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Heat Transfer Studies using Artificial Neural Network - a Review

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Abstract *– This review 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.

1. INTRODUCTION

Development of computer based algorithms for various heat transfer applications is emerging as a successful tool in the field of thermal engineering. Artificial intelligence algorithms used in this field are simple models of human intelligence and evolutionary experience. The enhancement of heat transfer is a significant area that attracts a great deal of researchers' attention. The methods used for such analysis include using fundamental equations, employing conventional correlations, or developing unique designs from experimental data through trial and error. Also the heat transfer problems are becoming increasingly more complex and that the need for modeling single steady phenomena requires dealing with dynamics, system performance, optimization, and control. To overcome this difficulty, a simple artificial neural network (ANN) method has been implemented in various heat transfer studies based on databases available from experimentation. ANN have been successfully employed for various heat transfer applications like solar energy, design of a steam generating plant, estimation of heating loads of buildings, prediction of air flows in a naturally ventilated test room, waste heat recovery heat exchangers, gas-solid fluidized beds as modeling and thermal process analysis [1]. The advantage of using ANNs to simulate thermal processes is that, once they are trained, they represent a quick and reliable way of predicting their performance. The ANN modeling includes numerous advantages, such as accurate approximations of complex problems, greater efficiency than phenomenological models even for multiple response computations, and greater effectiveness even with incomplete and noisy input data [2]. ANN does not need definition of correlations and iterative method; it needs only input/output samples for training a special neural network, in turn, obtaining output results as test samples fed into trained network [3]. The models using first principles are obtained by deductive process whereas the tendency of human being to learn any activity for a particular action/reaction process is by inductive process which goes on reducing the errors or increasing the accuracy and efficiency of an activity. The empirical models and correlations developed by conventional methods are complex in nature, difficult to predict non-linear relationship, less accurate, and require long computing time. ANN can provide a platform for solving such thermal processes with quick and reliable way of predicting their performance. The changes in the system can also be continuously updated easily. Neural network (NN) has the ability to learn highly non-linear relationship which processes information by its dynamic system response to external inputs [4].

The purpose of this study is to present the ANN structure, methodology and implemental issues in general heat transfer problems, important heat transfer applications like heat exchangers and fluidized bed heat transfer studies using ANN and their corresponding results. This review of the ANN methodology and applications in various heat transfer applications will encourage the thermal engineers to consider ANN for dealing the critical heat transfer problems which are

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difficult to treat by conventional methods. The author's own experimentation study: ANN modeling to predict heat transfer coefficient and Nusselt number for horizontal tube immersed in gas-solid fluidizing bed of large particles is explained in brief to strengthen the successful implementation of ANN in heat transfer studies.

2. ARTIFICIAL NEURAL NETWORK STRUCTURE AND METHODOLOGY

ANN is an information processing paradigm inspired by biological neuron system of human brain. It consists of a large number of highly interconnected processing elements called as neurons [5]. It is observed that in analysis, data used is very important which represents the past data and performance of real system and a suitable selection of neural network model. ANN can model the inherent relationship between any set of input and output data accurately without knowing a physical system. It also considers all the parameters affecting the physical system. The variable relations such as nonlinearity, multiple variables and parameters, and noisy and uncertain input and output data are considered easily. ANN consists of large number of processing units in the network which runs parallel data processing hence the methodology is more accurate. It also deals with dynamic modeling and adaptive control hence any sudden changes and control in the system can be adopted easily. Such simplicity cannot be implemented by traditional analysis methods in thermal engineering hence thermal system analysis and control can be implemented by ANN with more accuracy and less computing time. The large amount of experimental data available from various thermal processes helps in terms of input and output data required for training the neural network which is essential for the ANN implementation. The data available are mostly in the form of heat-transfer correlations. In thermal analysis we always need to validate theoretical models and hence available experimental data will be used in ANN analysis. In addition, experimental data obtained under specific dynamic conditions can also be used to train dynamic ANNs. 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 [6].

ANN consists of a large number of processing units fully interconnected as nodes or artificial neurons, organized in layers. There are, three groups of node layers in general, 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 synaptic connectors. Each connector is characterized by a synaptic weight. The input layer is used to designate the parameters for the problem under consideration, while the output-layer corresponds to the unknowns of the problem under consideration. The parameters in the input and output layer are need not to be all independent. The weights of the connectors are the weighting functions that determine the relative importance of the signals from all the nodes in the previous 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. 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 or not. The information by the connector and node operations starts at the input layer, moves forward toward the output layer [7]. Such a network is known as a feed-forward network as shown in Figure 1.

The error at each of the output node can be determined by comparing the calculated feed-forward data with the experimental output data. The training of the network performs the adjustment of node biases and weights in the network to minimize the errors between target output and desired output. The training procedure for feed-forward networks is known as the supervised back propagation (BP) learning scheme where the weights and biases are adjusted layer by layer from the output layer toward the input layer [8], [9]. The process of minimizing error continues till to achieve the performance level defined by user with backward learning. The first step in the training process is to assign initial values to all the synaptic weights and biases in the network. The values may be either positive or negative, and in general practice, are taken to be less than unity in absolute values. The next step is to complete all the node input and output calculations based on activation function used in the network. The activation functions such as step function, the logistic sigmoid function, the hyperbolic tangent, the Gaussian, the wavelet, have been proposed by various studies in recent past. The activation function may be changed from one hidden layer to another. The most popular and preferred activation functions is the continuous version of the step function, known as the logistic sigmoid function, which possesses continuous derivatives to avoid computational difficulties.

The learning rate of the network plays important role to scale down the degree of change made to the connectors and nodes. The larger the learning rate, the faster the network will learn, but there is a chance that the ANN may not reach the desired outcome due to oscillatory error behaviors. Its value is normally selected in the range 0.4–0.5. In some cases to further modulate the error-correction rates, a momentum term is added, characterized by a momentum rate based on the old weight and bias changes in the previous learning iteration [10]. An epoch or cycle of training decides computing a new set of weights and biases successively for all the runs in the training data. The calculations are then repeated over many cycles while recording an overall error quantity for a specific run within each epoch. After a cycle of the runs is completed, a maximum or average cycle error can be determined. The weights and biases are continually updated throughout the runs and cycles. The training is terminated when the last cycle error falls below a prescribed performance level defined by user. The final sets of weights and biases can then be used for prediction purposes, and the corresponding ANN becomes a model of the input-output relation of the given problem. As ANN is to be trained to interpret the relationship between input and output data, the data used for the training should be sufficient enough to understand the process by the network. Generally 75 to 80% of the total data is used for training the network whereas remaining 25 to 20% of the data is used as testing data to evaluate the accuracy of the network.

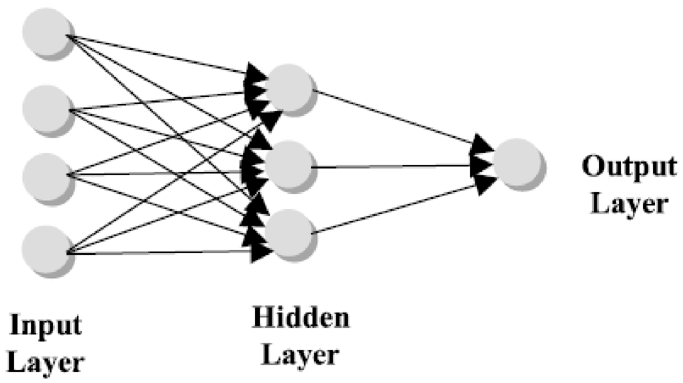

Fig. 1. Feed-forward neural network model.

3. ARTIFICIAL NEURAL NETWORK – THERMAL PROBLEMS

The thermal problems involve multidimensional fundamental disciplines with complex geometry. Experimentation plays important role in the development of thermal science and engineering. The experimental data correlates with dimensionless groups and are treated as physical models for performance prediction and design of thermal systems. It has been observed that there is a fundamental inadequacy in these correlated results. The existing experiment based database can be used to develop excellent ANN-based thermal models. Recent advances in the ANN methodology and good results are attracting an increasing number of thermal engineers to apply the ANN analysis to critical and challenging thermal problems. The heat transfer problems can be broadly classified in two categories: i) steady state ii) unsteady state or transient. Much of the current knowledge is based on heat-transfer correlations and unsatisfactory approximate theories. ANN analysis can be applied to obtain ANN-based models, which are significantly more accurate than the traditional correlated models.

Heat exchanger is one of the basic applications in heat transfer analysis. There are large numbers of phenomena associated with the heat exchangers like heat and flow geometries, turbulence in the flow, and existence of hydrodynamic and thermal entrance regions, non uniform local heat transfer rates, fluid temperatures, and heat conduction along tube walls, natural convection within the tubes and between fins [11]. The individual analysis of the phenomena is easy but when combined result in a system; it is very difficult to compute. The steady state as well as dynamic predictions needs to perform based on number of assumptions and simplifications and hence the results are not realistic. The common practice is to develop approximate theoretical models based on the use of overall heat transfer coefficients made of individual heat-transfer coefficients for each fluid obtained from correlations with experimental data in terms of dimensionless numbers [12]. Always assumptions are made, to predict the approximate model, such as, thermo physical properties of fluids and simplified geometrical parameters. As a result, the resulting heat-transfer rates do not predict well the actual heat-transfer performance of the heat exchangers under consideration. ANN analysis provides a very accurate tool for modeling the heat exchanger performance, which does not use any simplifying and artificial assumptions, but still considers all the physical effects that relate the input physical parameters to the heat exchanger performance.

One of the important thermal problems is heat transfer studies in gas-solid fluidized bed as fluidization techniques have found vast applications in chemical and mechanical industries in the recent past. The important industrial applications of fluidized beds are design of commercial catalytic reactors, design of fluidized nuclear reactor, fluidized bed drying and now a days waste heat recovery fluidized bed heat exchangers in mechanical industries [13]. Fluidized bed heat transfer includes the heat transfer between immersed surface and bed. The computation through neural network of these fluidized beds has proven that the ANN can represent system behavior more accurately than the dimensional analysis approach and analysis by first principles.

4. ANN INCORPORATING GENERAL HEAT TRANSFER PROBLEMS

Benjamin *et al.* [14] describe two frameworks: non-recurrent and recurrent, using ANN in approximate simulation of the behavior of physical system response. The study represented efficient modeling of physical systems by preprocessing the training data using any of a number of simplifying transformations like principal component analysis, modal filtering, elimination of statistically dependent components of motion and transformation of the components of motion to statistically independent, standard normal random signals. They found that satisfactory simulation of complex systems can be achieved with ANNs with computation times up to two orders of magnitude lower than phenomenological models. Solution of inverse heat conduction problem for the estimation of thermal conductivity and specific heat using combination of ANNs and Levenberg-Marquardt (LM) method was investigated by Soeiro *et al*. [15] The multi layer perceptron (MLP) [16] NN with BP algorithm was used. The combination of ANN-LM found in good agreement with the experimental data. Rafiq *et al*. [4] represented the practical guidelines for designing ANN for engineering applications. The major aspects like building NNs, pre-processing of training data, data selection for the neural network training, duration of NN training, speeding up the training process of three types of NN: MLP, radial basis functional network (RBFN) and normalized RBF (NRBF) are discussed. The results show that ANN is a powerful tool for solving some of the complicated problems even when input data contain errors and are incomplete. Three NNs were compared and proved that MLP and NRBF performed equally well but RBF showed a poorer performance.

A new method of predicting critical heat flux (CHF) with ANN was developed by Guanghui *et al*. [17]. The ANN was trained based on three conditions: upstream conditions, local or CHF point conditions and downstream conditions. The effects of main parameters such as pressure, mass flow rate, equilibrium quality and inlet sub-cooling on CHF were analyzed using ANN. The BP algorithm was adopted for weight adjustment. ANN was developed with one hidden layer in which there were 40 neurons. A net input v_j to a neuron in a hidden layer k is calculated by

$$v_j = \sum_{i=1}^{n} w_{ji} o_i + \theta_j \tag{1}$$

where n is number of k-1 layer neurons and the weights are denoted by $w_{ji},$ threshold offset by $\theta_j,$ The output of the neuron o_j is given by an activation function. The activation function used in this work was

$$o_j = \tanh(v_j) = \frac{\exp(v_j) - \exp(-v_j)}{\exp(v_j) + \exp(-v_j)} \tag{2}$$

The weights w_{ji} of the neurons were trained in such a way as to reduce the system error E_{AV} to a minimum

$$E_{AV} = \frac{1}{2N} \sum_{n=1}^{N} \sum_{j} (d_j(n) - o_j(n))^2 \tag{3}$$

where $d_j(n)$ is the desired output. The improved values of the weights were achieved by making incremental changes Δw_{ij} proportional to $\partial E_{AV}/\partial w_{ji}$

$$\Delta w_{ij} = -\eta \frac{\partial E_{AV}}{\partial w_{ji}} \tag{4}$$

where η is learning rate, chosen 0.9 in this analysis and new weight for $m+1$ step is given by

$$w_{ji}(m+1) = \alpha w_{ji}(m) + \eta \delta_j o_i \tag{5}$$

where α is momentum coefficient used to improve convergence and chosen 0.9 in this study.

$$\delta_k = 0.5(d_k - o_k) f'(v_k) \quad \text{For output neurons} \tag{6}$$

$$\delta_j = f'(v_k) \sum_k \delta_k w_{kj} \quad \text{For hidden neuron} \tag{7}$$

The ±10 % accuracy was achieved for predicting CHF based on CHF point conditions. Prediction of critical heat flux using ANN in round vertical-tube flow of water under low pressure and oscillating flow conditions for either natural or forced circulations was carried out by Su *et al.* [18]. The standard feed-forward algorithm was selected, but using hyperbolic-tangent activation function, with slight variation of the basic methodology. The training process was aided by the use of both optimized learning and momentum rates. The inputs included pressure, mean mass flow rate, relative amplitude, inlet sub-cooling, oscillation period, and geometrical ratio of the heated length to tube diameter. Additional input node was a numeral unity, providing a threshold to nodes in the next layer. The ten-node hidden layer also included a unity node for the same purpose. The single-node output layer was a dimensionless ratio of the critical heat flux with oscillation to that without oscillation given by the test data. The study utilized two separate trained networks: one with natural and the other for forced circulation data sets. It was demonstrated that the average parity ratios of the training sets were well within 10%, while the average error of the testing data. A simulation of natural convection heat transfer from a confined isothermal horizontal elliptic tube based on ANN was developed by Hayati *et al*. [19]. Previously Ashjaee *et al*. [20] developed an individual ANN network for each access ratio which was time consuming and computational speed was very less. Such problems were overcome by developing only one ANN for all axis ratios where axis ratio was considered as one of the input to the network. The average Nusselt number considered as a function of three variables: wall spacing to tube minor axis ratio, Rayleigh number and axis ratio. The feed-forward MLP network architecture was selected. The network configuration selected for the study is shown in Figure 2.

The transfer functions for the layers were tansig/tansig/tansig/purelin respectively. The details of the ANN parameters are shown in Table 1.

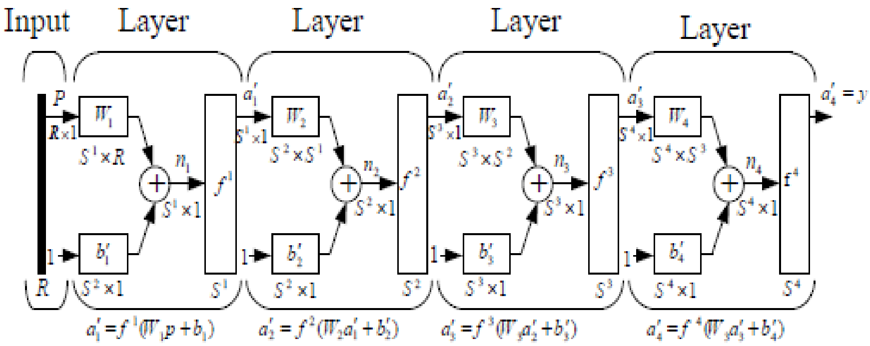

Fig. 2. Network configuration.

Table 1. Optimum parameters of ANN for the study.

ANN Parameters	Details
Neural Network	MLP
No. of hidden layers	2
No. of neurons in the input layer	5
No. of neurons in the first hidden layer	8
No. of neurons in the second hidden layer	18
No. of neurons in the output layer	1
Learning rate	0.5
No. of epochs	1000
Adaption learning function	Train lm
Training error	0.00001

The results showed that the maximum deviation for the train set was less than 0.325% and the maximum deviation for the test set was less than 1.89 %. That shows the best fit between the experimental and predicted data.

Unsteady state heat transfer is one of the important areas in heating and cooling industrial systems. Temperature profiles are required in different time elements for various geometries like flat plate, long cylinder and sphere. Developing the mathematical equation for the unsteady state heat conduction has been solved for various geometries by Gurney-Lurie and Heisler charts. The charts have been used for estimation of temperature at various locations within the material as a function of time. The algorithm MLP, trained with generalized delta rule was developed by Pandharipande *et al.* [21] as below.

$$W''_{kl}(t+1) = W''_{kl}(t) + \eta\delta_1 Y_1 + \beta_1[W''_{kl}(t) - W''_{kl}(t-1)] + \beta_2[W''_{kl}(t-1) - W''_{kl}(t-2)] \quad (8)$$

The data generated for these charts was used for training and it was observed that the predictions of these ANNs were so accurate that they can replace these charts and reduce the arbitrariness in reading the charts with high accuracy for interpolation. The new features in the algorithm were implemented like option with activation function, selection of either two or three previous time elements for error BP algorithm, numerical values of momentum function and learning rate can be changed in training mode. An attempt was made to use ANN to model the thermal transient process and the thermal behaviour of reciprocating mixer by Rakoczy *et al.* [22]. The mixing was varied out with a single perforated plates agitators with the different degree of perforation (ratio of hole-to-solid area of plate) oriented horizontally and reciprocating in a vertical direction. The agitator was always placed at half of the liquid height in the vessel. For practical application, RBF network was structured so that it can approximate the five characteristic quantities of thermal-transient curves and estimate the dynamic behaviour of temperature at unsteady heat transfer in the reciprocating mixer. The simulation results indicate that the MLP network model can appropriately predict the characteristic quantities of thermal transient processes such as the time lag of thermal process, the maximal value of temperature, the time of the achievement of maximal value of temperature, the time duration of thermal process and the quantity of area between the thermal response of transient process and the time axis by using the set of input operational parameters. The experimental investigation was performed by Scalabrin *et al.* [23] in forced convection heat transfer to supercritical carbon dioxide inside tubes using NNs, implemented multilayer feed forward NN with only one hidden layer. Four architectures were applied to the regression of heat transfer coefficients as functions of working conditions; NN in terms of dimensionless numbers, NN in terms of physical variables (2 Nos.) and NN accounting for property variation. The transfer function used here was a sigmoid function of the form:

$$f(x) = \beta \frac{1}{1+e^{-2\gamma x}} \tag{9}$$

Two positive parameters were applied in Eq. (9) to make the functions behavior more flexible: β changes the activation span and γ determines the steepness of the sigmoid function. The second architecture directly represents the heat transfer coefficient a as a function of the controlling physical quantities as independent variables, such as the reduced pressure, reduced temperature, mass flow rate, and heat flux. A third NN architecture was studied, that was similar to the first, but with slightly different inputs. From a functional point of view, this architecture strictly parallels the input/output variables of the conventional correlation. In this study, the error deviation, average absolute deviation and bias were evaluated for the validation of the results.

Heat transfer of a silver/water nanofluid in a two-phase closed thermosyphon (thermally enhanced by magnetic field) was predicted by Salehi *et al*. [24] using optimized ANN. A MLP neural network was used to estimate the thermal efficiency and resistance of a thermosyphon during application of a magnetic field and using nanoparticles in the water as the working fluid. The magnetic field strength, volume fraction of nanofluid in water and inlet power was used as input parameters and the thermal efficiency and thermal resistance were used as output parameters. The Genetic Algorithm (GA) ANN predicts the thermosyphon behavior correctly within the given range of the training data. In this study, a new approach for the auto-design of neural networks, based on a GA, was implemented to predict collection output of a closed thermosyphon. GA was implemented for optimizing the NN parameters such as number of neurons in the hidden layer, the coefficient of the learning rate and the momentum. The correlation coefficients between the desired parameters (efficiency and resistance) and the GA-MLP output found to be 0.98 and 0.99 with respect to experimental data. Modeling of a photovoltaic thermal collector in thermal and electrical along with NN was performed by Ravaeel *et al*. [25]. Ambient temperature of collector, cell temperature, and fluid temperature at duct inlet, fluid velocity in duct, solar identity and time were used as input layer and the thermal efficiency and electrical efficiency were outputs. Networks with different hidden layers used for modeling and performances evaluated with maximum correlation coefficient, minimum root mean square error (RMSE) and low coefficient of variance (COV). The results showed that the ANN with 1 hidden Layer and 10 neurons in this layer found to be with best performance.

$$COV = \frac{RMSE}{\sum_{i=1}^{N} a_i} X100 \tag{10}$$

The term a_i represents i^{th} experimental data. The controlling of photovoltaic collectors can well be modeled using ANN. Selection of the proper training function in NN technique decides success of modeling. Singh *et al*. [26] compared the performances of three training functions (TRAINBR, TRAINCGB and TRAINCGF) used for training NN for predicting the value of the specific heat capacity of working fluid, LiBr-H2O, used in vapour absorption refrigeration system. The parameters used for the comparison was on the basis of percentage relative error, coefficient of multiple determination, RMSE and sum of the square due to error. The inputs parameters are vapor quality and temperature and one output parameter selected was specific heat capacity. Training was continued up till the least value of mean square error (MSE) at definite value of epochs which was represented. Based on the results by performance parameters it was found that TRAINBR function showed better performance as compared to other two training functions. Elsayed [27] in his experimental work of small diameter helically coiled tubes for the evaporator of miniature refrigeration systems implemented NN techniques to predict the flow boiling heat transfer coefficients inside helically coiled tubes. He investigated the flow boiling of refrigerant R134a in helically coiled tubes with diameters ranging from 2.8 mm to 1.1 mm and coil diameter ranging from 30 mm to 60 mm. The normalized convective, boiling numbers and liquid heat transfer coefficient were used as the inputs for the developed network while the normalized ratio of the two-phase to liquid heat transfer coefficients was set as the network output. The ANN method produced a better prediction of the experimental results with ±30%.

5. ANN MDOELS INCORPORATING HEAT EXCHANGER

Heat exchanger is a useful device used in many engineering process for heating and cooling of flowing fluids. The major applications are in the field of refrigeration and air-conditioning systems, food processing systems, power plants, chemical industries, space applications etc. Prediction of heat transfer rates of heat exchangers is the core area in design of thermal systems under prescribed operating conditions. Conventional steady-state modeling approaches, used are development of correlations, provide predictions with large uncertainties. The experimental errors and assumptions in the analysis lead to uncertainties. Control of these devices needs dynamic simulations for which only a limited number of models are available. ANN techniques are used in heat exchanger for prediction of outputs and in control of operations. The simulation of time dependent behavior of a heat exchanger using ANN technique was performed by Diaz *et al*. [28]. Authors use the combined advantages of ANNs and internal model control to generate an efficient real time control scheme for a heat exchanger. The exchanger transfers heat from water to air, and the objective was to control a single output variable, the outlet air temperature by changing a single input variable, the air speed. It is observed that multilayer networks are universal approximators capable of approximating any measurable function to any desired degree of accuracy. To train the ANN, BP algorithm was used. The prediction in dynamics needs to consider the order of the system. One has to provide values of relevant variables at previous instants of time, because the ANN is simulating as differential equation of unknown order. Dynamic simulations using ANN technique was performed by training the NN with the information of the dynamic behavior of heat exchanger as shown in Figure 3. The variables involved in the problem were presented at time $t–\Delta t$ as an input to the network and the output corresponds to the variables at time t. It is rarely necessary to train the network with data from two previous time steps, as long as the chosen time step is reasonably small. It was proved that the ANN prediction was superior to that of the correlation.

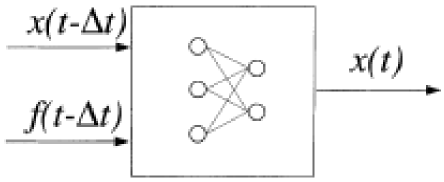

Fig. 3. Training method for dynamic problems.

The governing of dynamics of heat exchanger pilot plant was performed by Kharaajoo *et al*. [29] using NN based predictive controller. To develop a neural network model for the heat exchanger, outlet liquid temperature was considered as output and liquid flow rate as input data whereas steam temperature and inlet liquid temperature were kept constant. A MLP NN with 10 neurons in the hidden layer was used. Predictions were obtained and a quadratic form cost function was utilized to compute the prediction error and to derive the optimal predictive control strategy. For the estimation of non-linear process the NN must be trained until the optimal values on the weight vectors are found. The NARMAX model was used as given below;

$$y(k) = F[u(k-d-1),...,u(k-d-m), y(k-1),..., y(k-n)] \quad (11)$$

where $F(.)$ is a non linear function, d is a dead time, n and m are the orders of the nonlinear system model. The NN output was given by

$$y(k) = F^N[U(k-d-1), Y(k-1)] \quad (12)$$

where F^N is input output transfer function of the NN which replaces the nonlinear function F in previous equation $U(k\text{-}d\text{-}1)$, $Y(k\text{-}1)$ are vectors which contain m and n delayed elements of u and y respectively from the time instant $k\text{-}1$. ANN model was developed to predict the performance of a heat exchanger operating in real mechanical ventilation and air-conditioning system by Hu *et al*. [30]. The accurate prediction of steady state and dynamic behavior of heat exchangers was applied. In this study feed-forward network was chosen with BP algorithm. These ANN models were implemented under MATLAB, which provides a very convenient computing environment for the calculation of derivation of the ANNs. BP combines adaptive learning and momentum training using heuristic technique. Under steady state prediction the input parameters were: inlet chilled water temperature, outlet chilled water temperature, the inlet temperature of hot air, mass flow rate of chilled water and the mass flow rate of air. The output parameter was heat transfer rate. All the data from experimentation were normalized to [0, 1] range before providing to ANN. The total 445 sets of data were used, out of which 345 sets were used randomly for training and remaining data for testing purpose. The final structure of the ANN was determined by checking the error convergence by changing the hidden nodes. The result shows that 10 hidden nodes could achieve the convergence. The most of the predicted values were within 95-105% of the measured values. The mean relative error was 1.38% and the maximum relative error was 4.87%, it shows that the behaviour of heat exchanger in steady state and dynamic conditions can well predicted by ANN modeling. The NN prediction was performed of the overall and detailed heat transfer characteristics of a compact fin-tube heat exchanger [31], [32] under distorted flow conditions by Tan *et al*. [33]. The experiments were conducted with air and water/ethylene glycol anti-freeze mixtures as the exchanger fluids over a wide range of flow rates and inlet temperatures. The study also examines the use of an alternative type of NN, called as self-organizing map, to identify and classify the deterioration in exchanger performance associated with different degree of inlet obstruction. A multilayer feed forward NN was utilized. An ANN was developed initially to represent the overall behavior of the heat exchanger over the whole range of flow rates, inlet temperatures, liquid compositions and blockage ratio studied in the experiments. The single output neuron represented the overall rate of heat transfer between the two test fluids. There were total six hidden neurons found to be most suitable by a trial and error process. The NN predictions were in much closer agreement to the experimental data than corresponding predictions derived by the use of a conventional non-linear regression model. The performance parameters such as the RMSE and correlation coefficient were compared as given in Table 2.

Table 2. Comparison of ANN and non-linear regression model.

Performance indicators	Training Data		Test Data		Validation Data	
	ANN	NLR	ANN	NLR	ANN	NLR
Simulation 1						
MAE (%)	0.6	2.9	0.9	2.8	0.9	3.2
RSME	0.017	0.086	0.030	0.077	0.032	0.092
Corr-coeff	0.999	0.980	0.998	0.984	0.997	0.975
Simulation 2						
MAE (%)	0.7	8.2	2.3	5.2	1.8	5.1
RSME	0.022	0.227	0.062	0.163	0.053	0.143
Corr-coeff	0.999	0.980	0.991	0.935	0.995	0.946

Optimization of ANN architecture for shell and tube type heat exchanger was performed by Pandharipande *et al.* [34]. Estimation of exit temperatures of both the fluids as a function of inlet temperature conditions and flow rate was performed. ANN architecture with single, two and three hidden layers were tried for developing MLP feed forward NN. Numbers of neurons in hidden layers were varied and the process time required and error were checked to decide the efficient NN structure. Estimation of convective heat transfer coefficient and pressure drop in condensation of R134a flowing downward inside a vertical smooth copper tube was performed by Balcilar *et al.* [35]. R134a and water were used as working fluids in the tube side and annular side of a double tube heat exchanger, respectively. Input of the ANNs were the measured values of test section such as mass flux, heat flux, the temperature difference between the tube wall and saturation temperature, average vapor quality, while the outputs of the ANNs were the experimental condensation heat transfer coefficient and measured pressure drop in the analysis. Condensation heat transfer characteristics of R134a were modeled to decide the best approach using several ANN methods such as MLP, RBFN, generalized regression NN and adaptive neuro-fuzzy inference system. The performance of the method of MLP with 5-13-1 architecture and radial RBFN was found to be in good agreement. Xie *et al.* [3] implemented ANN for heat transfer analysis of shell-and-tube heat exchangers with segmental baffles or continuous helical baffles. Three heat exchangers were experimentally investigated. i) heat exchanger with segmental baffles ii) heat exchangers with continuous helical baffles, middle-in-middle-out (shell side flows) iii) heat exchangers with continuous helical baffles, side-inside-out (shell side flow). Prediction of the outlet temperature differences in each side and overall heat transfer rates were performed. Different network configurations were also studied by the aid of searching a relatively better network for prediction. Eight independent parameters were fed into the input layer of the network: Reynolds number and inlet temperature in each side, total number of tubes, diameter of center tube, total number of baffles and baffle pitch. The output layer contains three parameters: heat transfer rate, temperature differences in each side. The maximum deviation between the predicted results and experimental data was less than 2%. Ten different ANN configurations were tried to decide the best configuration.

$$R = \frac{1}{N}\sum_{i=1}^{N} R_i = \frac{1}{N}\sum_{i=1}^{N}\frac{A^e}{A^p} \quad (13)$$

$$\sigma = \sqrt{\sum_{i=1}^{N}\frac{(R-R_i)^2}{N}} \quad (14)$$

R represents the average accuracy of the prediction, while σ reflects the scatter of the prediction. For three layers, when the number of hidden nodes increased to 5, *R* is much closer to unity. This indicates that adding more hidden nodes may not improve the predicted results. Hence, configuration 8-6-5-3 was selected for testing with smallest R=1.089 and σ=0.1387 and the maximum relative error was less than 1.5%. Wu *et al.* [36] demonstrated the applicability and feasibility of ANN for estimating the performance of a wavy-fin gas cooler in CO_2 transcritical system. The effect of the five input parameters (inlet pressure, inlet temperature and mass flow rate of CO2, inlet temperature of air and inlet velocity of air) was examined individually by keeping the other four parameters constant. MLP model was applied to forecast the performance of the gas cooler, for the highly nonlinear relationship between the five input parameters and four output parameters, by searching an optimal weight in its weighting space. During the training process, the performance of the NN was evaluated by calculating RMSE values of the output data. The root mean square (RMS) value is defined as:

$$RMS = \sqrt{\frac{\sum_{j=0}^{p}\sum_{i=0}^{N}(d_{ij}-y_{ij})^2}{N.P}} \quad (15)$$

where, *P* is the number of the output processing elements; *N* is the number of exemplars in the data set;

y_{ij} is network output for exemplars at processing elements j; and d_{ij} is the output for exemplars at processing elements j. At the end of training process, the RMS found to be 0.062. It makes sure that the trained ANN has satisfactory performance within the trained data. Wu *et al*. [37] predicted the performance of the reversible used cooling tower under cross flow conditions as part of a heat pump system for service hot-water heating in winter by means of ANN technology and experimental test. The activation function was chosen as the tangent sigmoid function in the hidden layer and the linear transfer function in the output layer. The input layer has five nodes, including inlet air dry-bulb temperature, inlet air wet-bulb temperature, inlet $CaCl_2$ aqueous solution temperature, $CaCl_2$ aqueous solution mass flow rate and air mass flow rate. The output layer was with nine nodes, including heat absorption capacity, heating coefficient of efficiency, ratio of sensible heat transfer to the latent heat transfer, outlet air dry-bulb temperature, outlet air wet-bulb temperature, outlet $CaCl_2$ aqueous solution temperature, ratio of sensible heat transfer to the total heat transfer, ratio of latent heat transfer to the total heat transfer and humidity ratio of moist air difference between inlet and outlet. The data gathered from experiments was divided into input matrix and target matrix. All the training and testing data were normalized between 0 and 1 in order to improve the predicted agreement. The normalization and anti-normalization functions of training data were premnmx and postmnmx function, respectively, and the normalization and anti-normalization functions of testing data were tramnmx and postmnmx function. As number of variables in output layer was nine till ANN modeling handles it with easily.

6. ANN MODELS INCORPORTAING FLUIDIZED BED HEAT TRANSFER

Fluidized beds are widely used for different industrial applications, such as the coal combustors, boilers, and furnaces; the drying of solid particles; waste heat recovery heat exchangers; etc. In most applications, a fluidized bed consists of a vertically oriented column filled with particles (small or large), and a fluid (gas or liquid) is pumped upward through a distributor at the bottom of the bed [38]. The main characteristics of the fluidized bed are its isothermal nature and the high rate of heat transfer between the fluidized bed and the immersed surface [39]. Gas solid fluidized beds are aggregative in nature because of formation of bubbles of different sizes which results in non-uniform bed expansion and poor fluidization [40]. To improve the fluidization, disk and blade promoters were used in these beds. The authors [41] developed the correlation using dimensional analysis approach for the prediction of modified bed expansion ratio. The accurate behavior of system was represented by ANN models to predict bed expansion ratio. The BP algorithm for training was used in this study. In each case different ANN structures with varying number of neurons in hidden layer were tested keeping other parameters constant. The least error criteria used for the selection of final parameters of network. The dependent and independent variables were normalized so as to lie in the same range group of 0-1. Two models of ANN one for bed with disk and the other for bed with blade promoters were developed. The structure of NN models for test problem selected is as given in Table 3.

Table 3. Structures of NN model.

Bed Particulars	Input nodes	Hidden Nodes	Output Nodes	No. of cycles used For training
Blade with disk promoter	7	20	1	50,000
Bed with blade promoter	5	18	1	50,000
Network Parameters				Details
Learning rate				0.001-0.1
Momentum parameter				0.001
Slope for sigmoid function				0.7

Based on least error criterion, one system was selected for training of the input-output data in each problem. The number of cycles selected during training was high enough so that the ANN models can rigorously be trained. The weights during training phase were initialized randomly between -1 and 1. It was observed that the correlation developed using dimensional analysis approach as well as ANN models can satisfactorily be used for the prediction of bed expansion ratio. Also ANN models provide better prediction with reduced standard and mean deviations. The coefficient of determination for training and testing data obtained were in the range of 0.956-0.9854 which confirms that the ANN models were trained properly. Hence it can be inferred that the ANN model based on feed forward architecture and trained by BP technique represents system behavior more accurately than the dimensional analysis approach. The gas-liquid co-current down flow packed bed reactor, which is called as trickle bed reactor (TBR) is commonly used for the transfer of momentum, heat and mass using inert packing. The values of the heat transfer parameters like effective wall to bed heat transfer coefficient (h_w) and effective radial thermal conductivity of the bed (k_{er}) and change with the other variables are important for such TBRs. RBFN was applied for modeling these heat transfer parameters by Babu *et al*. [42]. The parameters like temperatures at four radial positions in the bed, liquid and gas rates, ratio of column to particle diameter were used as input neurons and k_{er}, h_w and the flow regime were used as output neurons. The experimentation includes the estimation of heat transfer parameters for air-water system over a wide range of flow rates of air and water covering trickle, pulse and dispersed bubble flow regimes in a 50 mm I.D. column with ceramic spheres (2 mm) and glass spheres (4.05 and 6.75 mm) and ceramic raschig rings (4 and 6.75 mm) as the packing materials. The RMSE was 0.1 and 0.12 for the two training set used in the analysis which is quite good. An attempt was made to study the effect of co-axial rod and disk promoters of different configuration on pressure drop in squared gas-solid fluidized bed using ANN model by Sahoo *et al*. [43]. The various parameters like flow rate, initial static bed height, particle size and density were varied and the bed pressure drop under fluidizing conditions was measured. A fluidized bed of size 8.2 cm X 8.2 cm X 100 cm was prepared with a conical section and multi orifice distributor. The disc promoter consists of six numbers of stars of Perspex material spaced at 10 cm gaps with a central rod 120 cm long. The rod promoter consists of three 6 mm dia. and 60 cm long steel rods which were placed at the vertices of an equilateral triangle with the fourth rod of 120 cm length placed at its centre. The pressure drop in terms of Euler number in fluidization condition was correlated to various system parameters from a dimensional analysis approach.

For un-promoted bed,

$$Eu = 17.817.\left(\frac{H_s}{D_c}\right)^{1.25}.\left(\frac{d_p}{D_c}\right)^{-0.45}.\left(\frac{\rho_s}{\rho_f}\right)^{0.23}.\left(\frac{U_f}{U_{mf}}\right)^{-1.88} \quad (16)$$

For disc-promoted bed,

$$Eu = 2.85x10^2.\left(\frac{H_s}{D_E}\right)^{0.045}.\left(\frac{d_p}{D_E}\right)^{-0.224}.\left(\frac{\rho_s}{\rho_f}\right)^{-0.025}.\left(\frac{U_f}{U_{mf}}\right)^{-0.184} \quad (17)$$

For a rod-promoted bed,

$$Eu = 31.223.\left(\frac{H_s}{D_E}\right)^{-0.234}.\left(\frac{d_p}{D_E}\right)^{-0.273}.\left(\frac{\rho_s}{\rho_f}\right)^{0.222}.\left(\frac{U_f}{U_{mf}}\right)^{-0.821} \quad (18)$$

ANN model was developed of a three layered feed forward NN. The network was trained with 60 sets of data, where each set consists of four system parameters (H_s/D_c, d_p/D_c, ρ_s/ρ_f, U_f/U_{mf}) and the corresponding value of experimental Euler number calculated from measured pressure drop. The system parameters were the input and the experimental Euler numbers were the output respectively. The network was exposed to the normalized set of data. The same set of data or other set of input data were taken as the testing data for which the target or output data was to be calculated. The weights were updated using the BP algorithm. The optimum parameters of ANN model are shown in Table 4.

Table 4. The optimum ANN parameters.

ANN Parameters	Un-promoted Bed	Disc Promoted Bed	Rod Promoted Bed
Error tolerance, (0.001-100)	0.001	0.001	0.001
Learning Parameter, (0.01 – 1.0)	1.0	0.5	1.0
Momentum Parameter, (0.01 – 1.0)	0.01	0.01	0.03
Noise factor, (0.0 – 1.0)	0.0	0.0	0.0
Slope, (0.1 – 1.0)	0.9	0.4	0.9
Maximum cycles	50000	50000	50000
Input units	4	4	4
No. of hidden layer	1	1	1

A modeling of a laboratory scale inverse fluidized bed reactor was studied using NN by Rajasimman *et al.* [44]. Degradation of starch wastewater in inverse fluidized bed bioreactor (IFBBR) was carried out continuously in different stages by varying initial substrate concentration and hydraulic retention time (HRT). Experimentation was performed to provide information of the process behavior and to train the network. The air flow rate was adjusted according to bed height for biomass growth. Continuous degradation (COD) in IFBBR was started with an initial concentration of 2250 mg and a HRT of 40 h. when the reactor reaches steady state, the HRT was reduced to 32 h and reduction in COD was monitored. Experiment was continued with various HRT (24 h, 16 h and 8 h). The performance of the reactor was studied based on COD removal efficiency. The RBF network was trained to predict the performance of IFBBR. The criterion used to evaluate the performance of the reactor was to determine the reduction in organic matter present in the starch industry wastewater. The NN was trained with the influent substrate concentration, hydraulic retention time and effluent concentration of the reactor. The data used for the training at various hydraulic retention times and at different initial substrate concentrations. The performance of the network was evaluated on the basis of an overall absolute error and RMSE. The absolute standard deviation (ABSD) and percentage RMSE used in the study is given as

$$ABSD = \frac{\sum (NN_{value} - Experimental_{value})}{N} \quad (19)$$

$$\%RMSE = \sqrt{\frac{\sum x^2}{N}} X100 \quad (20)$$

where x = ((experimental value – NN value)/experimental value) and N = number of data points. The low RMSE values indicate that the ANN modeling of IFBBR is justified for the treatment of starch industry wastewater. ANN approach to segregation characteristics of binary homogeneous mixtures in promoted gas solid fluidized beds was studied by Sahoo *et al*. [45]. A three layered feed-forward NN was considered with 92 data sets in each case, where each case set consists of four system parameters and the corresponding experimental value of the segregation distance. The BP algorithm was implemented using C-programming language. The sigmoid activation function used was as follows:

$$f(x) = 2.0X(\frac{1}{1+e-\lambda.x} - 0.5) \quad (21)$$

where, λ is the slope parameter. The maximum 30,000 number of epochs executed till the MSE is below the pre-defined threshold value. The final coefficient and exponents of correlation by ANN approach were determined by averaging the 98 sets of output data components. The values of segregation distance by dimensional analysis (DA) approach and ANN approach have been compared in Table 5. The NN structure model is as shown in Figure 4.

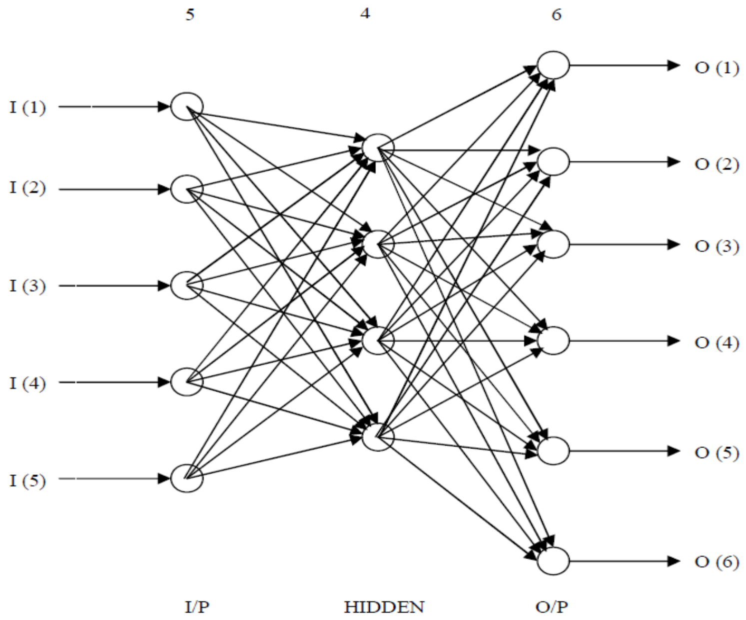

Fig. 4. Neural network model.

Table. 5. Comparison with dimensional analysis and ANN study.

BED	Un-promoted Fluidized bed		Rod Promoted Fluidized bed		Disc promoted fluidized bed	
Approach	DA Approach	ANN Approach	DA Approach	ANN Approach	DA Approach	ANN Approach
Standard Deviation %	5.88	5.84	5.92	5.88	5.996	6.57
Mean Deviation %	4.81	4.75	4.86	4.87	4.92	8.18

Investigations of heat transfer studies were carried out for small and large particles of tube bundles immersed in fluidized bed by Ravindranath [13]. Immersed tube heat transfer includes heat transfer coefficient between tube surface and particle which comprises of particle heat transfer by conduction, convection heat transfer by gas to surface and heat transfer by radiation [46]. A systematic approach to predict heat transfer parameters using ANN was implemented in feed forward network with BP structures Levelberg – Marquardt's learning rule. Batch training was used, while training, 70% of data was used for training and 30% for testing. Performance evaluation of the network was performed by regression analysis [47] and most of the results obtained match well with experimental data. The correlations developed were as follow:

For small particles Single Tube

$$Nu = 66.\left(\frac{Re}{Ar}\right)^{0.407}.\left(\frac{U-U_{mf}}{U_{mf}}\right)^{0.24}\left(\frac{D_t}{d_p}\right)^{0.364}(Pr)^{0.3} \quad (22)$$

For Multi tube

$$Nu = 66.\left(\frac{Re}{Ar}\right)^{0.407}.\left(\frac{U-U_{mf}}{U_{mf}}\right)^{0.24}\left(\frac{D_t}{d_p}\right)^{0.364}(Pr)^{0.3}.\left(1-0.18\left(\frac{Pt}{Dt}\right)^{-1.7}\right) \quad (23)$$

For large particles single bare tube

$$Nu = 2.86.\left(\frac{U-U_{mf}}{U_{mf}}\right)^{0.116}(Ar)^{0.044}(Re)^{0.147}(Pr)^{0.3} \quad (24)$$

Bare Tube Bundle (in-line and staggered)

$$Nu = 2.86.\left(\frac{U-U_{mf}}{U_{mf}}\right)^{0.116}(Ar)^{0.044}.(Re)^{0.147}.(Pr)^{0.3}.\left(1-0.18\left(\frac{Pt}{Dt}\right)^{-1.7}\right) \quad (25)$$

The regression value coefficient of correlation (R=1) obtained in training small and large particles for single bare tube and tube bundles shows that the network followed good trend in training. Test results, the value of R ranged from 0.899 to 0.999 strongly support that the network predictions were found to be in very good agreement with the experimentally observed values. The accuracy of the result of the ANN model based on feed forward architecture and trained by BP technique represents system behavior more accurately and is acceptable in site conditions and can be employed by engineers. Fluidized bed dryers are extensively used in the food industry for drying of moist food products. The fluid bed dryers significantly reduce drying time compared with the tray dryers due to good solid mixing, high rate of heat and mass transfer and easy material transport. A study conducted by Nazghelichi *et al*. [48] on integrated response surface methodology (RSM) and GA were recommended for developing ANNs with great chances to be an optimal one. A multi layer feed forward ANN was applied to correlate the outputs to the four inputs like drying time, drying air temperature, carrot cube size and bed depth. The RSM was used to build the relationship between the input parameters and output responses and used as the fitness function to measure the fitness value of the GA approach. Five parameters were used like number of neurons, momentum coefficient and step size in the hidden layer, number of epochs and number of training times. One hidden layer multi layer feed forward ANN with hyperbolic tangent sigmoid transfer function was selected for optimization process.

$$\tan sigm = \left(\frac{2}{1+e^{-2n}}\right) - 1 \quad (26)$$

The selected numerical parameters for optimization were the number of neurons in the hidden layer (2-40), momentum coefficient (0.1-0.7) and step size (0.1-0.4) in the hidden layer, epoch number (100-3000) and training times (1-5). The goodness of fit of the optimal ANN to the experimental data was based on coefficient of determination (R^2), MSE and mean absolute error (MAE) for the tested models.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(x_{pi}-x_{di})^2}{\sum_{i=1}^{N}(x_{pi}-\bar{x})^2} \quad (27)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_{pi}-x_{di})^2 \quad (28)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|x_{pi}-x_{di}\right| \quad (29)$$

x_{pi} is the network output from observation i, x_{di} is the experimental output from observation i, x is the average value of experimental output and N is the total number of data observation. For ANN simulation, significant reduction of the total computational effort with a relative good precision attained using coupled RSM and GA approach. Drying characteristics of green pea with an initial moisture content of 76% (db) was studied in a fluidized bed dryer assisted by microwave heating by Momenzadeh *et al*. [49]. ANN for predicting the drying time (output parameter) was investigated; microwave power, drying air temperature and green pea moisture content were considered as input parameters. Already the mathematical modeling of drying processes have been put forward by different researchers but such models are not used much because of their complexity and long time required for computation. ANN model with 50 neurons was selected for studying the influence of transfer functions and training algorithms. The results revealed that a network with the logsig transfer function and trainrp BP algorithm made the most accurate predictions for the green pea drying system. The random errors were within and acceptable range of ±5 % with a coefficient of determination of 98 %.

$$Logsig(n) = \frac{1}{1+e^{-n}} \quad (30)$$

A well trained ANN model should produce small MAE, RMSE and SE with large R^2 values.

7. ANN MODELING BY AUTHORS – EXPERIMENT BASED INVESTIGATION

The average heat transfer coefficient was determined between the fluidizing bed and horizontal tube surface immersed in the bed of large particles. The mustard (d_p=1.8 mm), raagi (d_p=1.4 mm) and bajara (d_p=2.0 mm) were used as particles in the bed. The effect of fluidizing gas velocity on the heat transfer coefficient in the immersed horizontal tube was discussed. The schematic diagram of the experiment's set up is shown in Figure 5. The results obtained by experiment were compared with correlations and ANN modeling. The parameters particle size, temperature difference between bed and immersed surface were used in the neural network modeling along with fluidizing velocity.

In the current study a multilayer feed-forward ANN model [33] has been developed. The network consists of an input layer with three neurons (particle diameter d_p, fluidizing velocity u and temperature difference between bed and tube surface ΔT'), an output layer of two neurons (heat transfer coefficient h and Nusselt number Nu), and hidden layer of five neurons. The schematic diagram of NN model selected for the current study is shown in Figure 6.

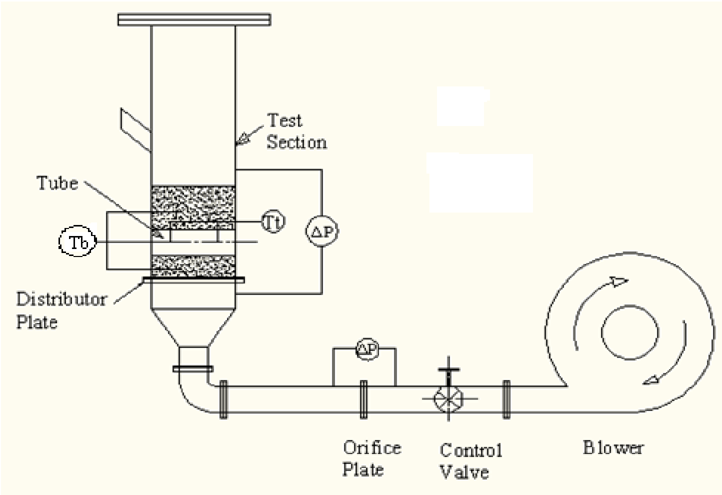

Fig. 5. Schematic diagram of experimental set-up.

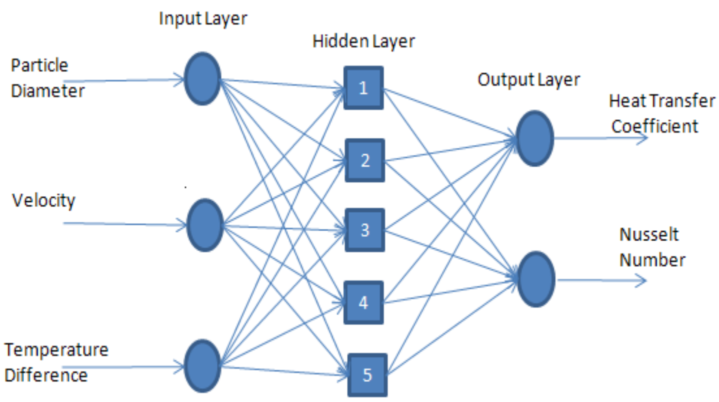

Fig. 6. ANN structure used in the study.

The supervised training, in which a network is trained for a particular set of inputs to produce the desired outputs, has been used. Initially, the weights of input vectors and bias were chosen randomly; however, the weights, subsequently, were adjusted to minimize the network performance function i.e., MSE with performance level 1×10^{-5}. The training was considered as completed when the NN reached user defined performance level. The network weights have been updated using the BP algorithm as implemented by Sahoo *et al*. [45]. Back propagation supervised learning technique in which the weights and biases have been adjusted by error derivative vectors is used for ANN. In this technique it uses a gradient descent algorithm [50] in which it updates the network weights and biases in the direction in which the performance function decreases most rapidly (i.e. along the negative of the gradient).

$$X_{k+1} = X_k - \alpha_k . g_k \tag{31}$$

X_k is vector of current weights and biases, α_k is learning rate and g_k is current gradient. The learning rate in training the network was set at 0.5. The algorithm used for the network training was Trainlm [19]. The training data sets have been fed for a maximum of 1000 epochs until the MSE was below a performance goal set. The weights and biases have been updated only after the entire training set has been applied to the network. The readings of input and output achieved during experimentation have been used for the training and testing of the network. The network was trained with 75 data sets (70% of data) and tested with 30 data sets (30% of data) hence in all 105 data sets were used in NN modeling. The post-training analysis has been performed with a regression analysis between the network response and the corresponding target. The resulting correlation coefficient between the ANN outputs and the targets decides the measure of the performance of the network. In order to obtain the optimum number of neurons in a hidden layer [51], [52] the ANN model was trained with a varying number of neurons with the Tansig transfer function and Trainlm algorithm. The maximum neurons checked were 15, starting with a minimum of one neuron and then increasing the network size in steps by adding a neuron every time. Based on the results, the minimum error found at five numbers of neurons hence selected. The experimental and predicted values of the heat transfer coefficient and Nusselt number match with a high level of accuracy.

$$MSE = \frac{1}{N}\sum[t_o(k) - a(k)]^2 \text{ , } (1 \le k \le N) \tag{32}$$

where a is network output, t_o is target output, and N is number of data points. The maximum percentage errors of heat transfer coefficient values predicted by ANN for trained and tested data are 0.074% and 0.2572% respectively. The maximum percentage errors of Nusselt number values predicted by ANN for trained and tested data are 0.1343% and 0.3588% respectively. The coefficient of determination value found to be 1 and 0.999 for trained and tested data respectively. It indicates that there is a good agreement between experimental and predicted results by ANN.

8. FUTURE SCOPE FOR ANN METHODOLOGY

The difficulties in heat transfer analysis by conventional methods like imperfect, uncertain and noisy experimental data, many assumptions in the analysis in terms of thermo physical properties of fluids, tedious fundamental equations, long computation time and less accuracy, direct correlations in terms of dimensionless numbers prove to be approximate analysis. These all drawbacks are being modified by ANN modeling without knowing the physical system in detail. It is seen that ANN methodologies represent a promising tool to approach and solve difficult heat transfer problems. There are some shortcomings like need of reliable experimental data and uncertainty in selection of ANN parameters in modeling which can be reduced by implementation this methodology in many heat transfer applications. The other tools available in artificial intelligence world can be combined to strengthen the ANN implementation.

9. CONCLUSION

This brief review concludes the successful implementation of ANN in difficult and complex heat transfer problems in the field of energy systems, hear exchangers, gas-solid fluidized beds, along with the authors own study of ANN implementation in gas-solid fluidized bed heat transfer. The basic structure and methodology of ANN implementation is discussed in general. The ANN modeling is explained in basic heat transfer areas in steady state and dynamic thermal modeling in general heat transfer applications. ANN results are shown in terms of accuracy and flexibility in its use, and also their computational and experimental validations. Thermal engineering analysis requires tedious equations and correlations to develop to satisfy the fundamental principles of the physical system which can be analyzed in a simple manner by implementing the ANN approach. The study shows that analysis with less and noisy input data and even non-linear relationship behavior can be properly fitted in ANN modeling. It is one of the easy ways to implement with multiple response computations and complex thermal systems. Based on the results achieved by researchers in their analysis, it can be concluded that the BP algorithm is the powerful learning algorithm with feed-forward structure in many heat transfer applications. These models provide better prediction with reduced standard and mean deviations. The regression value of R=1 obtained in training the network in many cases and in other some cases this value ranged from 0.899 to 0.999, strongly support that the network predictions are found to be in good agreement with the experimentally observed values. Once the ANN model trained for a particular thermal process, a reliable and quick response is possible even we can continue the updating these models for the changes in the system.

NOMENCLATURE

a’	Output of each neuron
Ar	Archimedes number
b’	Bias vector of each neuron
D_C	Column diameter of the fluidizer, [m]
D_E	Equivalent column diameter for promoted bed, [m]
d_p	Particle diameter, [m]
D_t	Diameter of tube, [m]
Eu	Euler number
f	Transfer function
f(t)	Time dependent function
H_s	Initial static bed height, [m]
n	Transfer function input
Nu	Nusselt number
p	Input vector
Pr	Prandtl number
P_t	Tube pitch, [m]
Re	Reynolds number
t	Time, s
U_f	Superficial fluidization velocity, [m/s]
U_{mf}	Minimum fluidization velocity, [m/s]
W	Weight vector
W_{kl}	Weights in between second hidden and output layer
x(t)	Variable in differential equation
Y	target activation of the output layer
Y_l	Desired output vector

Subscript

R	number of elements in input

Greek letters

β_1, β2	first and second momentum parameter
δ_l	mean error corresponding to output layer
Δt	time step, [s]
η	learning rate
ρ_f	fluid density, [kg/m^3]

ABBREVIATIONS

ABSD	absolute standard deviation
ANN	artificial neural network
BP	back propagation
CHF	critical heat flux
COV	coefficient of variance
DA	dimensional analysis
GA	genetic algorithm
HRT	hydraulic retention time
IFBBR	inverse fluidized bed bioreactor
LM	Levenberg-Marquardt
MAE	mean absolute error
MLP	multi layer perceptron
MSE	mean square error
NN	neural network
NRBF	normalized radial basis function
RBF	radial basis function
RMSE	root mean square error
RSM	response surface methodology
SE	standard error
TBR	trickle bed reactor

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