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Multi-Quality Prediction Model of CNC Turning Using Back-Propagation Network

[1]Tian-Syung Lan, [1]Chih-Yao Lo, [2]Ming-Yung Wang and [1]Yen-An Yu
[1]Department of Information Management, Yu Da College of Business, Miaoli County, Taiwan 361, Republic of China
[2]Department of Mechanical Engineering, Tatung University, Taipei, Taiwan 10451, Republic of China

Abstract: In this study, the four cutting parameters (cutting depth, feed rate, speed and tool nose runoff) with three levels (low, medium and high) are selected to determined the 3^4 = 81 sets of full experimental combinations. The ECOCA-PC3807 CNC lathe is utilized to diameter finishing turn the S45C. The surface roughness (Ra), tool wear ratio (μm^{-2}) and cutting force are additionally measured as quality objectives. The BPN is moreover introduced to learn the selected 45 sets of experimental results. The remaining 36 sets of experimental results are furthermore used to verify and construct a multiple quality predictor of CNC turning. Considering the learning rate as 1 and momentum factor as 0.5, the results of 4000 times of BPN training through a hidden layer indicated that the prediction of surface roughness reached 95.87% of accuracy, the quality objective of tool wear ratio reached 94.32% of accuracy, the quality of cutting force reached 92.29% accuracy and the overall prediction accuracy of the multiple quality process predictor could reach 94.16%. The results not only provide the CNC turning operations with an economic and prospective multiple quality analytic method but also establish machining references for CNC turning industry with profound insight. Under the considerations of multiple qualities, this study definitely explored, expanded and realized the prediction mechanism and values of cutting parameters.

Key words: Numerical control, Taguchi method, back-propagation neural network

INTRODUCTION

For metal cutting, the lathe is a common and basic operational process. In fact, the controllable parameters of cutting roughly include cutting depth, feed rate, speed and the choices of cutter materials and types. Nian *et al*. (1999) used Taguchi method to plan experiment and used S/N ratio and variable analysis model to find out the cutting conditions. In the research of optimal lathe cutting parameters. Lin *et al*. (2001) also used convergent network method to construct a surface roughness and cutting force models of lathe cutting. To be competitive, the industry should not only purchase ascendant equipments to introduce production automation and shorten work hours, reduce labor force, improve process and reduce cost but also consider how to economically establish a set of effective bases for process parameter. Particularly when the operators have demand of multiple qualities, they could not decide the optimal processing parameters by general experiences and know how complicated the interrelationship between process parameters.

Wang and Huang (2007) used commences by employing an orthogonal array using the Taguchi method to calibrate the factor levels of a heuristic algorithm and to estimate the percent contribution from various individual factors. Subsequently, the calibrated heuristic algorithm is used to optimize a Back-Propagation Network (BPN). They used BPN and combined the training of experimental data to simulate the results of processing by equation. But, their method also needs to input selected processing conditions to predict cutting force and surface roughness degrees. Yang and Lee (1999) also used Taguchi Orthogonal Arrays to compute the S/N ratio of convergence time of artificial neural network, carry out analysis of mean, analysis of variance to find out optimal parameter of artificial neural network that the artificial neural network may quickly converge.

In summarizing above-mentioned reasons, the research adopted BPN technology to establish a set of multiple quality process prediction models and take advantages of good input and output corresponding relationship between the artificial network itself and non-linear issues to complicated issue of process designs is deemed to be necessary. They will be able to provide practical numerical controlled cutting operation with a set of economic and prospective analytical method for multiple quality cutting parameters to shorten setup time of numerical controlled cutting operation and enhance the competitiveness of numerical controlled cutting industry.

Corresponding Author: Tian-Syung Lan, Department of Information Management, Yu Da College of Business, Miaoli County, Taiwan 361, Republic of China

MATERIALS AND METHODS

Machining theory: Lin *et al.* (2001) constructed the surface roughness and cutting force models of lathe cutting by convergent network method. Davim and Conceicao (2001) measured simultaneously cutting force, surface roughness and cutter life of Al matrix composites with feed rate and cutting speed as processing parameters. They also furthered to construct a mathematic model of lathe cutting processing and used cutting force equation to present surface roughness and tool life through weight evaluation before computing the optimal processing parameters with genetic algorisms. Besides, there are applications of artificial neural fuzzy system and genetic algorism to the optimization of multiple quality processing parameters (Galante *et al.*, 1998).

Through above-mentioned researches and after evaluating practical lathe cutting control parameters by literature review, we decided to adopt four lathe cutting control parameters (cutting speed, feed rate, cutting depth and the tool nose runoff) and the quality property of CNC turning including three experimental output objectives (surface roughness, cutter abrasion and cutting force).

Among parameters, the cutting speed is the surface speed of CNC lathe, cutting depth is the depth of each cut, the runoff of the tool nose is the circumrotation center of cutter tip and work piece at the same level. For the quality of the CNC lathe, the surface roughness is measured from the micro-geometrical shape formed by the smaller intervals and peaks and valleys on processed surface while the tool was the abrasion of cutter in cutting and synthesized results of cutting heat and the physical effects and chemical effects generated by the mechanic friction. Among them, Fig. 1 is the abrasion belt on the back of cutter, gap and cutting edge chipping, crescent moon and low-lying ground shape abrasions that are often shown on the front of cutter and ox pit as well as fissure-shape abrasion are shown on secondary back. The cutting force comes from the elastic-plastic deformation of work piece materials and the friction between cutter trimmings and the surface of work piece. When a cutter merges into the work piece, the work piece will have great plastic deformation; and in dividing trimmings, the cutter will take resistance from the work piece.

The three quality properties were selected as measured objectives in the research and were tested by the experimental standards established by Taguchi Method. The three objectives of surface roughness, cutter abrasion and cutting force were measured by instruments to make sure they were fit to the cutting properties.

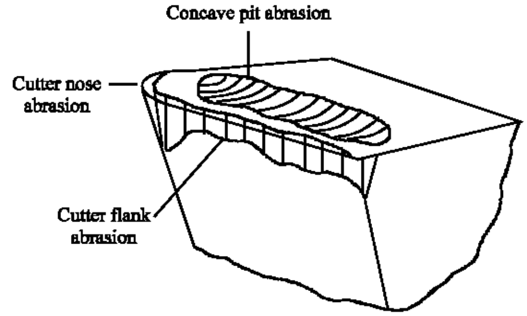

Fig. 1: Abrasion formation of cutter

Table 1: Standard orthogonal arrays

Orthogonal arrays	No. of rows	Maximum No. of factors	Maximum value of No. of rows at the standard: 2	3	4	5
L_4	4	3	3	-	-	-
L_8	8	7	7	-	-	-
L_9	9	4	-	4	-	-
L_{12}	12	11	11	-	-	-
L_{16}	16	15	15	-	-	-
L_{16}	16	5	-	-	5	-
L_{18}	18	8	1	7	-	-
L_{25}	25	6	-	-	-	6
L_{27}	27	13	-	13	-	-
L_{32}	32	31	31	-	-	-
L_{32}	32	10	1	-	9	-
L_{36}	36	23	11	12	-	-
L_{36}	36	16	3	13	-	-
L_{50}	50	12	1	-	-	11
L_{54}	54	26	1	25	-	-
L_{64}	64	63	63	-	-	-
L_{64}	64	21	-	-	21	-
L_{81}	81	40	-	40	-	-

Taguchi method: Essentially, traditional experimental design procedures are too complicated and not easy to use. A large number of experimental works have to be carried out when the number of the process parameters increases. To solve this problem, the Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with only a small number of experiments. Taguchi is the developer of the Taguchi method. Taguchi robust design method is a powerful tool for the design of a high-quality system (Su, 2002; Palanikumar, 2008). Table 1 includes 18 standard orthogonal arrays listed by Taguchi Method. For direct use of standard orthogonal arrays, the standard number of research-pending factors should be consistent with the standard number of the orthogonal arrays. Meanwhile, we should use the minimum orthogonal array that meets the requirements to save the expenditure of experiments.

Huh *et al.* (2003) and Anastasiou (2002) have applied Taguchi Method to plan metal cutting experiments in which both dry cut and wet cut were adopted to cut S1017C and S1045C materials by traditional lathe. And materials, cutter dip, speed, feed rate and cutting depth were selected as five factors to evaluate cutter life and surface roughness. However, the traditional lathe was no longer utilized.

To meet requirements of optimization of cutting practices, the research selected cutting depth, feed rate, speed, tool nose runoff as four control factors and $L_9(3^4)$ orthogonal arrays to layout the full experiments. Additionally, this study also used the cutting parameters recommendations to determine the range of standards (low, medium and high) to conduct researches on the parameters for multiple quality CNC turning.

Artificial neural network: Artificial Neural Network (ANN) means the simulation of computation system of biological neural network, including software and hardware and used a great deal of linking artificial neuron to simulate the ability of biological neural network. ANN is a parallel and distributed computation model that has properties of high parallelism, distributed associative memory, fault tolerance, adaptability and ability to learn from environment. It has been widely used in graphic identification, language identification and synthesis, signal processing, image compression, expert system construction, as well as policy-decision (Wang, 2007).

Most of applications of ANN to the researches on cutting are used to monitor cutter abrasion and construct prediction models of cutting force and establish learning model that could for the users' reference. Tamas (1999) adopted fixed cutter and work piece materials and used CNC lathe to carry out the experiment of cutting force with cutting speed, feed rate, speed and cutting depth as variables. He also used BPN to establish cutting force prediction model and confirmed that BPN might replace linear regression equation in predicting cutter abrasion in future.

Based on mentioned above, it is suggested that BPN could simply predict external factor and furthered to evaluate its value. It has excellent learning and prediction ability and can successfully solve many problems of optimization. Under the consideration of multiple quality cutting conditions, it should be able to establish a complete prediction model of multiple quality CNC cutting operation. After evaluation, it has been confirmed that BPN met the requirements of the research.

RESEARCH DESIGN

To respond current CNC lathe cutting processing, based on the experiments of $3^4 = 81$ groups designed by $L_9(3^4)$ orthogonal array, the research selected S45C as work piece to conduct experiments on ECOCA PC-3807

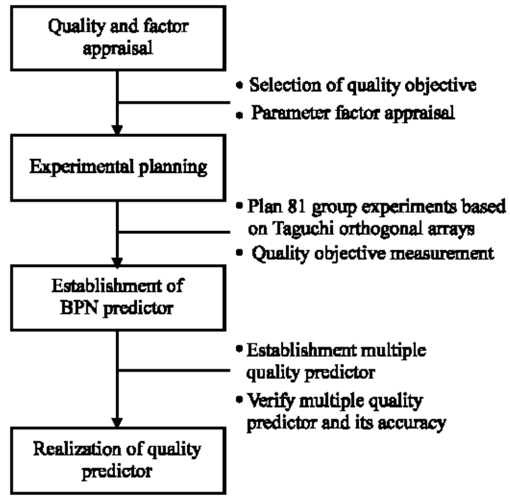

Fig. 2: Steps of multi-quality prediction model

CNC to establish appropriate cutting experiments. This study then furthered to wrote a multiple quality process predictor by Visual Basic and apply the technology of back-propagation algorism to verify the value of multiple quality process predictor. The main implementation process of the research planning is shown as Fig. 2.

Toshiba WTJNR2020K16 holder and Sumitomo Electric AC700G type TNMG-160404 disposal inserts were selected as turning tool, S45C medium carbon steel as processing materials for experiment on t ECOCA PC-3807. The size of diameter turning materials is φ 45×250 mm. Meanwhile, under the consideration of multiple standards of quality goals including surface roughness, cutter abrasion and cutting force, we used practical cutting for qualitative analysis to evaluate and confirm various affecting parameters and further to develop signal factor and noise strategy. The machined work pieces were measured by MITSUTOYO SURFTEST surface roughness meter right after each cutting. The trial piece was measured in three sections. We measured once every 30 mm from the end-face to obtain the surface roughness of the front, middle and back sections and took the average as the surface quality property of the trial piece.

According to the abrasion form of cutter, the research used electronic image microscope SONY COLOR VIDEO CAMERA MOLD to interpret the edge of cutter through gray level setting and measure the width criterion of flank abrasion V_{B2} (mm) (Fig. 3). The width criterion was then divided by total volume of removed materials and defined as tool wear ratio (μm^{-2}) for the quality property of the tool wear.

For the convenience of measurement and research of lathe cutting force, in general practices, F_r is divided into three mutual vertical component forces (Fig. 4): tangential force F_Z, radial force F_y and axial force F_X. Among them, F_Z is the greatest that its consumption of power is 95 to 99% of total cutting power. Therefore, this research focused the exploration of lathe cutting force on the key cutting force F_Z. In order to establish a cutting force measurement system, we modified the base of lathe cutter of ECOCA PC-3807 to install piezoelectric pressure sensors (KISTLER type 9001 Load Washer) at the bottom of cutter base that would function as dynamometer. The measured lathe cutting signal was amplified by electric charge before sampling and making record by PC through A/D card (Advantech PCL 816).

According to practical measurement of each quality, the research made up 81 groups of learning examples and made reference to recommending values in selecting 45 groups as training examples. Yeh (1998) used VB.NET language to develop BPN module. Meanwhile, according to related literature, we adopted a hidden layer to learn the experimental results of orthogonal arrays of Taguchi Method. This study selected cutting depth, feed rate, speed and the tool nose runoff as input layer while multiple qualities were selected as output nodes by output layer. Moreover, the analogy the relationship between input and output through relative small amount experimental data were used to construct multiple quality process predictors and know the results of corresponded process by each parameter.

Applying the results of the remaining 36 experiments (81-45 = 36) in the 45 groups of training pattern and the weight and bias of the training pattern, we analyzed the predictability of BPN prediction model through computation of error ratios between the prediction output goals and real output goals by BPN to verify the accuracy of multiple quality prediction mechanism of numerical controlled cutting.

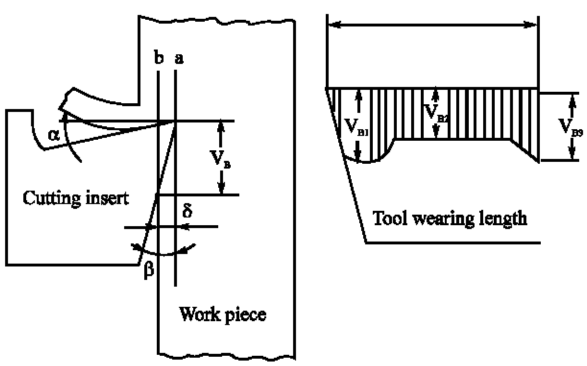

Fig. 3: Flank abrasion

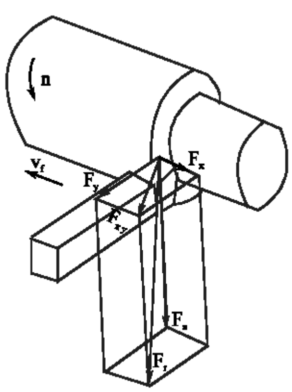

Fig. 4: Join force and component force

RESULTS AND DISCUSSION

This research adopted Visual Basic program language and MS SQL data to develop multiple quality predictor system. Input 45 groups of experiment as training pattern and explored the degree of convergence of BPN as shown as Fig. 5 and 6 through the error of BPN model (Table 2) in Mean Absolute Errors (MAE) and Root Mean Squared Error (RMSE) to further verify the accuracy of multiple quality process predictor.

The MAE and RMSE were designed to verify the BPN convergence status between predicted output

Table 2: Parameters of BPN training model

BPN model	No. of layers of hidden layer	No. of units processed by hidden layer	Learning rate	Momentum constant
A	1	6	1	0.5
B	2	6	1	0.5

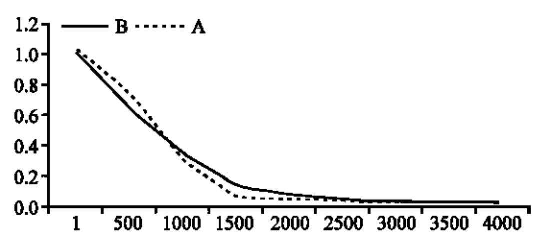

Fig. 5: Convergence process of MAE

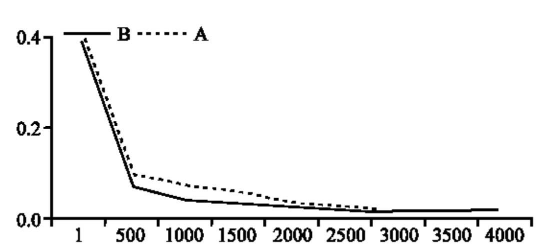

Fig. 6: Convergence process of RMSE

Table 3: Testing data of BPN

Control parameter				Surface roughness (µm)			Tool wear ratio (mm^{-2})			Cutting force (N)		
Speed ($m\ min^{-1}$)	Cutting depth (mm)	Feed rate ($mm\ rev^{-1}$)	Tool nose runoff (mm)	Practical measured value	Predicted output value	CPE (%)	Practical measured value	Predicted output value	CPE (%)	Practical measured value	Predicted output value	CPE (%)
250	1.5	0.10	-0.1	0.6666	0.6454	-3.18	3.67E-07	3.47E-07	-0.05	511.754	512.8080	0.21
250	1.5	0.10	0.0	0.6746	0.6470	-4.09	3.55E-07	3.51E-07	-1.12	510.286	513.4575	0.62
250	1.5	0.10	0.1	0.6566	0.6480	-1.31	3.49E-07	3.50E-07	0.29	513.334	513.7158	0.07
250	0.5	0.10	-0.1	0.7830	0.7573	-3.28	9.59E-07	9.23E-07	-3.75	170.316	147.1392	-13.61
200	0.5	0.02	0.1	1.0566	1.0177	-3.68	9.92E-07	9.25E-07	-6.75	65.111	64.3043	-1.24
250	0.5	0.10	0.1	0.6033	0.6463	7.13	9.76E-07	9.25E-07	-5.23	171.026	156.7741	-8.33
250	1.5	0.06	0.0	0.8866	0.8273	-6.69	2.68E-07	2.86E-07	6.72	373.224	358.7410	-3.88
250	0.5	0.10	0.0	0.7066	0.7589	7.40	8.46E-07	8.53E-07	0.83	170.654	150.1487	-12.02
250	1.0	0.10	0.0	0.7514	0.7591	1.02	3.62E-07	3.49E-07	-3.59	344.578	358.3986	4.01
250	1.0	0.10	-0.1	0.8033	0.8247	2.66	3.03E-07	3.41E-07	12.54	343.245	358.2970	4.39
250	0.5	0.06	-0.1	0.6166	0.6409	3.94	9.27E-07	9.23E-07	-0.43	124.221	147.0015	18.34
200	1.5	0.10	-0.1	0.7833	0.7577	-3.27	3.03E-07	3.42E-07	12.87	517.384	512.6427	-0.92
200	1.5	0.10	0.0	0.7634	0.7591	-0.56	3.55E-07	3.48E-07	-1.97	512.116	513.3991	0.25
250	0.5	0.02	-0.1	0.7773	0.7554	-2.31	8.62E-07	8.42E-07	-2.32	62.336	63.7789	2.31
200	1.5	0.10	0.1	0.7200	0.7596	5.50	3.09E-07	3.48E-07	12.62	515.764	513.6934	-0.40
250	0.5	0.06	0.0	0.7866	0.7587	-3.55	7.48E-07	7.95E-07	6.28	123.698	147.9423	19.60
250	1.5	0.02	-0.1	0.9766	0.9420	-3.54	3.49E-07	3.23E-07	-7.44	191.278	147.2362	-23.03
250	1.0	0.06	0.0	0.8223	0.8266	0.40	3.87E-07	3.43E-07	-11.37	248.759	247.0495	-0.69
200	1.0	0.06	-0.1	0.6200	0.6412	3.42	4.04E-07	4.39E-07	8.66	238.794	246.4819	3.22
150	0.5	0.10	0.0	0.7011	0.7587	8.22	6.50E-07	6.33E-07	-2.62	170.496	147.3913	-13.55
150	1.0	0.06	0.0	0.7300	0.7585	3.90	4.72E-07	4.42E-07	-6.36	247.120	246.9231	-0.08
150	0.5	0.10	0.1	0.6766	0.6446	-4.73	6.34E-07	6.37E-07	0.47	173.148	153.2798	-11.47
150	1.5	0.06	-0.1	0.6000	0.6415	6.92	2.74E-07	2.84E-07	3.65	378.541	358.4049	-5.32
150	1.0	0.02	0.1	0.8800	0.8271	-6.01	4.55E-07	4.44E-07	-2.42	125.129	149.9982	19.87
150	0.5	0.06	-0.1	0.5733	0.5227	-8.83	7.64E-07	7.94E-07	3.93	127.478	146.5726	14.97
150	1.5	0.06	0.0	0.5500	0.5312	-3.42	3.09E-07	3.38E-07	9.39	375.463	358.5977	-4.49
150	1.0	0.06	0.1	0.7266	0.7594	4.51	4.13E-07	4.44E-07	7.51	244.034	247.2423	1.31
150	1.5	0.06	0.1	0.5600	0.5351	-4.45	2.68E-07	2.87E-07	7.09	374.289	358.3420	-4.26
150	1.0	0.06	-0.1	0.6033	0.6398	6.05	4.21E-07	4.38E-07	4.04	245.468	246.3747	0.36
150	1.0	0.02	0.0	0.8014	0.8232	2.72	3.96E-07	3.15E-07	-20.45	127.249	146.3622	15.02
150	0.5	0.02	-0.1	0.6231	0.6350	1.91	6.67E-07	6.22E-07	-6.75	65.773	63.4755	-3.49
150	0.5	0.06	0.1	0.4700	0.4708	0.17	7.32E-07	7.95E-07	8.61	123.278	149.9632	21.65
200	1.5	0.02	0.0	0.5384	0.5310	-1.37	3.43E-07	3.33E-07	-2.92	188.354	148.6873	-21.06
150	0.5	0.02	0.0	0.5333	0.5278	-1.03	6.02E-07	6.31E-07	4.82	63.741	63.9840	0.38
150	1.0	0.02	-0.1	0.5850	0.5223	-10.72	4.29E-07	4.36E-07	1.63	126.472	146.6247	15.93
150	0.5	0.02	0.1	0.6011	0.6413	6.69	6.83E-07	6.36E-07	-6.88	60.113	64.2480	6.88

objective and real output objective in the process of 4000 trainings. Their formula are:

$$\mathrm{MAE} = \sum_{i=1}^{n} |T_i - E_i| / n$$

and

$$\mathrm{RMSE} = \frac{\sqrt{\sum_{i=1}^{n} (T_i - E_i)^2}}{n}$$

where, T_i is real output objective, E_i is prediction output objective, n is the number of times of execution and i is initial value.

From Fig. 5 and 6, it is found that the weight was allocated by random numbers randomly distributed from 0 to 1 that the initial value of MAE error rate was greater than 1. After 1500 trainings, BPN model A was close to flat and not converged at 2500. When BPN model B reached 1500 times of training, the convergence began to slow down and reached the effect of convergence until 3000 times. BPN model A reached a certain extent of flat status after 2000 times of RMSE training. Model B reached convergence only after 2500 times of training. For this, the BPN structure of one-layer hidden layer adopted by the research was quicker than two-layer hidden layer in reaching effective convergence. We could learn from it that giving 4000 times training to 45 groups of data of training neural network could help BPN train a group of effective weight and bias of prediction.

Through the weight and bias of training of BPN and after confirming the accuracy of convergence process of BPN, we applied initial 36 groups to the verification of BPN and used CPE and MAPE to reinforce the verification of the accuracy of BPN prediction. Table 3 shows the verification of CPE and MAPE for real cutting and prediction data.

CPE (cost percentage error) is designed to verify and test the difference between the output by BPN multiple quality predictor and real output. After the CPE test, we need to further verify the integral BPN prediction accuracy. Among them, the formula of CPE and MAPE is:

$$CPE = \frac{E(i) - T(i)}{T(i)} \times 100\%$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left(\frac{|E(i) - T(i)|}{T(i)} \times 100\%\right)$$

among them, T(i) is real output goals, E(i) is prediction output goals, n is the number of times of execution and i is initial value. There were 35 data of prediction output value of the surface roughness quality objective that their errors were within ±10% from real output except one that its error was greater than ±10% after CPE computation and 4.13% after MAPE computation. The prediction results showed that the research had significant prediction effect on the surface roughness quality prediction. The accuracy could reach 95.8%. There were 31 data of prediction output value of the cutter abrasion quality objective that their errors were within ±10% from real output except five data that their error were greater than ±10% after CPE computation and 5.68% after MAPE computation. Cutter abrasion quality goals might have greater prediction errors due to smaller difference of units of measured quality goals, but their prediction effect were still within 92.32% of scope of validity. There were 23 datum of prediction output value of the cutting force quality objective that their errors were within ±10% from real output except one that their error were greater than ±10% after CPE computation and 7.71% after MAPE computation. Thirteen data of the cutting force quality goals had inferior prediction accuracy due to uneven distribution of quality goals after measurement, but the integral average error still reached 92.29% of accuracy. The total average error of MAPE verification of total three quality goals were 5.84%. That is, the BPN predictor could reach 94.16% of accuracy.

CONCLUDING REMARKS

The lathe processing is an important basic process in metal cutting. The researches of cutting behaviors are more subtle with the increasingly strict requirements of processing. Due to more complicated design of industrial products, the improvement of process often needs more consideration on optimization of multiple properties of quality. Therefore, it is indispensable for the industry to have a prediction and analysis formula of quality improvement that is simple and easy to use. Through BPN, this research used 45 group samples to train BPN and compared the predictions with 36 groups of experimental data. The results confirmed that the model recommended by the research was a highly reliable quality prediction model. That is, it would have significant effect for process quality prediction through ANN. The contributions of the research are also follows:

- Application of Taguchi Method, comparing to traditional statistic skill that needs a large quantity of data and the data may provide accurate analytic results only if the data meet the requirements of assumption of distribution of parent body, Taguchi Method has conception of economy and material benefits in planning lathe cutting experiments.
- The research provides a simple and easy-to-use BPN quality prediction system to solve problems of process prediction and is capable to provide effective and quick data analyses under the consideration of cost and time.
- In future, we may combine BPN predictor with genetic algorism through the combinations of the fittest multiple lathe cutting parameters. We may also find out most optimal multiple lathe cutting parameters through global best solutions that without need of years of experiences, operating personnel, with only a small quantity of experimental data, could carry out processing and understand in advance possible results of processing corresponded to each parameter within application scope in entire prediction model. Meanwhile, we could develop toward multi-objective quality property and multi-aspect process, such as slice and end-face processing.

The application of BPN to the researches on the multiple quality predictor with lathe cutting parameters may not only develop a model for integrating multiple quality prediction but also provide operators with an economic and prospective multiple quality prediction by conducting practical CNC lathe operation through Taguchi Method for the industry. Meanwhile, it could establish the reference base for multiple quality cutting parameters to reduce cost of processing and even shorten setting time for CNC lathe operation that will effectively save the cost. In future, we could even expand the applications to related cutting processing industries.

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