IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 24, 2020, accepted September 1, 2020, date of publication September 8, 2020, date of current version September 25, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3022648

The Optimization of Lathe Cutting Parameters Using a Hybrid Taguchi-Genetic Algorithm

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This work was supported in part by the Ministry of Science and Technology of the Republic of China, Taiwan, under Grant MOST 108-2218-E-194-013.

ABSTRACT In this paper, the multi-objective Hybrid Taguchi-Genetic Algorithm is used to search for the best processing parameters with specified processing accuracy. The experimental cutting parameters used for the L9 orthogonal table process are cutting depth, cutting velocity and feed rate. The surface roughness of the machined workpiece surface was measured according to the standard of centerline average roughness. The Material Removal Rate will be calculated by measuring the diameter of the processed workpiece from the formula to give the Material Removal Rate. A linear regression model is constructed from the processed quality and the processing parameters of the orthogonal table, and the reliability of the model is confirmed by analysis of variance. A Hybrid Taguchi-Genetic Algorithm was used to calculate the optimal cutting parameters for multi-objective processing. The results of the experiments indicate that Hybrid Taguchi-Genetic Algorithm gave better convergence and robustness than the conventional Genetic Algorithm using the same number of iterations. This process produces multiple combinations of optimal cutting parameters for material removal rate and surface roughness. As the enhancement of material removal rate improved efficiency on the production line, the optimal cutting parameters were based on the tolerance range of Ra 1.6μm to 3.2μm according to the international standard of surface roughness. After actual processing with the selected optimum cutting parameters, the quality of processing is even better than the experimental design of the L9 Orthogonal table.

INDEX TERMS Regression analysis, genetic algorithm, multi-objective optimization.

NOMENCLATURE

Ra	Surface roughness
MRR	Material Removal Rate
ANOVA	Analysis of variance
HTGA	Hybrid Taguchi-Genetic Algorithm
GA	Genetic Algorithm
y, x	dependent variable
β_0	intercept of the prediction model
ε	error value of the prediction model
β_i, β_{ij}	simulated parameters based on the measured value of the dependent variable for the model
Df_B	degree of freedom for the model
Df_W	residual degree of freedom
Df_T	total degree of freedom
SS_B	sum of squares of the model
SS_W	residual sum of squares
SS_T	total sum of squares
a	value obtained by calculation using the created regression model and the independent variable
$\bar{a}$	mean of a
b	value of the dependent variable
MS_B	sum of mean squares of the model
MS_W	sum of mean squares of the residual difference
$F - value$	value for the determination of the model
R^2	coefficient of determination of the model
$R^2(adj)$	coefficient of determination after model adjustment
$f_1(x)$	objective functions Ra
$f_2(x)$	objective functions MRR

The associate editor coordinating the review of this manuscript and approving it for publication was Yunhua Li.

$maxf_1(x)$	maximum values of the objective function Ra
$maxf_2(x)$	maximum values of the objective function MRR
$f(x)$	multi-objective function
$w1$	value of the weight 1
$w2$	value of the weight 2
D_{before}	diameter before processing
D_{after}	diameter after processing
l	processing length
T	processing time
d	cutting depth
Vc	cutting velocity
f	feed rate

I. INTRODUCTION

CNC machined workpieces must reach a certain level of precision to be considered as a primary processing and the parameters are often chosen by an experienced machine operator who then sets the machine accordingly. Although this method frequently produces the required specifications, it may not be the best for large scale production [1]. In the machinery industry, one of the most important measures of finished product quality is surface roughness. The roughness tolerance range is an important indicator of the completeness of the cutting surface. That the finished surface roughness should be within the required tolerance depends on the settings, and these in turn, depend on the experience of the person making them [2]. Another processing quality indictor that needs attention is the MRR. The faster the removal rate the better the efficiency of the production line. Therefore, the highest MRR that will give the required surface roughness should be used [3]. The cost of the production process also needs consideration as well as the overall cost of the process to the environment and of the materials generated [4].

The design of the experiment needed a means of verification and the famous Taguchi method was used to search for the best parameter combinations [5]. The Taguchi method involves the use of an orthogonal table of the experimental control factors which greatly reduces the time and cost of an experiment [6] and there have been a vast number of academic applications of the Taguchi method [7], [8]. In addition, the experimental data in the table were used to perform regression analysis to create a prediction model [9]. Xiao, *et al.* [10] derived a surface roughness prediction model for the discharge turning of stainless steel using an orthogonal table and the Response Surface Method (RSM) with good results. In their project an L9 orthogonal table was used for the experimental design of processing parameters. The Ra and MRR data and the processing parameters obtained in their discharge turning experiments were used in an orthogonal table to create an Ra and MRR prediction model using linear regression. In another study, Alharthi, *et al.* [11], used an Artificial Neural Network (ANN) to create a surface roughness prediction model for the discharge turning of an AZ61 magnesium alloy and this was also verified by regression analysis which indicated good consistency. To verify the prediction model, some researchers have used the analysis of variance to verify the confidence of a model. For example, Gohil and Puri [12] created a surface roughness prediction model for the electrical discharge turning of a Ti-6Al-4V alloy where regression analysis was used to verify the confidence of the model by the analysis of variance. Davoodi and Tazehkandi [13] used a coated carbide tool to process an Inconel 738 alloy and simulated a quadratic model using the feed, thrust and cutting forces as well as surface roughness in the RSM. The confidence of their model was checked by ANOVA.

The created prediction model was used to find the best solution based on the optimization objective, and different optimization algorithms can be seen in the literature. Zeelanbasha, *et al.* [14] developed a prediction model for measurement of temperature rise and surface roughness. The Multi-Objective Genetic Algorithm (MOGA) found 18 sets of optimal processing parameters and confirmed the best processing parameters for achieving the minimum temperature rise and surface roughness. The discharge turning experiments made by Gupta, *et al.* [15] on Inconel-800 alloy employed Particle Swarm Optimization (PSO) and Teaching Learning-Based Optimization (TLBO) to find the optimal processing parameters. Solarte-Pardo, *et al.* [16] developed a system for the selection of tool and cutting parameters to find the lowest power consumption, the shortest processing time, and the most acceptable surface roughness for the working specifications using an Artificial Neural Network (ANN) and Genetic Algorithm (GA) optimized modelling. The use of GA combined with several other methods has shown to be better than the use of conventional GA alone. Garg [17] proposed a new penalty guided hybrid approach called PSO-GA. The optimization issue is treated under nonlinear constraint and PSO-GA gave better results that either method alone. The position of a space manipulator was investigated by Jiang and Wang [18] who used a hybrid LM-GA algorithm, a combination of the Levenberg-Marqurdt algorithm with the Genetic Algorithm, to find precise requirements for camera calibration. Their results showed that the hybrid LM-GA gave more precise non-linear camera error reduction. Among other optimization algorithms, we used HTGA as proposed by Jinn-Tsong, *et al.* [19] to search for multi-objective optimization. HTGA was derived from a hybrid of GA and the Taguchi method. The famous Taguchi method for finding the best combination of parameters through the experimental design of the orthogonal table and the experimental results. At HTGA, the Taguchi method is used to select better combinations of genes, while the Taguchi method's experiment has been used in most of the literature. As traditional GA is randomly selected for gene search, which makes them easier getting into local optimization, the use of HTGA can stabilize the results and prevent them from getting stuck in a local optimal solution [20] Hasan, *et al.* [21] howed that the use of HTGA for the adjustment of ACG controller parameters gave more stability than the conventional Genetic Algorithm. In addition, HTGA search is robust and has been used by many others [22], [23] and is useful for multi-objective optimization. Pirpinia, *et al.* [24] used the weighted combination method to study multi-objective machine learning with different combinations of weight. Zhang, *et al.* [25] proposed a cutting cost model and used the processing parameters as decision variables. They chose energy saving, noise reduction and cost saving for a multi-objective optimization model, and used the Non-dominant Sort Genetic Algorithm (NSGA-II) to choose the most suitable Pareto-optimal solution by multi-objective optimization of weighted combinations. The algorithm used in this article first compared the output results of GA and HTGA to ensure stable results. Finally, the Pareto-optimal solution obtained from the HTGA was chosen based on the tolerance range of surface roughness. The data measured after the processing was compared with the experimental design of the L9 orthogonal table to obtain a better material removal rate.

II. METHODS

This sections has three part. In the first part an orthogonal table was used to design the experiment to find the optimal processing parameters. In the second part, regression analysis was conducted to obtain a prediction model for workpiece quality and ANOVA was used to verify the confidence of the model. In the third part the optimization algorithm is used to output the optimal processing parameters. The experimental processes are as shown in Figure 1. The design of the orthogonal table is described in detail section A of part III, the regression analysis model section B of part III, and the multi-objective Genetic Algorithm section C of part III.

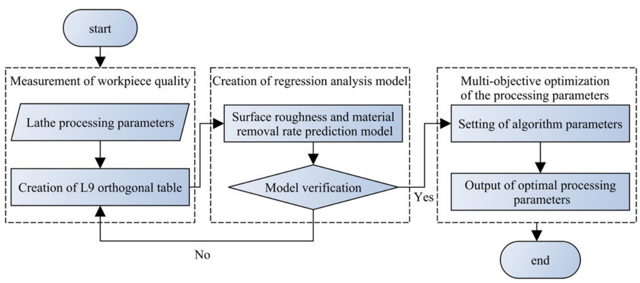


FIGURE 1. Experiment flow chart.

A. DESIGN OF THE ORTHOGONAL TABLE

First, we established the design method of the turning experiments and used the orthogonal table proposed by RA Fisher [26]. This method makes the levels of each control factor orthogonal to the others based on the scale of the experiment. It is important that the contribution level of the control factors are evenly distributed in order to conduct the experiment in a more efficient way. This paper refers to the often used application of L9 orthogonal table in mechanical processing for the application of such experimental research [27]. The selected processing parameters in the table for the lathe used in this study are: cutting depth, cutting velocity and feed rate. Three different levels within the processing range of each parameter are set, and the design of orthogonal table is as shown in Table 1.

TABLE 1. The experimental L9 orthogonal table.

No.	Levels of the processing parameters		
	Cutting depth(mm)	Cutting velocity(m/min)	Feed rate(mm/rev)
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	3
5	2	2	1
6	2	3	2
7	3	1	2
8	3	2	3
9	3	3	1

B. REGRESSION ANALYSIS MODEL

The processing parameters of L9 Orthogonal table in section A of part III were used as the independent variables to prepare a prediction model of processing quality (Ra and MRR). An interactive prediction model of surface roughness and material removal rate was obtained as shown in formula (1) [28]–[31].

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=j}^{k} \sum_{j=2}^{k} \beta_{ij} x_i x_j + \varepsilon \tag{1}$$

y is the dependent variable; β_0 is the intercept of the prediction model; k is the number of independent variables for the model; x is the independent variable; ε is the error value of the prediction model; β_i and β_{ij} are the simulated parameters based on the measured value of the dependent variable for the model. In this paper the MATLAB toolbox linear regression model was used to solve β_0, β_i, β_{ij} and ε.

ANOVA [32] was used to evaluate the precision of the prediction model. The degree of freedom for the analysed ANOVA value was determined using formulas (2), (3) and (4):

$$Df_B = k - 1 \tag{2}$$

$$Df_W = N - k \tag{3}$$

$$Df_T = N - 1 \tag{4}$$

Df_B is the degree of freedom for the model; Df_W is the residual degree of freedom; Df_T is the total degree of freedom; k is the number of groups; N is the number of samples.

After the degree of freedom of ANOVA was decided, the sum of squares could be used to calculate the coefficient of determination of the model. The sum of squares of the analysis value of ANOVA was determined using formulas (5), (6) and (7).

$$SS_B = \sum_{i=1}^{N} (a_i - \bar{a})^2 \tag{5}$$

$$SS_W = \sum_{i=1}^{N} (a_i - b_i)^2 \tag{6}$$

$$SS_T = SS_B + SS_W \tag{7}$$

SS_B is the sum of squares of the model; SS_W is the residual sum of squares; SS_T is the total sum of squares; a is the value obtained by calculation using the created regression model and the independent variable; $\bar{a}$ is the mean of a; b is the value of the dependent variable.

Divide the sum of squares by the corresponding degree of freedom to get the sum of mean squares, and then divide by the sum of mean squares of the model and the residual difference. The sum of mean squares for the analysed value of ANOVA was obtained using formulas (8), (9) and (10).

$$MS_B = \frac{SS_B}{Df_B} \tag{8}$$

$$MS_W = \frac{SS_W}{Df_W} \tag{9}$$

$$F - value = \frac{MS_B}{MS_W} \tag{10}$$

MS_B is the sum of mean squares of the model; MS_W is the sum of mean squares of the residual difference; $F - value$ is the data for the determination of the model.

The coefficient of determination R^2 of the model and the coefficient of determination $R^2(adj)$ after model adjustment can be found using formulas (11) and (12).

$$R^2 = 1 - \frac{SS_W}{SS_T} \tag{11}$$

$$R^2(adj) = 1 - \frac{\frac{SS_W}{Df_W}}{\frac{SS_T}{Df_T}} \tag{12}$$

Finally if the $F - value$ based on ANOVA is greater than the $F - value$ of 95% confidence, this can be used to decide the confidence level of the prediction model [33].

C. MULTI-OBJECTIVE GENETIC ALGORITHM

The Genetic Algorithm "imitates" biological evolution. It can quickly calculate linear and nonlinear optimization issues and is widely used in engineering [34]. From and initial number of genes, the fitness value of the environment is first evaluated before the required number of evolutions. Genes must selected for duplication, the higher the fitness of the gene the greater the probability of its being selected. This goes on until the number of duplications is equal to the initial number. The self defined crossover rate determines whether mating occurs. The mating process is a random selection of two genes which are rearranged as two newly generated ones. The new gene combination mutates and the proportion of genes is changed. The mutated gene is evaluated to determine whether it meets the environmental requirements; if not, duplication, mating and mutation will continue until the environmental fitness value, or the required number of evolutions, has been reached [35].

In this present study the Hybrid Taguchi-Genetic Algorithm proposed by Jinn-Tsong, *et al.* [19] was used for the optimization calculation. HTGA uses the roulette wheel method to select two genes at random during the cross selection. The size of the Taguchi orthogonal table was determined by the self defined variable and the better gene combinations were found. These gene combinations and the genes selected by the roulette wheel method were then used for cross selection. The selected genes mutated and evolved new genes based on the fitness value. Better combinations of genes were selected by the Taguchi method. Convergence was faster and the process was less likely to be stuck in a local optimal solution than the conventional Genetic Algorithm [36].

Consideration was given to two processing quality factors such as surface roughness and material removal rate, and multi-objective optimization was used to find the optimal processing parameters. It was necessary to optimize several objectives at the same time and this inevitably sacrificed other objectives. It was decided to find a set of compromise solutions based on the range of one important objective using the Pareto non-inferior solution (sometimes called the Pareto-optimal solution) [37]. The Das and Dennis method [38] was used for multi-objective optimization. This employs the weighted combination of two single objective issues to form a multi-objective function. The functions of the two objectives were conducted for normalization setting to prevent one from reaching the target value too fast as a result of the division of the maximum value. The original objective function was converted to the same range of output and then weighted to form a multi-objective function, as shown in the following formula(13), (14) and (15).

$$f_1(x) = \frac{f_1(x)}{maxf_1(x)} \tag{13}$$

$$f_2(x) = \frac{f_2(x)}{maxf_2(x)} \tag{14}$$

$$f(x) = w1 \times f_1(x) + w2 \times f_2(x) \tag{15}$$

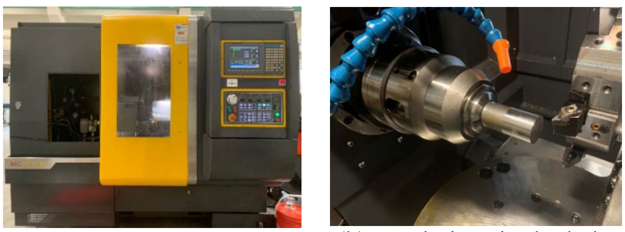
$f_1(x)$ and $f_2(x)$ are two different objective functions, Ra and MRR; $maxf_1(x)$ and $maxf_2(x)$ are the maximum values of the objective function; $f(x)$ is the multi-objective function after the combination; $w1$ and $w2$ are the objective functions with the weighted pattern $w1 + w2 = 1$ respectively.

III. EXPERIMENTAL RESULTS AND DISCUSSION

The experiments in this study were conducted by straight turning. The workpiece was clamped out 60mm long in the lathe collet and the turning portion was 30mm long. As the material diameters are a little different from the factory, the workpiece needs to be processed to the same diameter before the experiment in order to reduce the error of the experiment. Next, set the cutting parameters for the design of the orthogonal table in section A of part III to complete the machining for this experiment. The actual values of surface roughness and material removal rate were measured after turning to derive a prediction model for both using regression analysis. By using the Hybrid Taguchi-Genetic Algorithm for multi-objective optimization, we get many sets of cutting parameters from the results of the multi-objective optimization, and we choose the best processing parameters according to the quality of the surface roughness.

A. EQUIPMENT USED IN THE EXPERIMENTS

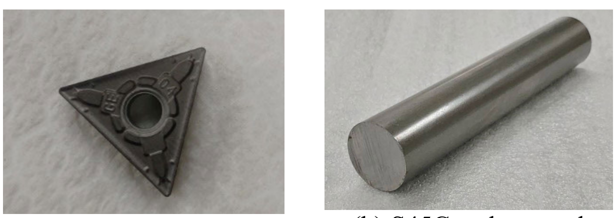
The lathe used in this study was a MC4200BL Mike Machine spherical CNC lathe with a SYNTEC 21-TA controller, as shown in Figure 2(a). The main shaft collet was a Posa TAC-10-CY, and the processing tool used was a CHAIN ETQNL-2020K16 as shown in Figure 2(b).



(a) Mike Machine spherical CNC lathe (b) Workpiece in the lathe collet and the cutting tool

FIGURE 2. Equipment used in the experiment.

The cutting tools used were SUMITOMO TNMG1604-04N-GE tungsten steel blade, see Figure 3(a). The S45C medium carbon steel workpieces were 30 mm in diameter and 175 mm long, see Figure 3(b).



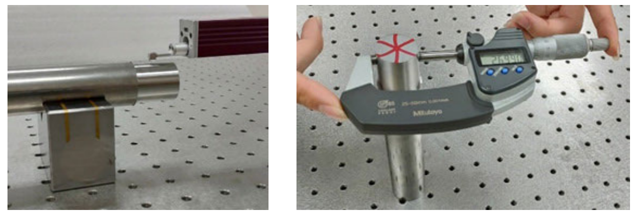
(a) Tungsten steel blade (b) S45C carbon steel workpiece

FIGURE 3. The tungsten steel blade and a workpiece.

A Mitutoyo SJ-210 surface roughness tester was used to measure workpiece roughness. The workpiece was supported in V-groove block on a surface plate and the average of six different measurements, taken at different angles, along the centre-line of the workpiece was used, as shown in Figure 4 (a). The calculation of MRR was done using formula (16).

$$MRR = \frac{(D_{before} - D_{after})^2 \times \pi \times l}{4 \times T} \tag{16}$$

D_{before} is the diameter (mm) before processing; D_{after} is the diameter (mm) after processing; l is the processing length (mm); T is the processing time (min).



(a) Ra measurement (b) Diameter measurement

FIGURE 4. Measuring the workpiece.

A Mitutoyo micrometer was used to measure the workpiece diameter used to calculate the MRR, see Figure 4 (b).

B. CREATING A PREDICTION MODEL FOR WORKPIECE QUALITY

An L9 orthogonal table as described in Section A of part IV was used and the processing parameter levels were set according to the range of processing parameters recommended by the tool manufacturer. The measured workpiece quality data after processing is shown in Table 2.

TABLE 2. L9 direct table and actual measures.

No.	Cutting depth (mm)	Cutting velocity (m/min)	Feed rate (mm/rev)	Ra (μm)	MRR (mm^3/min)
1	0.5	270	0.1	1.169	952.448
2	0.5	310	0.15	1.935	1637.121
3	0.5	350	0.2	3.308	2447.586
4	1.0	270	0.15	1.990	2900.089
5	1.0	310	0.2	3.341	4455.143
6	1.0	350	0.1	1.516	2506.250
7	1.5	270	0.2	4.154	6030.000
8	1.5	310	0.1	1.330	3470.852
9	1.5	350	0.15	2.502	5971.389

A regression model, as described in Section B of part IV, was used with the data in Table 2 to derive a first-order polynomial prediction model. This was based on the relationship between surface roughness and material removal rate using and as dependent variables, and cutting depth (d), cutting velocity (Vc) and feed rate (f) as independent variables. See formula (17) and (18):

$$\begin{aligned} Ra = & -1.2778 + 5.0764 \times d + 0.0120 \times Vc \\ & \ldots, -48.3805 \times f - 0.0252 \times d \times Vc \\ & \ldots, +23.5029 \times d \times f + 0.1370 \times Vc \times f \end{aligned} \tag{17}$$

$$\begin{aligned} MRR = & \; 4116.1024 - 4314.9735 \times d - 13.9828 \times Vc \\ & \ldots, -23208.2733 \times f + 14.4309 \times d \times Vc \\ & \ldots, +23120.4 \times Vc \times f + 74.144 \times Vc \times f \end{aligned} \tag{18}$$

The predictive range of the model is the upper and lower limits of the processing parameters 0.5mm $\leq d \leq$ 1.5mm;

270m/min $\leq$ Vc $\leq$ 350m/min; 0.1mm/rev $\leq$ f $\leq$ 0.2mm/rev.

On the basis of the model verification method described in Section B of part IV, the analysis results of surface roughness of the prediction model are as shown in Table 3. Assuming 95% confidence in the statistics, the validity of the ANOVA model generation and the degrees of freedom for residual differences, the prediction model had reached an F-value of: 19.32953 or higher.

TABLE 3. ANOVA (analysis of variance) of the prediction model for surface roughness.

Source	Df	Sum of Squares	Mean Squares	F-value	P-value
Model (SS_R)	6	8.5857	1.4310	132.5091	0.0075
Residual (SS_E)	2	0.0216	0.0108		
Total (SS_T)	8	8.6073			

Notes:R^2=0.997;R^2(adj) = 0.990; confidence level = 95%

Results of the analysis of material removal rate for the prediction model are shown in III-C. On the basis of 95% confidence in the statistics, as well as validity of the ANOVA model generation and the degrees of freedom for residual difference, the prediction model had reached an F-value of: 19.32953 or higher.

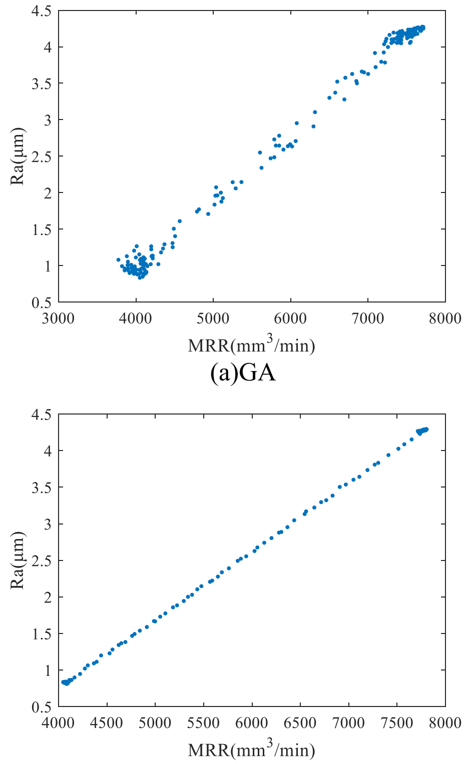
TABLE 4. ANOVA (analysis of variance) of the prediction model for material removal rate.

Source	Df	Sum of Squares	Mean Squares	F-value	P-value
Model (SS_R)	6	2577934 6.8383	4296557 .8064	993	0.00101
Residual (SS_E)	2	8650.332 0	4325.16 60		
Total (SS_T)	8	2578799 7.1703			

Notes：R^2=0.999;R^2(adj) = 0.999;confidence level = 95%

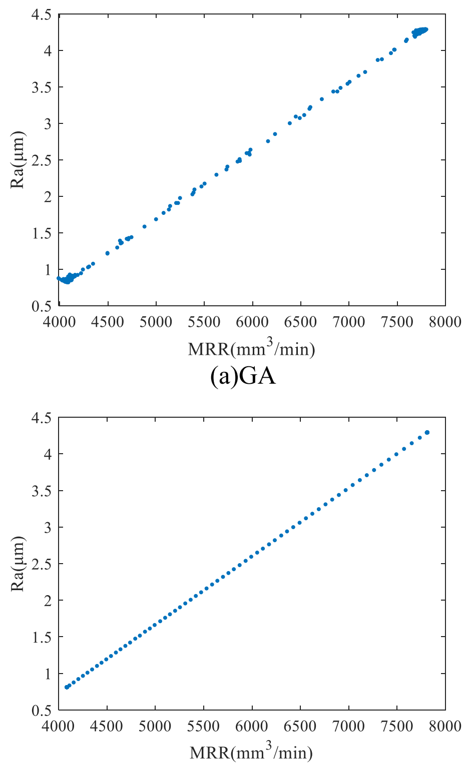
C. MULTI-OBJECTIVE OPTIMIZATION

To prove the superiority of the Hybrid Taguchi-Genetic Algorithm described in Section C of part IV, the conventional GA and HTGA were both run using the same parameters and comparisons were made at specific numbers of iterations. The setting of parameters were: initial population size 60,



(b)HTGA

FIGURE 5. Pareto-optimal solutions after 100 iterations.



(b)HTGA

FIGURE 6. Pareto-optimal solutions after 1000 iterations.

and the number of iterations used were 100, 1000 and 5000; the crossover rate was 0.7; the mutation rate 0.2; Set the $w1$

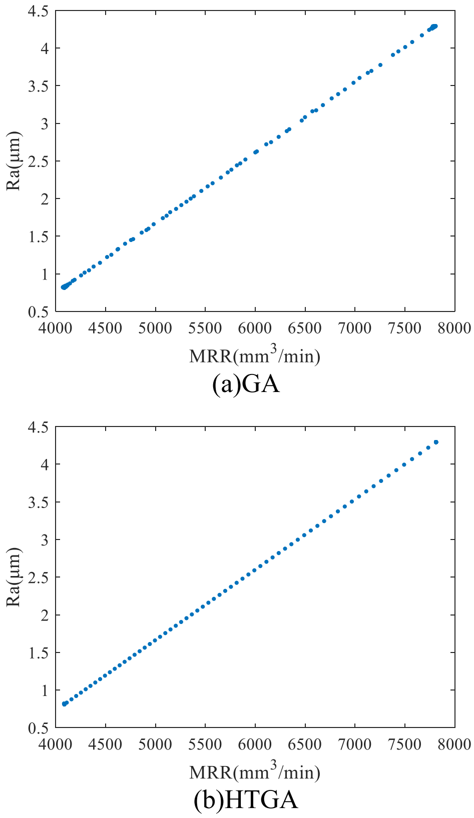


FIGURE 7. Pareto-optimal solutions after 5000 iterations.

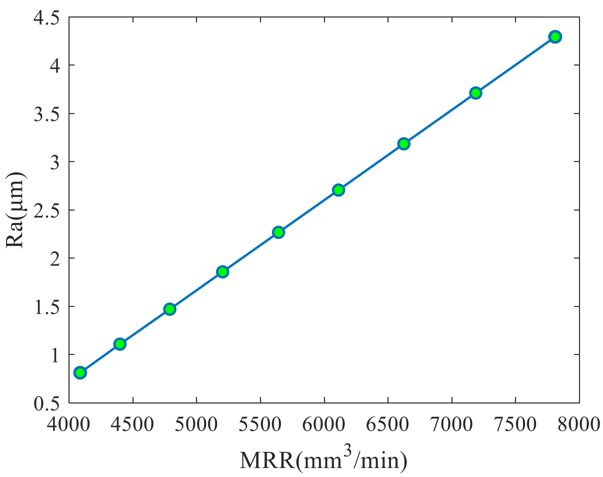


FIGURE 8. The Pareto-optimal solution for material removal rate and surface roughness.

TABLE 5. The optimal cutting parameters and Pareto-optimal solution.

Cutting parameters			Pareto-optimal solution	
Cutting depth (mm)	Cutting velocity (m/min)	Feed rate (mm/rev)	Ra (μm)	MRR (mm^3/min)
1.500	349.943	0.200	4.293	7811.022
1.500	349.973	0.200	4.293	7811.111
1.500	349.998	0.200	4.293	7810.597
1.500	349.977	0.200	4.291	7808.250
1.500	349.971	0.200	4.293	7811.222
1.500	349.992	0.200	4.293	7811.025
1.500	349.973	0.200	4.293	7811.634
1.500	349.881	0.200	4.293	7809.586
1.500	349.987	0.200	4.293	7811.308
1.500	349.989	0.200	4.294	7812.327
1.500	349.999	0.183	3.708	7185.751
1.500	349.923	0.168	3.186	6625.677
1.499	349.985	0.154	2.706	6111.292
1.500	349.973	0.142	2.267	5642.158
1.500	349.992	0.130	1.855	5202.532
1.500	349.998	0.119	1.471	4792.434
1.500	349.947	0.108	1.103	4397.909
1.500	349.983	0.100	0.811	4086.301
1.500	349.997	0.100	0.813	4087.452
1.500	350.000	0.100	0.812	4085.814
1.500	349.998	0.100	0.813	4087.437
1.500	349.971	0.100	0.811	4086.033
1.500	349.990	0.100	0.811	4086.892
1.500	349.957	0.100	0.812	4086.365
1.500	349.955	0.100	0.812	4084.940
1.500	349.943	0.200	4.293	7811.022
1.500	349.973	0.200	4.293	7811.111
1.500	349.998	0.200	4.293	7810.597
1.500	349.977	0.200	4.291	7808.250
1.500	349.971	0.200	4.293	7811.222
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1.500	349.987	0.200	4.293	7811.308
1.500	349.989	0.200	4.294	7812.327
1.500	349.999	0.183	3.708	7185.751
1.500	349.923	0.168	3.186	6625.677

weights of formula (7), the range of weighted adjustment was from 0.01 to the end of each iteration by increasing the value of 0.005 to 0.99 to the end. Each of the optimal parameter values of the weighted output were substituted into formula (17) and (18), to obtain the Pareto-optimal solution, as shown in Figure 5, Figure 6, and Figure 7.

Figure 5 shows that, after 100 iterations, the division of Pareto-optimal solutions for GA is rather messy while the division of Pareto-optimal solutions for HTGA has started to become completely stable. Figure 6 shows that, after 1000 iterations, the division of Pareto-optimal solutions for GA starts to become stable, while the division of Pareto-optimal solutions for HTGA is apparently completely stable. From Figure 7, it shows that after 5000 iterations, the Pareto-optimal solutions of GA and HTGA are clearly the same, but we can see that the Pareto-optimal solutions of HTGA are almost the same as those of 1000 iterations, which means that HTGA has completely converged at 1000 iterations, so we can know that HTGA has a faster convergence speed and better robustness when it is used for multi-objective optimization. It is clear the convergence speed of HTGA is faster and far more robust for multi-objective optimization.

TABLE 6. HTGA parametric actual processing and L9 experiment conform the quality of tolerance.

Results of the experiment	Work piece quality	
	Ra(μm)	MRR(mm^3/min)
HTGA	3.186	6625.677
Actual processing	2.615	6534.073
L9 Direct table experiment 2	1.935	1637.121
L9 Direct table experiment 4	1.990	2900.089
L9 Direct table experiment 9	2.502	5971.389

D. THE MULTI-OBJECTIVE OPTIMIZATION OF THE HYBRID TAGUCHI-GENETIC ALGORITHM

It is clear that HTGA provides superior multi-objective searches and in this section HTGA was used exclusively for this purpose. The parameters used were population size 60; iterations: 1000; crossover rate: 0.7; mutation rate: 0.2; Set the $w1$ weights of formula (7), the range of weighted adjustment was from 0.01 to the end of each iteration by increasing values of 0.04 to 0.99 to the end. Each of the optimal parameter values of the weighted output were substituted in formulas (17) and (18), to obtain the Pareto-optimal solution shown in Figure 8.

The corresponding processing parameters, surface roughness and material removal rate of all Pareto-optimal solutions obtained using HTGA objective optimization are shown in Table 5.

The experiments carried out in this study were based on the international standard ISO4287-1997 for surface roughness and Ra 1.6μm to 3.2μm were used as the tolerance range for workpiece quality [39]. The Ra value in Table 5 that was closest to the value of 3.2μm was selected to carry out the turning experiments, the processing parameters were: cutting depth 1.5 (mm); cutting velocity 349.923 (m/min); feed rate 0.168 (mm/rev), the quality of the workpiece: Ra 3.186μm; MRR 662.5677 (mm^3/min). The quality of the workpiece obtained after the processing was as shown in IV.

The enhancement of MRR is a clear demonstration of an improvement in processing efficiency. The experimental data shown in the L9 orthogonal table shows that working efficiency was higher using the processing parameters obtained from multi-objective optimization with HTGA.

IV. CONCLUSION

This study used workpiece surface roughness and material removal rate to model multi-objective optimization. The experiment is based on the Pareto-optimal solution obtained from the multi-objective optimization of weighted combinatorial method with HTGA, and the best process parameters for the specified accuracy have been found. This method can be implemented in other machine tools and with different materials. The prediction model of surface roughness and material removal rate can be found using an orthogonal table and a linear regression model. The confidence rate of the model was better that 95% and this was verified by ANOVA. For the algorithm part, after the same parameters are compared by the number of iterations of 100, 1000 and 5000, the HTGA can make the division of Pareto-optimal solution completely stabilize with only 1000 iterations as shown by the Pareto-optimal solutions, so the use of HTGA can get better convergence and robustness. Finally, the processing parameters of Pareto-optimal solution were selected according to the surface roughness range of tolerance for the turning experiment, and the quality of the measured workpieces was compared with that of the L9 orthogonal table experiment, and a better material removal rate was obtained by the multi-objective optimization of HTGA. Therefore a global search of the cutting parameters of a lathe based on the HTGA multi-objective optimization method can be used to obtain the best possible process parameters.

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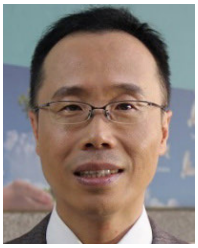

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