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Dynamic mean absolute error as new measure for assessing forecasting errors

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ABSTRACT

Accurate wind power forecast is essential for grid integration, system planning, and electricity trading in certain electricity markets. Therefore, analyzing prediction errors is a critical task that allows a comparison of prediction models and the selection of the most suitable model. In this work, the temporal error and absolute magnitude error are simultaneously considered to assess the forecast error. The trade-off between both types of errors is computed, analyzed, and interpreted. Moreover, a new index, the dynamic mean absolute error, *DMAE*, is defined to measure the prediction accuracy. This index accounts for both error components: temporal and absolute. Real cases of wind energy forecasting are used to illustrate the use of the new *DMAE* index and show the advantages of this new index over other error indices.

1. Introduction.

Renewable energy provides valuable benefits to the economy, public health, and the environment. The need to reduce CO_2 to mitigate global warming has resulted in the increasing use of renewable energy sources worldwide. Fig. 1 illustrates this situation in the case of Spain where, on average, more than one third of the electricity is produced by renewable sources. Therefore, having accurate wind power forecasts is essential for grid integration, system planning, and electricity trading in certain electricity markets. Consequently, analysing prediction errors is a critical task that will allow a comparison of prediction models and the selection of the most suitable model.

Wind has been the largest contributor to the growth of renewable energy during the early 21st century. In recent years, there has been rapid growth in wind electricity generation, and it is expected to account for a larger percentage of the generation mix in the next few decades [1,2]. However, this growing share in the energy mix produces difficulties in the management of the entire energy system and induces instability in electricity prices. Management problems arise from the inherent variability in the wind speed, which results in a fluctuating source of electrical energy. Problems are caused not only by this variability, but also by the inaccuracies in wind speed forecasting. Wind speed forecasting errors make it difficult to match the production to the demand and specify the participation of renewable companies in the electricity markets. Specifically, in the day-ahead electricity market, the suppliers of energy must declare the amount of energy that they are selling in each of the 24 h of the following day (see [3]). In the case of wind energy companies, these commitments of energy are made based on wind speed forecasts. Thus, errors in these will negatively impact the companys revenue because of penalties that must be paid when commitments are not fulfilled and the final electricity price, which can increase because of using more expensive and short-term alternate sources of energy to compensate for the shortages.

Therefore, having accurate wind power forecasts is essential for grid integration, system planning, and electricity trading in certain electricity markets. Consequently, analysing prediction errors is a critical task that will allow a comparison of prediction models and the selection of the most suitable model. In addition, a deeper knowledge of the nature of prediction errors will be very helpful to improve the quality of forecasting models and increase the economic benefits obtained by decision makers using appropriate forecasting methods.

There are many statistical indices to measure the difference between two time series that are used by scientists and engineers to assess the quality of forecasting methods, including the mean absolute error (*MAE*), root mean squared error (*RMSE*), mean squared error (*MSE*), standard deviation of error (*SDE*) and corresponding normalised estimates using the installed capacity of each wind farm. The book Forecast verification: a practitioners guide in atmospheric science, edited by Jolliffe and Stephenson [4], is an indispensable reference in forecast verification, providing a review of a wide range of forecast verification

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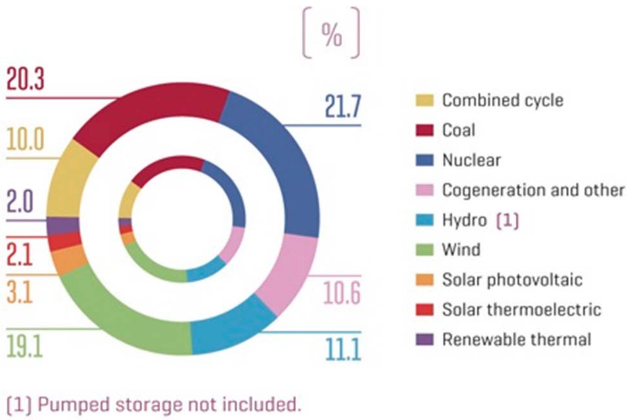

Fig. 1. Annual peninsular demand coverage for 2015 [3].

methods currently being employed in weather and climate forecasting centres. Madsen et al. [5,6] introduced a standardised protocol consisting of a set of criteria for the evaluation of short-term wind power prediction systems. These authors explained certain problems associated with the standard use of some of the usual statistics, and introduced a set of reference predictors such as persistence, the global mean, and a new reference model. This work was conducted within the framework of the European R&D project Anemos. The protocol was used to evaluate more than ten prediction systems [7]. Marti et al. [8], which was also part of Anemos, presented a comparison of nine of the most common power prediction models. This protocol, which is currently the most popular for the assessment of forecasting methods, does not consider any temporal component of error. Numerous recent studies have aimed at developing new forecasting systems for renewable sources e.g., a system based on series decomposition and support vector machines to obtain short-term wind energy forecasts [9], a short-term model based on Markov chains [10], different approaches based on neural networks [11,12], a combination of neural networks and wavelet decomposition [13], and autoregressive models [14]. However, in all these cases, only classic deviation measurements and their relative versions are used to assess the performance.

Tascikaraoglu et al. [15] presented a wind prediction model that includes spatio-temporal information when making forecasts. However, their validation procedure only used classic measurements. Giorgi et al. [16] compared the cumulative distribution functions of wind measurement and forecasts. Different probability distributions have been considered in the literature to model the distribution of wind power forecast errors, including hyperbolic [17,18], normal [19,20], Weibull [21], and beta [22] distributions, as well as kernel density estimation (KDE) [23]. All these indices and error analyses were based on the differences between the forecast series and true series at the same moments in time. None of them considered forecast failures due to mismatches in the time index. As a simple and clarifying example, consider Fig. 2, where the forecast series perfectly matches the true series, but has a one and a half hour lag. Forecasting the variability of the true series using a constant value (the blue[1] line in Fig. 3) can produce similar or better values for traditional indices such as MAE.

This artificial situation occurs with real forecasting methods as shown in Fig. 4, where temporal mismatches between the forecast series and true series are appreciated: some events such as the beginning of a production peak are forecast slightly soon or late, or the duration is over- or underestimated.

This paper considers the assessment of forecasting methods for renewable energy using a unique index, the dynamic mean absolute error

[1] For interpretation of color in 'Figs. 3, 6, 17, and 18', the reader is referred to the web version of this article.

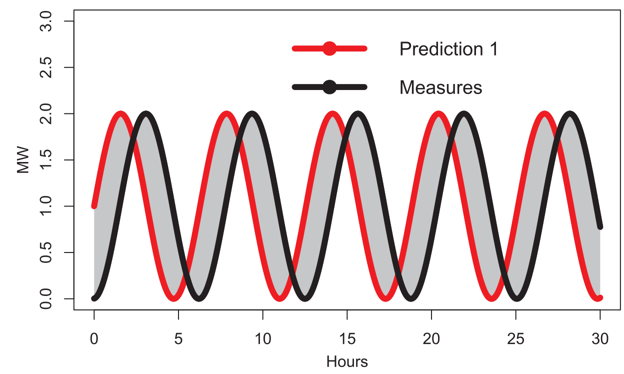

Fig. 2. Synthetic example 1.

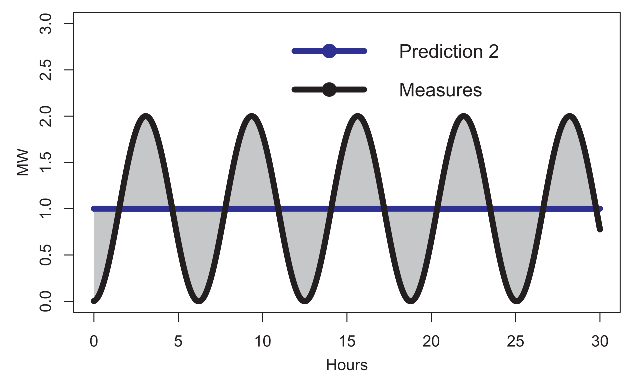

Fig. 3. Synthetic example 2.

(*DMAE*), which accounts for both the temporal error and absolute magnitude error. The definition of this new index is founded on the theoretical developments of [24,25], where a methodology to match two time series by transforming the time axis was introduced. The optimal alignment of both series is made under the criterion of minimising the *MAE* between the aligned series (the one resulting from the transformation of the temporal axis of the forecast series) and the reference one. The amount of change made in the time index to align both series is measured using the temporal distortion index (*TDI*). After the temporal dimension of the forecasting error is introduced, the error assessment problem becomes a bi-objective problem where both error criteria are simultaneously considered, with a greater temporal distortion for matching the series associated with a smaller MAE between the transformed and true series. The level of allowed temporal distortion to align the series can be controlled by a parameter. The *DMAE* index introduced in this paper accounts for both components of the error (temporal and absolute), becoming the only index to measure errors with such characteristics defined in the specialised literature. In summary, the novelties of this paper are as follows:

- The temporal error and absolute magnitude error are considered simultaneously to assess the forecast error, and the trade-off between them is computed, analysed, and interpreted.
- A new index (*DMAE*) is defined to measure the prediction accuracy, which accounts for both error components (temporal and absolute), and the properties of *DMAE* are presented.
- Real wind energy forecast cases are used to illustrate the use of the new index (DMAE), and its advantages compared to other error indexes are shown.

The paper is organised as follows. Section 2 presents a summary of the concepts and methodological results needed to assess the temporal prediction errors, which are the basis for the new developments shown in this work. In Section 3, the trade-off between the temporal and