The International Journal Of Engineering And Science (IJES)
|| Volume || 4 || Issue || 8 || Pages || PP -38-43|| 2015 ||
ISSN (e): 2319 – 1813 ISSN (p): 2319 – 1805

Modeling of LDO-fired Rotary Furnace Parameters using Adaptive Network-based Fuzzy Inference System

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ABSTRACT
In this paper a novel approach i.e. neuro-fuzzy technique is used for the first time in modeling rotary furnace parameters to predict the melting rate of the molten metal required to produce homogenous castings. The relationship between the process variables (input) viz. flame temperature, preheat air temperature, rotational speed of the furnace, excess air, melting time, and fuel consumption and melting rate (output) is very complex and is agreeable to neuro-fuzzy approach. The neuro-fuzzy model has been created out of training data obtained from the series of experimentation carried out on rotary furnace. The results provided by neuro-fuzzy model compares well with the experimental data. This work has considerable implications in selection and control of process variables in real time and ability to achieve energy and material savings, quality improvement and development of homogeneous properties throughout the casting and is a step towards agile manufacturing.

Keywords: *Adaptive Network - based Fuzzy Inference System (ANFIS), Light Diesel Oil (LDO), Rotary Furnace.*

Date of Submission: 13 June 2015 Date of Accepted: 20 August 2015

I. INTRODUCTION

To respond to changing demand scenarios, the system must be equipped with a comprehensive manufacturing planning and control system that incorporates vast amounts of manufacturing knowledge in a form that is accessible rapidly. The design and implementation of these systems is one of the major challenges faced by today's manufacturing engineers [1-2].

The basic idea of Rotary furnace technique is of using a dome rotating continuously to create homogeneity in the casting. The rotary furnace consists of a cylindrical structure, which rotates continuously about its axis. The furnace can be run by a variety of fuels but at present we are considering a Light Diesel Oil (LDO) fired furnace. This technique suits the conditions and requirements of the local foundries in terms of the cost of castings produced as well as their quality. Moreover the pollutants emitted by the furnace are well within the range specified by the Central Pollution Control Board (CPCB) of India [3].

The Rotary furnace is the most versatile and economical mode of melting iron in ferrous foundries. But it is very strange that a very little information is available in the form of literature on this furnace [4].

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, rotational speed, excess air, 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. 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. In order to meet this demand, an ANFIS model is developed that correlates well with the experimental data [5].

II. NEURO-FUZZY SYSTEMS

Neuro-fuzzy systems belong to a newly developed class of hybrid intelligent systems that combine the main features of artificial neural networks with those of fuzzy logic, using heuristic learning strategies derived from the domain of neural network theory to support the development of a fuzzy system. Modern neuro-fuzzy systems usually are represented as a multilayer feed-forward neural network. In neuro-fuzzy models, connection weights, propagation and activation functions differ from common neural networks [6].

The neuro-fuzzy system is capable of extracting fuzzy knowledge from numerical data and linguistic data into the system. The goal here is to avoid difficulties encountered in applying fuzzy logic for systems represented by numerical knowledge (data sets), or in applying neural networks for systems presented by linguistic information (fuzzy sets). Neither fuzzy reasoning systems nor neural networks are by themselves capable of solving problems involving at the same time both linguistic and numerical knowledge. A number of researchers have used the term hybrid systems to depict systems that involve in some ways both fuzzy logic and neural network features [7].

Neuro-fuzzy systems overcome the limitations of artificial neural networks (ANN) and fuzzy system. A neuro-fuzzy system is trained by a learning algorithm derived from neural network theory. The (heuristic) learning procedure operates on local information, and causes only local modifications in the underlying fuzzy system. The learning process is not knowledge-based, but data-driven [8].

A neuro-fuzzy system can be viewed as a special multi-layer, feed-forward neural network. The first layer represents input variables, the middle (hidden) layer(s) represent(s) fuzzy rules and the last layer represents output variables. Fuzzy sets are encoded as (fuzzy) connection weights. A neuro-fuzzy system can always be interpreted (i.e., before, during and after learning) as a system of fuzzy rules. It is possible both to create the system out of training data from scratch and to initialize it by prior knowledge in the form of fuzzy rules [9].

A neuro-fuzzy system approximates an n-dimensional (unknown) function that is given partially by the training data. It is possible to view a fuzzy system as a special neural network and to apply a learning algorithm directly (hybrid models).

Recently, several approaches were suggested for generating the fuzzy rules from numerical data automatically. Most notable is Jang's Adaptive Network - based Fuzzy Inference System (ANFIS).

ANFIS Developed by Jang, is an extension of the Takagi, Sugeno and Kang (TSK) fuzzy model. ANFIS represents a neural network approach to the design of fuzzy inference systems. An ANFIS network makes use of a supervised learning algorithm to determine a non-linear model of the input-output function, which is represented by a training set of numerical data. Because, under proper conditions it can be used as a universal approximator, an ANFIS network is suited particularly for solving function approximation problems in several engineering fields. The present model allows the fuzzy system to learn the parameters using hybrid learning algorithm [10-12].

III. MODELING OF ROTARY FURNACE PARAMETERS

In this section, the ANFIS modeling of rotary furnace parameters is described. The data is obtained from the experiments conducted on a self-designed and developed furnace as shown in the Figure 1, at Foundry Shop, Faculty of Engineering, DEI, Dayalbagh, Agra, INDIA and is used to train the ANFIS model.

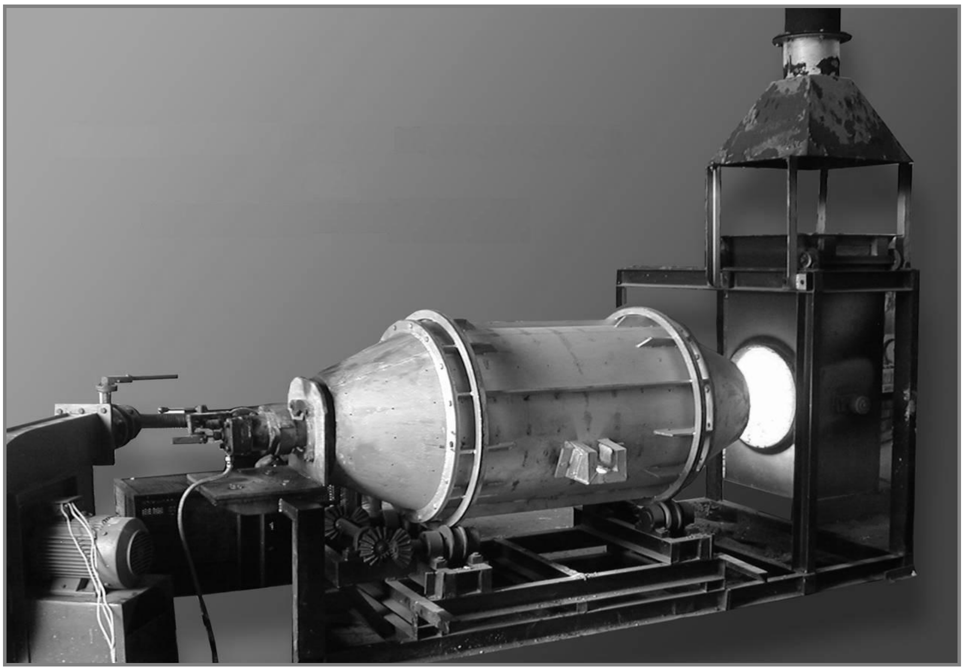

Fig. 1: Self designed and developed Rotary furnace.

In the experimentation, 200 *kg*. of the charge is melted in the rotary furnace. A Circular burner is used for burning LDO as a fuel. Total 201 numbers of experiments were conducted at different percentages of excess air; varying from 10% to 50% and varying in the amount of air preheat from 200°C to 400°C [13-14].

A six input ANFIS architecture is shown in the figure 2 with five layers. The description of each layer is given below:

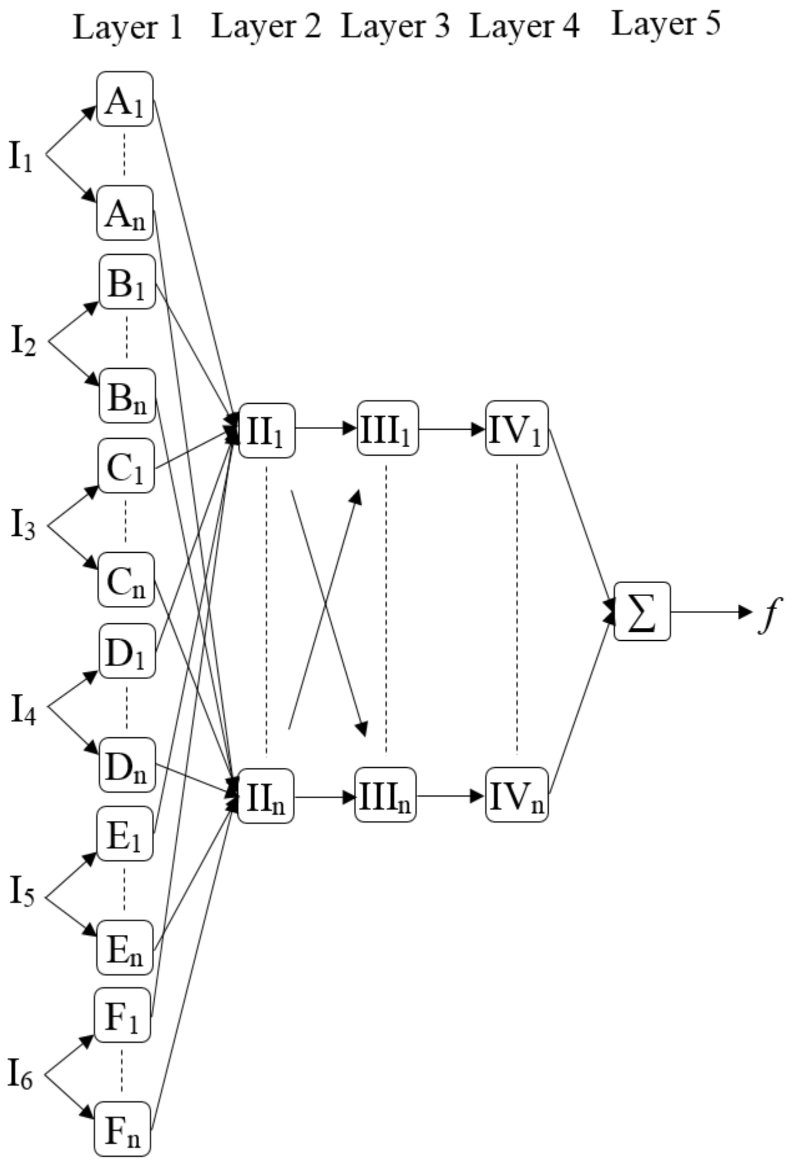

Fig. 2: ANFIS Architecture [15]

Layer 1: Every node in this layer is a square node, with a node function, $O_i^1 = \mu_{A_i}(\theta)$, where *O* is the input to node *i*, and A_i is the linguistic label associated with this node function. In this architecture, μ_{A_i} is bell shaped with maximum equal to 1 and minimum equal to 0.

$$\mu_{A_i}(\theta) = \frac{1}{1 + \left[\left(\frac{\alpha - c_i}{a_i}\right)^2\right]^{b_i}}$$; where $\{a_i, b_i, c_i\}$ are the premise parameters.

Layer 2: The function of node in this layer is to multiply the incoming signals and produce the product of all inputs. For instance,

$$w_i = \mu_{A_j}(\alpha) \times \mu_{B_k}(\beta) \times \mu_{C_l}(\gamma) \times \mu_{D_m}(\delta) \times \mu_{E_n}(\nu) \times \mu_{F_o}(\lambda)$$

$$i = 1, 2, 3, ..., 201 \qquad and \qquad j,\ k,\ l,\ m,\ n,\ o\ =\ 1,\ 2,\ 3,\ 4,\ 5,\ 6.$$

Each node output represents the firing strength of a rule.

Layer 3: The input firing strength is normalized in this layer and output is called normalized firing strengths.

$$\overline{w_i} = \frac{w_i}{w_1 + w_2 + ... + w_{201}}\ ; \quad i=1, 2, 3, …, 201.$$

Layer 4: Every node *i* in this layer is a parameterized function. The node function is:

$O_i^4 = \bar{w}_i f_i = \bar{w}_i \left(p_i\alpha + q_i\beta + r_i\gamma + s_i\delta + t_i\nu + u_i\lambda \right)$; where i =1, 2, …, 201 and $\bar{w}_i$ is the output of previous layer, and {p_i, q_i, r_i, s_i, t_i, u_i} is a parameter set. Parameters in this layer are referred as consequent parameters.

Layer 5: The single node in this layer computes the overall output as the summation of all incoming signals, i.e. $O_1^5 = overall\ output = \sum \bar{w}_i f_i$

The system is initialized with a number of membership functions and a rule base. Learning consists of two separate passes. In the forward pass, the consequent parameters are determined by least square method and antecedent parameters are updated by a gradient descent algorithm in the backward pass [16].

From the equations obtained in layer 4 and 5 it is observed that given the values of premise parameters, the overall output is expressed as linear combinations of the consequence parameters. The output *f* can be rewritten as:

$$f = \sum_{i=1}^{201} \bar{w}_i f_i$$

$$f = \sum_{i=1}^{201} (\bar{w}_1\alpha) p_i + (\bar{w}_1\beta) q_i + (\bar{w}_1\gamma) r_i + (\bar{w}_1\delta) s_i + (\bar{w}_1\nu) t_i + (\bar{w}_1\lambda) u_i$$

This is linear in the consequent parameters [17].

The forward pass of the learning algorithm continues up to nodes at layer 4 and consequent parameters are determined by the method of least squares. In the backward pass, the error signal propagates backward to update the premise parameters by gradient descent. The training information is as follows:

Number of nodes	= 193
Number of linear parameters	= 405
Number of non-linear parameters	= 36
Total number of parameters	= 441
Number of training data pairs	= 201
Number of checking data pairs	= 100
Number of fuzzy rules	= 81
Number of epochs	= 500.

IV. RESULT

The predicted values by ANFIS model used in this work are much closer to the experimental values as can be observed from the results. A partial set of the experimental results and the estimated values reported by ANFIS model are listed in Table 1.

Table 1: Comparison of Melting Rate obtained by Experimentation on Rotary furnace & by ANFIS Model

S. No.	Excess Air (*%*)	Flame Temperature (*°C*)	Rotational Speed (*RPM*)	Melting Time (*Min*)	Preheat Air Temperature (*°C*)	Fuel Consumed (*Liters*)	Experimental Values of Melting Rate (*MT/hr.*)	Estimated Values of Melting Rate (*MT/hr.*)
1.	10	2190	0.8	35	200	76	0.343	0.343
2.	10	2185	0.8	35	200	75	0.343	0.342
3.	10	2190	0.8	35	200	76	0.343	0.343
4.	10	2195	0.8	36	200	75	0.330	0.329
5.	10	2200	0.8	34	300	75	0.353	0.353
6.	10	2215	0.8	34	300	75	0.353	0.352
7.	10	2215	0.8	35	300	76	0.343	0.342
8.	10	2220	0.8	34	300	75	0.353	0.353
9.	10	2280	0.8	32	400	74	0.375	0.375
10.	10	2290	0.8	32	400	74	0.375	0.375
11.	10	2300	0.8	32	400	74	0.375	0.374
12.	10	2290	0.8	32	400	74	0.375	0.375
13.	10	2180	1.0	37	200	78	0.324	0.324
14.	10	2175	1.0	37	200	78	0.324	0.323
15.	10	2175	1.0	38	200	79	0.315	0.315
16.	10	2195	1.0	35	300	76	0.343	0.343
17.	10	2200	1.0	35	300	76	0.343	0.342
18.	10	2215	1.0	36	300	79	0.330	0.330
19.	10	2265	1.0	34	400	75	0.343	0.342
20.	10	2270	1.0	34	400	75	0.343	0.343
21.	10	2270	1.0	34	400	76	0.343	0.343
22.	10	2160	1.2	38	200	79	0.315	0.314
23.	10	2165	1.2	38	200	78	0.315	0.315
24.	10	2160	1.2	37	200	79	0.324	0.323
25.	10	2180	1.2	37	300	77	0.324	0.324
26.	10	2185	1.2	37	300	78	0.324	0.324
27.	10	2190	1.2	37	300	77	0.324	0.323
28.	10	2250	1.2	36	400	76	0.330	0.330
29.	10	2245	1.2	36	400	75	0.330	0.329
30.	10	2245	1.2	36	400	76	0.330	0.329
31.	10	2150	1.4	38	200	80	0.315	0.315
32.	10	2155	1.4	38	200	80	0.315	0.314
33.	10	2160	1.4	37	200	79	0.324	0.324
34.	10	2175	1.4	36	300	80	0.330	0.330
35.	10	2180	1.4	36	300	81	0.330	0.330
36.	10	2170	1.4	36	300	81	0.330	0.329
37.	10	2230	1.4	34	400	80	0.353	0.353
38.	10	2240	1.4	34	400	79	0.353	0.352
39.	10	2240	1.4	34	400	79	0.353	0.352
40.	10	2145	1.6	38	200	81	0.315	0.315
41.	10	2150	1.6	38	200	80	0.315	0.315
42.	10	2150	1.6	37	200	81	0.324	0.323
43.	10	2170	1.6	36	300	79	0.330	0.330
44.	10	2178	1.6	36	300	79	0.330	0.329
45.	10	2170	1.6	36	300	80	0.330	0.330
46.	10	2220	1.6	35	400	78	0.343	0.343
47.	10	2215	1.6	35	400	78	0.343	0.342
48.	10	2210	1.6	35	400	79	0.343	0.343
49.	10	2100	2.0	39	200	80	0.307	0.307
50.	10	2110	2.0	38	200	80	0.315	0.315

V. CONCLUSION

The developed neuro-fuzzy model in this paper can effectively estimate the melting rate based on input process variables viz. flame temperature, preheat air temperature, rotational speed of the furnace, excess air, melting time, and fuel consumption that correlates well with the experimental values. This technique easily captures the intricate relationship between various process parameters and can be easily integrated into existing manufacturing environment and also opens new avenues of parameter estimation, function approximation, optimization and online control of complex manufacturing systems.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the inspiration provided by the Most Revered Prof. P.S. Satsangi Sahab, Chairman, Advisory Committee on Education, Dayalbagh, Agra, INDIA.

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