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PREDICTING OF TOOL PATH EFFECT ON ROUGHNESS OF A MACHINED SURFACE USING ANN AND RSM

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Abstract- The surface roughness of a machined part is a very strong criterion for achieving good accuracy of functional surfaces in mechanical parts. It also indicates the quality of a machining process. The surface roughness is affected by many factors such as the workpiece material, feed rate, nose radius of tool, cutting speed, spindle speed, tool wear, and others, including non-controllable factors. Therefore, it is extremely difficult to model the roughness of a surface mathematically according to all these factors. In this paper, the R_a model is based on the following parameters: cutting speed V_c, axial depth a_p of cut, feed advanced speed or rate f and tool trajectory mode, to observe the tool path influence on surface roughness, the artificial neuro-network tool is used, then compare the obtained results with those of artificial neural network and those obtained by statistical methods, especially the surface response methodology. The first step to build an artificial neural network model is collecting training data. Several experiments have been carried out using the Taguchi DOE to decrease the number of tests or experiments. Four parameters (cutting speed, feed rate, spindle speed, and tool path mode) as the learning input were selected. The neural network targets the surface roughness Ra, the cutting time and the material removal rate MRR. In this study aims to predict the roughness of a machined surface and the effect of the tool path strategy without using roughness control tools. This paper also shows the accuracy of artificial intelligence models compared to the statistical model in a prediction type. Finally, an optimization is performed by using a Geometric Algorithm to derive the optimum cutting conditions for a minimal roughening of the surface.

Keywords: End Milling, Surface Roughness, Artificial Neural Network, Tool Trajectory, Cutting Parameters, Genetic Algorithm.

1. INTRODUCTION

Obtaining a mechanical part by material removal is one of the most widely used processes in several domains. In this machining process, to make good quality parts with a minimum cost. Therefore, modelling a cutting phenomenon is the key to understanding and estimating the appropriate cutting conditions. Among the modelling investigations that have been done, cutting forces modelling [1-3], temperature [2], stress [4], [5], chip formation [6], vibration [7], [8], tool wear [9], cutting power [10], and others.

The smoothness of a manufactured surface, which characterizes the workpiece quality is among the modelled cutting performance. To this end, several approaches to model surface roughness have been published in different scientific papers. These methods can be grouped in mathematical, statistical and machine learning techniques. Some researchers have used some statistical techniques [3], [11-13], or mathematical models, others used artificial intelligent techniques [8], [14-17], in which they have opted for different cutting parameters as neuron network inputs such as cutting speed (V_c) [18], feed rate (f), nose radius of tool (r), axial pass depth (D_a) and radial pass depth (D_r) or spindle speed (N), feed rate, and other cutting parameters.

The objective of the study is to apply the ANN and compare it with the statistical method. Also, to observe the tool path effect on the roughness of a machined surface. For this, steps are followed:
- Collection of the learning data;
- Achievements of the ANN models;
- Run simulation modellings;
- Selection of a good ANN;
- Prediction surface roughness machined by ANN and RSM;
- Comparison ANN, RSM, and experiment results;
- Estimation of the effect of the tool path on roughness.

The number of experiments realized is 27 experiments determined by the Taguchi design of experiments [19]. The data collected during experiments will be used to form a neural network to model the roughness according to input parameters (a_p, f, V_c and TP).

2. EXPERIMENTAL DETAILS

Taking the parameters; V_c, f, TP trajectory (see Figure 1). With three different levels, 81 experiments were required for the four independent factors [20]. By using the Taguchi design of experiments, the number of tests is limited to 27 instead of 81. The CNC milling machine with a quality control system was used for that purpose on the Al 2024 material. The machining parameters used, as well as their chosen levels, are presented in Table 1.

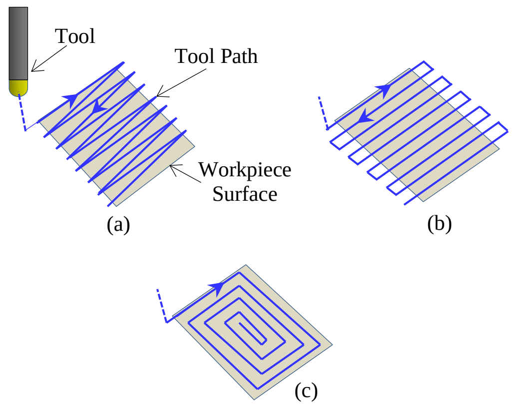

Figure 1. Tool path: (a) Zig, (b) ZigZag, (c) Contour

Table 1. Machining settings and levels

factors	Levels		
V_c	30	50	70
f	0.02	0.04	0.06
a_p	0.20	0.40	0.60
Tool trajectory (*TP*)	Zig	Zig-Zag	Contour

3. PREDICTING THE SURFACE ROUGHNESS

3.1. Artificial Neural Network (ANN)

The artificial intelligence techniques used in the field of mechanical parts manufacturing can be classified as follows;

• Clustering is a technique used to classify cutting parameters according to machining quality [21], [22];

• The prediction utilities use the artificial neural network to predict for example, the tool life, surface smoothness, and effect of parameters on the machining forces, it is also used to solve differential equations faced in machining or other domains;

• The neuro-Fuzzy tool is used to estimate the cutting performance in real time and monitor the machining process. [23].

The artificial neural network is one of the methods that enable a computer to simulate the behavior of neurons in the human brain by using training data of input and output variables. In the process of learning, the model structure is automatically adapted to the data and the final model can be used for making predictions. The basic process of training a neural network can be described as follows.

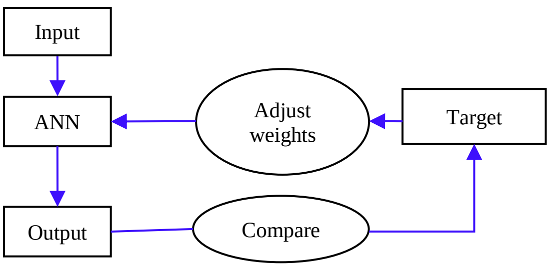

Figure 2. Steps to form an ANN

- Apply the input learning data to the ANN and calculate the value of the output;
- Compare the output value with the target and determine the error between the two;
- Determine the differences and signs of the weights to modify each weight to reduce the error;
- Determine the values of the new weights;
- Apply a weight correction;
- Repeat the preceding steps with all training data.

The structure of the model based on ANN is illustrated in Figure 3. There are four neurons in the input layer that are the four cutting parameters (V_c, f, a_p, *TP*). Three neurons in the output layer (R_a, *MRR* material removal rate, *CT* cutting time), and the hidden layers *HL* with n_N number of neurons in each one of them.

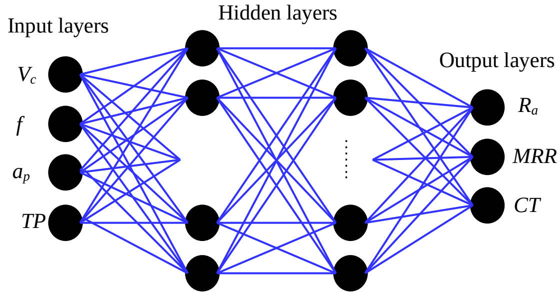

Figure 3. The structure of the model based on ANN

3.2. ANN Model of Surface Roughness *Ra*

Ranking [24] and normalization [25] of the training data are performed to facilitate the convergence of a cost function to the global minimum, compared to random and un-normalized data. The MATLAB software is used to train ANN and model the R_a using, V_c, f, a_p and *TP* as inputs and R_a, *MRR* and *CT* as targets. Some tests were performed on ANN by changing the *HL*, the n_N and the training algorithm. The error between expected roughness values and measured values is presented in Table 2.

In similar cases of ANN modelling, authors [8],[26], and others use the LM as the training algorithm, or the BR algorithm, the sigmoid as the activation function in the hidden layers, and linear in the output neurons.

Table 2. The effect of n_N and the training algorithm on ANN learning

No. ANN	[HL1 HL2]	Training algorithm	Mean error	Max error
1	[8 0]	LM	0.1100	0.0442
2	[10 0]	LM	0.0451	0.0122
3	[20 0]	LM	0.0423	0.0133
4	[8 8]	LM	0.0533	0.0237
5	[10 10]	LM	0.0312	0.0072
6	[20 20]	LM	0.0389	0.0063
7	[8 0]	BR	0.0099	0.0049
8	[10 0]	BR	0.0055	0.0012
9	[20 0]	BR	0.0127	0.0016
10	[8 8]	BR	0.0081	0.0015
11	[10 10]	BR	0.0033	0.0015
12	[20 20]	BR	0.0064	0.0015

To accurately estimate the value of surface roughness, the rate of material removal and cutting time, the ANN with two hidden layers, 10 neurons for each hidden layer [10 10] as shown in Figure 5, with a Bayesian Retrogradation Training Algorithm Regulation (BR) and a sigmoid activation function in the hidden layers, and the output layer uses a linear function, is the most adequate model as shown in Figure 4.

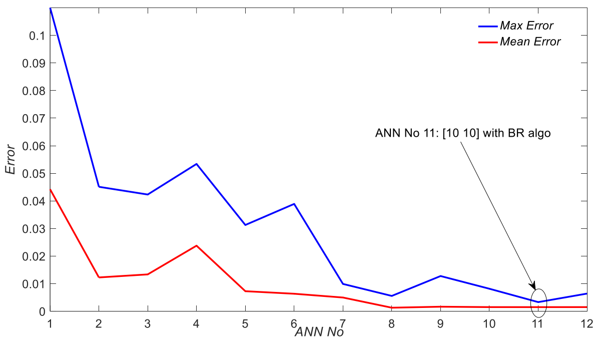

Figure 4. Error based on ANN

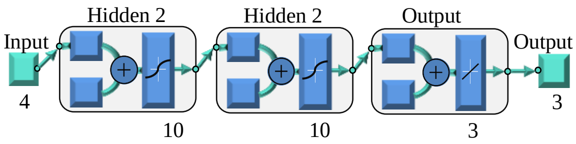

Figure 5. The neural network structure

The training correlation, validation, and testing are 1, 0.99517, and 0.95619, respectively, as Figure 6 illustrated. According to these values, it can be noted that there is a strong correlation between the output of the neural network and targets data, which makes the ANN model No. 11 more accurate than others as appeared in Figure 4.

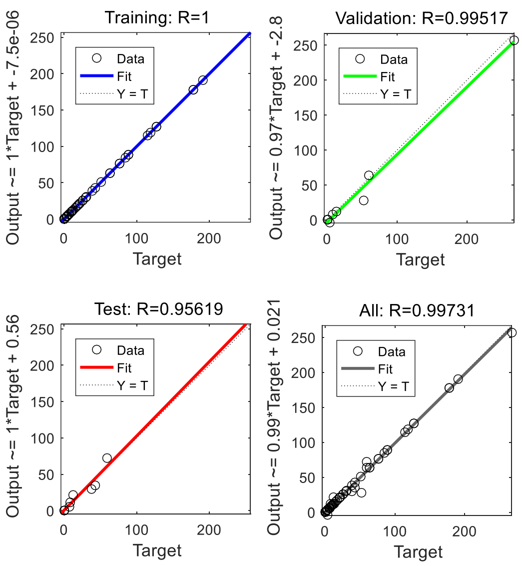

Figure 6. Correlation coefficients

3.3. The RSM

The RSM provides a solid statistical approach that can be used for modelling Figure 7, it aims to explore the relationships between the dependent and independent variables involved in an experiment. The principle of this method is to put the results of experiments which are also called responses in terms of input parameters (or stimuli variables) in a polynomial form. The method is used to link the response by a transfer function with the stimuli variables. The following articles [26], and [27] give more details on this statistical approach.

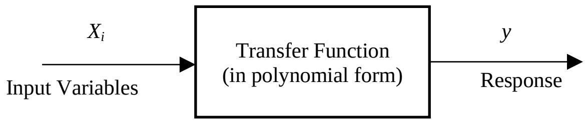

Figure 1. Polynomial transfer function

In this study, a polynomial equation of the second order is used and represented by Equation (1).

$$y = \sum_{i<1}^{k} X_i X_j b_{ij} + \sum_{i=1}^{k} X_i^2 b_{ii} + \sum_{i}^{k} X_i b_i + b_0 \tag{1}$$

where, y is the response (R_a, MRR and CT in this study), X is the input variable (V_c, f and a_p in the present work) and the coefficient of regression b. According to [20], the surface roughness model R_a is represented by Equations (2), (3) and (4) for the Zig, Zig-Zag and Contour toolpaths, respectively.

$$\begin{aligned} Ra &= 0.0694 - 0.000472V_c + 2.875f + 0.1576a_p - 11.11f^2 - \\ &- 0.0694a_p^2 - 0.00417V_c \times f - 0.000208a_p \times V_c - 1.111a_p \times f \end{aligned} \tag{2}$$

$$\begin{aligned} Ra &= 0.0793 - 0.000556V_c + 2.875f + 0.1576a_p - 11.11f^2 - \\ &- 0.0694a_p^2 - 0.00417V_c \times f - 0.000208a_p \times V_c - 1.112a_p \times f \end{aligned} \tag{3}$$

$$\begin{aligned} Ra &= 0.04670 - 0.000389V_c + 2.875f + 0.1576a_p - 11.11f^2 - \\ &- 0.0694a_p^2 - 0.00417V_c \times f - 0.000208a_p \times V_c - 1.111a_p \times f \end{aligned} \tag{4}$$

Based on the above models, surface roughness is calculated and presented in Table 3.

Table 3. R_a (μm) from RSM model for different tool path

Exp No.	Zig tool path	Exp No.	ZigZag tool path	Exp No.	Contour tool path
1	0.12034	10	0.14832	19	0.14808
2	0.17062	11	0.18860	20	0.14774
3	0.19757	12	0.19638	21	0.19650
4	0.10840	13	0.13387	22	0.13644
5	0.15618	14	0.17165	23	0.13640
6	0.18063	15	0.17942	24	0.18312
7	0.09646	16	0.11942	25	0.12480
8	0.14174	17	0.15470	26	0.12505
9	0.16369	18	0.16247	27	0.16975

4. PREDICTING THE SURFACE ROUGHNESS

4.1. The ANN and RSM Models

The results of the experiments and those predicted by the ANN and the RSM are presented in Figure 8. The values presented by ANN are very close to experimental results. the comparison between the RSM model and the ANN model is made by calculating the percentage deviation between the results of each model with the experiment's data. Figure 9 shows the percentage deviation of the models.

To determine the difference between the value of the experiments and the value derived from the models, A comparison of the measuring and predicting values of the two models (RSM and ANN) was made. It is noted that the ANN predicts surface roughness with a mean absolute deviation of 0.15%. However, the RSM model predicts it with an absolute mean deviation of 0.153%. This makes the ANN model more powerful and accurate for prediction than the RSM method.

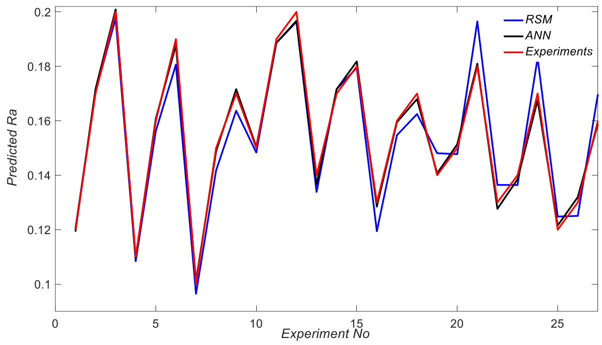

Figure 8. R_a value predicted by RSM and ANN models

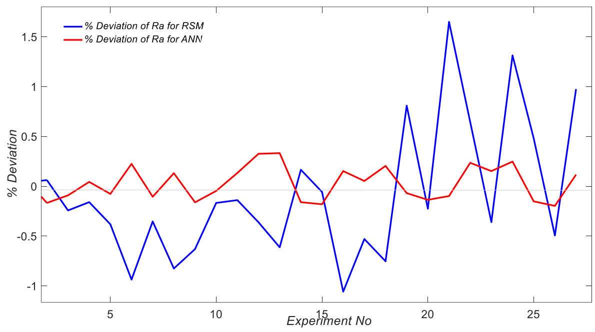

Figure 9. Difference between model results and measured R_a

4.2. Effect of Tool Trajectory on R_a

In this section, the *Ra* values are estimated using ANN by changing the cutting speed, the advance, and the trajectory of the tool, the pass depth maintained constant a_p=0.6 mm, to see the impact of each parameter on R_a, and especially the tool path.

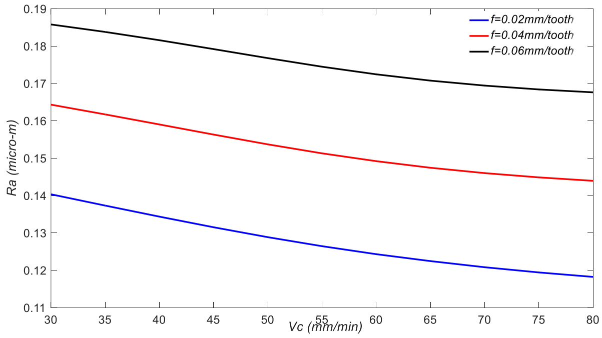

Figure 10. Effect of Contour *TP*, V_c, and *f* on R_a

The following Figures 10-12 show the cutting parameters' effect on roughness for a constant a_p. From these figures, it can be seen that the good surface condition results in a minimum value of the advance *f*, which confirms the results found by [29].

With the Zig path, it can be observed that at the highest cutting speed and the lowest feed rate, the roughness is minimal by a value R_a=0.1296 μm.

Similarly, in the case of a Zig-Zag trajectory, the surface roughness is minimal at the point (V_c=75 mm/min, *f*=0.02 mm/tooth but with a good surface condition than the Zig trajectory, the minimum value, in this case, is around of R_a=0.1292 μm. The Contour trajectory gives a minimum roughness value in the point (V_c=75 mm/min, *f*=0.02 mm/tooth) in the order of R_a=0.1194 μm with a deviation of 0.009μm from the Zig-Zag strategy, and a deviation of 0.01μm from the Zig strategy.

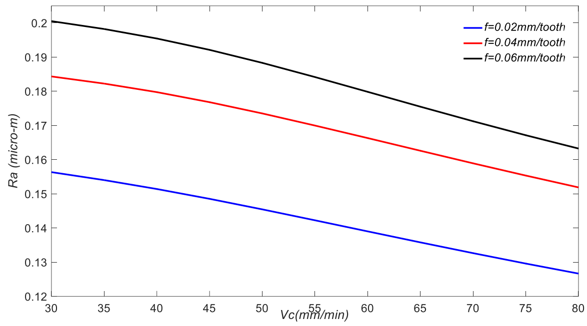

Figure 11. Effect of Zig *TP*, V_c and *f* on R_a

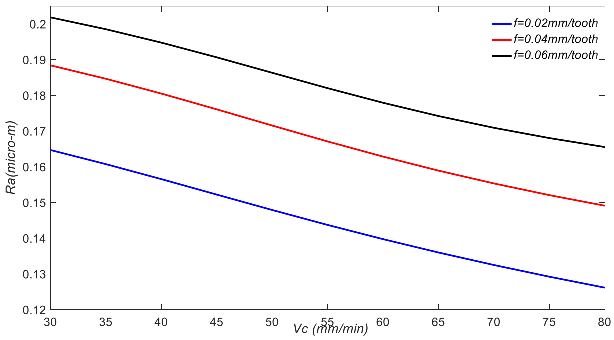

Figure 12. Effect of Zig-Zag *TP*, V_c and *f* on R_a

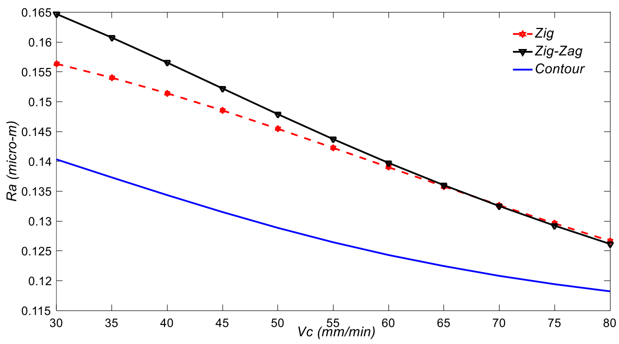

Figure 13. The roughness of the surface according to V_c and the type of trajectory

According to Figure 13, it can be observed that the condition of the surface given by the Zig trajectory is better compared to that of Zig-Zag in the margin of low-cut speeds (V_c<60 mm/min) beyond 65 mm/min the roughness state of Zig-Zag becomes lower than that given by the Zig trajectory. The Contour mode remains the best for a good surface condition at least within the margin of cutting speeds and the chosen advanced speed.

4.3. Cutting Parameters Optimization

The GA is used to optimize the cutting conditions in a way to have a good surface condition. To apply this algorithm, an objective function (R_a) is needed, and the intervals of the variables (V_c, *f*, a_p, and *TP*), *TP* is characterized by three values 1 for Zig strategy, 2 for Zig-Zag strategy, and 3 for Contour strategy. The fitness function is generated by MATLAB from a neural network, the function represented by Equation (5) is a function of the cutting parameters, the biases, and the ANN weights.

$$R_a = func(V_c, f, a_p, TP, b, w) \quad (5)$$

MATLAB optimization tool is used to minimize the Ra to obtain the best possible combination of cutting conditions. The initial parameters to solve the problem using GA are shown in Table 4.

Table 4. Initial parameters on genetic algorithm

Settings parameters	Level
Population size	50 for under 5 variables
Initialize population	Randomly
Scale function	Rank
Selector function	Tournament
Crossover	Tow point crossover
Mutation operator	Uniform mutation
Percent of cross over	P_c=0.8
Percent of mutation	P_m=0.01
Stopping criteria	400x (number of variables)

Several tests are performed to optimize the surface roughness as Table 5 presents, the maximum cutting speed, minimum feed rate, Contour strategy, and a_p=0.2315 mm give a smooth surface with a value of roughness $R_{a,\min}$=0.1123 μm.

Table 5. Optimal parameters for a R_a minimal in each run

Run No.	R_a	Cutting parameters			
		V_c	f	a_p	TP
1	0,12434	59,95210	0,02514	0,21320	3
2	0,11230	59,89850	0,02053	0,23150	3
3	0,13450	56,58710	0,03400	0,25480	3
4	0,13390	55,44757	0,03542	0,27477	3
5	0,13900	53,76507	0,03985	0,29557	3
6	0,14410	52,08257	0,04428	0,31637	3
7	0,14920	50,40007	0,04871	0,33717	3
8	0,15430	48,71757	0,05314	0,35797	3
9	0,15940	47,03507	0,05757	0,37877	3
10	0,16450	45,35257	0,06200	0,39957	3

5. CONCLUSION

The work presented in this paper consists of modelling the roughness of a machined surface by the artificial neural network and the RSM, to predict the values of R_a. The ANN is used to predict the optimal cutting parameters in order to obtain a minimum roughness value, with different cutting speeds, feed rate, and tool trajectories. The ANN is also used to assess the influence of the trajectory on the roughness of the machined surface. Optimized cutting parameters using GA to achieve minimum roughness are also employed. The results show that the ANN network with two hidden layers, a sigmoid activation function, and the LM algorithm for training can predict the surface roughness more accurately than the statistical RSM method, with an absolute mean deviation of 0.38%.

According to the results, it can be concluded that the feed rate is the most dominant factor that has a meaningful t effect on the roughness. Cutting speed and tool path have the smallest effect on the surface roughness. it can also be observed that the contouring tool path has a good effect on the surface finish at higher cutting speeds and minimum feed rate compared to other tool path strategies (Zig, Zig-Zag). The genetic algorithm is used to determine the optimum combination of cutting parameters for the most suitable surface finish (minimum surface roughness). The fitness function to be optimized is generated according to the ANN. The results of the optimization also show that the best combination is the one with maximum Cutting Velocity, minimum Feed Speed and Contour Toolpath, as illustrated in Table 5.

Expanding the margin of cutting parameters, the number of cutting parameters, and using other artificial intelligence methods such as image processing, and audio processing to predict and find optimal machining parameters with more accuracy in the different manufacturing processes, can be a part of the further work.

NOMENCLATURES

1. Acronyms

ANN Artificial Neural Network
BR Bayesian Regularization backpropagation
CNC Computer Numerical Control
DOE Design of Experiment
GA Genetic Algorithm
LM Levenberg-Marquardt Algorithm
RSM Response Surface Method

2. Symbols / Parameters

a_p: Axial depth of cut [mm]
CT: Cutting time [min]
D_a: Axial pass depth [mm]
D_r: Radial pass depth [mm]
f: Feed rate [mm/tooth]
HL: Number of Hidden Layer
MRR: Material Removal Rate [mm^3/min]
N: Spindle speed [RPM]
n_N: Number of Neurons in each Hidden Layer
r: Tool nose radius [mm]
R_a: Surface roughness [mm]
TP: Tool Path
V_b: Tool wear [mm]
V_c: Cutting speed[m/min]

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