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# OPTIMIZATION OF CUTTING PARAMETERS AND PREDICTION OF SURFACE ROUGHNESS IN TURNING OF DUPLEX STAINLESS STEEL (DSS) USING A BPNN AND GA

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**Abstract-** Among the metrological controls, the control of the roughness of a surface, this measurement activity has a cost that should not be underestimated in the parts manufacturing workshops, this cost includes the cost of the material, the cost of labor workers, in addition to the time spent for the measurement operations. In this paper, an artificial model (BBNN) is proposed to estimate the roughness of a machined surface with satisfactory accuracy according to four cutting parameters that have a major influence on the roughness of a surface, namely the cutting speed, the feed rate, the depth of cut, and tool nose radius. An optimal BPNN model was trained by adjusting its hyperparameters (i.e., learning algorithm, activation function, hidden layer number, number of neurons, etc.). The roughness function generated by the neural network is optimized with a genetic algorithm to determine the optimal cutting parameters. Then, several tests have been carried out to compare the optimized artificial neural network accuracy with other works, this comparison shows the good precision of the artificial model developed.

**Keywords:** Back-Propagation Neural Network, Optimization, Turning, Surface Roughness, Parameters, Genetic Algorithm.

## 1. INTRODUCTION

The roughness of a machined surface depends on 59 parameters [1] which makes surface roughness very difficult to model by mathematical methods, the Ishikawa diagram in Figure 1 exposes some of these parameters. For this reason, artificial intelligence comes into play to simplify these types of problems. Artificial intelligence tools are applied in serval domains such as medical [2], renewable energy [3, 4], image processing [5], and other fields.

Machining is also a domain where IA is applied to model specific cutting parameters such as cutting forces [6, 7], cutting power [8], the temperature in the cutting zone [9], tool or workpiece vibrations [10, 11], tool wear [10-12], the roughness of a machined surface [6], [12-14], and others. All these studies converge on the optimization of cutting parameters to predict them with good accuracy.

The artificial intelligence techniques used in manufacturing can be cited as follows;

- The classification techniques are used to classify the cutting parameters [15, 16],
- The prediction tools used the artificial neural network to predict for example tool wear, the surface roughness, the impact of parameters on cutting forces, this tool is also used to solve differential equations encountered in the field of machining or another field [17],
- Neuro-Fuzzy tool is used to predict cutting parameters in real-time [18].

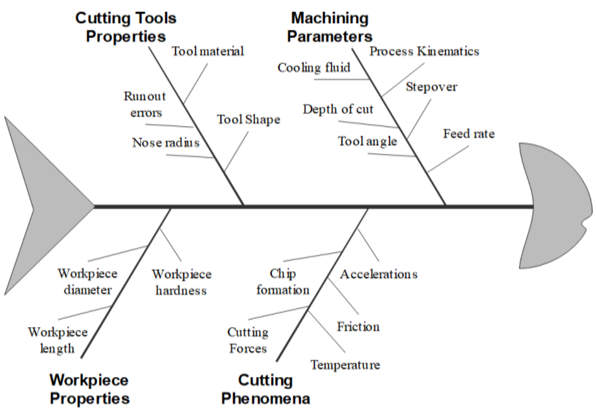


Figure 1. Parameters that affect surface roughness [19]

## 2. METHODOLOGY

The method aims to build an optimized BPNN to predict the roughness of a surface with good accuracy and to optimize the cutting parameters, the flowchart presented in Figure 2 allows us to detail the steps performed.

to train and build a neural network, training data is essential in the case of supervised machine learning, for this purpose, turning operations are carried out by choosing the major factors that affected the surface roughness. The feed rate (*f*) is recognized as the first factor which has a major impact on Ra, the second parameter is the nose radius according to [20]. Another study [21] recognized that the nose radius is more meaningful than the feed rate. Therefore, four parameters are chosen to perform the experiments, with five levels each, Table 1 shows the levels of each cutting parameter.

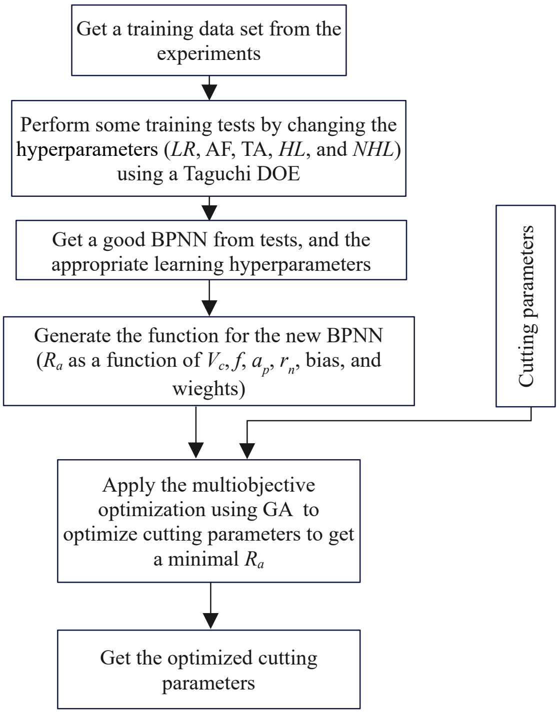


Figure 2. Methodology steps

Table 1. Cutting parameters and their levels

| Parameters | Levels | | | | |
|---|---|---|---|---|---|
| $V_c$ | 80 | 100 | 120 | 140 | 160 |
| $f$ | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 |
| $a_p$ | 2.5 | 3.0 | 3.5 | 4.0 | 4.5 |
| $r_n$ | 0.8 | 1.2 | 1.6 | 2.4 | 2.8 |

By using an orthogonal design of experiment, number of experiments is reduced to 30 experiments [22]. The turning operation is carried out by a tungsten carbide tool on a piece of AISI 4140 material. Table 2 shows roughness quality of a machining surface in each experiment.

Table 2. The experimental value of surface roughness [22]

| Exp No | cutting parameters | | | | |
|---|---|---|---|---|---|
| | $V_c$ (mm/min) | $f$ (mm/tooth) | $a_p$ (mm) | $r_n$ (mm) | $R_a$ (mm) |
| 1 | 120 | 0.4 | 3.50 | 1.6 | 2.47 |
| 2 | 100 | 0.5 | 3.00 | 1.2 | 3.01 |
| 3 | 140 | 0.5 | 3.00 | 1.2 | 2.01 |
| 4 | 100 | 0.3 | 4.00 | 2.4 | 2.86 |
| 5 | 120 | 0.4 | 4.50 | 1.6 | 2.74 |
| 6 | 100 | 0.3 | 3.00 | 2.4 | 2.91 |
| 7 | 140 | 0.5 | 4.00 | 1.2 | 2.29 |
| 8 | 140 | 0.3 | 4.00 | 2.4 | 2.43 |
| 9 | 120 | 0.4 | 3.50 | 1.6 | 2.53 |
| 10 | 120 | 0.4 | 3.50 | 1.6 | 2.52 |
| 11 | 140 | 0.5 | 4.00 | 2.4 | 2.21 |
| 12 | 120 | 0.4 | 3.50 | 1.6 | 2.45 |
| 13 | 80 | 0.4 | 3.50 | 1.6 | 3.39 |
| 14 | 120 | 0.4 | 3.50 | 1.6 | 2.52 |
| 15 | 100 | 0.5 | 4.00 | 1.2 | 3.34 |
| 16 | 120 | 0.4 | 3.50 | 1.6 | 2.47 |
| 17 | 140 | 0.3 | 3.00 | 1.2 | 2.17 |
| 18 | 120 | 0.6 | 3.50 | 1.6 | 2.69 |
| 19 | 140 | 0.3 | 4.00 | 1.2 | 2.51 |
| 20 | 100 | 0.3 | 3.00 | 1.2 | 2.86 |
| 21 | 140 | 0.5 | 3.00 | 2.4 | 2.31 |
| 22 | 100 | 0.5 | 4.00 | 2.4 | 2.97 |
| 23 | 120 | 0.4 | 2.50 | 1.6 | 2.31 |
| 24 | 100 | 0.5 | 3.00 | 2.4 | 3.01 |
| 25 | 120 | 0.2 | 3.50 | 1.6 | 2.74 |
| 26 | 100 | 0.3 | 4.00 | 1.2 | 3.23 |
| 27 | 160 | 0.4 | 3.50 | 1.6 | 1.88 |
| 28 | 120 | 0.4 | 3.50 | 2.8 | 2.72 |
| 29 | 140 | 0.3 | 3.00 | 2.4 | 2.54 |
| 30 | 120 | 0.4 | 3.50 | 0.8 | 2.7 |

## 3. BACK-PROPAGATION NEURAL NETWORK MODEL

### 3.1. Training Process of BPNN

In this section, a refined back-propagation neural network is provided to model and predict the roughness of a machined surface. These artificial neural networks can model complex linear or non-linear problems in this case, the neural network needs to be well-trained by adjusting these hyperparameters such as; the number of hidden layers (NHL), the number of neurons for each hidden layer (HL), the algorithm and learning rate, the activation function. More information on the effect of training hyperparameters on machine learning models can be found in this paper [23].

The structure of a BPNN model is shown in Figure 3, which contains four inputs for the four cutting parameters ($V_c$, $f$, $a_p$ and $r_n$), and an output represented by the roughness of the machined surface.

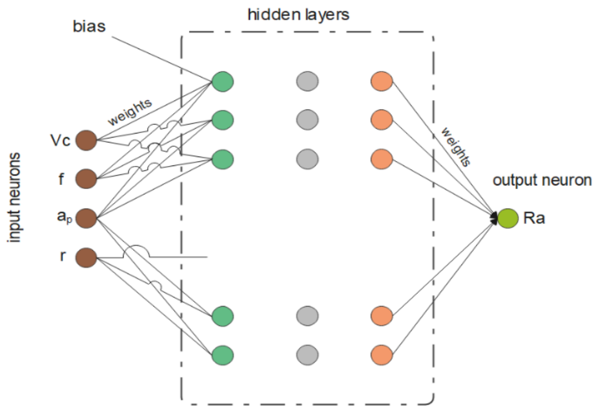


Figure 3. Structure of BPNN

In general, the BPNN follows the following steps for training, the training process is illustrated in Figure 5;
- Application of input data (in this case the values of $V_c$, $f$, $a_p$, and $r_n$).
- Comparation of the output value of ANN with the Target (target is the measured $R_a$ values).
- Calculation the error between Output $R_a$ and $R_a$ targeted.
- Determination and application of new weights.
- Repetition the steps until having a minimum possible error.

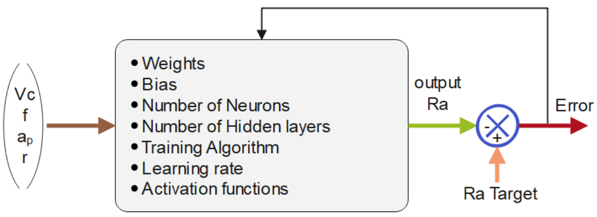


Figure 4. The training process of a BPNN

### 3.2. Tuning a BPNN

The more precise BPNN is generated, for this reason, it is necessary to choose a good combination of hyperparameters. Several tests were performed by changing the hyperparameters, using the Taguchi DOE, as other authors have done in these articles [24, 25], to determine the minimum possible tests and most significant. The chosen hyperparameters are represented in Table 3.

Table 3. Hyperparameters and their levels

| | *LR* | *HL* | *NHL* | AF | TA |
|---|---|---|---|---|---|
| Levels | 0.001 | 1 | 8 | Linear | LM |
| | 0.002 | 2 | 10 | ReLU | BR |
| | 0.01 | 3 | 12 | Sigmoid | GD |
| | 0.02 | 4 | 14 | Logsig | RP |

DOE of Taguchi orthogonal array gives a total of 16 tests instead of 1024 tests. For each simulation test, the *MSE* is derived, these tests are done by Matlab V2016a to have an excellent BPNN configuration. Classification and normalization of the training data are performed to facilitate the convergence of a cost function to the global minimum, in comparison to random data [26]. The Figure 5 illustrates the *MSE* and training time for each neural network simulation.

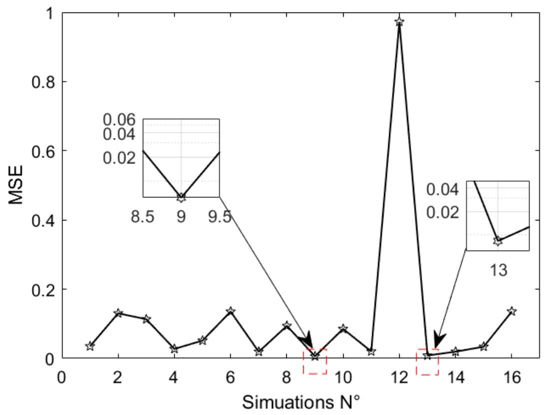


Figure 5. BPNN error

According to the tests shown in Figure 6, the best neural networks found, which have the minimum *MSE* appear on test number 9 which has an *MSE*=0.0062 mm$^2$, and No 11 with *MSE*= 0.0084 mm$^2$. Also, it can be seen that if the number of hidden layers increases the neural network becomes overfitting, represented by ANN number 12, and if the number of neurons is very small, it is an underfitting case. the training algorithm influences the learning time the BR takes more time for training than the LM algorithm, but it gives good accuracy.

For the next, the neural network number 9 is selected, with the hyperparameters as shown in Table 4.

Table 4. BPNN training hyperparameters

| *LR* | *HL* | *NHL* | AF | TA |
|---|---|---|---|---|
| 0.01 | 1 | 12 | Logsig | BR |

After training the neural network under the training conditions shown in the table above, the error between the measured roughness on the part and that predicted by the BPNN is calculated, Figure 7 plots the BPNN error of each experiment. It can be seen very well (in the boxed area) that there is a maximum absolute error of 0.6890 mm, this error is large and unacceptable. By the same training conditions of the neural network and adding the MRR as an additional output, a new BPNN has been trained, the error between the $R_a$ obtained by the experiment and the new BPNN gives a maximum absolute error of 0.0762 mm.

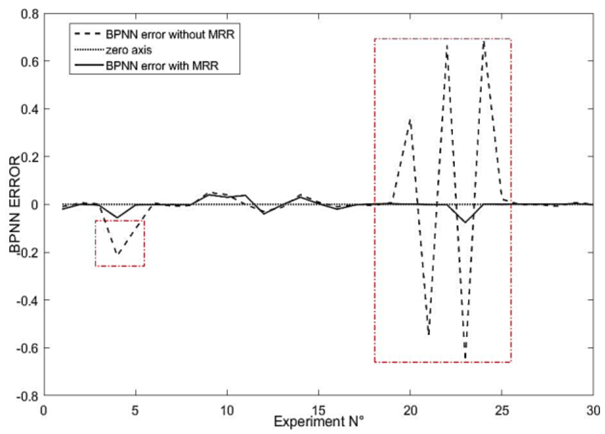


Figure 6. MSE for each simulation

With classified, normalized data, and by adding supplementary output for the network, the gradient descent converges very quickly (Figure 8) at the global minimum. The regression coefficient presented in Figure 9 becomes very close to 1; $R$=0.99991 for training, and $R$=0.99917 for testing, the gradient descent equals 6.3121E-5 in epoch 321, this indicates that the target values are very close to the output values, therefore a more accurate BPNN.

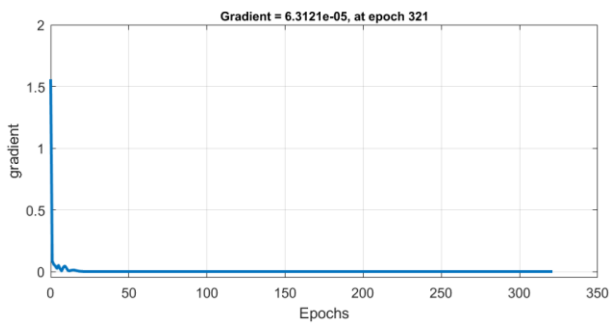


Figure 7. Gradient descent

## 4. GA OPTIMIZATION

The best condition of the surface is that which has a minimum roughness, the objective of this section is to optimize the cutting conditions in such a way to have a good surface condition, the genetic algorithm has a good ability to solve this type of problem (Figure 11 shows the flowchart of GA). To apply the optimization approach with the GA, a function to optimize (fitness function) is required, intervals of the variables (cutting parameters).

In this case, the fitness function is Ra generated from BPNN presented in Figure 10. It is a function of cutting parameters, weights, and biases are presented with Equation (1).

$$R_a = \text{fun}(Vc, f, a_p, r_n, b_1, b_2, W_{i-HL}, W_{HL-O}) \quad (1)$$

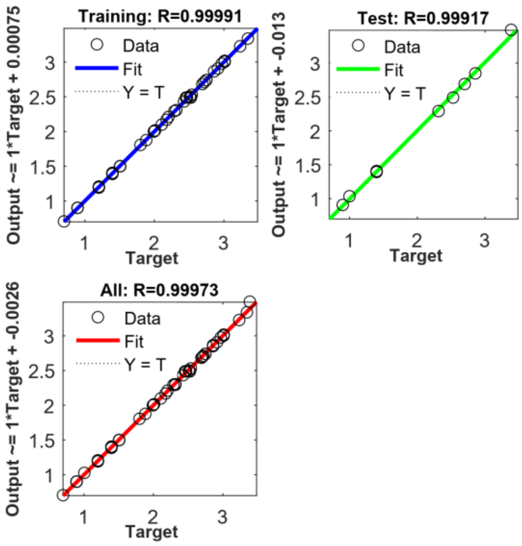


Figure 8. Regression coefficient

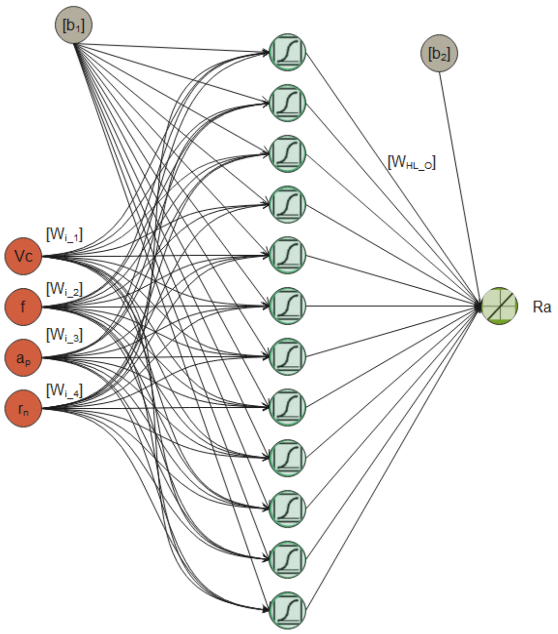


Figure 9. BPNN architecture of $R_a$

The weights and biases are represented as matrices, the activation functions are Logsig in the hidden layer, and Linear in the output layer.

MATLAB software is used to minimize the surface roughness to find a good combination of cutting parameters. The initial settings to solve the problem by using GA, are shown in Table 5.

Serval runs are made to get the best fitness value, As shown in Figure 11, the best fitness values of cutting parameters are in run No 4, which appears in generation 94.

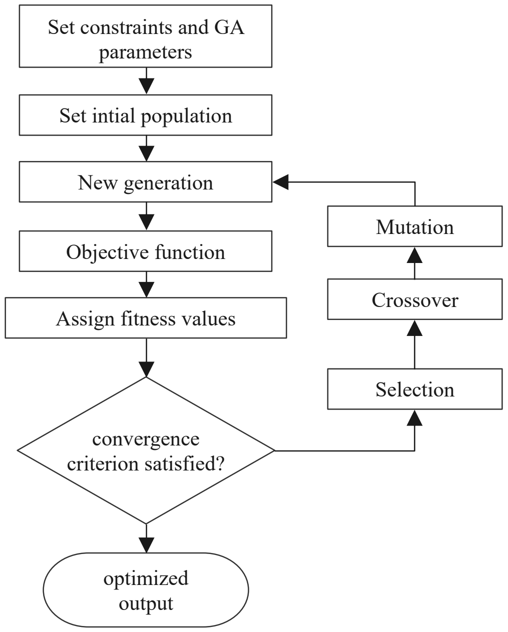


Figure 10. The flowchart of GA [27]

Table 5. Initial settings on GA

| Settings Parameters | Level |
|---|---|
| Population size | 50 for under 5 variables |
| Initialize population | Randomly |
| Scaling function | Rank |
| Selection function | Tournament |
| Crossover fraction | Tow point crossover |
| Mutation operator | Uniform mutation |
| Per cent of cross over | $P_c$=0.8 |
| Per cent of mutation | $P_m$=0.01 |
| Stopping criteria | 400×(number of Variables) |

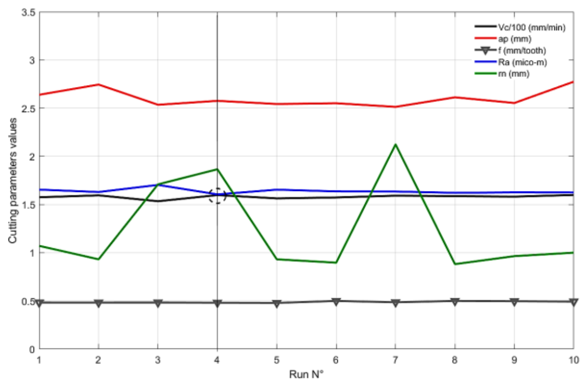


Figure 11. Optimum cutting parameters on each run

## 5. COMPARISON WITH OTHER WORKS

### 5.1. Neural Network

Table 6 shows the best ANN structure found by [22], and the model developed in this paper.

In the case of our model or M. Gopal model the number of HL, the activation function in the hidden layer, are the same, the difference appears in the number of neurons in the hidden layer, the activation function, and the training algorithm. It can be noticed that the descent gradient is converged more easily for our model at epoch 321.

Table 6. The architecture of ANN models

| | M. Gopal model | BPNN model |
|---|---|---|
| *HL* | 1 | 1 |
| *NHL* | 8 | 12 |
| AF in HL | Logsig | Logsig |
| AF in output | Sigmoid | Linear |
| TA | GD | BR |
| Global minimum | in epoch 1000 | in epoch 321 |

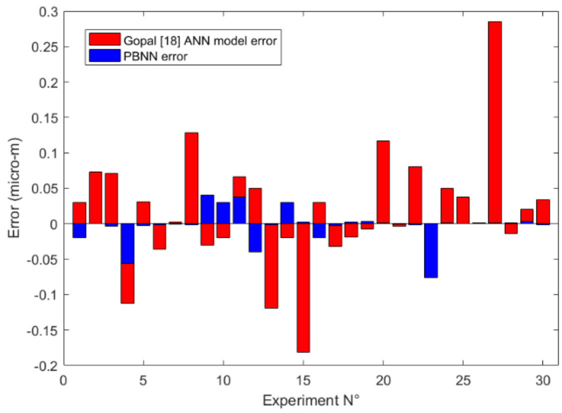


Figure 12. The error of two ANN models

For the same cutting parameter, same results of experiments for neural network training, and with different network architecture, this model gives a small error as Figure 12 shown compared to Gopal model.

### 5.2. Optimum Cutting Parameters

From the interaction results found by the same author using ANOVA, it can be seen that the optimum cutting parameters to minimize the surface roughness are very close to results from genetic algorithm optimization Table 8. The minimal surface roughness value found by ANOVA and those found by GA are successively 1.8800 mm and 1.6056 mm.

Table 7. Optimized parameters from ANOVA and GA

| | optimum | Optimized cutting parameters | | | |
|---|---|---|---|---|---|
| | $R_a$ | $Vc$ | $f$ | $a_p$ | $r_n$ |
| ANOVA [22] | 1.88 | 160 | 0.60 | 2.5 | 1.8 |
| GA | 1.606 | 159.812 | 0.481 | 2.576 | 1.866 |

## 6. CONCLUSION

The objective of this paper is to build a good BPNN optimized to predict the roughness of the surface and to optimize the four cutting parameters ($Vc$, $f$, $a_p$, and $r_n$) aiming at minimal surface roughness.

The back-propagation neural network is trained by different hyperparameters using Taguchi DOE, the right combination of training parameters was chosen as shown in Table 4. The optimization of cutting parameters is done by a genetic algorithm which gives significant results. Based on a comparative study, it can be found that the artificial neural model developed has good accuracy, as shown in Figure 12. The results indicate that Artificial intelligence (tools are very powerful in these modelling cases, which leads to several suggestions for future work, such as modelling other cutting conditions using different tools or coupling various Artificial intelligence tools.

## NOMENCLATURES

### 1. Acronyms

| | |
|---|---|
| AF | Activation Function |
| ANN | Artificial Neural Network |
| BPNN | Backpropagation Neural Network |
| BR | Bayesian Regularization backpropagation |
| DOE | Design of Experiment |
| GA | Genetic Algorithm |
| GD | Gradient Descent backpropagation algorithm |
| LM | Levenberg-Marquardt algorithm |
| TA | Training Algorithm |
| RP | Resilient backpropagation algorithm |

### 2. Symbols / Parameters

$a_p$: Depth of cut [mm]
$b_1$, $b_2$: Neural network Bias
$f$: Feed rate [mm/tooth]
$HL$: Number of Hidden Layer
$LR$: Learning Rate
$MRR$: Material Rate Removal
$NHL$: Number of Neurons in each Hidden Layer
$R_a$: Surface roughness [mm]
$r_n$: Tool nose radius [mm]
$Vc$: Cutting speed [m/min]
$W_{HL\text{-}O}$: Neural network Weights matrices from hidden layers to output layer
$W_{i\text{-}HL}$: Neural network Weights matrices from input to hidden layers

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