An advanced strategy for wind speed forecasting using expert 2-D FIR filters

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***Abstract*—Renewable energies such as wind and solar have become the most attractive means of electricity generation nowadays. Social and environmental benefits as well as economical issues result in further utilization of such these energy resources. In this regard, wind energy plays an important roll in operation of small-scale power systems like Micro Grid. On the other hand, wind stochastic nature in different time and place horizons, makes accurate forecasting of its behavior an inevitable task for market planners and energy management systems. In this paper an advanced strategy for wind speed estimation has been purposed and its superior performance is compared to that of conventional methods. The model is based on linear predictive filtering and image processing principles using 2-D FIR filters. To show the efficiency of purposed predictive model different FIR filters are designed and tested through similar data. Wind speed data have been collected during the period January 1, 2009 to December 31, 2009 from Casella automatic weather station at Plymouth. It is observed that 2-D FIR filters act more accurately in comparison with 1-D conventional representations; however, their prediction ability varies considerably through different filter sizing.**

***Index Terms*—Energy forecasting, FIR filters, Image processing, 2-D linear filtering, Wind speed**

I. INTRODUCTION

In recent times, new trend in electrical systems is developing toward substituting large power plants with smaller distributed generation units (DG) to avoid negative environmental footprints and energy deficiencies as well. Besides, considering a situation in which renewable energies are exploited at high levels, it is becoming more and more important to assess the amount of power obtained from such resources. Since wind is a widespread kind of renewable energy that can be easily converted into electricity therefore accurate wind speed estimation or its related power prediction becomes vital for secure operation of power grids. Furthermore, the stochastic nature of wind and its speed intermittency makes wind speed forecasting a challenging task in power market scheduling, i.e. because the amount of power available from a wind farm depends greatly upon the wind speed, unexpected changes at the farm output power can cause potential risks and additional costs for both supply and demand sides [1]. In this matter, providing a reliable means of wind speed or power forecasting, becomes the field of study for many authors and researches. Various types of forecasting tools are accessible at the present time and most of them are generally based on physical or statistical methods, hybrid models, artificial neural networks and some other compound methods [2-7]. For example, physical methods like Numerical Weather Forecasting (NWF) usually use several physical considerations such as meteorological or topological data to provide forecast objectives [8]. On the other side, Statistical methods are widely used because the atmosphere dynamic conditions form a nonlinear system, and forecasting can't be implemented in a deterministic sense. Such these methods are recursive Least Squares Regression (LSR) or Autoregressive Integrated Moving Average (ARIMA) models that provide satisfactory prediction on the basis of observed time series data and their mutual relations [9-11]. Artificial Neural Networks (ANNs) are some other types of popular tools in the field of forecasting that provide flexibility of applications as well as acceptable errors. As an example Lapedes et al. [12] proposed a feed-forward neural network for wind speed estimation using back-propagation error algorithm. Meanwhile, there exist other types of fuzzy predictive models or compound methods such as neuro-fuzzy algorithms that are used to a great extent [13-15].

This study focuses on an expert estimation of wind speed so that the maximum power generation from a typical wind farm can be calculated genuinely. The work origin is completely different from previously mentioned methods and it is mainly set up on rendering wind speed data in a 2-D image-like model as will be described in the next Section. Although such similar data representations can be found in articles [16], but the novelty of the idea is something specific in the field of wind speed prediction. During the work, first a brief description on image processing principles and predictive filtering is presented. After that mathematical modeling of FIR filters and coding concepts is discussed and lastly, several predictors based on expert FIR filters are designed and tested to verify the efficiency of purposed predictive models. Comparison of results shows that 2-D predictive filtering not only results more reliable and accurate estimation of wind speed but also provides a suitable mean for realizing wind speed correlations in different hours of a day or among any particular hours of different days. Moreover, since the 2-D modeling is fed by real recorded wind speed data which includes both surface effects and meteorological changes such as air pressure, relative humidity or even temperature, provides more reliable information for operators. The wind speed data used in the work are collected during the period January 1, 2009 - December 31, 2009 from Casella automatic weather station at Plymouth, UK. The weather station is located on the roof of the Fitzroy building which is approximately 50m above MSL and 15m above ground level. The anemometer is based upon a three cup rotor, with an accuracy of ±1% over 3m/sec. Starting velocity is 0.4m/sec and the maximum designed wind speed is 75m/sec.

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II. RENDERING WIND SPEED DATA TO AN IMAGING MODEL

Rendering wind speed data into a smart visual model yields several advantages. It offers an easier way for understanding meteorological information and their interdependencies in different time horizons; provides better interpretation of wind speed data and their related behaviors and finally assists to implement an efficient predictive filtering process. To construct the visual model, whole recorded wind speed data must be arranged in a n by m array initially (Eq. (1)). The number of rows reveal days of a year (n=1 to 365) and the number of columns shows different hours in a given day (m=1 to 24). Each element inside the 2-D array represents (v_{ij}) wind speed magnitude at a given hour of a particular day in the year.

$$V_{wind-speed} = \begin{bmatrix} v_{11} & \cdots & v_{1m} \\ \vdots & v_{ij} & \vdots \\ v_{n1} & \cdots & v_{nm} \end{bmatrix} \qquad (1)$$

$$m = 1, 2, \ldots, 24 \quad ; \quad n = 1, 2, \ldots, 365$$

$$v_{i,j} = wind\ speed\ at\ j^{th}\ hour\ of\ i^{th}\ day$$

Fig.1 shows the hourly wind speed data in a time plot (hour horizon) while Fig. 2 displays the similar values for wind speed in a 2-D surface plot (day and hour horizons).

Two important observations can be found from above figures. First the stochastic nature of wind data is obvious from both 1-D and 2-D representations, but it's hard to make distinction between wind speed through days and hours in Fig. 1 while this interpretation is easy to understand in Fig .2. To form the visual model based on the surface model of Fig. 2 all the available information about the magnitude of wind speed must be converted to a gray-scale image as shown in Fig. 3. In this image corresponding pixels represented by different gray values that range from white to black reveal hourly wind speed data in an expert pattern i.e. this kind of indexed sequential access method makes the estimation process a much more suitable structure for applying forecasting techniques via digital filters as will be explained in the next section.

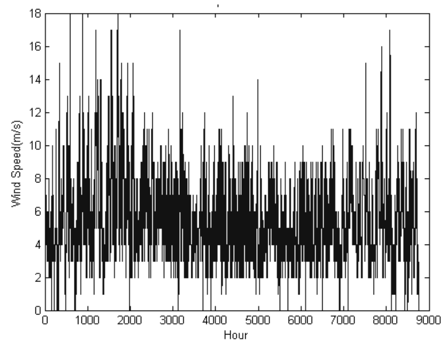


Fig. 1. Wind speed data time-plot

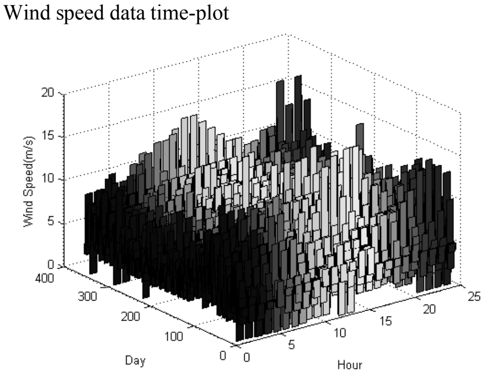


Fig. 2. Hourly wind speed data surface plot

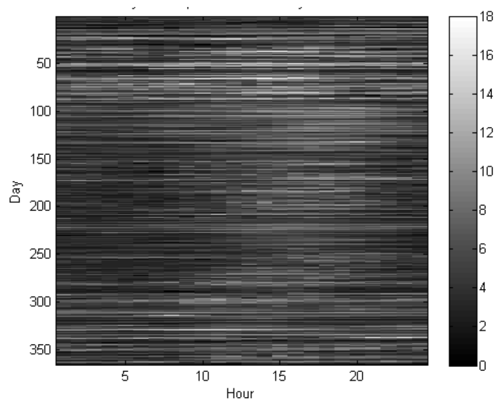


Fig. 3. Hourly wind speed data in a gray-scale-image model

As mentioned earlier, 2-D modeling makes it possible to grasp the meaning of data easily and perform the prediction more reliable in comparison with conventional 1-D representations. Moreover, forecasting techniques using image processing tools can be easily implemented considering correlations between pixels.

III. IMAGE PREDICTIVE FILTERING FUNDAMENTALS

Predictive filtering in image processing filed is defined as a particular operation in which the scalar value of any given pixel inside the image template can be calculated by applying some mathematical algorithms to the values of the pixels in the neighborhood of the corresponding target pixel. In this regard, Linear predictive filtering is explained as a common form of filtering in which the output pixel value can be determined as a linear combination of neighboring pixels magnitudes. Another explanation is that linear predictive filtering tries to estimate future values of the input signal on the basis of past signals. Generally, for a typical linear predictive coding (LPC) we derive an algorithm with two separate parts: first an encoding part and then a synthesis or decoding part. In an encoding part, the designed LPC takes the input samples in predefined blocks and determines the input time series signal and related filter taps in order to reproduce the current block of information. These output data is quantized and passed to the second part. In decoding section, the filter is reconstructed by LPC based on the received coefficients from previous part. The whole filter structure can be viewed as a tube that, when is fed by an input signal, produces required information (Forecasted values). In predictive coding, different types of filters can be designed and applied to the work but basically, there are two kinds of filters: Finite Impulse Response (FIR) filters and Infinite Impulse Response (IIR) filters. Table 1, shows a brief comparison of these two digital filters.

TABLE I. FIR FILTERS VS. IIR FILTERS

Characteristics	FIR filters	IIR filters
Architecture & Implementation	Easy and simple, single loop instruction, possible to implement using coefficients with magnitude of less than 1 and total gain of the filter can be adjusted at the output, no limit cycle, implemented just as a single summation of products.	Hard to implement, multiple loop instruction, might have limit cycles, it needs two summations of products for both feed-forward and feedback sections, implementations are restricted to application-specific designs.
Phase	Linear phase.	Usually nonlinear phase, difficult to control, no particular techniques available.
Feedback dependency	No feedback, Depends only on previous input samples.	Need feedback loop, depends on the previous input as well as output samples.
History	Require more memory, No analog history.	Require less memory, but Derived from analog filters.
Stability	Always stable.	Can be unstable for higher order tapping.
Application	Suited to multi-rate applications or to applications where we need a linear phase-characteristic.	Can be used in nonlinear applications or where linearity is not at the head of concern.

A. Characterizing digital FIR filters

There are several terms used for describing the design structure and performance of FIR filter as mentioned below [17]:

1. *Filter Coefficients (Tap weights)*: set of constants used to multiply against delayed sample values. In the case of an FIR filter the impulse response of the filter defines such coefficients.
2. *Impulse Response:* A sequence of time domain output when the input is an impulse.
3. *Tap:* FIR filter tap numbers indicate the amount of required memory, the amount of calculations which is needed, and the extent of filtering that it can provide. Basically, if more taps are considered for a typical FIR filter then it will result better attenuation through the stop band, less ripple amount and variations in the pass band and finally provides steeper roll off and a shorter transition between the pass band and the stop band.
4. *Multiply-Accumulate (MAC)*: In this regard, an operation in which a coefficient is multiplied by the corresponding delayed data sample and the result is accumulated in each step, called *"MAC"*. There is usually one MAC per tap.

Mostly, a causal N^{th} –order FIR filter is described by a transfer function A (z) given by Eq. (2)

$$A(z) = \sum_{n=0}^{N} a[n] z^{-n} , \qquad (2)$$

The operation of the above FIR filter is given by the time domain difference Eq. (3)

$$y[n] = \sum_{k=0}^{N} a[k]\, x(n-k) \qquad (3)$$

Common architecture of FIR filters can be seen in Fig. 4 – 6.

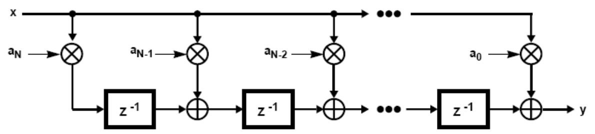


Fig. 4. Transposed FIR filter

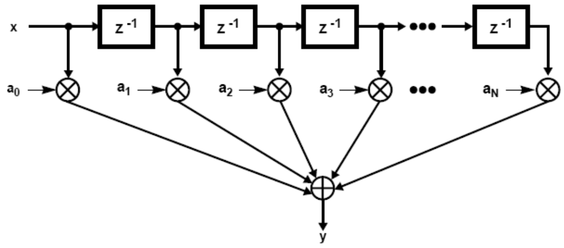


Fig. 5. Transversal FIR filter

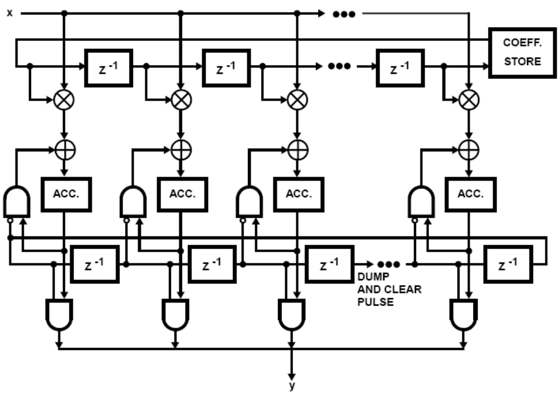


Fig. 6. Parallel multiplier-accumulator FIR filter

IV. DESIGNING LINEAR PREDICITVE DIGITAL FIR FILTERS

In linear forecasting, future samples or target outputs can be optimally estimated through an autoregressive process using a linear combination of past samples. In the case of FIR, the filter used by the synthesis part (decoder) to rebuild the original input block is established upon a set of taps or coefficients. It's mentioned earlier that during the encoding or analysis process all the coefficients are obtained from the real input and are passed to decoding part. Each separate segment has its own parameters or better to say filter coefficients that is used to reconstruct the target output. If *n* parameters are used in filtering procedure then it's called an n^{th} -order FIR filter. Now, to find optimal filter coefficients that best describe the current plan of action, first the error function must be minimized in the sense of mean squared error (Eq. (4)).

$$e_n^2 = (x_n - \sum_{i=1}^{M} a_i x_{n-i})^2 \qquad (4)$$

where $\{x_n\}$ includes an array of input samples for the current block and $\{a_i\}$ is the vector of filter coefficients. The most accurate tap vector $\{a_i\}$ can be found through minimization of the mean value of e_n^2 for all samples within the template by taking corresponding derivative (Eq. (5)).

$$\begin{aligned} &\frac{\delta}{\delta a_j} E[(x_n - \sum_{i=1}^{M} a_i x_{n-i})^2] = 0 \\ &\rightarrow -2E[(x_n - \sum_{i=1}^{M} a_i x_{n-i}) x_{n-j}] = 0 \\ &\rightarrow \sum_{i=1}^{M} a_i E[x_n x_{n-j}] = E[x_n x_{n-j}] \\ &(Note: E[x_n x_{n-j}] = 0 \ if \ j \neq 0) \end{aligned} \tag{5}$$

Taking the above derivatives yields M equations that can be written in the form of a matrix equation. Solving the mentioned equations for optimal filter coefficients needs an accurate estimation of $E[x_{n-i} x_{n-j}]$ value. To find the estimation value both autocorrelation and auto covariance approaches can be applied. In this paper, the autocorrelation approach is adopted and used for linear predictive coding objectives [18-19]. To apply the autocorrelation method two initial assumptions can be made for $\{x_n\}$ within the current template as stated below:

1. $\{x_n\}$ is stationary.
2. $\{x_n\} = 0$ beyond the current template range.

In the case of autocorrelation, each mathematical expectation such as $E[x_{n-i} x_{n-j}]$ is changed into an autocorrelation function in the form of $R_{xx}(|i-j|)$. Here, the estimation of the above function $R_{xx}(k)$ can be expressed as Eq. (6):

$$R_{xx}(k) = \sum_{n=n_0+1+k}^{n_0+N} x_n x_{n-k} \tag{6}$$

Using $R_{xx}(k)$, the M matrix equations obtained from derivatives of the total mean squared error can be written as Eq. (7).

$$RA = P \tag{7}$$

Where R is the correlation matrix and represents the correlation between an ensemble of samples that are separated by their distinct index, A is the vector of optimal filter coefficients and P is the output vector represents the correlations between the estimated value and any of the samples within the prediction template as described in detail by Eq. (8).

$$R = \begin{bmatrix} R_{xx}(0) & R_{xx}(1) & R_{xx}(2) & \cdots & R_{xx}(M-2) & R_{xx}(M-1) \\ R_{xx}(1) & R_{xx}(0) & R_{xx}(1) & \cdots & R_{xx}(M-3) & R_{xx}(M-2) \\ R_{xx}(2) & R_{xx}(1) & R_{xx}(0) & \cdots & R_{xx}(M-4) & R_{xx}(M-3) \\ \vdots & \vdots & \vdots & & \vdots & \vdots \\ \vdots & \vdots & \vdots & & \vdots & \vdots \\ R_{xx}(M-1) & R_{xx}(M-2) & R_{xx}(M-3) & \cdots & R_{xx}(1) & R_{xx}(0) \end{bmatrix} \tag{8}$$

$$A = [a_1 \ a_2 \ a_3 \ \cdots \ \cdots \ a_M]^T$$
$$P = [R_{xx}(1) \ R_{xx}(2) \ R_{xx}(3) \ \cdots \ \cdots \ R_{xx}(M)]^T$$

To calculate the filter coefficients first it's needed to compute the inverse of correlation matrix (R^{-1}). Since R is a symmetric matrix with similar diagonal elements, the inversion action can be done easily using some recursive approaches like Levinson-Durbin (L-D) which is computationally efficient while determining the filter coefficients using Eq. (9).

$$A = R^{-1}.P \tag{9}$$

It should be mentioned that for a time varying series the correlation coefficient (ρ) between two random variables indicates the amount of their mutual dependency. Basically, ρ is limited between -1 and +1 which +1 shows a perfect positive linear correlation, -1 indicates the same meaning but in a negative sense and 0 indicates no linear relationship between values. The population correlation coefficient $\rho_{X,Y}$ between two random variables X and Y with expected values μ_X and μ_Y and standard deviations σ_X and σ_Y is defined as Eq. (10).

$$\rho_{X,Y} = Corr(X,Y) = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y} \tag{10}$$

Where E is the mathematical expectation, $\mathrm{cov}(X,Y)$ means covariance between X and Y variables and, $Corr$ is a famous notation for Pearson's correlation [20].

A. Expert 2-D predictive FIR filters

In this section, different types of 2-D FIR filters are designed and their performances are compared in the case of forecasting ability with conventional 1-D types. It's proved in linear predictive coding that a precise and robust forecasting process relies on applying highly correlated information [21]. The more correlated data results the less prediction error and the more forecasting quality. Therefore, in the first step it is necessary to provide accurate information about the wind speed data interdependencies through the whole time domain. Table 2 shows such these correlations within a square template with 4 pixels in length and wide showing 4 consecutive hours a day and 4 consecutive days in a year respectively.

TABLE II. CORRELATION COEFFICIENTS WITHIN THE TEMPLATE

$\rho_{i,j}$	j = 0	j = 1	j = 2	j = 3
i = 0	1	0.97907	0.96336	0.94528
i = 1	0.86766	0.86632	0.86192	0.85527
i = 2	0.85136	0.85021	0.84583	0.83933
i = 3	0.86527	0.86353	0.85895	0.85212

As previously mentioned in introduction section (articles review) it's concluded that conventional methods for wind speed forecasting are generally based on utilizing past samples before the hour to be forecasted i.e. all related approaches are limited in a 1-D template which refers to a horizontal prediction [4] or 1-D horizontal filtering as shown in Fig. 7. It's observed from the first row of Table 2 that horizontal pixels which shows consecutive hours in a given day are highly correlated therefore they enhance forecasting capability greatly but it's worthy of note that using a high indexed i and j in the template (considering a larger template) may results to unreliable or imperfect forecasting. In this study different template sizes are chosen considering i, j = 0, 1, 2, 3 and 4.

$$\begin{bmatrix} x_{1,1} & & & \cdots & & x_{1,m} \\ \vdots & (\cdots \rightarrow & x_{i,j-2} \rightarrow & x_{i,j-1} \rightarrow & \langle x_{i,j} \rangle \;\; \cdots) & \vdots \\ x_{n,1} & & & & & x_{n,m} \end{bmatrix}$$

Fig. 7. Horizontal predictive filter(1-D FIR filter –Type 1)

The one dimensional forecasting can also be implemented in a vertical mode as shown in Fig. 8. In this case, vertical forecasting means to estimate wind speed in a given hour of a day using samples from previous days but the same hour. Although these sequential data have great mutual dependencies (the first column of Table 1 shows related interdependencies) but, since correlation coefficients through this template are lower than the previous one it's expected that the accuracy of forecasting decreases in comparison with the horizontal forecasting and the numerical results confirm it.

$$\begin{bmatrix} x_{1,1} & & \cdots & & x_{1,m} \\ & & \begin{pmatrix} \downarrow \\ x_{i-2,j} \\ \downarrow \\ x_{i-1,j} \\ \downarrow \\ \langle x_{i,j} \rangle \\ \vdots \end{pmatrix} & & \\ \vdots & \cdots & & \cdots & \vdots \\ x_{n,1} & & \cdots & & x_{n,m} \end{bmatrix}$$

Fig. 8. Vertical predictive filter (1-D FIR filter-Type 2)

Up until now some conventional methods are reviewed and their equivalence filters are discussed. Here, the plan of action changes from formal 1-D approaches to expert 2-D ones. This kind of 2-D predictive filtering takes advantages from both previous single direction forms and the filtering is established on high correlation coefficients within the template. Referring to Table 2, again it's observed that correlation coefficients decrease as long as i and j increase across the template. It means that neighboring pixels in multiple directions contain a strong correlation with each other while the others miss such high correlations, so considering a set of pixels with the highest correlations can be a decisive factor for implementation of expert 2-D FIR filters as shown in Fig. 9.

$$\begin{bmatrix} x_{1,1} & \cdots & & \cdots & x_{1,m} \\ & \begin{pmatrix} \vdots & \vdots & \vdots & \downarrow \\ \vdots & \vdots & \cdots & x_{i-2,j} \\ \vdots & \cdots & x_{i-1,j-1} & x_{i-1,j} \\ \rightarrow & x_{i,j-2} & x_{i,j-1} & \langle x_{i,j} \rangle \end{pmatrix} & & & \\ \vdots \;\; \cdots & & & & \cdots \;\; \vdots \\ x_{n,1} & \cdots & & \cdots & x_{n,m} \end{bmatrix}$$

Fig. 9. 2-D FIR predictive filter

B. Evaluating purposed FIR filters performance

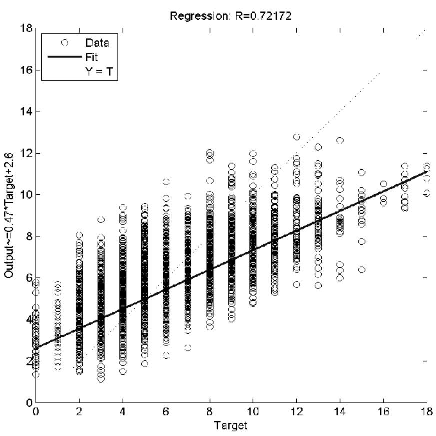
Here, to assess the performance of purposed filters 5 types of structures are constructed, two types of 1-D filtering (Horizontal and Vertical) and three types of 2-D filtering with different orderings, for example a 5^{th} -order filter applies a template which includes five pixels with the highest correlations in a 2-D domain. Similar wind speed data are used for all the models and the forecasting ability of structures compared in the field of maximum error, Root Mean Square Error (RMSE) and the maximum likelihood of predicted values against the actual ones. Optimal filters taps are also calculated using Eq. (9) and tabulated as shown below (Table 3):

TABLE III. OPTIMAL FILTER COEFFICIENTS

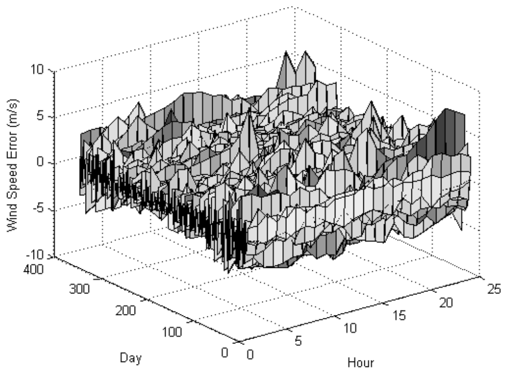
	1-D Type 1 Horizontal FIR Filter	1-D Type 2 Vertical FIR Filter	2-D Type 1 3^{rd}-order FIR Filter	2-D Type 2 4^{th}-order FIR Filter	2-D Type 3 5^{th}-order FIR Filter
h_1	0.8717	0.37769	0.82631	0.83191	0.08103
h_2	0.15923	0.2099	0.091404	0.14916	0.019701
h_3	-0.05037	0.3616	0.073031	-0.064192	0.048049
h_4	N/A*	N/A	N/A	0.10044	0.81171
h_5	N/A	N/A	N/A	N/A	-0.03866

* N/A: Not Available.

To assess the forecasting performance of purposed filter a set of data is fed into the prediction model and estimated values are obtained respectively. Fig. 10a shows the performance of a vertical filter in which target values are plotted against estimated ones. The prediction error is also shown in Fig. 10b. It should be mentioned that the vertical model uses 3 wind speed samples from previous days but the same hour before the hour to be forecasted. It's observed that regression between forecasted output and the real one is to some extent low (R=0.72172) and the maximum error reaches 9 (m/s) considering that the maximum wind speed in the year is 18 (m/s).



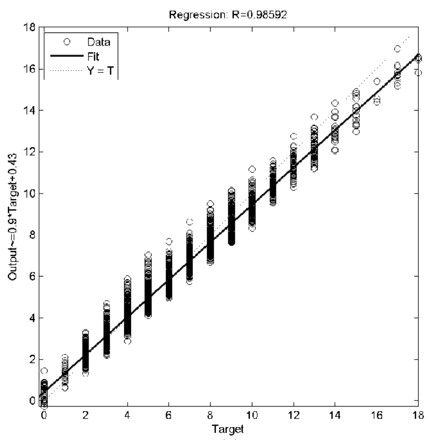
(a)



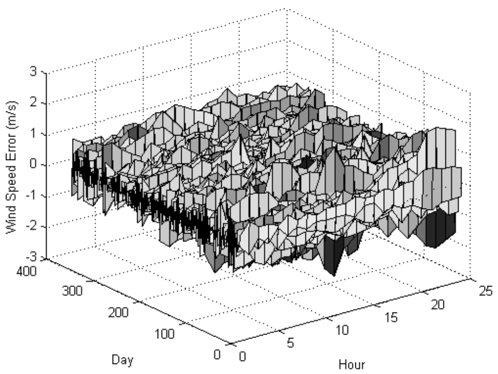
(b)

Fig. 10. Vertical forecasting performance

The second model indicates horizontal filtering whose performance and prediction error are depicted in Fig. 11a and Fig. 11b respectively. Again for this type of forecasting 3 wind-speed samples from previous hours in a same day are utilized and it's observed that estimation ability improves because correlation coefficients between wind speed data through this template are stronger than the previous one. This time regression rises to R=0.98592 and the maximum error falls to 2.2 (m/s) which demonstrates a further improvement.



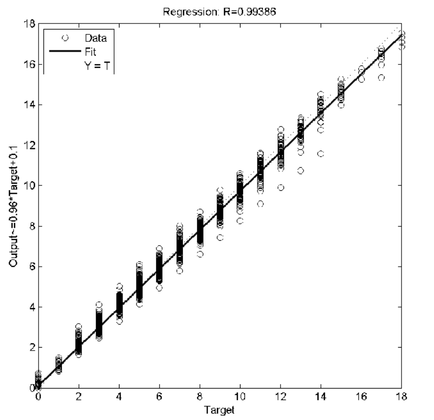
(a)



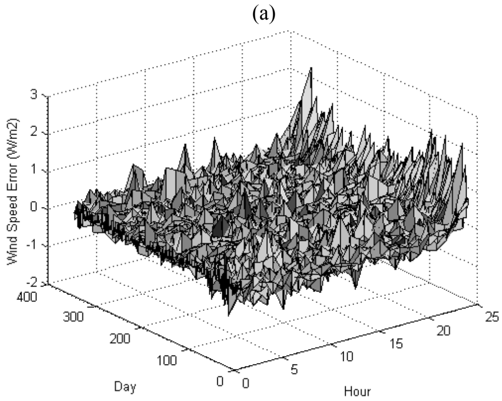
(b)

Fig. 11. Horizontal forecasting performance

The third model, which benefits a 2-D structure and reveals the intelligent idea of this paper, uses 3 samples from previous hours and days with the highest correlation inside the template for the forecasting process. As shown in Fig. 12 the forecasting performance improves to a great extent (R=0.99388). The purposed 2-D filtering indicates that wind speed behavior in a given hour of a day is highly resembles to that of previous hours or to that of previous days and the same hour therefore, to reach a reliable forecasting it's needed to apply wind speed samples from previous hours as well as samples from previous days.



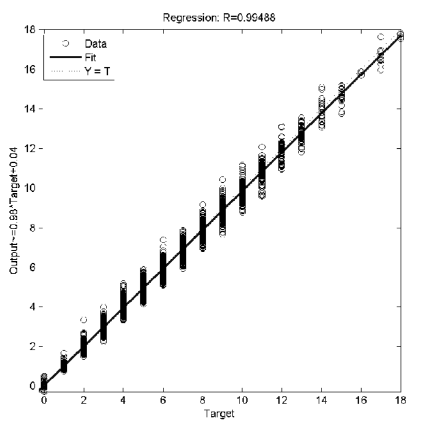
(a)



(b)

Fig. 12. 2-D forecasting performance (Type 1- 3rd-order FIR Filter)

In this regard, if we enlarge our template size by increasing i and j indices in both direction and use more past samples the performance shows further improvement but it should be considered using large template size not only requires extra memory for filtering process and data saving but also causes unreliable forecasting in some cases. Figs. 13-14 show the filter size extension to 4th and 5th -order respectively and the results indicate that using larger 2-D templates (to a limit range) together with optimal filter sizing ends in higher performance and more trustful forecasting in comparison with previously mentioned 1-D models.



(a)

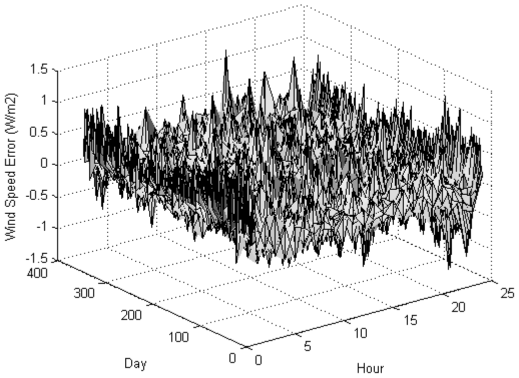


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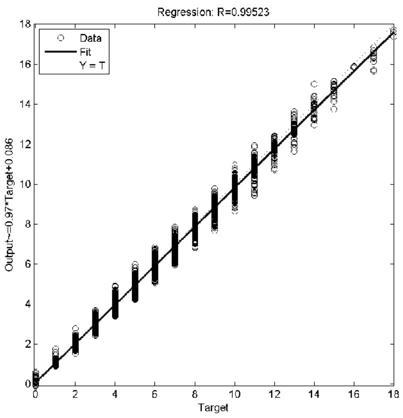
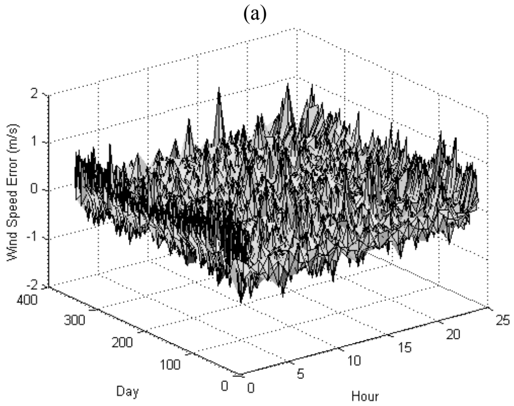
Fig. 13. 2-D forecasting performance (Type 2 - 4th-order FIR Filter)



(a)



(b)

Fig. 14. 2-D forecasting performance (Type 3 - 5th-order FIR Filter)

V. RESULTS AND DISCUSSIONS

Experimental observations indicate that image processing tools and predictive filtering can be powerful means to overcome the stochastic nature of wind. According to the 2-D image-like model it's observed that adjacent pixels in a given template are more correlated than the others in farther distances. On the other hand, using predictive filtering based on strong correlation values can improve the forecasting problem to a high amount. Furthermore, it was indicated that wind speed behavior at any time of a given day resembles highly to that of previous hour i.e. consecutive hours a day carrying high correlation values ($\rho \geq 0.97$). From the other point of view, wind speed data at a given hour among consecutive days are also correlated but in lower amounts ($\rho \geq 0.86$). Considering a 2-D template with a set of highly correlated pixels can be the best respondent to the forecasting needs and Table 4 is an approval to this statement. All the previously mentioned forecasting models are compared in the field of Root Mean Square Error (RMSE) and the maximum likelihood of predicted values against the actual ones($\rho_{est-act}$).

TABLE IV. COMPARISON BETWEEN FORECASTING MODELS

Filter Type	Max Error(m/s)	RMSE	$\rho_{est-act}$
1-D Type 1 Horizontal FIR Filter	2.1763	0.46054	0.98592
1-D Type 2 Vertical FIR Filter	8.6114	1.7621	0.72172
2-D Type 1 3rd-order FIR Filter	2.4317	0.28721	0.99386
2-D Type 2 4th-order FIR Filter	1.4118	0.257	0.99488
2-D Type 3 5th-order FIR Filter	1.5707	0.2511	0.99523

In order to get a better insight about the performance of 2-D predictive filters and compare their acts of forecasting with that of conventional predictors, a set of wind speed data from 25th day of the year is selected and used for testing the purposed models as shown in Figs. 15-19.

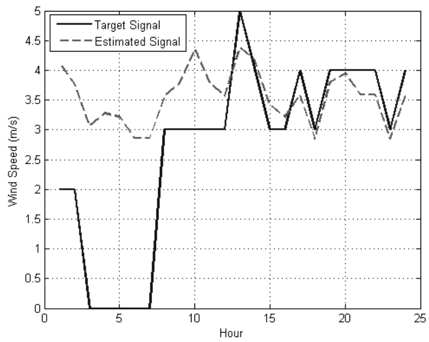


Fig. 15. Vertical filter performance in a 24-hour horizon

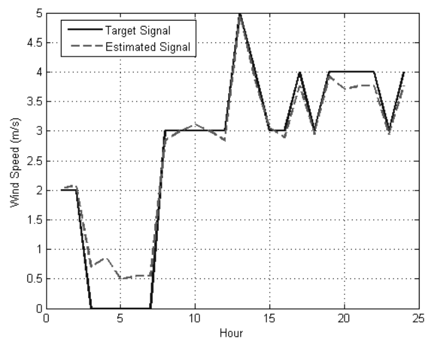


Fig. 16. Horizontal filter performance in a 24-hour horizon

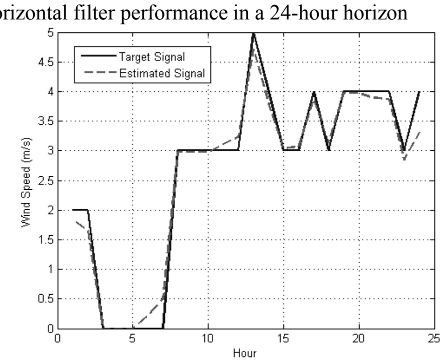


Fig. 17. 3rd-order FIR Filter performance in a 24-hour horizon

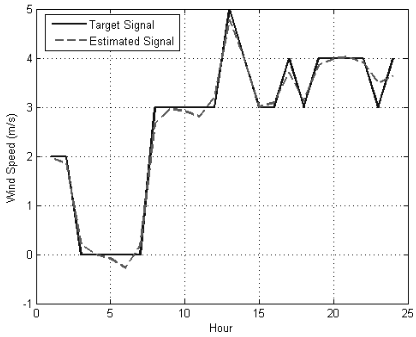


Fig. 18. 4th-order FIR Filter performance in a 24-hour horizon

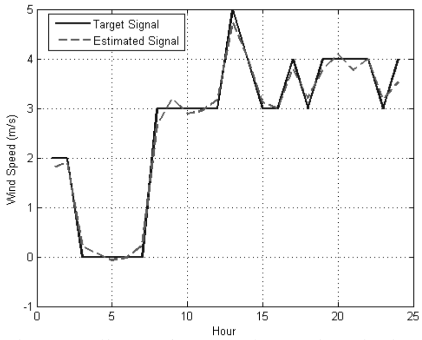


Fig. 19. 5th-order FIR Filter performance in a 24-hour horizon

From above illustrations it's observed that 2-D estimators acts surprisingly better than the 1-D representations in other words, well-designed 2-D FIR filters accompanied by higher order 2-D templates, produce more perfect forecasting in comparison with earlier models. On the whole, 2-D predictive filtering is a key means for improving the prediction capability through gathering strong correlated data in a template and using their similarity in estimation process.

VI. CONCLUSION

So far, many various models for predicting renewable energies have been purposed and mostly are based on physical methods or conventional statistical ones. Some others apply neural networks techniques or combined methods such neuro-fuzzy algorithms or wavelet transformation. Anyway, forecasting methods are generally based on one dimensional routine algorithm and few of them purposed two dimensional modeling [12], but the lack of accuracy can be found in all of them. On the other side, with high levels of renewable energy penetration in a Micro Grid the overall effect on grid operations will increase consequently therefore, there is a strong need to forecast max power generation from these resources accurately. In this work, various types of FIR filters are designed for wind speed forecasting and their performances are evaluated using similar data. It's indicated that an intelligent 2-D structure gives a better forecasting both in the case of RMSE and maximum likelihood, compared to the 1-D conventional types.

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