Solar Generation Prediction using Artificial Intelligence: A Review

Navareen Sohkhlet[1], Bikramjit Goswami[2]

[1,2] Department of Electrical and Electronics Engineering, School of Technology, Assam Don Bosco University
Airport Road, Azara, Guwahati-781017, Assam, INDIA
[1]navareensohkhlet@gmail.com, [2]bikramjit.goswami@dbuniversity.ac.in*

Abstract: ***Solar energy generation is one of the most promising and fastest-growing renewable energy sources for the generation of useful energy worldwide. Forecasting of solar power is the most essential for the planning of grid operations, mainly in residential microgrids, to optimize and manage the energy produced in a dispatchable trend. Due to the inability of deterministic methods to accurately forecast solar power generation due to their dependency on natural inputs, Artificial Intelligence (AI) based techniques are required to be implemented. AI techniques clubbed with stochastic methods are considered to be highly effective for solar generation forecasting. In this review, various artificial intelligence-based supervised and unsupervised learning methods for solar energy generation prediction are analyzed. The use of weather and environmental inputs for supervised learning is also compared. The accuracy of prediction of solar generation using several AI, Machine Learning, and Neural Network-based techniques are also analyzed in the paper. The paper presents an overall picture of the use of Artificial-Intelligence based techniques in solar generation prediction in the world.***

Keywords: Solar power forecast; Artificial Intelligence (AI); Artificial Neural Network; Regression.

Article history- Received: 17 July 2021 and Accepted: 15 October 2021.

1. Introduction

Solar energy generation is the fastest growing and most promising type of renewable energy source of power generation in the whole world. In today's world, electrical energy is one of the basic needs just after food, clothing, and shelter. The use of electrical energy is also a parameter for measuring the growth and development of a country. Therefore, there is always an increasing demand for it in the whole world. As the current major sources of electrical power, generated through fossil fuels (coals, fuel, diesel), etc. are of non-renewable types, with the sources depleting day by day, it is more important now to switch to renewable sources. Also, the use of fossil fuels raises serious environmental concerns. These are the main reasons that force the development and growth of renewable or non-conventional sources of energy, which are ecologically safe and renewable in nature. Renewable energy resources are becoming more applicable as a viable alternative to the use of fossil fuels [16].

Power generation globally is dominated by fossil fuels, which are also the main contributors to CO_2 in the atmosphere. Increasing CO_2 emission threatens the world by global warming, as pointed out in the "World Energy Outlook 2019" by the International Energy Agency [21]. Due to increasing CO_2 emissions, increasing the risk of global warming from the traditional power systems, governments all around the world are now supporting and encouraging renewable electric energy sources. Worldwide renewable energy growth in recent years has been such that, more than 50% of the net annual additions of power generating capacities have been renewable forms [9].

India has tremendous potential for sunlight-based PV and with support from the government; India can become a leader in the solar market. One of the primary components of the government's solar mission is to make the solar power generation limit of 20 GW by 2022 [7].

Forecasting or predicting the output of the solar PV systems will be an important issue for electricity departments to dispatch electricity in time, with increased reliability and also in reducing the spinning reserve capacity of generation systems. Solar Photovoltaic Power Production Prediction models that predict the output power of PV systems at short-term or long-term intervals are highly dependent on intermittent solar radiation [9].

Short-term power prediction methods for solar power plants are found to be primarily comprised of two classes: physical methods and statistical methods [10]. The most widely used forecast technique is the physical model, which depends on the physical properties of the weather, either as graphical or numerical data. Examples of some data sources for the physical method are satellite images, ground-based sky images, and numerical weather prediction methods. These models are highly dependent on the weather data and its properties such as cloud coverage, changes in temperature that help forecast the future state of the atmosphere [16]. The statistical methods use historical data for the prediction of solar generation, based on trend data analysis.

Section-1 presents the introduction of the paper. Section-2 explains the AI-based techniques for solar generation prediction. Section-3 presents the regression model of machine learning in solar generation prediction, whereas, Section-4 presents the conclusion regarding solar generation using artificial intelligence.

2. AI-based techniques for solar generation prediction

A. Mellit *et al.* [10] pointed out that the accuracy of forecasting of PV output power by the application of AI techniques is very high. The AI techniques used are of different types such as machine learning (ML), Deep learning, artificial neural networks (ANNs), genetic algorithms (GAs), and fuzzy logic (FL). The most effective ANN-based methods for solar generation prediction include MLP, RNN, and RBF. The ANN-based solar generation forecasting method uses weather and environment-based input parameters such as temperature, relative humidity, cloud index, wind speed, pressure, etc.

K. R. Kumar *et al.* [7] considered environmental factors such as solar irradiance, cloud cover, atmospheric pressure, and temperature as inputs to train and utilize the ANN and ANFIS (Adaptive neuro-fuzzy inference system) models for solar generation prediction. Installation angles, dust on a PV panel, and other random factors are also considered as input data for the forecasting models for higher accuracy. The data points taken for validation are being sampled to represent low, medium and, high values of the parameters which are required in the forecast model.

R. Kabilan *et al.* [21] show how power prediction of BIPV (Building Integrated Photovoltaics) can be done by using ANN, SVM (Support Vector Machine), and Decision tree, through machine learning technique algorithm. The algorithm is mostly focused to predict the load dispatch of a particular grid that is interconnected to the PV system in determining its accuracy and efficiency.

J. P. Lai *et al.* [14] pointed out the surveys of several machine learning models and their techniques that can be applied for predicting renewable energy. The data process techniques involved for the prediction are divided into four sections of data processing, determining proper parameters, training the model, and testing. For forecasting accuracy, the measurement parameters computed are- MAE (Mean of the Absolute Errors), MAPE (Mean Absolute Percentage Error), RMSE (Root Mean Square Error) and R squared (Coefficient of determination).

S. Al-Dahidi *et al.* [9] predicted the photovoltaic system power productions in terms of one day ahead of hourly predictions. Different ANN learning algorithms have been used for defining and investigating the ANN parameters. Several sets of inputs or data sets have been used for ANN prediction modes. Also, different algorithms and training datasets have been used for building ANN models.

The research of I. Jebli *et al.* [18] is mainly focused on predicting accurately the solar energy generation, applying architectures of RNN (Recurrent Neural Network), LSTM (Long Short-Term Memory), and GRU (Gated Recurrent Unit) algorithms, which provide suitable forecasting of the time series data. Three different DL models are used for the prediction of PV solar energy output in terms of half an hour ahead, i.e., RNN, LSTM, and GRU.

J. M. Barrera *et al.* [15] presents a PV solar energy prediction mechanism based on the ANN model. The three solar components that are considered for the inputs on solar energy production are: direct radiation, diffused radiation, and reflected radiation. The various factors that are additionally considered are- azimuth angle, air temperature, wind speed, and PV output. For this system various support vector machine algorithms have been considered for weather prediction, computing the parameters such as MAE, MSME, etc.

S. S. Ali *et al.* [11] have provided a broad and overall review to support many forecasting applications in a distributed smart grid. The paper indicates how various AI techniques are applied for supporting the combination of conventional generation with renewable energy resources. The various factors which are involved in smart grid systems, considered for modelings, such as markets, consumers, and energy production are presented in their paper [11].

R. Sabzehgar *et al.* [16] predict the solar irradiance based on the climate or weather parameters and by using the predicted values forecast the cost or amount of generated power in a microgrid. For this study, three forecast approaches are considered, viz., variable regression, neural networks, and support vector machines. Mean absolute percentage error (MAPE) and mean squared error (MSE) is computed to evaluate the accuracy of the forecast models of all three types.

H. Wang *et al.* [12] used AI algorithms-ML, deep learning, and fuzzy logic to predict the solar energy generation levels. The different ML algorithms used are ANN, SVM, ELM (Extreme learning machine), and RNN. In deep learning, it includes SAE (Stacked Automatic Encoders), DBN (Deep Belief Network), CNN (Convolutional Neural Network), and GAN (Generative Adversarial Networks). AI optimizer for solar predictions in this work includes PSO, GA, DE, etc. from the quantitative statistical standards measurements. It can be observed that all the forecasting methods considered in this study have different RMSE indices.

Figure 1 presents the process flow chart of the forecasting model using ML for solar generation forecasting. All other supervised learning algorithms also follow similar steps for the solar generation prediction using environmental inputs and historical data in the training phase.

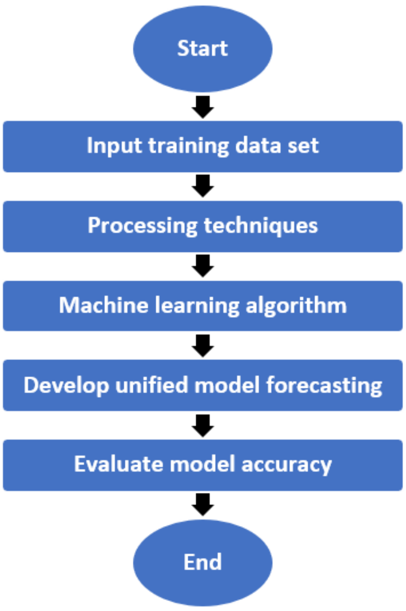

Figure 1: Process flow chart of the forecasting model using ML for solar generation forecasting [4]

3. Regression models of Machine Learning in solar generation prediction

The application of Machine Learning (ML) methods in environmental and renewable energy has expanded with recognition of its potential. Many of the renewable energy problems are exactly the types of problems, and issues for which the AI approach appears to be most applicable. ML models are suitable for forecasting due to their capabilities in learning. Some Examples of these models would include support vector machines (SVM), regression, and neural networks. With the increasing demand for solar power in residential usage, the use of ML has become highly imperative [16].

Machine learning has become increasingly common in predicting/forecasting and classification because of its capability to deal with nonlinear problems and for being able to reliably process complex data. It can differentiate the relationship between input and output variables, even when the representation is unlikely [20]. Some of the common machine learning algorithm techniques used in solar generation prediction are Support vector machine (SVM), Regression, Artificial Neural Network (ANN), Fuzzy logic, K-nearest neighbor algorithm (kNN), and decision tree-based techniques such as random forest (RF), etc. [9].

The most popular form of regression analysis is Linear regression because of its ease of use in predicting and forecasting. However, the complexity of input-output relationships prompts the use of polynomial regression in solar generation prediction problems.

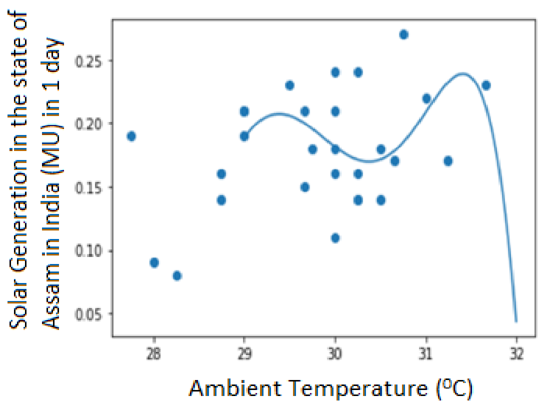

Figure 2: Polynomial regression plot solar generation (net MU) versus ambient temperature [4]

A linear, multi-variable, or polynomial equation obtained by the regression method which is best fits for data depends on the correlation between the dependent variable and various samples of independent variables [16].

The multivariate model of Regression helps in predicting and explaining the unique significance of each independent variable on the independent variable. Regression analysis helps in causal forecasting. It is possible to build a statistical model once the relationship is determined and forecast the variables of interest. Forecasting using regression analysis is more reliable and powerful than time series forecasting [3]. In solar power forecasts, the multiple linear regression analysis models perform well. The performance of such a model is better for near horizon forecasting. If the forecasting hours are with a clear sky, the prediction is more accurate. For cloudy hours, the performance of the models is often compromised [4].

Some of the more advanced machine learning techniques such as Deep Learning (DL) have created a good performance on several types of problems, including solar generation prediction. However, the application of DL in photovoltaics is still limited [10]. There is scope for the application of the same inaccurate prediction of solar generation using multiple input data from numerous sources.

4. Conclusion

In this paper, several solar generation forecast models have been presented, based on the different types of algorithms and techniques of AI used, such as ANN, ML, DL, etc. The PV output power using ML is determined by considering the short-term day-ahead power, long-term day-ahead power, and for different climatic conditions. The climatic variables taken into considerations are solar irradiance, temperature, humidity, precipitation, cloud cover, and wind direction. The output power of the PV changes depending on the climatic condition of that particular location or area during the day. Hence, for the accuracy of prediction, the ANN is dependent on how it is trained and on the quality of data used. The more weather data used for the prediction algorithm development more accuracy of solar power prediction is obtained. From the compared results of the works done by several researchers, it is observed that the Machine Learning models are more accurate and efficient in predicting the generated energy by the Solar PV sources. Also, the use of mixed algorithms makes the prediction more efficient and accurate. Out of all the variables used for solar generation prediction, the ambient temperature and weather conditions are found to be the most effective ones, with higher accuracy of prediction. However, it is also true that the selection of suitable variables depends on the location of solar generation. Hence, it can be concluded that the selection of suitable variables for solar generation prediction is to be done based on in-situ experimentation and validation.

References

[1] W. C. Wang, K. W. Chau, C. T. Cheng, and L. Qiu, “A comparison of the performance of several artificial intelligence methods for forecasting monthly discharge time series,” *Journal of Hydrology*, vol. 374, no. 3-4, pp. 294-306, Aug. 2009, doi: 10.1016/j.jhydrol.2009.06.019

[2] C. H. F. Toro, S. Gómez Meire, J. F. Gálvez, and F. Fdez-Riverola, “A hybrid artificial intelligence model for river flow forecasting,” *Applied Soft Computing*, vol. 13, no. 8, pp. 3449–3458, Aug. 2013, doi: 10.1016/j.asoc.2013.04.014

[3] U. Nalina, V. Prema, K. Smitha, and K. U. Rao, “Multivariate regression for prediction of solar irradiance,” in *2014 International Conference on Data Science & Engineering (ICDSE)*, Kochi, India, Aug. 2014, pp. 177–181, doi: 10.1109/ICDSE.2014.6974633

[4] M. Abuella and B. Chowdhury, “Solar power probabilistic forecasting by using multiple linear regression analysis,” in *Proc. of IEEE SoutheastCon 2015*, Fort Lauderdale, FL, USA, Apr. 2015, pp. 1-5, doi: 10.1109/SECON.2015.7132869

[5] M. Abuella and B. Chowdhury, “Solar power forecasting using artificial neural networks,” in *IEEE 2015 North American Power Symposium (NAPS)*, Charlotte, NC, USA, Oct. 2015, pp. 1-5, doi: 10.1109/NAPS.2015.7335176

[6] Z. M. Yaseen, O. Kisi, and V. Demir, “Enhancing Long-Term Streamflow Forecasting and Predicting using Periodicity Data Component: Application of Artificial Intelligence,” *Water Resources Management*, vol. 30, no. 12, pp. 4125–4151, Sep. 2016, doi: 10.1007/s11269-016-1408-5

[7] K. R. Kumar and M. S. Kalavathi, “Artificial intelligence based forecast models for predicting solar power generation,” *Materials Today: Proceedings*, vol. 5, no. 1, pp. 796–802, 2018, doi: 10.1016/j.matpr.2017.11.149.

[8] D. V. Tai, “Solar photovoltaic power output forecasting using machine learning technique,” *Journal of Physics: Conference Series*, vol. 1327, no. 1, p. 012051, Oct. 2019,

doi: https://doi.org/10.1088/1742-6596/1327/1/012051

[9] S. Al-Dahidi, O. Ayadi, J. Adeeb, and M. Louzazni, "Assessment of Artificial Neural Networks Learning Algorithms and Training Datasets for Solar Photovoltaic Power Production Prediction," *Frontiers in Energy Research*, vol. 7, article 130, Nov. 2019, doi: 10.3389/fenrg.2019.00130

[10] A. Mellit, A. Massi Pavan, E. Ogliari, S. Leva, and V. Lughi, "Advanced Methods for Photovoltaic Output Power Forecasting: A Review," *Applied Sciences*, vol. 10, no. 2, p. 487, Jan. 2020, doi: 10.3390/app10020487

[11] S. S. Ali and B. J. Choi, "State-of-the-Art Artificial Intelligence Techniques for Distributed Smart Grids: A Review," *Electronics*, vol. 9, no. 6, p. 1030, Jun. 2020, doi: 10.3390/electronics9061030

[12] H. Wang *et al.*, "Taxonomy research of artificial intelligence for deterministic solar power forecasting," *Energy Conversion and Management*, vol. 214, p. 112909, Jun. 2020, doi: 10.1016/j.enconman.2020.112909

[13] S. S. Ali and B. J. Choi, "State-of-the-Art Artificial Intelligence Techniques for Distributed Smart Grids: A Review," *Electronics*, vol. 9, no. 6, p. 1030, Jun. 2020, doi: 10.3390/electronics9061030

[14] J. P. Lai, Y. M. Chang, C. H. Chen, and P. F. Pai, "A Survey of Machine Learning Models in Renewable Energy Predictions," *Applied Sciences*, vol. 10, no. 17, p. 5975, Aug. 2020, doi: 10.3390/app10175975

[15] J. M. Barrera, A. Reina, A. Maté, and J. C. Trujillo, "Solar Energy Prediction Model Based on Artificial Neural Networks and Open Data," *Sustainability*, vol. 12, no. 17, p. 6915, Aug. 2020, doi: 10.3390/su12176915

[16] R. Sabzehgar, D. Z. Amirhosseini, and M. Rasouli, "Solar power forecast for a residential smart microgrid based on numerical weather predictions using artificial intelligence methods," *Journal of Building Engineering*, vol. 32, p. 101629, Nov. 2020, DOI: 10.1016/j.jobe.2020.101629

[17] M. Kuzlu, U. Cali, V. Sharma, and O. Guler, "Gaining Insight into Solar Photovoltaic Power Generation Forecasting Utilizing Explainable Artificial Intelligence Tools," *IEEE Access*, vol. 8, pp. 187814–187823, 2020, doi:10.1109/ACCESS.2020.3031477

[18] I. Jebli, F. Z. Belouadha, M. I. Kabbaj, and A. Tilioua, "Deep Learning based Models for Solar Energy Prediction," *Advances in Science, Technology and Engineering Systems Journal*, vol. 6, no. 1, pp. 349–355, Jan. 2021, doi: 10.25046/aj060140

[19] W. Guo, L. Che, M. Shahidehpour, and X. Wan, "Machine-Learning based methods in short-term load forecasting," *The Electricity Journal*, vol. 34, no. 1, p. 106884, Jan. 2021, doi: 10.1016/j.tej.2020.106884

[20] M. A. Majeed *et al.*, "Artificial Neural Network Modelling for Short Term Load Forecasting," in *2021 International Conference on Technology and Policy in Energy and Electric Power (ICT-PEP)*, Jakarta, Indonesia, Sep. 2021, pp. 302–306. doi: 10.1109/ICT-PEP53949.2021.9601105

[21] R. Kabilan *et al.*, "Short-Term Power Prediction of Building Integrated Photovoltaic (BIPV) System Based on Machine Learning Algorithms," *International Journal of Photoenergy*, vol. 2021, pp. 1–11, Apr. 2021, doi: 10.1155/2021/5582418

Authors' Profiles

Ms. Navareen Sohkhlet is pursuing an M.Tech. in the Department of Electrical and Electronics Engineering, School of Technology, Assam Don Bosco University. Her area of specialization is Power Systems. Her research areas include Power Systems, Machine Learning and Artificial Intelligence.

Dr. Bikramjit Goswami is working as an Assistant Professor in the department of Electrical and Electronics Engineering, School of Technology, Assam Don Bosco University, India. His research interests are Microwave Remote Sensing, Artificial Neural Networks, Renewable Energy and Disaster Forecasting.