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Ahmad Alzahrani

Jonathan W. Kimball
Missouri University of Science and Technology, kimballjw@mst.edu

Cihan H. Dagli
Missouri University of Science and Technology, dagli@mst.edu

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Predicting Solar Irradiance Using Time Series Neural Networks

Alzahrani, A*. Kimball, J.W. Dagli, C

Missouri University of Science and Technology,

Abstract

Increasing the accuracy of prediction improves the performance of photovoltaic systems and alleviates the effects of intermittence on the systems stability. A Nonlinear Autoregressive Network with Exogenous Inputs (NARX) approach was applied to the Vichy-Rolla National Airport's photovoltaic station. The proposed model uses several inputs (e.g. time, day of the year, sky cover, pressure, and wind speed) to predict hourly solar irradiance. Data obtained from the National Solar Radiation Database (NSRDB) was used to conduct simulation experiments. These simulations validate the use of the proposed model for short-term predictions. Results show that the NARX neural network notably outperformed the other models and is better than the linear regression model. The use of additional meteorological variables, particularly sky cover, can further improve the prediction performance.

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Keywords: Time Series Neural Network, NSRDB, NARX,

1. Introduction

Photovoltaic systems have been tremendously improved in the past few years. These improvements include those mad at the operational level. These improvements have increased the amount of research focused on predicting solar energy. Predicting solar radiation increases the economic benefit and reduces the renewable energy expansion constraints. Thus, models are needed that can predict solar irradiation and improve the operations. A number of models are available that can estimate solar radiation. Both physical models and stochastic models are most commonly used for these tasks. Physical models are good fit to sun radiation based on its mean bias error (MBE) and root mean square error (RMSE) tests [1].

* Ahmad Alzahrani. Tel.: +001-970-430-7813.
E-mail address: asakw9@mst.edu

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The physical model used in this study estimates sunrise and sunset times without using extra equations (as other physical models do). Starting by defining the declination δ and it was given for any day of the year as:

$$\delta = 23.45^{o} \sin\left[\frac{360\ (n-80)}{365}\right] \qquad (1)$$

where n is the day of the year, and 23.45° is the angle of the polar axis of the earth with the sun [10]. The indication took into account that angles north of the equator are positive; they are negative when located south of the equator. Figure 1 illustrates the declination at different times of the year. Time of solar noon can be calculated as:

$$t = 12 + \frac{\varphi_L - \phi_n}{15} \times 60 \qquad (2)$$

Where φ_L is the longitude for the point of interest, ϕ_n is the longitude at which the solar noon occurs relative to the local time zone, and (60 min/15°) is used because the earth needs 60 minutes to rotate 15 degrees. One essential connection exists between ϕ, δ, and ω. This relationship is to determine the position of the sun in term of α at a given location, time and date was defined as in the denominator of equation. Equation (3) was used to find the air mass coefficient (AM) to include the length of the path through the atmosphere. This path length is typically compared to a vertical path located at sea level. Therefore, the air mass was thus calculated as:

$$AM = \frac{1}{\sin\delta \sin\phi + \cos\delta \cos\phi \cos\omega} \qquad (3)$$

The sun radiation's received energy of the sun radiation at a specific location, on a specific day and time, can be estimated by

$$I = 1367 \times (0.7)^{AM} \qquad (4)$$

This equation is used to calculate unity AM. Nevertheless, according to the physical model [1], a better fit to the observed data is given as:

$$I = 1367 \times (0.7)^{AM^{0.678}} \qquad (5)$$

2. Prediction Using Neural Networks

There are many studies on how to predict solar irradiation using neural networks. In the literature, Raidal Bese Function Networks was used to predict solar irradiance. However, in this paper, time series neural networks were used to perform the prediction. In this study, a data set (containing time series measurements) was taken from the National Renewable Energy Laboratory in Golden, Colorado. It was collected between January 1991 and December 2005, and contains 131,400 observations (year# = 8760 observations). All observation were made at the Vichy National Airport in Rolla, MO. Variables were chosen in the data were chosen according to their variability. The data the information used are as in table 1.

Table 1: Different Inputs of Neural Networks

Experiment 1	**Experiment 2**	**Experiment 3**
Day (from 1 to 365)	Day (from 1 to 365)	Day (from 1 to 365)
Hour of the day (1 to 24)	Hour of the day (1 to 24)	Hour of the day (1 to 24)
Azimuth angle (degrees)	Azimuth angle (degrees)	Azimuth angle (degrees)
Zenith angle (degrees)	Zenith angle (degrees)	Zenith angle (degrees)
	Wind speed (mph)	Wind speed (mph)
	Wind direction	Wind direction
		Temperature (C)

2.1 Visualizing Data and Preprocessing

Solar irradiation was visualized in one year to determine if there is a correlation between the inputs and the output. Solar irradiations that were equal to zero were eliminated first. Doing so makes training data easier and aids in more readily identifying the neural network's pattern. This data presented in Fig. 4. Here, large portion of the year had a solar irradiation of zero.

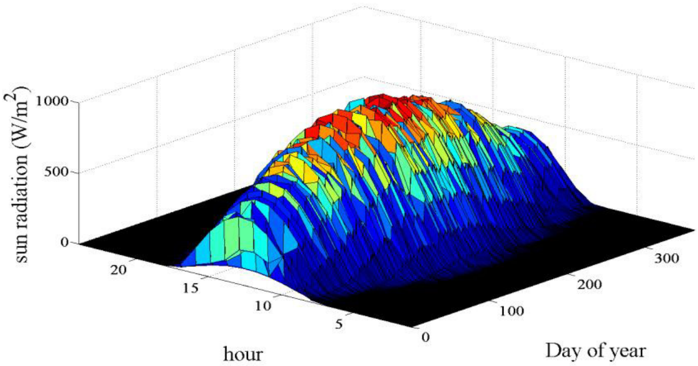

Figure 1: Solar Irradiation in One Year

Figure 2 depicts the data after the zero irradiation was removed. This data illustrates that days are longer during the summer than during the winter. After eliminating zero solar irradiation, all data points were normalized between -1 and 1 using the Matlab built-in function Mapminmax. This normalized data will use Mapminmax to de-normalize the data and present them in the output.

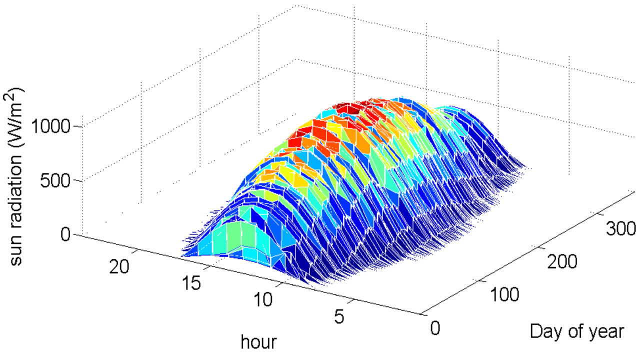

Figure 2: Data after Zero Irradiation is removed

2.2 Neural Network Design

The structural design of the selected back propagation neural network is depicted in Fig, 3. This design uses time delay to predict solar irradiation. A time delay neural network (TDNN) is a type of neural network. The primary aim of this type of networks is to figure on serial information. The TDNN units recognize options freelance of time-shift (i.e., sequence position) and are typically kind a part of a bigger pattern recognition system. They are most often used to change continuous audio into a stream of classified sound labels for speech recognition. A sign is increased with delayed copies as different inputs. The neural network is time-shift invariant since it has no internal state [5]. This network is referred to as NARX (nonlinear autoregressive with external input). It is given previous values of a time series so that it can learn to predict future values. The input received from the feedback is known as the external (or exogenous) time series [2].

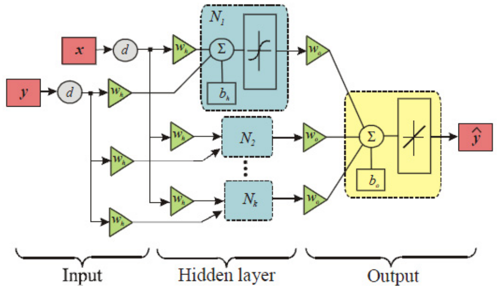

Figure 3. NARX Neural Network Architecture [10]

3. Case Studies

3.1 Case 1: Predicting Solar Irradiation Using Three Variables

Three variables were used in case 1 to predict irradiation: hours, zenith angle, and Azimuth angle. Feedback from the output was also used.

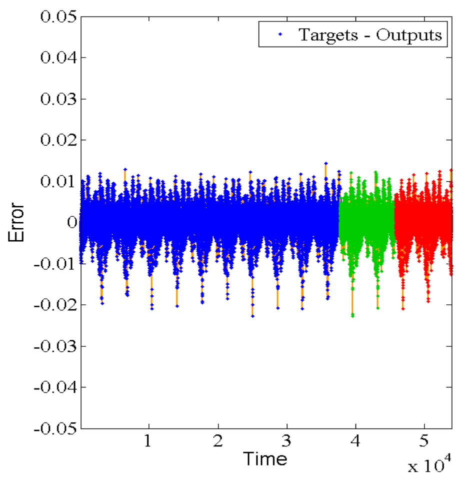

Figure 4: MSE Error

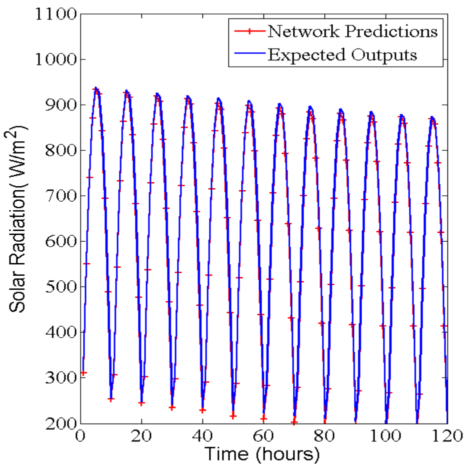

Figure 5: The predicted output vs. the actual output

This case gives very good result because the predicted output is matching the physical model. However, more cases were needed to make sure that this networks performance under the noise (shading conditions) was very accepted. The regression in Fig. 5 illustrates that the relationship between the predicted output and the actual output is approximately 1. Thus, the predicted output matches the actual output. Figure 4 illustrates that there is a small error comparing. It is oscillates around zero.

3.2 Case 2: Predicting Solar Irradiation Using Five Variables

Five variables were used in Case 2 to predict solar Irradiation: hours, zenith angle, Azimuth angle, wind speed, and wind direction. Feedback received from the output was also used.

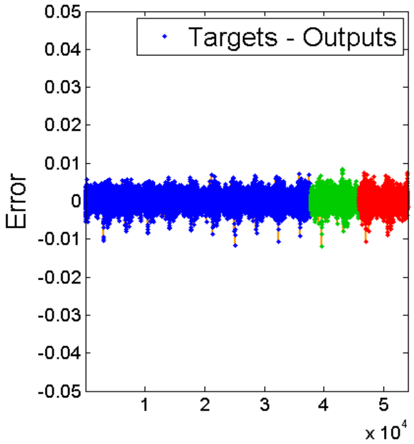

Figure 6: MSE Error

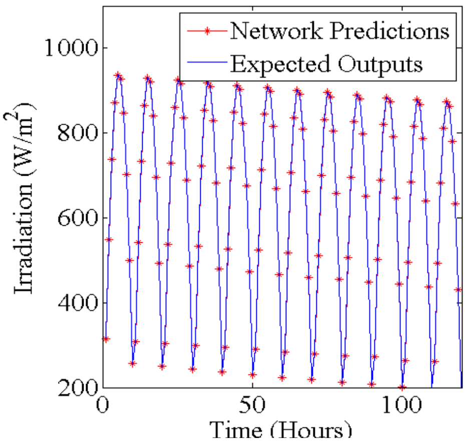

Figure 7: The predicted output vs. the actual output

3.3 Case 3: Predicting Solar Irradiance Using Six Variables

In these section different windows sizes which I used one back propagation training algorithm, as summarized in Table 2. A maximum number of epochs (1,0000) was used; the training goal value was 0. The Levenberg-Marquardt algorithm was used to reduce the error function. Overall, a window size of 3 is the best case where the smallest mean square error (MSE). Thus, this windows size used was to evaluate additional test values and cases.

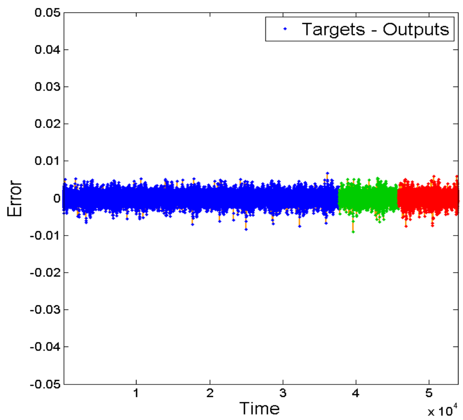

Figure 8: MSE Error

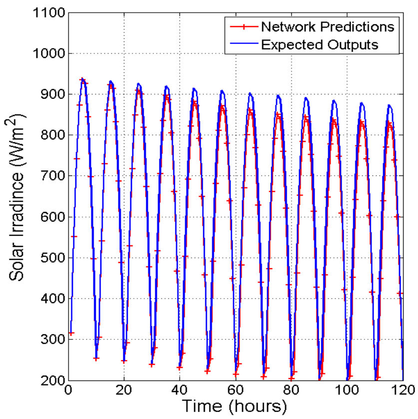

Figure 9: The predicted output vs. the actual output

The predicted output was not better than that for either Case 1 or Case 2 because the temperature (which fluctuates) was included.

4. Evaluating Different Window Sizes and Performance

The network was evaluated under different window sizes (see Table 2). The mean square error was used to compare the experiments to one another. The best performance occurred when three previous values were used and the convergence point was reached faster than other cases.

Table 2. Summary of Five different Windows Sizes

Algorithm	Number of Neurons Hidden Layer	Windows Size	Output MSE
Levenberg-Marquardt (trainlm)	21	2	5.7%
Levenberg-Marquardt (trainlm)	21	3	2.2%
Levenberg-Marquardt (trainlm)	21	4	7.6 %
Levenberg-Marquardt (trainlm)	21	5	11.02 %
Levenberg-Marquardt (trainlm)	21	6	15.33 %

The MSE was used to evaluate all three cases (see Table 3). Again, the use of three variables was found to yield the best performance because no strong correlation between temperature and irradiation exists (as in Case 3).

Table 3, Performance Evaluation of the cases

Case	Number of Neurons Hidden Layer	Window Size	Output MSE
Case 1	21	3	5.7 %
Case 2	21	3	5.5 %
Case 3	21	3	8.2 %

5. Conclusions

The completed back propagation neural network was successfully predicted the solar irradiation. Time series neural networks provided good predications as well. Three cases were conducted and tested. The output produced promising results. Different window sizes were tested. The best case occurred when three window sizes were used. Future studies should be conducted in which three networks are evaluated meticulously and compares them to other linear regression approaches, and other types of neural networks.

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