Neural Networks and Regression Modeling of Eco-friendly Melting Furnace Parameters using Bio-fuels

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ABSTRACT
Rotary furnaces apart from being pollution efficient can maintain the quality standards set by the present methods of casting. The rising demand for high quality castings necessitates that vast amount of manufacturing knowledge be incorporated in manufacturing systems. Rotary furnace involves several critical parameters like flame temperature, preheat air temperature, revolutions per minute of the furnace, excess air percentage, melting time, fuel consumption and melting rate of the molten metal which should be controlled throughout the melting process. A complex relationship exists between these manufacturing parameters and hence there is a need to develop models which can capture this complex interrelationship and enable fast computation. In this paper the applicability and the relative effectiveness of the artificial neural networks as function approximators for rotary furnace have been investigated. The results obtained by these models are found to correlate well with the experimental data. Results obtained by the regression modeling are also found correlating well with the experimental data. This indicates that NN models and regression models can very well be used to model this complex relationship amongst various parameters in an eco-friendly melting furnace.

General Terms
Regression modeling, Neural Network

Keywords
Rotary Furnace, Artificial Neural Networks (ANN), Back-Propagation (BP), Levenberg - Marquardt (LM) Approximation, Regression modeling.

1. INTRODUCTION
The voluminous production of Flue gases by cast iron foundries damages the environment since it contains gases like SO_2, CO_2, CO, H_2S which are poisonous. Almost all the foundries use coke fired cupolas for melting. However, melting by coke-fired cupola does not obey the environmental regulations. The problem of objections from environmentalists to 80% of the existing foundries is due to their exorbitant pollution emission level which has posed a serious threat to these foundries. The control on operation of foundries has been imposed by social organizations and by Honorable Supreme Court of India. In Agra, the city of foundries, the Honorable Supreme Court of India has totally banned the operation of Coke-fired Cupola. So, it has been essential to develop a substitute of coke as fuel in the foundries [1]. The Author had designed and developed a Rotary furnace of 200 kg. capacity and conducted lots of experiments to evaluate the performance of the furnace with different parameters.

The Rotary Furnace is very simple melting unit consisting mainly of a drum of required size having a cone on each side lined with refractory, fire bricks or ramming mortar generally having alumina as a constituent. This Furnace drum is placed on rollers which may be locked when the furnace is not rotated and may slowly rotate about their central axis when the furnace is rotated (for homogeneous mixture of molten metal and proper heat transfer). The rollers are driven by a small electric motor. At one end of the drum, a suitable burner is placed with appropriate blower system and combustion gases exit from other end. This drum or horizontal cylinder is flanked by two conical portions on both sides. One of the cones accommodate the burner whereas from the other cone hot flue gasses exit. Charging of the iron for melting is also done from this side. The cone on one side can accommodate different types of burners using the pure Jatropha and blends of Jatropha oil with Diesel. The tap hole is located in the cylindrical wall halfway between the ends. This tap hole is used to take out the molten metal. During the melting of metal this tap hole is closed.

There are a number of variables controllable to varying degrees which affect the quality and composition of the out-coming molten metal. These variables, such as flame temperature, preheat air temperature, revolutions per minute, excess air percentage, melting time, fuel consumption and melting rate play significant role in determining the molten metal's properties and should be controlled throughout the melting process [2]. However, even an experienced operator may find it difficult to select the optimum input parameters which would yield ideal molten metal and often he may choose them by guessing which may not be effective and economical.

Several investigators have carried out studies and developed mathematical models concerning the problem of choosing the optimum input parameters. Levi [3] was the first person to develop a mathematical model between carbon content in the charge and that of the tapped metal in cupola operations. Davis and Decrop [4] concluded that blast temperature has significant control over metal temperature and hence on carbon pick up. Pehle [5] developed the first thermo chemical model for predicting cupola performance under various operating conditions. Artificial neural networks (ANN) are useful tools for prediction, function approximation and classification. It is well suited to extracting information from imprecise and non-linear data. Karunakar and Datta [6] used ANN to model cupola furnace parameters with about 5% error. Regression techniques have a long history of use as forecasting tools in multiple disciplines. Regression models have the advantage of simple computation and easy implementation. Regression models are also used for decision making [7]. Vasin et al. [8] also developed practical crash prediction regression models for assessing the long-range safety impact of alternative freeway networks for urban areas.

2. OBJECTIVE OF STUDY

A Rotary Furnace was self-designed and developed at Foundry Shop, Faculty of Engineering, Dayalbagh Educational Institute (D.E.I), Dayalbagh, Agra, INDIA and experiments were conducted by taking the following input variables: 1) Percentage of Excess Air, 2) Flame Temperature, 3) Rotational Speed, 4) Melting Time, 5) Pre-heat Air Temperature, 6) Fuel Consumed for calculating the Melting Rate. And after conducting a number of experiments it has been observed that critical parameters affecting the Melting rate are Rotational speed of furnace dome, Melting time of metal and fuel consumed in melting the metals. So, only these three parameter observations are taken from 201 observations taken from 201 heats. Number of observation represented in table 1and 2 are the representative observations from a bigger set of 201 observations. So the main aim of this study was to randomly selecting 18 heats and to verify the influence of these critical parameters on the Melting Rate by developing Neural Network and Regression models.

3. METHODOLOGY

3.1 Experimental Setup and Data Collection

In the experimentation, 200 kg. of the charge is melted in the rotary furnace. A Circular burner is used for burning Jatropha oil with 50% blending with Diesel as fuel. Due to the heat transfer by conduction, when refractory material comes in contact with the molten charge, to have better heat transfer, the maximum time is given to refractory to be in contact with the charge. The quantity of fuel consumed is reduced in subsequent heats and normally it is found to be almost constant in third heat onwards.

Numbers of experiments were conducted at different percentage of excess air varying from 10% to 50% and amount of air preheat from 200°C to 400°C [9].

It was observed that it is difficult to achieve the rotation below 0.8 RPM from the fabricated rotary furnace. So, keeping this in view the experiments were carried out at rotational speed ranged from (0.8 - 2.0) RPM.

While conducting experiments it was observed that rate of melting varies with change of rotational speed. Charge of 200 kg. when melted in the furnace at 2 RPM, took 45 minutes. The rate of melting (MR) was obtained

= 0.266 MT (Metric Ton)/Hour

Under similar conditions, the total time taken for complete melting from third heat onwards was reduced to 35 minutes, when the rotational speed is reduced to 1 RPM. The rate of melting (MR) was obtained

= 0.343 MT (Metric Ton)/Hour

From above it can be interpreted that the rate of melting is high at slower rotational speed. During experimentation it was observed that the fuel consumption varies with rotational speed, percentage of excess air and air pre-heat temperature. Charge of 200 kg. when melted in the furnace at 2 RPM with 20 % excess air and 300°C air pre-heat, took 47 minutes and consumed 85 liters of LDO. The rate of fuel consumption obtained = 0.425 Liters/Kg.

Under similar conditions, the fuel consumption for complete melting of charge at the rotational speed of 1 RPM with 20 % excess air and 300°C air preheat was 81 liters. The rate of fuel consumption was obtained = 0.405 Liters/Kg.

From the above discussion it can be interpreted that the rate of fuel consumption is high at higher rotational speed.

Large numbers of heats were taken from the rotary furnace with the variations of the above mentioned parameters and finally a set of 201 heats was obtained from the furnace. This data was used to train the artificial neural network and also for the regression modeling.

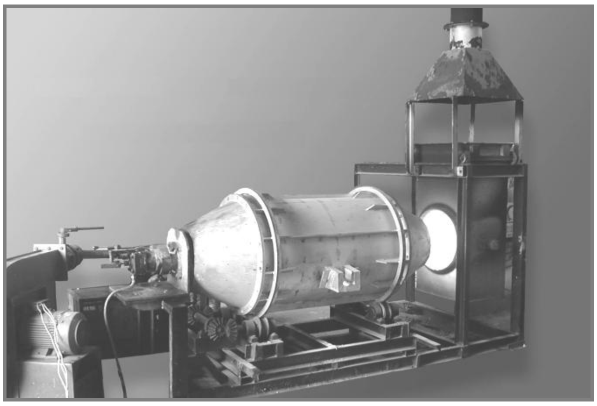

Fig 1: Designed and Developed Rotary Furnace at D.E.I., Dayalbagh

3.2 Artificial Neural Network

Artificial Neural Networks (ANNs) are massively parallel adaptive networks of simple nonlinear computing elements called neurons which are intended to abstract and model some of the functionalities of the human nervous system in an attempt to partially capture some of its computational strengths.

Artificial Neural Networks (ANNs) are currently gaining wide popularity in manufacturing field [10, 11]. ANNs are proposed to represent the relationship between the operating conditions and the process-related variables because of their data driven approach i.e. they can capture and model extremely complex relationships even without the help of an explicitly stated mathematical model. This property of ANNs is extremely useful in situations where it is difficult to derive the mathematical model that links the various parameters.

3.2.1 Back Propagation Neural Networks

The Back Propagation (BP) neural network is a multiple layer network with one input layer, one output layer and some hidden layers between input and output layers [12]. Its learning procedure is based on gradient search with least sum squared optimality criterion. Calculation of the gradient is done by partial derivative of sum squared error with respect to weights. After the initial weights have been randomly specified and the input has been presented to the neural network, each neuron computed weighted sums of inputs from all neurons in the preceding layer are used as inputs to succeeding layers and final the networks weighted sum is calculated. The sums and activation (output) values for each neuron in each layer are propagated forward through to entire network to compute an actual output and error of each neuron in the output layer. The error for each neuron is computed as the difference between actual output and its corresponding target output, and then the partial derivative of sum-squared errors of all the neurons in the output layer is propagated back through the entire network and the weights are updated. In course of the BP learning, a gradient search procedure is used to find connection weights of the network, but it tends to trap itself into the local minima. The local minima may be avoided by adjusting value of the momentum. This algorithm can be expressed succinctly in the form of a pseudo-code as given below:

1. Pick a rate parameter R.
2. Until performance is satisfactory.

For each sample input
Compute the resulting output.
Compute β for nodes in the output layer using

$$\beta_z = D_z - O_z \quad \dots (1)$$

Where D represents the desired output and O represents the actual output of the neuron
Compute β for all other nodes using

$$\beta_j = \sum_k W_{j \to k} O_k (1 - O_k) \beta_k \quad \dots (2)$$

Compute weight changes for all weights using

$$\Delta W_{i \to j} = r\, O_i O_j (1 - O_j) \beta_j \quad \dots (3)$$

Add up the weight changes for all sample inputs and change the weights.

3.2.2 Levenberg - Marquardt (LM) Approximation

The standard BP algorithm suffers from the serious drawbacks of slow convergence and inability to avoid local minima. Therefore, BP with Levenberg - Marquardt (LM) approximation is used in this work. LM learning rule uses an approximation of the Newton's method to get better performance [13]. This technique is relatively faster but requires more memory. The LM update rule is:

$$\Delta W = (J^T J + \mu I)^{-1} J^T e \quad \dots (4)$$

Where J is the Jacobean matrix of derivatives of each error to each weight, μ is a scalar and e is an error vector. If the scalar is very large, the above expression approximates the Gradient Descent method; while it is small the above expression becomes the Gauss - Newton method. The Gauss Newton method is faster and more accurate near error minima. Hence, the aim is to shift towards the Gauss - Newton as quickly as possible. The μ is decreased after each successful step and increased only when the step increases the error.

3.2.3 Network Training and Development of Model

A two layer feed forward network with three input neurons, three neurons in the first hidden layer (S_1), two neurons in the second hidden layer (S_2), and one output neurons in the output layer is designed and trained with LM learning rule. The logarithm of sigmoid function is used in the first hidden layer, tangent of sigmoid in the second hidden layer and the output layer has pure linear neurons. The neural network architecture is shown in the figure 2.

The input parameters are:
1. Rotational Speed (R.P.M)
2. Melting Time (min.)
3. Fuel Consumed (Liters)
Melting Rate is taken as single output parameter.
The training parameters are as follows:
Frequency of progress displays (in epochs) = 20
Maximum number of epochs to train = 300
Sum-squared error goal = 10-8
Neurons in layer 1, S1 = 3
Neurons in layer 2, S2 = 2
Number of epochs = 130

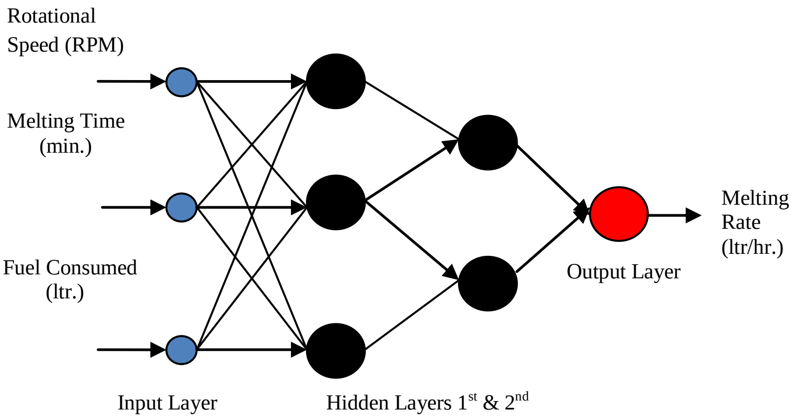

Fig 2: Proposed Neural Network Architecture

3.3 Regression Modeling

Captions Statistical methods such as cluster analysis, pattern recognition, design of experiments, factor analysis, and regression analysis are some of the statistical techniques which enable one to analyze the experimental data and build empirical models to obtain the most accurate representation of physical situations. In case of Rotary furnace which is designed and developed in Faculty of Engineering, D.E.I. numbers of heats were produced varying some of the critical parameters and output as melting rate was observed from the regressive experiments. In order to accurately model the melting rate in Rotary furnace one needs to determine the critical parameters affecting the melting rate. To keep the experiments manageable, major variables with their nominal values are selected.

The Critical input Parameters affecting the melting rate are:

1. Rotational Speed (in RPM)
2. Melting Time (in Minutes)
3. Fuel Consumed (in Liters)

Melting Rate is taken as single output Parameter.
Melting Rate (M), which is a function of Rotational Speed (R), Melting Time (T) and Fuel Consumed (F), is as follows:

$$M = C_0 \times R^{C1} \times R^{C2} \times R^{C3} \quad \dots\dots (5)$$

on taking logarithm of both the sides,

$$\ln M = \ln C_0 + C_1 \ln R + C_2 \ln T + C_3 \ln F \quad \dots\dots (6)$$

The regression model for this problem involves three variables; therefore their dependency relationship can be mathematically expressed as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \quad \dots\dots (7)$$

which is a natural extension of the simple linear regression model.
In matrix notation, it can be written as:

$$Y = X\beta + \varepsilon \quad \dots\dots (8)$$

Data for developing multiple regression model is shown in Table 2. Response of Eighteen observations on model Y and on the three variables X_1, X_2 and X_3 can be written as follows:

$$Y = \begin{bmatrix} 5.7291 \\ 5.7817 \\ 5.4806 \\ 5.5215 \\ 5.5215 \\ 5.5215 \\ 5.8663 \\ 5.5215 \\ 5.6791 \\ 5.7038 \\ 5.8091 \\ 5.6791 \\ 5.7817 \\ 5.7038 \\ 5.6315 \\ 5.9269 \\ 5.8373 \\ 5.7038 \end{bmatrix}, \quad \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix}, \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \vdots \\ \varepsilon_n \end{bmatrix}, \quad X = \begin{bmatrix} 1 & 0.693147 & 3.663562 & 4.356709 \\ 1 & 0.693147 & 3.610918 & 4.369448 \\ 1 & 0.693147 & 3.912023 & 4.382027 \\ 1 & 0.470004 & 3.871201 & 4.454347 \\ 1 & 0.470004 & 3.871201 & 4.430817 \\ 1 & 0.470004 & 3.871201 & 4.442651 \\ 1 & 0.336472 & 3.526361 & 4.369448 \\ 1 & 0.336472 & 3.871201 & 4.430817 \\ 1 & 0.336472 & 3.713572 & 4.382027 \\ 1 & 0.182322 & 3.688879 & 4.394449 \\ 1 & 0.182322 & 3.583519 & 4.343805 \\ 1 & 0.182322 & 3.713572 & 4.369448 \\ 1 & 0 & 3.610918 & 4.369448 \\ 1 & 0 & 3.688879 & 4.369448 \\ 1 & 0 & 3.7612 & 4.394449 \\ 1 & -0.22314 & 3.465736 & 4.304065 \\ 1 & -0.22314 & 3.555348 & 4.330733 \\ 1 & -0.22314 & 3.688879 & 4.369448 \end{bmatrix}$$

The method of lest square stipulates that one should select $\{\beta_0, \beta_1, \beta_2$ and $\beta_3\}$ such that the selection minimizes the sum of squares of the errors $\sum \varepsilon_i^2$. For the model in equation we have:

$$\sum \varepsilon_i^2 = \sum (Y_i - \beta_0 - \beta_1 X_{i1} - \beta_2 X_{i2} - \beta_3 X_{i3})^2 \qquad \text{………. (9)}$$

Differentiation of the above equation with respect to β_0, β_1, β_2 and β_3 separately gives normal equations, written in matrix notation as $X^T X\beta = X^T Y$. The solution to this equation is $\beta = (X^T X)^{-1} X^T Y$. Therefore β comes out to be as follows:

$$\beta = \begin{bmatrix} 9.3896 \\ -0.000044367 \\ -0.99999 \\ 0.0007019 \end{bmatrix}$$

This estimates the model parameters $\{\beta_0, \beta_1, \beta_2$ and $\beta_3\}$.
Now,
C_0=11963, C_1= -0.000044367, C_2= -0.99999, C_3= 0.00070192
So, Melting Rate from equation (5) comes out to be as follows:

$$M = 11963 \times R^{-0.000044367} \times T^{-0.99999} \times F^{0.0007019} \qquad \text{…. (10)}$$

Values of M estimated by multiple regression model is shown in Table 2.
Taking natural logarithm of equation (10) gives:

$$\ln M = \ln 11963 - 0.000044367 \ln R - 0.99999 \ln T + 0.00070192 \ln F \qquad \text{……. (11)}$$

4. COMPARISON OF RESULTS

Table 1: Comparison of the experimental values of output (actual melting rate) and ANN modeled melting rate

S.No.	Rotational Speed (RPM)	Melting Time (Minutes)	Fuel Consumed (Liters)	Melting Rate (Liters/Hour) Experimental	Melting Rate (Liters/Hour) ANN model	Percentage Variation
1.	2.0	39	78	307.692	307.68	0.004011
2.	2.0	37	79	324.324	324.3076	0.005171
3.	2.0	50	80	240	240.0018	-0.00074
4.	1.6	48	86	250	250.0028	-0.00114
5.	1.6	48	84	250	249.9967	0.001301
6.	1.6	48	85	250	250.0003	-0.00012
7.	1.4	34	79	352.941	352.8833	0.016391
8.	1.4	48	84	250	250.0081	-0.00324
9.	1.4	41	80	292.683	292.7295	-0.01593
10.	1.2	40	81	300	300.0311	-0.01038
11.	1.2	36	77	333.333	333.2917	0.012488
12.	1.2	41	79	292.683	292.696	-0.00445
13.	1.0	37	79	324.324	324.2701	0.01673
14.	1.0	40	79	300	299.9873	0.004232
15.	1.0	43	81	279.07	279.0821	-0.00441
16.	0.8	32	74	375	374.99	0.002677
17.	0.8	35	76	342.857	342.9214	-0.01875
18.	0.8	40	79	300	299.9883	0.003907

Table 2: Comparison of the experimental values of output (actual melting rate) and Regression modeled melting rate

S.No.	Rotational Speed (RPM)	Melting Time (Minutes)	Fuel Consumed (Liters)	Melting Rate (Liters/Hour) Experimental	Melting Rate (Liters/Hour) Regression model	Percentage Variation
1.	2.0	39	78	307.692	307.685	0.002415
2.	2.0	37	79	324.324	324.319	0.001574
3.	2.0	50	80	240	239.999	0.00039
4.	1.6	48	86	250	250.014	-0.00564
5.	1.6	48	84	250	250.01	-0.00398
6.	1.6	48	85	250	250.012	-0.00481
7.	1.4	34	79	352.941	352.941	0.000076
8.	1.4	48	84	250	250.011	-0.00458
9.	1.4	41	80	292.683	292.686	-0.00099
10.	1.2	40	81	300	300.008	-0.00253
11.	1.2	36	77	333.333	333.33	0.001135
12.	1.2	41	79	292.683	292.685	-0.0008
13.	1.0	37	79	324.324	324.329	-0.0015
14.	1.0	40	79	300	300.005	-0.00158
15.	1.0	43	81	279.07	279.079	-0.00341
16.	0.8	32	74	375	374.992	0.002243
17.	0.8	35	76	342.857	342.856	0.000281
18.	0.8	40	79	300	300.008	-0.00257

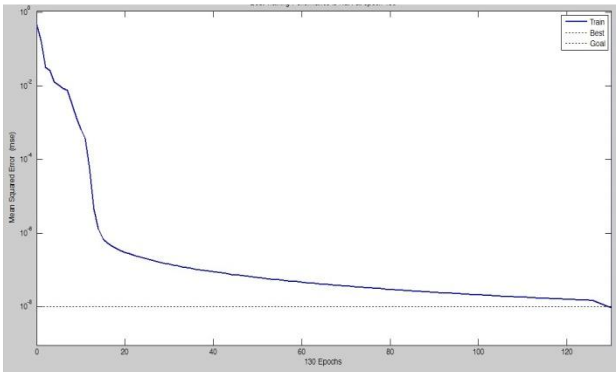

Fig 3: Training Graph

Table 1 is representing the experimental value of melting rate and the estimated value by the NN model. Similarly, Table 2 is representing the experimental value and the estimated value by Regression model. The percentage variations shown in Table 1 and 2, show that both ANN and regression models have approximately same results as was obtained from the experimentations. It was also observed that, the critical parameters Rotational speed, Melting Time, and Fuel consumed are the main factors which affect the Melting Rate.

The training graph between sum squared error and number of epochs is shown in Figure 3. Figure 4 is representing the variation in the percentage error by Regression and ANN modeling. And it shows that both the models are giving the error less than 5%. The results predicted are with lesser error as compared to the prediction of Karunakaran and Dutta [6].

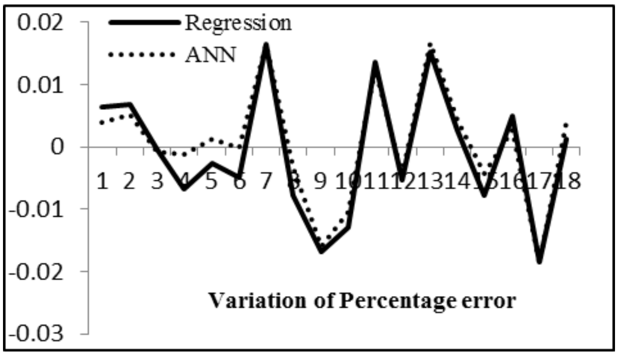

Fig 4: Variation of Percentage Error with ANN and Regression Modeling

5. CONCLUSION

The neural network models developed in this paper can effectively estimate the melting rate based on Rotational Speed, Melting time, and Fuel consumption. The results obtained using most critical input parameters of furnace and Levenberg - Marquardt training for back propagation neural network give good estimation and are validated with experimental values with an error much lesser than 5% error. These performance figures suggest that ANN is a powerful tool for modeling and predictive applications. The ANN models have emerged as a new alterative to model manufacturing processes. Similarly Regression modeling also gives good estimation and validated with experimental data with less than 5% error. Results show that these techniques easily capture the intricate relationship between various process parameters and can be readily integrated into existing manufacturing environment. These techniques open new avenues of parameter estimation, function approximation, optimization and online control of complex manufacturing systems.

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