Improved Kalman Filtered Neuro-Fuzzy Wind Speed Predictor For Real Data Set Collected At Egyptian North-Western Coast

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Abstract: *Wind energy plays an important role as a contributing source of energy, as well as, and in future. It has become very important to predict the speed and direction in wind farms. Effective wind prediction has always been challenged by the nonlinear and non-stationary characteristics of the wind stream. This paper presents three new models for wind speed forecasting, a day ahead, for Egyptian North-Western Mediterranean coast. These wind speed models are based on adaptive neuro-fuzzy inference system (ANFIS) estimation scheme. The first proposed model predicts wind speed for one day ahead twenty four hours based on same month of real data in seven consecutive years. The second proposed model predicts twenty four hours ahead based only one month of data using a time series predication schemes. The third proposed model is based on one month of data to predict twenty four hours ahead; the data initially passed through discrete Kalman filter (KF) for the purpose of minimizing the noise contents that resulted from the uncertainties encountered during the wind speed measurement. Kalman filtered data manipulated by the third model showed better estimation results over the other two models, and decreased the mean absolute percentage error by approximately 64 % over the first model.*
Keywords: *Kalman Filtering, Forecasting, State Estimation, Time series, Adaptive Neuro-Fuzzy Inference System.*

I. Introduction

Exponential increase in energy demand globally is leading to rapid depletion of existing fossil fuel resources [1], [2]. This has led the power industry to explore renewable energy sources such as wind, solar, and tidal energies. Renewable energy resources attracted more attention recently owing to their pollution free energy generation capabilities. Wind as a potential source for electricity generation on a large scale has been receiving much attention recently. [1], [3]

Egypt now relies on burning fossil fuels to satisfy about 85% of its electricity demand, which is growing at a rate of 8% per year[4]. The Arab countries' fossil fuel supply is expected to dry up within the next 30-50 years [4]. The National Renewable Energy Authority (NREA) states that Egypt generated 600 MW of power from wind in 2010 with a goal to generate 7.2 GW of wind power by 2020, about 12% of its total electricity production [4].

Due to the unpredictable nature of wind gust, accurate wind prediction is difficult but much needed. Therefore, researchers have focused on deriving accurate stochastic models for wind speed, wind direction, and consequently wind power prediction. These wind models are based on soft-computing either using probabilistic modeling (using random process estimation theories) or based on approximate reasoning using expert systems like neural networks, fuzzy logic, and hybrid systems [4].

In this paper, new time series forecast models for wind-speed prediction are proposed for Egypt's north-western coast, since Egypt is a very promising country for wind energy generation. All models are based on real data gathered for that site. The proposed method doesn't require much data in order to give a prediction with respectable accuracy; the inputs are correlated over severalyears to take into account seasonal changes. The resultant models are used to predict twenty four hours ahead based on same month of real data in seven consecutive years and predicts twenty four hours ahead based only one month of data using a time series predication schemes. The predicted wind-speed is compared to the actualdata to validate the obtained models.

II. Wind-Speed Forecasting

Integration of accurate wind prediction in the management and control regimes involved in the wind energy conversion system (WECS) provides a significant tool for optimizing operating costs and improving

reliability [5]. However, due to highly complex interactions and the contribution of various meteorological parameters, wind forecasting is a very difficult task. Stochastic techniques depend on collecting wind-speeds data for wind atlas preparations, wind sites monthly and annual production, and wind turbines optimum sites prediction using a Weibull statistical model for predicting the performance of hybrid wind systems and their annual production, consumption of fuel, and costs [4].

Very short-term forecastingis defined as look ahead periods from a few minutes up to an hour, while short-term forecasting, which is proposed in this paper,will indicate hours out to a few days ahead. This difference between the two forecasting time periods is important when trying to create a prediction system .Three main classes of techniques have been identified for wind forecasting. These techniques are numeric weather prediction (NWP) methods, statistical methods, and methods based upon artificial intelligence [6].

Fuzzy sets were introduced to represent and manipulate data and information that possesses non-statistical uncertainty. Fuzzy sets are a generalization of conventional set theory that was introduced as a new way to represent vagueness in the data. It introduces vagueness (with the aim of reducing complexity) by eliminating the sharp boundary between the members of the class from nonmembers [4].These approaches are problem dependent to a large extent and converge slowly and even may diverge in certain cases.

Weibulldistribution is the most commonly used probability density function to describe and evaluate the frequency of wind-speed at the selected sites [4].Weibull distribution can be described by (1) [7];

$$f_{wB}(w) = \frac{v}{\varsigma}(\frac{w}{\varsigma})^{v-1} e^{-(\frac{w}{\varsigma})^{v}} \qquad (1)$$

Where$v$is a shape parameter, ς is a scale parameter, and independent variable w is the wind-speed. If the shape parameter equals 2, the Weibull distribution is known as the Rayleigh distribution. For the Rayleigh distribution the scale factor, c, given the average wind speed ($\overline{w}$) can be found from (v=2, and $\varsigma = \frac{2}{\sqrt{\pi}}\overline{w}$) [4].
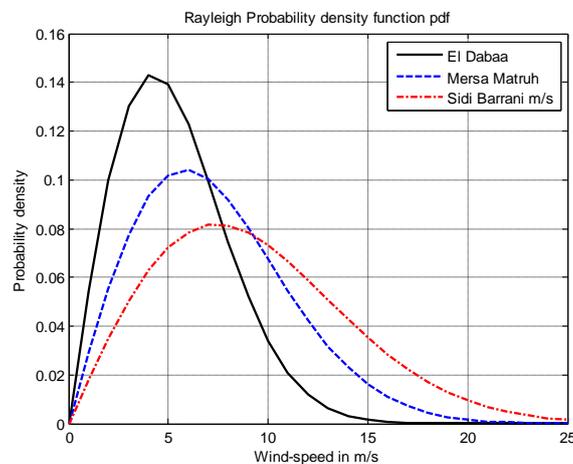
Figure 1. *Probability density of the Rayleigh distribution for selected sites*

In Fig. 1, the wind-speed probability density function (pdf) of the Rayleigh distribution is plotted. The average wind speeds in the figure are 5m/s, 5.3 m/s, and 5.4 m/s correspond to the wind speed in SidiBarrani, MersaMatruh and El Dabaaas three important candidate regions in Egypt's North-Western coast [7].

In this paper, three different wind-speed prediction models are proposed. The differences between these models are the size of wind-speed data block required and the scheme by which ANFIS is implemented. All proposed models are short-term based models, twenty four hours ahead of wind-speed forecasting.

III. Proposed Approach

The proposed approach in this paper is based on Kalman filter and ANFIS as a superior soft-computing technique. 3.1) Kalman Filter (KF)

The Kalman filter was created by Rudolf E. Kalman in 1960, though Peter Swerling actually developed a similar algorithm earlier [8]. It was developed as a recursive solution to the discrete-data linear filtering problem. Kalman filter is based on recursive data processing algorithm and Generates optimal estimate of desired quantities given the set of measurements.

Kalman Filtering is so popular because Good results in practice due to optimality and structure.

In order to use the KF to estimate the internal state of a process given only a sequence of noisy observations; the following matrices must be specified, which is represented as a linear stochastic difference equation.

$$x_k = A_k x_{k-1} + B_k u_k + w_k \tag{2}$$

Where:

x_k = state vector

A_k = state transition model which is applied to the previous state x_{k-1}

B_k = control-input model which is applied to the control vector u_k

w_k = process noise which is assumed to be drawn from a zero mean multivariate normal distribution with covariance Q, $P(w) \square N(0, Q)$

The relationship between the process state and the measurementvaluescanbe represented as [8]:

$$Z_k = H_k x_k + v_k \tag{3}$$

Where:

Z_k = measurement of system state

H_k = the observation (or measurement) z_k of the true state space into the covariance R

v_k = measurement noise; $p(v) \sim N(0, R)$

To find an equation that computes an a posteriori state estimate as $\hat{x}_k$ a linear combination of an a priori estimate $\hat{x}_k^-$ and a weighted difference between the actual measurement z_k and a measurement prediction $H\hat{x}_k^-$ [8].

$$\hat{x} = \bar{\bar{x}} + K(Z_k - H\bar{\hat{x}}_k) \tag{4}$$

The difference $(z_k - H\hat{x}_k^-)$ iscalled innovation or residual. Residual of zero;meansthat, the twoterms are in complete agreement and k is the gain or blending factor thatminimizes the posteriori error covariance.

Matrix k is the gain thatminimizes the a posteriori error covariance. The equationsthatneed to beminimized,

$$\hat{x}_k = \hat{x}_k^- + K(Z_k - H\bar{\hat{x}}_k) \tag{5}$$

Ongoing Discrete Kalman Filter CycleProject the state ahead,

$$\hat{x}_k^- = A_k \hat{x}_{k-1} + B_k u_k \tag{6}$$

Project the error covariance ahead

$$P_k^- = A_k P_{k-1} A_k^T + Q \tag{7}$$

Compute the Kalman gain

$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1} \tag{8}$$

Update estimate with measurement z_k

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - H\hat{x}_k^-) \tag{9}$$

Update the error covariance [8]

$$P_k = (1 - K_k H) P_k^- \tag{10}$$

3.2) Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

Adaptive Neuro Fuzzy Inference System (ANFIS) is a fuzzy mapping algorithm that is based on Tagaki-Sugeno-Kang (TSK) fuzzy inference system.ANFIS is integration of neural networks and fuzzy logic and have the potential to capture the benefits of both these fields in a single framework. ANFIS utilizes linguistic information from the fuzzy logic as well learning capability of an ANN for automatic fuzzy if-then rule generation and parameter optimization [9].

A conceptual ANFIS consists of five components: inputs and output database, a Fuzzy system generator, a Fuzzy Inference System (FIS), and an Adaptive Neural Network. The Sugeno- type Fuzzy Inference System, which is the combination of a FIS and an Adaptive Neural Network, was used in this study for rainfall-runoff modeling. The optimization method used is hybrid learning algorithms [9].

For a first-order Sugeno model, a common rule set with two fuzzy if-then rules is as follows:

Rule 1: If x_1 is a_1 and x_1 is b_1, then

$$f_1 = a_1 x_1 + b_1 x_1 + c_1 \tag{11}$$

Rule 2: If x_1 is a_2 and x_2 is b_2, then

$$f_2 = a_2 x_2 + b_2 x_2 + c_2 \tag{12}$$

Where, x_1 and x_2 are the crisp inputs to the node and a_1, b_1, a_2, b_2 are fuzzy sets, a_i, b_i and c_i (i = 1, 2)are the coefficients of the first-order polynomial linear functions.

It is possible to assign a different weight to each rule based on the structure of the system, where, weights w_1 and w_2 are assigned to rules 1 and 2 respectively and f = weighted average .

ANFIS network is composed of five consequent layers. Each layer contains several nodes described by the node function. Let O_i^j denote the output of the ith node in layer j[9], [10].

In layer 1, every node *i* is an adaptive node with node function

$$O_i^1 = \mu A_i(x), \qquad i = 1, 2 \tag{13}$$

Or

$$O_i^1 = \mu B_{i-2}(y), \qquad i = 3, 4 \tag{14}$$

Where x (or y) is the input to the ith node and A_i (or B_{i-2}) is a linguistic label associated with this node. The membership functions for A and B are usually described by generalized bell functions [11], e.g.

$$\mu A_i(x) = \frac{1}{1 + \left| \dfrac{x - r_i}{p_i} \right|^{2q_i}} \tag{15}$$

where $\{p_i, q_i, r_i\}$ is the parameter set. Any continuous and piecewise differentiable functions, such as triangular-shaped membership functions, are also qualified candidates for node functions in this layer [4]. Parameters in this layer are referred to as premise parameters.

In layer 2, each node $\prod$ multiplies incoming signals and sends the product out

$$O_i^2 = w_i = \mu A_i(x) \times \mu B_i(y), \qquad i = 1, 2 \tag{16}$$

Each node output represents the firing strength of a rule.

In layer 3, each node *N* computes the ratio of the ith rule firing strength to the sum of all rules' firing strengths

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \qquad i = 1, 2 \tag{17}$$

The outputs of this layer are called normalized firing strengths. In layer 4, each node computes the contribution of the ith rule to the overall output

$$O_i^4 = \overline{w}_i z_i = \overline{w}_i(a_i x + b_i y + c_i), \qquad i = 1, 2 \tag{18}$$

Where $\overline{w}_i$ is the output of layer 3 and $\{a_i, b_i, c_i\}$ is the parameter set. Parameters of this layer are referred to as consequent parameters.

In layer 5, the single node $\sum$ computes the final output as the summation of all incoming signals

$$O_i^5 = \sum_i \overline{w}_i z_i = \frac{\sum_i w_i z_i}{\sum_i w_i} \tag{19}$$

Thus, an adaptive network is functionally equivalent to a Sugeno-type fuzzy inference system. ANFIS is an embedded tool in the MATLAB fuzzy toolbox. This approach is based on using the neural networks training capability to adjust the membership functions' (MF) parameters of the proposed fuzzy inference system (FIS).

The proposed ANFISs utilize a subtractive clustering technique in which Gaussian MFs are used. Subtractive clustering generates an initial model for ANFIS training. This subtractive clustering method partitions the data into groups called clusters, and generates an FIS with the minimum number of rules required to distinguish the fuzzy qualities associated with each of the clusters. Subtractive clustering avoids the curse of dimensionality of grid partitioning method. Subtractive clustering is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data. It is especially used if there is no clear idea about how many clusters should be assigned for a given set of data.

The real-data sets used to build the proposed models were obtained through a huge database website for weather recordings that covers almost all countries around the globe [12]. These recordings are based on real hourly-based measurements for the corresponding sites. The study proposed is done for MersaMatruh site as one of the candidate sites in Egypt that has sufficient wind resources [7].

IV. Simulation Results And Discussions
In this paper the study is based on a real wind speed data gathered from Egypt north-western coast [12]. This location has been selected based on the evaluation done in [7], as it can be considered one of the most promising locations at the north coast. Each subsection has a model to forecast the wind-speed for a certain period of time and a different data block size to obtain with four different models by the end of this section.

1.1. Model-I: 24-Hrs Ahead Based on Yearly Data Recordings

The first model is based on a single month's wind-speed data in seven consecutive years e.g. the month of July of years 2007, 2008, 2009, 2010, 2011, 2012 and 2013. In order to train an ANFIS, complete data sets of inputs along with their corresponding desired output data are needed. Thus, wind-speed data from 2007-2012 are used as six inputs with data sets of 2013 are used as a corresponding output. Since July is 31 days, only 30 days data (5040 data points) were used for training and the 31st whole day is to be predicted using the obtained model. The monthly data is selected in the same season to avoid the climate change between seasons.

$$Data(k) = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 & x_5 & x_6 \end{bmatrix} \tag{20}$$

The output training data corresponds to the trajectory prediction.

$$T\arg et(k) = \begin{bmatrix} x_7 \end{bmatrix} \tag{21}$$

Where: x_1 through x_7 are wind-speed data in seven consecutive years e.g. the month of July of years 2007, 2008, 2009, 2010, 2011, 2012 and 2013 respectively.

The training input/output data is a structure whose first component is the six-dimensional input $Data(k)$ as in (20), and its second component is the output $T\arg et(k)$ as in (21).

Fig. 2 presents the wind-speed data sets in m/s for July in 2007 through 2013 from upper graph down respectively, these data sets were obtained from [9]. The data are hourly recordings, thus for 31 days a total of 744 data point are shown per graph, but only 720 points per graph are used for training purposes and the last 24 hours are to be predicted. Fig. 3 shows the generated FIS using subtractive clustering using ANFIS toolbox that provides a single output Takagi-Sugeno-Kang (TSK) type with linear MFs for the output.

The upper graph of Fig. 4 shows the root mean square error (RMSE) that resulted during the ANN training epochs. The resultant ANFIS model is used for the purpose of testing and validation to predict 24-Hrs ahead. The middle graph of Fig. 4 shows the wind-speed forecasting in m/s for one complete day ahead for the end of July. The error over one day between actual and predicted wind-speed is shown in the lower graph of Fig. 4. The mean value of the error (ME) is found to be around 0.2645 m/s with a mean absolute error (MAE) of 1.6319 m/s. Figure 5 gives scattered plot for actual speed verses predicted speed month data.
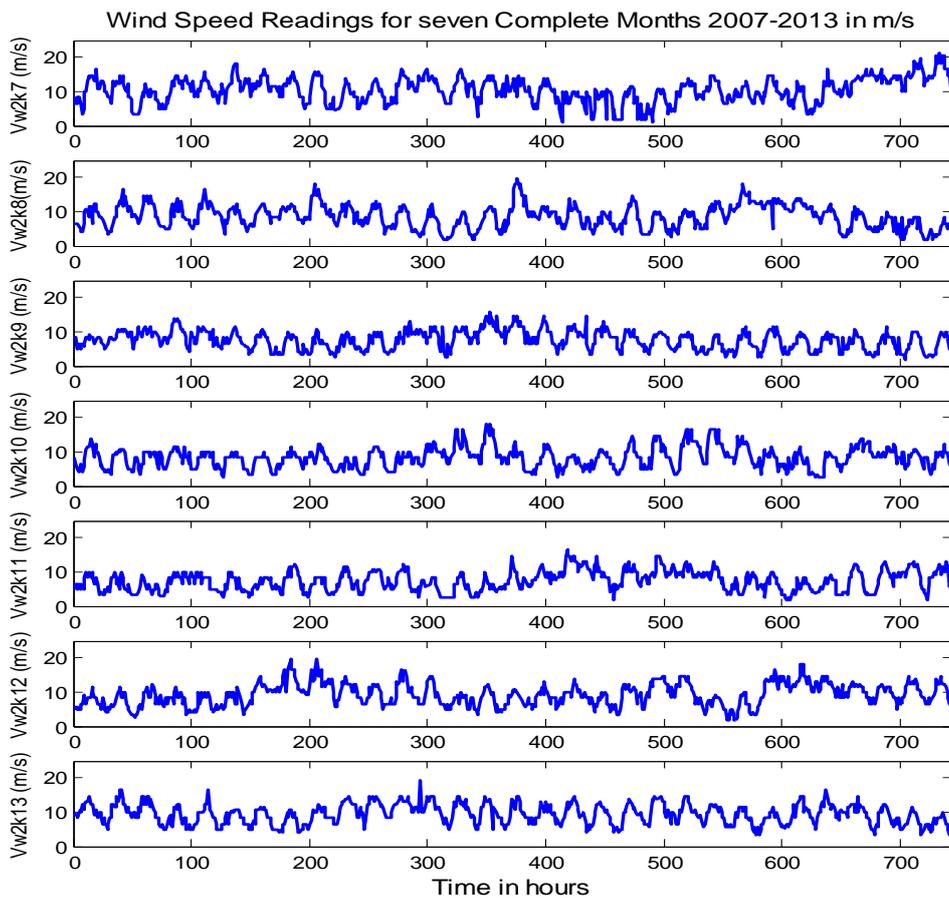
Figure 2. Real wind-speed data for 7 months all in July (2007-2013).
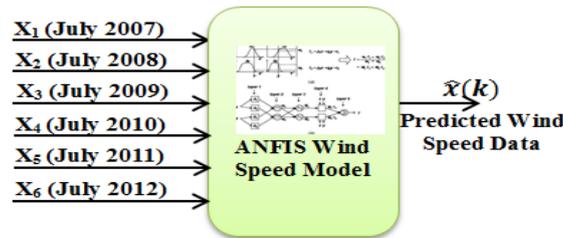
Figure 3. Proposed TSK-FIS for model-I based onReal Wind Speed Data Input
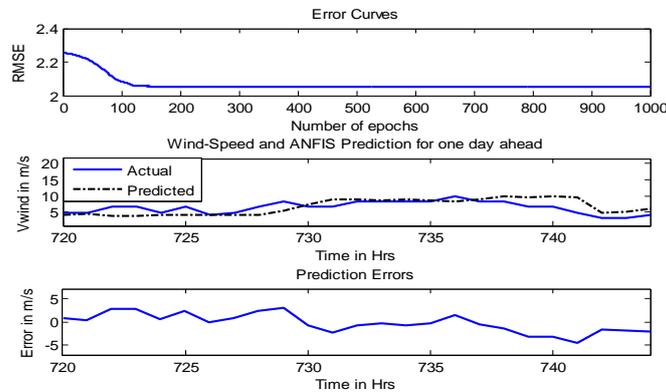
Figure 4. Upper graph is RMSEresult for the model-I, Middel graph is actual and prediction of 24-Hrs ahead ,where the lower graph shows the prediction error
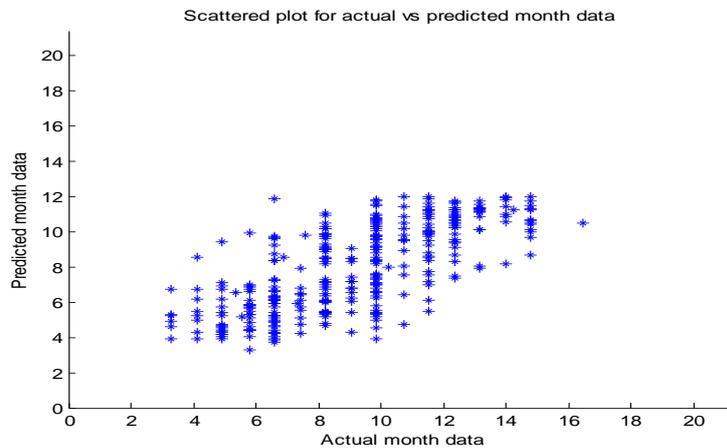
Figure 5. Scattered plot for actual vs predicted month data

1.2. Model-II: 24-Hrs Ahead Based on one month Data

This model is based on only one month wind-speed data, e.g. July 2013. In this model, one month of hourly based wind-speed recordings are required. Data are rearranged to create a mapping from 4 samples wind-speed data points, sampled every 24 hours, to a predicted future of 24 hoursas shown in Fig. 6.
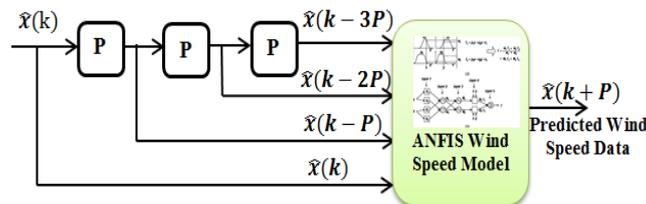
Figure 6. Block diagram of ANFIS without Kalman Filter (KF)

$$Data(k) = \begin{bmatrix} x(k-3p) & x(k-2p) & x(k-p) & x(k) \end{bmatrix} \tag{22}$$

The output training data corresponds to the trajectory prediction.

$$Target(k) = x(k + P) \tag{23}$$

Where k is the time instant in hours and P is the period to be predicted ($P = 24$ in this case). The training input/output data is a structure whose first component is the four-dimensional input $Data(k)$ as in (22), and its second component is the output $Target(k)$ as in (23). There are 720 input/output data points. These data points are used for the ANFIS training (these became the training data set), while only part of them are used as checking data to validate the identified fuzzy model.
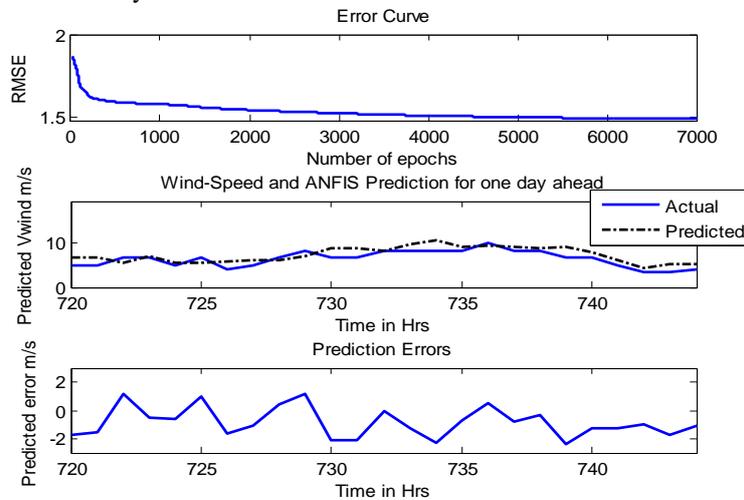
Figure 7. Upper graph is RMSE result for the model-I, Middel graph is actual and prediction of 24-Hrs ahead ,where the lower graph shows the prediction error

The one month data points (July 2013) were plotted earlier as the last graph of Fig. 2 to illustrate the data used for the training. These data points are then rearranged as five vectors of shifted wind-speed recordings (each vector is 24-Hrs shifted from its corresponding consequent vector). Training the ANFIS is done based on the concept of time-series prediction. RMSE resulted from the training epochs of the ANN is shown in theupper graph of Fig. 7. Data is then used to validate the ANFIS by predicting 24-Hrs ahead. The prediction of July 31st is shown in middle graph of Fig. 7, while the lower graph illustrates the prediction error which shows a quite similar prediction error for model-II as for model-I. The mean value of the error is found to be around 0.8545 m/s with MAE of 1.1975 m/s. The results obtained by model-II is similar to the results of the previous model (model-I), but it has a significant advantage over model-I. This advantage is that model-I has much more data points used in the training step (model-II uses only 14% of model-I data points). Thus, model-II is preferred over model-I. Figure 8 gives scattered plot for actual speed verses predicted speed month data of model II
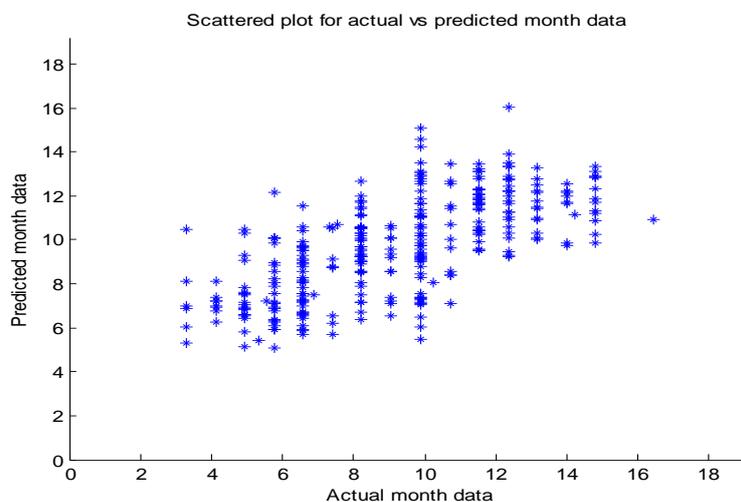
Figure 8. Scattered plot for actual vs predicted month data

1.3. Model-III: 24-Hrs Ahead Based on one month Data with Kalman Filter

The statistical uncertainty is the randomness or error that comes from different sources; the five types of uncertainty that emerge from the imprecise knowledge are:

- Process uncertainty: dynamic randomness.
- Modeling uncertainty: wrong specification of the model structure.
- Measurement uncertainty: error on observed quantities.
- Implementation uncertainty: consequence of the variability.
- Estimate uncertainty: appear from any source of uncertainties or a combination of them, and it is called inexactness and imprecision.

Wind speed measurements obtained from [12], are subjected to some sort of uncertainties which are presented as vagueness of the wind speed value due to noise contents. KF is commonly used to filter out noisy data as it is considered the best linear unbiased estimator (BLUE). In Model-II; data set is allowed to pass initially through KF for the purpose of minimizing the error covariance exhibited by the data set as shown in Fig. 9. Estimated (filtered) data are then rearranged to create a mapping from four samples wind-speed data points, sampled every twenty four hours, to a predicted future of twenty four hours.
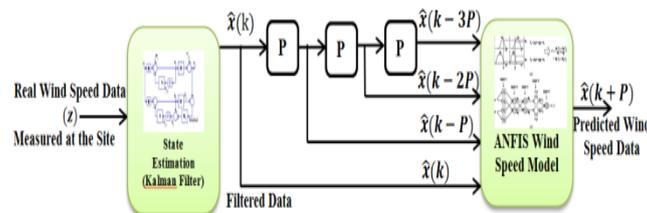
Figure 9. Block diagram of ANFIS with Kalman Filter (KF)

$$E_{Data}(k) = \begin{bmatrix} \hat{x}(k-3p) & \hat{x}(k-2p) & \hat{x}(k-p) & \hat{x}(k) \end{bmatrix} \qquad (24)$$

Where:

$E_{Data}(k)$ = Estimated data Vector

The output training data corresponds to the trajectory prediction.

$$\text{Estimated Target}\,(\text{k}) = \hat{x}(k+p) \qquad (25)$$

Where k is the time instant in hours and p is the period to be predicted ($p = 24$ in this case). The training input/output data is a structure whose first component is the four-dimensional input $E_{Data}(k)$ as in (24), and its second component is the output Estimated Target (k) as in (25). There are 720 input/output data points. These data points are used for the ANFIS training (these became the training data set), while only part of them are used as checking data to validate the identified fuzzy model.
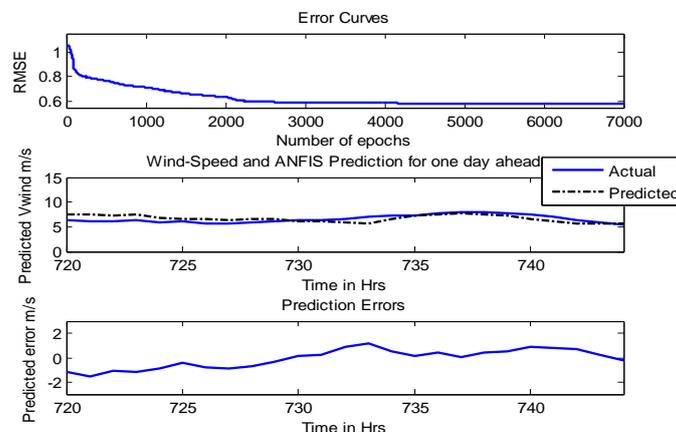
Figure 10. Upper graph is RMSE result for the model-I, Middel graph is actual and prediction of 24-Hrs ahead ,where the lower graph shows the prediction error

RMSE resulted from the training epochs of the ANN is shown in upper graph of Fig.10. Data is then used to validate the ANFIS by predicting 24-Hrs ahead. The prediction of July 31st is shown in middle graph of Fig. 10, while the lower graph illustrates the prediction error. The mean value of the error is found to be around

0.0804 m/s with MAE of 0.6624 m/s. The results obtained by model-III arebetter than the results of the previous model (model-II), because it has a significant advantage over model-II. This advantage is that model-III has low mean absolute error this mean the prediction is more accurate by 55.5%. Thus, model-III is preferred over model-II. Figure 11 gives scattered plot for actual speed verses predicted speed month data of model III
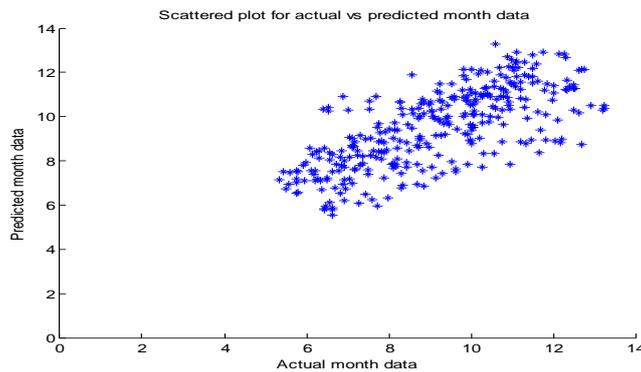
Figure 11. Scattered plot for actual vs predicted month data

Table I. shows accuracy study between the three proposed models including the used forecasting period which is twenty four hours during seven months for the first model and one month for the next both of models. The comparison discusses: RMSE, ME, MAE and Mean Absolute Percentage Error (MAPE).

Model-III using KF showed better accuracy based on error calculation. Thus; model-III is better than model-I because MAPE has been improved by 51.45% as shows in equation (26):

$$\text{Enhancement Ratio} = (1 - \frac{\text{MAPE of Model-III}}{\text{MAPE of Model-I}}) \qquad (26)$$

$$= (1 - \frac{10.31}{28}) = 63.17\%$$

And model-III is better than model-II because MAPE has been improved by 51.45% as shows in equation (27):

$$\text{Enhancement Ratio} = (1 - \frac{\text{MAPE of Model-III}}{\text{MAPE of Model-II}}) \qquad (27)$$

$$= (1 - \frac{10.31}{21.24}) == 51.45\%$$

Table I. Accuracy study for wind-speed forecasting.

	Model-I	**Model-II**	**Model-III**
Forecasting Period	24-Hrs	24-Hrs	24-Hrs
Amount of data points	5040	720	720
RMSE (m/s)	1.9782	1.3466	0.7652
Mean Error (m/s)	0.2645	0.8545	0.0804
MAE (m/s)	1.6319	1.1975	0.6624
MAPE (%)	28.00	21.24	10.31

V. Conclusion

In this paper, three effective time series stochastic wind models for Egypt's north-western coast were proposed and optimized using ANFIS and Kalman filter.

Model-I based on real wind-speed data sets for the month of July in the years 2007 through 2013; the target was to predict wind-speed 24-Hrs ahead. Model-I accuracy (MAE)is 1.6319 m/s. Model-II and model-III are both based on one month of data to predict 24-Hrs (July 2013);which have the advantage of using only 14% of the data block size and improve the accuracy in the same time. In model-III an initial stage of kalman filter has been added. KF stage has filtered out noise exhibited from measurement uncertainty. Model-III showed better accuracy over model-I by approximately 63.17% mean absolute error and by approximately 51.45% mean absolute error for model-II.

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