Short Term Solar Forecasting

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Abstract

Electricity generated from solar power is highly variable and the need to predict these variations in the short term is driven by the operations of power plants and grid balancing. A Nonlinear Autoregressive Neural Network with Exogenous Inputs (NARXNET) approach was used to analyze data in order to predict total normal solar irradiance ten minutes in the future. The proposed model uses current and past inputs (e.g. solar zenith angle, relative humidity, wind speed, wind direction, and total downward short wave irradiation) to make these predictions. While the proposed NARXNET model outperformed other approaches during the forecasting phase, the model had difficulty predicting sudden changes in irradiance yielding results that were inconclusive.

1 Introduction

Solar power systems generate electricity using photovoltaic systems and solar irradiance. Solar irradiance is a clean and abundant resource, however it is difficult to predict in the short term. Accurate predictions are needed to implement solar power for large-scale energy production in order for this resource to be used to its fullest potential. Machine learning techniques can provide these accurate predictions and lower the cost of implementing solar power. Therefore, it is important to use these techniques to predict solar irradiance when forecasting the time horizon of 10 minutes for power plant operation, grid balancing and trading.

2 Methods

The output prediction will be solar irradiance ten minutes into the future for all the models used. Autoregressive model and a nonlinear autoregressive neural network use only past observations of the dependent variable to make a prediction. Neural Networks can also use selected exogenous variables to make predictions more accurate.

2.1 Autoregression

Autoregression is a linear forecasting model that predicts the value of a single time series using a window of observations from that time series. The prediction is in series with the observations in the window. This means that AR predicts a single minute into the future using current and past conditions. Consider the time series of total broadband irradiance $y_n|n \in N$, we use the first w [1] observations to make prediction w +1.

$$\hat{y}_{w+1} = c + \Sigma_{i=0}^{w-1} \Phi_i (y_{w-i}) \tag{1}$$

[1] w = window size

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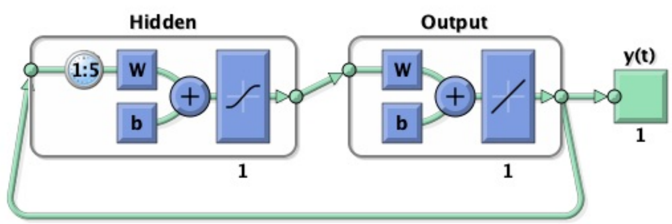
To push our prediction farther into the future we use predicted values in place of observed values. The variable t ranges from one to ten, this variable projects forecast to ten minutes in the future. At t equals one we use observed values in the regression, at t equals two we use the first prediction in place of y_w, at t equals ten, $\hat{y}$ is ten minutes in the future and Φ_1 is multiplied by the prediction y_{w+9}. The tenth prediction is saved, and the window of observed values is shifted forward in time by one. Repeating this process, we obtain a prediction for each minute in the test set after time 10+w.

$$\hat{y}_{w+t} = c + \Sigma_{i=0}^{w-1} \Phi_i (y_{w+(t-1)-i}) \tag{2}$$

2.2 Nonlinear Autoregressive Neural Network

An autoregressive neural network is a non-linear forecasting model that receives a window of inputs like the autoregressive model also relying on linear weights phi and a constant term. Also to forecast farther into the future a closed loop is implemented, feeding the prediction back into the network. However this neural network uses nonlinear log-sigmoid transfer function f and a linear transfer function l to make the prediction.

$$\hat{y}_{w+1} = l(d + f(c + \Sigma_{i=0}^{w-1} \Phi_i (y_{w-i}))) \tag{3}$$



The most effective window size and number of layers in network must be found. The model will use the most effective window size from autoregression and then the best number of layers will be found.

2.3 Autoregressive Neural Network with Exogenous Inputs

A nonlinear neural network can use observations of external variables to help predict changes in the target time series. Each single minute prediction requires up to date observations of exogenous variables. To predict the target time series ten minutes into the future a vector of predictions for each exogenous variable must be created. These predictions are made using uniform neural networks with the same number of neural layers and window lengths. Each variable has an individual network trained for predictions. However, these predictions are not optimized using test data.

$$\hat{y}_{w+1} = f(x(w+1), x(w)..., x(1), y(w), y(w-1)..., y(1)) \tag{4}$$

3 Evaluation

3.1 Experimental Setting

This experiment uses supervised learning methods. Using known future values, we can train and evaluate the accuracy of different prediction models.

The data was collected in one-minute intervals for five consecutive days, 7200 observations. However, the observations where irradiance was less than zero were removed, cutting our usable observations down to 2758. Variables measured include broadband total irradiance, solar zenith angle, relative humidity, wind speed, wind direction, and total downward shortwave irradiation. Total broadband irradiance is the test variable. Solar zenith angle, relative humidity, wind speed, wind direction, and total downward shortwave irradiation are dependent variables used to forecast.

Data is not randomly assigned to the training and testing sets. Doing this would not allow us to exploit the serial correlation in the data. Instead, the data set was divided in a way so that both sets have sunny and cloudy days and the sets consist of entire days from dawn to dusk. See figure 1. Model parameters are learned using the training data and evaluated using the test set.

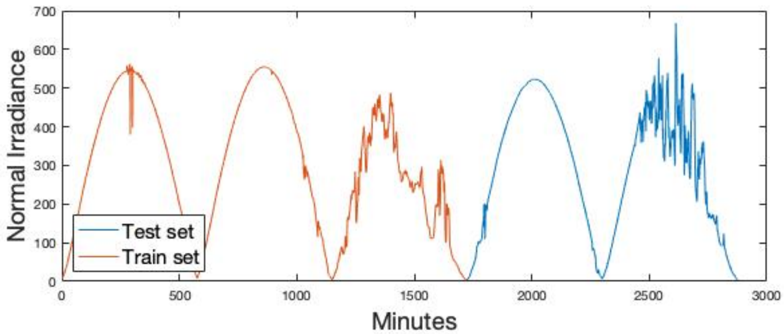


Figure 1: Data Set

3.2 Results

In order to make predictions, a window of observed values must be considered first. Using those known values we make a series of one-minute predictions. After every tenth prediction is saved, the window of observed values shifts forward in time by one. The saved predictions are compared to the actual values using normalized root mean square error (NRMSE), a measure that is more sensitive to large errors and well suited for utility applications where large errors can be especially costly. This error measure was used to compare window sizes, hidden layers in the network, and combinations of inputs.

Error data was gathered for window size from one to ten, AR and NARNET models were most effective at a size of ten. While, NARXNET was most effective at a window size of six. The range for Auto Regression (AR) error was minimal, from 0.254 to 0.256, compared to the larger error range for NARNET, which had a 0.025 difference, from 0.186 to 0.211, for all window sizes tested. However, NARXNET had the greatest error range with a difference of 1.33, from 0.170 to 1.50.

Hidden layers in the neural networks were sequentially added, starting at one and ending at ten, but the addition of layers produced less accurate predictions.

Case studies of different inputs were created to maximize the accuracy rate of NARXNET and capture the effectiveness of this model. These case studies yielded very similar results, the best error from case 1 is 0.167 and in case 2 is 0.164. The case studies are shown in the charts below.

Case 1	Case 2
Solar Zenith Angle	Solar Zenith Angle
Relative Humidity	Relative Humidity
Wind Speed	Wind Speed
Wind Direction	Wind Direction
-	Total Downward Shortwave Irradiation

Table 1: Case Studies

As shown in Table 2, NARNET has a smaller minimum error at 18 % while the error for the AR model measured 25 %. Therefore, concluding AR was the least effective model. With all variables in place, Table 2 shows the best error rate for each model. According to the data in Table 2, NARXNET outperformed the other two models making it the best approach to use to predict future solar irradiance. However, when comparing the NARXNET and NARNET models, Table 2 shows they performed similarly on the test data, 16 % and 18 % respectively.

	Auto Regression	Nonlinear Autoregressive Neural Network	NARXNET
Window Size	10	10	6
Hidden Layers	-	1	1
Exogenous Variables	-	-	5
NRMSE	% 25.41	% 18.47	% 16.45

Table 2: Model Comparison

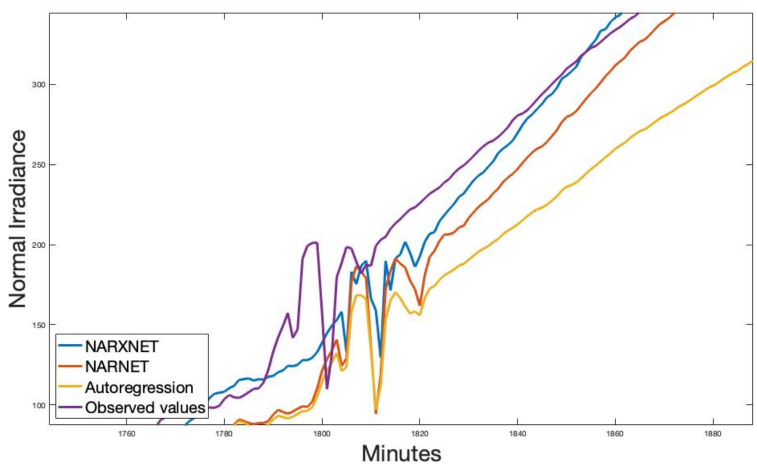


Figure 2: Model Comparison

3.3 Critical Analysis

Well known cloud and transparency predictions are available and future studies should consider the model developed by Allan Rahill of the Canadian Meteorological Center. The NARXNET model makes the most accurate predictions, however the model had difficulty predicting sudden changes in irradiance (See figure 3). During the test, cloudy day, NRMSE was 22.47 %, less when compared to the other models but not close compared to the 6 % NRMSE during the test, sunny day. It should also be noted that better prediction of exogenous variables has the possibility to make NARXNET predictions even more accurate.

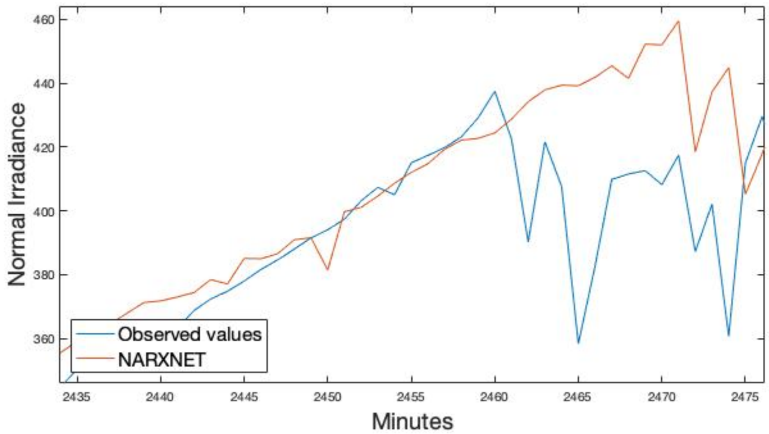


Figure 3: Neural Network with Exogenous Variables

4 Conclusion

NARXNET was the best model when it came to predicting future total normal solar irradiation. Two cases were conducted and tested. The results from both studies were similar. Different number of layers and window sizes were tested. The test yielding the best prediction results occurred when there was only one layer and the window size of six was used. Future studies should be conducted in which cloud cover and transparency are predicted.

5 Citation

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