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# Specific Energy Consumption Prediction Method Based on Machine Tool Power Measurement

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**Abstract:** Accurate prediction on energy consumption in machining is helpful to evaluate process energy characteristics and choose process methods for energy saving. Specific energy consumption expresses the required energy consumption when cutting unit volume material. The Back Propagation (BP) neural network prediction method for specific energy consumption in machining is set up in the paper. The prediction method bases on machine tool power signal measurement by power analyzer and shunt sensors. In the developed BP neural network, the input layer neurons include spindle speed, feed rate, depth of cut and material removal rate; and the output layer neurons includes specific energy consumption in machining. The power signal measurement system is built up in the computer numerical control (CNC) milling machine tool, and the prediction method for specific energy consumption is tested with cutting data. The prediction results show that the introduced method is effective to predict specific energy consumption in machining. *Copyright © 2014 IFSA Publishing, S. L.*

**Keywords:** Shunt sensor, Power measurement, Specific energy consumption, Machining, BP neural network

## 1. Introduction

The global energy crisis and climate warming situation become more and more serious [1]. Recently, the low carbon revolution aimed to high energy efficiency and low emissions is carried out by some developed countries in the world, to cope with environment deterioration, climate change and energy crisis [2-3]. The developed countries and the international organization for standardization have launched a series of standards and laws related with energy-saving, low carbon technology. The manufacturing field is the state Pillar industry. For one thing, it lays a solid foundation for improving the humankind spiritual civilization and material civilization. For another thing, it will consume a lot of resources and energy, and result in unnecessary losses and serious environmental pollution [4]. Consequently, the urgent task of the manufacturing industry is how to reduce the manufacturing resources, energy consumption and environmental pollution [5-6].

Based on thermal dynamics, Gutowski divided the energy consumption of the manufacturing process into two parts, the energy consumption to produce materials and the energy consumption to process products [7]. And the former relates to the used material nature, material purity and manufacturing technology. The carbon emission in machining comes from energy consumption mainly, especially the electric energy. The energy consumption in manufacturing fields account for about 60% of the total energy consumption in China, and more than 70% of emissions to cause environmental pollution come from manufacturing industry [8]. In sum, how to reduce energy consumption and environment pollution caused by manufacturing industry is an urgent problem to deal with [9].

The computer numerical control (CNC) machine tools are powerful, and have a lot of energy consumption parts, which include the spindle servo drive system, feed servo drive system, cooling and lubricating system, CNC device and PLC part, lighting device, fan, chip system, cutter change device and other auxiliary system. The energy consumption includes cutting energy consumption, motors power loss, generalized energy storage, friction energy consumption, electrical components energy consumption, and auxiliary system energy consumption [10]. The CNC machine tools components are divided into two categories by Mori [11]. One is the spindle motor and feed motor, whose energy consumption depends mainly on the cutting force, inertia force and friction force to move spindle box and table; the other is cooling lubrication peripheral equipment, whose energy consumption depends mainly on working time.

Shi analyzed the machine tool main motor power transmission characteristics and the mechanical transmission system characteristics, and established the dynamic power balance equations of the main drive system [12]. Hu *et al*. divided the main transmission system input power $P_{in}$ into the no-load power $P_u$, cutting power $P_c$, and additional load loss power $P_a$ further [13]:

$$P_{in} = P_u + P_c + P_a \,, \tag{1}$$

where $P_u$ has connection with friction, damping and rotation rate; $P_c$ depends on the cutting parameters; and $P_a$ is the function of cutting power $P_c$.

Balogun neglected the spindle system power losses due to friction, bearing vibration and heat when analyzing the main transmission system no-load power, and arrived at a conclusion that the no-load power $P_u$ is a piecewise linear function of the spindle motor rotation speed $N$ [14].

To sum up, energy consumption reduction is very important to protect environment and achieve sustainable manufacturing. So accurate prediction on energy consumption in machining is helpful to evaluate process energy characteristics and choose process methods for energy saving. But CNC machine tools have many function parts and the energy consumption is difficult to calculate precisely. The existing energy consumption prediction methods are analyzed, and the Back Propagation (BP) neural network prediction method for specific energy consumption in machining is built up in the paper. The prediction method bases on CNC machine tool power signal measurement by power analyzer and shunt sensors. The power signal measurement system is built up in a CNC milling machine tool, and the prediction method for specific energy consumption is testified with cutting data.

## 2. The Existing Machine Tool Energy Consumption Prediction Methods

In modern CNC machining process, the energy consumption of cutting movement is less than 15%, while the energy consumption of auxiliary systems occupies about 85%. The auxiliary systems include blanking, cutting fluid pump, start and brake, CNC system, cooling, lighting and so on [7]. The existing machine tool energy consumption prediction methods include prediction methods based on machine tool function components and prediction methods based on empirical model mainly.

### 2.1. The Energy Consumption Prediction Methods Based on Machine Tool Function Components

After establishing energy model of each CNC machine tool function component, Braun predicted the energy consumption in machining according to process parameters, cutters, work piece materials [15]. Zhang divided the CNC machine tool energy consumption $E$ into cutting energy consumption $E_c$, air cutting energy consumption $E_a$ during non cutting stage, and tool change energy consumption $E_t$ [16]:

$$E = E_c + E_a + E_t \,, \tag{2}$$

Balogun divided the energy consumption $E$ in machining into the standby energy consumption $E_{basic}$, the preparatory work energy consumption $E_{ready}$, and the energy consumption $E_{cutting}$ when cutting [14]:

$$E = E_{basic} + E_{ready} + E_{cutting} \,, \tag{3}$$

Liu established the CNC machine tool service process energy consumption prediction model according to three kinds of sub process, including start, no-load and processing [17]. With the prediction model, the energy consumption in machining can be predicted according to process parameters. He *et al*. analyzed the energy characteristic of CNC machine tool function components, and set up the energy consumption prediction model [18]:

$$\begin{aligned} E = &\int_{t_{ms}}^{t_{me}} p_m dt + \int_{t_{cs}}^{t_{ce}} p_c dt + \sum_{i=1}^{m} \int_{t_{fs}}^{t_{fe}} p_i dt + \\ &p_{tool} t_{tool} + p_{cool}(t_{coe} - t_{\cos}) + \\ &(p_{servo} + p_{fan})(t_e - t_s) \end{aligned} \,, \tag{4}$$

The variables meaning are as follows:

$E$ is the total energy consumption when running the CNC codes;

$p_m$ is the power enabling the operating state of the spindle transmission system;

$t_{ms}$ is the spindle system rotation starting time;

$t_{me}$ is the spindle system rotation ending time;

$p_c$ is the power of material removal;

$t_{cs}$ is the cutting starting time;

$t_{ce}$ is the cutting ending time;

$p_i$ is the $i_{th}$ axis feed servo motor power;

$t_{fs}$ is the starting time of the $i_{th}$ axis servo motor;

$t_{fe}$ is the ending time of the $i_{th}$ axis servo motor;

$p_{tool}$ is the power of the tool change motor;

$t_{tool}$ is the tool change time;

$p_{cool}$ is the coolant pump motor power;

$t_{coe}$-$t_{cos}$ is the coolant pump motor working time;

$p_{servo}$ is the servos system power;

$p_{fan}$ is the fan motors power;

$t_e$-$t_s$ is the machine tool running time.

### 2.2. The Energy Consumption Prediction Methods Based on Empirical Model

CNC machine tools have a lot of function components, and the energy consumption calculation in machining is very complex. The empirical models are advisable means to calculate energy consumption in machining [19]. Gutowski established machine tool efficiency model and energy consumption model, and considered that machine tools consume energy even at no-load operation state [7]. The extra energy consumption in machining is directly proportional to the material process rate, and the power balance equation is as follows:

$$P = P_0 + k\dot{v}, \qquad (5)$$

The variables meaning are as follows:

$P$ is the total power in the cutting process in kW;

$P_0$ is the idle power in kW;

$k$ is constant in kJ/cm$^3$;

$\dot{v}$ is the material processing rate in cm$^3$/s.

Kara developed the specific energy consumption prediction method for turning and milling process [20]:

$$SEC = \mathrm{C}_0 + \frac{C_1}{MRR}, \qquad (6)$$

where:

$SEC$ is the machine tool specific energy consumption in kJ/cm$^3$;

$C_0$ and $C_1$ are constants;

$MRR$: the material removal rate in cm$^3$/s.

Considering the CNC machine tool spindle drive system, no-load power consumption, standby power consumption and cutting energy consumption, Li put forward specific energy consumption prediction model in dry cutting condition [21]:

$$SEC = k_0 + k_1 \cdot \frac{N}{MRR} + \frac{k_2}{MRR}, \qquad (7)$$

The variables meaning are as follows:

$k_0$ is the specific energy requirement in cutting operations;

$k_1$ is the specific coefficient of spindle motor;

$k_2$ is the constant coefficient of machine tool;

$N$ is the spindle speed;

$MRR$ is the material removal rate in cm$^3$/s.

## 3. The Specific Energy Consumption Prediction Method Based on BP Neural Network

### 3.1. The Process Parameters and Energy Consumption in CNC Turning and Milling

Generally, CNC machine tool includes the spindle drive system, feed drive system, electric control system, lighting system, cooling system, lubricating system and chip system. The spindle drive system and feed drive system are defined as machine tool transmission system. The structure of CNC machining system is shown in Fig. 1.

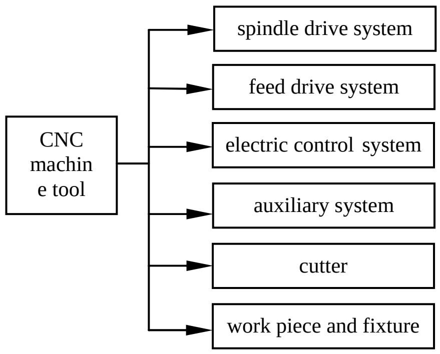



**Fig. 1.** The structure of CNC machining system.

In CNC turning and milling, the cutting elements commonly include the spindle speed, feed rate and cutting depth. Specifically, the spindle speed is used to specify the CNC machine tool spindle rotation rate in r/min; feed rate is the moving speed of the tool relative to work piece on the feed direction in mm/min; and cutting depth is the vertical distance between the machined surface and the unprocessed surface in mm.

Machining process is a dynamic system, which cuts work piece material with cutter, fixture, lubricating oil and coolant, and finally obtains the semi-finished or finished products. All of the process stages need to consume energy. Each subsystem of mechanical processing is accompanied with the energy input, storage and release, loss and output. In general, the energy required for machining system is electric energy.

### 3.2. The Specific Energy Consumption Prediction Method Based on BP Neural Network

The specific energy consumption expresses the required energy consumption when cutting unit volume material. The advantage of specific energy consumption is that it can reflect the mapping relationship between the cutting energy consumption and the material removal rate. In other words, as long as the specific energy consumption is achieved, the machine tool energy consumption in machining can be predicted accurately.

In CNC machining, the specific energy consumption depends on both the material removal rate and the specific cutting parameters. However, the existing specific energy consumption prediction models depend on material removal rate mainly, not considering specific cutting parameters such as the spindle speed, feed rate and cutting depth. So the BP neural network prediction method for specific energy consumption in machining is set up in the paper, which bases on CNC machine tool power signal measurement by power analyzer and shunt sensors.

The machine tool power signal measurement system structure is shown in Fig.2. The voltage signal and current signal are measured from three phase power lines of CNC machine tool. The machine tool large current signals are converted into small voltage signals by shunt sensors to input power analyzer. The USB interface is used to achieve communication between power analyzer and personal computer (PC). The CNC machine tool power signals are measured and stored in PC, which provides data information for the specific energy consumption calculation.

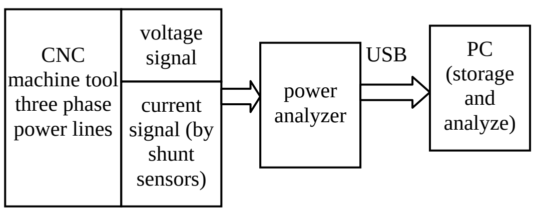



**Fig. 2.** The machine tool power signal measurement system.

BP network is an artificial neural network based on error back-propagation algorithm. As shown in Fig. 3, the developed BP neural network for specific energy consumption prediction is a single hidden layer feedforward neural network, which includes input layer, hidden layer and output layer. The input layer consists of four neurons, such as the spindle speed, feed rate, depth of cut and material removal rate; while the output layer includes only one neuron, which is the specific energy consumption. In the BP neural network, each layer neurons connect fully only with the adjacent layers neurons, no connection between neurons in the same layer, and no feedback connections between the neurons in each layer.

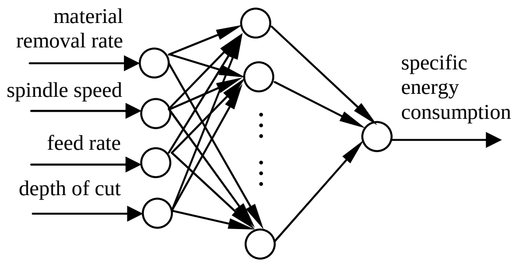



**Fig. 3.** The BP neural network for specific energy consumption prediction.

## 4. The Specific Energy Consumption Prediction Experiments in CNC Milling

### 4.1. The Power Signal Measurement in Milling Process

The process experiments are surface rough milling in the three-axis vertical milling CNC machine tool, with a hard alloy end mill cutter whose diameter is 32mm, with cooling liquid in the milling process, and the cutting width $b_D$ is 30mm, the work piece dimension is 400mm*150mm*75mm. In the machining process, the CNC milling machine tool power signals are measured with power analyzer and shunt sensors according to the hardware structure shown in Fig. 2. The machine power signals are stored and analyzed in PC, and the PC software interface is shown in Fig. 4.

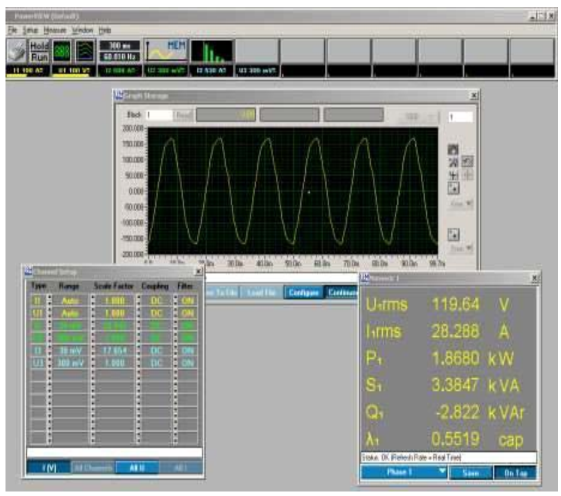



**Fig. 4.** The machine tool power signals acquisition and processing.

The process parameters and power signals are shown in Table 1. The material removal rate *MRR* is calculated according to depth of cut $a_p$, feed rate $F$, and cutting width $b_D$. The specific energy consumption *SEC* is computed according to machine tool power signals $p_{in}$ and material removal rate *MRR*.

### 4.2. The Specific Energy Consumption Prediction with BP Neural Network

As shown in Fig. 3, the introduced BP network for specific energy consumption prediction is a single hidden layer feedforward neural network. The input layer neurons number $n$ is 4, such as the spindle speed, feed rate, depth of cut and material removal rate. The output layer neuron number $m$ is 1, the specific energy consumption. In general, the hidden layer neurons number $n_1$ is determined according to empirical formula:

$$n_1 = \sqrt{nm}\,, \tag{8}$$

$$n_1 = \log 2^n\,, \tag{9}$$

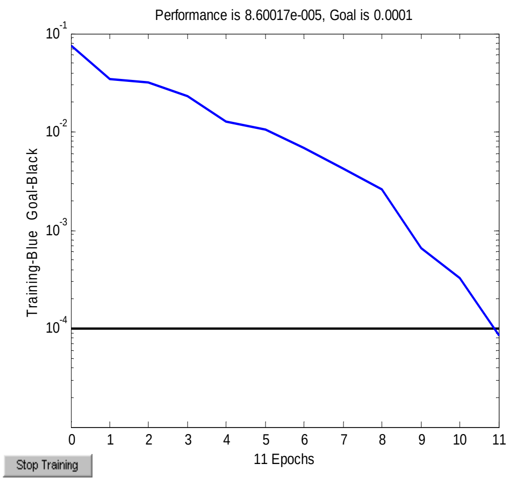
$$n_1 = n + 0.618\times(n-m)\,, \tag{10}$$

$$n_1 = 2n+1 \tag{11}$$

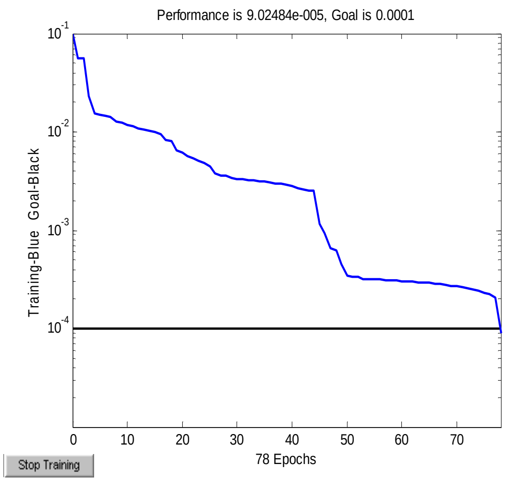
Therefore, choose hidden layer with 3 to 12 neurons to train the BP network respectively. The BP network training curve with different hidden layer neurons number is shown in Fig. 5, and the mean square error (MSE) is shown in Table 2. Consequently, it can be seen from Fig. 5 and Table 2, the BP neural network mean square error is least with 11 hidden layer neurons.

**Table 1.** The process parameters and power signals.

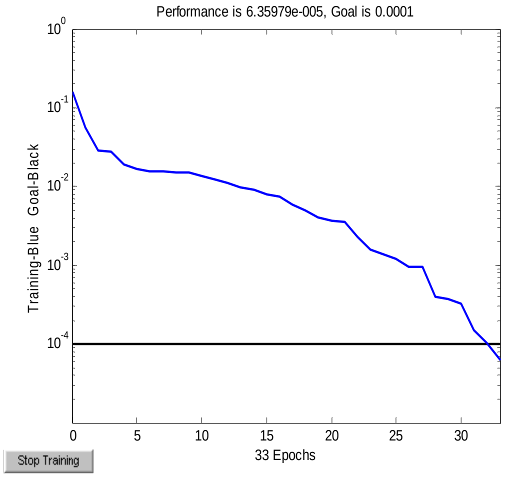
| No. | $N$(r/min) | $F$(mm/min) | $a_p$(mm) | $P_{in}$(kW) | $MRR$(cm$^3$/min) | $SEC$(KJ/cm$^3$) |
|---|---|---|---|---|---|---|
| 1 | 310 | 250 | 3 | 2.75 | 22.5 | 7.33 |
| 2 | 290 | 220 | 5 | 4.12 | 33.0 | 7.49 |
| 3 | 310 | 240 | 4 | 3.57 | 28.8 | 7.44 |
| 4 | 310 | 300 | 2 | 2.19 | 18.0 | 7.30 |
| 5 | 260 | 200 | 9 | 6.79 | 54.0 | 7.54 |
| 6 | 290 | 220 | 6 | 5.05 | 39.6 | 7.65 |
| 7 | 270 | 200 | 8 | 5.63 | 48.0 | 7.04 |
| 8 | 250 | 125 | 12 | 5.66 | 45.0 | 7.55 |
| 9 | 250 | 100 | 15 | 5.68 | 45.0 | 7.57 |
| 10 | 250 | 100 | 14 | 5.30 | 42.0 | 7.57 |
| 11 | 210 | 50 | 20 | 4.09 | 30.0 | 8.18 |
| 12 | 250 | 80 | 18 | 5.41 | 43.2 | 7.51 |
| 13 | 250 | 150 | 10 | 5.58 | 45.0 | 7.44 |
| 14 | 250 | 90 | 16 | 5.37 | 43.2 | 7.46 |



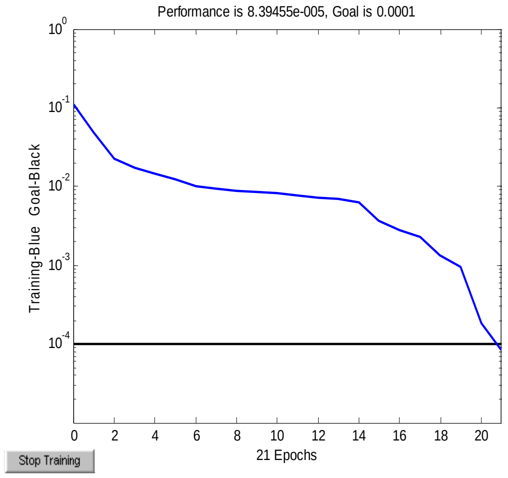

(a) Hidden layer with 3 neurons



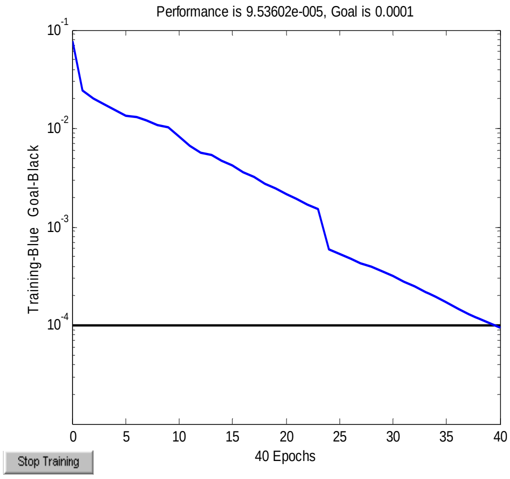

(b) Hidden layer with 4 neurons



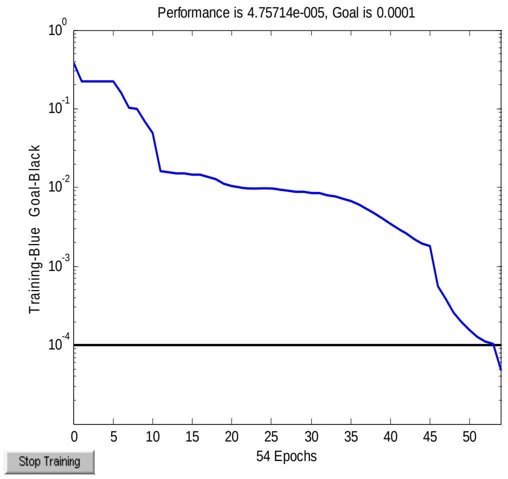

(c) Hidden layer with 5 neurons



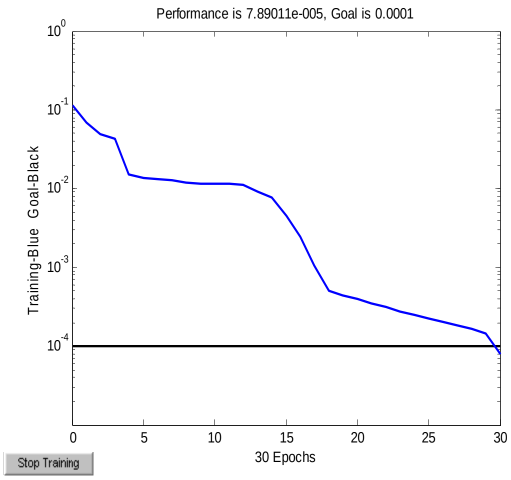

(f) Hidden layer with 8 neurons



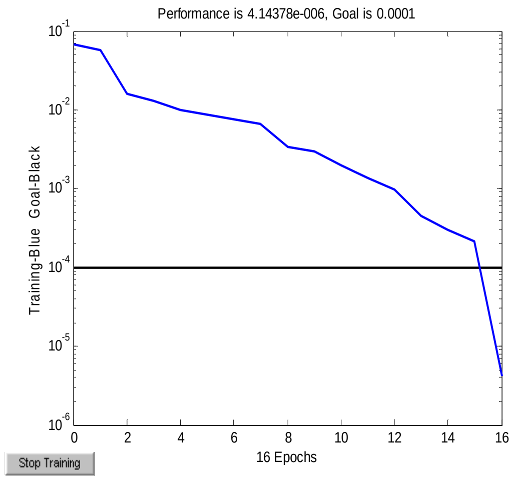

(d) Hidden layer with 6 neurons



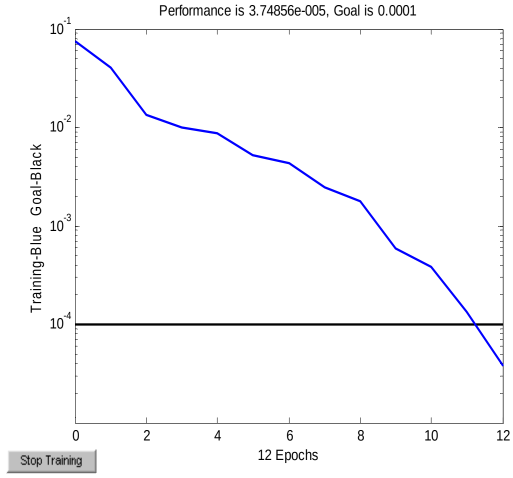

(g) Hidden layer with 9 neurons



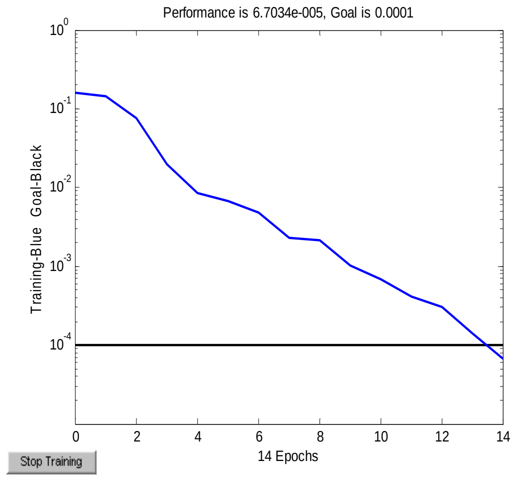

(e) Hidden layer with 7 neurons




(h) Hidden layer with 10 neurons




(i) Hidden layer with 11 neurons




(j) Hidden layer with 12 neurons

**Fig. 5.** The BP network training curve with different hidden layer neurons number.

**Table 2.** The BP network training results.

| **Hidden layer neurons number** | **MSE** | **Hidden layer neurons number** | **MSE** |
|---|---|---|---|
| 3 | 8.60017e-005 | 8 | 8.39455e-005 |
| 4 | 9.02484e-005 | 9 | 4.75714e-005 |
| 5 | 6.35979e-005 | 10 | 4.14378e-005 |
| 6 | 9.53602e-005 | 11 | 3.74856e-005 |
| 7 | 7.89011e-005 | 12 | 6.7034e-005 |

Consequently, the BP prediction network adopts 4-11-1 structure. There are 4 neurons in the input layer, 11 neurons in the hidden layer, and 1 neuron in the output layer respectively. The BP network is trained with the No.1-No.12 group data in Table 1. Then the trained network is tested with the No.13-No.14 group data in Table 1. The predicted *SEC* are 7.3752 and 7.5397, and the prediction error are 0.87% and 1.07% relative to the actual *SEC* of the No.13-No.14 group data in Table 1. In conclusion, the network prediction value is very close to the actual measurement value, and the developed BP network can predict specific energy consumption in milling process accurately after training.

## 6. Conclusions

The research on energy consumption in machining is helpful to analyze the machine tool energy characteristics, optimize process parameters and machine tool components for energy saving. Specific energy consumption expresses the required energy consumption when cutting unit volume material. The BP neural network prediction method for specific energy consumption in machining is set up in the paper. The prediction method bases on machine tool power measurement by power analyzer and shunt sensors. The BP network adopts 4-11-1 structure. There are 4 neurons in the input layer, which express the spindle speed, feed rate, depth of cut and material removal rate. There is 1 neuron in the output layer, which express the specific energy consumption in machining. The CNC milling machine tool power signal measurement system is built up, and the prediction method for specific energy consumption is tested with cutting data. The prediction results show that the introduced method is effective to predict machine tool specific energy consumption.

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## References

[1]. Joost R. Duflou, John W. Sutherland, David Dornfeld, Towards energy and resource efficient manufacturing: A processes and systems approach, *CIRP Annals - Manufacturing Technology*, 61, 2, 2012, pp. 587-609.

[2]. Chris Yuan, Qiang Zhai, David Dornfeld, A three dimensional system approach for environmentally sustainable Manufacturing, *CIRP Annals - Manufacturing Technology*, 61, 1, 2012, pp. 39-42.

[3]. Vijayender Singh, P. Venkateswara Rao, S. Ghosh, Development of specific grinding energy model, *International Journal of Machine Tools & Manufacture*, 60, 2012, pp. 1–13.

[4]. Rajesh Kumar Bhushan, Optimization of cutting parameters for minimizing power consumption and maximizing tool life during machining of Al alloy SiC particle composites, *Journal of Cleaner Production*, 39, 2013, pp. 242-254.

[5]. A. Vijayaraghavan, D. Dornfeld, Automated energy monitoring of machine tools, *CIRP Annals - Manufacturing Technology*, 59, 1, 2010, pp. 21-24.

[6]. J. Jeswiet, S. Kara, Carbon emissions and CESTM in manufacturing, *CIRP Annals – Manufacturing Technology*, 57, 1, 2008, pp. 17–20.

[7]. Timothy Gutowski, Jeffrey Dahmus, Alex Thiriez, Electrical energy requirements for manufacturing processes, in *13th CIRP International Conference of Life Cycle Engineering*, July 2006.

[8]. Huajun Cao, Hongcheng Li, Yanbin Du, Current Situation and Development Trend of Low-Carbon Manufacturing, *Aeronautical Manufacturing Technology*, 9, 2012, pp. 26-31.

[9]. M. F. Rajemi, P. T. Mativenga, A. Aramcharoen, Sustainable machining: selection of optimum turning conditions based on minimum energy considerations, *Journal of Cleaner Production*, 18, 10-11, 2010, pp. 1059-1065.

[10]. Zhou Dan, Liu Guangfu, Heping, Study on Extracting Method of Energy Design Factors for NC Machine, *China Mechanical Engineering*, 22, 3, 2011, pp. 351-355.

[11]. M. Mori, M. Fujishima, Y. Inamasu, Y. Oda, A study on energy efficiency improvement for machine tools, *CIRP Annals - Manufacturing Technology*, 60, 1, 2011, pp. 145-148.

[12]. Shi Jinliang, Liu Fei, Xu Dijian, Xie Dong, Power Balance Equation about the Numerical Control Machine Tool's Main Driver System Driven by Variable Voltage Variable Frequency, *Journal of Mechanical Engineering*, 46, 3, 2010, pp. 118-124.

[13]. Shaohua Hu, Fei Liu, Yan He, Tong Hu, An on-line approach for energy efficiency monitoring of machine tools, *Journal of Cleaner Production*, 27, 2012, pp. 133-140.

[14]. V.A. Balogun, P.T. Mativenga, Modelling of direct energy requirements in mechanical machining processes, *Journal of Cleaner Production*, 41, 2013, pp. 179-186.

[15]. S. Braun, U. Heisel, Simulation and prediction of process-oriented energy consumption of machine tools, in *19th CIRP International Conference on Life Cycle Engineering*, April 2012, pp. 245-250.

[16]. Zhang Zhe, Li Haolin, Quantitative analysis and comparison method for cutting process scheme energy consumption of machine tools, *Manufacturing Technology & Machine Tool*, 12, 2013, pp. 21-23.

[17]. Liu Fei, Liu Shuang, Multi-period Energy Model of Electro-mechanical Main Driving System during the Service Process of Machine Tools, *Journal of Mechanical Engineering*, 48, 21, 2012, pp. 132-140.

[18]. He Y., Liu F., Wu T., Zhong F-P, Analysis and estimation of energy consumption for numerical control machining, *Proceedings of the Institution of Mechanical Engineers Part B-Journal of Engineering Manufacture*, 226, B2, 2012, pp. 255-266.

[19]. W. Li, S. Kara, An empirical model for predicting energy consumption of manufacturing processes: a case of turning process, *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 225, B9, 2011, pp. 1636-1646.

[20]. S. Kara, W. Li, Unit process energy consumption models for material removal processes, *CIRP Annals - Manufacturing Technology*, 60, 1, 2011, pp. 37-40.

[21]. Lin Li, Jihong Yan, Zhongwen Xing, Energy requirements evaluation of milling machines based on thermal equilibrium and empirical modeling, *Journal of Cleaner Production*, 52, 2013, pp. 113-121.