Construction of Processing Prediction Model and Parameter Optimization Model for Ultrasonic Assisted Turning

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Abstract- Ultrasonic assisted turning is a technique capable of reducing cutting force and tool wear while increasing manufacturing quality in optical components or materials that are difficult to cut. Taguchi method was used to determine the optimal combination of parameters (A1B1C3D2) for ultrasonic assisted turning. Rotational speed was the most significant factor influencing the quality of surface roughness, followed by feed rate, with ultrasonic type and depth of cutting demonstrating less influence. This study combines Taguchi method with artificial neural networks (Taguchi-neural network) to construct a predictive model for ultrasonic assisted turning. The Levenberg-Marquardt method was then incorporated into the predictive model to establish parameters to provide an optimization model for ultrasonic assisted turning. The optimal parameters derived using the resulting model include feed rate at 0.1625 (0.0015 mm/rev), depth of cutting at 0.1625 (0.0015 mm), rotational speed of 0.843 (475 rpm), and ultrasonic as the ultrasonic type. Surface roughness Ra_{pre} *was predicted to be 1.71*μm*; the tested experimental value was 1.69* μm*, resulting in a 1.2 % error between predicted and experimental values.*

Keywords: Ultrasonic assisted turning, Surface roughness, Taguchi method, Levenberg -Marquardt method

I. INTRODUCTION

In metal working, turning is an important process of which the goal is often to achieve the proper surface roughness. So it is particularly important to establish a prediction model that predicts surface roughness quality. For optical components, hard-to-cut materials, and other processing applications, ultrasonic vibration assisted turning effectively reduces cutting force and tool wear while enhancing quality. For industries demanding machinery with high efficiency and precision, it achieves high product quality optimization at low cost. For hard rigid or special materials in particular, ultrasonic vibration assisted applications generate much better results.

Ultrasonic-assisted turning technology in hard metal alloy processing has been confirmed to reduce cutting force [1-4]. Compared with traditional turning, it improves surface quality by up to 50 % while reducing noise levels [5, 6]. Ultrasonic-assisted turning achieves mirror-like surface quality using reduced cutting friction and lower average cutting force [7, 8].

The Taguchi method is commonly used in industry to improve product quality. Through an orthogonal array, the number experimental iterations can be decreased. And calculating the signal-noise ratio (S/N ratio) can estimate the output variance to reduce product loss. The Taguchi experimental method adopts the arrangement of the orthogonal array experiment to investigate the optimal control factor combination and predict values of product processes [9, 10].

Artificial neural networks are an excellent tool for building decision-making systems. They are commonly used in process analysis and much-recognized Back propagation (BP) artificial neural networks [11-13]. Tay and Butler [14] has used data from Taguchi L18 orthogonal arrays for artificial neural network training examples, with 80% used as study samples and the rest as test samples. Lin and Yang [15] combined the Taguchi method and neural networks for the prediction model of near-field photolithographic fabrication, accurately predicting the experimental results of the process.

The conventional optimization methods most used, which involve the conjugate gradient method, Gauss-Newton method and Levenberg-Marquardt method, are to solve a set of acceptable approximate solutions. The optimization method uses the relationship between an objective value and numeric expression value to determine the optimized size and direction of each step. The residual system value must first be defined. With an addition of regularization, it becomes to a non-linear problem. This approach is commonly known as the Tikhonov Regularization method [16]. This modified method, which is based on the least squares method, can smooth the optimization process by adding a smooth parameter. Thus, an optimized value analytical method can be applied to a non-linear problem. The common value optimization method uses the Gauss-Newton method to acquire the best size and direction of each step. With an addition of modified parameter Λ, known as the Marquardt parameter, in the Gauss-Newton method, the best step of the Levenberg-Marquardt method can then be acquired. Schnur and Nicholas [17] applied the Levenberg-Marquardt method to backward calculate the material characteristics and material interface properties of elastic materials.

Traditional Taguchi analysis often uses L18 or L27 orthogonal arrays for experimentation, with considerable test sequences for Run 18 or Run 27. This is both time-consuming and expensive. Moreover, traditional Taguchi analysis only provides one set of optimal processing parameters, which cannot predict combination results for non-controlling factor levels. This study proposes a progressive Taguchi-neural network model, which combines the Taguchi method with neural network construction to form a prediction model for surface roughness in ultrasonic-assisted turning. First, use Taguchi orthogonal array experimental factors with orthogonal properties for ultrasonic-assisted turning of the L9 orthogonal array, and apply the orthogonal array experimental data as initial neural network (ANN) training examples. With results from the factor responses table, determine the important factor and light factor of ultrasonic-assisted turning. Apply the light-factor, once determined in Stage-2 refining-network as training examples. Finally, use important factors and best Taguchi factor combination to determine the supplemental critical experimental training examples for Stage-3. Last, perform supplemental experiments with network training to complete high-accuracy prediction using artificial neural.

The Levenberg-Marquardt method was then incorporated into the predictive model to optimize the parameters for manufacturing with ultrasonic assisted turning. The error between the objective value and the predicted value in surface roughness is the objective function. Using the Levenberg-Marquardt method in conjunction with reasonable convergence criteria, we identified the optimal combination of processing parameters corresponding to the objective values and predicted values.

II. ULTRASONIC-ASSISTED TURNING AND TAGUCHI ANALYSIS

A. Laboratory Equipment

As seen in Fig. 1, inputting the current adjustment for the ultrasonic-assisted turning machine may cause the frequency (18,000 ~ 24,000 Hz) of ultrasonic oscillator to change. In this study, an ultrasonic frequency of ~ 23000 Hz and amplitude of ~15μm were entered via computer-control as processing and path conditions. The cutting material used was diamond-turning lathe with processing material of 10 × 120 mm in carbon steel. Measuring instrument made by ACCRETECH measured surface roughness. The measurement positions of the work piece from the end face were 10, 40, and 70 mm, respectively.

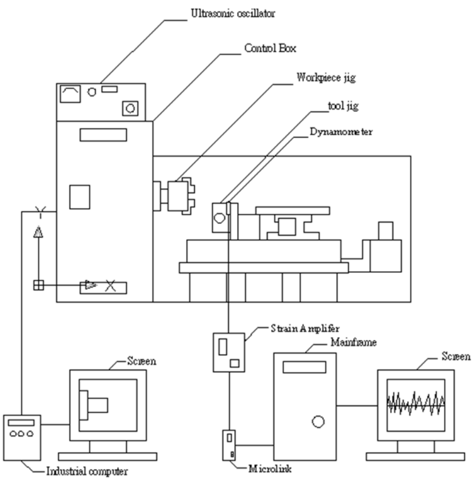

Fig. 1 Ultrasonic-assisted turning machine

B. Taguchi method of control factor level

Table 1 shows the four control factors and three levels. The control factors included A. feed rate (mm/rev), B. depth of cutting (mm), C. rotational speed (rpm), and D. ultrasonic type. The three levels of ultrasonic type: Level 1 for non-ultrasonic vibration, Level 2 and Level 3 for ultrasonic vibration, with vibration frequencies of 23000 Hz. For Level 3, a sleeve was added between the cutting tool and oscillator (Fig. 2). For the four factor and three level situations, traditional experimental methods required 81 (34) trials. The smallest Taguchi factor level orthogonal array in line with this experiment was the L9 (34) orthogonal array, composed of four factors, three levels, and nine experiments. Table 2 shows each experimental configuration [9]. Nine experimental results investigated the impact of each controlling factor on surface roughness.

Table 1 Control factors and their levels in the Taguchi method

control factor	A. feed rate (mm / rev)	B. depth of cutting (mm)	C. rotational speed (rpm)	D. ultrasonic type
level 1	0.002	0.002	100	X
level 2	0.006	0.006	275	V
level 3	0.01	0.01	450	V (sleeve)

Table 2 Experimental planning in ultrasonic-assisted turning

Run	A. feed rate (mm / rev)	B. depth of cutting (mm)	C. rotational speed (rpm)	D. ultrasonic type
1	0.002	0.002	100	X
2	0.002	0.006	275	V
3	0.002	0.01	450	V (sleeve)
4	0.006	0.002	275	V (sleeve)
5	0.006	0.006	450	X
6	0.006	0.01	100	V
7	0.01	0.002	450	V
8	0.01	0.006	100	V (sleeve)
9	0.01	0.01	275	X

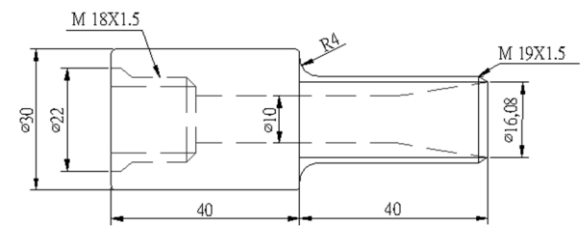

Fig. 2 Ultrasonic-assisted turning sleeve

C. Taguchi method of data analysis

Based on Table 2 of L9 orthogonal array for ultrasonic-assisted turning, after turning each work piece, three points measured surface roughness. Since smaller surface roughness in ultrasonic-assisted turning means better cutting quality, this study aspired for small S/N ratio characteristics. A small S/N ratio characteristic was defined as follows [9]:

$$\eta = -10 \times \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{1}$$

Where, η is the signal-to-noise ratio (S/N); n the number of measuring points; y_i the surface roughness value of the measurement position. By multiplying S/N ratio by a negative sign, a smaller quality loss with larger S/N ratio could be reached. Table 3 shows that after the experiment, surface roughness measurements were substituted into Eq. 1 to obtain the S/N ratio for surface roughness.

Table 3 Experimental results and S/N value in ultrasonic-assisted turning

Run	A	B	C	D	surface roughness (μm)			S/N(dB)
1	1	1	1	1	2.3	2.1	1.98	-6.57
2	1	2	2	2	1.87	1.92	1.89	-5.55
3	1	3	3	3	1.74	1.81	1.63	-4.75
4	2	1	2	3	2	1.95	1.97	-5.9
5	2	2	3	1	2.12	1.95	1.43	-5.37
6	2	3	1	2	2.34	2.1	1.81	-6.42
7	3	1	3	2	1.88	1.64	1.93	-5.21
8	3	2	1	3	2.5	2.36	2.18	-7.42
9	3	3	2	1	2.15	2.18	2.11	-6.64

After the experiment completion, on the experimental results of L9 table were analyzed. After sorting out data from Table 3, the factor response table and factor response graph were processed. Table calculations were based on signal-to-noise ratio (S/N) calculations. The signal-to-noise ratio of each control parameter level as it occurred in accordance with Table 3 of its position, added up the positions, and then divided the summed total by the number of occurrences, in order to determine the signal-to-noise ratio at each level. Table 4 displays the results. Furthermore, Fig. 3 shows the factor response table was expressed as a graph, called the factor response graph. Using the S/N response table, the best parameter level combination for ultrasonic-assisted turning was A1B1C3D2. Among the factors affecting surface roughness quality, rotational speed was the most significant, followed by feed rate. The effects of ultrasonic type and depth of cutting were not obvious.

Table 4 Control factor S/N factor response table of surface roughness

mean S/N ratios	A. feed rate (mm / rev)	B. depth of cutting (mm)	C. rotational speed (rpm)	D. ultrasonic type
level 1	-5.61	-5.89	-6.80	-6.19
level 2	-5.90	-6.10	-6.01	-5.71
level 3	-6.42	-5.94	-5.11	-6.02
Effect	0.8	0.22	1.69	0.46

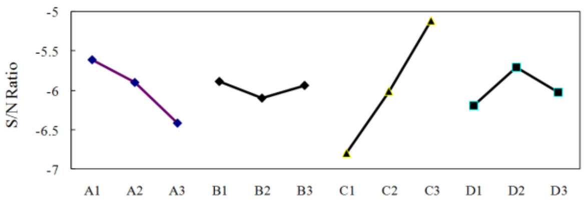

Fig. 3 Factor response graph

III.PROGRESSIVE TAGUCHI-NEURAL NETWORK MODEL CONSTRUCTIONS

This study proposed the progressive Taguchi-neural network model, combining the Taguchi method and neural network to construct a surface roughness prediction model of ultrasonic-assisted turning.

A. Stage-1 initial-network construction

This paper adopts a back propagation (BP) ANN for the system structure; its construction procedures are [15]:

1) Planning the network structure
2) Input module and output modules for network training example
3) Normalization
4) Network training
5) Network prediction output module

B. Stage-2 refining-network

This study ignored the role of the light factor in planning Stage-2 refining-network training examples. Using calculations derived from the additive model of the Taguchi method, the non-implementation of level combinations of signal-to-noise ratios from the light factor were implemented by experimental parameters. The additive model equation for S/N values was follows [18]:

$$S/N\,(A\,B\,C\,D)=\overline{S/N}+(A-\overline{S/N})+(B-\overline{S/N})+(C-\overline{S/N})+(D-\overline{S/N}) \quad (2)$$

Where, A, B, C and D were S/N average values from each control parameter level.

The light factor was the B factor (depth of cutting). So assuming that (A B1 C D) were for parameter combinations of implemented experiments, the signal-to-noise ratio was expressed in Eq. 3a using the additive model. (A B2 C D) were for light factor parameter combinations from non-implemented experiments. The signal- to-noise ratio was expressed in the additive model Eq. 3b. Equations 3a and 3b are as follows:

$$S/N\,(A\;B1\;C\,D)=\overline{S/N}+(A-\overline{S/N})+(B1-\overline{S/N})+(C-\overline{S/N})+(D-\overline{S/N}) \quad (3a)$$

$$S/N(A\,B2\,C\,D)=\overline{S/N}+(A-\overline{S/N})+(B2-\overline{S/N})+(C-\overline{S/N})+(D-\overline{S/N}) \quad (3b)$$

Where, the values of B1 and B2 were already known from Taguchi experimental analysis. Eq. 3b was further expressed as:

$$S/N(A\,B2\,C\,D)=\overline{S/N}+(A-\overline{S/N})+(B1-\overline{S/N})+(C-\overline{S/N})+(D-\overline{S/N})+(B2-\overline{S/N})-(B1-\overline{S/N}) \quad (4)$$

Therefore, the signal-to-noise ratio S/N(AB2CD) from non-implemented experimental light factor (A B2 C D) parameter combinations is derived from the signal-to-noise ratio of implemented experimental parameter combination (A B1 C D) and from B1, B2 signal-to-noise ratio known from Taguchi analysis. Its equation is:

$$S/N(A\,B2\,C\,D)=S/N(A\,B1\,C\,D)+B2-B1 \quad (5)$$

The nine groups of training examples for the Stage-1 initial-network were used as examples. If each group of test example extracted one controlling factor (depth of cutting) as the light factor, then signal-to-noise values from the two groups were calculated using the additive model of the Taguchi method Eq. 5. For the nine groups of training examples in the Stage-1 initial-network, the light factor additive model calculation generates 27 runs of training examples for Stage-2 refining- network.

C. Stage-3 supplemental critical experiments and completion of high-accuracy prediction using artificial neural networks

Based on best factor combination of Taguchi analysis and important factor supplemental critical experiments, supplemental experiments were performed with network training. Important factor was supplemented by adding one set of experimental values in between two key factor levels. Other settings were similar to best factor combination from Taguchi analysis.

The Levenberg-Marquardt method was then incorporated into the predictive model to establish parameters to provide an optimization model for ultrasonic assisted turning.

Using the Levenberg-Marquardt method to search for the optimal combination of parameters requires the identification of the relationship between the processing objective value and the computed values to deduce the optimal size and direction of every step. Here, the processing objective value for ultrasonic assisted turning is surface roughness. First, we define the residual value of this study as:

$$r_i(p) = Ra_{obj} - (Ra_{pre})_i \tag{6}$$

where Ra_{obj} is the objective value for surface roughness, and Ra_{pre} is the predicted surface roughness derived using the predictive model. The error function was defined by the minimum sum of squares in the residual value E(p)

$$E(p) = \frac{1}{2}\sum_{i=1}^{2} r_i(p)^2 = \frac{1}{2}\vec{r}(p)^T \vec{r}(p) \tag{7}$$

where $\vec{r}(p)$ represented the vectors constructed by the residual value of the system, T represented the matrix transpose, and p represented the unknown parameters of the system, which, in this paper, are the combination of parameters for ultrasonic assisted turning. For Eq. 7 when i = 2, the error function E(p) is precisely equal to the residual sum of squares. The gradient of residues in Eq. 7 is

$$\nabla E = J(p)^T r(p) \tag{8}$$

where J is the Jacobian Matrix. The residual value is expressed as the following matrix:

$$J = \begin{bmatrix} \dfrac{\partial r_1(p)}{\partial p} \\ \\ \dfrac{\partial r_2(p)}{\partial (p)} \end{bmatrix}_{2\times 1} \tag{9}$$

$$r = \begin{bmatrix} r_1(p) \\ \\ r_2(p) \end{bmatrix}_{2\times 1} \tag{10}$$

By using the general numerical method of optimization, the best step of the Gauss-Newton method is [19]:

$$\delta = -(J^T J)^{-1} J^T r \tag{11}$$

If a modified parameter Λ, called Marquardt parameter, is added to the Gauss- Newton equation, one can obtain the best step of the Levenberg-Marquardt method as [19]:

$$\delta = -(J^T J + \Lambda)^{-1} J^T r \tag{12}$$

To determine the value of this unknown parameter which matches the physical condition, one must give a constraint to this unknown parameter as following:

$$c(p) > 0 \tag{13}$$

where c(p) is the constrained function, here they are the optimal parameters combination of ultrasonic assisted turning and c(p)>0.

To ensure a smooth search, the concept of the Tikhonov method [16] is used and a modified term is added to Eq. 7; thus, the objective function of the system can be expressed as

$$E^*(p) = \frac{1}{2}\sum_{i=1}^{2}(Ra_{obj} - (Ra_{pre})_i)^2 + \Psi(p) \tag{14}$$

where Ψ(p) is known as an inverse barrier function, which was proposed by Carroll, and is expressed as following [17]:

$$\Psi(p) = \frac{\phi}{c} \tag{15}$$

where ϕ is a penalty function weight.

Thus, when calculates the optimal parameters combination of ultrasonic assisted turning using Levenberg-Marquardt method, an appropriate initial guess $p^{(0)}$ is given in Eq. 16, one can obtain increment of parameter δ(k) in each iteration [17]:

$$(J^{(k)^T} J^{(k)} + \Lambda^{(k)} + H^{(k)})\delta^{(k)} = -J^{(k)^T} r^{(k)} + g^{(k)} \tag{16}$$

where

$$g = -\frac{d\Psi}{dp} \tag{17a}$$

$$H = \frac{d^2\Psi}{dp^2} \tag{17b}$$

where k is the iterative count, T represents the transpose of matrix, J the Jacobian Matrix, and Λ Marquardt parameter [20], which is an adjustable variable. Obviously, this parameter is related to the value and direction of each step.

From Eq. 17, after the differential is performed, one can acquire:

$$g = \frac{\phi}{c^2} \tag{18a}$$

$$H = \frac{2\phi}{c^3} \tag{18b}$$

Subsequently, Eq. 16 can be rewritten as

$$(J^T J + H + \Lambda)\delta = -J^T r + g \tag{19}$$

Therefore,

$$\delta = (-J^T r + g)/(J^T J + H + \Lambda) \tag{20}$$

Plus the initial guess to the increment of parameter obtained from Eq. 20, the actual value of the modified parameter of the next step can be acquired as:

$$p^{(k+1)} = p^{(k)} + \delta^{(k)} \tag{21}$$

By substituting the new parameter value of p(k+1) acquired by Eq. 21 back into the ultrasonic assisted turning prediction model, a new output value and new objective function can be acquired. Comparison the objective function of the new one with the old, and if the new is smaller, then, the Marquardt parameter, Λ, is reduced, and from Eq. 19, the increment of parameter is increased. Conversely, when the new objective function is larger, one must increase Λ and the increment of parameter must be decreased. The convergent criterion used in the analysis of inverse elasticity adopted by Schnur and Nicholas [17] is $\sum_{i=1}^{n}\left|\delta_i^{(k)}\right| \Big/ \left(10^{-5} + \sum_{i=1}^{n}\left|p_i^{(k)}\right|\right) < 10^{-4}$. Using the Levenberg-Marquardt method described above, an optimal combination of processing parameters conforming to the defined convergence criteria was identified. The procedure of obtaining the optimal rotational speed using the parameter optimization model in this study is shown in Fig. 4.

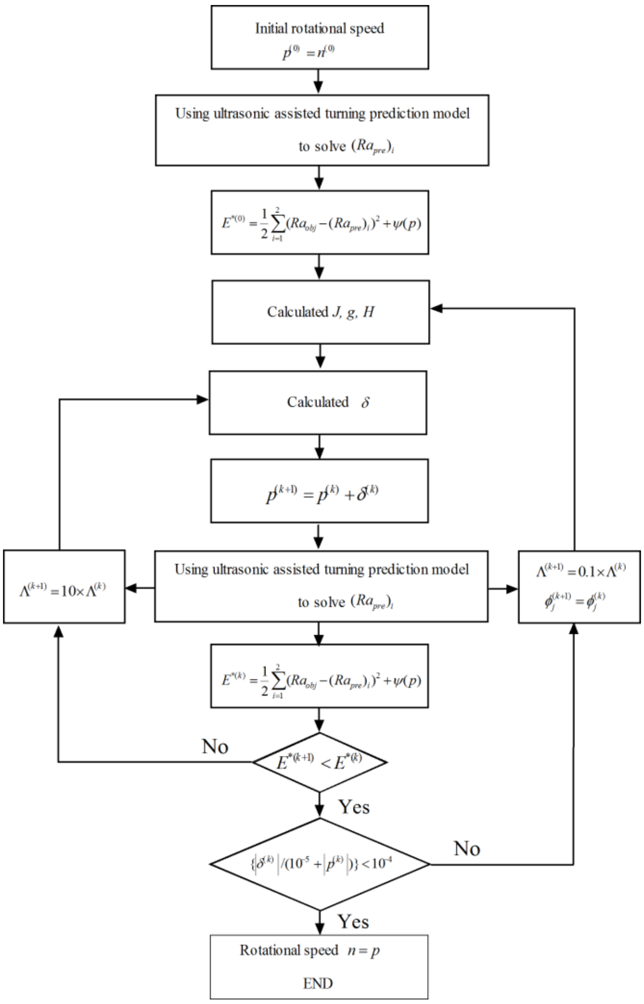

Fig. 4 Procedure of parameter optimization model

A. Results from Taguchi method of analysis

After the aforementioned ultrasonic-assisted turning data analysis, factor response table and graph analysis were performed in order to understand the significance of various processing parameters. As derived from Table 4 of S/N factor response table and Fig. 3 of the S/N factor response graph, the best parameter level combination using Taguchi analysis for ultrasonic-assisted turning was A1B1C3D2. Among the factors affecting surface roughness quality, rotational speed was the most significant. High rotational speeds of 450 rpm were better than low rotational speeds of 100 and 275 rpm. The reason for this was that front vibration amplitude of high rotational speeds was smaller. The second most significant factor was the turning feed rate. A low feed rate of 0.002 mm/rev was better than a high feed rate of 0.006 and 0.01 mm/rev because high feed rate created greater cutting force. Ultrasonic-assisted turning was better than traditional turning because ultrasonic-assisted turning lowered cutting force [1-4] and raised cutting quality [5]. Additionally, adding a sleeve in between the cutting tool and oscillator lowered the cutting system's rigidity, reducing cutting quality [21].

Table 4 Control factor S/N factor response table of surface roughness

mean S/N ratios	A. feed rate (mm / rev)	B. depth of cutting (mm)	C. rotational speed (rpm)	D. ultrasonic type
level 1	-5.61	-5.89	-6.80	-6.19
level 2	-5.90	-6.10	-6.01	-5.71
level 3	-6.42	-5.94	-5.11	-6.02
Effect	0.8	0.22	1.69	0.46

B. Examples of progressive Taguchi-neural network model development

1) Construction of Stage-1 initial-network

After using a single hidden layer of 4×6×1, the network was transmitted for training, with the network learning rate set at 0.1, learning impulse set at 0.1, and learning number set at 20000 times. Table 5 shows that the network used the nine group experimental factor combinations for Stage-1 training examples.

Table 5 Stage-1 training examples in neural network using L9 orthogonal array data

run	setup value				
	at input layer				at output layer
	feed rate	cutting depth	rotational speed	ultrasonic type	Stage-1
1	0.2	0.2	0.2	0.2	0.39101
2	0.2	0.5	0.5	0.5	0.62022
3	0.2	0.8	0.8	0.8	0.8
4	0.5	0.2	0.5	0.8	0.54157
5	0.5	0.5	0.8	0.2	0.66067
6	0.5	0.8	0.2	0.5	0.42472
7	0.8	0.2	0.8	0.5	0.69663
8	0.8	0.5	0.2	0.8	0.2
9	0.8	0.8	0.5	0.2	0.37528

2) Stage-2 refining-network

This study ignored the role of the light factor in planning network expansion training examples. Based on Table 4 factor response table analysis results, B. depth of cutting was the light factor of ultrasonic-assisted turning.

The nine groups of network training examples were used to plan 1a, 1b, 2a, 2b, etc. In total, 27 groups from Table 6 were used as the light factor expansion training examples in Stage-2 network refining. The purpose of refining the network was to achieve accurate and positive results and carry out training with similar neuron numbers in the network hidden layer and parameters. Table 7 shows that the squared error for Stage-1 network and 27 group predictions in the Taguchi additive model was 0.087733, while the Stage-2 network and 27 group predictions in the Taguchi additive model was 0.055906. The results show that network learning improved.

Table 6 Stage-2 training examples in neural network using light factor

run	setup value				
	at input layer				at output layer
	feed rate	cutting depth	rotational speed	ultrasonic type	Stage-2
1	0.2	0.2	0.2	0.2	0.391011236
1a	0.2	0.5	0.2	0.2	0.341573034
1b	0.2	0.8	0.2	0.2	0.379775281
2	0.2	0.5	0.5	0.5	0.620224719
2a	0.2	0.2	0.5	0.5	0.669662921
2b	0.2	0.8	0.5	0.5	0.658426966
3	0.2	0.8	0.8	0.8	0.8
3a	0.2	0.2	0.8	0.8	0.811235955
3b	0.2	0.5	0.8	0.8	0.761797753
4	0.5	0.2	0.5	0.8	0.541573034
4a	0.5	0.5	0.5	0.8	0.492134831
4b	0.5	0.8	0.5	0.8	0.530337079
5	0.5	0.5	0.8	0.2	0.660674157
5a	0.5	0.2	0.8	0.2	0.71011236
5b	0.5	0.8	0.8	0.2	0.698876404
6	0.5	0.8	0.2	0.5	0.424719101
6a	0.5	0.2	0.2	0.5	0.435955056
6b	0.5	0.5	0.2	0.5	0.386516854
7	0.8	0.2	0.8	0.5	0.696629213
7a	0.8	0.5	0.8	0.5	0.647191011
7b	0.8	0.8	0.8	0.5	0.685393258
8	0.8	0.5	0.2	0.8	0.2
8a	0.8	0.2	0.2	0.8	0.249438202
8b	0.8	0.8	0.2	0.8	0.238202247
9	0.8	0.8	0.5	0.2	0.375280899
9a	0.8	0.2	0.5	0.2	0.386516854

3) Stage-3 supplemental critical experiments and completion of high-accuracy predictions of neural networks

Based on best factor combination in Taguchi analysis and important factor, the critical supplemental experiment training examples were determined. Table 8 shows information on Stage-3 network training examples.

VI. RESULTS OF PARAMETER OPTIMIZATION MODEL FOR PROCESSING WITH ULTRASONIC ASSISTED TURNING

The maximum and minimum control factors (A. feed rate, B. depth of cutting, and C. rotational speed) set as 0.85 and 0.15. Three choices are available for D. ultrasonic type: D=0.2 (X), 0.5 (V), and 0.8 (sleeve). During implementation of the parameter optimization model, the four control factors were initially set at 0.5. The other initial input conditions are as follows: convergence value ε=10^{-4}, and the Marquardt parameter Λ=0.0001. From the S/N responses in Table 5, it is apparent that while processing with ultrasonic assisted turning: C. rotational speed has the largest influence on the processing, followed by A. feed rate; D. ultrasonic type and B. depth of cutting exert less influence. Consequently, rotational speed was the first priority in identifying the optimal combination for parameters in this study, followed by feed rate, ultrasonic type, and depth of cutting.

Table 7 Stage-1, Stage-2 networks and Taguchi additive model prediction comparison

no	Combined factors	prediction		
		Add mode	Stage-1 network	Stage-2 network
1	A2B1C1D1	0.32809	0.269	0.299
2	A2B1C1D2	0.435955	0.290	0.338
3	A2B1C1D3	0.366292	0.313	0.367
4	A2B1C2D1	0.505618	0.497	0.509
5	A2B1C2D2	0.613483	0.535	0.545
6	A2B1C2D3	0.54382	0.569	0.565
7	A2B1C3D1	0.7078652	0.690	0.717
8	A2B1C3D2	0.8157303	0.726	0.737
9	A2B1C3D3	0.7460674	0.756	0.743
10	A2B2C1D1	0.280899	0.301	0.292
11	A2B2C1D2	0.388764	0.328	0.332
12	A2B2C1D3	0.319101	0.355	0.360
13	A2B2C2D1	0.458427	0.509	0.499
14	A2B2C2D2	0.566292	0.550	0.531
15	A2B2C2D3	0.496629	0.589	0.551
16	A2B2C3D1	0.6606742	0.682	0.701
17	A2B2C3D2	0.7685393	0.721	0.728
18	A2B2C3D3	0.6988764	0.754	0.735
19	A2B3C1D1	0.316854	0.326	0.299
20	A2B3C1D2	0.424719	0.358	0.332
21	A2B3C1D3	0.355056	0.390	0.343
22	A2B3C2D1	0.494382	0.511	0.489
23	A2B3C2D2	0.602247	0.556	0.535
24	A2B3C2D3	0.532584	0.598	0.542
25	A2B3C3D1	0.6966292	0.669	0.699
26	A2B3C3D2	0.8044944	0.710	0.735
27	A2B3C3D3	0.7348315	0.746	0.728
squared sum error			0.087733	0.055906

Table 8 Stage-3 network training examples

run	setup value				
	at input layer				at output layer
	feed rate	cutting depth	rotational speed	ultrasonic type	Stage-3
27 training examples of Stage-2					
S1	0.2	0.2	0.8	0.5	0.84277
S2	0.2	0.2	0.345714	0.5	0.57125
S3	0.2	0.2	0.645714	0.5	0.74652

Table 9 shows the optimal combination of parameters for the proposed model. Run1 is the supposed ideal values for feed rate, depth of cutting, and rotational speed without restricted conditions. The normalized values of Run 1 were: feed rate = 0.15 (0.00134 mm/rev); depth of cutting = 0.15 (0.00134 mm), rotational speed = 0.85 (479.5 rpm), and ultrasonic type = 0.5 (supersonic). The normalized value of the predicted value Ra_{pre} was 0.821. Using the signal-to-noise ratio formula of Eq. (3), a minimum predicted surface roughness Ra_{pre} of 1.71μm was derived.

Table 9 Optimal combination of parameters

Run	Constraint condition	optimal parameters combination				predicted value Ra_{pre}	check
		feed rate	depth of cutting	rotational speed	ultrasonic type		
1	D=0.2, 0.5, 0.8	0.15	0.15	0.85	0.5	0.821	
	D=X, V, sleeve	0.0013	0.0013	479.5	V	1.71	
2	D=0.2, 0.5, 0.8	0.1625	0.1625	0.843	0.5	0.816	0.843
	D=X, V, sleeve	0.0015	0.0015	475	V	1.71	1.69

Run 2 used the experimental values for feed rate, depth of cutting, and rotational speed with restricted conditions. During experimentation, feed rate, depth of cutting, and rotational speed were, in fact, discontinuous functions; therefore, this study conducted further experiments to obtain the optimal parameter combination using restricting conditions. The normalized values of Run 2 are feed rate = 0.1625 (0.0015 mm/rev), depth of cutting = 0.1625 (0.0015 mm), rotational speed = 0.843 (475 rpm), and ultrasonic type = 0.5 (ultrasonic); the normalized value of the predicted Ra_{pre} is 0.816. Using Eq. (3), a minimum surface roughness Ra_{pre} was 1.71μm. The experimental value was 1.69μm, resulting in a 1.2 % error between predicted and experimental values. As seen in Table 9, the error between the predicted results derived using the parameter optimization model established for ultrasonic assisted turning in this study and experimental values is within 5 %. The predicted results are close to the order of experiments, which is within the accepted range of error.

VII. CONCLUSIONS

In optical components, ultrasonic assisted turning can effectively reduce cutting force and tool wear with materials that are difficult to cut and increase processing quality. The S/N response table shows the optimal combination of parameter levels of be A1B1C3D2. Among the factors influencing the quality of surface roughness, rotational speed had the greatest impact. Rotational speed of 450 rpm provided results superior to those of 100 rpm and 275 rpm, due to the fact that the vibration amplitudes in the turning bit were smaller at higher rotational speeds. Cutting feed rate also had considerable influence and a lower feed rate of 0.002 mm/rev was superior to 0.006 mm/rev and 0.01 mm/rev because high feed rates created higher cutting force. Ultrasonic assisted turning was superior to conventional turning as it reduced cutting force and increased cutting quality. In addition, adding a sleeve between the cutting tool and the oscillator reduced the rigidity of the cutting tool system, which decreased cutting quality.

This study combines Taguchi method with artificial neural networks (Taguchi-neural network) to construct a predictive model for ultrasonic assisted turning that is highly precise and yet requires fewer experiments. In addition, we incorporated the Levenberg-Marquardt method into the predictive model, resulting in a parameter optimization model for ultrasonic assisted turning. The optimal parameter combination obtained by the model was feed rate = 0.1625 (0.0015 mm/rev), depth of cutting = 0.1625 (0.0015 mm), rotational speed = 0.843 (475 rpm), and ultrasonic type = 0.5 (ultrasonic). The minimum surface roughness Ra_{pre} was predicted to be 1.71μm; the experimental value was 1.69 μm, resulting in a 1.2 % error between predicted and experimental values. The parameter optimization model established for ultrasonic assisted turning in this study is capable of increasing processing precision, with reference value for applications of ultrasonic assisted turning.

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