Renewable Energy 76 (2015) 637–647

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Daily wind speed forecasting through hybrid KF-ANN model based on ARIMA

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ARTICLE INFO

Article history:
Received 20 August 2014
Accepted 25 November 2014
Available online

Keywords:
Wind speed forecasting
Forecasting accuracy
Hybrid KF-ANN
ARIMA
Kalman filter
ANN

ABSTRACT

The accuracy of wind speed forecasting is important to control, and optimize renewable wind power generation. The nonlinearity in the patterns of wind speed data is the reason of inaccurate wind speed forecasting using a linear autoregressive integrated moving average (ARIMA) model. The inaccurate forecasting of ARIMA model reflects the uncertainty of modelling process. The aim of this study is to improve the accuracy of wind speed forecasting by suggesting a more appropriate approach. An artificial neural network (ANN) and Kalman filter (KF) will be used to handle nonlinearity and uncertainty problems. Based on the ARIMA model, a hybrid KF-ANN model will improve the accuracy of wind speed forecasting. First, the effectiveness of ARIMA will be helped to determine the inputs structure for KF, ANN and their hybrid model. A case study will be carried out using daily wind speed data from Iraq and Malaysia. The hybrid KF-ANN model was the most adequate and provided the most accurate forecasts. In conclusion, the hybrid KF-ANN model will result in better wind speed forecasting accuracy than its separate components, while the KF model and ANN separately will be provide acceptable forecasts compared to ARIMA model that will provide ineffectual wind speed forecasts.

1. Introduction

Frequent, extreme wind speeds and the nonlinear nature of wind speed data makes forecasting a complex process. Some authors have proposed using ARIMA models, a classical statistical approach, to forecast wind speeds. Finding the appropriate wind speed ARIMA model can be accomplished by following the methodology proposed by Box–Jenkins. Benth and Benth [1] proposed an ARIMA model for estimating and forecasting wind speeds for three different wind farms in New York State. Shi, Qu and Zeng [2] adopted a simplified ARIMA model for direct and indirect short-term forecasting methods then compared the performances of both approaches using the wind speed and power production data from an offshore 2-MW wind turbine. Zhu and Genton [3] reviewed statistical short-term wind speed forecasting models, including autoregressive models and traditional time series approaches, used in wind power developments to determine which model provided the most accurate forecasts. AR, ARIMA, or seasonal ARIMA models have been used for comparing and for determining KF state equation structures and ANN inputs structure such as those proposed by Refs. [4–9].

The nonlinear pattern of wind speed data may be one reason for the inaccuracy of ARIMA forecasting, which is a linear time series model [5]. An ANN was used to handle the nonlinear nature of wind speed data. Cadenas and Rivera [4] presented a comparison of ARIMA and ANN approaches for wind speed forecasting using seven years of wind speed data. Six years of data was used for training and one year of data was reserved for validation. Li and Shi [10] compared one hour ahead forecasts for hourly wind speeds in North Dakota using three different types of artificial neural networks. They used an autocorrelation function (ACF) and partial autocorrelation function (PACF) to determine the ANN input variables. Pourmousavi-Kani and Ardehali [11] used ANN to develop very short-term wind speed forecasts after combining the ANN with a Markov chain to create an ANN–MC hybrid model. Assareh, Behrang, Ghalambaz, Noghrehabadi and Ghanbarzadeh [12] forecasted wind speeds using twelve years of data from the Manjil station. The final year of data was used for testing and the first eleven years were used for training. ANN was proposed as a way to represent the relationship among wind speeds, as an output, and other meteorological time series data, and to accurately forecast

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http://dx.doi.org/10.1016/j.renene.2014.11.084
0960-1481/

wind speed. Bilgili and Sahin [13] used ANN to forecast daily, weekly, and monthly wind speeds using data from four different measuring stations in the Aegean and Marmara regions of Turkey. They obtained successful forecasting results. Peng, Liu and Yang [14] suggested an individual ANN and hybrid strategy based on physical and statistical approaches for short term wind power forecasting. The individual ANN approach resulted in highly accurate forecasts.

In this paper, an ANN was constructed based on an autoregressive order to simulate the ANN structure. An autoregressive order can be determined by observing PACF. Khashei and Bijari [15] and Khashei and Bijari [16] explained the use of an autoregressive order (p) for determining the inputs structure of ANN. Guo, Zhao, Haiyan and Wang [9] proposed many methods for wind speed forecasting. One of these methods was a feed-forward neural network whose input variables were determined using a partial autocorrelation function that was dependent on the autoregressive order. Liu, Tian and Li [6] confirmed that the performance of the hybrid method in terms of its wind speed predictions was consistently better than that of its components. They proposed two types of hybrid methods. One method has been called a new ARIMA-ANN hybrid method, while it contains using ANN based on AR(p) model and it performed well.

Although an ARIMA model is the perfect statistical model for forecasting, it leads to inaccurate results for wind speed forecasting. The KF model can be used for meteorological purposes, such as wind speed forecasting. To obtain the best initial parameters for the KF, an ARIMA model will be used to create the structure of the KF model that will be regarded as the best model for handling the stochastic uncertainty and improve wind speed forecasting. An ARIMA model will be used with the KF model to construct the structure of the state-space equation. This model is also called a hybrid ARIMA-KF.

Malmberg, Holst and Holst [17] used the KF model based on an AR to model and forecast the large scale component of bounded areas of near-surface ocean wind speeds. Galanis, Louka, Katsafados, Pytharoulis and Kallos [18] proposed implementing nonlinear polynomial functions in classical linear Kalman filter algorithms as a new methodology that would improve regional weather forecasts. Louka, Galanis, Siebert, Kariniotakis, Katsafados, Pytharoulis and Kallos [19] applied the KF model as a post-processing method for numerical wind speed forecasting and employed two limited area atmospheric models with different horizontal resolution to improve wind speed forecasts. Cassola and Burlando [20] proposed a mixed approach based on the use of a NWP model coupled with a statistical model based on the KF model to generate a way to forecast wind speed and wind power data sets collected from two anemometric stations located in the eastern Liguria. Liu, Tian and Li [6] proposed two new ARIMA-ANN and ARIMA-Kalman hybrid methods for wind speed forecasting, and compared their performance. They combined an ARIMA with ANN and the KF model in order to create the structure of an ANN model and initialize the state equation for a KF. Zhu and Genton [3] suggested using traditional time series statistical models of wind speed forecasting, including a KF method, to handle uncertainty in the system, noise, and observation noise. Tatinati and Veluvolu [7] proposed many approaches for short term wind speed forecasting. One of these approaches was a hybrid model that combined the KF model with an AR model to improve forecasting accuracy.

In this paper, a hybrid KF-ANN model was proposed based on an ARIMA model to further improve the forecasting accuracy of wind speed. Artificial neural network (ANN) and Kalman filter were useful for handling nonlinearity and stochastic uncertainty problems associated with wind speed data. Many recent studies have also combined the KF model to handle stochastic uncertainty, with another approach, such as support vector machines which handle the nonlinearity of wind speed. Tatinati and Veluvolu [7] proposed several approaches for short term wind speed forecasting such as a the KF model based on AR, a least squares version of support vector machine (SVM), an empirical mode of decomposition (EMD), and their hybrid model for average wind speed and the direction in Beloit for the period 2003–2004. Chen and Yu [8] integrated unscented Kalman filter (UKF) with support vector regression (SVR) based on a state-space model. The hybrid SVR–UKF approach was employed firstly to handle a nonlinear state-space model via studying support vector regression and then stochastic uncertainty via studying an unscented KF. In the proposed KF-ANN approach, first the KF state (system) and observation (measurement) equations were created based on an ARIMA model. In a second step, the inputs variables of the ANN approaches were generated from the new state series that was the output of the state equation, while the target was the original wind speed series. As a result, the output of the ANN represents the final fitted or forecasting series.

This paper is organized as follows: Section 2 states the framework of this study and presents a hybrid KF-ANN based on ARIMA through ARIMA, KF, hybrid ARIMA-KF, and ANN theoretically. Section 3 displays and discusses the forecasting results and the computational steps of the methods in Section 2. Section 4 provides the conclusion of this study.

2. Material and method

2.1. Data and framework used in the study

In this study, daily wind speed data from two meteorological stations was collected. The first data set was collected from the Mosul Dam Meteorological Station in Mosul, Iraq. It covered four hydrological years (1 October 2000–30 September 2004) which was used for training. Another four months' of hydrological data (1 October 2004–31 January 2005) was reserved for testing. The other data set was collected from the Muar Meteorological Station in Johor, Malaysia. It covered four hydrological years (1 October 2006–30 September 2010) which was used for training. An additional three months' of hydrological data (1 October 2010–31 December 2010) was used for testing.

The framework of this study includes the following:

a. Determining the most appropriate ARIMA model following Box–Jenkins methodology.
b. Constructing the most appropriate ANN based on AR.
c. Constructing the most appropriate hybrid ARIMA-KF model.
d. Combining the KF model and ANN based on ARIMA to create a hybrid KF-ANN model.
e. Comparing the studied approaches to determine what model would provide the best forecasts. Fig. 1 demonstrates the framework of this study.

2.2. Mathematical models

2.2.1. Autoregressive integrated moving average (ARIMA) model

An ARIMA model was used to forecast wind speed. The modelling strategy followed Box–Jenkins methodology through the identification, estimation, diagnostic checking, and forecasting stages. A general expression of the seasonal ARIMA$(p,d,q)(P,D,Q)_s$ model is shown below:

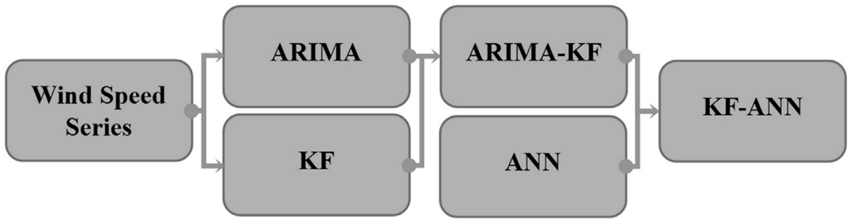

Fig. 1. The framework of the study.

$$\underbrace{\left(1-\phi_1 B-\phi_2 B^2-\cdots-\phi_p B^p\right)}_{\mathrm{AR}(p)} \times \underbrace{\left(1-\Phi_1 B^s-\Phi_2 B^{2s}-\cdots-\Phi_P B^{Ps}\right)}_{\mathrm{AR_s}(P)} \underbrace{(1-B)^d}_{\mathrm{I}(d)} \underbrace{(1-B^s)^D}_{\mathrm{I_s}(D)} Y_t = \underbrace{\left(1-\theta_1 B-\theta_2 B^2-\cdots-\theta_q B^q\right)}_{\mathrm{MA}(q)} \times \underbrace{\left(1-\Theta_1 B-\Theta_2 B^{2s}-\cdots-\Theta_Q B^{Qs}\right)}_{\mathrm{MA_s}(Q)} a_t \tag{1}$$

where AR(p) is a pth order of the autoregressive component, MA(q) is a qth order of moving average component, $I(d)$ is a dth non-seasonal difference, $\mathrm{AR_s}(P)$ is a Pth order of seasonal autoregressive component, $\mathrm{MA_s}(Q)$ is a Qth order of seasonal moving average component, $\mathrm{I_s}(D)$ is a Dth seasonal difference, s is a period of the seasonal pattern, B^i is an ith order of backshift operator, and $\phi,\ \Phi,\ \theta,\ \Theta$ are the parameters of the ARIMA model.

The Box–Jenkins methodology steps were developed by Ref. [21]. The identification stage includes satisfying the stationarity of mean and variance. An ARIMA expression in Equation (1) can be reformulated after performing many computational processes as follows:

$$\begin{aligned} Y_t = {} & \begin{pmatrix} \left(\phi_1 B-\phi_2 B^2-\cdots-\phi_p B^p\right)+\left(\Phi_1 B^s-\Phi_2 B^{2s}-\cdots-\Phi_P B^{Ps}\right) \\ -\left(\phi_1 B-\phi_2 B^2-\cdots-\phi_p B^p\right)\left(\Phi_1 B^s-\Phi_2 B^{2s}-\cdots-\Phi_P B^{Ps}\right) \end{pmatrix} Y_t \\ & -\left(\left(1-\phi_1 B-\phi_2 B^2-\cdots-\phi_p B^p\right)\left(1-\Phi_1 B^s-\Phi_2 B^{2s}-\cdots-\Phi_P B^{Ps}\right)\right)(W_t-Y_t) \\ & -\begin{pmatrix} \left(\theta_1 B+\theta_2 B^2+\cdots+\theta_q B^q\right)+\left(\Theta_1 B+\Theta_2 B^{2s}+\cdots+\Theta_Q B^{Qs}\right) \\ -\left(\theta_1 B+\theta_2 B^2+\cdots+\theta_q B^q\right)\left(\Theta_1 B+\Theta_2 B^{2s}+\cdots+\Theta_Q B^{Qs}\right) \end{pmatrix} a_t + a_t \end{aligned} \tag{2}$$

2.2.2. Artificial neural network (ANN)

Use of the multilayer feed-forward back propagation neural network for time series forecasting was supported by the ANN toolbox in MATLAB software. The proposed ANN in this study was able to handle nonlinear wind speed data and this affected the accuracy of the ARIMA forecasting. Using ANN toolboxes after determining the ANN training algorithms, training function, transfer functions types of input and hidden layers, initial weights, bias value, and other requirements, meant that it was necessary to create an ANN structure to provide accurate forecasting. The types of transfer functions that can be used in hidden and output layers are tan-sigmoid that generates nonlinear outputs between -1 and $+1$, log-sigmoid that generates nonlinear outputs between 0 and 1, and linear transfer functions that generates linear outputs between -1 and $+1$. Selecting a transfer function for the hidden and output layers is important for obtaining good results and depends on the nature of the data.

The best training functions for back propagation algorithms are Levenberg–Marquardt and Bayesian regularization. The number of neurons in a hidden layer must be correctly calculated to create an ANN that can handle nonlinear data [22–24].

An AR(p) model was used to determine the inputs structure of the ANN. The inputs structure of the ANN depended on the number of autoregressive parameters of the ARIMA model. AR variables, which are those on the right side of Equation (2) regardless of the parameters and signs, will be used to determine the inputs structure of the ANN. Proposing an AR model, regardless of several time series conditions, resulted in a simple input structure for the ANN that, subsequently, provided more accurate forecasting [6–8]. ACF and PACF were used for the original time series data and for the first difference series to provide an idea about the p, d, q, P, D, and Q of the ARIMA model. To measure the adequacy of the ARIMA model, the Akaike information criterion (AIC) will be plotted.

2.2.3. Hybrid ARIMA-KF model

To handle the stochastic uncertainty, a KF model was used for more accuracy of wind speed forecasting. The KF model was named after Scientist Rudolf Emil Kalman. Due to its good performance in meteorological applications, it was used for wind speed forecasting [17–19]. The KF model can be introduced as a statistical approach for estimating and forecasting the unmeasured state space. In recent papers in this field, researchers proposed using hybrid AR-KF model instead of hybrid ARIMA-KF model to maintain simplicity when the parameters of moving average and integration parts become zero [6–8]. In this paper, the KF model was initialized based on ARIMA(p,d,q)(P,D,Q)$_s$ to obtain a hybrid ARIMA-KF model.

Based on the ARIMA model in Equation (2), the state equation (SE) and the observation equation of the KF model process can be written in state space form as follows [25]:

$$X_t = AX_{t-1} + C^T a_t \tag{3}$$

$$Y_t = CX_t \tag{4}$$

where X_t is m-dimensional state vector. Vector elements are the same as the input variables used for the ARIMA model, which are those on the right side of Equation (2) regardless of the parameters and signs.

$$X_t = \left[X_{1,t} \quad X_{2,t} \quad \ldots \quad X_{m,t}\right]^T;$$

A is $m \times m$ state transition matrix

$$A = \begin{bmatrix} K_1 & K_2 & K_3 & \cdots & K_m \\ 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}_{m \times m}$$

and C is $1 \times m$ observation transition matrix

$$C = [1 \quad 0 \quad 0 \quad \cdots \quad 0]_{1 \times m}$$

where Y_t is the observation transpose vectors that will be the same as the output series shown on the left side of Equation (2) and a_t is the current residual transpose vectors. m is the number of Y_t's lagged series and all residual series on the right side of ARIMA model in Equation (2). $(K_1, \ K_2, \ K_3, \ \ldots, \ K_m)$ are all parameter values of Y_t's lagged series and all residual series on the right side of ARIMA model in Equation (2) except a_t.

The SE in Equation (3) and OE in Equation (4) can be reformulated as follows:

$$X_t = AX_{t-1} + Bu_{t-1} + C^T a_t \tag{5}$$

$$Y_t = CX_t \tag{6}$$

where X_t is a state vector, which includes all previous lags of original series on the right side of the ARIMA model in Equation (2)

$$X_t = \begin{bmatrix} X_{1,t} & X_{2,t} & \ldots & X_{m,t} \end{bmatrix}^T; \quad m = \max((p+P),(q+Q))$$

u_t is a residuals vector, which includes all previous lags of residual series on the right side of the ARIMA model in Equation (2)

$$u_{t-1} = \begin{bmatrix} u_{1,t-1} & u_{2,t-1} & \ldots & u_{m,t-1} \end{bmatrix}^T$$

A is $m \times m$ state transition matrix

$$A = \begin{bmatrix} K_1 & K_2 & K_3 & \cdots & K_m \\ 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}_{m \times m}$$

B is $m \times m$ residuals transition matrix

$$B = \begin{bmatrix} R_1 & R_2 & R_3 & \cdots & R_m \\ 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}_{m \times m}$$

and C is $1 \times m$ observation transition matrix

$$C = [1 \quad 0 \quad 0 \quad \cdots \quad 0]_{1 \times m}$$

where $(K_1, \ K_2, \ K_3, \ \ldots, \ K_m)$, and $(R_1, \ R_2, \ R_3, \ \ldots, \ R_m)$ are the parameter values of previous lags of the original series and previous lags of the residual series, respectively, on the right side of the ARIMA model in Equation (2).

Both of previous methods above lead to convergent results. The first method was the simplest practically and intelligibly for both hybrid ARIMA-KF and KF-ANN models. After initializing the SE and OE equations, the KF model was used for wind speed forecasting using a KF recursive step such as the one found in Refs. [18,19,26]. By observing the state equation in Equation (3), the state vector combined linear and nonlinear parts of the ARIMA model. Combining linear and nonlinear parts improved the accuracy of wind speed forecasting and was more capable of handling stochastic uncertainty. The output of OE represented the fitted series or the forecasting series. The difference $Y_t - CX_t$ for Equations (4) and (6) was the error forecasting of KF. MAPE will be computed for the error forecasting of the KF model to evaluate the accuracy of the forecasts.

2.2.4. Hybrid KF-ANN model

The linear nature of the ARIMA model made it inappropriate for studying nonlinear time series data. Instead, an ANN and KF model were used to handle the nonlinearity and the stochastic uncertainty problems associated with wind speed data. Combining these approaches in one hybrid model will be more useful for improving forecasting accuracy. In this paper, a hybrid KF-ANN model was proposed based on the ARIMA model to further improve the accuracy of the wind speed forecasts. SE and OE of KF model will be created initially based on the ARIMA model as mentioned in hybrid ARIMA-KF model section previously. Determining the structure of the ANN input variables will be performed using the contents of SE output, while the target will be the original wind speed series. The dimension of the ANN inputs matrix is $m \times n$(m is the number of variables in SE and n is the length of data series), while the dimension of the ANN target is $1 \times n$. As a result, the output of this ANN represents the fitted series for the training stage and the forecasting series for the testing stage. The equations and other details of the hybrid KF-ANN model were briefly mentioned in the subsections of ANN and the hybrid ARIMA-KF model.

3. Results and discussion

The wind speed data from Iraq for the period spanning (1 October 2000–31 January 2005) and the wind speed data from Malaysia for the period spanning (1 October 2006–31 December 2010) are plotted in Fig. 2.

Fig. 2 shows monthly seasonal periods based on data line behaviour. The data was recorded daily and it exhibited monthly peaks or valleys. As a result, the order of seasonality was equalled to 12.

3.1. ARIMA model

The best empirical ARIMA model of Iraqi wind speed was ARIMA(0,1,3)(0,0,2)$_{12}$, while the best empirical ARIMA model of Malaysian wind speed was ARIMA(0,1,2)(0,1,1)$_{12}$. All the parameter estimators for both ARIMA models were significant. The testing values and other details are shown in Table 1.

The ARIMA(0,1,3)(0,0,2)$_{12}$ model for the wind speed data from Iraq can be expressed as follows:

$$W_t = \left(1 - \theta_1 B - \theta_2 B^2 - \theta_3 B^3\right)\left(1 - \Theta_1 B^{12} - \Theta_2 B^{24}\right) a_t$$

$$\begin{aligned} Y_t = Y_{t-1} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \theta_3 a_{t-3} - \Theta_1 a_{t-12} - \Theta_2 a_{t-24} \\ + \theta_1 \Theta_1 a_{t-13} + \theta_1 \Theta_2 a_{t-25} + \theta_2 \Theta_1 a_{t-14} + \theta_2 \Theta_2 a_{t-26} \\ + \theta_3 \Theta_1 a_{t-15} + \theta_3 \Theta_2 a_{t-27} \end{aligned} \tag{7}$$

where

$$W_t = (1 - B) Y_t = Y_t - Y_{t-1}$$

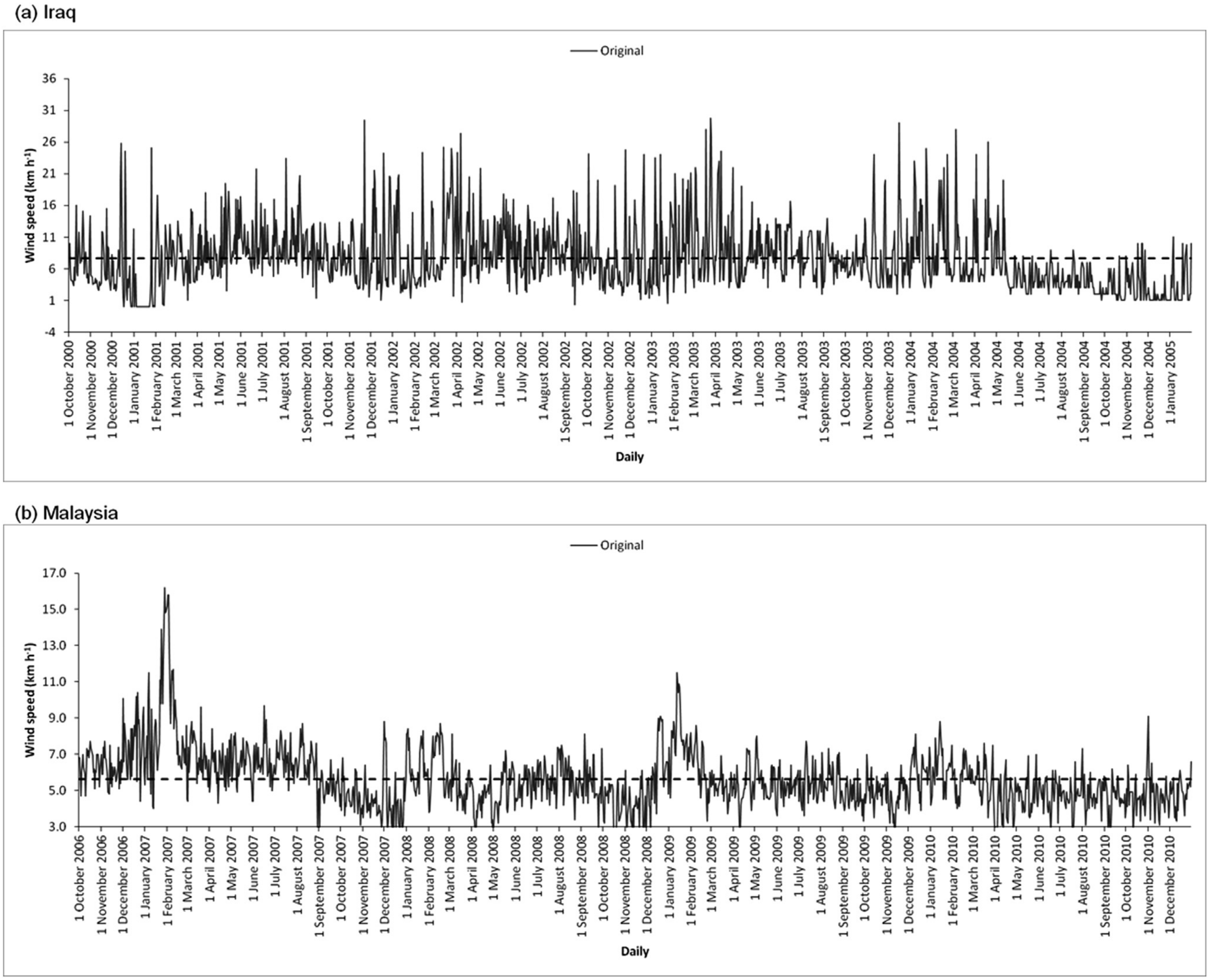

Fig. 2. Time series plot of wind speed for Iraq and Malaysia.

After substituting the parameters in (7) for their estimated values in Table 1, the ARIMA(0,1,3)(0,0,2)$_{12}$ model will be as follows:

$$\begin{aligned} Y_t &= Y_{t-1} + a_t - 0.618a_{t-1} - 0.236a_{t-2} - 0.097a_{t-3} \\ &\quad + 0.081a_{t-12} - 0.065a_{t-24} - 0.050a_{t-13} + 0.040a_{t-25} \\ &\quad - 0.019a_{t-14} + 0.015a_{t-26} - 0.008a_{t-15} + 0.006a_{t-27} \end{aligned} \tag{8}$$

The ARIMA(0,1,2)(0,1,1)$_{12}$ model for the wind speed data from Malaysia can be expressed as follows:

$$\begin{aligned} W_t &= \left(1 - \theta_1 B - \theta_2 B^2\right)\left(1 - \Theta_1 B^{12}\right)a_t \\ Y_t &= Y_{t-1} + Y_{t-12} - Y_{t-13} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \Theta_1 a_{t-12} \\ &\quad + \theta_1 \Theta_1 a_{t-13} + \theta_2 \Theta_1 a_{t-14} \end{aligned} \tag{9}$$

where

$$\begin{aligned} W_t &= \left(1 - B^{12}\right)(1 - B)Y_t = \left(1 - B - B^{12} + B^{13}\right)Y_t \\ &= Y_t - Y_{t-1} - Y_{t-12} + Y_{t-13}. \end{aligned}$$

After substituting the parameters in (9) for their estimated values in Table 1, the ARIMA(0,1,2)(0,1,1)$_{12}$ model will be as follows:

$$\begin{aligned} Y_t &= Y_{t-1} + Y_{t-12} - Y_{t-13} + a_t - 0.426a_{t-1} - 0.240a_{t-2} \\ &\quad - 0.978a_{t-12} + 0.417a_{t-13} + 0.235a_{t-14} \end{aligned} \tag{10}$$

In the ARIMA models, the mean absolute percentage error (MAPE) was used to reflect the forecasting accuracy of 123 observations based on the Iraqi testing series and 92 observations based on the Malaysian testing series. Table 1 reveals that all ARIMA parameters are significant with p values smaller than the significant level of 5% for Iraqi and Malaysian wind speed data. Tables 2 and 3 contain the MAPE values of Iraqi and Malaysian ARIMA forecasting

Table 1
The parameter estimators and the testing values of ARIMA.

Parameters	Estimate	t-test	p-value
ARIMA(0,1,3)(0,0,2)$_{12}$			
θ_1	0.6180	27.40	<.0001
θ_2	0.2362	8.06	<.0001
θ_3	0.0971	3.73	<.0001
Θ_1	−0.0810	−3.04	.0020
Θ_2	0.0653	2.47	.0140
ARIMA(0,1,2)(0,1,1)$_{12}$			
θ_1	0.4261	16.68	<.0001
θ_2	0.2404	9.41	<.0001
Θ_1	0.9780	276.75	<.0001

Table 2
Measurement of training forecasts accuracies.

Method	MAPE
ARIMA(0,1,3)(0,0,2)$_{12}$: Iraq	58.02
ARIMA(0,1,2)(0,1,1)$_{12}$: Malaysia	15.50
ANN	
Iraq	43.32
Malaysia	14.32
Hybrid ARIMA-KF	
Iraq	26.13
Malaysia	9.99
Hybrid KF-ANN	
Iraq	16.52
Malaysia	8.10

Table 3
Measurement of testing forecasts accuracies.

Method	MAPE
ARIMA(0,1,3)(0,0,2)$_{12}$: Iraq	137.51
ARIMA(0,1,2)(0,1,1)$_{12}$: Malaysia	19.27
ANN	
Iraq	118.25
Malaysia	18.17
Hybrid ARIMA-KF	
Iraq	43.95
Malaysia	17.20
Hybrid KF-ANN	
Iraq	36.17
Malaysia	11.29

errors for training and testing periods, respectively. The training forecasts of ARIMA were 58.02 and 15.50 for Iraqi and Malaysian wind speed respectively, while the testing forecasts of ARIMA were 137.51 and 19.27 for Iraqi and Malaysian wind speed, respectively.

3.2. ANN approach

The inputs structure of ANN depended on the number of autoregressive parameters of ARIMA model. AR variables, which are those on the right side of Equation (2) regardless of the parameters and signs, will be used to determine the inputs structure of the ANN. Using an AR model, regardless of several stationarity conditions, resulted in a simple input structure for the ANN and may be provided more accurate forecasting. The stationarity condition was omitted, because the ARIMA model was used only for determining the structure of the input layer for the ANN [6–8].

The ACF and PACF for the original series reflected the number of significant orders for the ARIMA model for both data sets. Fig. 3 illustrates the ACF and PACF of the original Iraqi wind speed data set, and it also demonstrates the ACF and PACF from the original Malaysian wind speed data set.

Fig. 3 illustrates the slow dying out style exhibited by the autocorrelation functions of the Iraqi and Malaysian non-stationary data. The partial autocorrelation function in Fig. 3 illustrates the cutting off style after 12 for the Iraqi data set and after 7 for the Malaysian data set. AR(12) and AR(7) were proposed based on the ACF and PACF results from the Iraqi and Malaysian data sets, respectively. The inputs structure of the ANN for both data sets was based on the autoregressive order of the AR(12) and AR(7) models. In other words, the ANN inputs are the 12th and 7th sequent lags from the original series for the Iraqi and Malaysian data sets, respectively. Inputs data have been divided into training inputs and testing inputs. The inputs variables must be inserted as rows into one variable for training and into one variable for testing. The targets of ANN were the original time series data for Iraqi and Malaysian wind speed. Target series have been divided into training inputs and testing inputs. The target series must be inserted as rows into one variable for training and into one variable for testing.

AIC was used to confirm the results, Fig. 4 shows the AIC of AR(1), AR(2), …, AR(20) for the original Iraqi and Malaysian data set series. Fig. 4 illustrates the quick fading of the AIC values that stabilized after the 12th and 7th value for the Iraqi and Malaysian data sets, respectively.

The AIC plots confirmed that the selection of AR(12) and AR(7) was performed correctly.

MATLAB has improved some of its toolboxes for neural networks. Neural network toolboxes in MATLAB use many types of training algorithms, training functions and transfer functions. The structure of ANN has been constructed by determining the following requirements:

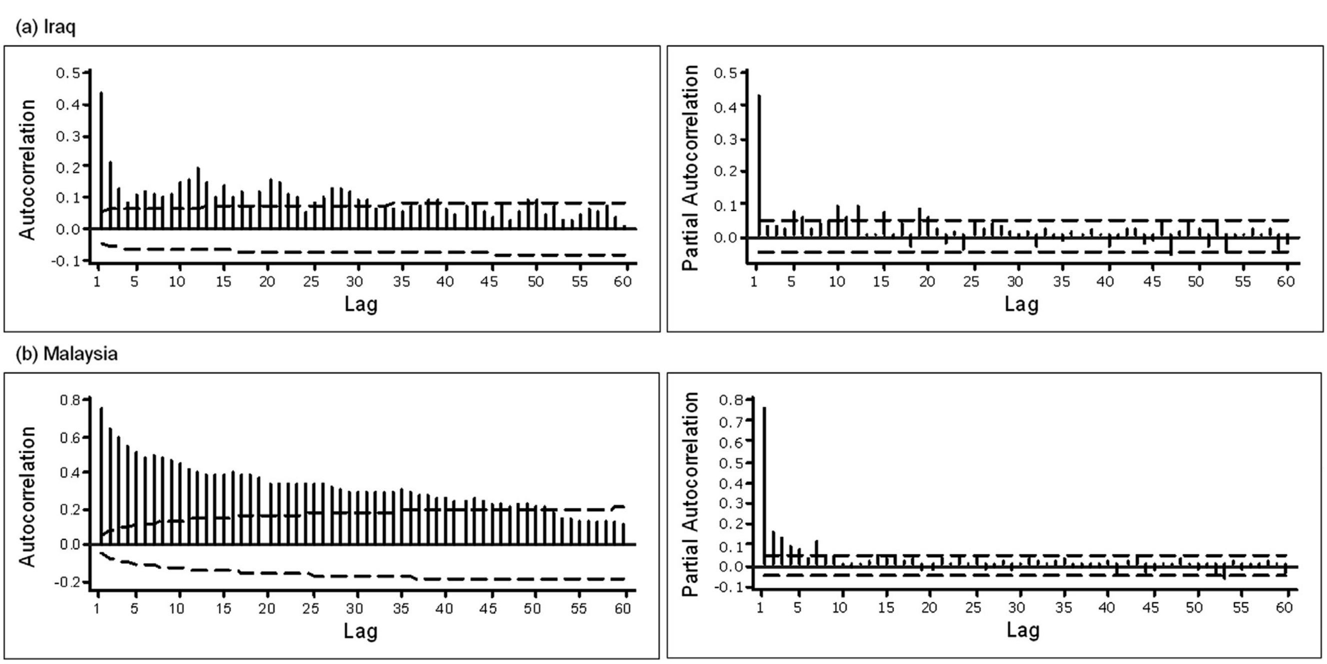

Fig. 3. ACF and PACF for Iraqi and Malaysian wind speeds.

a. Feed-forward back propagation must be determined as a network type.
b. The inputs of ANN for Iraqi wind speed data were $(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-12})$ and for Malaysian wind speed data were $(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-7})$. Training input and training target data must be imported to construct ANN structure.
c. Only Levenberg Marquardt and Bayesian regularization training algorithms were used as training function in this study.
d. The weights and biased part were determined randomly depended on ANN toolboxes strategies.
e. The number of neurons in the hidden layer was determined to be $(\text{no. of inputs} * 2 + 1)$ neurons [27]. The number of neurons in the hidden layer was 25 and 15 for the Iraqi and Malaysian data sets, respectively.
f. The nonlinearity of wind speed data was obligated to choose a nonlinear transfer function such as tan-sigmoid or log-sigmoid for hidden layer to filter the nonlinearity. Determining a transfer function for output layer depended on forecasting accuracy.

After completing ANN construction, training and testing processes were the next and final steps to obtain the fitting and forecasting series. Training and testing processes only need to import the input and target variables for training and testing periods, respectively.

Tables 2 and 3 show the MAPE values for the most minimum Iraqi and Malaysian ANN forecasting errors for the training and testing periods, respectively. The best training forecasts for ANN were 43.32 and 14.32 for Iraqi and Malaysian wind speed data, respectively, while the best testing forecasts of ANN were 118.25 and 18.17 for Iraqi and Malaysian wind speed data, respectively. The most minimum Iraqi ANN forecasting error has been obtained by determining the Bayesian regularization as training function, and log-sigmoid and tan-sigmoid transfer functions for hidden and output layers, respectively. The most minimum Malaysian ANN forecasting error has been obtained by determining the Bayesian regularization as training function, and log-sigmoid and linear transfer functions for hidden and output layers, respectively. Fig. 5 demonstrates Iraqi and Malaysian ANN structures were result in better forecasting accuracy.

Tables 2 and 3 show that for both the Iraqi and Malaysian data sets, the wind speed forecasting values for training and testing periods found using ANN were better than those found using the ARIMA model. These results confirm that ANN as a nonlinear approach improved the forecasting results compared to the ARIMA model.

3.3. Hybrid ARIMA-KF model

ARIMA modelling must be performed before a hybrid ARIMA-ANN model can be created. In this study, the Box–Jenkins Methodology was applied after satisfying the stationarity of the time series data. To handle stochastic uncertainty, the KF model was used for more accurate wind speed forecasting. In this paper, the KF model initialized SE of ARIMA$(p,d,q)(P,D,Q)_s$ within hybrid ARIMA-KF model to obtain the hybrid KF-ANN model based on ARIMA, which was discussed earlier. The state vector inputs of the KF model were similar to the ARIMA inputs on the right side of Equations (8) and (10) except a_t. Based on the ARIMA model in (8) after applying $Y_{t-i} = Y_{i,t}$ and $a_{t-i} = a_{i,t}$, SE and OE of the KF model process in (3) and (4) can be formulated for Iraqi wind speed as follows:

$$\begin{pmatrix} Y_{1,t} \\ a_{1,t} \\ a_{2,t} \\ a_{3,t} \\ a_{12,t} \\ a_{24,t} \\ a_{13,t} \\ a_{25,t} \\ a_{14,t} \\ a_{26,t} \\ a_{15,t} \\ a_{27,t} \end{pmatrix} = \begin{pmatrix} 1 & -0.618 & -0.236 & \cdots & 0.015 & -0.008 & 0.006 \\ 1 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 1 & 0 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & 0 & \cdots & 1 & 0 & 0 \\ 0 & 0 & 0 & \cdots & 0 & 1 & 0 \end{pmatrix}_{12\times12} \times \begin{pmatrix} Y_{1,t-1} \\ a_{1,t-1} \\ a_{2,t-1} \\ a_{3,t-1} \\ a_{12,t-1} \\ a_{24,t-1} \\ a_{13,t-1} \\ a_{25,t-1} \\ a_{14,t-1} \\ a_{26,t-1} \\ a_{15,t-1} \\ a_{27,t-1} \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} a_t \tag{11}$$

$$Y_t = [1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0]_{1\times12} \times \begin{pmatrix} Y_{1,t} \\ a_{1,t} \\ a_{2,t} \\ a_{3,t} \\ a_{12,t} \\ a_{24,t} \\ a_{13,t} \\ a_{25,t} \\ a_{14,t} \\ a_{26,t} \\ a_{15,t} \\ a_{27,t} \end{pmatrix}_{12\times1} \tag{12}$$

where Y_t and a_t are the transpose vectors of observations and residuals, respectively.

Based on the ARIMA model in (10), after applying $Y_{t-i} = Y_{i,t}$ and $a_{t-i} = a_{i,t}$, SE and OE of KF process in (3) and (4) can be formulated for Malaysian wind speed as follows:

$$\begin{pmatrix} Y_{1,t} \\ Y_{12,t} \\ Y_{13,t} \\ a_{1,t} \\ a_{2,t} \\ a_{12,t} \\ a_{13,t} \\ a_{14,t} \end{pmatrix} = \begin{pmatrix} 1 & 1 & -1 & -0.426 & -0.240 & -0.978 & 0.416 & 0.235 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & 0 \\ 0 & 0 & 0 & 0 & \cdots & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 & 1 & 0 \end{pmatrix}_{8\times8} \times \begin{pmatrix} Y_{1,t} \\ Y_{12,t} \\ Y_{13,t} \\ a_{1,t} \\ a_{2,t} \\ a_{12,t} \\ a_{13,t} \\ a_{14,t} \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} a_t \tag{13}$$

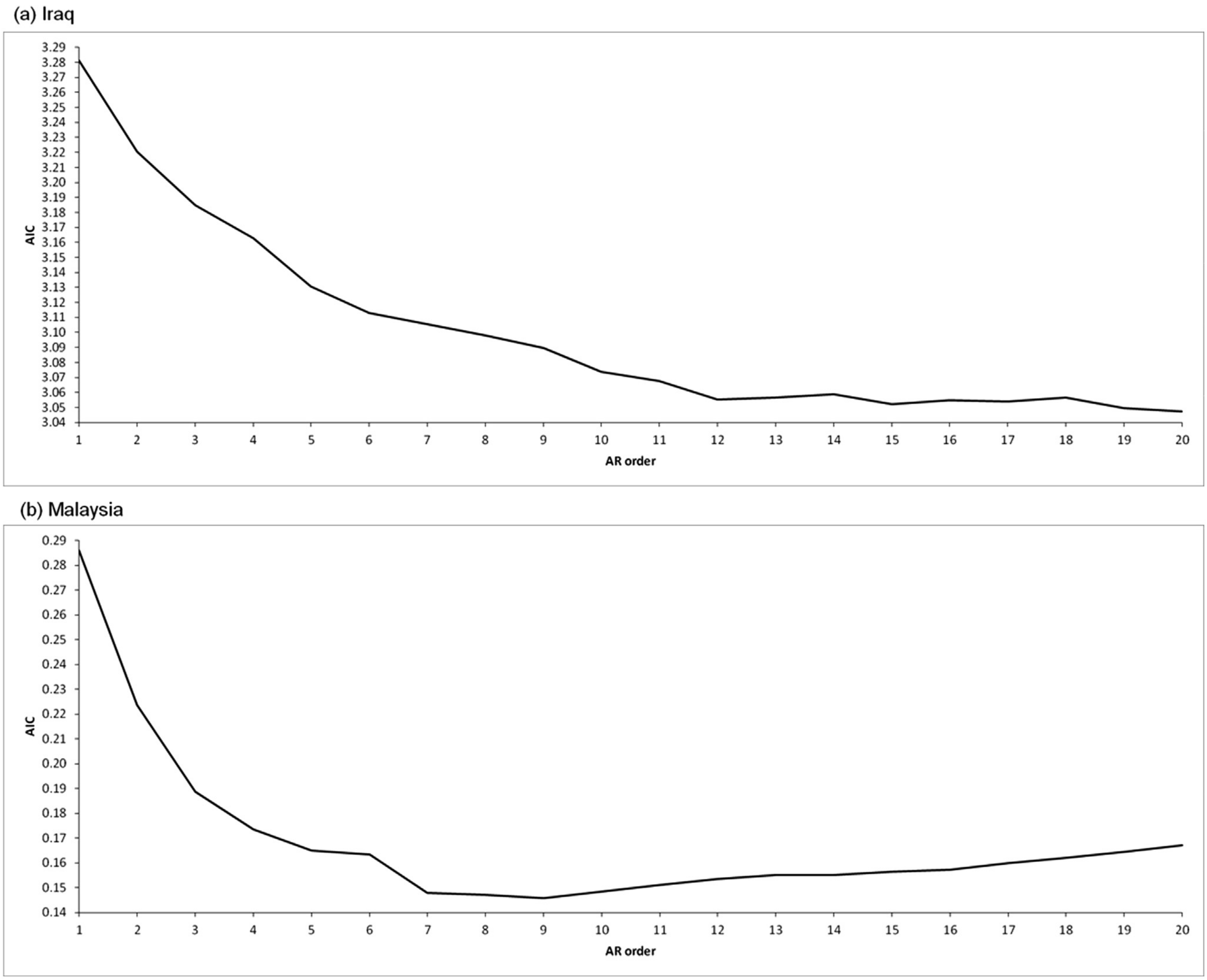

Fig. 4. AIC of the ARIMA for Iraqi and Malaysian data sets.

$$Y_t = \begin{bmatrix}1 & 0 & 0 & 0 & 0 & 0 & 0 & 0\end{bmatrix}_{1\times 8} \times \begin{pmatrix} Y_{1,t} \\ Y_{12,t} \\ Y_{13,t} \\ a_{1,t} \\ a_{2,t} \\ a_{12,t} \\ a_{13,t} \\ a_{14,t} \end{pmatrix}_{8\times 1} \tag{14}$$

where Y_t and a_t are the transpose vectors of observations and residuals respectively.

After initializing the SE and OE equations for Iraqi and Malaysian wind speed data, the KF model was used for wind speed forecasting using a KF recursive step, such as the one found in Refs. [18,19,26]. The state vector combined linear and nonlinear parts of the ARIMA model, such as in (11) and (13). Combining linear and nonlinear parts improved the accuracy of wind speed forecasting and was more capable of handling stochastic uncertainty. The output Y_t of observation equation represents the fitted series or the forecasting series. The difference $Y_t - CX_t$ is the forecasting errors for the KF model. The MAPE was computed for forecasting error of Iraqi and Malaysian wind speeds to evaluate the accuracy of the forecasts.

Tables 2 and 3 present the MAPE values for the hybrid ARIMA-KF forecasting errors for the training and testing periods in Iraq and Malaysia, respectively. The training forecasts for hybrid ARIMA-KF model were 26.13 and 10.00 for Iraqi and Malaysian wind speeds, respectively, while the testing forecasts for the hybrid ARIMA-KF model were 43.95 and 17.20 for Iraqi and Malaysian wind speeds, respectively. The training and testing forecasts for the hybrid ARIMA-KF model were more accurate than those for ARIMA and ANN. The reason behind the accuracy of the hybrid ARIMA-KF forecasting was due to the superior performance of the KF model in regards to handling stochastic uncertainty.

3.4. Hybrid KF-ANN model

The nonlinearity and the stochastic uncertainty problems in wind speed data can be handled by combining ANN and KF in one hybrid model. In this paper, a hybrid KF-ANN model was proposed that was based on the ARIMA model to further improve the accuracy of wind speed forecasting. The first step for performing a hybrid KF-ANN forecast based on the ARIMA model was done after the state equation for Iraqi wind speed data in Equation (11) and the state equation for Malaysian wind speed data in Equation (13) were created and the new state vectors for Equation (11) and

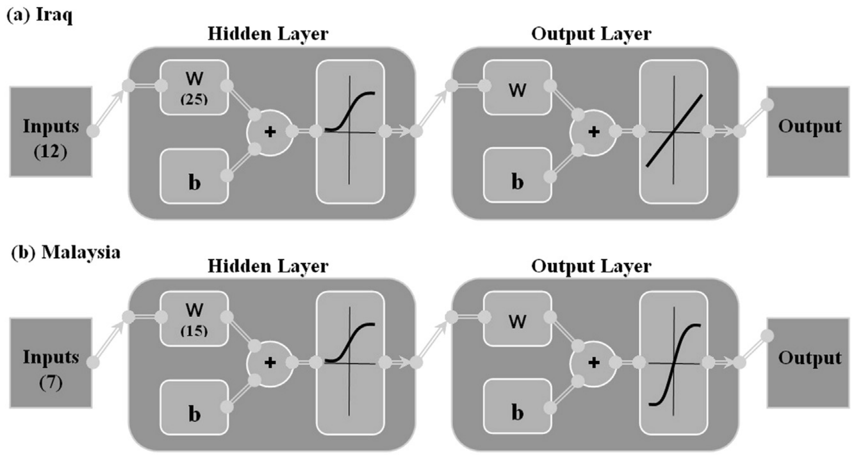

Fig. 5. ANN structure with more appropriate transfer function types.

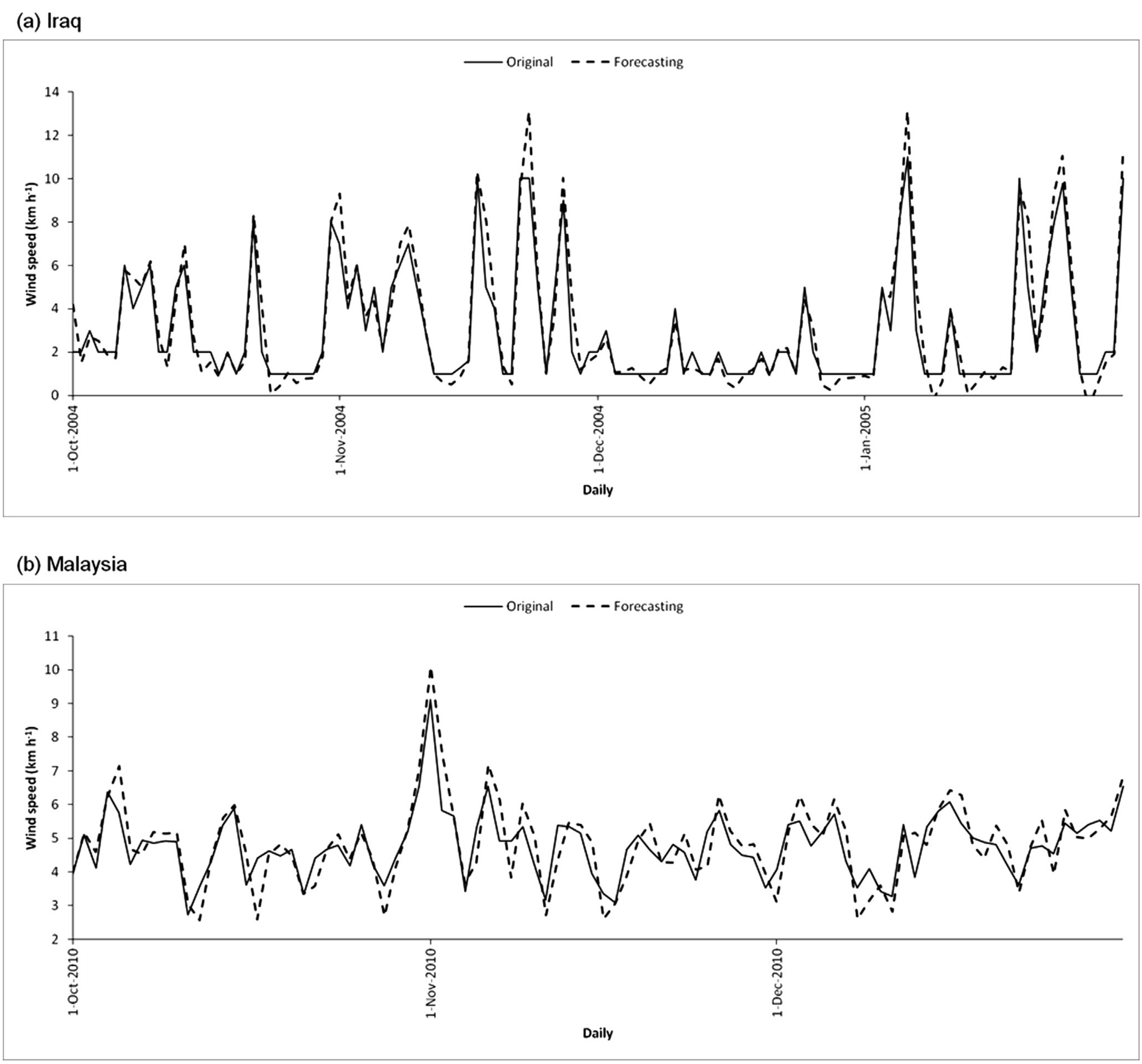

Fig. 6. Testing forecast and the original plots for Iraqi and Malaysian wind speed.

Equation (13) were obtained. All variables within the new state vectors in Equation (11) and Equation (13) represent ANN inputs variables for Iraqi and Malaysian wind speed data. Inputs data have been divided into training inputs and testing inputs. The inputs variables must be inserted as rows into one variable for training and into one variable for testing. The target for ANN was the original wind speed series. Target series have been divided into training inputs and testing inputs. The target series must be inserted as rows into one variable for training and into one variable for testing. The dimension for the ANN inputs matrix was $m \times n$ (n was the length of data series), while the dimension for the ANN target was $1 \times n$.

ANN toolboxes in MATLAB use many types of training algorithms, training functions and transfer functions. The structure of ANN in this stage has been constructed by determining the following requirements:

a. Feed-forward back propagation must be determined as a network type.
b. (Y_{t-1}, a_{t-1}, a_{t-2}, a_{t-3}, a_{t-12}, a_{t-24}, a_{t-13}, a_{t-25}, a_{t-14}, a_{t-26}, a_{t-15}, a_{t-27}) represents the 12 ANN input variables for Iraqi wind speed data, while (Y_{t-1}, Y_{t-12}, Y_{t-13}, a_{t-1}, a_{t-2}, a_{t-12}, a_{t-13}, a_{t-14}) represents the 8 ANN input variables for Malaysian wind speed data. Training input and training target data must be imported to construct ANN structure.
c. Only Levenberg Marquardt and Bayesian regularization training algorithms were used as training function in this study.
d. The weights and biased part were determined randomly depended on ANN toolboxes strategies.
e. The number of neurons in the hidden layer was determined to be (no. of inputs $^* 2 + 1$) neurons [27]. The number of neurons in the hidden layer was 25 and 17 for the Iraqi and Malaysian data sets, respectively.
f. Tan-sigmoid and log-sigmoid has been chosen for hidden layer. Determining a transfer function for output layer depended on forecasting accuracy.

As a result, the outputs of the training and testing processes for ANN represent the fitted series for the training stage and the forecasting series for testing stage. The difference between the ANN output and the ANN target is the error forecasting for the hybrid KF-ANN model. The accuracy of the forecasting was evaluated by determining the MAPE for the forecasting errors of the Iraqi and Malaysian wind speeds.

Tables 2 and 3 present the MAPE values for the Iraqi and Malaysian hybrid KF-ANN forecasting errors for the training and testing periods, respectively. The training forecasts for the hybrid KF-ANN model were 16.52 and 8.10 for Iraqi and Malaysian wind speeds, respectively, while the testing forecasts for the hybrid KF-ANN model were 36.17 and 11.29 for Iraqi and Malaysian wind speeds, respectively. The most minimum Iraqi ANN forecasting error has been obtained by determining the Levenberg Marquardt as training function, and log-sigmoid and linear transfer functions for hidden and output layers, respectively. The most minimum Malaysian ANN forecasting error has been obtained by determining the Bayesian regularization as training function, and tan-sigmoid and linear transfer functions for hidden and output layers, respectively. Fig. 6 outlines the consistency between the original and testing forecast series obtained by using the hybrid ARIMA-KF model.

Tables 2 and 3 confirm that the forecasting accuracy of the hybrid KF-ANN model exceeded the forecasting accuracy of the ARIMA and ANN models and it also surpassed the forecasting accuracy of the hybrid ARIMA-KF. Fig. 6 demonstrates that the testing forecasts series was consistent with the original Iraqi and Malaysian data sets.

The reason behind the consistency and the high level of forecasting accuracy was due to the hybridization of the linear and nonlinear parts of the ARIMA model, the use of a KF to handle stochastic uncertainty, the use of ANN to handle the nonlinearity within the hybrid KF-ANN model. The differences in forecasting accuracy rates for the Iraqi and Malaysian wind speed data may have been caused by the differences in the meteorological environments of Iraq and Malaysia. Additionally, Iraq has four seasons yearly, whereas Malaysia has only two, making the Iraqi data set more complex.

4. Conclusion

A hybrid KF–ANN approach was proposed to improve the accuracy of wind speed forecasting. Two wind speed data sets from different meteorological environments were used. The results showed that ARIMA, ANN, hybrid ARIMA-KF and hybrid KF–ANN model were effective. However, the MAPE results indicated that the hybrid KF-ANN model was the most effective tool for improving the accuracy of wind speed forecasts. The advantages of the hybrid model were the result of hybridizing the linear and nonlinear parts of the ARIMA model and combing it with a KF to handle stochastic uncertainty and ANN to handle the nonlinearity within hybrid KF-ANN model.

References

[1] Benth JŠ, Benth FE. Analysis and modelling of wind speed in New York. J Appl Stat 2010;37:893–909.
[2] Shi J, Qu X, Zeng S. Short-term wind power generation forecasting: direct versus indirect ARIMA-based approaches. Int J Green Energy 2011;8:100–12.
[3] Zhu X, Genton MG. Short-term wind speed forecasting for power system operations. Int Stat Rev 2012;80:2–23.
[4] Cadenas E, Rivera W. Wind speed forecasting in the south coast of Oaxaca, México. Renew Energy 2007;32:2116–28.
[5] Cadenas E, Rivera W. Wind speed forecasting in three different regions of Mexico, using a hybrid ARIMA-ANN model. Renew Energy 2010;35:2732–8.
[6] Liu H, Tian H, Li Y. Comparison of two new ARIMA-ANN and ARIMA-Kalman hybrid methods for wind speed prediction. Appl Energy 2012;98:415–24.
[7] Tatinati S, Veluvolu KC. A hybrid approach for short-term forecasting of wind speed. Sci World J 2013;2013.
[8] Chen K, Yu J. Short-term wind speed prediction using an unscented Kalman filter based state-space support vector regression approach. Appl Energy 2014;113:690–705.
[9] Guo Z, Zhao W, Haiyan L, Wang J. Multi-step forecasting for wind speed using a modified EMD-based artificial neural network model. Renew Energy 2012;37:241–9.
[10] Li G, Shi J. On comparing three artificial neural networks for wind speed forecasting. Appl Energy 2010;87:2313–20.
[11] Pourmousavi-Kani SA, Ardehali MM. Very short-term wind speed prediction: a new artificial neural network–Markov chain model. Energy Convers Manag 2011;52:738–45.
[12] Assareh E, Behrang MA, Ghalambaz M, Noghrehabadi AR, Ghanbarzadeh A. An analysis of wind speed prediction using artificial neural networks: a case study in Manjil, Iran. Energy Sources Part A Recovery Util Environ Eff 2012;34:636–44.
[13] Bilgili M, Sahin B. Wind speed prediction of target station from reference stations data. Energy Sources Part A Recovery Util Environ Eff 2013;35:455–66.
[14] Peng H, Liu F, Yang X. A hybrid strategy of short term wind power prediction. Renew Energy 2013;50:590–5.
[15] Khashei M, Bijari M. An artificial neural network (p,d,q) model for time series forecasting. Expert Syst Appl 2010;37:479–89.
[16] Khashei M, Bijari M. A novel hybridization of artificial neural networks and ARIMA models for time series forecasting. Appl Soft Comput 2011;11:2664–75.
[17] Malmberg A, Holst U, Holst J. Forecasting near-surface ocean winds with Kalman filter techniques. Ocean Eng 2005;32:273–91.
[18] Galanis G, Louka P, Katsafados P, Pytharoulis I, Kallos G. Applications of Kalman filters based on non-linear functions to numerical weather predictions. Ann Geophys 2006;24:2451–60.
[19] Louka P, Galanis G, Siebert N, Kariniotakis G, Katsafados P, Pytharoulis I, et al. Improvements in wind speed forecasts for wind power prediction purposes using Kalman filtering. J Wind Eng Ind Aerodyn 2008;96:2348–62.

[20] Cassola F, Burlando M. Wind speed and wind energy forecast through Kalman filtering of numerical weather prediction model output. Appl Energy 2012;99: 154–66.
[21] Liu L-M. Time series analysis and forecasting. 2nd ed. Illinois, USA: Scientific Computing Associates Corp.; 2006.
[22] Forshed J, Andersson FO, Jacobsson SP. NMR and Bayesian regularized neural network regression for impurity determination of 4-aminophenol. J Pharm Biomed Anal 2002;29:495–505.
[23] Mahamad AK, Saon S, Hiyama T. Predicting remaining useful life of rotating machinery based artificial neural network. Comput Math Appl 2010;60: 1078–87.
[24] Tien Bui D, Pradhan B, Lofman O, Revhaug I, Dick OB. Landslide susceptibility assessment in the Hoa Binh province of Vietnam: a comparison of the Levenberg–Marquardt and Bayesian regularized neural networks. Geomorphology 2012;171:12–29.
[25] Gould PG, Koehler AB, Ord JK, Snyder RD, Hyndman RJ, Araghi FV. Forecasting time series with multiple seasonal patterns. Eur J Oper Res 2008;191:207–22.
[26] Madsen H. Time series analysis. CRC Press; 2007.
[27] Sheela KG, Deepa S. Review on methods to fix number of hidden neurons in neural networks. Math Probl Eng 2013;2013.