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Daily Wind Speed Forecasting Through Hybrid AR-ANN and AR-KF Models

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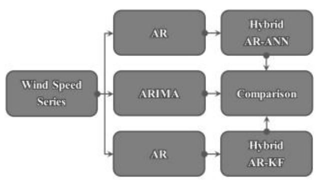
Graphical abstract



The framework of the study

Abstract

The nonlinearity and the chaotic fluctuations in the wind speed pattern are the reasons of inaccurate wind speed forecasting results using a linear autoregressive integrated moving average (ARIMA) model. The inaccurate forecasting of ARIMA model is a problem that reflects the uncertainty of modelling process. This study aims to improve the accuracy of wind speed forecasting by suggesting more appropriate approaches. An artificial neural network (ANN) and Kalman filter (KF) will be used to handle nonlinearity and uncertainty problems. Once ARIMA model was used only for determining the inputs structures of KF and ANN approaches, using an autoregressive (AR) Instead of ARIMA may be resulted in more simplicity and more accurate forecasting. ANN and KF based on the AR model are called hybrid AR-ANN model and hybrid AR-KF model, respectively. In this study, hybrid AR-ANN and hybrid AR-KF models are proposed to improve the wind speed forecasting. The performance of ARIMA, hybrid AR-ANN, and hybrid AR-KF models will be compared to determine which had the most accurate forecasts. A case study will be carried out that used daily wind speed data from Iraq and Malaysia. Hybrid AR-ANN and AR-KF models performed better than ARIMA model while the hybrid AR-KF model was the most adequate and provided the most accurate forecasts. In conclusion, the hybrid AR-KF model will result in better wind speed forecasting accuracy than other approaches, while the performances of both hybrid models will be provided acceptable forecasts compared to ARIMA model that will provide ineffectual wind speed forecasts.

Keywords: Wind speed forecasting; ARIMA; KF; ANN; hybrid forecasting

1.0 INTRODUCTION

Extreme wind speeds and the nonlinear nature of wind speed data makes forecasting a complex process. Some authors have proposed using ARIMA models to forecast wind speeds. Benth and Benth proposed an ARIMA model for estimating and forecasting wind speeds for three different wind farms in New York State [1]. Shi *et al.* 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 [2]. Zhu and Genton reviewed statistical short-term wind speed forecasting models, including AR model and traditional time series approaches, used in wind power developments to determine which model provided the most accurate forecasts [3].

An ANN can be used to handle the nonlinear nature of wind speed data. Many recent papers have proposed using ANNs to improve the forecasting accuracy of nonlinear data. Cadenas and Rivera presented a comparison of ARIMA and ANN approaches for wind speed forecasting using seven years of wind speed data [4].

The nonlinear pattern of wind speed data is the reason for the inaccuracy of ARIMA forecasting, which is a linear model [5]. Pourmousavi-Kani and Ardehali used ANN to develop very short-term wind speed forecasts after creating a hybrid ANN–MC model [6]. Assareh, *et al.* forecasted wind speeds using twelve years of data. They proposed ANN as a way to represent the relationship between wind speed, and other meteorological data [7]. Bilgili and Sahin used ANN to forecast daily, weekly, and monthly wind speeds using data from four different measuring of Turkey [8]. They obtained successful forecasting results. Peng *et al.* [9] suggested an individual ANN and hybrid strategy based on physical and statistical approaches for short term wind power forecasting [9]. The individual ANN approach resulted in highly accurate forecasts.

In this study, an ANN based on AR was proposed to improve the forecasting accuracy. This method is called a hybrid AR-ANN model. Li and Shi compared one hour ahead forecasts for hourly wind speeds using three different types of artificial neural networks [10]. They used an autocorrelation function (ACF) and a partial autocorrelation function (PACF) to determine the ANN inputs. Guo, *et al.* proposed many methods for wind speed forecasting [11]. One of these methods was a feed-forward neural network whose inputs were determined based on the AR order. Liu, *et al.* proposed new ARIMA-ANN and ARIMA-Kalman hybrid methods [12]. Their new hybrid ARIMA-ANN method was similar to hybrid AR-ANN model that will be studied in the current study. They confirmed that the performance of their hybrid method in terms of its predictions was consistently better than that of ARIMA.

Although an ARIMA is a preferable statistical model for forecasting, it leads to inaccurate wind speed forecasting. The KF model can be used for wind speed forecasting. To obtain the best initial parameters for the KF, an AR will be used to create the structure of the KF model to handle the stochastic uncertainty and improve forecasting. An AR will be depended to construct the structure of the state equation (SE) of KF. This model is called a hybrid AR-KF that is proposed in the current study. In the proposed AR-KF model, the SE and the observation equation (OE) will be created based on AR model.

Malmberg, *et al.* used the KF model based on AR to forecast the large scale component of bounded areas of near-surface ocean wind speeds [13]. Galanis, *et al.* proposed implementing non-linear polynomial functions in classical linear KF algorithm as a new methodology that would improve regional weather forecasts [14]. Louka, *et al.* applied the KF model for numerical wind speed forecasting and employed two limited area atmospheric models with different horizontal resolution to improve forecasts [15]. Cassola and Burlando proposed a mixed approach based on the use of a NWP model coupled with a statistical model based on the KF model to forecast wind speed and wind power data collected from two anemometric stations [16]. Liu, *et al.* proposed two new hybrid ARIMA-ANN and ARIMA-KF methods for wind speed forecasting, and compared their performance [12]. Their hybrid ARIMA-KF method was similar to hybrid AR-KF model in the current study. The performance of their method in terms of its predictions was consistently better than that of ARIMA. Zhu and Genton suggested using traditional statistical models of wind speed forecasting, including a KF method, to handle uncertainty [3]. Tatinati and Veluvolu proposed many approaches for short term wind speed forecasting [17]. One of these approaches was a hybrid AR-KF model to improve forecasting accuracy.

AR, ARIMA, or seasonal ARIMA models have been used for comparing and determining KF and ANN inputs structures such by several researchers [4, 5, 11, 12, 17, 18]

This paper is organized as follows: Section 2 states the framework of this study and presents the proposed hybrid AR-ANN and AR-KF models theoretically. Section 3 displays and discusses the forecasting results of the methods in Section 2. Section 4 provides the conclusions of this study.

■2.0 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 2010–31December 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 KF based on AR.
d. Comparing the studied approaches to determine what model would provide the best forecasts. Figure 1 demonstrates the framework of this study.

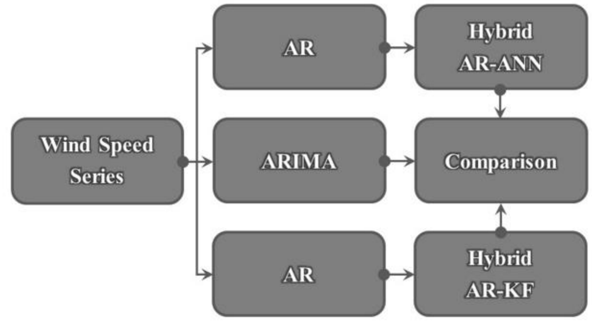


Figure 1 The framework of the study

2.2 Mathematical Models

2.2.1 ARIMA Model

An ARIMA model was used to forecast wind speed. The modelling strategy followed Box-Jenkins methodology. A general expression of the seasonal ARIMA(p,d,q)(P,D,Q)$_s$ model is shown in Equation (1).

$$\underbrace{(1-\phi_1B-\phi_2B^2-\cdots-\phi_pB^p)}_{AR(p)}\underbrace{(1-\Phi_1B^s-\Phi_2B^{2s}-\cdots-\Phi_PB^{Ps})}_{AR_s(P)}W_t = \underbrace{(1-\theta_1B-\theta_2B^2-\cdots-\theta_qB^q)}_{MA(q)}\underbrace{(1-\Theta_1B\ -\Theta_2B^{2s}-\cdots-\Theta_QB^{Qs})}_{MA_s(Q)}a_t \tag{1}$$

where

$$W_t=\underbrace{(1-B)^d}_{I(d)}\underbrace{(1-B^s)^D}_{I_s(D)}Y_t$$

where Y_t is the time series variable, W_t is the time series variable after the successive and seasonal differences, a_t is the residual series at the current time, where *AR(p)* is a p^{th} order of the autoregressive component, *MA(q)* is a q^{th} order of moving average component, *I(d)* is a d^{th} non-seasonal difference, $AR_S(P)$ is a P^{th} order of seasonal autoregressive component, $MA_S(Q)$ is a Q^{th} order of seasonal moving average component, $I_S(D)$ is a D^{th} seasonal difference, *s* is a period of the seasonal pattern, B^i is an i^{th} order of backshift operator, and ϕ,Φ,θ,Θ are the parameters of the ARIMA model.

The Box–Jenkins methodology steps were developed by [19]. An ARIMA expression in Equation (1) can be reformulated after performing many computational processes as per Equation (2).

$$Y_t=\begin{pmatrix}\left(\phi_1B-\phi_2B^2-\cdots-\phi_pB^p\right)+\left(\Phi_1B^s-\Phi_2B^{2s}-\cdots-\Phi_PB^{Ps}\right)\\-\left(\phi_1B-\phi_2B^2-\cdots-\phi_pB^p\right)\left(\Phi_1B^s-\Phi_2B^{2s}-\cdots-\Phi_PB^{Ps}\right)\end{pmatrix}Y_t$$
$$-\left((1-\phi_1B-\phi_2B^2-\cdots-\phi_pB^p)(1-\Phi_1B^s-\Phi_2B^{2s}-\cdots-\Phi_PB^{Ps})\right)(W_t-Y_t)$$
$$-\begin{pmatrix}(\theta_1B+\theta_2B^2+\cdots+\theta_qB^q)+(\Theta_1B\ +\Theta_2B^{2s}+\cdots+\Theta_QB^{Qs})\\-(\theta_1B+\theta_2B^2+\cdots+\theta_qB^q)(\Theta_1B\ +\Theta_2B^{2s}+\cdots+\Theta_QB^{Qs})\end{pmatrix}a_t+a_t \tag{2}$$

2.2.2 Hybrid AR-ANN Model

ANN will be proposed to handle the nonlinearity of wind speed data and to improve the forecasting accuracy. Use of the multilayer feed-forward back propagation neural network for time series forecasting was supported by the ANN toolbox in MATLAB software. Determining the training function, transfer functions types of hidden and output layers, and other requirements was necessary to create the most appropriate ANN structure.

The types of transfer functions are tan-sigmoid, which generates nonlinear outputs between -1 and +1, log-sigmoid which generates nonlinear outputs between 0 and 1, and linear transfer functions which generates linear outputs between -1 and +1. Selecting a suitable transfer function is important for obtaining good results. 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 appropriate ANN.

The nonlinearity of wind speed data is obligated to choose a nonlinear transfer function such as tan-sigmoid and log-sigmoid for hidden layer to filter the nonlinearity. In these situations, determining a linear transfer function for an output layer is preferable, especially after the nonlinearity filtration. Figure 2 demonstrates the structure of feed-forward back propagation and the differences among the types of transfer functions.

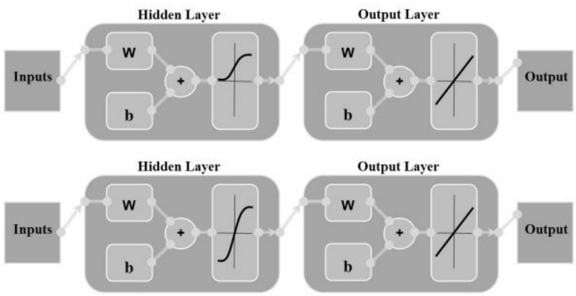


Figure 2 ANN structure and transfer function types

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. This approach can just be called ANN [20, 21] or it can also be called hybrid AR-ANN model [12]. Using an AR model Instead of ARIMA model, regardless of several time series conditions, resulted in a simple input structure for the ANN. Hybrid AR-ANN model has been proposed in the current study to improve the accuracy of forecasting.

Hybrid AR-ANN model combines the regularity of the pure statistical AR model with the high forecasting accuracy of nonlinear ANN. In the first stage, the AR model will be constructed. An AR model was used to determine the inputs structure of the ANN.

2.2.3 Hybrid AR-KF Model

To handle the stochastic uncertainty, a KF model was used for more accuracy of wind speed forecasting. Due to its good performance in meteorological applications, it was used for wind speed forecasting [13-15]. The KF model can be introduced as a statistical approach for estimating and forecasting the unmeasured state space. In this study, the KF model will be initialized based on AR model to obtain a hybrid AR-KF model. A hybrid AR-KF model is proposed instead of hybrid ARIMA-KF model to maintain simplicity when the parameters of moving average (MA) part become zero [12, 17, 18]. The SE inputs of the KF model were the same as the AR variables, which are those on the right side of Equation (2) regardless of the parameters. Based on the AR model, SE and OE of the KF model can be written in state space form as per Equation (30) and Equation (4) [22]:

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

$$Y_t = CX_t \quad (4)$$

where X_t is m-dimensional state vector

$X_t = \begin{bmatrix} X_{1,t} & X_{2,t} & \dots & X_{m,t} \end{bmatrix}^T$;

A is $m \times m$ state transition matrix

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

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

$C = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \end{bmatrix}_{1 \times m}$

where $(K_1, K_2, K_3, \dots, K_m)$ are all AR parameter values, which are those on the right side of Equation (2) after seasonal and non-seasonal differencing, and m is the number of these parameters. Y_t and a_t are the observation and the residual transpose vectors, respectively.

After initializing the SE and OE, the KF model will be used for wind speed forecasting using KF recursive steps such as the one found in [14, 15, 23]. The output of OE represented the fitted series or the forecasting series. The difference $Y_t - CX_t$ is the error forecasting of KF. The mean absolute percentage error (MAPE) will be computed for the error forecasting of the KF model to evaluate the accuracy of the forecasts.

3.0 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 Figure 3.

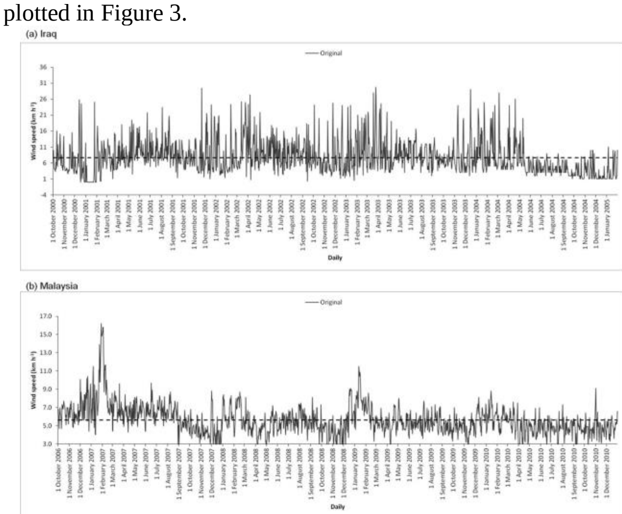


Figure 3 Time series plot of wind speed for Iraq and Malaysia

Figure 3 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 ARIMA model of Iraqi wind speed was ARIMA(0,1,3)(0,0,2)$_{12}$, while the best 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 Iraqi wind speed data can be expressed as per Equation (5).

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

$$Y_t = Y_{t-1} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \theta_3 a_{t-3} - \Theta_1 a_{t-12} - \Theta_2 a_{t-24} + \theta_1\Theta_1 a_{t-13} + \theta_1\Theta_2 a_{t-25} + \theta_2\Theta_1 a_{t-14} + \theta_2\Theta_2 a_{t-26} + \theta_3\Theta_1 a_{t-15} + \theta_3\Theta_2 a_{t-27} \quad (5)$$

where

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

After substituting the parameters in Equation (5) for their estimated values in Table 1, the ARIMA(0,1,3)(0,0,2)$_{12}$ model will be as per Equation (6):

$$Y_t = Y_{t-1} + a_t - 0.618a_{t-1} - 0.236a_{t-2} - 0.097a_{t-3} + 0.081a_{t-12} - 0.065a_{t-24} - 0.050a_{t-13} + 0.040a_{t-25} - 0.019a_{t-14} + 0.015a_{t-26} - 0.008a_{t-15} + 0.006a_{t-27} \quad (6)$$

The ARIMA(0,1,2)(0,1,1)$_{12}$ model for Malaysian wind speed data can be expressed as per Equation (7):

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

$$Y_t = Y_{t-1} + Y_{t-12} - Y_{t-13} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \Theta_1 a_{t-12} + \theta_1\Theta_1 a_{t-13} + \theta_2\Theta_1 a_{t-14} \quad (7)$$

where

$$W_t = (1-B^{12})(1-B)Y_t = (1-B-B^{12}+B^{13})Y_t = Y_t - Y_{t-1} - Y_{t-12} + Y_{t-13}.$$

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
Hybrid AR-ANN		
	Iraq	43.32
	Malaysia	14.32
Hybrid AR-KF		
	Iraq	28.74
	Malaysia	10.15

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
Hybrid AR-ANN		
	Iraq	118.25
	Malaysia	18.17
Hybrid AR-KF		
	Iraq	42.22
	Malaysia	15.55

After substituting the parameters in Equation (7) for their estimated values in Table 1, the ARIMA(0,1,2)(0,1,1)12 model will be as per Equation (8):

$$Y_t = Y_{t-1} + Y_{t-12} - Y_{t-13} + a_t - 0.426a_{t-1} - 0.240a_{t-2} - 0.978a_{t-12} + 0.417a_{t-13} + 0.235a_{t-14} \quad (8)$$

In the ARIMA models, MAPE was used to reflect the forecasting accuracy of 123 observations for the Iraqi testing series and 92 observations for the Malaysian testing series.

Table 1 reveals that all ARIMA parameters are significant. Table 2 and Table 3 contain the MAPE values of Iraqi and Malaysian ARIMA forecasting errors for training and testing periods, respectively.

The training forecasts of ARIMA were 58.02 and 15.50 for Iraq and Malaysia respectively, while the testing forecasts of ARIMA were 137.51 and 19.27 for Iraq and Malaysia, respectively.

3.2 Hybrid AR-ANN Model

Neural network toolboxes in MATLAB can use many types of training algorithms and training functions. Feed forward and back-propagation algorithm with the Levenberg Marquardt and the Bayesian regularization training algorithms were used in this study to improve forecasting accuracy.

The partial autocorrelation function (PACF) for the original series reflected the number of significant orders for the AR model. The stationarity conditions were omitted in this stage, because the AR model was used only for determining the structure of the input layer for the ANN. Figure 4 illustrates the ACF and PACF of the original Iraqi and Malaysian wind speed data set.

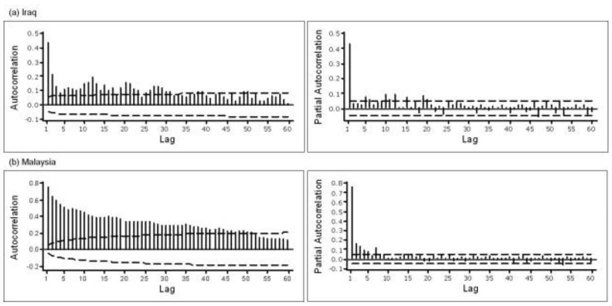


Figure 4 ACF and PACF for Iraqi and Malaysian wind speeds

From Figure 4, ACF exhibited the slow dying out style of the Iraqi and Malaysian non-stationary data. The PACF in Figure 4 illustrates the cutting off style after 12 for the Iraqi data set and after 7 for the Malaysian data set. Therefore, AR(12) and AR(7) can be proposed based on the ACF and PACF results for the Iraqi and Malaysian data sets, respectively. The Akaike information criterion (AIC) will be plotted to measure the adequacy of the best AR model. AIC was used to confirm these results (Figure 5) for the original Iraqi and Malaysian data set series for AR(1), AR(2), …, AR(20).

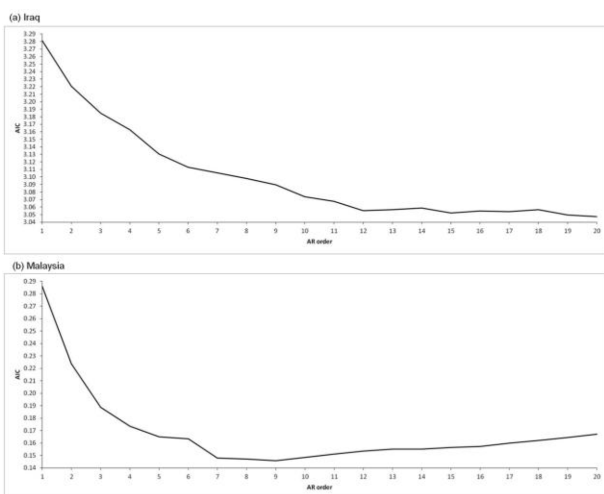


Figure 5 AIC of the ARIMA for Iraqi and Malaysian data sets

Figure 5 shows the quick dying out style of the AIC values that stabilized after the 12th and 7th values for the Iraqi and Malaysian data sets, respectively. The AIC plots confirmed that the selection of AR(12) and AR(7) was performed correctly.

The input structure of the ANN for both data sets can be considered based on the autoregressive order of the AR(12) and AR(7) models. In other words, the ANN inputs are equalled to 12 and 7 for the Iraqi and Malaysian data sets, respectively.

Figure 6 outlines the consistency between the original and testing forecast series obtained by using the hybrid AR-ANN model for Iraqi and Malaysian wind speed data sets, respectively.

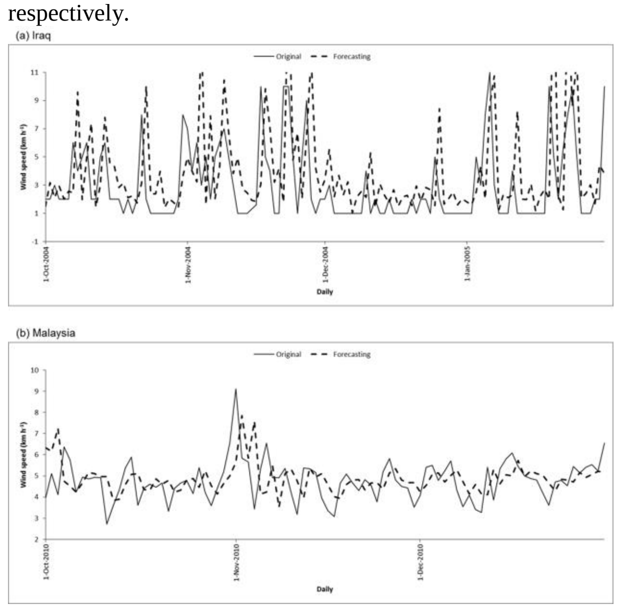


Figure 6 Hybrid AR-ANN testing forecast and the original plots for Iraq and Malaysia

Figure 6 demonstrates that the consistence between the testing forecasts series and original data sets was acceptable for Iraq and Malaysia with some of over forecasting situation for Iraqi data set. Table 2 and Table 3explains the MAPE values for Iraqi and Malaysian hybrid AR-ANN forecasting errors for the training and testing periods, respectively. From Table 2 and Table **3**, the MAPE values for the hybrid AR-ANN training forecasts were 43.32 and 14.32 for Iraqi and Malaysian wind speed data, respectively, while the MAPE values for the testing forecasts of the hybrid AR-ANN were 118.25 and 18.17 for Iraqi and Malaysian wind speed data sets, respectively. Table 2 and Table 3 shows that for both the Iraqi and Malaysian data sets, the wind speed forecasting values for training and testing periods found using AR-ANN were better than those found using the ARIMA model. These results confirm that the hybrid AR-ANN model improved the forecasting accuracy compared to the ARIMA model.

3.3 Hybrid AR-KF Model

To handle stochastic uncertainty, the KF model was used for more accurate forecasting. AR modelling has been performed in the previous section successfully. Therefore, the state vector inputs of the KF for both data sets can be considered based on AR(12) and AR(7) models. In other words, the state vector inputs are equalled to 12 and 7 for the Iraqi and Malaysian data sets, respectively.

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

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \\ Y_{3,t} \\ Y_{4,t} \\ Y_{5,t} \\ Y_{6,t} \\ Y_{7,t} \\ Y_{8,t} \\ Y_{9,t} \\ Y_{10,t} \\ Y_{11,t} \\ Y_{12,t} \end{pmatrix} = \begin{pmatrix} 0.426 & 0.025 & 0.034 & 0.001 & 0.072 & 0.055 & 0.027 & 0.044 & 0.034 & 0.087 & 0.035 & 0.128 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \times \begin{pmatrix} Y_{1,t} \\ Y_{2,t} \\ Y_{3,t} \\ Y_{4,t} \\ Y_{5,t} \\ Y_{6,t} \\ Y_{7,t} \\ Y_{8,t} \\ Y_{9,t} \\ Y_{10,t} \\ Y_{11,t} \\ Y_{12,t} \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} a_t \quad (9)$$

$$Y_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}_{1\times 12} \times \begin{pmatrix} Y_{1,t} \\ Y_{2,t} \\ Y_{3,t} \\ Y_{4,t} \\ Y_{5,t} \\ Y_{6,t} \\ Y_{7,t} \\ Y_{8,t} \\ Y_{9,t} \\ Y_{10,t} \\ Y_{11,t} \\ Y_{12,t} \end{pmatrix}_{12\times 1} \quad (10)$$

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

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \\ Y_{3,t} \\ Y_{4,t} \\ Y_{5,t} \\ Y_{6,t} \\ Y_{7,t} \end{pmatrix} = \begin{pmatrix} 0.615 & 0.068 & 0.081 & 0.0359 & 0.062 & -0.010 & 0.140 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \times \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ Y_{3,t-1} \\ Y_{4,t-1} \\ Y_{5,t-1} \\ Y_{6,t-1} \\ Y_{7,t-1} \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} a_t \quad (11)$$

$$Y_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}_{1\times 7} \times \begin{pmatrix} Y_{1,t} \\ Y_{2,t} \\ Y_{3,t} \\ Y_{4,t} \\ Y_{5,t} \\ Y_{6,t} \\ Y_{7,t} \end{pmatrix}_{7\times 1} \quad (12)$$

After initializing the SE and OE for Iraq and Malaysia, the hybrid AR-KF model will be used for forecasting by using KF recursive steps, such as the one found in [14, 15, 23]. The outputs Y_t of OE in Equation (10) and (12) represent the Iraqi and Malaysian hybrid AR-KF fitted or forecasting series respectively. The difference $Y_t - CX_t$ is the forecasting errors for the hybrid AR-KF model. Figure 7 outlines the consistency between the original wind speed data and hybrid AR-KF testing forecast.

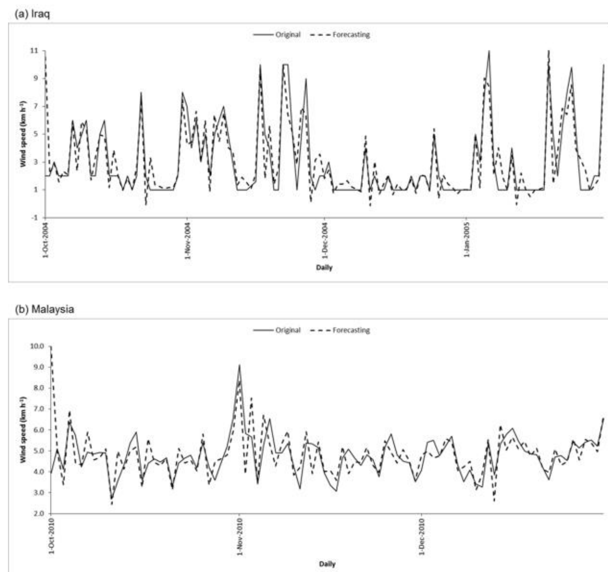


Figure 7 Hybrid AR-KF testing forecast and the original plots for Iraq and Malaysia

Figure 7 demonstrates that the hybrid AR-KF testing forecasts for Iraq and Malaysia were more consistent with the original data sets than the hybrid AR-ANN testing forecasts.

The MAPE was computed for Iraqi and Malaysian forecasting error to evaluate the forecasting accuracy. Table 2 and Table 3 present the MAPE values for the training and testing hybrid AR-KF forecasting errors in Iraq and Malaysia, respectively. The MAPE for training hybrid AR-KF forecasts for Iraq and Malaysia were 28.74 and 10.15, respectively, while the MAPE for testing hybrid AR-KF forecasts for Iraq and Malaysia were 42.22 and 15.55, respectively.

As a result, the training and testing forecasts for the hybrid AR-KF model were more adequate and more accurate than those for ARIMA and hybrid AR-ANN models. The reason behind the accuracy of the hybrid AR-KF forecasting was due to the superior performance of the KF model in regards to handling stochastic uncertainty.

The differences in forecasting accuracy rates for the Iraqi and Malaysian 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 wind speed more complex.

■4.0 CONCLUSION

Hybrid AR-ANN and AR-KF models were proposed to improve the wind speed forecasting accuracy. Two wind speed data sets from different meteorological environments were used. The results showed that the hybrid AR-ANN and AR-KF models were effective. However, the MAPE results indicated that the hybrid AR-KF model was the most effective tool for improving the forecasting accuracy. The hybrid AR-KF forecasting was more accurate than those for ARIMA and AR-ANN models. The advantage of the hybrid AR-KF model was due to the superior performance of the KF model in regards to handling stochastic uncertainty.

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