Short Term Forecasting of Global Solar Irradiance by k-Nearest Neighbor Multilayer Backpropagation Learning Neural Network Algorithm

by Unit Three Kartini

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ABSTRACT
The paper proposes based on meteorology data, especially for optimizing the operation of power generating electricity from photovoltaic energy. This paper proposes a novel methodology for very short term forecasting of hourly global solar irradiance (GSI). This methodology is a combination of k-nearest neighbor algorithm (k-NN) modelling and multilayer backpropagation learning neural network (BPLNN) model. The k-NN-multilayer BPLNN model is designed to forecast GSI for 1 hours ahead based on meteorology data for the target PV station which position is surrounded by eight other adjacent PV stations. The forecasting for global solar irradiance using k-NN-multilayer BPLNN modelling is a very powerful technique to determine the behaviour of time series data. The first method implements k-NN as a preprocessing technique prior to backpropagation learning method. The error statistical indicators of k-NN- multilayer BPLNN models used momentum (mc) = 0.8 the root-mean-square error (RMSE) is 176.5 W/m^2. The models forecasts are then compared to measured data and validation results indicate that the k-NN-BPLNN based method presented in this study can estimate hourly GSI with satisfactory accuracy.

CCS Concepts
• **Information systems→Mobile information processing systems**

Keywords
Global solar irradiance; photovoltaic; gradient descent adaptive rate and momentum; forecasting; k-nearest neighbor; multilayer backpropagation NN.

1. INTRODUCTION
Nowadays, forecasting global solar irradiance is an essential task to perform, particularly related to the rise of photovoltaic solar energy as a source of power. Since solar power is categorized as intermittent energy sources, the forecasting is paramount to regulate electricity load in power network. It also functions to optimize power delivery and unit commitment and in extension, minimize the operating cost of power system. Moreover, distribution of load, electric energy storage, and energy supply will be maximized and more reliable.

The performance of photovoltaic systems (PV) is heavily influenced by some meteorological conditions, consisting of a temperature, global irradiation, humidity, wind speed and wind direction. The relation is clear: electrical energy generated by the photovoltaic (PV) solar depends on the amount of the global solar irradiance received by photovoltaic panels. Previous research have presented a variety of mathematical modelling for global solar irradiance forecasting in relation to meteorological variables. Mark et.al. [1] and Liu et.al. [2] presented Augmented Efficient BackProp as a strategy for applying the backpropagation algorithm to deep autoencoders and explain multilayer BP gradient descent with adaptive momentum. Zhang et. al.[3] presented a novel BP algorithm for condition recognition. The forecasting GSI with statistical methods kNN. Fatih [4] and Hugo et.al. [5] presented modelling of solar irradiation. Sancho et.al. [6] worked on the prediction of daily global irradiation using temporal Gaussian process. Dazhi et.al. [7] and [8] studied the forecasting of global horizontal irradiance by exponential smoothing. Spatiotemporal pattern recognition for global horizontal irradiance forecasting has been proposed as well by Licciardi et.al. [9]. In Badia et.al. [10], ANN based on daily local forecasting for global solar radiation was explained, and Wong et.al. [11] presented the solar radiation model.

To get multi-horizon irradiation forecasting for Mediterranean, time series models have been proposed by Paolia et.al. [12]. Elke et.al. [13] presented irradiance forecasting for the power prediction of grid-connected photovoltaic systems. Wang et.al. [14] studied short term solar irradiance forecasting model based on ANN. Another study on GSI forecasting using ANN was performed by Adel et.al. [15] which they applied the prediction to a grid-connected PV plant. Optimizing short term forecasting of solar radiation using statistical approach of satellite data have been proposed by Hammer et.al. [16]. Xiao et.al. [17] have presented about optimization models for feature selection of decomposed nearest neighbor. Validation of short and medium term operational solar radiation forecasts was studied by Richard et.al. [18]. Forecasting of global and direct solar irradiance using

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stochastic methods, have been proposed by Marquez et.al. [19]. For prediction of global solar irradiance based on time series analysis, Luis and zarzalejo applied the analysis to solar thermal power plants energy production planning [20]. Remus et.al. [21] have presented about functional fuzzy approach for forecasting daily GSI and very short term forecasting of the global horizontal irradiance using a spatiotemporal autoregressive model have been proposed by Dambreville et.al. [22]. Review of solar irradiance forecasting methods and a proposition for small-scale insular grids have been proposed by Diagne et.al. [23]. Short term solar power prediction using a support vector machine have been proposed Zeng et.al. [24]. Dong et.al. [25] have presented about short term solar irradiance forecasting using exponential smoothing state space model. Ren et. al. [26] have presented about short term wind speed forecasting by empirical mode decomposition model. ANN model for prediction solar radiation data have been proposed by Mellit et.al [27]. Farhad et. al. [28] have presented k-nn and artificial neural network for approach in bloggers classification with hybrid. A multilayer neural network with an adaptive learning algorithm is designed for short term load forecasting have been proposed by Long et. al. [29].

The aforementioned studies elaborated on GSI forecasting at one target PV station, but have yet to forecast GSI at PV station which position is surrounded by other PV stations. This paper presents a part of a research in progress seeking to estimate and forecast global solar irradiation at PV station for energy production by one hours ahead. In this study, a novel methodology that combines k-NN modelling and multilayer BPLNN with gradient descent adaptive rate and algorithm used weight initialization nguyen widrow modelling techniques has been developed. The remainder of the paper is organized as follows: Section 2 describes the modelling PV station, section 3 describes the methodology, while Section 4 presents study cases of the modelling in forecasting and its measured error. Finally, Section 5 presents some concluding remarks.

2. MODELLING

The global solar irradiance measurements were performed continuously every 5 minutes in fourteen hours. The dataset contains fourteen hours of data (from 5:10 a.m. to 18.00 p.m.) on 08-June 2012. For this study, the very short-term forecasts of global solar irradiance (GSI) was only provided by PV station S which position was at the center. The k-NN locations surrounding station S were Station A, Station B, Station C, Station D, Station E, Station F, Station G and Station H we can see in Fig. 1.

Figure 1. Modelling station S which is surrounded by eight other photovoltaic-station.

3. METHODOLOGY

This section explains basic idea of the developed methodology for GSI forecasting, namely k-NN-multilayer BPLNN with gradient descent adaptive rate and momentum algorithm used weight initialization nguyen-widrow model.

3.1 k-Nearest Neighbors (k-NN)

The k-NN forecast is computed using the features assembled in the matrices. To find the K nearest neighbors based on the Euclidean distance, this equation is used:

$$d(x,y) = \sqrt{\sum_{j=1}^{d} w_j^2 \left(x_j - y_j\right)^2} \qquad (1)$$

where d is the number of forecast instances in the optimization set.

3.2 Multilayer Backpropagation Learning NN

Backpropagation is an efficient and popular supervised learning method for training multilayer BPLNN, the net inputs are given by:

$$y_k = f\left(y\_net_k\right) = \frac{1}{1+e^{-\delta\_net_k}} \qquad (2)$$

where net_j is the input signal from the external sources to node j in the input layer

3.2.1 *Weight Initialization Nguyen Widrow*

The nguyen widrow scale factor (β) is defined as:

$$\beta = 0.7H^{1/N} \qquad (3)$$

where H is the number of hidden units, N is the number of input units and β is the scale factor, the weights are randomly selected in the interval [-1,1] and then scaled by :

$$v = \frac{\beta v}{\|v\|} \qquad (4)$$

where v is the first layer weight vector while weight in the hidden layer which is the bias given a random value between -β and β.

4. ANALYSIS OF SIMULATION RESULT

This section discusses the result of k-NN-multilayer BPLNN with gradient descent adaptive rate and momentum used weight initialization Nguyen Widrow model.

4.1 k-NN Modelling

The procedure of k-NN for regression is as follows:

1) Form d-dimensional feature from the historical data and form n-dimensional distance

$$ds_j^i(c,nxy) = \sqrt{\sum_{q=1}^{k}\left(c_p^i - nxy_{pj}^i\right)^2} \qquad (5)$$

Sort $ds_j^i(c,nxy)$ in ascending order

2) Form a Kernel function $K(j) = \dfrac{1/j}{\sum_{j=1}^{K} 1/j}$

i = 1,2,3,...,5 as weighted averaging factor for k-NN aggregation.

The procedures are described in Fig. 2 which explain the global solar irradiance forecasting process using hybrid k-NN-multilayer BP learning neural network modelling.

4.1.1 Multilayer backpropagation

The proposed model in this research is used to predict the GSI values for the next hours or one hour ahead, forecasting based on meteorology data. Research composition for parameter momentum is $mc_1 = 0.6$, $mc_2 = 0.7$, $mc_3 = 0.8$ and $mc_4 = 0.9$. The proposed k-NN-multilayer BPLNN model has to forecast GSI values for the next hour or 1 hours ahead by taking into account the forecasting data based on meteorology data. In figure 3 explained about the proposed forecasting model using k-NN-multilayer BPLNN model. To model the existing relationship between k-NN model forecasts and the real values of GSI at the target location.

4.1.2 Proposed k-NN-multilayer BP learning neural network modelling and validation

Using k-NN-multilayer BPLNN with gradient descent adaptive rate and momentum used weight initialization Nguyen Widrow model, it is expected that a valid result of GSI forecast will be produced. The design forecast is divided into two stages:

- The first stage is calculating d-dimensional feature and n-dimensional distance based on the Euclidean (k-NN model).
- The second stage is using multilayer BPLNN with gradient descent adaptive rate and momentum used weight initialization Nguyen Widrow based on the assumption that the existing data input is a combination the results obtained from k-NN model.

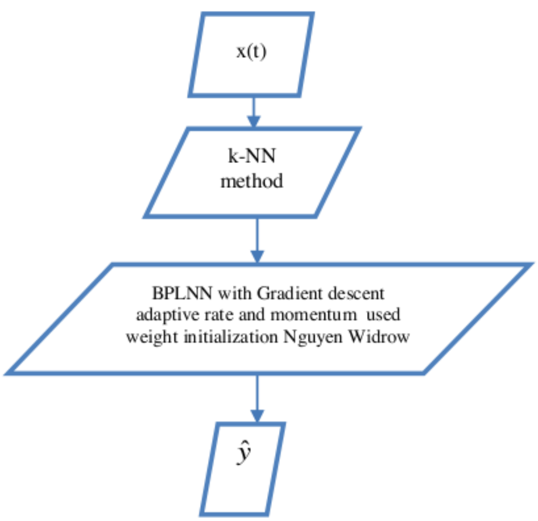

Figure 2. Flowchart Hybrid model used k-NN-multilayer BP learning Neural Network algorithm

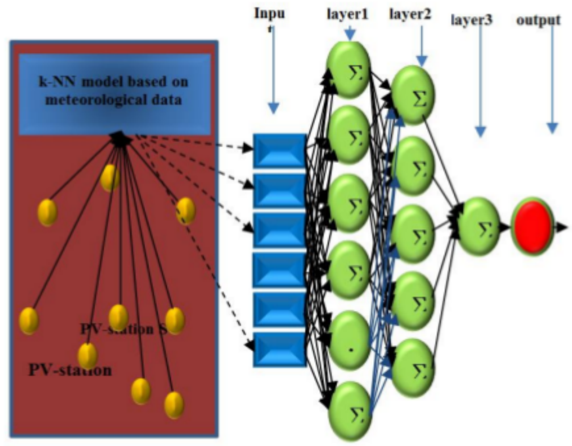

Figure 3. The proposed forecasting model using k-NN-multilayer BP learning neural network model

The research model proposed in this study seeks to estimate and forecast a PV station production 1 hours ahead, which position is located at the center and surrounded by eight other PV stations. Root mean square error (RMSE) was used as error statistical indicator. The estimation from k-NN-multilayer BPLNN model was then compared with k-NN model and mean average of meteorological data forecasts. Fig. 4 shows k-NN-multilayer BP LNN algorithm with gradient descent adaptive rate and with different parameter momentum, i.e $mc_1 = 0.6$, $mc_2 = 0.7$, $mc_3 = 0.8$ and $mc_4 = 0.9$ comparison for predicted, actual data and k-NN of three subsets: training, validation, and test set. As seen in Fig. 4, there is a good fit between actual and predicted data with parameter momentum value is $mc_3 = 0.8$ for very short term GSI forecasting in station target S.

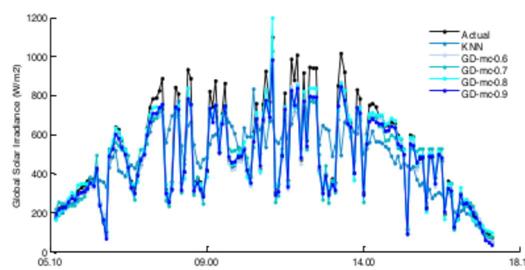

Figure 4. Very short term GSI forecasting based k-NN-learning NN gradient descent and momentum learning algorithm model, actual data, and k-NN method

Fig. 5 illustrates the comparison of GSI forecasting in fourteen-hours based on k-NN-multilayer BPLNN model, actual data, and k-NN method. The result shows that very short term forecasting simulation using k-NN-multilayer BPLNN algorithm method with gradient descent adaptive rate and momentum value ($mc_3 = 0.8$) during fourteen hour window gives better result compared to k-NN method. And Fig. 5 illustrates very short-term (1 hours ahead) GSI forecast using k-NN-multilayer BP learning rate with different value parameter momentum (mc_3) = 0.8 and its comparison with another value momentum (mc_1, mc_2, and mc_4) and actual data. It is evident that k-NN-multilayer BP with gradient descent adaptive rate and momentum ($mc_3 = 0.8$) is in a good agreement with measured data in the object station. To evaluate the performance of the models, error statistical indicators including measurement was used in the experiment, namely the root mean square error (RMSE). Fig. 6 shows RMSE coefficient between actual data and very short term (1hours ahead) forecasting performance using k-NN and multilayer BP learning neural network algorithm model used value parameter momentum which different. It is evident that k-NN-multilayer BP learning neural network algorithm model with value parameter (mc_4) = 0.8 displays better prediction than k-NN model.

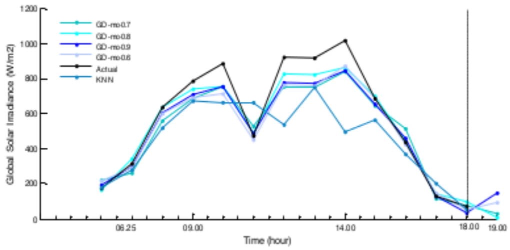

Figure 5. Very short term (1 hours ahead) GSI forecast using k-NN- learning NN gradient descent and momentum algorithm model versus actual data

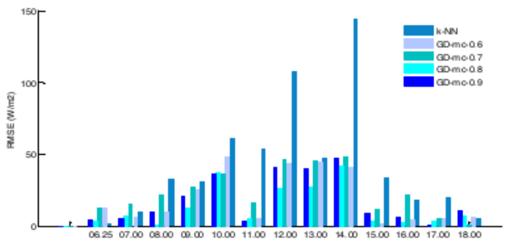

Figure 6. RMSE coefficient between actual data and GSI forecast using k-NN- learning NN gradient descent and momentum algorithm model in the test set.

The performance of the proposed k-NN-multilayer BP with gradient descent adaptive rate and momentum value (mc_3) = 0.8 value used weight initialization nguyen widrow learning neural network algorithm model is more better compared with another value momentum and k-NN model.

5. CONCLUSIONS

In this work we proposed a novel methodology for GSI forecasting using a combination of k-NN modelling and multilayer backpropagation with gradient descent adaptive rate and momentum used weight initialization nguyen widrow learning neural network algorithm model.

The novelty of this article is to predict global solar irradiance on a PV station which position is at the center and surrounded by eight other adjacent PV stations. With the same location presents RMSE is 176.5492W/m2, for the same location target PV station.

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FINAL GRADE

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GENERAL COMMENTS

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