Solar Penetration Analysis Techniques for Photovoltaic Energy and Smart Grid Management

Zahoor Ahmed\textsuperscript{1}, Junaid Zaffar\textsuperscript{2}, Rashid Aleem\textsuperscript{3}, Ehtasham-ul-Haq\textsuperscript{4}, Nurali Pyarali\textsuperscript{5}, Mehr E Munir\textsuperscript{6}

\textsuperscript{1, 5}Department of Electrical Engineering, Bahria University, Karachi, Pakistan
\textsuperscript{2, 3, 4, 6}Department of Electrical Engineering, Iqra National University, Peshawar, Pakistan

*Corresponding author: Zahoor Ahmed Email: zahoor.ahmed@hotmail.com

https://doi.org/10.26782/jmcms.2019.08.00005

Abstract

As the world thrives for power in order to strengthen its industrial demands and economy, traditional power sources are becoming more and more difficult to fulfill the rising demands. Renewable energy demand in the world whether third world countries or leading ones of the era, has seen a boost in recent decades. Photovoltaic and solar energy is an ongoing trend in power system designers, researchers and companies. As sun is the free source of energy, the world now a days achieves 30% of its total energy from it. Solar power is sporadic and is not constant, as solar source at the ground level is extremely reliant on clouds density, atmospheric conditions with other restrictions. These limitations become a challenging task for engineers and energy managers to focus the energy constraints and came up with managing plan in order to produce and manage energy efficiently in smart grids. This paper focuses on energy constraints of both solar resource and PV power alongside smart grid energy management.

Keywords: Solar energy, PV cells, energy forecast, smart grid management.

I. Introduction

Solar cells are unique energy transducers that convert the photovoltaic energy to electrical power energy. Solar energy as directly comes from the sun, now a days the leading crisis of the energy in the world has forced designers and power engineers to utilize it. Traditional power energy resources has lead a rise in temperature of the world and Global warming has become a major cause of concern for humankind. This energy crisis over the past few decades have motivated the use and expansion of substitute, maintainable, and unsoiled energy sources such as solar, wind and other clean forms of energy. The world leading economies have already invested in solar form of energy in fact Germany has invested such massive amount in green energy that it has even surpassed United States of America and now its half of industries are running on green power ranking itself as top consumer of Solar power with 40GW of energy [I-IV]. PV power generation has familiarized noteworthy monetary and ecological benefits to the communal societal attentiveness, such as decreasing discharges of harmful Carbon dioxide as well as generating service [V]. PV power is...
getting advanced and sophisticated infiltration equals in the smart grids [VI]. A significant feature of the smart grid is its extraordinary capability to assimilate renewable energy generation.

However, as recurrent energy source, PV generation presents noteworthy instability in smart grid, which calls out severe tasks to system stability [VII], electric power balance [VIII], reactive power compensation [IX], frequency response [X], etc. The solar energy converted by the panels are stored in battery as direct energy and with inverter is converted to AC which is further distributed in home appliances and further. In order to guarantee safe and monetary combination of PVs into the smart grid, precise PV power prediction has turn out to be a curious and key element of energy management systems. PVs output directly depends on solar penetration on ground levels. It helps in improving power quality of network and decreases the supplementary costs related to overall instability [XI]. Solar penetration in ground level is a tough task for energy management in smart grids since temperature conditions, humidity levels, dust particles with wind make it a tough task. The solar penetration in smart grids determines the controllability of solar cells and their operations [XII]. The determination of solar penetration on ground level addresses power scheduling and grid regulation activities. There are four methods used for forecasting the solar penetration for PV generations. These methods are statistical approach, artificial intelligence (AI) approach, physical approach, and hybrid approach.

The historic data on weather conditions for specific region and area defines the statistical method for PV generation. Artificial intelligence use specific algorithms for certain conditions and implement then accordingly but the algorithms are defined in AI on the basis of statistical models [XIV] [XV]. Physical methods use likelihood of weather probability like rain and sunny conditions with help of images taken through satellite and correspondingly make operations management [XVI] [XVII]. In last the most advance method use for smart grid management is hybrid approach which is combination of all three methods. This paper presents an analysis of techniques and approaches used for forecasting analysis and their impact on PV generation.

II. Characteristics of Solar Penetration:

Solar estimation usually yields solar power. The solar energy input is based on such mathematical models and predictions that include forecasting of rain and related variables over given horizon consistently performance assessment catalogues are announced for evolving novel solar energy predictors.

II.i. Factors Effecting PV Generation and Maximum Power Point (MPPT):

The input of solar power depends upon factors such as reflection of light, temperature of given area under normal weather conditions the dust particles density and humidity levels. As solar power is usually converted through inverters, the total efficiency of inverters and its operating power also plays an important role in determination of PV plant. Equation 1 shows the maximum power output of PV.

\[
P_R = \eta Ki [1 - 0.05(S_0 - 25)]
\]  

\( P_R \) = \( \eta Ki [1 - 0.05(S_0 - 25)] \)
Where K represents the cells area while $\eta$ efficiency and $S_0$ the temperature conditions in Celsius.

Chasing the maximum power point (MPPT) of a PV array is typically vital fragment in order to increase the efficiency [19]. In this method voltage $V_R$ and the current $I_R$, is driven automatically in area which PV array functions capably to attain the concentrated power production $P_R$ under a assumed temperature, as verified in Fig. 1.

![Power Curve MPPT Characteristics](image)

Fig 1: Power Curve MPPT Characteristics

### II.i. Major Forecasting Features:

While making statistical models and physical models, the predictions are based on variables chosen to observe. These variables measure the efficiency of models which provides basis of PV plants output [20]. They variables chosen to be input associated but not restricted to the historical data of Generation of PV, descriptive variables depth knowledge which can be said as wind conditions its speed over several intervals of monthly to hourly basis, humidity conditions and clouds effecting solar penetration on ground levels. In practical terms while implementation, on the models provided the decision is based on 4 scenarios which is shown in Table 1.
### Table 1. Decision Scenarios of Smart Grid

| S.No | Decision | Duration       | Description/Use                                                                 |
|------|----------|----------------|---------------------------------------------------------------------------------|
| 1    | VST      | 0-5 minutes    | Very Short Term decision for storage purposes                                    |
| 2    | ST       | 2 to 3 Days    | Short term decision implements in power operation units commitment in grid installation management. |
| 3    | MT       | 3 Days to 1 week | Medium term decision implements in power operation maintenance over system failures and sudden surge |
| 4    | LT       | 2 weeks to year | Long Term decision are implemented when installing and designing the new plant over a given horizon |

Usually the first two decisions are frequently used as compared to last two. Fig. 2 shows the decision making over given horizons we can conclude from this easily that mostly models made are based on very short and short term use.

![Fig 2: Decision production Events.](image)

*Copyright reserved © J. Mech. Cont.& Math. Sci.*  
*Zahoor Ahmed et al.*
III. Neural Networks in Artificial Intelligence:

The neural networks are parts of Artificial intelligence that use mathematical and statistical models. The Neural network is a set of commands that are executed on the historical data provided over a given horizon and is consisted on 3 layers or parts as shown in figure 3. The input layer is a data set of samples over hidden functions. Ranging from 2 and above the input shows usually the factors effecting PV plant operations and the hidden layer is a set of statistical models that are implemented constantly in order to achieve maximum power efficiency of plant in smart grid. The output layer is a chain of commands implemented and their operation such as shifting directions through automated motors in direction of solar penetration, immediately execution of plant operation over storm conditions etc.

The examples of neural networks in AI is Radial Basis Function neural network (RBFNN) which was introduced first in 1988 specifically use for time series prediction. Another network model least-square support vector machine (LS-SVM) monitors and executes commands over specific hourly weather conditions.

IV. Smart Grid Management:

As in huge-scale saturation of Photovoltaic power, the adverse effects if unchecked over networks particularly over smart grid management is gaining a lot of consideration in designing features. Models particularly statistical and Neural are being designed in order to overcome power surge losses, short circuits scenarios, and voltage fluctuations problems. Effective models have been proved to operate and manage grid electricity well for operators and situation holders in electric power plant management. Neural networks in Artificial Intelligence have been employed with specific models in order to prevent short term fluctuations losses in cloud coverage cases and their alternative solution and back up [21-22]. This range in seconds to minutes efficiently prevents large fluctuations and system failures and smoothing PV curves. In order to bind the incline proportion of PV productions, numerous...
approaches like ramping generators, battery storages in AI have been implemented to smooth the PV outputs.

V. Conclusion:

This paper presented the solar forecasting importance for smart grid management as the world is utilizing it to fulfill its needs. The statistical models provide base for hybrid and Artificial intelligence based models. The forecasting predictions provide basis for Short term and Very short term decisions which are mostly used scenarios. The models in smart grid management play a key role in effecting overall performance and they can be changed regularly depending upon statistical models.

IV. Acknowledgement:

The authors acknowledge the support provided by Iqra National University, Peshawar, Pakistan.

References

I. A. Sfetsos and A. H. Coonick, “Univariate and multivariate forecasting of hourly solar radiation with artificial intelligence techniques,” Solar Energy, vol. 68, no. 2, pp. 169–178, Feb. 2000.

II. B. Kumar Sahu, “A study on global solar PV energy developments and policies with special focus on the top ten solar PV power producing countries,” Renewable & Sustainable Energy Reviews, vol. 43, no. 0, pp. 621–634, Mar. 2015.

III. D. Yang, C. Gu, Z. Dong, P. Jirutitijaroen, N. Chen, and W. M. Walsh, “Solar irradiance forecasting using spatial-temporal covariance structures and time-forward kriging,” Renewable Energy, vol. 60, no. 0, pp. 235–245, Dec. 2013.

IV. E. Geraldi, F. Romano, and E. Ricciardelli, “An advanced model for the estimation of the surface solar irradiance under all atmospheric conditions using MSG/SEVIRI data,” IEEE Transactions on Geoscience and Remote Sensing, vol. 50, no. 8, pp. 2934–2953, Aug. 2012.

V. F. Bizzarri, M. Bongiorno, A. Brambilla, G. Gruosso, and G. S. Gajani, “Model of photovoltaic power plants for performance analysis and production forecast,” IEEE Transactions on Sustainable Energy, vol. 4, no. 2, pp. 278–285, Apr. 2013.

VI. F. Ueckerdt, R. Brecha, and G. Luderer, “Analyzing major challenges of wind and solar variability in power systems,” Renewable Energy, vol. 81, no. 0, pp. 1–10, Sep. 2015.

VII. H.-T. Yang, C.-M. Huang, Y.-C. Huang, and Y.-S. Pai, “A weather-based hybrid method for 1-day ahead hourly forecasting of PV power output,” IEEE Transactions on Sustainable Energy, vol. 5, no. 3, pp. 917–926, Jul. 2014.

VIII. IEA-PVPS, “Annual Report 2014 (AR2014),” May 2015.

IX. M. Hosenuzzaman, N. A. Rahim, J. Selvaraj, M. Hasanuzzaman, A. B. M. A. Malek, and A. Nahar, “Global prospects, progress, policies, and environmental impact of solar photovoltaic power generation,” Renewable & Sustainable Energy Reviews, vol. 41, no. 0, pp. 284–297, Jan. 2015.
X. P. Bacher, H. Madsen, and H. A. Nielsen, “Online short-term solar power forecasting,” Solar Energy, vol. 83, no. 10, pp. 1772–1783, Oct. 2009.

XI. R. G. Wandhare and V. Agarwal, “Reactive power capacity enhancement of a PV-grid system to increase PV penetration level in smart grid scenario,” IEEE Transactions on Smart Grid, vol. 5, no. 4, pp. 1845–1854, Jul. 2014.

XII. R. Shah, N. Mithulananthan, R. C. Bansal, and V. K. Ramachandaramurthy, “A review of key power system stability challenges for largescale PV integration,” Renewable & Sustainable Energy Reviews, vol. 41, no. 0, pp. 1423–1436, Jan. 2015.

XIII. R. Perez, E. Lorenz, S. Pelland, M. Beaubarnois, G. Van Knowe, K. Hemker Jr, et al., “Comparison of numerical weather prediction solar irradiance forecasts in the US, Canada and Europe,” Solar Energy, vol. 94, no. 0, pp. 305–326, Aug. 2013.

XIV. R. Perez, S. Kivalov, J. Schlemmer, K. Hemker Jr, D. Renne, and T. E. Hoff, “Validation of short and medium term operational solar radiation forecasts in the US,” Solar Energy, vol. 84, no. 12, pp. 2161–2172, Dec. 2010.

XV. S. J. Steffel, P. R. Caroselli, A. M. Dinkel, J. Q. Liu, R. N. Sackey, and N. R. Vadhari, “Integrating solar generation on the electric distribution grid,” IEEE Transactions on Smart Grid, vol. 3, no. 2, pp. 878–886, Jun. 2012.

XVI. S. D. Campbell and F. X. Diebold, “Weather forecasting for weather derivatives,” Journal of the American Statistical Association, vol. 100, no. 469, pp. 6–16, Mar. 2005.

XVII. S. I. Nanou, A. G. Papakonstantinou, and S. A. Papathanassiou, “A generic model of two-stage grid-connected PV systems with primary frequency response and inertia emulation,” Electric Power Systems Research, vol. 127, no. 0, pp. 186–196, Oct. 2015.

XVIII. S. Eftekharnejad, G. T. Heydt, and V. Vittal, “Optimal generation dispatch with high penetration of photovoltaic generation,” IEEE Transactions on Sustainable Energy, vol. 6, no. 3, pp. 1013–1020, Jul. 2015.

XIX. T. Sueyoshi and M. Goto, “Photovoltaic power stations in Germany and the United States: A comparative study by data envelopment analysis?” Energy Economics, vol. 42, no. 0, pp. 271–288, Mar. 2014.

XX. T. Esram and P. L. Chapman, “Comparison of photovoltaic array maximum power point tracking techniques,” IEEE Transactions on Energy Conversion, vol. 22, no. 2, pp. 439–449, 2007.

XXI. Z. Dong, D. Yang, T. Reindl, and W. M. Walsh, “Satellite image analysis and a hybrid ESSS/ANN model to forecast solar irradiance in the tropics,” Energy Conversion and Management, vol. 79, no. 0, pp. 66–73, Mar. 2014.

XXII. Z.-Y. Zhao, S.-Y. Zhang, B. Hubbard, and X. Yao, “The emergence of the solar photovoltaic power industry in China,” Renewable & Sustainable Energy Reviews, vol. 21, no. 0, pp. 229–236, May 2013.