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Solar Forecasting using ANN with Fuzzy Logic Pre-processing

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Abstract

Lack of predictability of solar power remains one major hindrance to the introduction of large-scale solar energy production. Comprehensive solar forecasting technologies are required to manage the intermittent nature of solar energy supply. However, one of the most challenging aspects of solar forecasting is the requirement for very short-term forecasting (in terms of minutes ahead) due to cloud movement, ambient temperature variation and humidity levels, which result in rapid ramp up and ramp down rates. This paper proposes an improved solar forecasting algorithm based on artificial neural network (ANN) model with fuzzy logic pre-processing. A three-layer (input layer, hidden layer and output layer) feed forward with back-propagation model is proposed as the neural network training algorithm. In this paper, an error correction factor based on the previous 5-min forecasted output is included to the input layer to minimize the forecast error. This is expected to produce a more accurate forecast. Weather information is a key input for the ANN model. In the case of rapid changes in solar irradiation or temperature on the forecast day, produced solar power changes greatly and forecast error would sensibly increase. In traditional prediction methods, the ANN uses all similar days' data to learn the trend of similarity. However, learning all similar days' data is quite complex, and it does not help if weather conditions change suddenly during the same day. Therefore, it is necessary to integrate into the ANN, a pre-processing stage that could perform real time analysis of weather information and factor it into the forecasting output. A fuzzy pre-processing toolbox is introduced into the proposed ANN model to find data correlation between cloud cover, temperature, wind speed, and wind direction with irradiance value. The accuracy of the proposed forecasting algorithm is compared with other ANN forecast algorithms.

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Keywords: Solar energy; intermittency; forecasting; fuzzy logic; artificial neural network; cloud cover.

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1. Introduction

Solar photovoltaic (PV) is on the verge of achieving its grid parity with the decline in cost due to increase in global PV installations and overcapacities in production. In Singapore, the levelized cost of electricity (LCOE) from solar energy is between S$0.19/kWh and S$0.27/kWh [1]. Despite reducing solar cost, lack of predictability of solar power remains one major hindrance to the introduction of large-scale solar energy production in Singapore. Solar power production is affected by solar irradiance which in turn is affected by weather conditions, such as cloud cover, wind speed and wind direction. Comprehensive solar forecasting technologies are required for grid control and dispatch to manage the intermittent nature of solar energy supply. However, one of the most challenging aspects of solar forecasting is the requirement for very short-term forecasting (in terms of minutes ahead) due to cloud movement, cloud formation and dissipation which result in rapid ramp up and ramp down rates.

Current research are focused on developing more accurate solar forecasting in order to better prepare the power system operator to manage the fluctuations in the solar PV power output. Different solar forecasting timescales, i.e., intra-hour, intra-day and day ahead, are required for different grid operator activities such as ramping events, unit commitment and electricity future markets [2]. Global horizontal irradiance (GHI) forecasting is the fundamental process in most solar power prediction tools. The data set used in the forecast will determine the forecast timescale. Medium- to longer-term forecasts are performed using numerical weather prediction (NWP) models and satellite-based forecasts such as those presented in [3] and [4] respectively. Research done in [5] utilizes satellite-derived data and a numerical weather prediction model to improve intra-day solar forecasting. Improved forecasting is achieved in [6] with the use of ground images of cloud movement. Although numerical based forecasting can achieve realistic predictions of changes in the weather conditions but it is inadequate when constrained by space and time due to the high emphasis to achieve overall coherence.

Computationally efficient and more accurate short-term solar forecasting is also widely researched as the accuracy of day-ahead models are further deteriorate by the unpredictable weather pattern experienced today [7]. Linear statistical models such as autoregressive (AR) and autoregressive moving average (ARMA) that uses real-time measurement data have been successfully applied for short-term forecasting [8], [9]. Auto-Regressive Integrated Moving Average (ARIMA) model which combines the autoregressive component to a moving average (MA) is also widely researched for application in solar forecasting. In these linear models, the relationship between the input variables and the forecasted variable are derived through statistical analysis. However, non-linear characteristics caused by variation in weather including cloud cover and atmospheric particulates further complicates the short-term forecasting [10].

Artificial intelligence or machine learning techniques are widely researched as an alternative solution for estimating processes associated with non-linear functions. In [11], artificial neural network (ANN) is used for short-term solar forecasting based on multiple input variable such as temperature, humidity, pressure and wind. A mixed wavelet neural network (WNN) is presented in [12] for short-term solar irradiance forecasting. Autoregressive fuzzy logic model is proposed in [13] to establish the clearness index function for improved solar forecasting. In these models unknown non-linear function and non-stationary environmental parameters are trained using historical data. In this paper, a hybrid combination of ANN with fuzzy logic pre-processing is proposed to further improve solar forecasting accuracy. A three-layer feed forward with back-propagation model is proposed. A fuzzy logic pre-processing stage is included to tune the relationship functions of various weather data in order to improve the accuracy of the solar forecast. In order to further improve the forecasting accuracy, an error correction factor based on the previous 5-min forecasted output is included to the input layer.

The paper is organized as follows. Section 2 describes in detail the clear sky radiation model used in this paper. In Section III, the ANN and the fuzzy logic preprocessing is described. Section IV presents the numerical results and discussion. Section V concludes.

2. Clear Sky Radiation Model

All grid-connected solar PV inverters usually operate in the Maximum Power Point Tracking (MPPT) mode with relatively constant power conversion efficiency. This indicates that once a PV system has been constructed, its AC power output is mainly determined by the solar irradiation and the operation temperature at its. Therefore, if the solar irradiation at the mounting location of the PV panels can be predicted accurately, the PV system's AC power output can be forecasted. The clear sky model used in this paper is adopted from [14]. The total radiation incident on an inclined PV panel, G_T is composed of the beam, diffuse, and reflected components as given by

$$G_{\mathrm{T}} = G_{ON}\left[(\tau_b \cdot \cos\theta_s) + (\tau_d \cdot \cos\theta_z \cdot \sigma) + (\rho \cdot \tau_r \cdot \cos\theta_z \cdot \sigma)\right] \tag{1}$$

where G_{ON} is the extra-terrestrial solar radiation, θ_s is the angle between the normal to the surface and the direction to the sun (in deg), θ_z solar zenith angle (in rad), and ρ is the average reflectance of the ground. τ_b, τ_d and τ_r are the atmospheric transmittance for beam, diffuse and reflected components, respectively. σ is the inclination angle factor which is given by

$$\sigma = \left(\frac{1+\cos\beta}{2}\right) \tag{2}$$

where β is the PV panel inclination angle from the surface (in deg). The extra-terrestrial solar radiation, G_{ON} can be obtained using (3) where G_{SC} is the solar constant and D is the day of the year. In this paper, G_{SC} is taken as 1367 W/m^2.

$$G_{\mathrm{ON}} = G_{SC}\left[1 + 0.033 \cdot \cos(360 \cdot D/365)\right] \tag{3}$$

The atmospheric transmittance for beam, τ_b, diffuse, τ_d and reflected, τ_r are given by

$$\tau_{\mathrm{b}} = a_0 + a_1 \cdot e^{(-k/\cos_Z)} \tag{4}$$

$$\tau_{\mathrm{d}} = 0.271 - 0.294 \cdot \tau_b \tag{5}$$

$$\tau_{\mathrm{r}} = 0.271 + 0.706 \cdot \tau_b \tag{6}$$

where

$$a_0 = r_0\left[0.4237 - 0.00821(6 - A)^2\right] \tag{7}$$

$$a_1 = r_1\left[0.5055 + 0.00595(6.5 - A)^2\right] \tag{8}$$

$$k = r_k\left[0.2711 + 0.01858(2.5 - A)^2\right] \tag{9}$$

A is the altitude of the panel installation location in km while r_0, r_1 and r_k are the climate correction factors. The angle between the normal to the surface and the direction to the sun, θ_s and the solar zenith angle, θ_z are given by (10) and (11) respectively.

$$\begin{aligned}\cos\theta_S &= \sin\delta \cdot \sin\phi \cdot \cos\beta - \sin\delta \cdot \cos\phi \cdot \sin\beta \cdot \cos\alpha + \cos\delta \cdot \cos\phi \cdot \cos\beta \cdot \cos\omega \\ &\quad + \cos\delta \cdot \sin\phi \cdot \sin\beta \cdot \cos\alpha \cdot \cos\omega + \cos\delta \cdot \sin\alpha \cdot \sin\omega \cdot \sin\beta\end{aligned} \tag{10}$$

$$\cos\theta_Z = \cos\delta \cdot \cos\phi \cdot \cos\omega + \sin\delta \cdot \sin\phi \tag{11}$$

where, ϕ is the latitude of the solar PV installation (in deg), and α is the azimuth angle of the normal of the surface. The δ solar declination (in deg) can be obtained from (12) and ω is the hour angle (in deg) from (13). LMT is the Local Mean Time which is given from the range of 0 to 24 hour while TZ is the time zone.

$$\delta = 23.45 \sin\left[360 \cdot (D + 284) / 365 \right] \tag{12}$$

$$\omega = (LMT - TZ - 12) \cdot 15^{\circ} \tag{13}$$

Figure 1 shows the hourly solar radiation incident on the solar PV panel based on the clear sky radiation model discussed earlier. In this paper, r_0, r_1 and r_k are taken as 0.95, 0.98, and 1.02 respectively to represent the Singapore's tropical climate [14]. The solar PV panel inclination angle β is taken as 15° and the average reflectance of the ground ρ for concrete material used for building roof-top is taken as 0.33 [15]. The altitude of the panel installation location A is 0.04km to represent a typical 15-storey Housing Development Board (HDB) residential building in Singapore. LMT is obtained from the input data time while TZ is taken as -1 as Singapore is located at GMT+7 but takes GMT+8 as the time reference. The clear sky model output is compared with the peak irradiance recorded for that particular time during the year 2016 at a weather station located at Singapore (1.341003N, 103.963014E). The peak irradiance data is used to represent the closest resemblance of a clear sky irradiance experienced on that particular time. It can be seen that the clear sky model output is able to closely represent the actual irradiance profile in Singapore. The Mean Absolute Percentage Error (MAPE) between the actual peak irradiance data and the clear sky model peak output is 17.8%. This error is mainly due to the high vapour content in the atmosphere and frequent cloud cover experienced in Singapore. The clear sky model will be one of the input for the ANN model.

3. ANN with Fuzzy Logic Model

A three-layer (input layer, hidden layer and output layer) feed forward with back-propagation model is proposed in this paper. The Levenberg-Marquardt optimization method is used as the neural network training algorithm. The neural network shown in Figure 2 consists of 8 inputs in the input layer, 1 output in the output layer and 25 hidden neurons. A tangent sigmoid is used as the activation function for all the neurons in the neural network.

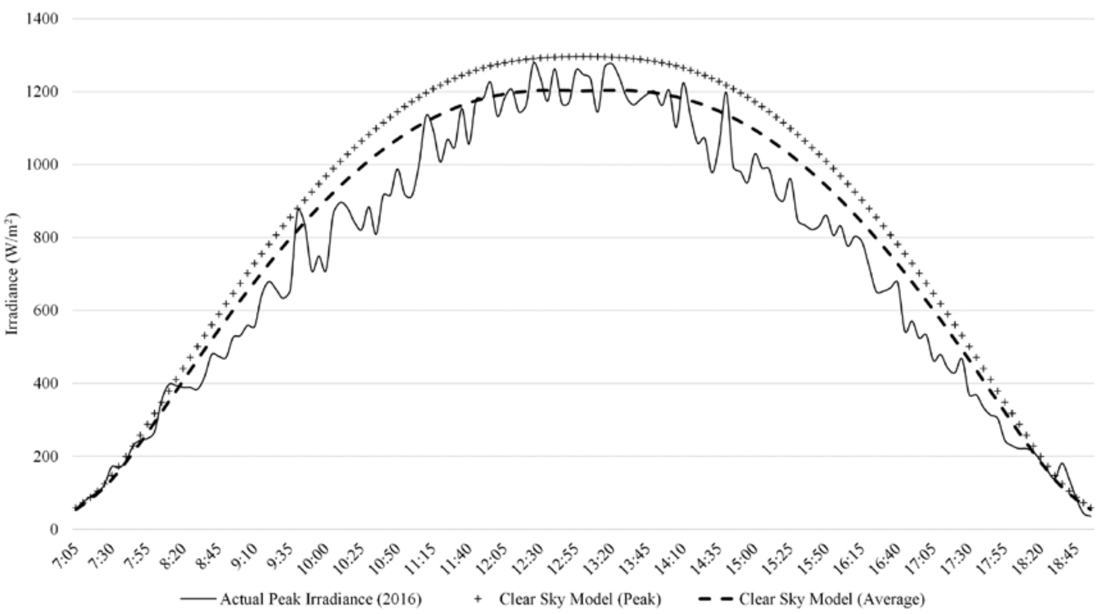

Figure 1: Irradiance output using clear sky model

However, weather information is a key input for the ANN based solar forecasting algorithm. In the case of rapid changes in solar irradiation or temperature on the forecast day, produced solar irradiance changes greatly and forecast error would sensibly increase. In traditional prediction methods, the ANN uses all similar days' data to learn the trend of similarity. However, learning all similar days' data is quite complex, and it does not help if weather conditions change suddenly during the same day or lack of data on similar day profile. Therefore, it is necessary to integrate into the ANN a system that could perform real time analysis of weather information coming from the weather sensors. The paper proposes the use of fuzzy filtering for dealing with the complexity of inputs involved in the available weather data. A fuzzy pre-processing toolbox is introduced into the neural system to find data correlation between relative humidity, rainfall and the time of the day to classify the cloud cover index as another input to the neural network (i_8). The membership functions for relative humidity are low, average and high, while the membership function for rainfall are binary "1" and "0". The membership functions of both relative humidity and rainfall are determined through statistical analysis of their probability distribution. Besides producing more accurate forecast results, the proposed method will also eliminate the need for very expensive sky imaging system to provide information on cloud cover. In addition, an error correction factor is proposed to compute the error between the output of the neural network (n^{th} interval) and the clear sky model (n^{th} interval) and then propagated back from the output layer back to the input layer of the neural network to minimize the error for the next 5-min forecast ($n+1^{th}$ interval). The input on the error correction factor (i_7) for the improved ANN model is given by

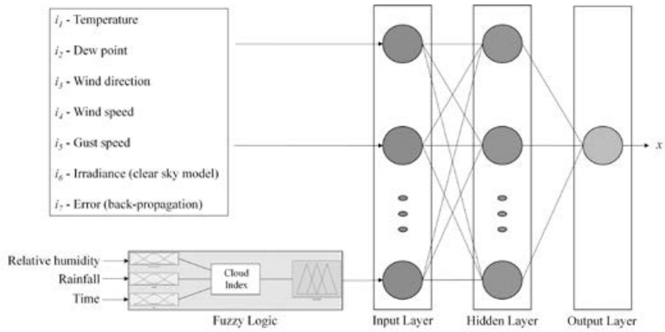

Figure 2: Proposed ANN with fuzzy logic and improved back-propagation model.

$$i_{7,n+1} = x_n / i_{6,n} \tag{14}$$

4. Numerical Results and Discussions

The proposed improved ANN with back-propagation algorithm and fuzzy logic pre-processing is implemented using MATLAB. The input weather data is obtained from a weather station located at Singapore (1.341003N, 103.963014E). The ANN algorithm is trained using the last 3 months weather data (January to March 2017) to forecast irradiance for April 2017. It must be noted that the training data does not include previous similar day data for the month of April 2016 and as such higher error rate is expected. This is mainly due to the unavailability of data to train the model. However, this is acceptable as the objective of this paper is to prove that the inclusion of the fuzzy logic pre-possessing and improved back-propagation algorithm will improve forecast error compared to a pure ANN model. The MAPEs of Model (i) - pure ANN, Model (ii) - ANN with fuzzy logic pre-processing, and Model (iii) - improved ANN with error correction factor and fuzzy logic pre-processing are shown in Table 1 and Figure 3. It is evident that the

Table 1. Numerical results

Model	MAPE
Model (i)	46.3%
Model (ii)	43.1%
Model (iii)	29.6%

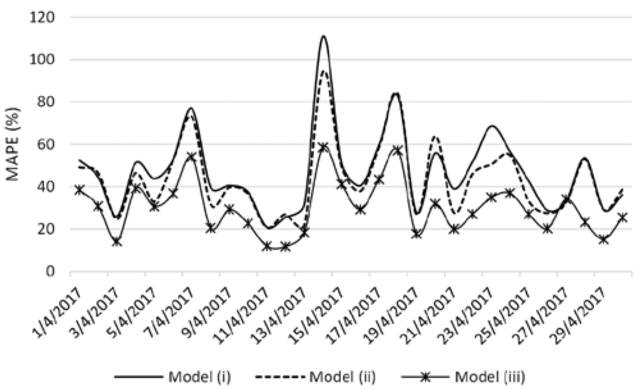

Figure 3: Daily MAPE for month of April 2017.

proposed improved ANN with error correction factor and fuzzy logic pre-processing is able to improve the accuracy of pure ANN and ANN with fuzzy logic by 16.7% and 13.5% respectively. It can also be observed that the ANN with fuzzy logic is able to improve the forecast accuracy of pure ANN model by 3.2%. Figure 3 shows the daily MAPE error for all three models. It can be seen that the proposed improved ANN with error correction factor and fuzzy logic pre-processing performs better that the other two model consistently throughout most days in the month of April 2017. Specifically, on 14 April 2017, the proposed model achieves a 52.48% improvement on forecast accuracy compared to the pure ANN model. This improvement is mainly attributed to the adaptive error correction mechanism and as such the forecasting algorithm does not require large-scale historical weather data.

5. Conclusion

This paper has proposed an improved solar forecasting algorithm based on artificial neural network (ANN) model with fuzzy logic pre-processing. The proposed model also includes an improved error correction factor aimed at minimizing the forecast error by incorporating the error from previous 5-min forecasted output to the input layer. The clear-sky model and weather data obtained from a weather station in Singapore are used for training the developed model. The numerical result prove that the error correction factor coupled with a pure ANN can significantly improve solar irradiance forecast accuracy due to the adaptive error correction ability. A slight improvement can also be achieved by incorporating a fuzzy logic pre-processing to classify cloud cover index based on relative humidity, rainfall and the time of the day. Further work will focus on developing a more comprehensive multi-layer ANN model and using more significant dataset to train the ANN model in order to achieve a higher forecast accuracy.

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References

[1] J. Luther and T. Reindl, "Solar photovoltaic (PV) roadmap for Singapore," Solar Energy Research Institute of Singapore, 2014.
[2] V. Kostylev and A. Pavlovski, "Solar power forecasting performance – towards industry standards," in *Proc. 1st 1st International Workshop on the Integration of Solar Power into Power Systems*, Oct. 2011.
[3] P. Mathiesen and J. Kleissl, "Evaluation of numerical weather prediction for intra-day solar forecasting in the CONUS," Solar Energy, vol. 85, no. 5, pp. 967–977, May 2011.
[4] L. Nonnenmacher and C.F.M. Coimbra, "Streamline-based method for intra-day solar forecasting through remote sensing," Solar Energy, vol. 108, pp. 447–459, Oct. 2014.
[5] M. Thomson and D. G. Infield, "Impact of widespread photovoltaics generation on distribution systems," IET Renewable Power Generation, vol. 1, no. 1, pp. 33-40, Mar. 2007.
[6] T. Y. Tiam and D. S. Kirschen (2007), "Impact on the power system of a large penetration of photovoltaic generation," in *Proc. IEEE Power Engineering Society General Meeting*, pp. 1-8, Jun. 2007.
[7] L. Mazorra Aguiar, B. Pereira, P. Lauret, F. Díaz, and M. David, "Combining solar irradiance measurements, satellite-derived data and a numerical weather prediction model to improve intra-day solar forecasting," Renewable Energy, vol. 97, pp. 599-610, Jun. 2016.
[8] G. Reikard, "Predicting solar radiation at high resolutions: a comparison of time series forecasts," Solar Energy, vol. 83, no. 3, pp. 342–349, Mar. 2009.
[9] P. Bacher, H. Madsen, and H.A. Nielsen, "Online short-term solar power forecasting, vol. 83, no. 10, pp. 1772–1783, Oct. 2009.
[10] F. Wang, Z. Mi, S. Su, and H. Zhao, "Short-term solar irradiance forecasting model based on artificial neural network using statistical feature parameters," Energies, vol. 5, no. 5, pp. 1355–1370, 2012
[11] F.-V. Gutierrez-Corea, M.-A. Manso-Callejo, M.-P. Moreno-Regidor, and M.-T. Manrique-Sancho, "Forecasting short-term solar irradiance based on artificial neural networks and data from neighboring meteorological stations," Solar Energy, vol. 134, pp. 119-131, Sep. 2016.
[12] V. Sharma, D. Yang, W. Walsh, and T. Reindl, "Short term solar irradiance forecasting using a mixed wavelet neural network," Renewable Energy, vol. 90, pp. 481–492, May 2016.
[13] R. S. Boata and P. Gravila, "Functional fuzzy approach for forecasting daily global solar irradiation," *Atmospheric Research*, vol. 112, pp. 79-88, Aug. 2012.
[14] C. Tao, D. Shanxu, and C. Changsong, "Forecasting power output for grid-connected photovoltaic power system without using solar radiation measurement", *Proc. 2nd IEEE Int. Symp. Power Electron. Distrib. Gener. Syst. (PEDG)*, pp. 773-777, Jun. 2010.
[15] A. McEvoy, T. Markvart, and L. Castaner, Practical handbook of photovoltaics, Elsevier, 2012.