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Improved week-ahead predictions of wind speed using simple linear models with wavelet decomposition

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ABSTRACT

Simple linear methods are widely used for time series modelling and prediction and in particular for the forecast of wind speed variations. Linear prediction models are popular for their simplicity and computational efficiency, but their prediction accuracy generally deteriorates beyond a few time steps. In this paper we demonstrate that the prediction accuracy of simple auto-regressive (AR) models can be significantly improved, by as much as 60.15% for day-ahead predictions and up to 18.25% for week-ahead predictions, when combined with suitable time series decomposition. The comparison with new reference forecast model (NRFM) also shows similar accuracy gain of week ahead predictions. The combined model is capable of forecasting wind speed up to 7 days ahead with an average root mean square error less than 3 m/s. We also compare the performance of AR and f-ARIMA models in wind speed prediction and observe that the f-ARIMA model is no better than the AR model when used in combination with time series decomposition.

1. Introduction

Wind is widely recognized as one of the fastest growing alternate sources of energy all over the world. Wind energy is clean, economically viable and safe for the environment and is available in abundance. Compared to power produced from gas or coal, each MWh of wind power saves no less than 500 kgs of green house effect gases from being released into the atmosphere and this makes wind power one of the most eco-friendly sources of energy [1,2]. Over the last few years there has been a steady growth of the generation and use of wind power and as of 2013, the total installed capacity of wind power stands at 318 GW. According to European Wind Energy Association, if the growth of wind power generation continues at the current rate, it would account for more than 12% of the total energy demands by the year 2020 [3]. A major factor affecting wind power production is the highly fluctuating nature of wind speed, under the influence of numerous meteorological factors. These variations occur at all time scales ranging from seconds to months and even years and being able to predict these fluctuations is a key factor in the production and management of wind energy. Based on the length of the forecasting period, wind speed predictions are generally classified as short-term (up to 6 h ahead), medium term (6 h–1 day ahead) and long-term (1 day–1 week ahead) [4], and improving the accuracy of predictions at all these time-scales is crucial at various stages of wind energy production and management. Short term forecasts ranging from milliseconds to a few minutes are needed for active turbine control and managing wind energy at electricity grids [5,6] and forecasts in the range of a few hours up to a few days are useful in energy management and trading, especially in liberalized electricity markets where users devise best bidding strategy based on expected power production [7]. Long-term forecasts of up to several days ahead are useful in managing the maintenance of wind farms and transmission lines [8]. Methods for accurate prediction of wind speed has therefore emerged as an important research area in recent years.

Various models for wind prediction include physical models, which use complex mathematical equations to describe the physical relationship between various atmospheric parameters and local topography, statistical models which use time series of past data or probability distribution of wind speed for future predictions and also hybrid models which combine physical models with

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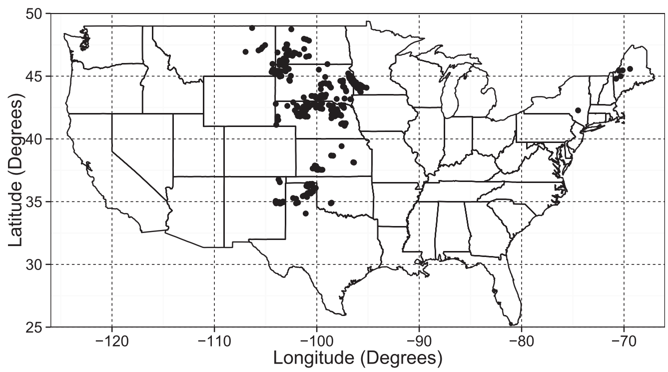

Fig. 1. The geographical locations, denoted by filled circles, for the 234 sites selected for wind speed data analysis and prediction.

statistical tools [9]. A thorough review of the current status of wind power forecast models, especially of the meteorology based approaches, can be found in Refs. [10] and [11]. Provided the meteorological conditions do not change dramatically over short term, time series models, which use past history of wind speed to predict future values, are found to perform reasonably well. They include moving average models such as ARMA, ARIMA and its variants fitted to the time series of wind speed [12–14], models based on artificial neural networks [13,15–17] and deterministic prediction models suitable for chaotically varying wind speed dynamics [18,19]. Most of these methods are capable of reasonably accurate predictions up to a few hours, but the range of predictability often varies significantly over topography and other local conditions [4].

Wind speed data usually exhibit long range correlations and f-ARIMA models are especially suited for making short to medium term forecasts of such data. Kavasseri and Sreetharaman [14] have applied f-ARIMA models to forecast hourly average wind speeds up to a period of two days ahead, with an improvement of prediction accuracy up to 42% compared to the elementary method of persistence. In this work we demonstrate that decomposition of the wind speed data into selected frequency components before applying the forecasting technique can dramatically improve the accuracy and longevity of prediction. The decomposition of wind speed data is achieved by the use of wavelet transform technique, while the actual forecasts on the component series are made by simple prediction tools such as auto-regressive (AR) model or f-ARIMA model.

2. AR and f-ARIMA models of prediction

A popular model for prediction of time series is the autoregressive (AR) model which uses a linear combination of p past observations and a random error. An AR-model AR(q) of order p has the form,

$$x_t = c + \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_t$$

where ϕ_i s are suitably chosen coefficients, c is a constant and ε_t is

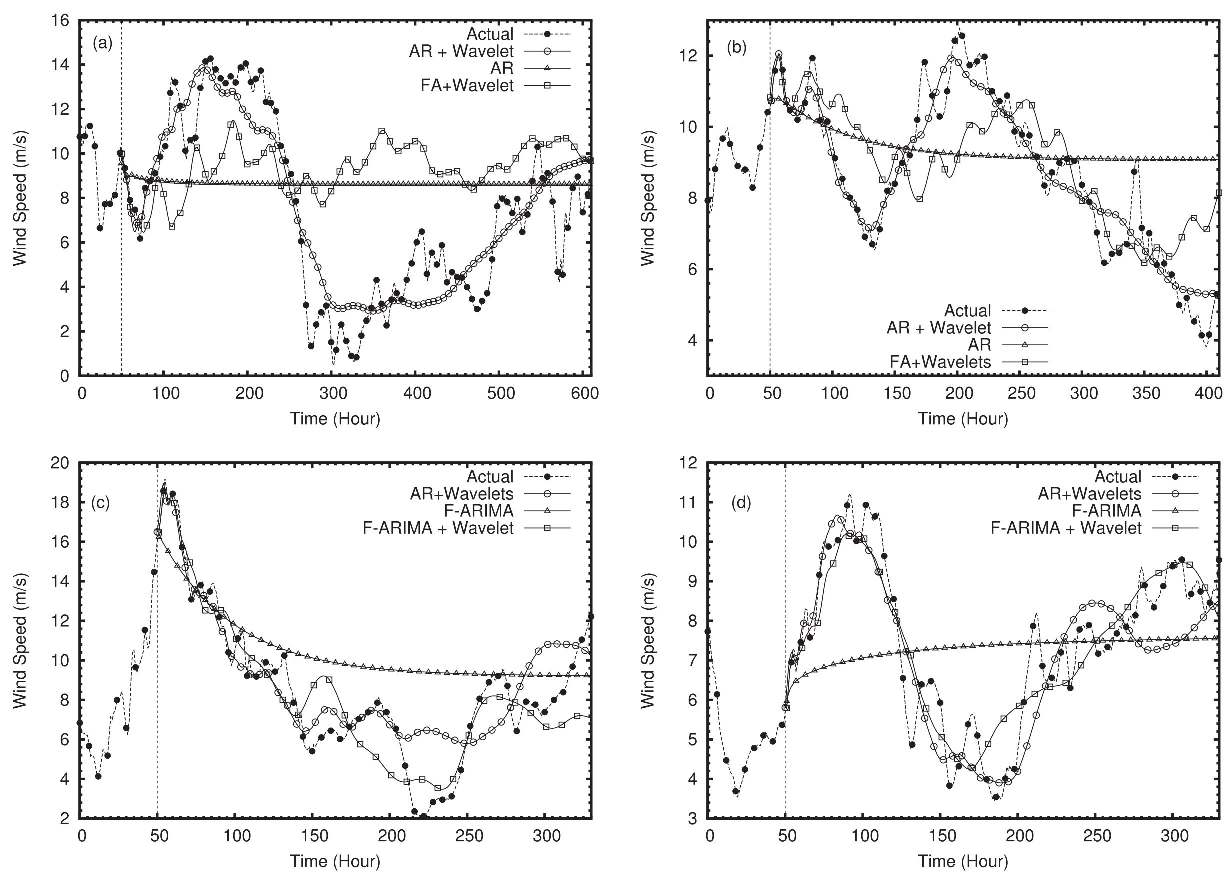

Fig. 2. Comparison of predicted values with actual data for AR and f-ARIMA models with and without wavelet decomposition. (a) Latitude: 44.34406°N Longitude: 99.61266°W, prediction start time: 2004-12-26 12:10:00 (b) Latitude: 45.39850°N Longitude: 103.51002°W, prediction start time: 2006-03-21 12:10:00 (c) Latitude: 44.95404°N Longitude: 96.60688°W, prediction start time: 2005-09-22 12:10:00 (d) Latitude: 38.67878°N Longitude: 98.59783°W, prediction start time: 2004-01-31 12:10:00.

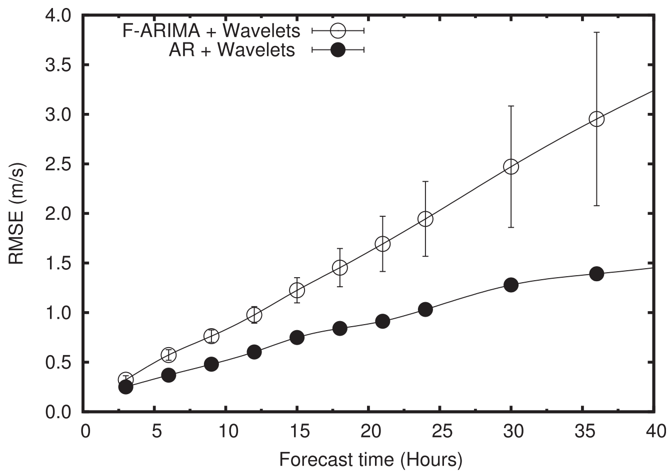

Fig. 3. Comparison of location and time averaged RMSE of hourly mean wind speed data between AR and f-ARIMA models both combined with wavelet decomposition.

the random error at time t [20]. For the analysis reported in this paper we have adopted Burg's method [21] for estimating the parameters as implemented in the *stats* package of *R*. For time series having predominantly deterministic character, AR model is expected to perform better in prediction compared to other linear methods. A moving average (MA) model, on the other hand, uses a linear combination of past errors. An MA-model MA(q) of order q has the form,

$$x_t = \mu + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

where ϕ_i s are suitably chosen coefficients, μ is the mean of the series and the random errors ε_{t-j} are assumed to be independent and identically distributed with zero mean and constant variance [20].

An auto-regressive model of order p and a moving average model of order q can be effectively combined to form the more useful ARMA(p,q) model, which has the general form,

$$x_t = c + \varepsilon_t + \sum_{i=1}^{p} \phi_i x_{t-i} + \sum_{j=1}^{q} \theta_j x_{t-j}$$

Using the operators,

$$\Phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$$
$$\Theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q$$

the ARMA(p, q) model can be written as,

$$\Phi(B) x_t = c + \Theta(B) \varepsilon_t$$

where B is the backward-shift operator so that $Bx_t = x_{t-1}$.

ARMA models are commonly used in forecasting time series of stationary processes. Time series of non-stationary processes are best modelled using integrated ARMA models or ARIMA models, which additionally uses differencing operation to remove stationarity. An ARIMA(p, d, q) model has the general form,

$$\Phi(B) \Delta^d x_t = c + \Theta(B) \varepsilon_t$$

where $\Delta = 1 - B$ is the differencing operator and d is an integer [20].

f-ARIMA is a generalization of ARIMA where the parameter d is allowed to have a fractional value with the operator $(1 - B)^d$ interpreted to have the binomial expansion [22],

$$(1 - B)^d = 1 - \mathrm{d}B + \frac{d(d-1)}{2!} B^2 + \cdots$$

The possibility of wide range of choices for the parameters p, d, q and the constants ϕ_i and θ_i give the model great flexibility and wider applicability.

One of the features that distinguishes a *f-ARIMA* process from an *ARIMA* process is that the former is characterized by a slow decay in its auto-correlation function compared to the latter. This feature makes *f-ARIMA* model an attractive choice for data sets that exhibit long range correlations such as the wind speed data [14].

3. Wavelet transform

Wavelet transform allows us to decompose data or other functions into its frequency components and then study each component with a resolution matched to its scale. Whereas traditional Fourier transform methods use superposition of sines and cosines of different amplitudes and frequency to represent functions, the wavelet transform does this using a collection of wavelet functions, all of which can be generated by scaling and translating a single base wavelet called *mother wavelet*. The mother wavelet and all wavelets generated from it are, unlike sines and cosines, localized in space and the given function or data is approximated by a series of scaled and translated versions of these localized functions. This allows processing of data at different scales or resolutions, with lower scales giving finer details of the high frequency components and higher scales yielding grosser features of the low frequency components of the data. Measured data such as wind speed data are inherently multi-scale due to contributions from events occurring with different localizations in time and frequency, and wavelets are more suited for analysis of this kind of data.

Mathematically, a mother wavelet is a square integrable function $\psi(t)$, which satisfies the *admissibility condition* [23],

$$0 < c_\psi = \int_{-\infty}^{\infty} \frac{|\widehat{\psi}(\omega)|}{|\omega|} < \infty$$

where $\widehat{\psi}(\omega)$ is the Fourier transform of $\psi(t)$ and preferably a regularity condition which requires that $\psi(t)$ be fast decaying or be non-zero only on a finite interval [23]. To decompose a given function, wavelet transforms use a family of wavelet functions $\psi_{s,\tau}(t)$ obtained from the mother wavelet $\psi(t)$ by dilations and translations;

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t-\tau}{s}\right), \quad s, \tau \in \mathbb{R}, s \neq 0$$

where s is the scale parameter and τ is the location parameter. The continuous wavelet transform of a function $x(t)$ is then defined by,

$$W_x(s,\tau) = \int_{-\infty}^{\infty} x(t) \psi^*_{s,\tau}(t) \mathrm{d}t$$

where * denotes the complex conjugate. The admissibility condition of $\psi(t)$ ensures that $x(t)$ can be recovered from $\psi_{s,\tau}(t)$ by the inverse transform [23].

$$x(t) = \frac{1}{c_\psi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W_x(s,\tau) \psi_{s,\tau}(t) \frac{\mathrm{d}\tau \mathrm{d}s}{s^2},$$

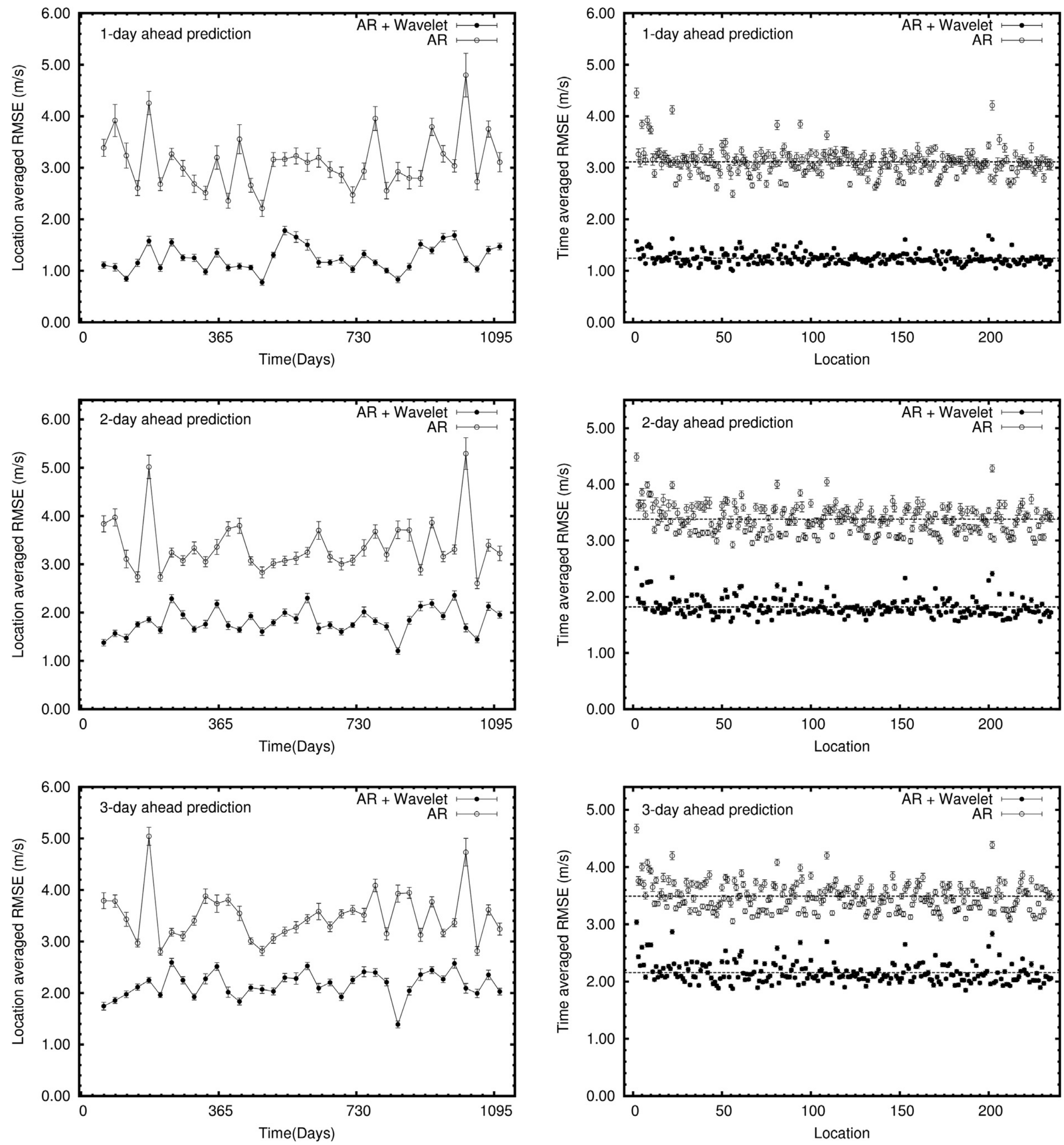

Fig. 4. Plots of averaged RMSE of 1–3 day ahead predictions at different locations as well as points of time. The left panel shows location averaged RMSE of predictions at different points of time whereas the right panel shows the time averaged RMSE of at different locations.

and this is called the wavelet decomposition of $x(t)$.

The variation of the scale and location parameter of the wavelet over a continuum of values in the continuous wavelet decomposition leads to undesirable redundancy in the calculation of wavelet coefficients. In practical applications it is more convenient to sample the parameters s and τ on a discrete set of values in the scale–time plane. This leads to *discrete wavelets* defined for suitably chosen grid points on the s–τ plane,

$$\psi_{j,k}(t) = s_0^{-j/2}\psi\left(s_0^{-j}t - k\tau_0\right), \quad j,k\in\mathbb{Z}$$

where $s_0 > 1$ and τ_0 are fixed dilation and translation factors [23]. The so called *dyadic sampling* corresponds to the choice $s_0 = 2$ and $\tau_0 = 1$. The discrete wavelet transform(DWT) is then defined by,

$$W_x(i,j) = \int_{-\infty}^{\infty} x(t)\psi_{j,k}^*(t)\mathrm{d}t.$$

If the set of wavelets $\psi_{j,k}(t)$ forms an orthogonal basis, the above transform can be inverted leading to the *discrete wavelet decomposition* of $x(t)$ given by,

$$x(t) = \frac{1}{c_\psi}\sum_{j,k\in\mathbb{Z}} W_x(j,k)\psi_{j,k}(t).$$

The DWT is especially suited for time series data sampled at

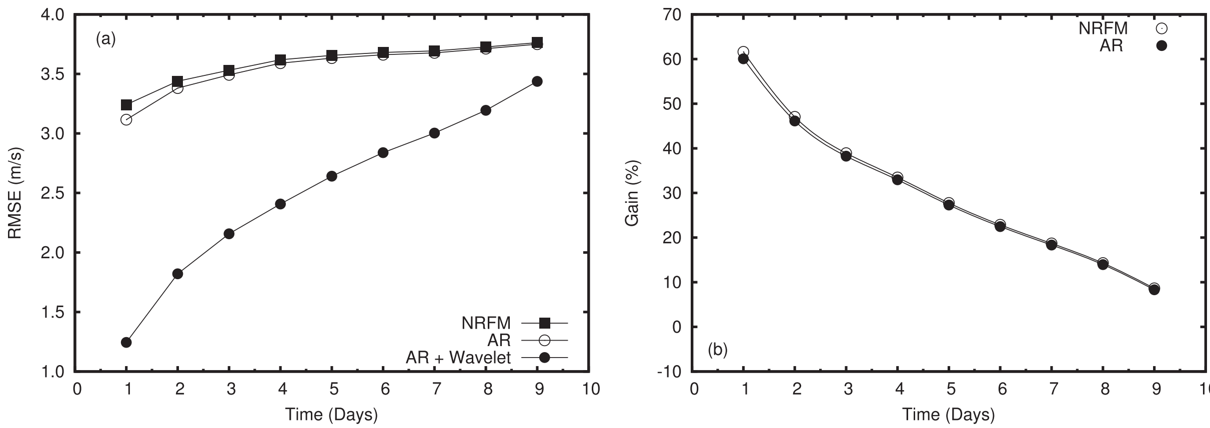

Fig. 5. (a) Location and time averaged RMSE for predictions up to 9 days ahead. (b) Percentage gain of accuracy in terms of RMSE for the AR model and the New Reference Forecast Model (NRFM) method of persistence when used in combination with wavelet decomposition.

equal intervals of time. We use a specific version of DWT, called Maximal Overlap DWT (MODWT) which has some advantages over traditional DWT. First, it is well defined for all sample sizes N, unlike DWT which requires N to be multiple of J for a complete decomposition of J scales. MODWT is highly redundant over DWT and also non-orthogonal, but the redundancy allows better comparison of the series with its decomposition [24].

At each scale J, the MODWT transforms an N dimensional vector X, which represents the given data, into $J+1$ new vectors each of dimension N. These vectors consists of J vectors $W_1, W_2, \cdots W_J$ of MODWT wavelet coefficients corresponding to the scales τ_j, $j = 1,2,\ldots J$ and a vector V_J containing the so called MODWT scaling coefficients. We can invert this procedure and recover the original vector X from these wavelet and scaling coefficients. This leads to a decomposition known as multi-resolution analysis(MRA), expressed as [24,25],

$$X = \sum_{j=1}^{J} D_j + S_J$$

The vector D_j contains the details of the data associated with the average variations on a scale of τ_j and is computed exclusively from the wavelet coefficients in W_j. On the other hand, S_J is calculated from the scaling coefficients in V_J and is associated with the averages at scales $2\tau_J$ and higher, which separates the smoother part of the data [24,25]. Thus the MRA expresses the given data as a sum of a smoother part and a set of component parts giving details of the variations at various scales.

4. Results and discussion

In earlier works we have demonstrated that random like fluctuations found in time series of wind speed could actually arise from an underlying chaotic dynamics [18], and that in such situations deterministic forecasting methods can make significantly accurate short term predictions of wind speed [19]. However, the chaotic behaviour essentially limits the possibility of accurate long-term predictions using chaotic prediction methods due to exponential divergence of nearby trajectories. A time series of wind speed is the result of interplay between numerous dynamical factors of various scales and frequencies and with a systematic procedure to keep track of the various frequencies it could be possible to bypass these limitations to some extent and make fairly accurate long-term predictions taking advantage of the underlying determinism. We demonstrate that wavelet decomposition of wind speed data combined with simple auto-regressive prediction models can make long-term predictions as far as a week ahead possible with root mean square error below 3 m/s.

For the present analysis we have used the wind speed data sampled at 10-min intervals, for the period from January 2004 to January 2007, for 234 locations spread across an area ranging from 34.05911°N, 106.95718°W to 48.84354°N, 69.40916°W as available from National Renewable Energy Laboratory (http://www.nrel.gov), USA as shown in Fig. 1. Our prediction method starts with an MRA of the given time series, thus decomposing it into time series of various scales by applying MODWT with Daubechies wavelet of order 8. We have set $J = 12$ giving rise to 12 detail series $D_j, j = 1,2,\ldots 11$ (at scales $2^j, j = 1,2,\ldots 11$) and the smooth series S_{12} of variations at scales greater than 2^{11}. A part of this component series is then selected as the model data for prediction which is then used to forecast several time steps into the future using AR or f-ARIMA method. The resulting series are then combined, again using MRA, to reconstruct the original series along with the predicted values.

Fig. 2 shows the results of predictions made by AR and f-ARIMA models, for some hundred hours, on the wind speed data from four different locations, plotted along with the actual data. Also plotted in the Fig. 2 are the predictions by each of these models in combination with wavelet decomposition technique as described earlier. These plots clearly show that both the AR and f-ARIMA predictions are remarkably improved when combined with wavelet decomposition. Whereas the forecasts by the plain models diverge from the actual data after a few time steps, when combined with wavelet decomposition, they yield fairly accurate predictions for a longer period of time and pick up the dynamics of the original series more or less faithfully.

To further investigate the reliability of this technique combining prediction models with wavelet decomposition, and also to demonstrate their wider applicability in wind speed prediction, we have carried out a statistical analysis of the wind speed forecasts made at a range of different geographical locations. The analysis consists of computing and comparing wind speed prediction errors at a total of 234 geographical locations mentioned earlier. We use spatial averages of prediction errors over the various locations, as well as time averages over various periods of time at each location, to compare the prediction accuracies of the forecast models when used directly and in combination with wavelet decomposition. The prediction errors are measured in terms of the root mean squared error (RMSE) defined as follows. Suppose that from a given time series of $n+k$ observed values $x_1, x_2, \ldots x_{n+k}$, we choose the first n values as constituting the model data for prediction and obtain the forecasts $x^p_{n+1}, x^p_{n+2}, \ldots, x^p_{n+k}$ for the next k values. The root mean squared error is then given by,

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=n+1}^{n+k}\left(x_i - x_i^p\right)^2}{k}}$$

For each location we obtained predictions for 1–9 days ahead at intervals of 30 days for the 3-year period from 2004 to 2006, using the AR or f-ARIMA model alone at first and then in combination with wavelet decomposition. Wind speed data of previous 30 days were used to build suitable models for predictions in all cases. The time-averaged RMSE for each location was computed by averaging over the RMSEs of the predictions at intervals of 30 days at the location. The location averaged RMSE at a particular time was calculated by averaging over the RMSEs of predictions at various locations at the time.

To compare the performance of AR and f-ARIMA models in the presence of wavelet decomposition, we computed both location and time averaged RMSE for predictions up to 6 h ahead, which evaluates to 0.01627287 ± 0.00017 for AR model and to 0.05017721 ± 0.00075 for f-ARIMA model. We have repeated this comparison for hourly mean wind speed data and the results are shown in Fig. 3. These results indicate that when used in combination with wavelet decomposition, the AR model fares much better, with considerably less computational cost, than the f-ARIMA model. The f-ARIMA model also shows the tendency to diverge for certain scales of the data. Hence the rest of the analysis was carried out using exclusively the AR model as the base prediction tool in combination with wavelet decomposition.

Fig. 4 shows average RMSEs for 1–3 day ahead predictions with the left panel showing the location-averaged RMSEs and the right panel showing the time averaged RMSEs. These results clearly demonstrate that wavelet decomposition significantly improves the prediction accuracy of the AR model and that the performance edge of the combined model is more or less maintained at the same level across all locations and all time periods. The order of AR model was between 34 and 36 in almost all cases. In predictions up to 3 days ahead, the combined model is accurate to within an average relative error of about 7–8%, which is roughly 5–6% less than what AR model produces when used directly. For 4–9 days ahead predictions the accuracy is certainly lower than the earlier set of forecasts, but the combined method of AR with wavelet decomposition continues to deliver much better accuracy than the singular AR method. Fig. 5(a) shows the overall performance of forecasting methods for predictions up to 9 days ahead by plotting the time and location averaged RMSE against the number of days of predictions. For comparison, we have also computed the RMSE of predictions using the New Reference Forecast Model (NRFM), which is an effective modification of the persistence forecast model for forecast lengths of more than a few hours [26]. NRFM uses a weighting between the persistence for the short term and the data mean for the long term, where the weighting parameters depend on the correlation and are chosen to minimize the mean square error. This makes the long term predictions by the model approximate the climatology better. The AR prediction based on wavelet decomposition is able to make fairly accurate predictions for up to a week ahead, consistently across all locations and seasons, with an average relative error of about 11% or less. As shown in Fig. 5(b) the major benefit of the method proposed in this paper is the significant gain in accuracy of the AR model obtained by the use of wavelet decomposition. In terms of location and time averaged RMSE, this gain is 60.15% for 1-day predictions and 46.24% for 2-day predictions. Comparison of the combined model with new reference forecast model also shows similar performance advantage. For week-ahead predictions, the use of wavelet decomposition returns an average 18.25% of accuracy gain for the AR model. The exponential decay of the accuracy gain, as seen in the figure, may be due the chaotic behaviour of underlying dynamics of wind speed variations [18,19]. Prediction accuracy of a chaotic time series is bound to decay exponentially as time length of the predicted value increases. However, decomposition of time series before prediction is seen to slow down this decay process appreciably.

5. Conclusion

Accurate prediction of wind speed is an important aspect of the control and management of electricity produced at the wind farms and consequently wind speed forecasting has emerged as a major research area in recent years. Majority of the techniques reported in the literature for wind speed forecasting use linear time series models. While attractive for their computational efficiency and simplicity, their prediction accuracy beyond a few time steps is generally very poor. In this paper we have demonstrated through numerical computations that the prediction accuracy of simple linear models can be remarkably improved, even for forecasts beyond a week, by properly decomposing the time series before prediction. Wind speed forecasts by an auto-regressive model combined with wavelet based decomposition of time series are found to be accurate within an average error of 7–8% for predictions up to 3 days ahead. A statistical analysis of the predictions made at 234 different locations reveal that time series decomposition improves the accuracy of AR models by an average 60.15% for day-ahead predictions and up to 18.23% for week-ahead predictions. Since the entire analysis has been carried out on high resolution data of 10 min intervals, the results reported here are of greater practical relevance.

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