Wind Prediction Enhancement by Supplementing Measurements with Numerical Weather Prediction Now-Casts

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Abstract **– This paper explores how the accuracy of short-term prediction of wind speed and direction can be enhanced by considering additional spatial measurements. To achieve this, two different data sets have been used: (i) wind speed and direction measurements taken over 23 Met Office weather stations distributed across the UK, and (ii) outputs from the Consortium for Small-scale Modelling (COSMO) numerical weather model on a grid of points covering the UK and the surrounding sea. A multivariate complex valued adaptive prediction filter is applied to these data. The study provides an assessment of how well the proposed model can predict the data one hour ahead and what improvements can be accomplished by using additional data from the COSMO model.**

I. INTRODUCTION

THE growth of wind power requires improvements in short-term wind forecast at wind energy sites. As the wind penetration becomes more and more important in the national grids, the accuracy of the wind farms' power output is of fundamental importance for power system operators and for trading on the energy market. The reliability and stability of power systems are decreased, and the operational costs increased, by the high uncertainty in wind. Therefore, it is essential to improve wind prediction at wind farms sites [4], [5] particularly for short forecast periods.

In literature, several different methods have been used to reduce the uncertainty in the forecast of wind speed and direction. Numerical Weather Prediction (NWP) models are mathematical models of the atmosphere and oceans that use current weather observations as inputs. Although these models have a good performance in forecasting the wind speed, their computational time is highly demanding and therefore they are run typically only every six hours. Hence, as NWP models do not provide hourly wind forecasts, many study in recent years have focused their attention to the problem. In order to achieve hourly wind prediction, statistical methods have been employed that do not require long running time and expert knowledge to be used. Moreover, the spatial resolution of NWP is such that a statistical method based on measurements at the site of interest would still out perform the NWP if it could be run quickly.

In previous works, it has been considered the spatio-temporal prediction of wind speed and direction by means of linear complex valued prediction filters [2], [3]. In this paper, it is investigated how the accuracy of temporal prediction can be enhanced by considering additional spatial measurements.

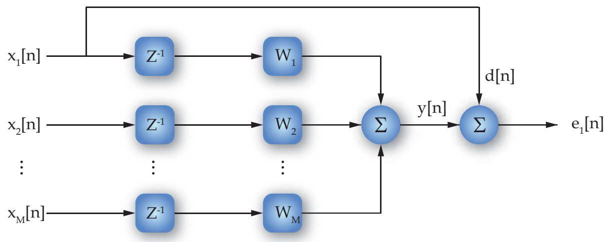

Fig. 1: Multi-channel filter.

II. SPATIO-TEMPORAL PREDICTION

A. Complex Multichannel Data

This study uses hourly mean time series of wind speed and direction measured in M geographically separate sites. These time series are converted in complex-valued vector time series $x_m[n] \in \mathbb{C}$, $m = 1 \ldots M$, where the wind speed is the magnitude of the complex variable, the wind direction is the phase, and n is a discrete time index. Moreover, the mean of the time series is calculated and removed to create zero-mean signals.

Using the expectation operator $\mathscr{E}\{\cdot\}$, the cross-covariance of the data is given by $r_{x_ix_j}[\tau] = \mathscr{E}\{x_i[n]x_j^*[n-\tau]\}$, $i, j = 1 \ldots M$, which for $i = j$ provides the special case of the covariance for site i. From the values of $r_{x_ix_j}[\tau]$, a covariance matrix $\mathbf{R}$ and $\mathbf{p}_m$ will be defined later. For simplicity, it will be assumed a stationarity model so that the covariance matrix will depend only on the lag time τ.

B. Minimum Mean Square Error Prediction

To predict the time series $x_m[n]$ at the m site at time index n, we utilised past measurements from this site and other sites, whereby $m = 1 \ldots M$, with M the total number of sites available. The structure of the predictor, exemplary for $m = 1$, is shown in Figure 1, representing an M channel linear predictor with prediction coefficients $\mathbf{w}_{1,m} \in \mathbb{C}^N$, where N is the temporal window over which prediction is performed. A tap delay line vector

$$\mathbf{x}_m[n] = \begin{bmatrix} x_m[n] \\ x_m[n-1] \\ \vdots \\ x_m[n-L+1] \end{bmatrix} \quad (1)$$

holds this data window at the mth site during iteration n.

The adjustment of the coefficients $\mathbf{w}_{i,m} \in \mathbb{C}^N$, $i, m = 1 \ldots M$ is performed such that the prediction error

$$e_m[n] = d_m[n] - \sum_{i=1}^{M} \mathbf{w}_{i,m}\mathbf{x}_i[n] = d_m[n] - \mathbf{w}_m^{\mathrm{H}}\mathbf{x}[n] \quad (2)$$

with $d_m[n] = x_m[n+1]$ is minimised in the mean square error (MSE) sense, with the vectors $\mathbf{w}_m$ and $\mathbf{x}[n]$ formed from concatenations of $\mathbf{w}_{i,m}$ and $\mathbf{x}_i[n]$, $i = 1 \ldots M$, such that

$$\mathbf{x}[n] = \begin{bmatrix} \mathbf{x}_1[n] \\ \mathbf{x}_2[n] \\ \vdots \\ \mathbf{x}_M[n] \end{bmatrix}, \qquad \mathbf{w}_m[n] = \begin{bmatrix} \mathbf{w}_{1,m}[n] \\ \mathbf{w}_{2,m}[n] \\ \vdots \\ \mathbf{w}_{M,m}[n] \end{bmatrix} . \quad (3)$$

contain all measurement time series and filter coefficients, respectively.

The MSE of the prediction error $e_m[n]$ is given by

$$\begin{aligned} \xi_m &= \mathscr{E}\{e_m[n]e_m^*[n]\} & (4) \\ &= \sigma_{x_m}^2 - \mathbf{w}_m^{\mathrm{H}}\mathbf{p}_m - \mathbf{p}_m^{\mathrm{H}}\mathbf{w}_m - \mathbf{w}_m^{\mathrm{H}}\mathbf{R}\mathbf{w}_m \quad . & (5) \end{aligned}$$

By minimising the mean-squared error the result

$$\mathbf{w}_{m,\mathrm{opt}} = \mathbf{R}^{-1}\mathbf{p}_m, \quad (6)$$

is known as the Wiener-Hopf solution [2], [7], where $\mathbf{R} = \mathscr{E}\{\mathbf{x}[n]\mathbf{x}^{\mathrm{H}}[n]\}$ is the covariance matrix of the data, and $\mathbf{p}_m = \mathscr{E}\{d_m[n]\mathbf{x}^*[n]\}$ the cross-covariance vector between the desired signal $d_m[n]$ for site m and the data vector. Its minimum value for the MSE in (5) can be calculated by inserting (6),

$$\xi_{m,\min} = \sigma_{x_m}^2 - \mathbf{p}_m^{\mathrm{H}}\mathbf{R}^{-1}\mathbf{p}_m \quad . \quad (7)$$

Therefore, the prediction is made by using N previous values of the M time series that are weighted by the optimal coefficients, $\mathbf{w}_{m,\mathrm{opt}}$, with the objective to minimise the MSE of the forecast at site m, $m = 1 \ldots M$.

C. Thinning of the Predictor

In order to investigate which of the remaining $M-1$ sites have the greater contribution on the wind forecast for a target site m, the aim is to create a sparse prediction filter combining only dominant contributions. The effect of not taking particular spatial/temporal information into account can be investigated based on reduced or thinned versions of the covariance matrix and cross-correlation vector in (6)

Thinning of $\mathbf{R}$ and $\mathbf{p}_m$ has been computed by removing a tap at position k, $k \in [1; K]$ and discarding the appropriate entries from $\mathbf{R}$ and $\mathbf{p}_m$ using a matrix

$$\mathbf{V}_{K,k} = \begin{bmatrix} \mathbf{I}_{k-1} & \underline{0} & \mathbf{0} \\ \mathbf{0} & \underline{0} & \mathbf{I}_{K-k} \end{bmatrix} \in \mathbb{Z}^{(K-1)\times K} \quad . \quad (8)$$

Thinning is applied recursively to eliminate an increasing number of coefficient. Generally, at the ith iteration the coefficient is removed that minimises the minimum mean-squared error (MMSE). At each iteration the MMSE is calculated, and the removed coefficient is noted. Therefore, after L iterations, only $MN - L$ dominant coefficient remain.

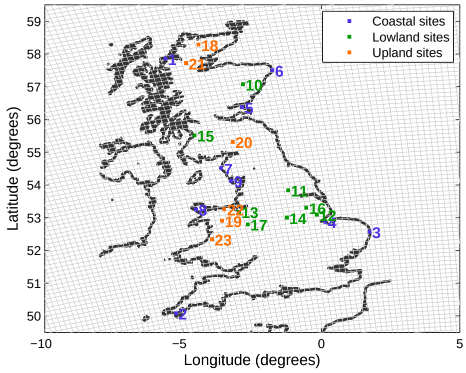

Fig. 2: Map of the Met Office sites overlapping the COSMO model grid.

III. WIND DATA

For this study, two different type of data set have been used to test the prediction filter, which are described below.

A. Met Office Data

The British Atmospheric Data Centre [6] provided the Met Office Integrated Data Archive System (MIDAS) set of onshore weather data from 37 weather stations across the UK, from which a selection of 23 sites with at least 98% of good data has been made shown in Figure 2. The observations are taken at 10m from ground and provide wind speed [knots] and direction [deg] sampled every hour. The time window chosen for this study is of two years, starting from 00:00h on 1/01/2006 to 23:00h on 31/12/2007.

B. COSMO Model Data

The Consortium for Small-scale Modelling (COSMO) [1] has developed a non-hydrostatic limited-area atmospheric prediction model. The data provided are the zonal and meridional wind speeds [m/s], u and v respectively, at 10m above ground and Figure 2 shows the area covered by the model grid points. The resolution of the data is of 0.1deg; the original resolution of the model has been reduced. For the purpose of this study, data for the two years of interest, 2006 and 2007, have been selected and converted in to complex-valued time series.

IV. RESULTS

The algorithm has been tested on the MIDAS and COSMO data set. The filter coefficients have been calculated using the data from 2006 as training data, and then the prediction algorithm has been tested on the data from 2007.

A. Prediction Based on MIDAS Data Set

To analyse the spatial and temporal correlation between the different sites, the elements of the covariance matrix have been investigated. In figure 3, it is shown a colour plot of the covariance matrix for the 23 Met Office weather stations: on the main diagonal there are the covariance of each site and on the off-diagonal the cross-covariance between different

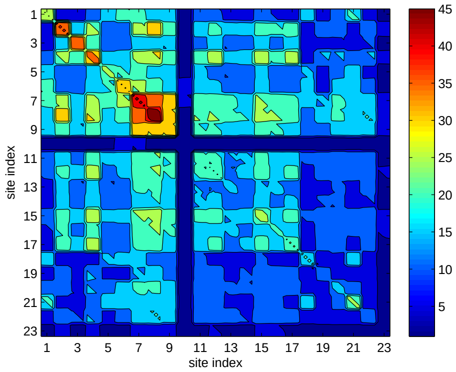

Fig. 3: Colour plot of the covariance matrix for the 23 Met Office weather stations.

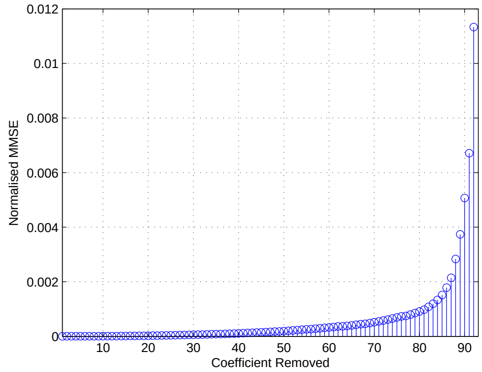

Fig. 4: Plot of the normalised MMSE for site 7 as a function of the removed coefficients from the covariance matrix.

Site 8 analysis:	Site 7 analysis:
Normalised MMSE: 0.0539	Normalised MMSE: 0.0664
site 8, lag 0: 99.4[%]	site 7, lag 0: 98.9[%]
including site 8, lag 2: 99.5[%]	including site 8, lag 0: 99.3[%]
including site 2, lag 0: 99.6[%]	including site 8, lag 3: 99.5[%]
including site 7, lag 0: 99.7[%]	including site 9, lag 0: 99.6[%]
including site 1, lag 0: 99.7[%]	including site 1, lag 0: 99.7[%]

TABLE I: Dominant coefficients that contribute to the MMSE for the prediction of sites 8 and 7.

sites. As evident from figure 3, some sites have a high cross-correlation; e.g. sites 7, 8 and 9 which are situated in the Gwynedd and Cumbria areas respectively. Whereas other wind measurements are poorly correlated together. In particular, sites 10 (in Aberdeenshire) and 23 (in Dyfed) have negligible variance with all the stations.

To investigate the contribution of each site to the prediction of one target site, the respective coefficients inside the covariance matrix have been removed one by one and the mean-squared error calculated at each step. Results from two interesting sites are shown in table I, where the MMSE obtained for the prediction of each site is reported together with the contribution to the MMSE from the first 5 more important sites. It is interesting to note that, for site 8, one important contribution appears to be from site 2 (situated on the coast of Cornwall, see figure 2) that is upstream to site 8. In fact, site 2 together with the target site 8 contribute more than 99% to the MMSE. Results for site 7 shows the correlation between sites 7, 8 and 9, as mentioned earlier. Considering the relative position of each weather station, it can be deduced that sites located upstream have the major impact on the prediction of the target site. This is confirmed by results in table I where sites 8 and 9 contribute up to 99.6% of the MMSE for the prediction at site 7.

Another interesting aspect to notice is that only few sites contribute to the MMSE, as evident from figure 4. The plot shows the contribution to the MMSE for the prediction at site 7; it is apparent that only the last coefficients have a significant impact on the error. Similar results are obtained for all the 23 MIDAS sites.

B. Prediction with Additional COSMO Data

The attention was focused on the analysis of only site 8. The procedure previously described has been carried out using other two data sets: one set considers only the measurements from the MIDAS site 8 (the target site) and the surrounding data from the COSMO model, and the other data set contains all the 23 MIDAS sites plus the COSMO data around site 8. The COSMO data have been selected considering the closest grid point to the target site and then selecting the data every 5 grid points from a 20x20 grid around it.

Table II shows the normalised minimum mean-squared error of the prediction for site 8. The MMSE previously obtained with all the MIDAS site was 0.0539 (see table **??**). It is evident that the addition of the COSMO data provides an improvement in the prediction, especially when added to all the MIDAS sites; where the MMSE is reduced by more than 8%.
In table II are also reported the first five more important contributions to the error from each site or COSMO grid point. It is evident that the most important contribution comes from the previous measurements of the target site. It is interesting to note that, when the COSMO data are added to the Met Office weather data, the next contributions come from neighbouring COSMO grid points instead of site 7 that is situated downstream to site 8. As expected, the COSMO grid points 44 and 46 are situated respectively south-west and south to site 8. This result suggests that depending on the position of the target site and the prevailing direction of weather systems, the contribution to the prediction can be improved by including only the appropriate data. When considering only the measurements from the site 8 and the COSMO data, the prediction error is the same as for the case with all 23 sites. From table II, it can be seen that the most important COSMO grid points are the closest one (grid point 13) and the one south to the target site.

C. Wind Forecast

Finally, the algorithm prediction has been tested for all the sites. It has to be noticed that, to avoid transient behaviours and problems in the prediction, it is necessary that the time series considered do not have missing data. For this purpose, a

MMSE contributions [%]
Prediction made with site 8 and COSMO data:
Normalised MMSE: 0.0530
site 8, lag 0: 99.3
including site 8, lag 1: 99.4
including COSMO grid point 13, lag 0: 99.4
including COSMO grid point 24, lag 0: 99.5
including COSMO grid point 9, lag 2: 99.6
Prediction made with all MIDAS Site and COSMO data:
Normalised MMSE: 0.0492
site 8, lag 0: 98.9
including site 8, lag 1: 99
including COSMO grid point 2, lag 0: 99.1
including COSMO grid point 44, lag 0: 99.1
including COSMO grid point 46, lag 0: 99.2

TABLE II: Dominant coefficients that contribute to the MMSE for the prediction of site 8 using 3 different data set.

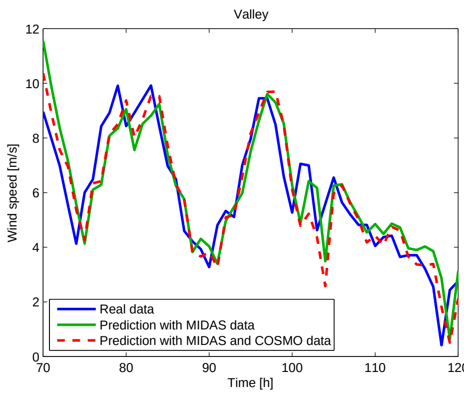

Fig. 5: Time series from site 8 (in blue), prediction with only MIDAS sites (in green) and COSMO data (in red). Zoom on the time window between hours 70 and 120

time window of 170 hours has been selected, from 8/02/2007 to 15/02/2007.

As an example, the forecast for site 8 is shown in figure 5, where a zoom in has been made for a better legibility. The prediction has been made in two different ways; the first method uses all the 23 Met Office sites, and the second technique considers additional COSMO model data to the wind measurements from MIDAS sites. To compare the two forecasts the root-mean-square error has been calculated. As confirmation of the previous results, the prediction made using additional COSMO data has a smaller error than the other; 1.89 and 1.94 respectively.

In general the COSMO data do help in the prediction of MIDAS site time series. However, it has to be mentioned that for few exceptions the additional data from the model are not beneficial for the forecast. It is important to note that the results depend on the method and criteria used to select the COSMO data to add to the MIDAS time series. Moreover, in this study the selection of the COSMO data has been carried out using the same method for all sites. It is believed that, by adapting the selection technique for the model data to the target site, the COSMO data can improve the prediction for all sites. This aspect certainly requires further investigations.

V. CONCLUSION

This paper has analysed the relative importance of each time series within the prediction algorithm in order to achieve the lowest forecast error with the minimum number of data. The results showed that some sites have a strong correlation and therefore only few sites contribute to minimise the prediction mean-squared error. This suggests that the computational time for the forecast can be reduced and optimised without compromising its accuracy.

Moreover, it has been analysed whether the addition of data from the COSMO model has an impact in the forecast performance. The effect of the COSMO data depends on the position of the target site respect to other MIDAS weather stations and the criteria chosen for the selection of the additional data from the model. In general, with few exceptions, COSMO data do aid in the prediction of MIDAS site time series. A particular case has been analysed more in detail; the selected measurements were from Valley (site 8) on the north-western coast of Wales. In that case the prediction error has been reduced by adding some data from neighbouring points around the target site.

As several methods can be used to include additional data from the COSMO model, this requires further investigation on the best technique to select the data. It has to be noticed that the results seem to be site specific, therefore a deeper analysis of this aspect is needed.

Further improvement can certainly be achieved by considering the non stationarity of wind. Annual cycles as well as seasonal variation in wind regimes have motivated the development of a cyclo-stationary Wiener filter [3]. Future work is planned to test the cyclo-stationary filter with the additional COSMO model data. In addition to this, diurnal variations, as sea breeze regimes, remain to be analysed and need to be explored.

ACKNOWLEDGEMENTS

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REFERENCES

[1] COSMO (Consortium for Small-scale Modelling): available at: www.cosmo-model.org

[2] J. Dowell, S. Weiss, D. Hill, and D. Infield, *A Complex-Valued Multi-channel Filter Approach to Short Term Directional Wind Forecasting*. Wind Energy, 2013.

[3] J. Dowell, S. Weiss, D. Hill, and D. Infield, *A Cyclo-Stationary Complex Multichannel Wiener Filter for the Prediction of Wind Speed and Direction*. In 21^{st} European Signal Processing Conference, Marrakech, Morocco, September 2013.

[4] T. Gneiting, K. Larson, K. Westrick, M. Genton and E. Aldrich, *Calibrated Probabilistic Forecasting at the Satellite Wind Energy Center: The Regime-Switching Space-Time Method.* Journal of the American Statistical Association, **vol.101** (2006), No. 475, pp. 968-979.

[5] A. Hering, and G. Genton, *Powering Up with Space-Time With Forecasting.* Journal of American Statistical Association, **vol.105** (2010), No. 489, pp. 92-104.

[6] UK Meteorological Office. Met Office Integrated Data Archive System (MIDAS) Land and Marine Surface Stations Data (1853-current), [Internet].NCAS British Atmospheric Data Centre, 2012. Available from http://badc.nerc.ac.uk/view/badc.nerc.ac.uk__ATOM__dataent_ukmo-midas.

[7] B. Widrow, and S. D. Stearns, *Adaptive Signal Processing.* Prentice Hall, Englewood Cliffs, New York, 1985.