ANN Based Model Development for Material Removal Rate in Dry Turning in Indian Context

Mangesh R. Phate, V. H. Tatwawadi

Abstract—This paper is intended to develop an artificial neural network (ANN) based model of material removal rate (MRR) in the turning of ferrous and nonferrous material in a Indian small-scale industry. MRR of the formulated model was proved with the testing data and artificial neural network (ANN) model was developed for the analysis and prediction of the relationship between inputs and output parameters during the turning of ferrous and nonferrous materials. The input parameters of this model are operator, work-piece, cutting process, cutting tool, machine and the environment.

The ANN model consists of a three layered feedforward back propagation neural network. The network is 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.

Keywords—Field data based model, Artificial neural network, Simulation, Convectional Turning, Material removal rate.

I. INTRODUCTION

TURNING is a widely used machining process in manufacturing. Therefore, a best selection of cutting parameters to make happy an economic objective within the constraints of turning operations is a very significant assignment. Traditionally, the selection of cutting conditions for metal cutting is left to the machine operator Surface roughness, power consumption, material removal rate and productivity has received serious attention for many years. A considerable number of studies have investigated the general effects of the speed, feed, and depth of cut on the turning process [1]. Some researchers studied on the machinability of aluminum-silicon alloys [2]-[7]. The influence of several factors (speed, feed, and depth of cut) on cutting force and surface roughness has investigated by using orthogonal tests in turning Si-Al alloy [3]. The results showed that the surface roughness may be improved by using diamond tool. Recently, in order to obtain reasonable cutting parameters in turning casting aluminum alloy ZL108. The main influential factors of cutting force have been investigated by using carbide tool YG8 [4]. The results indicated the depth of cut had great influence

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on stability of whole cutting process in rough machining. The experimentation has carried out to simplify best analysis for non-ferrous materials [3].

For cast iron (CI) and steels, they employed the criteria of reducing the machining cost to a minimum. Several monograms were worked out to facilitate the practical determination of the most cost-effective machining environment. They pointed out that the more tricky- to-machine materials have a restricted range of parameters over which machining can be carried out and thus any attempt at optimizing their costs are artificial. They have suggested the use of Lagrangian multipliers for optimization of the constrained problem of part cost, with cutting power as the main restraint. In 1970, the researchers have discussed the use of goal programming and geometric programming to selection of machine they optimized cutting speed and feed rate to yield minimum production cost [9], [16]. In 1991, the researchers have described the design and development of an analytical tool for the selection of machine parameters in drilling [13]. Geometric programming was used as the basic methodology to determine values for feed rate and cutting speed that minimize the total cost of machining SAE 1045 steel with cemented carbide tools of ISO P-10 grade. Surface finish and machine power were taken as the constraints while optimizing cutting speed and feed rate for a given depth of cut [10]-[12].

II. MODEL FORMULATION BY ARTIFICIAL NEURAL NETWORK

A. Process Variables under Investigation

The term variables are used in a very general sense to apply any physical quantity that undergoes change. If a substantial quantity may be altered independent of the other quantities, then it is an independent variable. If a substantial quantity changes in reaction to the variation of one or more number of independent variables, then it is termed as dependent or response variable. If a physical quantity that affects our test is changing in random and uninhibited manner, then it is called an inappropriate variable. The variables affecting the efficiency of the phenomenon under consideration are operator data, single point cutting tool, lathe machine, work piece, process parameters and the environmental parameters. The dependent or the response variables in this case of turning operation is material removal rate. The list of various process variables that affects the machining phenomenon is as shown in Table I.

B. Reduction of Variables by Buckingham's Pi Theorem

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 logical set he needs, the only condition being that his variables must be expressible in his system [8], [14], [15]. 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 are as shown in Table II.

The dimensions of the finished work piece are as shown in Fig. 1. The dimensionless pi term for the various input are as shown in the Table II [17], [18].

TABLE I
LIST OF PROCESS VARIABLES

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

C. Workpiece Geometry and Properties
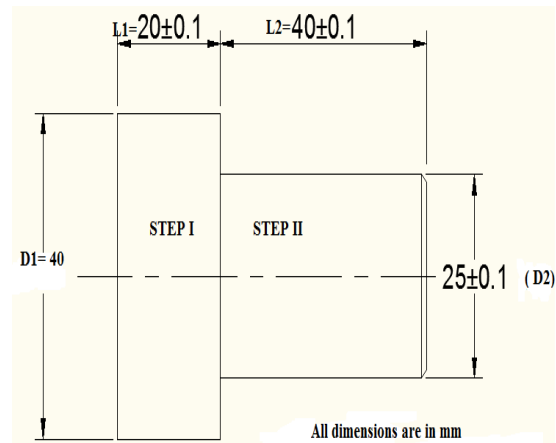
Fig. 1 Geometry of the finished Work-piece

D. Ann Based Model Formulation

Dry turning is a machining technique used for the manufacturing of cylindrical component like parts without any application of cutting fluids. In recent years, it has gained renewed interest for its potential environmental and economic benefits. However, the dimensional accuracy, which is the fundamental quality requirements for component parts, may suffer due to application of this technique. This paper presents experimental and analytical results of a preliminary investigation into dimensional accuracy in dry turning. The ANN is used to determine the effects of the operator, work piece, tool, machine, cutting process and the machining environment on dimensional error of the finished components. The various model obtained for the dimensional accuracy of the turned ferrous and nonferrous materials are as follows.

TABLE II
LIST OF DIMENSIONLESS PI TERM

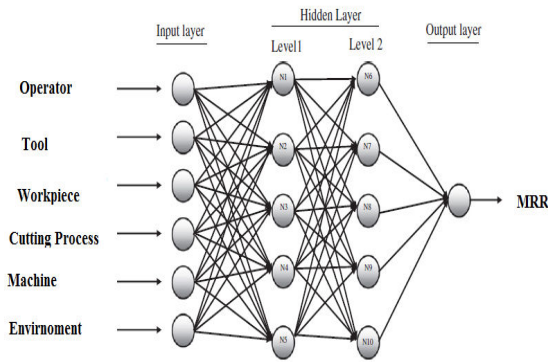| S. N.	Pi Term	Dimensionless Ratio	Nature
1	π_1	An*SBP*SK*Ag*Wp*SPO2/ DBP*PS*EDU*EX*BSG*D^3	Operator
2	π_2	AR * r * β * BHNT * LT*LP*LS / α * LO* SW * SH * WG	Cutting Tool
3	π_3	BHNW * W raw* LR * τ / D * FC * ϱ * DR	Work piece
4	π_4	f * FT * N * θ_{wp}* VB $_{Tool}$ / VB $_{Machine}$ * FC*VC	Cutting Process
5	π_5	SP * P_{HP} * $W_{m/c}$ / AGM* FC^2	Machine
6	π_6	HUM*DTO *Vf *DB*VC*FC/ LUX*D^3	Environment
7	π D_1	MRR /D^2*VC	**MRR**

Fig. 2 Basic of ANN topology
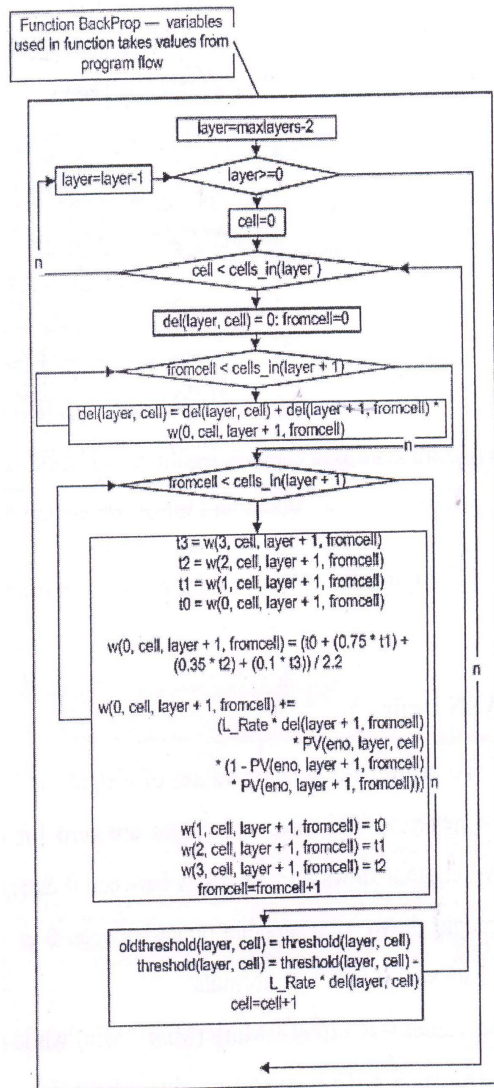

Fig. 3 Flow for back propagation in ANN

1. Model I: MRR Model for Ferrous and Nonferrous Materials

- Correlation Coefficient = 0.93162198441
- Root Mean Square =0.025164096
- Reliability = 98.80619006 %

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

where

$$sum(layer\ 1\ cell\ 0) = -1.56755 * X_{0,1} + 1.27957 * X_{0,2} - 1.31085 * X_{0,3} + 0.75105 * X_{0,4} + 0.15151 * X_{0,5} + 0.02717 * X_{0,6} + 0.4928$$

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

where

$$sum(layer\ 1\ cell\ 1) = 2.83919 * X_{0,1} + 0.89278 * X_{0,2} - 3.86722 * X_{0,3} + 4.03925 * X_{0,4} - 0.62060 * X_{0,5} - 0.62060 * X_{0,6} + 2.8336$$

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

where

$$sum(layer\ 1\ cell\ 2) = 2.73878 * X_{0,1} - 0.28556 * X_{0,2} - 0.71144 * X_{0,3} - 0.24587 * X_{0,4} + 0.44711 * X_{0,5} + 1.22458 * X_{0,6} + 0.2325$$

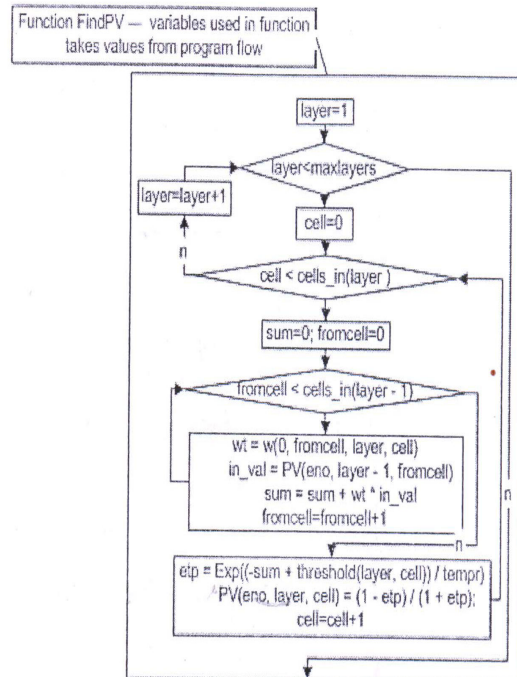Fig. 4 Flow for Determination of PV in ANN

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

where

$sum \ (layer \ 1 \ cell \ 3) = -0.49424 \quad * \ X_{0,1} - 1.06837 \quad * \ X_{0,2}$
$+ 2.58675 \quad * \ X_{0,3} - 1.45148 \quad * \ X_{0,4} - 4.99645 \quad * \ X_{0,5}$
$+ 9.41658 \quad * \ X_{0,6} + 1.6233$

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

where

$sum \ (layer \ 1 \ cell \ 4) = 1.03164 \quad * \ X_{0,1} + 0.95381 \quad * \ X_{0,2}$
$+ 0.99700 \quad * \ X_{0,3} + 0.32728 \quad * \ X_{0,4} + 0.46278 \quad * \ X_{0,5}$
$+ 2.62370 \quad * \ X_{0,6} - 0.4292$

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

where

$sum \ (layer \ 2 \ cell \ 0) = -0.21177 \quad * \ X_{1,1} + 0.86090 \quad * \ X_{1,2}$
$+ 0.35073 \quad * \ X_{1,3} - 0.60897 \quad * \ X_{1,4} + 0.61507 \quad * \ X_{1,5}$
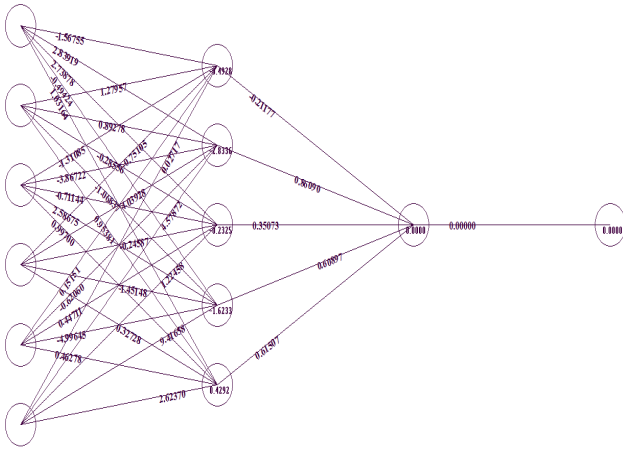$- 0.00000$

$$(1)$$

Fig. 5 6-5-1 ANN Network for MRR in the turning of ferrous and nonferrous material
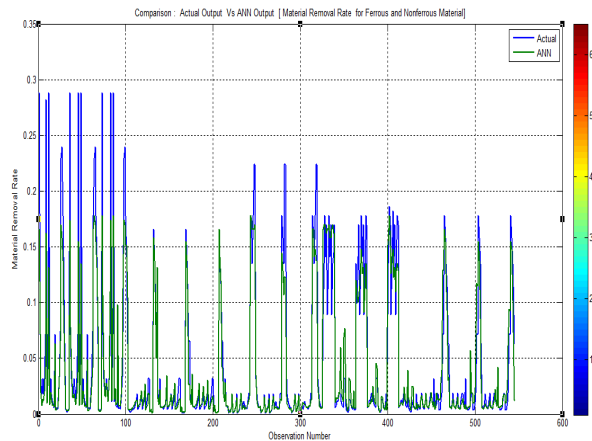

Fig. 6 Comparison between actual and ANN MRR for ferrous and nonferrous materials

2. Model II: MRR Model for Ferrous Materials

- Correlation Coefficient = 0.90876919211034
- Root Mean Square = 0.035117015297
- Reliability = 98.05573796061%

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

where

$sum \ (layer \ 1 \ cell \ 0) = 0.55484 \quad * \ X_{0,1} - 0.06176 \quad * \ X_{0,2}$
$+ 0.51481 \quad * \ X_{0,3} + 0.65062 \quad * \ X_{0,4} + 0.14857 \quad * \ X_{0,5}$
$+ 0.94237 \quad * \ X_{0,6} + 0.4729$

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

where

$sum \ (layer \ 1 \ cell \ 1) = 0.30050 \quad * \ X_{0,1} + 0.19075 \quad * \ X_{0,2}$
$+ 0.08964 \quad * \ X_{0,3} + 0.62011 \quad * \ X_{0,4} - 0.59247 \quad * \ X_{0,5}$
$+ 1.87723 \quad * \ X_{0,6} + 1.2168$

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

where

$sum \ (layer \ 1 \ cell \ 2) = 0.99506 \quad * \ X_{0,1} + 0.52449 \quad * \ X_{0,2}$
$+ 0.15191 \quad * \ X_{0,3} + 1.11283 \quad * \ X_{0,4} + 0.17832 \quad * \ X_{0,5}$
$+ 0.90380 \quad * \ X_{0,6} + 0.1193$

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

where

$sum \ (layer \ 1 \ cell \ 3) = 0.3403 \quad * \ X_{0,1} - 0.16705 \quad * \ X_{0,2}$
$+ 1.28832 \quad * \ X_{0,3} + 0.06407 \quad * \ X_{0,4} - 0.47462 \quad * \ X_{0,5}$
$+ 2.26729 \quad * \ X_{0,6} + 0.6696$

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

where

$sum \ (layer \ 1 \ cell \ 4) = 0.29565 \quad * \ X_{0,1} + 0.60947 \quad * \ X_{0,2}$
$+ 0.89084 \quad * \ X_{0,3} + 0.66821 \quad * \ X_{0,4} + 0.83378 \quad * \ X_{0,5}$
$+ 1.17056 \quad * \ X_{0,6} + 0.0170$

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

where

$sum \ (layer \ 2 \ cell \ 0) = 0.33164 \quad * \ X_{1,1} + 0.79261 \quad * \ X_{1,2}$
$+ 0.12408 \quad * \ X_{1,3} + 1.24680 \quad * \ X_{1,4} + 0.15857 \quad * \ X_{1,5}$
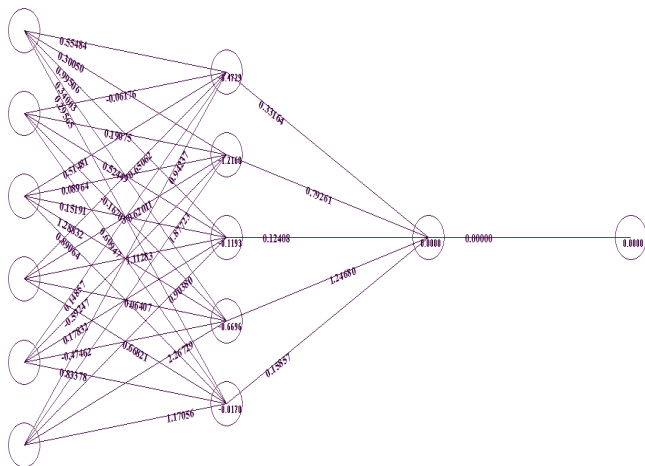$- 0.00000$

$$(2)$$

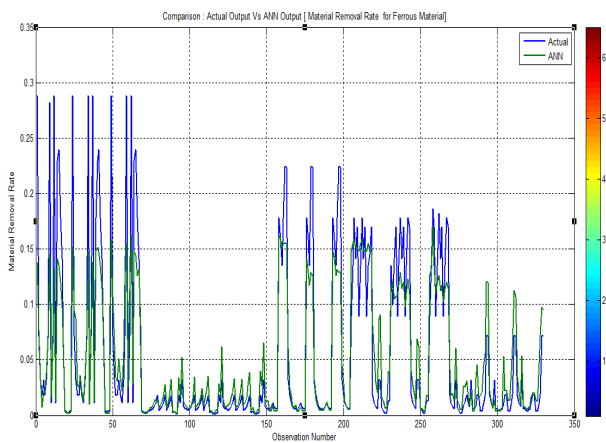Fig. 7 6-5-1 ANN Network for MRR in the turning of ferrous material

Fig. 8 Comparison between actual and ANN MRR for ferrous materials

3. Model III: MRR Model for Nonferrous Materials

- Correlation Coefficient = 0.944114257469
- Root Mean Square =0.01450621217
- Reliability =99.25868812 %

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

where

$sum\ (layer\ 1\ cell\ 0) = 1.91534\ *\ X_{0,1} - 0.65303\ *\ X_{0,2} + 1.54936\ *\ X_{0,3} + 0.98445\ *\ X_{0,4} - 0.09669\ *\ X_{0,5} + 0.88269\ *\ X_{0,6} + 0.6479$

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

where

$sum\ (layer\ 1\ cell\ 1) = -0.62138\ *\ X_{0,1} + 2.02822\ *\ X_{0,2} - 0.96843\ *\ X_{0,3} + 0.92048\ *\ X_{0,4} - 0.64141\ *\ X_{0,5} + 3.88090\ *\ X_{0,6} + 1.2168$

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

where

$sum\ (layer\ 1\ cell\ 2) = 2.42747\ *\ X_{0,1} + 0.06923\ *\ X_{0,2} + 1.29002\ *\ X_{0,3} + 0.55795\ *\ X_{0,4} - 0.42152\ *\ X_{0,5} + 0.68212\ *\ X_{0,6} + 0.2774$

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

where

$sum\ (layer\ 1\ cell\ 3) = 1.56161\ *\ X_{0,1} + 0.46987\ *\ X_{0,2} + 2.15194\ *\ X_{0,3} - 0.05987\ *\ X_{0,4} - 0.79298\ *\ X_{0,5} + 1.11086\ *\ X_{0,6} + 0.4629$

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

where

$sum\ (layer\ 1\ cell\ 4) = -1.35627\ *\ X_{0,1} + 1.52712\ *\ X_{0,2} - 0.73626\ *\ X_{0,3} + 0.20481\ *\ X_{0,4} + 0.36948\ *\ X_{0,5} - 0.97157\ *\ X_{0,6} - 0.3173$

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

where

$sum\ (layer\ 2\ cell\ 0) = 0.07738\ *\ X_{1,1} + 0.90245\ *\ X_{1,2} + 0.70275\ *\ X_{1,3} + 0.51354\ *\ X_{1,4} - 0.76849\ *\ X_{1,5} + 0.00000$
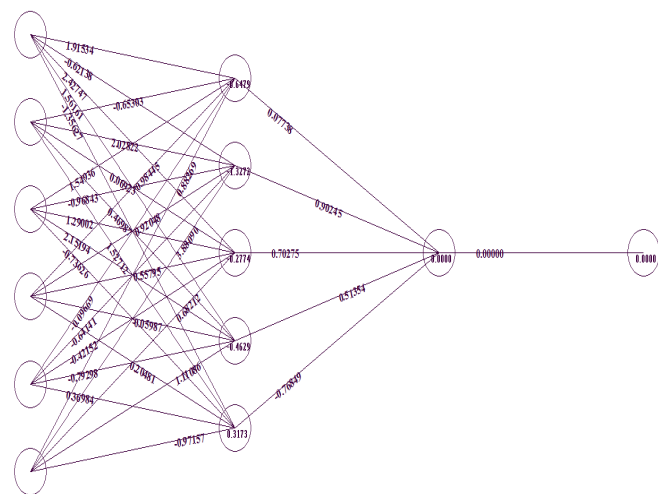
(3)

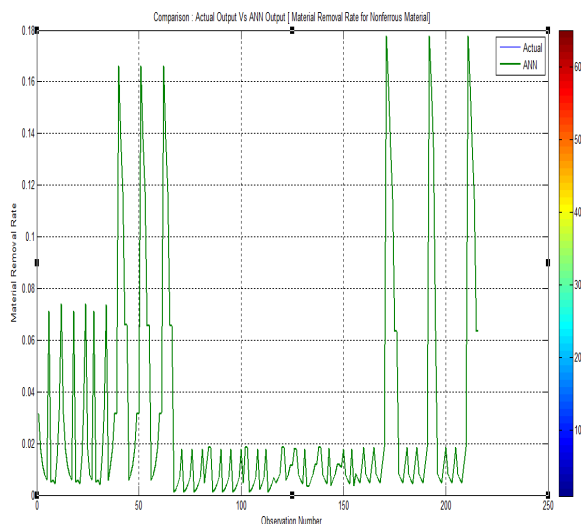Fig. 9 6-5-1 ANN Network for MRR in the turning of nonferrous material

Fig. 10 Comparison between actual and ANN MRR for non ferrous materials

III. Conclusion

According to the previous studies and investigations, the ANN model showed higher accuracy than traditional statistical. Artificial neural networks possess many desirable features that have made them suitable for practical financial and manufacturing applications. In this paper, we have provided a brief description of ANN and the model formulation that are most commonly used in the machining application. Interested readers are also directed to more detailed descriptions of the algorithms for their relative advantages and disadvantages for further information. Specific areas in finance and manufacturing that have experienced remarkable results by modeling with neural networks are described and some of the important and relevant works are reported.

Acknowledgment

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