Global Solar Radiation Prediction using Artificial Neural Network Models for New Zealand

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Abstract

In this study, nonlinear autoregressive recurrent neural networks with exogenous input (NARX) were used to predict global solar radiation across New Zealand. Data for nine hourly weather variables recorded across New Zealand from January 2006 to December 2012 were used to create, train and test Artificial Neural Network (ANN) models using the Levenberg−Marquardt (LM) training algorithm, with global solar radiation as the objective function. In doing this, ANN models with different numbers of neurons (from 5 to 250) in the hidden layer as well as different numbers of delays were experimented with, and their effect on prediction accuracy was analyzed. Subsequently the most accurate ANN model was used for global solar radiation prediction in ten cities across New Zealand. The predicted values of hourly global solar radiation were compared with the measured values, and it was found that the mean squared error (MSE) and regression (R) values showed close correlation. As such, the study illustrates the capability of the model to forecast radiation values at a later time. These results demonstrate the generalization capability of this approach over unseen data and its ability to produce accurate estimates and forecasts.

Keywords-Solar Radiation; Levenberg-Marquardt; Neural Network

1. Introduction

Building reliable solar energy systems requires information about global solar radiation (GSR) in the region where the system is to be built. Recently the need for precise modeling, forecasting and prediction of solar irradiance has increased due to increased interest in renewable energy systems implementation worldwide. One reason for this is that predicting solar irradiance 24 hours in advance would help efficiently optimize energy distribution between the buildings and the local grid.

The traditional way of determining the amount of GSR is to install pyranometers in as many locations as possible, significantly increasing the cost of GSR data collection. In most cases limited coverage of radiation measuring networks prompts the development of models for estimating the GSR using climatological parameters [1]. Several models have been developed in order to estimate and generate the solar irradiance data, in different scales. These models include empirical [2], analytical [3] and numerical models as well as neural network approaches [4]. A significant amount of literature has also used physics-based models [5–7] and statistical forecasting for solar data [8].

Models based on statistical processes such as autoregressive, moving-average, autoregressive moving-average, autoregressive-integrated moving-average and Markov chain have been used widely for modeling and prediction of solar irradiance data. However, these models need some statistical transformations to the data before they are applied to the network to be used. Due to these transformations, we cannot

be sure that the results are accurate and represent a precise correlation with the measured solar irradiance values [9]. Therefore it is necessary to develop a more accurate method of modeling and predicting hourly solar irradiance [10].

ANN techniques offer a promising alternative to conventional techniques and are used in a number of solar energy applications. Kalogirou [11] has reviewed the use of ANN in renewable energy systems applications. Similarly [12, 13] have reviewed ANN for sizing of photovoltaic systems and for photovoltaic applications.

More generally, [14] predicted global solar radiation using ANN model with wind speed, relative humidity, air temperature and soil temperature as inputs for La Serena in Chile. Regression values were found to be 94%, indicating strong correlation between hourly global solar radiation and meteorological data. Rehman and Mohandes [15] used day, global solar radiation, ambient temperature and relative humidity as inputs to a radial basis function (RBF) network for modeling of diffuse and direct normal solar radiation for sites in Saudi Arabia. A mean absolute percentage error (MAPE) of 0.016 and 0.41 for diffuse solar radiation was achieved using 50 hidden neurons and 0.1 spread constant in the RBF network. Finally, [16] used global solar irradiation on a horizontal surface, declination and hour angles as input parameters for generalized regression neural networks (GRNN) to predict solar radiation on tilted surface in Iskenderun, Turkey. Regression and MAPE were found to be 98.7% and 14.9Wh/m^2 respectively.

In most cases reported in the literature, measured input weather data is normalized and randomized to remove spikes and significant variations when training an ANN. It is supposed that these increase network processing times and achieve good correlation between measured and predicted values. This preprocessing of input weather data could reduce the accuracy of predicted values [9]. As such, this study aims to explore the accuracy of ANNs for predicting global solar radiation in New Zealand cities using real measured data.

2. Methodology

In this study seven years of hourly data for Temperature (T_{max}, T_{min}), Air Pressure (P), Relative Humidity (RH), Solar Zenith Angle (SZA), Azimuth Angle (Az), Rain amount (Ra), Wind speed (Ws) and Wind direction (Wd) were taken from the National Institute of Water and Atmospheres CliFlo database to train the ANN with Global Solar Radiation as the target variable.

The data was presented in an unprocessed format, to study the effect of real input variables on target and predict output. Input and target data from 1 January 2006 to 31 December 2012 were used to train, validate and finally, test the networks ability to predict the global solar radiation from 1 January 2013 to 31 December 2013.

The prediction accuracy of ANN models is found to be dependent on the combination of weather predictor variables, training algorithm and ANN architecture configuration [17]. One of the key tasks in time series prediction is the selection of the input variables. For the proposed non-linear ANN models there is no systematic approach that can be followed [18], so there is a risk of omitting important variables. In this study the same process is used as in [19], where a two-step technique is applied called “sensitivity analysis”. This technique is based on trial and error. Once the most significant variables are determined, the network is trained with every selected variable, until the training error is minimized and the influence of each variable is removed by replacing it with its mean value or zero. As there are 512 possible combinations of nine weather predictor variables testing the network with all

combinations was not possible. Therefore, to simplify the process, the twelve most significant combinations of the nine weather predictor variables were tested as shown in Table 1 in order to investigate their effect on the global solar radiation prediction accuracy.

Table 1. Models based on different combinations of input variables

Model	Input Parameters	Model	Input Parameters
1	T_{max}, T_{min}, P, RH, SZA, Az, Ra, Ws, Wd	7	P, RH, SZA, Az, Ra
2	T_{max}, T_{min}, P, RH, SZA, Az, Ra	8	T_{max}, T_{min}, SZA
3	T_{max}, T_{min}, P, RH, SZA, Az	9	T_{max}, T_{min}, P, SZA, Az
4	P, RH, SZA, Az, Ra, Ws, Wd	10	RH, SZA, Az, Ra
5	T_{max}, T_{min}, P, RH, SZA	11	T_{max}, T_{min}, P
6	T_{max}, T_{min}, SZA, Az	12	T_{max}, T_{min}, Ws, Wd

Neural networks for radiation prediction

There are two basic solar irradiance models: parametric and decomposition [20]. Parametric models require detailed information of atmospheric conditions and estimate irradiance components based on weather, time and geographical data. Decomposition models use irradiance values, for example global irradiance, and then compute other components such as direct and diffuse solar irradiance using the main component. In this study a parametric model for global solar irradiance was developed using different combinations of the weather predictor variables described previously. This model is known as a NARX recurrent dynamic network, with feedback connection.

The NARX model is based on the linear ARX model, which is commonly used in time-series modeling.

The equation for the NARX model is given by (1):

$$y(t) = f\left(y(t-1), y(t-2), \dots, y\left(t-n_y\right), u(t-1), u(t-2), \dots, u(t-n_u)\right) \quad (1)$$

where, the next value of the dependent output signal $y(t)$ is regressed on previous values of the output signal and previous values of an independent input signal. The NARX model is implemented using a feed-forward neural network to approximate the function f. A diagram of the resulting network is shown in Fig. 1, where the $y(t)$ output series is predicted given past values of $y(t)$ and another input series $x(t)$.

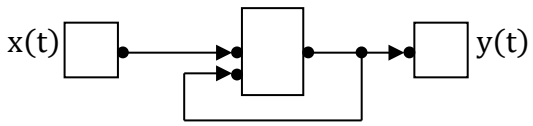


Figure 1. NARX block diagram

There are different connection styles and learning algorithms in neural networks, the most common being the Back Propagation algorithm. The Back Propagation algorithm consists of two phases: a training phase and recall phase [21]. Before the training phase starts, the weights of the network are randomly initialized. Then the output of the network is calculated and compared to the desired value. At each step during training the error of the network is calculated by means of gradient methods and used to adjust the weights of the output layer [22]. In the case of more than one

network layer the error is propagated backward to adjust the weights of the previous layers. Once the weights are determined, after several training steps and correlation between different combinations of input variables with targets are finalized, the recall phase may run. In doing this the network output computations are performed using finalized iterations of input data and weights from the training phase.

The training phase is important as it determines the success of the resulting network. In back propagation, there are two methods of updating the weights. In the first method, weights are updated for each of the input patterns using an iteration method. In the second method, used in this study, the mean value of input and output patterns of the training sets is calculated [23]. As soon as the weight update values are obtained, the new weights and biases can be calculated using (2)

$$W_{ij,n} = U_n + \alpha W_{ij,n} - 1 \qquad (2)$$

where $W_{ij,n}$ is a vector of current weights and biases, α is the momentum factor rate which determines how the past weights will reflect to the current value, and U_n is the update function which can be chosen according to the problem and data type.

According to [20] and [23] the most commonly used equation solving algorithm is the LM algorithm. It can be considered as an alternative to the conjugate methods for second derivative optimization. In LM, the update function, U_n can be calculated using (3)

$$U_n = -[J^T \times J + \mu I]^{-1} \times J^T \times e \quad (3)$$

where J is the Jacobian matrix that contains the first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The parameter μ is a scalar number and I is the identity matrix. Depending on when the μ parameter is large, the update function U_n becomes identical to the basic back propagation (with a small step size). During processing the μ value decreases after each successful step and should be increased only when a tentative step increases the error term or performance function. Consequently the performance function is guaranteed to reduce or get bounded at each iteration [24].

A significant number of networks were designed and trained in the course of this study to predict global solar radiation with the lowest possible MSE values. In order to investigate the performance of developed ANN models quantitatively and verify whether there was any underlying trend in performance of ANN models, regression (R), the mean square error (MSE), and the mean bias error (MBE) values were analyzed. MSE provides information on the short term performance which is a measure of the variation of predicated values around the measured data. The lower the MSE, the more accurate is the estimation. MBE is an indication of the average deviation of the predicted values from the corresponding measured data and can provide information on long term performance of the models; the lower MBE the better the long term model prediction. A positive MBE value indicates the amount of overestimation in the predicated global solar radiation and vice versa. The expressions for the aforementioned statistical parameters are shown in (4) and (5):

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(I_{p,i} - I_i) \qquad (4)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i=1}}^{\mathrm{N}}(\mathrm{I_{p,i}} - \mathrm{I_i})^2} \quad (5)$$

where $\mathrm{I_{p,i}}$ is the predicted solar irradiance in $\mathrm{MJ/m^2}$, $\mathrm{I_i}$ is the measured solar irradiance in $\mathrm{MJ/m^2}$, and N denotes the number of observations.

3. Results and Discussion

Number of Hidden Neurons and Delays

More computation is required if the number of neurons or the number of delays are increased and vice versa. Increasing the number of neurons and delays has a tendency to overfit the data when the numbers are set too high, but it allows the network to solve more complicated problems. During experiments both the number of neurons in hidden layer and the number of delays in the tapped delay lines were continuously increased until the network performed well in terms of the mean square error (MSE) and the error autocorrelation function.

Therefore, the effect of changing the number of neurons in the hidden layer, increasing and decreasing the number of delays was also investigated. The number of hidden neurons, network delays and time steps for training, validation and test were varied for best performance. The number of neurons was changed between 5 and 250 and delays between 1 and 5 were tested in order to come up with the most suitable ANN prediction model. Taking Model 2 as an example, Table 2 shows the MSE and Regression values for various numbers of neurons in the hidden layer. Processing time was also observed and it was noted that time increases exponentially with increasing number of neurons or delays. After several trials, it was decided that the most suitable network had 90 hidden neurons and 2 delays in the tapped delay lines, considering its accuracy and processing time. Processing time was closely monitored because if the model is implemented on a hardware platform, processing power and memory are very limited compared to desktop resources.

Table 2. MSE and Regression values for different number of neurons and delays.

Neurons	Delays	MSE	R	Model	Time
10	2	0.0774	0.951	2	0:00:24
20	2	0.0747	0.952	2	0:00:22
30	2	0.0709	0.955	2	0:00:48
40	2	0.0659	0.957	2	0:00:53
50	2	0.0689	0.956	2	0:00:50
50	3	0.0624	0.964	2	0:01:02
90	2	0.0591	0.963	2	0:01:20
90	3	0.0543	0.966	2	0:02:20
90	5	0.0486	0.969	2	0:04:42
150	2	0.0634	0.963	2	0:02:02
200	2	0.0632	0.963	2	0:04:33
250	2	0.0613	0.964	2	0:05:10

Mean Squared Error

The MSE is the mean squared normalized error performance function which is the difference between the output and target values. Network training can be stopped early by the validation vectors if the network performance on the validation vectors

fails to improve or remains the same, as indicated by an increase in the mean square error of the validation samples. Test vectors are used as a further check that the network is generalizing well, but do not have any effect on training. The best validation performance for model 2 is 0.072828 at epoch 9 with seven input variables as shown in Figure 2. It is shown that training, validation and testing errors decreased and merges with the dotted line on epoch 9 which demonstrates the best validation performance.

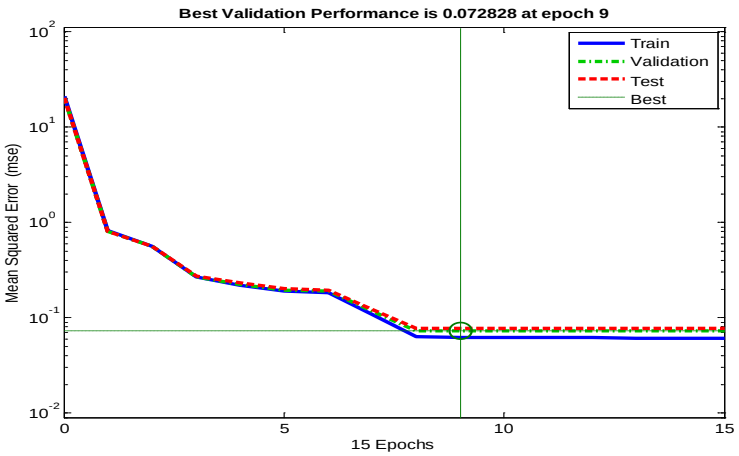


Figure 2. The best validation performance is 0.072828 at epoch 9 with seven input variables (Tmax, Tmin, P, RH, SZA, Az, Ra).

Regression Analysis

The network outputs with respect to targets for training, validation, and test sets are shown in Figure 3. The dashed line in each axis represents the perfect result, that is: outputs = targets. The solid line represents linear best fit between the outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R=1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets. When the network outputs are equal to the targets, the data should fall along a 45 degree line which will show a perfect fit. For this problem, the fit is reasonably good for all data sets, with the overall R values as high as 0.9633.

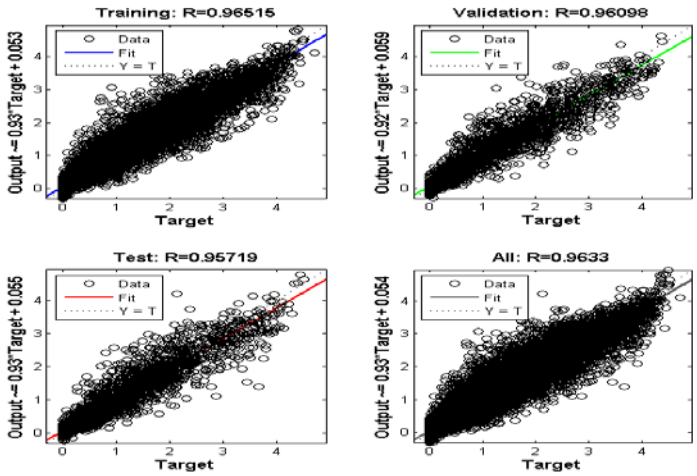


Figure 3. Regression analysis of the network outputs with respect to targets for training, validation and test sets.

For the twelve models described in Table 1, the NARX network architecture with LM training algorithm was trained, validated and tested. Values of Mean Squared Error (MSE) and Regression (R) were closely monitored to find the best model, Table 3 below shows the MSE and R values for 90 neurons in the hidden layer.

Table 3. MSE and Regression values for all 12 ANN models

Model	MSE	Regression (R)	Model	MSE	Regression (R)
1	0.0670	0.956	7	0.0732	0.953
2	**0.0591**	**0.963**	8	0.0733	0.953
3	0.0659	0.957	9	0.0668	0.956
4	0.0711	0.953	10	0.0749	0.952
5	0.0722	0.953	11	0.0779	0.949
6	0.0676	0.956	12	0.0769	0.950

Figure 4 illustrates this point further, by showing for a single day, that for the first six models there is close correlation between the measured and ANN predicted values for global solar radiation in Auckland. However, in Table 3, it can be seen that Model 2 is the best among all 12 models with 0.0591 MSE and 0.963 Regression value.

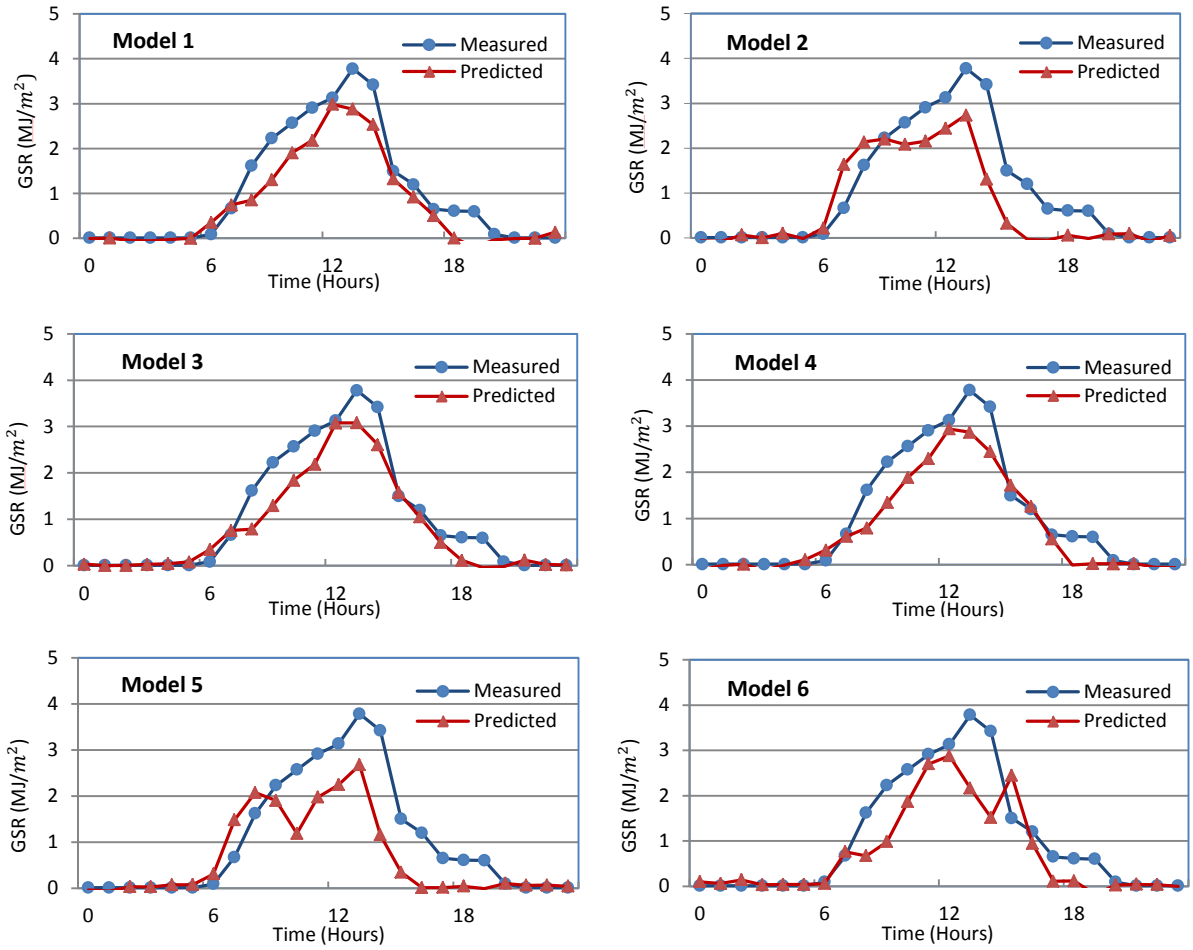
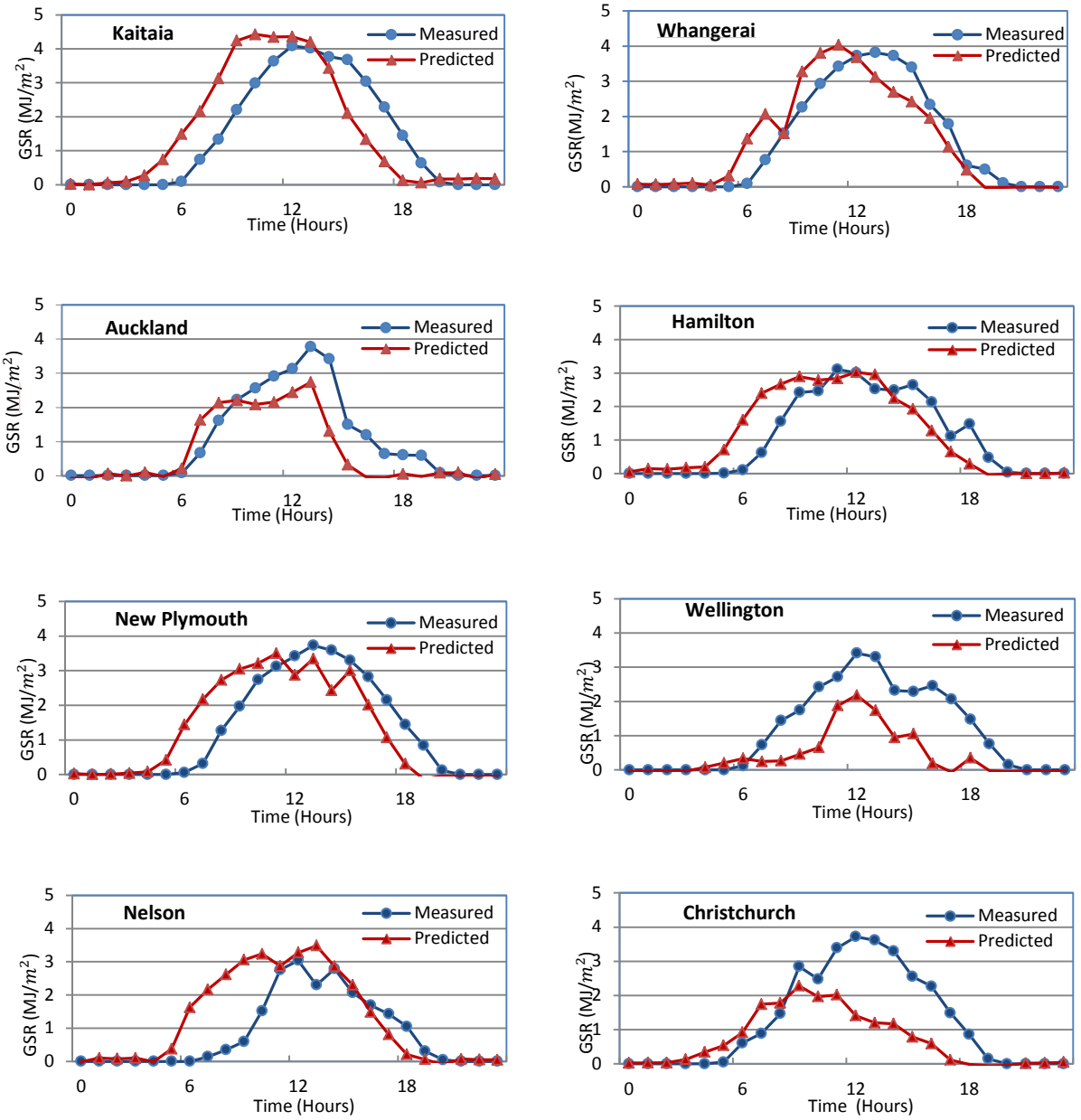


Figure 4. Measured and predicted radiation values for Auckland

Radiation Prediction for New Zealand Cities

Having determined the most suitable configuration of ANN, Model 2 was used for ten cities across New Zealand to predict global solar radiation in $\mathbf{MJ/m2}$ as shown in Figure 5. In Figure 5 it can be seen that using real data to train the ANN gives predicted values of GSR similar to those measured for all locations. In this regard, it suggests that the ANN with the LM training algorithm offers a suitable predictive tool for GSR in New Zealand. Moreover, it shows that training neural networks with real data can deliver satisfactory prediction of the output variable.



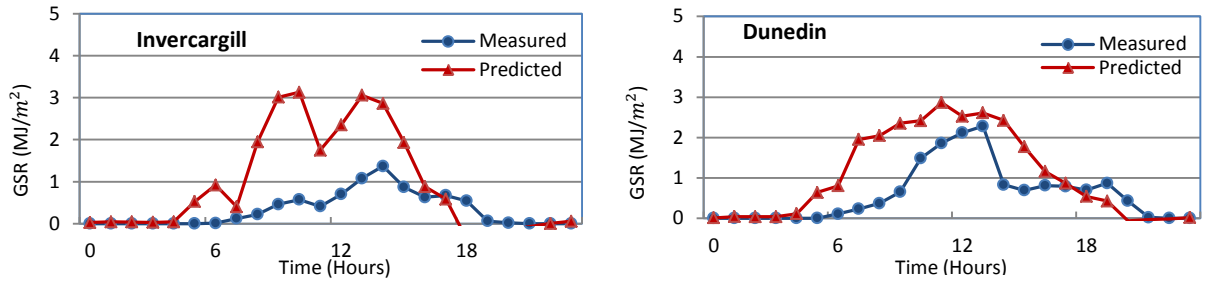


Figure 5. Predicted radiation for New Zealand cities

Conclusion

This paper proposed predictive model based on recurrent neural networks trained with Levenberg-Marquardt backpropagation learning algorithm to forecast global solar radiation using seven years historical weather data. Twelve different combinations of nine weather predictor variables were used to train, validate and test using twelve ANN models. Real-time input and target data were used without normalizing to study the real effects of input variables on outputs. One model with the lowest Mean Square Error and highest Regression value was used to predict global solar radiation in ten major cities across New Zealand. Predicted values were compared with measured data and showed close correlation. Based on the experimental results including mean squared error analysis, error autocorrelation function analysis, regression analysis and time series response, the proposed ANN model illustrated the capability to predict global solar radiation values at a later time. These results further demonstrated the generalization capability of this approach and its ability to produce accurate estimates and forecasts for GSR.

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