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Review of Different Error Metrics: A Case of Solar Forecasting

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***Abstract*—Renewable energy systems (RES) are no longer confined to being used as a stand-alone entity in the modern era. These RES, especially solar panels are also used with the grid power systems to supply electricity. However, precise forecasting of solar irradiance is necessary to ensure that the grid operates in a balanced and planned manner. Various solar forecasting models (SFM) are presented in the literature to produce an accurate solar forecast. Nevertheless, each model has gone through the step of evaluation of its accuracy using some error measures. Many error measures are discussed in the literature for deterministic as well as probabilistic solar forecasting. But each study has its own selected error measure which sometimes landed on a wrong interpretation of results if not selected appropriately. As a result, this paper offers a critical assessment of several common error metrics with the goal of discussing alternative error metrics and establishing a viable set of error metrics for deterministic and probabilistic solar forecasting. Based on highly cited research from the last three years (2021-2019), error measures for both types of forecasting are presented with their basic functionalities, advantages & limitations which equipped the reader to pick the required compatible metrics**

***Index Terms*—Error measures, deterministic forecasting, probabilistic forecasting, solar forecasting, root mean square error.**

I. Introduction

Among various renewable energy resources (RES), solar energy has been recognized as one of the potential solutions to the electricity demand [1]. However, the intermittent and uncertain behavior of solar photovoltaic (PV) output is one of the biggest challenges to the grid integrated power systems. As a result, solar forecasting or PV power forecasting (commonly both referred to as solar forecasting) has received unprecedented attention from the various communities of researchers. Progress in solar forecasting has been steadily increasing since the end of the nineteenth century, with the goal of providing accurate solar forecasting models (SFM) [2]. While searching the publications for the keyword "solar forecasting" and "PV forecasting", Google scholar (a reputed technical research database) returns 19300 and 16000 results respectively since the year 2020 as on date of 17th August 2021, 11:58 p.m.

From consideration of this abundant literature of solar forecasting, numerous new SFM has been developed and also being developed. Many researchers have also been presented an extensive review on various SFMs. Table 1 presented the top 10 review studies on the SFMs published in recent years. These papers are selected from the year 2019-2021 based on the number of citations from google scholar (as on date 17th Aug., 2021).

TABLE I
RECENTLY PUBLISHED LITERATURE REVIEW ON SOLAR/ PV FORECASTING

Ref.	YOP	Title
[1]	2019	A review of deep learning for renewable energy forecasting
[4]	2019	Modeling of solar energy systems using artificial neural network: A comprehensive review

The publications mentioned in table 1 only presented the details of different forecasting models and their fundamental methodologies. Nevertheless, these studies are based on a limited number of papers and can only provide a brief of recent works among total selected publications. In other words, these publications act like local optima instead of a global solution in an optimization problem. Moreover, these publications aware the researcher's community about the recent development in the solar forecasting models only.

In parallel, to estimate the performance of any SFM, some statistical measures are adopted by the developers. In the last two decades, various accuracy measures or error measures have been used by developers to evaluate their models. These measures provide the necessary feedback to the decision-maker for refining and calibrating the measured model to optimize the preciseness of the model. Upon searching the abundant literature of solar forecasting/PV forecasting, no universal or single error metrics has been found that has been accepted by every researcher to evaluate their model. Each study has its own adopted statistical measure on the unexplained ground to prove its accuracy best. Sometimes in practical problems, some of the popular metrics are failed to provide easily interpretable results. For instance, the mean absolute percentage error (MAPE) is one of the popular metrics to evaluate any SFM, but is vulnerable to the outliers [3]. Lastly, despite of developments of various SFMs, the solution of universal single error metrics for all models is still controversial.

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[5]	2019	Review on forecasting of photovoltaic power generation based on machine learning and met heuristic techniques
[6]	2020	A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization
[2]	2019	A current perspective on the accuracy of incoming solar energy forecasting
[7]	2019	Sustainability perspectives- a review for solar photovoltaic trends and growth opportunities
[8]	2019	Clear sky solar irradiance models: A review of seventy models
[9]	2020	Advanced Methods for photovoltaic output power forecasting: A review
[10]	2020	A comprehensive review of hybrid models for solar radiation forecasting
[11]	2020	Solar irradiance measurement instrumentation and power solar generation forecasting based on Artificial Neural Networks (ANN): A review of five years research trend

Based on the above ground, this paper provides a review of various popular error measures for the case of solar forecasting/ PV forecasting. This paper discusses the different error measures used in deterministic as well as probabilistic forecasting. The critical findings from various studies about the error measures are thoroughly discussed in the presented manuscript.

This paper is organized is as follows: section 2 discusses the different error measures for the deterministic and probabilistic solar forecasting. Section 3 provides the critical analysis of the error measures used by recent studies. The key findings are also discussed in this section. Section 4 presents some cautions about referring the previous work and section 5 conclude the paper.

II. Error Measures

By examining the recent literature of solar forecasting, the numerous error measures have been obtained. All the measures can be categories for the type of forecasting: deterministic solar forecasting and probabilistic solar forecasting. Fig. 1 shows the two types of solar forecasting along with their respective error measures.

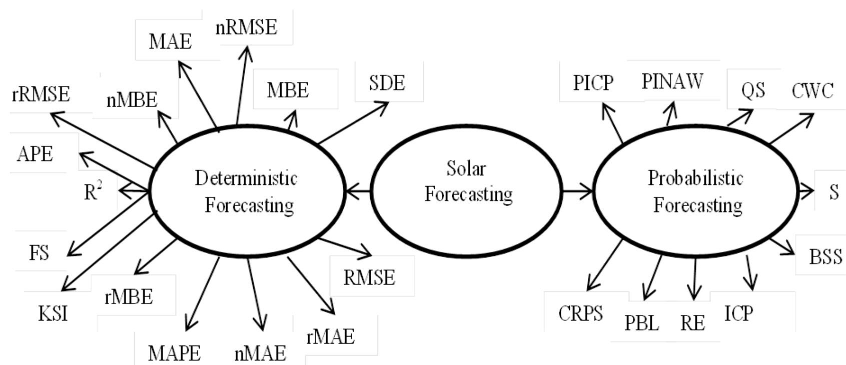

Fig.1. Different errors used in solar forecasting

A. Error Measures of deterministic forecasting

If M is the total samples of solar/ PV data series, F_t is the original solar/ PV series and $\widehat{F}_t$ is the forecasted solar /PV series at any time stamp t then error measures can be represented mathematically as [3]:

Mean Bias Error (MBE): MBE is used to calculate the average bias in the forecast.

$$MBE = \frac{1}{M}\sum_{t=1}^{M}(\widehat{F}_t - F_t) \tag{1}$$

The value of MBE in positive direction represents the overestimation by the SFM whereas, negative value represents the underestimation.

Mean Absolute Error (MAE): A uniform estimation of error is identified by this measure.

$$MAE = \frac{1}{M}\sum_{t=1}^{M}\left|\widehat{F}_t - F_t\right| \tag{2}$$

Standard Deviation Error (SDE): This measure used to estimate the deviations from the mean.

$$SDE = \sqrt{\frac{1}{M}\sum_{t=1}^{M}(\widehat{F}_t - F_t - MBE)^2} \tag{3}$$

Root Mean Square Error: It is one of the popular error measures used to evaluate the performance of SFM. This measure identifies the largest error in the forecasted sequence.

$$RMSE = \sqrt{\frac{1}{M}\sum_{t=1}^{M}\left(\widehat{F}_t - F_t\right)^2} \tag{4}$$

$$RMSE^2 = MBE^2 + SDE^2$$

Mean Absolute Percentage Error (MAPE): This is simply the representation of uniform error (MAE) in percentage form.

$$MAPE = \frac{1}{M}\sum_{t=1}^{M}\left|\frac{\widehat{F}_t - F_t}{F_t}\right| \tag{5}$$

Normalized RMSE: It is RMSE on a different scale. It can be calculated from RMSE of the forecasted output to the mean of forecasted data.

$$nRMSE = \frac{\sqrt{\frac{1}{M}\sum_{t=1}^{M}\left(\widehat{F}_t - F_t\right)^2}}{mean(\widehat{F}_t)} \tag{6}$$

Normalized MBE: It is MBE on a different scale. It can be calculated from MBE of the forecasted output to the mean of forecasted data.

$$nMBE = \frac{MBE}{mean(\widehat{F}_t)} \tag{7}$$

Normalized MAE: It is MAE on a different scale. It can be calculated from MAE of the forecasted output to the mean of forecasted data.

$$nMAE = \frac{MAE}{mean(\hat{F}_t)} \tag{8}$$

Forecast Skill: It is a unit less measure to evaluate the effectiveness of the SFM. It can be computed with reference to any benchmark model in term of RMSE, MAPE, and MAE etc.

For a case of RMSE, $FS = 1 - \frac{RMSE_{observed}}{RMSE_{ref}}$ (9)

Kolonogorov-Smirnov test Integral (KSI): It is another notable error measure in case of point or deterministic solar forecasting. Unlike other error measure, it compares the cumulative distribution function (CDF) of the forecasted series and the actual series. It can be represented as:

$$KSI = \int_{x_{\min}}^{x_{\max}} K_n dx \tag{10}$$

Where x_{min} & x_{max} are the minimum and maximum values from the forecasted data, K_n = Difference in the two CDFs.

A zero value of KSI interpreted as the equal CDF of both series.

Correlation Coefficient: It represents the strength in the linear relationship between the forecasted values and the observed values.

$$R = \frac{\sum_{t=0}^{M}\left(\hat{F}_t - avg(\hat{F}_t)\right)\left(F_t - avg(F_t)\right)}{\sqrt{\sum_{t=0}^{M}\left(\hat{F}_t - avg(\hat{F}_t)\right)^2}\sqrt{\sum_{t=0}^{M}\left(F_t - avg(F_t)\right)^2}} \tag{11}$$

Table II represents the different error measure applications by the various highly cited studies in the recent years to observe the performance of the SFM. The used measure is denoted by the symbol of tick against each paper. However, the Colum "other" comprises of small error measures like SDE, Bias, skewness, kurtosis etc.

TABLE II

ERROR MEASURES OF DETERMINISTIC SOLAR FORECASTING IN RECENT PUBLICATIONS

Ref.	YOP	RMSE	MAPE	MAE	MBE	nRMSE	nMAE	nMBE	FS	R^2	Others
[12]	2021					✓	✓	✓	✓		✓
[13]	2021	✓			✓				✓		
[14]	2021										
[15]	2021	✓		✓	✓				✓		
[16]	2021	✓		✓						✓	✓
[17]	2021	✓		✓					✓	✓	✓
[18]	2021	✓		✓						✓	
[19]	2021	✓		✓						✓	
[20]	2021	✓									✓
[21]	2021		✓								✓
[22]	2020	✓	✓		✓						
[23]	2020	✓		✓							✓
[24]	2020	✓								✓	
[25]	2020	✓	✓		✓						
[26]	2020	✓	✓			✓				✓	
[27]	2020	✓	✓							✓	
[28]	2020					✓	✓				
[29]	2020	✓		✓		✓	✓			✓	
[30]	2020	✓						✓		✓	
[31]	2020		✓			✓			✓		
[32]	2019	✓									
[33]	2019	✓		✓		✓	✓				
[34]	2019	✓	✓	✓							
[35]	2019	✓	✓	✓							
[36]	2019		✓								✓
[37]	2019					✓		✓	✓		
[38]	2019	✓								✓	
[39]	2019	✓		✓						✓	
[40]	2019	✓	✓	✓							✓
[41]	2019		✓	✓		✓	✓				✓

B. Error measures of probabilistic forecasting

Prediction interval nominal confidence (PINC): The prediction interval (PI) is one of the prime parameters in the probabilistic forecasting which depicts about the probability of lying forecasting values within any specified range. In parallel, the PI directly affected by the value of significance level α. So, PINC is the calculation of probability for the future value of solar output that falls within the PI.

$$PINC = 100(1-\alpha)\% \tag{12}$$

In addition, the PI for a time t and significance level α can be represented as:

$$P_t = U_t - L_t$$

where U_L & L_t are the upper and lower level of PI respectively.

Prediction interval coverage probability (PICP): it is used to evaluate the distributions of the forecasted values and can be expressed as:

$$PICP = \frac{1}{M}\sum_{t=0}^{n} C_t \tag{13}$$

where M is the total sample in the observations and C_t is

$$C_t = \begin{cases} 1, & if\ \hat{F}_t \in P_t \\ 0, & otherwise \end{cases}$$

Prediction interval normalized average width (PINAW):

$$PINAW = \frac{1}{MR}\sum_{t=0}^{n} P_t \tag{14}$$

where R is the range of observed values.

Coverage width-based criterion (CWC):

This measure used the values of PICP and PINAW to evaluate the SFM.

$$CWC = PINAW\left[1 + \beta(PICP)e^{-\gamma(PICP-\varepsilon)}\right] \tag{15}$$

where β (PICP) is a step function that can be represented as:

$$\beta(PICP) = \begin{cases} 0, & if\ PICP \geq \varepsilon \\ 1, & if\ PICP < \varepsilon \end{cases}$$

Continuous ranked probability score (CRPS): This is one of most widely used error measure in case of probabilistic forecasting. Like MAE in deterministic forecasting, it also generalizes in MAE for the probabilistic forecasting.

$$CRPS = \frac{1}{M}\sum_{t=0}^{M}\int_{0}^{P}\left(CDF_t - \eta\left(F_t - \hat{F}_t\right)\right)^2 dF \tag{16}$$

where η is the Heaviside step function represented as:

$$\eta = \begin{cases} 0 & if\ F_t < \hat{F}_t \\ 1 & otherwise \end{cases}$$

To analyze the popularity of each probabilistic error measure, table III has been prepared from the highly cited publication of recent years.

TABLE III
ERROR MEASURES OF PROBABILISTIC SOLAR FORECASTING IN RECENT PUBLICATIONS

Ref.	YOP	CRPS	RE	S	PICP	PINAW	BSS	CRPSS	QS	CWC	PBL	Other
[42]	2021	✓	✓		✓							✓
[43]	2021	✓	✓				✓	✓				
[44]	2021	✓						✓				
[45]	2021	✓						✓	✓			
[46]	2021				✓	✓						✓
[47]	2021	✓						✓				
[48]	2021	✓	✓	✓								
[49]	2020	✓			✓	✓						
[50]	2020	✓	✓	✓		✓						
[51]	2020			✓								✓
[52]	2020				✓	✓						
[53]	2020	✓					✓					✓
[54]	2020	✓	✓			✓		✓				✓
[55]	2020	✓				✓						
[56]	2020		✓		✓	✓		✓			✓	
[57]	2020	✓			✓			✓	✓			
[58]	2020	✓			✓	✓					✓	
[59]	2020		✓	✓							✓	
[60]	2020	✓						✓				
[61]	2020				✓	✓				✓		
[62]	2020				✓							✓
[63]	2020	✓	✓									
[64]	2019	✓				✓		✓				
[65]	2019					✓				✓		
[66]	2019	✓					✓					✓
[67]	2019											

In table III, each error measure according to their application in respective study is mark with the symbol "tick". The other matrices represent the average coverage error (ACE), barrier score (BS) etc. In addition, based on these references, the percentage share of each error metrices in deterministic and probabilistic forecasting is shown in fig. 2. It is evident from the fig. 2(a), RMSE has greatest share among all error metrices, represents the first choice of researchers to represents the forecasting accuracy of their models. Whereas, the MAPE & MAE scored with the same percentage. Similarly, as can be seen in fig. 2(b), the CRPS and PINAW are the mostly used error metrices for the evaluation of probabilistic forecasting.

III. CRITICAL REVIEW

This section provides the critical findings of the entire survey of the error measures. From the critical examinations of several measures, a question arises that what is the ideal error measure? Some studies suggested a measures, that are capable of interpret the results easily and sensitive to the outliers i.e., robustness. On the other hand, some have been suggested that the criteria of forecast evaluation must correspond to the criteria of forecast optimization. While some are in favour of the scale independent error measures. Therefore, the following are the critical observations on the popular error measure that have been used by most cited papers as mentioned in table II & III.

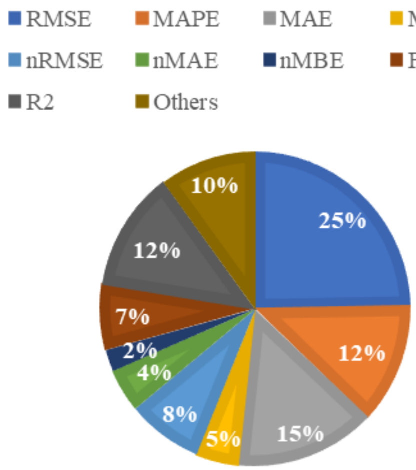

Fig. 2 (a) Percentage share of different error metrices in deterministic forecasting.

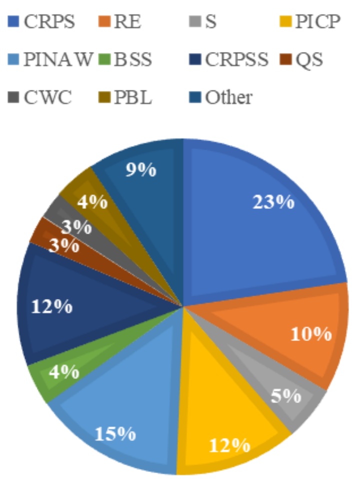

Fig. 2 (b) Percentage share of different error metrices in probabilistic forecasting.

A. Key findings: Deterministic forecasting

It is apparent from table II and fig. 2 (a), the RMSE is most popular and common error measure used to evaluate the SFM. It is widely used to observe the model performance in case of determining solar forecast. It is due to the fact that the largest errors in the solar forecasting are highly undesirable. RMSE penalize the model performance for the highest errors present in the final results [11].

MAE and MBE are the second most widely used error measure after RMSE for the evaluation of SFM. However, they are scale dependent measures and can show biased results for different scales. These error measures are only useful in case where the results achieve the Gaussian distribution [69].

MAPE is a highly unsuitable error measure for examination of the accuracy of the SFM. The results of this measure are highly affected by skewed and diffused distributions. The interpretation of MAPE results also becomes inefficient in large skewed distributions due to the high influence of outliers. Moreover, the MAPE penalizes the positive values of error instead of negative values which also leads to biased results [3]. However, many of the authors mentioned in table 2 used this measure to shows the average errors in percentage but statistically; it is a poor measure due to non-symmetric losses and extreme percentages.

MASE is used to overcome the problem of MAPE, MASE is considered to evaluate the performance of a SFM. It is another MAE but scaled by the MAE of benchmark/ reference model [11]. However, MAAPE; another version of MAPE is uncommon in the literature of solar forecasting but also used by some of the potential studies [70]. It transforms the MAPE into MAAPE measure using the arctangent function. This measure not only removes the shortcomings of the MAPE but also preserve the original characteristics of the MAPE. Therefore, MAAPE could be a good statistical error measure for observing the performance of SFM instead of MAPE.

KSI is another notable error measure to evaluate the accuracy of the point forecast of solar irradiance. This measure never compares the forecasted values of a SFM to its respective actual values as in other measures. Instead, a gathering of forecast distribution of the SFM makes it more popular. Furthermore, it is popularly used in the case of time series-based forecasting where its emphasis is on the variability of forecasted values with respect to actual values. In other words, by using this error measure, the lesser variability in the forecast can be detected by obtaining the larger value of KSI [11].

B. Key findings: Probabilistic forecasting

Apart from point forecast, probabilistic forecast produces highly satisfactory results in solar forecasting. Point forecast provides a fixed forecast at a specific interval of time. Whereas, probabilistic forecast provides the detail of uncertainty in forecasted results using a range of expectations in terms of prediction interval (PI), where the forecast value will fall. In other words, PI forecasting generates to achieve a density function of the desired value.

PICP, PINAW are the two most commonly used parameters to observe the reliability of a PI. However, PICP determines the probability of the forecast fall within the range. In parallel, PINAW refers to the width of the PI. Therefore, these two are conflicting measures as both are required either high or low in a good forecast [42]. Another most common measures in probabilistic forecasting are CWC, which is the combination of PICP and PINAW. The main point in the CWC is that it penalizes the invalid PIs which indirectly enforce the good forecast to achieve valid PICP. Lastly, CRPS is global measure in the probabilistic forecasting and can be understood as MAE in deterministic forecasting. Unlike other metrics, the CRPS is calculated by determining the cumulative distribution function (CDF) of the forecast. So, probabilistic forecasting is, however, a better forecasting method but observed lesser work on it compared to deterministic forecasting.

IV. Cautions

While working with solar forecasting, either in deterministic forecasting or probabilistic forecast, it is necessary to use the terms cautiously. With the huge literature on deterministic forecasting, many of the studies altered the universal naming conventions as well as used different acronyms for a known error measure. For instance, Gueymard et al. (2014) obtained the percentage value of RMSE, MAE and MBE but the acronyms of error metrics were not changed [68]. Likewise, the word "deviation" was used many times instead of the actual word "error". Moreover, a normalization of any error measure can be obtained by dividing the mean of the sample. But sometimes, to represents the lesser values of normalized error measures, studies divided it by the maximum value from the sample [69].

V. CONCLUSION

While developing a solar forecasting model, a clear understanding of the error measures is highly desirable. Since, an unclear and inappropriate selection of the error measure leads to a different conclusion. This paper is designed with an aim to present a clear representation of different error measures of deterministic and probabilistic forecasting in solar/ PV forecasting. Various key findings are obtained from the highly cited studies of the latest literature. From this study of highly cited papers from latest literature (year 2021-2019), it is found that the RMSE, MAE, MAPE and R^2 are the most common error metrics in deterministic forecasting with the 25%, 15%, 12% and 12 % respectively. On the other hand, CRPS, PINAW, PICP and RE are the most common error metrics in probabilistic forecasting with 23%, 15%, 12% and 10% respectively share among all. Conclusively, it is observed that the performance of a solar forecasting model is highly dependent on the type of geographical area as well as the type of weather. Therefore, a scale-dependent error measure like "forecast skill" is advised to compare the performance of the different models for different datasets. Therefore, for a solar forecasting model, the discussed error measures are recommended in practice. However, for a future prospectus, a new error measure can be developed with the characteristics of scale independence and free from bias.

ABBREVIATIONS

APE: Absolute percentage error; BSS: Brier skill score; CRPS: Continuous ranked probability score; CWC: Coverage width-based criterion; FS: Forecast skill; ICP: Interval coverage probability; KSI: Kolonogorov-Smirnov test Integral; MAE: Mean absolute error; MAPE; Mean absolute percentage error; MBE: Mean bias error; PINAW: Prediction interval normalized average width; PICP: Prediction interval coverage probability; PINC: Prediction interval nominal confidence; QS: Quantile score; RMSE: Root mean square error; rMAE: relative mean absolute error; rMBE: Relative mean bias error; rRMSE: relative root mean square error; R2: Coefficient of determination; RE: reliability; S: sensitivity; SDE: standard deviation error;

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