# ANN BASED PREDICTION OF BLAST FURNACE PARAMETERS

**Sujit Kumar Bag**
*School of Electrical Sciences,Vellore Institute of Technology, Vellore -632 014, India*
*E-mail: sujitbag@yahoo.com*

***ABSTRACT***

*The paper presents a method to predict blast furnace parameters based on artificial neural network (ANN). The prediction is important as the parameters cause the degradation of the production process. The productivity as well as quality can be improved by knowing these parameters in advance. In this context, the iron making process in the modern blast furnace is briefly illustrated. Characterisation of the input and the output parameters as well as the design of a feed forward neural network (FFNN) is outlined. The implementation issues are discussed to predict the parameters like hot metal temperature (HMT) and percentage of impurity of silicon content in molten iron. The simulation and plant trial results are compared to show the effectiveness of the approach.*

***Keywords:*** *ANN Prediction Technique, Feed Forward, Optimal Neural Network*

## 1. INTRODUCTION

Artificial Neural Network (ANN) computing is a soft-computing method that attempts to emulate the basic structure and functionality of the human brain. ANN has long been used for prediction of unknown parameters in both engineering and non-engineering fields. This paper presents the works on a prediction mechanism using ANN. It is observed that the hot metal temperature (HMT) of the blast furnace in most of the steel plants suddenly drops because of natural occurring. This is a serious problem, as the production process has to be stopped until the operational temperature is raised up again to the standard level. Sometimes, the re-heating process takes hours due mainly to the large time constant of the overall system. This will result in the wastage of resources, time and money. Similarly there are other parameters like silicon, sulphur etc. which cause the production of poor quality of steel. This can be prevented by predicting the process parameters in advance. Moreover, the inputs that are required to maintain a desired temperature and minimise the impurities should be predicted. To achieve these, various processes and mathematical modelling that have been tried and many of them have been successfully implemented. One of the techniques is artificial neural network (ANN) modelling. A feed forward neural network is sufficient to predict the output parameters. However, in order to predict the quantity of the inputs, the neural network must be inverted and optimised. However, this is not under the scope of this paper. It is necessary to monitor the blast furnace to make sure the hot metal temperature of the furnace does not fall below the recommended range. In this paper, the hot metal temperature (HMT) and the percentage of impurity of silicon content have been predicted using feed forward neural network (FFNN). The preparation of input dataset to the ANN and implementation issues will be discussed.

The paper is outlined as follows: Section 2 briefly introduces the blast furnace process and explains the problems. The design and principles of artificial neural network technique are discussed in section 3. The major implementation issues and the plant trial results are illustrated in sections 4 and 5 respectively.

## 2. BLAST FURNACE PROCESS

Steel is known as an alloy of ferrous and carbon and is produced by employing a complex procedure [1]. A mass of iron ore and charcoal were heated in the furnace. The ore is reduced to metallic iron with some slag and charcoal ash. The modern blast furnaces are the refinement of the traditional furnaces but equipped with instruments and control architecture [2]. The most important parts of the production process are the operation and control of blast furnace in terms of controlling the internal temperature at various segments and monitoring the impurity levels on-line. In this stage the molten iron, commonly known as pig iron which is the raw material for the steel, is produced [3]. The main purpose of the blast furnace is to remove the oxygen from the iron, create the molten material and control the impurities.

The process of steel making begins with three basic materials, limestone, iron ore, and coal. The coal is first heated in coke ovens to produce the coke. This process is called carbonisation and produces a gas that is used to fuel other parts of the steel plant. Once the coke is preheated and passed through this procedure it is brought out of the oven for cooling. Simultaneously iron ore and limestone are granulated, mixed and preheated in a sinter plant in a moving belt where the materials are ignited helping them to fuse together to form a porous material known as sinter whose main purpose is to speed up the process in the blast furnace. Thereafter both the sinter and coke are passed into the blast furnace to produce the pig iron. In the blast furnace, pellets of coke, and iron ore are added to the top by a conveyor belt. From the bottom of the furnace hot air of temperatures over 1450 ˚C is blasted through nozzles, called tuyeres [4;5]. Oxygen is combusted with the coke to form carbon monoxide (CO). This process generates a tremendous amount of heat in the furnace. Sometimes oil is blasted into the furnace with the air to ensure proper combustion. The CO gas, which is produced during combustion, then flows through the entire furnace and removes the oxygen from the iron ore, leaving behind the pure iron. Subsequently, the heat from the furnace helps in melting the iron turning it into a liquid form. The impurities are floated on top of this molten iron and it is known as slag. This is removed at various stages to produce pure pig iron. Once the hot metal is ready with a correct consistency it flows into torpedo ladles, which are specially constructed railway containers used to transport the pig iron to the LD furnace. At the LD furnace the oxygen is added to the molten iron and then passed through a caster and cooled into slabs and rolled into sheets. This is the finished steel which can be shipped to manufacturing plants for further processing. In other words the blast furnace must always stay at a consistent temperature and should not be allowed to cool down and maintain the correct composition. High or low temperature would cause damage to the furnace lining and may introduce impurities into the molten iron.

Steel Companies are greatly concerned about the production rate, cost and quality that they encounter at steel manufacturing plants. One serious problem that the steel plants are facing is the sudden drop of hot metal temperature in the blast furnace. The temperature of the blast furnace at below 1350 ˚C causes a stop in it production of liquid iron. It does not ensure the proper production of quality of carbon steel as well as the melting; hence impurities will result in the steel. Therefore it is highly important to maintain the temperature of the blast furnace between the ranges of 1350 ˚C to 1550 ˚C which ensures the iron is properly melted with right consistency to make top quality steel.

When the temperature drops below 1400 ˚C, the production must be stopped until the temperature rise again. The operators at the plant increases the inputs to the furnace for quick action but the temperature does not rise as fast due to time lag between the inputs action and their effect. Once this is reached, the production of hot metal can be continued. Simply adding the raw materials to the blast furnace does not automatically increase the temperature of the furnace. Since the coke added to the furnace must be combusted to form CO gas which heats the iron. There is a time delay associated with the addition of materials and the point when proper temperature is once again reached in the furnace. This is a waste of time, hence production, manpower and money lost.

Hence if the temperature drop is predicted in advanced, the operators can add the correct amount of the inputs at the right time to prevent this situation. The mathematical modelling of the blast furnace based on artificial neural network can help the operators to predict the temperature as well as other parameters that affect the quality of the steel production. Hence, design of a proper ANN is an important task that could predict the parameters accurately.

## 3. DESIGN OF NEURAL NETWORK

Neural network has been used for online or offline prediction of parameters in various fields. Its use is not limited to engineering but applied to many non-engineering fields include metrology, inventory, decision and policy making, and commerce etc. [6-9]. The method has the capability to learn which allows them to gain knowledge through input - output relationships in the training data. Instead of having to program them to perform a certain way, one can just subject them to various data sets and let them induce the relationships between them [10]. There are many types of neural networks but the problem of prediction that is associated above can easily be mapped by a feed forward neural network (FFNN). A feed forward network can be made to map the relationship between the input and the output and it has the ability to model complex non-linear behaviour of the system. This mapping is called forward mapping and provides relation for a one to many mapping because each output can correspond to a number of inputs.

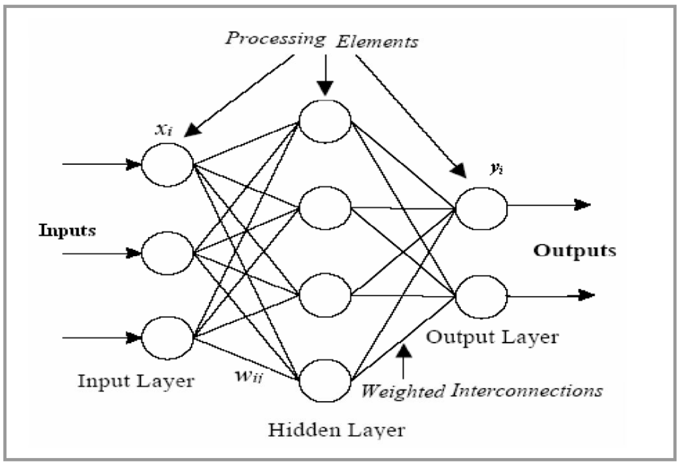


***Figure 1: A feed forward neural network***

A typical feed forward network consists of inputs, weights, an activation function and one or more outputs as shown in figure 1. The output of any neuron is the function of the sum of inputs INi (i = 1, 2, 3…etc) multiplied by the weights Wij (j = 1, 2, 3 … etc) if there is no bias added to the network and each neuron has an activation function. In the picture above, the feed forward network has three layers. An input layer, where the inputs being feed into the neuron which is a processing element and has a mathematical function [11;12]. The output of the neuron is then passing into a weighing function. The middle layer is called hidden layer. Sometimes there are more than one hidden layers but it is revealed from the research that the increase of number of hidden layer does not improve the performance of the neural network [13;14]. Hence, most of the application uses one hidden layer. However the number of neurons in the hidden layer affects the performance. This is selected during optimisation of the performance of the network. The relationship between one layer input and the next hidden layer is determined by the weights and the transfer function of the network. In Figure 1 it is shown that a line is connected from each node in the hidden layer with every node in the input layer. This is because the value of each node in the hidden layer is determined by all of the values of the input layer. Each line connecting an input node with a node in the hidden layer has an associated weight with it.

The last layer is known as output layer, where the outputs are collected. Therefore the values of each node can be calculated as follows.

$$O_n = \sum_{i=1,\, j=1}^{N} IN_i \ x \ W_{ij} \qquad (1)$$

where $O_n$ is the output and N is the total number of inputs of the network. Similarly, multiplying the hidden nodes with their weights and adding them together to determine the output.

Another class of feed forward neural network can be constructed which may have a bias; this is a number between 0 and 1 and is added to the sum of inputs and weights to reach the output. Regardless of how many layers the network contains, the relationship from one layer to another layer is always the same; the value at each node in a layer is equal to the value the nodes of the previous layer multiplied by the weights and addition of a bias (if any). Therefore in general the output (y) of the forward neural network can be expressed as a function of its weights $w_{ij}$, and input $x_i$ as

$$y = f\,(x,w) \qquad (2)$$

It is convenient to use linear functions in the input and output layers and nonlinear function in the hidden layer. The weights and the number of neurons as well as their combination are decided during optimisation routine. Normally raw data from the plant are pre-processed before it goes for optimisation and these issues are discussed in the following section.

## 4. IMPLEMENTATION ISSUES

The blast furnace is the central point of any steel plant. Inside the blast furnace, the oxygen is removed from the iron oxides to yield nearly pure liquid iron. This liquid iron, or pig iron, is the raw material for steel production. The most important factors that determine the quality are (i) the amount and composition of impurities, and (ii) the temperature of the hot metal when it is tapped from the blast furnace. The quality of the pig iron determines the cost of its steel production, its use and the types of steel that can be made from the pig iron. Therefore, it is important that hot metal temperature should be maintained within an optimal range to minimise the impurities [15]. It is difficult to physically model a blast furnace due to the complex flow relationship between mass and heat transfer. Hence, ANN approach can be suitable for modelling the furnace behaviour. For many years, blast furnace operators have been aware of the fact that there are no universally accepted methods for accurately controlling blast furnace operation and predicting the outcome.

The hot metal temperature and silicon content are important parameters that indicate the internal state of a blast furnace as well as the quality of the pig iron. The production of pig iron involves with complex heat and mass transfer and their relationships among the various chemicals used. However, an Artificial Neural Networks (ANN) technique can be used easily to model these complex and non-linear inter-variable relationships in simple manners.

Most of the modern blast furnaces are connected with state of-the-art instrumentations and level three automation technologies, hence automatically collect and store data at periodic intervals on a number of input and output parameters for future analysis. This will ease the task. The measuring instruments are connected to the data server through Programmable Logic Controller (PLC) or directly depends their range of outputs. A computer server runs software called Supervisory Control and Data Acquisition (SCADA) system [16], which fetches the data at certain interval and stores for several months to several years. Further details on SCADA are available in the literature of Bag [17]. The hot metal temperature is normally measured using pyrometer and directly feed into the server but silicon content is based on chemical analysis of the sample in the laboratory at certain frequency as there is no such device available to measure it online. However, it may possible to do so in the future. These data are finally correlated with other data logged into the server and time. Any mathematical model or ANN system can be run on the same server to feed the inputs online and display the outputs on the screen or send to the desired actuators or other systems. Modelling the relationships between various input variables and the desired output variables of the blast furnace has been quite difficult task using standard statistical techniques due to the existence of non-linearity [18]. Therefore, many academicians, researchers and engineers have tried to model using neural networks in order to predict various blast furnace parameters. For example, Bulsari and Saxen [19] used feed-forward neural networks to classify the state of a blast furnace based on the measurement of blast furnace temperatures. Bulsary et al. [20] used multi-layered feed-forward neural networks to predict the silicon content of hot metal from a blast furnace. Singh et. al. [21] tried several different artificial neural network models in order to predict the silicon content of pig iron using the parameters like coke rate, hot blast temperature, slag rate, top pressure, slag basicity and the logarithm of blast kinetic energy. The difficulties associated in the blast furnace modelling also involved consistency, reliability, accuracy and availability etc.

The raw data collected from the instrumentation of the blast furnace are not consistent enough for direct usage during modelling. It ranges from problems inherent to the associated data, such as missing or very anomalous values, or more subtle flaws such as not taking into account the effect of time lags in the production process. Hence, pre-processing is needed on the dataset before it is used in the training of the neural network. The output of the neural network can not be expected as desired due to pre-processing. Hence post processing of the dataset is essential.

For example, the extremely abnormal data values stored in the server and can be adjusted to make the data consistent. Values that are more than two standard deviations from the mean can be modified so that they must fall within two standard deviations from the mean. In some cases a minimum value for a variable can be specified. If two standard deviations below the mean is smaller than the minimum then the data are adjusted to the minimum value. In this process, it is possible to remove many outliers from the dataset. A major problem with the original data is inaccurate values from its instruments. Linear interpolation between measurements can generate approximate values for the missing data points. The scan time of data may vary for different variables. Some of the inputs have very fast changes and others are slow. Since the temperature changes slowly over a longer period of time, these short term changes do not have a noticeable affect on the output. An effective change of data can be considered for half to one hour interval depending the time delay associated with that input. This problem can be solved by re-sampling the data. Therefore, groups of data points can be averaged to create one data point. This may reduce the number of data points available for training the network. A moving window technique can be used to avoid this problem. This technique can allow the use of almost the same number of data points as in the original dataset. In case the dataset involved is laboratory data, those must be arranged accordingly to fit the time scale and bring into the consistency level. Once the missing values and abnormality of the dataset are removed, the lag of each input variables must be adjusted based on operator experienced or experimentally or calculated by any other means like correlation factors. A normalised dataset generated is more reliable to use in neural network than raw data. Hence each input and output dataset is brought into the range between 0 and 1 dividing by the highest number. The dataset is now ready for training the neural network. The training process starts with selection of number of inputs and outputs as well as optimisation parameters like number of neurons in each layer, learning rate, epochs, error goal etc.

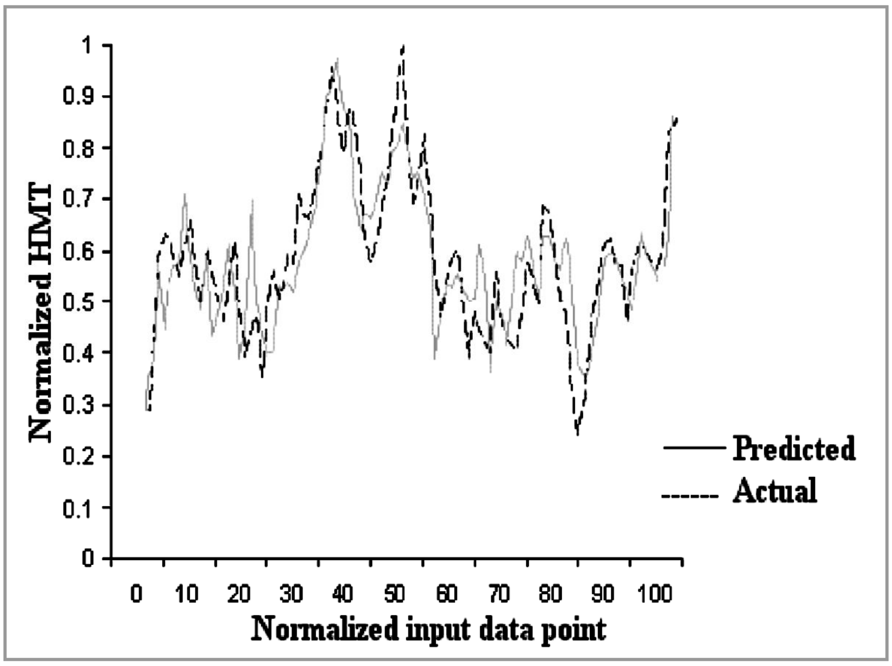


*Figure 2a: Effectiveness of HMT prediction at six hours in advance*

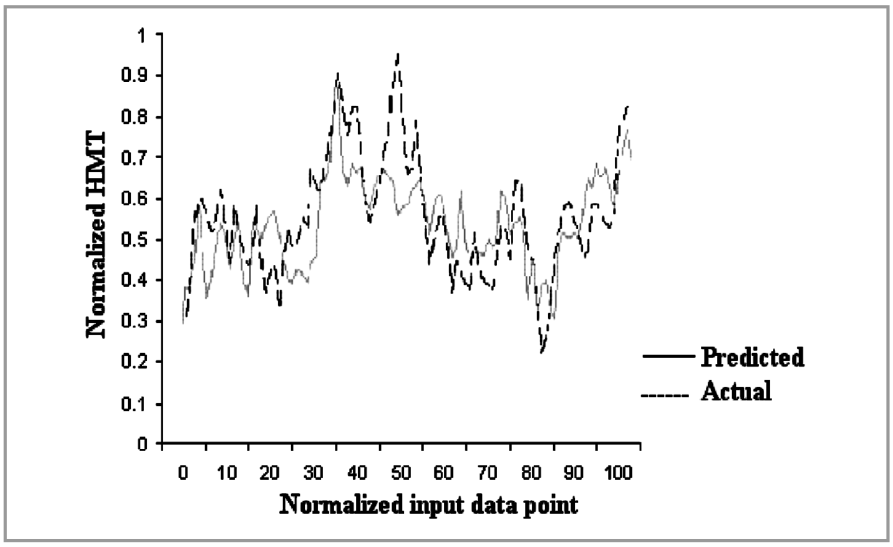


*Figure 2b: Effectiveness of HMT prediction at eight hours in advance*

There are a number of input parameters (approximately 39) available in a medium size blast furnace data acquisition system. Analysis showed that redundancy exists in the input variables and others are not useful in prediction of hot metal temperature or silicon content. This is normally found using correlation method of different inputs to one of the output. If the correlation value between a particular input and the output is high then that particular input variable is "important". The threshold value has to be decided based on the experience of the operator and analysis of the data. Therefore, such a variable should be included in the dataset. Gupta et al. [7] used this technique and found 11 input variables that are important for determining the hot metal temperature of the blast furnace. The author had used 12 inputs for his application, i.e. total coke, carbon oxide, hydrogen, steam, group 1 heat flux, group 2 heat flux, ore to coke ratio, actual coke injection, oxygen enrichment (%), charge time for 10 semi charges, hot blast temperature (˚C) and the previously measured hot metal temperature. It is found that the previously measured hot metal temperature plays an important role in maintaining the current temperature in the blast furnace. Hence, inclusion of this variable improves the prediction accuracy.

A similar method is used for silicon prediction with additional variables such as coke ash, coke V.M., C.S.R., C.R.I., RDI, CaO, $SiO_2$, MgO, $Al_2O_3$, FeO and Fe when compared with 9 inputs ANN based silicon content model developed by Zheng et al.[22]. This also improves the prediction accuracy. These data are available from the Coke and Sinter plants datasets [23], hence appropriate action should be taken to incorporate them. Silicon is measured at less frequency compared to the hot metal input variables; in addition the silicon column data has large, contiguous regions of the output variable that had the same constant value. Therefore, linear interpolation, hourly averaging and the usual practices of implementing the best lags is performed and normalised for each of the input variables before training the neural network.

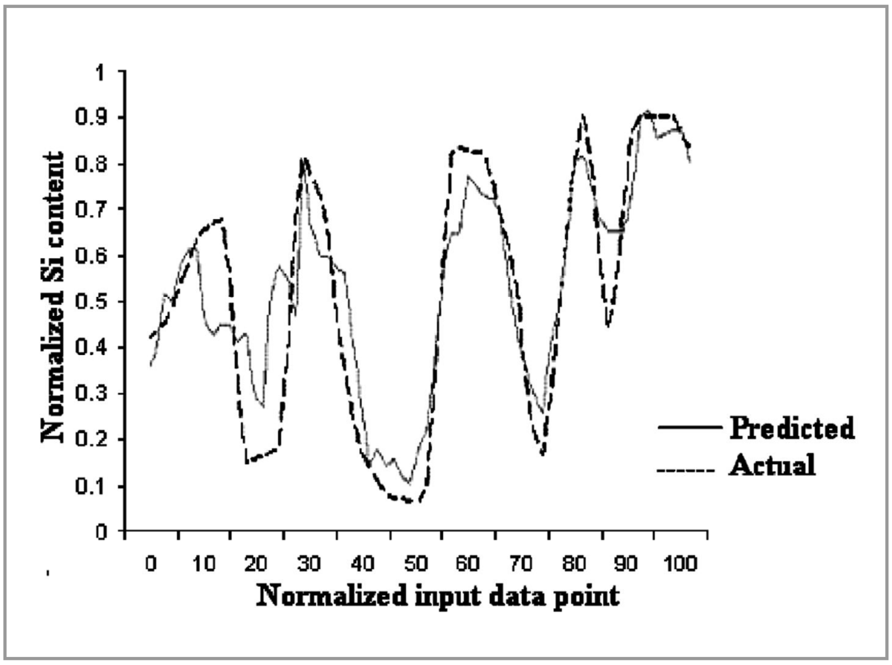


*Figure 3a: Effectiveness of silicon content prediction at six hours in advance*

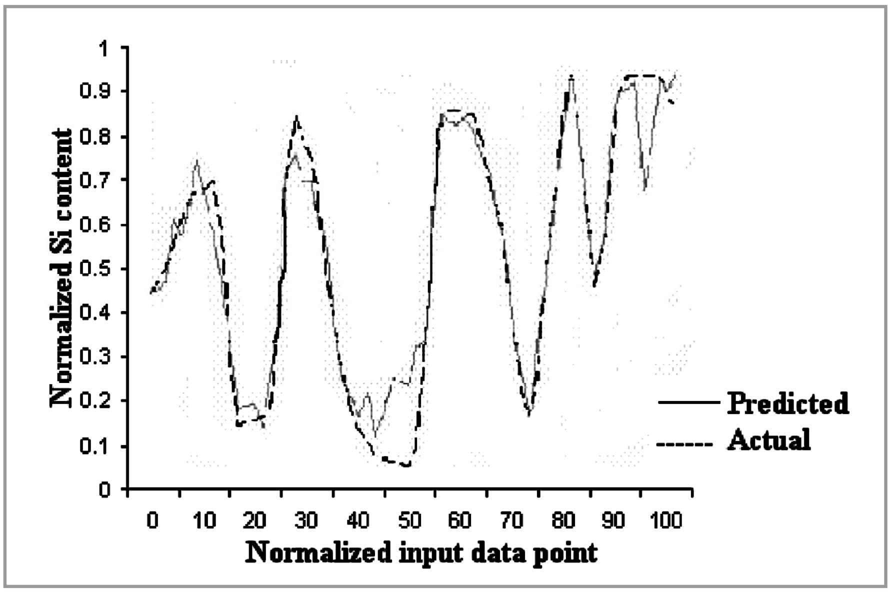


*Figure 3b: Effectiveness of silicon content prediction at eight hours in advance*

Once the neural network is trained and ready to accept the inputs, it is first tested offline using collected data and compared to the real temperature. The network can be put online using VB or C programming. Since MATLAB is used during design of the network, it is convenient to translate the network into C/C++ executable file. Care must be taken for pre and post processing stage. The section below will discuss the effectiveness of the technique.

## 5. SIMULATION AND PLANT TRIAL RESULTS

To present the effectiveness of the prediction of blast furnace parameters using artificial neural network, the predicted results from modelling of hot metal temperature and silicon content are presented in the Figures 2 and 3 respectively.

Figure 2 shows the graph of predicted hot metal temperature in six and eight hours in advance, againts the subsequent observed values.

Figure 2 shows that the prediction accuracy decreases as the time elapses. Similar analysis is performed for silicon content prediction as shown in Figure 3. It indicates the future condition of the blast furnace based on the current conditions. The same conclusion can be made. This is extremely useful when the blast furnace operator alters the current conditions to keep the future conditions within desirable range. In order to perform the task, the relationships between the variables being controlled and the variables affecting them must be known.

The first step towards controlling the conditions of a blast furnace involves finding out which input variables are most influential in producing an output. Since the network can predict HMT with a relatively high degree of accuracy, it is possible to find what kind of importance the neural network itself assigns each input variable when predicting HMT. This can be done using inversion of the ANN model [24; 25].

## 6. CONCLUSIONS

The paper has presented neural network based design and implementation approach of prediction of process parameters in blast furnace of the medium-scale steel plants. The results show the effectiveness of the method. Some of the important hints and tips to this approach are outlined. The neural network based prediction method deals with real time data, and the most difficult problems encountered are at the data preparation stage. This is encountered during the design of ANN and implementation period. Linearisation and moving windows techniques are preferred choice and have been used to overcome difficulties like missing data compensation and data point reduction respectively. The variations on the number of nodes may affect the overall efficiency in other case studies as reported by others, but in this case the different algorithms did not produce very significant differences.

## ACKNOWLEDGEMENTS

The author has carried out this work during his service in Tata Steel, India and gratefully acknowledges his sincere thank to Mr. Ajit Kothari, and Dr. Debasish Bhattacharjee to understand the blast furnace operation. ■

## REFERENCES


[1] A. K. Biswas, Principles of Blast Furnace Iron making, SBA Publications, 1984.

[2] L. Osamu, Y. Ushijima, and S. Toshiro, "Application of AI Techniques to Blast Furnace Operations", Iron and Steel Engineer, October 1992.

[3] Tata Steel, "Graduate Training Manual: A report prepared by training school"; http://www.tatasteel.com/steelmaking/default.asp.

[4] P. H. Winston, Artificial Intelligence, 3rd Ed., Addison-Wesley, 1992.

[5] H. Demuth and M. Beale, Neural Network Toolbox User Guide, The Math Works Inc. 1997.

[6] K. Bansal, S. Vadhavkar, and A. Gupta, "Neural Networks based Data Mining: Applications for Medical Inventory Problems", Int. J. of Agile Manufacturing, Vol. 1(2), pp. 187-200, 1998.

[7] A. Gupta, S. Vadhavkar, and S. Au, "Data Mining for Electronic Commerce," Electronic Commerce Advisor, Vol. 4(2), pp. 24-30, 1999.

[8] K. Bansal, A. Gupta, and S. Vadhavkar, "Neural Networks based Forecasting Techniques for Inventory Control Applications," Data Mining and Knowledge Discovery, Vol. 2, 1998.

[9] A. Dedecker, P. Goethals, W. Gabriels, and D. Pauw, "Optimisation of ANN Model Design for Prediction of Microinvertebrate Communities in the Zwalm River Basin", IEMSS proceedings, Vol. 20, 2002.

[10] C. Knoblock, "Neural Networks in Real-world Applications," IEEE Expert, pp 4-10, 1996.

[11] A. K. Sadhukhan, S. K. Bag, "Prediction of Air Separation Column Behaviour of Oxygen Plant based on Static Neural Network", Journal of Tata Search, 2000.

[12] R. J. Williams, "Inverting a Conncetionist Network Mapping by Backpropagation Error", Proc. of 8th Annual Conference of the Cognitive Science, 1986.

[13] A. A. Gorni, "The Application of Neural Networks in the Modeling of Plate Rolling Processes", E-journal of Materials under computer tools for materials, April 1997.

[14] E. Jeong, I. Fang Chung, and S. Miyano, "A Neural Network Method for Identication of RNA-Interacting Residues in Protein", Genome Informatics 15(1), 105 - 116, 2004.

[15] R. K. Sarma, "Using Neural Networks to Predict the Hot Metal Temperature of the G - Blast Furnace at Tata Steel" MS Thesis, MIT, 1999.

[16] N. P. Mahalik, J. Ryu, B. H. Ahn, "Simulation Integrated Management Layer for Real-time Embedded Distributed Control Network", Int. J. of Computer Standards and Interfaces, Elsevier Science, Vol. , 2004.

[17] S. K. Bag, "Characteristics of SCADA Architecture and its Applications", National Conference of Systems Society of India, No. 26, December 2005.

[18] M. Smith, Neural Networks for Statistical Modeling, Van Nostrand Reinhold, New York, 1993.

[19] Bulsari A. and Saxen H., "Classification of blast furnace probe temperatures using neural networks," Steel Research. Vol. 66, 1995.

[20] A. Bulsari, H. Saxen, and B. Saxen, "Timeseries Prediction of Silicon in Pig Iron using Neural Networks," Int. Conf. on Eng. App. of Neural Networks, 1992.

[21] H. Singh, N. Sridhar, and B. Deo, "Artificial Neural Nets for Prediction of Silicon Content of Blast Furnace Hot Metal," Steel Research, Vol. 67(12) 1996.

[22] Zheng D., Liang R., Zhou Y., and Wang Y., "A Chaos Genetic Algorithm for Optimising an Artificial Neural Network of Predicting Silicon Content in Hot Metal", J. of University of Sc. and Tech., Beijing Vol.10 (2), 68, April 2003.

[23] D. Bhattacharjee, S. K. Dash, and A. K. Das, "Application of Artificial Intelligence in Tata Steel", Journal of Tata Search, 1999.

[24] S. Lee , and R. M. Kil, "Inverse Mapping of Continuous Functions using Local and Global Information", IEEE Trans. on Neural Networks, Vol. 5(3), 1989

[25] B. L. Lu, H. Kita, and Y. Nishikawa, "Inverting Feedforward Neural Networks using Linear and Nonlinear Programming," IEEE Trans. on Neural Networks, Vol. 10, 1999.


## PROFILE

Prof. Dr Bag is a Professor in the School of Electrical Sciences, Vellore Institute of Technology, India. His academic interest includes control systems, data mining, neural network, industrial application of real-time systems. He has graduated from IIT, Kharagpur, in 1990 and received his Ph.D. from Leicester University, UK in 1997. He has been a visiting research fellow to the University of Leeds, U.K. He has long experiences in industry and implemented many projects. He has published papers in reputed national and international journals and conferences. He has been worked funded projects from EPSRC (UK) and European Commission (EC) and successfully completed them. He has supervised many B. Tech. and M. Tech. projects and guiding Ph. D students. He has been invited as guest editor and reviewer of international journals related to his area of research. He is involved in many professional societies both in India and abroad.