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Advances in the Temporal Distortion Index and their use to analyze and compare wind energy forecasts models

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ABSTRACT

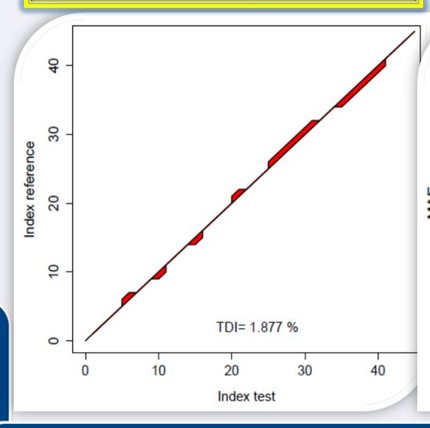
Wind has been the largest contributor to the growth of renewal energy during the early 21st century. However, the natural uncertainty that arises in assessing the wind resource implies the occurrence of wind power forecasting errors which perform a considerable role in the impacts and costs in the wind energy integration and its commercialization. The main goal of this work is to provide a deeper insight in the analysis of timing errors which leads to the proposal of a new methodology for its control and measure. A new methodology, based on Dynamic Time Warping, is proposed to be considered in the estimation of accuracy as attribute of forecast quality. A new dissimilarity measure, the Temporal Distortion Index, among time series is introduced to complement the traditional verification measures found in the literature. Besides a set of new families of the basic functions of the Dinamic Time Warping has been defined. This functions are defined to be more efficient in the case of wind energy series. Furthermore we provide a bi-criteria perspective to the problem of comparing different forecasts.

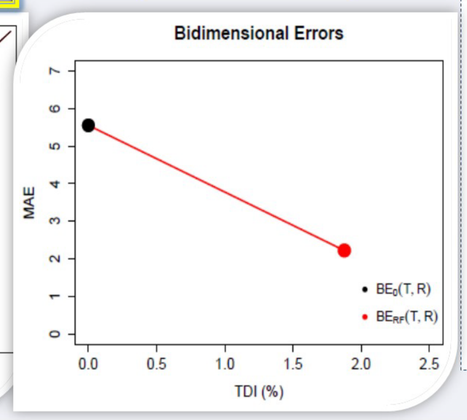
$$P_l = \int_{i_l}^{i_{l+1}} \left(x - \frac{(x-i_l)(j_{l+1}-j_l)}{(i_{l+1}-i_l)} + j_l\right) dx$$

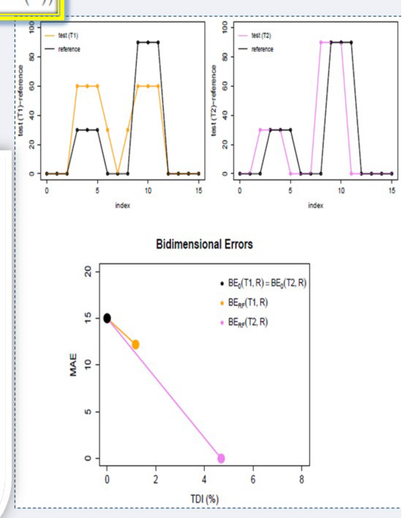
$$TDI = \frac{2\sum_{l=1}^{k-1}|P_l|}{N^2}$$

$$BE_{RF}(T,R) = (TDI, MAE(S))_{RF} \quad BE_0(T,R) = (0, MAE(T))$$

$$MAE(S) = \sum_{i=1}^{N} \frac{|S_i - R_i|}{N}$$







CONTROL AND MEASUREMENT OF THE TIMING ERROR COMPONENT. Methodology to obtain the bi-dimensional measure for the forecast error assessment: AN ILLUSTRATIVE EXAMPLE

We work with two time series, the test (or query) series T = (T1,T2,…,TN) and the reference series R =(R1,R2,...,RM)

1 As first step, we define the local distance between pairs of elements T_i and R_j as a non-negative function $f : \Phi \times \Phi \longrightarrow \mathbb{R}_{\geq 0}$:

$$f(T_i, R_j) = d(T_i, R_j) = d_{ij} = \|T_i - R_j\| \geq 0$$

The DTW algorithm begins by the setting-up of a matrix of local distances ($d \in \mathbb{R}^{N \times N}$) -called Local Cost Matrix- that contains all pairs of corresponding distances between both series.

2 Once the Local Cost Matrix is defined the concept of path between series is introduced as a sequence of points $w = (w_1 = (i_1, j_1), w_2 = (i_2, j_2), \ldots, w_l = (i_l, j_l), \ldots, w_k = (i_k, j_k))$ $k \in \mathbb{N}$, where $w_l = (i_l, j_l) \in [1:N] \times [1:N]$ for $l \in [1:k]$ under the following restrictions:

- Boundary conditions: $w_1 = (1,1)$ and $w_k = (N,N)$. This condition requires that the path must begin and end on the first and last points, respectively, of the sequences.
- Monotonicity condition: Given $w_l = (i_l, j_l)$ then $w_{l-1} = (i_{l-1}, j_{l-1})$ being $i_l - i_{l-1} \geq 0$ and $j_l - j_{l-1} \geq 0$. This condition ensures that through the path the points are sorted according to time.
- Condition of continuity or step size: Given $w_l = (i_l, j_l)$ then $w_{l-1} = (i_{l-1}, j_{l-1})$ being $i_l - i_{l-1} \leq 1$ and $j_l - j_{l-1} \leq 1$. This condition ensures that the path does not present big jumps, even more, it is restricted to neighbouring points.

3 Now, the total cost associated to a path w between series T and R, with respect to its local distance, is identified by $c_w(T,R)$ and is calculated with the next expression: $c_w(T,R) := \sum_{l=1}^{k} d(T_{i_l}, R_{j_l})$ *where* $(i_l, j_l) = w_l$

4 Accordingly, an optimal path between the series T and R is a path w^* that presents a minimum total cost taking into account all the possible paths:

$$c_{w^*}(T,R) = min\{c_w(T,R) \mid w \text{ is a path}\}$$

5 The optimal path w^* is obtained by using dynamic programming. Dynamic programming (DP) is a procedure that solves optimization problems by breaking them down into simpler problems.

We identify the sequences $T(1:i) := (T_1, T_2, \ldots, T_i)$ where $i \in [1:N]$ and $R(1:j) := (R_1, R_2, \ldots, R_j)$ where $j \in [1:N]$ and we define:

$$D(i,j) = c_{w^*}(T(1:i), R(1:j))$$

Then, $D(i,j)$ express the cost associated to the best path matching the series $(T_1, T_2, ...T_i)$ and $(R_1, R_2, ..., R_j)$. So, the values $D(i,j)$ define a matrix $D \in \mathbb{R}^{N \times N}$ which is refereed by the name of accumulated cost matrix (Cost Matrix). Clearly $D(N,N) = c^*_w(T,R)$.

Taking into account the constraints cited in the path definition, the calculation of the Cost Matrix elements can be automatized using dynamic programming by means of the following recursive formula:

$$D(i,j) = min \begin{cases} D(i\text{-}1,j) + d(i,j) \equiv \text{Branch (1)} \\ D(i,j\text{-}1) + d(i,j) \equiv \text{Branch (2)} \\ \underbrace{D(i-1,j-1)}_{\text{Cumulative Cost}} + \underbrace{d(i,j)}_{\text{Actual Cost}} \equiv \text{Branch (3)} \end{cases}$$

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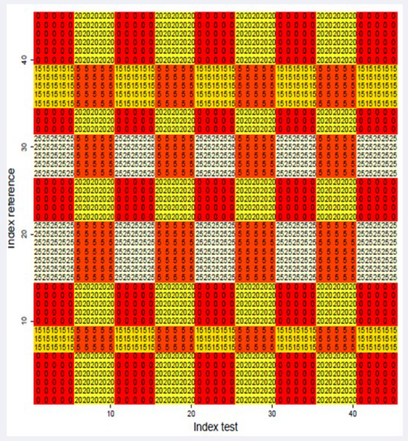
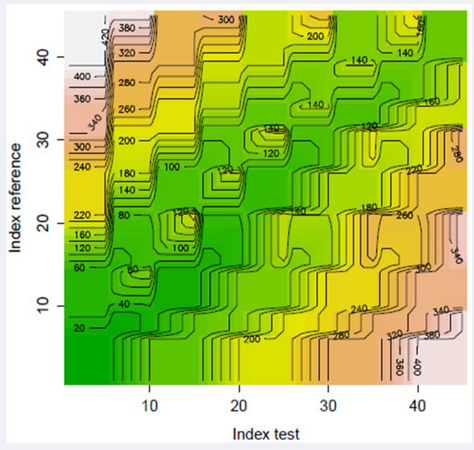
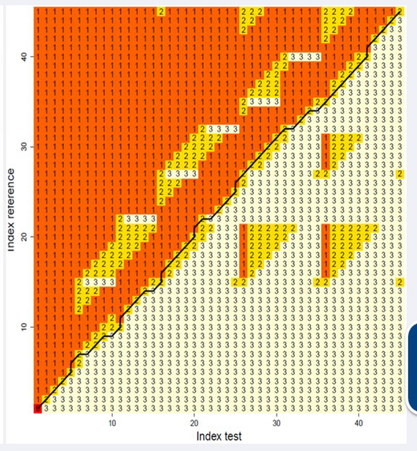
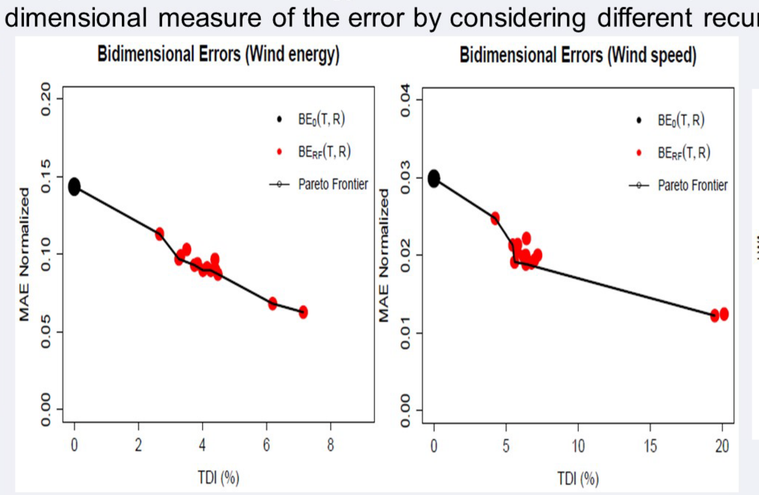


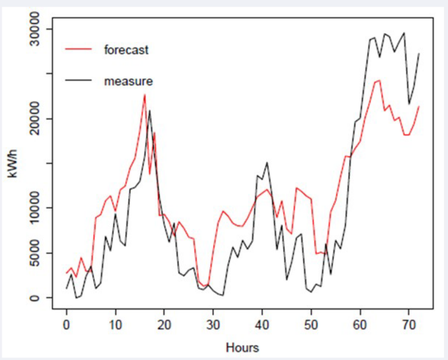




Bidimensional error measurement: a real case

In this section we test the methodology by using real data series: a real wind energy series is compared with a wind energy forecast. Furthermore, we provide a deeper insight in the bi-dimensional measure of the error by considering different recursive formulas.

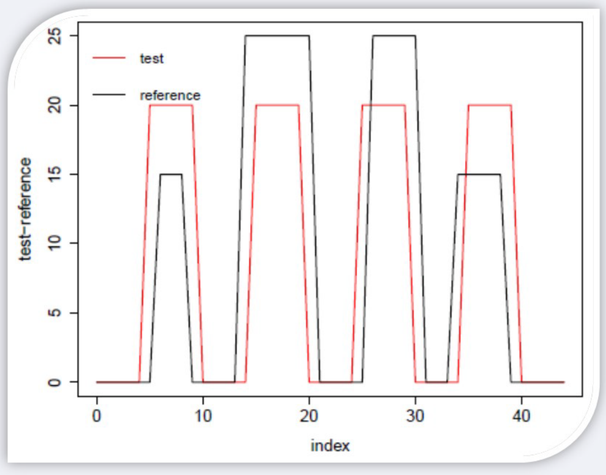


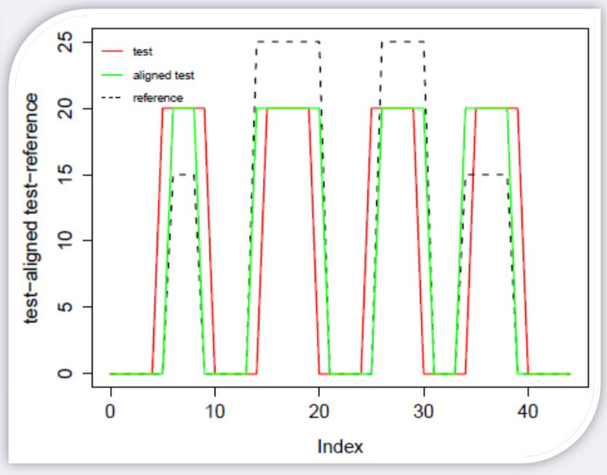


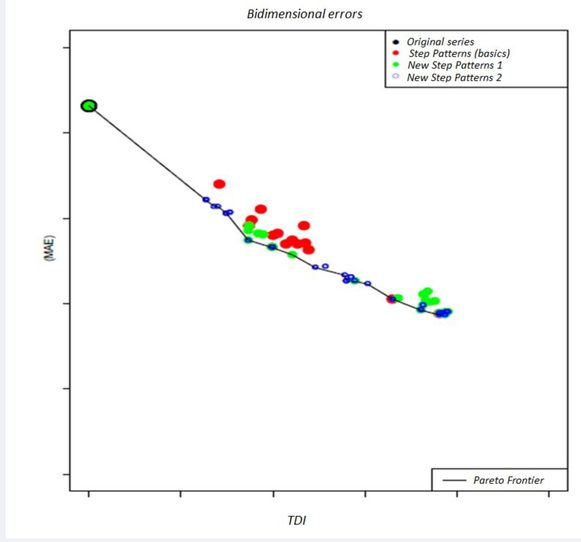
To illustrate this behavior we have considered a set of recursive formula that differ among them in amplitude of the allowed steps as well as in the weighs assigned to different movements. In general, it is observed that an increase in the temporal error is accompanied by a reduction in the static error, although it is not always the case: there is some recursive formula providing a better value for both components of the error than other ones. In these cases we can discard the dominated recursive formula and only keep to the error analysis the non-dominated ones. In this way a Pareto Frontier [5] is obtained. This Pareto Frontier better characterizes the error in the forecast than only one value or pair of values. Nevertheless, in order to simplify the assessment of forecast errors and for ease the comparison between different methods one or few representative points should be selected. More precisely, in the plot of the Pareto Frontier the first error assessment will reduce much static error but at some point the marginal gain will drop, giving an angle in the graph. A representative bidimensional error assessment should be chosen at this zone, and hence the "elbow criterion".

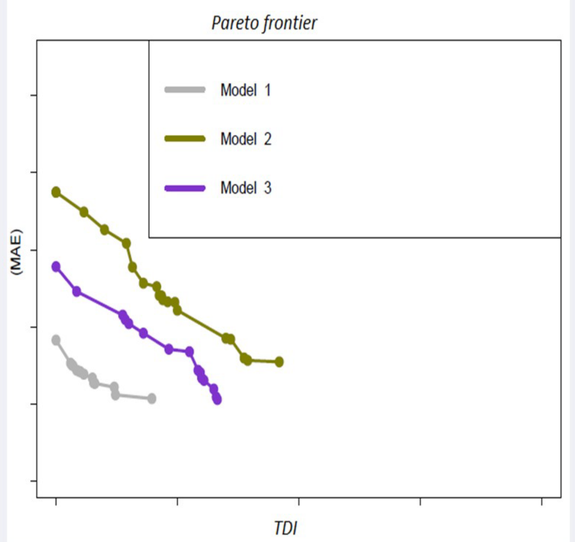
DEFINING NEW FAMILIES OF RECURSIVE FORMULAS:

PREDICTION MODEL COMPARISIONS:









The test series is transformed, using the optimal path, in a new series called aligned series and denoted by S = (S1,S2,…,SN) ,with a smaller vertical difference to the reference series than the test series.
The resulting aligned series is the one, among all those series associated to an optimal path, providing a minor temporal misalignment of the test series. Equivalently, the aligned series is the one whose associated optimal path is the closest to the identity path.

Hence, a global measure of the temporal distortion carried out in the test series, in order to obtain the aligned series, is provided by the area between the resulting optimal path and the identity path, which is denoted by TDI (Temporal Distortion Index). So, this parameter will serve to describe the temporal component of the error:

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