

Low-dimensional Models in Spatio-Temporal Wind Speed Forecasting

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Abstract—Integrating wind power into the grid is challenging because of its random nature. Integration is facilitated with accurate short-term forecasts of wind power. The paper presents a *spatio-temporal* wind speed forecasting algorithm that incorporates the time series data of a target station and data of surrounding stations. Inspired by Compressive Sensing (CS) and structured-sparse recovery algorithms, we claim that there usually exists an intrinsic low-dimensional structure governing a large collection of stations that should be exploited. We cast the forecasting problem as recovery of a *block-sparse* signal x from a set of linear equations $b = Ax$ for which we propose novel structure-sparse recovery algorithms. Results of a case study in the east coast show that the proposed Compressive Spatio-Temporal Wind Speed Forecasting (CST-WSF) algorithm significantly improves the short-term forecasts compared to a set of widely-used benchmark models.

I. INTRODUCTION

A. Variable Energy Resources

Many countries in the world as well as many states in the U.S. have mandated aggressive Renewable Portfolio Standards (RPSs). Among different renewable energy resources, wind energy itself is expected to grow to provide between 15 to 25% of the world’s global electricity by 2050. According to another study, the world total wind power capacity has doubled every three years since 2000, reaching an installed capacity of 197 GW in 2010 and 369 GW in 2014 [1], [2]. The random nature of wind, however, makes it difficult to achieve the power balance needed for its integration into the grid [3], [4]. The use of ancillary services such as frequency regulation and load following to compensate for such imbalances [5]–[8] is facilitated by accurate forecasts [9], [10].

B. Wind Energy Forecasting Methods

One can directly attempt to forecast wind power. An alternative approach is to forecast the wind speed and then convert it to wind power using given power curves. This approach will accommodate different wind turbines installed in a wind farm experiencing the same wind speed but resulting in different wind power generation. We focus on wind speed forecasting in this paper. Wind speed forecasting

methods can be categorized to different groups: (i) model-based methods such as Numerical Weather Prediction (NWP) vs. data-driven methods, (ii) point forecasting vs. probabilistic forecasting, and (iii) short-term forecasting vs. long-term forecasting. This paper is concerned with short-term point forecasting using both temporal data as well as spatial information. For a more complete survey of wind speed forecasting methods see [11] and [12] among others.

C. Spatio-Temporal Wind Speed Forecasting

There is a growing interest in the so-called *spatio-temporal* forecasting methods that use information from neighboring stations to improve the forecasts of a target station, since there is a significant cross-correlation between the time series data of a target station and its surrounding stations. We review some of the spatio-temporal forecasting methods. Gneiting et al. [13] introduced the Regime Switching Space-Time Diurnal (RSTD) model for average wind speed data based on both spatial and temporal information. This method was later improved by Hering and Genton [14] who incorporated wind direction in the forecasting process by introducing Trigonometric Direction Diurnal (TDD) model. Xie et al. [15] also considered probabilistic TDD forecast for power system economic dispatch. Dowell et al. [16] employed a multi-channel adaptive filter to predict the wind speed and direction by taking advantages of spatial correlations at numerous geographical sites. He et al. [17] presented Markov chain-based stochastic models for predictions of wind power generation after characterizing the statistical distribution of aggregate power with a graph learning-based spatio-temporal analysis. Regime-switching models based on wind direction are studied by Tastu et al. [18] where they consider various statistical models, such as ARX models, to understand the effects of different variables on forecast error characteristics. A methodology with probabilistic wind power forecasts in the form of predictive densities taking the spatial information into account was developed in [19]. Sparse Gaussian Conditional Random Fields (CRFs) have also been deployed for probabilistic wind power forecasting [20]. See [21] for a comprehensive review of the state-of-the-art methods.

D. Our Contribution

Inspired by Compressive Sensing (CS) and structured-sparse recovery algorithms, we claim that there usually exists an intrinsic low-dimensional structure governing the interactions among a large collection of weather stations. Such low-dimensional models should be exploited in the forecasting process. To this end, we cast the forecasting problem as the recovery of a *block-sparse* signal x from a

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$$\begin{aligned}
\underbrace{\begin{bmatrix} y_{n+1}^i \\ y_{n+2}^i \\ \vdots \\ y_{n+M}^i \end{bmatrix}}_{\mathbf{b} \in \mathbb{R}^M} &= \underbrace{\begin{bmatrix} y_n^1 & \cdots & y_1^1 & \cdots & \cdots & y_n^P & \cdots & y_1^P \\ y_{n+1}^1 & \ddots & \vdots & \cdots & \cdots & y_{n+1}^P & \ddots & \vdots \\ \vdots & \ddots & \vdots & \cdots & \cdots & \vdots & \cdots & \vdots \\ y_{n+M-1}^1 & \cdots & y_M^1 & \cdots & \cdots & y_{n+M-1}^P & \cdots & y_M^P \end{bmatrix}}_{A \in \mathbb{R}^{M \times N}} \underbrace{\begin{bmatrix} X_1^{\text{tr}}(1, i) \\ \vdots \\ X_n^{\text{tr}}(1, i) \\ \hline \vdots \\ \vdots \\ X_1^{\text{tr}}(P, i) \\ \vdots \\ X_n^{\text{tr}}(P, i) \end{bmatrix}}_{\mathbf{x} \in \mathbb{R}^N} \quad (1)
\end{aligned}$$

} Block 1
} Block P

set of linear equations $\mathbf{b} = A\mathbf{x}$ for which we propose novel structure-sparse recovery algorithms. As a case study, we apply our proposed forecasting algorithm to the data recorded from 57 measuring locations (a combination of airports and weather stations) in a region in the east coast including Massachusetts, Connecticut, New York, and New Hampshire. The results lead to a considerable improvement of the short-term forecasts compared to a set of widely-used benchmark models and advanced spatio-temporal approaches.

E. Paper Organization

In Section II, we formulate the forecasting problem. The proposed forecasting algorithms and related concepts are presented in Section III. We apply the proposed methods to real wind speed data and compare the results with other benchmark methods in Section IV. Section V presents our concluding remarks and possible future directions.

II. MULTIVARIATE AUTOREGRESSIVE (M-AR) MODEL

Autoregressive (AR) models assume that the output variable of a system can be well presented as a weighted linear combination of its own previous values. Multivariate Autoregressive (M-AR) (a.k.a., Vector Autoregressive) models generalize this approach to multivariate time series. Let $\mathbf{y}(t) \in \mathbb{R}^P$ be a P -dimensional output measurement (e.g., wind speeds at P weather stations) at time t . An M-AR model of order n is written as

$$\begin{aligned}
\mathbf{y}(t) &= X_1 \mathbf{y}(t-1) + \cdots + X_n \mathbf{y}(t-n) + \mathbf{e}(t) \\
&= \sum_{j=1}^n X_j \mathbf{y}(t-j) + \mathbf{e}(t), \quad (2)
\end{aligned}$$

where $X_j \in \mathbb{R}^{P \times P}$ is a coefficient matrix associated with the j -th time lag and $\mathbf{e}(t)$ is a Gaussian noise. Using a different notation, let y_t^i be the wind speed of the i -th station at sample time t for $t = 1, 2, \dots, M+n$. For each station, the M-AR model (2) can be re-written in a matrix-vector product format as in (1), where $N := nP$. In the training stage, the goal is to find a coefficient vector $\mathbf{x} \in \mathbb{R}^N$ that best explains the observations $\mathbf{b} \in \mathbb{R}^M$ and $A \in \mathbb{R}^{M \times N}$. As seen from (1), \mathbf{x} has a block structure as the coefficients corresponding to each station appear in one vector-block.

III. COMPRESSIVE SPATIO-TEMPORAL WIND SPEED FORECASTING (CST-WSF)

We believe that among a large collection of stations, only a few of them have a strong correlation with the target station. We show that under the assumption of *sparsity* of the interconnections (that is, assuming only a few weather stations contribute to the output of the target station), there will be a distinct structure to the solution \mathbf{x} that we are seeking. In particular, a typical coefficient vector \mathbf{x} under our model assumptions will have very few non-zero entries, and these non-zero entries will be clustered in few locations. Vectors with such structure are called *block-sparse*. The number of blocks corresponds to the number of links that contribute to the output of the target station. For a given target station, we then solve the minimization problem:

$$\min_{\mathbf{x}} \|\mathbf{b} - A\mathbf{x}\|_2 \quad \text{subject to} \quad (\mathbf{x} \text{ is block-sparse}). \quad (3)$$

We call this approach Compressive Spatio-Temporal Wind Speed Forecasting (CST-WSF), as it is inspired by Compressive Sensing (CS) and structured-sparse recovery.

A. Background on CS

CS enables recovery of an unknown signal from its underdetermined set of measurements under the assumption of sparsity of the signal and under certain conditions on the measurement matrix A [22]. The CS recovery problem can be viewed as recovery of a K -sparse signal $\mathbf{x} \in \mathbb{R}^N$ from its observations $\mathbf{b} = A\mathbf{x} \in \mathbb{R}^M$ where $A \in \mathbb{R}^{M \times N}$ is the measurement matrix with $M < N$ (in many cases $M \ll N$). A K -sparse signal $\mathbf{x} \in \mathbb{R}^N$ is a signal of length N with K non-zero entries where $K < N$. Since the null space of A is non-trivial, there are infinitely many candidate solutions to the equation $\mathbf{b} = A\mathbf{x}$; however, CS recovery algorithms exploit the fact that, under certain conditions on A , only one candidate solution is suitably sparse. An interested reader can refer to [23], [24] for several proposed recovery conditions.

B. Uniform CST-WSF

We adapt our CST-WSF algorithm from tools proposed in the CS literature for recovery of a block-sparse signal \mathbf{x} .

Definition 1 (Block K -Sparse Signal): Let $\mathbf{x} \in \mathbb{R}^N$ be a concatenation of P vector-blocks $\mathbf{x}_i \in \mathbb{R}^n$, i.e.,

$$\mathbf{x} = [\mathbf{x}_1^{\text{tr}} \cdots \mathbf{x}_i^{\text{tr}} \cdots \mathbf{x}_P^{\text{tr}}]^{\text{tr}},$$

where $N = nP$. A signal $\mathbf{x} \in \mathbb{R}^N$ is called *block K -sparse* if it has $K < P$ non-zero blocks. \square

Several extensions of the standard CS recovery algorithms can account for additional structure in the sparse signal to be recovered [25], [26]. Among these, the Block Orthogonal Matching Pursuit (BOMP) algorithm [26] is designed to exploit block sparsity due to its flexibility in recovering block-sparse signals of different sparsity levels and its low computation complexity [27]. In a more general setting, BOMP has been recently used for topology identification of interconnected dynamical systems (e.g., see [28]).

C. Nonuniform CST-WSF

In a uniform CST-WSF, the assumption is that a uniform M-AR model as given in (1) is governing the interactions between stations. In other words, we assume that the target station and its surrounding stations are related by AR models of the same order. In this section, we consider a more generalized version of the CST-WSF algorithm where the target station and its surrounding stations are related by AR models of different orders. This model structure, called Nonuniform Multivariate Autoregressive (NM-AR) distinguishes between the stations with high and low cross-correlation with the target station. Let n_i be the order associated with the i -th station for $i = 1, 2, \dots, P$. An NM-AR version of (1) can be considered as given in (4), where $n_{\max} \geq \max_i n_i$ and $N := \sum_{i=1}^P n_i$. This results in a *nonuniform* block-sparse coefficient vector \mathbf{x} whose blocks have different length.

Definition 2 (Nonuniform Block K -Sparse Signal): Let $\mathbf{x} \in \mathbb{R}^N$ as a concatenation of P vector-blocks $\mathbf{x}_i \in \mathbb{R}^{n_i}$ where $N = \sum_{i=1}^P n_i$. A signal $\mathbf{x} \in \mathbb{R}^N$ is called *nonuniform block K -sparse* if it has $K < P$ non-zero blocks. \square

Remark 1: One should note that our definition of nonuniform block K -sparse signals is a generalization of the conventional definition of block K -sparse signals (Definition 1) where all blocks have the same length, i.e., $n_i = n, \forall i$. \square

Given $\{n_i\}_{i=1}^P$, the BOMP algorithm can be used for recovery of \mathbf{x} with $A_i \in \mathbb{R}^{M \times n_i}$. In order to find the set of order $\{n_i\}_{i=1}^P$, we use a correlation analysis. We then adjust the orders to achieve the best prediction performance.

IV. CASE STUDY OF 57 STATIONS IN EAST COAST

We apply our proposed CST-WSF algorithms to real wind speed data. East coast states are good candidates for our study because: (i) wind speed profiles are higher and (ii) there are more stations in a close vicinity in these states.

A. Data Description

We use hourly wind speed data from Meteorological Terminal Aviation Routine (METAR) weather reports of 57 stations in east coast including Massachusetts, Connecticut, New York, and New Hampshire [29]. Fig. 1 depicts the area under study and the location of these 57 stations. The target

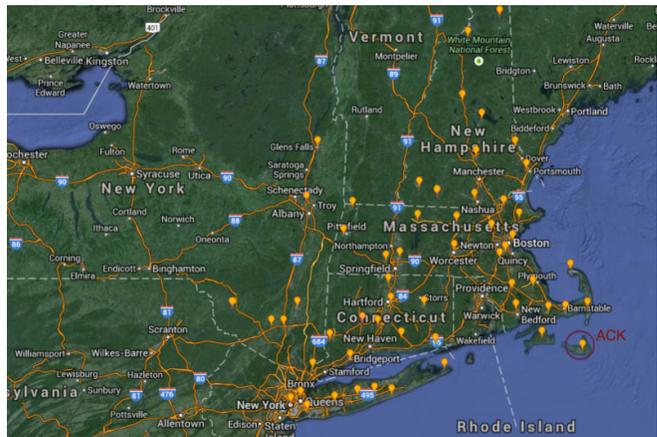


Fig. 1. Map of the area under study. The 57 measuring locations in east coast are shown with yellow points. Circled in red is the target station ACK.

station Nantucket Memorial Airport (ACK) (circled in red) is located on an island and is subject to wind profiles with high ramps and speeds due to the fact that the surrounding surface has very low roughness heights. Furthermore, this area has good correlations with other stations owing to the fact the prevailing wind direction of this region is mainly northwest or southeast. A time period from January 6, 2014 to February 20, 2014 is considered in our simulations. This time period has the most unsteady wind conditions throughout the year. The data is divided to two subsets: (i) training subset from January 6, 2014 to February 6, 2014 (a period of 30 days) and (ii) validation subset from February 6, 2014 to February 20, 2014 (a period of 14 days).

B. Comparison with Other Benchmark Algorithms

In order to better gauge the effectiveness of the proposed algorithm, we compare CST-WSF with other proposed benchmark algorithms in temporal and spatio-temporal wind speed forecasting. For temporal wind speed forecasting, we first consider *persistence forecasting* method which simply uses the last measured value for the forecast interval. Any algorithm that can improve upon persistence forecasting is judged to be an effective algorithm. We also consider AR models as well as an advanced prediction model that combines Wavelet Transform (WT) with Artificial Neural Network (ANN). The latter method is shown to have the capability of capturing nonlinearity in the wind speed time series. In this model, briefly, the volatile wind speed series is first cut up by the WT into a number of better-behaved sub-series in various frequency bands. Subsequently, estimates of each extracted sub-series are carried out separately employing the ANN mode. Speed predictions are then reconstructed except for the highest frequency band which represents the most fluctuating part of the wind speed series (see [30] for more details). Multi-step predictions were performed in a recursive manner for a period of 14 consecutive days with 6 hour-ahead updates. The prediction results are given in Fig. 2. As can be seen, the considered temporal prediction methods provide reasonable forecasting compared to persistence

$$\begin{aligned}
\underbrace{\begin{bmatrix} y_{n_{\max}+1}^i \\ y_{n_{\max}+2}^i \\ \vdots \\ y_{n_{\max}+M}^i \end{bmatrix}}_{\mathbf{b} \in \mathbb{R}^M} &= \underbrace{\begin{bmatrix} y_{n_{\max}}^1 & \cdots & \cdots & \cdots & y_{n_{\max}-n_1+1}^1 & \cdots & y_{n_{\max}}^P & \cdots & y_{n_{\max}-n_P+1}^P \\ y_{n_{\max}+1}^1 & \ddots & \ddots & \ddots & \vdots & \cdots & y_{n_{\max}+1}^P & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots & \cdots & \vdots & \ddots & \vdots \\ y_{n_{\max}+M-1}^1 & \cdots & \cdots & \cdots & y_{n_{\max}-n_1+M}^1 & \cdots & y_{n_{\max}+M-1}^P & \cdots & y_{n_{\max}-n_P+M}^P \end{bmatrix}}_{\mathbf{A} \in \mathbb{R}^{M \times N}} \underbrace{\begin{bmatrix} X_1^{\text{tr}}(1, i) \\ \vdots \\ \vdots \\ X_{n_1}^{\text{tr}}(1, i) \\ \vdots \\ X_1^{\text{tr}}(P, i) \\ \vdots \\ X_{n_P}^{\text{tr}}(P, i) \end{bmatrix}}_{\mathbf{x} \in \mathbb{R}^N}
\end{aligned} \tag{4}$$

model. ANN-based model outperforms the AR model.

We also consider two spatio-temporal forecasting methods. We first employed an advanced ANN-based spatio-temporal model [31]. We also employed a Least Squares (LS) M-AR spatio-temporal forecasting approach [18]. Fig. 3 depicts how incorporation of spatial information improves the forecasting performance as compared to temporal methods.

C. Uniform and Nonuniform CST-WSF

We now apply our proposed uniform and nonuniform CST-WSF methods. Note that in our simulations a new coefficient vector \mathbf{x} is obtained every 6 hours (equivalently, every 6 time steps as each time step is 1 hour). This is the considered prediction time horizon. Also, we follow a recursive approach in prediction. That is, the wind speed predictions at time $n + M + 1$ for all stations ($\hat{y}_{n+M+1}^i, \forall i$) are included in the A matrix for predicting the wind speed at time $n + M + 2$ ($\hat{y}_{n+M+2}^i, \forall i$) and so on. This recursive process goes on for 6 time steps. The elements of A are then completely updated with real measurements and the recursive process continues for another 6 time steps.

Figure 4(a) shows the result of the uniform CST-WSF. The result is superior to all benchmark approaches discussed in the previous section. We then apply the nonuniform CST-WSF algorithm. The result is illustrated in Fig. 4(b). In order to demonstrate the effectiveness of the proposed forecasting models, the associated Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values, which are the most common performance metrics in the wind forecasting literature, are listed in Table I for all of the wind speed forecasting methods considered in this paper. The MAE provides the average deviation between the measured and predicted data while the RMSE gives higher weights to larger error values by squaring the differences. Moreover, the Normalized Root Mean Squared Error (NRMSE) which is the RMSE normalized by the range of observed data, is calculated to provide a scale-independent error measure. Evidently the proposed uniform and nonuniform CST-WSF methods outperform the other considered temporal and spatio-temporal methods. The best prediction is provided by the nonuniform CST-WSF. Considering the NRMSE as

TABLE I
STATISTICAL ERROR MEASURE COMPARISON OF DIFFERENT METHODS

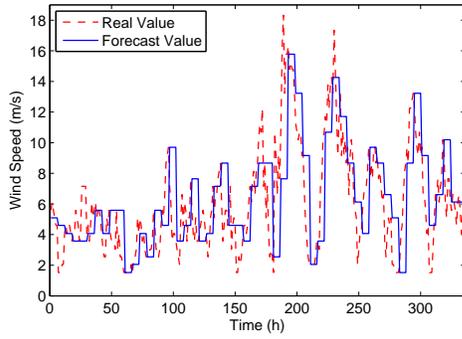
Forecasting approach	MAE (m/s)	RMSE (m/s)	NRMSE (%)
Persistence Forecasting	2.1441	2.8334	16.86
AR of order 1	2.0742	2.7629	16.44
AR of order 3	2.0696	2.7560	16.40
WT-ANN	1.8200	2.4671	14.68
ANN-based ST	1.7981	2.2997	13.69
LS-based ST	1.7234	2.1983	13.08
CST-WSF of order 3	1.5665	2.0595	12.25
Nonuniform CST-WSF	1.3442	1.7586	10.46

an example, nonuniform CST-WSF approach provides a reduction of 38%, 36.2% and 28.7% as compared to the considered temporal methods (persistence forecasting, AR of order 3, and WT-ANN models) and a reduction of 24% and 20% as compared to the considered spatio-temporal methods (ANN-based ST and LS-based ST), respectively.

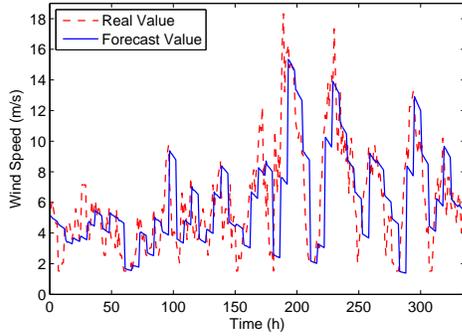
Fig. 5 illustrates the corresponding block-sparse coefficient vectors for the uniform and nonuniform CST-WSF methods at the training stage. As can be seen, only a few of the blocks in uniform and nonuniform CST-WSF are non-zero, resulting in a block-sparse \mathbf{x} . This block-sparse structure appears in all of the other calculated coefficient vectors (with different block-sparsity pattern) as we move over prediction horizon time and further confirms our motivation behind exploiting the intrinsic low-dimensional models in spatio-temporal wind speed forecasting. It is worth noting that the proposed CST-WSF methods have a much shorter computational time as compared to other ANN-based methods and the average computational time for other proposed short-term forecasting methods in the literature [15], [32]. For instance, the total simulation time of nonuniform CST-WSF approach is almost the half of the time required for the predictions with WT-ANN model and approximately 15% smaller than that of LS M-AR spatio-temporal model in this study.

V. CONCLUSION

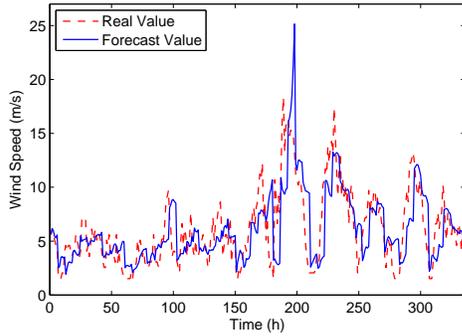
We proposed two spatio-temporal wind speed forecasting methods, called uniform and nonuniform CST-WSF. The methods are inspired by CS and structured-sparse recovery



(a) Persistence forecasting



(b) AR model of order 3

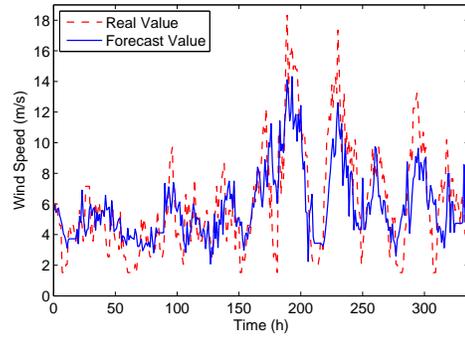


(c) WT-ANN model

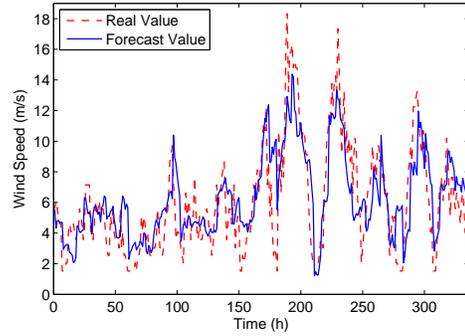
Fig. 2. Comparison of different temporal forecasting algorithms.

algorithms, where we claim that there usually exists an intrinsic low-dimensional structure governing a large collection of stations. The results of a case study show that the proposed approaches considerably improves the short-term forecasts compared to a set of widely-used benchmark models.

As future directions, we plan to apply the proposed CST-WSF to a much larger set of stations. Incorporating other variables (such as temperature, pressure, etc.) in the wind speed forecasting is another research path. Yet another direction is to investigate using sparsity-based ideas in probabilistic forecasting methods. Such information about the forecast errors are useful for Transmission System Operators (TSOs), Independent Power Producers (IPPs), etc., in evaluating the economic and technical risks due to uncertainty.

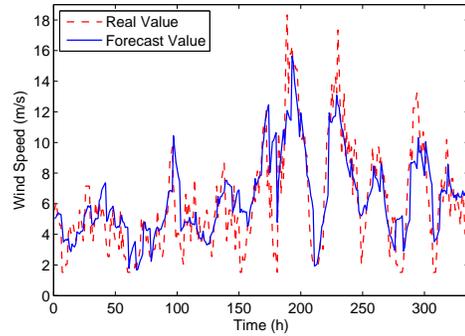


(a) Spatio-temporal ANN model

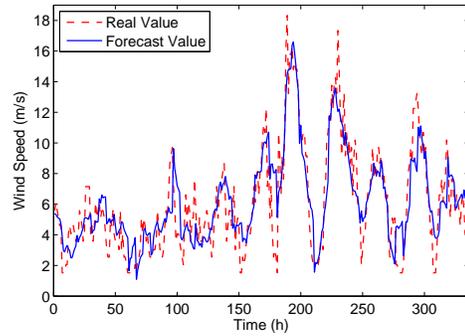


(b) Spatio-temporal LS M-AR model

Fig. 3. Comparison of different spatio-temporal forecasting algorithms.



(a) Uniform CST-WSF with equal orders of 3.



(b) Nonuniform CST-WSF with nonuniform orders.

Fig. 4. Comparison of the uniform and nonuniform CST-WSF.

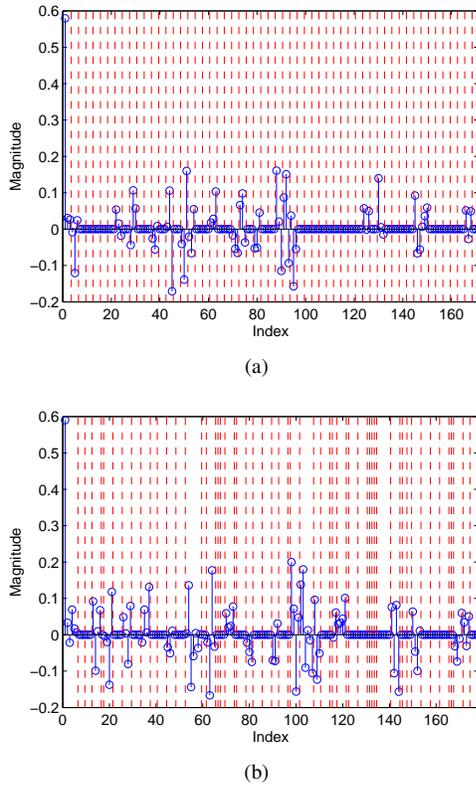


Fig. 5. Block-sparse coefficient vector. The red dashed lines specify 57 vector-blocks of the coefficient vector. (a) Uniform CST-WSF of order 3. (b) Nonuniform CST-WSF with different orders (vector-block lengths).

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