State-Of-The-Art Solar Energy Forecasting Approaches: Critical Potentials and Challenges

Haoying Ye¹, Bo Yang¹, Yiming Han¹* and Nuo Chen²

¹Faculty of Electric Power Engineering, Kunming University of Science and Technology, Kunming, China, ²China Southern Power Grid EHV Transmission Company, Kunming, China

Keywords: solar energy forecasting, statistical methods, physical methods, artificial intelligence methods, potentials and challenges

INTRODUCTION

For decades, solar energy has taken an increasingly important part, which will continue to rise, driven by carbon peaking and carbon neutrality strategic goals, in the energy consumption of China (Yang et al., 2021a; Mahidin et al., 2021). Due to the intermittence and volatility of sunlight, photovoltaic (PV) power generation is more erratic than conventional power which results in some problems of the grid: frequency instability (Liu et al., 2020; Murty and Kumar, 2020), dispatch difficulty (Peng et al., 2020; Tummala, 2020), and voltage and current surges (Bozorg et al., 2020; Yang et al., 2021b). Hence, accurately forecasting the power generation of the PV system is one of the major issues of PV system’s engineering practice to settle the aforementioned problems (Huang et al., 2021a; Yang et al., 2021c).

According to the modeling means of prediction, the prevailing PV power prediction methods are broadly divided into three categories, namely, physical, statistical, and artificial intelligence (AI) forecasting technologies (Yang et al., 2021d). Furthermore, the applicable ranges of different forecasting technologies are given in Figure 1. Moreover, these PV power forecasting technologies face different challenges. First, it is difficult for physical forecasting technology to obtain accurate future weather forecast information and determine output characteristic model parameters. Second, statistical forecasting technology is not demanding for geographical location and other information of PV systems but requires masses of historical data to deduce statistics laws. As for AI forecasting technology, it is easy to trap in the local optimum because of internal defects of the AI algorithm. This work aims to clarify aforementioned problems and give some perspectives on various PV power prediction methods.

PHYSICAL PREDICTION METHOD

The physical prediction method refers to a technology that excavates the factors related to PV power generation from the principle and then creates a physical model. Specifically, physical method modeling is based on numerical weather prediction (NWP) by utilizing atmospheric physical data including wind speed, temperature, rainfall, humidity, length of day (Urquhart et al., 2013), and cloud image via a total sky imager (Shen et al., 2019) or satellite (Tuohy et al., 2015). Besides, it can be further classified as a simple physical model method and a complex physical model method. A simple physical model needs power system parameters, weather data, satellite observations, and so on (Hammer et al., 1999). The literature (Peder et al., 2009) applies a simple physical prediction model combined with the HIRLAM mesoscale weather pattern to forecast the future power generation of 21 small PV power stations in the Jutland peninsula but obtains a relatively poor predictive value.
literature (Inman et al., 2013) verifies that the PV power prediction model of wavelength-independent only absorbs light of aqueous vapor after experiments. In order to ensure the stable operation of the bulk power grid, the prediction of power generation of the PV microgrid system must be more accurate. In terms of this issue, work (Lorenz et al., 2011) creates a complex physical prediction model based on the local weather forecast data and performs prediction tests based on an actual PV power station to assess the accuracy of the model.

NWP models which can be classified into two categories of wide-area prediction models and local area models prediction are utilized to forecast the solar illumination intensity and cloud distribution. Local area models are usually used for short-term forecasting of the PV plant power. So far, NAM (Mathiesen and Kleissl, 2011), MM5 (Fernandez-Jimenez et al., 2012), and WRF (Lima et al., 2016) are developed and applied in the PV power prediction of local area models. NAM takes SURFRAD actual measurement data as inputs and takes MBE and RMSE as the evaluation index of the model performance. Moreover, the prediction results utilizing with the NAM model prove that applying the irradiance as the model output variable can decrease the error and offset of power forecasting. The MM5 model can provide power production prediction values of each hour in the following day through analyzing historical information of hourly power outputs and estimation values of climate parameters in the past 1.5 years. The investigation of the wide-area PV power prediction model is worth paying more attention due to its well accuracy in estimating cloudy and cloudless sky situations. GFS and ECMWF (Mathiesen and Kleissl, 2011) are two typical models for the wide-area PV power prediction method.

Under the condition of reasonable model parameters, the physical PV power forecasting method can accurately predict the results of the future power output. However, the physical forecasting approach has the disadvantage of requiring a complex model of the solar radiation output and a characteristic model of the PV power generation system, as well as the precise future weather forecast information. In addition, determining the parameter values of the output characteristic model is more complicated for different types of generating unit systems (Perez et al., 2002).

### STATISTICAL PREDICTION METHOD

The statistical method needs to collect a large number of data related to the power output of the PV power generation system to regress some unknown constants and further obtain the functional relationship between the output power and the measurable unknown. According to the amount of unknowns, the statistical method can be divided into the unary linear regression method, multiple linear regression method, and nonlinear regression method. Because there are many factors affecting PV system power generation, the prediction result is not satisfactory by using the unary linear regression method. The multiple linear regression method adopted in the literature (Li et al., 2011) takes solar radiation intensity and ambient temperature as two main factors to build a multiple linear regression model of the PV system and finally obtains the linear function relation of the output power on six unknowns, including radiation intensity and temperature. By using this linear function, the output power of the PV power generation system can be predicted as long as the value of corresponding solar radiation and ambient temperature is obtained. The literature (Li and Li, 2008) employs the support vector machine (SVM) to design a regression algorithm of the solar farm power prediction model. Because the SVM is based on the principle of risk minimization and has a strong ability of generalization, the error of solving results is relatively smaller even though there are fewer training samples. Furthermore, the
TABLE 1 | Classification of PV power prediction methods.

| Basis of classification | Prediction methods              | Definition                                                                 | Characteristic                                                                 |
|------------------------|---------------------------------|----------------------------------------------------------------------------|--------------------------------------------------------------------------------|
| Forecasting process    | Direct prediction method        | Direct prediction based on historical PV power data                        | Suitable for cases of sufficient historical PV power data; difficult for modeling |
|                        | Indirect prediction method      | Power forecasting combined with the correlation model based on the solar irradiance prediction of PV panels | Suitable for cases of lacking historical data but available solar irradiance and temperature historical data |
| Time scale             | Short-term prediction           | PV power forecasting of 1 day                                              | Providing power variation information in short-term; used to make the power market scheduling plan |
|                        | Medium- and long-term prediction| PV power forecasting of 1 day to 1 year                                    | Forecasting PV power information for a long term in the future |
| Spatial scale          | Single-plant prediction method  | Power prediction for a single PV system                                    | Applied to the optimal operation of the PV system |
|                        | Regional prediction method      | Power prediction for all PV systems in an area                             | Helpful for dispatching departments to predict the fluctuation of PV power |
| Modeling method        | Physical prediction method      | Power prediction by the power calculation model based on the solar altitude angle, geographic location, temperature, and solar irradiance etc. | Complex models; highly depend on reasonable parameters |
|                        | Statistical prediction method   | Power prediction based on the statistical relationship between input and output data of the prediction model | Not require physical internal information of the PV plant |
|                        | AI prediction method            | Training the prediction model by AI algorithms with sample data           | Strong self-learning and self-adaptation ability; need lots of historical data |

SVM learning algorithm is used to solve the convex quadratic optimization problem; hence, the solution obtained by the SVM is the global optimal solution. In reference (Zhu and Tian, 2011), the least squares support vector machine (LSSVM), which is the improved version of the SVM mentioned earlier, is used to predict the output power of the PV power generation system.

NARX and NARMAX (Di Piazza et al., 2016) are representative nonlinear regression models which take solar irradiance, temperature, and day time as input variables of prediction models. The literature (Bouzerdoum et al., 2013) proposes the SARIMA model and studies its performance in power prediction of solar farms. Moreover, SARIMA enhances the prediction accuracy of real solar farms. In the literature (Pedro and Coimbra, 2012), the ARIMA model which is the linear non-stationary method is applied to forecast a local 1 MW PV plant. This model takes hourly power output values for the past half year as input variables and the mean absolute percentage error (MAPE) calculated by Eq. 1 as the performance metrics of the model. The experimental results indicate that the ARIMA model is more sensitive and accurate in reflecting the shape changes of solar irradiance. Similarly, the ARIMAX (Pedro and Coimbra, 2012) model which adopts the former solar irradiance as inputs also achieves approximate goals compared to the ARIMA model. However, the influence of weather factors other than solar illumination is not fully considered for both ARIMA and ARIMAX models.

\[
MAPE = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{P_{\text{pre}} - P_{\text{meas}}}{P_0} \right|, \tag{1}
\]

where \( P_{\text{pre}} \) is the predicted power value, \( P_{\text{meas}} \) represents the mean of actual power values, \( P_0 \) is the capacity of tested solar farm, and \( n \) is the sample size.

These aforementioned regression prediction models try to modify the models through the deviation between the measured and predicted values of PV power generation. In particular, the multiple linear regression method can enhance the prediction accuracy without extra measurement data, which is a method worthy of further study. The merits of the statistical method are simple operation, fast prediction, and good relation expression between the factors and the output power, hence more suitable for fitting the new situation. However, the statistical method has the complexity and difficulty in establishing the regression equation due to its high accuracy demand of the distribution rule and historical sample data. Thus, it has a lower prediction accuracy.

AI PREDICTION METHOD

Nowadays, PV power forecasting based on the AI algorithm is a very popular research area because of its strong self-learning and self-adaptation ability. In the literature (Kaushika et al., 2014), the PV array generation sequence, weather type, irradiance intensity, and temperature are adopted to build the backpropagation (BP) neural network prediction model. But this method requires a large number of historical power data and massive calculation. Moreover, it is not suitable for new or under-construction power stations due to unavailable historical data. In the literature (Tang et al., 2016), the extreme learning machine (ELM) is employed to forecast the extracted power of solar farms. Particularly, combined entropy is introduced to the prediction model and observably promotes the forecasting accuracy and the convergence. However, neural networks often need a large number of training samples to obtain a good accuracy and generalization ability (Huang et al., 2021b; Yang et al., 2021c).
As a result, its prediction performance will be greatly reduced in the case of small samples. In addition, the structure and parameters of the neural network are not easy to determine. Moreover, the existing training algorithms often lead to parameters falling into local minimum (Zhang et al., 2021). Therefore, it is urgent for developing a new training algorithm to train the neural network model of PV power prediction.

**DISCUSSION AND CONCLUSION**

The efficient PV power forecasting technology can not only improve the grid connection ability and security but also effectively reduce light discarding. Also, various prediction technologies of the aforementioned PV plant are summarized and evaluated in Table 1.

But the PV power forecasting technology still faces many challenges. Recommendations and limitations for future research studies are shown as follows:

1) Pre-processing of the mass of experimental data is manually performed; hence, efficient algorithms should be developed to effectively summarize and extract information data and establish connections among them;
2) It is urgent for developing a swarm intelligence algorithm to train the neural network model of PV power prediction;
3) Regional prediction is important for power dispatching which should be further analyzed and studied;
4) Many works only consider cloud cover as a meteorological factor to represent the extent of sky cover but ignore that the partial shading of the PV panel caused by a cloud will lead to the multi-peak phenomenon of the PV curve. This issue requires further research for more accurate power prediction.

**AUTHOR CONTRIBUTIONS**

HY: writing the original draft and editing. BY: conceptualization. YH: visualization and contributed to the discussion of the topic. NC: formal analysis.

**REFERENCES**

Bouzerdoum, M., Mellit, A., and Massi Pavan, A. (2013). A Hybrid Model (SARIMA-SVM) for Short-Term Power Forecasting of a Small-Scale Grid-Connected Photovoltaic Plant. *Solar Energy* 98, 226–235. doi:10.1016/j.solener.2013.10.002

Bozorg, M., Bracale, A., and Caramia, P. (2020). Bayesian Bootstrap Quantile Regression for Probabilistic Photovoltaic Power Forecasting. *Prot. Control. Mod. Power Syst.* 5 (3), 218–229. doi:10.1186/s41601-020-00167-7

Di Piazza, A., Di Piazza, M. C., and Vitale, G. (2016). Solar and Wind Forecasting by NARX Neural Networks. *Renew. Energy Environ. Sustain.* 1, 39–44. doi:10.1051/reese/2016047

Fernandez-Jimenez, L. A., Muñoz-Jimenez, A., Falces, A., Mendoza-Villena, M., Garcia-Garrido, E., Lara-Santillan, P. M., et al. (2012). Short-term Power Forecasting System for Photovoltaic Plants. *Renew. Energy* 44, 311–317. doi:10.1016/j.renene.2012.01.018

Hammer, A., Heinemann, D., Lorenz, E., and Lückehe, B. (1999). Short-term Forecasting of Solar Radiation: a Statistical Approach Using Satellite Data. *Solar Energy* 67 (1–3), 139–150. doi:10.1016/s0038-092x(00)00038-4

Huang, K., Li, Y., and Zhang, X. (2021). Research on Power Control Strategy of Household-Level Electric Power Router Based on Hybrid Energy Storage Droop Control. *Prot. Control. Mod. Power Syst.* 6 (2), 178–190. doi:10.1186/s41601-021-00190-2

Huang, S., Wu, Q., Liao, W., Wu, G., Li, X., and Wei, J. (2021). Adaptive Droop-Based Hierarchical Optimal Voltage Control Scheme for VSC-HVDC Connected Offshore Wind Farm. *IEEE Trans. Ind. Inf.* 17, 8165–8176. doi:10.1109/TII.2021.3065375

Inman, R. H., Pedro, H. T. C., and Coimbra, C. F. M. (2013). Solar Forecasting Methods for Renewable Energy Integration. *Prog. Energy Combustion Sci.* 39 (6), 535–576. doi:10.1016/j.pecs.2013.06.002

Kaushika, N. D., Tomar, R. K., and Kaushik, S. C. (2014). Artificial Neural Network Model Based on Interrelationship of Direct, Diffuse and Global Solar Radiations. *Solar Energy* 103, 327–342. doi:10.1016/j.solener.2014.02.015

Li, G., Liao, H., and Li, J. (2011). Discussion on the Method of Grid-Connected PV Power System Generation Forecasting. *J. Yunnan Normal Univ.* 31 (2), 33–38. doi:10.3969/j.issn.1007-9793.2011.02.006

Li, R., and Li, G. (2008). Photovoltaic Power Generation Output Forecasting Based on Support Vector Machine Regression Technique. *Electric Power 41* (2), 74–78. doi:10.3969/j.issn.1004-9649.2008.02.019

Lima, F. J. L., Martins, F. R., Pereira, E. B., Lorenz, E., and Heinemann, D. (2016). Forecast for Surface Solar Irradiance at the Brazilian Northeastern Region.
Tuohy, A., Zack, J., Haupt, S. E., Sharp, J., Ahlstrom, M., Dise, S., et al. (2015). Solar Forecasting: Methods, Challenges, and Performance. IEEE Power Energ. Mag. 13 (6), 50–59. doi:10.1109/MPW.2015.2461351

Urqhart, B., Ghonima, M., Nguyen, D., Kurtz, B., Chow, C. W., and Kleissl, J. (2013). Sky-Imaging Systems for Short-Term Forecasting. Solar Energ. Forecast. Resource Assess., 195–232. doi:10.1016/b978-0-12-397177-7.00009-7

Yang, B., Guo, Z., Yang, Y., Chen, Y., Zhang, R., Su, K., et al. (2021). Extreme Learning Machine Based Meta-Heuristic Algorithms for Parameter Extraction of Solid Oxide Fuel Cells. Appl. Energ. 303, 117630. doi:10.1016/j.apenergy.2021.117630

Yang, B., Shao, R., Zhang, M., Ye, H., Liu, B., Bao, T., et al. (2021). Socio-inspired Democratic Political Algorithm for Optimal PV Array Reconfiguration to Mitigate Partial Shading. Sustainable Energ. Tech. Assessments 48, 101627. doi:10.1016/j.seta.2021.101627

Yang, B., Ye, H., Wang, J., Li, J., Wu, S., Li, Y., et al. (2021). PV Arrays Reconfiguration for Partial Shading Mitigation: Recent Advances, Challenges and Perspectives. Energy Convers. Manag. 247, 114738. doi:10.1016/j.enconman.2021.114738

Yang, B., Zhong, L., Wang, J., Shu, H., Zhang, X., Yu, T., et al. (2021). State-of-the-art One-Stop Handbook on Wind Forecasting Technologies: an Overview of Classifications, Methodologies, and Analysis. J. Clean. Prod. 283, 124628. doi:10.1016/j.jclepro.2020.124628

Yang, B., Zhu, T., and Cao, P. (2021). Classification and Summarization of Solar Irradiance and Power Forecasting Methods: a Thorough Review. Csee Jpes. doi:10.17775/CSEEJ/PES.2020.04930

Zhang, K., Zhou, B., Or, S. W., Li, C., Chung, C. Y., and Voropai, N. I. (2021). Optimal Coordinated Control of Multi-Renewable-To-Hydrogen Production System for Hydrogen Fueling Stations. IEEE Trans. Ind. Applicat., 1. doi:10.1109/TIA.2021.3093841

Zhu, Y., and Tian, J. (2011). Application of Least Square Support Vector Machine in Photovoltaic Power Forecasting. Power Syst. Tech. 35 (7), 54–59. doi:10.3354/cr00999

Conflict of Interest: NC was employed by China Southern Power Grid EHV Transmission Company.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher’s Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors, and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Copyright © 2022 Ye, Yang, Han and Chen. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.