New Time Horizon Based Classification of PV Power Generation Forecasting Techniques

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***Abstract*—Among the common renewable energy sources (RES), photovoltaic (PV) energy holds an increasing share in the global energy market. The depending on various environmental aspects, weather conditions and non-linear characteristics create the main challenge in PV based installations specially on large farms level. Load variations and future expectations play a critical role in calculating the reserve stand-by units for vally-filling; a major challenge for grid-control authorities. Consequently, PV power generation forecasting is unavoidable for robust, reliable and cost-effective grid control from both operation and maintenance aspects. Despite the available review articles, recent forecasting techniques are not well classified or aggregated with solid benchmark assessments. This paper presents a novel criteria for classifying all the developed PV power generation forecasting techniques based on time horizon classification. In addition, inputs, outputs, forecasting methodology and performance metric are included in the proposed criteria. Detailed classification and comparison tables are concluded with detailed discussion and survey outcomes. The presented paper acts as a robust road-map for researchers concerned with this current topic as it accommodates all the available techniques with novel classification and comparison.**

***Index Terms*—Forecasting, PV generation, Machine learning, Artificial intelligence, Numerical weather predictor**

I. INTRODUCTION

Nowadays, electrical energy has a major share in several daily applications along with the rapid demand increase due to world globalisation and modernisation. Conventional sources of energy have caused several environmental problems in addition to massive depletion of fossil fuels. Consequently, the need of alternative source of energy arises where renewable energy sources (RES) witnessed booming interest globally.

The most dominant source among RES is the photovoltaic (PV), characterized by high penetration rate in energy markets. PV based generation has great potential in electrification of both rural and urban areas in addition to other forms of utilization like heating/cooling generation, passive systems and combined power. Also, it has advantages of low maintenance cost, long lifetime, increased robust and reliable operation [1]–[3].

PV power generation is affected by the weather condition and the amount of solar irradiance arriving on the earth. These conditions are varying from deterministic to probabilistic. Sun and earth motion are good example of deterministic aspects. Probabilistic aspects like clouds, block the sun's rays in a stochastic way. To overcome these circumstances, an accurate output solar power forecasting is necessary to guaranty power system reliability, stability, and quality. It serves in reducing the power uncertainty impact on the grid. Also, accurate forecasting is required for operation cost reduction as a proper forecast leads to massive reduction the number of the hot standby units.

There is no standard way of evaluation measures for the forecasting techniques that leads to difficulty in the comparison between them. Also, all the literature reviews and surveys considered illustrating the existing work by listing the used algorithms and performance metrics with no collective comparison based on any solid criteria [4]–[6]. Therefore, in this paper a new classification criteria is proposed in order to review the available PV power forecasting techniques in more illustrative way to be a useful guide for the researchers in this area. The proposed classification is based on the time horizon that categorize the forecasting processes according to the prediction time as shown in fig. (1). For each time horizon, the classification is carried out considering: (i) the input variable to the model, (ii) the predicted output, (iii) the used forecasting technique and (iv) the assessment metric of the model.

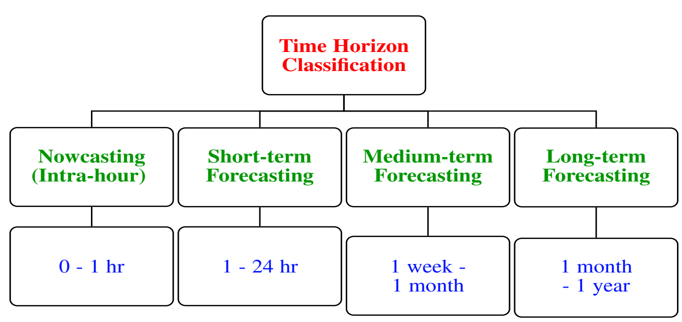

Figure 1. Proposed Time Horizon Classification Criteria of PV Power Forecasting

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The paper is structured as follows: Section 2 illustrate the classification criteria that will be considered in the paper. Section 3 includes the proposed classification based on time horizon. Section 4 discuss the concluded benefits of the proposed classification for the researchers in the field.

II. Classification Criteria

The proposed classification is based on time horizon as mentioned in the introduction. For each forecasting time duration, the previous work is grouped based on certain classification aspects which are listed in fig. (2). These factors are crucial for the proposed comparison assessment of the forecasting performance.

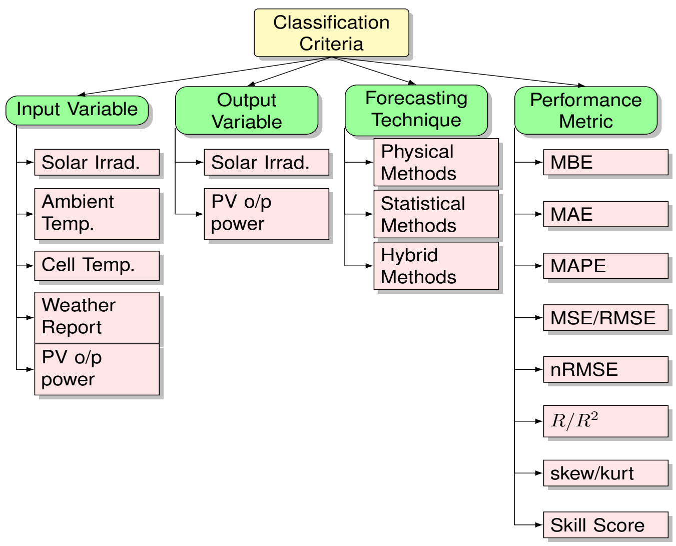

Figure 2. Proposed Internal Classification Criteria

A. Input Variable

Each model basically depends on the input variables which may be a present and/or delayed time-series for the PV power production records. Also, the input may come from local measurements such as cell temperature or information from satellite images, sky imagers, numerical weather predictions (NWP) like irradiance, ambient temperature, cloud cover, etc..., values from other meteorological data base. In the presented classification the mostly common used input variables are considered.

B. Output Variable

The targeted variable of the prediction process has been categorized into two main categorise (i) solar irradiance and (ii) power output. These two approaches are considered as indirect and direct ways to predict the power. For the first approach after estimating the irradiance of the sun the pv performance model of the plant can be used to obtain the power generated. The second approach calculate directly the produced power of the plant. The indirect approach of forecasting is related to the physical model and the direct prediction of the power using the statistical and machine learning methods.

C. Performance Metric

In order to evaluate the accuracy level of the model used in the forecasting process, several statistical measure are used [7]–[9]. The mostly common used performance metrics are:

1) Mean Bias Error (MBE):

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}(i) - y(i)) \tag{1}$$

2) Mean Absolute Error (MAE):

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}(i) - y(i)| \tag{2}$$

3) Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\hat{y}(i) - y(i)}{y(i)}\right| \tag{3}$$

4) Mean Square Error (MSE)/ Root MSE (RMSE):

$$RMSE = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}(i) - y(i))^2 \tag{4}$$

5) Normalized Root Mean Square Error (nRMSE):

$$RMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}(i) - y(i))^2}}{\bar{y}} \tag{5}$$

6) Correlation Coefficient (R)/ Coefficient of Determination (R^2):

$$R = \frac{(Cov(y(i) - \hat{y}(i)))^2}{Var(\hat{y}(i))} \tag{6}$$

$$R^2 = 1 - \frac{Var(y(i) - \hat{y}(i))}{Var(\hat{y}(i))} \tag{7}$$

7) Skewness (skew) / Kurtosis (kurt):

$$skew = \frac{N}{(N-1)(N-2)}\sum_{i=1}^{N}\left(\frac{nE - n\hat{E}}{SD}\right)^3 \tag{8}$$

$$kurt = \left[\frac{N(N-1)}{(N-1)(N-2)(N-3)}\sum_{i=1}^{N}\left(\frac{nE-n\hat{E}}{SD}\right)^4\right]\cdot\frac{3(N-1)^2}{(N-2)(N-3)} \tag{9}$$

8) Skill Score:

$$ss = 1 - \frac{MSE_{forecated}}{MSE_{refrence}} \tag{10}$$

D. Forecasting Techniques

Classical PV power prediction techniques are commonly based on mathematical techniques which are devided into two subcategories: (i) persistence model and (ii) statistics method. These methods deliver forecasting with low level of accuracy and fail to process non-linear data. According to these limitations, more advanced techniques are of recent interest. These techniques; used for forecasting the generated power of the PV or solar irradiance; are categorized into three main groups [10]–[12]:

- Physical Methods
- Statistical and Numerical Methods
- Hybrid Methods

1) Persistence Model: This model is considered as the benchmark of the developed model for testing the accuracy of forecasting . Therefore, many studies present their work using skill score. It uses the historical data and deliver a prediction of spam time 1 hr for the solar power where it is assumed that the forecasting power is equal to output power of the measured for the past or upcoming day. Also, it is called a naive predictor. The predicted power for the next day can be expressed as follow, [13]–[18]:

$$P_t(t+h) = P_{pd}(t) \tag{11}$$

where, $P_t(t+h)$ is the forecasted power and $P_{pd}(t)$ is the prior day output power at the same time.

Due to stochastic nature of irradiance variability; this approach is not suitable for intra-hour prediction. So, other approaches were developed to overcome this problem by decomposing the production of the solar power into both the stationary and the stochastic component [9].

2) Physical Methods: This method is based on the interaction between the solar radiation dynamic motion and the physical state which is used for irradiance forecasting and hence solar power. Also, it is called the PV performance model that is classified into three groups:

- Numerical weather prediction (NWP) model
- Sky imagery model
- Satellite imaging or Remote sensing model

NWP models has three types which are global, mesoscale and regional [19]. For forecasting in short-term time horizon the used technique is Sky imagery models that deal with clouds variable motion creating small scale variability [10]. For both remote sensing or the satellite imaging models, there is no need for ground sensors.

3) Statistical and Numerical Methods: As the climate conditions are the main factors that affect the power generation which is a non-stationary type of data; classical statistics methods fail in dealing with non-linear data. Therefore, stochastic techniques and machine learning models are considered to work with these limitations. Machine learning is suitable for handselling the problems that explicit algorithms can not solve and it can evolve a relation between the past meteorological parameters and output power or irradiance. It is capable to use the historical data to extract information to be able to forecast time series. This group of forecasting method contains the following models:

- Statistical models:
  1) Regression methods
  2) Autoregressive Moving Average (ARMA)
  3) Markov Chain
- Machine Learning:
  1) Artificial Neural Network (ANN)
  2) Support Vector Machine (SVM)
  3) Support Vector Regression (SVR)

4) Hybrid Methods: Each of the previous two forecasting methods has its own weakness. In order solve that hybrid methods were proposed to solve this issues and to enhance their strength and accuracy although it leads to increase the complexity of the computations. The hybrid methods are mainly consists of combination of machine learning, optimization techniques and physical methods to deliver high level of accuracy for solar forecasting that is more sufficient for time horizons intervals of medium/long terms [20]. Also, the combination of one of the optimization techniques with any of the earlier two mentioned methods can improve the speed of the convergence during the training stage. The classes of hybrid methods are:

- Physical model and Machine learning
- Machine learning and optimization technique
- Statistical model and optimization technique

III. Proposed Time Horizon based Classification of PV Power Generation

Literature articles that classify PV forecasting techniques commonly utilize one or more of the core aspects mainly time interval, adopted algorithms and meteorological data. Integrating all the classification aspects in one review was not presented before although it will improve the analysis of the previous work and give valuable insights on the forecasting results. This is the core motivation of the current article.

Forecast time horizon is defined as the time span into future for which it is used to predict the PV power outputs. The accuracy level varies depending on time horizon for same forecasting model and parameters. So, time horizon must be taken into consideration in advance of the model designing process. Although there is no clear establishing strategy for classifying time horizon, most researches adopt the four groups mentioned earlier. PV forecasting is crucial due to its importance to wide applications as but not limited to: scheduled grid equipment maintenance, power grid stability, and storage/spinning reserve planning. An extensive survey is carried out in this article based on the novel proposed classification criteria mentioned in previous section fig. (2) of PV power generation forecasting categorized based on time horizon as shown in fig. (1).

A. Nowcasting (Intra hour)

The intra-hour forecasting involves few second to several minutes investigation. This period is vital for decision making especially for real time applications like decentralized load dispatch and energy storage management. For high renewable energy penetrated grids, short time manoeuvring with renewable energy resources and associated storage strengthen the grid stability mainly when sudden islanding/fault scenarios occur.

Commonly, historical and/or meteorological records are utilized for now casting assessment noticing degradation performance of NWP based techniques. Recently elaborated image processing of sky captures acn lead to promissing results.

B. Short-term Forecasting

This time horizon forecasting is useful to increase the grid security. Satisfactory results were obtained using a wide range of methods of forecasting short-term horizon which is also called intra-day. Therefore, it is difficult here to select a single suitable technique. The commonly recommended models were ANN, SVR and regressive methods. Also, for this time frame, NWP variables were extensively used. Cloud accumulation and motion detection can reveal promising results while benefiting from neighbouring PV plants forecasting.

C. Medium-term Forecasting

Medium-term forecasting, like other time horizons, it is difficult to get conclusion about which are the best predictor due to the diversity of techniques used. However, the use of NWP variables give promising prediction performance. Noticeable trade-off is recorded between complexity and accuracy of the data based model that relies on weather condition instead of previous days.

D. Long-term Forecasting

This time horizon is not investigated in many studies as power grid operators commonly utilize shorter time horizons for decision making. NWP variables are recommended to be used as information from neighbouring PV plants won't be beneficial due to low spatio-temporal correlation.

Table (I) summarizes the investigated studies based on two aspects the input/output variables to the model of forecasting. This is categorized for the adopted classification time horizon.

The proposed time horizon based classification of the forecasting of PV power generation is presented in the following tables categorized according to the prediction technique into: (A)-Physical Methods, (B)-Statistical and Numerical Methods, and (C)-Hybrid Methods, table (II), (III), (IV), respectively.

IV. Discussion and Conclusion

PV performance models outweigh statistical ones from various aspects. Among them, the irrelevance to historical data is the core. On the contrary, dependency on NWP exhibits reported resolution errors.

Regarding various interval forecasting assessments, statistical techniques suffer a tradeoff between accuracy and interval period. From the proposed classification it can be concluded that the statistical methods are suitable for short-term forecasting while machine learning techniques can present better performance for medium term studies.

Among all the investigated techniques the presented study shows that hybrid methods that combines advanced machine learning with physical and/or optimization techniques offer highest performance from both accuracy and forecasting period aspects.

From the authors points of view, research regarding optimal determination of input variables (like: temperature, humidity, ...) and how this selection affects the forecasting accuracy will be the elaborating investigation area in the field of PV forecasting.

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Table I
CLASSIFICATION BASED ON INPUT/OUTPUT VARIABLES OF PV POWER GENERATION FORECASTING

Output Variable	Time Horizon	Input Variable				
		Weather Rep.	***Solar Irradiance***	***Ambient Temp.***	***Cell Temp.***	***PV o/p power***
Solar Irradiance	**T1**	[21]–[27]	[23], [24], [28]–[34]	[29], [34]		
	T2	[21]–[23], [36]–[44], [78]	[23], [31], [36], [39], [40], [78], [36], [45]–[56]	[45], [47], [48], [52], [54]–[57], [78]		
	T3	[38], [43]	[54], [48], [58], [59]	[54], [48], [58], [59]		
	T4	[60]		[60]		
PV output Power	**T1**	[61]	[62]–[66]	[62]–[64]		[61]–[67]
	T2	[61], [68]–[77]	[65], [78]–[87]	[71], [72], [79]–[88]	[81], [82], [87]	[61], [65], [67], [73], [77], [80], [84], [86], [87] [89]–[91]
	T3	[73]	[92]	[92]		[73]
	T4					

T1: Nowcasting, T2: Short-term forecasting, T3: Medium-term forecasting, T4: Long-term forecasting

Table II
PROPOSED TIME HORIZON BASED CLASSIFICATION OF PV POWER GENERATION FORECASTING (A-PHYSICAL METHODS)

Forecasting Technique	Time Horizon	Performance Metrics							
		MAE	***MBE***	***MAPE***	***MSE/RMSE***	***nRMSE***	**R/R^2**	***skew/kurt***	***SS***
NWP	**T1**								
	T2	[40], [85]	[38]		[38], [73], [39]	[90]			[40]
	T3		[38]		[38], [73]				
	T4								
Sky imagery	**T1**	[24]			[24]	[25]	[30]		
	T2								
	T3								
	T4								
Satellite image	**T1**								
	T2								
	T3								
	T4								

T1: Nowcasting, T2: Short-term forecasting, T3: Medium-term forecasting, T4: Long-term forecasting

Table III
TIME HORIZON BASED CLASSIFICATION OF PV POWER GENERATION FORECASTING (B-STATISTICAL/NUMERICAL METHODS)

Forecasting Technique	Time Horizon	Performance Metrics							
		MAE	***MBE***	***MAPE***	***MSE/RMSE***	***nRMSE***	**R/R^2**	***skew/kurt***	***SS***
Regression	**T1**								
	T2	[89]	[80], [50]	[71], [72]	[50], [71], [72], [89]	[80]		[80]	
	T3								
	T4								
ARMA	**T1**	[22], [27]			[22], [27]				
	T2	[22]	[49]		[49], [22]	[78]			
	T3								
	T4								
Markov Model	**T1**	[64]							
	T2								
	T3								
	T4			[60]	[60]		[60]		
ANN	**T1**	[28], [31], [61], [32], [33]	[28], [61]		[62], [28], [63], [31], [61]	[31]	[45], [28], [63]	[34]	[31]
	T2	[91], [31], [61], [83], [42], [55]	[45], [79], [80], [61], [83]	[37], [41], [42], [57]	[45], [79], [31], [61], [83], [54], [41], [53], [42], [77], [55]	[78], [37], [80], [81], [31], [83]	[45], [79], [80], [41], [42], [55]		[31]
	T3				[58], [92], [54]				
	T4								
SVM	**T1**	[33]	[29]	[29]	[29], [26]		[29], [26]		
	T2	[70], [55]		[70]	[69], [46], [47], [55]	[81]	[46], [47], [55]	[84]	
	T3								
	T4								
SVR	**T1**				[65]				
	T2	[83]	[83]		[59], [83]	[83]			
	T3								
	T4								

T1: Nowcasting, T2: Short-term forecasting, T3: Medium-term forecasting, T4: Long-term forecasting

Table IV
TIME HORIZON BASED CLASSIFICATION OF PV POWER GENERATION FORECASTING (C-HYBRID METHODS)

Forecasting Technique	**Time Horizon**	**Performance Metrics**							
		MAE	***MBE***	***MAPE***	***MSE/RMSE***	***nRMSE***	**R/$\mathbf{R^2}$**	***skew/kurt***	***SS***
ANN+ physical	**T1**		[23]		[23]				
	T2	[74], [75], [85]	[23], [39]		[21], [23]	[39], [75]	[21], [39], [76]		
	T3								
	T4								
ANN+ optimization	**T1**					[66]			
	T2	[44]	[44]	[86]	[43], [56], [44]		[44]		
	T3				[43]				
	T4								
ANN+ WT	**T1**	[67]	[21]	[67]	[67]	[21]			
	T2	[67]		[67]	[67]				
	T3								
	T4								
SVM+ WT	**T1**								
	T2			[48]	[48]		[48]		
	T3			[48]	[48]		[48]		
	T4								
SVM/SVR+ optimization	**T1**					[66]			
	T2				[88], [87]	[82], [51]	[82]		
	T3			[59]	[59]		[59]		
	T4								
ARMA+ ANN	**T1**								
	T2				[52]	[52]			
	T3								
	T4								
Fuzzy+ NN	**T1**								
	T2	[68]		[36]	[68]				
	T3								
	T4								

T1: Nowcasting, T2: Short-term forecasting, T3: Medium-term forecasting, T4: Long-term forecasting

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