Short-term Prediction of Photovoltaic Output Power for Grid Integration

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Summary
The photovoltaic (PV) output power prediction is fundamental in increasing the generation of solar power into the electrical grids. Precise short-term PV output power predictions contribute to the optimization of power systems operation and control. The model was to construct to utilize a reduced set of PV output power representatives for predicting short-term PV output power. Further, the efficiency of the representative PV output power resulting from a well-established clustering methodology were tested by the application on a real data set. The error between the actual data and predicted data ranged between 19.374 and 25.983, and 9.034 and 14.692 for RMSE and MAE, respectively. The correlation coefficient values were all above 97.8%. The results of the prediction model using the representatives validate the efficiency of the presented model and could potentially contribute to the optimization of power systems operation and control, and further the integration of such systems into the electrical grid.

Keywords:
Grid integration, photovoltaic, smart grids, solar panel,

1. Introduction

The integration of photovoltaic (PV) solar systems into the electrical grid is contemplated to be a challenging task due to the uncertainty of the solar irradiation. A fundamental method to solve this difficulty is to precisely predict short-term PV output power generation. The PV output power prediction is fundamental in increasing the generation of solar power into the electrical grids. Precise short-term PV output power predictions contribute to the optimization of power systems operation and control. However, the precision predicting PV output power depends mainly on meteorological and climatic circumstances. Due to the uncertainty of meteorological circumstances, predicting PV output power becomes certainly a challenging task.

Generally, PV output power is mainly affected by the solar irradiation. Numerous models have been proposed for predicting the amount of solar irradiance. These models are mainly classified into two main categories [1]: physical predicting models and statistical predicting models. Physical predicting models utilize mathematical representations intensively to describe the dynamics and physics of the atmosphere, which essentially affects the solar irradiation [2]. Physical predicting models perform properly for medium and long-term solar predictions [1]. Statistical predicting models function by analyzing time-series data. Accordingly, they feature lower complexities than physical predicting models. Further, those models have the ability to perform adequately for short-term solar predictions. Statistical predicting models include utilizing artificial neural networks (ANN) [3], [4], autoregressive (AR), autoregressive moving average (ARMA) [5], and support vector machine (SVM) [1] models. Such models have presented their efficiency in predicting solar irradiation. Utilizing solar irradiation for predicting PV output power has been an area of interest. For that, this paper presents a model for short-term predictions of PV power. The approach of this model uses a dedicated formulation to evaluate the efficiency of the photovoltaic power pattern prediction (PVPP) cluster representatives obtained by following the method of [6].

The remainder of the paper is structured as follows. Section 2, presents the photovoltaic output power prediction model. The application of the prediction model on a real data set is presented in Section 3. The conclusions are drawn in Section 4.

2. PV Output Power Prediction Model

At time (t), the presented short-term prediction model predicts the PV output power at future time-steps $(t+1, t+2, \ldots, t+f)$. The prediction of future time-steps is associated with the past observations of ambient temperature, solar irradiation, and representative PVPPs at $(t-1, t-2, \ldots, t-n)$. Accordingly, the prediction is based on the classification of the past PVPP time-steps to the

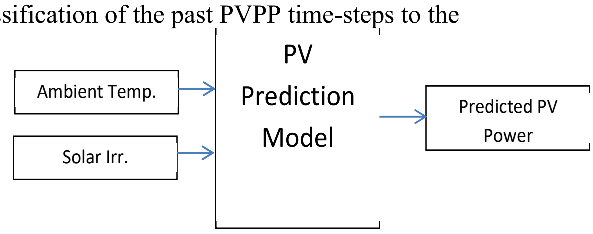

Figure 1: Illustration of the prediction model.

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representative PVPPs, subsequently the future values are obtained from the nearest PVPPs. The illustration of the short-term PV output power prediction model in shown in Fig. 1 and the steps are as follows:

1- The observations of ambient temperature and solar irradiation preceding to the interval to be predicted *(t-1,t-2,...,t-n)* are attained.
2- The corresponding AC power output for the time sequence *(t-1,t-2,...,t-n)* is computed utilizing:

$$T_c = T_{amb} + \left(\frac{NOCT - 20}{0.8}\right). S \tag{1}$$

$$P_{dc} = P_{max}\left(S/1000\right)\left[1 - 0.005\left(T_c - 25\right)\right] \tag{2}$$

where T_c is the cell temperature, T_{amb} is the ambient temperature, S is the irradiance, $NOCT$ is the operating cell temperature at Standard Test Conditions (STC: S=1000W/m^2, T_{amb}=25ºC), and P_{max} is the maximum rated power.

3- The "distance" between the obtained sequence and the corresponding time sequence of each representative PVPP is computed using the Euclidean distance metric:

$$D_{ij} = \sqrt{\sum_{l=1}^{d}\left(x_{il} - x_{jl}\right)^2} \tag{3}$$

4- The closest pair of PVPPs are obtained, and the mean distance between the pair is computed. Consequently, the result is three PVPPs.
5- The distance between the obtained sequence from *step 2* and the corresponding time sequence of the three PVPPs from *step 4* is computed.
6- The future PV output power values *(t+1,t+2,...,t+f)* are obtained from the closest PVPP.

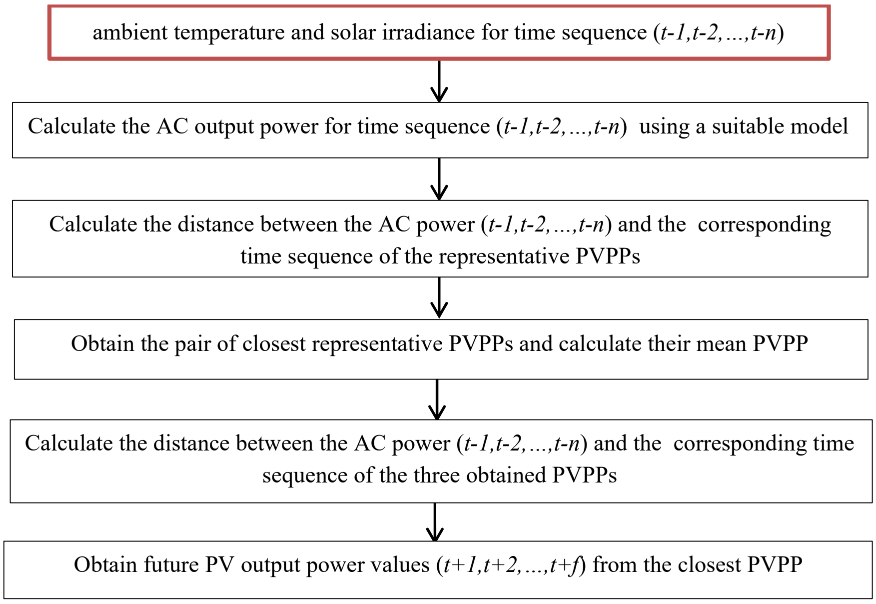

Figure 2: Flowchart of the short-term PV output power prediction model.

The flow chart of the short-term PV output power prediction model in shown in Figure 2.

3. Application of The PV Output Power Prediction Model

The presented short-term PV output prediction model is applied on a real dataset for predicting the sequence of ten-minute time steps of 30 minutes, 60 minutes, and 120 minutes ahead. The utilized data is a real data set concerning three consecutive years (2010-2012) with ten-minute time-steps of ambient temperature and solar irradiation from the Solar Radiation Research Laboratory [7]. The location of the obtained data has a latitude of 39.74ºN and a longitude of 105.18ºW. The irradiance data with this high time resolution (ten minutes) can lead to better accuracy due to the autocorrelation coefficients that will have higher positive values as compared to those obtained for data with lower time resolutions [8]. The PVPP cluster representatives are obtained by applying the methodology of [6] using the Bat WCBCR clustering algorithm. The application on three consecutive years for the data resulted in 32 representative PVPPs. The ambient temperature and solar irradiation for a following year were converted to AC power and the test data was achieved by choosing every tenth day of that year. Consequently, 36 daily PVPPs are achieved. The results of predicting the future 30 minutes, 60 minutes, and 120 minutes ahead from the time sequence of the past 30 minutes, 60 minutes, 120 minutes, and 240 minutes are shown in Table 1. The results were evaluated utilizing the RMSE, MAE, and correlation coefficient:

$$\text{RMSE} =? \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_{observed} - P_{predicted})^2} \tag{3}$$

$$\text{MAE} =? \frac{1}{N}\sum_{i=1}^{N}\left|P_{observed} - P_{predicted}\right| \tag{4}$$

$$\text{Correlation Coefficient} =? \frac{\sum_{i=1}^{N}\left(P_{observed} - \mu_{observed}\right)\cdot\left(P_{predicted} - \mu_{predicted}\right)}{\sqrt{\sum_{i=1}^{N}\left(P_{observed} - \mu_{observed}\right)^2}\sqrt{\sum_{i=1}^{N}\left(P_{predicted} - \mu_{predicted}\right)^2}} \tag{5}$$

where $P_{observed}$ and $P_{predicted}$ are the observed and predicted daily PVPPs, respectively; $\mu_{observed}$ and $\mu_{predicted}$ are the mean values of $P_{observed}$ and $P_{predicted}$, respectively.

The evolution metrics were computed between the actual observations and the predicted values, and the RMSE and MAE arranged between 19.374 and 25.983, and 9.034 and 14.692, respectively. The correlation coefficient values were all above 97.8%. Lower values of RMSE and MAE suggest superior prediction performance of the model. Also, greater positive correlation coefficient values indicates that the actual and predicted values are more correlated. It can be observed that when the time sequence of the prediction increased, the error increased. Also, increasing the past time sequence observations does not improve the prediction. Figure 3 presents the comparison between the actual and predicted PV output power for predicting 60 minutes from the past 30 minutes.

Figure 4 shows the correlation between the actual and predicted PV output power. From the slope of the fitting line, it can be witnessed that the predictions fall close to the diagonal line. Therefore, the predicted values closely match the actual observations, which indicates to higher accurate predictions of PV output power.

Table 1: Initial results during the data preparation step in the DMKD process

Past time sequence (min)	Predicted time sequence (min)	RMSE	MAE	Corr.
30	30	19.374	9.034	0.988
30	60	21.542	11.133	0.985
30	120	25.983	14.692	0.978
60	30	19.320	9.378	0.988
60	60	21.860	11.318	0.984
60	120	25.716	14.451	0.978
120	30	19.584	10.161	0.987
120	60	21.749	11.620	0.985
120	120	25.687	14.677	0.978
180	30	20.499	10.741	0.987
180	60	22.366	11.887	0.985
180	120	24.906	13.611	0.981
240	30	20.533	10.367	0.988
240	60	22.283	11.171	0.986
240	120	24.846	13.267	0.982

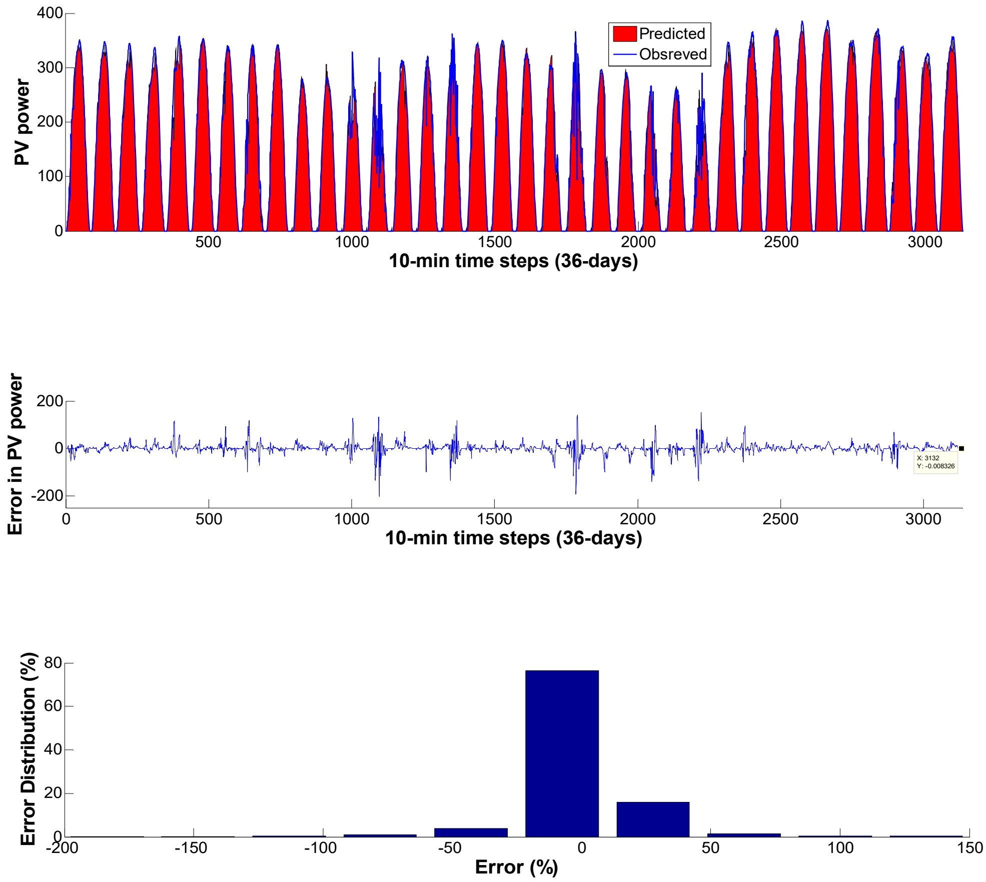

Figure 3: Comparison between the actual and predicted PV power for predicting 60 minutes from the past 30 minutes..

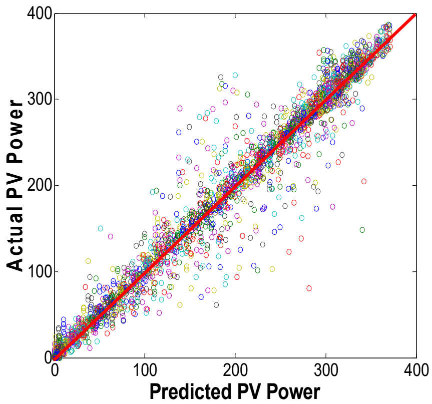

Figure 4: Correlation between the actual and predicted PV power

4. Conclusions

This paper presented a short-term PV output power prediction model. The model was to construct to utilizes a reduced set of PVPP representatives for predicting short-term PV output power. Further, the efficiency of the representative PVPPs resulting from the PVPP clustering methodology were tested by the application on real data. The error between the actual data and predicted data ranged between 19.374 and 25.983, and 9.034 and 14.692 for RMSE and MAE, respectively. The correlation coefficient values were all above 97.8%. It was observed that when the sequence of the prediction increased, the error increased. Further, it was observed that increasing the past time sequence does not improve the prediction accuracy for future PV output power. The results of the prediction model using the representatives validate the efficiency of the presented model and potentially contribute to the optimization of power systems operation and control, and further the integration of such systems into the electrical grid.

References

[1] J. Zeng, and W. Qiao, “Short-term solar power prediction using a support vector machine,” Renewable Energy, vol. 52, pp. 118-127, 2013.

[2] V. Badescu, Modeling solar radiation at the earth surface, Springer, 2008.

[3] A. Koca, H. F. Oztop, Y. Varol, and G. O. Koca, “Estimation of solar radiation using artificial neural networks with different input parameters for mediterranean region of anatolia in turkey,” Expert Systems with Applications, vol. 38, pp. 8756-8762, 2011.

[4] S-H. Cao, J-B. Chen, W-B. Weng, and J-C. Cao, “Study of daily solar irradiance forecast on chaos optimization neural networks,” Natural Science, vol. 1, pp. 30-36, 2009.

[5] G. Reikard, “Predicting solar radiation at high resolutions: a comparison of time series forecasts,” Solar Energy, vol. 83, pp. 342-349, 2009.

[6] A. Munshi, and Y. A.-R. I. Mohamed, “Comparisons among Bat algorithms with various objective functions on grouping photovoltaic power patterns,” Solar Energy, vol. 144, pp. 254-266, 2017.

[7] Solar Radiation Research Laboratory (BMS) available online at: http://www.nrel.gov/midc/srrl_bms. Retrieved January 2014.

[8] C. Craggs, E. M. Conway and N. M. Pearsall, “Statistical investigation of the optimal averaging time for solar irradiance on horizontal and vertical surfaces in the UK,” Solar Energy, vol.68, pp. 179–187, 2000.