ARTIFICIAL NEURAL NETWORK AND KALMAN FILTER APPROACHES BASED ON ARIMA FOR DAILY WIND SPEED FORECASTING

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To my dearest father and mother,

And

My beloved wife and dear children.

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ABSTRACT

The wind speed forecasting is important to observe the wind behaviour in the future and control the harms caused by high or slow speeds. Daily wind speed is more consistent and reliable than other time scales by providing vast monitoring and effective planning. Although a linear autoregressive integrated moving average (ARIMA) model has been used for wind speed forecasting in many recent studies, but the model is unable to identify the nonlinear pattern of wind speed data. ARIMA modelling process causes the stochastic uncertainty as a second reason of inaccurate forecasting results. Wind speed data collection process faces several problems such as the failure of data observing devices or other casual problems that lead losing parts of data. Therefore, wind speed data naturally contains missing values. In this study, an ARIMA-artificial neural network (ANN) and ARIMA-Kalman filter (KF) methods are proposed to improve wind speed forecasting by handling the nonlinearity and the uncertainty respectively. A new hybrid KF-ANN method based on the ARIMA model improves the accuracy of wind speed forecasting by rectifying both nonlinearity and uncertainty jointly. These proposed methods are compared with others such as AR-ANN, AR-KF, and Zhang's method. AR-ANN method is also used to impute the missing values. It is capable to overcome the missing values problem in wind speed data with nonlinear characteristic. It is compared with linear, nearest neighbour, and state space methods. Two different daily wind speed data from Iraq and Malaysia have been used as case studies. The forecasting results of the ARIMA-ANN, ARIMA-KF and the new hybrid KF-ANN methods have shown in better forecasting than other compared methods, while AR-KF and AR-ANN methods provided acceptable forecasts compared to ARIMA model. The ARIMA-ANN and the new hybrid KF-ANN methods outperformed all other methods. The comparison of missing values imputation methods has shown that AR-ANN outperformed the others. In conclusion, the ARIMA-ANN and the new hybrid KF-ANN can be used to forecast wind speed data with nonlinearity and uncertainty characteristics more accurately. The imputation method AR-ANN can be used to impute the missing values accurately in wind speed data with nonlinear characteristic.

ABSTRAK

Ramalan kelajuan angin adalah penting untuk memerhatikan tingkah laku angin di masa depan dan mengawal kemudaratan yang disebabkan oleh kelajuan tinggi atau perlahan. Kelajuan angin harian yang lebih konsisten dan lebih dipercayai daripada skala masa lain boleh disediakan dengan pemantauan yang luas dan perancangan yang lebih berkesan. Walaupun model bergerak autoregresi linear bersepadu purata (ARIMA) telah digunakan untuk ramalan kelajuan angin dalam banyak kajian baru-baru ini, model ini tidak dapat mengenal pasti pola linear kelajuan angin. Proses pemodelan ARIMA mengenalpasti ketidakpastian stokastik sebagai sebab kedua keputusan ramalan yang tidak tepat. Proses pengumpulan data kelajuan angin menghadapi pelbagai masalah seperti kegagalan peranti data atau masalah kasual lain yang membawa kepada kehilangan bahagian data pemerhatian. Oleh itu, data kelajuan angin semulajadi akan mengandungi nilai-nilai yang hilang. Dalam kajian ini, model ARIMA-Rangkaian neural tiruan (ANN) yang diubahsuai dan penapis ARIMA-Kalman (KF) dicadangkan untuk meningkatkan ramalan kelajuan angin dan mengendalikan ketidaklinearan dan ketidakpastian masing-masing. Kaedah hibrid baru KF-ANN berdasarkan model ARIMA meningkatkan ketepatan ramalan kelajuan angin dengan memperbaiki kedua-dua ketidaklinearan dan ketidakpastian bersama. Kaedah ini dibandingkan dengan kaedah lain seperti AR-ANN, AR-KF, dan Zhang. Kaedah AR-ANN juga digunakan untuk menggantikan nilai-nilai yang hilang. Ia mampu mengatasi masalah nilai-nilai yang hilang dalam data kelajuan angin dengan sifat tak linear. Ia dibandingkan dengan kaedah linear, jiran terdekat, dan kaedah keadaan ruang. Dua data yang berbeza kelajuan angin setiap hari dari Iraq dan Malaysia telah digunakan sebagai kajian kes. Keputusan ramalan daripada kaedah ARIMA-ANN yang diubahsuai, ARIMA-KF dan kaedah hibrid KF-ANN baru telah menunjukkan keputusan ramalan yang lebih baik berbanding kaedah lain, manakala kaedah AR-KF dan AR-ANN yang digunakan memberikan ramalan yang boleh diterima pakai berbanding model ARIMA. ARIMA-ANN yang diubah suai dan kaedah hibrid KF-ANN baru mengatasi semua kaedah lain. Perbandingan kaedah untuk mengatasi nilai yang hilang menunjukkan bahawa AR-ANN mengatasi yang lain. Kesimpulannya, ARIMA-ANN yang diubahsuai dan hibrid baru KF-ANN boleh digunakan untuk meramal data kelajuan angin yang tidak linear dan ciri-ciri yang tidak menentu dengan lebih tepat. Kaedah imputasi AR-ANN juga boleh digunakan untuk menggantikan nilai-nilai yang hilang dengan tepat untuk data kelajuan angin yang bersifat tidak linear.

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LIST OF ABBREVIATIONS

ARIMA	-	Autoregressive Integrated Moving Average
AR	-	Autoregressive
MA	-	Moving Average
ANN	-	Artificial Neural Network
KF	-	Kalman Filter
ACF	-	Autocorrelation Function
PACF	-	Partial Autocorrelation Function
FFBP	-	Feed-Forward Back Propagation
LM	-	Levenberg-Marquardt
BR	-	Bayesian Regularization
SE	-	State Equation
OE	-	Observation Equation
MSE	-	Mean Square Error
MMSE	-	Minimum Mean Square Error
MAE	-	Mean Absolute Error
MAPE	-	Mean Absolute Percentage Error
RMSE	-	Root Mean Square Error
AIC	-	Akaike Information Criterion
MLE	-	Maximum Likelihood Estimation
RBF	-	Radial Basis Function
NWP	-	Numerical Weather Prediction
ERNN	-	Elman's Recurrent Neural Networks
SVR	-	Support Vector Regression
SVM	-	Support Vector Machines
EKF	-	Extended Kalman Filter
EMD	-	Empirical Mode of Decomposition

UKF	-	Unscented Kalman Filter
SOM	-	Self-Organizing Map
MLP	-	Multi-Layer Perceptron

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CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Frequent, extreme wind speeds and the nonlinear nature of wind speed data makes forecasting a complex process. The accuracy of wind speed forecasting is important to secure, control, optimize, and improve renewable wind power generation. The chaotic fluctuation in the pattern of wind speed data is often the reason of the nonlinearity.

Some authors have proposed using autoregressive integrated moving average (ARIMA) model, a classical statistical approach, to forecast wind speeds (Benth and Benth, 2010; Shi *et al.*, 2011). AR, ARIMA, or seasonal ARIMA models have been used for comparing with other methods by (Cadenas and Rivera, 2007, 2010; Chen and Yu, 2014; Guo *et al.*, 2012; Liu *et al.*, 2012b; Tatinati and Veluvolu, 2013). Finding the appropriate wind speed ARIMA model can be accomplished by following the approach proposed by Box-Jenkins. Zhu and Genton (2012) 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. Although an ARIMA model is the preferable statistical model for forecasting, it can lead to inaccurate results for wind speed forecasting.

The nonlinear pattern of wind speed data may be one reason for the forecasting inaccuracy of ARIMA model, which is a linear time series model (Cadenas and Rivera, 2007, 2010). An ANN can be used to handle the nonlinear nature of wind speed data. ANN was proposed to improve the forecasting accuracy of nonlinear time series data by (Assareh *et al.*, 2012; Bilgili and Sahin, 2013; Peng *et al.*, 2013; Pourmousavi-Kani and Ardehali, 2011).

A hybrid ARIMA-ANN model is proposed in this study in order to accommodate all the linear and nonlinear components of wind speed data and combine them in one distinct approach. The proposed hybrid model depends on all ARIMA inputs and their intersections which are those on the right side of ARIMA equation to determine the inputs structure of the ANN and provides the most accurate forecasts.

Several recent studies have proposed different hybrid approaches that combine ARIMA and ANN. Zhang's hybrid model that combines both ARIMA and ANN models was proposed by (Zhang, 2003) and used by Aladag *et al.* (2009); and Cadenas and Rivera (2010). Zhang's hybrid model combined linear and nonlinear components of ARIMA and improved just the residual of ARIMA using ANN.

An ANN can be constructed based on the autoregressive (AR) in order to simulate the ANN structure, this approach can be called hybrid AR-ANN model (Liu *et al.*, 2012b) or only ANN (Khashei and Bijari, 2010, 2011; Zhang, 2003). It was used and compared with other approaches by Guo *et al.* (2012); Li and Shi (2010); and Liu *et al.* (2012b). Khashei and Bijari (2010) proposed a hybrid ANN using ARIMA model called an artificial neural network (p,d,q) model.

The inaccurate forecasting of ARIMA model is a problem that reflects the stochastic uncertainty of modelling process as another reason of inaccurate wind speed forecasting results. The Kalman Filter (KF) model can be used for meteorological purposes, such as wind speed forecasting (Cassola and Burlando, 2012; Galanis *et al.*, 2006; Louka *et al.*, 2008). To obtain the best initial parameters for the KF, an ARIMA model is used to create the structure of the KF model that is regarded as the best model for handling the stochastic uncertainty and improve wind speed forecasting. An ARIMA model is used with the KF model to construct the structure of the state equation. This model can be called a hybrid ARIMA-KF. Determining KF state equation structures and ANN inputs structure has been done based on AR, ARIMA, or other time series models by Cadenas and Rivera (2007, 2010); Chen and Yu (2014); Guo *et al.* (2012); Liu *et al.* (2012b); Malmberg *et al.* (2005); Tatinati and Veluvolu (2013); and Zhu and Genton (2012).

In this study, a new hybrid KF-ANN model is proposed based on an ARIMA model to further improve the forecasting accuracy of wind speed. ANN and KF are useful for handling nonlinearity and stochastic uncertainty problems associated with wind speed data. Therefore, ANN and KF improve the accuracy of wind speed forecasting. Many recent studies combined the KF model to handle stochastic uncertainty, with another converged approach, such as support vector machines which handle the nonlinearity of wind speed (Chen and Yu, 2014; Tatinati and Veluvolu, 2013). In the proposed KF-ANN approach, first the KF state (system) and observation (measurement) equations are created based on an ARIMA model. In a second step, the inputs variables of the ANN approaches are generated from the new state series that is the output of the state equation, while the target is the original wind speed series. As a result, the output of the ANN represents the final fitted or forecasting series.

The hybrid ARIMA-ANN and hybrid KF-ANN models resulted in better wind speed forecasting accuracy than their components, while the KF model and ANN separately provided acceptable forecasts compared to ARIMA model that provided ineffectual forecasts. The hybrid ARIMA-ANN model outperformed all other studied methods.

The collection process of wind speed data as one of meteorological time series data faces several tactical problems such as thunderstorms, failure of data observing devices, or other unforeseen errors that lead to increased complexity in data analysis. A sequential dataset is required for performing analysis and modelling processes. Therefore, the missing values in wind speed data should be filled and imputed. Missing values imputation can be accomplished using simple methods such as linear, nearest neighbour or others. Although complex methods require additional expertise and specialization, they often outperform the simple methods. The classical methods such as linear, nearest neighbour, and state space may not provide accurate imputations when the wind speed data contains nonlinearity.

In most meteorological time series datasets, nonlinearity is problem that may hamper time series analysis using linear methods as mentioned previously. In particular, wind speed data suffer from nonlinearity in addition to the missing values. In recent studies, ANN was introduced to impute missing values and to handle the nonlinearity of meteorological time series datasets in general and wind speed dataset in particular (Coulibaly and Evora, 2007; He *et al.*, 2013; Junninen *et al.*, 2004; Kim and Pachepsky, 2010; Yozgatligil *et al.*, 2013). Using ANN to impute missing values was not limited to meteorological time series data as Kornelsen and Coulibaly (2012) introduced ANN as the most effective method for missing values infilling in soil moisture as hydrometeorological time series dataset.

In this study, a hybrid AR-ANN method is proposed to reform the problems of this study by imputing missing values and jointly handling the nonlinearity problem. Feed-forward back propagation is used as a neural network algorithm. AR model is used only for determining the structure of the input layer for the ANN. AR order can be determined by observing the significant lags in partial autocorrelation function (PACF). Listwise deletion is also used as the simplest method before AR modelling to handle missing value problems in wind speed time series datasets. AR-ANN method has been used in many recent papers for handling the nonlinearity in full dataset of wind speed without any missing value as mentioned previously.

The stationarity conditions for the wind speed data were omitted in this stage, and the parameters, signs, and residual series were also omitted from the terms of AR equation, because the AR model was used only for determining the structure of the input layer for the ANN (Khashei and Bijari, 2010; Liu *et al.*, 2012b).

In many studies, AR model was also used purely as missing values imputation method (Alosh, 2009; Choong *et al.*, 2009; Honaker and King, 2010). Applying the listwise deletion was suggested to produce consistent and unbiased attributes of parameters especially for performing data analysis and modelling using model or software that requires a sequential dataset (Cheema, 2014; Honaker and King, 2010).

Many other methods of missing values imputation are compared with AR-ANN method proposed in this study. Linear method and nearest neighbour method are presented as more simple methods for imputing missing values. ANN method and state space method are presented as complex methods that need more expertise and scientific specialization. A linear method is summarized by connecting two data points with a linear equation line. It was used for comparing with more complex methods in many recent papers such as in (Junninen *et al.*, 2004; Kornelsen and Coulibaly, 2012; Norazian *et al.*, 2008). A nearest neighbour method is the simplest imputation method of missing values that can be summarized by replacing the missing values by the nearest neighbour data point. A nearest neighbour method was used as a simple method for comparing with other proposed methods such as in (Junninen *et al.*, 2004; Liew *et al.*, 2011; Siripitayananon *et al.*, 2003; Waljee *et al.*, 2013). The state space model has been proposed and used as an imputation method of missing values in (Sarkka *et al.*, 2004; Tsay, 2005). Root mean square error (RMSE) measurement is computed for the error of missing values imputation for all imputation methods and all datasets as a statistical criterion to evaluate the adequacy and accuracy of these methods. AR-ANN method has been compared with linear, nearest neighbour, and state space methods. The proposed ANN method outperformed other imputation methods. The results have shown that ANN outperformed the other imputation methods.

In conclusion, the wind speed data with nonlinearity and uncertainty characteristics can be forecasted more accurately using the hybrid models KF-ANN and ARIMA-ANN. The missing values in wind speed data with nonlinear characteristic can be imputed more accurately using a hybrid AR-ANN method.

1.2 Problem Statement

Although an ARIMA model is the preferable statistical model for forecasting, it can lead to inaccurate results for wind speed forecasting. The nonlinear pattern of wind speed data may be one reason for the forecasting inaccuracy of ARIMA model, which is a linear time series model (Cadenas and Rivera, 2007, 2010). It is important to propose an appropriate method to accommodate all the linear and nonlinear components of wind speed data and combine them in one distinct approach in order to handle the nonlinearity.

The inaccurate forecasting of ARIMA model is a problem that reflects the stochastic uncertainty of modelling process as another reason of inaccurate wind speed forecasting results. Proposing a method that handles the stochastic uncertainty problem is important to obtain accurate forecasting. Handling nonlinearity and stochastic uncertainty problems jointly associated with wind speed data using a suitable method is requested for more forecasting accuracy.

The collection process of wind speed data as one of meteorological time series data faces several tactical problems such as thunderstorms, failure of data observing devices, or other unforeseen errors that lead to increased complexity in data analysis. A sequential dataset is required for performing analysis and modelling processes. Therefore, the missing values in wind speed data should be filled and imputed. Missing values imputation can be accomplished using the classical methods such as linear, nearest neighbour, and others. The classical methods may not provide accurate imputations when the wind speed data contains nonlinearity.

1.3 Research Question

(a) What are the methods proposed in this study to improve the forecasting accuracy?

(b) What are the most appropriate forecasting methods among the classical and the hybrid methods for Iraqi and Malaysian wind speed data?

(c) What are the methods used to impute the missing values in Iraqi and Malaysian wind speed data?

(d) What is the most appropriate method for missing values imputation among the classical and the proposed methods?

1.4 Research Objectives

The following objectives are recognized to achieve the aims of the research:

(a) To develop ARIMA-ANN hybrid model to handle the nonlinearity in wind speeds and to develop ARIMA-KF hybrid model to handle the stochastic uncertainty.

(b) To develop a new KF-ANN hybrid model to handle nonlinearity and stochastic uncertainty problems jointly those associated with wind speed data.

(c) To evaluate the forecasting performance of classical and proposed methods.

(d) To develop hybrid AR-ANN model to impute the missing values in wind speed data.

(e) To evaluate the performance of classical and proposed methods for imputing the missing values in wind speed datasets.

1.5 Significance of the Research

Some authors have proposed using ARIMA model, a classical statistical approach, to forecast wind speeds. It can lead to inaccurate results for wind speed forecasting. The nonlinear pattern of wind speed data may be one reason for the forecasting inaccuracy of ARIMA model, which is a linear time series model (Cadenas and Rivera, 2007, 2010). An ANN can be used to handle the nonlinear nature of wind speed data. A hybrid ARIMA-ANN model is proposed in this study in order to accommodate all the linear and nonlinear components of wind speed data and combine them in one distinct approach for more handling of the nonlinearity. The hybrid ARIMA-ANN model depends on all ARIMA inputs and their intersections which are those on the right side of ARIMA equation to determine the inputs structure of the ANN and provides the most accurate forecasts. Several recent studies have proposed different hybrid approaches that also combine ARIMA and ANN. Zhang's hybrid model that combines both ARIMA and ANN was proposed by (Zhang, 2003) and used by Aladag *et al.* (2009); and Cadenas and Rivera (2010). Zhang's hybrid model only improved the residuals of ARIMA by using ANN. Constructing an ANN based on AR to simulate the ANN structure was used and compared with other approaches by Guo *et al.* (2012); Li and Shi (2010); and Liu *et al.* (2012b). The advantages of the new hybrid ARIMA-ANN model were hybridizing the linear ARIMA model and a nonlinear ANN and combining their components in one distinct approach to improve wind speed forecasting accuracy.

The inaccurate forecasting of ARIMA model reflects the stochastic uncertainty of modelling process as another reason of inaccurate wind speed forecasting. An ARIMA model is used with the KF model to construct the structure of the state-space equation. In recent studies, 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 (Chen and Yu, 2014; Liu *et al.*, 2012b; Tatinati and Veluvolu, 2013). In this study, the KF model is initialized based on ARIMA$(p,d,q)(P,D,Q)_s$ to obtain a hybrid ARIMA-KF model. ARIMA-KF model combines all the components of both ARIMA and KF in distinct approach for more forecasting accuracy than AR-KF model.

In this study, a new hybrid KF-ANN model is proposed based on an ARIMA model as a unique method for handling the nonlinearity and uncertainty jointly to further improve the forecasting accuracy of wind speed. The wind speed data with nonlinearity and uncertainty characteristics can be forecasted more accurately using the hybrid models KF-ANN and ARIMA-ANN.

A sequential dataset is required for performing analysis and modelling processes. Missing values imputation can be accomplished using classical methods such as linear, nearest neighbour or others. The classical methods may not provide accurate imputations when the wind speed data contains nonlinearity. In this study, a hybrid AR-ANN model was proposed to reform the missing values problem by imputing missing values and jointly handling the nonlinearity problem. This method can be called hybrid AR-ANN model (Liu *et al.*, 2012b) or ANN (Khashei and Bijari, 2010, 2011; Zhang, 2003). The missing values in wind speed data with nonlinear characteristic can be imputed more accurately using AR-ANN model.

1.6 Scope of the Study

In this study, daily wind speed data from two meteorological stations were collected. The first dataset was collected from the Mosul dam meteorological station in Mosul, Iraq [1]. 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 dataset was collected from the Muar meteorological station in Johor, Malaysia [2]. 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. These samples of data are applied to test the proposed methods. Appendix E and Appendix F include full Iraqi and Malaysian wind speed datasets respectively.

[1] Dam and Water Resources Research Center, University of Mosul, Mosul, Iraq.

[2] Departments of Environment, Ministry of Natural Resources and environment, Malaysia.

Missing values datasets have been generated by distributing the missing values into the training periods of wind speed datasets. The missing values have been distributed into three different parts 1, 3, 6 randomly. Three different proportions 10%, 20%, 30% have been considered percentages of missing values. Five datasets is the total number of missing datasets for each of Iraq and Malaysia. First three datasets include 10% of missing values that were distributed into one, three, and six equal parts respectively. 10% requires advanced methods for handling as mentioned in (Acuña and Rodriguez, 2004). Last two datasets were distributed into six equal parts that includes 20%, and 30% of missing values respectively. Acuña and Rodriguez (2004) mentioned that any percentage of missing values more than 15% may impact the scientific interpretation. .

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