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Evaluation for NDWCT Performance with Different Types of Packing Fills in Iraq Using ANN

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Abstract: *Artificial Neural Network (ANN) is used to predicate experimental results for Natural Draft Wet Cooling Tower (NDWCT) rig using Levenberg-Marquardt back propagation algorithm in MATLAP. The experimental tests are done in hot and dry weather (Iraqi weather as an example). ANN results show good agreements with experimental results where average correlation coefficient (R) for all results is (0.994), average root mean square errors (RMSE) are (5.99, 0.91, 0.24, 0.51, 0.49, 0.2, and 5.46), and average of mean ratio between the errors and the network output values (MRE) are (1.72%, 1.32%, 3.93%, 1.78%, 3.77%, 8.4%, and 1.05%) for relative humidity change, tower range, water to air mass flow ratio, cooling capacity, heat rejected to air, effectiveness, and air enthalpy change respectively.*
Keywords: *Cooling Tower, Packing Fill, Natural Draft, Artificial Neural Network, Back Propagation.*

I. Introduction

ANN recently growing areas of artificial intelligence and it is started to be used in cooling tower area because of it is ability to deal with many inlet and outlet parameters while their relations are linear or nonlinear. ANN usually used as a part of Excel or MATLAP programs depend on complicity and programmers experiences. One of the main important features of ANN is its Ability to learn. Learning or training algorithms can be categorized into supervised training and unsupervised training. Supervised training uses pairing of both input vector with a target vector which represents the desired output. So, this training required a teacher. Unsupervised training is employed in self-organizing neural nets. Unsupervised training does not require a teacher, **Sivanandam, [1].** Figure (1) shows the supervised and unsupervised training. Seven learning rules are tabulated and compared in terms of the single weight adjustment formulas, supervised versus unsupervised learning mode, weight initialization, and required neuron activation function. Learning rules are: Delta, Perceptron, Hebbian, Widro-Hoff, Correlation, Winner-take-all, and Outstar, **Zurada, [2]**.

ANN is widely used in many engineering fields, in this survey will focus on its use in NDWCT only. **Gao et al., [3]**, experimentally studied the performance of natural draft counter-flow wet cooling in terms of heat transfer for cases with cross-wind conditions. It is concluded experimentally that ΔT and η are influenced by the cross-wind, and ΔT and η can decrease by 6% and 5%, respectively. When the critical (Fr) number is less than 0.174 (wind velocity = 0.45 m/s), ΔT and η decrease with increasing cross-wind velocity, and when it is greater than 0.174, ΔT and η increase with increasing cross-wind velocity, ANN is used in this research to predicate experimental results. **Gao et al., [4]**, applied and developed ANN model for prediction of thermal performance on natural draft wet cooling towers using five, six, three nodes at input, hidden , and output layers. The nodes were dry bulb temperature of inlet air, wet-bulb temperature, circulating water inlet temperature, circulating water inlet mass flow rate and inlet wind velocity and output layer included circulating water outlet temperature, temperature difference and cooling efficiency coefficient. The correlation coefficient (R) and mean square error (MSE) are used to measure the performance of ANN model where the correlation coefficient in the range of 0.993–0.999, and the MSE values for the ANN training and predictions were very low relative to the range of the experiments. **Jiasheng et al., [5]**, used artificial neural network (ANN) technique. Huge data required for training and predication so extensive field experimental work has been carried out. Tangent sigmoid transfer function at hidden layer used with ANN model where eleven nodes and a linear transfer function at output layer with back-propagation (BP) training technique. The predictions have good agreement with the experimental values with a satisfactory correlation coefficient in the range of (0.9249–0.9988), the absolute fraction of variance in the range of (0.8753–0.9976), and the mean relative error in the range of (0.0008–0.54%). **Gao et al., [6]**. Developed a three-layer back propagation (BP) network model which has one hidden layer based on the level Froude number (Frl), and four, eight, six nodes at input, hidden, and output layer respectively. The results were MRE and R in the range of (0.48%-3.92%) and (0.992-0.999), respectively, and RMSE values for the ANN training and predictions were very low relative to the range of the experiments.

In this research, Levenberg-Marquardt back propagation used to predicate NDWCT experimental results which are validated firstly by direct comparison and secondly using R, MRE, and RMSE. A software package for Artificial Neural Network using MATLAP is used to exam experimental results with Delta learning rule. ANN structure including (I×H×O) which represent input, hidden, and output layer respectively. Eight neurons are used as input and seven neurons as output where hidden neurons are varied according different theories

II. Experimental and Artificial Neural Network

[7], describes experimental work and results recorded from experimental test rig which is shown in figure (2) to evaluate and compare three types of packing fills namely splash, honey cell, and trickle fill where results show that trickle fill has better heat performance that other fills.

Levenberg-Marquardt back propagation algorithm is used to predicate experimental results because it has better convergence properties than the conventional back propagation method but required higher storage capacity. ANN with three layers constructed from eight, ten, and seven neurons at input, output, and hidden layers respectively as shown in figures (3) and (4). The total operation will early stop if error reaches to (1*10-7) or it will continue till (1000 iterations) which represent an optimum number using Levenberg-Marquardt back propagation algorithm. Data divided automatically and randomly into (70%) for training ANN, (15%) for validation, and the rest (15%) for testing samples. Working by ANN required many tests and huge number of data to achieve network training. Huge experimental results are recorded from rig by changing water mass flow rate six times, cross wind velocity five times, **[8]**, three type of fills, and four different thicknesses. These results are divided as followed.

1 Data collected for different thickness of honey cell fill to study increasing water flow rate effects.
2 Data collected for different thickness of honey cell fill to study effect of cross wind velocity.
3 Data collected for different thickness of splash fill to study increasing water flow rate effects.
4 Data collected for different thickness of splash fill to study effect of cross wind velocity.
5 Data collected for (5) cm thickness of honey cell, splash, and trickle fills to study increasing water flow rate effects.
6 Data collected for (5) cm thickness of honey cell, splash, and trickle fills to study effect of cross wind velocity.
7 Data collected for (10) cm thickness of honey cell, splash, and trickle fills to study increasing water flow rate effects.
8 Data collected for (10) cm thickness of honey cell, splash, and trickle fills to study effect of cross wind velocity.

Validation of all results can be shown by comparison between experimental results and predicated results using ANN by direct comparison between exact and predicated results or by checking R, MRE, RMSE values where exact solution if (R=1) and good agreeing if approach to (1) while approaching to (-1) means that results are not valid, The less MRE is the better fit predicted results are, and (RMSE) better fit when its value approaches to zero. First path needs to draw experimental with predicated results together as in figures (5) to (24). Second path can give all results together in one package as in figure (25).

III. Results validation

Number of hidden nodes in hidden layer are determined by many theories mentioned in detail at [2] which include different theories submitted by **Hecht-Nielson, [9], Xin, [10], Ding, [11], Xie, [12], Yao** and **Wang, [13]**. Applying these theories, a range of hidden numbers are found so eight to fifteen nodes are tested to find the best suitable number. Table (1) list correlation coefficient (R) values using different number of hidden nodes used to predicate (120) experimental results for honey cell type when water flow is changed from (0.8) to (2.4) gpm and it is found that best value is (Rall =0.99653) when 10 hidden nodes are used. Up on that ten hidden nodes will be used to predicate all results in this research.

Validation of predicated and experimental results will be determined by the use of MRE, RMSE, and R where:

$$MRE(\%) = \frac{1}{N}\sum_{i=1}^{N}\left|100\frac{a_i - b_i}{a_i}\right| \qquad \text{……………..} (1)$$

MRE, shows the mean ratio between the error and the network output values, **Hosoz et al., [14].**

(ai and bi) represent experimental and network output values, respectively. (N) Represents the sample number.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(a_i - b_i)^2} \qquad \text{……………..} (2)$$

Root mean square error (RMSE), better fit when its value approaches to zero. **Gao et al., [1, 2]**.

$$R = \frac{\mathrm{cov(a, b)}}{\sqrt{\mathrm{cov(a, a).cov(b, b)}}} \qquad \text{……………..} (3)$$

IV. Results predication using ANN

Eight inputs are used {water flow rate (Liter/min), air inlet temperature (˚C), inlet air relative humidity (%), inlet water temperature (˚C), fill thickness (cm), wind velocity (m/s), air velocity at outlet (m/s), and pressure difference (mm water)} and seven outlets {change in relative humidity (%), range (˚C), water to air mass flow rate ratio, cooling capacity (kW), heat transfer to air (kW), effectiveness (%), and air enthalpy change (kJ/kg)}.

Table (2) list RMSE and MRE for each case as mentioned before. Table shows that maximum RMSE between predicated and experimental results are (15.25, 4.203, 0.475, 1.508, 0.801, 0.458, and 9.663) found at cases (5, 5, 1, 5, 4, 8, and 3) and minimum values are (2.288, 0.0183, 0.002, 0.014, 0.272, 0.016, and 0.846) found at cases (2, 7, 2, 7, 3, 3, and 5) for relative humidity change, tower range, water to air mass flow rate ratio, cooling capacity, heat rejected to air, effectiveness, and enthalpy change respectively. Maximum and minimum values of MRE as followed (8.010%, 5.953%, 22.642%, 5.687%, 11.503%, 28.714% and 1.847%) for cases (5, 5, 4, 5, 8, 8, and 3) and (0.235%, 0.005%, 0.108%, 0.457%, 0.332%, 0.352%, and 0.320%) for cases (1, 8, 2, 6, 3, 3, and 5) respectively. Correlation coefficient (R) Values for 8 cases are listed in table (3) where (Rall) values (all means total predicated results for each case including results used for training, validation, and test) are (0.99653, 0.99562, 0.99397, 0.99548, 0.99201, 0.994, 0.9907, and 0.99445). Remembering that R approach to (+1) means agreed relation between predicated and experimental results where (R) approach to (-1) means reverse relation and R approach to zero mean no relation between them. Better results (R= 0.99653) found in case one and less one is found at case seven (R=0.9907). Figure (25) shows relations between experimental (target) and predicated (output) results using ANN for eight cases. Best relation between experimental and predicated results are listed in table (4).

V. Conclusions

1 Using Artificial Neural Network shows a very good matching with experimental results which can be expressed by direct comparison or using R, MRE, and RMSE.

2 Best R, MRE, and RMSE are (0.99653, 0.005%, and 0.002) recorded at cases 1, 8, and 2 respectively.

3 ANN can be used to find best fit relation for predicated (output) and experimental (target) results, the best relation is (output= target+0.019) found at case (8).

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Table (1) List regressions values using different hidden number of nodes to predicate results using honey cell fill.

No. of hidden nodes	R Training	R Validation	R Tests	R All
8	0.99397	0.99021	0.98514	0.99179
9	0.99687	0.98871	0.98682	0.99412
10	0.99866	0.9923	0.9896	**0.99653**
11	0.99775	0.99442	0.99269	0.99626
12	0.9989	0.99199	0.99014	0.99592
13	0.99333	0.98677	0.98906	0.99151
14	0.99529	0.99058	0.99457	0.99379
15	0.99622	0.99296	0.99461	0.99533

Table (2) List RMSE and MRE for eight cases and seven parameters using ANN

Parameter type / Result type		ΔRH %	ΔT_w °C	$\dot{m}_w/\dot{m}_a$	ΔQ_w kW	ΔQ_a kW	η %	Δi kJ/kg
1	RMSE	4.179	0.021	0.475	0.255	0.317	0.178	4.760
	MRE	0.235%	0.466%	1.723%	1.958%	2.890%	5.401%	0.517%
2	RMSE	2.289	1.149	0.002	0.693	0.747	0.038	6.930
	MRE	0.365%	1.424%	0.108%	2.276%	2.137%	7.850%	1.720%
3	RMSE	11.400	0.120	0.078	0.354	0.272	0.016	9.664
	MRE	2.198%	0.024%	0.567%	0.629%	0.332%	0.352%	1.847%
4	RMSE	5.458	1.543	0.346	0.137	0.801	0.162	8.703
	MRE	1.227%	2.341%	22.64%	1.382%	7.181%	5.820%	1.652%
5	RMSE	15.256	4.203	0.007	1.508	0.741	0.394	0.846
	MRE	8.010%	5.953%	0.358%	5.687%	2.869%	3.809%	0.320%
6	RMSE	2.395	0.055	0.423	0.524	0.406	0.214	2.356
	MRE	0.666%	0.320%	2.362%	0.457%	0.457%	2.060%	0.475%
7	RMSE	3.459	0.018	0.402	0.014	0.311	0.173	3.816
	MRE	0.794%	0.023%	2.393%	1.159%	2.806%	13.15%	1.140%
8	RMSE	3.487	0.152	0.193	0.605	0.344	0.458	6.604
	MRE	0.274%	0.005%	1.310%	0.706%	11.50%	28.71%	0.710%

Table (3) List correlation coefficient values for eight cases.

Correlation coefficient / Case number	R Training	R Validation	R Tests	R All
1	0.99866	0.9923	0.9896	0.99653
2	0.99853	0.99221	0.98705	0.99562
3	0.99782	0.99153	0.9771	0.99397
4	0.99642	0.99177	0.99597	0.99548
5	0.9918	0.99665	0.98836	0.99201
6	0.99823	0.99378	0.97748	0.994
7	0.99916	0.99446	0.94695	0.9907
8	0.9969	0.99469	0.98963	0.99445

Table (4) List best relation between experimental and predicated values

Case number	Fit relation for all results
1	Output= 0.98*target+0.12
2	Output= 0.99*target+0.16
3	Output= 0.97*target+0.24
4	Output= 0.98*target+0.078
5	Output= 0.94*target+0.32
6	Output= 0.99*target+0.18
7	Output= 0.99*target+0.28
8	Output= target+0.019

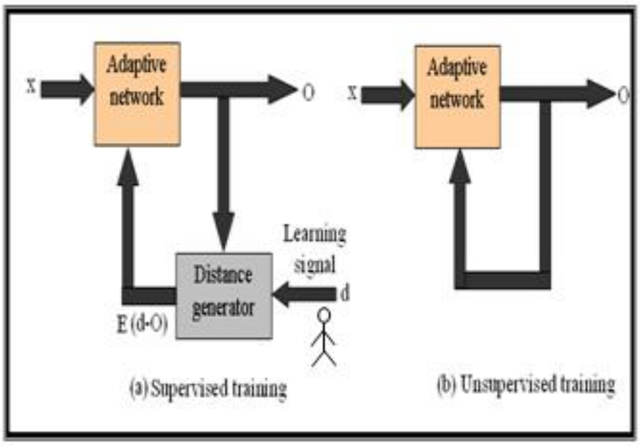


Fig. (1) Block diagram of basic learning modes, **[6].**

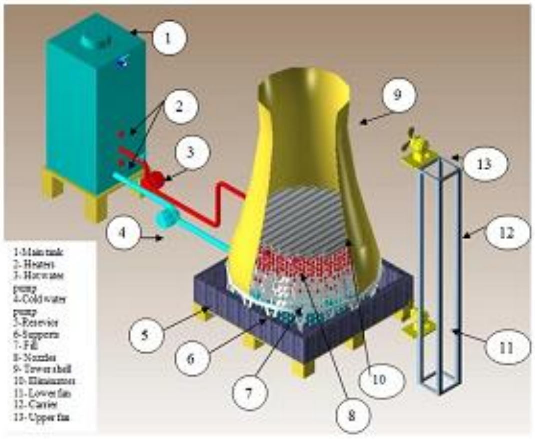


Fig. (2) Experimental rig, **[15]**.

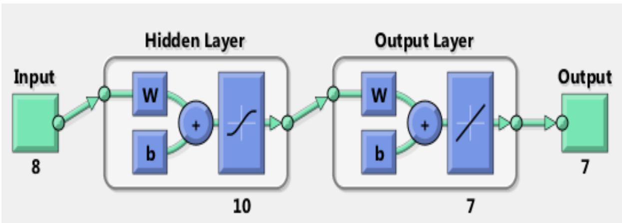


Fig. (3) Schematic diagram for sigmoid hidden neurons and linear output neurons using 10, 7, and 8 neurons at input, hidden, and output layers respectively.

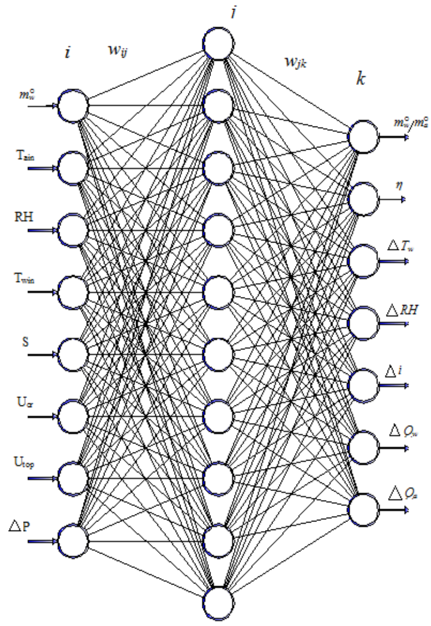


Fig. (4) Structure of ANN used to model experimental tests.

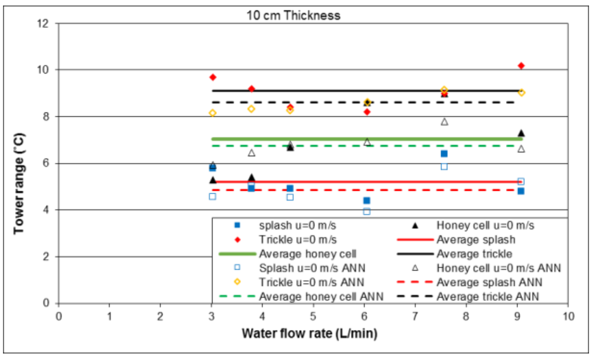


Fig. (5) Tower range due to water mass flow rate change for different fill types, (u=0 m/s), (experimental and ANN).

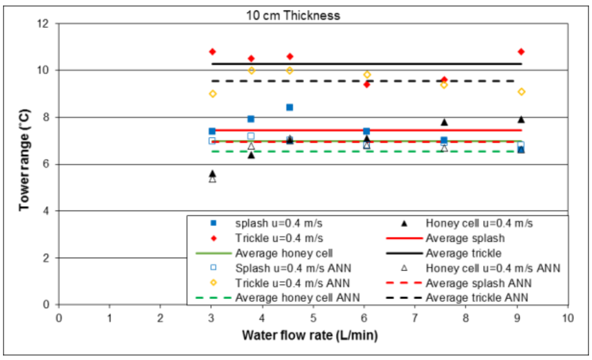


Fig. (6) Tower range due to water mass flow rate change for different fill types, (u=0.4 m/s), (experimental and ANN).

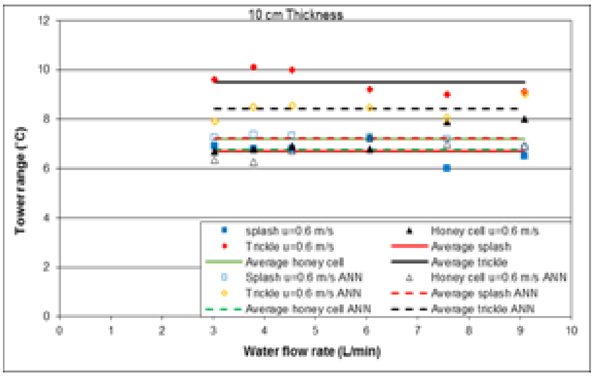


Fig. (7) Tower range due to water mass flow rate change for different fill types, (u=0.6 m/s), (experimental and ANN).

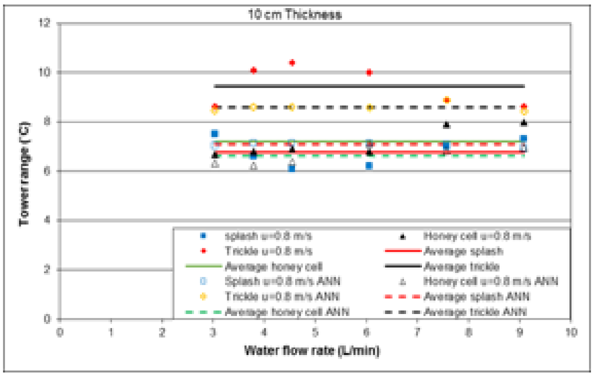


Fig. (8) Tower range due to water mass flow rate change for different fill types, (u=0.8 m/s), (experimental and ANN).

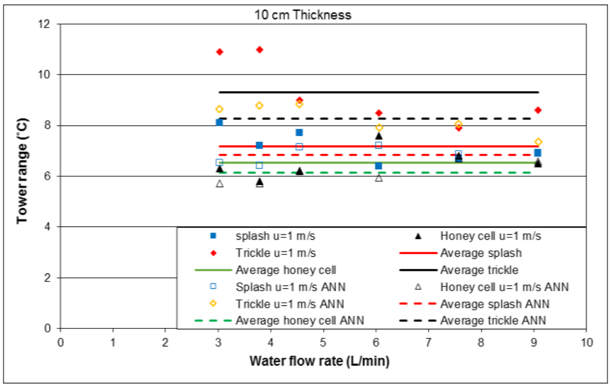


Fig. (9) Tower range due to water mass flow rate change for different fill types, (u=1 m/s), (experimental and ANN).

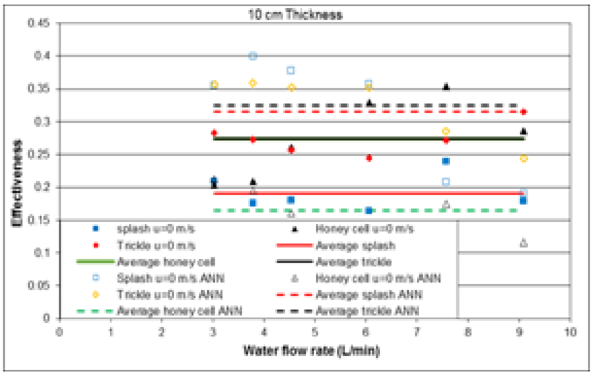


Fig. (10) Effectiveness due to water mass flow rate change for different fill types, (u=0 m/s), (experimental and ANN).

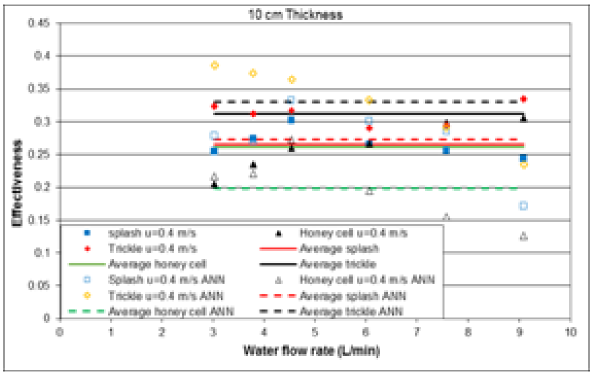


Fig. (11) Effectiveness due to water mass flow rate change for different fill types, (u=0.4 m/s), (experimental and ANN).

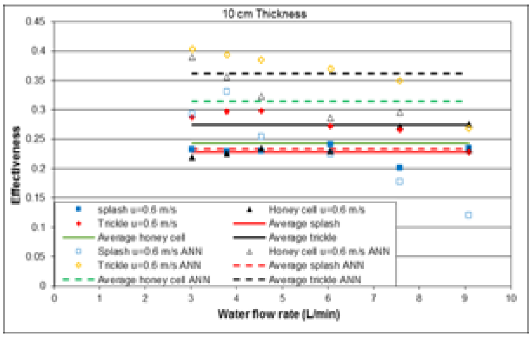


Fig. (12) Effectiveness due to water mass flow rate change for different fill types, (u=0.6 m/s), (experimental and ANN).

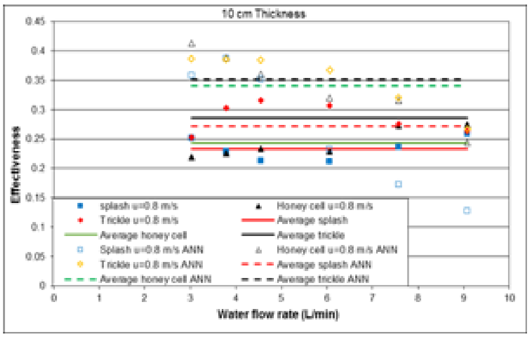


Fig. (13) Effectiveness due to water mass flow rate change for different fill types, (u=0.8 m/s), (experimental and ANN).

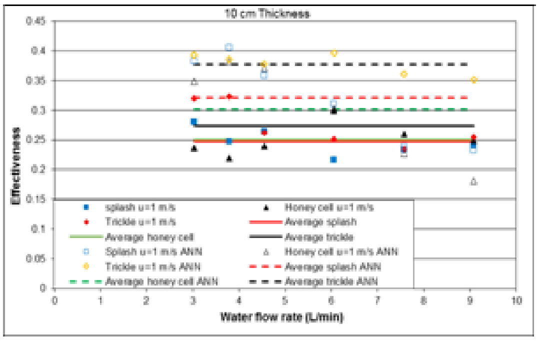


Fig. (14) Effectiveness due to water mass flow rate change for different fill types, (u=1 m/s), (experimental and ANN).

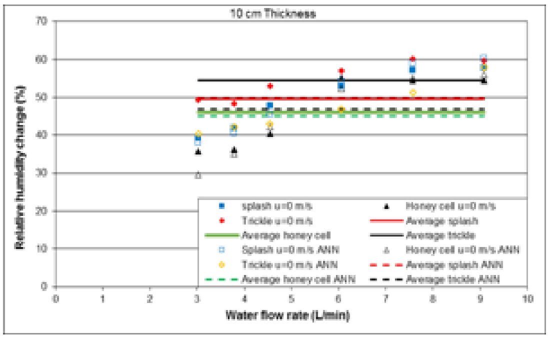


Fig. (15) Air relative humidity change due to water mass flow rate change for different fill types, (u=0 m/s), (experimental and ANN).

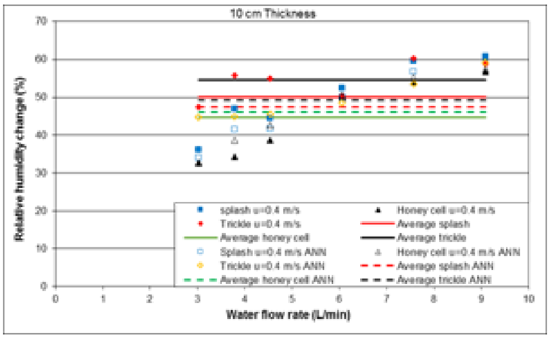


Fig. (16) Air relative humidity change due to water mass flow rate change for different fill types, (u=0.4 m/s), (experimental and ANN).

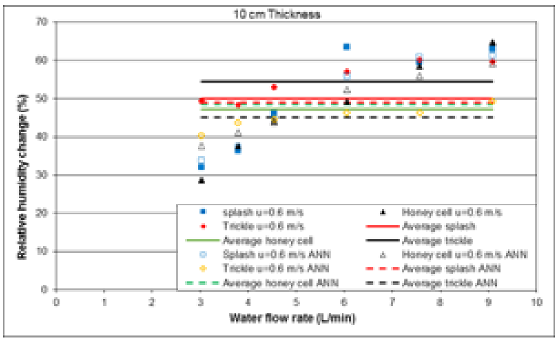


Fig. (17) Air relative humidity change due to water mass flow rate change for different fill types, (u=0.6 m/s), (experimental and ANN).

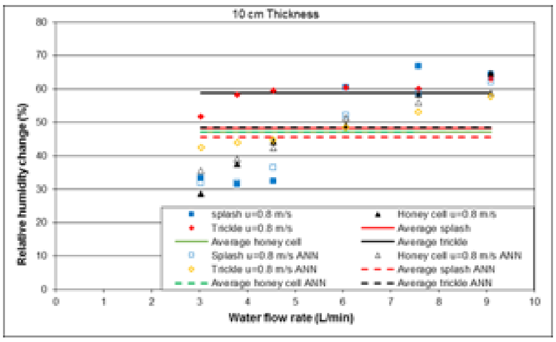


Fig. (18) Air relative humidity change due to water mass flow rate change for different fill types, (u=0.8 m/s), (experimental and ANN).

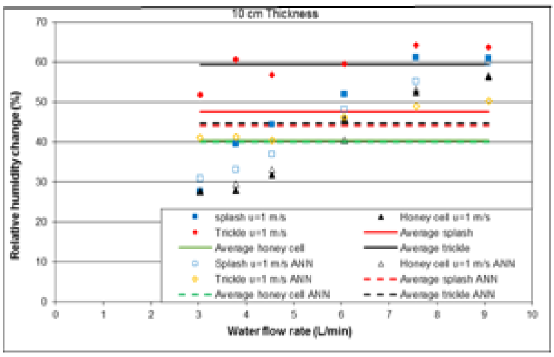


Fig. (19) Air relative humidity change due to water mass flow rate change for different fill types, (u=1 m/s), (experimental and ANN).

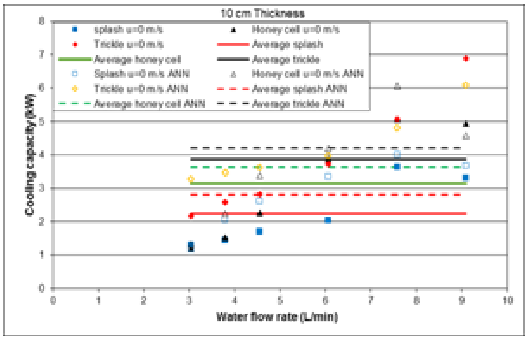


Fig. (20) Cooling capacity due to water mass flow rate change for different fill types, (u=0 m/s), (experimental and ANN).

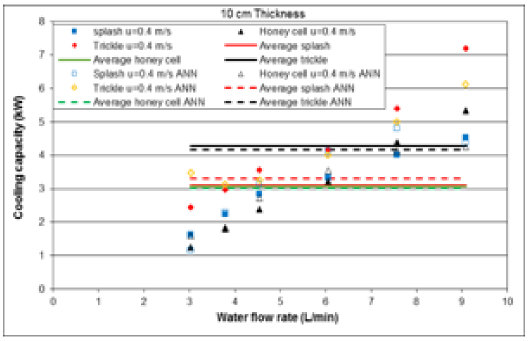


Fig. (21) Cooling capacity due to water mass flow rate change for different fill types, (u=0.4 m/s), (experimental and ANN).

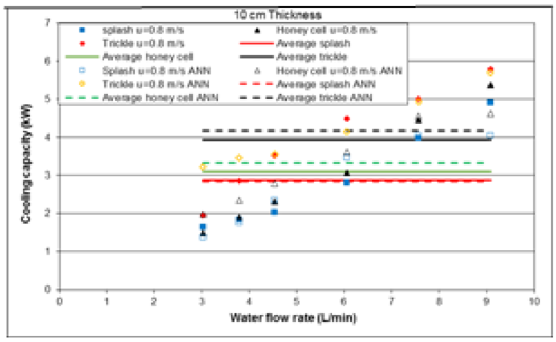


Fig. (22) Cooling capacity due to water mass flow rate change for different fill types, (u=0.6 m/s), (experimental and ANN).

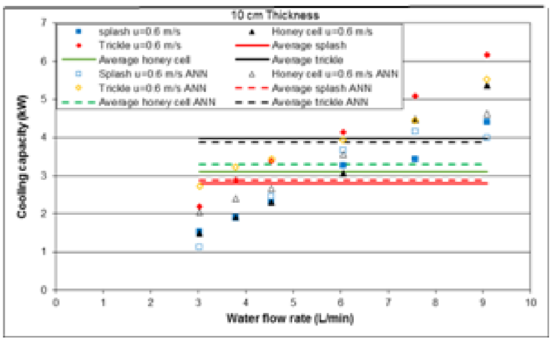


Fig. (23) Cooling capacity due to water mass flow rate change for different fill types, (u=0.8 m/s), (experimental and ANN).

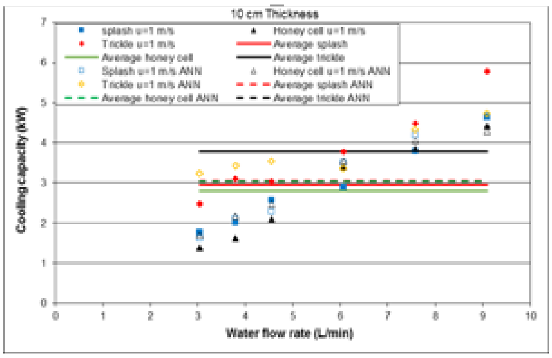
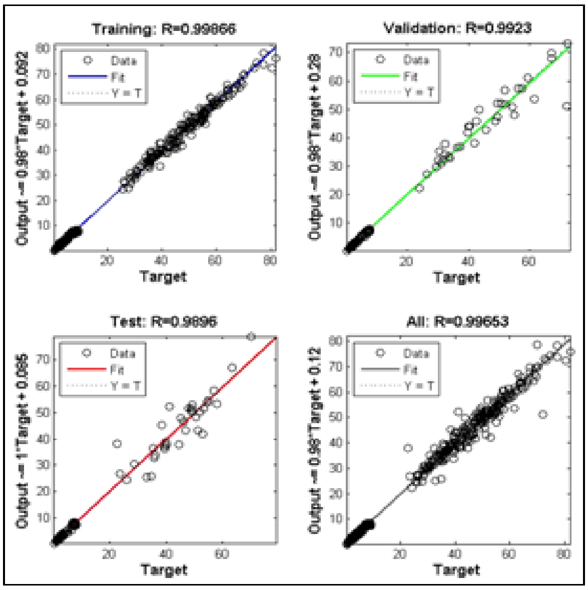
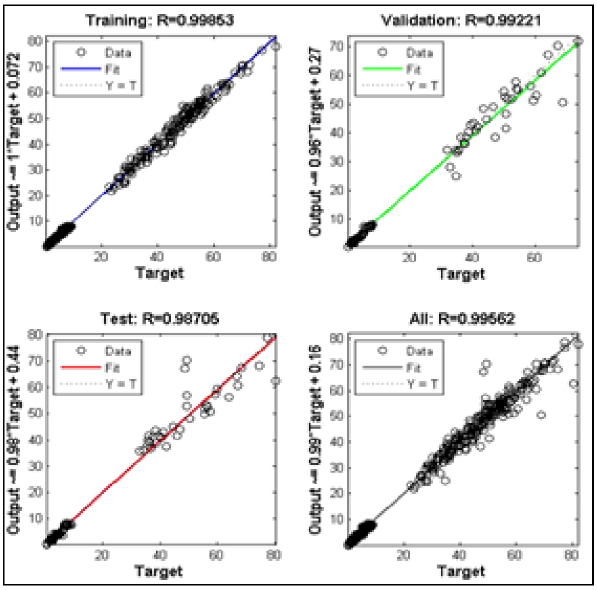


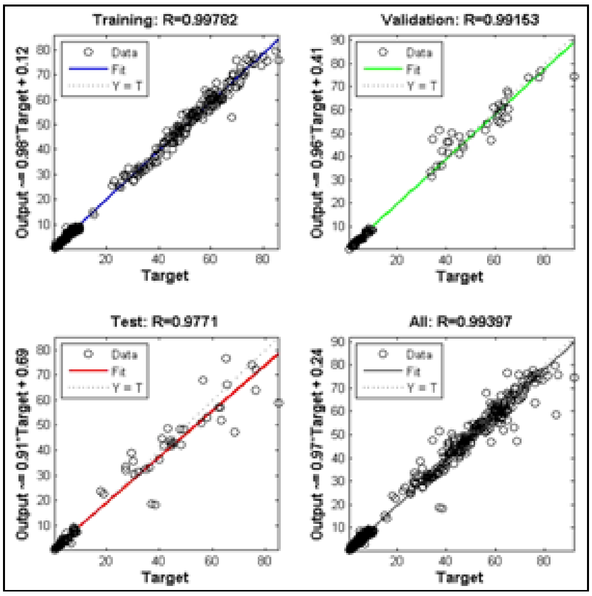
Fig. (24) Cooling capacity due to water mass flow rate change for different fill types, (u=1 m/s), (experimental and ANN).



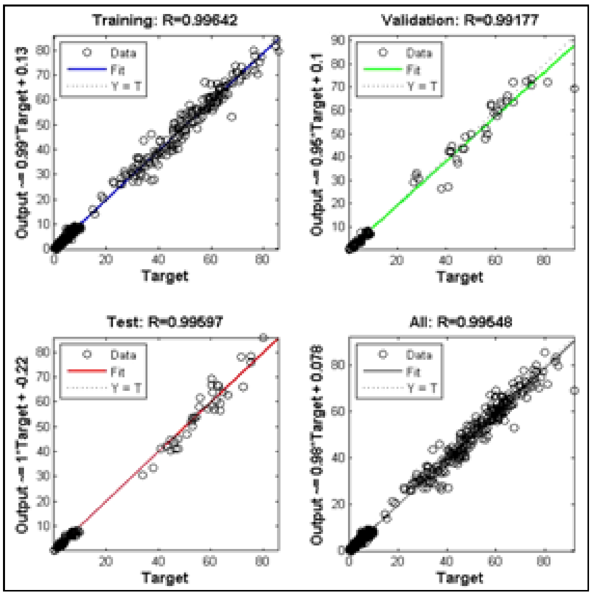
Case (1).



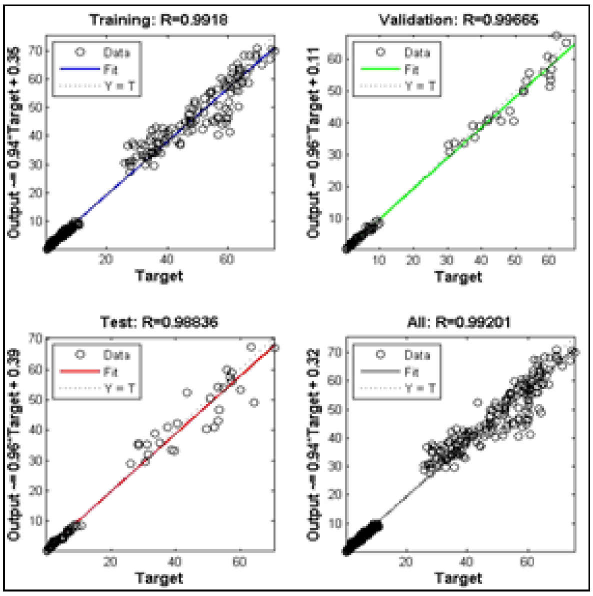
Case (2).



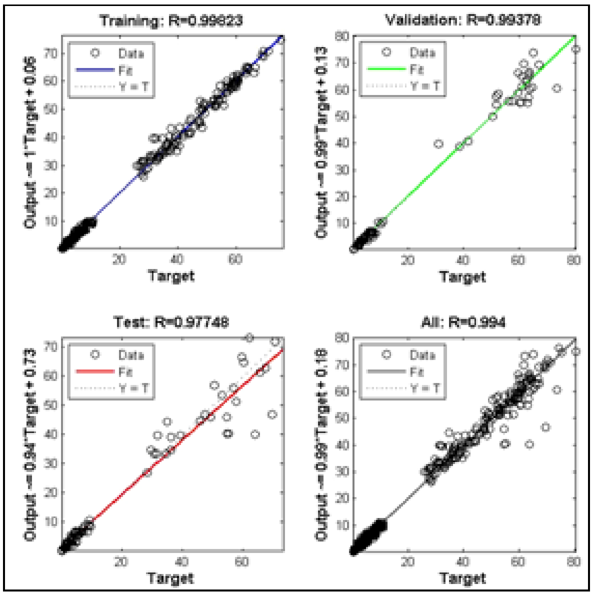
Case (3).



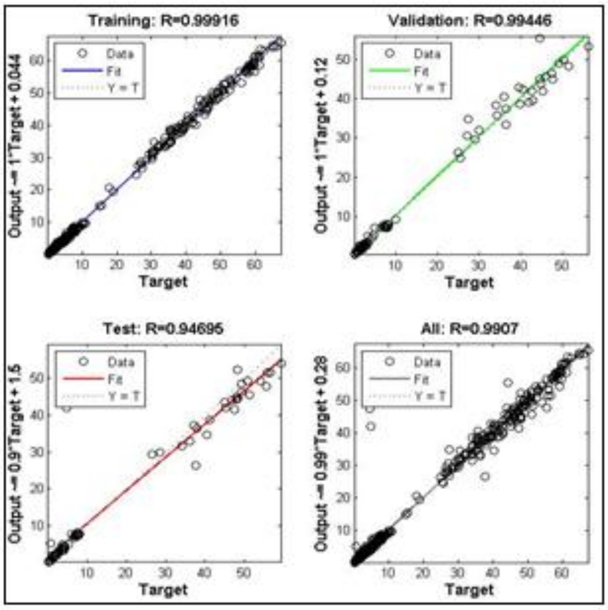
Case (4).



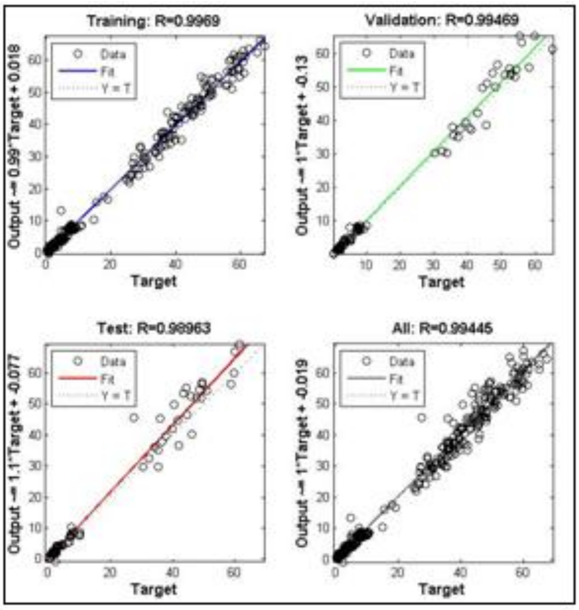
Case (5).



Case (6).



Case (7).



Case (8).

Figure (25) Experimental (target) and predicated (output) results using ANN for eight cases.