K-NN Decomposition Artificial Neural Network Models for Global Solar Irradiance Forecasting Based on Meteorological Data

by Unit Three Kartini

K-NN Decomposition Artificial Neural Network Models for Global Solar Irradiance Forecasting Based on Meteorological Data

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Abstract: This paper proposes a novel methodology for forecasting of one hourly global solar irradiance (GSI). This methodology is a combination of k-NN decompotition method and artificial neural network (ANN) algorithm modelling. The k-NN Decomposition-ANN method is designed to forecast *GSI* for 60 min ahead based on meteorology data for the target PV station which position is surrounded by eight other adjacent PV stations. The novelty of this method is taking into account the meteorology data. A set of *GSI* measurement samples was available from the PV station in Taiwan which is used as test data. The first method implements k-NN Decomposition as a preprocessing technique prior to ANN method. The error statistical indicators of k-NN Decomposition- ANN model and the root-mean-square error (*RMSE*) is 20 W/m2. The models forecasts are then compared to measured data and simulation results indicate that the k-NN Decomposition-ANN-based model presented in this research can calculate hourly *GSI* with satisfactory accuracy.

Key words: Forecasting, decomposition, artificial neural network, global solar irradiance, meteorological, photovoltaic.

1. Introduction

The photovoltaic energy forecasting is a rapidly evolving field, especially forecasting toward the GSI. The GSI forecasting is challenging due to use changing metheorology data patterns, solar radiation, and potential error within mathematical modelling since this depends on the variability of weather conditions that cannot be predicted and controlled. Hourly the global solar irradiance data forecasting has significant consequences in most solar applications such as energy system sizing and meteorological estimation. Accurate forecasting of the GSI will be improves the efficiency of the outputs of many applications. Moreover, the distribution of load, the electric energy storage and fulfillment of electrical energy will be maximized and reliable when done well to forecast the GSI on the photovoltaic system. The performance of photovoltaic systems (PV) at this paper is heavily influenced by some meteorological conditions consisting of a temperature, global irradiation, humidity, wind speed and wind direction. It is obvious that the electric energy generated by the photovoltaic (PV) solar depends on the magnitude of the GSI received by photovoltaic panels at every PV station. In previous research work which presents a variety of mathematical modelling for forecasting the

GSI as well as forecasting the GSI regardless and not dependent on of the meteorological variables. As the authors [1], [2] have presented nearest-neighbor methodology for prediction of intra-hour global horizontal. The authors of [3]-[7] have presented about ANN based daily local forecasting for global solar radiation. And the authors of [8], [9] have explained about prediction of solar radiation using ANN for short term forecasting PV generator.

To get the resulting a hybrid method based on a new clustering technique have been proposed in [10]. The authors of [11]-[19] have presented about univariate and multivariate methods for very short-term solar photovoltaic power forecasting. Combining solar irradiance measurements, satellite derived data and a numerical weather prediction model weather prediction model to improve intra day solar forecasting have been proposed in [20], [21]. Solar radiation forecasting with multiple parameters neural networks have been proposed in [22]. The authors of [23] have presented about estimation of hourly global solar irradiation on tilted absorbers from horizontal one using ANN have been proposed in [24]. However, all of the aforementioned only consider one station and do not consider the station its surround. Our main goal is to compare the performance of these models for very short term photovoltaic power forecasting and especially to investigate if the meteorological weather data helps to improve the accuracy. The rest of this paper is organized as follows. Section 2, we describe data station PV. Section 3 describes our methodology. Section 4 presents and discusses the results model forecasting the GSI and measured error. Section 5 summarizes the main results and concludes the paper.

2. Models and Data Description

In this work, measured the GSI hourly data from meteorological data ground stations photovoltaic are used to forecast the GSI for the next day [12]. The data representing position the GSI can see in Table 1 which explains geographical location altitude of the nine stations in Taiwan.

Table 1. Geographical Location of the Stations

Stations	Locations	Altitudes (Km)
A	0	8.3
B	36	10.5
C	93	10.8
D	140	10.5
E	180	10
F	250	4.3
G	280	5.4
H	310	9.1
S	0	0

3. Methodology

The purpose of this study is the improvement of forecasting results using k-NN Decomposition method combined with ANN methods. The simulation of the k-NN Decomposition ANN method can be programmed in a few minutes ahead after the recording of the initial measurements.

3.1. K-Nearest Neighbor (K-NN)

The k-NN method is one of the simplest methods among the machine learning algorithms. The process calculate the Euclidan distance between, as in

$$ds_j^i(c,nxy)=\sqrt{\Sigma_{q=1}^{k}\left(c_p^i-nxy_{pj}^i\right)^2} \qquad p=\ 1,\ 2,\ 3...m \qquad (1)$$

where in the matrix is the scalar distance of two vectors C and nxy of the matrix with the size of a dimension.

3.2. Artificial Neural Network (ANN)

ANN is a mathematical model that is inspired by the structure and information processing of biological neural networks, and ANN are intelligent systems that have the capacity to learn. The neurons have five basic components namely input, weight-bias, threshold, summing junction and output as illustrated in Fig. 1.

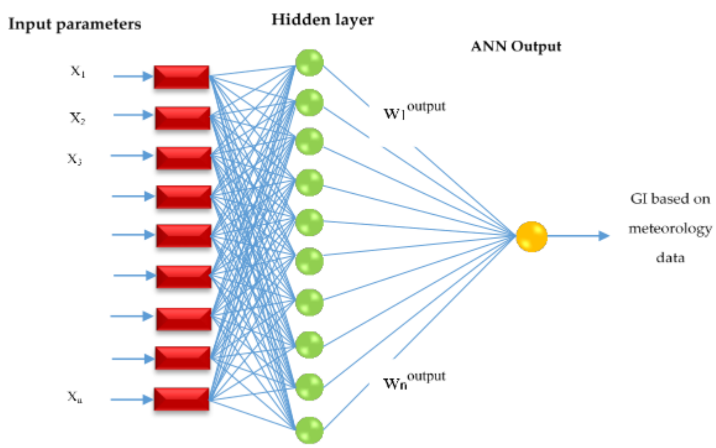


Fig. 1. Basic structure architecture of a simple artificial neuron.

3.3. STL Decomposition Method

The proposed technique for forecasting hourly the GSI data of Taiwan electric utility with a classical decomposition method. Decomposition method is a very powerful technique to determine the behaviours of time series data. The GSI data time series can be decomposed into the separated component the seasonal, trend, cyclical and residual. The seasonal component indicates the changes in the data that depend on the weather. Normally, the trend and cyclical components are combined together to make a trend-cycle. The general form decomposition techniques can be expressed as:

$$Y_t = T_t \times S_t \times C_t \times R_t \tag{2}$$

where Y_t is the time series (or observation) at time t, T_t is the trend component at time t, C_t is the cyclical component at time t, S_t is the seasonal component at time t, R_t is the residual component at time t.

3.4. K-NN Decomposition ANN Modelling

K-NN Decomposition ANN is characterized by a combination of any or two or more of the methods described previously. This approach is trying to decipher patterns of the basic time series into sub patterns and combined with four components, namely, the trend (T), seasonal (S), cyclical (C) and error (R) component. The decomposition method is based on the assumption that the existing data are a combination of several components, are simply described as follows:

$$\begin{aligned} \text{Data} &= \text{pattern} + \text{residual} \\ &= f(\text{k} - \text{NN} - \text{ANN}, \text{cyclical}, \text{seasonal}) + \text{residual} \end{aligned} \tag{3}$$

For the k-NN Decomposition ANN modelling can see Fig. 2. And this section discussed configurations of proposed modelling for process forecasting the GSI.

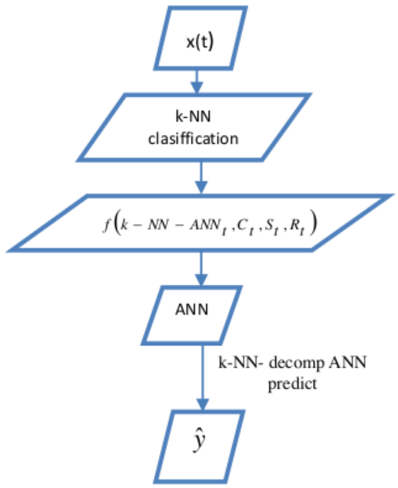
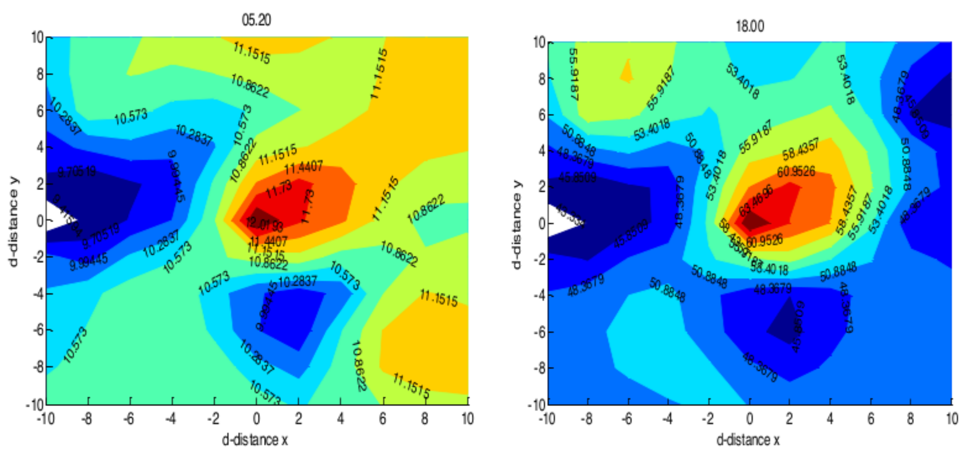


Fig. 2. Flowchart process k-NN-decomposition ANN forecasting model.

4. Result and Discussion

In this section of the hybrid model is used to forecast future global solar irradiance by using a 60 minutes ahead forecasting procedure. Particularly, researcher tested our model using the previously described databases with wind direction, wind speed, pressure, temperature, and humidity.

4.1. Performance of Forecasting Techniques



(a) (b)

Fig. 3. (a) d-Distance PV station based on the Euclidean (k-NN model) in time 5:20 a.m. on 8 June 2012; and (b) d-Distance PV station based on the Euclidean (k-NN model) in time 18:00 p.m. on 8 June 2012.

Modelling design used in hybrid modelling of the GSI forecasting has a design by giving a valid result. The d-dimensional feature and n-dimensional distances based on the Euclidean (K-NN model) every hour for all of PV station are shown in Fig. 3. From the simulation results using the k-NN method based on meteorological data values, respectively.

All of them are used as pre-processing data in the ANN method, which can be calculated by the polynomial Equation (4):

$$f(x,y) = p_{00} + p_{10}x + p_{01}y + p_{20}x^2 + p_{11}xy + p_{02}y^2 \tag{4}$$

where $f(x, y)$ is the *GSI* value of the k-NN method and variable x, y is the coordinate value's position of the PV station. In which the polynomial equation above is the result of the simulation on 5:20 a.m. for Fig. 3a and 18:00 p.m. hours for Fig. 3b using the k-NN method for Station S. Moreover that polynomial equation also can be implemented for the other PV stations. Consider an hourly the GSI time series over a period of fourteen hours as showed in Fig. 4. Explain about the global solar irradiance time series can be decomposed into the seasonal, trend and residual component using a decomposition model.

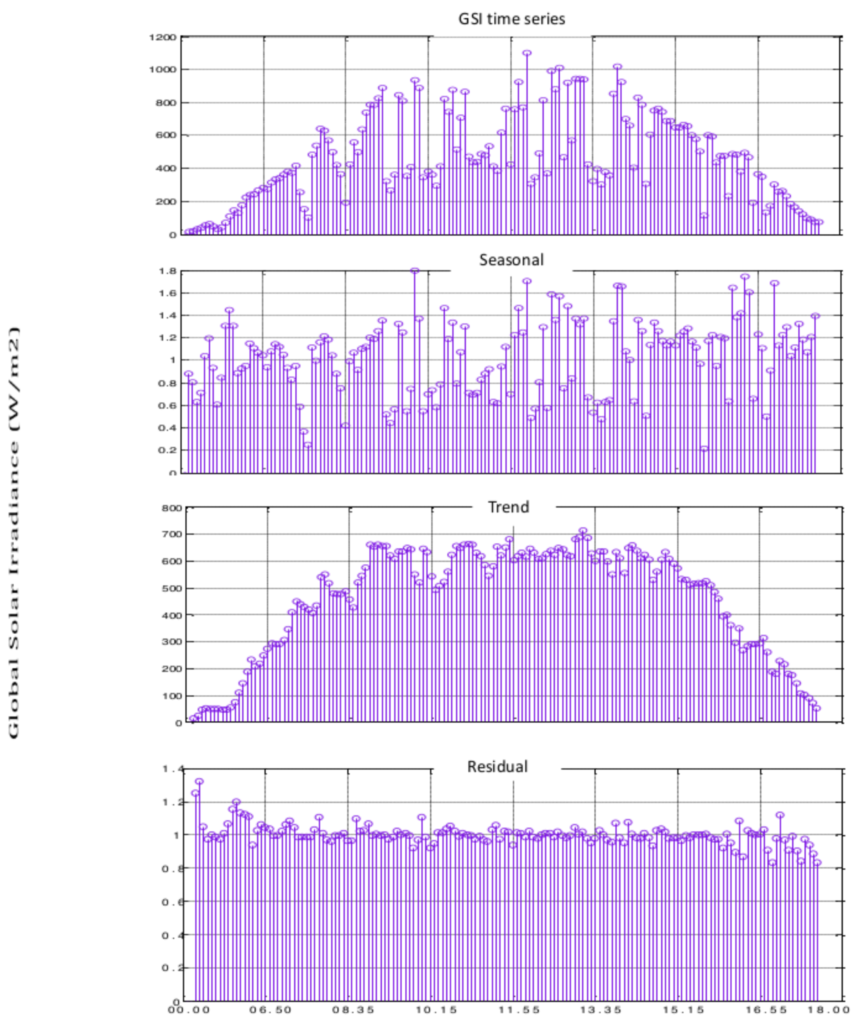


Fig. 4. STL decomposition for hourly the global solar irradiance time series. The GSI for Taiwan June 8, 2012. The three panels show the decomposed seasonal, trend and residual component.

From Fig. 5 we can see illustrates the result forecasting performance the GSI with k-NN Decomposition ANN model is better than and closer to the actual data in PV station target. For average error calculation with a Root mean squared error (RMSE) formula of k-NN Decomposition ANN modelling is 20 W/m². Fig. 6 Shows indicative results from the performance the GSI of the model k-NN Decomposition ANN approach for short term GSI forecasting with time fourteen hours in (5:20 a.m to 18:00 p.m) on June 8, 2012, is comparable with actual data, k-NN method and k-NN ANN method. From result value calculation, GSI forecast it shows that the general trend of the GSI is learned with well in modelling of k-NN decomposition ANN model as compare with to k-NN method and k-NN ANN method as well as hybrid model is closely matched with actual data. In the Fig. 7 depicts calculation result of very short term forecast the GSI k-NN Decomposition ANN model versus the actual for 60 minutes ahead.

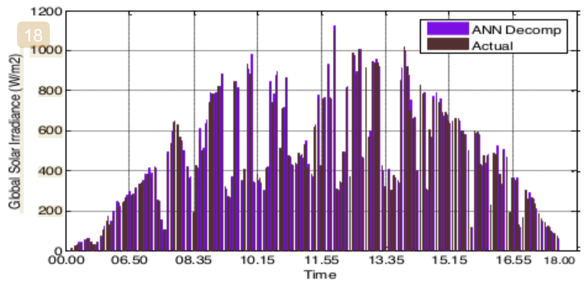


Fig. 5. Short term forecasting the GSI with k-NN Decomposition ANN model vs actual data in PV station target.

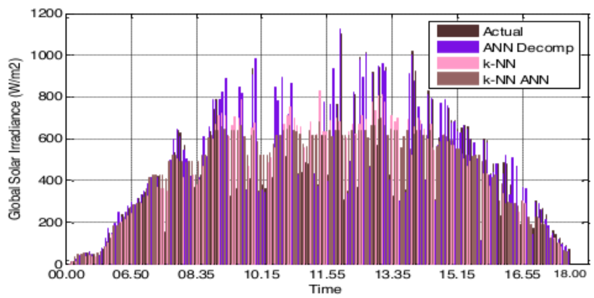


Fig. 6. Short term the GSI forecasting with k-NN Decomp ANN model, actual, k-NN, and k-NN-ANN method.

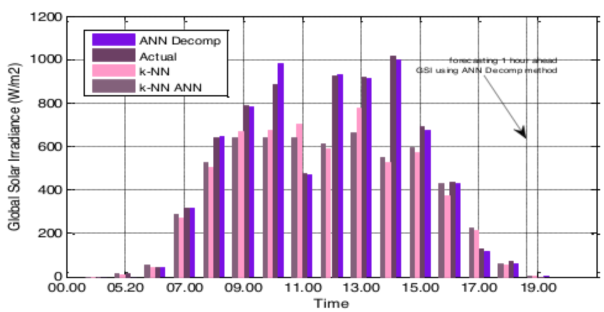


Fig. 7. The forecast the GSI using k-NN Decomp ANN method 60 minutes ahead.

Many diagnostic statistics to measurement error formula commonly used in the GSI forecasting, using root mean square error (RMSE). Fig. 8 illustrates the *RMSE* coefficients for the actual data and the forecasting performance using *k*-NN, the *k*-NN-ANN and k-NN Decomp ANN model. The error statistical indicators of the *k*-NN-ANN model are *RMSE* 169 W/m^2.

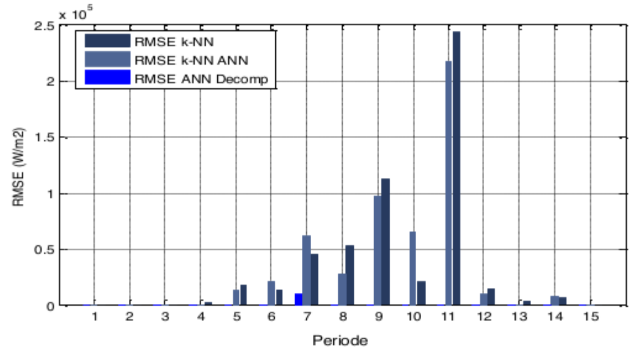


Fig. 8. RMSE coefficients between actual data and GSI forecasts using the k-NN, k-NN ANN, and ANN decomp model on the test data set.

On the other hand, the error statistical indicators for the proposed model (k-NN Decomp-ANN model) are RMSE 20 W/m^2 and the k-NN model are RMSE 164 W/m^2. It is evident that k-NN-Decomposition ANN model displays better predictions than the k-NN and k-NN ANN model.

5. Conclusion

In the present study, a novel methodology k-NN Decomposition ANN based model combination of k-NN-decomposition model, ANN model was developed to forecast the GSI at the surface. The following conclusions can be drawn from this research:

- A different formulation for very short term GSI forecasting using k-NN-decomposition ANN modelling based on meteorology data is proposed. The proposed model attempting to shape the patterns of a polynomial equation shows that the proposed model forecasting is better. The variable meteorology data weather is of great very importance and affects the resulting GSI forecasting output.
- The new model proposed in this study is a combination of k-NN decomposition modelling and an ANN model. The model is employed to forecast *GSI* data for forecasting period based on meteorology data. It clearly shows that the *GSI* forecasting using a different k-NN decomposition-ANN model for every hour based on meteorological data giving a better result output, which means the *GSI* forecasting largely depends on variable meteorological data, where the meteorology data variables consist of *GI*, wind speed, wind direct, humidity and temperatures.

Finally, the proposed k-NN-decomposition ANN model can be effectively used as an appropriate alternative for the *GSI* forecasting which the resulting simulation better than another method as well as very closely matching with actual data.

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PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9