Prediction and Optimization of Blast Furnace Parameters using Artificial Neural Network

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Abstract— Blast furnace (BF) is a giant countercurrent reactor and heat exchanger, and is the first step towards the production of the steel. It is one of the most complex industrial reactor and is impossible to model mathematically. The operation and control of an industrial blast furnace is a serious problem, hence to overcome this we are using Artificial Neural Network (ANN). It is very important to predict the various temperatures i.e., Raceaway Adiabatic Flame Temperature (RAFT), Stack temperature and uptake temperature. Optimizing these temperature distribution would lead to considerable savings of input material of blast furnace. Productivity as well as quality can be improved by knowing these parameters in advance. In this paper, we are using the multi input multi output (MIMO) artificial neural network. By this we have to optimize overall efficiency, minimize operational cost, and reduce fuel consumption which leads to improve productivity. The input parameters used are Oxygen enrichment, Blast volume, Blast pressure, Top gas pressure, Hot Blast temperature, steam injection rate, cold blast flow, cold blast temperature and Pulverized coal injection rate. For prediction and optimization back propagated, feed forward artificial neural network is applied. All the input data were collected from the Vizag steel plant (VSP) during the period of 5 months.

Keywords: ANN, Blast Furnace, RAFT, MIMO

I. INTRODUCTION

Blast Furnace is used from the very early days of 1700 B.C. Most of Europe. The iron preparation from the ancient to the end of the medieval ages is the same alternating layer of ore and wood that was heated until molten ore was obtained. The molten ore was fired to get the raw iron that is completely forged to remove impurities. A few away from the heart, the metal was ready. Initially simple to taper opening in the floor, the heart developed into a furnace, progressively becoming

Ideal. The quantity of iron produced in the early century was only a few kilograms first then later reached 55 to 65 kg in the medieval age. From that time on, iron was manufactured enhanced with carbon steel.

A series of chemical and thermal reactions take place inside the blast furnace. Many variables are involved as a process so that the exact mathematical process is difficult to model due to its complexity. Today, many iron makers around the world have used modern technology to improve the efficiency of the blow furnace by improving the quality of the molten iron.

A very complex process usually takes place in the blast furnace for the production of pig iron, which is gradually developing as a conventional furnace. The blast furnace melts down the ore by burning the coke. Pig iron is produced as a blast furnace output by a series of several equations. The blast furnace process is very difficult to replicate as the co-existence of the mass and heat transfer phases. Predicting the outcome and controlling the blast furnace operation is very difficult, and operators are aware of this fact.

The blast furnace manufacturing is based on the chemical analysis of temperature and pig iron. It also depends on the slag condition. These factors affect the output parameters in the blast furnace operation.

So we need to optimize the parameters of the blast furnace. We need a model that can predict RAFT, shaft temperature, and uptake temperature automatically. In this sector, there has been so much use of neural networks. Predicting the parameters to enable operators to effectively regulate the process. In order to optimize the expected temperature, we will then apply these expected parameters to the genetic algorithm. Our task is to first develop a predictive model and then optimize the predicted results with the help of the neural network and the genetic algorithm in particular. We need the historical information of blast furnace for the development of these models.

The neural network is an art, it is not a science. There are only a few system sets to track and it is extremely difficult to predict which type of model would be suitable for the known data collection. We have several methods to minimize the root mean square value in this present work by training the data several times.

A. Blast Furnace:

Steel is known as a ferrous and carbon alloy and is manufactured using a complex process. In the furnace, a mass of iron ore and charcoal were heated. With some slag and charcoal ash, the ore is reduced to metallic iron.

Modern blast furnaces are the refinement of traditional furnaces, but they are equipped with instruments and architecture control. The molten iron, commonly known as pig iron that is the steel's raw material, is produced at this stage. The blast furnace's main purpose is to remove the oxygen from the iron, create the molten material, and control the impurities. The steel production process starts with three basic materials, limestone, iron ore and coal. The coal is first heated to produce the coke in coke ovens. This process is called carbonization and produces a gas used as fuel to other steel plant parts.

Once the coke has been preheated and passed this procedure, it is removed for cooling from the oven. At the same time, iron ore and limestone are granulated, mixed and preheated in a sinter plant in a moving belt where the materials are ignited to fuse together to form a porous material known as sinter whose main purpose is to speed up the blast furnace process. The sinter and coke are then transferred into the blast furnace to produce the pig iron. In the blast furnace, a conveyor belt adds coke pellets and iron ore to the top. Through nozzles, called tuyeres, the hot air of temperatures above 1450 C is blasted from the bottom of the furnace. To form carbon monoxide (CO), oxygen is combusted with coke

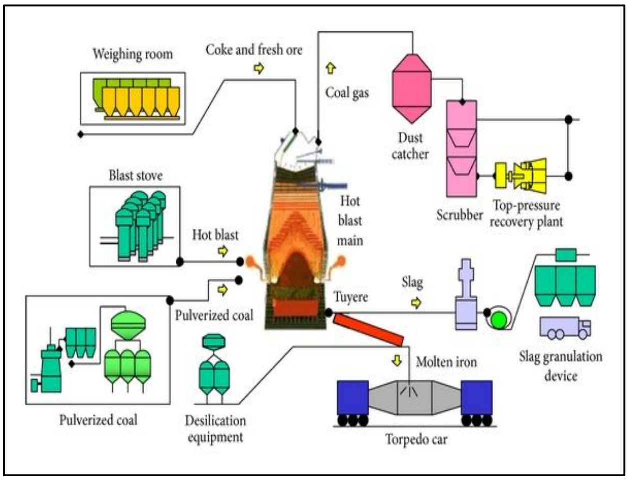

Fig. 1.1: Schematic-diagram-of-a-typical- BF-ironmaking-process

The heat from the furnace subsequently helps to melt the iron and turn it into a liquid form. On top of this molten iron, the impurities are floated and it is known as slag. This is removed to produce pure pig iron at different stages. Once the hot metal is ready, it flows into torpedo ladles, which are specially built railway containers used to transport the pig iron to the LD furnace. The oxygen is added to the molten iron at the LD furnace and then passed through a caster and cooled into slabs and rolled into sheets. This is the finished steel that can be shipped to manufacturing plants for further processing. In other words, the blast furnace must remain at a consistent temperature at all times and should not be allowed to cool down and maintain the proper composition. The furnace lining would be damaged by high or low temperatures and may introduce impurities into the molten iron. The production rate, cost and quality they encounter at steel manufacturing plants are of great concern to Steel Companies.

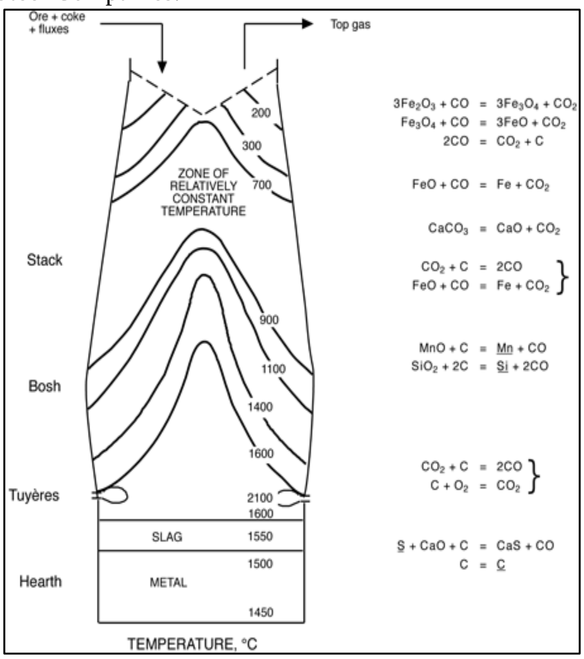

Fig. 1.2: Technical description of blast furnace operation

One serious issue steel plants are facing is the sudden drop of hot metal temperature in blast furnace. The blast furnace temperature below 1350 ˚C causes the stop in production of liquid iron. It does not ensure proper carbon steel quality production as well as melting; therefore, the steel will result of impurities. Therefore it is very important to maintain the temperature of the blast furnace between the ranges from 1350 ˚C to 1550 ˚C which ensures that the iron is properly melted with the correct consistency to produce steel of the highest quality. When the temperature drops below 1400 ˚C, the production must be stopped until the temperature rise again.

The plant operators increase the inputs to the furnace for rapid action, but due to the time lag between the action of the inputs and their effect, the temperature does not rise quickly. Once this is achieved, it is possible to continue the production of hot metal. Simply adding the raw materials to the blast furnace does not increase the furnace temperature automatically.

Since the coke added to the furnace must be combusted in order to form CO gas that heats the iron. There is a time delay associated with materials being added and the point when proper temperature is once again reached in the furnace. This is a waste of time, resulting in the loss of production, manpower and money. Therefore, if the temperature drop is predicted in advance, the operators can add the correct amount of inputs at correct time to prevent this situation. Blast furnace mathematical modeling based on artificial neural network can help operators predict the temperature and other parameters affecting steel production quality.

B. Artificial Neural Network:

In many industrial branches, neural networks are used. They are an alternative to the problem-solving analytical approach. Neural networks can be used for all areas predictive, classification or control-related problems. In the 40s of the previous century, the idea of building artificial neural networks appeared. The work began with a simplified neuron mathematical description. ANN is very similar to our human nervous system, our human brain. Normally, ANN is used to identify, classify, predict, pattern recognize, match and optimize. It solved complicated mathematical issues where there are no variables. They present a good nonlinear system with several advantages, they are easy to program, they solve multi nonlinear problems.

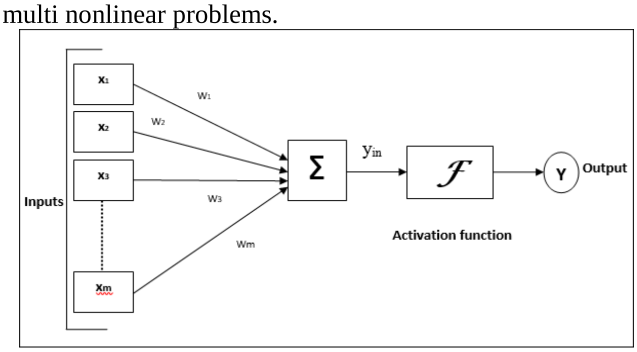

Fig. 1.3: ANN model diagram

However, our work has to do with predicting the parameters using previous data. The sufficient data should be in hand to develop new or existing system. Prediction depends primarily on the parameters of the selected input. The algorithm speed and memory capacity problem will occur when comparatively more parameters are considered than required. On the other hand, the output of the model will not be able to predict correctly if there are fewer parameters for input. The input parameters will therefore be taken in a way that reduces the complexity of the algorithm and improves accuracy.

Neural network is used to solve non-linear relationship issues that are highly complex. It established the relationship with a set of no-connected series nodes between a set of input variables and output. The NN model has three layers, known as input layer, hidden layer and output layer. On the basis of problems hidden layer will be selected. But from the experiments we find that increasing the hidden layer does not improve the network's performance by much however by varying the hidden layer nodes, the network's performance is affected.

Feed-forward Neural network was used to predict and control the temperatures of the different blast furnace zones using 9 input variables. Back propagation algorithm has been used in the forward neural network feed. Back propagation is used for the weight and bias algorithm corresponding to the hidden layer and the output layer. Biases are supplied to the network to adjust the error across the hidden layer and output layer. The back propagation algorithm computes the derivative to calculate the error. It provides us a procedure for calculating the error and relate with the derivative. The predicted values from output layer compared with the teaching input and then error is found between the output layer and the teaching layer. These errors are propagated backwards to the input layer to minimize the error by training the data again.

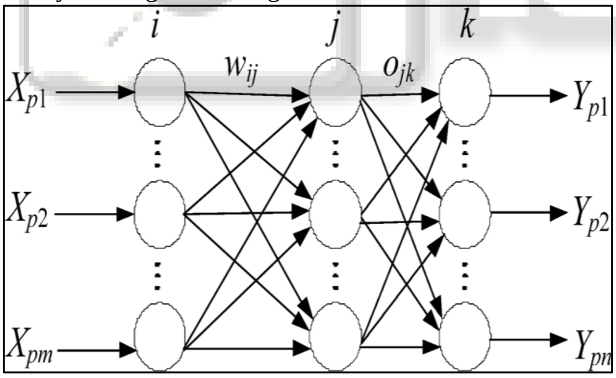

Fig. 1.4: Multi input multi output ANN with back propagation model

Xp1 to Xpm reflects the neuron numbers in the input layer, w is the weight corresponding to each node bias is given to adjust the error between the output layer and the hidden layer. Yp1 to Ypn is the network calculated output. Used transig feature for the input algorithm in the hidden layer and output layer. Multiple output is calculated here.

C. Genetic Algorithm:

Genetic algorithms are often used in the preparation of neural networks. There are numerous neural networks that bundle a genetic algorithm for the preparation stage. The output produced of genetic algorithms is reasonable. As they take the type of parameters in the wellness capacities, the results can be connected effectively. Genetic algorithm used to discover ideal qualities most of the time. They are not limited to the type of information-the length of the information can be spoken to as a series of altered length bits. They do not promise optimality despite the fact that the genetic algorithm is suitable for improvement. They may be hitting an optimum neighborhood and certainly not finding the best arrangement. Genetic algorithms can be calculated to be escalated; items that join them along these lines tend to undertake level items that continue to run on effective servers.

II. LITERATURE SURVEY

Marc A. Duchesne et al was developed an artificial neural network model to predict slag viscosity over a wide range of temperatures and slag compositions. They created an ANN model to predict slag viscosity over a wide range of temperatures and slag compositions. To avoid over fitting a lot of measurements were taken. For find out the effect of various fluxing agents, slag viscosity predictions were made for Genesee coal ash. After the fluxing agents considered, the one with high magnesium at ease has the most effect when it comes to minimizing the necessary temperature for slag removal.

Jerzy FELIKS et al have studied prediction model based on multilayer artificial neural network for the prediction of iron ore demand. Historical data of iron ore demand as well information regarding the current situation on steel market and the iron ore stock volume of a given metallurgical company. They designed the model for the prediction of iron ore for next month with the help of previous data. The algorithm used for learning the network was Levenberg-Maguardt algorithm. To efficiently reduce uncertainty and risk of logistics decision-making in the sphere of iron ore supply the hybrid intelligent decision support system will be used.

Sujit Kumar Bag studied a method to predict the blast furnace parameters based on artificial neural network (ANN). Predicted the parameters in advance for improving the quality as well as productivity of hot metal. Predicted the parameters advance in 6hrs and 4hrs for HMT and silicon content. Designed the feed forward neural network for the characterization of input and output parameters. Hot metal temperature and percentage of impurities of silicon content in molten iron can be predicted to improve the quality. Because of natural occurring it is observed hot metal temperature of the blast furnace suddenly drops. For the elimination of this problem a predictive model (ANN) has been developed to know the process parameters in advance.

III. METHODOLOGY

A. Data Collection:

Data required for the exercise input and output were extracted from the blast furnace records spanning three years. For ANN processing, nine input parameters and three output parameters were used. The research inputs are the ones that are most sensitive to the outputs from literature. The inputs are interrelated, i.e. Changing one parameter affects the other. The inputs are Oxygen enrichment, Blast volume, Blast pressure, Top gas pressure, Hot Blast temperature, steam injection rate, cold blast flow, cold blast temperature and Pulverized coal injection rate. The output parameters on the other hand are raceaway adiabatic flame temperature, stack temperature and uptake temperature. These inputs and outputs are fed into a MATLAB-based ANN system to establish an optimum model.

B. Input Parameters:

We took nine input variables to predict RAFT, Stack temperature and uptake temperature. The input variables are tabulated in the form of table. Selected the input variable as time in dependent. Variables depending on time are the ore / coke ratio. This is time-dependent. Instant effect is not shown on the furnace when we put the charge in the blast furnace. It takes 7-8 hours to reach the combustion zone so there is no immediate effect on the hot metal temperature.

NO.	PARAMETERS	RANGE	UNITS
1	OXYGEN ENRICHMENT	1.6 -1.7	%
2	BLAST VOLUME	5194 – 5209	Nm³/mm
3	BLAST PRESSURE	3.32 – 3.37	Kg/cm^2
4	TOP GAS PRESSURE	1.96 – 2.04	Kg/cm^2
5	HOT BLAST TEMPERATURE	992 – 1008	^{0}C
6	STEAM INJECTION RATE	3.5 – 9.5	T/hr
7	COLD BLAST FLOW	2561 - 3612	Nm³/mm
8	COLD BLAST TEMPERATURE	984 – 1113	^{0}C
9	PULVERIZED COAL INJECTION RATE	13.84 – 35.45	T/hr

Table 1: Input parameters with range and units

C. Oxygen Enrichment:

For every 1 percent increase in hot blast oxygen enrichment, there is 2 to 2.5 percent increase in blast furnace productivity. When coke burnt at the tuyere nitrogen of the blast are also heated by 4-5 unit with every unit of weight. Some amount of gasses in the shaft or stack zone are valuable for heat transfer. The presence of nitrogen in the blast restricts the temperature generated in the combustion zone. By increasing the oxygen content in the blast, we can improve this temperature in the combustion zone by decreasing the nitrogen content in the blast. Oxygen reduces nitrogen in the burden for every 2 percent of oxygen enrichment reduces nitrogen by 4 units in the burden per unit weight of coke and higher temperature in the combustion zone is possible.

In front of the tuyere there is a limit of higher temperature as excess temperature causes stock bridging and sticking and also more silicon content in the molten iron which is undesirable for pig iron quality. Another endothermic reaction must engross excessive heat generated in front of the tuyere.

The oxygen enrichment up to 25% in the blast is advantageous by the balance of adequate humidification. The combined effect of both the enrichment of oxygen and the humidification of blast provides good temperature control in the combustion zone.

Any increase in the percentage of oxygen enrichment results in an increase of 3 to 4 percent in the production rate and also save the coke rate. When moisture cracking occurs that gives the hydrogen and acts in the stack as a reducing gas. As shown in the figure, oxygen enrichment increases productivity.

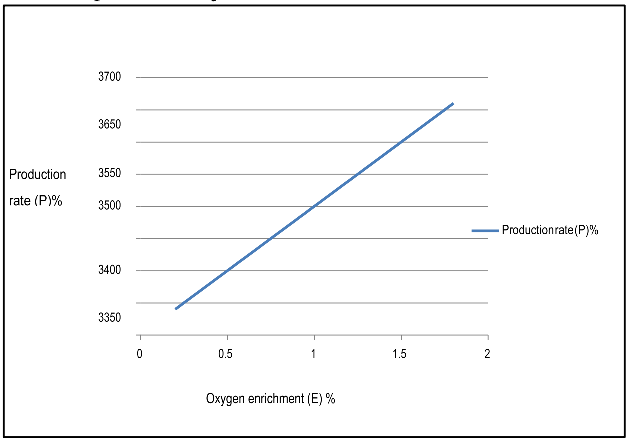

Fig. 3.1: Effect of oxygen enrichment on production rate

The effect of enriching oxygen is as illustrated in the figure. If we increase 1% of the oxygen, the productivity will increase by 2-3%.

The rate of production depends not only on the values of oxygen enrichment, but also on other variables such as blast temperature, blast volume, injection rate of steam.

Additives can also affect the furnace's performance as it maintains the RAFT. It is helpful to control RAFT in a range that is neither maximum nor minimum. It affects the combustion chamber's melting zone under both conditions.

D. Hot Blast Temperature:

The hot blast enters the furnace through base known as tuyeres. After leaving the stove, it enters the blast furnace through the tuyeres. It has reacted with coke, ore and fluxes and emerges as a top gas, containing carbon monoxide and carbon dioxide in particular. There is a 1.4 bar pressure drop across the burden, regardless of the top gas pressure. As the pressure variation is present, the furnace's permeability is good and the materials are moving down at the appropriate speed through the furnace so that the reduction can occur. If the temperature of the hot blast is constant, a good furnace efficiency can be maintained. We must therefore keep the temperature of the blast constant in the combustion zone. As the hot blast leaves the stoves cool down the hot blast temperature decreases so that we need to mix the hot blast with the cold blast in the mixing chamber to maintain a constant temperature. The controlling chamber that contains the control module controls the proportion of the hot to clod blast. Blast temperature is an important parameter that affects the blast furnace's productivity. The productivity will be improved by 1% with the 100^{0}C increase in the blast temperature. There is also a decrease of 0.1% in the Sulphur content of coke, which improves productivity by 0.7% to 1.2%.Hot blast temperature can produce 2400-2500^{0}C as a RAFT that can be used, as RAFT increases the combustion chamber's melting zone and affects pig iron quality. The combination of blast temperature, humidification, oxygen enrichment, injection of pulverized coal and natural gases brings down the RAFT to normal 1900-2000^{0}C The appropriate values to bring the RAFT as normal are 150-200kg / thm pulverized coal injection or 100-150Nm3 natural gas injection with 3-5% oxygen enrichment and 5-10% blast humidification. All these variables combinations bring the RAFT as normal. By the use of pulverized coal injection coke rate is decreases.

E. Humidification of Blast:

RAFT is the best required factor for smooth blast furnace operation. RAFT depends on the blast's moisture content as it varies from season to season. In rainy season, humidity is maximum and minimum in dry summer. By adding some additives with the blast, we can increase the blast temperature without increasing the RAFT.

Steam is introduced to the stove in the cold blast before it is preheated for blast moisture. If we add steam to the hot blast then the hot blast temperature is reduced as the steam temperature is very low compared to the hot blast and therefore has a cooling effect that is undesirable. The best advantage of humidification is that it reduces the day-to-day level of humidity that always varies and eliminates the major variable that affects the operations of the blast furnace.

Steam requires energy to be generated and is not cheap either. It is found that the endothermic process will compensate for an increase of 20g / Nm3 of moisture in the blast by an increase of 200^{0}C in the blast preheat. This is the thumb rule for adding additional moisture.

Some variables are time-dependent and some are time-independent, which means that the immediate effect on the molten metal cannot be seen. The time-dependent variable is the ore / coke ratio as it cannot effect immediately. It takes time for the charge to come down to the hearth. But there are some instant variables that can instantly control the process. These variables are blast rate, blast temperature and blast pressure also oxygen enrichment.

If RAFT increases beyond the usual value melting zone at tuyere level, it will start to increase. On the other hand, when the RAFT begins to drop, then the smelting capacity and reduction process decreases and the furnace's thermal heat balance will be faded. When the flame temperature value increases suddenly, then the melting zone becomes uneven. Oxygen enrichment of the hot air blast is normally accompanied by fuel injected at the tuyere level. The injection of oxygen into the air blast reduces the specific gas flow causing the top temperature to decrease and the RAFT to increase. Thus the injection of fuel additives such as pulverized coal injection, natural gas, etc. can compensate for these effects.

Blast pressure and volume of blast affect the furnace's injection rate. If the blast pressure is below 10psi, coal could be injected. If the pressure is within 10-15psi, the injection rate will be half. The blast pressure would be above 15psi for better furnace performance. We included some changes to the tuyere level for the uniform injection. . For the effective operation of the lance the injecting lance angle should be 11^0.

F. Output Parameters:

To generate hot metal temperature for steel production, a blast furnace is used. The quality and quantity in front of the tuyere level depends on the temperature. In the blast furnace, an enormous amount of heat is generated. Hot blast air is injected into the tuyere together with oxygen enrichment and other fuel additives for the iron ore combustion. This thesis focuses primarily on prediction and optimization. The prediction of RAFT, shaft temperature & uptake temperature with the use of 9 input variables. The neural network is used for the prediction. By optimizing these output parameters, we can improve productivity.

No.	PARAMETERS	RANGE	UNITS
1	RAFT	1900 – 2100	^{0}C
2	UPTAKE TEMPERATURE	150 – 250	^{0}C
3	STACK TEMPERATURE	800 – 900	^{0}C

Table 2: Output parameters with range and units

G. RAFT:

There is a runway or raceway in front of each tuyere zone where the flame travels as the gasses smoothly expand through the whole cross section of the furnace. As the gasses expanded, the first raceway is horizontal, then it changes the direction as vertical through the furnace cross section. The temperature found in this zone is known as raceway adiabatic flame temperature (RAFT). RAFT should be in the range neither maximum nor minimum. As RAFT increases the melting zone also increases consequently, the sudden drop of the RAFT faded the furnace accordingly and also reduces the process's reduction. Theoretically the RAFT should be maintained at 1900^{0}C but in actual the RAFT varied up to 2000^{0}C in the blast furnace as we have noted the data from VSP. Sulphur remains unaltered but the silicon content goes up to 1 to 1.36 which can be controlled by the oxygen enrichment.

H. Uptake Temperature:

By the large vertical pipes called uptakes, the effluent gases are going out of the furnace. There are four main uptakes in number. By combining the two adjacent uptakes, a single duct is formed and two such ducts are again combined into one duct. For the cleaning of gases, the effluent gases are going down to the dust catcher. Effluent gas temperature is known as the uptake temperature. Through the gas pipe, the unreduced gasses left the furnace. The uptake temperature is found in this zone and varies from 150 ^{0}C to 250^{0}C.

I. Stack Temperature:

The temperature in the stack zone or shaft zone is known as shaft temperature. The shaft temperature varies 800 ^{0}C to 900^{0}C in the blast furnace as reading noted from the VSP. The reduction of the reaction starts from the starting of this zone. Various reactions takes place inside the BF reduction of the iron ores in the process. Indirect reaction takes place inside the blast furnace at the upper zone

J. Procedure:

- Collected the data of blast furnace from VSP during the operating period of 5months.
- As the input variables are varying in large amount such as oxygen enrichment & some are varying less known as blast pressure so we need to normalize the input variable and as well as output variable.
- Use the Neural network tool for the prediction of RAFT, shaft temperature and uptake temperature.
- Train the network again and again to minimize the error.
- Compare the predicted data with actual data and find out the error.

IV. DATA ANALYSIS

We trained the data for several times to minimise the error as varying hidden nodes and hidden layer & select the one when we get less MSE & more R value as shown in table.

NN model	MSE	R value
9-2-15-3	0.0319	87%
9-2-20-3	0.0144	79%
9-1-9-3	0.0183	78%
9-1-10-3	0.0125	84%
9-1-15-3	0.003	96%
9-1-20-3	0.0011	98%
9-1-25-3	3.89	88%
9-1-30-3	8.22	86%

Table 3: NN Training table

From the above table we find that the best neural network model suited for 9 input variables and 3 output variables are with one hidden layer and 20 no. of neurons gives 98% regression values and mean square error is 0.00112.

- The activation function used at hidden layer and output layer is transig function is given as

$$\frac{1 - e^{-2x}}{1 + e^{-2x}}$$

- The output from a given neuron is determined by applying a transfer function to a weighted summation of its input to give an output

$$O_n = \sum_{i=1, j=j}^{N} IN_i W_{ij} + B$$

N= Total no of input nodes inputs in neural network W= weight of the ith & jth layer
B= bias; O= total no of output

Gradient Descent algorithm changes weights and predispositions relative to subsidiaries of system keeping in mind the end goal to minimize the mistake. Gradient Descent algorithm is moderately moderate as it obliges littler preparing rate for more steady learning and this is an unmistakable downside because of now is the right time expending procedure. Both Levenberg-Marquardt and Gradient Descent algorithms are utilized as a part of this study to assess conceivable impacts and execution of the preparing algorithms of neural systems models. ANN likewise can be incorporated with numerous different methodologies including connection master frameworks to enhance the forecast quality advance.

Neural network model progress during training process.

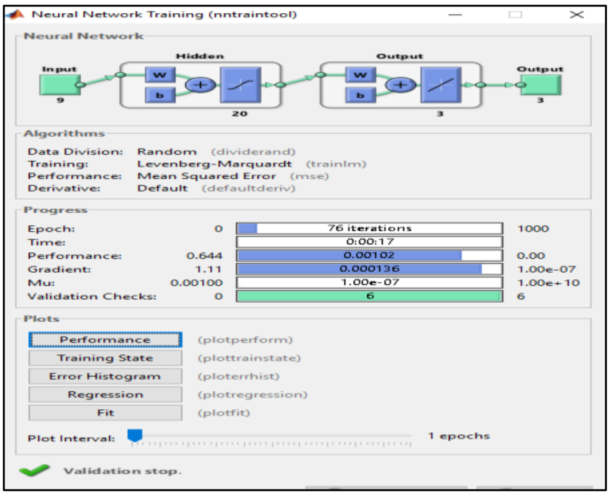

Fig. 4.1: Training process of the neural network.

In the above figure it shows the training progress of the neural network. Levenberg- Marquardt algorithm is used for the process of the training. Epoch showing in the progress goes up to 1000 iterations. Validation checks also done for the 1000 iterations.

Neural network training regression plot is shown in the figure.

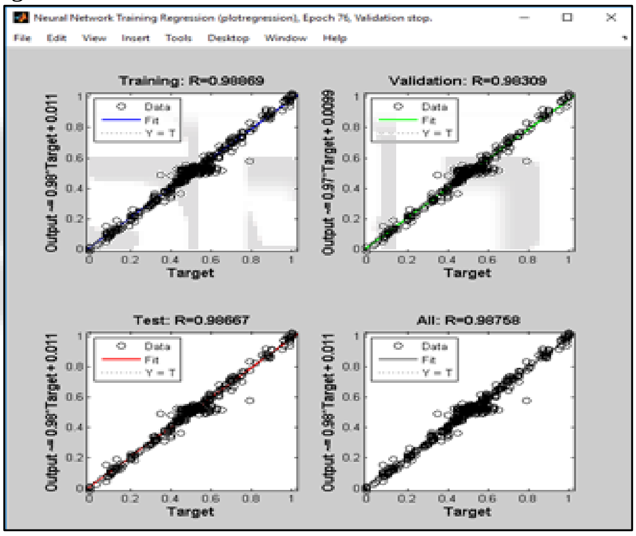

Fig. 4.2: Regression plot for training, validation & testing

This is the regression plot for training, validation and testing. We have taken the data 70% for training, 15% for validation and 15% for testing. Training data represents the no of weights and bias corresponding to minimize the error. Validation data represents the untrained values for the network. Testing data represents the best performance of the model. In training 70% of data were taken for trained the values as it shown in the plot and 15%, 15% data were taken validation and testing. The regression values for training plot are 0.98860. If the regression values will be 1 then there is exact linear relationship between output and target and if the regression value is 0 then there is exact non-linear relationship between output and target. Similarly the regression values for validation and testing is 0.98309 and 0.98366 respectively. Solid line represents the best fit linear regression plot between the output and target data. Dashed line represents the best result between output and target.

Performance curve plot for training, validation and testing along the no of epochs.

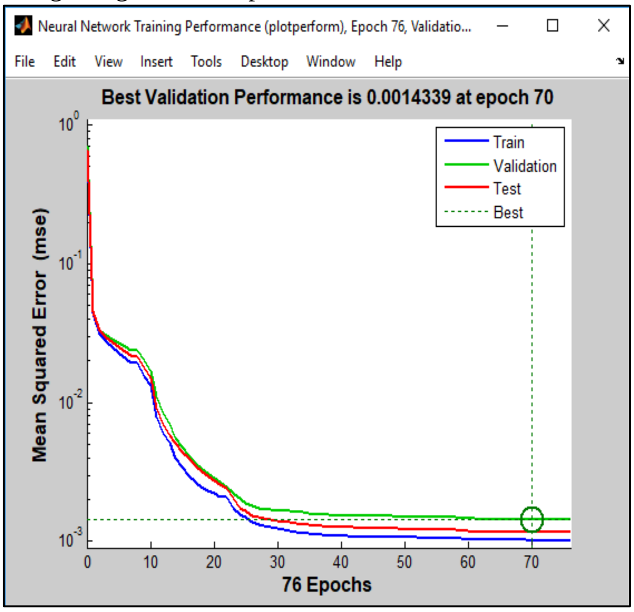

Fig. 4.3: Training performance curve

This figure shows the performance curve for training, testing and validation. It varies along the no. of epochs with mean square error 0.00112. The best validation performance is 0.0011. The blue lines shows the training curve variation along the no of epochs, green is for validation and red one for testing curve. The dotted line shows the best validation performance curve.

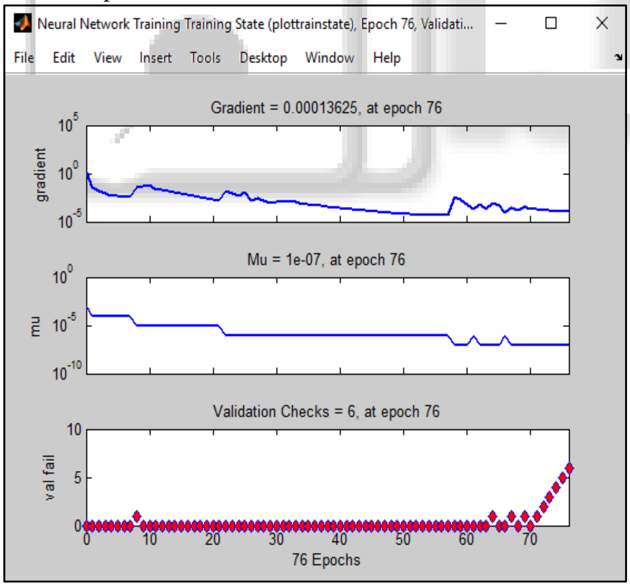

Fig. 4.4: Shows gradient, mu values and validation failure across the no of epochs

This curve shows the training state when the training performance is done. Validation failure varies linearly along the no of epochs. Validation is stop when the maximum no of epochs reached. Validation failure also run for 1000 epochs. Mu values varies between 0.00100 to 1.00e+10. Validation check for 1000 epochs. Gradient values varies from (1.41e+03 to 1.00e-07) and values of gradient is 4.26e-06.

V. RESULT

Graph for variation between actual normalised RAFT v/s predicted normalised RAFT.

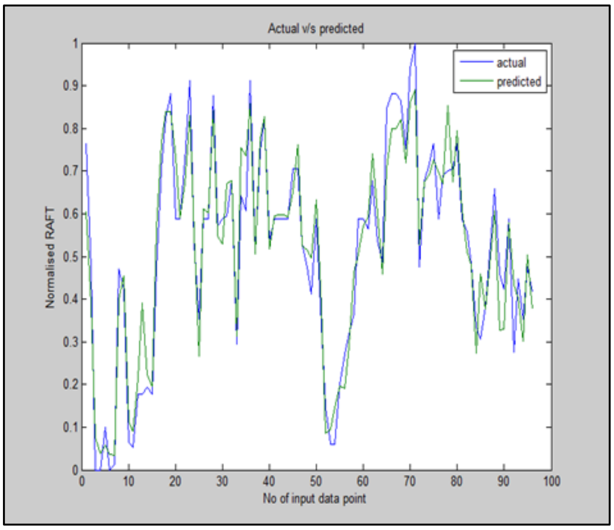

Fig. 5.1: Variation of predicted V/s Actual RAFT with 9 input variables.

The variation between actual and predicted is shown in the figure. Normalised RAFT prediction has been done with the 9 input variables across 96 data points. The blue line shows the actual normalised RAFT and green shows the predicted RAFT. The MSE between actual and predicted RAFT is 0.0121. The 9 input variables were taken during the operating period of 1 month.

Graph for variation between actual shaft temperature and predicted shaft temperature.

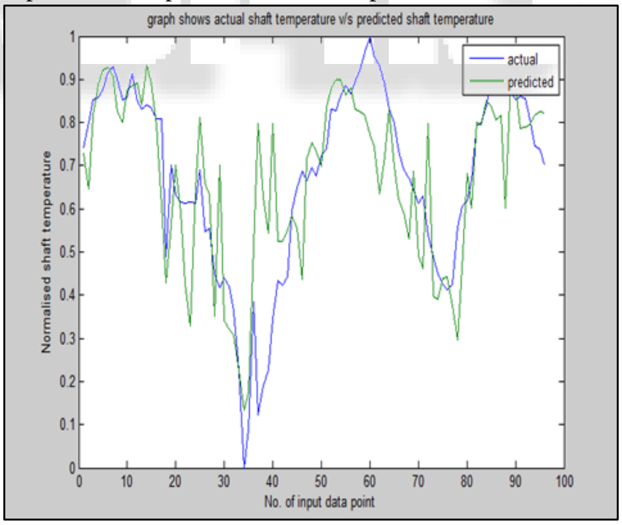

Fig. 5.2: Variation with actual shaft temperature V/s predicted Shaft temperature with 9 input variable.

Variation of actual shaft temperature v/s predicted shaft temperature. The mean square error between actual and predicted is 0.0521. 96 data points were taken for the prediction corresponding to 9 input variables. In this graph somehow there is more error as compared to RAFT and uptake temperature. This error is more because we trained the data with multi output. The error can be minimized by taking all the output variables single.

VI. CONCLUSIONS

Artificial neural networks are a very good tool for the modeling of various dependences. The paper presents the properties of artificial neural networks used for the blast furnace process modeling. The output parameter for the network was the RAFT, Stack temperature and the input parameters were the variables, which describe the BF process. The results of the BF process modeling have been satisfactory and more network improvements are still possible. During the process modeling operation a correct selection of input data is of a primary importance. Neural networks can be used as a tool for modeling many different complicated processes.

- Applied the artificial neural network successfully for the prediction of output and find the mean square error as 0.11% with 20 no. of hidden nodes using 1 hidden layer.
- For metallurgical point of view maximize the shaft temperature, minimize the uptake temperature and put in range of RAFT.
- The multiple output model give more error as compared with the single output neural network model.

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