Artificial Neural Networks Model for Short Term Forecasting Global Irradiation at Center station in the Nine Station Photovoltaic

by Unit Three Kartini

Artificial Neural Networks Model for Short Term Forecasting Global Irradiation at Center station in the Nine Station Photovoltaic

Chao Rong Chen
Dept. Electrical Engineering
National Taipei University of Technology
Taipei, Taiwan
E-mails: crchen@ntut.edu.tw

Unit Three Kartini
Dept. Electrical Engineering
National Taipei University of Technology
Taipei, Taiwan
E-mail: t101319021@ntut.edu.tw , uunitthree@gmail.com

***Abstract*— This article will studies of forecasting global irradiation (GI) for the short term at one station photo voltaic system (PV) which the station is located at center point between the eight other photovoltaic stations. Short-term forecasting model which is known as Artificial Neural Networks (ANNs) is divided into two models, the first model without taking into account temperature and the second model based on data from meteorological temperature. In this article proposes forecasting which use a combination of exponential smoothing models as preprocessing of data and ANNs as a technique for predicting GI 60 minutes ahead. The simulation results with ANNs forecasting model will be compared with measured data. The result performance of our scheme show good results and have a satisfactory accuracy which can be obtained RMSE value 6.28% without consider of temperature and 5.18% consider data temperature, respectively.**

Keywords- Artificial Neural Network (ANNs); forecasting; global irradiation.

I. INTRODUCTION

The evolution of human technology has developed very fast, the source of solar energy can be used for solar power generation. Solar energy is a renewable energy which can be used freely and can be applied to meet human demands, especially electric energy in daily life. The usage of energy, particularly solar energy can be utilized as an alternative energy in order to reduce dependence on energy conventional (un-renewable) or a hydrocarbon-based energy. The usage of solar energy is one of the best choices to fulfill the needs of electricity, as solar energy provides energy troop numbers are very abundant, especially in the area which have high sunlight intensity. Photovoltaic systems have reliability in meeting consumer demand for electrical energy, which need meteorology data, i.e. temperature, which are part of very important in influencing the operation of solar energy. The operation of the photovoltaic system (PV) need several conditions of the data variable meteorology. It obviously that the electricity is generated by the photovoltaic system (PV) solar energy is strongly influenced by the great number of GI. The concentration of the solar radiation on each photovoltaic panel have varies according to geographic location, the time and the concentration of sunlight by photovoltaic panel system. It is clearly that variable solar radiation a very significant and give a major influence on the behavior of the solar force that will be generated. Because of the diversity of the global solar radiation as well as providing an enormous influence on the performance of the PV-system. The authors of [1] and [2] have presented the forecasting GHI with a novel method at the ground level from satellite images using NN, prediction of daily global solar irradiation using temporal Gaussian process in paper explain about evaluate the estimation of solar irradiation used Gaussian process regression (GPR).

The several literatures have presented numerous models prediction for PV modules, especially forecasting model for GI which are popular and many research, discuss about global solar irradiation forecasting using mathematical models, among the others, namely artificial neural network based daily local forecasting for global solar radiation. The authors of [3] have presented about implementing methodology which design model of artificial neural networks (ANN) for local forecasting of daily global horizontal irradiance (GHI) based on daily weather forecasts. The authors of [4] have presented ANNs based on meteorological data for input forecast solar irradiation at the surface, spatiotemporal pattern recognition and nonlinear PCA for global horizontal irradiance forecasting. The forecasting global solar radiation with estimation method based on ambient temperature and relative humidity for prediction which use two method, i.e. first method use decision matrix, while the second method use regression correlation of meteorological parameters. To get the result estimation global radiation for predicting the average daily and hourly global radiation and diffuse radiation have been proposed in [5]. The authors of [6] have presented about dataset which consist of each parameter input data hourly and daily clearness index and diffuse fraction at a tropical station. An accurate forecast of solar irradiation is required for various solar energy applications and environmental impact analysis one of modeling for hourly and daily solar irradiation forecast using diagonal recurrent wavelet neural networks have been presented in [9-19]. Time series modeling and large scale global solar radiation forecasting from geostationary satellites data have been presented in [20-21]. Direct normal irradiance forecasting and its application

2374-8400/15 $25.00 © 2015 IEEE
DOI 10.1109/AMS.2015.11

to concentrate solar thermal output forecasting and prediction of hourly solar radiation using a novel hybrid model of ARMA and TDNN have been presented in [22-23]. The authors of [24] have presented nearest-neighbor methodology for prediction of intra-hour global horizontal and direct normal irradiances which explain about a novel forecasting methodology for intra hour solar irradiance based on optimized pattern recognition using k-NN algorithm. However, all of aforementioned only consider one station and do not consider station its surround.

In this article proposes for short term forecasting solar irradiation (GI) at PV-system for 60 minutes ahead of time which be located at point center and consider its surround of PV-system. The proposed can be achieved by modeling location PV-system which is represented in Fig 1. For to get accurate short term forecasting ahead of time results, the proposed use meteorology weather data, which is known as global irradiation data and temperature data. The rest of this paper is organized as follows: Section 2 describes a location model and data position of the nine station PV-system. Section 3 explains and present about the neural networks methodology for forecasting solar irradiation while the modeling proposed for the analysis of result simulation presented in section 4. Finally, some conclusions are given in section 5.

II. MODEL LOCATION STATION PV-SYSTEM

Position information about each station can be seen in Figure 1. In Figure 1 illustrates the placement of nine stations PV-systems which are neighbors to one another. While the station S is located in a central position and its surrounded by eight other PV-systems.

Data is taken based on the measurement of PV-system nine locations are conducted continuously every 5 minutes during two hours from 5:10 till 7: 00 on June 8, 2012. To generate parameter information, meteorological research, with data per hour measured irradiation global (GI) (W/m2) and ambient temperature (Ta) (°C). In this article, carried only a short-term forecasting for station PV-systems which the station S is located in the center as shown in Figure 1.

III. METHODOLOGY

In this article, based on the methodology which consider for short-term forecasting of global irradiation (GI). Forecasting methodology as follow, the first aimed at short-term forecasting for global irradiation (GI) on the PV system is located in the center, namely S stations. The modeling of position or placement of nine places around the PV-system, and between the PV and the other one next to each other and have a short distance to the station S. Modeling or design of nine PV- system is carried out based on the distance and measured based on data, meteorology of each PV-system, especially the data environment temperature. The GI and meteorological data (temperature) is taken an average value per 5 minutes to various hours.

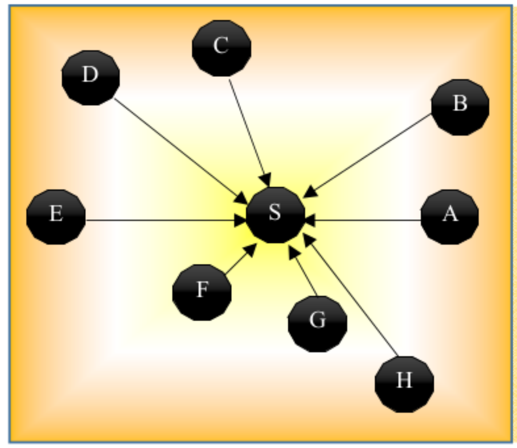


Figure 1. PV-system design models with nine stations.

The time information of data for each station PV-system in one hour, where in one minute is composed of six data. The second goal is to make short-term forecasting of GI for 60 minutes next to the station S. For forecasting GI, the data is measured by taking into account the meteorological data such as temperature and forecasting carried out without taking into account the temperature of eight stations PV-system that surrounds the location the target station (station S) and close proximity to each other. Forecasting model GI of target station will use neural networks as shown in Figure 2.

In addition, the method of forecasting neural networks can be programmed to forecasting in a few hours later have been carried out, periodically measured data is then processed to obtain the input data to be pre-processing. After getting the data pre-processing to forecasting GI then the data will be used based on the information input data for forecasting GI 60 minutes ahead. Because of the pre-processing performance is good and perfect will get the average value data for global irradiation as well as taking into account the meteorology data, it will get better forecasting results. Thus, forecasting a good GI can later be used as input variables when calculating of the energy is generated by the photovoltaic products fuel.

Exponential smoothing given time series modeling using simple linear regression equation, forecasting based approach to the value of global irradiation (W/m2) in a central position between eight PV- systems which its surround each other and have close proximity to each other, where the intercept $a_0(t)$ and slope $b_0(t)$ are varying slowly over time. In this article, the rate of exponential

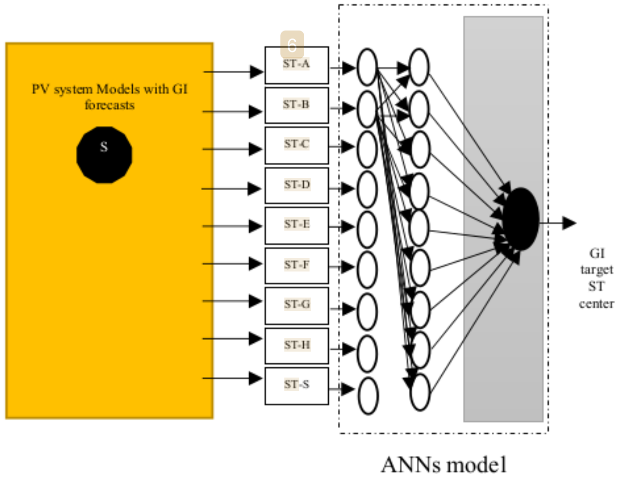


Figure 2. The proposed forecasting GI at the target station center modelling with Neural Networks.

decay is taken with alpha = 0.9 and use this value for alpha (α), because the value is considered to be the closest and provide short-term forecasting results for GI (W / m2) is good. Equation for forecasting exponential smoothing, which can be defined by [25] as shown in Eq. (1)

$$S_{At} = \alpha P_t + (1-\alpha) S_{At-1} \quad (1)$$

For more detail about our proposed can be seen in figure 3 which explain modelling, forecasting GI with neural networks for the center station S photovoltaic system.

IV. ANALYSIS OF SIMULATION RESULT

In this article, the input data is used as parameters in the simulation forecasting (GI) with neural network method which use two models, the first model without taking into account temperature and the second model taking into account the data of meteorological forecasting temperature. Thus, for meteorological data that will be used in forecasting GI at one of the stations as much as 2 input variables (GI and temperature) PV-system data.

Model of design to that used in the neural network for forecasting system in accordance with the model design has a processing stage that can give more valid results. Where to System forecasting, modeling ANNs consists of input, determination, determination of output and determines network architecture that will be used. For multi-layer neural networks will perform with different processing, which is considered to get a better mapping between input and output on ANNs modeling.

Possible combinations of variables that will be considered as the data input of ANNs modeling is the data of GI and

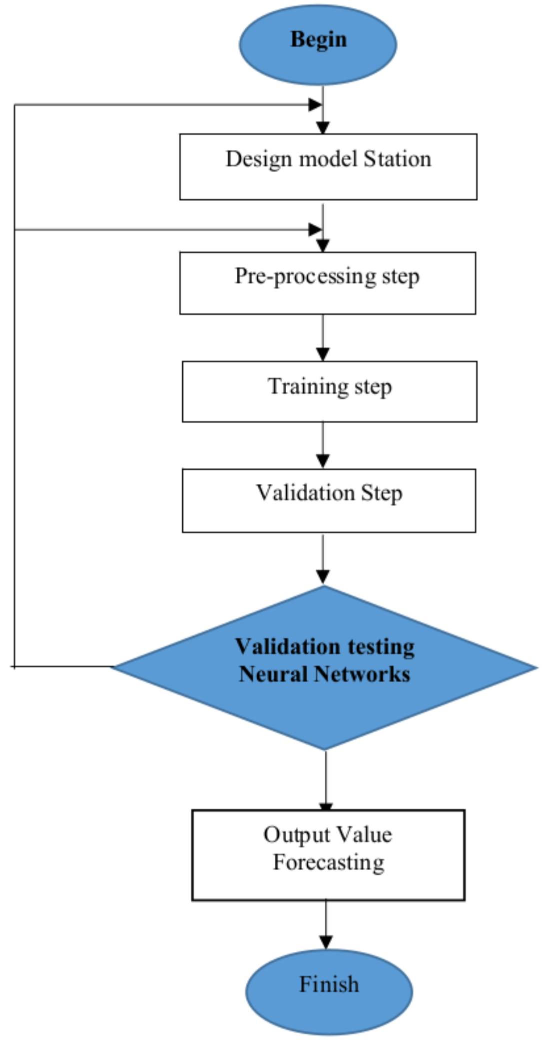


Figure 3. The flow chart of the ANNs modelling, forecasting GI.

ambient temperature for a short-term forecasting.

The proposed scheme is a short-term forecasting for GI value of 60 minutes ahead which target location is surrounded by eight stations PV-system adjacent to one another. Because the processing of short-term forecasting for GI for 60 earlier on the target station depend on the value of GI and temperature values from another station.

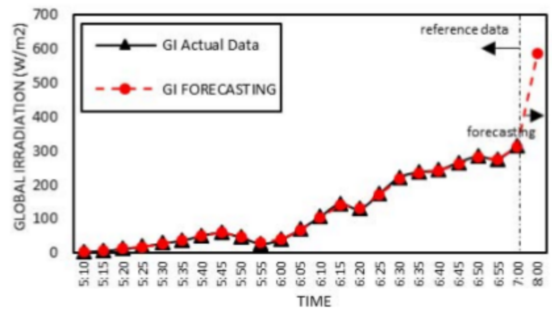
In this article use two step models, the first step model with 9 station PV-system consist of one station target position at the center and surrounded by 8 station PV system where each other is located adjacent to each other. Forecasting is done for only two hours, each hour divided into 12 periods in a row, and each period is divided in 5 minutes at any location station PV-system. Thus, for the amount of data entered in the GI regardless of forecasting temperature has

108 inputs and 1 output GI forecasting results on the target station. The second step model also use 9 station PV system taking into account the data of meteorological temperature as the input data 216 is comprised of 12 for input data GI and 12 period as input data of temperature and 1 output as forecasting results GI on the target.

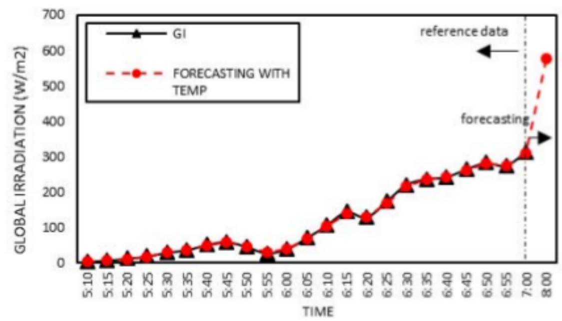
$$GI_{norm} = \frac{GI_t - GI_{t\min}}{\left(GI_{t\max} - GI_{t\min}\right)} \qquad (2)$$

In order to calculate of the normalization, the value of GI use great value or infinitive. Then, the normalization of GI value for model ANNs per hour is calculated by the equation (2). After that perform simulation forecasting of GI value on the target station use nine GI value at each station for training ANNs and testing models. The result of normalization of center station value for 60 minutes ahead of time can be shown in Figure 4 and is explained for each part. In Figure 4. (a) Describe the results of simulation modeling ANNs for forecasting GI value without taking into account the data on the temperature meteorology station S. And the image (b) Describe the results of simulation modeling ANNs for forecasting GI value taking into account the data of meteorological temperature. The overall performance for GI at the station S for two hours and at the same time depending on the performance of GI on other stations surround the station S, the process of training the ANNs using the location model design nine photovoltaic system thus providing the possibility to study meteorological data connected between temperature and GI which is used to build the global evolution of irradiated forecast for the next 60 minutes, and can be shown the results of forecasting in Fig.4. In Figure 4. Show the results of the processing of training and testing of modeling ANNs with alpha = 0.9 with two input values models. The verification has been done before the process of training with ANN model with data input variables normalized with predetermined criteria, because with data de-normalization can be obtained optimal results and speed up the process of calculation in the training system in the ANN model itself.

In fact, if the used data in the training process with different scales, which will get variable results with different data, it also will get the value of the error conduct output is higher, so that it has greater value errors. In modeling architecture used for layer perceptron ANN two hidden layers, the first layer using 16 neurons and a second layer using one neuron. Whereas, for the sigmoid activation function which has been used in every layer and activation functions are used for forecasting simulation using sigmoid-trainlm with 1 output. Furthermore, the calculation of the acquisition performance results ANNs GI value forecasting for the next 60 minutes compared with the measured data or actual data on the station S.



(a)



(b)

Figure 4. Result of normalization of the center station values for 60 min ahead of time from the used data base: (a) GI norm without temperature forecasting (b) with temperature forecasts at station S

Modeling and design, as well as the architecture of the building which is started by ANNs based on database receives, which has a variety of steps, for database standard procedures give an accurate picture of the behavior of a system that will be modeling. After the process performance validation has been done which to get the output target value corresponding to the minimum error, then the model is ready for use. The proposed used ANNs forecasting model gives limitation with twice the training, in order to obtain good results. The results of the calculation value, namely GI in the data is compared with the results of the forecasting value of GI using ANNs. The GI value forecasting simulation results will be compared with the GI measured to obtain minimum error. In this article, performance using ANNs with architectural training is given 100 iterations at each simulation process. Hence the tendency of the results obtained in the form of better forecasting and always have a small error value. The statistical method for measuring the error and are typically used in the forecast, namely:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(G_i - \hat{G}_i\right)^2}{N}} \tag{3}$$

For the calculation results with statistical methods RMSE error unchanged, whereas the ANNs modeling RMSE values is declining, which is used as the learning of GI on the target station that its location at the center between the station PV-system to another and adjacent and can be seen in figure 5. Figure 5, represents a variation calculation results with statistical estimation at the target location, where the error calculation for RMSE results obtained vary at any period of time between modeling ANNs compared with actual data. Therefore, the amount of data used for learning and training process will greatly affect the results forecast for the next 60 minutes.

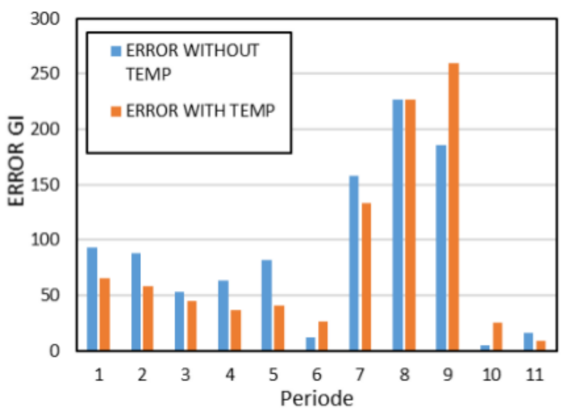


Figure 5. RMSE with ANNs based design model test validation for forecasting at station S

The amount of data that is too little or too much will cause to learning outcomes and design training ANNs has an error value (RMSE) high. If the amount of data that architecture is too little ANNs only recognizes data slight variations, so it does not get the best results for forecasting, as well as the quantity of data that is too much on modeling ANNs also does not give good results. Interval of forecasting is determined by the method of ANNs with excellent performance with 0.06285 coverage without use data meteorological temperature and a second model has an error rate of 0.05184, taking into account data temperature.

V. CONCLUSION

In this article, proposed a modeling ANNs to forecast GI with nine stations on the surface of the PV-system is divided into two models. The first model regardless of the data in temperature meteorology, and a second model uses meteorological data, which based on the ambient temperature. The main modeling of this article is that ANNs modeling shows one method of forecasting with better ability, so it can be used for short-term forecasting of GI on PV-station system where the target station has a central position and surrounded station PV system other and have the closest distance to the station PV- system between each other. Simulation of short-term forecasting GI with ANNs taking an alpha value of = 0.9 is expected to obtain the results for short-term forecasting with a time of 60 minutes better forward and has a small error value. Interval of forecasting is determined by the method of ANNs with excellent performance with a high probability of 6.285% coverage without of data meteorological temperature and a second model has an error rate of 5.184% with the data temperature.

REFERENCES

[1] Sancho Salcedo-Sanz, Carlos Casanova-Mateo, Jordi Muñoz-Marí, and Gustau Camps-Valls. Prediction of Daily Global Solar Irradiation Using Temporal Gaussian Processes. IEEE Geoscience and Remote Sensing Letters 2014; Vol. 11, No. 11: 1936-1940.

[2] Badia Amrouche, Xavier Le Pivert. Artificial neural network based daily local forecasting for global solar radiation. Applied Energy 2014; 130: 333–341.

[3] G. A. Licciardi, R. Dambreville, J. Chanussot, and Stéphanie Dubost, Spatiotemporal Pattern Recognition and Nonlinear PCA for Global Horizontal Irradiance Forecasting IEEE Geoscience And Remote Sensing Letters, 2015; Vol. 12, No. 2:284-288.

[4] Dimas Firmanda Al Riza, Syed Ihtsham ul Haq Gilani and Mohd. Shiraz Aris, Hourly Solar Radiation Estimation Using Ambient Temperature and Relative Humidity Data, International Journal of Environmental Science and Development, Vol. 2, No. 3, June 2011.

[5] L.T. Wong, W.K. Chow, Solar radiation model, Applied Energy 69 (2001) 191–224.

[6] E. C. Okogbue, J. A. Adedokunb and B. Holmgrenc, Hourly and daily clearness index and diffuse fraction at a tropical station, Ile-Ife, Nigeria, INTERNATIONAL JOURNAL OF CLIMATOLOGY, Int. J. Climatol. 29: 1035–1047 (2009).

[7] Gilles Notton a, Christophe Paoli b, Siyana Vasileva c, Marie Laure Nivet b, Jean-Louis Canaletti a,Christian Cristofaria, Estimation of hourly global solar irradiation on tilted planes from horizontal one using artificial neural networks, Energy 39 (2012) 166-179.

[8] Gilles Notton a, Christophe Paoli b, Liliana Ivanova c, Siyana Vasileva c, Marie Laure Nivet b, Neural network approach to estimate 10-min solar global irradiation values on tilted planes, Renewable Energy 50 (2013) 576-584.

[9] Jiacong Cao, Xingchun Lin, Study of hourly and daily solar irradiation forecast using diagonal recurrent wavelet neural networks, Energy Conversion and Management 49 (2008) 1396–1406.

[10] Ricardo Marquez, Carlos F.M. Coimbra, Forecasting of global and direct solar irradiance using stochastic learning methods, ground experiments and the NWS database, Solar Energy 85 (2011) 746–756.

[11] I. Drezga, S. Rahman, Short-Term Load Forecasting With Local ANN Predictors, IEEE Transactions on Power Systems, Vol. 14, No. 3, August 1999.

[12] Elke Lorenz, Johannes Hurka, Detlev Heinemann, and Hans Georg Beyer, Irradiance Forecasting for the Power Prediction of Grid-Connected Photovoltaic Systems, IEEE journal of selected topics in applied earth observations and remote sensing, vol. 2, no. 1, march 2009.

[13] Ching-Tsan Chiang, Yung-Sheng Lee and Xiao Ru Li, Chiung-Chou Liao, A RSCMAC Based Forecasting for Solar Irradiance from Local

Weather Information, WCCI 2012 IEEE World Congress on Computational Intelligence June, 10-15, 2012.
[14] Falayi E. O, The Impact of Cloud Cover, Relative Humidity, Temperature and Rainfall on Solar Radiation in Nigeria, Energy and Power 2013, 3(6): 119-127.
[15] M. S. Okundamiya , A. N. Nzeako, Empirical Model for Estimating Global Solar Radiation on Horizontal Surfaces for Selected Cities in the Six Geopolitical Zones in Nigeria, Hindawi Publishing Corporation Journal of Control Science and Engineering, Volume 2011.
[16] Antonio Bracale, Pierluigi Caramia, Guido Carpinelli, Anna Rita Di Fazio, and Gabriella Ferruzzi, A Bayesian Method for Short-Term Probabilistic Forecasting of Photovoltaic Generation in Smart Grid Operation and Control, Energies 2013, 6, 733-747.
[17] Kurt Spokas, Frank Forcella, Estimating hourly incoming solar radiation from limited meteorological data, Weed Science, 54:182–189. 2006.
[18] Ugwu, A. I, Ugwuanyi, J. U., Performance assessment of Hargreaves model in estimating solar radiation in Abuja using minimum climatological data, International Journal of the Physical Sciences Vol. 6(31), pp. 7285 - 7290, 30 November, 2011.
[19] Rachid Chenni, Ernest Matagne, Messaouda Khennane, Study of Solar Radiation in View of Photovoltaic Systems Optimization, Smart Grid and Renewable Energy, 2011, 2, 367-374.
[20] Cyril Voyant , Pierrick Haurant, Marc Muselli, Christophe Paoli, Marie-Laure Nivet, Time series modeling and large scale global solar radiation forecasting from geostationary satellites data, Solar Energy 102 (2014) 131–142.
[21] Changsong Chen, Shanxu Duan, Tao Cai, Bangyin Liu, Online 24-h solar power forecasting based on weather type classification using artificial neural network, Solar Energy 85 (2011) 2856–2870.
[22] Edward W. Law, Abhnil A. Prasad, Merlinde Kay, Robert A. Taylor, Direct normal irradiance forecasting and its application to concentrated solar thermal output forecasting – A review, Solar Energy 108 (2014) 287–307.
[23] Ji Wu, Chee Keong Chan, Prediction ofhourly solar radiation using a novel hybrid model of ARMA and TDNN, Solar Energy 85 (2011) 808–817.
[24] Hugo T.C. Pedro, Carlos F.M. Coimbra, Nearest-neighbor methodology for prediction of intra-hour global horizontal and direct normal irradiances, Renewable Energy (2015) 770-782.
[25] Joseph J. LaViola Jr.,Double Exponential Smoothing: An Alternative to KalmanFilter-Based Predictive Tracking, Brown University Technology Centerfor Advanced Scientic Computing and VisualizationPO Box 1910, Providence, RI, 02912, USA, 2003.

Artificial Neural Networks Model for Short Term Forecasting Global Irradiation at Center station in the Nine Station Photovoltaic

ORIGINALITY REPORT

9%	8%	8%	3%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	econpapers.repec.org Internet Source	1%
2	downloads.hindawi.com Internet Source	1%
3	ijesd.org Internet Source	1%
4	www.ijcaonline.org Internet Source	1%
5	uksim.info Internet Source	1%
6	digitalcommons.cedarville.edu Internet Source	1%
7	www.semanticscholar.org Internet Source	1%
8	Submitted to Universitaet Hamburg Student Paper	<1%

9	thermalscience.vinca.rs Internet Source	<1%
10	www.iariajournals.org Internet Source	<1%
11	Shih-Cheng Hu. "Short-term Electricity Forecasting of Air-conditioners of Hospital Using Artificial Neural Networks", 2005 IEEE/PES Transmission & Distribution Conference & Exposition Asia and Pacific, 2005 Publication	<1%
12	dblp.dagstuhl.de Internet Source	<1%
13	Amit Kumar Yadav, S.S. Chandel. "Solar radiation prediction using Artificial Neural Network techniques: A review", Renewable and Sustainable Energy Reviews, 2014 Publication	<1%
14	L.T. Wong, W.K. Chow. "Solar radiation model", Applied Energy, 2001 Publication	<1%
15	courses.nus.edu.sg Internet Source	<1%
16	www.ijrer-net.ijrer.org Internet Source	<1%
17	G. A. Licciardi, R. Dambreville, J. Chanussot,	

	Stephanie Dubost. "Spatiotemporal Pattern Recognition and Nonlinear PCA for Global Horizontal Irradiance Forecasting", IEEE Geoscience and Remote Sensing Letters, 2015 Publication	<1%
18	Shamkant B. Navathe. "Predictive filtering", Proceeedings of the 1st international workshop on Data management for sensor networks in conjunction with VLDB 2004 - DMSN 04 DMSN 04, 2004 Publication	<1%
19	os.unil.cloud.switch.ch Internet Source	<1%
20	Dazhi Yang, Jan Kleissl, Christian A. Gueymard, Hugo T.C. Pedro, Carlos F.M. Coimbra. "History and trends in solar irradiance and PV power forecasting: A preliminary assessment and review using text mining", Solar Energy, 2018 Publication	<1%
21	Mousavi, Seyyed Mohammad, Elham S. Mostafavi, Alireza Jaafari, Arefeh Jaafari, and Fariba Hosseinpour. "Using measured daily meteorological parameters to predict daily solar radiation", Measurement, 2015. Publication	<1%

Artificial Neural Networks Model for Short Term Forecasting Global Irradiation at Center station in the Nine Station Photovoltaic

GRADEMARK REPORT

FINAL GRADE

/0

GENERAL COMMENTS

Instructor

PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6