameter, spindle speed and feed rate are the inputs to the network, and drill wear is the output. Drilling experiments were carried out over a wide range of cutting conditions to map the relationship between the input information and a tool wear. The performance and the architecture of the neural network have been validated with experiments, and a good agreement in an estimation of the tool condition was found. The results show that this method can be effectively used to verify and determine the tool wear.

Key words: mechanical project, monitoring, drilling projects.

1. Introduction

Drill wear is a very important issue in manufacturing processes, since it affects not only surface roughness of a hole, but also tool life. Moreover, drilling is one of the most common operations in machining, e.g., in automobile or aircraft industries. It was reported that drilling accounts for nearly 40% of all the metal removal operations in the aerospace industry [1]. Therefore, drill wear monitoring has gained a considerable importance in manufacturing industry.

Tool wear monitoring methods can be classified into two categories, i.e., direct and indirect methods. With direct methods it is possible to determine tool wear directly, which means that these methods really measure tool wear as such. In spite of many attempts, the direct methods such as visual inspection or computer vision, etc. have not yet proven to be very attractive economically or technically. This is probably the reason why many of the TCMSs proposed in the literature are indirect methods.

Drill wear is a progressive process that takes place at the outer margin of the flutes of the drill due to the chip-workpiece contact at high temperatures [2]. Moreover, under constant cutting conditions a drill failure can be consider a stochastic process. Among the main reasons for this consideration are the in-homogeneities in the workpiece and tool material, the irregularities in the cutting fluid motion, and the unavoidable asymmetry introduced during the grinding of the cutting edges [3].

Many TCMSs use the cutting forces and torque [4, 5], mainly due to the fact that these two forces increase as tool wear increases. Other works have studied tool condition monitoring in drilling using different sensor signals, such as vibrations [6] or spindle motor power [7]. Among the sensors used for tool condition monitoring, motor current sensing constitutes a major method, since these sensors do not disturb the machining process. Moreover, it can be applied in the manufacturing environment at almost no extra cost [8].

In this work, drill wear condition monitoring is based on spindle and feed motor current signals. The novelty of this paper is the signal processing method used to analyzed the monitoring signals. Different statistical parameters are obtained and principal component analysis (PCA) is then applied to reduce the number of variables in the proposed model. With the resulting components, an artificial neural network (ANN) is trained to predict tool condition.

2. Methodology

Drilling experiments were performed on a vertical drilling machine. The monitoring signals were acquired during machining, taking into account an expected tool life. The workpiece material was C45 steel. Flank wear of the drills was consecutively measured after a number of holes were drilled. HSS drills with different diameters were used in the experiments. The experiments were carried out over a wide range of cutting conditions to map the relationship between the input information and the output information, i.e., the tool flank wear. Figure 1a shows a schematic diagram of the experimental set-up.

The AC current signals of the drilling machine were measured with Hall current sensors, sampled at 1000 Hz. Table 1 shows the experimental cutting conditions.

Table 1. Experimental data used for preparing the TCMS.

Exp.	Speed [rpm]	Feed rate [mm/rev]	Drill diameter [mm]	Tool flank wear [mm]
1	300	0.1	5	0.31
2	300	0.5	7.5	0.24
3	400	0.3	10	0.19
4	400	0.3	7.5	0.42
5	500	0.4	10	0.25
6	500	0.5	5	0.61
7	600	0.2	7.5	0.54
8	600	0.1	5	0.42
9	600	0.2	10	0.37
10	300	0.5	5	0.26
11	800	0.1	7.5	0.17
12	400	0.4	10	0.72
13	600	0.3	5	0.24
14	800	0.2	7.5	0.39
15	800	0.3	7.5	0.44
16	300	0.5	10	0.52
17	400	0.7	5	0.63
18	800	0.5	10	0.55
19	600	0.3	5	0.37
20	400	0.4	5	0.28
21	800	0.2	7.5	0.34
22	300	0.5	10	0.25
23	1000	0.3	10	0.33
24	1000	0.1	7.5	0.45
25	300	0.3	5	0.67
26	500	0.2	10	0.29
27	1000	0.5	7.5	0.32
28	600	0.3	10	0.15
29	500	0.2	7.5	0.44
30	400	0.5	5	0.32
31	600	0.7	10	0.27
32	1000	0.3	5	0.59
33	800	0.4	7.5	0.54
34	600	0.1	10	0.28
35	1000	0.4	7.5	0.69

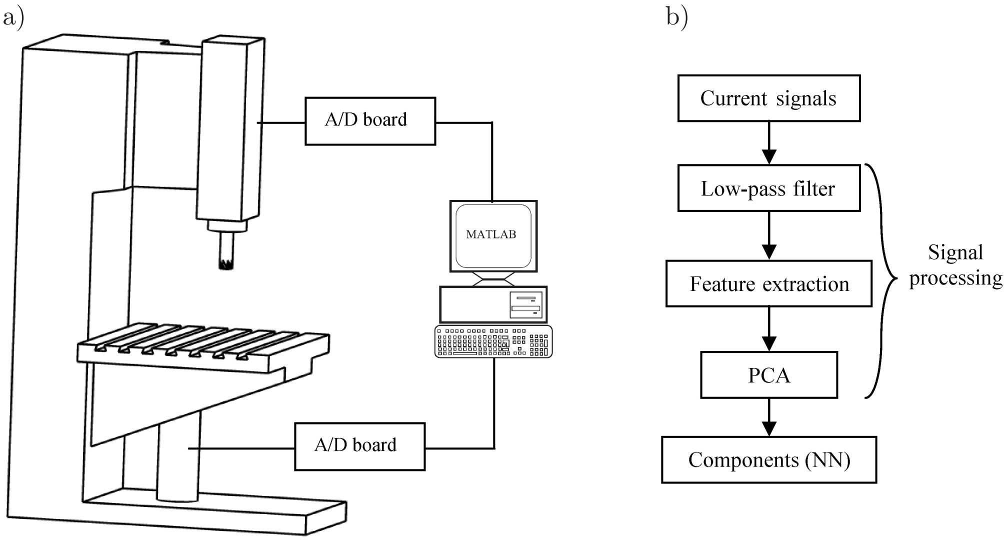

FIG. 1. a) Schematic diagram of the experimental set-up, b) schematic diagram of the monitoring strategy.

Table 2 lists 14 statistical features that were extracted from the monitoring signals. The suffixes S and F refer to the spindle motor current and the feed motor current respectively. To estimate the tool condition, a selection was made of only those features that present a monotonic variation with flank wear. Interestingly, these were the same statistical features, i.e., the variance, the RMS and the skewness for the two current signals.

Table 2. Extracted features from monitoring signals.

Signal features	Spindle current	Feed motor current
Mean	$\overline{X}_S$	$\overline{X}_F$
Variance	σ_S^2	σ_F^2
RMS	RMS_S	RMS_F
Range	R_S	R_F
Median	M_S	M_F
Skewness	SK_S	SK_F
Kurtosis	K_S	K_F

The six features selected for developing the TCMS were reduced to three by applying principal component analysis (PCA) in order to develop a more effective decision making strategy. In particular, the main objective of this data dimension reduction is to reduce the computing time. The three new features along with the cutting conditions are the features introduced to the network to predict the tool wear.

3. Results and discussion

An ANN – a multilayer perceptron – was used to estimate the tool condition in view of the good results yielded by ANNs in estimating the tool wear in other works. Furthermore, the robustness of ANNs with respect to perturbations in the input information makes them ideal for TCMS development. Another interesting fact is that an appropriate choice of the learning rate and the momentum parameter allows to obtain a fast convergence with low error, and a relatively small number of training iterations.

The inputs to the network are the cutting conditions (speed, feed and drill diameter) and the selected features of the vibration signals (the three features obtained under PCA) – six inputs in total. Figure 2 shows a schematic diagram of the multilayer neural network.

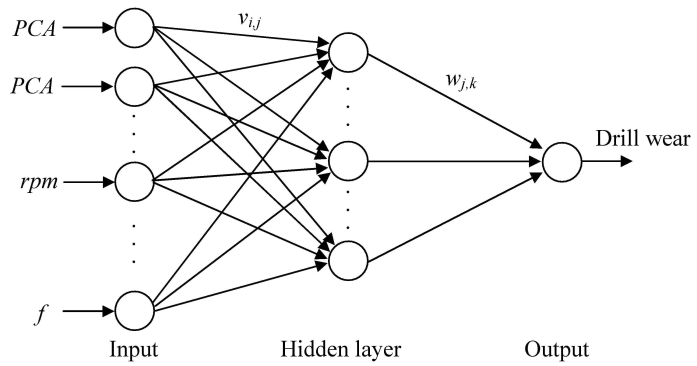

Fig. 2. Schematic diagram of multilayer neural network.

To select the best architecture of the neural network, the number of iterations in the training process was fixed at 20000, and then the errors were calculated with the validation data. Table 3 shows the validation data used in the development of this TCMS. The $v_{i,j}$ are the weights between i-th neuron of the input layer and j-th neuron of the hidden layer, and $w_{j,k}$ the weights between j-th neuron of the hidden layer and k-th neuron of the output layer. From the results, the architecture that has been identified as optimal is a 6-3-1 network based on the minimum RMS error. There was no improvement obtained by having two hidden layers in the architecture.

Analyzing the monitoring signals, it was found that, in general, the current amplitude increases as the tool flank wear increases. Another interesting result is that the variance, RMS and skewness for both the spindle motor current

Table 3. Experimental data used to validate the TCMS.

Exp.	Speed [rpm]	Feed rate [mm/rev]	Drill diameter [mm]	Tool flank wear [mm]
1	500	0.1	7.5	0.31
2	400	0.5	5	0.24
3	300	0.1	7.5	0.19
4	400	0.4	10	0.42
5	600	0.3	5	0.25
6	500	0.5	7.5	0.61
7	500	0.1	5	0.54
8	600	0.4	5	0.42
9	400	0.3	7.5	0.37
10	300	0.1	5	0.26
11	800	0.4	10	0.17
12	500	0.3	7.5	0.72
13	600	0.5	5	0.24
14	500	0.4	10	0.39
15	800	0.3	7.5	0.44

and feed motor current increase when the feed increases. These results are in agreement with the findings of PATRA *et al.* [8]. Moreover, it is important to notice that the increase in spindle motor current is linear until 0.35 mm of a tool flank wear and for greater wears this relationship becomes nonlinear. Especially, this effect is observed when the feed rate is greater than 0.3 mm/rev.

Figure 3 shows the estimation errors (in percentages) with the validation data. A good correlation between the estimated tool flank wear and the measured one is observed.

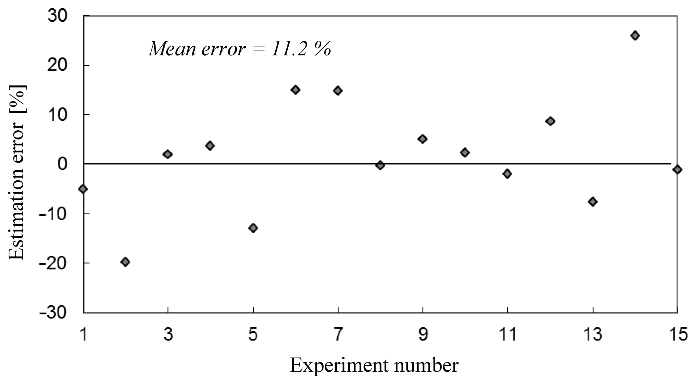

FIG. 3. Estimation error obtained with the validation data and 6-3-1 neural network (NN) architecture.

4. Conclusions

It is possible to reduce the dimensional space of the features without reducing the success rate of the proposed TCMS. In particular, when applying the PCA technique, the feature dimension has been reduced by 50%, which reduced the computing time due to the dimensional reduction. The mean error obtained with the validation data is 11.2%. Another interesting result is that the variance, RMS and skewness for both the spindle motor current and feed motor current increase when feed increases. This effect has been also detected but with a great magnitude when a drill diameter increases. Moreover, it is important to notice that the increase in spindle motor current is linear until 0.35 mm of tool flank wear, and for larger wears this relationship becomes nonlinear.

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