A Comparative Study of Types, Tools and Techniques in Solar Irradiance Forecasting

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ABSTRACT

The existing solar irradiance forecasting methods can be classified, according to the duration of forecast, into three classes: short, medium, and long techniques. The methods are breakdown into three approaches: statistical, physical, and hybrid. The purpose of this classification is to analyze the forecasting techniques that seem to embrace more potential for effectively forecasting a given data. The research evaluates the performances of different tools and techniques for selecting and constructing the most suitable solar irradiance forecasting model. This comparative study clears proper selection and structuring criterion, necessary for getting best results from forecasting model on given dataset. Lastly the paper outlines the future research directions and challenges faced by existing solar irradiance forecasting techniques.

Keywords: artificial, neural, network, solar, photovoltaic, system, irradiance, forecasting

1. INTRODUCTION

Heat and light are the two forms of solar energy. Solar energy is a renewable source because nothing is paid out to consume it on earth. This natural source of energy is also environment friendly with no harmful emissions or waste like other conventional energy sources. Solar energy is economical, with reduced distribution and transmission costs as it is located anywhere where there is sunlight. Even so, use of solar energy is not without its challenges.

The objective of review is to choose an appropriate forecasting technique, depending on a type of load, and then to propose a suitable model whose speculative characteristics are well-matched with the numerical properties of the particular data set. The generalized process is split into three steps: 1) data-preprocessing, 2) estimation, and 3) diagnostic checking. Solar irradiance forecasting is acquiring a lot of attention due to its auspicious applications in multiple fields. It is very costly and hard to install massive infrastructure in residential and industrial sector for communication between different fields as illustrated by **Error! Reference source not found.**. So the use of existing models and techniques is recommended [1]. Comparison between different forecasting types with their durations, strengths and drawbacks are shown in Table 4.Further these types are breakdown into three categories of forecasting approaches as depicted in the following Table 5. These categories of approaches have multiple techniques to facilitate the forecasting process .

The novelty of this paper lies in reviewing and classifying solar irradiance forecasting types, tools and techniques. The research gives the basis for forecast in photovoltaic systems, a concise analysis of forecasting techniques and their performance evaluation as discussed in the literature. It is difficult to rank the performance of all reviewed tools and techniques at this point because these are developed for different environments and scenarios. So, all the techniques are organized under the categories of types and nature of approaches.

All tools, approaches and techniques that are compared in this paper to give a complete understanding of each scheme and their behavior in various environments. This comparison will pave the way for further research of developing different solar irradiance forecasting models. The remainder of the paper is arranged as follows. Section 340 introduces solar irradiance forecasting, including methods and approaches.

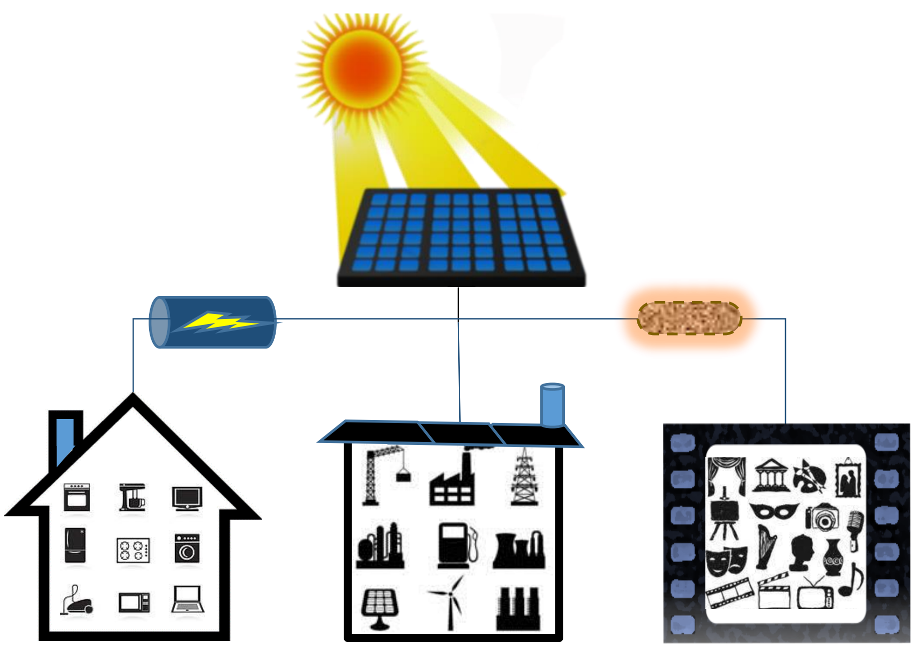

Figure 7 Applications and transmission strategies of solar energy

In section 3, a basic research upon forecasting classification is made. Besides this, forecasting strategies, approaches, classification, advantages, and disadvantages are also analyzed in this section.Then, in section 0, all solar irradiance forecasting tools are reviewed in detail. In this section, the tabulated summaries of existing tools are also presented. Section 0 and 0 enlist the general forecasting steps and research challenges respectively. Finally, section 0 concludes the paper by highlighting findings. The future work and research directions is discussed and suggested in section 0.

2. LITERATURE REVIEW

Global horizontal irradiance (GHI) forecasting gives a more accurate modeling and forecasting for solar power. Several solar irradiance forecast models and approaches are based on the time horizon, and applications. Long term solar irradiation estimation in Morocco by using a three layered and back propagated ANN model [3]. Multi-nonlinear regression neural network to estimate solar radiance in Turkey [4].The spectrum methods like the Autoregressive model (AR) and the Autoregressive moving average model (ARMA) [5], are competent for forecasting the future value of adaptive time series data. The fame of the ARMA method within the scientific research lies in its ability of mining stimulating statistical tools, in accumulation with adoption of the renowned Box-Jenkins method [6].Non-stationary solar irradiance data needs pre-processing. Lauret et al. [7] proposed a benchmarking of several machine learning techniques and an AR model. Bird clear sky model [8] is used to make stationary solar irradiance data. Recently, David et al. [9] extend the same pre-processing work to forecast solar irradiance with recursive ARMA-GARCH models. Many artificial intelligence (AI) techniques including artificial neural networks (ANN), expert systems (ES), genetic algorithms (GA), fuzzy logic (FL) and many hybrid systems were introduced for irradiance forecasting [10]. As the irradiance forecasting techniques including support vector machines, generic algorithms, regression series and all the variations of Artificial Neural Networks (ANN) are well efficient and have the capability to work even more efficiently then before by considering the climate variables (maximum temperature, sunshine duration, relative humidity, cloud cover, longitude, latitude and altitude) while training and producing an output as supported by various studies [11].

3. CLASSIFICATIONS OF SOLAR IRRADIANCE FORECASTING METHODS

Accurate predictions are needed over different time horizons: from very short-term to long-term horizon. There are three different types of irradiance forecasting approaches including statistical, physical and hybrid. Physical models utilize the current atmospheric observations and make future predictions with supercomputers. The statistical models predict the future value by considering the historic trend. Hybrid models (also known as combined models) combine two or more forecasting techniques to increase the forecast accuracy. Hybrid models are meant for overwhelming any insufficiency of using distinct model, such as regression models, to take the benefit of each distinct model and combine them to decrease forecast errors. It is vital to keep in mind that significant concerns like solar irradiance modules, clear sky models, air mass, Linked turbidity and clearness's indices have not been stated at this point because here we deal with Global Horizontal Irradiance (GHI) which is suitable for solar PV systems and do not require direct components of solar irradiance.

The forecasts aid the power system operators in ensuring supply reliability as well as optimal operation planning to allow dispatch of existing renewable generation.

Table 4. Comparison between forecasting types

Forecast Types	Duration	Strengths	Drawbacks	Well-suited Approaches
Short	1h to a week	Best for forecasting Load on holidays	Slow Processing	Statistical
Medium	1 month to an year	Fast to compute, model and trend tracking	Frequent changes in variables like gold price cannot be incorporated easily.	Physical
Long	several years	Minimizes the penalties and ensures the reliable operation	Complex training and forecasting process on Long term historic data	Hybrid

Table 5. Comparison of existing forecasting approaches

Forecasting Approaches	Input Data	Mean Absolute percentage error (MAPE) [12]	Example Technique	Limitation	Strength
Statistical	historical data	8.29% to 10.8% under different weather conditions	AR, MA, ARMA, ARIMA, ANN	Unable to retrieve data in remote areas	Ability of self-organize, learn and adapt
Physical	Environmental description	10% to 12% In case of long term forecasting	(NWP) and satellite cloud imagery	Hard time to provide predictions	More accurate long term planning
Hybrid	Environmental and historical data	7.65%	Fuzzy Logic Cao and Cao	Requires meteorological data even in remote areas	Show good generality capabilities irrespective of environment

3.1 Statistical Methods

Statistical methods additionally incorporate the persistence, which conjectures the future forecasting accepting that it is like past esteem. The perseverance technique is the least complex kind of gauge and is the most widely recognized reference show for brief time skyline conjectures [12].Linear factual models have a place with the class of time-arrangement forecast strategies .They are the most broadly executed and customary strategies exhibit in the writing as contrasting options to the physical techniques. Conventional factual procedures incorporate autoregressive (AR), moving normal (MA), ARMA and different variations of comparative models. The general type of such a model is given by the creators of [14]. In a few examinations, the attention has been on determining the power yield from a PV plant in view of comparative methods for irradiance estimating. In an investigation by Bacher et al. [15], both AR and AR with exogenous info (ARX) models were to anticipate the hourly estimations of sun based power for skylines up to 36 h. Another measurable approach is the Coupled AR and Dynamical System (CARDS) show discussed by [16] to figure out sun oriented radiation time arrangement for one day ahead forecast. Since sunlight based radiation displays regularity, the sun oriented radiation information was utilizing Fourier arrangement and power range examination as exhibited in Boland. Measurable methodologies require noteworthy volume of authentic time arrangement information. ANNs are propelled by the normal insight and the capacity of the human cerebrum to adjust its subjective

Table 6 Comparison of existing techniques

Techniques	Problem Type	Average predictive accuracy	Training speed	Prediction speed	Automatic feature interactions learning?	Parametric
Logistic regression	Classification	High	Fast	Fast	No	Yes
ARIMA	Either	Low	Fast	Fast	Yes	No
ANN	Either	Low	Slow	Moderate	Yes	No
Linear Regression	Regression	Low	Fast	Fast	No	No
SVM	Classification	High	Fast	Fast	Yes	Yes
NWP	Either	Medium	Fast	Fast	Yes	No
GFS	Either	Low	Fast	Moderate	Yes	Yes

procedure to tackle complex issues. The plan of ANNs empowers them to gain as a matter of fact and to exhibit solid summing up the competences. These models are information driven procedures which can speak to a complex non-direct relationship and are fit for extricating the reliance between the information and yield factors through the preparation and learning process. What's more, they have the capacity of self-association, learning and adjustment [17], hence, they are an effective and adaptable tool for forecasting. ANNs are arranged in two structures: encourage forward neural systems (FFNNs) and intermittent neural systems (RNNs) [18]. These systems normally have layers of information and yield neurons with at least one shrouded layers. The hidden neurons in function in innermost layers, to create important associations between the outside sources of info and the system yields. On alternate hand, RNNs are portrayed by the nearness of in reverse associations makes RNNs especially valuable in the demonstrating of dynamic frameworks [19].

3.2 Physical Methods

Physical forecasting techniques can be categorized in two basic groups; those that are satellite based (cloud imagery) and those based on numerical weather prediction (NWP).Various NWP- are typically marketable and are settled and functioned by meteorological stations, utilities and private companies [20]. Almost 14 operating global NWP models can be utilized by solar irradiance forecasting [21]. Integrated Forecast System (IFS) and Global Forest System (GFS) are another important contribution in literature. ECMWF forecasts fifteen day ahead solar irradiance and cloud parameters. The satellites and sky images are related to evaluation of cloud structures and motion from historical as well as current data to forecast their location and size in future and hence directly related to solar irradiance [22].

3.3 Hybrid Methods

Hybrid methods take advantage from different forecasting models. Few solar based forecast methods that exist in the literature are appeared in Table IV. Hybrid models have been executed in three diverse ways; linear, nonlinear and both of them. With the goal to enhance the anticipating exactness, half and half methodologies has been proposed by numerous scientists [23]. Fuzzy Logic includes non-straight mapping of information factors to the yield with persistent scope of participation works in the range [24]. Different investigations have used fuzzy methodologies in the anticipating of based irradiance and PV control generation. The handiness of these models is especially unique in circumstances where the correct model of the framework isn't accessible or deficient, or when the issue definition includes vulnerability or equivocalness. In [25], the creators utilized estimated temperature and irradiance to acquire fuzzy logic models. Interim sort 2 fuzzy models are utilized to represent the vulnerability intrinsic in the sun oriented irradiance expectation. The majority of these strategies required meteorological information as info, which may not be promptly accessible in remote territories. The blunders in the meteorological information influence the nature of sun based irradiance figures. Moreover, climate data is generally illustrative yet not evaluated [27]. Cao and Cao in [28] built up a hybrid model for anticipating arrangements of aggregate every day sun powered irradiance, which joins ANN with wavelet investigation. Ji and Chee [29] utilize a cross breed model [30] of ARMA and TDNN to enhance the forecast precision. They assume that the everyday solar based irradiance arrangement is created by linear and nonlinear methods [31] and utilize the ARMA model to fit the direct segment and the TDNN model to locate the nonlinear pattern lying in the residual. Every single mixture display can possibly outfit the interesting highlights and qualities of blend of models instead of utilizing the models independently [32].

4.SOLAR IRRADIANCE FORECASTING TOOLS

For the comparative analysis of tools some parameters are defined for tool evaluation .Each tool is checked against each parameter and find whether the tool have that feature or not. Only those parameters which are common for all tools like each tool must have some import and export formats and supported parameters (time horizon etc.) are defined. A parameter of release date to find out that how many years of solar irradiance dataset it contains. Other parameters include user how convenient it is for the user to operate the interface (user friendly GUI), either the tool have partially free (for specific time or with certain features). Platform independence or cross platform support (it can run on multiple platforms) is another plus for any tool. Every tool has its unique as well as common parameters for example clear sky index, meteorological factors like temperature and parameters related to solar geometry are common among all. Tools are mentioned below with their reference websites for complete description and help.

Table 7. Comparison of solar irradiance tools

Ref.	Tools	User Friendly GUI	Parameter supported	Import Formats	Export Format	Cost	Cross Plat-form	Release Year
[33]	Area Solar Radiation	Medium	19	.sa	.apk	Full Free	Yes	2000
[34]	Points Solar Radiation	Medium	18	.dbf,.txt	.apk	Full Free	Yes	1999
[35]	Solar Radiation Graphics	Low	20	.dbf, .sa	.pdf,.apk	Partial Free	Yes	1990
[36]	Meteonorm	High	13	.csv	36 formats	Partial Free	Yes	1981
[37]	PVGIS	Medium	24	.MET, *.SIT	.txt, .pdf	Full Free	Yes	1981
[38]	NASA SSE	Medium	58	.txt	.txt,.xml	Full Free	Yes	1983

We have done the analysis on the basis of the above mentioned parameters. The analysis is given in the Table 4. The analysis shows that all the tools are cross platform supported. Majority of the tool convert text (.txt) or database (.csv, .dbf) to text portable (.pdf) or executable (.apk) format. All tools are quite user friendly but Meteonorm is highly user friendly. Both Meteonorm and PVGIS are mature tools as compared to others as they have solar irradiance data since 1981.

5.FORECASTING METHODOLOGY IN GENERAL

This section explains a set of three generic steps of data pre-processing, estimation, and diagnostic checking as shown by Fig. 2

Step 1: Data Pre-Process
This step is meant for data labeling and modification before giving it as input into the forecasting tool. The preprocessing includes: removing nighttime GHI values, detruding, and normalization.

Step 2: Estimation
In this step, the pre-handled information are acquainted with the anticipating tool. The recorded GHI information are sustained to the model as an info and the real GHI is nourished as an objective. The model is set up by the particular data sources as inputs. The chronicled information is prepared utilizing distinctive preparing techniques and the blunder is investigated. The preparation procedure proceeds until the mistake between the determined and the real GHI is limited given the information sources, weights and by utilizing different parameters.

Step 3: Diagnostic Checking
After getting an output from the model, errors are calculated and solution accuracy is determined. Models like NWP require diagnostic checking for modification of systematic deviations; that includes indirect and not standardized parameters delivered by the NWP models as output (e.g., solar surface irradiance); consolidate the yield of various models in an ideal way. The resultant estimated information from organize two speak to the daytime GHI esteems in standardized shape. In this way, organize three is the turnaround of the primary step. Step three incorporates three procedures: denormalization, including evening hours, and figuring the GHI. The handled information is denormalized e.g. through increasing the hourly pinnacle clear sky GHI by the hourly yield GHI from step 2.

6.SOLAR IRRADIANCE FORECASTING CHALLENGES

GHI forecasting is less accurate due to multiple reasons:

- Despite of considerable increase in the size and installed capacity; intermittent (i.e., unavailability) and fluctuating (i.e., constantly change in time) nature of renewable generation is a challenge.

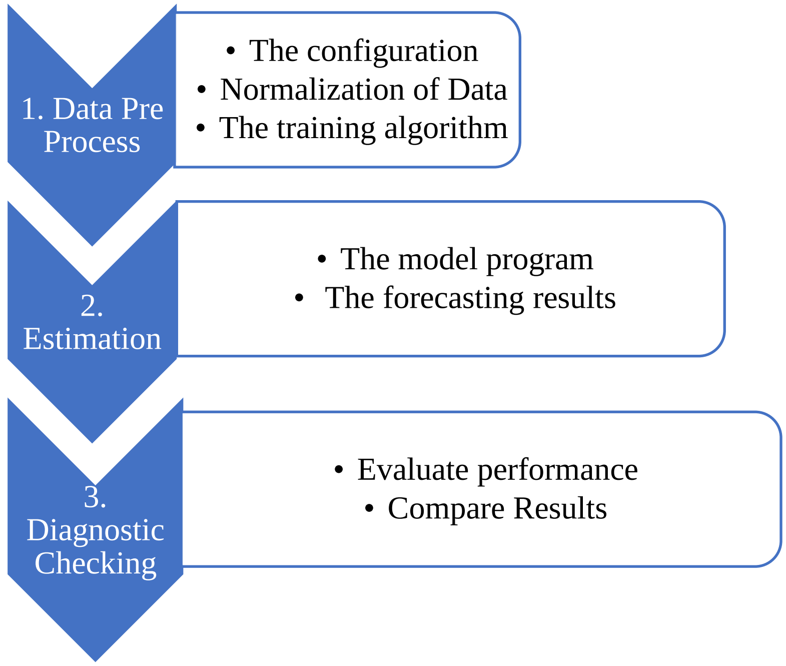

Figure 8 Generalized Forecasting Steps

- Failure to forecast the timing and severity of the fluctuations.
- The irregularity of solar data pattern due to climate change has imposed significant limitations to forecasting models [39]. So, sunny climate has noticeable patterns as compared to foggy climate hence less forecasting error.
- Different times of same day (like the sunset and the sunrise) imposes limitations to forecasting horizon.
- The long-term forecasting usually requires training on long-term historical solar irradiance data to extract patterns of the time series.
- To assure the regulation of supply to demand, providers and managers have to schedule the energy distribution and to guarantee that the generated power meet the consumer's demands plus the electricity cost.

7.CONCLUSION

This paper has offered different forecasting types according to their various selection techniques and principles. An expansive number of existing forecasting techniques have been looked into. Types of solar irradiance forecasting ranges from couple of minutes to a year, has received an immense consideration from industrial and academic scientists. The accuracy of forecasting reduces the energy consumption, distribution and transmission overhead by meeting the future energy demand in an effective manner. The comparison between types, tools and techniques for solar irradiance forecasting is made upon the various parameters of forecasting such as being MAPE, cost, interface type etc. The process of the forecasting routing is divided into three generic step it is not possible to review the performance of every techniques, which are meant for different environments. Therefore, few important techniques are reviewed along with their functionality, performance, strengths, drawbacks and applications in various environments.

FUTURE WORK

Vulnerabilities and intermittent nature of natural resources like solar irradiance to enhance solar irradiance forecasting over temporal and spatial horizons. Sky image techniques will also need to be integrated with the methods like ARIMA and WRF for more accurate forecast product with different time horizons of forecast.

REFERENCES

1. Tuohy J. Zack, Haupt S.E., Sharp J. at all. "Solar Forecasting: Methods, Challenges, and Performance," *IEEE Power Energy Mag.*, vol. 13, no. 6, pp. 50–59, Nov. 2015.
2. Ela E., Diakov V., Ibanez E. and Heaney M. "Impacts of variability and uncertainty in solar photovoltaic generation at multiple timescales," *Contract*, vol. 303, pp. 275–3000, 2013.
3. Honeyman S. Kann, Baca J. "U.S. SOLAR MARKET INSIGHT 'Executive Summary' 2015 Year in Review." Solar Energy Industries Association | SEIA and GTM Research, Mar-2016.
4. Chupong and Plangklang B. "Forecasting power output of PV grid connected system in Thailand without using solar radiation measurement," *Energy Procedia*, vol. 9, pp. 230–237, 2011.
5. Chen S. Duan, Cai T., and Liu B. "Online 24-h solar power forecasting based on weather type classification using artificial neural network," *Sol. Energy*, vol. 85, no. 11, pp. 2856–2870, Nov. 2011.
6. Watetakarn S., Premrudeepreechacharn S. "Forecasting of solar irradiance for solar power plants by artificial neural network," I *Smart Grid Technologies-Asia (ISGT ASIA), 2015 IEEE Innovative*, 2015, pp. 1–5.
7. Diagne H.M., Lauret P., David M. "Solar irradiation forecasting: state-of-the-art and proposition for future developments for smallscale insular grids," in *WREF 2012-World Renewable Energy Forum*, 2012.
8. Stefferud K., Kleissl J., Schoene J. "Solar forecasting and variability analyses using sky camera cloud detection & motion vectors," in *Power and Energy Society General Meeting, 2012 IEEE*, 2012, pp. 1–6.
9. Kleissl J. *Solar Energy Forecasting and Resource Assessment*. Academic Press, 2013.
10. Diagne M., David M., Lauret P., Boland J., Schmutz N. "Review of solar irradiance forecasting methods and a proposition for smallscale insular grids," *Renew. Sustain. Energy Rev.*, vol. 27, pp. 65–76, Nov. 2013.
11. Diagne H.M., Lauret P., David M. "Solar irradiation forecasting: state-of-the-art and proposition for future developments for smallscale insular grids," in *WREF 2012-World Renewable Energy Forum*, 2012.

12. Huang R., Huang T., Gadh R., Li N. “Solar Generation Prediction using the ARMA Model in a Laboratory-level Micro-grid,” in *Smart Grid Communications (SmartGridComm), 2012 IEEE Third International Conference on*, 2012, pp. 528–533.
13. Pillai J. S., Pillai M.J. “An Algorithm for Retrieving Skyline Points based on User Specified Constraints using the Skyline Ordering”, *International Journal of Computer Applications*, vol. 104, no. 11, pp. 24-29, 2014.
14. Zhang Y., Beaudin M., Taheri R., Zareipour H., Wood D. “Day- Ahead Power Output Forecasting for Small-Scale Solar Photovoltaic Electricity Generators,” *IEEE Trans. Smart Grid*, pp. 1–1, 2015.
15. “Solar Data 1991-2010 Site #725650.” [Online]. Available: http://rredc.nrel.gov/solar/old_data/nsrdb/19912010/hourly/siteonthefly.cgi?id=725650. [Accessed: 16-Sep-2014].
16. Webberley A., Wenzhong Gao D. “ Study of Artificial Nectial Network based short term Irradiance forecasting” Power and Energy Socie-ty General Meeting (PES), 21-25 July 2013, 1-4.
17. Hesham K. Alfares and mohammad Nazeeruddin, Electrical Irradiance Forecasting Literature Survey and Classification of Methods, International Journal of Systems Science 33 (1), 2002, 23-24.
18. Ke Li, Tai N., S. Zhang S. “Research and application of climatic sensi-tive short - term irradiance forecasting,” *2015 IEEE Power & Energy Socie-ty General Meeting*, Denver, CO, 2015, pp. 1-5.
19. Farah A., Farah N. “Multi-model approach for electrical irradiance forecasting,” 2015 SAI Intelligent Systems Conference (IntelliSys), London, 2015, pp. 87-92.
20. Munkhammar J., Widén J. "Correlation modeling of instantaneous solar irradiance with applications to solar engineering", Solar Energy, vol. 133, pp. 14-23, 2016.
21. Lim P., Nayar C. "Solar Irradiance and Load Demand Forecasting based on Single Exponential Smoothing Method", International Journal of Engineering and Technology, vol. 4, no. 4, pp. 451-455, 2012.
22. Tofallis C. “A better measure of relative prediction accuracy for model selection and model estimation” Journal of the Operational ResearchSociety vol. 66 no. 8 pp. 1352-1362 Nov 2014.
23. Genyong C., Jingtian S. “Study on the methodology of short-term irradiance forecasting considering the accumulation effect of tempera-ture,”2009 International Conference on Sustainable Power Generation and Supply, Nanjing, 2009, pp. 1-4.
24. Pavan M., Pavan A.M. “A 24-h forecast of solar irradiance using artificial neural network: Application for performance prediction of a grid-connected PV plant at Trieste, Italy,” Sol. Energy, vol. 84, no. 5, pp. 807–821, May 2010.
25. Huang Y., Lu J., Liu C., Xu X., Wang W., Zhou X. “Comparative study of power forecasting methods for PV stations,” in 2010 International Conference on Power System Technology, 2010, pp. 24–28.
26. Zhang Y., Beaudin M., Taheri R., Zareipour H., Wood D. “Day-Ahead Power Output Forecasting for Small-Scale Solar Photovoltaic Electricity Generators,” IEEE Trans. Smart Grid, pp. 1–1, 2015.
27. Marquez R., Coimbra C.F.M. “Forecasting of global and direct solar irradiance using stochastic learning methods, ground experiments and the NWS database,” Sol. Energy, vol. 85, no. 5, pp. 746–756, May 2011.

28. Stefferud K., Kleissl J., Schoene J. “Solar forecasting and variability analyses using sky camera cloud detection & motion vectors,” in Power and Energy Society General Meeting, 2012 IEEE,2012, pp. 1–6.
29. Chupong C., Plangklang B. “Forecasting power output of PV grid connected system in Thailand without using solar radiation measurement,” Energy Procedia, vol. 9, pp. 230–237, 2011.
30. Chen C., Duan S., Cai T., Liu B. “Online 24-h solar power forecasting based on weather type classification using artificial neural network,” Sol. Energy, vol. 85, no. 11, pp. 2856–2870, Nov. 2011.
31. Singh V.P., Vaibhav K., Chaturvedi D.K. “Solar power forecasting modeling using soft computing approach,” in Engineering (NUiCONE), 2012 Nirma University International Conference on,2012, pp. 1–5.
32. Diagne H.M., David M., Lauret P., and Boland J. “Solar irradiation forecasting: state-of-the-art and proposition for future developments for small-scale insular grids,” American Solar Energy Society, 2012.
33. “Area Solar Radiation—Help | ArcGIS for Desktop”, Desktop.arcgis.com, 2017. [Online]. Available: http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/area-solar-radiation.htm. [Accessed: 12- Oct- 2017].
34. “Points Solar Radiation—Help | ArcGIS for Desktop”, Desktop.arcgis.com, 2017. [Online]. Available: http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/points-solar-radiation.htm. [Accessed: 12- Oct- 2017].
35. “Solar Radiation Graphics—Help | ArcGIS for Desktop”, Desktop.arcgis.com, 2017. [Online]. Available: http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/solar-radiation-graphics.htm. [Accessed: 12- Oct- 2017].
36. “Meteonorm: Irradiation data forevery place on Earth”, Meteonorm.com, 2017. [Online]. Available: http://www.meteonorm.com/. [Accessed: 12- Oct- 2017].
37. “JRC's Directorate C: Energy, Transport and Climate - PVGIS - European Commission”, Re.jrc.ec.europa.eu, 2017. [Online]. Available: http://re.jrc.ec.europa.eu/pvgis/. [Accessed: 12- Oct- 2017].
38. “Surface meteorology and Solar Energy”, Eosweb.larc.nasa.gov, 2017. [Online]. Available: https://eosweb.larc.nasa.gov/sse/. [Accessed: 12- Oct- 2017].
39. Lam J., Tang H., Li D. "Seasonal variations in residential and commercial sector electricity consumption in Hong Kong", Energy, vol. 33, no. 3, pp. 513-523, 2008.