Research on Real-time Monitoring for Milling Cutter Wear Based on Neural Network

HUANG Zhigang
School of Mechanical and Electronical Engineering, East China Jiaotong University, Nanchang Jiangxi Province, China, 330013
1.huangzg7301@163.com, 2.huangzg@ecjtu.jx.cn

Abstract: The tool's abrasion causes part's shape and dimension change. Since the machine tool input power change is connected with the cutting state, the tool's wearing quantity is gained by measuring power signal indirectly. The average cutting power signal for a single tooth can reflect the cutting state farthest. Recur to the difference principle, it is easy to separate the normal cutting power and abrasion cutting power. Using BP neural network, we can identify the tool's two states: normal and wear off. Some experiments have been fulfilled under different cutting parameters. This system was able to identify the tool's abrasion state with high reliability. The results illuminate that the method used in the system is effective.

Key words: wear; real-time monitoring; neural network; compensation

1. Introduction

The milling process is a very important form in machining. It executes cutting with multi-blades and the cutting parameters vary continually in the whole processing. The two typical characteristics are:1) each milling cutter is composed of several teeth, each tooth works and rests alternately in a cycle;2) when the tooth takes part in cutting, the thickness of cutting varies in different point, therefore, the difficulty of monitoring the milling process is added. The disadvantages brought by tool wear in machining are: machine tool's vibration, workpiece surface quality and dimension precision descent, severely causing such failures as tool breakage, workpiece rejection, machine tool's abnormal stopping. According to the statistics, approximately 75% equipment abnormal stopping comes of tools' invalidation. So, the tool wear's real-time monitoring is very important to the modern machining. The process is often composed of computer and sensor technology.

2. Principle of Wear'S Monitoring

Tool wear is caused by various mechanical physical factors, including the blade's plastic deformation, adherence, friction and thermal fatigue. After the tool wear, the rear edge's angle is zero, the interface between rear surface and workpiece increases. Meanwhile, the knifepoint radius's augment brings on the friction getting acute between tool and workpiece. Consequently, the machine tool's cutting power is increased. Depend on monitoring the major electromotor input power and some given recognition strategy, we can detect the tool wear in detail. The electromotor power monitoring method transfers the force measurement from cutting area to electromotor, and the force parameters are translated into electrical parameters relevantly. This method can be incorporated into the category of cutting force monitoring.

Due to this method's merits such as being highly sensitive to tool wear, simple measurement signal, avoidance of cutting scrap、oil、smoke、vibration, no disturbance to manufacture, it is used widely in tool state's monitoring and real-time control. Machine tool's power is the major electromotor output power. It is related to the status of machining and contains the cutting power P_c which is correlative to the state of the tool. On account of the difficulty in detecting the electromotor output power, we measure the major electromotor input power P_t in practice. After some predigesting, we can analyze the relation between p_t and p_c from the energy transfer in machine tool. The result is:

$$P_t \approx \alpha_t P_c + M_0\omega + B\omega^2 + J\omega\frac{d\omega}{dt} \qquad (1)$$

ω—electromotor angular velocity; $\mathbf{M_0}$—non-load coulomb friction equivalent moment gained by converting machine tool's transmission system to the electromotor shaft; B—damp viscosity coefficient; **J**—moment of inertia; $\boldsymbol{\alpha_t}$—system load waste coefficient.

We can make out that the effective cutting power signal consists in the electromotor input power signal. When tool wear takes place, there certainly will be alteration in cutting force and power. Three-phase hall

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power level detector is used in measuring electromotor input power signal. In figure 1, the part's material is 40Cr; tool's material is YT5; cutting depth is 0.5 millimeter. It is obvious that tool wear degree increases along with the electromotor input power augment in time

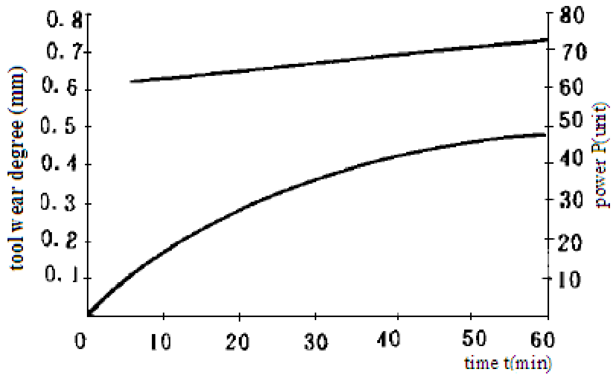

Fig 1 the relation among tool wear degree, power and time

history form. The variation range is 63 to 72 units. In figure 2, there is an approximate linear relationship between tool wear degree and input power.

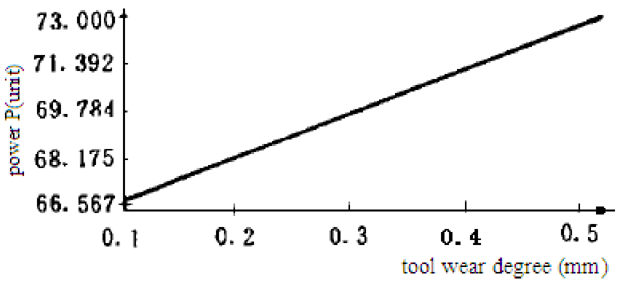

Fig2 the relation between tool wear degree and input power

3. Character Extraction and Identification

3.1 Wear'S Character Signal Processing

Electromagnetism disturbance is caused by the overlapped 50Hz industrial electric power. In order to eliminate the disturbance, we have designed a low pass filter. For milling process, the instantaneous power signal is not important in a tooth cycle. The most important signal is mean power signal which reflects the tooth's cutting effect. Therefore, the filtered power signal is averaged in a tooth region (cycle) and is regarded as basic processing unit. In the processing, when a tooth is worn, the place which it should cut will be accomplished by the next tooth. This phenomenon will cause the cutting load varies with a trend: fall, increase, comeback normal. Using difference to compare the two next teeth's cutting power P_c, we can identify the normal teeth and the worn teeth. Due to the influence of machine tool's inertia part, the machine tool's input power **pt** dose not vary immediately while the j +1 tooth's cutting load increase for j tooth's wear. The increased power will appear after a little delay until the j+2 tooth takes part in cutting. Base on this reason, our system uses difference methodology. When the tool's state is normal, the power signal's difference value and unitary value are small. However, when tool occurs wear, the two values are obviously more lager. Utilizing appropriate sensor and sampling frequency, we can extract useful information and identify the wear state in time.

3.2 Tool State Identification

Tools have two states: normal and wear. Because of the reasons for tool wear are complex, it is difficult to distinguish different instances by conventional methods. We make use of neural network via self-study to form required decision-making area. BP network is favored by reason of its practicality and simpleness. It is especially remarkable that this network can approach non-linear function with discretional precision. The process of artificial network monitoring the milling cutter can be divided into two stages: (1) training: concentrated training network weights (W1, W_2) and threshold values (b1, b2) using a series of measured wear quantities; (2) extending application: according to the trained network weights to predict (calculate) the tool wear.

The model of neural network used to monitoring tool state adopts three layers perceptive cell. Its output layer just uses one node. The network model is illustrated in figure 3. Three inputs are principal axis power difference, axial cutting depth a_p , instantaneous cutting thickness respectively. To sort and arrange experimental data which are collected on different cutting conditions.

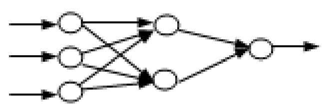

Figure. 3 the BP network structural sketch map

By choosing several groups typical experimental data, we can train the neural network. Finally, we have established the tool wear monitoring and controlling model. When the output node's value is 1, it shows that the tool is being worn badly. When the output node's value is 0, it shows that the tool is in normal state. The more hidden layers and nodes exist in the model, the lower efficient the system is. So we ensure that there are three layers in our model.

4. System Constitution and Realization

Machine tool: XA5032 stand-up milling machine; Tool: 25 millimeter milling cutter; Power level detector; Sampling and Holding device; neural network data process module; Compensation device (NC); Industrial Computer; Displaying and Printing module. The system's composition diagram is shown in figure 4. All these transducers are insulative to the ground. The loop disturbance to the measuring signal is eliminated. When the tool cutter is in normal state, scheduled program and algorithm are executed to perform compensation strategy so as to adjust the cutting track and to ensure the right dimensional precision. When the tool wear is out of the error limitation, a photo-sonic alarming is activated to instruct supervisor to stop the machine and to replace the worn tool. The system's composition is shown in figure 4. In this system, the collected data

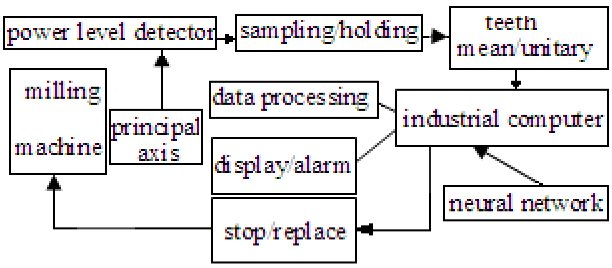

Figure.4 system composition sketch map

from forward path is processed by the network algorithm. Thus, the two tool states are identified resorting to this method. The output of I/O module is switching value. The proclitic control circuit is comprised of triode, relay, diode, pull-up resistor and indicator light. The contr olling principle is shown in figure 5.

The triode's base is in conducting state only when the output of I/O module is high level. Then, the relay begins to work so as to stop the electromotor. The diode is an overload protection device. The high level drives alarm circuit working and indicates the supervisor to change the worn tool in time. In order to simplify the narration, we substitute a lamp for the control circuit. When the output of I/O module is low level, the triode's base is in cut-off state. The relay and the alarm circuit do not work. This means that the tool is normal and the machine can be operating continually. Thus, the machine's efficiency and productivity can be guaranteed.

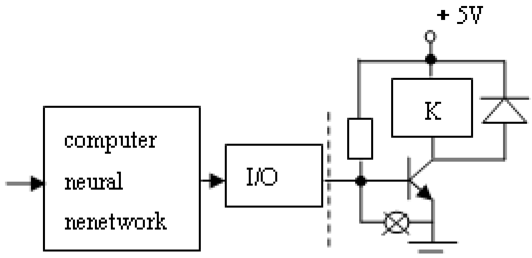

Figure.5 system control principle's sketch map

5. Conclusion

We have experimented several times under the laboratory condition. The accuracy rate of the system can almost achieve 90%. But, the probability of misinformation is little higher in the course of small cutting depth and feed. Furthermore, we have found that the more full-scale the sample is, the higher accuracy the network model is. So, we can make a conclusion that the network method is able to work well in a large range with satisfactory reliability. The whole system's configuration is popular and its cost performance is very high.

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