Neuro - Fuzzy Modeling of an Eco-friendly Melting Furnace Parameters using Bio-fuels for the Agile Production of Quality Castings

Purshottam Kumar
Dayalbagh Educational Institute
Dayalbagh, Agra-282005, U.P., INDIA - 282110

Ranjit Singh
Dayalbagh Educational Institute
Dayalbagh, Agra-282005, U.P., INDIA - 282110

ABSTRACT
In this paper neuro-fuzzy technique is used for the first time in modeling eco-friendly furnace parameters to predict the melting rate of the molten metal required to produce homogenous and quality castings. The relationship between the process variables (input) viz. flame temperature, preheat air temperature, rotational speed of the furnace dome, percentage of excess air, melting time, fuel consumption and melting rate (output) is very complex and is agreeable to neuro-fuzzy approach. The neuro-fuzzy model has been developed out of training data obtained from the series of experimentation carried out on eco-friendly self designed and developed 200 kg capacity rotary furnace using bio-fuels. 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.

General Terms
Neuro-Fuzzy, ANFIS, Neural Network

Keywords
Neuro-Fuzzy, Rotary Furnace, Bio-fuel, Artificial Neural Network (ANN), Adaptive Network - based Fuzzy Inference System (ANFIS), Agile Manufacturing Systems (AMS).

1. INTRODUCTION
AGILE Manufacturing Systems (AMS) are respond to rapid changes in designs and demand without intervention by humans. Agility, specifically, has the following principal components: quality, speed to market, widening customer choice and expectation, the competitive priorities of responsiveness, new product introduction, readiness for change, respect for human knowledge and skills, and a synthesized use of the developed and well-known technologies and methods of manufacturing. In order to take advantage of speed to market and new product introductions, management must invest in technologies that confer operational flexibility.

So as 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 [1-3].

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 is shown in figure 1. The furnace can be run by a variety of fuels but at present we are using Jatropha (bio-fuel) blended with diesel for firing the furnace 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 (C.P.C.B.) of India.

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.

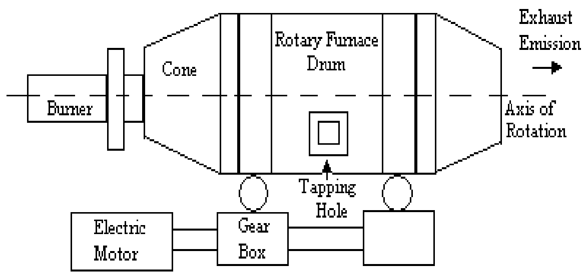

Fig. 1. Layout of Rotary Furnace

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 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. 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, a neuro-fuzzy model is developed that correlates well with the experimental data. This work also has implications in the 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 process [4].

2. 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.

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 [5-7].

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.

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.

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) [8].

ANFIS Developed by Jang, is an extension of the Takagi, Sugeno and Kang (TSK) fuzzy model [9]. 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 [10-13].

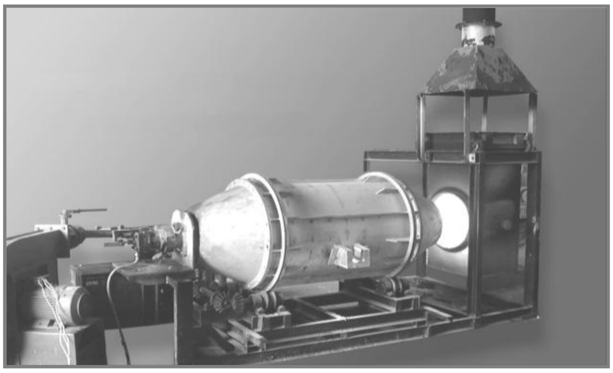

Fig. 2. Self Designed and Developed Rotary Furnace at Foundry Shop, Faculty of Engineering, Dayalbagh Educational Institute, Dayalbagh, Agra

3. NEURO-FUZZY MODELING OF ROTARY FURNACE PARAMETERS

In this section, the Neuro-fuzzy 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 2, at Foundry Shop, Faculty of Engineering, D.E.I., Dayalbagh, Agra, INDIA and is used to train the neuro-fuzzy model.

In the experimentation 200 kg. of the charge is melted in the rotary furnace. A Circular burner is used for burning Bio fuel which is used 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 [14-15].

Architecture of ANFIS

The ANFIS is a fuzzy Sugeno Model put in the framework of adaptive systems to facilitate learning and adaptation. Such framework makes the ANFIS modeling more systematic and less reliant on expert knowledge. A six input neuro - fuzzy network architecture with five layers is shown in the figure 3.

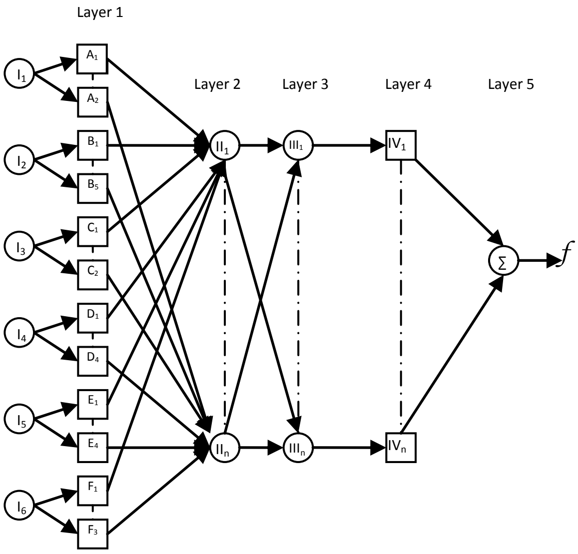

Fig. 3. An ANFIS Architecture used in predicting results

The data set comprises of six input viz. percentage of excess air in % (EA), flame temperature in °C (FT), rotational speed in RPM (RS), melting time in Minutes (MT) , preheat air temp in °C (PAT), fuel consumed in Liters (FC) and one output Melting rate (MT/hr.).

The description of each layer is given below:

Layer 1: Every node in this layer is a square node and each node outputs the membership value of input.

Layer 2: The function of node in this layer is to multiply the incoming signals and produce the product of all inputs to compute the rule matching factor.

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.

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

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.

ANFIS Computational Complexity

Layer #	L-Type	# Nodes	# Parameter
Layer 1	Value	(p*n)	3*(p*n)=|S1|
Layer 2	Rules	p^n	0
Layer 3	Normalize	p^n	0
Layer 4	Lin. Function	p^n	$(n+1)* p^n= \|S2\|$
Layer 5	Sum	1	0

Where:

- p is the number of fuzzy partitions of each variable
- n is the number of input variables
- S1 represents the fuzzy partitions used in the rules LHS
- S2 represents the coefficients of the linear functions in the rules RHS

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 [8, 9, 16]. The shape of the membership functions to be used in ANFIS depends on parameters, and changing these parameters change the shape of the membership function. Instead of just looking at the data to choose the membership function parameters, we selected 3 different memberships function (MF) parameters using ANFIS GUI. The 3 Membership function used in ANFIS are (a) triangular membership function (trimf), (b) Gaussian membership function (gaussmf), (c) difference between two sigmoidal functions (dsigmf) and the simulkated results are calculated for the data obtained through the experiment. Inspite of fixing the number of epoch we used different number of epoch for different MF until the error is reduced to its global minima

The training information is as follows:

Table: 1

ANFIS Information	
Total no of inputs	6
No of membership Function for each input	[2 5 2 4 4 3]
Membership Function used	1. GAUSSMF
	2. TRIMF
	3. DSIGMF
Number of nodes	1969
Number of linear parameters	960
Number of nonlinear parameters	60
Total number of parameters	1020
Number of training data pairs	132
Number of checking data pairs	69
Number of fuzzy rules	960

The ANFIS structure shown in figure 3 was implemented by using MATLAB software package (MATLAB version 7.0 with fuzzy logic toolbox) using 201 experimental data sets, among which 132 data sets are used for training and rest 69 are used validating the model given in Table 4.

4. SIMULATION RESULTS

In training model, number of membership functions associated with each input are given as [2 5 2 4 4 3] according to the preference of input on output. The same model is run on same MF (trimf, gaussmf and dsigmf) and it is found that the predicted values by ANFIS model used in this work are much closer to the experimental values as can be observed from the results. The chart between RMS error with number of epoch for GAUSSMF, DSIGMF, TRIMF is shown in Figure 4, Figure 5 and Figure 6 respectively. The Error chart shows that the RMS error converges rapidly with minimum number of epoch for TRIMF in comparison with GAUSSMF, while in DSIGMF the RMS error curve do not converge till 200 epochs, and the computational time too increases with each epoch. The results in Table 2 and Figure 7 showing difference between desired and predicted values by the three membership function are also satisfying RMS chart shown in Figure 4, Figure 5 and Figure 6. Some of the data sets obtained by experiments on Rotary Furnace for various parameters are listed in Table 4. A comparison of experimental results and the estimated values reported by ANFIS model are listed in Table 3.

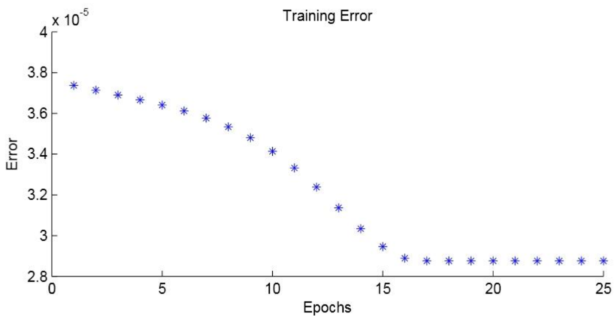

Fig. 4. Graph between RMS Error and number of Epochs using Gauss

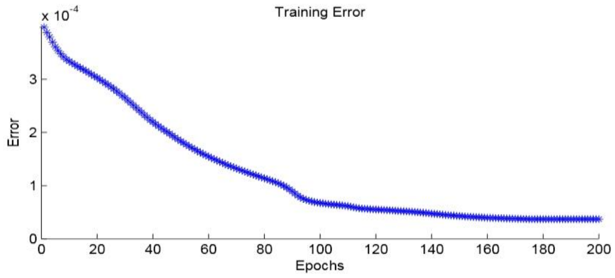

Fig 5: Graph between RMS Error and number of Epochs using DSIGMF

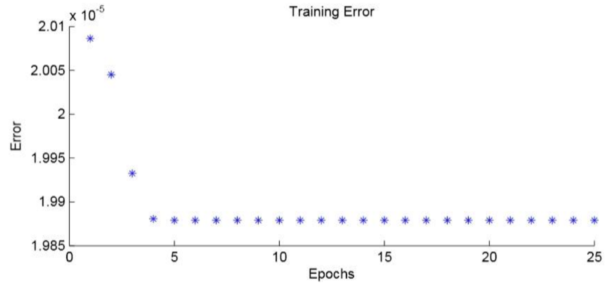

Fig 6: Graph between RMS Error and number of Epochs using TRIMF

Table: 2

Difference between desired and predicted values		
Gauss error in %	Average	0.00392579
	Minimum	0
	Maximum	0.1844907
DSIGMF error in %	Average	0.00532441
	Minimum	0
	Maximum	-0.299267598
TRIMF error in %	Average	0.002858178
	Minimum	-0.0000280
	Maximum	0.148277499

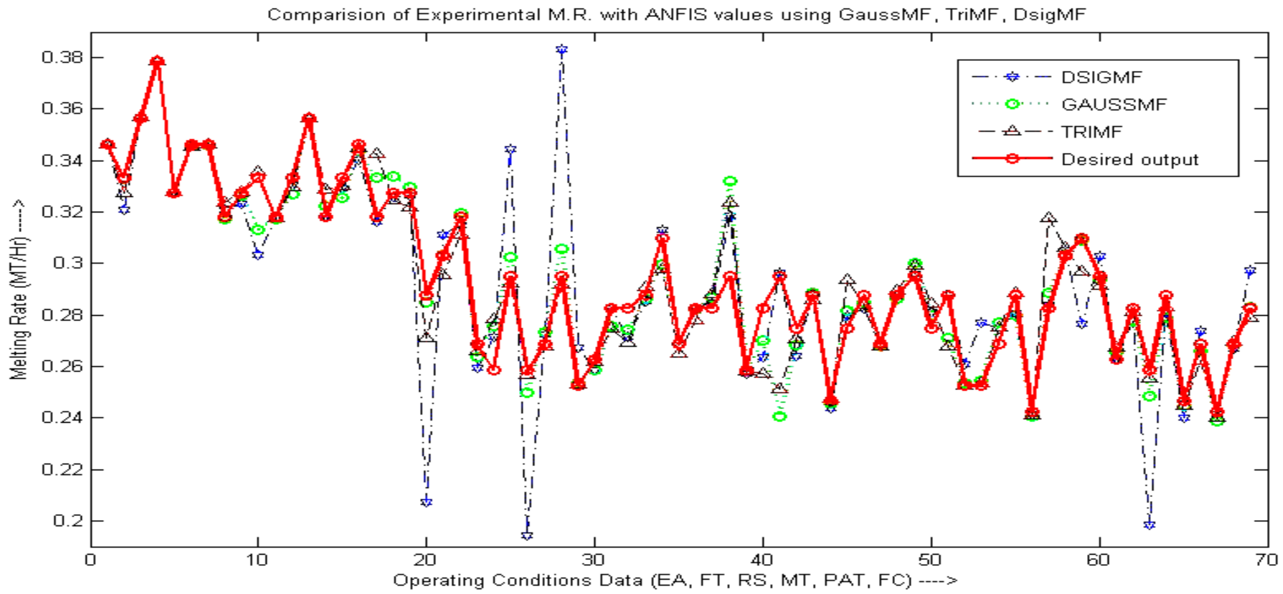

Fig 7. Comparison of 3 Membership Function with desired output

5. 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 drum, excess air percentage, melting time, and fuel consumption that correlates well with the experimental values. It is found that for our model does not give satisfactory result with DSIGMF in comparisons to GAUSSMF and TRIMF as the error is high in case of DSIGMF. Since the average error is minimum in the case of TRIMF. So, this may be selected as the membership function for evaluating the melting rate. The results demonstrate that the ANFIS can be applied successfully and provide high accuracy and reliability for estimating the melting rate of the molten metal in foundries. 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.

REFERENCES

[1] S. L. Goldman, R. N. Nagel, and K. Preiss, “Agile Competitors and Virtual Organizations: Strategies for Enriching the Customer”, Van Nostrand Reinhold, New York, 1995.

[2] Y. Y. Yusuf, M. Sarhadi, and A. Gunasekaran, “Agile Manufacturing: The Drivers, Concepts and Attributes”, International Journal of Production Economics, Vol. 62, 1999, pp. 33-43.

[3] P. T. Kidd, “Agile Manufacturing: Forging New Frontiers”, Addison - Wesley Reading, M.A., 1994.

[4] R. Singh, G. Das, and R. Setia, “Parametric Modeling of a Rotary Furnace for Agile Production of Castings with Artificial Neural Networks,” International Journal of Agile Manufacturing, Vol. 10, Issue 2, 2007, pp. 137–147.

[5] H. R. Berenji, and P. Khedkar, “Learning and Tuning Fuzzy Logic Controllers Through Reinforcements”, IEEE Trans. Neural Networks, Vol. 3(5), 1992, pp. 724-740.

[6] J. J. Buckley, and Y. Hayashi, “Fuzzy Neural Networks: A Survey”, Fuzzy Sets and Systems, Vol. 66, 1994, pp. 1-13.

[7] J. J. Buckley, and Y. Hayashi, “Neural Networks for Fuzzy Systems”, Fuzzy Sets and Systems, Vol. 71, 1992, pp. 265-276.

[8] J. S. R. Jang, “ANFIS: Adaptive-Network-Based Fuzzy Inference Systems” IEEE Transaction on Systems, Man & Cybernetics, Vol. 23, 1993, pp. 665-685.

[9] T. Takagi, and M. Sugeno, “Fuzzy Identification of Systems and its Application to Modeling and Control”, IEEE Transaction on Systems, Man & Cybernetics, Vol. 15, 1985, pp. 116-132.

[10] S. K. Halgamuge, and M. Glesner, “Neural Networks in Designing Fuzzy Systems for Real World Applications”, Fuzzy Sets and Systems, Vol. 65, 1994, pp. 1-12.

[11] D. Nauck, and K. Kruse, “Designing Neuro - fuzzy Systems Through Back - propagation”. In Witold Pedrycz, editor, Fuzzy Modelling: Paradigms and Practice, 1996, pp. 203-228, Kluwer, Boston.

[12] D. Nauck, and K. Kruse, “Neuro-fuzzy Systems Research and Applications Outside of Japan” (in Japanese), Fuzzy-Neural Networks (in Japanese), Soft Computing Series, 1996, pp. 108-134, Asakura Publications, Tokyo.

[13] S. K. Halgamuge, and M. Glesner, “Neural Networks in Designing Fuzzy Systems for Real World Applications,” Fuzzy Sets and Systems, Vol. 65, 1994, pp. 1-12.

[14] R. Singh, R. Setia, and G. Das, “Modeling and Optimization of Rotary Furnace Parameters using Artificial Neural Networks and Genetic Evolutionary Algorithms,” Proceedings of 31st National Systems Conference, MIT, Manipal, December 14–15, 2007, P.No.–75.

[15] R. Singh, G. Das, and R. K. Jain, “Modeling and Optimization of Rotary Furnace Parameters using Regression and Numerical Techniques,” Proceedings of 68th World Foundry Congress & 56th Indian Foundry Congress, Chennai Trade Centre, Chennai, February 7–10, 2008, P.No. OP-62, pp. 333-339.

[16] M. Sugeno, and G. T. Kang, “Structure Identification of Fuzzy Model”, Fuzzy Sets and Systems, Vol. 28, 1998, pp. 15-33.

TABLE : 3

Sl. No.	COMPARISON OF MELTING RATE OBTAINED BY EXPERIMENTATION ON ROTARY FURNACE & BY ANFIS MODEL						
	Values				Error in %		
	Desired	**gmf**	**dsigmf**	**trimf**	**gmf**	**dsigmf**	**trimf**
1	0.34643	0.34641	0.34643	0.34642	0.0000577	0.0000000	0.0000289
2	0.3333	0.33283	0.32103	0.32734	0.0014101	0.0368137	0.0178818
3	0.35653	0.3567	0.35652	0.35701	-0.0004768	0.0000280	-0.0013463
4	0.37875	0.37858	0.37874	0.37873	0.0004488	0.0000264	0.0000528
5	0.32724	0.32755	0.32785	0.32806	-0.0009473	-0.0018641	-0.0025058
6	0.34643	0.34605	0.3464	0.34565	0.0010969	0.0000866	0.0022515
7	0.34643	0.34599	0.34647	0.34622	0.0012701	-0.0001155	0.0006062
8	0.31815	0.31706	0.32115	0.32363	0.0034261	-0.0094295	-0.0172246
9	0.32724	0.32661	0.32338	0.32792	0.0019252	0.0117956	-0.0020780
10	0.3333	0.31314	0.30349	0.33588	0.0604860	0.0894389	-0.0077408
11	0.31815	0.31738	0.31791	0.31783	0.0024202	0.0007544	0.0010058
12	0.3333	0.32714	0.33072	0.32952	0.0184818	0.0077408	0.0113411
13	0.35653	0.35653	0.35653	0.35654	0.0000000	0.0000000	-0.0000280
14	0.31815	0.3225	0.31877	0.32863	-0.0136728	-0.0019488	-0.0329404
15	0.3333	0.32552	0.32945	0.33027	0.0233423	0.0115512	0.0090909
16	0.34643	0.34347	0.34025	0.34483	0.0085443	0.0178391	0.0046185
17	0.31815	0.33339	0.31647	0.34261	-0.0479019	0.0052805	-0.0768820
18	0.32724	0.33385	0.32618	0.32473	-0.0201992	0.0032392	0.0076702
19	0.32724	0.32972	0.32645	0.32197	-0.0075785	0.0024141	0.0161044
20	0.28785	0.28495	0.20754	0.271	0.0100747	0.2789995	0.0585374
21	0.303	0.30356	0.31113	0.29553	-0.0018482	-0.0268317	0.0246535
22	0.31815	0.31936	0.31471	0.31122	-0.0038032	0.0108125	0.0217822
23	0.26866	0.26378	0.25929	0.26588	0.0181642	0.0348768	0.0103477
24	0.25856	0.27568	0.27142	0.27835	-0.0662129	-0.0497370	-0.0765393
25	0.29492	0.30262	0.34472	0.29242	-0.0261088	-0.1688594	0.0084769
26	0.25856	0.24994	0.19449	0.25681	0.0333385	0.2477955	0.0067683

27	0.26866	0.27343	0.27246	0.26776	-0.0177548	-0.0141443	0.0033500
28	0.29492	0.30579	0.38318	0.29169	-0.0368575	-0.2992676	0.0109521
29	0.2525	0.25346	0.26731	0.25324	-0.0038020	-0.0586535	-0.0029307
30	0.2626	0.25837	0.25869	0.26175	0.0161081	0.0148896	0.0032369
31	0.2828	0.27562	0.2827	0.27498	0.0253890	0.0003536	0.0276521
32	0.2828	0.27429	0.27133	0.2693	0.0300919	0.0405587	0.0477369
33	0.28785	0.28622	0.28524	0.29088	0.0056627	0.0090672	-0.0105263
34	0.31007	0.29971	0.31314	0.29771	0.0334118	-0.0099010	0.0398620
35	0.26866	0.26893	0.26815	0.26515	-0.0010050	0.0018983	0.0130648
36	0.2828	0.28203	0.28284	0.27798	0.0027228	-0.0001414	0.0170438
37	0.2828	0.28695	0.28502	0.28837	-0.0146747	-0.0078501	-0.0196959
38	0.29492	0.33199	0.31859	0.32363	-0.1256951	-0.0802591	-0.0973484
39	0.25856	0.25812	0.25698	0.25806	0.0017017	0.0061108	0.0019338
40	0.2828	0.27015	0.26349	0.25708	0.0447313	0.0682815	0.0909477
41	0.29492	0.24051	0.29641	0.25119	0.1844907	-0.0050522	0.1482775
42	0.27472	0.26828	0.2642	0.27041	0.0234421	0.0382935	0.0156887
43	0.28785	0.28847	0.2875	0.2857	-0.0021539	0.0012159	0.0074692
44	0.24644	0.24564	0.24359	0.24761	0.0032462	0.0115647	-0.0047476
45	0.27472	0.28183	0.27997	0.29383	-0.0258809	-0.0191104	-0.0695617
46	0.28785	0.28487	0.28273	0.28394	0.0103526	0.0177870	0.0135835
47	0.26866	0.26777	0.2685	0.26791	0.0033127	0.0005955	0.0027916
48	0.28785	0.28618	0.28791	0.28953	0.0058016	-0.0002084	-0.0058364
49	0.29492	0.30015	0.29597	0.29913	-0.0177336	-0.0035603	-0.0142751
50	0.27472	0.27973	0.28139	0.28431	-0.0182368	-0.0242793	-0.0349083
51	0.28785	0.27095	0.28785	0.26806	0.0587111	0.0000000	0.0687511
52	0.2525	0.25337	0.2611	0.2524	-0.0034455	-0.0340594	0.0003960
53	0.2525	0.25447	0.27729	0.2534	-0.0078020	-0.0981782	-0.0035644
54	0.26866	0.27685	0.27486	0.2754	-0.0304846	-0.0230775	-0.0250875
55	0.28785	0.28005	0.28071	0.28858	0.0270974	0.0248046	-0.0025360
56	0.2424	0.24044	0.24158	0.24087	0.0080858	0.0033828	0.0063119
57	0.2828	0.28884	0.28408	0.31788	-0.0213579	-0.0045262	-0.1240453
58	0.303	0.30353	0.30511	0.306	-0.0017492	-0.0069637	-0.0099010
59	0.31007	0.30871	0.27666	0.29702	0.0043861	0.1077499	0.0420873
60	0.29492	0.29379	0.30306	0.29136	0.0038315	-0.0276007	0.0120711
61	0.2626	0.26559	0.26329	0.2675	-0.0113861	-0.0026276	-0.0186596
62	0.2828	0.27731	0.27762	0.28118	0.0194130	0.0183168	0.0057284
63	0.25856	0.24836	0.19849	0.25547	0.0394493	0.2323252	0.0119508
64	0.28785	0.27888	0.28084	0.28306	0.0311621	0.0243530	0.0166406
65	0.24644	0.24475	0.24029	0.24485	0.0068577	0.0249554	0.0064519
66	0.26866	0.2662	0.27378	0.26218	0.0091566	-0.0190575	0.0241197
67	0.2424	0.23878	0.24155	0.24	0.0149340	0.0035066	0.0099010
68	0.26866	0.26817	0.26683	0.26983	0.0018239	0.0068116	-0.0043549
69	0.2828	0.28286	0.2974	0.27905	-0.0002122	-0.0516266	0.0132603

TABLE : 4

Melting Rate obtained by Experiment on Rotary Furnace using Bio-fuel showing relationship with various parameter used in ANFIS model							
Sl. No.	**Excess Air (%)**	**Flame Temperature (°C)**	**Rotational Speed (RPM)**	**Melting Time (Minutes)**	**Preheat Air Temperature (°C)**	**Fuel Consumed (Liters)**	**Experimental Values of Melting Rate (MT/Hr.)**
1	10	2212	0.8	36	200	77	0.34643
2	10	2217	0.8	37	200	76	0.3333
3	10	2222	0.8	35	300	76	0.35653
4	10	2303	0.8	33	400	75	0.37875
5	10	2197	1	38	200	79	0.32724
6	10	2222	1	36	300	77	0.34643
7	10	2293	1	35	400	76	0.34643
8	10	2187	1.2	39	200	79	0.31815

9	10	2207	1.2	38	300	79	0.32724
10	10	2267	1.2	37	400	76	0.3333
11	10	2177	1.4	39	200	81	0.31815
12	10	2202	1.4	37	300	82	0.3333
13	10	2262	1.4	35	400	80	0.35653
14	10	2172	1.6	39	200	81	0.31815
15	10	2200	1.6	37	300	80	0.3333
16	10	2237	1.6	36	400	79	0.34643
17	10	2131	2	39	200	81	0.31815
18	10	2156	2	38	300	80	0.32724
19	10	2192	2	38	400	79	0.32724
20	20	2010	0.8	43	200	79	0.28785
21	20	2086	0.8	41	300	79	0.303
22	20	2151	0.8	39	400	79	0.31815
23	20	1959	1.2	46	200	85	0.26866
24	20	2005	1.2	44	300	84	0.25856
25	20	2040	1.2	42	400	82	0.29492
26	20	1858	1.4	48	200	85	0.25856
27	20	1909	1.4	46	300	83	0.26866
28	20	1970	1.4	42	400	81	0.29492
29	20	1737	1.6	49	200	87	0.2525
30	20	1808	1.6	47	300	85	0.2626
31	20	1838	2	44	400	83	0.2828
32	30	1924	0.8	44	200	81	0.2828
33	30	2015	0.8	43	300	80	0.28785
34	30	2121	0.8	40	400	78	0.31007
35	30	1990	1	46	200	82	0.26866
36	30	2030	1	44	300	81	0.2828
37	30	1985	1.2	44	300	82	0.2828
38	30	2020	1.2	42	400	80	0.29492
39	30	1833	1.4	48	200	86	0.25856
40	30	1889	1.4	44	300	83	0.2828
41	30	1985	1.4	42	400	82	0.29492
42	30	1783	1.6	45	300	84	0.27472
43	30	1808	1.6	43	400	83	0.28785
44	30	1752	2	50	200	88	0.24644
45	40	1914	0.8	45	200	81	0.27472
46	40	1990	0.8	43	300	80	0.28785
47	40	1975	1	46	200	82	0.26866
48	40	2015	1	43	300	81	0.28785
49	40	2081	1	42	400	80	0.29492
50	40	1964	1.2	45	300	82	0.27472
51	40	2015	1.2	43	400	82	0.28785
52	40	1808	1.4	49	200	85	0.2525
53	40	1727	1.6	49	200	85	0.2525
54	40	1762	1.6	46	300	83	0.26866
55	40	1793	1.6	43	400	81	0.28785
56	40	1737	2	51	200	88	0.2424
57	50	1879	0.8	44	200	81	0.2828

58	50	1975	0.8	41	300	80	0.303
59	50	2060	0.8	40	400	79	0.31007
60	50	2020	1	42	400	81	0.29492
61	50	1904	1.2	47	200	83	0.2626
62	50	1934	1.2	44	300	81	0.2828
63	50	1788	1.4	48	200	84	0.25856
64	50	1939	1.4	43	400	81	0.28785
65	50	1712	1.6	50	200	87	0.24644
66	50	1752	1.6	46	300	84	0.26866
67	50	1722	2	51	200	88	0.2424
68	50	1768	2	46	300	84	0.26866
69	50	1778	2	44	400	83	0.2828