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Thermal Analysis of Shell and Tube Heat Exchanger Using Artificial Neural Network

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Abstract- This explains the effective utilization of artificial neural network (ANN) modeling in various heat transfer applications like steady and dynamic thermal problems, heat exchangers, gas-solid fluidized beds etc. It is not always feasible to deal with many critical problems in thermal engineering by the use of traditional analysis such as fundamental equations, conventional correlations or developing unique designs from experimental data through trial and error. Implementation of ANN tool with different techniques and structures shows that there is good agreement in the results obtained by ANN and experimental data. The purpose of the present review is to point out the recent advances in ANN and its successful implementation in dealing with a variety of important heat transfer problems. Based on the literature it is observed that the feed-forward network with back propagation technique implemented successfully in many heat transfer studies. The performance of the network trained were tested using regression analysis and the performance parameters such as root mean square error, mean absolute error, coefficient of determination, absolute standard deviation etc. The authors own experimental investigation of heat transfer studies of tube immersed in gas-solid fluidized bed using ANN is included for strengthening the said review. The results achieved by performance parameters shows that ANN can be used reliably in many heat transfer applications successfully.

Keywords: - Artificial Neural Network, back propagation, heat exchanger, heat transfer, multi layer perceptron.

I. INTRODUCTION

Heat exchangers are devices that allow the flow of thermal energy between two or more fluids at different temperatures [1]; they are complex systems due to their geometric configuration that seeks increasing efficiency in the heat transport.

Simulations of heat exchangers and other components of thermal systems usually address the steady-state behavior for heat rate prediction required for system design. The temperature gradients depend directly of the geometry of the heat exchanger in relationship to the distribution and position of the elements that transport the fluids. In power generation plants, where heat exchangers are used for the energy generation, the heat exchanger performance depends on several key parameters such as water flow, turbine efficiency and electric generator efficiency, which are related with the cooling capacity during regular operation.

Thus, it is important to develop design that allow for the proper selection of the heat exchanger configuration and its material, possibly including operation parameters such as maintenance cycles and replacement time due to fouling. Heat transfer and fluid behavior in different heat exchanger configurations have been studied for over 40 years [2,3]. More recently assisted by numerical simulations to describe the flow and heat transfer behavior [4-8], including Computational Fluid Dynamics approaches for the analysis [9]. Software packages, such as Fluent, have been applied for 2D and 3D simulations of heat exchangers, achieving a better understanding of the influence of the geometry and materials [1].

Improving the efficiency of the heat exchanger design and the development of tools for such a purpose, remain, for the most part, and active research topic [2-9].

In this contribution, Computational Fluid Dynamics (CFD) is applied for the analysis of a cross flow heat exchanger seeking to establish more efficient strategies for finding the optimum design; Data generated from CFD simulations are used to build a surrogate ANN model that includes the material type as part of the variables.

Such model may ease the effort in finding the appropriate material taking into account such factors as maintenance and replacement cycles. ANNs have been used to predict the heat transfer coefficients, performance, pressure drop and dynamic control in thermal systems [2]. ANN also have been used to substitute the dynamical heat exchanger models for complex geometries and predict outlet temperatures, mass flow rates [2], Nusselt numbers and friction factors for finned tubes heat exchangers [3].

II. PROBLEMS FORMULATION

Now ANN is widely used in various application areas such as function fitting, dynamic control, data clustering, pattern recognition, and system identification. In the thermal system, ANN is applied for performance prediction, heat transfer analysis, and dynamic control.

For example, Yang and Sen [1] reviewed the work on dynamic modeling and controlling of heat exchangers using ANN and GA. Wang et al. [9, 21, and 22] did much work on the performance prediction and analysis of the heat transfer and friction for heat exchangers through the ANN methods. Hosoz et al. [8] and Gao et al. [3] predicted the performances of cooling towers with ANN. Akbari et al. [5] predicted the steady state and the transient performance of a run-around membrane energy exchanger for yearly nonstop operation. Zdaniuk et al. [6] correlated the heat transfer and friction in helically finned tubes using ANNs, and it was concluded that ANNs were well suited for the application to helically finned tubes.

Then, Zdaniuk et al. [7] made a comparison of ANNs with symbolic-regression-based correlations for optimization of helically finned tubes in heat exchangers. It was concluded that the predictive capability of the ANNs was superior to empirical correlations obtained by symbolic regression, when considering only their applicability to the available datasets, but much care must be exercised when using ANNs for optimization purposes to enhance the heat transfer.

Mohanraj et al. [8] made a review about the applications of ANN for the energy analysis of refrigeration, air conditioning, and heat pump systems (RACHP). It was concluded that ANN could be successfully applied in the field of RACHP systems with acceptable accuracy.

Besides, ANN is also used in the optimization of the HVAC system energy consumption in a building [9] and the type of the helical wire inserted tube in heat exchangers [4], and to predict thermal performances of the thermoelectric generator for the waste heat recovery [3] and the carbon nano tube nano fluid in a tube [2]. From the for mentioned successful applications of ANN in the thermal system, it can be seen that ANN is a significant tool for thermal analysis in the engineering system, especially in heat exchangers.

Furthermore, there is a widespread problem that the air inlet direction is not always perpendicular to the heat exchanger surface in many cases for the direct and indirect air cooling systems. The air oncoming flow direction has an important effect on the heat transfer and pressure drop performances of the air-cooled radiator.

So the research and development of air inlet angles' influence on the air-side performances of heat exchangers have been paid more attention. Liu et al. [3] numerically studied the effect of the air inlet angles on the air-side performance of plate-fin heat exchangers in automotive radiators. Also the experiments were accomplished on finned oval-tube heat exchangers under four different air inlet angles in the author's previous studies [6].

After the experiment has been completed, a high accuracy of dimensionless correlations on the heat transfer and friction is always expected according to the limited experimental data. However, the experiment conditions are limited. So it needs to cost much energy to acquire more experiment data to improve the precision. Besides, during the procedure of reducing experimental data to get the experimental correlation for heat transfer and friction, certain errors are always generated by the traditional methods.

Pacheco-Vega et al. [9] applied the ANN approach to accurately model thermal performances for the fin-tube refrigerating heat exchanger with limited experimental data, and the results showed that the ANN methodology gave an upper bound of the estimated error in the heat rates and the ANN procedure could also help the manufacturer to find where new measurements are needed.

Peng and Ling [7] applied ANN to predict the thermal characteristics on plate-fin heat exchangers with limited experimental data. The predicted values were found to be in good agreement with the actual values from the experiments. However, they only researched on the effectiveness of ANN to predict thermal performances for fin-tube refrigerating heat exchangers and plate-fin heat exchangers with the limited experimental data, while few on the comparison of the predicted performances of ANN with those of experimental correlations of finned oval-tube heat exchangers and few on the difference between the heat transfer and flow characters predicted together and predicted separately.

In view of the aforementioned facts, this study proposes a dimensionless experimental correlation equation including air inlet angles to make the correlation have a wide range of applicability. It uses the air inlet angle divided by 90 degrees to make the angle dimensionless. Then, this study shows the procedure of an ANN fitting tool to predict the heat transfer and resistance performances on a finned oval-tube heat exchanger under four air inlet angles with the limited experimental data. Then, the performances of the results predicted by ANN are compared with those by experimental correlations. The results of Nu and f predicted separately are compared with those of Nu and f predicted together. Finally, the predicted performances when the data of the four air inlet angles are fitted separately are compared with those when they are fitted together to predict Nu and f. The results can provide the theoretical support for the application of the artificial intelligence in the heat exchanger performance prediction and optimization.

III. PROPOSED METHODOLOGY ARTIFICIAL NEURAL NETWORK (ANN)

Analysis Despite the apparent popularity of fuzzy-logic control in the relatively narrow HVAC applications see examples in Refs. 2–4, ANNs are now unquestionably the leading soft-computing methodology for the general thermal problems.

There are several significant reasons for this. First of all, it has a powerful ability to recognize accurately the inherent relationship between any set of input and output without a physical model, and yet the ANN results do account for all the physics relating the output to the input. This ability is essentially independent of the complexity of the underlying relation such as nonlinearity, multiple variables and parameters, and noisy and uncertain input and output data. This essential ability is known as pattern recognition as the result of learning.

Secondly, the methodology is inherently fault tolerant, due to the large number of processing units in the network undergoing massive parallel data processing.

Thirdly, its learning ability also gives the methodology the ability to adapt to changes in the parameters. This ability enables the ANN to deal with time dependent dynamic modeling and adaptive control by means of neuro controllers. This ability significantly enables thermal engineers to delve into system analysis and control, a complexity which simply cannot be treated by any traditional analysis at the present time.

Finally, the basic ANN methodology has much flexibility to incorporating elements of other soft-computing methodologies such as fuzzy logic and GA, for example, to further improve its capability to deal with additional complexity in thermal problems. On the other hand, despite these capabilities of the

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basic ANN methodology, it must be pointed out that input-output data sets must be available in the learning process to train the neural networks. Even though this requirement seems to be a serious shortcoming of the ANN analysis, it is, however, not really the case.

The reality is the existence and availability of a large amount of experimental data sets for various thermal phenomena and device performances accumulated over a long time. They are mostly in the form of heat-transfer correlations. Such available data sets are the perfect vehicle for use with the ANN analysis.

Furthermore, experimental data for thermal problems will always be available, in general, as they normally are required to validate theoretical models and analysis. In addition, experimental data obtained under specific dynamic conditions can also be used to train dynamic ANNs. Furthermore, the neural network can be trained in real time when the experimental data are being obtained at the same time, a feature useful in the development of dynamic adaptive control schemes.

Here again, the complexity of the problem under consideration is not an issue. In the next section, the ANN analysis in its basic methodology will be described, along with the discussion of the various issues of implementation. Examples of thermal problems with increasing complexity that have been treated by the ANN analysis with promising results are then shown and discussed.

The description that follows is essentially that of Schalkoff. The structure and function of the ANN attempt to mimic that of the biological neural network. The most popular fully interconnected ANN consists of a large number of processing units known as nodes or artificial neurons, organized in layers.

There are, in general, three groups of node layers, namely, the input layer, one or more hidden layers, and an output layer, each of which is occupied by a number of nodes. All the nodes of each hidden layer are connected to all nodes of the previous and following layers by means of internodes synaptic connectors or simply connectors. Each of the connectors, which mimic the biological neural synopsis, is characterized by a synaptic weight. The nodes of the input layer are used to designate the parameter space for the problem under consideration, while the output-layer nodes correspond to the unknowns of the problem under consideration. The parameters in the input layer need not to be all independent, and this is also true in the output layer. At each hidden-layer node, the node input consists of a sum of all the node outputs from the nodes in the previous layer modified by the individual interconnector weights and a local node bias, which represents the propensity of the combined input to trigger a response at the node.

It is thus clear that the weights are simply weighting functions that determine the relative importance of the signals from all the nodes in the previous layer. At each hidden node, the node output is determined by an activation function, which plays the role to determine whether the particular node is to activate "fire" or not. It is thus seen that by the connector and node operations, information, which starts at the input layer, moves forward toward the output layer. Such a network is known as a fully connected feed-forward network.

Formation-processing paradigm that is inspired by the way the biological nervous system, such as the brain, processes information. It is composed of large number of highly interconnected processing elements (neurons) working in unison to solve specific problem. The most common for chemical engineering application is Multi Layer Perception (MLP), which is a feed forward neural network. It consists of multilayer hierarchical structure, which apart from input and output layers, has at least one layer of processing units in between them.

The layers between the input and output layers are termed "hidden" since they do not converse with the outside world directly. The nodes between the two successive layers are fully connected by means of weights. That is outputs from the input layer are fed to the hidden layer units, which in turn, feed their outputs to the next hidden nodes. The hidden node passes the net activation through a nonlinear transformation of a linear function, such as the logistic sigmoid or hyperbolic tangent to compute their outputs.

For the training of such a MLP error back propagation algorithm suggested by Rumelhart5 is popular. This is based on a nonlinear version of the Windrow-Hoff rule known as Generalized Delta Rule (GDR).

It is now clear that the overall ANN analysis involves just a few deterministic and algebraic steps repeated many times on the computer, while keep tab on the propagation of cycle errors in the training process.

On the other hand, the methodology does involve a relatively large number of free parameters and choices. They include the number of hidden layers, the number of nodes in each layer, the initial weights and biases, the learning rate, the minimum number of training data sets, and sometimes also the choice of input parameters. All these do have a material effect on the ANN results.

While literature does provide some semi rational suggestions and recommendations, past experience and numerical trials and experimentation still represent the best guides. As pointed out by Yang, studies are being pursued currently to provide a more rational basis for some of the choices. Several guidelines may be of some interest. Despite the simple computational steps, overall effort is still an important issue, and does depend on the total number of nodes in the network, as a large number of nodes also tend to slow down the training process.

The general idea is to seek a number of hidden layers and a number of nodes in each hidden layer as low as possible, but still permit efficient flow of information from the input layer to the output layer. In a new thermal problem, there are likely more input parameter nodes than output nodes. One reasonable practice is that the first hidden layer should have the same number of nodes as that in the input layer, and this number decreases toward the output layer, and the number of hidden layers depends on problem complexity.

One flexibility in the ANN methodology is that both numbers of the hidden layer and the corresponding nodes can be increased at will from training cycle to training cycle, if the cycle errors do not decrease as expected. On the other hand, it must be cautioned that too many nodes may suffer the same fate as using polynomial curve-fitting schemes by collocation at specific data points, thus creating large errors in attempting interpolation between successive data points. One interesting strategy regarding the node-number issue is suggested by Kramin by first training a large network, which can then be reduced in size, and by removing those nodes, which do not significantly affect the training result. There is another suggestion based on a reversed strategy by adding nodes systematically as training proceeds. These practices suggest that the network architecture, relative to the node number, can be freely modified throughout a single training cycle.

A more rational procedure of optimizing the ANN architecture based on evolutionary programming is also available, as will be discussed separately in a later section. The issue of assigning initial weights and biases is always difficult in a new application. Without past information or data, the current practice is simply to generate a set of initial data from a random number generator of bounded numbers.

A more rational, but complex method is that suggested by Lehtokangas et al. based on an orthogonal least-squares algorithm. The choice of the training rate has not been rationally studied so far, and at the same time, the only guide is by numerical experimentation. As mentioned previously, a value somewhere between 0.4 and 0.5 can be used as a starting point, and reasonable results can be expected.

Finally, the sigmoid activation function, as already pointed out, is a surrogate for a step function with continuous derivatives, thus avoiding possible computational difficulties. However, it also possesses asymptotic limits of and may cause difficulties when these limits are approached. Therefore, the usual practice is to normalize all physical variables in an arbitrarily restricted range such as to limit the computational efforts.

Finally, there is another common and recommended practice in the way that the experimental data sets are utilized for training. Since the ANN is to be trained to recognize the input-output relations, which are generally somewhat noisy and do contain experimental uncertainties, it is desirable to include as many training data sets as possible. However, it is also important to set aside about one-quarter of the entire data sets to serve as testing data sets to evaluate the accuracy of the ANN results.

The soul of the above model lies in the fact that the system so developed tries to mimic the working of the human brain in terms of the following:

- It works in a complex parallel computation manner
- High speed of performance due to the parallel architecture.
- It learning and adapt according to the modified link weights.

Work on ANN has been inspired right from its inception by the acknowledgement that the human brain computes in an entirely different way from the conventional digital computer.

ANN has an astonishing ability to find a relationship between completely non-linear data's which can be implemented successfully to detect trends and thus find the pattern followed by our targets which are impossible for human brains to notice.

ANN poses great ability to train itself based on the data provided to it for initial training. It has the tendency of self-organization during learning period and it can perform during real time operation.

ANN process input data information to learn and get knowledge for forecasting or classifying patterns etc. type of works. All information processing is done within neuron only. In above figure connections between neurons is shown in which learning algorithm is applied to train using historical data [2].The links between neurons consist of some value which is termed as weights. These weights are responsible for scaling input values to a new value which will be responsible for forecasting accurate value.

The value of weights is decided in the basis of input and target data and on the choice of activation function (usually nonlinear). The value of weight is utilized to successfully solve some certain complex forecasting or classification problem. The weights are continuously changed while training to improve accuracy [1] [2].

Through the input layer of neural network input data is passed first and then transferred to other layers through links after some alteration. This links possesses some strength whose value is also changed which is also called as weights. Our main aim is to calculate the most possible optimum values of these weights. Hidden layers neurons are further connected to output layer neurons. The activation function of hidden layer neurons is the main factor in deciding values of weights. The weight of this connection between hidden and the output layer is also needed to be optimized with prior weights.

The number of hidden layer neurons which will give the best result is difficult to find since there is no particular method to calculate that. Hence, we will vary the number of hidden layer neurons till we get required satisfactory result. A number of input layer neurons are equaled to a number of input signals and a number of output layer neurons is equal to the number of output variables which in our present case is one i.e. present load.

Below figure 3.1 depicts the working of a back propagation network in the form of the flow chart. From the chart, it is clear that after the initiation of training initial values of weights are to be assumed. Then input data is processed in sets.

After all sets of input data are processed, then the error is calculated. If the error is within tolerant range, then network weights are saved and training is ended. If the error is not in the range of tolerance range, then check for a number of epochs. If epochs exceeded the maximum value, then show failure massage and end training else retrain network until required results are obtained.

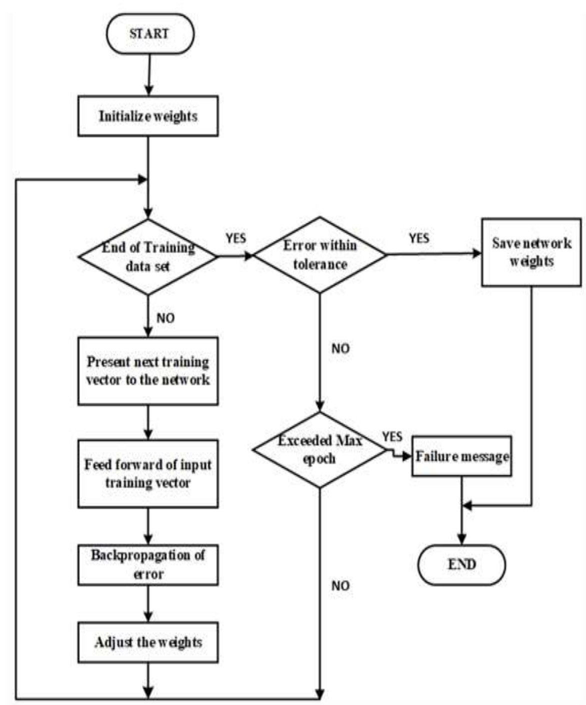

Fig 1. Block Diagram of Back propagation Neural Network (BNN). [6]

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IV. RESULT AND SIMULATION

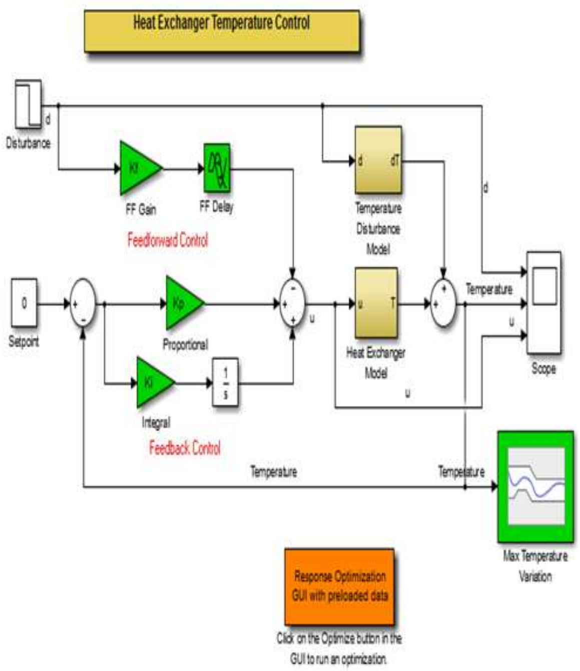

Fig 2. MATLAB simulation modeling Optimize plotting.

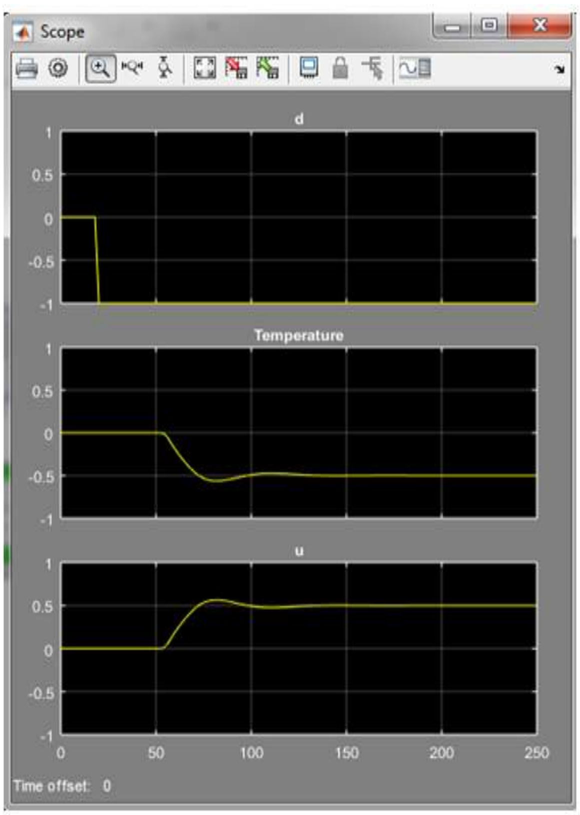

Fig 3. Temperature and Heat flow Rate across time scale.

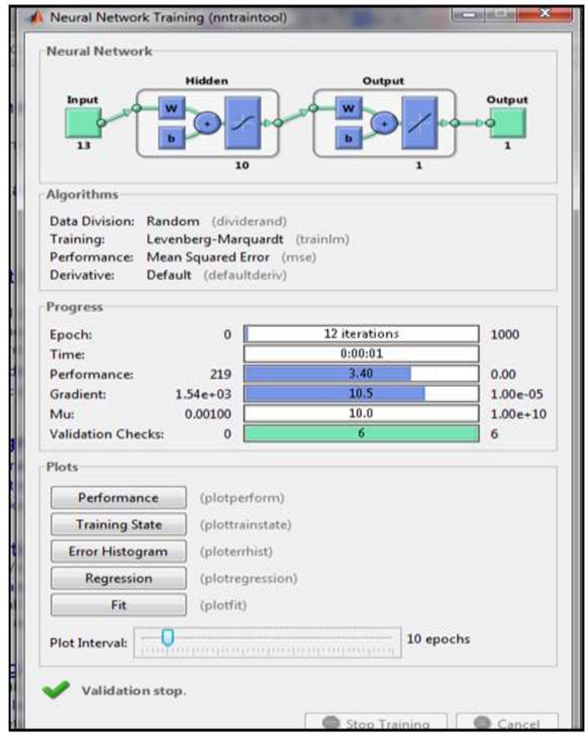

Fig 4. NN Training State.

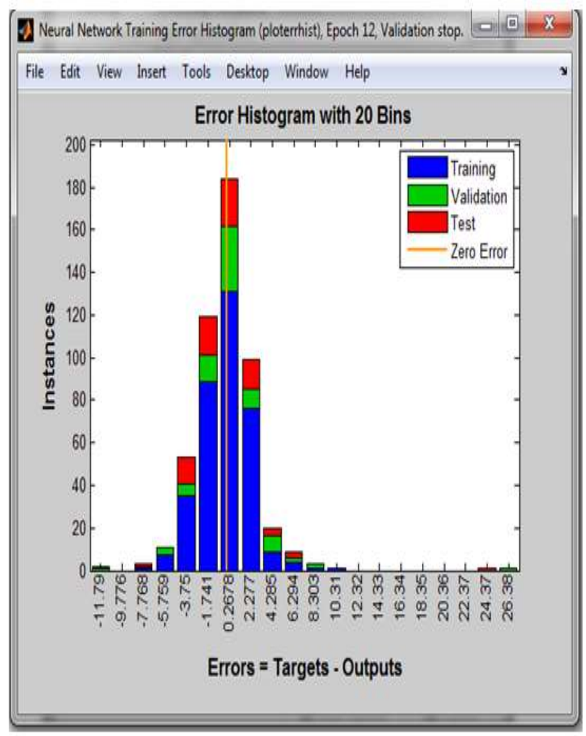

Fig 5. Error of histogram.

MSE Analysis represents histogram for multiple layer option. The irregular result provide to neural network. So 0.2678 Error histogram with 20 bins is the highest value of this graph represent.

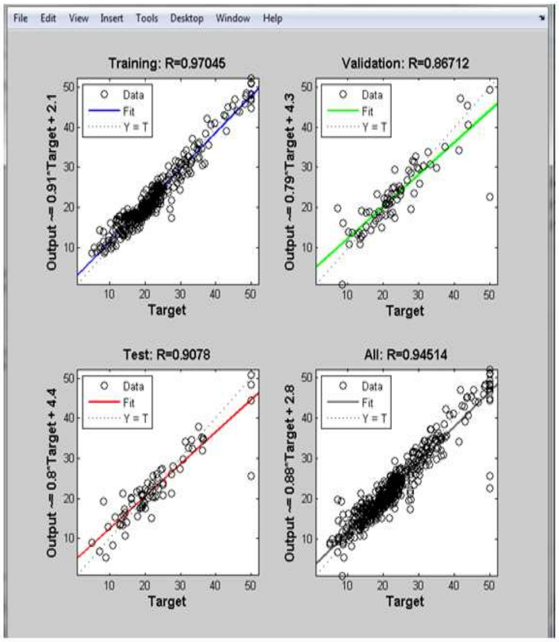

Fig 6. output Error.

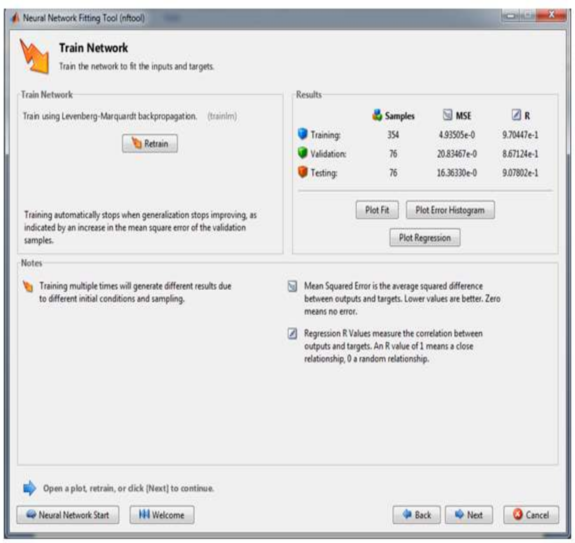

Fig 7. Import data.

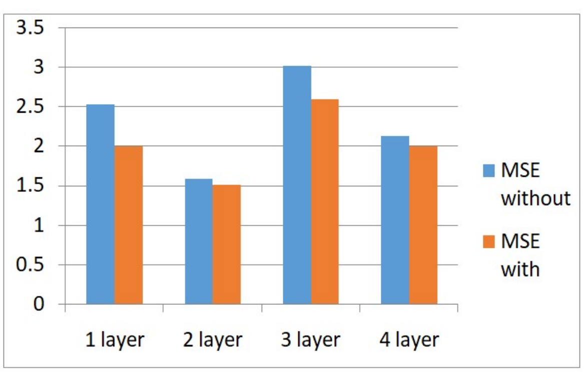

Fig 8. MSE Layer of Analysis Neural Network.

The previous chapter introduces the proposed methodology. This chapter describes the related future work and schedule plan of excursion.

Table 1. MSE Analysis of Neural Network.

Layers	MSE Analysis Without Neural Network	MSE Analysis With Neural Network
1 Layer Training	2.53	0.2678
2 Layer Training	1.59	-0.127
3 Layer Training	3.01	0.739
4 Layer Training	2.13	-0.1447

Table 2. Accuracy and Precision of base paper and our proposed work.

S.N.	Accuracy Base paper	Proposed ANN based Accuracy
1.	96.2	98.24

The previous chapter introduces the proposed methodology. This chapter describes the related future work and schedule plan of excursion.

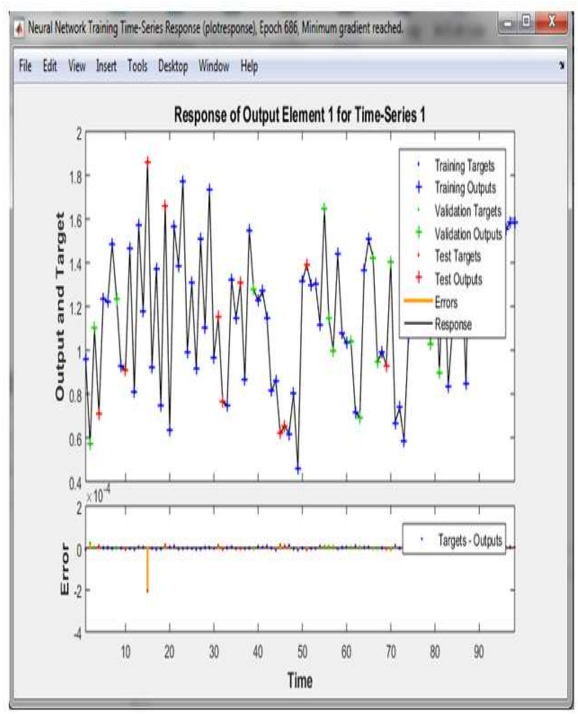

Fig 9. Time series Analysis of ANN.

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This curve is show the load based building durability in days with also find maximum accuracy of optimization.

V. CONCLUSIONS

The study of the physics involved in convective evaporation has increased its complexity since the appearance of enhanced surfaces for evaporators and new environmentally-friendly refrigerants.

This enhanced complexity has made it more difficult to develop accurate correlations for the prediction of the thermal performance of evaporators. Reports in the literature clearly show that predictions based on models that consider forced convection and flooded evaporation as separate phenomena are severely degraded and new alternatives like artificial neural networks (ANNs) are necessary.

We have developed neural network models of a mini-tube evaporator that may be able to accurately predict the thermal performance under several operating conditions. Results obtained using the ANN technique, as developed in this investigation, are very promising. The prediction of heat transfer obtained in this work has a maximum error of 2.46% and a mean quadratic error of 0.26%, which is by far lower than the 5% obtained by other authors that use conventional correlation techniques.

The technique of artificial neural networks is therefore an excellent option for reliable and precise characterization of thermal systems where evaporation processes occur, such as in refrigeration and air conditioning units, and when appropriately trained, the predictions obtained from neural network models are of the order of the experimental uncertainty.

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