Prediction of Wall temperature of Supercritical Boilers using Artificial Neural Network (ANN)

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***Abstract* :** One critical factor that influences the structural integrity of the boiler and has to be well understood is the wall temperature. It has to be predicted and modeled perfectly to ensure a safe and reliable operation. In this work, an expert system has been formulated and presented for prediction of wall temperatures of boiler tubes. Two Artificial Neural Network (ANN) models have been formulated to predict the wall temperature. One model uses a Feed Forward Back Propagation Neural Network, while the other model is based on Cascade Forward Back Propagation Neural Network. The system is modeled on inputs like internal tube diameter, pressure inside the boiler tubes, heat flux, mass flux and bulk fluid temperature. The results of the proposed models are validated against the results of experimentation and also been validated by calculating the Normalized Root Mean Square (NRMS) value between the experimental value and the temperature predicted by the proposed model. The results exhibit a closer correlation with values of experimentation and are quantified through RMSE and NRMSE. The results are further validated through Pearson correlation coefficient. The results demonstrate the suitability of the proposed approach in predicting wall temperature.

Key words – wall temperature, supercritical, ANN, expert system.

I. INTRODUCTION

Energy is the essence behind economic development of any nation. The growth index of any country is influenced by its energy means and how the needs are satisfied. The world as such is going through a transformation with a rapid phase of development happening in different countries. The speed of the development and the volume of development is fueling the need for more energy. It is becoming imperative to quench this ever increasing demand for energy. The only way to do this is to increase the energy supply to satisfy the demand. In spite of the developments in renewable and alternate sources of energy, steam still remains the primary prime mover. The concerns about the climate change and the necessity to shift to alternate sources of energy may have underlined the importance of renewable energy but they have not impacted the conventional forms of energy generation greatly. Heat transfer of water at super critical pressure has remained one of the active areas of research. It is primarily due to this fact that it is important to understand the behavior of water at supercritical pressures so that we can ensure optimal design and safe operation of systems at supercritical pressure. This is more complicated by the fact that the Thermo-physical properties exhibit random and rapid changes there by rendering the heat transfer of supercritical pressure water flowing inside a tube a unique one [1,2]. It is important to predict the metal temperature for such complex heat transfer conditions. In most of the conventional approaches to predict metal temperature, usually experimentation is conducted for a desired range and a variety of influencing parameters. These parameters include fluid pressure, temperature, heat flux, mass flux, tube inner diameter etc. Also in an experimental setup the metal temperature at different / each combination of these parameters are usually measured. Typically experimental Nusselt Number is calculated using heat flux and the difference between inner wall and fluid temperature. In addition to this non – dimensional Reynolds Number and Prandtl Number are also computed for corresponding fluid parameters and flow conditions. Based on these numbers, an experimental correlation is developed which is subsequently used for predicting the metal temperature for a given condition. This is a very complex process which involves lots of data reduction and calculations for ensuring correlation from these experiments. Also there is a chance of computational errors and other possible inaccuracies creeping into the process. Similarly, there are different experimental formulae that can possibly be chosen depending upon a particular range of operating parameter. In addition to this, most of these experimental formulations have been based on linear assumptions and most of which may not be suitable in a highly non – linear situation experienced in supercritical heat transfer. Another way of predicting metal temperature is Analytical Models. Unfortunately, Analytical Models for predicting heat transfer encountered in a supercritical turbulent flow have a very limited scope. This is due to the fact that the complex nature of the flow and abrupt changes in fluid properties render the analytical models less effective. This is also complicated by the fact that heat transfer behavior at supercritical condition is much different and cannot be correlated to the changes in wall temperature. Since the prediction of wall temperature using Analytical route is not reliable and using the experimentation setup is complex, it is imperative to engineer methods that can predict the wall temperatures accurately with enough robustness and reliability. In this work, an expert system that uses two ANN models one based on Feed Forward Back Propagation Neural Network and other based on Cascade Forward Back Propagation Neural Network to predict the wall temperature of metal tubes used in supercritical boilers is presented. The training data set for the proposed ANN model has been drawn from different experimentations conducted for different tube diameters, heat flux, mass flux, pressure and fluid bulk temperature. The experimental results presented in [6, 19, 20] are harvested and used as training data set for the ANN models. The heterogeneous nature of the data set has rendered the model the ability to deliver better prediction of fluid wall temperature. The proposed ANN model considers the tube internal diameter, pressure of the fluid, heat flux and mass flux as inputs to predict the tube wall temperature. The results of the proposed system are validated by comparing with experimentation results available in [6, 19, and 20]

II. STATE OF ART OF SUPERCRITICAL BOILERS

In the quest for efficiency enhancement in energy conversion, supercritical fluids are attractive options. Schuster et al. [3] have investigated the supercritical Organic Rankine Cycles (ORC), which primarily use the low-temperature heat sources (such as geothermal energy, solar desalination and waste heat recovery) and the supercritical organic fluids. The thermal efficiency is improved by more than 8%, compared with the subcritical state. Chen et al.[4] have proposed a supercritical Rankine Cycle (SRC) based on zeotropic mixture working fluids, which shows 10 -30% enhancement in the thermal efficiency over the conventional subcritical ORC.For supercritical fluids, often the Brayton or supercritical Rankine cycle is suggested. In both the cycles, either heat rejection or heat addition takes place at constant pressure in the near-critical region (Feher [5]). This region is prone to heat transfer deterioration due to the abrupt changes of thermophysical properties, as evidenced by the erstwhile experiments tracing back to the 1960s (Swenson et al, [1]; Ackerman, [25]; Yamagata et al [6]; Hall and Jackson, [7]). The tube wall temperature significantly increases due to the poor heat transfer between the tube wall and the bulk fluid. The heat transfer deterioration not only reduces the thermal efficiency but also presents a threat to the safety of the system. Therefore, prior identification of such a problem will help the engineers to mitigate it. Along this direction, advanced correlations considering non-constant properties have been developed based on the experimental data (Krasnoshchekov and Protopopov [8], Bishop et al. [9] Jackson [10]) and are still extensively used after half a century. Large efforts have been made in the past to predict the heat transfer of supercritical water and CO2 with CFD (Heet al [11]; Pucciarelli et al [12]; Zhang et al., [13]). However, CFD studies using turbulence models seem to be unreliable at the supercritical pressure. Recently, Artificial Neural Networks (ANN) has received overwhelming attention (Schmidhuber,[14] Deng and Yu,[15]). Among the limited studies that investigate heat transfer of supercritical fluids with ANNs, most target supercritical CO2. A multi-layer feed forward neural network has been developed in Scalabrin and Piazza [16] for forced convection heat transfer to supercritical CO2. An ANN is proposed in Pesteei and Mehrabi [17] for calculating local heat transfer coefficient of supercritical CO2 in a vertical tube with the diameter of 2 mm at low Reynolds numbers (<2500). In a paper by Dhanuskodi et al. [18] an ANN is trained with in-house experimental data for a supercritical boiler design. The authors report 100% prediction accuracy for the training data at a deviation level of $\pm 7 \circ$ C, which drops to about 80% in the validation. Experimental, numerical and analytical methods are complex, cumbersome and time consuming. Models based on historical data have widely been used in different domains of science and technology for forecasting and prediction.

III. DATA SET

The data set that is required for training has been obtained from different experimental results available in the literature. The experimental conditions along with the test parameters and Tube inner diameter applicable for each experimentation were individually tabulated and subsequently used for training the Artificial Neural Network (ANN) .The different experimentations used for forming the data set can be listed as below –

a. Experiments of Vikherv et. al [19]
b. Experiments of Yamagata et. al [6]
c. Experiments of Loewenberg et. al [20]

a. Experiments of Vikherv et. al [19]

Two sets of data were populated from this experimentation. The Bulk Fluid Temperature was correlated with Inner Wall Temperature (ºC) for two different set of test conditions. For Test Condition – 1, a tube Inner Wall Diameter (ID) of 20.4 mm, the Pressure (P) of 265 bar, Heat Flux (q) of 570 KW/m^2, Mass Flux (G) of 495 Kg/m^2s were selected. For Test Condition – 2, the Tube Inner Wall Diameter and Pressure were maintained same as that of Condition – 1 while the Heat Flux (q) of 1160 KW/m^2 and the Mass Flux (G) of 1400 Kg/m^2s were opted.

b. Experiments of Yamagata et. al [6]

Yamagata et. al performed experiments under two different operating conditions. For Test Condition – 1, a tube Inner Wall Diameter (ID) was 7.5 mm, the Pressure (P) was 245 bar, Heat Flux (q) was 233 KW/m^2, Mass Flux (G) was 1260 Kg/m^2s. For Test Condition – 2, the Tube Inner Wall Diameter and Pressure are same as that of Condition – 1 while the Heat Flux (q) was 930 KW/m^2 and the Mass Flux (G) was 1260 Kg/m^2s. For this experimentation, the Bulk Fluid Temperature was considered between 340 °C to 380 °C.

c. Experiments of Loewenberg et. al [20]

Experiments were conducted under two different operating conditions and two sets of data were obtained. A tube Inner Wall Diameter (ID) of 20 mm, the Pressure (P) of 250 bar, Heat Flux (q) of 300 KW/m^2, Mass Flux (G) of 1000 Kg/m^2s were considered for Test Condition – 1. The tube Inner Wall Diameter (ID) was same as that of Test Condition – 1 while a Pressure (P) of 235 bar, Heat Flux (q) of 1200 KW/m^2, Mass Flux (G) of 2250 Kg/m^2s were considered for Test Condition – 2. The experiments were carried out for Bulk Fluid Temperature variation from around 270 °C to 410 °C.

IV. PROPOSED PREDICTION MODEL

Artificial neural networks are biologically inspired; they are composed of elements that perform in a manner that is analogous to the most elementary functions of the biological neuron. The important characteristics of artificial neural networks are learning from experience; generalize from previous examples to new ones, and abstract essential characteristics from inputs containing irrelevant data. Neural networks commonly have three layers: input, hidden, and output layers as shown in Figure 1. The numbers of nodes in each layer varies and are user-dependent [21]. The input variables can be PV array parameters like VOC and ISC, atmospheric data like irradiance and temperature, or any combination of these. The output is usually one or several reference signal(s) like a duty cycle signal used to drive the power converter to operate at or close to the MPP. How close the operating point gets to the MPP depends on the algorithms used by the hidden layer and how well the neural network has been trained

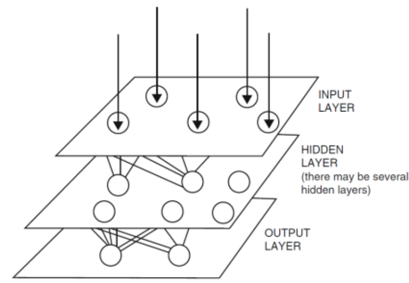

Figure (1): A Simple Neural Network illustration

An artificial neural network (ANN) includes selection of inputs, outputs, network topology and weighed connection of node. Input features will correctly reflect the characteristics of the problem. Another major work of the ANN design is to choose network topology. This is done experimentally through a repeated process to optimize the number of hidden layers and nodes according to training and prediction accuracy. In this work two types of neural networks are considered ANN model-1 uses a Feed Forward Back Propagation Neural Network illustrated using figure 2, while ANN model- 2 is based on Cascade Forward Back Propagation Neural Network illustrated using figure 3. The details of the ANN used this work is list in the table 1.

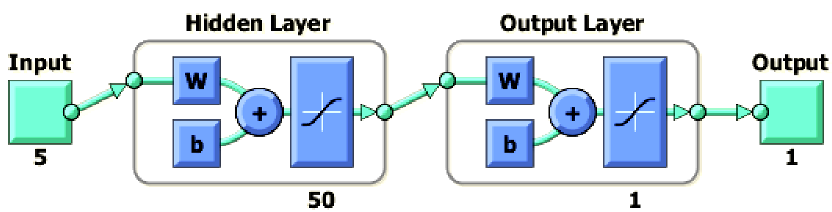

Figure (2): ANN Model -1 employing Feed Forward Back Propagation Neural Network

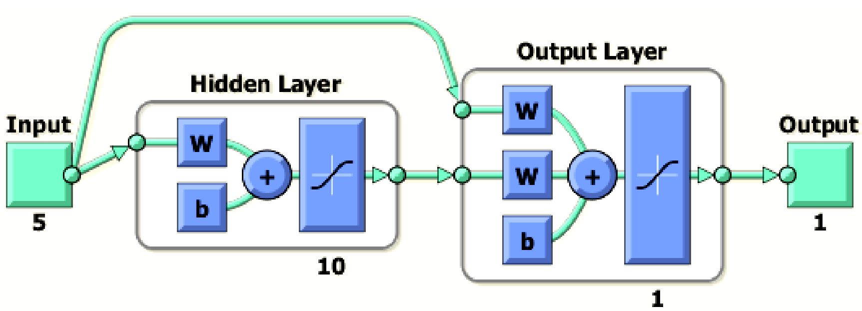

Figure (3): ANN Model -2 employing Cascade Forward Back Propagation Neural Network

Table 1: Details about the ANN model used in this work

		ANN Model-1	ANN Model-2
1	Number of Neurons in the Input	5	5
2	Number of Neurons in the Hidden Layer	50	10
3	Type of Neural Network	Feed Forward Back Propagation	Cascade Forward Back Propagation
4	Activation function used for the input layer	tansig	tansig
5	Activation function used for the output layer	purelin	purelin
6	Training function	trainlm Levenberg-Marquardt (LM) optimization.	trainlm Levenberg-Marquardt (LM) optimization.

The proposed prediction model considered 5 inputs in the form of the Bulk Fluid Temperature (BFT), Inner Wall Diameter (ID Pressure (P), Heat Flux (q) and Mass Flux (G). Wall temperature is predicted based on these inputs.

Regression plot, which shows the relationship between the outputs of the network and the targets, is depicted in Figure 4 while the performance plot is depicted in Figure 5. The dashed line in each axis represents the perfect result – outputs = targets. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets. From Figure 4 it can be observed that R values are above 0.9 and close to 1 indicating a liner relationship pointing to an accurate fit and subsequently better prediction.

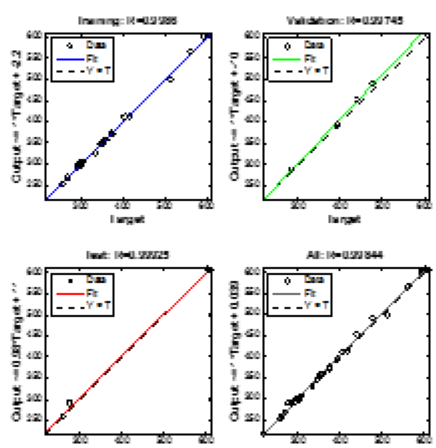

Figure (4): Regression Plot of ANN Model -2

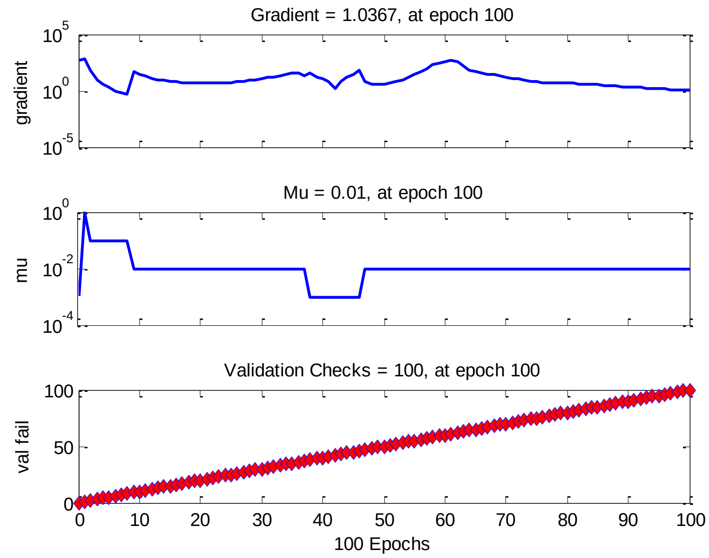

Figure (5): Performance Plot of ANN Model -2

V. RESULTS AND DISCUSSION

The forecasting model is coded using Matlab R 2012 b and the simulations are run in a Pentium i3 system with a RAM of 4 GB. For the experiments of Vikherv et. al [6] the data points that are considered for prediction and the results of the prediction using the proposed model is tabulated using table 2 and table 3. For the experiments of Yamagata et. al [6] the data points that are considered for prediction and the results of the prediction using the proposed model is tabulated using table 4 and table 5. For the experiments of Loewenberg et. al [20] the data points that are considered for prediction and the results of the prediction using the proposed model is tabulated using table 6 and table 7. It is observed that, the predicted wall temperatures using proposed models are very close to experimental values. It is worth full to note that, the % Error is low at high temperature and high at low temperature. Further the proposed model is quantified by calculating Root Mean Square Error (**RMSE**) (also called the root mean square deviation, RMSD) and Normalized Root Mean Square Error (NRMSE). The ANN model -2 shown better performance than ANN Model -1

Table 2: Results of wall temperature prediction for experimental data set 1 of Vikherv et. al [19]

Tube Internal Diameter (ID) = 20.4 mm, Pressure (P) =265 bar, Heat Flux (q) =570 KW/m^2, Mass Flux (G) =495 Kg/m^{2}s				
S.No	Bulk Fluid Temperature (°C)	Wall Temperature Experimental (°C)	Wall Temperature predicted using ANN Model 1 (°C)	Wall Temperature predicted using ANN Model 2 (°C)
1	62	226.68	232.56	231.67
2	108	246.59	251.98	250.32
3	248	362.07	368.34	365.53
4	285	387.51	390.71	390.23
5	330	451.26	455.86	453.23

Table 3: Results of wall temperature prediction for experimental data set 2 of Vikherv et. al [19]

Tube Internal Diameter (ID) = 20.4 mm, Pressure (P) =265 bar, Heat Flux (q) =1160 KW/m^2, Mass Flux (G) =1400 Kg/m^2s				
S.No	Bulk Fluid Temperature (°C)	Wall Temperature Experimental (°C)	Wall Temperature predicted using ANN Model 1 (°C)	Wall Temperature predicted using ANN Model 2 (°C)
1	148	259.14	264.65	263.98
2	225	320.16	329.26	327.54
3	358	458.67	456.73	454.87
4	395	513.26	516.72	514.99
5	405	551.26	553.86	553.12

Table 4: Results of wall temperature prediction for experimental data set 1 of Yamagata et. al [6]

Inner Wall Diameter (ID) :7.5 mm, Pressure (P) :245 bar, Heat Flux (q) :233 KW/m^2, Mass Flux (G) =1260 Kg/m^2s				
S.No	Bulk Fluid Temperature (°C)	Wall Temperature Experimental (°C)	Wall Temperature predicted using ANN Model 1 (°C)	Wall Temperature predicted using ANN Model 2 (°C)
1	335	350	356.65	354.38
2	350	358	361.72	360.79
3	393	385	382.98	381.90
4	400	391	394.13	393.87
5	405	399	401.99	401.82

Table 5: Results of wall temperature prediction for experimental data set 2 of Yamagata et. al [6]

Inner Wall Diameter (ID) :7.5 mm, Pressure (P) :245 bar, Heat Flux (q):930KW/m^2, Mass Flux (G) =1260 Kg/m^2s				
S.No	Bulk Fluid Temperature (°C)	Wall Temperature Experimental (°C)	Wall Temperature predicted using ANN Model 1 (°C)	Wall Temperature predicted using ANN Model 2 (°C)
1	341	392	394.12	393.19
2	358	400	401.87	400.93
3	376	411	415.68	414.83
4	380	419	421.46	421.21
5	382	421	422.85	422.28

Table 6: Results of wall temperature prediction for experimental data set 1 of Loewenberg et. al [20]

Inner Wall Diameter (ID) : 20 mm, the Pressure (P) :250 bar, Heat Flux (q) : 300 KW/m^2, Mass Flux (G) : 1000 Kg/m^2s				
S.No	Bulk Fluid Temperature (°C)	Wall Temperature Experimental (°C)	Wall Temperature predicted using ANN Model 1 (°C)	Wall Temperature predicted using ANN Model 2 (°C)
1	273	300	308.12	307.68
2	312	334	337.21	337.07
3	381	384	392.23	391.88
4	385	399	405.54	404.21

5	406	427	430.76	431.23

Table 7: Results of wall temperature prediction for experimental data set 1 of Loewenberg et. al [20]

Inner Wall Diameter (ID) : 20 mm, the Pressure (P) :235 bar, Heat Flux (q) : 1200 KW/m^2, Mass Flux (G) : 2250 Kg/m^{2}s				
S.No	Bulk Fluid Temperature (ºC)	Wall Temperature Experimental (ºC)	Wall Temperature predicted using ANN Model 1 (ºC)	Wall Temperature predicted using ANN Model 2 (ºC)
1	273	321	325.67	324.88
2	370	396	399.11	398.76
3	382	402	405.34	405.01
4	390	433	438.36	437.24
5	407	467	469.18	467.37

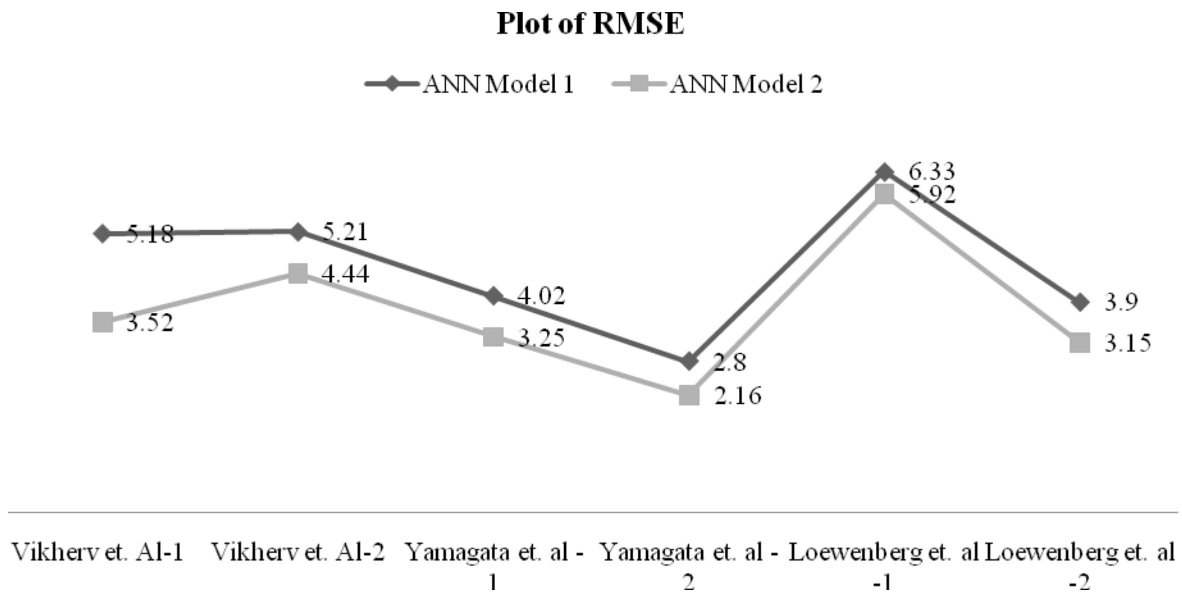

Figure (6): RMSE for the proposed prediction model for different data sets for the two ANN models

The Root Mean Square Error (**RMSE**) (also called the root mean square deviation, RMSD) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modeled. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power.

The RMSE of a model prediction with respect to the estimated variable X_{model} is defined as the square root of the mean squared error:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (X_{obs,i} - X_{model,i})^2}{n}} \qquad (1)$$

Where X_{obs} is observed values and M_{odel} is modeled values at time/place i.

The RMSE for the prediction model is illustrated using the figure 6, it can be inferred from the figure that for all the data sets that have been tested the RMSE error is below 10 ºC Similarly it can be observed the least RMSE value is 2.16 ºC while the highest being 6.33 ºC

In order to further validate the proposed model since the data points considered are of different range and heterogeneous, Normalized Root Mean Square Error (NRMSE). In this work the RMSE is normalized to the range of observed value and is given as;

$$\%NRMSE = \frac{RMSE}{X_{obs,\max} - X_{obs,\min}} X100 \quad (2)$$

The NRMSE % as illustrated using figure 7 also validates the performance of the proposed approach.

It can also be observed from the measurements that average RMSE, for all the data sets for prediction using ANN model -1 is 4.57 ºC and for ANN model -2 it stands at 3.74 ºC. Similarly the average NRMSE % for ANN model-1 is 4.95 % and ANN model -2 is 3.99%

The performance of the proposed model is also evaluated using Pearson correlation coefficient (r) Correlation – often measured as a correlation coefficient . This indicates the strength and direction of a linear relationship between two variables (for example model output and observed values). The Pearson product-moment correlation coefficient (also called Pearson correlation coefficient or the sample correlation coefficient), is obtained by dividing the covariance of the two variables by the product of their standard deviations. The Pearson product-moment correlation coefficient can be used to estimate the correlation between model and observations. The Pearson product-moment correlation is represented using equation (3)

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (3)$$

The correlation is +1 in the case of a perfect increasing linear relationship, and -1 in case of a decreasing linear relationship, and the values in between indicates the degree of linear relationship between for example model and observations. A correlation coefficient of 0 means the there is no linear relationship between the variables. The Pearson product-moment for the three methods discussed here are presented in the figure 8. From the figure (8) it can be inferred that the Pearson product-moment correlation is higher for the proposed method validating the veracity of the proposed approach in predicting the wall temperature that correlates well with experimental value.

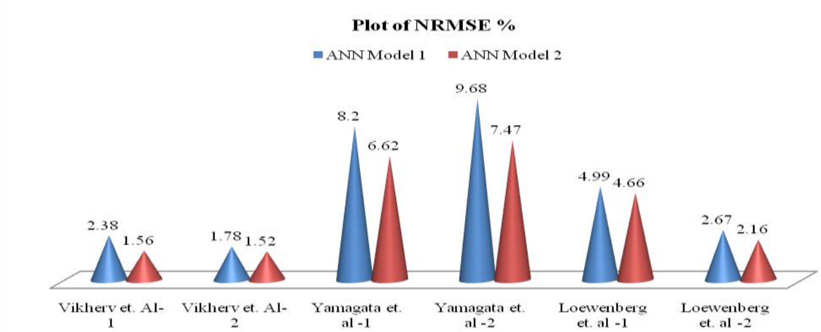

Figure (7): NRMSE % for the proposed prediction model for different data sets for the two ANN models

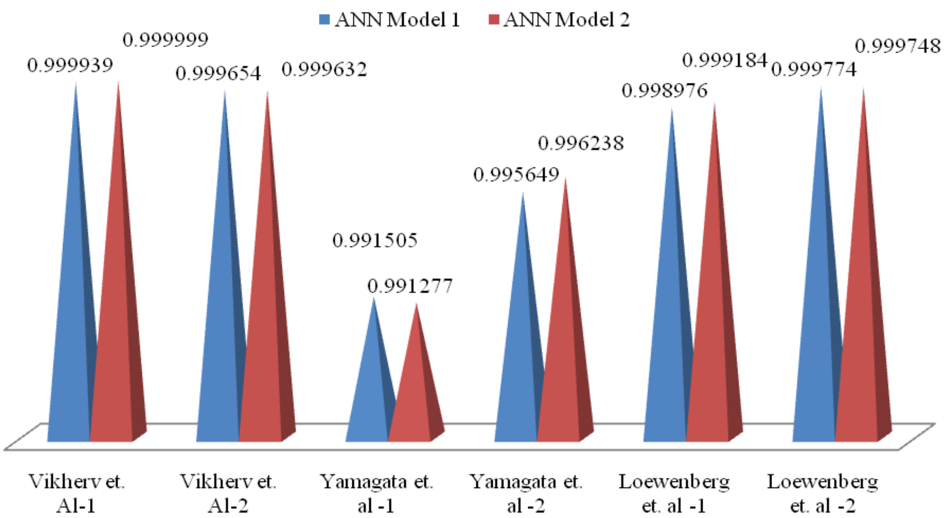

Figure (8): Plot of Pearson correlation coefficient for the two ANN models

VI. CONCLUSION

In this work, a prediction model based on ANN has been designed and presented. Since the model was trained using heterogeneous data derived from different experimentations, it was able to successfully capture the nonlinear variation of tube wall temperature. This has been clearly demonstrated and can be inferred through comparative analysis of the results. The proposed approach has delivered results with a lesser error % captured using NRMSE and that are closer to results of experimentation. It can be inferred from the results, that though both model deliver a satisfactory prediction, the ANN model -2 delivers a slightly better prediction as quantified through average RMSE and NRMSE. The results of Pearson correlation coefficient also demonstrate the performance of the proposed model.

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