MODELING AND OPTIMIZING SURFACE ROUGHNESS IN TURNING 40X STEEL BASED ON GENETIC PROGRAMMING AND GREY WOLF OPTIMIZATION ALGORITHMS

Duong Xuan Bien[1,*], Do Manh Tung[2], Nguyen Van Nam[1], Le Van Tan[3], Do Tien Lap[1], Ta Huu Vinh[1], Le Thanh Binh[1]

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ABSTRACT

This paper presents the results of establishing a predictive model and optimizing the surface roughness (SR) value when turning 40X steel using genetic programming (GP) algorithm and grey wolf optimization (GWO) algorithm. The regression equation is built by GP algorithm on the basis of 63 practical experiments with cutting parameters including rotary tool tilt angle, depth of cut, feedrate and cutting speed. The GWO algorithm is used to find the most suitable cutting parameters corresponding to the minimum SR value. Furthermore, the influence of these parameters on the SR value is also considered. The research results allow to evaluate the effectiveness of the algorithms used as well as the basis for improving the surface quality in dry turning with selt-driven rotary tool in some specific application cases.

Keywords: *Self-rotary turning tool, regression model, surface roughness, genetic programming, GWO.*

[1]Advanced Technology Center, Military Technical Academy, Vietnam
[2]Faculty of Mechanical Engineering, Military Technical Academy, Vietnam
[3]Faculty of Engineering, Dong Nai University, Vietnam
[*]Email: duongxuanbien@lqdtu.edu.vn
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1. INTRODUCTION

The self-driven rotary tool hard turning method is one of the cutting machining methods that has been developed for a long time ago [1]. The self-driven rotary cutting tool is widely used in machining hard materials and can replace grinding and polishing operations. The self-rotating nature of the insert tool as well as its shape has a good response to surface quality based on reducing cutting heat and increasing tool life [2].

Surface roughness is always a factor of leading research interest in machining because of its importance. There has been a lot of research on this issue with different prediction models including Response Surface Methodology (RSM) [3], Intelligent algorithm application methods such as artificial neural network (ANN) [4], Fuzzy and Adaptive Neuro Fuzzy Inference System (ANFIS) [5], Multi-regression analysis (MRA) [6], GP [7-14]. The model for predicting R_a value using the GREY system theory is described in [3] in end-milling operation with 20 experiments and 3 input cutting parameters. The online modeling technique integrated into the system greatly reduces the setup time of the R_a value prediction system.

Recently, the GP method is also utilized and developed to establish regression model. GP is a method quite different from other methods in constructing nonlinear regression model. There are numerous studies that have applied GP technique in surveying and creating nonlinear regression model such as in [7-14]. The predicted result in [7] is 15% different from the measured data. The feedrate has the greatest effect on the R_a value. In [8], tool wear was studied in turning Ti-6Al-4V materials through MRA and GP prediction models. GP is more effective than MRA. The GP model in [9] is applied to predict the R_a value with an accuracy of 91%. Furthermore, GP is proved to be the most effective and reliable method in [10]. With the Pareto fronts defined, the improved GP model in [11] shows superiority over other methods such as genetic algorithm (GA) or ANN in building the model robust enough to compensate for the uncertainty in the 43 experiments dataset. The GP-M5 hybrid model is proposed [12] in order to model the rapid prototyping process by fused deposition modeling. This model is compared with SVM and ANFIS methods. Research results confirm that the GP-M5 hybrid method has a higher degree of compatibility. Extended GP in [13] is proven to be more efficient than traditional GP and ANN. In [14], cutting parameters influence on geometric structure of materials after heat treatment are studied in laser processing on industrial robots. Prediction accuracy by GP model reached 98.59%.

This paper presents the establishing results of a model to predict and optimize the R_a value in dry turning 40X steel with a turning self-driven rotating tool. The GP method is used to build the prediction model with specific quality evaluation criteria including R^2, RMSE and MAPE. The optimal results of R_a value with the corresponding set of cutting parameters are found based on the GWO algorithm.

Accordingly, the influence of pairs of cutting parameters on R_a value is also considered and described in detail.

2. RESEARCH CONTENTS

2.1. Experiment setup

The experimental model for rotary tool hard turning is presented with 64 experiments (Ex). These were designed to fully satisfy 4 inputs including tool axis tilt angle θ (deg), depth of cut a_p (mm), feed rate f_r (mm/rev) and cutting speed v_c (m/min). The workpiece material 40X-GOST4543 steel with achieve hardness. An EMCOTURN E45 lathe and an INGERSOLL RHHW1605MOTN rotary cutter were used to perform experiments. The ingredients and mechanical properties off 40X steel after heat treatment are shown in Table 1.

Table 1. Material ingredients of 40X steel after heat treatment

Chemical composition (%)	Mechanical properties
(0.36 ÷ 0.44)%C; (0.5 ÷ 0.8)%Mn; 0.035%P; 0.035%S; (0.17 ÷ 0.37)%Si; (0.8 ÷ 1.1)%Cr; %Ni ≤ 0.3	Yield strength:293 MPa; Tensile strength: 572MPa; Ductility: 28.6%; Hardness: (43 ÷ 46)HRC

The machine system with the workpiece and rotary cutting tool is shown in Fig. 1. The roughness measuring device is a HUATEC-SRT6200 tester.

Fig. 1. Machining system and workpieces

Limits of cutting parameters are divided 3 levels as shown in Table 2.

Table 2. Levels and value ranges of cutting parameters

Symbols	Parameters	Levels		
		Level 1 (-1)	Level 2 (0)	Level 3 (1)
x_1	θ (deg)	15	25	35
x_2	a_p (mm)	0.2	0.4	0.6
x_3	f_r (mm/rev)	0.1	0.3	0.5
x_4	v_c (m/min)	100	150	200

Criteria R^2 [14], MSE [15] and MAPE [7] are used to evaluate the model. The dataset of 63 experiments measured in practice and predicted from the GP algorithm is shown in the appendix.

2.2. GP and GWO algorithms

2.2.1. GP algorithm

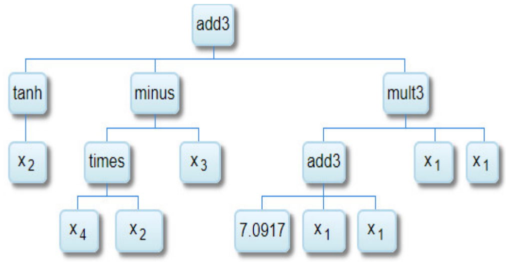


Fig. 2. Tree structure of a model gene

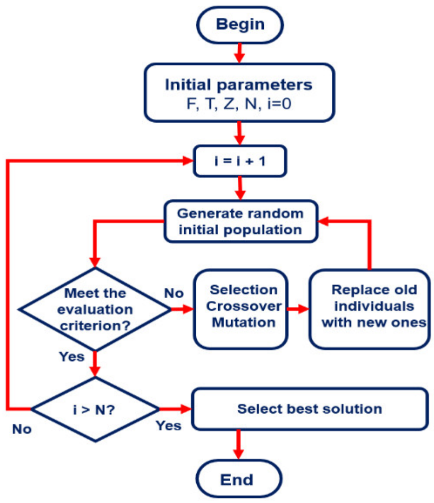


Fig. 3. Algorithm implementation steps in GP

Basically, GP is an AI-ML platform and can be considered as a genetic programming technique with polygenic individuals to establish nonlinear regression model [10]. The final nonlinear regression model is the evolutionary set of polygenic models. These models can be developed to be simple or complex depending on the weights of the genes. These weights are obtained from the calculation of the least squares in evolution. The reliability of the predicted model is also evaluated based on the training and test dataset in reality compared with the predicted data from the GP model. Fig. 2 depicts a tree structure illustrating a gene in the general model of GP method. Fig. 3 describes the steps to implement the GP algorithm. In which, $\mathbf{F}=\{+,-,*,/,\text{mult3},\text{add3},...\}$ is the set of functional genes, $\mathbf{T}=\{x_1,x_2,x_3,x_4\}$ is the set of terminal genes, and **Z** is the set of arguments corresponding to the set of **F** and N is the number of generations.

2.2.2. GWO algorithm

The Grey Wolf Optimizer algorithm was first introduced in 2014 by S. Mirjalili [16]. This algorithm is implemented based on mimicking the leadership hierarchy and hunting mechanism of gray wolves in the wild. Four grey wolf positions arranged in the order α, β, δ and ω were used to simulate the very tight leadership hierarchy in the wolf pack. Individual wolf α is considered to be the leader of the pack and dominates the pack. The members of the pack must obey its orders. Individual wolf β is the subordinate wolf, helps α in decision making and is considered the best candidate to become α. The individual wolf δ is a wolf subject to α and β, but they dominate ω. Wolf individual ω is the lowest ranked individual or considered the least important individual in the pack and it is only allowed to eat last. Accordingly, three main steps are implemented to perform the optimization algorithm: search, surround and attack the prey.

Stage 1. Encircling the prey

To mathematically model the prey encirclement behavior of wolves, the following equations are proposed as

$$\vec{\mathbf{D}} = \left|\vec{\mathbf{C}}.\vec{\mathbf{X}}_p(t) - \vec{\mathbf{X}}(t)\right|;\ \vec{\mathbf{X}}(t+1) = \vec{\mathbf{X}}_p(t) - \vec{\mathbf{A}}.\vec{\mathbf{D}} \quad (1)$$

In which, $\vec{\mathbf{D}}$ is the distance vector between the prey and any wolf. The t value represents the current iteration. $\vec{\mathbf{A}}$ and $\vec{\mathbf{C}}$ are the coefficient vectors. The $\vec{\mathbf{X}}_p$ is the position vector of the prey. The $\vec{\mathbf{X}}$ is the position vector of any gray wolf in the pack. The values of the coefficients $\vec{A}$ and $\vec{\mathbf{C}}$ are calculated as follows

$$\vec{\mathbf{A}} = 2\vec{\mathbf{a}}.\vec{\mathbf{r}}_1 - \vec{\mathbf{a}};\ \vec{\mathbf{C}} = 2\vec{\mathbf{r}}_2 \quad (2)$$

In which, $\vec{\mathbf{a}}$ is the hunting velocity. The hunting process is repeated continuously, so this value is reduced linearly from 2 to 0. The random coefficient vectors $\vec{\mathbf{r}}_1$ and $\vec{\mathbf{r}}_2$ take values in the range [0, 1].

Stage 2. Moving and approaching prey

Grey wolves have the ability to recognize the location of their prey and surround them. The hunt is usually guided by wolves α, β, and δ. In the search space, the prey position is not the optimal position. According to the simulation of hunting behavior of grey wolves, the positions of wolves α, β, and δ are the best solutions, respectively, because they have the best skills to always find potential locations best to approach prey. Accordingly, the positions of three individuals α, β, and δ will always be updated and saved until the end of the loop of the hunting process. The wolves in the pack (including wolf ω) are required to update their position according to the position of the leader wolf. The location update is described as follows:

$$\begin{aligned}
&\vec{D_\alpha} = \left|\vec{C}_1.\vec{X_\alpha} - \vec{X}\right|;\ \vec{D_\beta} = \left|\vec{C}_2.\vec{X_\beta} - \vec{X}\right|;\\
&\vec{D_\delta} = \left|\vec{C}_3.\vec{X_\delta} - \vec{X}\right|;\ \vec{X}_1 = \vec{X_\alpha} - \vec{A}_1.\vec{D_\alpha};\\
&\vec{X}_2 = \vec{X_\beta} - \vec{A}_2.\vec{D_\beta};\ \vec{X}_3 = \vec{X_\delta} - \vec{A}_3.\vec{D_\delta};\\
&\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}
\end{aligned} \quad (3)$$

In which, $\vec{\mathbf{D}}_\alpha, \vec{\mathbf{D}}_\beta$ and $\vec{\mathbf{D}}_\delta$ are the distance from wolves α, β, and δ to the prey. Their position is respectively $\vec{\mathbf{X}}_1, \vec{\mathbf{X}}_2$ and $\vec{\mathbf{X}}_3$. The positions of the prey for each leader wolf are $\vec{\mathbf{X}}_\alpha, \vec{\mathbf{X}}_\beta$ and $\vec{\mathbf{X}}_\delta$.

Stage 3. Attacking the prey

Grey wolves end their hunt by attacking their prey when it stops moving. For mathematical modeling of prey approach, the value of vector $\vec{a}$ is decremented. This means that the distance between the wolves and the prey decreases. Note that the amplitude of the oscillation value of $\vec{\mathbf{A}}$ also decreases with $\vec{\mathbf{a}}$. In other words, $\vec{\mathbf{A}}$ is a random value in the interval [-2a; 2a]. In which, the value of $\vec{a}$ decreases from 2 to 0 during the iteration. When the random values of $\vec{\mathbf{A}}$ are in [-1; 1] then the wolf's next position can be anywhere between its current position and the position of the prey.

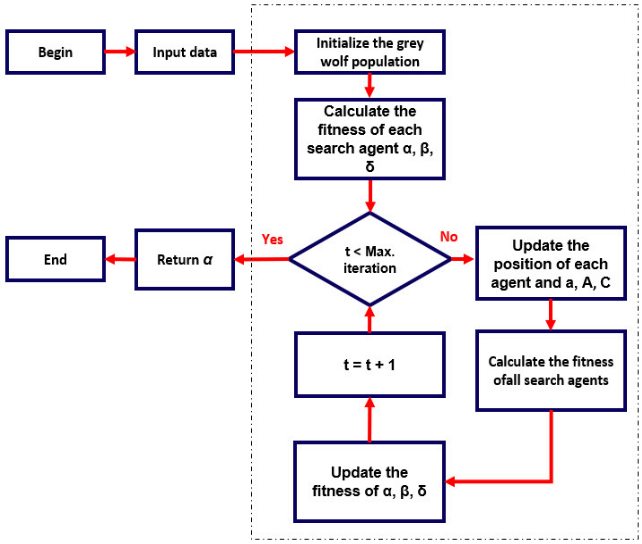


Fig. 4. GWO algorithm diagram

In general, the process of finding the optimal solution in the GWO begins with the generation of a random population of gray wolves. Each wolf is a solution in the optimization algorithm. During iterative foraging and hunting, wolves α, β, and δ estimate where prey can move to. Each wolf in the pack updates their distance from their prey based on the estimates of the pack leaders. The GWO algorithm terminates when a final criterion is satisfied (about the loop limit or the optimal distance needed by wolves α, β, and δ to attack the prey). The schematic diagram of the algorithm is shown in Fig. 4.

2.3. Predictive model and optimal value

The key parameters in the GP algorithm described above include Population size: 350; Max. Generations: 200; Input variables: 04; Tournament size: 30; Maximum genes: 20; Maximum tree depth: 20; Crossover probability: 0.84; Mutation probability: 0.14; Training data set: 90%; Test data set: 10%; Function set: Times, minus, plus, tanh, mult3, add3.

The regression equation set up based on the GP algorithm is shown as follows

$$\begin{aligned} R_a = &-8.73 + 0.735x_1 + 6.15x_2 + 9.2x_3 + 0.0209x_4 \\ &+ 0.874\tanh(x_2x_4^2) - 0.44x_1x_2 - 0.00129x_1x_4 \\ &+ 0.00764x_1^2x_2 + 0.012x_1^2x_3 + 2.64\times10^{-5}x_1^2x_4 \\ &- 3.3\times10^{-5}x_2x_4^2 - 0.00247x_3^2x_4 - 0.734x_1\tanh(x_3) \\ &- 0.0135x_1^2 + 0.0629x_1x_2x_3 - 1.97\times10^{-4}x_1x_3x_4 \end{aligned} \quad (4)$$

The results of the regression model evaluation criteria with 54 Ex during training and 9 Ex testing are described in Table 3.

Table 3. Results of regression model evaluation

Criteria	54 Ex			9 Ex		
	R^2	MSE	MAPE (%)	R^2	MSE	MAPE (%)
Values	0.997	0.014	4.75	0.98	0.082	11.94

The predicted results in 54 Ex and verify in 9 EEx of GP are depicted in Fig. 5 and Fig. 6.

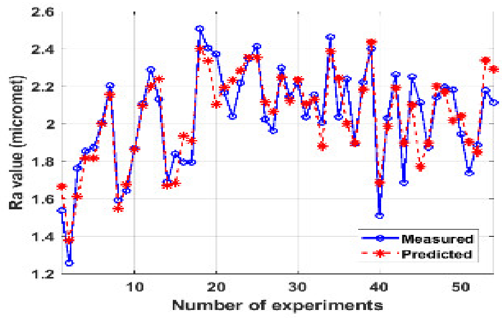


Fig. 5. R_a values in 54 Ex

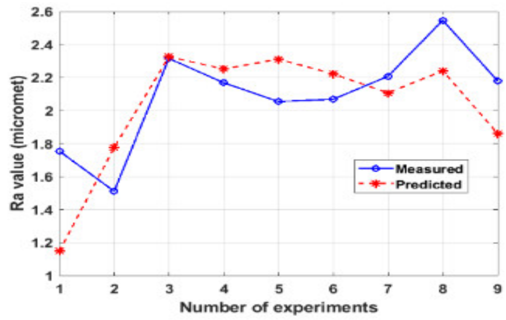


Fig 6. R_a values in 9 Ex

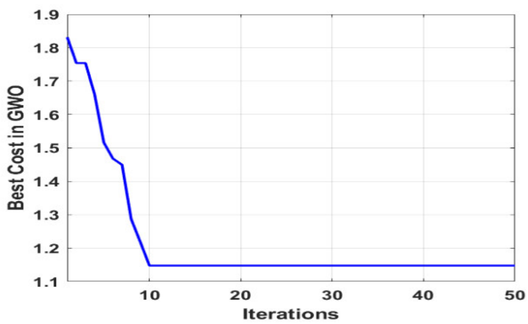
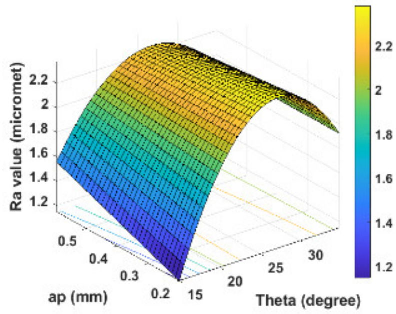


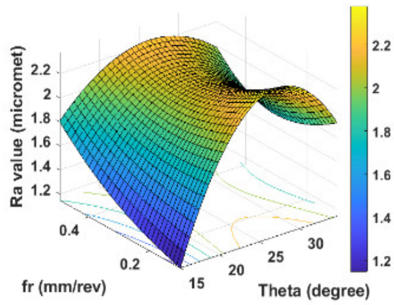
Fig 7. Fitness function value

Based on the regression equation (4) built from the GP algorithm, the optimal R_a value and the corresponding cutting parameters are determined according to the GWO algorithm. The main parameters used in GWO include: Number of search agents: 10; Maximum interations: 50; $\mathbf{r_1}$, $\mathbf{r_2}$ get random values in the interval [0,1]; the value of **a** decreases from 2 to 0; Lower limit: [15; 0.2; 0.1; 100]; Upper limit: [35; 0.6; 0.5; 200]. The results of the fitness function calculation are shown in Fig. 5. The Fig. 7 depicts the optimal results of the Ra value. The optimal value achieved is 1.147µm. The cutting parameters corresponding to the optimal value are θ = 15 (deg), a_p = 0.2 (mm), f_r = 0.1 (mm/rev), v_c = 100 (m/min).



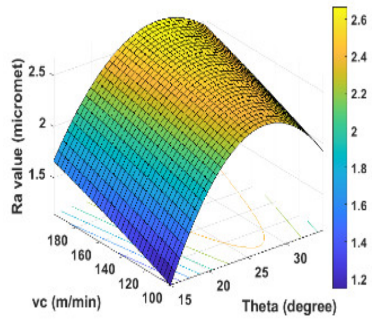
$f_r = 0.1;\ v_c = 100$

Fig. 8. Effect of θ and a_p



$a_p = 0.2;\ v_c = 100$

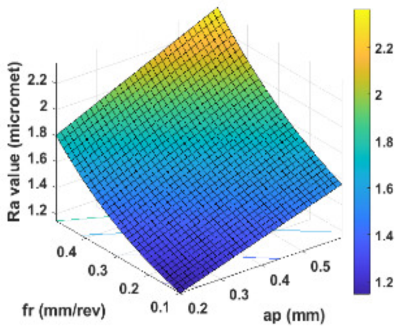
Fig. 9. Effect of θ and f_r



$a_p = 0.2,\ f_r = 0.1$

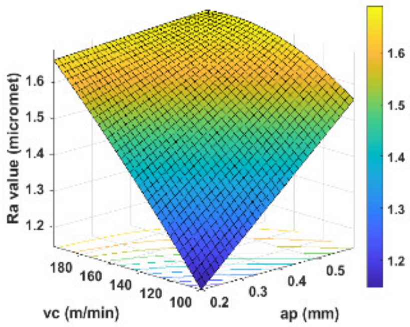
Fig. 10. Effect of θ and v_c

Fig. 8 shows the influence of the parameters pair (θ and ap) on the R_a value when f_r = 0.1 (mm/rev) and v_c = 100 (m/min) are fixed. Accordingly, the angle of inclination of the cutting tool affects the R_a value more than the depth of cut parameter. The larger the angle of inclination, the lower the surface quality is. The R_a value does not increase as the cutting depth increases. The influence of the parameter pair (θ and f_r) is depicted in Fig. 9.



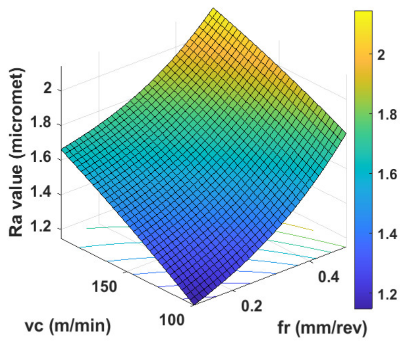
$\theta = 15^0$, $v_c = 100$

Fig. 11. Effect of a_p and f_r



$\theta = 15^0$, $f_r = 0.1$

Fig. 12. Effect of a_p and v_c



$\theta = 15^0$, $a_p = 0.2$

Fig. 13. Effect of f_r and v_c

Similarly, the angle of inclination θ affects the R_a value higher than that of the feedrate parameter. The effect of the parameters pair (θ and v_c) is also not significantly different (Fig. 10). However, when fixing the angle θ = 15^0, the influence of the parameter pairs (a_p; f_r) in Fig. 11, (a_p; v_c) in Fig. 12 and (v_c; f_r) in Fig. 13 are shown more clearly. The f_r parameter affects R_a value more than a_p parameter (Fig. 11) and v_c parameter (Fig. 13). The R_a value increases sharply when simultaneously increasing the cutting speed and depth of cut (Fig. 12).

3. CONCLUSION

In summary, the problem of modeling and optimizing the Ra value in dry turning 40X steel by self-driven rotary tool has been described and presented in detail. The GP algorithm is used to create the Ra value prediction model. The assessmented results the predictive model through the criteria show high accuracy and reliability with a large enough number of experiments in both training and verification stages. The optimization value and the corresponding set of cutting parameters are determined based on the GWO algorithm. Thereby, the influence of cutting parameters pairs is mentioned and evaluated specifically. Some results can be described as follows

- The GP algorithm gives a simple to complex predictive model based on the tuning parameters in it. However, GP allows to create a fairly general model and shows complex relationships between cutting parameters.

- The value of the tool inclination angle has the greatest influence on the Ra value of the four parameters considered.

- The feedrate value has a greater influence on the Ra value than the cutting speed and depth of cut.

- As the value of cutting speed and depth of cut increases, the surface quality decreases.

The above results have important implications in choosing reasonable cutting parameters both in terms of their priority and value when applying the machining method described in this study. Moreover, the GP and GWO algorithms show the efficiency in setting the predictive model and optimize the objective function also show them to be a good choice in similar studies.

APPENDIX

Table A1. Measurement and predicted results of R_a value with 54 Ex

No	Cutting Parameters				Actual	Predicted
	θ	a_p	f_r	v_c	R_a value	R_a value
1	15	0.2	0.1	200	1.536	1.667
2	15	0.2	0.3	100	1.258	1.377
3	15	0.2	0.3	150	1.764	1.613
4	15	0.2	0.3	200	1.854	1.817
5	15	0.2	0.5	100	1.875	1.815
6	15	0.2	0.5	150	2.007	2.002
7	15	0.2	0.5	200	2.204	2.157
8	15	0.4	0.1	150	1.593	1.548
9	15	0.4	0.1	200	1.644	1.675
10	15	0.4	0.3	200	1.868	1.863
11	15	0.4	0.5	100	2.107	2.097
12	15	0.4	0.5	150	2.290	2.202
13	15	0.4	0.5	200	2.132	2.241
14	15	0.6	0.1	150	1.689	1.672
15	15	0.6	0.1	200	1.839	1.684
16	15	0.6	0.3	150	1.797	1.937
17	15	0.6	0.3	200	1.795	1.910
18	15	0.6	0.5	150	2.507	2.402
19	25	0.2	0.1	100	2.403	2.336

20	25	0.2	0.3	100	2.372	2.104
21	25	0.2	0.3	150	2.167	2.194
22	25	0.2	0.5	100	2.039	2.235
23	25	0.4	0.1	100	2.218	2.287
24	25	0.4	0.1	150	2.349	2.353
25	25	0.4	0.1	200	2.414	2.354
26	25	0.4	0.3	100	2.025	2.118
27	25	0.4	0.3	200	1.964	2.067
28	25	0.4	0.5	150	2.300	2.250
29	25	0.4	0.5	200	2.146	2.122
30	25	0.6	0.1	100	2.214	2.237
31	25	0.6	0.1	200	2.036	2.107
32	25	0.6	0.3	100	2.155	2.131
33	25	0.6	0.3	200	2.007	1.882
34	25	0.6	0.5	100	2.464	2.387
35	25	0.6	0.5	150	2.036	2.243
36	25	0.6	0.5	200	2.240	2.000
37	35	0.2	0.1	100	1.897	1.898
38	35	0.2	0.1	150	2.222	2.185
39	35	0.2	0.1	200	2.400	2.438
40	35	0.2	0.3	100	1.511	1.685
41	35	0.2	0.5	100	2.032	1.988
42	35	0.2	0.5	200	2.263	2.193
43	35	0.4	0.1	100	1.686	1.898
44	35	0.4	0.1	150	2.250	2.102
45	35	0.4	0.3	100	2.114	1.773
46	35	0.4	0.3	150	1.875	1.898
47	35	0.4	0.5	150	2.143	2.200
48	35	0.4	0.5	200	2.197	2.171
49	35	0.6	0.1	150	2.182	2.019
50	35	0.6	0.1	200	1.947	2.042
51	35	0.6	0.3	150	1.736	1.904
52	35	0.6	0.3	200	1.886	1.847
53	35	0.6	0.5	100	2.179	2.340
54	35	0.6	0.5	150	2.114	2.294

Table A2. Measurement and prediction results of R_a value with 9 Ex

No	Cutting Parameters				Actual R_a value	Predicted R_a value
	θ	a_p	f_r	v_c		
1	15	0.2	0.1	100	1.754	1.148
2	15	0.4	0.3	150	1.511	1.775
3	15	0.6	0.5	200	2.315	2.325
4	25	0.2	0.3	200	2.168	2.251
5	25	0.4	0.5	100	2.054	2.311
6	25	0.6	0.1	150	2.068	2.221
7	35	0.2	0.5	150	2.207	2.107
8	35	0.4	0.1	200	2.546	2.240
9	35	0.6	0.3	100	2.180	1.861

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