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MATLAB BASED ARTIFICIAL NEURAL NETWORK MODEL FOR PREDICTION OF MELT DOWN TEMPERATURE IN STEEL MAKING

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ABSTRACT

Steel making is conversion of liquid Iron produced in the blast furnace, which is known as hot metal in steel making, by removing the impurities such as Carbon, Silicon, Phosphorous and Sulfur from hot metal. This is done by directly blowing oxygen into the bath, thus oxidizing the metalloids. Steel making is a batch process. Quantity of Raw materials used varies depending upon the quality, availability of inputs and the quality of steel required to be made. Steel making process made the prediction of these parameters difficult and the reliability was low. The procedure is to measure the parameters at various stages intermittently and establish a relation among them, such as temperature increase, carbon drop rate etc. and predict the parameters in co-relation with these measurements.This paper presents an analysis and selection of various techniques/parameters in developing a suitable feed forward neural network for performing process analysis using MATLAB 7.9 NEURAL NETWORK TOOLBOX. Further various toolbox functions such as different types of feed forward neural network, training functions, activation functions, learning functions, initialization functions and performance functions available are tested and the most suitable combination is selected. We summarize the analysis comparing the results with each training function and conclude the suitability of ANN training for Temperature Assessment.

KEYWORDS – Steelmaking, neural network, feed forward neural networks, process analysis, temperature assessment.

INTRODUCTION

Steel making is conversion of liquid Iron produced in the blast furnace, which is known as hot metal in steel making, by removing the impurities such as Carbon, Silicon, Phosphorous and Sulfur from hot metal. Carbon is brought down from 4.5% to 0.04%, Si from 0.60% to nil, Phosphorous from 0.16% to 0.025% and Sulfur from 0.05% to 0.03%. This is done by directly blowing oxygen in to the bath, thus oxidizing the metalloids [2,3]. To take care of the heat generated due to the exothermic reactions of the metalloids oxidation scrap is added as coolant and lime as flux material for easy removal of the oxide resultants generated. Steel making is a batch process. Quantity of Raw materials used varies depending upon the quality, availability of inputs and the quality of steel required to be made [3,4].

A mathematical model – called Charge Balance model or static model- which is a complete heat, mass and chemistry balance of the reactions involved in the Steel Making Process was being used to predict the various parameters of the process at various stages of the process [2]. But the uncertainties of the working conditions and dynamic variation of the requirement of the complicated steel making process made the prediction of these parameters difficult and the reliability was low. To encounter these problems the procedure followed is to measure the parameters at regular intervals and arrive at the end point subsequently. Another procedure is to measure the parameters at various stages intermittently and establish a relation among them, such as temperature increase, carbon drop rate etc. and predict the parameters in co-relation with these measurements. The total requirement of Oxygen for one heat, turndown temperature & carbon etc. can be predicted with certain accuracy to some extent. One of the best suitable and available tools to formulate a numerical description of this kind of complex process is the ARTIFICIAL NEURAL NETWORKS. Artificial Neural Networks (ANN), or commonly known as neural networks, have been attractive for applications in complex function modeling and classifications due to the fact that neural networks have very different computing approaches from traditional computing machine [5].

Application of Artificial Neural Network (ANN) to the above mentioned problem has attained increasing importance mainly due to the efficiency of present day computers. Moreover real-time use of conventional methods in an energy management center can be difficult due to their significant large computational times. One of the main features, which can be attributed to ANN, is its ability to learn nonlinear problem offline with selective training, which can lead to sufficiently accurate online response. The neural network system has an ability to construct the rules of input-output mapping by itself. Thus, the designer of the system does not need to know the internal structure and instructions of the system, or the functional rules like traditional systems. Instead, the neural network system requires the feed-in's of input-output patterns to "learn" before the system can function correctly. Due this flexibility neural networks have gained increasing interest in different fields of material science and other ferrous metallurgical areas [8,9]. The ability of ANN to understand and properly classify such a problem of highly non-linear relationship has been established in most of them and the significant consideration is that once trained effectively ANN can classify new data much faster than it would be possible with analytical model. The conditions of the twin hearth furnace from one plant to the other and from one twin hearth furnace to another in the same plant may vary. Taking these into consideration in this paper, an attempt has been made to predict the intermediate temperature required by using Feed Forward Back Propagation algorithm using the previous heats data of an integrated Steel Plant.

METHODOLOGY

The approach used for investigating the different parameters and functions in the MATLAB TOOLBOX, is given by the following algorithm.

Step1:
Obtain a database for the Input vector in the following form [scrap, Hot Metal, Total(HM +SCRAP), C, Mn, Final C, Final Mn, Oxygen ppm, Final Temp ,Oxygen C(CU.M)] from heats tapped in Twin Hearth -3 of Steel melting shop –I of Bhilai Steel plant. Scrap is the scrap amount, HM is the hot metal in tons, Tot represents the total, C is the carbon content, Mn is the manganese content, F.C is the final carbon, F.Mn is the final manganese, Oppm is the oxygen in ppm, F.Temp is the final temperature, OxyC is the total oxygen consumed. Target vector is the melt down temperature.

Step 2:
The database is divided into four parts, two parts used for training, one part for validation of model, one part for testing on new data.

Step 3:
Find the minimum and maximum values of the input vector, remove redundancies and normalize to suit to train the selected feed forward neural network.

Step 4:
Select the set of parameters to train the network. The main parameters selected are number of epochs, learning increment and rate, performance goal with Mean Squared Error (MSE) and minimum and maximum gradient.

Step 5:
Train the network based on a set of activation functions and number of neurons. The number of neurons in each layer is varied initially and optimum combination is found out depending on the training period and performance error.

Step 6:
Check the performance of the network for behavioral accuracy. If not change the activation functions and check the network again. Find the most suitable combination of the activation function.

Step 7:
Change the training function keeping same transfer functions and optimum number of neurons in each layer.

Step 8:
Find the most suitable network based on the simplicity least possible Mean Square Error and computational speed. Further use various test functions to confirm the effectiveness of the proposed neural network. At this state the functions and all the parameters are finalized for this combination.

NETWORK ARCHITECTURE AND ANALYSIS OF THE FUNCTIONS

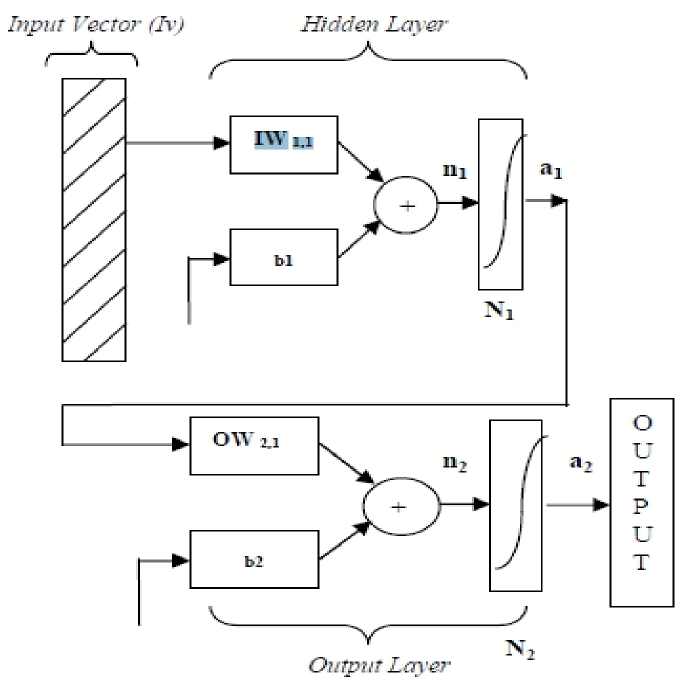

Figure. 1: Proposed Feed Forward Neural Network (FFNN) architecture

Figure 1 shows the proposed feedforward neural network. The architecture consists of an input layer, a hidden layer and an output layer. Input vector is fed to the Input layer for all the buses of the selected system. The network weights and biases are adjusted using the 'dotprod' function in the toolbox and adaptation is done using 'adaptwb' function which changes both weights and biases. First to obtain the best combination of number of neurons, training and activation function a test system is developed and the toolbox parameters are applied. Following Toolbox functions are analyzed based on the above methodology [9]:

- Neural network architecture and types
- Training functions
- Activation functions
- Learning function
- Initialization functions
- Performance functions

It was found that Levenberg Marquardt (LM) training algorithm performs the best considering the criteria's as Mean Square Error for predicting the melt down temperature values, training time and overall accuracy. Moreover, sigmoid activation functions ('logsig') for the Input and hidden layer and the linear activation functions ('tansig') for the output layer were the most suitable [9].

Following functionality are incorporated in the developed ANN algorithm. Initially from the selected Input data set the minimum and maximum values are found out. Then the FFNN architecture is selected defining the number of neurons, training and activation functions. Further the Input data is normalized and filtered for redundancy. In the next step, network training parameters such as learning ratio (0.01), learning increment (1.05), number of epochs (1000), Minimum and Maximum Gradient (1e-10 and 1e-10 respectively) have been set based on the analysis done. After training the network for the set of samples, network performance is evaluated with a new set of non simulated data and output is compared. The trained network nomenclature is assigned and further a new set of NN is trained for contingencies.

RESULTS AND DISCUSSION

Keeping the suitable activation functions, each of the training function is analyzed for two different conditions. Initially the training was conducted for same network with constant number of neurons in all the layers to identify the performance of each function and also to calculate the CPU time. It was observed that the computational time for 'TRAINGDX' and 'TRAINGDA' functions are same (3seconds) but the Mean Square Error as 0.21553 and 0.21554 and regression was R= 0.89618 and 0.8912 respectively. Thus it can be concluded that 'TRAINGDX' function is the most suitable one if both the computational time is considered as the most critical criteria. With the same number of layers and neurons and activation function TRAINLM was the fastest (1second) .The Mean Square Error was 0.21354 and Regression was 0.89735. It can be seen that 'TRAINLM' function is the optimal Table 1 compiles the performance of each of these training functions for same number of neurons (cond.1) and best suitable neurons in each layer (cond.2).

To check the response of the network trained a post regression analysis has been conducted between the target and the output. It was observed that the correlation coefficient is 0.899 while training with 'TRAINLM'. Figure 2 shows the slope and Y-intercepts of the analysis.

TABLE-1

Performance Comparison for various Training Functions

Comparison between various most suitable Training Functions in Back Propagation network

Type of network	**Description of training pattern**	**Training Function**	**Performance Goal(MSE)**	**Regression**
Condition1		Train LM	0.21356	R= 0.89735
Feed Forward Network	(23 ,22,1) logsig tansig purelin	Train GDX	0.21553	R=0.89618
		Train GDA	0.21554	R=0.8962
Condition2	(24,1) logsig tansig	Train LM	0.219	R=0.89634
	(23,22,1) logsig tansig purelin	Train GDX	0.21989	R=0.88735
	(28,23,1) tansig tansig purelin	Train GDA	0.2356	R=0.87878

CONCLUSIONS

Highly nonlinear problems like this can be solved using single hidden layer neural network and propose its ability in assessment of intermediate temperature in steel making. It is found that in such an analysis, the training algorithm is the most important factor in the performance and accuracy of the network, since any variation to be done in the number of neurons and the network parameters is limited. Post regression analysis and the comparison of the output at each bus shows that the output obtained are sufficiently accurate if well organized training is conducted reducing the redundancy and normalizing the inputs as well as outputs. Moreover, the performance of each of the training algorithms depends also on the size of the data of the network under consideration. The results show that training function LM was the best of all the three having minimum mean square error as well as high value of R(correlation coefficient). The value of R is the estimate of how close the developed model predicted the melt down temperatures.

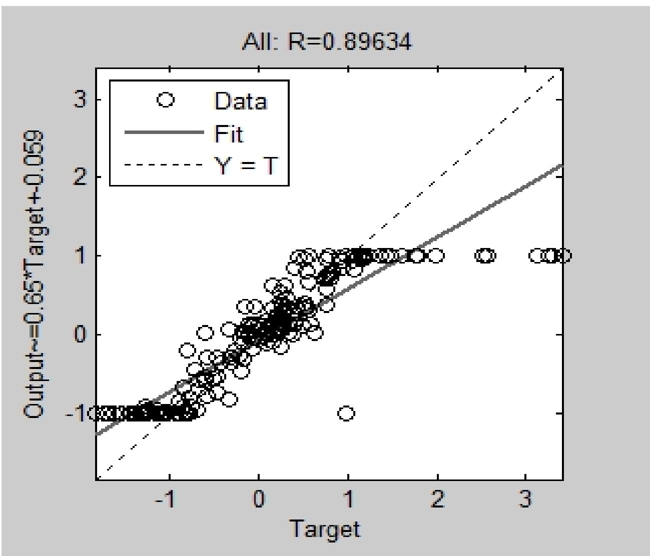

Fig.2: Post Regression Analysis on TRAINLM

REFERENCES

[1] G. Horvath, B. Pataki et al., "Black box modeling of complex Industrial process". Technical university of Budapest.

[2] Narra Rajesh et al., " Feed Forward Neural Network for Prediction of end Blow Oxygen in LD Converter Steel Making"Materials Research. 2010; 13(1): 15-19

[3] H.Gutte et al "Process control in Oxygen Steel production", ACTA METALLURGICA SINICA, Vol 13.no.6 pp-1101-1112,December 2000.

[4] Ke Hongdi et.al., "AOD furnace smelt ferro alloy end-point forecast" 978-1-4244- 8217-7/10/$26.00 ©2010 IEEE

[5] Bogdan M. Wilamowski et al "Efficient Algorithm for Training Neural Network with one hidden layer", IEEE 1999,0-7803-5529-6/99

[6] Rudolf Jaksa et.al., "Neural Network Model of the Backpropagation Algorithm, Technical University of Koˇsice

[7] Martin T**.** Hagan and Mohammad B**.** Menhaj "Training Feedforward Networks with The Marquardt algorithm, IEEE TRANSACTIONS ON NEURAL NETWORKS, VOL.*5,* NO. *6,* NOVEMBER **1994 989**

[8] H. Meradi, S. Bouhouche, and M. Lahreche "Prediction of Bath Temperature using Neural Networks", World Academy of Science, Engineering and Technology 24 2006

[9] The Mathworks Inc. Neural Network TOOLBOX, Users guide-for using in MATLAB, 2010.

[10] Z. Guo, W. Sha *," Modelling the correlation between processing parameters and properties of maraging steels using artificial neural network *", Computational Materials Science 29 (2004) 12–28

[11] Xiying Ding et al , "Predictive Model of BOF Based on LM-BP Neural Network Combining with Learning Rate", 978-0-7695-3888-4/09 $26.00 © 2009IEEE 2009.192