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Comparative study of BOF Steelmaking Process based on ANFIS and GRNN Model

Sarita Chauhan, Mahendra Singh, Vivek Kumar Meena
ECE Department, MLVGTEC Bhilwara

Abstract*— BOF steelmaking process is most important process to obtain the desired quality of steel consideration of two parameter end point temperature and end point carbon percentage by two model ANFIS and GRNN. The main aim of present paper is steelmaking through Basic Oxygen Furnace (BOF) to achieve higher productivity and the lower production cost in the minimum time by desired endpoint carbon content and temperature of raw material (molten steel). It is a very complicated physical chemical process however most of the industries use it. To achieve this various modeling are used such as mechanistic model, statistical model, regression and neural network models. Neural Network usages Fuzzy Logic Controllers is adaptive in nature and gives superior and faster results, without using of accurate mathematical model and well response for complex non-linear multi dimensional system. The present paper about predict the end point of carbon content and temperature in the basic oxygen furnace process using ANFIS and GRNN model. After that we compared both result. ANFIS has provided a new method for solving the problem of prediction and control of end point carbon content and end point temperature of complex BOF process. ANFIS model have five layers but GRNN have only two that's the main reason behind the more accuracy of ANFIS model.

***Index Terms*— BOF, ANFIS Model, GRNN Model, FLC.**

I. INTRODUCTION

This project based on to develop model for end point carbon and temperature with the help of latest methodology i.e., Adaptive Neural Fuzzy Inference System (ANFIS) and Generalized Regression Neural Networks (GRNN) and then have brought out the comparison of the results to achieve predicted accuracy in measured carbon content and temperature. Fuzzy logic controllers (FLC) [1] yield superior and faster results, adaptive in nature and gives robust performance for nonlinear system. The main design problem lies in the determination of the consistent and complete rule set and the shape of the membership functions. Neuro-Fuzzy software tools work as an intelligent assistant to the design. It helps to generate and optimize membership functions as well as the rule base from the simple data provided [4].

In steelmaking there are two processes one is basic oxygen furnace and another is Electric Arc Furnace. 67% steel is made from BOF across worldwide. In general, the main task of BOF is two: one is the carbon percentage decrease from approximately 4% in hot metal to less than 0.08% in liquid steel, and the other is the temperature increase from approximately 1250°C in hot metal to more than 1650°C.

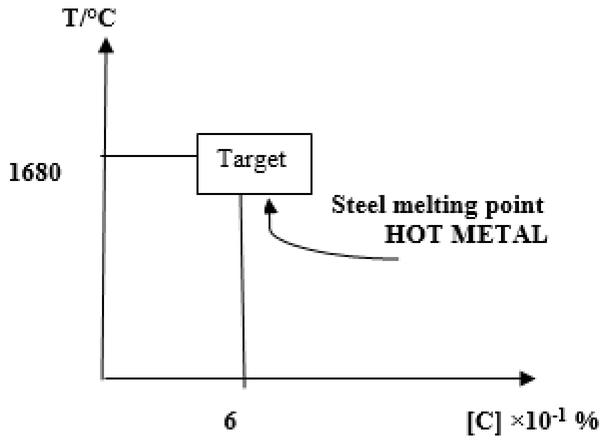

Fig. - End point BOF Steelmaking process

II. BACKGROUND

Generally steel making process are very complicated, time consuming and low productivity means wastage of raw materials. The process like as mechanistic models, statistical models of steel making is complicated and not completely understood as it involves multiphase physical chemical reaction at high temperature. The usages of neural network such as ANFIS and GRNN model gives higher productivity at low production cost and various steelmaking processes can be implemented. These processes are easily understood and give precious results for complex non-linear system.

III. BASIC OXYGEN FURNACE

Basic Oxygen Furnace **(**BOF**)** is a steel making furnace, in which molten pig iron and steel scrap convert into steel due to oxidizing action of oxygen blown into the melt under a basic slag. BOF is a widely preferred steel making method due to its higher productivity and considerably low production cost. About 67% of the crude steel in the world is made in the Basic Oxygen Furnaces (BOF) [2]. The process is very complex physical chemical process due to harsh environment and high temperature [9]. The amount and quality of scrap iron change from batch to batch; the grades of steel vary frequently and also change the height of the oxygen lance during each heat. The main objective is to obtain the prescribed parameters. In practical acceptance of molten steel is decided by the endpoint carbon content C and temperature T [10]. The three most important reactions in the process are:

$[C] + O2 \rightarrow CO$

$[C] + [O] \rightarrow CO$

$CO + O2 \rightarrow CO2$

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There are various steps in steelmaking process from raw materials up to the final products. These steps can be summarized as follows:

Step 1: Charging raw materials into the furnace as being either iron ore or scrap iron, depending on the process. These are converted into molten steel. The ore-based process uses a blast furnace + BOF and the scrap-based process uses an electric arc furnace only.

Step 2: For both routes is pouring the molten steel from the furnace and it is eventually solidified in a continuous caster.

Step 3: These semi-finished products are transformed, or "rolled" into finished products. Some of these undergo a heat treatment, known as "hot rolling". More than half of the hot rolled sheet is subsequently rolled again at ambient temperatures (known as "cold rolling"). It can then be coated with an anti-corrosion protective material.

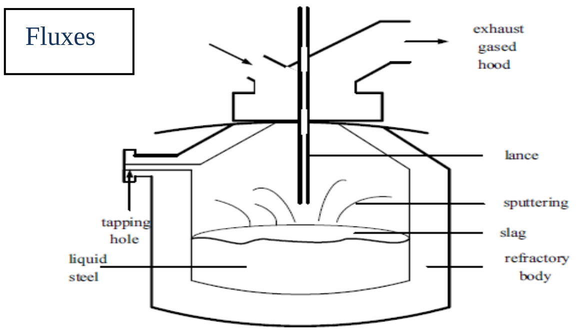

Fig.:- General View of BOF

The basic oxygen furnace is a steel shell lined with refractory materials. The body is slightly cylindrical, open at the top to receive raw materials and the oxygen lance which is then hooded to collect the waste gases into extensive air-treatment facilities. The principal raw material used in the converter is molten pig iron from a blast furnace. Besides Hot metal, steel scrap, fluxes such as the calcined lime or Dolomite form the part of the charge to the converter. 99.5% pure Oxygen at 15-16 kg/cm^2 pressure is blown into the converter through an oxygen lance. Oxygen oxidizes the impurities such as carbon, phosphorus, manganese etc. present in the hot metal which are fixed as slag with basic fluxes such as lime. During the process heat is generated by exothermic reaction of the oxidation of the metalloids via silicon, manganese, phosphorus and carbon and temperature to 1700°C enabling refining and slag formation.

IV. ANFIS MODEL

ANFIS stands for Adaptive Neural Fuzzy Inference System. The ANFIS was developed by professor Jang in 1992 and is used in the GUI of Mat lab software. The properties of neuro-fuzzy systems are the accurate learning and adaptive capabilities of the neural networks, together with the generalization and fast-learning capabilities of fuzzy logic systems. To explain the ANFIS architecture, the first order Sugeno model should be understood [5]. Using a given input/output data set, the toolbox function anfis constructs a fuzzy inference system (FIS) whose membership function parameters are adjusted using either a back propagation algorithm alone, or in combination with a least squares type of method[6]. Fuzzy logic and neural network has proved to be an excellent tool for modeling process. During the fuzzy modeling, the membership functions and rule base can be determined by experts only, thus the Modeling of best fitting boundaries of membership functions and number of rules is very difficult [7] .Sugeno type of rule base with the following two rules

If u1 is A1 and u2 is B1 then y1=c11u1+ c12u2+ c13u3
If u1 is A2 and u2 is B1 then y2=c21u1+ c22u2+ c23u3

Also neural network cannot be used for processing fuzzy information. Thus to overcome these demerits, a hybrid adaptive neuro fuzzy interface system was developed by researchers [11] [12].

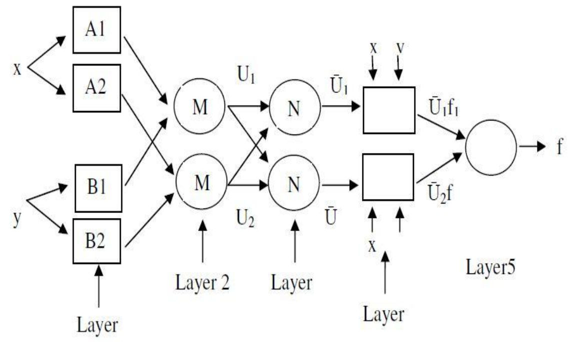

Figure 1 ANFIS architecture

V. GRNN MODEL

A generalized regression neural network (GRNN) is often used for function approximation. GRNNs training times are faster and can model non-linear functions, and shown to perform very well in noisy environments if given enough data. These are known as kernel regression and originally reported in the statistics literature [8].

GRNNs are comprised of two layers. The first layer consists of radial basis neurons, whose transfer function is a Gaussian function with a bias or spreading factor b_i. First layer weights are simply the transpose of input vectors from the training set. A Euclidean distance is calculated between an input vector and these weights, which are then scaled by the spreading factor (b_i). The radial basis output a_i, is then calculated as the exponential of the negatively weighted distance:

$$d_1 = (\sum (p - iw)^2)^{0.5}$$

$$a_i = e^{-d_j^2 b_j^2}$$

Where p is input vector, iw = initial weight matrix, b= spreading factor, i= number of data patterns

Therefore, if a neuron weight is equal to the input vector, distance between the two is 0 giving an output of 1. This type of neuron gives an output characterizing the closeness between input vectors and weight vectors. The weight matrix size is defined by the size of the training dataset (m

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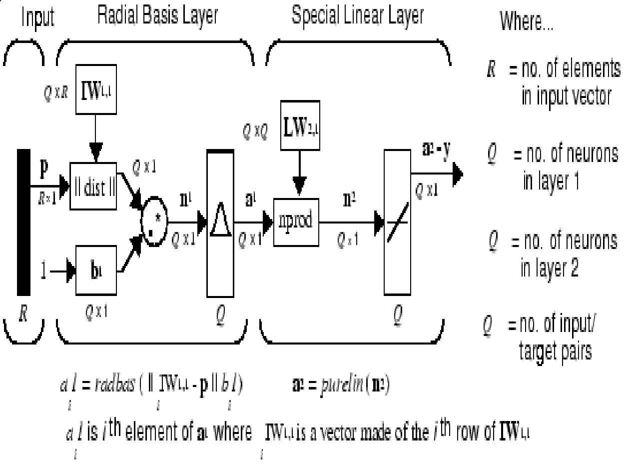
parameters x n data points), while the number of neurons is the number of input vectors (n) [16].

The architecture for the GRNN is shown below. It is similar to the radial basis network, but has a slightly different second layer.



The second layer consists of neurons with a linear transfer function. Hidden layer weights, lwi, are set to target values. The output of second layer tp (output corresponding to input vector, p) is:

$$t_p = \frac{\sum lw_i * a_i}{\sum a_j}$$

As the spreading factor b increases, the radial basis function decreases in width. The network will respond with the target vector associated with the nearest design input vector. As the spreading factor b becomes smaller, the radial basis function increases in width. Several neurons may then respond to an input vector. This is because the network computes a weighted average of corresponding target vectors. As radial basis function gets wider and wider, more neurons contribute to the average resulting in a smoother model function. For this study, the spreading factor was held constant for all neurons and is optimized through calibration of the network.

VI. SIMULATION AND RESULTS

In prediction of end point of BOF steelmaking we use the MATLAB 2010b version for ANFIS we use fuzzy logic toolbox and GRNN we use neural network toolbox. Through domain knowledge of the process and after lot of research in this process six process Parameters were chosen for end point carbon prediction and seven parameters for end point temperature.

PROCESS PARAMETERS:-

Input for Temperature	Input for Carbon
Carbon content in HM	Qnt. of Hot Metal
Qnt. of Oxygen blown	Qnt. of Scrap Steel
Temp. of HM	Qnt. of Coke
Qnt. of Limestone	Carbon content in HM
Qnt. of HM and Scrap Steel	Oxygen blown
Qnt. of Additives	Temp. of HM
Qnt. of Aluminum	

RESULT OF ANFIS:-

In the result of ANFIS predict end point carbon gives root mean square error (RMSE) is 4.7784e-006 and R (error) is 0.27484. The end point temperature gives root mean square error is 0.01851 and the R (error) is 0.22.

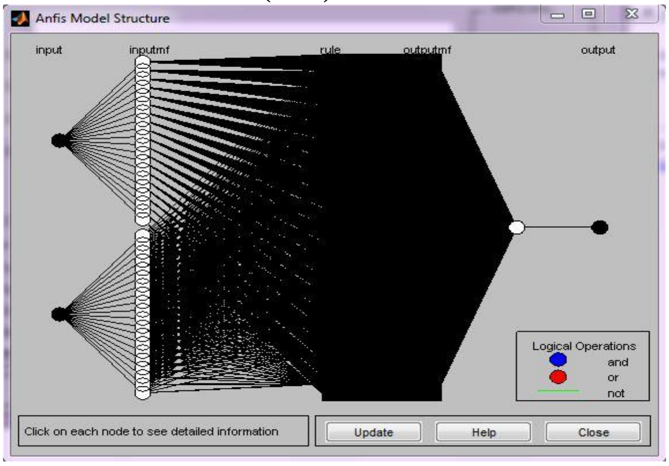


Fig. – ANFIS model of carbon percentage and temperature.

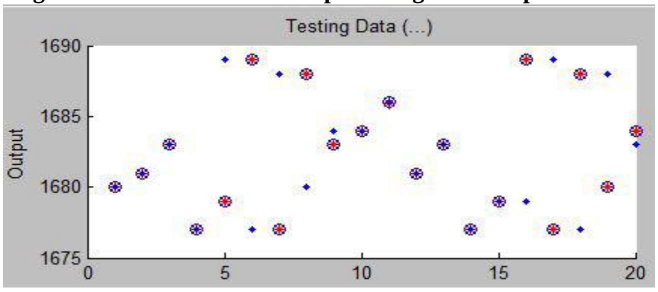


Fig. - Prediction of end point temperature

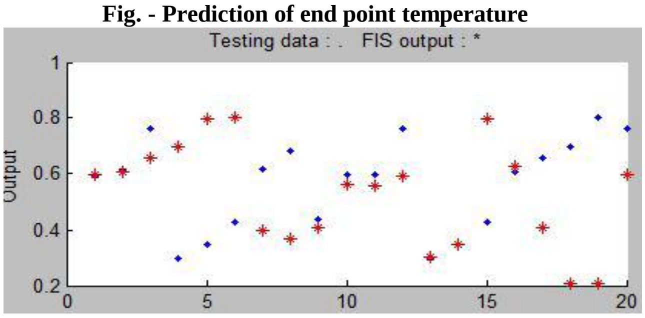


Fig. - Prediction of end point carbon percentage.

ANFIS MODEL PARAMETERS:-

ANFIS Temp. model	ANFIS Carbon model
No. of Nodes 4426	No. of Nodes 1503
Number of linear parameter 2187	Number of linear parameters 729
Number of nonlinear parameter 63	Number of nonlinear parameter 36
No. of parameter 2250	No. of parameter 765
Number of training data pairs 20	Number of training data pairs 20
No. fuzzy rules 2187	No. fuzzy rules 729

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RESULT OF GRNN:-

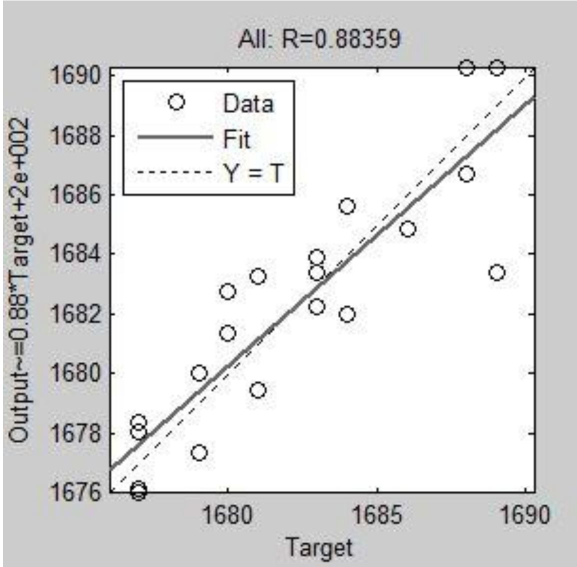

Fig. - Prediction of end point temperature

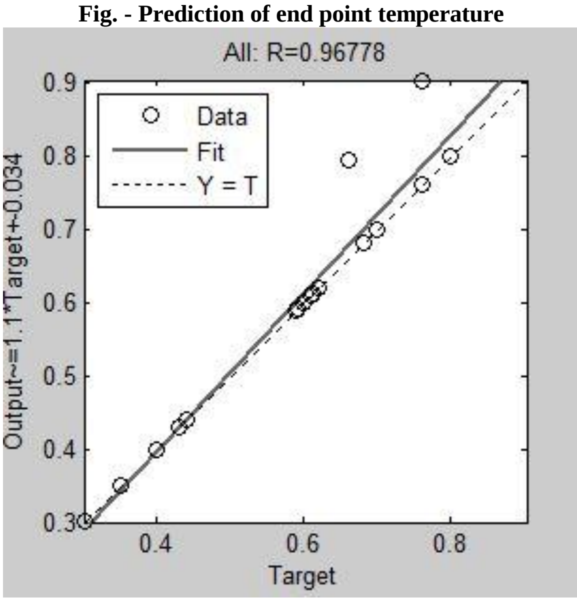

Fig. - Prediction of end point Carbon percentage

In the results of GRNN predict end point carbon root mean square error is obtain 3.5147e-3 and the R (error) is 0.92166e-1. For end point Temperature root mean square error is 3.670 and the R (error) is 0.9441.

COMPARISON OF RESULTS OF ANFIS AND GRNN:-

COMPARISON OF RESULTS OF ANFIS AND GRNN

INPUTs	CARBON		TEMPERATURE	
Model	ANFIS	GRNN	ANFIS	GRNN
RMSE	4.7784e-6	3.5147e-3	0.01851	3.6706
R(error)	0.27484	0.92166	0.2200	0.9441

VII. CONCLUSIONS AND FUTURE SCOPE

ANFIS Model has 5 layers and GRNN have only 2 layer of neural network. The result of ANFIS is better than GRNN. In prediction of end point carbon root mean square error of ANFIS is 4.7784e-6 and root mean square error of GRNN is 3.5147e-3. In prediction of end point temperature root mean square error of ANFIS is 0.01851 and root mean square error of GRNN is 3.6706. ANFIS Model can be implement in Stainless steel, Silicon steel, Tool steel (tungsten or manganese), Bullet steel, Chromalloy (chromium, molybdenum), Crucible steel, Damascus steel, HSLA steel, High speed steel, Mar aging steel, Reynolds 531, Wootz steel, alloy making process.

Robust relevance vector machine (RRVM) and adaptive-network-based fuzzy Inference system (ANFIS) proposes a dynamic control model for oxygen furnace (BOF) steelmaking process. The noise variance coefficients of outliers gradually decrease by introduce individual noise variance coefficient to each training sample proposed in RRVM to improve the robustness of the model [13]. ANFIS model based on kernel and greedy components is future scope of this paper. This kind of model can improve the endpoint predicting precision of the steel carbon contents and temperature in BOF.

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AUTHOR BIOGRAPHY

Sarita Chouhan received her B. Eng. Degree in Electronics & Communication from Rajeev Gandhi Proudyogiki Vishwavidyalaya, Bhopal, India in 2002 and M.Tech degree in VLSI design from Mewar University, Chittorgarh, Rjasthan, India. Currently she is an Assistant Prof. in Electronics and Communication department in Manikya Lal Verma Govt. Textile & Engg. College, Bhilwara, Rajasthan, India. Her area of interest are applied electronics, Microelectronics, VLSI, VHDL, Verilog, EDA, Analog CMOS designing and Low Power optimization.

Mahendra Singh is a student of final year B.Tech. Pursuing his Degree in Electronics & Communication from Rajasthan Technical University, Kota, India .His area of interest are in VLSI design and MATLAB. He presented papers in National and International conferences on ANFIS model currently working on neural network toolbox and HSPICE toolbox.

Vivek Kumar Meena is a student of final year B.Tech. Pursuing his Degree in Electronics & Communication from Rajasthan Technical University, Kota, India .His area of interest is in VLSI design and MATLAB. He presented papers in National and International conferences on ANFIS model currently working on RRVM.