A REVIEW: POWER QUALITY MEASURMENT IN SOLAR PHOTOVOLTIC SYSTEM USING ANN CONTROLLER

SAPNA XALXO	MANISH KUMAR CHANDRAKAR
Mtech Scholar	Assistant Professor
Dept of Electrical, RSR Rungta college of engineering and technology	Dept of Electrical, RSR Rungta college of engineering and technology

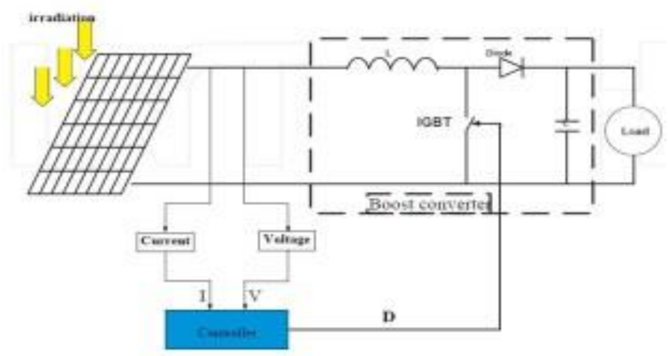
Abstract:

Power electronics and D.E.R. have contributed to rising power quality problems on the utility grid. The power quality must be kept constant under both steady and fault circumstances, regardless of the load. Distribution grid power quality may be enhanced with FACTS's Unified Power Quality Conditioners. The reactive and actual power imbalances are corrected by the Unified Power Quality Conditioner at the same time. Combining reactive power control and unit vector template control is the proposed control algorithm for the Unified Power Quality Conditioner. By combining the Unified Power Quality Conditioner with D.E.R.s like solar panels, converter power ratings may be lowered while still meeting demand. When applied to power electrical devices, reinforcement learning algorithms, in particular the Neural-Network method, can significantly boost efficiency. Superior power generation is achieved by using an Artificial Neural Network controller in a solar-integrated Unified Power Quality Conditioner system. The controller can adjust to new conditions on its own. The system is put through its paces with balanced and unbalanced loads in MATLAB-SIMULINK. The per-unit method simplifies analysis. Non-linear load distortion can be eliminated by solar integration at the DC link and hybrid management of the series and shunt converters. Short voltage dips and spikes are needed for IEEE 1159. In just 50 ms, the Computer and Business Equipment Manufacturers Association curve glides over the brief dip or spike that can last anywhere from half a second to three. The suggested control mechanism naturally reduced harmonics in the load-side current. Both power factor and distribution dependability are protected in this way. An artificial neural network controller in a solar integrated Unified Power Quality Conditioner was shown to be superior to a traditional Proportional-Integral controller in reducing harmonics of varying orders by 12.72 percentage points. Total Harmonic Distortion was lowered to below IEEE 519 limits thanks to a controller based on artificial neural networks. The goal of achieving several harmonic orders was met.

Keywords—solar radiation prediction; solar energy modeling;artificial intelligence; artificial neural networks(ANN)

1. INTRODUCTION

Data about solar radiation is absolutely necessary for study and engineering pertaining to solar energy. In point of fact, having a grasp of the supply as well as the fluctuation in the intensity of solar radiation is essential for the functioning of solar devices, flat plate collectors, photovoltaic structures, the thermal load on houses, the study of environmental effect, and agriculture [2-7]. There is an issue caused by the large number of meteorological stations that measure sun energy using pyrometers that are dependable and calibrated. Instruments for measuring the sun's radiation are both costly and require regular maintenance [8, 9]. In addition, maximum stations only have a limited number of parameters that can be measured, such as relative humidity, temperature, wind speed, and the amount of time that the sun is out. As a result of the ease with which these parameters can be obtained all over the world, it is possible to use them to estimate the amount of solar radiation that is present and then apply the appropriate models to obtain the information that is required. Since the introduction of the primary models [10, 11], techniques using artificial intelligence (AI) have proven to be useful in the context of exchange strategies. To be more specific, ANNs are capable of carrying out a computational simulation and have a high capability to modeless complex, nonlinear, and time-varying input-output systems [12]. ANNs had been hired on a large scale to estimate the amount of radiation emitted by the sun on a global scale using a variety of geographical and meteorological parameters. The purpose of this study is to highlight realistic methods that are available in the literature for predicting solar radiation, and as such, a review on Artificial Neural Network techniques is presented here. Our contribution consists of compiling an exhaustive list of significant works along with the most recent research that has been conducted on this topic up until the year 2016. The objective is to make it simpler for future researchers to locate published papers by requiring them to specify the prediction horizon, the structure of the ANN, and the overall performance indicators that correspond to those signs. One more thing that can be done is to factor out the challenges that have been encountered in the research and to endorse recommendations and outlooks for future research initiatives. After providing statistical indications and performing a review of solar radiation models in the following sections (Sections II and III), this article moves on to Section V, where it presents a discussion, guidelines, and a conclusion.



UnifiedDiagramofPVSystem

PVTechnologyReview: At this point in time, renewable energy strategies for the production of power are dependable and have reached maturity. The photovoltaic (PV) power is the maximum promising source of electricity due to the fact that it does no longer emit any pollutants and is to be had in abundance everywhere in the international. Solar photovoltaic (PV) electricity is particularly useful in remote locations, such as deserts and rural areas, where the absence of power grid lines and the challenges involved in transporting traditional resources render their utilization impossible.

2. The Application of Statistical Indicators in Literature

In the research that has been done on artificial neural networks (ANN), numerous well-known indices that measure prediction accuracy have been implemented. Our careful examination of the publications that were under review made it possible to extract the list from the desk that was Table I..

TABLE I. Indicators Used In The Underlying Studied Works

Performance indicators	Formula
R (correlation coefficient)	$\frac{\Sigma_i^n\left(o_i-\left(\frac{1}{n}\Sigma_i^n(o_i)\right)\right)\left(t_i-\left(\frac{1}{n}\Sigma_i^n(t_i)\right)\right)}{\sqrt{\Sigma_i^n\left(o_i-\frac{1}{n}\Sigma_i^n(o_i)\right)^2\Sigma_i^n\left(t_i-\frac{1}{n}\Sigma_i^n(t_i)\right)^2}}$
R^2 (coefficient of determination)	$1-\left(\frac{\Sigma_i^n(t_i-o_i)^2}{\Sigma_i^n(o_i)^2}\right)$
RMSE (root mean square error)	$\sqrt{\frac{1}{n}\sum_i^n(o_i-t_i)^2}$
MAPE (mean absolute percentage error)	$\frac{1}{n}\sum_i^n\left\lvert\frac{o_i-t_i}{t_i}\right\rvert\times 100$
MBE (mean bias error)	$\sqrt{\frac{1}{n}\sum_i^n(o_i-t_i)}$
RMBE (relative mean bias error)	$\frac{\Sigma_i^n(o_i-t_i)}{\frac{1}{n}\Sigma_i^n(o_i)}\times 100$
MAE (mean absolute error)	$\frac{\Sigma_i^n\lvert o_i-t_i\rvert}{n}$
MRV (mean relative variance)	$\frac{\Sigma_i^n(t_i-o_i)^2}{\left(t_i-\left(\frac{1}{n}\Sigma_i^n(t_i)\right)\right)^2}$
DA (degree of agreement)	$1-\frac{\Sigma_i^n(o_i-t_i)^2}{\Sigma_i^n\left(\left\lvert o_i-\frac{1}{n}\Sigma_i^n(t_i)\right\rvert-\left\lvert t_i-\frac{1}{n}\Sigma_i^n(t_i)\right\rvert\right)^2}$

EVALUATION OF ANNS FOR PREDICTING SOLAR RADIATION

A. The requirements for participation

An automatic search became done on the databases of the most prominent publishers, and other criteria were employed, in order to make certain that the publications that we examined were of a high satisfactory. This allowed us to ensure that the publications that we evaluated were of a high quality. Following this, a listing was compiled with the aid of incorporating works that were mentioned in guides that had been chosen in the past. This was done in order to ensure that the listing had as much information as possible. We did not take into consideration conference articles, running papers, comments, or ebook appraisal pieces while conducting our search [13].

B. The dissemination of researches on previous works of literature Following this section, we will present the distribution of the reviewed publications based on the journal publisher (figure 1.a) and prediction horizon (figure 1.b).

Prediction of the solar radiation every month, every day, and every hour We find multiple prediction horizons in the works that have already been conducted, including monthly, daily, and hourly levels. In point of fact, month-to-month prediction makes it possible to realise a pre-sizing of sun devices, whereas daily and hourly sun radiation values are required for a reliable and precise sizing. Together, these values are essential for determining the appropriate size. In point of fact, the first standards of our research are to classify papers through the utilisation of the prediction horizon. Tables III and IV, respectively, provide an illustration of the obtained results for the daily/hourly sun radiation prediction category as well as the monthly sun radiation prediction category. In these tables, we have arranged the classes in a chronological order by specifying the expected factor, the ANN architecture, the location, and the overall performance assessment signs that correspond to that factor. When compared with diffuse and beam (direct) additives, the tables demonstrate that significantly more work was accomplished in the prediction of global solar radiation. In addition, we have found that the chosen studies can destroy up to forty neurons in a single hidden layer, and only a small percentage of them attempt to use two hidden layers with a total of up to 69 neurons. The ANN models each made use of their own unique set of input parameters, which were determined by the available geographical and meteorological statistics. When it comes to the maximum indicators of overall performance, the R2, MAPE, RMSE, and MBE are the ones that are used in the articles that are examined. According to [14], the found MAPE values fall within the range of [0.3 - 10.1], which indicates a high level of prediction accuracy. Every one of the models exhibits good performance, with a coefficient of determination (R2) that falls between 0.82 and 0.99.

3. CONVERSATION AND FUTURE RESEARCH WORKS RECOMMENDATIONS

During our analysis of the previously mentioned papers, we came across a number of issues and observations, which we will discuss in the following section along with our suggestions for how these issues should be addressed.

• Long-term climate data are required in order to examine and validate models that predict the power output of the sun. However, such data are not easily accessible because of the prohibitively high cost of measuring devices and the problem of inaccessibility of the measuring sites. This presents a significant challenge when attempting to conceive of models that are dependable and accurate. Based on our review of the scholarly literature, we have concluded that there is currently no up-to-date database that features a large number of different entry kinds in addition to recording periods of data. If you want to categories data with 90% precision, a decent rule of thumb is to have an education set size that's 10 times the community weights [47]. Furthermore, the database type's training and evaluation subsets should be statistically representative for reliable models. Empirical methods (which may need a massive computer assessment) are currently the only accepted method for optimizing the number of hidden layers and associated neurons in ANN models. This is a difficult and unanswered question that has to be considered in follow-up studies. The use of optimization techniques such as genetic algorithms, particle swarm optimization, and simulated annealing are all possibilities here..

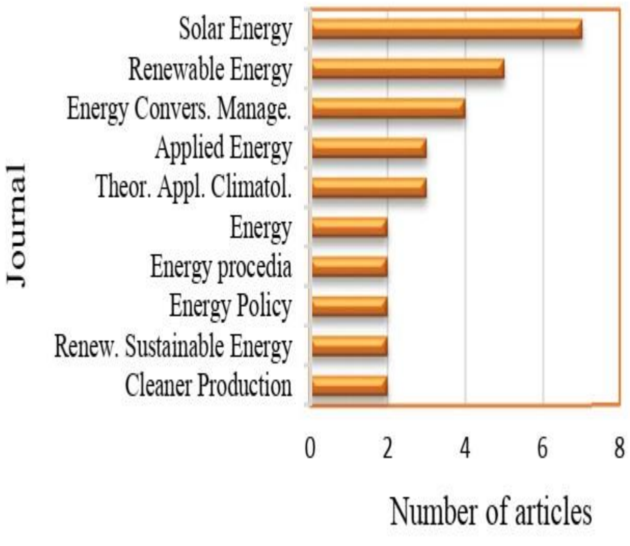


Fig. 1. Journal (a) and prediction (b) distributions of the reviewed articles.

TABLE III. MONTHLY SOLAR RADIATION PREDICTION PUBLICATION OF OUR STUDY0

Component	Reference	Authors	Journal	Year	The ANN architecture	Performance indicators	Location
Global	[15]	M.Laidi,et al.	Theor.Appl.Climatol.	2016	One Hidden Layer (8-35-1)	RMSE (Wh/m^2)= 5.750 R^2=0.999	Algeria
Global	[16]	E.F.Alsina et al.	Energy Conver. Manage.	2016	One Hidden Layer (7-4-1)	MAPE (%) = about 1.67 NRMSE(%)= 1.01	Italy
Global	[17]	O.Celik et al.	Cleaner Production.	2016	One Hidden Layer (6-3-1)	MAPE (%) = >99 R^2(%)= around 5.0	Turkey
Global	[18]	Waewsak etal.	Energy Procedia	2014	One Hidden Layer (6-9-1)	RMSE= 0.0031 to 0.0035 MBE= 0.0003 to 0.0011	Bangkok ,Thailand
Global	[19]	A.K. Yadav et al.	Renew. Sustainable Energy Rev.	2014	One Hidden Layer (5-10-1)	MAPE (%) = 6.89	India
Diffuse	[20]	Y.Jiang	Energy Policy	2008	One Hidden Layer (2-5-1)	R^2=0.90 MPE(%)=1.55 MBE(MJ/m^2)= 0 .040 RMSE(MJ/m^2) =0.746	China
Global	[21]	J.Mubiru et al.	Solar Energy	2008	One Hidden Layer (6-15-1)	R=0.974 MBE(MJ/m^2)= 0	Uganda
Beam	[22]	S.Alam et al.	Renewable Energy	2006	One Hidden Layer (7-3-1)	RMSE (%)= from 1.65 to 2.79	India
Global	[23]	F.S. Tymvios et al.	Solar Energy	2005	Two Hidden Layer (3-46-23-1)	MBE(%)= 0.12 RMSE(%)= 5.67	Cyprus , Athen
Global	[24]	A.Sozen et al.	Energy Coners. Manage.	2004	Two Hidden Layer	MAPE(%)= 6.735	Turkey
Global	[25]	A.Sozen et al.	Applied Energy	2004	(6-N/A-1)	MAPE (%) = <6.73 R2(%)= 99.89	Turkey
Global	[26]	A.S.S.Dorvlo et al.	Applied Energy	2002	(5-N/A-1)	RMSE(%)= 0.83	Oman
Global	[27]	M.Mohandes et al.	Solar Energy	1999	One Hidden Layer (5-10-1)	MAPE= 10.1	Saudi Arabia
Global	[28]	S.M.Al-Alawi et al.	Renewable Energy	1998	One Hidden Layer (8-15-1)	MAPE(%)= 5.43 R2(%)= 95	Sultanate of Oman
Global	[29]	M.Mohandes et al.	Renewable Energy	1998	One Hidden Layer (4-10-1)	MAPE (%) = from 6.5 to 19.1	Saudi Arabia

- According to the published research, the best desire for geographical and meteorological entry characteristics are critical to forecasting solar radiation with more reliability and precision. With the exception of a few research now being undertaken in this topic [19, 43], there is currently no automated approach that can sport out the selection of the most significant input variables for ANN models.

• The importance of the daylight period on forecast accuracy has been emphasised in the study done by *19+. This insight must be generalised if the influence of each variable on the overall performance of the ANN model is to be investigated.

• With regard to tables III and IV, which show the scarcity of papers on predicting diffuse and beam solar radiation using ANN, and taking into account the importance of those components for power systems, additional research must be conducted in future works.

• In order to pick the finest artificial neural network (ANN) prediction models, it is required to compare many ANN designs such as MLP, RBF, Generalised Regression Neural Network, and so on. We have obtained the conclusion [35, 36] in the field of solar radiation forecasting. Regrettably, the comparison of ANN with different prediction models has received less attention [23, 48, 49].

• As stated in *14+, unique ANN models must be created utilising latitude, longitude, altitude, and extraterrestrial radiation as input factors, and then correctness must be verified. This procedure must be carried out again. Even if it is determined that range and longitude have a negligible influence on solar radiation forecast, as proven in [19], this might be beneficial in areas where there are no meteorological stations. This might be beneficial in areas where no meteorological stations have been installed..

1. CONCLUSION

In this research, a detailed assessment of several methods employing artificial neural networks to estimate solar energy was offered. To successfully offer clean solar energy, one needs have an in-depth understanding of the availability and unpredictability of solar radiation. This is a prerequisite for achieving success in this endeavour. Due to its great potential to replicate the complex, nonlinear, and time-varying input-output systems, ANN models have been shown to be capable of properly predicting solar radiation. This discovery was made possible by the fact that ANN models have been used. When compared to other models that already exist, this one has a number of advantages. Because of this, one-of-a-kind research articles that are mostly based on artificial neural network models that are utilised to anticipate solar radiation are described in this study. These models are employed to predict solar radiation. Our inquiry consists of a review that is up to date and can be of assistance in the process of conducting more research in this field. Along with the prediction horizon, ANN structure, and overall performance metrics that correlate to it, it makes use of a bibliography that was selected with a great deal of care. In addition, the objective of analysing those guides is to bring to light difficulties such as the lack of a generic database (having an enormous range of input types with records recording durations) and the lack of a scientific method optimising the ANN structure. Both of these issues have become the purpose behind analysing those guidelines. The purpose of this research has evolved into drawing attention to these issues. In addition, there is no technique to carry out the selection of the input variables that are the most significant for ANN models, thus until a few research are working on this subject, there is no way to accomplish it. This is the situation regardless of the fact that there have been some research conducted on this matter. Also, we've discovered that there aren't many studies focusing on the prediction of the beam and diffuse components of the sun's radiation, which employs artificial neural networks. This is something that we've noticed. This is something that has come to our attention.

REFERENCES

[1] M. Iqbal, "A study of Canadian diffuse and total solar radiation data-llMonthly average hourly horizontal radiation," Solar Energy,vol.22,issue1, pp. 87-90, 1979.

[2] Y. Sukamongkol, S. Chungpaibulpatana, and W. Ongsakul, "A simulationmodel for predicting the performance of a solar photovoltaic system withalternating current loads," Renewable Energy, vol.27, issue 2, pp.237-258, 2002.

[3] A. Mellit, and A. M. Pavan, "A 24-h forecast of solar irradiance usingartificial neural network: Application for performance prediction of a grid-connected PV plant at Trieste, Italy," Solar Energy, vol. 84, issue 5,pp. 807-821, 2010.

[4] L.T. Wong, and W.K. Chow, "Solar radiation model," Applied Energy,vol. 69, pp.191–224, 2001.

[5] T. Muneer, S. Younes, and S. Munawwar, "Discourses on solar radiationmodeling," Renewable and Sustainable Energy Reviews,vol.11,issue4,pp. 551-602, 2007.

[6] A. Mellit, and S. A. Kalogirou, "Artificial intelligence techniques forphotovoltaic applications: A review," Progress in Energy andCombustion Science, vol.34, issue 5, pp. 547-632, 2008.

[7] S. Zekai, "Solar Energy Fundamentals and Modelling Techniques:Atmosphere, Environment, Climate Change and Renewable Energy,"Springer-Verlag London, 2008.

[8] T. Khatib, A. Mohamed, and K. Sopian, "A review of solar energymodeling techniques," Renewable and Sustainable Energy Reviews, vol.16, issue 5, pp. 2864-2869, 2012.

[9] J. Mubiru, and E.J.K.B. Banda, "Estimation of monthly average dailyglobal solar irradiation using artificial neural networks," Solar Energy,vol. 82, issue 2, pp. 181-187, 2008.

[10] A. Whillier, "The determination of hourly values of total solar radiationfrom daily summations," Arch. Met. Geoph. Biokl. B., vol.7,issue2,pp.197-204, 1956.

[11] B. Y. H. Liu, and R. C. Jordan, "The interrelationship and of direct,diffuse and characteristic distribution total solar radiation," Solar Energy,vol. 4, issue 3, pp.1-19, 1960.

[12] A. Gani, “Day of the year-based prediction of horizontal global solarradiation by a neural network auto-regressive model,” Journal of CleanerProduction, vol. 104, pp.01-12, 2015.

[13] A. Qazi, H. Fayaz, A. Wadi, Ram Gopal Raj, N.A. Rahim, “The artificialneural network for solar radiation prediction and designing solar systems:a systematic literature review,” Theor Appl Climatol, vol. 125, issue 3,pp. 679-689, 2016.

[14] A. K. Yadav, and S. S. Chandel, “Solar radiation prediction usingartificialneural network techniques: A review,” Renewable and SustainableEnergy Reviews, vol. 33, pp. 772-781, 2014

[15] M. Laidi et al., “Supervised artificial neural network-based method forconversion of solar radiation data (case study: Algeria),”Theor.Appl.Climatol., pp. 1–13, 2016.

[16] E. Federico Alsina, M. Bortolini, M. Gamberi, and A. Regattieri,“Artificial neural network optimisation for monthly average daily globalsolar radiation prediction,” Energy Conversion and Management, vol.120, pp. 320-329, 2016.

[17] Ö. Çelik, A. Teke, and HB. Yildirim, “The optimized artificial neuralnetwork model with Levenberg-Marquardt algorithm for global sola rradiation estimation in Eastern Mediterranean Region of Turkey,” Journalof Cleaner Production, vol. 116, pp. 1-12, 2016.

[18] J. Waewsak, C. Chancham, M. Mani, and Y. Gagnon, “Estimation ofmonthly mean daily global solar radiation over Bangkok,Thailandusingartificial neural networks,” Energy Procedia, vol. 57, pp.1160-1168,2014.

[19] A. K. Yadav , H. Malik , and S.S. Chandel, “Selection of most relevantinput parameters using WEKA for artificial neural network based solarradiation prediction models,” Renewable and Sustainable EnergyReviews, vol. 31, pp. 509-519, 2014.

[20] Y. Jiang, “Prediction of monthly mean daily diffuse solar radiation usingartificial neural networks and comparison with other empirical models ,” Energy Policy, vol. 36, issue 10, pp. 3833-3837, 2008.

[21] J. Mubiru, and E.J.K.B. Banda, “Estimation of monthly average dailyglobal solar irradiation using artificial neural networks,” Solar Energy,vol.82, pp. 181-187, 2008.

[22] S. Alama, S.C. Kaushikb, and S.N. Garg, “Computation of beam solarradiation at normal incidence using artificial neural network,” Renewable Energy, vol. 31, issue 2, pp.1483-1491, 2006.

[23] F.S. Tymvios, C.P. Jacovides, S.C. Michaelides, and C. Scouteli,“Comparative study of Ångström’s and artificial neural networks’methodologies in estimating global solar radiation,” Solar Energy, vol.78, issue 6, pp. 752-762, 2005.

[24] A. Sözen, E. Arcaklioğlu, and M. Özalp, “Estimation of solar potential inTurkey by artificial neural networks using meteorological and geographical data,” Energy Conversion and Management, vol. 45, issue18–19, pp. 3033-3052, 2004.

[25] A. Sözen, E. Arcaklioğlu, and M. Özalp, E. G. Kanitc “Use of artificialneural networks for mapping of solar potential in Turkey,” AppliedEnergy, vol. 77, issue 3, pp. 273-286, 2004.

[26] A. S. S. Dorvlo, J. A. Jervase, and A. Al-Lawati, “Solar radiationestimation using artificial neural networks, ” Applied Energy, vol. 71, pp.307-319, 2002.

[27] M. Mohandes, A. Balghonaim, M. Kassas, S. Rehman, and T. O.Halawani, “Use of radial basis functions for estimating monthly meandaily solar radiation,” Solar Energy, Vol. 68, issue2, pp. 161-168, 2000.

[28] S. M. AI-Alawi, and H. A. AI-Hinai, “An ANN-based approach forpredicting global radiation in locations with no direct measurementinstrumentation,” Renewable Energy, Vol. 14, issue 1-4, pp. 199–204,1998.

[29] M. Mohandes, S. Rehman, and T. O. Halawani, “Estimation of globalsolar radiation using artificial neural networks,” Renewable Energy, Vol.14, issue 1–4, pp. 179-184, 1998.

[30] K. Chiteka, and C.C. Enweremadu, “Prediction of global horizontal solarirradiance in Zimbabwe using artificial neural networks,” Journal ofCleaner Production, vol. 135, 2016, pp. 701-711, 2016.

[31] M. Shaddel, D. S. Javan , and P. Baghernia, “Estimation of hourly globalsolar irradiation on tilted absorbers from horizontal one using artificial neural network for case study of Mashhad,” Renewable and SustainableEnergy Reviews, vol. 53, 59-67, 2016.

[32] M. Vakilia, S-R. Sabbagh-Yazdi, K. Kalhorb, and S. Khosrojerdi, “Usingartificial neural networks for prediction of global solar radiation in Tehran considering particulate matter air pollution,” Energy Procedia, vol. 74,pp.1205-1212, 2015.

[33] B. Ihya, A. Mechaqrane, R. Tadili, and M. N. Bargach, “Prediction ofhourly and daily diffuse solar fraction in the city of Fez (Morocco),”Theor Appl Climatol, vol. 120, issue 3, pp. 737-749. 2014.

[34] A. Mellit, and A. M. Pavan, “A 24-h forecast of solar irradiance usingartificial neural network: Application for performance prediction of a grid-connected PV plant at Trieste, Italy,” Solar Energy, vol. 84, issue 5,pp.807-821, 2010.

[35] T. Khatib, A. Mohamed, K. Sopian, and M. Mahmoud, “Modeling ofdaily solar energy on a horizontal surface for five mainsites in Malaysia,” International Journal of Green Energy, vol. 8, issue 8, pp.795-819,2011.

[36] A. Sfetsos, and A. H. Coonick, “Univariate and multivariate forecastingof hourly solar radiation with artificial intelligence techniques,” SolarEnergy, vol 68, issue 2, pp. 169-178, 2000.