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# Empirical Modeling of End Milling and optimization of process parameters using Artificial Neural networks

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**Abstract.** The Empirical modeling of the process parameters of manufacturing problems in the present days is mainly done using Artificial Neural Networks (ANN). In manufacturing environments, main focus is given to the finding of Optimum machining parameters. Therefore the present research is mainly focused on the empirical modeling of the End milling process. The End milling process is a widely used machining process in aerospace industries and many other industries ranging from large manufacturers to a small tool and die shops, because of its versatility and efficiency. The reason for being widely used is that it may be used for the rough and finish machining of such features as slots, pockets, peripheries and faces of components. The present research work involves the prediction of models using Artificial Neural Networks for the variables of End Milling process i.e speed, feed and depth of cut, whereas the metal removal rate (MRR) and tool wear resistance were taken as the output.

***Keywords*— End Milling Process, Design of experiments, ANN, AISI Steel.**

## 1. INTRODUCTION

The most widely used operation for metal removal in various industries Automobile, Aerospace and heavy industries is End milling operation. In the above industries quality is the most concern in the production of moulds /dies slots and pockets. The End mills are used in various milling applications like tracer milling, profile milling, face milling, and plunging. The end mills are used for light operations like cutting slots, machining accurate holes producing narrow flat surfaces and for profile milling operations. End milling is an operation of machining vertical or horizontal surfaces by using end milling. The operation is usually performed on vertical milling machine. Azlon zain, Haron and sharif observed the effect of different parameter like cutting speed, feed and rake angle in surface roughness. They compared the result of regression modeling and genetic algorithm. Hence the optimization of this process is particularly more important to save cost and time. Experimental optimization of end milling is a difficult task. It depends on mainly the experience of the operator. But as end milling contains more number of parameters to be controlled, it is needed to develop a method for the optimal selection. The present work involves the estimation of optimal values of the process variables like, speed, depth of cut and feed, whereas the metal removal rate (MRR) and tool wear resistance were taken as the output. In Matlab Software ANN module is used for finding the relationships between output and input process parameters, which is available in MATLAB. Later the models given by ANN can be used for optimizing the process.

Industrial Engineering Journal
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## 2. EXPERIMENTAL WORK

The experiments are done by using 3-axis CNC vertical machining center as shown in Fig. 3. AISI S2 is taken as the work piece material for investigation. It is a Shock-Resisting Steel grade *Tool Steel*. It is composed of (in weight percentage) 0.40-0.55% Carbon (C), 0.30-0.50%, 0.30-0.60% Manganese (Mn), 0.90-1.20% Silicon (Si), 0.30% Nickel (Ni), Molybdenum (Mo), 0.50% Vanadium (V), 0.25% Copper (Cu), 0.03% Phosphorus (P), 0.03% Sulfur (S), and the base metal Iron (Fe). It has excellent fine wear resistance and toughness will find various applications in cutting tools for heavy plate, shear blades, cold punching and upsetting and used in various cutting tools.

The specimen is prepared with the dimensions of 150mm x 250mm x 20mm and ceramic insert is used for experimentation. It was found from the experiments and literature survey that the process parameters such as spindle speed ($x1$), feed ($x2$), and axial depth of cut ($x3$) is the decision (control) variables and the MRR, Tool wear both as output responses. The ranges of the process control variables are given in table 1. The output responses were measured and recorded and is shown in the Table 2 for the experiments conducted as per the DOE.

Table 1. Cutting parameter Ranges

| **Input Variables** | **Units** | **Notation** | **Feasible range** | |
|---|---|---|---|---|
| | | | **Lower Limit** | **Upper Limit** |
| Cutting Speed | Rpm | $x_1$ | 900 | 1500 |
| Feed | mm/min | $x_2$ | 30 | 60 |
| Depth of Cut | mm/min | $x_3$ | 0.4 | 0.6 |

Table 2. Experimental dataset

| **S.No** | **SPEED (X1)** | **FEED (X2)** | **DEPTH OF CUT (X3)** | **M.R.R** | **WEAR** |
|---|---|---|---|---|---|
| 1 | 1500 | 30 | 0.6 | 5.587 | 0.163 |
| 2 | 900 | 30 | 0.4 | 3.487 | 0.09 |
| 3 | 1500 | 60 | 0.5 | 8.294 | 0.209 |
| 4 | 1200 | 45 | 0.6 | 7.59 | 0.199 |
| 5 | 1200 | 30 | 0.5 | 4.888 | 0.13 |
| 6 | 900 | 30 | 0.6 | 5.587 | 0.139 |
| 7 | 1500 | 30 | 0.4 | 3.492 | 0.115 |
| 8 | 1200 | 60 | 0.4 | 5.924 | 0.145 |
| 9 | 900 | 45 | 0.4 | 4.744 | 0.145 |
| 10 | 1200 | 45 | 0.5 | 6.641 | 0.174 |
| 11 | 900 | 45 | 0.5 | 6.641 | 0.149 |
| 12 | 1200 | 30 | 0.4 | 3.497 | 0.115 |
| 13 | 1200 | 45 | 0.4 | 4.744 | 0.148 |
| 14 | 1500 | 45 | 0.6 | 7.605 | 0.207 |
| 15 | 1500 | 60 | 0.6 | 9.479 | 0.225 |

Industrial Engineering Journal

ISSN: 0970-2555

Volume : 51, Issue 12, December 2022

| | | | | | |
|---|---|---|---|---|---|
| 16 | 900 | 45 | 0.6 | 7.59 | 0.175 |
| 17 | 1500 | 45 | 0.4 | 4.744 | 0.11 |
| 18 | 900 | 60 | 0.6 | 9.479 | 0.225 |
| 19 | 900 | 30 | 0.5 | 4.888 | 0.13 |
| 20 | 1500 | 30 | 0.5 | 4.888 | 0.116 |
| 21 | 900 | 60 | 0.5 | 8.294 | 0.189 |
| 22 | 1500 | 60 | 0.4 | 5.924 | 0.175 |
| 23 | 1200 | 60 | 0.5 | 8.294 | 0.202 |
| 24 | 1500 | 45 | 0.5 | 6.654 | 0.188 |
| 25 | 1200 | 60 | 0.6 | 9.479 | 0.235 |
| 26 | 900 | 60 | 0.4 | 5.924 | 0.173 |
| 27 | 1200 | 30 | 0.6 | 5.594 | 0.143 |

## 3. MODELLING USING ANN

ANN inspired by biological nervous systems and composed of simple elements that are operating in parallel and are as shown in Fig. 2.

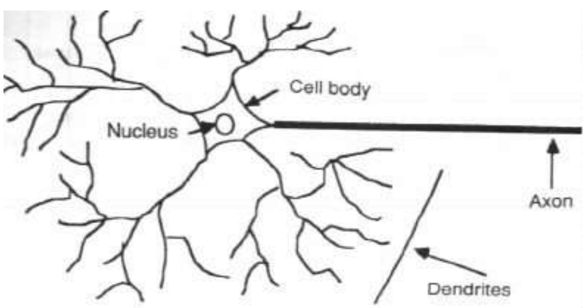


Fig. 2. Biological nervous system

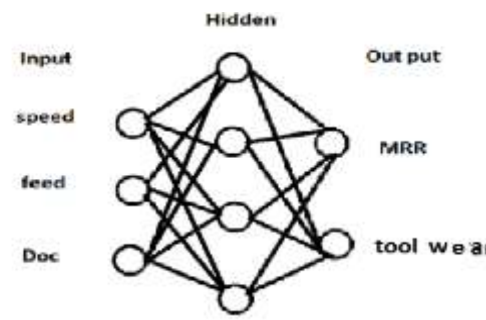


Fig. 3. Layers in Neural Networks

The models using ANN i.e 2 in number one is for MRR and next is for Tool wear. The Levenberg-Marquardt algorithm networks are used due to its high accuracy in similar approximation. A regularization scheme is used to improve the network model. The input/output dataset is divided randomly intotraining dataset and test dataset. The first step is training network and second step test the network with data, which were not used for training. in this paper Back propagation network is used as a tool. For ANN Modeling, the Input data, Testing Data set & Target Data set used are taken from the experimental data set developed according to Design experiments.

### 3.1. ANN model design for prediction of Material Removal Rate (MRR)

The model design for MRR & Tool wear consists of the following steps. First step is the fixing of nodes in both input and output layers. Then normalization of output and input is followed. Later the hidden layers number is fixed. Single and double hidden layers networks are used for solving these types of problems

### 3.2. Network model for MRR

Industrial Engineering Journal
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Feed forward back propagation trained using Levenberg Maquardtl algorithm is used for MRR network model development. The layers are 2 and 1 for output. Number of neurons are between 0 to10. The results show that at 71 epochs best regression plot is obtained. Based on the minimum error, the hidden layer node number is fixed. In this case, at 8 Nodes, the error is minimum in first hidden layer and at 4 nodes in second hidden layer and is given in Table 3.

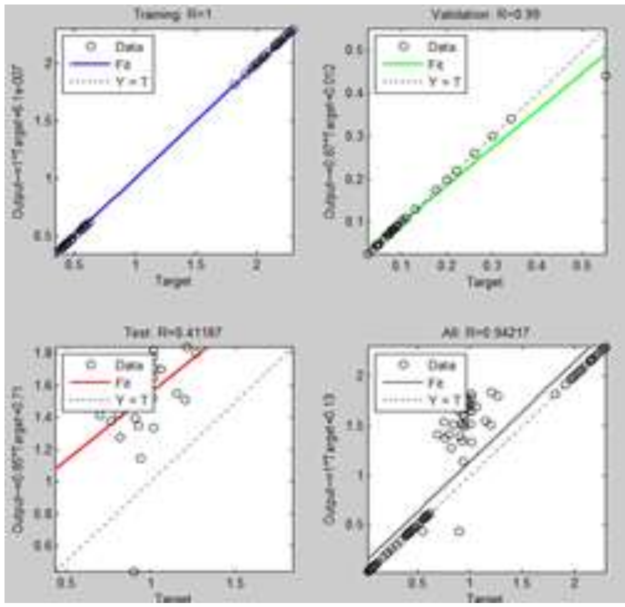

Fig. 4: Best MRR Regression plot

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Table 3. Best performance error with hidden nodes for MRR

| Hidden Layer | Best performance error |
|---|---|
| 2 | 0.012 |
| 5 | 0.098 |
| 10 | 0.0018 |
| 15 | 0.031 |
| 20 | 0.062 |

### 3.3. Network model for Tool Wear Resistance

The network developed for Tool wear are on feed forward back propagation. Training function is TRAINLM, Tran Sigmoid as the hidden layer transfer function and the output layer transfer function as the Pure linear. The adaption of learning rate set as LEARNGDM. The results show that at 84 epochs best regression plot is obtained. To obtain best performance i.e with minimum error, the hidden layer nodes are changed. For this the best performance error is less at nodes 17and the 18 and is given in Table 4.

Industrial Engineering Journal

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Volume : 51, Issue 12, December 2022

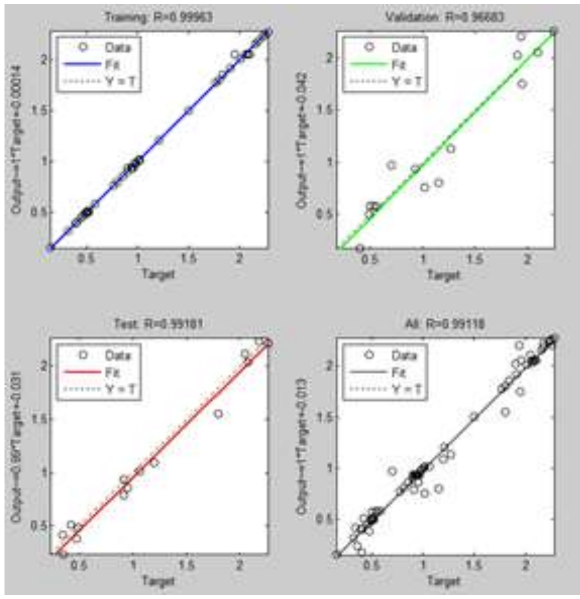


Fig. 5: Best Regression plot for Tool wear

Table 4. Best performance error with hidden nodes for Tool wear

| Hidden Layer | Best performance error |
|---|---|
| 16 | 0.0272 |
| 17 | 0.0123 |
| 18 | 0.0043 |
| 19 | 0.076 |
| 20 | 0.0987 |

The predicted values and experimental values of material removal rate and tool were resistance for both training and testing are shown in the fig 6 & 7. From both the figures it is evident that network responded well for the testing data as well.

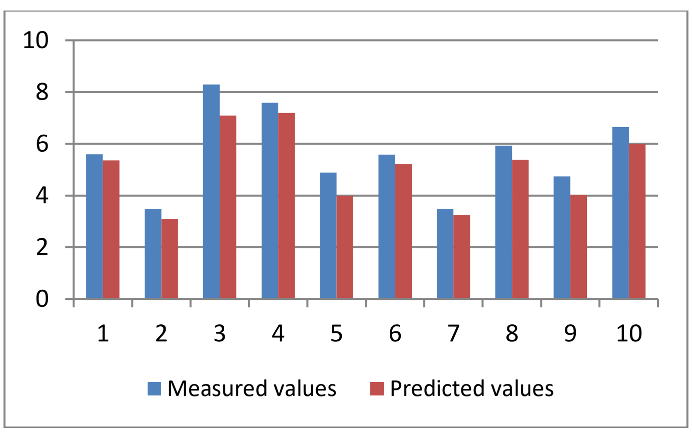


Fig. 6. Experimental and Predicted MRR values

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 51, Issue 12, December 2022

Table 5. Measured and predicted MRR values

| Exp no | Experimental Values | ANN Predicted Values | Percentage of error |
|---|---|---|---|
| 1 | 5.587 | 5.356 | 5.58 |
| 2 | 3.487 | 3.087 | 11.47 |
| 3 | 8.294 | 7.094 | 14.46 |
| 4 | 7.59 | 7.19 | 5.27 |
| 5 | 4.88 | 4 | 18.03 |
| 6 | 5.58 | 5.21 | 6.63 |
| 7 | 3.49 | 3.25 | 6.88 |
| 8 | 5.92 | 5.38 | 18.5 |
| 9 | 4.74 | 4.02 | 15.2 |
| 10 | 6.641 | 5.984 | 9.9 |
| 11 | 6.641 | 5.982 | 9.9 |
| 12 | 3.497 | 3.01 | 14 |
| 13 | 4.744 | 3.981 | 16 |
| 14 | 7.605 | 7.01 | 8 |
| 15 | 9.479 | 8.989 | 6 |
| 16 | 7.59 | 7.35 | 3.165 |
| 17 | 4.744 | 4.2 | 11.5 |
| 18 | 9.479 | 9.1013 | 4 |
| 19 | 4.888 | 4.5 | 7.93 |
| 20 | 4.888 | 4.32 | 11.62 |
| 21 | 8.294 | 8.021 | 3.3 |
| 22 | 5.924 | 6.01 | 2 |
| 23 | 8.294 | 8.102 | 2.32 |
| 24 | 6.654 | 6.322 | 5 |
| 25 | 9.479 | 9.149 | 11 |
| 26 | 5.924 | 5.638 | 5 |
| 27 | 5.594 | 5.212 | 13.172 |

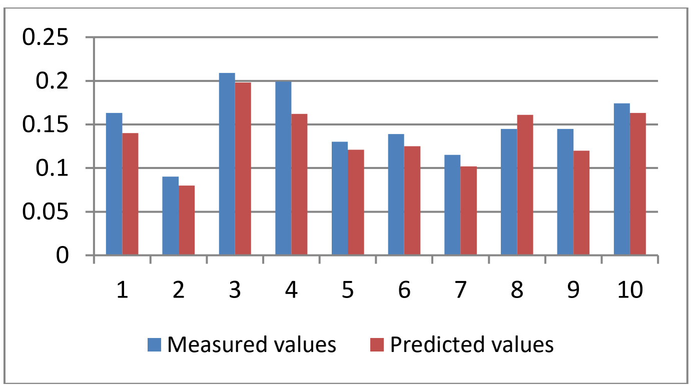


Fig. 7.Experimental and Predicted tool were resistance values

Table 6. Measured and predicted tool wear values

| Exp no | Experimental Values | ANN Predicted Values | Percentage of error |
|---|---|---|---|
| 1 | 0.163 | 0.14 | 14 |
| 2 | 0.09 | 0.08 | 11.11 |
| 3 | 0.209 | 0.198 | 5.27 |
| 4 | 0.199 | 0.162 | 18.59 |
| 5 | 0.13 | 0.121 | 6.63 |
| 6 | 0.139 | 0.125 | 10.01 |
| 7 | 0.115 | 0.102 | 11.305 |
| 8 | 0.145 | 0.161 | 11 |
| 9 | 0.145 | 0.12 | 13.79 |
| 10 | 0.174 | 0.163 | 6.32 |
| 11 | 0.149 | 0.139 | 6.711 |
| 12 | 0.115 | 0.109 | 5.22 |
| 13 | 0.148 | 0.12 | 18.91 |
| 14 | 0.207 | 0.2 | 3.4 |
| 15 | 0.225 | 0.21 | 6.67 |
| 16 | 0.175 | 0.19 | 8.58 |
| 17 | 0.11 | 0.1 | 9.09 |
| 18 | 0.225 | 0.21 | 6.67 |
| 19 | 0.13 | 0.118 | 9.23 |
| 20 | 0.116 | 0.137 | 18.11 |
| 21 | 0.189 | 0.158 | 3.6 |
| 22 | 0.175 | 0.153 | 12.5 |
| 23 | 0.202 | 0.19 | 5.95 |
| 24 | 0.188 | 0.162 | 13.83 |
| 25 | 0.235 | 0.21 | 10.64 |
| 26 | 0.173 | 0.197 | 13.83 |
| 27 | 0.143 | 0.122 | 13.986 |

## CONCLUSIONS

In this research paper, 3-Axis CNC vertical machining center is used for doing experiments, employing a variable continuously spindle speed up to a maximum of 6000 rpm and maximum spindle power of 5.5kW. The feed rates is set to a maximum of 10m/min. Experiments are done as per Design of experiments (DOE). Depth of cut, Cutting speed and Feed is taken as process parameters and the output responses are Material removal rate and Tool wear resistance. In MATLAB software, ANN module is available which is used to predict the relationships of input process parameters and the output variables. The models were developed to predict the MRR and Tool wear resistance through ANN. For different network configurations, As per the value of performance error obtained, best model is identified and selected. The models were evaluated by calculating the percentage deviation using predicted values and actual values.

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