A hybrid physical/statistical day-ahead direct PV forecasting engine

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Abstract

Photovoltaic (PV) penetration to the grid is growing rapidly, and more and more business models try to maximise their benefits in the context of smart grid services. Nevertheless, their volatile and intermittent behaviour remains a critical challenge for fully exploiting their potential while retaining overall grid stability and reliability, especially during planning day-ahead operation. Towards that direction, multiple PV generation forecasting algorithms and tools have been introduced by both research and industry, but without significant accuracy being achieved, especially for small scale PV installations. The presented approach combines a physical model to calculate the actual generation based on numerical weather forecast and PV plant technical specifications, and state-of-the-art machine learning algorithms to correct the error introduced by the limited accuracy of the online weather forecasting tools in the specific location of interested and using historical generation data. The proposed forecasting engine has been applied to a small-scale PV installation in Northern Greece. The engine's performance is assessed via well-known metrics (mean absolute error, root mean square error), along with a newly designed metric that can better evaluate the examined challenge, the weighted relative squared error. Experimental results acquired demonstrate a very good performance rendering the proposed algorithm a very promising tool in the energy-related domain.

1 Introduction

Photovoltaic (PV) penetration has been growing rapidly over the past decade, with the installed capacity reaching 518 GW in 2018 [1] and approximately 23% belonging to European countries. This huge amount of PV generation, provided for roughly 2.5% (around 600TWh) of the global electricity production. On top of that, the ambitious goals set by the European Commission for renewable energy penetration share to reach 32% and 100% in 2030 [2] and 2050 [3] respectively, has created further expectations for an exponential increase in PV capacity.

Although this new reality promotes a "greener" carbon footprint, it also comes with significant challenges that need to be addressed. The volatile and intermittent nature of such generation introduces significant risks to the stability and reliability of both the transmission and distribution networks [4]. PV plants (regardless size) do not comply to the "fit and forget" principle of generation units, thus unexpected shortage or excess can lead to severe imbalance between supply and demand, requiring mitigation actions from the system operator.

To avoid such circumstances, a lot of effort has been invested on forecasting ahead of time (from few seconds to months) the generation capacity. Either through physical (or analytical), time-series statistical, or combined (hybrid) models, quite interesting results have been presented, with forecasting error quite bellow 1% [5, 6]. Nevertheless, in most cases, these results are limited to either clear sky scenarios, or very strict assumptions that limit their scalability and replicability.

Following a slightly different approach, the work presented not only combines a physical and two machine learning models into one novel hybrid model for day-ahead PV output power forecasting. The engine requires knowledge of the installed PV plant along with on-site historical generation and weather measurements. In order to produce the quarterly day-ahead forecast the forecasting engine is fed with the hourly day-ahead weather forecast. The proposed forecasting engine aims towards identifying the on-site error introduced by the weather forecast through machine learning approach towards improving the results of the physical model. To the authors knowledge this has not been researched before, and it provides an optimal combination of forecasting approaches into a uniform, adaptive and scalable model, that can be applied regardless of the installation. This model, could significantly assist both power system planning and operating stages. Experimental data from a small PV plant located in Northern Greece are presented and key performance indicators are calculated demonstrating the good performance of the proposed PV power forecasting engine.

The manuscript is structured as follows: Section 2 provides an overview of related research findings in the literature. Section 3 introduces the methodology adopted, followed by the experimental results in Section 4. The paper is concluded in Section 5.

2 Related Work

Research on PV generation forecasting has undergone a drastic increase recently, which is supported by the considerable amount of review articles only in the last couple of years [7–11]. In general, PV forecasting can be performed directly (via predicting the power PV output) or indirectly (via forecasting the solar irradiance) [12]. Either approach can be based upon physical, statistical or hybrid methods. Physical methods aim towards mathematically modelling either either the entire PV system (direct forecasting), given as input numerical weather prediction (NWP) [13], or the complex atmospheric phenomena (indirect forecasting). For this method to work, significant infrastructure details are required to be known, while the accuracy of the produced forecast relies on NWP accuracy since physical models propagate the error of NWP (due to the low spatio-temporal accuracy [14]) to the PV generation forecast. Physical direct and indirect methods are proven superior in providing very long-term forecasting, i.e. several days or months-ahead time horizons [15], but are lacking in short term.

Towards tackling the poor performance of physical methods in short-term forecasting (few to 24-hour ahead), statistical approaches have gained a significant momentum due to the rise of AI technologies, with machine learning (ML) and deep learning (DL) approaches competing in terms of efficiency. Similarly to physical methods, ML/DL are used to forecast either output power or solar irradiance [11]. PV forecasting is mainly a regression problem, while clustering or optimisation methods can be used complementary to improve the overall performance. Artificial Neural Networks (ANN) are the most ML-based technique used in PV forecasting, including multilayer perceptron neural network (MLP) [17, 18], Radial Basis Function Networks (RBF-NN) [19] etc. ANNs have grown in popularity thanks to their high performance in mapping the high non-linearity of relationships between PV production and its related variables [20]. Apart from ANNs, other ML techniques commonly encountered in literature are classic timeseries forecasting algorithms such as autoregressive-integrated-moving-average (ARIMA) and its variants, support vector machine (SVM) [12] and support vector regression (SVR) [21] and k-nearest neighbors (k-NN) [22]. DL has started recently to be explored in the field of PV forecasting, with recurrent (RNN), convolutional neural networks (CNN) and long-short term memory (LSTM) techniques exploited.

A critical comparative analysis of these different ML/ DL approaches is a daunting task since each published work uses different metrics and the application varies (e.g. hour-ahead or day-ahead forecasts, for small or large PV plants). In the field of day-ahead PV power forecast for small-scale PV installations, the majority of published works uses as input the day-ahead NWP and ML is usually employed to model the non-linearities of the examined PV plant (e.g. [23]) under different weather conditions. Performance varies significantly, with the reasoning eluding justification since the impacting variables are multiple (different ML models, NWP providers, examined PV installations scales). Therefore, it can be stated that no particular model encountered in PV forecasting literature is proven superior over others consistently [22]. Furthermore, it should be noted that published works use a variety of performance metrics, which cannot be compared to each other. However, the outcome that can be derived from literature is that ANNs are the best performing models, with MAPE ranging from 1.08% (sunny days [24]) to 54.44% (cloudy days [25]). It can argued that using as input another forecast - in this particular case, a NWP - is not pure ML. To that end, there are particular efforts on direct PV forecast based only on historical measurements of output power combined in some cases with historical weather data. For example, in [26], an SVR-based forecasting engine is built for hourly and day-ahead direct PV forecast. Though results were promising, only sunny days were used for demonstration, thus omitting covering the forecast problem of less ideal days (cloudy, rainy etc.).

Beyond the two above research pathways, there are quite a few findings that support hybrid models that combine either physical and statistical models, or even multiple statistical models into one solution in order to take advantage of the combined strengths of different approaches. One field that is particularly unexplored is the hybrid statistical-physical forecasting engines. In fact, these approaches constitute only 6% of the published research [7]. In [27], a probabilistic direct forecast based on Bayesian inference and Monte Carlo simulation, is proposed using the analytical function connecting the hourly sky clearness index to the maximum power point production of a PV plant. Despite the good experimental results in determining the probability distribution function of output power, the method under performs if only one value is requested as estimator of the forecasted photovoltaic power. Another approach for day-ahead direct PV forecast based on a decision system that selects between a physical or an ANN-based (MLP) model, is described in [20], with the deciding factor being the cloud coverage percentage. Though in clear sky days, this approach demonstrates good results, poor performance in cloudy days is presented, demonstrating the shortcomings of the MLP model.

3 Methodology

Long-term forecasting is one of the key challenges identified for effectively managing the distribution network, in many aspects. Thus, the presented engine has been developed towards forecasting day-ahead PV generation, building upon a 24-hour-ahead NWP. The system is triggered at the end of the previous day and presents results for the next day, delivering the next 96 slots (15-min resolution) starting at midnight.

As depicted in Fig. 1 there are three main steps in the methodology followed in the proposed hybrid forecasting engine. Namely, the analytical calculation (physical model), the clear sky correction and the cloud correction, in case the total cloud coverage is above a certain threshold, defined via trial-and-error. Each step, including the input data required, the analysis performed and the outcome derived are explained in detail in the following sub sections.

3.1 PV Analytical/ Physical Model

In general, the performance of PV systems is well known and documented, hence analytical calculation of the total PV power output is a concrete calculation method, provided that system parameters are accurately defined. Analytical methods make the exact calculation of the PV power output feasible, since they are based on equations that derive from the photoelectric effect and extensive material science. To that end, an open source software (i.e. Pvlib v.0.7.1 [16]) has been employed in order to calculate the actual performance of the installed PVs using the real-life hardware infrastructure. By doing so, the proposed engine aims to deliver a model capable of adjusting more efficiently to the data analysed, avoiding complex, time consuming and computationally intensive processes that deliver similar or in most cases worse results in the time horizon explored. The physical model selected, allows in depth analysis of the PV system, defining the following parameters:

- *Location and time*: Given those data, a function pinpoints the exact position of the sun. Then, the solar irradiance components are calculated, assuming clear sky conditions.
- *PV configuration*: Tilt and azimuth angle, as well as the number and type of PV modules are defined. PV panels and inverter type are specified.
- *Weather data*: Cloud coverage data are also taken into consideration for the calculation of the solar irradiances, while temperature data are utilized for a more precise calculation of the PV system's performance.

3.2 NWP Error Correction Models

The concept of developing error correction models in order to improve the analytical method's PV output derives from the intuition that forecasting errors follow some certain patterns. This intuition was confirmed by conducting experiments, utilizing ground truth data that were obtained from the PV installation of the current study. Two types of errors were recognized: 1) clear sky error, which is proportionate to the solar irradiance and exists at all cases and 2) cloud coverage error, which varies depending on the propagating error introduced by the weather forecast. Hence following a similar, yet quite different approach than authors in [20], on top of the physical model two machine learning (ML) approaches (one for each of the above errors) have been developed towards identifying the exact error the weather forecast introduces for the infrastructure examined. As the literature presents quite good results in almost any ML approach for the first step, the clear sky scenario, a Random Forest Regression (RFR) solution has been used given the complexity and the amount of data analysed. On the other hand, for the rather challenging task of correcting the cloud coverage, two different techniques have been evaluated: a) ANN with 3 fully connected dense layers and rectified linear unit (ReLU) activation function, since they seem to deliver the optimal results according to the literature, and b) RFR with fine-tuned parameters using grid-search, again due to the volume of the dataset used.

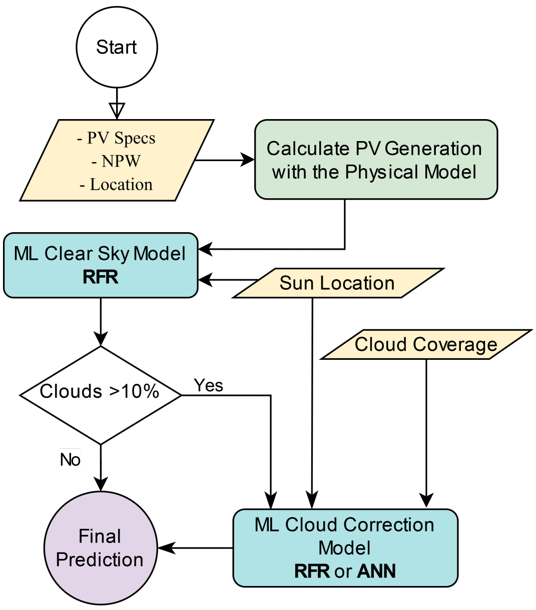

Fig. 1: Flow diagram depicting the hybrid combination of physical and machine learning models.

3.2.1 Clear Sky Model: At clear sky conditions, the physical model is expected to calculate PV power output, approaching near optimal accuracy. As it is revealed from the actual generated power, this does not happen and there may be several reasons for that. Starting with the installation of the PVs, the tilt and azimuth angles are provided with certain estimations. On top of that, forecasted weather conditions always come with a certain error, even in actual clear sky conditions (i.e. slightly different temperature, wind, very sparse clouds, etc.), especially when examining a very specific geographical area. Finally, such models assume that all hardware components are and operate in optimal conditions, which is not always true. This is even worse on installations in which often maintenance is not performed. All of the above reasons introduce an error that leads to certain slight differences between forecasted results and generation measurements. In Fig. 2, the average deviation from the actual PV output value for every hour of the day, reveals an obvious daily error pattern. As it is already mentioned, this error exists at all times, it remains constant under certain conditions and it can be isolated on clear sky days.

3.2.2 Cloud Coverage Model: Solar irradiance is the main factor that affects PV generation. In clear sky days, knowing the exact position of the sun is enough for a precise irradiance calculation. Cloudy days make this calculation more demanding as cloud coverage is provided by weather forecasts. Each weather forecast has limited accuracy due to the weather's stochasticity. As a result, the forecasting accuracy is expected to be poorer on cloudy days. With the cloud coverage model it was attempted to investigate the existence of specific error patterns on cloudy days PV generation. In fact, the hypothesis that PV generation error varies accordingly to the weather forecasting error, each hour of the day, was examined. The

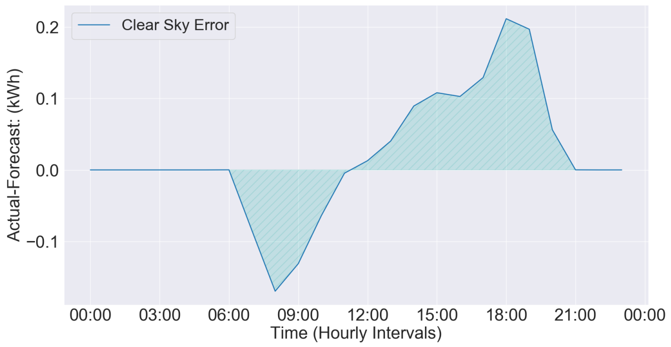

Fig. 2: Clear Sky deviation pattern.

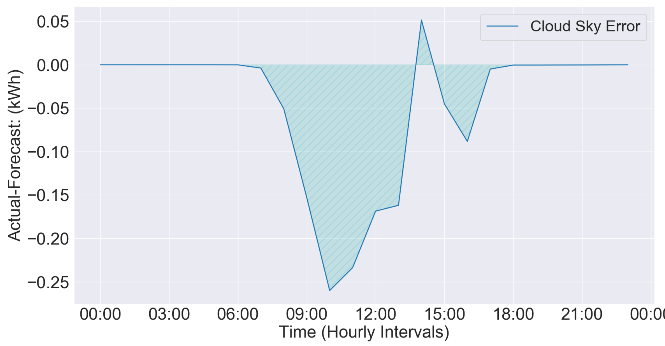

Fig. 3: Cloud Coverage deviation pattern.

above hypothesis is empirically verified, as shown in Fig.3 which presents the hourly PV generation error of the studied PV installation. Apart from the weather stochasticity, another reason for inaccurate weather forecast is that weather APIs provide forecasts according to the data obtained by specific weather stations. The distance between the weather station and the PV plant may be the cause of weather forecasting inaccuracies that can be detected by the outcome of the PV generation if these data are available. In the current study, two different free weather APIs were concurrently used as it was found that their weighted combination provided optimal weather forecasting results. Then, assuming as cloudy days, the days with more than 10% cloud coverage, PV generation ground truth data were used for the training of the model.

4 Experimental Results

4.1 Experimental Setup

The data used for the presented analysis were retrieved from a real-life small PV installation on the roof of a two floor house in Thessaloniki, Greece. The installation consists of 58 CIS (copper, indium, and selenium) solar panels with 165Wp nominal power each, divided into 9 strings that form in total 9.57kWp. The panels are facing 255°south-west with a tilt angle of 18°. The strings are inserted into two MPPT inputs of a 10kW inverter, which allows detailed monitoring through Modbus TCP/IP. The surrounding buildings are far and in lower height than the PV leading to the avoidance of shading regardless of the height of the sun from the horizon.

On the other hand, for the weather data, both real-time and day-ahead forecasted, two online APIs were utilised: Weatherbit and DarkSky. Both APIs provide the updated weather data in hour and 15-minute interval for the forecasted and the real-time respectively, while the closest weather station is little far from the PV installation.

4.1.1 Evaluation Metrics: Following suggested metrics from the literature, the forecasting results of the examined engine are evaluated in terms of Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and a newly introduced metrics named Weighted Relative Squared Error (WRSE).

The MAE metric measures the average magnitude of the errors without considering their direction, while the RMSE squares the errors before averaging them, giving a relatively high weight to large errors. WRSE is created in order to demonstrate the relative error in terms of magnitude of the evaluated generation. As depicted in Eq. 3, it takes into account the direction of the error and provides a uniform weighting for all errors. Finally, zero production values are disregarded.

$$MAE = \frac{1}{N}\sum_{i=1}^{i=N} \mid P_f(i) - P_A(i) \mid \tag{1}$$

$$RMSE = \sqrt{\sum_{i=1}^{i=N} \frac{(P_f(i) - P_A(i))^2}{N}} \tag{2}$$

$$WRSE = \frac{\left[\sum_{i=1}^{i=M}\left[\sqrt{\frac{\left(P_f(i)-P_A(i)\right)^2}{P_A(i)}}\right]\right]^2}{M\sum_{i=1}^{i=M} P_A(i)} 100\% \tag{3}$$

where,

- $P_f(i)$: forecasted PV output power at timeslot $i \in [0, N]$
- $P_A(i)$: measured PV output power at timeslot $i \in [0, N]$
- N: number of forecasted steps ahead (M steps of daylight).

4.2 Day-ahead Direct Forecast Results

A total of 9 months' data were available from the studied PV installation. 2/3 of each month's data were used for training and the rest 1/3 was kept for testing. Both error correction model implementations are based on the architecture of Fig.1, with the RFR outperforming the ANN approach when evaluating all examined metrics in total. Following suggested metrics from the literature, the forecasting results of the examined engine are evaluated in terms of Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Weighted Relative Squared Error (WRSE). The MAE metric measures the average magnitude of the errors without considering their direction, while the RMSE squares the errors before averaging them, giving a relatively high weight to large errors. WRSE metric is created in order to demonstrate the relative error in terms of magnitude of the produced PV output power.

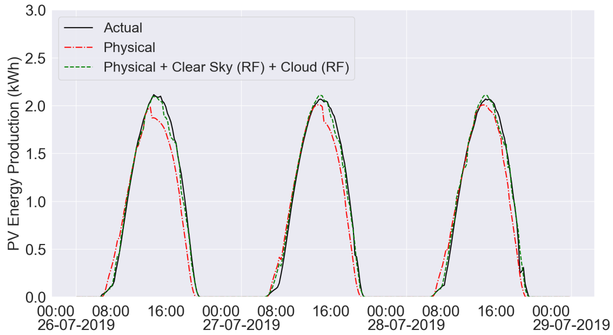

Fig. 4: Day-ahead PV forecast for 3 indicative clear sky days.

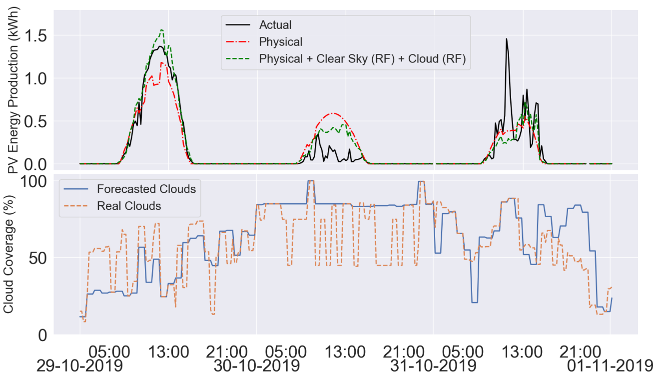

Fig. 5: Day-ahead PV forecast for 3 indicative cloudy days.

Commencing with the clear sky scenario, Fig.4 presents results for three consecutive summer days with minimum cloud coverage. Given the cloud coverage, the comparison between just the physical and clear sky models can be demonstrated. It is evident, that even in clear sky conditions a correction is needed in order to optimally reach the desired accuracy in terms of forecasting. The suggested method fits better the actual PV generation curve. Interestingly enough, it is also confirmed that the physical method presents a similar error pattern each hour of the day, during sunny days.

The same comparison is conducted respectively for cloudy days in Fig.5. In this case also, the error correction model seems to perform better than the physical, capturing the trend of the PV power generation with higher accuracy. However, it needs to be pointed out that the 15-min time resolution results to a steeper curve due to short-term weather changes that are almost impossible to capture. Moreover, the cloud coverage forecast is not always accurate, introducing a propagating error to the PV forecast, regardless of the correction models.

Fig. 6 presents the WRSE results per month for both the physical and the hybrid model. The latter is explored on each different step, namely the RF clear sky, RF cloud, and ANN cloud models. The first thing observed is that even the clear sky correction offers occasional improvements, a fact that validates the constraints described when using solely physical models for predicting PV generation. Furthermore, a rather interesting, and difficult to rationalize, finding is that in certain months the ANN works better than the RF (e.g. Nov), and for some

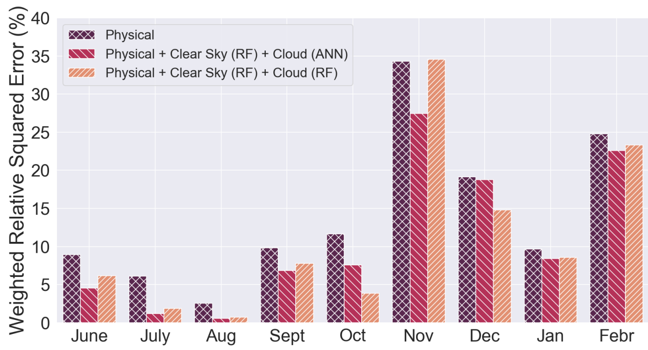

Fig. 6: WRSE for 9 months for the physical and hybrid models.

Table 1 Error Metrics for Physical (P), ANN and RF models.

	MAE (kWh)			RMSE (kWh)			WRSE (%)		
	P	**ANN**	**RF**	**P**	**ANN**	**RF**	**P**	**ANN**	**RF**
06/19	0.15	**0.11**	0.13	**0.26**	**0.26**	0.27	8.92	**4.53**	6.17
07/19	0.12	**0.07**	**0.07**	0.21	0.19	**0.17**	6.1	**1.2**	1.86
08/19	0.07	**0.04**	**0.04**	0.13	**0.1**	**0.1**	2.55	**0.55**	0.72
09/19	0.14	**0.11**	0.12	0.31	**0.3**	0.31	9.8	**6.84**	7.77
10/19	0.07	**0.04**	**0.04**	0.14	0.1	**0.09**	11.64	7.57	**3.88**
11/19	0.1	**0.09**	**0.09**	**0.21**	0.22	**0.21**	34.31	**27.47**	34.55
12/19	0.09	0.09	**0.08**	0.22	0.23	**0.21**	19.14	18.79	**14.79**
01/20	0.09	0.09	**0.07**	0.2	0.22	**0.18**	9.64	**8.4**	8.57
02/20	0.17	0.16	**0.15**	0.35	0.33	**0.32**	24.76	**22.57**	23.3

other months vise versa (e.g. Oct). Nevertheless, in general, as can be seen in Table 1 both the RF and the ANN implementations outperform the physical method in most cases. In terms of the evaluation metrics suggested, an overall reduction of 19.7% in MAE, 6.2% in RMSE, and 3% in WRSE is observed, with quite different results per month (i.e. October versus November). As expected, the error is rather low on months in which clear sky conditions are more often, and higher on those that cloud coverage occupies most of days instead.

5 Conclusion & Future Work

In this work a novel hybrid PV generation forecast is presented. The model introduces an innovative approach that targets the error introduced by available NWP tools as input to a well defined physical PV aspects. The forecasting engine combines both a physical model and a machine learning approach, that improve the results of the former by identifying the on-site error introduced by the weather forecast, either under clear sky or extensive cloud coverage conditions.

The findings suggest that the overall engine improves in general the results from the physical model and can provide quite limited error when predicting PV generation even in small-scale installations and without extensive on-site knowledge on weather conditions. An added values of this work is also the introduction of a new metric, the WRSE, that is believed to more accurately express the error of this particular challenge. Future work includes the evaluation of the proposed method to further installations and forecast horizons. Moreover, examining the impact of precipitation, wind speed, high, medium and low clouds, could lead to adding more features to our model.

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7 References

[1] Taylor, N., Jäger-Waldau, A.: Low Carbon Energy Observatory Photovoltaics Technology Market Report 2018 – Public Version, EUR 29935 EN, (European Commission, 2019), pp. 1–58

[2] 'EC 2030 Climate & Energy' Framework, https://ec.europa.eu/clima/policies/strategies/2030_en, accessed 08 April 2020.

[3] 'Energy roadmap 2050', https://ec.europa.eu/energy/sites/ener/files/documents/2012_energy_roadmap_2050_en_0.pdf, accessed 08 April 2020.

[4] Qi, B., Hasan, K. N., Milanović, J. V.: 'Identification of Critical Parameters Affecting Voltage and Angular Stability Considering Load-Renewable Generation Correlations', IEEE Transactions on Power Systems, 2019, 34, (4), pp. 2859-2869

[5] Han, Y., Wang, N., Ma, M., et al.: 'A PV power interval forecasting based on seasonal model and non parametric estimation algorithm', Sol. Energy, 2019, 184, pp. 515–526.

[6] Wang, K., Qi, X., Liu, H.: 'A comparison of day-ahead photovoltaic power forecasting models based on deep learning neural network', Appl. Energy, 2019, 251, 113315

[7] Antonanzas, J., Osorio, N., Escobar, R., et al.: 'Review of photovoltaic power forecasting', Solar Energy, 2016, 136, pp. 78–111

[8] Das, U.K., Tey, K.S., Seyedmahmoudian, M., et al.: 'Forecasting of photovoltaic power generation and model optimization: A review', Renew. Sustain. Energy Rev., 2018, 81, pp. 912-–928

[9] Akhter, M.N., Mekhilef, S., Mokhlis, H., et al.: 'Review on forecasting of photovoltaic power generation based on machine learning and metaheuristic techniques', IET Renew. Power Gener., 2019, 13, pp. 1009–1023

[10] Wang, H., Lei, Z., Zhang, X., et al.: 'A review of deep learning for renewable energy forecasting', Energy Conversion and Management, 2019, 198, pp. 111799

[11] Mellit, A., Massi Pavan, A., Ogliari, E., et al.: 'Advanced Methods for Photovoltaic Output Power Forecasting: A Review', Applied Sciences, 2020, 10, (2), pp. 487

[12] Shi, J., Lee, W. J., Liu, Y., Yang, Y., Wang, P.: 'Forecasting power output of photovoltaic systems based on weather classification and support vector machines', IEEE Transactions on Industry Applications, 2012, 48, (3), pp. 1064-1069

[13] Pelland, S., Galanis, G., Kallos, G.: 'Solar and photovoltaic forecasting through post-processing of the Global Environmental Multiscale numerical weather prediction model', Prog. Photovolt. Res. Appl., 2013, 21, pp. 284–296

[14] Dolara, A., Leva, S., Manzolini, G.: 'Comparison of different physical models for PV power output prediction', Solar energy, 2015, 119, pp. 83-99

[15] Voyant, C., Motte, F., Notton, G., et al.: 'Prediction intervals for global solar irradiation forecasting using regression trees methods', Renewable energy, 2018, 126, pp. 332-340

[16] Holmgren, W.F., Hansen, C.W., Mikofski, M.A.: 'pvlib python: a python package for modeling solar energy systems', Journal of Open Source Software, 2018, 3, (29), pp. 884

[17] Mellit, A., 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', 2010, Solar Energy, 84, (5), pp. 807-821

[18] Ehsan, R. M., Simon, S. P., Venkateswaran, P. R.: 'Day-ahead forecasting of solar photovoltaic output power using multilayer perceptron', 2017, Neural Computing and Applications, 28, (12), pp. 3981-3992

[19] Chen, C., Duan, S., Cai, T., et al.: 'Online 24-h solar power forecasting based on weather type classification using artificial neural network'. 2011, Solar energy, 85, (11), pp. 2856-2870

[20] Mosaico, G., Saviozzi, M.: 'A hybrid methodology for the day-ahead PV forecasting exploiting a Clear Sky Model or Artificial Neural Networks'. Proc. Int. Conf. IEEE EUROCON 2019-18th International Conference on Smart Technologies, Novi Sad, Serbia, July 2019, pp. 1-6

[21] Liu, J., Fang, W., Zhang, X., et al.: 'An improved photovoltaic power forecasting model with the assistance of aerosol index data', 2015, IEEE Transactions on Sustainable Energy, 6, (2), pp. 434-442

[22] Zhang, Y., Beaudin, M., Taheri, R., et al.: 'Day-ahead power output forecasting for small-scale solar photovoltaic electricity generators', 2015, IEEE Transactions on Smart Grid, 6, (5), pp.2253-2262

[23] Pierro, M., Bucci, F., De Felice, M., et al.: 'Multi-Model Ensemble for day ahead prediction of photovoltaic power generation', 2016, Solar energy, 134, pp. 132-146

[24] Al-Dahidi, S., Ayadi, O., Adeeb, J., et al.: 'Extreme learning machines for solar photovoltaic power predictions', 2018, Energies, 11, (10), pp. 2725

[25] Chen, C., Duan, S., Cai, T., et al.: 'Online 24-h solar power forecasting based on weather type classification using artificial neural network', Solar energy, 2011, 85, (11), pp. 2856-2870

[26] Das, U. K., Tey, K. S., Seyedmahmoudian, M., et al.: 'SVR-based model to forecast PV power generation under different weather conditions', 2017, Energies, 10, (7), pp. 876

[27] Bracale, A., Caramia, P., Carpinelli, et al.: 'A Bayesian method for short-term probabilistic forecasting of photovoltaic generation in smart grid operation and control', 2013, Energies, 6, (2), pp.733-747