Neural Network – Comparing the Performances of the Training Functions for Predicting the Value of Specific Heat of Refrigerant in Vapor Absorption Refrigeration System

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ABSTRACT
The objective of this work is to compare performances of three training functions (TRAINBR, TRAINCGB and TRAINCGF) used for training neural network for predicting the value of the specific heat capacity of working fluid, LiBr-H_2O, used in vapour absorption refrigeration system. The comparison is shown on the basis of percentage relative error, coefficient of multiple determination R-square, root mean square error and sum of the square due to error.

Keywords: ANN (Artificial Neural Network), VAR (Vapour Absorption Refrigeration System),R^2 (Coefficient of multiple determination), LiBr-H_2O.

1. INTRODUCTION
Effective utilization of energy is very necessary in this decade due to rapidly increasing demand of energy [1-4]. Therefore, it is necessary that computation should be up to the highest accuracy for appropriate analysis of the performance of thermodynamic system [5-7]. But in modern technology era, computational intelligence is attracting researchers in engineering for solving various engineering calculation of non linear nature. Artificial neural network is vital tool for analyzing computational intelligence [9-17]. The success of modeling a neural network depends on the selection of the training function. In this work, authors are comparing the performance of three training functions TRAINBR, TRAINCGB and TRAINCGF on the basis of percentage relative error and coefficient of multiple determination R-square.

2. ARCHITECTURE OF NEURAL NETWORK
Among many types of neural networks, authors have designed the neural network as shown in the figure 1. In the neural network the simple processing element is called neuron. The neural network is structured with 10 neurons in input and 1 neuron in output layer. Our designed network is the feed forward type network which is powered by back propagation algorithm [9-17]. This algorithm is used by many researchers because of its successful applicability in much complex engineering problems. The activation function, log sigmoid, is used in the hidden layer mentioned in equation (1) and tansig function is used in output layer mentioned in equation (2).

2.1 Methodology
The two inputs parameters are vapor quality (x in percentage fraction) and temperature (t in ^{0}C) and one output parameter is specific heat capacity. The pattern set of training data and testing data is mentioned in table 1 [8].These analyses are performed in the MATLAB2008a educational environment. The range of temperature is 10-190 ^{0}C and the range of vapour quality is 5-75 %. Selected data is given to the network during the training session with one particular training function. After completion of the training, some set of data of experimental results is used to test the network for validating the network. Test data is not used in training session. The normalization is important due to the nature of log sigmoid training function [9-17]. Range of the data after normalization is [0.15 1].

3. RESULTS AND ANALYSIS
Firstly, the authors have trained the neural network using three training functions named TRAINBR, TRAINCBG and TRAINCGF and this training is continued up till the least value of mse (mean square error) at definite value of epochs which has been represented in figure 1, 2 and 3 respectively are attained. Table 2 shows the comparison between the values from the experiment [8] to the values obtained from the networks using three different training functions. In table 3, authors have calculated the percentage relative error of the values obtained from the neural network test data session, for validating the training functions [9-17]. The validation of the training function is also based on the value of coefficient of multiple determinations R-square [9-17]. Function TRAINBR has achieved the value of R^2 almost closest to unity as shown in figure 4, while TRAINCBG and TRAINCGF have achieved the values 0.9937 and 0.9626 respectively with inferior performance than TRAINBR as shown in Figure 5 and 6. Moreover, the values of SSME, Adjusted R^2 and RSME are presented in Table 4. After analyzing all results TRAINBR function has shown better performance as compared to other two training functions which have been taken in this modeling.

Table 1: Experimental data used for modeling of artficial neural network.

x% Vapour Quality

t(^{O}C)	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75
10	3.845	3.563	3.304	3.065	2.844	2.640	2.455	2.291	2.123	1.961	1.797	-	-	-	-
20	3.852	3.579	3.329	3.097	2.882	2.685	2.506	2.347	2.208	2.077	1.925	1.764	-	-	-
30	3.865	3.602	3.360	3.135	2.926	2.734	2.559	2.404	2.267	2.140	2.01	1.860	-	-	-
40	3.873	3.616	3.379	3.158	2.952	2.762	2.589	2.434	2.297	2.170	2.040	1.896	-	-	-
50	3.881	3.628	3.396	3.179	2.976	2.788	2.616	2.462	2.324	2.196	2.065	1.923	1.768	-	-
60	3.887	3.638	3.408	3.193	2.993	2.803	2.632	2.477	2.341	2.208	2.077	1.936	1.782	-	-
70	3.892	3.643	3.412	3.194	2.991	2.801	2.627	2.468	2.325	2.190	2.055	1.908	1.751	-	-
80	3.904	3.659	3.432	3.218	3.018	2.831	2.659	2.502	2.360	2.223	2.089	1.948	1.790	-	-
90	3.914	3.667	3.438	3.221	3.019	2.829	2.653	2.493	2.348	2.212	2.074	1.927	1.769	-	-
100	3.928	3.682	3.452	3.236	3.032	2.842	2.666	2.506	2.358	2.221	2.084	1.936	1.780	-	-
110	3.945	3.696	3.466	3.249	3.051	2.856	2.678	2.519	2.370	2.233	2.095	1.949	1.792	1.629	-
120	3.964	3.717	3.487	3.272	3.066	2.879	2.703	2.543	2.396	2.261	2.120	1.975	1.824	1.660	-
130	3.982	3.731	3.508	3.280	3.087	2.897	2.720	2.556	2.405	2.256	2.115	1.968	1.817	1.654	-
140	4.000	3.750	3.515	3.294	3.086	2.893	2.714	2.552	2.403	2.263	2.124	1.980	1.829	1.668	1.511
150	4.023	3.770	3.533	3.309	3.101	2.905	2.726	2.562	2.412	2.273	2.135	1.991	1.841	1.684	1.527
160	4.051	3.792	3.554	3.329	3.119	2.924	2.743	2.579	2.431	2.294	2.158	2.016	1.867	1.717	1.563
170	4.077	3.817	3.572	3.341	3.128	2.930	2.747	2.583	2.432	2.292	2.156	2.015	1.868	1.715	1.563
180	4.111	3.842	3.595	3.359	3.143	2.942	2.758	2.592	2.442	2.303	2.168	2.027	1.883	1.732	1.582
190	4.149	3.876	3.619	3.381	3.158	2.955	2.770	2.603	2.452	2.314	2.179	2.040	1.898	1.749	1.602

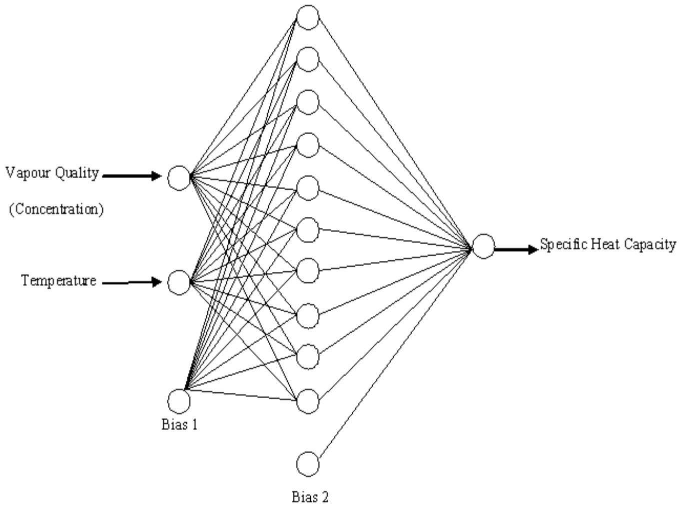

Figure 1 : Architecture of Neural Network

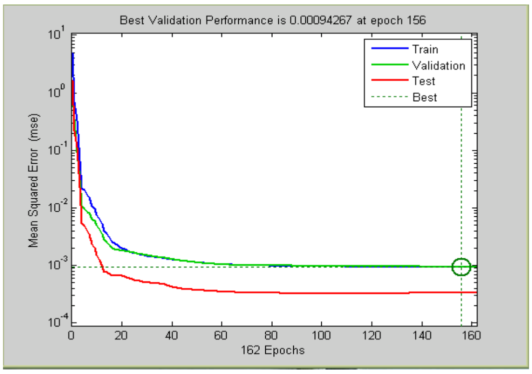

Figure 2: Training behavior of function TRAINBR during training.

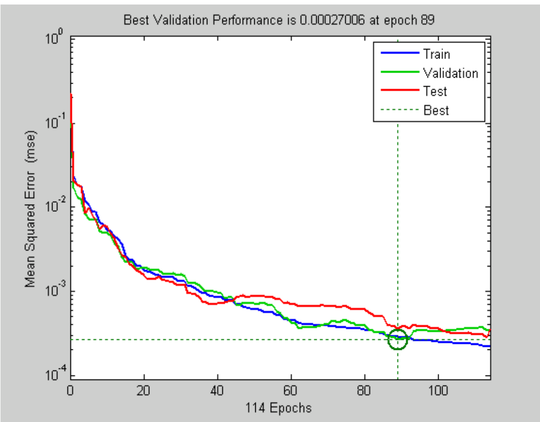

Figure 3: Training behavior of function TRAINCBG during training

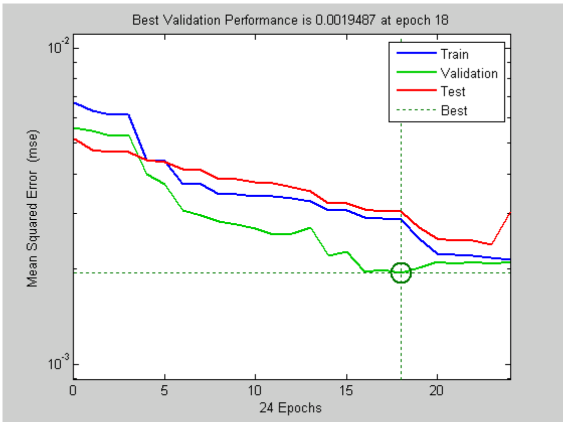

Figure 4: Training behavior of function TRAINCGF during training

Table 2: Comparative values of specific heat capacity by two ANN training functions with the experimental values.

x (wt%)	Temperature (^{0}C)	Values from Experiment[8]	Values from TRAINBR	Values from TRAINCBG	Values from TRAINCGF
5	80	3.904	3.9066	3.8492	3.7573
10	130	3.731	3.7341	3.7716	3.7455
15	140	3.515	3.51	3.5277	3.5329
20	150	3.309	3.3101	3.2403	3.406
25	170	3.128	3.1335	3.0457	2.9141
30	90	2.829	2.8331	2.8523	2.6109
35	20	2.506	2.5193	2.6162	2.4191
40	100	2.468	2.4843	2.4697	2.5466
45	60	2.341	2.3316	2.2338	2.4948
50	100	2.221	2.2205	2.1832	2.4601
55	90	2.074	2.0796	2.1081	2.2757
60	110	1.949	1.9495	2.0274	1.9508
65	120	1.824	1.8058	1.8257	1.6069
70	150	1.684	1.6823	1.6339	1.5166
75	160	1.563	1.5641	1.543	1.511

Table 3: Comparative % relative error of specific heat capacity by two ANN training functions with the experimental values.

x (wt%)	Temperature (^{0}C)	Values from Experiment[8]	% Relative Error (TRAINBR)	% Relative Error (TRAINCBG)	% Relative Error (TRAINCGF)
5	80	3.904	-0.0666	+1.4037	+3.7577
10	130	3.731	-0.0831	-1.0881	-0.0389
15	140	3.515	+0.1422	-0.3613	-0.5093
20	150	3.309	-0.0332	+2.0761	-2.9314
25	170	3.128	-0.1758	+2.6310	+6.8382
30	90	2.829	-0.1449	-0.8236	+7.7094
35	20	2.506	-0.5307	-4.3975	+3.4677
40	100	2.468	-0.6604	-0.0689	-3.1847
45	60	2.341	+0.4015	+4.5792	-6.5698
50	100	2.221	+0.0225	+1.7019	-10.7694
55	90	2.074	-0.2700	-1.6441	-9.7252
60	110	1.949	-0.0257	-4.0226	-0.0924
65	120	1.824	+0.9978	-0.0932	+11.9024
70	150	1.684	+0.1010	+2.9751	+9.9406
75	160	1.563	-0.07038	+1.2795	+3.3269

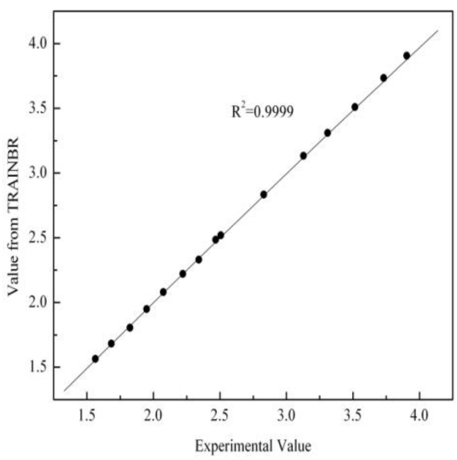

Figure 5: Regression Analysis for TRAINBR.

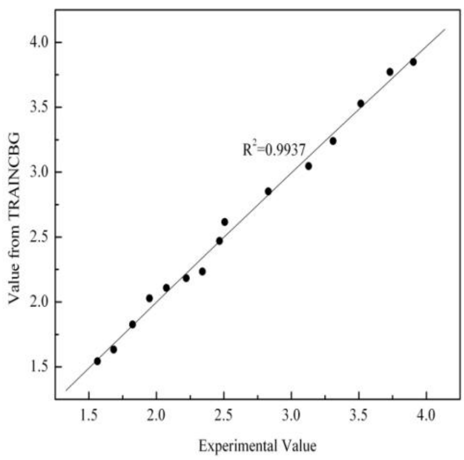

Figure 6: Regression Analysis for TRAINCBG.

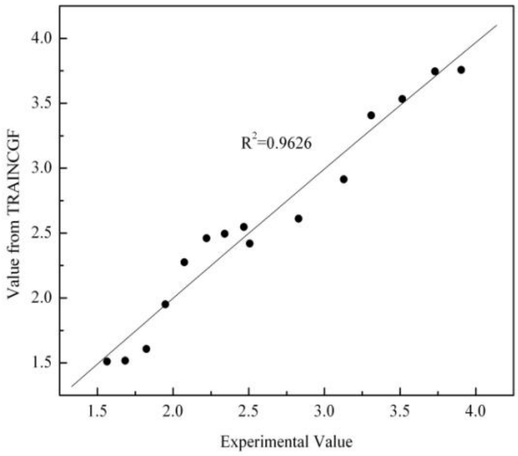

Figure 7: Regression Analysis for TRAINCGF.

Table 4: List of various errors obtained from training function test with the trained network.

Training Function	SSME	Adjusted R^2	RMSE
TRAINBR	0.0008295	0.9999	0.008314
TRAINCBG	0.05015	0.9927	0.06465
TRAINCGF	0.3067	0.9564	0.1599

4. CONCLUSION & FUTURE SCOPE

The training function TRAINBR is the most suitable training function with the experimental data of specific heat capacity among the three functions which has been chosen for the analyses. This work can help researchers in the selection of training function during the modeling of the neural network for any other energy or exergy analyses.

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