

Formulation of Artificial Neural Network (ANN) Based Model for the Dry Machining of Ferrous & Non-ferrous Material used in Indian Small Scale Industries

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Abstract: An artificial neural network (ANN) based models has been formulated for investigation and prediction of the relationship between various machining process parameters and the power consumption during turning of material such as En8, En1A, S.S.304, Brass and Aluminium. The input parameters of the ANN model are the cutting tool parameters, machine specification, work piece parameters, environmental parameters and the cutting process parameters. The output parameter of the model is power consumed during the turning process. The model consists of a three layered feed forward back propagation neural network. The network is trained with pairs of inputs/outputs database generated when machining of ferrous and nonferrous material. A very superior performance of the neural network, in terms of conformity with experimental data, was achieved. The model can be used for the analysis and prediction of the multifaceted relationship between input and output parameter. This paper presents the ANN model for predicting the power consumption performance measure in the machining process by considering the Artificial Neural Network (ANN) as the essential technique for measuring power consumption. Utilization of ANN-based modeling is also presented to show the required fundamental elements for predicting power consumption in the turning process. In order to investigate how competent the ANN technique is at estimating the prediction value for power consumption, a real machining experiment is performed in this study. In the experiment, more than 200 samples of data concerned with turning process using field data based approach of experimentation. It was found that the 13–10–1 network structure gave the best ANN model in predicting the power consumption value

Key words: Artificial Neural Network, comprehensive model, Dry Turning, Machining process.

1. Introduction

Machining is a most important manufacturing process and wide application in the modern technology. The aim of present study is to develop an effective and easy approach based on field data to decide the strengths and weakness of the existing process. Artificial Neural Network (ANN) has been used by various researchers to understand and effectively implement the ANN tool in various field of engineering. A multipass turning optimization by using genetic algorithm (GA) (**A. Belloufi et.al., 2013**) to minimize the production cost under a set of machining constraints. The convergence characteristics and robustness of the presented method have been explored through comparisons with results reported in literature. The

obtained results indicate that the hybrid genetic algorithm by using a sequential quadratic programming was effective compared to other techniques carried out by different researchers. From the experimental findings, it was cleared that the hybrid GA-SQP can achieve much better results than other approaches. The present method was a generalized solution method so that it can be easily employed to consider the optimization models of turning regarding various objectives and constraints. In the machining models, no specific work piece and tool was identified. Therefore, the solution approach can be used with any work piece for turning optimization problems.

The artificial neural network (ANN) tool has been used (**Gaitonde et.al., 2011**) in the performance analysis of conventional and wiper ceramic inserts in hard turning .The two artificial intelligence approaches – artificial neural network and genetic algorithm has been used (**Girish Kanta & Kuldip Singh Sangwan, 2015**) for optimization of a machining parameters to minimize the surface roughness. A number of experiments have been carried out to check the capability of the model for prediction and optimization of surface roughness. The experimental findings shows that the presents tools has been effectively used for the analysis of the machining process. An artificial neural network (ANN) based model has been formulated (**Mangesh R. Phate & Dr. V.H.Tatwawadi, 2012-2014**) for material removal rate (MRR) in the turning of ferrous and nonferrous material in a Indian small scale industry. Artificial neural network (ANN) model was developed for prediction of the responses during the turning of ferrous and nonferrous materials. The input parameters of this model were operator, work piece, cutting process, cutting tool, machine and the environment. The ANN model consists of a three layered feed forward back propagation neural network. The network was trained with pairs of independent/dependent datasets generated when machining ferrous and nonferrous material. A very good performance of the neural network, in terms of contract with experimental data, was achieved. The model may be used for the testing and forecast of the complex relationship between dependent and the independent parameters in turning operations.Principal Component Analysis (PCA) has been used (**Meenu Gupta & Surinder Kumar, 2015**) to investigate the machinability of unidirectional glass fibre reinforced plastics (UD-GFRP) composite in turning process. Taguchi L18 orthogonal array was used for experimental design. The tool nose radius, tool rake angle, feed rate, cutting speed, cutting environment (dry, wet and cooled) and depth of cut were considered as an influencing parameters to investigate the effect on output responses. Surface roughness and material removal rate model has been formulated by using principal component analysis. From the experimental results, it was cleared that the surface roughness increases as feed rate increases. It was found that feed rate was more significant factor followed by depth of cut and cutting speed. The ANN tool has been effectively used (**M. V. R. D. Prasad et.al., 2015**) to find out the best set of input parameters which minimize the surface roughness. The parameters like cutting speed, feed and depth of cut were considered as a input parameters for the investigation. Taguchi's design of experiments approach was used for conducting the experimentation. The work piece material used for the investigation was Inconel 718. The cutting tool used for the machining was Cubic Boron Nitride (CBN10) tool insert. The experimental finding shows that the surface roughness increases with increase in the feed rate and increase in cutting speed reduces the surface roughness. The predicted values obtained from ANN were very close to those the experimental values. The result of the prediction was favourable with 2.78% average percentage of error, that means neural network was capable to predict the surface roughness up to 97.22% accurate.Response Surface method was used (**Nexhat et.al., 2015**) to determine the correlation between a criterion variable and a combination of prediction variables. The machining parameters such as feed rate, tool geometry, nose radius, and machining time were considered for the investigation of surface produced in dry turning process. A three level factorial design has been used for the experimentation. Multiple Regression Analysis (MRA) and Artificial Neural Networks (ANN) have been used (**Rajendra Singh et.al., 2014**) to optimize the surface

roughness of 316L stainless steel pipe by using CNC lathe. The ANN model indicates that the feed rate cutting speed, feed rate, axial depth and radial depth were considered as an influencing parameters which affects the surface roughness. The ANN model indicates that the feed rate was the most significant factor affecting surface roughness. The result from this research is helpful to be implemented in both time-consuming and painstaking works in industry to reduce time and cost. Model has been developed (**Varaprasad.Bh et.al., 2015**) to predict tool flank wear of hard turned AISI D3 hardened steel using Response Surface Methodology (RSM). The combined effects of parameters such as cutting speed, feed rate and depth of cut were investigated using contour plots and surface plots. RSM based Central Composite Design (CCD) was applied as an experimental design. The satisfactoriness of the developed models was checked using Analysis of Variance (ANOVA). Main and interaction plots were drawn to study the effect of process parameters on output responses.

2. Material & Method

In traditional dry turning (DT), there are numerous factors affecting the power consumption such as machine operator data, tool parameters, work piece parameters, cutting process parameters, machine specifications and the environmental parameters. Machine operator consists of operator anthropometric data, experience, parameters, skill etc. Tool parameters consist of tool material, nose radius, tool vibration, tool geometry, etc., while work-piece parameters comprise material, hardness, raw dimension and finish dimension. Machine specifications consist of machine dimensions, motor HP and age of the machine. Furthermore, cutting conditions include spindle revolution, speed, feed, and depth of cut, cutting and tangential force. Since the dry turning process contains many parameters hence it is very complicated to select the proper cutting conditions and other parameters for achieving the maximum power consumption. Field data base approach [**H. Schenck Jr. (1951)**] was used to find out the strengths and weaknesses of the existing system or process. The list of various parameters affects the DT are as shown in table 1. The variables under investigation are correlated by the following equation 1. [**Tatwawadi et.al (2010) & Phate et.al (2012 - 2015)**].

$$PC = f(AN, EX, \tau, LR, DR, VC, f, D, FC, FT, VB, TM, HUM, DT, VF, LUX) \quad (1)$$

General form can be defined as

$$f(AN, EX, \tau, LR, DR, VC, f, D, FC, FT, VB, TM, HUM, DT, VF, LUX, PC) = 0 \quad (2)$$

Total number of variables = 17; All these variables can be expressed in terms of three primary dimensions i.e. mass (M), Length (L) and Time (T). According to Buckingham's theorem [**H. Schenck Jr. (1951)-Chapter 4**]; One should get = $17 - 03 = 14$ dimensionless terms. These pi terms will be correlated by eqn. 3.

$$f(\Pi_1, \Pi_2, \Pi_3, \Pi_4, \Pi_5, \Pi_6, \Pi_7, \Pi_8, \Pi_9, \Pi_{10}, \Pi_{11}, \Pi_{12}, \Pi_{13}, \Pi_{14}) = 0 \quad (3)$$

Choosing D, VC and FC as repeating variables

$$\Pi_1 = D^a VC^b FC^c AN \quad (4)$$

$$M^0 L^0 T^0 = L^a (LT^{-1})^b (M^1 L^1 T^{-2})^c (M^0 L^0 T^0) \quad (5)$$

$$ForM : O = c$$

$$ForL : O = a + b + c$$

$$ForT : O = -b - 2c$$

$$\therefore a = 0, \quad b = 0, \quad c = 0, \quad \Pi_1 = AN$$

Similarly for other pi terms are evaluated and dimensionless terms are formed as shown in Table 2. General equation for the power consumption is given by equation (6)

$$PC / VC * FC = f(AN, EX * VC / D, \tau * D^2 / FC, LR / D, DR / D, f / D, FT / FC, VB / D, TM, HUM, DT, VF / VC, LUX * D^3 / VC^2 * FC) \quad (6)$$

Table 1. The List of Process Variables under Investigations.

| S.N | Descriptions | Symbol | Nature | Dimensions |
|-----|---|-----------|------------------|---|
| 1 | Operator Anthropometric ratio | AN | Independent | M ⁰ L ⁰ T ⁰ |
| 2 | Experience | EX | Independent | M ⁰ L ⁰ T ¹ |
| 3 | Shear stress of the work piece material | τ | Independent | M ¹ L ⁻¹ T ⁻² |
| 4 | Length of the raw work piece | LR | Independent | M ⁰ L ¹ T ⁰ |
| 5 | Diameter of the raw work piece | DR | Independent | M ⁰ L ¹ T ⁰ |
| 6 | Cutting Speed | VC | Independent | M ⁰ L ¹ T ⁻¹ |
| 7 | Feed | f | Independent | M ⁰ L ¹ T ⁰ |
| 8 | Depth of cut | D | Independent | M ⁰ L ¹ T ⁰ |
| 9 | Cutting force | FC | Independent | M ¹ L ¹ T ⁻² |
| 10 | Tangential Force. | FT | Independent | M ¹ L ¹ T ⁻² |
| 11 | Machine Vibration | VB | Independent | M ⁰ L ¹ T ⁰ |
| 12 | Cutting Tool Temperature | TM | Independent | M ⁰ L ⁰ T ⁰ |
| 13 | Atmospheric Humidity | HUM | Independent | M ⁰ L ⁰ T ⁰ |
| 14 | Atmospheric Temperature | DT | Independent | M ⁰ L ⁰ T ⁰ |
| 15 | Air Flow | VF | Independent | M ⁰ L ¹ T ⁻¹ |
| 16 | Light Intensity | LUX | Independent | M ¹ L ⁰ T ⁻⁴ |
| 17 | Power consumption | PC | Dependent | M¹ L² T⁻² |

The experiments were conducted on five different specification lathe machine with a Various speed range En1A, En8 and S.S.304 were consider as a ferrous material and Brass and Aluminum were considered as a nonferrous work piece. The chemical compositions of the work piece are given in Tables 3 and 4 respectively. The power consumption is measured by using clamp meter. The clamp meter gives readings in terms of voltage and the current for three phase connection. The power consumption was measured by using following equation (7).

$$PowerConsumption = \sqrt{3}VI \cos\phi / 1000 \quad (7)$$

where , I is the current in ampere ,V is the voltage and cosφ is the power factor which is the direct method for estimation the energy consumption by the machine tool during all the stages of the machining.

The chemical composition of the various ferrous and nonferrous materials under investigation is as shown in the following table 3 and table 4. The dimensions of the required standard work piece component and the experimental set up are as shown in figure 1 and 2 respectively.

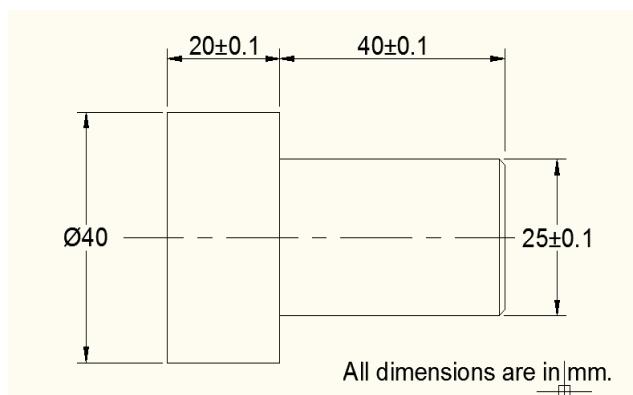


Fig. 1. Dimensions of Finished Components.



Fig. 2. Experimental Set up for CDT Process.

Table 2 . The List of Basic Dimensionless (Pi) Terms.

| S.N | Number | Ratio | Nature |
|-----------|-----------------------------|------------------------------|---|
| 1 | Π_1 | AN | Operator Anthropometric ratio |
| 2 | Π_2 | $EX*VC/D$ | Experience |
| 3 | Π_3 | $\tau *D^2/FC$ | Shear stress of the work piece material |
| 4 | Π_4 | LR/D | Length of the raw workpiece |
| 5 | Π_5 | DR/D | Diameter of the raw workpiece |
| 6 | Π_6 | f/D | Feed |
| 7 | Π_7 | FT/FC | Tangential Force. |
| 8 | Π_8 | VB/D | Machine Vibration |
| 9 | Π_9 | TM | Cutting Tool Temperature |
| 10 | Π_{10} | HUM | Atmospheric Humidity |
| 11 | Π_{11} | DT | Atmospheric Temperature |
| 12 | Π_{12} | VF/VC | Air Flow |
| 13 | Π_{13} | $(LUX*D^3/VC^2*FC)$ | Light Intensity |
| 14 | ΠD_1 | $PC/FC*VC$ | Power Consumption |

Table 3. Chemical Composition of Ferrous Material Under Investigation.

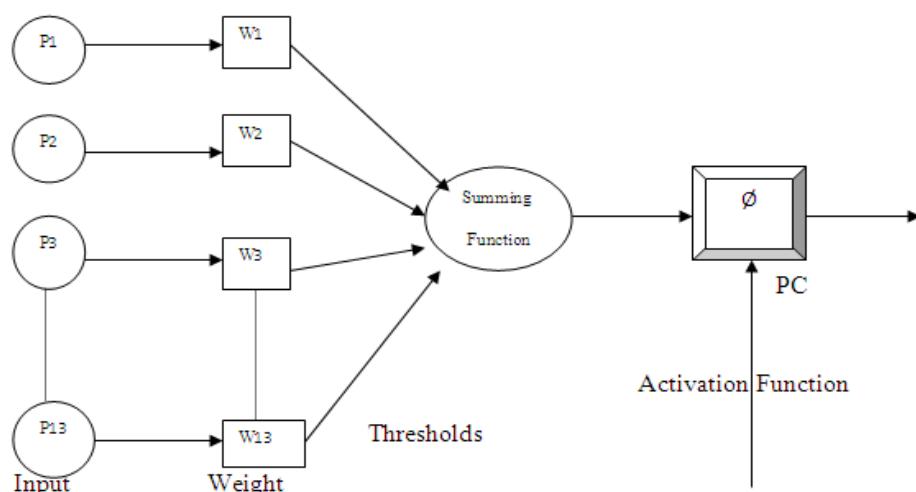
| S.N | Material | C% | Si% | Mn % | S % | P % | Ni % | Cr % | Fe % |
|-----|----------|------|------|------|-------|-------|------|------|-----------|
| 1 | EN8 | 0.4 | 0.25 | 0.8 | 0.015 | 0.015 | - | - | Remaining |
| 2 | EN1A | 0.15 | 0.1 | 1.2 | 0.3 | 0.7 | - | - | Remaining |
| 3 | S.S.304 | 0.08 | 0.03 | 2 | 0.03 | 0.045 | 10.5 | 20 | Remaining |

Table 4. Chemical Composition of Non-Ferrous Material Under Investigation.

| S.N | Material | C% | Si% | Mn % | S % | P % | Ni % | Cr % | Fe % |
|-----|---------------|------|-----|------|-----|-----|------|------|---------|
| 1 | Brass | 0.63 | 3.5 | 0.4 | - | - | 34 | - | Max 0.1 |
| 2 | Aluminum 6063 | 0.1 | 0.9 | - | 0.1 | 0.2 | 0.1 | 97.5 | 0.35 |

3. Artificial Neural Network (ANN) Model Formulation

Artificial neural networks (ANN) can replicate numerous functions of human behavior, which are formed by a predetermined number of layers with altered computing elements called neurons. In order to build a network, the neurons are interrelated. The crowd of connections determines the form and objectives of the ANN. The processing capacity of the network is stored in the inter unit connection strengths, or weights, which are tuned in the learning process. The training algorithm is defined as a procedure that consists of adjusting the weights and biases of a network that minimize selected function of the error between the actual and desired output. Neural network models provide an alternative approach to analyze the data. An easy process element of the ANN is shown in Fig. 3. The network has three layers; the input, hidden, and output layers. The input and output layers are defined as nodes and the hidden layer provides a relation between the input and output layers. Initially, the weights of the nodes are random and the network has not any knowledge. For a given input pattern, the network produces an associated output pattern. The various input and output parameters are as shown in Fig. 4.

**Fig. 3. Basic of ANN Methodology.**

ANN modelling and prediction of various responses has been increase in the various research applications. The various input/ output are as shown in figure 4. The various input parameters of ANN model are anthropometric data, operator experience, work piece stress, turning work piece length and diameters, cutting speed, feed and depth of cut, cutting force, tangential force, machine vibration, tool- work piece interface temperature, humidity, atmospheric temperature, light illumination and the air flow. The

output parameter is power consumption. The various steps used in the formulation of ANN based model to correlate the various input and output are as follows:

3.1. Pre-processing of the Data (Scaling)

The performance capability of the neural network is essentially dependent on the pre-processing of the actual data set .With any experimentation the numbers of inputs are set and corresponding output values are recorded in the present context there are four/six/thirteen such inputs and five outputs. Say inputs are X_1, X_2, \dots, X_{13} and output is y . If numbers of experiments are carried out then realized values of variables X_1 exhibit the range $X_{1\min}$ to $X_{1\max}$. Such minimum and maximum occurs for all the variables. The real values are non process able on the NN primarily because every value on NN must be between '0' and '1'.The process of converting real values to range '0' to '1' is called as scaling. For example in an experiment number of 50 values of X_1 say 30. If all the experiments are considered then the minimum value of X_1 is 16 and maximum value of X_1 is 62. The scaled value of X_1 for the experiment number 50 is given by equation (8)

$$X_{1s}(50) = [X_1(50) - X_{1\min}] / [X_{1\max} - X_{1\min}]$$

$$X_{1s}(50) = [30 - 16] / [62 - 16] = 0.304348 \quad (8)$$

This method guarantees the values between zero and one after scaling. This process is carried out for all the input and output variables for all the experiments. NN produces scaled output only. For its real time interpretation de-scaling (reverse process of scaling) should be applied at the time of interpretation. For example Y_{cs50} is the scaled output value for experimentation number 50. If it is to be compared with Y_{e50} (i.e. experimental output to the experiment number 50) then Y_{cs50} must be computed as follows (Equation 9):

$$Y_{cd}(50) = Y_{cs}(50)[Y_{\max} - Y_{\min}] + Y_{\min}$$

$$\text{Error} = Y_e(50) - Y_{cd}(50) \quad (9)$$

This error is with real output. Since NN is capable of handling the values between zero and one only, the real data quite often may be beyond this range. It is for this reason the entire set of input and output for each experiment must be scaled before loading the neural network.

3.2. Training, Testing and Simulation of the Data

Del value computation: Del value is the difference between computed and actual. For the last layer, both values are available, hence del (4) (0) = ($y_a - y_c$) .This del value (difference) is the combined effect of all the values cell (4,0) is receiving. There are three cells in layer 3, hence there are three inputs for final layer. This del value should be distributed into three parts and weight and threshold should be adjusted so that y_c will improve in the direct of y_a .refer equation 10.

$$S(4,0) = W(0,4,0)Pv(3,0) + W(1,4,0)Pv(3,1) + W(2,4,0)Pv(3,1)$$

$$Pv(4,0) = \frac{1}{(1 - e^S)} \quad (10)$$

Weight correction: The weight should be corrected as equation 11;

$$W = w + (\text{LearningRate}) * \text{DelValue} * T \quad (11)$$

Where T is the Pv of the cell

While applying this correction there can be a sudden change in the weight which may be undesirable. In order to stabilize the value of weights, not only the correct value of the weight should be considered but also the weight on earlier iteration should be honored. Say w(0) is the correct weight, w(1) is the weight (Refer equation 12) of earlier iteration, w(2) is the weight before two iteration, w(3) is the weight before three iterations. Weighted average of these four values is recommended for stability criterion.

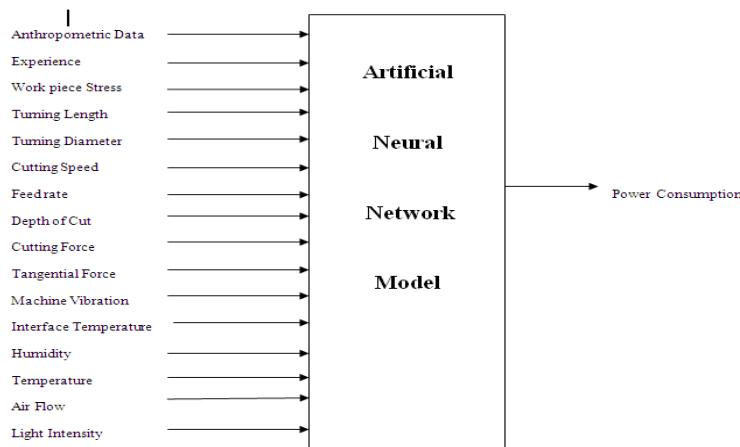


Fig. 4. Schematic Model Of Artificial Neural Network For Prediction Of Power Consumption For Dry Turning.

Say new w = Weighted average x correction

where; Weighted average = $[w(0) + 0.75w(1) + 0.35w(2) + 0.13w(3)]/2.2$

The coefficients used here are not very rigid and may be altered judiciously. Such changes should be done to award more importance to latest values.

$$\begin{aligned} NewW &= Correction + (LearningRate) * DelValue * Pv \\ W &= [w(0) + 0.75w(1) + 0.35w(2) + 0.13w(3)]/2.2 + LearningRate * DelValue * Pv \end{aligned} \quad (12)$$

Threshold correction:

Threshold is corrected by difference value i.e.

$$NewThreshold = OldThreshold - learningrate * DelValue$$

Computation of Del value of hidden layer (refer equation 13)

$$Del(3,0) = Pv(4,0) * Pv(4,0) * CF \quad (13)$$

Where CF (refer equation 14) is the correction factor, which considers output from this cell (3,0) as deficient. In this case there is only one correction from (3,0) to (4,0), Thus

$$CF = \sum w * Del(Layer, Cell)$$

$$CF = W(0,4,0) * Del(4,0) \quad (14)$$

Learning rate: It has the value between 0 and 1. Very small values of learning rate will cause smaller correction on weight and threshold. Large value of learning rate implies oscillating values of weight and thresholds. These extreme situations are not desirable. A steady improvement on weight and threshold without any oscillation is ideal. The optimal value of learning rate has direct dependence on intricacies of relationship between input and output. A judicious method is to try different values of learning rate. Present work is tried with 0.1, 0.2,-----, 0.9 for 1000 iterations and it has understood that error after 1000 iterations are lowest between learning rate 0.2 to 0.3. Further search between these two limits helped to decide learning rate precisely.

The results of such as a stabilized network are stored in the form of output file. This output file indicates weights for each connection and threshold for each cell. If some new inputs are now available then the value of Y (dependent variable) can now be computed in single iteration. In this manner the model acts as a predictive network and can decide output values for variety of inputs.

3.3. 13-10-1 ANN Network Construction

ANN is one of the most efficient and accurate modelling techniques. ANN is used for modelling complex relationships which are difficult to describe with physical models. ANN has been broadly applied in modelling many metal-cutting operations such as turning, milling, and drilling. However, this work was inspired by the model formulation to develop the relation between dependent and the independent parameters. The parameters such as number of data, number of hidden layers, learning rate, and processing function used affect the accuracy and the reliability of the ANN model. It is seen that both the processing functions, logsig and tansig, produce almost the same performance in different problems. The tansig processing function and single hidden layer have been used. A trial and error scheme has been used to determine the appropriate number of hidden neurons. The number of hidden neurons was determined as ten neurons. Since the input parameters were in different ranges, this parameters were normalized within specific ranges in order to prevent the simulated neurons from being driven too far into saturation. The maximum number learning rate values for each run were selected as 0.9.

The field data based modelling has been achieved based on observed data for the thirteen dependent pi terms. Simulation consists of three layers. First layer is known as input layer. No. of neurons in input layer is equal to the no. of independent variables. Second layer is known as hidden layer. It consists of ten number of neurons. The third layer is output layer. It contains one neuron as one of dependent variables at a time. Multilayer feed forward topology is decided for the network. 13-10-1 topology is used for the ANN network. The error during the learning called as mean squared error (MSE) is calculated as by equation (15).

$$RMSE = 1/N \sum_i |(t_i - t_o)^2| \quad (15)$$

where t_i is the targeted value and t_o is the output value. N is the number of experiments. The weights between hidden layer and output layer are adjusted and are again calculated using the chain rule of differentiation by equation (16).

$$\Delta w_{ji}(n) = \alpha \Delta w_{ji}(n-1) + \eta \delta_j(n) y_i(n) \quad (16)$$

where

- η = The learning rate parameter and
- α = The momentum coefficient

3.4. Formulation of a Model for the ANN network Obtain

The ANN model in terms of weights and thresholds related to the turning of ferrous and nonferrous is given by equation 17.

$$X_{1,1} = (1 - e^{-1*sum(layer1Cell0)}) / (1 + e^{-1*sum(layer1Cell0)})$$

where

$$\begin{aligned} Sum(layer1Cell0) = & 3.745297713 * X_{0,1} + 0.851430041 * X_{0,2} + 1.726120042 * X_{0,3} + 0.341669406 * X_{0,4} + \\ & 0.488410049 * X_{0,5} - 0.79931398 * X_{0,6} - 0.72102681 * X_{0,7} + 2.296032596 * X_{0,8} + 3.625995449 * X_{0,9} + \\ & 1.788433786 * X_{0,10} + 1.7657470 * X_{0,11} + 3.460183256 * X_{0,12} - 0.61366443 * X_{0,13} + 3.7481638 \end{aligned}$$

$$X_{1,2} = (1 - e^{-1*sum(layer1Cell1)}) / (1 + e^{-1*sum(layer1Cell1)})$$

where

$$\begin{aligned} Sum(layer1Cell1) = & 2.345062155 * X_{0,1} - 3.08726271 * X_{0,2} - 3.69504353 * X_{0,3} + 0.661745799 * X_{0,4} + \\ & 1.7399954725 * X_{0,5} - 0.13427043 * X_{0,6} - 0.96773004 * X_{0,7} + 0.150210896 * X_{0,8} - 0.17739114 * X_{0,9} + \\ & 0.344055425 * X_{0,10} - 1.82431336 * X_{0,11} + 0.503975777 * X_{0,12} + 0.534115499 * X_{0,13} - 0.823777223 \\ X_{1,3} = & (1 - e^{-1*sum(layer1Cell2)}) / (1 + e^{-1*sum(layer1Cell2)}) \end{aligned}$$

where

$$\begin{aligned} Sum(layer1Cell2) = & -1.710748 * X_{0,1} - 0.27665817 * X_{0,2} + 2.938171558 * X_{0,3} + 5.99570029 * X_{0,4} + \\ & 3.375021702 * X_{0,5} + 2.307321702 * X_{0,6} + 2.150321902 * X_{0,7} + 1.685218402 * X_{0,8} + 3.874957577 * X_{0,9} - \\ & 1.16449537 * X_{0,10} + 1.668932585 * X_{0,11} - 2.32885806 * X_{0,12} + 4.41405046 * X_{0,13} + 4.63359699 \\ X_{1,4} = & (1 - e^{-1*sum(layer1Cell3)}) / (1 + e^{-1*sum(layer1Cell3)}) \end{aligned}$$

where

$$\begin{aligned} Sum(layer1Cell3) = & -2.72785443 * X_{0,1} + 1.371796087 * X_{0,2} - 1.34263123 * X_{0,3} + 0.078675077 * X_{0,4} + \\ & 2.132348433 * X_{0,5} - 0.44714221 * X_{0,6} + 0.353559785 * X_{0,7} + 1.045764335 * X_{0,8} + 2.044842323 * X_{0,9} + \\ & 0.679840098 * X_{0,10} + 1.461904188 * X_{0,11} + 2.067278878 * X_{0,12} - 1.811783377 * X_{0,13} + 1.68478773 \\ X_{1,5} = & (1 - e^{-1*sum(layer1Cell4)}) / (1 + e^{-1*sum(layer1Cell4)}) \end{aligned}$$

where

$$\begin{aligned} Sum(layer1Cell4) = & 2.767428727 * X_{0,1} + 4.093989014 * X_{0,2} - 3.4141247 * X_{0,3} + 3.707141159 * X_{0,4} + \\ & 2.474428392 * X_{0,5} + 0.241979189 * X_{0,6} - 1.910930939 * X_{0,7} + 0.265968189 * X_{0,8} - 0.11920592 * X_{0,9} + \\ & 0.478513519 * X_{0,10} + 3.386187242 * X_{0,11} - 1.19873616 * X_{0,12} - 0.98697079 * X_{0,13} + 1.94255073 \\ X_{1,6} = & (1 - e^{-1*sum(layer1Cell5)}) / (1 + e^{-1*sum(layer1Cell5)}) \end{aligned}$$

where

$$\begin{aligned} Sum(layer1Cell5) = & -1.71434382 * X_{0,1} - 0.20527044 * X_{0,2} - 0.59482846 * X_{0,3} + 2.118099368 * X_{0,4} + \\ & 4.544825633 * X_{0,5} + 9.296859437 * X_{0,6} + 2.475629732 * X_{0,7} + 0.012643898 * X_{0,8} - 1.25854877 * X_{0,9} + \\ & 0.354807126 * X_{0,10} + 2.793029486 * X_{0,11} + 0.547359049 * X_{0,12} - 1.47662247 * X_{0,13} + 7.13536638 \\ X_{1,7} = & (1 - e^{-1*sum(layer1Cell6)}) / (1 + e^{-1*sum(layer1Cell6)}) \end{aligned}$$

where

$$\begin{aligned} Sum(layer1Cell6) = & 0.647064044 * X_{0,1} + 1.920454359 * X_{0,2} + 0.738700441 * X_{0,3} + 2.167387841 * X_{0,4} + \\ & 0.19100231 * X_{0,5} + 0.89332344 * X_{0,6} + 0.416624462 * X_{0,7} - 0.12545268 * X_{0,8} - 0.22325893 * X_{0,9} + \\ & 2.602458614 * X_{0,10} - 1.77726299 * X_{0,11} - 0.1714199 * X_{0,12} + 3.302598046 * X_{0,13} + 1.5264872 \\ X_{1,8} = & (1 - e^{-1*sum(layer1Cell7)}) / (1 + e^{-1*sum(layer1Cell7)}) \end{aligned}$$

where

$$\begin{aligned} Sum(layer1Cell7) = & -2.56386295 * X_{0,1} - 0.61889979 * X_{0,2} + 2.437212315 * X_{0,3} + 4.118528089 * X_{0,4} + \\ & 2.193527827 * X_{0,5} - 0.75161021 * X_{0,6} - 0.86175305 * X_{0,7} + 1.385575217 * X_{0,8} - 0.17360507 * X_{0,9} + \\ & 0.090992868 * X_{0,10} + 2.084672747 * X_{0,11} + 1.20543432 * X_{0,12} + 0.440684219 * X_{0,13} + 3.59174526 \\ X_{1,9} = & (1 - e^{-1*sum(layer1Cell8)}) / (1 + e^{-1*sum(layer1Cell8)}) \end{aligned}$$

where

$$\begin{aligned} \text{Sum(layer1Cell8)} &= 5.348459128 * X_{0,1} - 0.15459546 * X_{0,2} + 3.000182352 * X_{0,3} + 0.837113645 * X_{0,4} + \\ &2.601466514 * X_{0,5} + 4.596201758 * X_{0,6} - 0.22306825 * X_{0,7} - 0.13864495 * X_{0,8} + 0.6 + 0.9163278 * X_{0,9} + \\ &0.075802859 * X_{0,10} - 0.47529408 * X_{0,11} - 0.86014453 * X_{0,12} - 3.61127236 * X_{0,13} + 3.90522911 \\ X_{1,10} &= (1 - e^{-\text{sum(layer1Cell9)}}) / (1 + e^{-\text{sum(layer1Cell9)}}) \end{aligned}$$

where

$$\begin{aligned} \text{Sum(layer1Cell9)} &= -0.24168363 * X_{0,1} - 0.72580031 * X_{0,2} - 1.92666531 * X_{0,3} - 1.4183627 * X_{0,4} + \\ &0.714626317 * X_{0,5} - 1.0193888 * X_{0,6} + 0.733933636 * X_{0,7} + 2.175587658 * X_{0,8} + 0.428549901 * X_{0,9} + \\ &1.956621044 * X_{0,10} - 0.59300805 * X_{0,11} + 0.114523609 * X_{0,12} - 0.21258278 * X_{0,13} + 0.53392305 \\ \Pi D1 &= (1 - e^{-\text{sum(layer2Cell0)}}) / (1 + e^{-\text{sum(layer2Cell0)}}) \end{aligned}$$

where

$$\begin{aligned} \text{Sum(layer2Cell0)} &= 0.511979993 * X_{1,1} - 1.17628302 * X_{1,2} + 0.450303181 * X_{1,3} - 0.69805729 * X_{1,4} - \\ &1.05164677 * X_{1,5} + 1.079437041 * X_{1,6} + 0.771485314 * X_{1,7} + 0.896350576 * X_{1,8} + 1.304631653 * X_{1,9} - \\ &0.63981783 * X_{1,10} - 0.401842058 \end{aligned} \quad (17)$$

Similarly, using the same logic the models are formulated for the ferrous material data and nonferrous materials data separately. The sample observations are as shown in appendices.

3.5. Post Processing of the Result (De-Scaling)

Scaled value is further translated to its physical values by reverse scaling calculation. In this way once the network has gone through the learning process, it is capable of predicting output parameters. The complex relationship in manipulation of the output is not truly known, but the numerical results are obtainable. Moreover, these results are least affected by discrepant error. The adjustable neural network was tailored for three different situations earlier model using Buckingham's pi theorem. The comparison between experimental and ANN response is as shown in Fig. 5 - 7.

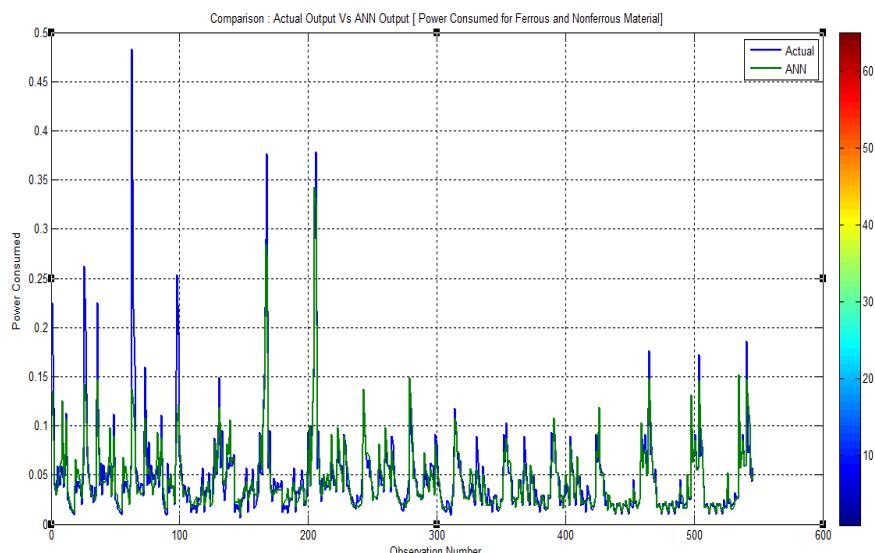


Fig. 5. Comparison between actual and ANN Output for Ferrous and Nonferrous Material.

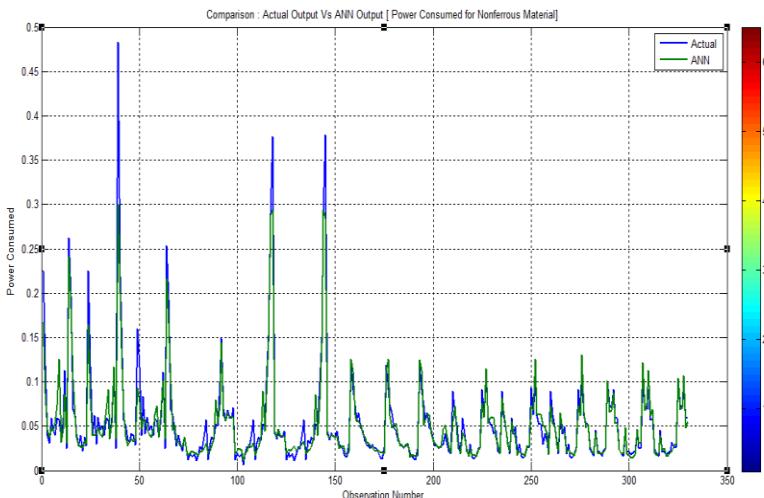


Fig. 6. Comparison between actual and ANN Output for Ferrous Material.

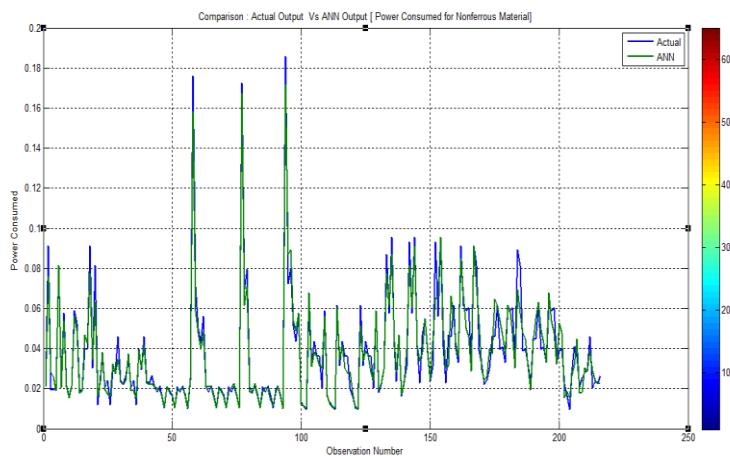


Fig. 7. Comparison between actual and ANN Output for Nonferrous Material.

4. Results & Discussion

Multilayer feed-forward back propagation artificial neural network was applied to model and predict the power consumption in the convectional dry turning operations. The experimental data were utilized to build the ANN model. The back-propagation training algorithms, Levenberg–Marquardt (LM), were used for ANNs training. The best the results were obtained with this algorithm compared to other training algorithms. One ANN structure 13-10-1, was tested. This means 1 node output layer, 10 node hidden layers, and 13 node input layer for input variables. The neural networks software was coded using the visual basic. The learning parameters of the proposed ANN structure are presented in Table 5. The Correlation, root mean square error and the reliability of the model are as shown in table 6.

$$Y_{cd}(50) = Y_{cs}(50)[Y_{\max} - Y_{\min}] + Y_{\min}$$

$$\text{Error} = Y_e(50) - Y_{cd}(50) \quad (18)$$

This error (Eqn 18) is with real output. Since NN is capable of handling the values between zero and one only, the real data quite often may be beyond this range. It is for this reason the entire set of input and output for each experiment must be scaled before loading the neural network.

Table 5. The training parameters used for 13-10-1 ANN Network.

| S.N | Training Parameters | |
|-----|-------------------------------------|-----------------------------------|
| 1 | The Number of layers | 3 |
| 2 | The Number of Neurons on the layers | Input-13, Hidden -10 and Output-1 |
| 3 | The initial weights | Between 0- 1 |
| 4 | Activation function | Sigmoid |
| 5 | Learning rate | 0.01 |
| 6 | Momentum constant | 0.95 |
| 7 | Normalization of data | 0.1-0.9 |
| 8 | Number of iterations | 20,000 |

Table 6. The training parameters used for 13-10-1 ANN Network.

| S.N | Material | Parameters | Values |
|-----|----------------------|-------------------------|---------------|
| 1 | Ferrous & Nonferrous | Correlation coefficient | 0.971508466 |
| 2 | Ferrous & Nonferrous | Root Mean square Error | 0.0233658445 |
| 3 | Ferrous & Nonferrous | Reliability in % | 98.9875534861 |
| 4 | Ferrous | Correlation coefficient | 0.95513400265 |
| 5 | Ferrous | Root Mean square Error | 0.00117758138 |
| 6 | Ferrous | Reliability in % | 99.089324752 |
| 7 | Nonferrous | Correlation coefficient | 0.9709900886 |
| 8 | Nonferrous | Root Mean square Error | 0.006654671 |
| 9 | Nonferrous | Reliability in % | 99.587375914 |

5. Conclusion

In this study, artificial neural network approach was used to predict the power consumption in the dry turning of ferrous and nonferrous materials in Indian scenario. The parameters such as operator, work piece, cutting process parameters and environmental parameters were measured by means of random plan of experimental design and the Indian seasonal condition. The data obtained were used to develop the approximate generalized power consumption models. The anthropometric ratio, shear stress, machine vibration, tool work piece interface temperature and light illumination are the dominant factor affecting the power consumption while tangential force, humidity, atmospheric and the air flow are least affecting parameters. The back-propagation NN training algorithms was used for ANNs training. The best result having the minimum error was obtained by ANN with 13-10-1 ANN network. The developed models were evaluated for their prediction capability with actual power consumption values. The predicted values were found to be close to the actual power consumption values. The developed models can be used effectively to predict the power consumption in the convectional step turning process. The overall correlation coefficient for training data, testing and prediction data shows the formation of best fit model. The advantages of the ANN compared to other methods are simplicity, speed, and capacity of learning, the ANN is a powerful tool in predicting the power consumption.

Appendix

Sample Observations

| Exp No | Actual | ANN | Exp No | Actual | ANN |
|---------------|---------------|-------------|---------------|---------------|-------------|
| 1 | 0.224905461 | 0.123026877 | 311 | 0.009549926 | 0.023988329 |
| 2 | 0.118576875 | 0.108893009 | 312 | 0.027542287 | 0.033884416 |
| 3 | 0.039810717 | 0.063095734 | 313 | 0.040738028 | 0.034673685 |
| 4 | 0.030902954 | 0.048977882 | 314 | 0.118032064 | 0.158489319 |
| 5 | 0.058884366 | 0.057543994 | 315 | 0.091201084 | 0.11994993 |
| 6 | 0.045708819 | 0.045708819 | 316 | 0.074131024 | 0.066069345 |
| 7 | 0.039810717 | 0.056234133 | 317 | 0.057543994 | 0.054954087 |
| 8 | 0.058884366 | 0.070794578 | 318 | 0.064565423 | 0.050118723 |
| 9 | 0.057543994 | 0.109144034 | 319 | 0.047863009 | 0.051286138 |
| 10 | 0.037153523 | 0.038904514 | 320 | 0.044668359 | 0.039810717 |
| 11 | 0.058884366 | 0.074131024 | 321 | 0.033884416 | 0.030902954 |
| 12 | 0.112719746 | 0.111173173 | 322 | 0.027542287 | 0.029512092 |
| 13 | 0.025118864 | 0.033884416 | 323 | 0.028183829 | 0.028840315 |
| 14 | 0.021379621 | 0.026915348 | 324 | 0.024547089 | 0.026915348 |
| 15 | 0.016218101 | 0.019952623 | 325 | 0.028840315 | 0.027542287 |
| 16 | 0.013182567 | 0.022387211 | 326 | 0.029512092 | 0.063095734 |
| 17 | 0.010964782 | 0.018197009 | 327 | 0.041686938 | 0.048977882 |
| 18 | 0.009549926 | 0.015848932 | 328 | 0.033113112 | 0.039810717 |
| 19 | 0.0616595 | 0.050118723 | 329 | 0.021877616 | 0.025703958 |
| 20 | 0.031622777 | 0.045708819 | 330 | 0.018620871 | 0.023442288 |
| 21 | 0.043651583 | 0.060255959 | 331 | 0.089125094 | 0.051286138 |
| 22 | 0.036307805 | 0.033884416 | 332 | 0.063095734 | 0.033884416 |
| 23 | 0.036307805 | 0.034673685 | 333 | 0.050118723 | 0.033884416 |
| 24 | 0.019952623 | 0.030199517 | 334 | 0.033113112 | 0.021379621 |
| 25 | 0.058884366 | 0.045708819 | 335 | 0.018620871 | 0.019952623 |
| 26 | 0.261818301 | 0.136458314 | 336 | 0.058884366 | 0.058884366 |
| 27 | 0.196788629 | 0.111943788 | 337 | 0.041686938 | 0.043651583 |
| 28 | 0.069183097 | 0.075857758 | 338 | 0.021877616 | 0.025703958 |
| 29 | 0.0616595 | 0.057543994 | 339 | 0.018620871 | 0.021379621 |
| 30 | 0.041686938 | 0.031622777 | 340 | 0.036307805 | 0.018620871 |
| 31 | 0.028183829 | 0.023442288 | 341 | 0.020892961 | 0.017782794 |
| 32 | 0.039810717 | 0.025703958 | 342 | 0.025118864 | 0.018197009 |
| 33 | 0.022387211 | 0.035481339 | 343 | 0.011748976 | 0.017782794 |
| 34 | 0.03801894 | 0.02630268 | 344 | 0.028183829 | 0.019054607 |
| 35 | 0.028183829 | 0.024547089 | 345 | 0.028840315 | 0.019498446 |
| 36 | 0.225423921 | 0.116144861 | 346 | 0.029512092 | 0.024547089 |

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References

- [1] Belloufi, A., Assas, M., & Rezgui, I. (2013). Optimization of Turning Operations by Using a Hybrid Genetic Algorithm with Sequential Quadratic Programming. *Journal of Applied research and Technology*, 8(2), 88-94.
- [2] Gaitonde, V. N., Karnik, S. R., Figueira, L., & Davim, J. P., (2011). Performance comparison of conventional and wiper ceramic inserts in hard turning through artificial neural network modeling. *International Journal Advance Manufacturing Technology*, 52, 101–114.
- [3] Girish, K., & Kuldip S. S. (2015). Predictive Modelling and Optimization of Machining Parameters to Minimize Surface Roughness using Artificial Neural Network Coupled with Genetic Algorithm. *15th CIRP Conference on Modeling of Machining Operations*, 31, 453-458.
- [4] Schenck, H. Jr (1954). *Theories of Engineering a Experimentation*. McGraw Hill Book Co, New York.
- [5] Mangesh R. P., & Tatwawadi, V. H. (2015). ANN Based Model Development for Material Removal Rate in Dry Turning in Indian Context. *International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering*, 8(1), 130-135.
- [6] Meenu, G., & Surinder, K. (2015). Investigation of surface roughness and MRR for turning of UD-GFRP using PCA and Taguchi method. *Engineering Science& Technology, An International Journal*, 18. 70-81.
- [7] Prasad, M. V. R. D., Yelamanchili, S., & Karri S. T. (2015). Study of the Influence of Process Parameters on Surface Roughness When Inconel 718 Is Dry Turned Using CBN Cutting Tool by Artificial Neural Network Approach. *International Journal of Materials, Mechanics and Manufacturing*. 2(4), 335-338.
- [8] Nexhat Q., Kaltrine J., Avdyl B., Mirlind B., Hysni O. (2015). Effect of Machining Parameters and Machining Time on Surface Roughness in Dry Turning Process. *25th DAAAM International Symposium on Intelligent Manufacturing and Automation*, 100, 135-140.
- [9] Phate, M. R., Tatwawadi, V. H., Modak, J. P. (2012). Formulation of A Generalized Field Data Based Model For The Surface Roughness of Aluminum 6063 In Dry Turning Operation, *New York Science Journal*, 5(7): 38-46.
- [10] Rajendra S., Rahul K. G., & Jitendra K. T. (2014). Surface roughness analysis and compare prediction and experimental value for cylindrical stainless steel pipe (SS316l) in CNC lathe turning process using ANN method for re-optimization and cutting fluid. *The International journal of Engineering and Science*. 3(7), 58-71.
- [11] Tatwawadi, V. H., Modak, J.P. & Chibule, S. G. (2010). Mathematical Modeling and simulation of working of enterprise manufacturing electric motor, *International Journal of Industrial Engineering*, 17(4), 341-35.
- [12] Varaprasad. B., SrinivasaRao.Ch, & Vinay, P. V. (2014). Effect of Machining Parameters on Tool Wear in Hard Turning of AISI D3 Steel. *12th Global Congress on Manufacturing And Management, GCMM ,2014*, 97, 338-345.
- [13] Phate, M. R., & Tatwawadi, V. H. (2014). ANN Based Model For Prediction Of Human Energy In Conventional Machining of Nonferrous Material from Indian Industry Prospective. *Journal of Production Engineering*. 17(1), 1-6.
- [14] Phate, M. R., & Tatwawadi, V. H. (2015). Mathematical Model of Material Removal Rate and Power Consumption for Dry Turning of Ferrous Material using Dimensional Analysis in Indian Prospective. *Jordon Journal of Mechanical and Industrial Engineering*. 9 (1), 351-362.



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