

# Modeling of a Glass Tank Furnace Using Artificial Neural Network

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**Abstract:** Modeling of an Industrial side port regenerative glass tank furnace for float glass manufacturing has been done using a Radial Basis Function (RBF) neural network to connect various input and output parameters applying conjugate gradient learning. RBF neural network is an intelligent technique that can model non-linear problems by learning from the operating data and can be used for the prediction of output parameters. The glass tank furnace is a complex unit with a large number of input and output parameters such as 54 inputs and 44 outputs. In the present work a methodology has been developed to identify the most important input-output parameters using co-linearity analysis of the raw data obtained from the industry as well as carrying out sensitivity analysis on the developed RBF neural network model. After achieving sufficient reduction in the number of parameters, the RBF network is reconfigured to estimate the output parameters with Normalized Mean Square Error (NMSE) and correlation coefficient(r) as performance criteria. The NMSE and 'r' values of the output parameters range from 0.0572-1101.2768 and 0.022-0.9787 respectively.

**Keywords:** Glass tank furnace; RBF model; Neural network; Co-linearity analysis.

## I. INTRODUCTION

The role of Glass Tank Furnace in a float line is monumental for obtaining the desired grade of glass manufacturing. However, operating the furnace efficiently is cumbersome due to the existence of a large number of operating parameters. This also poses problem in modeling the unit as the input parameters are correlated nonlinearly with output parameters. Thus, to develop an effective and efficient model it is necessary that only pertinent input-output parameters should be screened out and a non-linear multivariable relationship between these be established. This can be effectively done using artificial neural network (ANN) models.

An exhaustive literature review shows that a considerable number of CFD based models are available for glass tank furnaces to simulate different aspects of glass production [1]-[7]. However, the same is not true for ANN based models. It appears from the available literature, that only one NN model is present that has been used for predicting glass furnace outputs to meet production schedules [8] which does not come in the domain of present study. Thus, it can be safely concluded that ANN models have hardly been used for To bring turbulence to induce mixing, bubblers are used and to give uniform temperature, mild electric heating is done in the glass melter.

Downstream of the 'neck' region there is a refiner section where removal of the dissolved and trapped gases in the melt takes place. Refining agents, which are involved in the equilibrium redox reactions producing or consuming gases,

modeling complex glass tank furnaces where the demand of production, for different colored glasses, changes with time. The absence of ANN models for Glass Tank furnaces in open literature has provided the required motivation to develop ANN model using data obtained from a typical Glass Industry situated in the Northern part of India.

### A. Glass Tank Furnace

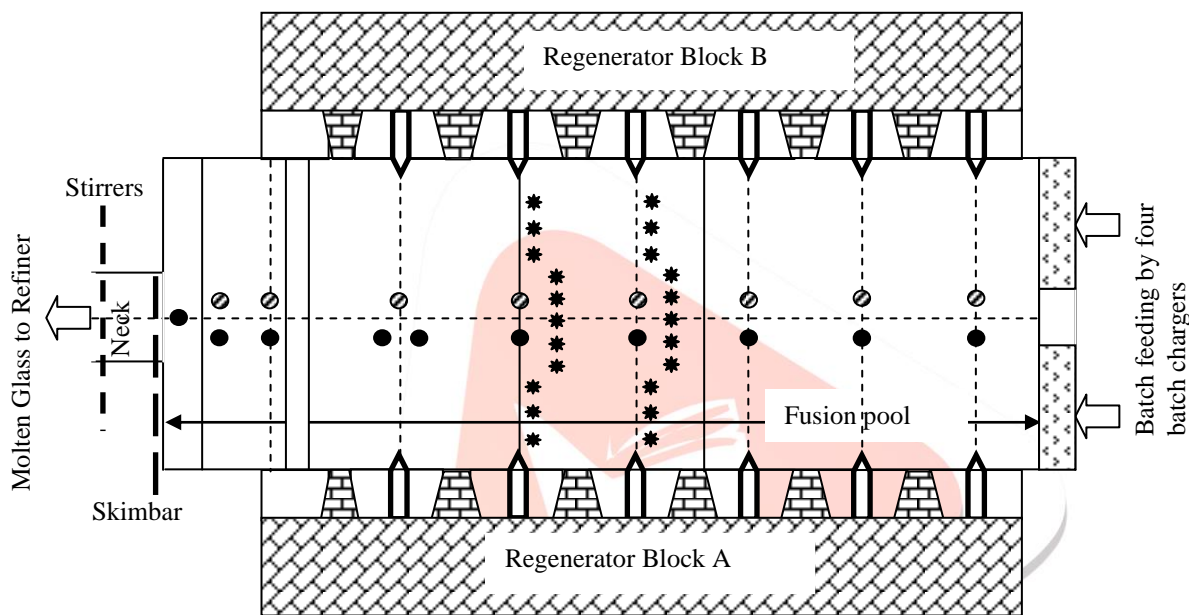
Fig. 1 shows the melter section of a Glass Tank furnace in a float line. It has 4 main sections such as batch feeding section, Regenerator block, bubbler area and neck. Some of the input (I/P) and output (O/P) variables, as given in Table 1, that are associated with different sections of the melter are provided in the table presented with Fig. 1.

The glass melter section is a complex unit due to the fact that a large number of unit operation as well as reactions take place in this section. In the melter section, the raw materials coming from batch preparation unit are charged via four batch chargers situated at the rear. The batch feeding section is known as the dog house. On both sides of the fusion pool, there are burners and their ports are positioned for efficient injection of fuel for combustion inside the chamber. The furnace is fired with furnace oil at alternate cycles of about 20 minutes from each side of fusion pool. Two regenerators (Block A & B) along the left and right side of the furnace function for preheating the combustion air and recovering heat from the exhaust gases. The regenerators are constructed with refractory bricks and the temperature inside the regenerator chamber is that of the exhaust gas. Heat is transferred to the reactants and glass melts both by convection and radiation. The reactions in the feed material take place on entering the feed zone and it forms a melt at around 1400-1500°C. The fining or primary removal of bubbles in molten glass is achieved by the operation of gas bubblers which also bring turbulence in the melt and induce mixing. The melt flows around the 'neck' (a narrow region downstream of the melting area) where the forced homogenization of glass takes place through mechanical stirring. One would find the neck region water cooled with auxiliary equipment to improve the quality of melt glass.

are usually added to the batch in order to remove undesirable bubbles from the glass melt. Proper temperature profile needs to be maintained in this section for better refining efficiency. The temperature in the refiner varies from 1300°C to 1100°C as the float line progresses. From the refiner section the glass melt flows to the tin bath section.

Amongst the input parameters the oil flow, secondary air flow, Batch% (the amount of fresh feed), pull (Throughput), chimney dampener opening are main parameters of interest for combustion in furnace. The various output parameters such as dog house temperature, crown temperature, refiner temperature, canal temperature, feed end temperature and regeneration flue gas temperature are the result of combustion to transfer heat to the glass melt. A proper temperature profile in the glass melting tank is essential to meet the quality of the glass produced. In the tank the temperature first increases and then decreases as feed moves from feed end towards the refiner. Thus, a maximum

temperature is found at around the middle of the furnace. This is done to promote the formation of circulation loops in the glass melt which enhances mixing and leads to formation of a uniform melt with desired properties. The same can be seen from the fuel flows which are highest near the middle port. Crown temperatures determine radiative heat transfer to the glass melt and the unmelted batch. The amount of heat required to melt a fresh batch is more as compared to melt recycled glass (cullet). The throughput is limited to the acceptable maximum temperatures in the furnace which is dictated by the selection of the associated refractory for the furnace walls.



Symbol	Details	Parameters	I/P no.	O/P no.
●	Crown T.C	FCT		O3-O10
⊙	Pavement T.C	DHT, FBT		O1-O2, O11-O17
*	Bubbler	BP	I38-I48	
— — —	Stirrer	SRPM	I36	
▨	Regenerator	SA, CDO, RFGT, MFGT, CBT	I20-I25, I51	O28-O41, O43, O44
▧	Batch Charger	BCRPM, Batch %	I32-I35, I53	
⤴	Burner	Oil Flow, % Valve O.P, BPP, MOP	I1-I6, I7-I12, I13-I18, I19	
— — —	Skimbar	SP	I37	

Fig.1 Schematic diagram of the Melter section of Glass Tank furnace

Table 1 List of input-output parameters for Float Glass Melting Furnace

INPUT PARAMETER							OUTPUT PARAMETER							
I/P parameter: Oil Flow(m <sup>3</sup> /hr)							O/P parameter: Dog house Temperature (DHT) (°C)							
I/P No.→	I1	I2	I3	I4	I5	I6	O/P No.→					O1	O2	
Oil Flow	1P	2P	3P	4P	5P	6P	DHT					TD1	TD2	
I/P parameter: % Valve O.P. for oil flow							O/P parameter: Furnace Crown Temperature(FCT)(°C)							
I/P No.→	I7	I8	I9	I10	I11	I12	O/P No.→	O3	O4	O5	O6	O7	O8	O9
% Valve O.P.	1P	2P	3P	4P	5P	6P	FCT	T1	T2	T3	T4	T5	T6	T7
I/P parameter: Burner Port Pressure(BPP)(kg/cm <sup>2</sup> g)							O/P No.→							
I/P No.→	I13	I14	I15	I16	I17	I18	FCT							O10
BPP	1P	2P	3P	4P	5P	6P	O/P parameter: Furnace Bottom Temperature(FBT)(°C)							
I/P parameter: Main oil Pressure(MOP) (kg/cm <sup>2</sup> g)							O/P No.→							
I/P No.→						I19	FBT	B1	B2	B3	B4	B5	B6	B7

MOP								IP	O/P parameter: Refiner Temperature(RT)							
I/P parameter: Secondary Air(SA) (m <sup>3</sup> /hr)									O/P No.→							
I/P No.→		I20	I21	I22	I23	I24	I25		RT					O18	O19	O20
SA		1P	2P	3P	4P	5P	6P		O/P parameter: Neck Bottom temperature(NBT) (°C)							
I/P parameter: % Valve O.P for SA									O/P No.→							
I/P No.→		I26	I27	I28	I29	I30	I31		NBT							O21
% Valve O.P.		1P	2P	3P	4P	5P	6P		O/P parameter: Working End Temperature(WET) (°C)							
I/P parameter: Batch Charger r.p.m. (BCRPM)									O/P No.→							
I/P No.→					I32	I33	I34	I35	WET					O22	O23	O24
BCRPM					BC1	BC2	BC3	BC4	O/P parameter: Canal Temperature ( CT) (°C)							
I/P parameter: Stirrer r.p.m.(SRPM)									O/P No.→							
I/P No.→								I36	CT						O26	O27
SRPM								S1	O/P parameter: Regenerator Flue Gas Temperature(RFGT) (°C)							
I/P parameter: Skimbar position(SP)									O/P No.→							
I/P No.→								I37	RFGT	L1	L2	L3	L4	L5	L6	L7
SP								SP1	O/P No.→	O35	O36	O37	O38	O39	O40	O41
I/P parameter: Bubbler Position(BP)									RFGT							
I/P No.→	I38	I39	I40	I41	I42	I43	I44		O/P parameter: Furnace Pressure (FP)(mmWC)							
BP	BP1	BP2	BP3	BP4	BP5	BP6	BP7		O/P No.→							
I/P No.→				I45	I46	I47	I48		FP							PV
BP				BP8	BP9	BP10	BP11		O/P parameter: Main Flue Gas Temperature ( MFGT) (°C)							
I/P parameter: G.L/S.P(cm)									O/P No.→							
I/P No.→								I49	MFGT							O43
G.L./S.P.								G1	O/P parameter: Chimney Base Temperature (CBT) (°C)							
I/P parameter: Draft (mmWC)									O/P No.→							
I/P No.→								I50	CBT							O44
Draft								D1								CT1
I/P parameter: Chimney damper Opening (%) (CDO%)																
I/P No.→								I51								
CDO%								CD1								
I/P parameter: Heat Exchanger temp. 2(HXT)(°C)																
I/P No.→								I52								
HXT								HX1								
I/P parameter: Batch %																
I/P No.→								I53								
Batch								BT1								
I/P parameter: Pull(TPH)																
I/P No.→								I54								
Pull								P1								

**II. DEVELOPMENT OF RBF NN MODEL**

The Radial Basis Function neural network (RBF NN) with the Gaussian activation function is among the best and most widely used feed forward universal approximators for ANN. There are a total of 54 I/P and 44 O/P for this section as given in Table 1. Due to limitation on page number the values of these data are not shown here. In total, there are 199 data points. Amongst these 140 points are assigned to training set, 20 to cross-validation set and remaining to the testing set. Total data is randomized and divided such that the mean and standard deviation for the training and testing data sets are comparable [9]. A set of input and output parameters that are treated as important from operational point of view are I1 to I6, I20-I25, I37, I51, I52, I53, I54, O3, O4, O5, O6, O7, O8, O9, O43 and O44. These parameters are maintained throughout the development of RBF NN models. The basis for maintaining these parameters are further substantiated from the results of statistical analysis of co-linearity (Correlation coefficient of the above parameters are >0.9) and also from the values of sensitivity coefficients (> 0.1335 which is the average value for the entire I/O parameter set considered for sensitivity study) obtained for these parameters.

For the development of a RBF NN model a considerable amount of input output data of the system is required. For this purpose, operating data of the glass tank furnace has been collected from a nearby glass industry.

In this paper, the stop and performance criteria for the RBF networks are defined. The methodology to identify the most important input-output parameters based on co-linearity analysis of the raw data as well as sensitivity analysis on the basis of developed neural network model is also presented. Finally, a RBF network is developed to estimate the important output parameters based on pertinent input parameters screened using above technique.

**A. Stop Criterion for training**

The learning curve for supervised learning is given by the plot of mean square error (MSE) versus number of iterations. The MSE is given by

$$MSE = \frac{\sum_{j=0}^P \sum_{i=0}^N (d_{ij} - y_{ij})^2}{NP} \tag{4}$$

The MSE will keep decreasing in the training set, during supervised learning with the increase in the number of iterations but may start to increase in the cross validation test set also. This happens when the network starts "memorizing" the training patterns. The stopping criterion for training is given by the minimum MSE in the Cross validation set.

### B. Performance Criteria for Testing

The performance of the network is defined by two parameters: normalized mean square error (NMSE), which should be minimum and correlation coefficient (r), which should have a value near unity. These two parameters are defined as:

$$NMSE = \frac{PN(MSE)}{N} \quad (5)$$

$$= \frac{\sum_{j=0}^P \left[ N \sum_{i=0}^N d_{ij}^2 - \left( \sum_{i=0}^N d_{ij} \right)^2 \right]}{N}$$

$$r = \frac{\sum_{i=0}^N (y_i - \bar{y})(d_i - \bar{d})}{N} \quad (6)$$

$$= \frac{\sqrt{\sum_{i=0}^N (y_i - \bar{y})^2} \sqrt{\sum_{i=0}^N (d_i - \bar{d})^2}}{N}$$

## III. METHODOLOGY FOR MODEL DEVELOPMENT

The method adopted for model development is given in the following steps:

- I. The data collected is tested against co-linearity to remove dependent input and output parameters.

## IV. RESULTS AND DISCUSSION

In the following sections results of two different RBF NN are discussed.

### A. RBF NN-1 Model

The input and output parameters screened using co-linearity test, discussed in Section III.A, is now used for the development of the model RBF NN-1 with the topology (TOPO-1). This topology consists of 40, 40, 24 and 5100 nodes in input layer, nodes in hidden layer, nodes in output layer and no. of epochs, respectively. The model has 40 inputs and 24 outputs.

The number of nodes in the hidden layer is found by trial and error procedure such that the minimum MSE in the cross validation set is 0.03 during the training phase. It corresponds to the best possible 'NMSE' and 'r' values for the output parameters during the testing phase of TOPO-1 as given in Table 2. It shows that ranges of 'NMSE' and 'r' are 0.0826-1393.857 and -0.092-0.9591, respectively.

### B. Sensitivity Analysis

- II. RBF NN model is established based on the screened input and output variables obtained from Step-I.
- III. Based on the developed RBF NN model (in Step-II) a sensitivity analysis is performed to select important input parameters which affect the output most. Based on this analysis a set of important input parameters are selected.
- IV. Based on the input parameters screened in Step-III and screened independent output parameters from Step-I a revised RBF NN is developed.

### A. Co-linearity Analysis

The input as well as outputs data sets should be independent. To confirm this, the given input and output data sets are tested against co-linearity to eliminate dependent variables. For a given data set (input or output), correlation coefficient, r, is computed for each variable with respect to the other. In fact, variables I36 and I37 are not considered for co-linearity test as these are constant parameters. In case, the variable has a correlation coefficient equal to 0.9 or more (maximum is 1) with respect to the other, one parameter out of the two is dropped from set of parameters. In such cases, if one of the parameter is important as discussed in Section II, it is kept whereas the other is dropped. Based on value of r the parameters considered are I1, I2, I3, I4, I5, I6, I7, I8, I9, I10, I11, I12, I13, I14, I15, I16, I17, I18, I19, I20, I21, I22, I23, I24, I25, I26, I27, I28, I29, I30, I31, I32, I33, I38, I49, I50, I51, I52, I53 and I54. However, I36 and I37 are not considered for this analysis. It shows that total 12 parameters are dropped. Thus, total 40 input parameters out of 54 are selected for further analysis. Similarly, after co-linearity analysis 24 output parameters out of 44 are considered. The dropped output parameters are O10, O12, O13-O17, O20, O24, O29-O34 and O36-O40.

In order to further refine the number of inputs for the final RBF NN model to be developed, sensitivity analysis is carried out using RBF NN-1. In this method, first the mean and standard deviation is computed for each input parameter. The input is varied from (mean - standard deviation) to (mean + standard deviation) and the corresponding output is computed using RBF NN-1. These computed outputs are then used to evaluate the sensitivity coefficient between each input and output parameters.

In order to select the input parameters which affect the output parameters most the mean of the sensitivity matrix is computed, which is 0.1335. The input parameters, which have sensitivity coefficient greater than mean value, are considered for analysis otherwise dropped. In this analysis the important parameters discussed in Section II are accounted irrespective of the value of sensitivity coefficient. Thus, dropped input parameters are I7-I12, I26, I27, I29, I30, I32, I33, I38, I49 and I50. In the present work a parameter is considered for further analysis if it is affecting more than 30% of total outputs, which is 8 outputs from 24. The number of input and output parameters after sensitivity analysis reduces to 25 and 24, respectively.

### C. RBF NN-2 Model

A final RBF NN model is developed with the topology (TOPO-2). It has 25, 28, 24 and 5100 nodes in input layer, nodes in hidden layer, nodes in output layer and no. of epochs, respectively. The 'NMSE' and 'r' values for the output parameters in testing phase of RBF NN-2 are given in Table 3. It shows that ranges of 'NMSE' and 'r' are 0.0515-1101.277 and -0.329-0.9787, respectively. Further, if average value of 'r' is computed from results shown in Table 2 and 3 it is found as 0.63 for both models i.e. RBF

NN-1 and RBF NN-2. It shows that 25 I/P parameters selected for RBF NN-2 correlate the output parameters in the same manner as that is predicted by RBF NN-1 with 40 I/P parameters. Thus, the present methodology can be effectively used to screen best input which can control a given output.

Table 2 NMSE and r values of the testing data for RBF NN-1

	O1	O2	O3	O4	O5	O6	O7	O8	O9	O11	O18	O19
NMSE	0.0826	0.9962	1.9936	0.8641	0.4546	1.3900	0.9611	1.1884	0.5209	0.2631	17.6428	0.5079
r	0.9591	0.5349	0.7082	0.6053	0.8881	0.3399	0.2676	0.4867	0.8528	0.8852	0.8134	0.8532
	O21	O22	O23	O25	O26	O27	O28	O35	O41	O42	O43	O44
NMSE	0.7838	1.3652	0.1531	0.7419	2.1423	1.1698	1.1480	1.1745	1.4056	1393.8573	0.1150	0.2097
R	0.8625	0.8897	0.9362	0.5214	0.9284	0.7413	-0.074	-0.092	0.1428	0.2262	0.9503	0.8917

Table 3 NMSE and r values of the testing data for RBF NN-2

	O1	O2	O3	O4	O5	O6	O7	O8	O9	O11	O18	O19
NMSE	0.0572	0.9324	0.9653	1.8751	0.3983	1.1593	0.4509	0.9344	0.4922	0.2121	9.0307	0.3570
r	0.9736	0.5439	0.4441	-0.329	0.8804	0.3920	0.7993	0.4761	0.7914	0.9033	0.8870	0.8928
	O21	O22	O23	O25	O26	O27	O28	O35	O41	O42	O43	O44
NMSE	0.7415	18.8030	0.2765	0.0515	0.1298	0.2136	1.0751	1.0187	1.3173	1101.2768	0.3274	0.0631
r	0.6116	0.8979	0.9332	0.9787	0.9707	0.9212	0.0220	0.1658	0.1192	0.0394	0.8340	0.9714

## V. CONCLUSION

The multi-input, multi-output system characterizing the operation in a glass tank furnace has been modeled using RBF neural network approach. A methodology has been developed to reduce important input parameters from 54 to 44 and output parameters from 25 to 24, using co-linearity and sensitivity analysis. The NMSE and r ranges from 0.0515-18.803 and -0.329-0.9787, respectively, for all parameters. The developed model can be further used to carry out parametric study to find out the most effective inputs for a given output.

## NOMENCLATURE

$d_i$	Desired response for $i^{\text{th}}$ exemplar
$d_{ij}$	Desired output for exemplar 'i' at processing element 'j'
$\bar{d}$	Mean desired value for the dataset considered
N	Number of exemplars in the dataset
P	Number of nodes in output layer
r	Coefficient of correlation
$y_i$	Network output for exemplar 'i'
$y_{ij}$	Network output for exemplar 'i' at processing element 'j'
$\bar{y}$	Mean network output value for the dataset considered

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