Modeling of Power Consumption in Turning of Ferrous and Nonferrous Materials using Artificial Neural Network.

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Abstract—**Development of artificial neural network (ANN) for prediction of power consumption in the turning of ferrous and nonferrous materials has been the subject of the present paper. ANN was trained through field data obtained on the basis of random plan of experimentation. Various influential machining field parameters were taken into consideration. The inputs were machine operator, work piece, cutting tool, cutting process parameters, machine specification and the machining field environmental parameters while the output was power consumed during the machining of ferrous and nonferrous materials. It was illustrated that a multilayer perception neural network could efficiently model the power consumption as the response of the network, with a minimum error. The performance of the trained network was verified by further observations.6-5-1 topology has been used for getting simulated result. The results of ANN were compared with the results of conventional turning (CT) observations.**

Keywords— **Artificial Neural Network, Mathematical Model, Turning Process, ferrous and nonferrous material & convectional machining.**

I. INTRODUCTION

Artificial neural networks (ANN) have already been applied to various aspects of machining processes, such as optimization of machining parameters [5]-[6], prediction of cutting load [7]-[8], surface roughness modeling[8]- [14], tool wear detection [15]-[16] and estimation of cutting tool stress [17]. Finesa and Agah [18], and El-Sonbaty et al [18] used neural network for positioning error compensation. Hao used ANN and genetic algorithm for modeling the thermal error in turning. This literature survey indicates that responses in cutting operations are well apt to be modeled by neural networks. To the knowledge of the authors, no work can be mentioned to have been done on the application of neural networks to convectional turning (CT). The authors have recently developed an ANN model for prediction of power consumption in the turning of ferrous and nonferrous material in CT. This work has been extended to include S.S.304, EN1A and EN8 as ferrous material and Aluminium 6063 and brass as a nonferrous material for the present study.

ANNs offer a computational approach that is quite different from conventional digital computation. Digital computers operate sequentially and can do arithmetic computation extremely fast. Biological neurons in the human brain are extremely slow devices and are capable of performing a tremendous amount of computation tasks necessary to do everyday complex tasks, commonsense reasoning, and dealing with fuzzy situations. The underlining reason is that, unlike a conventional computer, the brain contains a huge number of neurons, information processing elements of the biological nervous system, acting in parallel. ANNs are thus a parallel, distributed information processing structure consisting of processing elements interconnected via unidirectional signal channels called connection weights. Although modeled after biological neurons, ANNs are much simplified and bear only superficial resemblance. Some of the major attributes of ANNs are: (a) they can learn from examples and generalize well on unseen data, and (b) are able to deal with situation where the input data are erroneous, incomplete, or fuzzy.

II. PROCESS VARIABLES AFFECTING THE POWER CONSUMPTION

A. *List of Variables under consideration*

The list of various parameters is as shown in table 1.

B. *Reduction of Variables by Buckingham's Pi Therom*

According to the theories of engineering experimentation by H. Schenck Jr. the choice of primary dimensions requires at least three primaries, but the analyst is free to choose any reasonable set he wishes, the only requirement being that his variables must be expressible in his system. There is really nothing basis or fundamental about the primary dimensions. For this case ,the variables are expressed in mass (M), length (L) , time (T), temperature (θ) and angle (Δ).The final dimensionless pi term id as shown in table 2.

TABLE I
LIST OF PROCESS VARIABLES

S. N.	Process variables affecting the turning process		
	Description	**Symbol**	**Dimensions**
1	Anthropometric dimensions ratio of the operator.	An	$M^0 L^0 T^0 \theta^0 \Delta^0$
2	Weight of the operator.	W_p	$M^1 L^0 T^0 \theta^0 \Delta^0$
3	Age of the operator.	AGP	$M^0 L^0 T^1 \theta^0 \Delta^0$
4	Experience	EX	$M^0 L^0 T^1 \theta^0 \Delta^0$
5	Skill rating	SK	$M^0 L^0 T^0 \theta^0 \Delta^0$
6	Educational qualifications	EDU	$M^0 L^0 T^0 \theta^0 \Delta^0$
7	Psychological Distress	PS	$M^0 L^0 T^0 \theta^0 \Delta^0$
8	Systolic Blood pressure	SBP	$M^0 L^0 T^1 \theta^0 \Delta^0$
9	Diastolic Blood pressure	DBP	$M^0 L^0 T^0 \theta^0 \Delta^0$
10	Blood Sugar Level during Working	BSG	$M^1 L^{-3} T^0 \theta^0 \Delta^0$
11	Cutting Tool angles ratio.	CTAR	$M^0 L^0 T^0 \theta^0 \Delta^0$
12	Tool nose radius	R	$M^0 L^1 T^0 \theta^0 \Delta^0$
13	Tool overhang length	Lo	$M^0 L^1 T^0 \theta^0 \Delta^0$
14	Approach angle	α	$M^0 L^0 T^0 \theta^1 \Delta^0$
15	Setting angle	β	$M^0 L^0 T^0 \theta^1 \Delta^0$
16	Single point cutting tool Hardness	BHN	$M^0 L^0 T^0 \theta^0 \Delta^0$
17	Lip or Nose angle of tool	LP	$M^0 L^0 T^0 \theta^1 \Delta^0$
18	Wedge angle	WG	$M^0 L^0 T^0 \theta^1 \Delta^0$
19	Shank Length	LS	$M^0 L^1 T^0 \theta^0 \Delta^0$
20	Total length of the tool	LT	$M^0 L^1 T^0 \theta^0 \Delta^0$
21	Tool shank width	SB	$M^0 L^1 T^0 \theta^0 \Delta^0$
22	Tool shank Height	SH	$M^0 L^1 T^0 \theta^0 \Delta^0$
23	Work piece hardness	BHNW	$M^0 L^0 T^0 \theta^0 \Delta^0$
24	Weight of the raw work piece.	W	$M^1 L^0 T^0 \theta^0 \Delta^0$
25	Ultimate Shear stress of the workpiece material	σ_{sut}	$M^1 L^{-1} T^{-2} \theta^0 \Delta^0$
26	Density of the workpiece material	DST	$M^1 L^{-3} T^0 \theta^0 \Delta^0$
27	Length of the raw workpiece	LR	$M^0 L^1 T^0 \theta^0 \Delta^0$
28	Diameter of the raw workpiece	DR	$M^0 L^1 T^0 \theta^0 \Delta^0$
29	Cutting Speed	VC	$M^0 L^1 T^{-1} \theta^0 \Delta^0$
30	Feed	f	$M^0 L^1 T^0 \theta^0 \Delta^0$
31	Depth of cut	D	$M^0 L^1 T^0 \theta^0 \Delta^0$
32	Cutting force	FC	$M^1 L^1 T^{-2} \theta^0 \Delta^0$
33	Tangential Force.	FT	$M^1 L^1 T^{-2} \theta^0 \Delta^0$
34	Spindle revolution	N	$M^0 L^0 T^{-1} \theta^0 \Delta^0$
35	Machine Specification ratio	MSP	$M^0 L^0 T^0 \theta^0 \Delta^0$
36	Power of the Machine motor	HP	$M^1 L^2 T^{-3} \theta^0 \Delta^0$
37	Weight of the machine	Wm	$M^1 L^0 T^0 \theta^0 \Delta^0$
38	Age of the machine	AGM	$M^0 L^0 T^1 \theta^0 \Delta^0$
39	Atmospheric Humidity	Φ	$M^0 L^0 T^0 \theta^0 \Delta^0$
40	Atmospheric Temperature	DT	$M^0 L^0 T^0 \theta^0 \Delta^1$
41	Air Flow	Vf	$M^0 L^1 T^{-1} \theta^0 \Delta^0$
42	Light Intensity	LUX	$M^1 L^0 T^{-4} \theta^0 \Delta^0$
43	Sound level	DB	$M^0 L^0 T^0 \theta^0 \Delta^0$
44	Power consumption	PC	$M^1 L^2 T^{-3} \theta^0 \Delta^0$

C. Experimental plan

For multifactor experiments two types of plans viz. classical plan or full factorial and factorial plan are available, in this experimentation conventional plan of experimentation is recommended. In all data was collected from total 585 experiments of five material S.S.304, EN1A, EN8, Al 6063 and Brass. The experimental set up is as shown in figure 1.

III. MODEL FORMULATION BY ARTIFICIAL NEURAL NETWORK

Artificial neural network (ANN) takes their name from the network of nerve cells in the brain. Recently, ANN has been found to be an important technique for classification and optimization problem. Artificial Neural Networks (ANN) has emerged as a powerful learning technique to perform complex tasks in highly nonlinear dynamic environments. Some of the prime advantages of using ANN models are their ability to learn based on optimization of an appropriate error function and their excellent performance for approximation of nonlinear function.

Fig. 1 Experimental setup for the turning operation

TABLE III
LIST OF DIMENSIONLESS PI TERM FORMULATED

S. N	Pi term	Dimensionless ratio	Nature of basic physical quantities
1	π_1	An*SBP*SK*Ag*Wp *SPO2 / DBP*PS*EDU*EX*BSG*D^3	Machine operator data
2	π_2	AR * r * β * BHNT * LT*LP*LS / α * LO* SW * SH * WG	Single point cutting tool
3	π_3	BHNW * W raw* LR * τ / D * FC * DST * DR	Work piece material
4	π_4	f * FT * N * $Temp_{wp}$* VB_{Tool} / $VB_{Machine}$ * FC*VC	Cutting process parameters
5	π_5	SP * P_{HP} * $W_{m/c}$ / AGM* FC^2	Lathe Machine
6	π_6	HUM*DTO *V_f *DB*VC*FC/ LUX*D^3	Environmental data
7	π_{D1}	**PC/ FC * V**	**Power Consumption**

A. Need of ANN

The ANN is capable of performing nonlinear mapping between the input and output space due to its large parallel interconnection between different layers and the nonlinear processing characteristics. An artificial neuron basically consists of a computing element that performs the weighted sum of the input signal and the connecting weight. The sum is added with the bias or threshold and the resultant signal is then passed through a nonlinear function of sigmoid or hyperbolic tangent type. Each neuron is associated with three parameters whose learning can be adjusted; these are the connecting weights, the bias and the slope of the nonlinear function. For the structural point of view a NN may be single layer or it may be multilayer. In multilayer structure, there is one or many artificial neurons in each layer and for a practical case there may be a number of layers. Each neuron of the one layer is connected to each and every neuron of the next layer.The functional-link ANN is another type of single layer NN. This type of network the input data is allowed to pass through a functional expansion block where the input data are on linearly mapped to more number of points. The basic ANN model is as shown in figure 2. This is achieved by using trigonometric functions, tensor products or power terms of the input. The output of the functional expansion is then passed through a single neuron. The learning of the NN may be supervised in the presence of the desired signal or it may be unsupervised when the desired signal is not accessible. Here in
this paper ANN is supervised learning. Rumelhart developed the Back propagation (BP) algorithm, which is central to much work on supervised learning in MLP. A feed-forward structure with input, output, hidden layers and nonlinear sigmoid functions are used in this type of network. In recent years many different types of learning algorithm using the incremental back-propagation algorithm, evolutionary learning using the nearest neighbour MLP and a fast learning algorithm based on the layer-by-layer optimization procedure.
Intricate behaviour of output parameters can be studied using simulation techniques. In fact an approximate behaviour can be explained using regression analysis. The true intricacies take the shape of non-linear behaviour. Regression fails to explain any such deviation from assumed relationship. Multiplicity of behaviour cannot be combined in regression because it generates complicated relationship, which may not be resolved mathematically. In order to understand the fine behaviour of output parameters, simulation using ANN was the best proposition. The neural network used in this case was predictive in nature. It was range bound for all input factors. In neural network terminology total Input output cells were 7. A network with five hidden layers was reasonable to simulate. Mathematically both these numbers – number of layers and cells are justified in present day theories of neural network. All the input parameters were scaled down between zero and one using their maximum and minimum values. This is the requirement to make the data flow on neural network. The values of synaptic weights and thresholds were chosen randomly between zero and one. The data was iterated forward and backward to achieve accuracy at sixth place of decimal. The weights and threshold were corrected in every iteration. The values of weights and thresholds obtained at the end were matured values and indicated the end of learning process of the network. Thus it was very easy to answer what will be the output parameter if input factors are known. A separate program was written for this prediction. This program simulates the structure of entire network using final values of weights and thresholds. It carries out the single iteration using scaled values of input factors to generate the scaled values of output parameter. This scaled value is further translated to its physical value by reverse scaling calculations. In this way once the network has gone through the learning process, it is capable of predicting output parameters Viz. Value addition and human energy input immediately. 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. Separate network was not required for situation after improvement but it was essential to train the network about changed relationship between input output parameters after incorporating improvements in assembly system. Both the situations were truly viewed and difference in behaviour could be easily computed the network developed by ANN for all three models are as shown if figure 3,5 and 7 and the comparison between actual and the ANN outputs are as shown in figure 4,6 and 8. The true power and advantage of neural networks lies in their ability to represent both linear and non-linear relationships and in their ability to learn these relationships directly from the data being modelled. Traditional linear models are simply inadequate when it comes to modeling data that contains non-linear characteristics. Neural networks are designed to work with patterns - they can be classified as pattern classifiers or pattern associates.

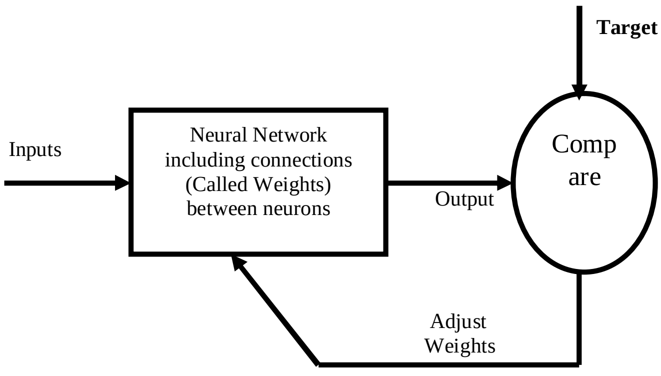

Fig-2: Basic ANN Model

B. Formulation of ANN Model

The optimum value of parameters used to train the ANN network is as shown in table 3.The ANN models are as given by equation 1,2 and 3.

TABLE IIIII

OPTIMUM PARAMETERS USED TO TRAIN THE ANN NETWORK

S.N.	Parameters	Optimum value
1	Number of hidden layer	1
2	Learning factor	0.1
3	Transfer function used	Sigmoid
4	Number of hidden neurons	5
5	Number of epochs	1000
6	Momentum factor	0.5

Model 1: For Turning of Ferrous and nonferrous materials

- Correlation Coefficient =0.9161179771956546
- Root Mean Square =0.157733431267774
- Reliability =

87.80989011%

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

Where

$$sum(layer1cell0) = -3.92600 * X_{0,1} - 0.95984 * X_{0,2} + 1.15693 * X_{0,3} + 3.95621 * X_{0,4} - 10.17656 * X_{0,5} + 0.32753 * X_{0,6} - 2.0614$$

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

Where

$$sum(layer1cell1) = 1.16225 * X_{0,1} + 0.48958 * X_{0,2} + 4.48538 * X_{0,3} - 0.09865 * X_{0,4} - 3.15324 * X_{0,5} - 0.62258 * X_{0,6} + 1.5942$$

$$X_{1,3} = (1 - e^{-1*Sum(layer1Cell2)})/(1 + e^{-1*Sum(layer1Cell2)})$$

Where

$$sum(layer1cell2) = 3.42859 * X_{0,1} + 0.43029 * X_{0,2} + 4.62208 * X_{0,3} + 9.71165 * X_{0,4} + 3.66868 * X_{0,5} + 3.31096 * X_{0,6} - 1.1261$$

$$X_{1,4} = (1 - e^{-1*Sum(layer1Cell3)})/(1 + e^{-1*Sum(layer1Cell3)})$$

Where

$$sum(layer1cell3) = 4.93480 * X_{0,1} - 1.11872 * X_{0,2} - 2.94682 * X_{0,3} - 3.43607 * X_{0,4} - 1.27769 * X_{0,5} - 1.27769 * X_{0,6} + 1.0003$$

$$X_{1,5} = (1 - e^{-1*Sum(layer1Cell4)})/(1 + e^{-1*Sum(layer1Cell4)})$$

Where

$$sum(layer1cell4) = 1.16632 * X_{0,1} - 0.21854 * X_{0,2} + 0.20694 * X_{0,3} - 0.46583 * X_{0,4} - 0.47970 * X_{0,5} + 0.19439 * X_{0,6} + 0.9168$$

$$PC = (1 - e^{-1*Sum(layer2Cell0)})/(1 + e^{-1*Sum(layer2Cell0)})$$

Where

$$sum(layer2cell0) = 1.3815 * X_{1,1} + 1.25564 * X_{1,2} - 0.46085 * X_{1,3} + 1.04069 * X_{1,4} - 3.02215 * X_{1,5} + 0.00000$$

(Eqn.1)

Model 2 : For turning of Ferrous Material

- Correlation Coefficient =0.90789834590931
- Root Mean Square =0.146175451030486
- Reliability =88.87272727 %

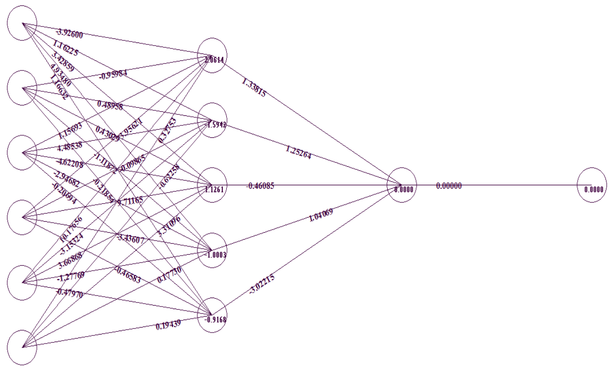

Fig-3: 6-5-1 ANN Model for turning of All Material data.

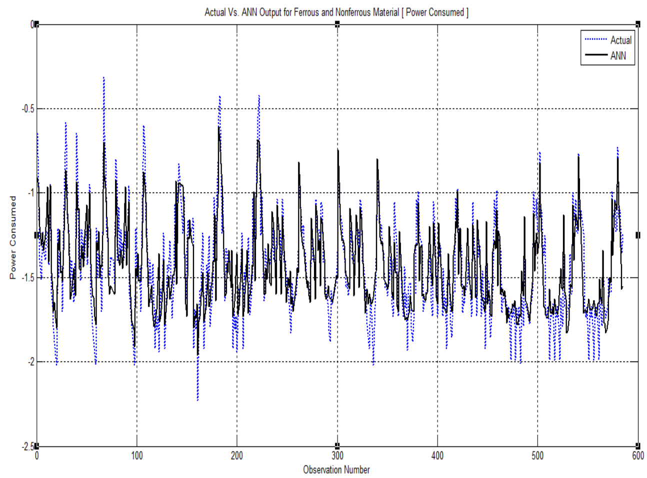

Fig-4: Comparison between Actual and ANN model for All material.

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

Where

$$sum(layer1cell0) = -2.21789 * X_{0,1} - 0.31074 * X_{0,2} - 1.93307 * X_{0,3} - 5.72529 * X_{0,4} + 15.17661 * X_{0,5} + 0.23898 * X_{0,6} - 3.9346$$

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

Where

$$sum(layer1cell1) = 2.30318 * X_{0,1} + 2.30318 * X_{0,2} + 0.78437 * X_{0,3} - 1.90586 * X_{0,4} + 1.72566 * X_{0,5} + 1.44385 * X_{0,6} - 0.8833$$

$$X_{1,3} = (1 - e^{-1*Sum(layer1Cell2)})/(1 + e^{-1*Sum(layer1Cell2)})$$

Where

$$sum(layer1cell2) = -0.556830 * X_{0,1} + 0.19367 * X_{0,2} - 0.18648 * X_{0,3} + 2.51526 * X_{0,4} + 1.54239 * X_{0,5} + 0.76082 * X_{0,6} - 0.3423$$

$$X_{1,4} = (1 - e^{-1*Sum(layer1Cell3)})/(1 + e^{-1*Sum(layer1Cell3)})$$

Where

$$sum(layer1cell3) = 0.94223 * X_{0,1} - 4.45814 * X_{0,2} + 0.73124 * X_{0,3} - 1.83730 * X_{0,4} - 0.24247 * X_{0,5} + 4.35527 * X_{0,6} - 2.0429$$

$$X_{1,5} = (1 - e^{-1*Sum(layer1Cell4)})/(1 + e^{-1*Sum(layer1Cell4)})$$

Where

$$sum(layer1cell4) = 1.74585 * X_{0,1} + 0.31055 * X_{0,2} - 3.88275 * X_{0,3} - 3.04742 * X_{0,4} + 1.08793 * X_{0,5} + 1.78056 * X_{0,6} + 1.4393$$

$$PC = (1 - e^{-1*Sum(layer2Cell0)})/(1 + e^{-1*Sum(layer2Cell0)})$$

Where

$$sum(layer2cell0) = 2.07441 * X_{1,1} + 0.64091 * X_{1,2} - 1.97879 * X_{1,3} + 0.31121 * X_{1,4} - 1.04151 * X_{1,5} + 0.00000$$

(Eqn.2)

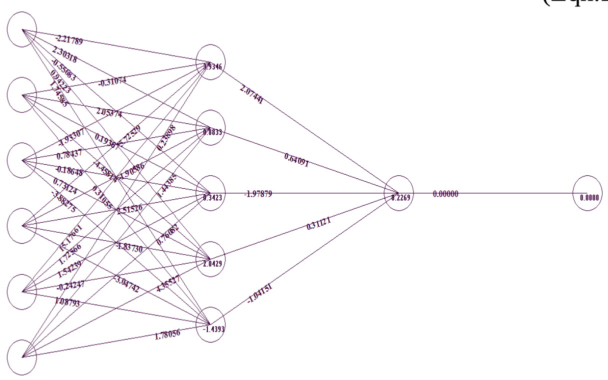

Fig-5: 6-5-1 ANN Model for turning of ferrous Material data.

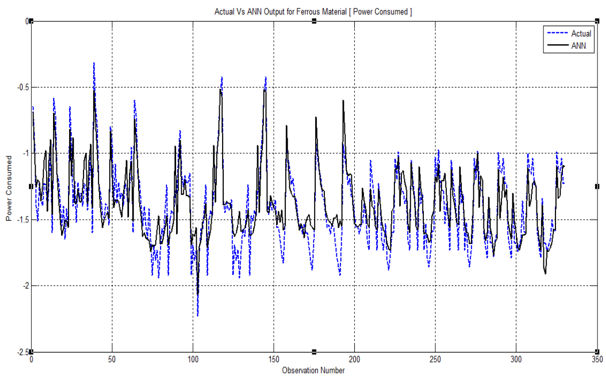

Fig-6: Comparison between Actual and ANN model for ferrous material.

Model 3 : For turning of Nonferrous Material

- Correlation Coefficient =0.917322928741176
- Root Mean Square =0.130248431675137
- Reliability = 90.24166667%

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

Where

$$sum(layer1cell0) = 4.44212 * X_{0,1} + 14.01318 * X_{0,2} + 16.36121 * X_{0,3} + 11.51879 * X_{0,4} + 7.59484 * X_{0,5} + 7.76097 * X_{0,6} - 5.7216$$

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

Where

$$sum(layer1cell1) = -3.68775 * X_{0,1} - 0.40033 * X_{0,2} + 0.71806 * X_{0,3} - 1.29215 * X_{0,4} - 0.95935 * X_{0,5} - 1.79097 * X_{0,6} + 0.2704$$

$$X_{1,3} = (1 - e^{-1*Sum(layer1Cell2)})/(1 + e^{-1*Sum(layer1Cell2)})$$

Where

$$sum(layer1cell2) = 0.12400 * X_{0,1} - 2.76638 * X_{0,2} - 6.04964 * X_{0,3} + 15.95501 * X_{0,4} - 15.223226 * X_{0,5} + 2.97805 * X_{0,6} - 3.3621$$

$$X_{1,4} = (1 - e^{-1*Sum(layer1Cell3)})/(1 + e^{-1*Sum(layer1Cell3)})$$

Where

$$sum(layer1cell3) = 4.74921 * X_{0,1} + 0.14112 * X_{0,2} - 0.40964 * X_{0,3} + 1.68634 * X_{0,4} + 0.43721 * X_{0,5} + 2.07350 * X_{0,6} - 0.51199$$

$$X_{1,5} = (1 - e^{-1*Sum(layer1Cell4)})/(1 + e^{-1*Sum(layer1Cell4)})$$

Where

$$sum(layer1cell4) = 14.15752 * X_{0,1} + 2.07703 * X_{0,2} - 6.45692 * X_{0,3} + 1.73585 * X_{0,4} - 12.98890 * X_{0,5} + 9.46460 * X_{0,6} - 3.2115$$

$$PC = (1 - e^{-1*Sum(layer2Cell0)})/(1 + e^{-1*Sum(layer2Cell0)})$$

Where

$$sum(layer2cell0) = 0.48587 * X_{1,1} + 6.89699 * X_{1,2} - 0.61445 * X_{1,3} + 6.80064 * X_{1,4} - 0.74602 * X_{1,5} + 0.00000$$

(Eqn.3)

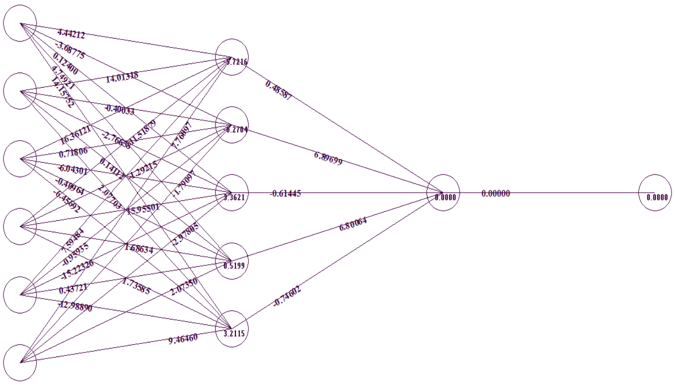

Fig-7: 6-5-1 ANN Model for turning of nonferrous Material data.

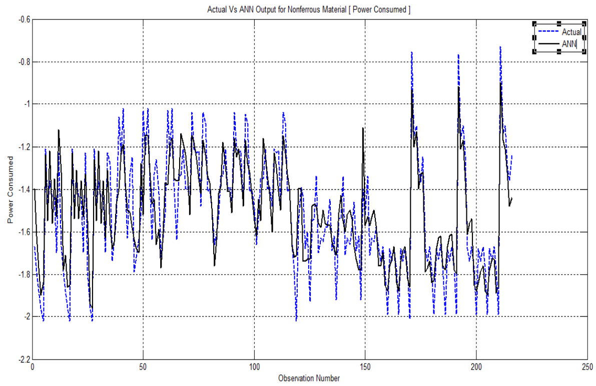

Fig8: Comparison between Actual and ANN model for nonferrous material.

IV. Conclusions

The power consumption for turning of ferrous and nonferrous maternal was modelled by artificial neural network, in the present study. The following characteristics of the network and training data could yield sufficiently accurate results: Multilayer perception was used for this purpose. The network was trained with field data carried out on the basis of random plan of experimentation and observation .The trained network was verified with separate observed data. Totally, 546 (330 for ferrous and 216 for nonferrous material) observations were taken for training and testing the network. Three-layered back propagation network was proposed for modelling the power consumption. Sigmoid function and one hidden layer accommodating five neurons could converge to acceptable output accuracy after 950 epochs. The test of the trained networks showed good agreement existing between their predictions and the experimental results.

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