Short-Term Forecasting of Wind Speed and Direction Exploiting Data Non-Stationarity

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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 the diurnal variation of the wind. The wind speed and direction are modelled as the magnitude and phase of a complex-valued time series. The prediction is performed by a multichannel filter using the spatio-temporal correlation between measurements at different geographical locations and the past values of the target site. A multichannel complex-valued non-stationary prediction Wiener filter is proposed that takes into account both the seasonal and diurnal variation of the wind. Using hourly wind speed and direction measurements from over 22 Met Office weather stations distributed across the UK, we demonstrate that there can be a benefit for predicting one hour ahead when taking into account the diurnal and seasonal cyclo-stationary nature of the wind.

Keywords: Non-stationarity, short-term wind forecast, multichannel predictive filter

1 Introduction

As worldwide more and more windpower sources are integrated into the national transmission systems, it is essential to accurately forecast power and therefore predict wind speed and direction [1, 2]. For instance, the stability and reliability of power system operations are highly dependent on the predicted power outputs. Moreover, wind farm operators can make financial savings from improved wind power forecasts, as these will result in more accurate bids on the energy market, thus avoiding penalties for not producing the power they declared in advance [3]. In addition to this, Operation and Maintenance (O&M) costs would be reduced, especially for offshore sites; for example with accurate weather forecast a better schedule of the vessel hire would be possible [4].

There are currently two main approaches to predict wind speed and direction: one method uses numerical weather prediction (NWP) models, while the other is based on statistical models. The choice is usually made considering the time scale of the desired forecast; for look-ahead times of more than 6 hours, NWP models are more accurate [5, 6]. In contrast for short-term forecasts of between one and up to six hours ahead, the statistical approach is preferred since NWPs are typically run only every 6 hours due to their computational complexity [5, 7]. Therefore, 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 outperform the NWP if it can be run quickly.

Many different models use the statistical approach. Some linear [6, 8] and non-linear methods [9–11] have been proposed to predict wind speed using the spatial correlation between geographically separated measurements. Despite the non-linear nature of the system, the use of linear methods has been justified considering their less complex structure and implementation. It has to be noted that some of the above mentioned models do not consider the wind direction and their forecast is computed for wind speed only.

When forecasting, it is important to take into account the direction of the wind as well, since wind farm power can depend on wind direction due to wake effects and terrain [12]. Wind direction can be introduced as the phase in a complex-valued time series, with the wind speed forming the magnitude of the complex variable [6, 13, 14]. In previous works, Dowell *et al.* [6] proposed an algorithm which uses a complex-valued wind data model that considers both wind speed and direction and the spatial correlation of measurements at different graphical locations. Moreover, a cyclo-stationary Wiener filter has been proposed by Dowell *et al.* [6], which exploits the seasonally and diurnally cyclic statistical properties of the wind. This provides predictions with greater accuracy than persistence, i.e. expecting no change in wind speed or direction over the next time period.

In this paper, the cyclo-stationary model proposed by Dowell *et al.* [6] is expanded to consider not only the seasonal variation of the wind signal but also its diurnal oscillation. It is investigated how the accuracy of the forecast can be improved by taking into account the non-stationary nature of the system.

In Section 2 the algorithm and approach to prediction are detailed: the stationary complex multichannel data model is introduced in Section 2.1 and derived in Section 2.2, and the cyclo-stationary model explained in Section 2.3. Section 3 is dedicated to the dataset and results. Conclusions are presented in Section 4.

2 Methodology

This section, based on the data model in Section 2.1, introduces a multichannel linear predictor in Section 2.2. To investigate the non-stationarity of the data, the cyclo-stationary model previously introduced by [6] to include the seasonal variation of the wind is now extended to consider the diurnal component, this new model is presented in Section 2.3.

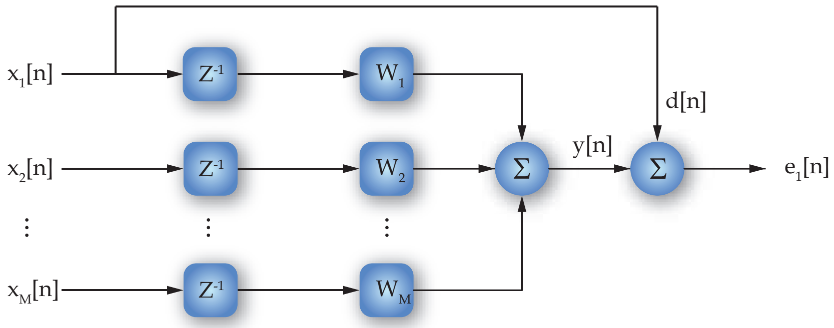

Fig. 1: Multi-channel prediction filter.

2.1 Complex Multichannel Data

This study uses complex-valued vector time series $x_m[n] \in \mathbb{C}$, $m = 1 \ldots M$, derived from hourly mean time series of wind speed and direction measured in M geographically separate sites. 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 $r_{x_i x_j}[n,\tau] = \mathscr{E}\{x_i[n]x_j^*[n-\tau]\}$, $i,j = 1 \ldots M$, which for $i = j$ provides the special case of the covariance for site i. The potential non-stationarity is highlighted by the inclusion of the time parameter n in the statistical quantities. From the values of $r_{x_i x_j}[n,\tau]$, a covariance matrix $\mathbf{R}[n]$ and a correlation vector $\mathbf{p}_m[n]$ will be defined later.

2.2 Minimum Mean Square Error Prediction

The prediction of the time series $x_m[n]$ at site m at time index n is performed using past measurements from all the M 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 $\mathbf{w}_{1,m}[n] \in \mathbb{C}^N$, where N is the temporal window over which prediction is performed. A tap delay line vector

$$\mathbf{x}_m[n] = \begin{bmatrix} x_m[n] \\ x_m[n-1] \\ \vdots \\ x_m[n-N+1] \end{bmatrix} \tag{1}$$

holds this data window at the m^{th} site during iteration n.

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

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

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

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

contain all measurement time series and filter coefficients, respectively.

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

$$\begin{aligned} \xi_m &= \mathscr{E}\{e_m[n]e_m^*[n]\} & (4)\\ &= \mathscr{E}\{(d_m[n] - \mathbf{w}_m^{\mathrm{H}}[n]\mathbf{x}[n])(d_m^*[n] - \mathbf{x}[n]^{\mathrm{H}}\mathbf{w}_m[n])\} & (5)\\ &= \sigma_{x_m}^2 - \mathbf{w}_m^{\mathrm{H}}[n]\mathbf{p}_m[n] - \mathbf{p}_m^{\mathrm{H}}[n]\mathbf{w}_m[n] - \mathbf{w}_m^{\mathrm{H}}[n]\mathbf{R}[n]\mathbf{w}_m[n] \quad . & (6) \end{aligned}$$

By minimising the mean-squared error, i.e. equating the first derivative of (5) with respect to the coefficients $\mathbf{w}_m$ to zero, the result

$$\mathbf{w}_{m,\mathrm{opt}}[n] = \mathbf{R}^{-1}[n]\mathbf{p}_m[n], \tag{7}$$

is known as the Wiener-Hopf solution [6, 15, 16], where $\mathbf{R}[n] = \mathscr{E}\{\mathbf{x}[n]\mathbf{x}^{\mathrm{H}}[n]\}$ is the covariance matrix of the data, and $\mathbf{p}_m[n] = \mathscr{E}\{d_m[n]\mathbf{x}^*[n]\}$ the cross-covariance vector between the desired signal $d_m[n]$ for site m and the data vector. The minimum MSE (MMSE) in (6) can be calculated by inserting (7),

$$\xi_{m,\min} = \sigma_{x_m}^2 - \mathbf{p}_m^{\mathrm{H}}[n]\mathbf{R}^{-1}[n]\mathbf{p}_m[n] \quad . \tag{8}$$

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

2.3 Cyclo-stationary Model

The cyclo-stationary model is based on the complex-valued multichannel Wiener filter where hypothesis on the non-stationarity of the data are made. Previously [6], it was assumed that the data are stationary on windows of length L, and that during that time period the statistics are the same during the corresponding time windows across all years. Additionally, in this study the diurnal variation is taken into account, therefore it is assumed that the data are stationary during a number h of hours of each day. Therefore, within the time window

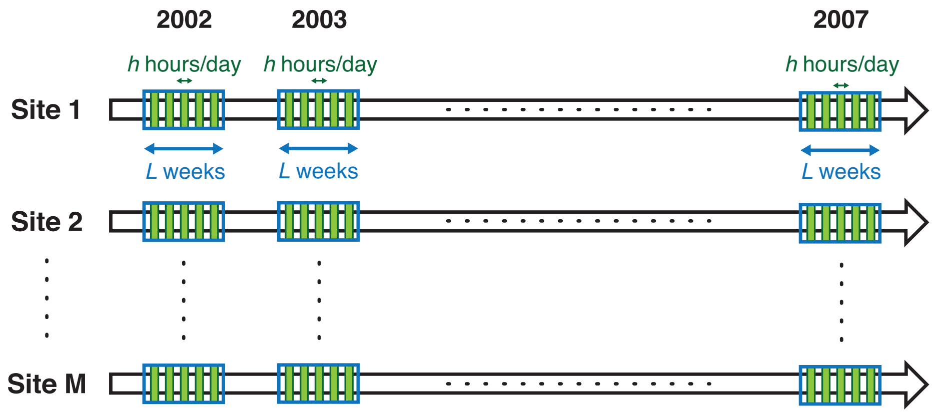

Fig. 2: Data selection for the cyclo-stationary model: time window of length L and number of hours per day h.

of length L, only h hours per day are selected to calculate the statistics. Figure 2 shows the selection of data for the diurnal case.

The statistics are calculated in the same way as described in 2.2. The difference between the two models resides in the selection of the data: in the stationary model all the data are selected, whereas in the cyclo-stationary model only h hours per day of the data in the time window of length L are considered. The mean is therefore both calculated and removed from only the selected data.

3 Data, Testing, and Results

3.1 Dataset

The British Atmospheric Data Centre [17] provided the Met Office Integrated Data Archive System (MIDAS) set of onshore weather data used for this study. The observations are taken at a height of 10m from ground and provide wind speed [knots] and direction [deg] sampled every hour. The time period chosen is of 5 years, starting from 00:00h on 1/01/2002 to 23:00h on 31/12/2007. For this window of time, 22 weather stations have been selected considering those with less than 2% missing and invalid data .
Figure 3 shows the locations of the 22 stations, with further details listed in table 1.

3.2 Testing and Results

The algorithm described in Section 2 has been tested on the MIDAS dataset. The filter coefficients have been calculated using the data from 2002 until 2006 as training data, and then the prediction algorithm has been tested on the data

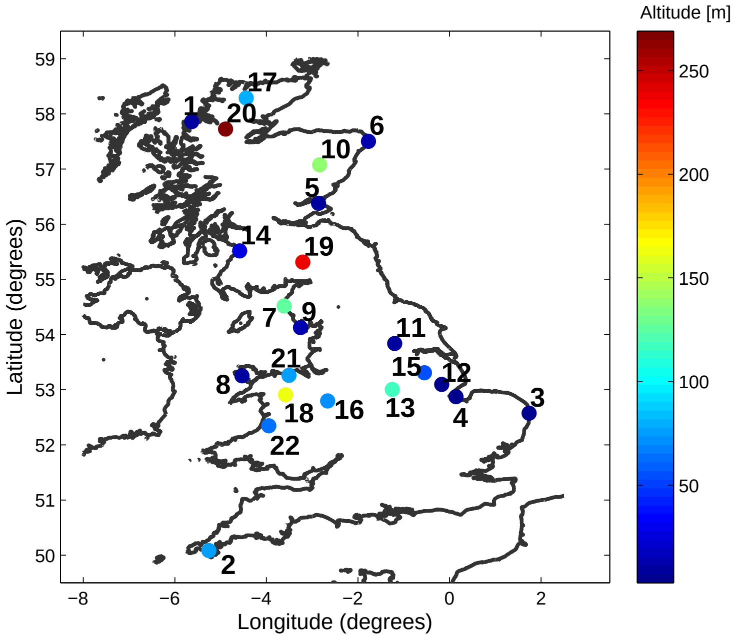

Fig. 3: Map of the UK Met Office sites.

from 2007. While invalid data can be discarded and poses no problem for calculating the statistics, performing a filter operation with the adjusted predictor is problematic because of resulting transient behaviour. Therefore to demonstrate the prediction of time-series, the adjusted filter is only run over shorter periods of time where all site have recorded valid data. We consider two different cases: 48 hours during winter ($15^{\text{th}} - 18^{\text{th}}$ January 2007) and summer ($23^{\text{rd}} - 25^{\text{th}}$ July 2007). Furthermore, this paper reports forecast results for look-ahead time of 1 hour.

The multichannel Wiener filter has been compared with the reference method: persistence. In the case of persistence, the predictor states that the future wind speed will be the same as the last measured value, i.e. the wind speed predicted for time n is assumed to the same as measured at time $n-1$. The algorithm has been tested considering four different models:

1. a stationary Wiener filter, which calculates its solution across all 5 years under assumption that the data are stationary;
2. Cyclo-stationary Wiener filter: data are assumed to be stationary over a windows of length $L = 15$ weeks and for h hours per day. Here 3 different cases have been tested:
   (a) 6 hours per day
   (b) 12 hours per day

Site Name	**Latitude** [deg]	**Longitude** [deg]	**Elevation** [m]
1. Aultbea	57.8592	-5.63159	11
2. Culdrose	50.0838	-5.25609	76
3. Gorleston	52.5716	1.74002	4
4. Holbeach	52.8729	0.14021	3
5. Leuchars	56.3774	-2.86051	10
6. Perterhead Harbour	57.5027	-1.77257	15
7. St Bees Head	54.5177	-3.61345	124
8. Valley	53.2524	-4.53524	10
9. Walney Island	54.1247	-3.25657	15
10. Aboyne	57.076	-2.83948	140
11. Church Fenton	53.8356	-1.1973	8
12. Coningsby	53.0935	-0.17119	6
13. Nottingham	53.0053	-1.24969	117
14. Prestwick	55.5153	-4.58343	27
15. Scampton	53.3066	-0.54649	57
16. Shawbury	52.7943	-2.66329	72
17. Altnaharra	58.2881	-4.44101	81
18. Bala	52.9073	-3.58303	163
19. Eskdalemuir	55.3118	-3.20545	236
20. Loch Glascarnoch	57.7251	-4.89419	269
21. Rhyl	53.259	-3.50754	77
22. Trawsgoed	52.3439	-3.94683	63

Table 1: Details on the 22 Met-Office stations used for the data analysis.

(c) 24 hours per day (which corresponds to the cyclo-stationary case addressed in [6]).

The window length, L, has been set equal to 15 weeks which has been established as the optimum window size in [6] on the basis of seasonal cyclo-stationarity only. The additionally assumed diurnal cyclo-stationary assumed here may lead to a different solution for L, and test are currently being carried out.

Prediction results from the cyclo-stationary algorithms and the stationary Wiener filter have been compared with persistence in terms of root mean-squared error (RMSE). Moreover, wind speed and direction forecasts have been performed and compared with persistence. Figures 4 and 5 show the summer and winter results for Aultbea (site 1 in Figure 3), while results for the same time periods at Coningsby (site 12) are displayed in Figures 6 and 7.

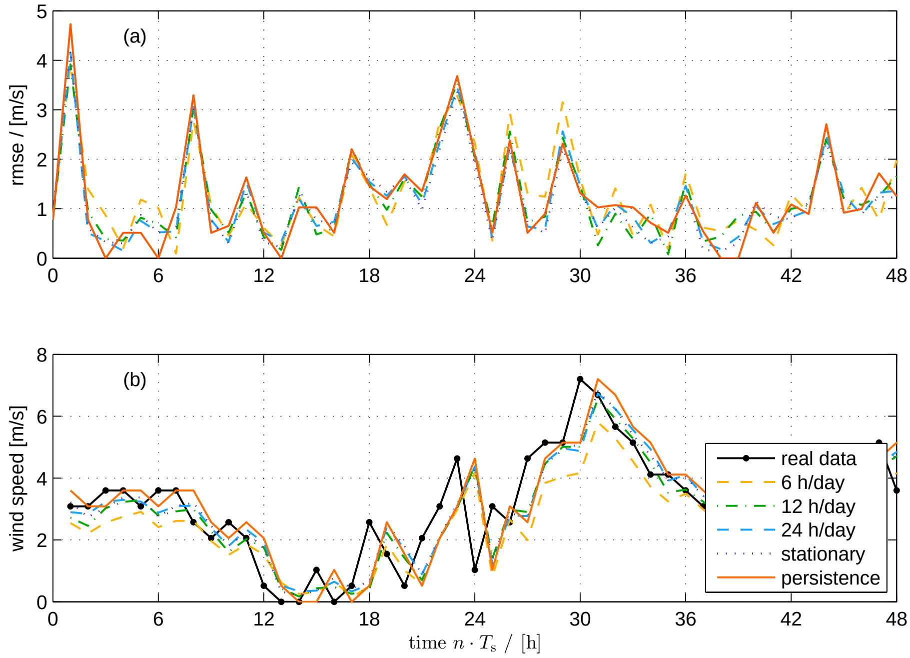

Fig. 4: (a) RMS and (b) predicted wind speed for site 1 (Aultbea) during summer.

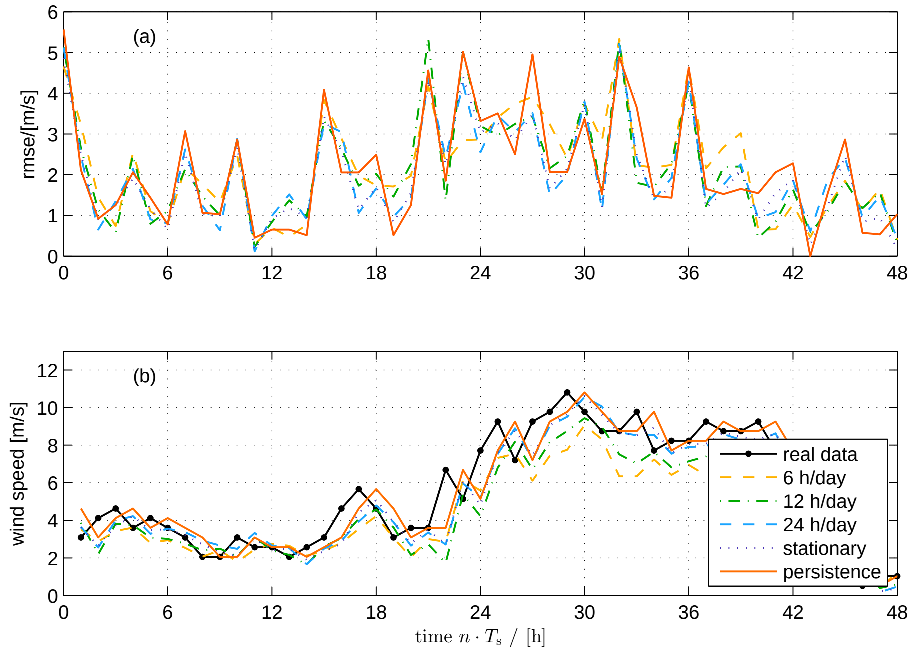

Fig. 5: (a) RMS and (b) predicted wind speed for site 1 (Aultbea) during winter.

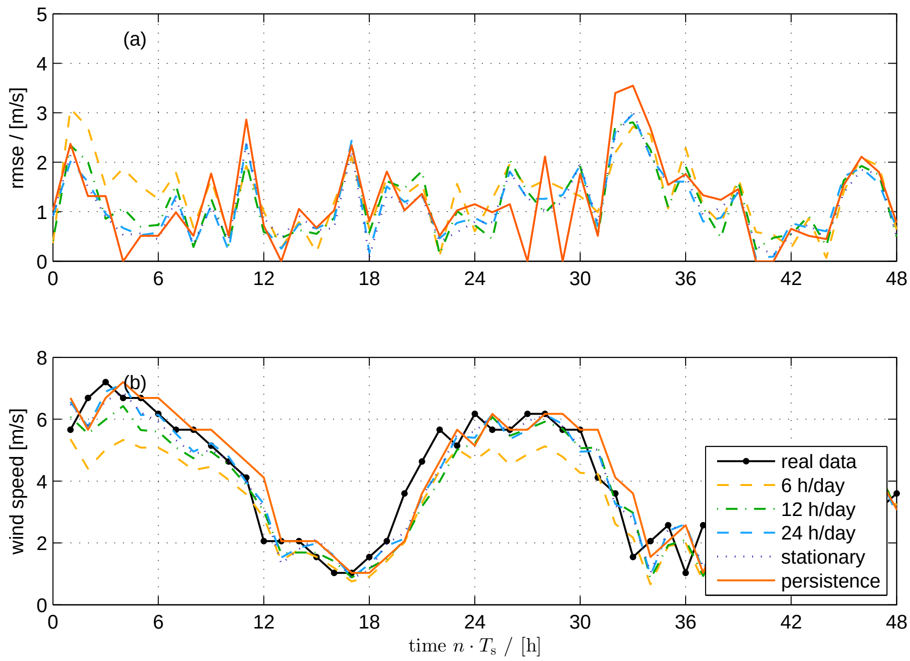

Fig. 6: (a) RMS and (b) predicted wind speed for site 12 (Coningsby) during summer.

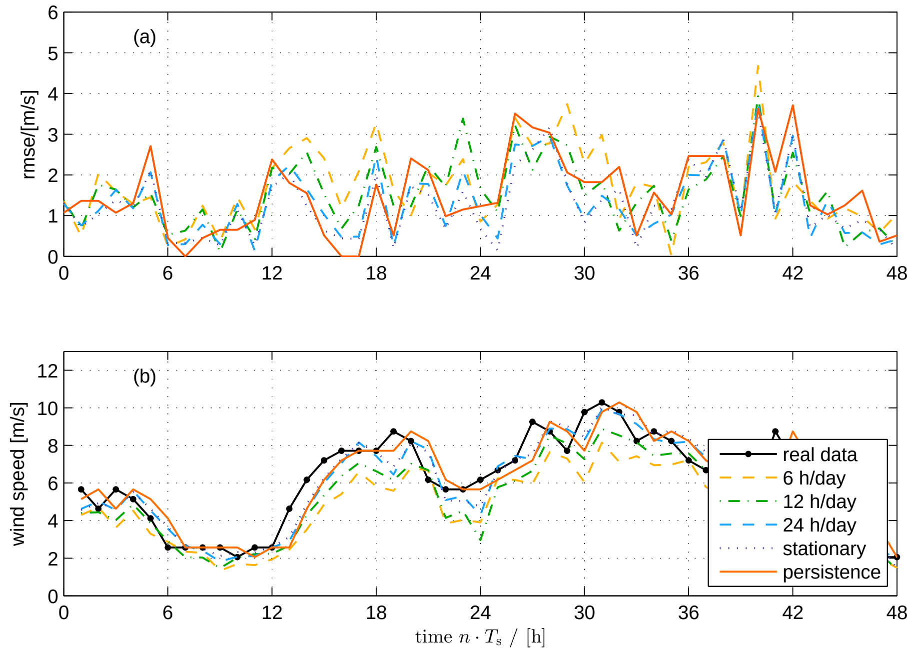

Fig. 7: (a) RMS and (b) predicted wind speed for site 12 (Coningsby) during winter.

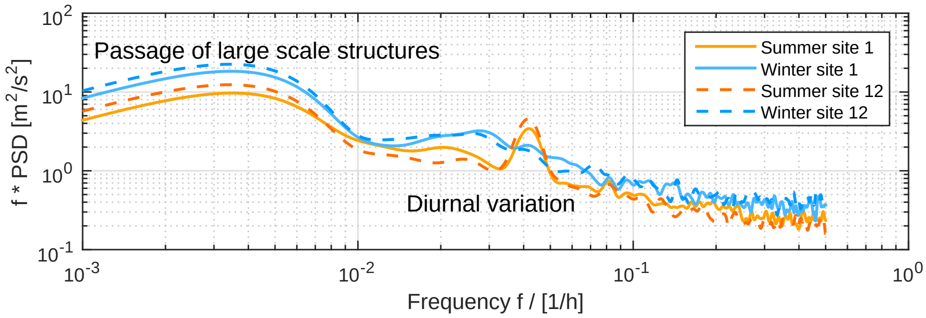

Fig. 8: Wind spectrum for site 1 and 12, in summer and winter.

3.3 Discussion

The models have been tested on two different time period of 48 hours each; during summer and winter. The motivation behind this choice was to highlight seasonal changes in the wind pattern and therefore find the way to use those variations to achieve better predictions. Moreover, a 48 hours time period has been chosen in order to investigate diurnal patterns. However, this is a preliminary attempt and further work is planned to expand the analysis also in spring and autumn and over a longer time period of at least 1 week.

Results are found to be very site specific, even though it is possible to identify some common features. Comparing the summer and winter results for each site, it is evident that on average wind speeds are higher in winter than in summer. The corresponding RMSEs are generally higher in winter for site 1 (Aultbea) as it is possible to see comparing Figures 4(a) and 5(a). However, from Figures 6(a) and 7(a), the RMSEs for site 12 (Coningsby) appear similar for both seasons.

The real wind speed data from site 12 in Figure 6(b) presents a clear diurnal variation, whilst in the winter case (Figure 7(b)) the changes in wind speed do not show that periodicity. It is possible to observe the same patterns for site 1: whereas in Figure 4(b) the wind speed during summer exhibits a diurnal variation, even if less evident than for site 12, in winter, Figure 5(b), the data seem to have a lower frequency variation. Even though only results for 48 hours are shown, we have found these generally representative of the data set. This can be explained by considering the wind spectrum for each site for summer and winter time. Figure 8 shows the wind speed spectral density function for site 1 and 12 in summer and winter. The peak corresponding to the diurnal variation is particularly event for the summer in both sites. Whilst for winter time, the peak is shifted towards lower frequencies which means that the wind varies over a longer time period. This explains why, from the graphs in Figures 5 and 7, in winter it is not possible to identify the typical 24 hours period of the diurnal variation.

It is interesting to analyse the position of the peaks in the RMSE plots and compare them to the real wind speed data. It is noticeable that some peaks correspond to abrupt changes in the wind pattern (either rises or falls). This will require further investigation in order to understand whether steep changes in the wind speed lead to higher prediction errors.

In general, by analysing the results in Figures 4–7, is it worth summarising that

– the performance of the cyclo-stationary algorithms is frequently outperforming both persistence and the stationary Wiener filter;
– in winter, forecast errors tend to be greater than in summer;
– all models seem to have poor performances when there are abrupt changes in the wind speed; in fact some peaks in the RMSE corresponds to sharp rises or falls in the wind speed.

4 Conclusions

In this article a preliminary attempt to include diurnal variation is proposed. The suggested model is a complex-valued multichannel Wiener filter where it is assumed that the data are stationary on windows of length L during h hours per day. Therefore, the coefficients depend on statistics that are the same during that time period in all years. The motivation behind this model was to capture the diurnal pattern of the wind.

The algorithm has been tested considering a window length $L = 15$ weeks in summer and winter, and 3 different cases: selection of 6, 12 and 24 hours per day. This model has been compared with the stationary Wiener filter and the persistence method.

Results showed that improvements can be achieved using a non-stationary Wiener filter that takes into account the diurnal variation of the wind. In general, the mean RMS errors of the 12 h/day case were outperforming persistence. Moreover, the 6 h/day model shows, in some cases, improvements over persistence. Encouraging results have been found that need more investigation and should be validated considering a longer period of time.

Further analysis is planned as it is believed that there is room for improvement. Future work will carry out a statistical analysis considering different lengths L of the time window in order to determine if the forecast error could be reduced by having a varying time window length throughout the year.

Finally, the forecast horizon considered in this work was of 1 hour. In previous works [6], it has been shown that improvements of the prediction error of the cyclo-stationary Wiener filter over persistence depends on the look-ahead time. In fact, the cyclo-stationary model performance increases as look-ahead times rises up to 6 hours.

Acknowledgements

The authors gratefully acknowledge the UK Meteorological Office and the British Atmospheric Data Centre for their supply of meteorological data and the support of the UK's Engineering Physical Sciences Research Council *via* the University of Strathclyde's Wind Energy Systems Centre for Doctoral Training, grant number EP/G037728/1.

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