Optimization of blast furnace parameters using artificial neural network

A THESIS SUBMITTED IN PARTIAL FULLFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

Master of Technology

In

Metallurgical and Materials Engineering

(Steel Technology)

By

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CERTIFICATE

*This is to certify that the work in this thesis report entitled "***Optimization of blast furnace parameters using artificial neural network"** *which is being submitted by* ***Mr. Dhirendra Kumar*** *(Roll no: 213MM2479) of Master of Technology, National Institute of Technology Rourkela, has been carried out under my supervision in partial fulfilment of the requirements for the degree of Master of Technology and is an original work. To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University / Institute for the award of any Degree or Diploma.*

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Abstract

Inside the blast furnace (BF) the process is very complicated and very tough to model mathematically. Blast furnace is the heart of the steel industry as it produces molten pig iron which is the raw material for steel making. It is very important to minimise the operational cost, reduce fuel consumption, and optimise the overall efficiency of the blast furnace and also improve the productivity of the blast furnace. Therefore a multi input multi output (MIMO) artificial neural network (ANN) model has been developed to predict the parameters namely raceway adiabatic flame temperature (RAFT), shaft temperature and uptake temperature. The input parameters in the ANN model are oxygen enrichment, blast volume, blast pressure, top gas pressure, hot blast temperature (HBT), steam injection rate, stove cooler inlet temperature, & stove cooler outlet temperature. For the optimisation of the predictive output back propagation ANN model has been introduced. In this present work, Artificial Neural Network (ANN) has been used to predict and optimise the output parameters. All the input data were collected from Rourkela steel plant (RSP) of blast number IV during the one month of operation.

Keywords: Blast furnace, ANN, RAFT, HBT

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Chapter - 1

Introduction

1. Introduction

Blast Furnace is used from the very earliest days 1700B.C. around in Europe. The preparation of iron from the ancient to ending of medieval ages are same alternating layer of ore and wood were heated until molten ore was obtained. For the removing of impurities the molten ore was hammered to get the raw iron which is complete forged. The metal was prepared a few away from the hearth. Initially easy tapering opening in the ground, the hearth evolved into a furnace, and was slowly perfect. In the early century's quantity of iron produced was few kilogram first then later its reached 55 to 65 kg at the medieval ages. From that period iron enriched with carbon steel were produced.

Inside the blast furnace a series of chemical and thermal reactions takes places. Many variables are involved as a process so as because of complexity exact mathematical process is difficult to model. In the present days many iron makers across the world wide used the modern technique to enhance the efficiency of the blast furnace by improving the quality of the molten iron.

In the blast furnace a very complex process takes place for the production of pig iron, which develops gradually as of the conventional furnace. A blast furnace melt downwards ore by the burning of the coke. Pig iron is produced as the output from the blast furnace by the series of several equations. The process of the blast furnace is very hard to replica as the coexistence of the phases with mass and heat transfer. The predicting of the outcome and controlling the blast furnace operations is very tough, operators are aware of this fact.

The production of the blast furnace is base on the temperature and pig iron chemical analysis. It also depend on the condition of the slag. These variables effect the output parameters in the operation of the blast furnace. [3].

So we have to optimise the blast furnace parameters. We needs a model that can automatically predict RAFT, shaft temperature and uptake temperature. There have been so many neural network use in this field. To predict the parameters so that operators can control the process efficiently. After then we will apply these predicted parameters to the genetic algorithm to optimise the predicted temperature. Our task is to developed a predictive model first then optimise the predicted outcomes particularly with the help of neural network and genetic algorithm. For the developing these models we need the historical data of blast furnace. All the data were collected from RSP during the operation for one month.

The neural network is not a science, it is an art. There are only some set of system to track and it is extremely hard to forecast what type of model would employ fit for the known collection of data. In this present work we have trial several method to minimise the root mean square value by training the data several time.

2.0 Background:

2.1 Blast furnace

The blast furnace is the generally most significant unit for the steel plant. Molten iron is the raw material for the production of steel. Molten iron is produced by the blast furnace and tapped at irregular interval of time. Slag floats on the upper layer of molten iron as its density is low. So, the main principle of the blast furnace is to take away the oxygen from iron oxides, producing pig iron as the main product. In the blast furnace enormous amount of heat is produced for the reduction of iron ore.

Three main raw materials are used in blast furnace for the production of pig iron known as iron ore, and limestone. Coke is used to provide the heat inside the blast furnace. Hot blast is injected through the tuyere level to burn the coke. This coke increases internal temperature high enough for the reduction of iron ore. Ore and coke are present in the alternate layer inside the blast furnace. As coke used for the reduction of ore so itself it act as a reducing agent. For the removal of impurities from the iron ore flux is used. Limestone and dolomite used as a flux.

For producing pig iron first coke is produced. This is done by the process carbonisation. For producing coke, coke oven is used. Coal is heated in coke oven. After the completion of the process coke has taken out from the oven. Coke has following properties:

It acts as fuel by providing the thermal requirement of the fuel, it provides CO for the oxidation of iron oxide, it provides the permeability in dry zone as well as wet zone and mechanical support to charge, it also reduces the melting point by carburises the iron. The main source of iron ore in BF is pellet which consists highly concentrated iron composition as oxides of iron. Sinter is the inferior iron source that is produced in plants.

Coke, sinter, pellet and limestone are primary efficient in material treatment and then forward to the plant according to the charging principle of BF. Oxygen is injected through the tuyere nozzles always to pressurised hot blast composition using the air compressors and heated up 1100 – 1200ºC with the help of stove system. Extremely pressurised blast creates a combustion reaction with coke and inner temperature rises to 2000 – 2500ºC in the furnace. The charge is to be oxidised by further moving reacting with the carbon monoxide. For the reduction of the iron bearing materials carbon monoxide rises up through the permeable bed. The incompletely oxidised gas ultimately leaves the process from the top of the blast furnace at a temperature approximately 100ºC. The coke is oxidised to carbon monoxide in the lower zone of the furnace. The temperature in the furnace varies broadly: from few 100 - 2000ºC. The oxygen is eliminated from the iron ore by the carbon monoxide gas.

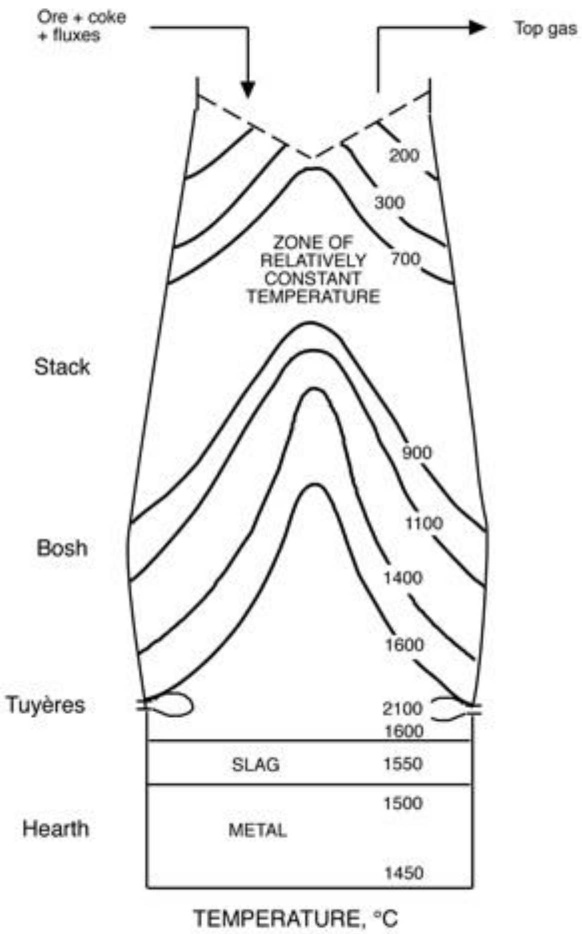

Figure 1 Temperature profile of blast furnace

Ref- Donald B. Wagner, Background to the Great Leap Forward in Iron and Steel

The temperarure profiles of blast furnace varying along the furnace is as shown in the figure. At the tuyere level the temperature is vary with 1600ºC to 2100ºC. At the shaft or stack zone the temperature is varies from 210 to 550ºC and the exhaust gas which leaves out from the furnace known as uptake gas. The temperature carried with this gas is uptake gas temperature. Metal is tapped from the opening of the furnace at the irregular interval of time.

2.2 Artificial Neural network (ANN):

ANN is very similar to our human brain that is human nervous system. ANN is normally used for identification, classification, prediction, pattern recognition, matching and optimisation and. It solved complicated mathematical problems where a no of variables are present. They have several advantages a good nonlinear system presents, easy to program, solve multi non linear problem.

However our work is related to prediction of the parameters with the use of previous data. For developing new or existing system the enough data should be in hand. Prediction mainly depend on the selected input parameters. When comparatively more parameters are considered than required then algorithm speed and memory capacity problem will occur. On the other hand model output will not able to predict properly if a fewer no of input parameters are available. Therefore the input parameters will be taken in a manner so that reduce the algorithm complexity and improve accuracy [8].

Neural network is used to solve for highly complex non-linear relations problems. It established the relation between a set of input variables and output with a set of no connected series nodes. There are several layers in the NN model 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 the increasing the hidden layer does not improve the much performance of the network however by varying the nodes of hidden layer affect the performance of the network.

Feed-forward Neural network have been applied to predict and control the temperatures of different zones of blast furnace by the use of 8 input variables. Back propagation algorithm have been used in the feed forward neural network. Back propagation is used for the algorithm of weights and biases corresponding to the hidden layer and output layer. Biases are supplied to the network for adjusting the error across the hidden layer and output layer. For calculating the error the back propagation algorithm computes the derivative. It gives us a procedure to compute 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 backward again to the input layer for minimising the error by training the data again.

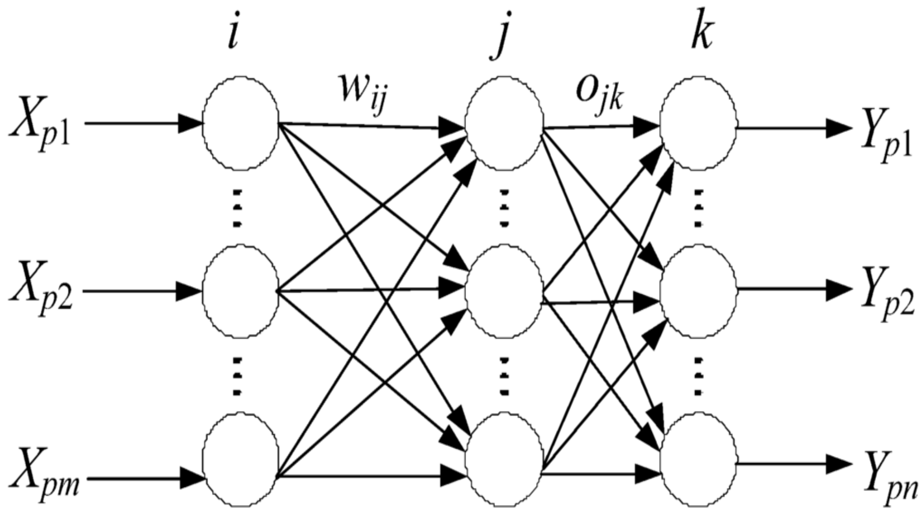

Figure 2 Multi input multi output ANN with back propagation model

Ref- Liu lang, Dezheng Lao

X_1 to Xn represents the no of neurons in the input layer w is the weight corresponding to each nodes bias is provided to adjust the error between output layer and hidden layer. Y_{p1} to Y_{pn} are the output calculated by the network. Used transig function at the hidden layer and output layer for the algorithm of output. Here multi output is calculated.

2.3 Genetic Algorithm:

Genetic algorithm are oftentimes utilized to prepare neural nets. Numerous neural nets bundle fuse genetic algorithm a possibility for the preparation stage. Genetic algorithm produce comes about that are reasonable. The outcomes can be effectively connected since they take the type of parameters in the wellness capacities. Much of the time, genetic algorithm utilized for discovering ideal qualities. They are not restricted to the sorts of information - the length of the information can be spoken to as a series of bits of an altered length. Despite the fact that genetic algorithm suitable in improvement, they don't promise optimality. They may hit a neighbourhood optima and certainly not locate the best arrangement. Genetic algorithm can be calculated escalated; along these lines items joining them have a tendency to be undertaking level items that keep running on effective servers.

Chapter - 2

LITREATURE REVIEW

Juan JIMENEZ et al[1] have developed parametric models by using neural network. They included the time variable for improving the consistency. They developed models which are able to calculate approximately blast variables known as hot metal temperature as a function of input variables. They used both models NOE & NARX. NOE models areindependent previous actual outputs, opening the door to the process simulation & NARX model is used for control system of a blast furnace.

Marc A. Duchesne et al [2] 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 [3] 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.

Jian Chen [4] developed a analytical system for blast furnaces by assimilating a neural network with qualitative analysis. The qualitative trend of the process is predicted through fundamental analysis and qualitative reasoning, and the neural network model developed the relation between input and output. The neural network is trained with appropriate data. Valuation can be made with the predicted data with the observed data. Si content in pig iron is predicted through the model. Predictive system helps the operators make the right decision. Qualitative reasoning is a way for treating the complex variable problems with quantitative method.

F. Pettersson et al [5]have studied a genetic algorithms based multi-objective optimization technique was utilized in the training process of a feed forward neural network, using noisy data from an iron blast furnace. They minimise the training error along with the network size with the design of the inferior part of the network and weight used them kept as variable. For optimising the task predator- prey algorithm efficiently used. Multi-objective analysis is not only beneficial for steel producers but also interest of soft computing researchers at large scale where a trade off between learning and generalisation is known to occur.

Yasin TUNCKAYA et al [6] have studied prediction of flame temperature of blast furnace using artificial intelligence. Also statistical method had been used to analyse the parameter .They predicted actual flame temperature and inhibited correctly, then operator be able to control fuel distribution and other operating parameters such as cold blast temperature, oxygen enrichment, pulverized coal injection, blast moisture, , coke to ore ratio and cold blast flow parameters in advance allowing for the thermal state changes .For forecasts the flame temperature they employed model Artificial Neural Networks (ANN) comapared with Multiple Linear Regression (MLR) and Autoregressive Integ*r*ated Moving Average (ARIMA) models by the error calculated between actual and predicted by selection of the most proper inputs so that it affect process parameter.

SK Das et al [7] have studied for predicting an output parameter an improved network has been developed.The network is based on multi-input-multi-output (MIMO) artificial neural network model. Output parameteres which has been predicted are grade and recovery to distinguish the separation behaviour of a high intensity magnetic separator for handing out iron ore in the particle size range of 75~300 µm. The input parameters are magnetic field intensity, particle size and pulp density for the composition of % SiO_2, %Al_2O_3 and % Fe have been feed to the model of the neural network. An best concurrence between the measured and the optimized model values related to recovery and grade for magnetic separation. The best result has beeen shown by the regression fit between the actual and predicted values.

Yoshihisa OTSUK et al [8] studied forecasting model level for decreasing heat level in order to stable the heat level in blast furnace using neural network model. Wall temperature measured at various points in the vertical and circular directions. Neural network technology is used to measured the distributed pattern as a temperature rising points. Supervised learning model and unsupervised learning model are two groups of learning style in neural network. After a rise in a wall temperature, sometimes there is a decrease in heat level noticed by operators but they were not able to find which pattern causes decrease the heat level which means no teaching data for supervised model. Unsupervised neural network models is the self organisation feature map model which recognises and classify the wall temperature rising patterns. Forecasting model using the classified wall temperature pattern gives better forecasting accuracy heat for heat level decrease than a forecasting model using the total amount of wall temperature rising point.

Yikang WANG et al [9] studied a prediction model was proposed based on support vector machine (SVM) and mutual information (MI) for feature selection. These models were proposed for the prediction of silicon content in hot metal. The proper input variable which depends on multivariate time series based on MI. The selected input has a maximum relevance to output variable and minimum redundancy between them. An SVM model based on MI has better performance than without feature selection. The proposed approach seems capable and can be determinant in providing the experts with the right tools for the selection of the relevant factors and for the prediction in this complicated problem, and it can satisfy the requirements of on-line prediction of silicon content in hot metal.

V.R. Radhakrishnan et al [10] studied a supervisory control system, neural network estimator and an expert system to improve the hot metal quality. Silica and sulphur are the important parameters to improve the quality of hot metal. Spectrographic techniques used for the measurement of the composition. A neural network based model is developed and trained with output variables with a set of thirty three process variables. The output variables consist of the quantity of hot metal and slag as well as their composition with respect to all important parameters. The process can be measured on line and so soft sensor technique used on line to predict the output parameters. The soft sensor technique has been able to predict the variables with an error less than 3%.

Sujit Kumar Bag [11] 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 characterisation 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 elimation of this problem a predictive model (ANN) has been developed to know the process parameters in advance.

Joachim Angstenberger [12] studied blast furnace analysis with neural network. In the upper part of the furnace temperature profile were analysed. Optimised the temperature distribution and find great savings of input materials. For the optimisation quantitative relations between furnace parameters are required. He developed a model neural network using fuzzy methods. Application of fuzzy clustering and neural network were used to classify temperature profiles and build a model of the interdependence between process operation parameters and resulting temperature profile. Neural network able to approximate the temperature profile with good precision. Neural network model achieved a high correlation between actual and estimated temperature profile.

MarcA. Duchesne et al [13] developed an artificial neural network to predict slag viscosity over a broad range of temperatures and slag compositions. Slag viscosity prediction are required in advance for combustion and gasification model. Genesee coal ash viscosity prediction were made to investigate the effect of adding limestone and dolomite. Magnesium in the fluxing agent provides better viscosity reduction than calcium for the threshold slag tapping temperature range. Fluxing agent like limestone and dolomite which generally reduces the slag viscosity. Since the ANN does not depend upon theoretical relations, it can easily be expanded to include other factors such as atmosphere composition and new components of the fluxing agents studied, the one with high magnesium content has the most effect when it comes to minimizing the required temperature for slag removal.

Angela X. Ge [14]studied a neural network approach to the modelling of blast furnace. A new method in this area is developed by using artificial neural network associated with complex system which includes many variables. Predicted the hot metal temperature which is the most important parameters of the blast furnace as output. Prediction of hot metal temperature based on eleven inputs variables. The actual output value are taken from the previous time period. They minimise the mean square error between the predicted hot metal temperature and the actual hot metal temperature. Exactness was got increasingly when one use the past data of the hot metal temperature in the phase of training, a number of variables which is used here had little impact. Different types of settings of neural algorithm were used for experiment by varying different numbers of nodes in the hidden layer and also by different learning rates. By varying the number of nodes in the hidden layer does not give very efficient result while a little bit changes had found also different algorithm did not produce the same. It shows that these factors are not as significant. A range of learning rates, from 0.01 to 9, were used for trial. The good result found by working with lower lerning rates as higher learning rates provides over fit of data.

Cahit Bilim et al [15] studied an artificial neural networks was carried out to predict the compressive strength of ground granulated blast furnace slag concrete. 45 concretes were shapedin the laboratory was utilized in the ANN study. The concrete mixture parameters were three different water–cement ratios, three different cement dosages and four partial slag replacement ratios. Compressive strengths of moist cured specimens (22 ± 2 C) were measured at 360 days. By using these data ANN can be constructed, training and testing for the minimisation of error. Six input parameters data used for ANN model that face the cement, ground granulated blast furnace slag, hyper plasticizer, water, aggregate and age of samples and, an output parameter called compressive strength of concrete. ANN can be an alternative approach for the predicting the compressive strength of ground granulated blast furnace slag concrete using concrete ingredients as input parameters.

Debashis Mohanthy et al [16] studied Genetic algorithms based multi-objective optimization of an iron making rotary kiln. The product sponge iron continuously discharge from the downstream end while the waste gases in counter flow exit through the uphill end. The outputs exhibit inconsistent trends at the production level – an increase in daily production results in a decrease in the product’s metallic iron content and vice versa. Artificial neural network (ANN) established the relationship between the various input and output being very complex. The optimisation task was carried out using multi-objective genetic algorithm and the pareto-front were analysed. Waste gas in the rotary kiln can be utilised to generate economical power for use in electrical steel making. This study signifies the efficacy of an evolutionary analysis to access and augmented the performance of an industrial rotary kiln. The interaction with a knowledgeable decision maker is often critical for the direct execution of the computed results, as the choices provided by a multi-objective analysis are often far too many, and it requires some actual plant experience to pick and choose the correct option.

Debashish Bhatacharjee et al [17]studied feed-forward neural networks for predicting several quality parameters such as hot metal temperature.for the first set they used twenty four inputs variables which reduced to fifteen input variables based on the method that measures the entropy of different input variables while categorizing the output HMT. Result indicate that by using one hidden layer with multi-layer perceptron networks and employing back-propagation algorithm were competent to predict the leaning value of HMT in daily basis. The value of correlation between the actual and predicted was relatively high, which can be equal to 0.78 in most of cases.

Nikus et Al [18] utilizes neural networks for predicting the thermal environment of the blast furnace.The data measured were analyzed at a minute interval. And prediction range of horizon which lies between one to twenty minutes for the future. For recognising optimum number of hidden nodes a Single hidden-layer networks is taken. A network which has five hidden nodes and seven inputs is found to be best performance. In addition to the lagged predicted values it was found that they fed into the network as added inputs. The mean squared errors of the testing data is varies in the range from 0.0036 to 0.0051. Even though the granularity of the data set is different from the hourly data which is used in the current paper, the results of provide reason for improved optimism that ANNs capacity be achieved in the present work.

Bloch et al [19] applied neural networks to manage precise processes in a steel plant, which is the strip temperature of the plant's induction furnace. For modelling the inverse of the induction furnace a method called multi-layered neural network is used. These give the current strip temperature and inputs and also demonstrate how one can modify the input variables so as to reach at a dissimilar required temperature level. Infect this is a inverse of the temperature prediction problem. Although initial results shows that additional effort in this area needed to be accomplished.

Chapter -3

Methodology

3.1 Output Parameters

A blast furnace is used to generate hot metal temperature for the production of steel. The quality and quantity is depend up on the temperature in front of the tuyere level. Enormous amount of heat is generated inside the blast furnace. Hot blast air is injected through the tuyere along with the oxygen enrichment and other additives fuels for the combustion of the iron ore. This thesis mainly focuses on the prediction and optimisation. The prediction of RAFT, shaft temperature & uptake temperature with the use of 8 input variables. The prediction can be done by the neural network. We can improve the productivity by optimising these output parameters. We have collected the data from RSP during the operating period of 1 month and noted the variation as given in the table.

Table 1 Variation of values of the output variables

S.No.	Output Variables	Minimum values	Maximum values
1	RAFT	1800 (^{o}C)	1970 (^{o}C)
2	Uptake temperature	65.5 (^{o}C)	126.5 (^{o}C)
3	Shaft temperature	211.5 (^{o}C)	535 (^{o}C)

3.1.1 RAFT

In front of the each tuyere zone there exists a runway or raceway in which the flame travels as the gases expanding smoothly through the entire cross section of the furnace. The first raceway is horizontal as the gases expanded, then its changes the direction as vertical through the cross section of the furnace. The temperature found in this zone is known as raceway adiabatic flame temperature (RAFT). RAFT should neither be maximum nor be minimum it should be in the range. As RAFT increases the melting zone is increases consequently sudden drop of the RAFT faded the furnace. And also reduces the reduction of the process.

Theoretically the RAFT should be maintained at 1900^{o}C but in actual the RAFT varied up to 1970^{o}C in the blast furnace as we have noted the data from RSP. Sulphur remains unaltered but the silicon content goes up to 1 to 1.36 which can be controlled by the oxygen enrichment.

3.1.2 Uptake Temperature

The effluent gases are goes out of the furnace by the large vertical pipes called uptakes. Mainly uptakes are four in number. By combining the two adjacent uptakes one single duct will form and again combining two such ducts form one ducts. The effluent gases are goes downwards to the dust catcher for the cleaning of the gases. The temperature of the effluent gases is known as the uptake temperature. The unreduced gases left the furnace through the uptake gas pipe. In this zone the uptake temperature is found and is varies from 65 ^{o}C to 125^{o}C.

3.1.3 Shaft Temperature

The temperature in the stack zone or shaft zone is known as shaft temperature. The shaft temperature varies 210 ^{o}C to 550^{o}C in the blast furnace as reading noted from the RSP. 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.

3.2 Input parameters

We have taken 8 input variables for the prediction of RAFT, Shaft temperature and uptake temperature. The input variables are oxygen enrichment, blast volume, blast temperature, top gas pressure, steam injection rate, blast pressure, stove cooler inlet temperatre and stove cooler outlet temperature. The input variables are tabulated in the form of table. Selected the input variable as time in depended. Time depended variables are ore/coke ratio. This depend on time. When we put the charge in the blast furnace then instant effect is not shown on the furnace. The charge takes 7- 8 hours to reach the combustion zone so instant effect on hot metal temperature is not seen.

Table 2 Variation of Input Variables

Serial number	Input variables	minimum values	maximum values	Units
1	Oxygen Enrichment	472	3034	Nm^3/hr
2	Blast Volume	75	144	Nm^3/hr
3	Blast temperature	860	965	ºC
4	Top Gas pressure	0.09	0.65	mm of water column
5	Blast pressure	0.66	1.69	Kg/cm^2
6	Steam injection rate	3.3	9.5	T/hr
7	Stove cooler Inlet temperature	36.2	42.9	ºC
8	Stove cooler outlet temperature	38	43.7	ºC

3.2.1 Oxygen enrichment

For every increase of 1% of oxygen enrichment of hot blast there is 2 to 2.5% of increase of productivity of the blast furnace. 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 gases are valuable for heat transfer in the shaft or stack zone. The presence of nitrogen in the blast restricts the temperature generated in the combustion zone. We can improve this temperature at combustion zone by decreasing the nitrogen content in the blast its means by increasing the oxygen content in the blast. Oxygen reduces the nitrogen in the burden for every 2% of oxygen enrichment reduces the nitrogen by 4 unit in the burden per unit weight of coke and there is a possibility of higher temperature in the combustion zone. There is a limit of higher temperature in front of the tuyere as excess temperature causes bridging and sticking of stock and also more silicon content in the molten iron which is undesirable for the quality of the pig iron. Excessive heat generated in front of the tuyere must be engrossed by some other endothermic reaction. By the balance of adequate humidification the oxygen enrichment up to 25% in the blast is advantageous. Combined effect of both the oxygen enrichment and humidification of blast offers a good control in the combustion zone of the temperature.

There is every increase of oxygen enrichment[19] percentage results increase in production rate of 3 to 4% and also saving the coke rate. When cracking of moisture take place which gives the hydrogen and acts as a reducing gas in the stack. Oxygen enrichment enhances the productivity as shown in the figure.

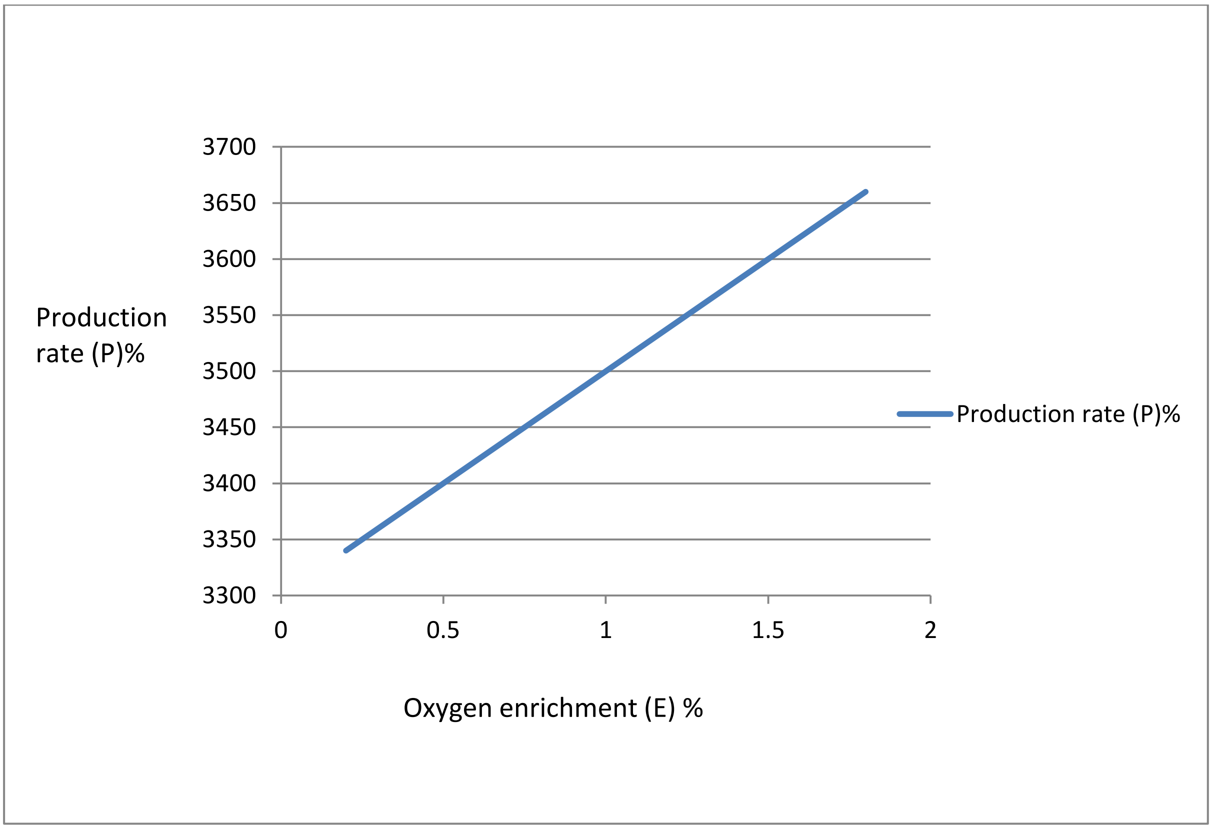

Figure 3 effect of oxygen enrichment on production rate

The effect of oxygen enrichment is as shown in the figure. If we increase 1% of the oxygen then productivity increases 2- 3%.

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

Additives can also effects the performance of the furnace as it maintains the RAFT. It helpful to control RAFT in a range neither be in a maximum range nor be in a minimum range. In both conditions it affects the melting zone of the combustion chamber.

3.2.2 Hot blast temperature

The hot blast enters through the base of the furnace known as tuyeres. After leaving the stove it enters through the tuyeres in to blast furnace. It reacted with coke, ore, fluxes and emerges as a top gas, mainly contain carbon monoxide and carbon dioxide. There is a pressure drop 1.4 bar across the burden, without consideration of the top gas pressure. As the pressure variation is there so permeability of the furnace is good and the materials moves downwards through the furnace at the appropriate speed so the reduction can takes place. If the hot blast temperature will be constant then a good efficiency of the furnace can be maintained. So we need to keep constant blast temperature in the combustion zone. As the hot blast leaves the stoves cools down the temperature of the hot blast decreases so to maintain a constant temperature we need to mix the hot blast with the cold blast in the mixing chamber. The proportion of the hot to clod blast is controlled by the control chamber which contains control module. Blast temperature is a important parameter which affects the productivity of the blast furnace. With the 100^{o}C increase of the blast temperature the productivity will be improved by 1%. Also there is decrease in sulphur content of coke by 0.1% then it improves the productivity by 0.7% to 1.2%. Hot blast temperature is capable of producing 2400-2500^{o}C as RAFT which can be used because RAFT increases the melting zone of the combustion chamber and affects quality of the pig iron. The combination of blast temperature, humidification, oxygen enrichment, pulverised coal injection and natural gases brings down the RAFT to normal 1900-2000^{o}C. The appropriate values for bringing the RAFT as normal is 150-200kg/thm pulverised coal injection or 100- 150Nm^3 of natural gas injection with 3 to 5% of oxygen enrichment and 5- 10% of humidification of blast. The combinations of all these variables bring the RAFT as normal. By the use of pulverised coal injection coke rate is decreases.

3.2.3 Humidification of blast

For the smooth blast furnace operation the best requisite factor is RAFT. RAFT is depended on the moisture content of the blast as moisture is vary from season to season. In rainy season moisture is maximum and minimum in dry summer. We can increase the blast temperature without increase in the RAFT by adding some additives with the blast.

Steam is introduced in the cold blast before the preheated to the stove for the humidification of blast. If we add steam to the hot blast then there is a reduction in the hot blast temperature as the temperature of steam compared to the hot blast is very low and hence have a cooling effect which is not desirable. The best advantage of the humidification is that it reduces day to day humidity level which varies always and eliminates the major variable which affects the blast furnace operations.

Steam requires energy for its generation and also is not cheap. It is found that an increase of 20g/Nm^3 moisture in the blast the endothermic process will be compensated by an increase of 200^{o}Cin the blast preheat. This the thumb rule for further moisture addition.

Some variables are time dependent and some independent of time that means the instant effect cannot seen on the molten metal. Ore/coke ratio is the time dependent variable as its cannot effect instantly. For the descending of the charge to the hearth takes times. But there are some instantly variables which can control the process instantly. These variables are blast rate, temperature and pressure also oxygen enrichment.

- Collected the data of blast furnace no IV from RSP during the operating period of 1 month.
- 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 normalise 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 minimise the error .
- Compare the predicted data with the actual data and find out the error.

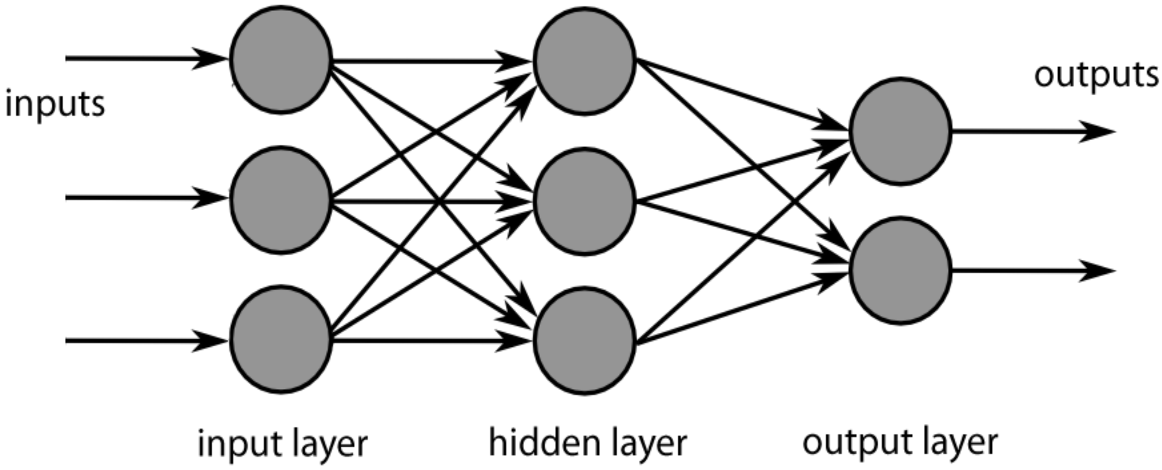

Figure 4 MIMO neural network

Ref- Leonard Giura

Table 3 Output Variable

S.No.	Output Variables	Units
1	Raceway Adiabatic Flame temperature	ºC
2	Shaft Temperature	ºC
3	Uptake Temperature	ºC

As given in the table these are the output variables which will be predicted by the neural network .

If RAFT rise additional than the usual value melting zone on tuyere level is begin increasing. On the other hand when the RAFT start dropping then smelting capacity and reduction process will decrease & the thermal heat balance of the furnace will be faded. When a sudden

sudden increase in flame temperature value then melting zone becomes uneven. Fuel injected at the tuyere level is normally accompanied by oxygen enrichment of the hot air blast. The injection of oxygen to the air blast reduces the specific flow of gas causing a reduction in the top temperature and an increase in RAFT. So these affects can be compensated by the injection of fuel additives like pulverised coal injection, natural gas, etc.

Blast pressure and blast volume affects the injection rate of the furnace. Coal could be injected if the pressure of the blast below 10psi. Injection rate will be half if the pressure would be in the range of 10-15psi. For better performance of the furnace the blast pressure would be above than 15psi. For the uniform injection we included some changes which would be done at the tuyere level. For the effective operation of the lance the injecting lance angle should be 11^{o}.

Chapter- 4

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.

Table 4 NN Training table

NN model	MSE	R value
8-2-15-3	0.0319	87%
8-2-20-3	0.0144	79%
8-1-8-3	0.015	89%
8-1-10-3	0.01121	91%
8-1-15-3	0.051	81%
8-1-20-3	0.017	89%
8-1-25-3	0.0143	88%
8-1-30-3	0.028	86%

From the above table we find that the best neural network model suited for 8 input variables and 3 output variables are with one hidden layer and 10 no. of neurons gives 91% regression values and mean square error is 0.01121.

- 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

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

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 [18].

Neural network model progess during training process.

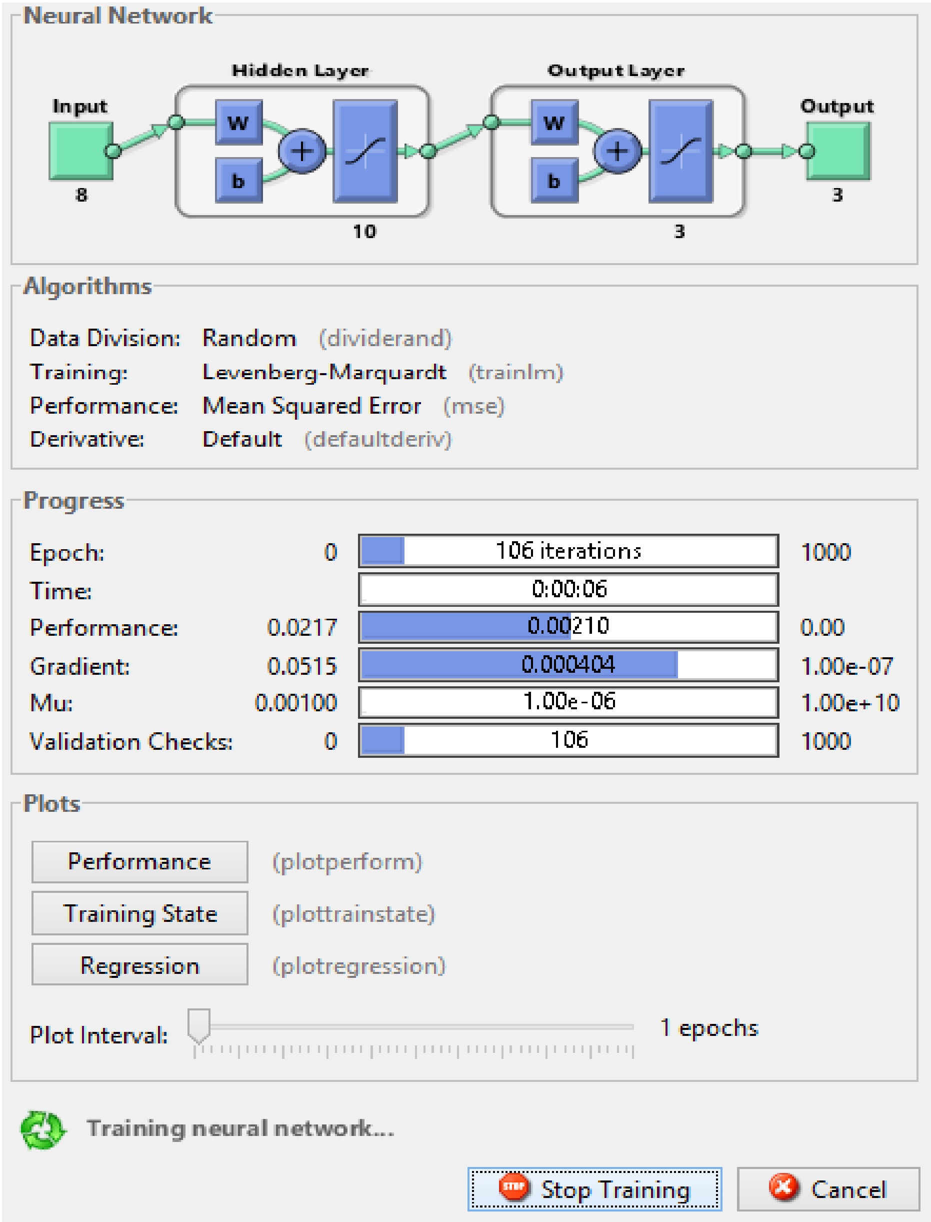

Figure 5 training process of the neural network.

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.

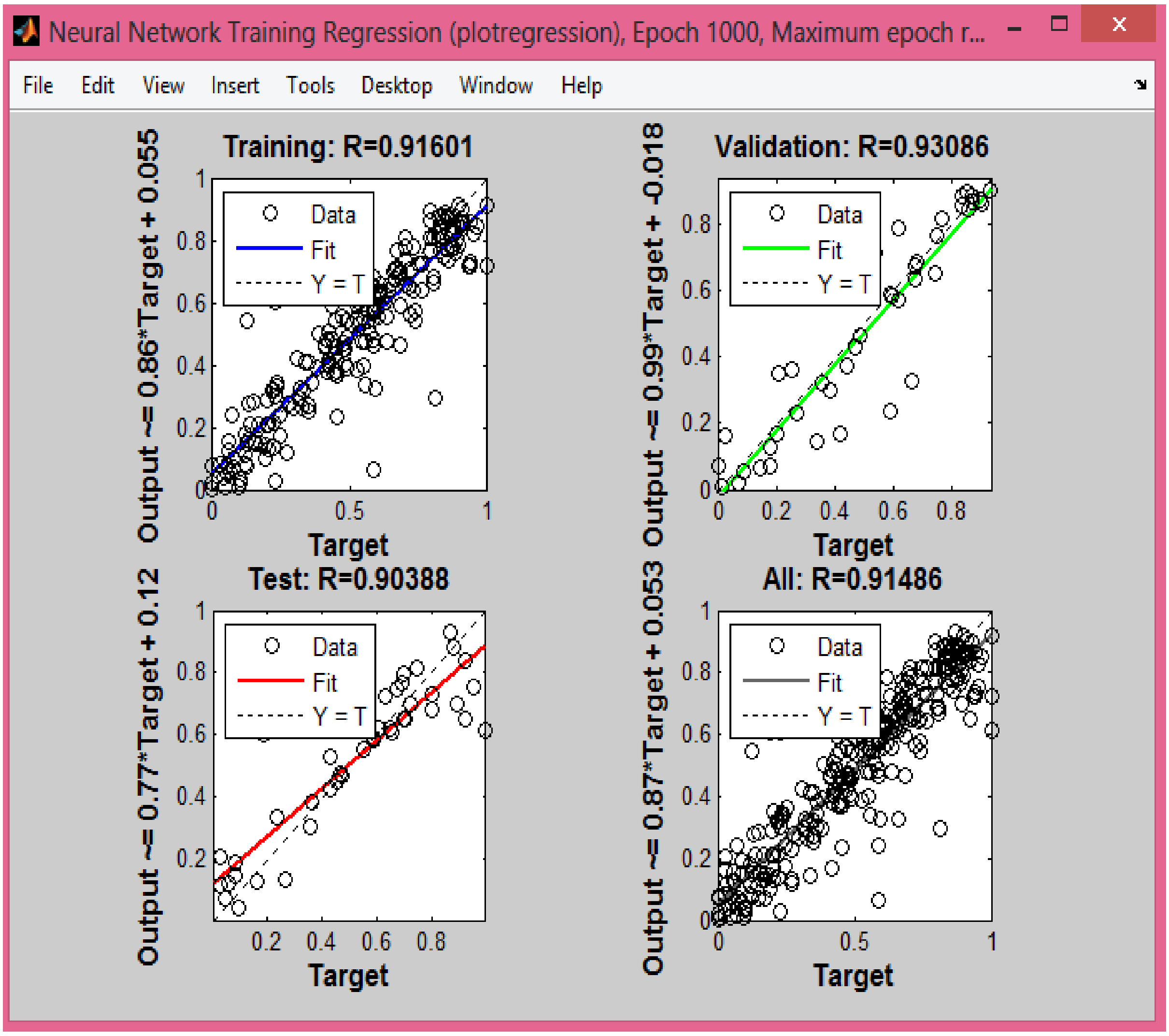

Figure 6 Regression plot for training, validation & testing

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 minimise 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 0.91601. 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 0.93086 and 0.90388 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.

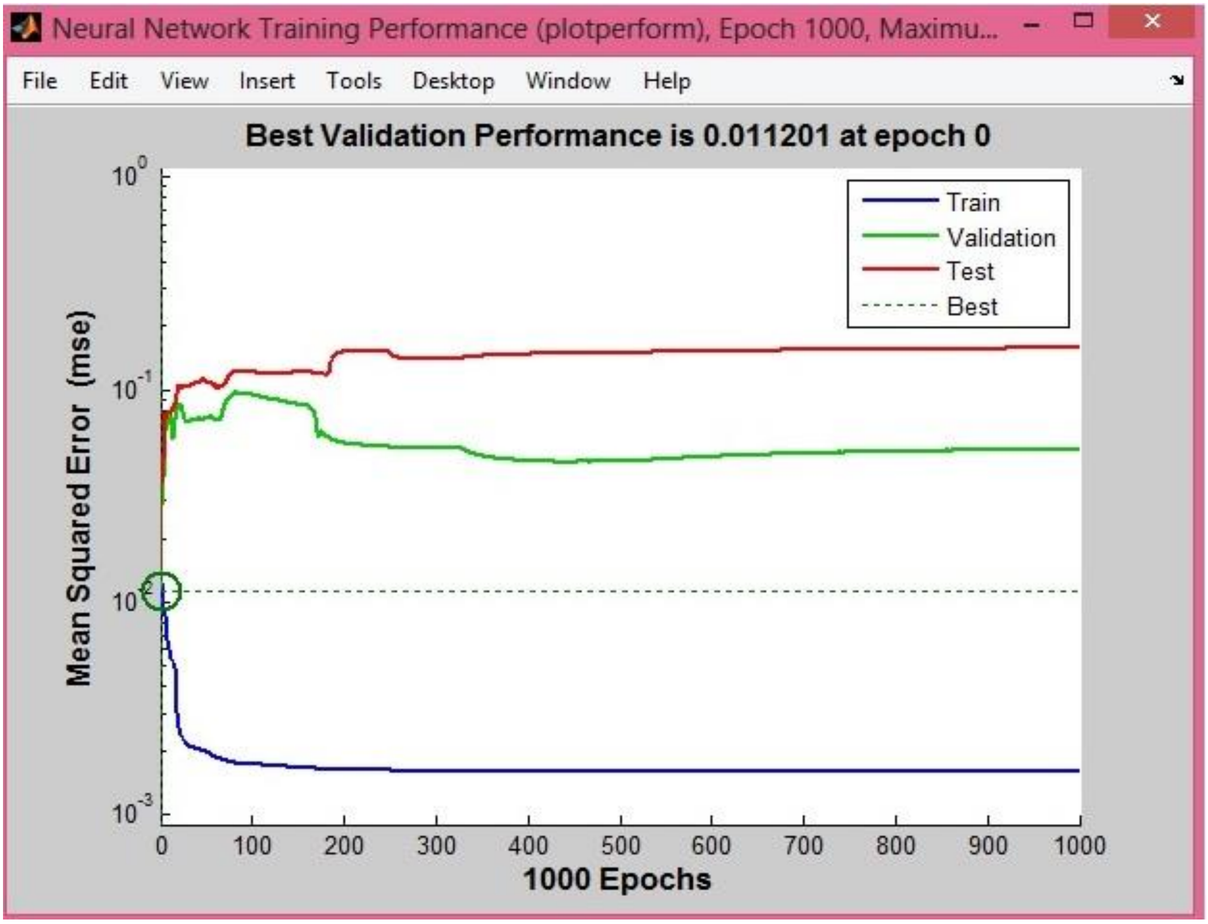

Figure 7 Training performance curve

This figure shows the performance curve for training, testing and validation. It varies along the no. of epochs with mean square error 0.01121. The best validation performance is 0.011. 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.

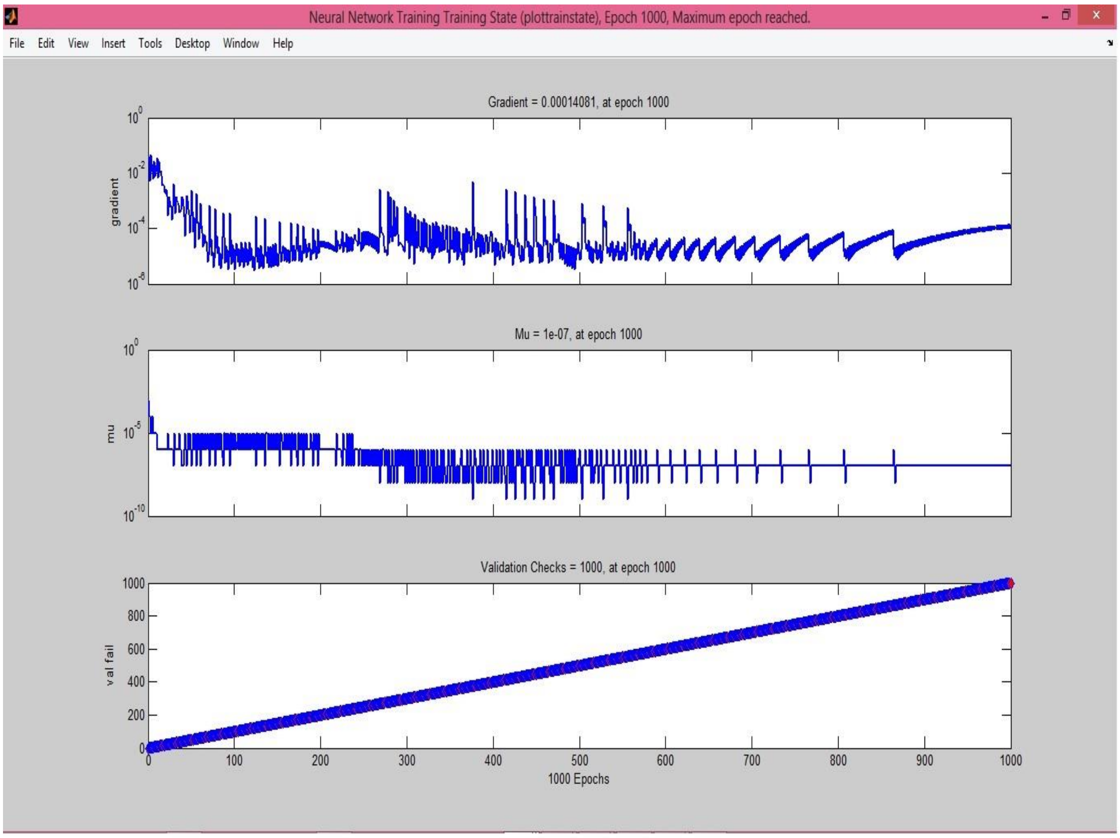

Figure 8 shows gradient, mu values and validation failure across the no of epochs

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.

Chapter- 5

Result and discussion

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

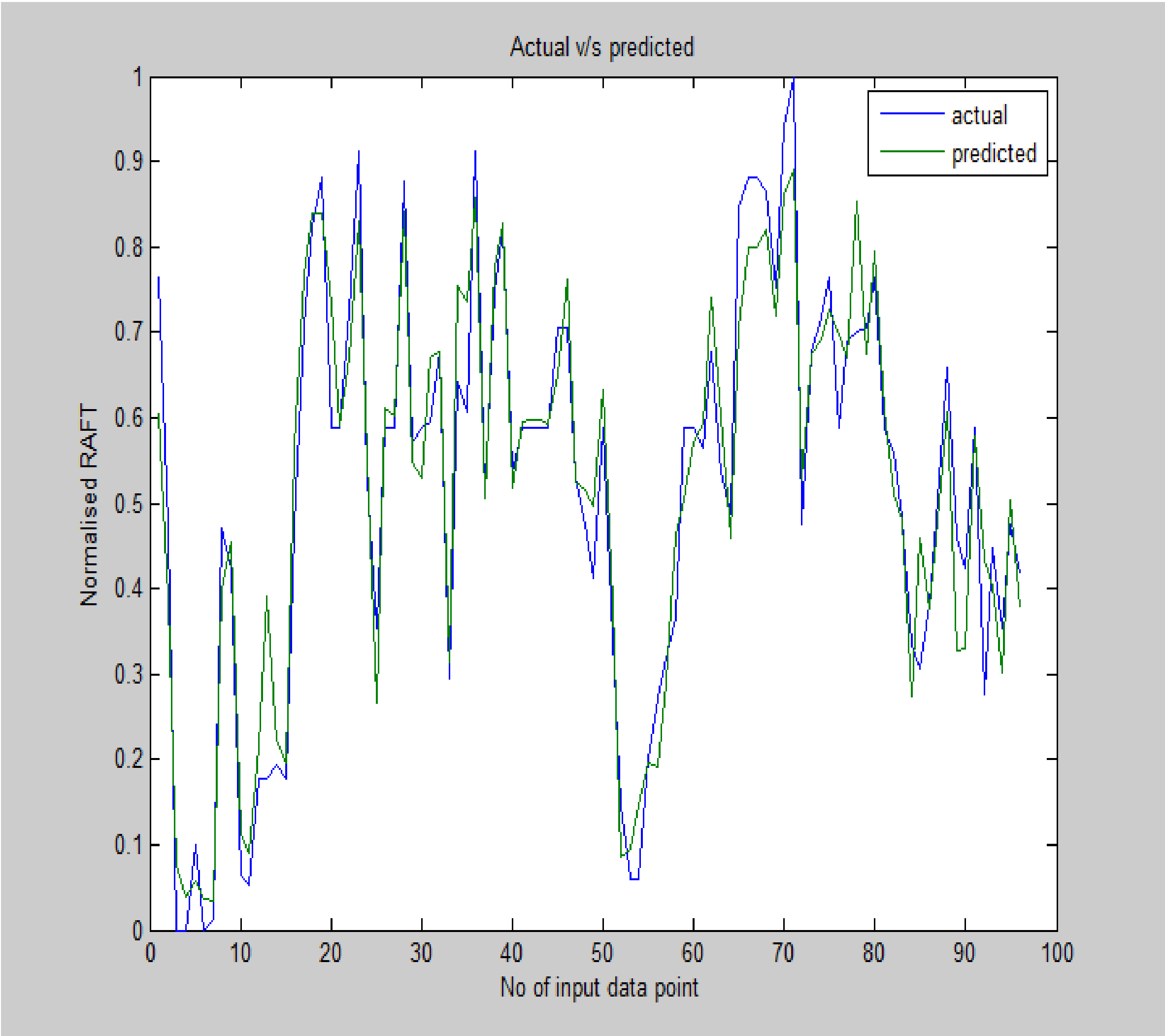

Figure 9 Variation of predicted V/s Actual RAFT with 8 input variables.

The variation between actual and predicted is shown in the figure. Normalised RAFT prediction has been done with the 8 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 8 input variables were taken during the operating period of 1 month.

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

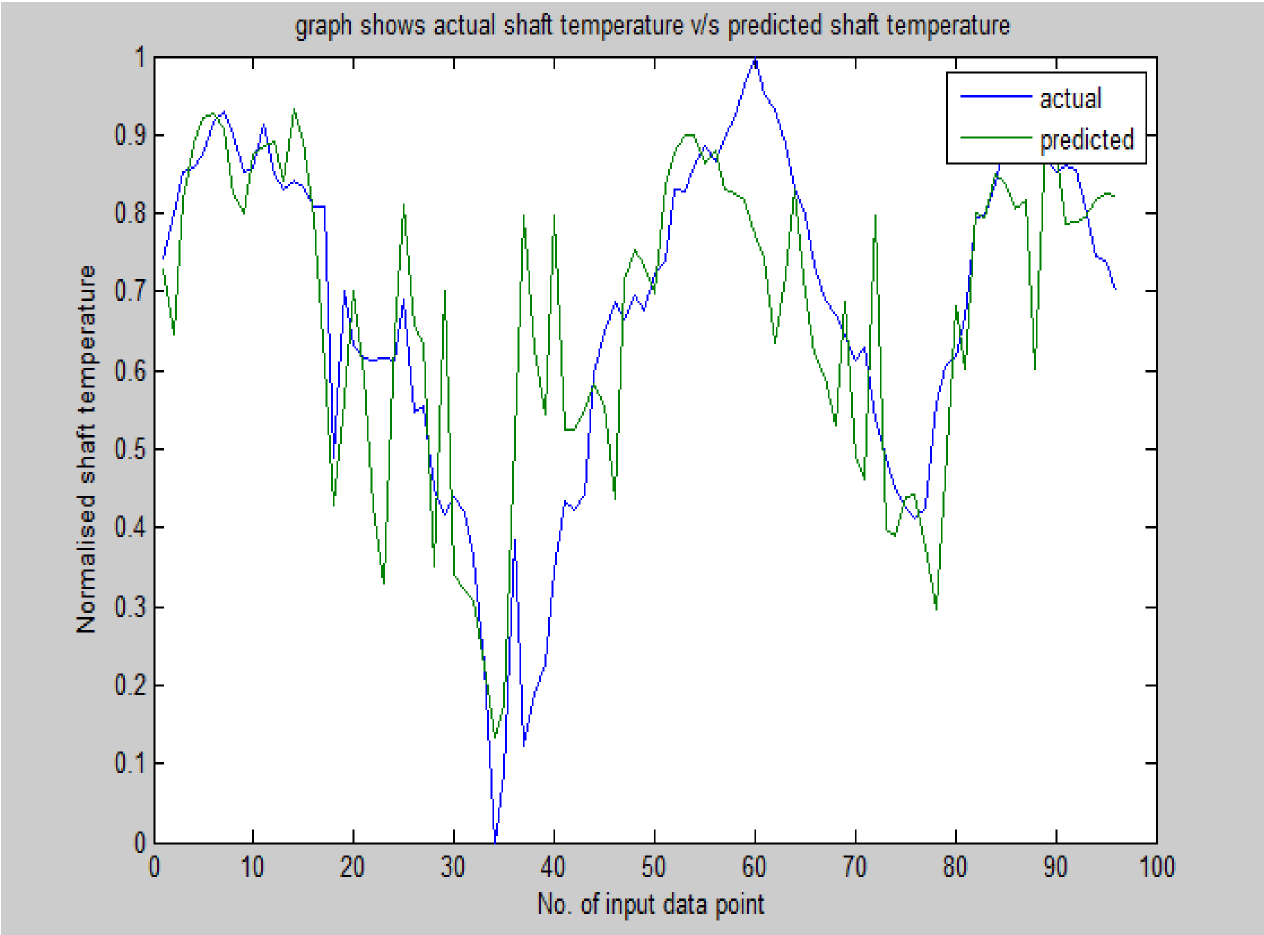

Figure 10 Variation with actual shaft temperature V/s predicted Shaft temperature with 8 input variable.

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 8 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 minimised by taking all the output variables single.

Chapter -6

Conclusions

- Applied the artificial neural network successfully for the prediction of output and find the mean square error as 1.15% with 10 no. of hidden nodes using 1 hidden layer.

- For metallurgical point of view maximise the shaft temperature, minimise the uptake temperature and put in range of RAFT.

- The multiple output model give more error as compared with the single ouput neural network model.

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