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Development of Neural Networks for Enhancement of Thermal Energy Storage using Phase Change Material

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Abstract

Three Artificial Neural Network models (Feedforward, Elman, and Nonlinear Autoregressive Exogenous (NARX) networks) were used to find the performance of a thermal energy storage system with and without a phase change material. Previously obtained experimental data was used to train the neural network. Time, mass of water, mass flow rate, number of balls containing the PCM, hourly solar radiation, ambient temperature and inlet water temperature were used in the input layer of the network. The outlet water temperature was in the output layer.

The obtained results were verified against previously obtained experimental data. It was found that Artificial Neural Network technique could be used to estimate the outlet temperature with excellent accuracy with the coefficient of determination of Elman, feedforward and NARX models were found to be 0.95006, 0.99411 and 0.88185, respectively. The obtained results showed that feedforward model had the best ability to estimate the required performance, while NARX and Elman network had the lowest ability to estimate it.

Keywords: *Thermal energy storage, Phase change material, Artificial Neural Network, Elman, NARX, Feedforward.*

1. Introduction

Being time-dependent, as well as having an unsteady characteristic through the day, solar energy, although it is obviously powerful, but could not be considered a reliable permanent source of energy. In other words, solar energy could not be considered a perfect replacement for the usage of non-renewable sources of energy which are currently used in the field of residential water heating. Over the years, many researches have been working with the aim of enhancing the usage of solar energy, and coping with its unsteady nature .Some of which were concerned with an issue beyond improving the means of using solar energy; they were concerned with finding out means to store this energy, making it –somehow- more controllable and more usable. Undoubtedly, when something is to be stored, it needs a medium to be stored in. This applies also to storing solar energy as well, which is stored in our case as heat, i.e. latent and sensible. The medium to store solar energy as heat has been the theme for all the researches and studies related to solar energy storage, but, recent researches and studies indicated that a Phase Change Material (PCM) is the most appropriate medium to store heat.

The study of Hamid El Qarnia [1] about thermal behavior and performance of a solar latent heat storage unit, tested with three kinds of phase change materials as storage mediums, thermal behavior and performance have been studied theoretically, under the summer climatic conditions of Marrakech city. A mathematical model was developed and validated by comparing numerical results and experimental data. Anant Shukla et al. [2] summarized the investigation and analysis of thermal energy storage incorporating with and without PCM for use in solar water heaters. The relative studies are classified on the basis of type of collector and the types of storage used, i.e. sensible or latent. A thorough literature investigation into the use of phase change material (PCM) in solar water heating has been considered. It has been demonstrated that for a better thermal performance of solar water heater a phase change material with high latent heat and with large surface area for heat transfer is required.

Regin et. El., [3] studied the behavior of a packed bed latent heat thermal energy storage system. The packed bed is composed of spherical capsules filled with paraffin wax as PCM usable with a solar water heating system. The effects of mass flow rate and phase change temperature range on the thermal performance of the capsules of various radii have been investigated. The results indicate that for the proper modeling of performance of the system the phase change temperature

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range of the PCM must be accurately known, and should be taken into account; consequently they conclude that the complete solidification time is much longer compared to the melting time.

In the work of Benmansour et el., [4] a two-dimensional separate phases formulation is used to develop a numerical analysis of the transient response of a cylindrical packed bed thermal energy storage system, which is randomly packed with spheres having uniform sizes and encapsulated the paraffin wax as a phase change material (PCM), with air as a working fluid flowing through the bed. In their study a theoretical and experimental investigation was performed for phase change thermal energy storage unit using spherical capsules.

In order to improve hot water heat stores, Mehling et al. [5] presented a work, which included experimental results and numerical simulation of the system using an explicit finite difference method. Experiments and simulations were carried out using different cylindrical PCM modules. With only 1/16 of the volume of the store being phase change material (PCM), (3/16) of water at the top of the store was held warm for 50% to 200% longer and the average energy density was increased by 20% to 45%. Furthermore, this (3/16) of water was reheated by the heat from the module after being cooled down in only 20 minutes.

Thermal energy storage systems required for any engineering application must be carefully selected based on the performance of these systems; such performance is found experimentally however, this is too difficult due to various measurement and heat transfer processes. In order to simplify this, computer codes are used for the estimation of the performance of systems. The algorithms employed are usually complicated, involving the solution of complex equations and such programs usually require large computer power and need a considerable long computational time.

Instead artificial neural network (ANN) has been becoming increasingly popular in thermal engineering applications during the last decade. A number of studies have been introduced about using ANN in thermal applications [6-13].The main objective of this study is to investigate the ability of ANN to outlet temperature (Tout) of the thermal energy storage. The models to be used include nonlinear autoregressive exogenous model (NARX), Elman Network and feedforward network. The results obtained were tested against previously experimental results.

2. Experimental Study

A schematic diagram of the experimental setup is shown in Fig.1. It consists of three main parts: solar collectors, PCM container, and a water storage tank. Three south facing flat plate copper pipes solar collectors are fixed with a tilt angle of 30°. The collectors have ordinary single glass covers and black painted absorber plates. The dimensions of each collector are (170 x 73) cm. The collectors are connected to the main water supply and the hot water storage tank through pipes and valves to allow for closed loop operation.

A cubic galvanized steel storage tank with dimensions of (50 x 50 x 50) cm is used in this setup. A standard 90W circulation pump, with a maximum capacity of 10 L/min, is also available on the collectors-storage tank loop to enable forced circulation investigations.

Water flow meter was installed at the inlet of the solar collector. The flow rate can be controlled and measured using the flow meter and a valve. During this work copper constantan thermocouples (200-350 oC) were used to record the temperatures of both atmospheric and the water flowing through the system. The water temperature was recorded at both inlet and outlet of the collectors.

Having been heated up as it flows through the collectors, the hot water is introduced into an insulated cubic tank, which is used as a storage system. Within this tank the hot water heats up the domestic water. Initially the tank is filled up only with water whose inlet and outlet temperatures were recorded. Having reached a maximum and constant water temperatures, paraffin wax (PCM) contained in plastic spheres was introduced into the tank, consequently the quantity of the PCM may be controlled through the number of the spheres.

Thermal storage experimental data were carried out between 9.00 and 16.00 h of July 2009 and August 2009 under Jordan climate conditions and tests were carried out for 12 days. The data were originally collected to find the effect of introducing the PCM on the inlet and outlet water temperature as it flows through the collectors at an optimum mass flow rate.

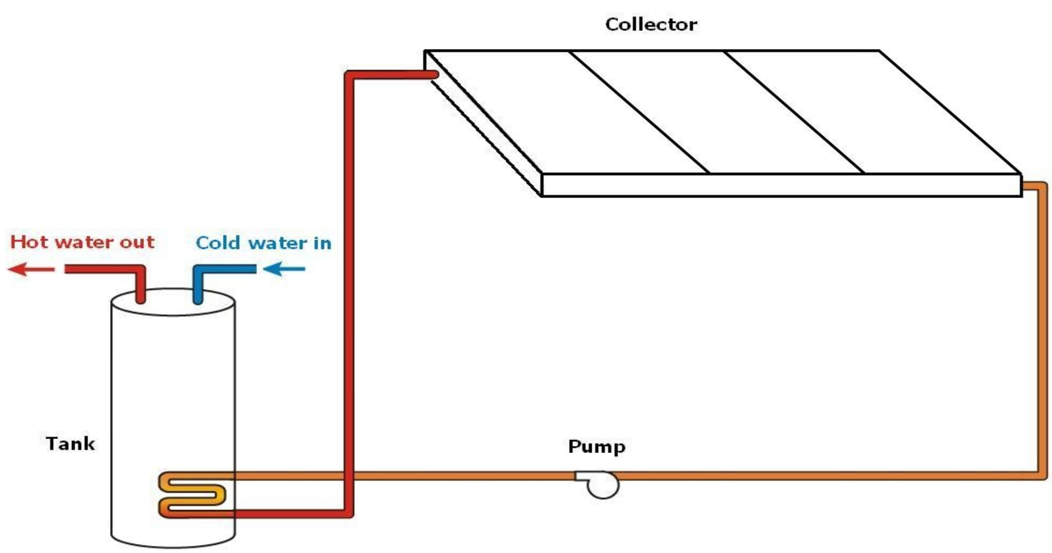


Figure 1: Experimental setup.

3. Artificial Neural Networks (ANN)

ANNs are commonly known as biologically inspired, highly sophisticated analytical techniques, being able to model extremely complex non-linear functions [15]. In general, they are composed of three layers, which are an input layer, some hidden layers, and an output layer [16]. Each layer can have many computational hidden nodes or neurons [17]. ANN has been used in a wide range of applications. These include pattern recognition, function approximation, Optimization, simulation, prediction, automatic, among many other application areas [18, Ref suggested].

To develop an ANN model, there is three steps must be followed. Firstly, the input is introduced with the desired output to the network together. Secondly, the network is trained to estimate the output in the training step. Finally, the testing step, in this step estimating output data are obtained by using the input data, which are not used in the training step. More details about these steps is found in [16].

In the current PCM storage application, the three layers network structure is shown in fig. 2. Seven inputs variables (time, mass of water (mw), flow rate (Q), number of balls (N), hourly solar radiation (Gt), ambient temperature (Ta), Inlet temperature (Tin)) are used in training three models of ANN network. One output variable is outlet temperature (Tout) of the thermal energy storage. The models to be used in the ANN include nonlinear autoregressive exogenous model (NARX), Elman and feedforward network. A brief introduction to the three neural network models to be used in this study is found in [19].

The aim of the below ANN is to estimate outlet temperature (Tout) of the thermal energy storage. Three types of ANN is constructed and tested by using MATLAB neural network module to solve this problem and to test the ability of each ANN to estimate outlet temperature (Tout) of the thermal energy storage. The performance of the proposed model has been carried out using three global statistics: coefficient of determination (R2), root mean squared error (RMSE) and mean bias error (MBE). More details about these parameters is found in [16].

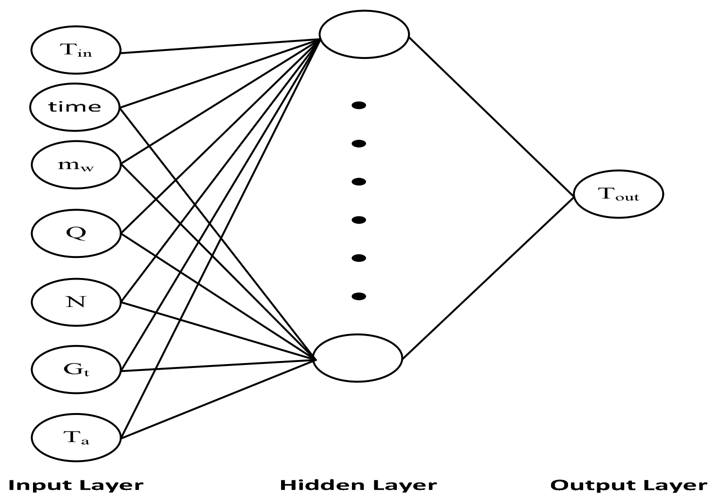


Figure 2: The architecture of ANN used for this study.

Three types of ANN network with neuron numbers (6, 10, 1) was constructed and tested within the MATLAB environment. Total data consists of 96 samples were obtained from previously experimental data is used as the input of ANN network. Totally, 40% of this data is used for training, 30% is used for validation and 30% is used for testing. In network, it was used RProp (trainrp) algorithm function. The number of the hidden layer was selected as 10 in this study after many trails and errors. Tangent sigmoid function was applied for the hidden layer, and linear transfer function is used in the output layer.

Table 1: Training Parameters

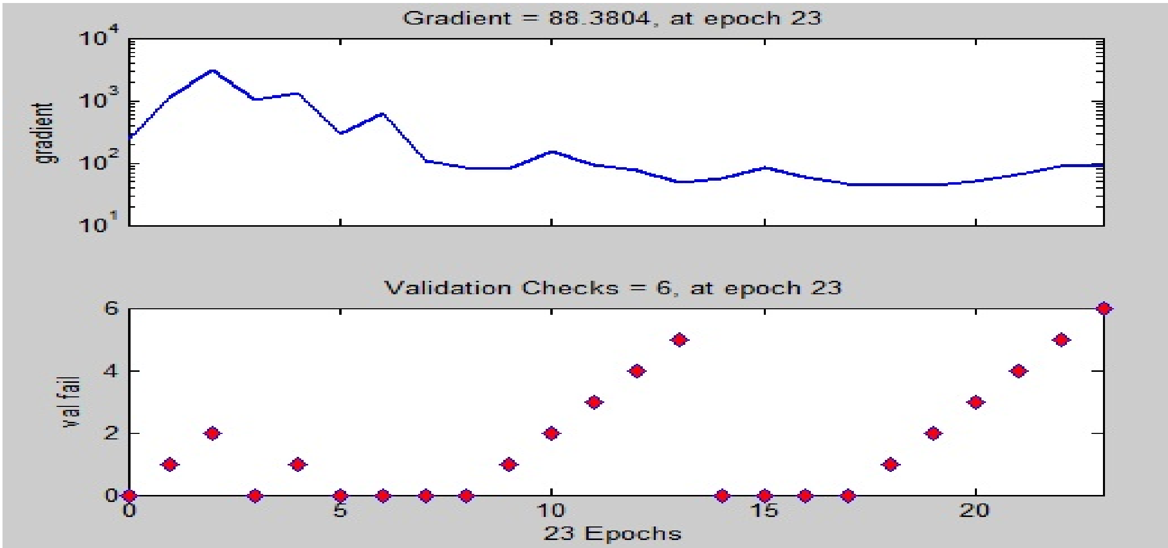
Epochs between displays	1
Maximum number of epochs to train	200
Maximum time to train in seconds	inf
Performance goal	0
Maximum validation failures	6
Factor to use for memory/ speed Tradeoff	1
Minimum gradient error	1*10-6

4. Results and Discussions

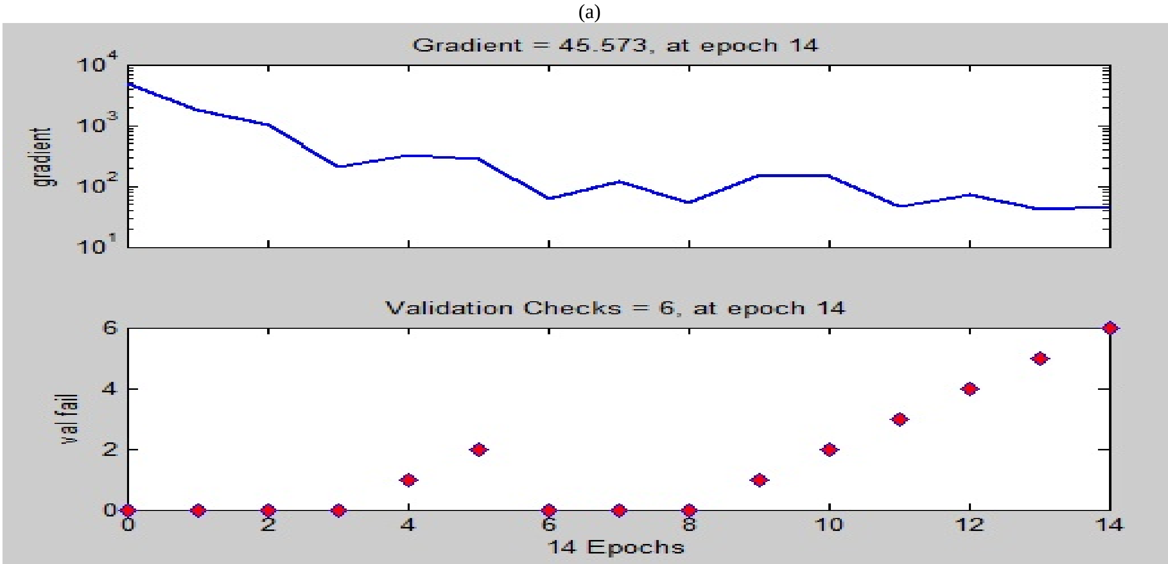
In Elman network, NARX network and Feedforward Network the training was stopped after 23, 14 and 93 epochs respectively with trainrp function.

Variation of the gradient error, value of μ and validation checks at each epoch are shown in Fig.3 for all model, the gradient error for the best model is 1.0752, and the number of validation checks is 6 at 93 epoch.

Scatter plot of training, validation, testing of experimental data are shown in Fig.4, as it may be noticed in this figure, it was found that the values of R for the best model is in training period, validation period, and testing period are 0.99947, 0.99371 and 0.98934, respectively. The maximum performance was found to be 15.7125 at 17 epoch, 2.0857 at 87 epoch and 43.6105 at 8 epoch for Elman Network, Feedforward Network and NARX Network, respectively.



(a)



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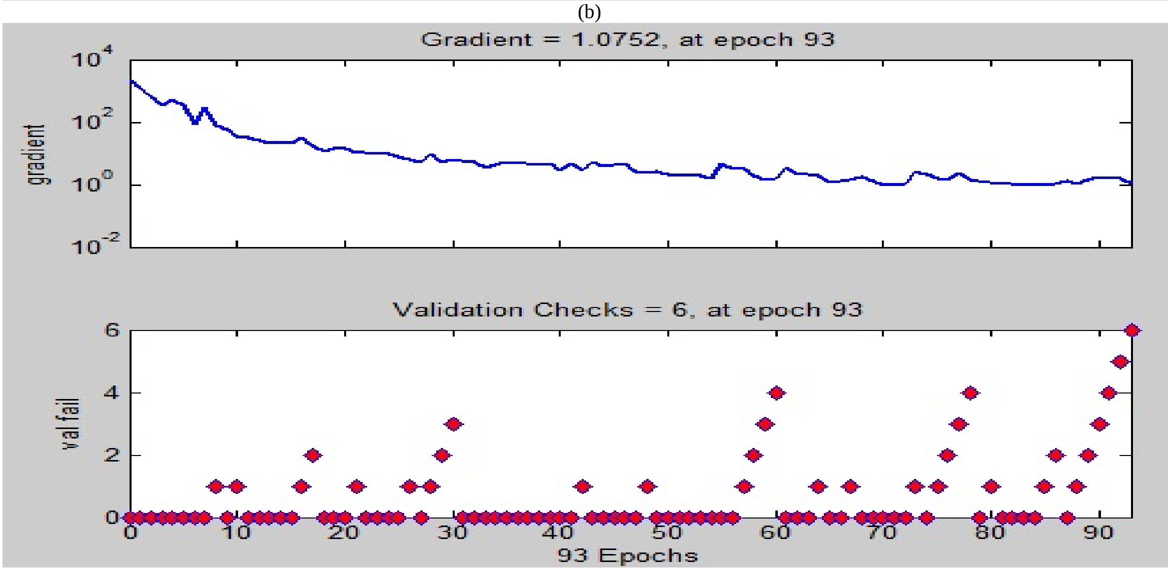
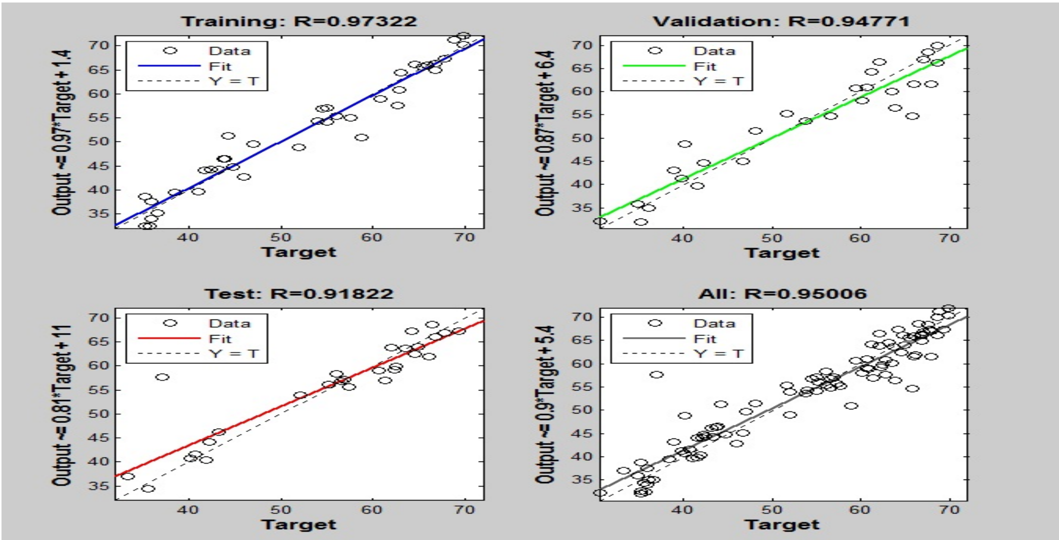
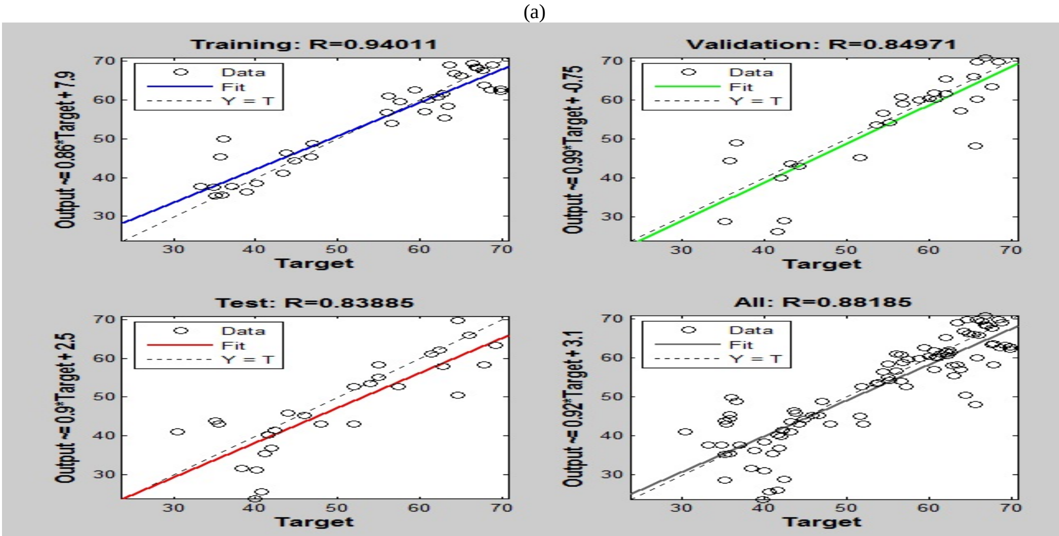


(c)

Figure 3: The variation of gradient error, and validation checks to a) Elman Network b) NARX Network c) Feedforward Network.



(a)



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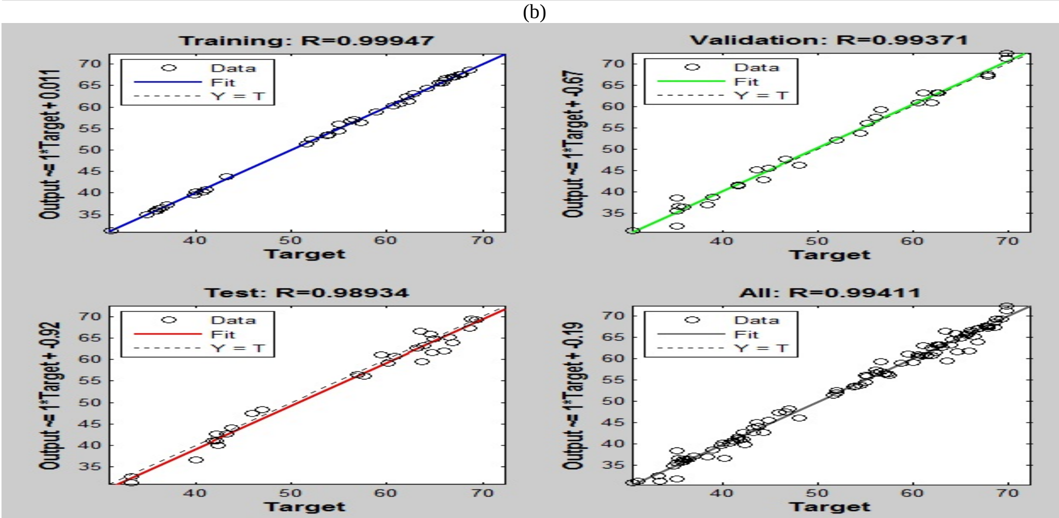

(c)

Figure 4: scatter plot of training, validation, test and all data to a) Elman Network b) NARX Network c) Feedforward Network.

The comparison between the obtained experimental data and the estimated efficiency for the three ANN networks are shown in fig. 5. The three global statistics: coefficient of determination (R), root mean squared error (RMSE) and mean bias error (MBE) are represented in table (2), which may be used to compare the estimation ability of the three models as shown in this table.

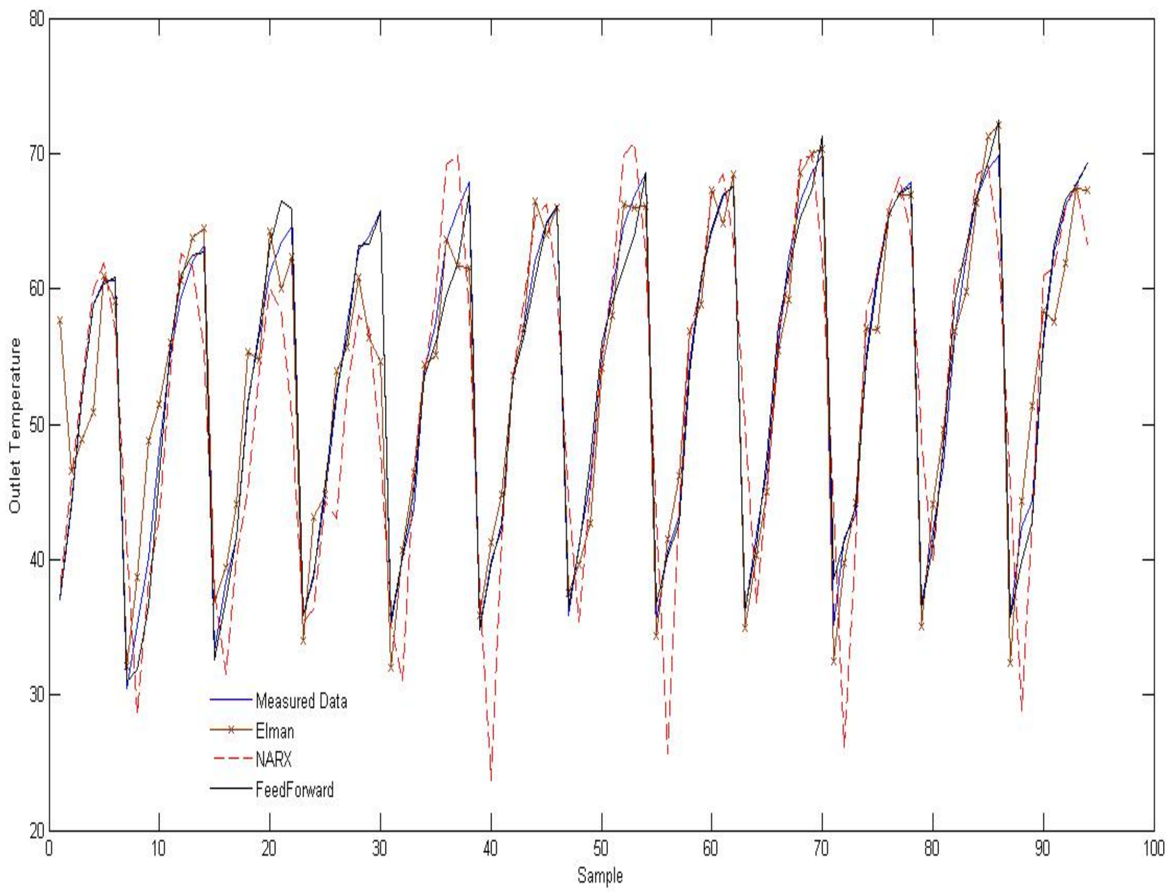

Figure 5: Comparison between experimental and estimated outlet temperature of the thermal energy storage.

Table (2): Comparison of performance of the used models.

	RMSE		MBE		R	
	Training	Validation	Training	Validation	Training	Validation
Elman	2.7005	3.9639	2.1094	3.0160	0.97322	0.94771
Feedforward	0.3908	1.4442	0.2943	1.1290	0.99947	0.99371
NARX	4.2935	6.6038	3.1623	4.5452	0.94011	0.84971

From the above table and figures for the three ANN model, it may be noticed that Feedforward is characterized by more accurate results compared with those of Elman network and NARX network. Consequently, this model may be used to estimate the output temperature data with a high accuracy.

5. Conclusion

In this study, an overview of the phase change material was presented. Artificial neural network models using Rprop learning algorithm were successfully used to estimate the relation between the experimental obtained data and the inputs variables of thermal storage system. The comparisons between the estimated data from three models and obtained data from the experiments showed that Feedforward model has the best ability to recognize the relationship between inputs and output variables. In addition, the statistical error analysis showed the accuracy of this model. NARX model and Elman model have the least ability for the estimation of the outlet temperature of the thermal storage system.

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