JJMIE
Volume 7, Number 1, December. 2013
ISSN 1995-6665
Pages 11 - 18
Jordan Journal of Mechanical and Industrial Engineering

Hourly Solar Radiation Prediction Based on Nonlinear Autoregressive Exogenous (Narx) Neural Network

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Abstract:

In this study, Nonlinear Autoregressive Exogenous (NARX) model was used to predict hourly solar radiation in Amman, Jordan. This model was constructed and tested using MATLAB software. The performance of NARX model was examined and compared with different training algorithms. Meteorological data for the years from 2004 to 2007 were used to train the Artificial Neural Network (ANN) while the data of the year 2008 were used to test it. The Marquardt–Levenberg learning algorithm with a minimum root mean squared error (RMSE) and maximum coefficient of determination (R) was found as the best in both training and validation period when applied in NARX model.

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Keywords: Solar Radiation Prediction; Nonlinear Autoregressive Exogenous; Neural Network.

1. Introduction

Solar radiation data are a fundamental input for solar energy applications. The data should be reliable and readily available for design, optimization and performance evaluation of solar technologies for any particular location. Unfortunately, for many developing countries, solar radiation measurements are not easily available. Therefore, it is necessary to develop methods to estimate the solar radiation on the basis of the more readily available meteorological data.

Many models have been developed to estimate the amount of global solar radiation on horizontal surfaces using various climatic parameters, such as sunshine duration, cloud cover, humidity, maximum and minimum ambient temperatures, wind speed, etc. Chakhchoukh [1] and Wu [2] used the metrological data of Nanchang station (China) from 1994 to 2005 to predict the daily global solar radiation from sunshine hours, air temperature, total precipitation and dew point. Z. Sen [3] proposed a nonlinear model for the estimation of global solar radiation from available sunshine duration data. This model is an Angstrom type model with a third parameter which appears as the power of the sunshine duration ratio that gives the nonlinear effects in solar radiation and sunshine duration relationship.

A simple model for estimating the monthly average of the daily global solar radiation data on horizontal surfaces was recently proposed by R. Perdomo, E. Banguero, and G. Gordillo in [4]. The model is based on a trigonometric function, which has only one independent parameter, namely the day of the year. It was found that the model can be used for estimating monthly average of daily global radiation for 68 provinces of Turkey with a high accuracy. Janjai [5] proposed a model for calculating the monthly average hourly global radiation in the tropics with high aerosol load using satellite data. This model was employed to generate hourly solar radiation maps in Thailand.

In literature, Artificial Neural Networks (ANN) has been widely used as time series predictors. Many techniques have been developed in the general framework of time series prediction. These methods can be classified into two main categories: classical statistical methods, and intelligent based methods. Statistical methods (such as Fractional difference model, Structure model, Bayesian method, Threshold AR model, alterable variance model, Zhang [6] and Ji [7], and the Ratio-of-Medians Estimator (RME) method) are used for the estimation of the autoregressive moving-average (ARMA) parameter model and time series prediction [1] and [8-10]. Most time series prediction methods based on intelligent used Artificial Neural Network (ANN) technique, such as multilayer perceptrons with back propagation, recurrent neural networks, and a radial basis function (RBF) neural network [11-13].

Traditional statistical methods are very easy to understand and implement, but they are not tractable in complex time series with a fast alteration and complicated evolvement Zhang [6]. ANNs are good for tasks involving incomplete data sets, fuzzy or incomplete information, and

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for highly complex and ill-defined problems. They can learn from examples, and are able to deal with non-linear problems Kalogirou [14].

As indicated above, several conventional models have been presented by researchers to predict global solar radiation (GSR) using different meteorological variables. However, using ANN has proved its efficiency as a prediction tool to predict factors through other input variables which have no specified relationship. Meteorological and climatological variables are most comprehensive and important factors for indicating the amount of solar radiation in a selected reign (Behrang [15], and Hrayshat [16]).

The main objective of this study is to investigate the ability of NARX model to predict the hourly solar radiation data in Amman, Jordan. NARX model, with different training algorithms, is examined and compared using MATLAB software.

2. Artificial Neural Network (ANN)

ANNs, commonly known as biologically inspired, highly sophisticated analytical techniques, are able to model extremely complex non-linear functions Chena [17]. In general, they are composed of three layers, which are an input layer, some hidden layers, and an output layer [18]. The advantages of the ANNs are speed, simplicity and ability to train past data to provide the necessary predictions. ANNs are used to solve complex functions in various applications such as control, data compression, forecasting, optimization, pattern recognition, classification, speech, vision Sözen [19].

To develop an ANN model, 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 are found in Caner [18].

In this Study, Nonlinear Autoregressive Exogenous (NARX) neural network, shown in Figure (1), is used to investigate its ability to predict the hourly solar radiation data in Amman, Jordan, using different training algorithms based on the results obtained in Moghaddamnia [20]. It was found that NARX model is the best network that can be used to predict solar radiation. More details about this model is found in Moghaddamnia [20]. The recorded hourly solar radiation for four years (from 2004 to 2007) were used as training data, while the data recorded in the year 2008 were used as target data. The input hourly solar data were provided by the National Center for Research and development, Energy Research Program in Amman, Jordan. They were obtained using a metrological station located in Amman. The performance of the model has been carried out using three global statistics: coefficient of determination (R^2), root mean squared error (RMSE) and mean bias error (MBE). More details about these parameters are found in Caner [18]. These three parameters are given by:

$$R^2 = 1 - \frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \tag{1}$$

$$RMSE = \sqrt{\frac{\sum_j (t_j - o_j)^2}{p}} \tag{2}$$

$$MBE = \frac{\sum_j (t_j - o_j)}{p} \tag{3}$$

Where:
t_j is the target value,
o_j is the output value and
p is the pattern

ANN network with neuron numbers (4, 20, 1) was constructed and tested by MATLAB software Beale [21]. Previously obtained experimental data of 8670 sample were used as the input of ANN network. Among this data, 40% were used for training, 30% for validation, and 30% for testing. The number of the hidden layer was selected as 20 following trail and error technique. Tangent sigmoid function was applied for the hidden layer, and linear transfer function is used in the output layer. Training parameters used in algorithms are shown in Table (1) with their values. The performance of all models have been carried out using three global statistics: coefficient of determination (R^2), root mean squared error (RMSE) and mean bias error (MBE).

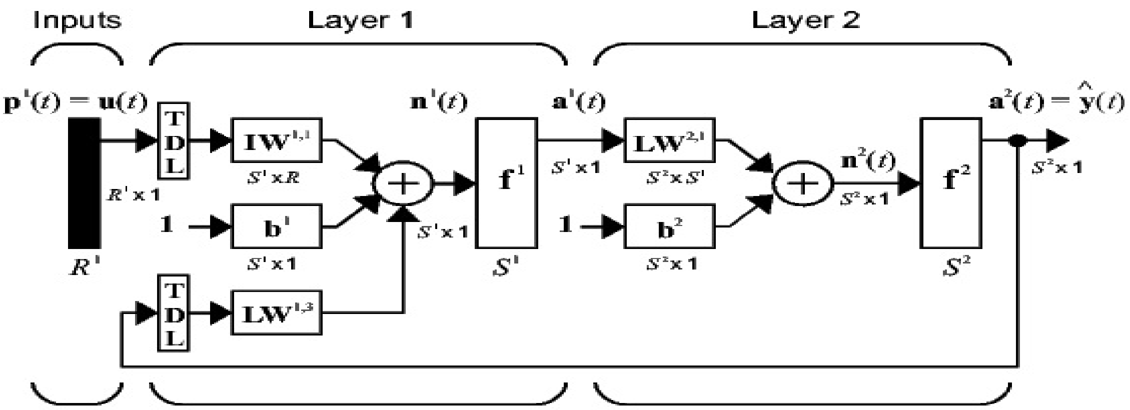


Figure 1. A typical neural network auto-regressive with exogenous inputs (Beale, Hagan, & Demuth, 2007).

Table 1. Training parameters.

Epochs between displays	1
Maximum number of epochs to train	800
Maximum time to train in seconds	inf
Performance goal	0
Maximum validation failures	15
Factor to use for memory/ speed Tradeoff	1
Minimum gradient error	$1*10^{-5}$
Initial µ	$1*10^{-3}$
µ decrease factor	0.1
µ increase factor	10
Maximum µ	$1*10^{10}$

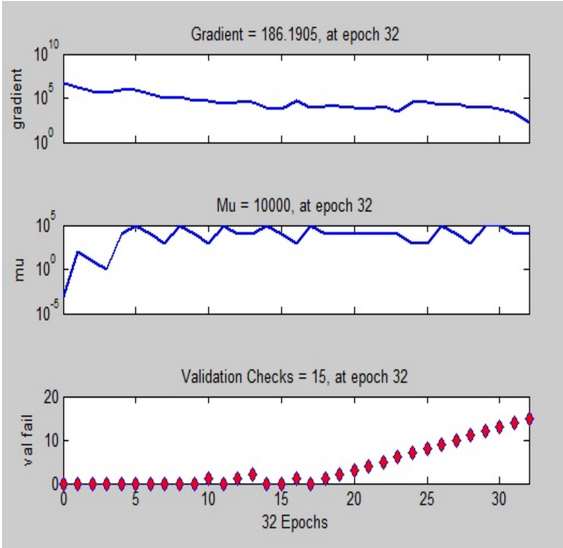
3. Results and Discussion

The data measured between January 1st 2004 and December 31st 2007 were used for training, testing, and validation of ANN. Once the ANN is trained, which means that all the weights and bias are set, it can be tested.The proposed network was trained using seven training algorithms: Levenberg-Marquardt (trainlm), Resilient Backpropagation (trainrp), Scaled Conjugate Gradient (trainscg), Conjugate Gradient with Powell/Beale Restarts (traincgb), Fletcher-Powell Conjugate Gradient (traincgf), Polak-Ribiére Conjugate Gradient (traincgp), and One Step Secant (trainoss).

Variation of the gradient error, value of µ, and validation checks at each epoch results produced by the seven training algorithms based NARX network are shown in Figure (2). In Figure (3), the scatter plots of training, testing, and validation are shown. The mean square error at each epoch for the training algorithms is shown in Figure (4). As shown in Figures (2) and (4), the NARX network trained with Levenberg-Marquardt algorithm converges faster than other algorithms; where the training stopped after 32 epochs. The mean square error (MSE) of training period was found to be 42.8367 MJ/m2/hour, and RMSE of validation period was found to be 48.3991 MJ/m2/hour. Figure (3) shows quite close results of the scatter plot during training, validation, and testing of the experimental data using different training algorithms. For Levenberg-Marquardt algorithm, it was found that it has the highest values of R in training, validation, and testing are 0.99157, 0.98916 and 0.98935 respectively.

Figures (5) and (6) show a comparison of measured and predicted values using the proposed NARX network. This comparison was based on seven training algorithms taken data on summer day (6th of August 2008) and on winter day (16th of December 2008).

The comparative analysis of different training algorithms using some basic statistics (coefficient of determination (R^2), root mean squared error (RMSE) and mean bias error (MBE)) has been carried out and is shown in Table (2), where trainlm algorithm provided the best performance, i.e., the lowest RMSE and highest R^2, for the training period and validation period. The results of the research indicate that the predictive capability of Scaled Conjugate Gradient (trainscg) algorithm is poor compared with other training algorithm in hourly solar radiation modelling.



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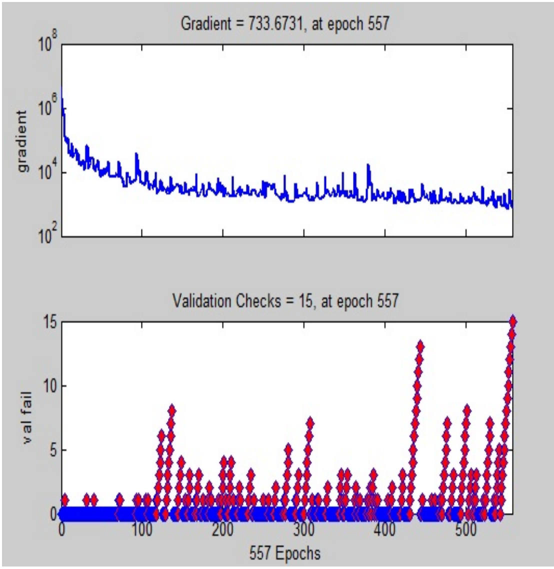

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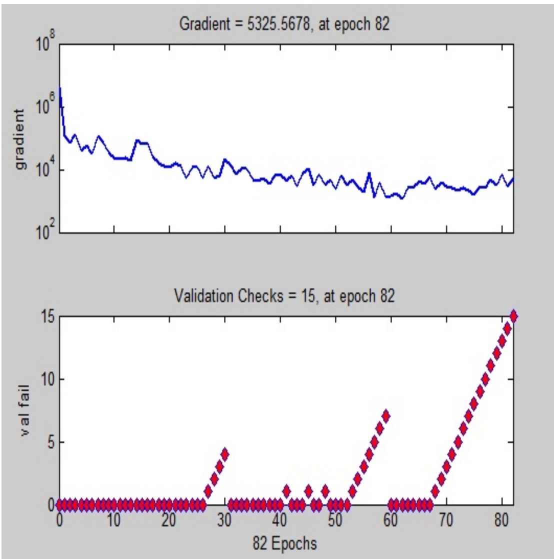

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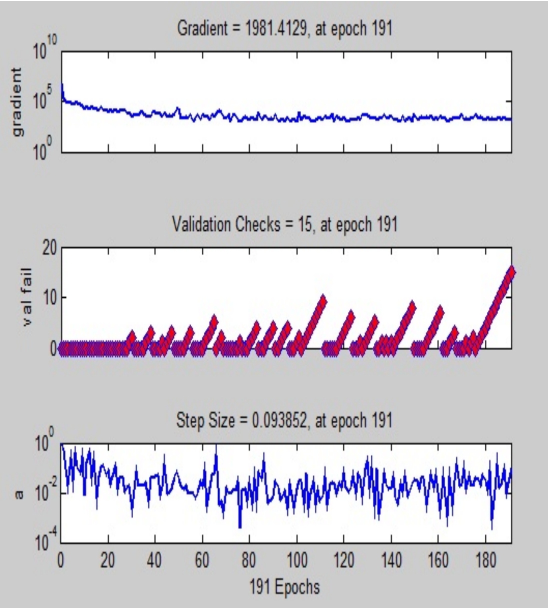

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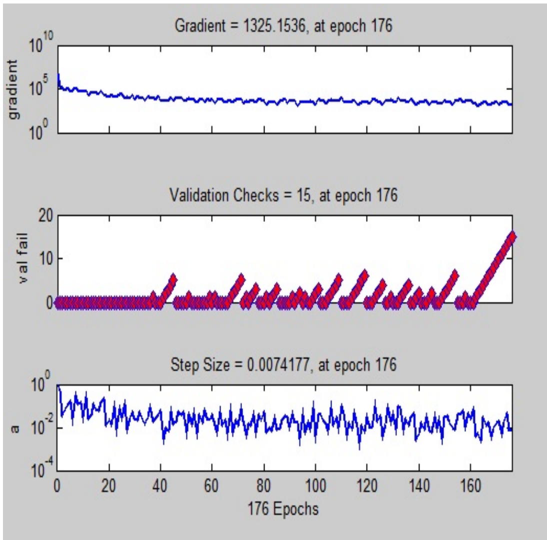

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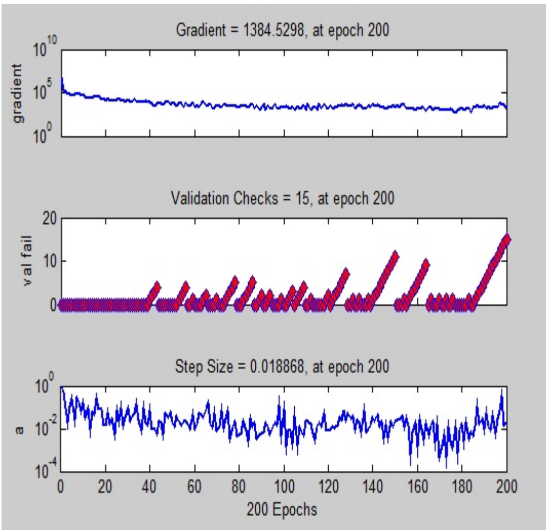

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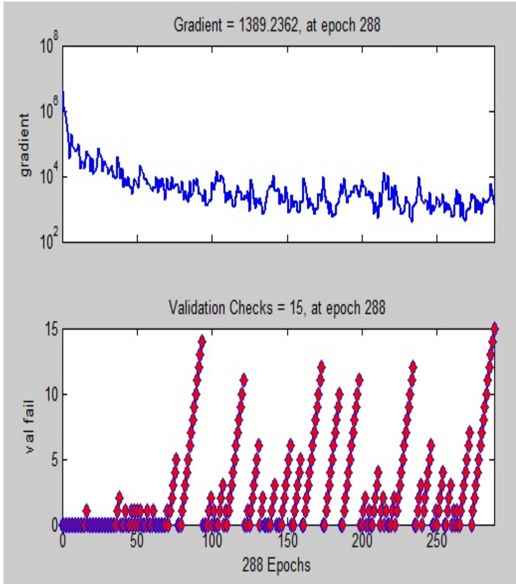

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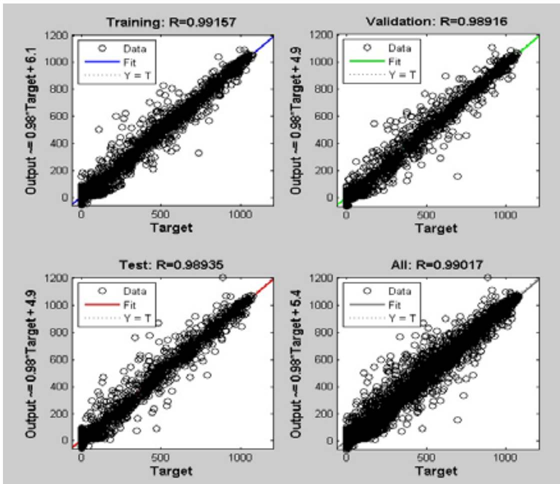
Figure 2. Comparison of variation of gradient error and validation checks using (a) trainlm, (b) trainrp, (c) trainscg, (d) traincgb, (e) traincgf, (f) traincgp, and (g) trainoss.



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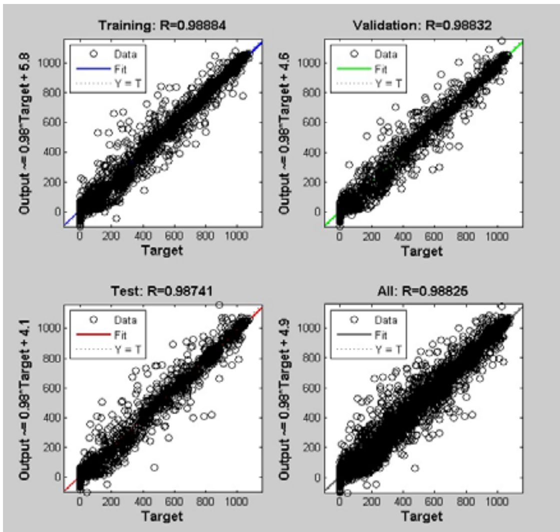

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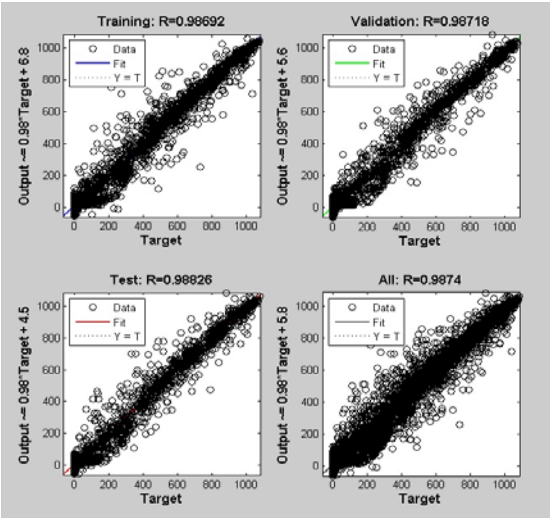

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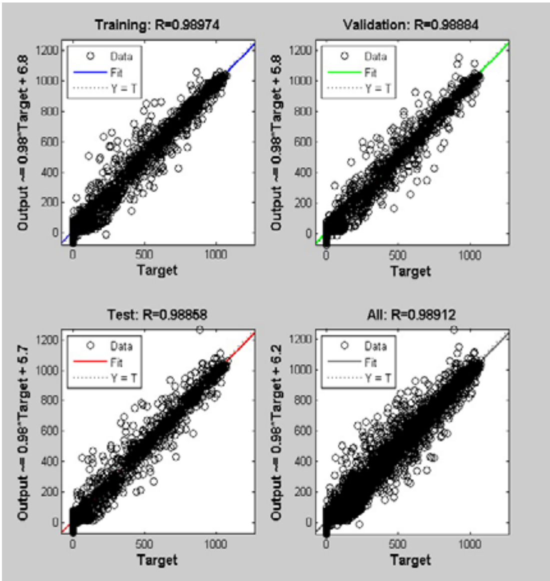

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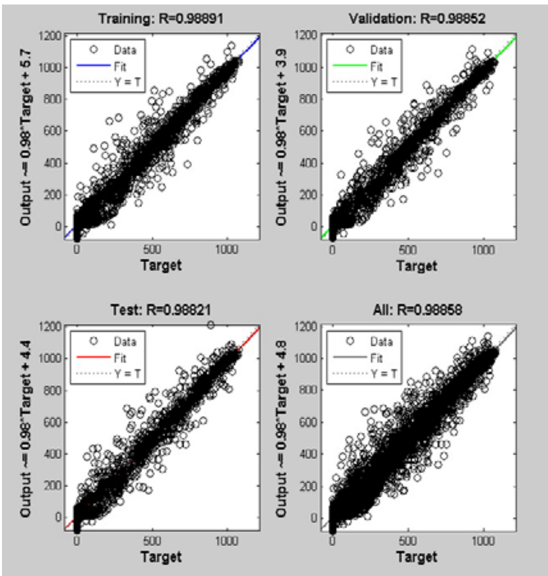

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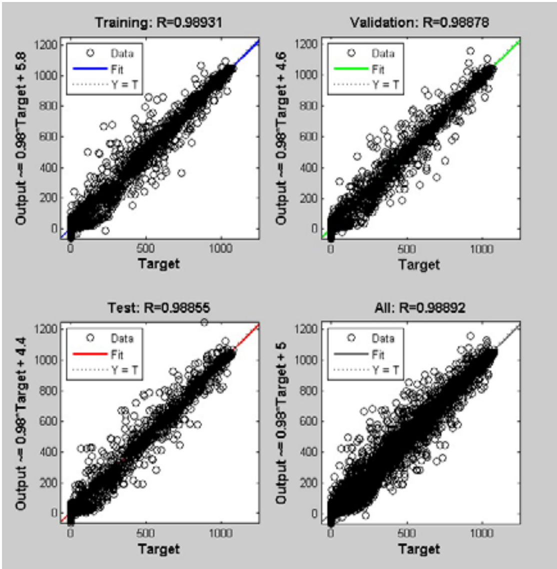

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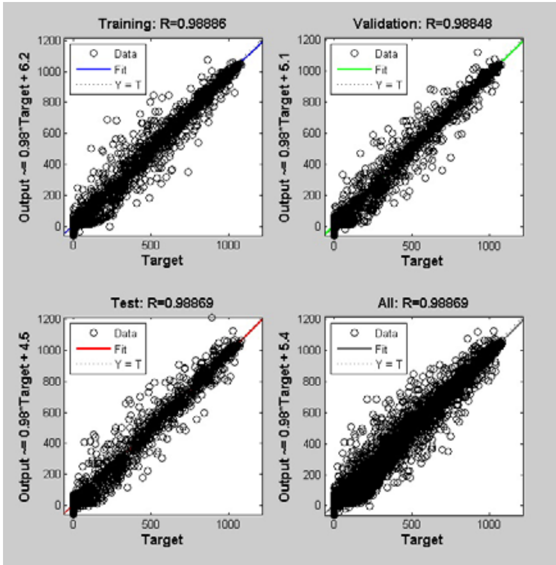

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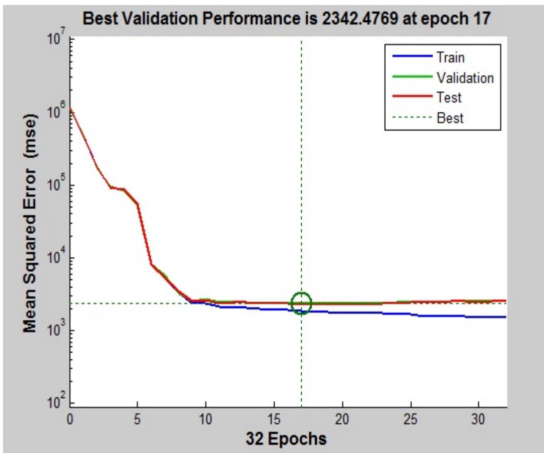
Figure 3. Comparison of scatter plots of the models used for solar radiation. (a) trainlm, (b) trainrp, (c) trainscg, (d) traincgb, (e) traincgf, (f) traincgp, and (g) trainoss.



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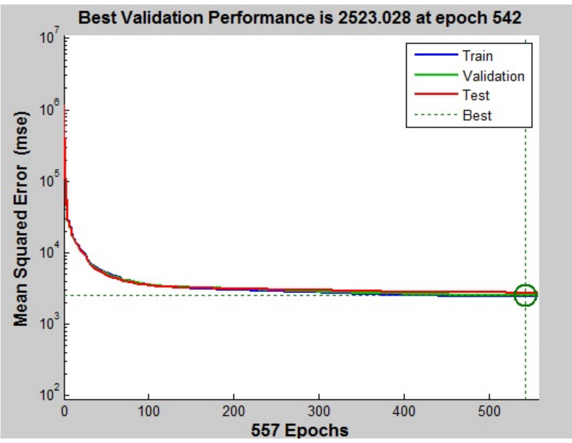

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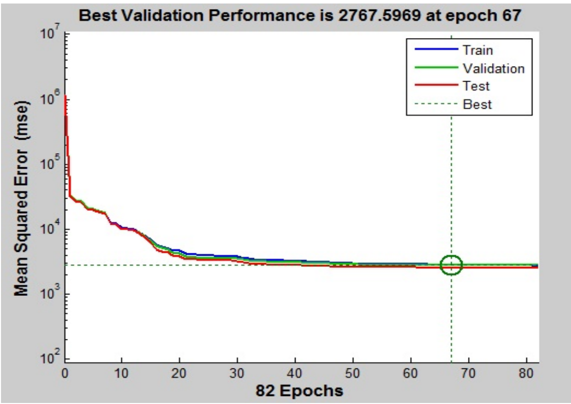

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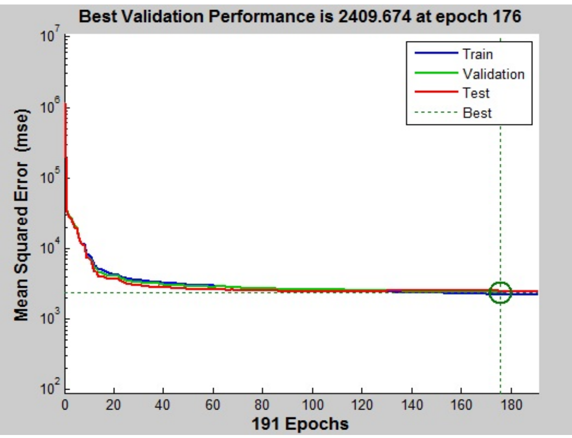

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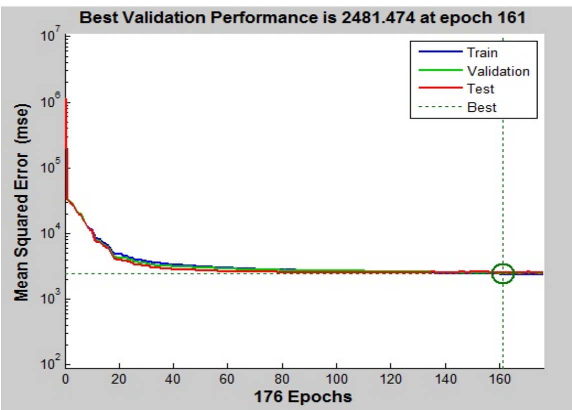

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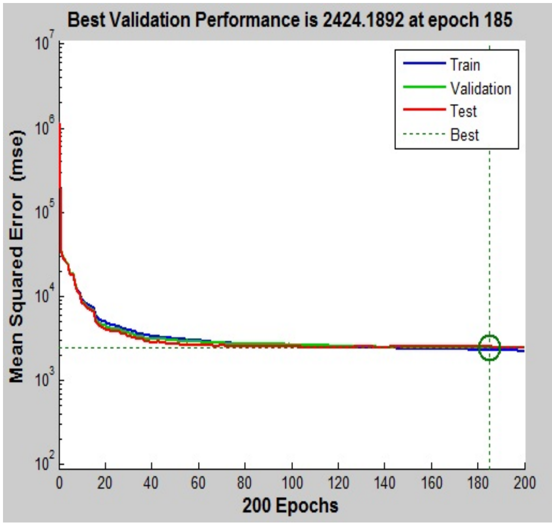

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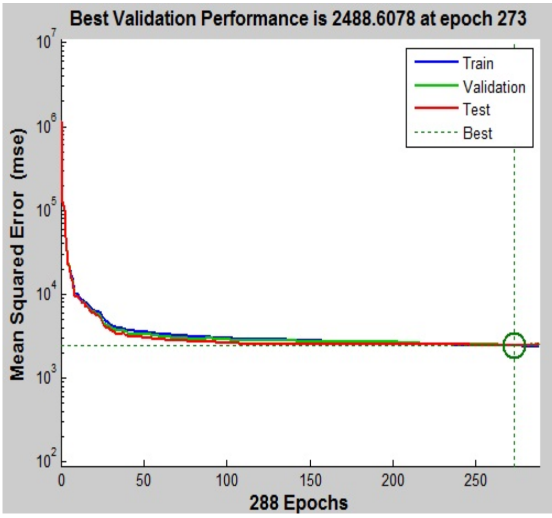

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Figure 4. Comparison of Mean Square Error (MSE) training performance of the ANN for a given training dataset. (a) trainlm, (b) trainrp, (c) trainscg, (d) traincgb, (e) traincgf, (f) traincgp, and (g) trainoss.

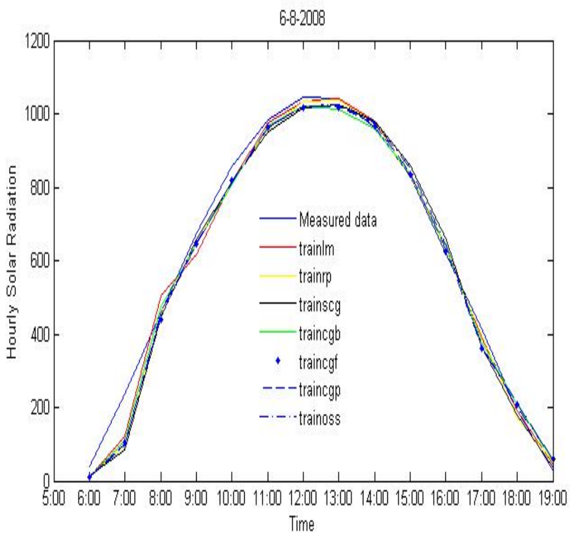

Figure 5. Comparison between measured and estimated hourly solar radiation at 6/8/2008.

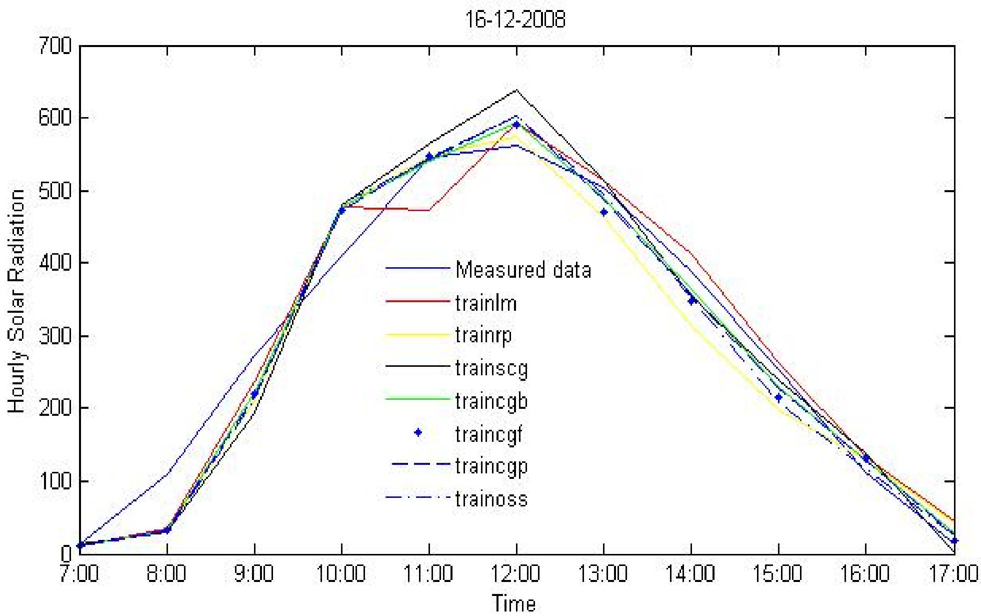

Figure 6. Comparison between measured and estimated hourly solar radiation at 16/12/2008.

Table 2. Comparison of performance of different training algorithms based on statistical criteria.

Algorithm	RMSE		MBE		R	
	Training	Validation	Training	Validation	Training	Validation
trainlm	42.8367	48.3991	25.5612	28.5317	0.99157	0.98916
trainrp	49.2078	50.2298	28.9444	30.6432	0.98884	0.98832
trainscg	53.2732	52.6080	31.3656	32.5375	0.98692	0.98718
traincgb	47.2268	49.0884	28.0998	29.7275	0.98974	0.98884
traincgf	49.0563	49.8144	29.5055	30.9015	0.98891	0.98852
traincgp	48.1758	49.2361	28.3929	29.9944	0.98931	0.98878
trainoss	49.1726	49.8859	28.7343	30.1949	0.98886	0.98848

4. Conclusion

In this study, an approach to estimating hourly solar radiation from meteorological data sets, based on NARX model using different training algorithms, was developed. The comparative analysis between the estimated data and measured data showed that NARX model has the ability to recognize the relationship between the input and output variables and predict hourly solar radiation accurtly. The statistical error analysis shows the prediction accuracy based on NARX model.

Different training algorithms were compared to select the best suited algorithm. The Marquardt–Levenberg learning algorithm with a minimum root mean squared error (RMSE) and maximum coefficient of determination (R) was found as the best in both training and validation period when applied in NARX model. Based on our results, NARX network is recommended for hourly solar radiation prediction in Jordan and nearby regions.

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