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A Review of using Neural Network and Kalman Filter based on ARIMA for Wind Speed Forecasting

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Abstract

The wind speed forecasting is important to observe the wind behaviour and control the harms caused by extreme speeds. A linear ARIMA 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. In this study, a review of an ARIMA-artificial neural network (ANN) and ARIMA-Kalman filter (KF) methods is presented. ANN and KF based on ARIMA are used to improve wind speed forecasting by handling the nonlinearity and the uncertainty respectively. This hybrid method will improve the accuracy of wind speed forecasting. Usually, the forecasting results of the hybrid methods will be in better forecasting than other compared methods. In conclusion, the proposed hybrid methods especially the hybrid ANN-KF based on ARIMA method can be used to forecast wind speed data with nonlinearity and uncertainty characteristics more accurately.

Keywords: ARIMA, Artificial neural network, Kalman filter, Uncertainty, Nonlinearity, Hybrid method, Forecasting .

دراسة مراجعة في استخدام الشبكات العصبية ومرشح كالمن بالاعتماد على ARIMA للتكهن بسرعة الرياح

المستخلص

ان التكهن بسرعة الرياح من الأهمية بمكان لدراسة سلوك الرياح والتحكم بالاضرار الناتجة عن السرع المتطرفة. ان نموذج ARIMA الخطي غير قادر على تشخيص النمط غير الخطي لبيانات سرعة الرياح. ان نمذجة البينات باستخدام ARIMA ربما يتسبب بمشكلة عدم التأكدية كسبب ثاني لعدم دقة نتائج التكهن. في هذه الدراسة سيتم تقديم طرق هجينة مثل ARIMA-ANN و ARIMA-KF. تم استخدام النموذج الهجين ANN-KF بالاعتماد على ARIMA

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لمعالجة مشكلتي عدم الخطية وعدم التأكدية في آن واحد. ان نتائج التكهن اثبتت ان النماذج الهجينة وخصوصا نموذج ANN-KF الهجين أدق بكثير من نتائج الطرق التقليدية. وبالتالي نستنتج ان استخدام النماذج الهجينة يعالج مشاكل بيانات سرعة الرياح ويؤدي بالتالي الى تكهنات ادق.

1. Introduction

Time series forecasting is important for future planning, controlling, and monitoring of economic, business, production, inventory, industry, and decision making processes (Box *et al.*, 2008; Palit and Popovic, 2006; Yaffee and McGee, 2000). Forecasting time scales have been classified to short, medium, and long. The future forecasting periods for many days, weeks, or months reflect short time scale, while the medium time scale is for one to two years. Future forecasting for many years reflects long time scale. Short time scale is more consistent and reliable than other time scales by providing vast monitoring and effective planning (Marquis *et al.*, 2011; Montgomery *et al.*, 2011; Zhu and Genton, 2012).

Wind speed forecasting is important to observe the wind behaviour in the future and to control the harms caused by high or slow speeds. Extreme wind speeds and the chaotic fluctuation in the pattern of wind speed data makes forecasting a complex process (Lerner *et al.*, 2009; Niu *et al.*, 2015).

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 will be reviewed as one of important method in this study in order to accommodate all the linear and nonlinear components of wind speed data and combine them in one distinct approach. This 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 based on an ARIMA model is reviewed as one of important method 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 will result 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 will outperform all other studied 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.

2. Wind Speed Forecasting Methods

ARIMA will be reviewed as a classical method that has been used in this study for forecasting and for assisting to construct the structure of other methods. A nonlinear ANN method improves wind speed forecasting by handling the nonlinear pattern of wind speed. KF also improves wind speed forecasting by handling the stochastic uncertainty of modelling process. ANN and KF methods in addition to their hybrid methods are also reviewed in this section.

2.1ARIMA

In many recent studies, AR, ARIMA, and seasonal ARIMA models as classical statistical forecasting methods have been reviewed and used for of wind speed forecasting. Kamal and Jafri (1997) used ARMA(p,q) model for more ease stochastic simulation for hourly average wind speeds in Quetta, Pakistan. It will give suitable forecasting results. Sfetsos (2000) compared various time series forecasting methods for mean hourly wind speed data. One of these approaches was the traditional ARMA model. Torres *et al.* (2005) used the ARMA and persistence models for hourly wind speed forecasting to five different areas in Navarre and to nine years. ARMA model in that study improved significantly the wind speed forecasts as compared to persistence models. Cadenas and Rivera (2007) compared ARIMA and seasonal ARIMA models with other methods for wind speed forecasting in the South Coast of the state of Oaxaca, Mexico. Seasonal

ARIMA will result better sensitivity for wind speed forecasting. Diaz-Robles *et al.* (2008) used an ARIMA and other methods to forecast wind speed as one of meteorological data in Temuco, Benth and Benth (2010) proposed an ARIMA model for estimating and forecasting wind speeds for three different wind farms in New York State. Cadenas and Rivera (2010) used ARIMA model for comparing with other methods to do the wind speed forecasting in three different regions of Mexico. Erdem and Shi (2011) employed four approaches based on ARIMA to perform the forecasting of wind speed and direction for two wind datasets in North Dakota, USA. Shi *et al.* (2011) 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. Hill *et al.* (2012) forecasted U.K. wind speed datasets using AR and persistence models. ARIMA model have been employed for comparing with the proposed methods to reflect the performance of the proposed methods for wind speed forecasting in China in (Guo *et al.*, 2011; Liu *et al.*, 2012a; Liu *et al.*, 2010; Liu *et al.*, 2012b, 2015a). Chen and Yu (2014) compared the forecasting results of AR model and other methods for wind speed data in three different sites in Massachusetts, USA. Safee and Ahmad (2014) used univariate time series models and Box-Jenkins consists of ARIMA and SARIMA for forecasting the climate index in Sitiawan. The importance of ARIMA model was reviewed as one method in wind speed and wind power forecasting by bibliographical survey in (Jung and Broadwater, 2014; Lei *et al.*, 2009; Soman *et al.*, 2010; Zhu and Genton, 2012).

2.2 Artificial neural network

An ANN can be used to handle the nonlinear pattern of wind speed data. In this study, ANN was reviewed as one of important method to improve the forecasting accuracy of nonlinear wind speed data. Many recent papers have proposed different types of ANN methods to improve the forecasting accuracy of nonlinear time series data. ANN methods were also reviewed with many other methods for wind speed and wind power forecasting by bibliographical survey in (Jung and Broadwater, 2014; Lei *et al.*, 2009; Soman *et al.*, 2010; Zhu and Genton, 2012).

Cadenas and Rivera (2007, 2010) used ARIMA and ANN and compared their forecasting performances with other methods such as Naïve, ARIMA, adaptive linear element, SARIMA, and ANN for wind speed data in La Venta, Oaxaca, Mexico, while Cadenas and Rivera (2009) applied four different proposed ANN to forecast wind speed in the same regions of Mexico. Liu *et al.* (2012a); Liu *et al.* (2010); Liu *et al.* (2015b);

Wang *et al.* (2014) compared their proposed methods with different types of ANN methods to forecast wind speed in different regions of China.

Pourmousavi-Kani and Ardehali (2011) used ANN to improve wind speed forecasts after combining the ANN with a Markov chain to create a hybrid ANN – MC model. Assareh *et al.* (2012) proposed ANN as a way to represent the relationships between wind speed, as an output, and other meteorological time series data, and to accurately forecast wind speed for the Manjil wind speed data. Bilgili and Sahin (2013) 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. Peng *et al.* (2013) suggested an individual ANN and hybrid strategy based on physical and statistical approaches for short term wind power forecasting. Chitsaz *et al.* (2015) modified wavelet neural network method as a novel method to forecast wind power and wind speed in Alberta, Canada and used many types of ANN such as multi-layer perceptron (MLP) and radial basis Function (RBF) neural networks for comparison.

2.3 Kalman Filter

Using ARIMA as a linear statistical model to model nonlinear wind speed data caused the stochastic uncertainty that reduce the accuracy of wind speed forecasting. Due to its good performance in meteorological applications, KF model can be used for meteorological purposes, such as wind speed forecasting to handle the stochastic uncertainty for more accuracy of wind speed forecasting. The recent forecasts with parameter (weighs) that reduce the corresponding biases are recursively combined with time series observation using Kalman filter. The KF model can be introduced as a statistical approach for estimating and forecasting the unmeasured state space. The KF model was named after Scientist Rudolf Emil Kalman (Bossanyi, 1985; Harvey, 1990; Kalman, 1960; Kalman and Bucy, 1961). Jung and Broadwater (2014); Lei *et al.* (2009); Zhu and Genton (2012) presented a bibliographical survey for using KF and many other methods for wind speed and wind power forecasting.

Wikle and Cressie (1999) applied KF to space time forecasting that accomplished dimension reduction in the analysis of near surface wind speed datasets in Pacific Ocean. Crochet (2004) improved the accuracy of temperature and wind-speed forecasts derived from a numerical weather prediction (NWP) in Iceland using an adaptive KF method. Galanis *et al.* (2006) proposed implementing non-linear polynomial functions in classical linear KF algorithms as a new approach that would improve regional weather forecasts. Cheng and Steenburgh (2007) proposed KF for improving the accuracy of temperature, dew point, and wind forecasts by the Eta/North American Meso Model. Louka *et al.* (2008) 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 (2012) proposed a mixed approach based on the use of NWP model coupled with a statistical model based on the KF model to generate a way to forecast wind speed and wind power datasets collected from two anemometric stations located in the eastern Liguria. Zhao *et al.* (2012) integrated KF in the system of wind forecasting in China to minimize wind speed forecasting errors and improved forecasting accuracy. Stathopoulos *et al.* (2013) employed KF algorithm to reduce systematic biases and minimize the forecasting errors of wind speed and wind power datasets over two areas of Greece: Lynch *et al.* (2014) used a KF for wind speed forecasting in the Cork Institute of Technology (CIT) college campus. They proposed KF to forecast the biases for a campus based turbine as an origin and NWP model for Cork Airport as an output.

2.4 Hybrid Methods

Many types of hybrid methods have been proposed in a lot of recent studies to enhance the forecasting accuracy by accommodating wide range of components and characteristics of wind speed data and combining them in one distinct approach to enhance the forecasting accuracy.

Several recent studies proposed different hybrid approaches that combine ARIMA model and ANN. Zhang (2003) proposed his special hybrid model that combines both ARIMA and ANN models. Zhang’s hybrid model combined the linear components of ARIMA with the improved residual of ARIMA by using ANN. Diaz-Robles *et al.* (2008) studied the forecasting of air quality and the forecasting wind speed as one of meteorological time series data in Temuco, Chile. They used a novel hybrid model combining ARIMA and ANN to improve the accuracy of forecasting in urban areas. Aladag *et al.* (2009) used Zhang’s hybrid model by combining Elman's recurrent neural networks (ERNN) and ARIMA models. Their suggested hybrid model provided accurate forecasts for Canadian Lynx time series data. Cadenas and Rivera (2010) used an ANN to improve a nonlinear component of the ARIMA model. Then they combined it with a linear component of ARIMA within Zhang’s hybrid ARIMA-ANN model for data from three different regions in Mexico. They compared the ARIMA and the ANN approaches to Zhang’s hybrid model. They found that Zhang’s hybrid ARIMA-ANN forecasting will more accurate than ARIMA forecasting, which will no better than ANN forecasting. Khashei and Bijari (2010) proposed a hybrid artificial neural network using ARIMA model called an artificial neural network (p,d,q)

model. They used this model to create a forecasting model that will more accurate than a pure artificial neural network. The results of this hybrid model will more general and provided a little bit accurate forecast than AR-ANN and Zhang's hybrid ARIMA-ANN models. A hybrid ARIMA-ANN model was reviewed in this study as one of important method in order to accommodate all the linear and nonlinear components of wind speed data and enhance the forecasting of nonlinear wind speed datasets.

Constructs an ANN can be based on the AR model in order to simulate the ANN structure. This approach can be called hybrid AR-ANN or hybrid ARIMA-ANN model (Liu *et al.*, 2012b) or it can just be called ANN (Khashei and Bijari, 2010; Zhang, 2003). Li and Shi (2010) 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 PACF to determine the ANN input variables. Guo *et al.* (2012) proposed many methods for wind speed forecasting. One of these methods was a feed-forward neural network whose input variables were determined using PACF that was depended on the order of AR model. Liu *et al.* (2012b) proposed new ARIMA-ANN and ARIMA-KF hybrid methods. Their ARIMA-ANN hybrid method was similar to hybrid AR-ANN model, entirely, that has been studied and compared in the current study. They confirmed that the performance of their hybrid method in terms of its wind speed predictions will consistently better than that of ARIMA. In this study, a hybrid AR-ANN was also reviewed as one of important method for comparison purposes and suggested for other tasks also.

To handle the stochastic uncertainty that belongs to model nonlinear wind speed data using ARIMA model, KF method have been used based on ARIMA model in many recent studies. This method is called a hybrid ARIMA-KF. Gardner *et al.* (1980) used ARMA model to create the structure of state space equation within KF and also calculated the exact likelihood function of ARMA model by means of the KF. Malmberg *et al.* (2005) 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. Liu *et al.* (2012b) proposed ARIMA-KF hybrid model that is similar to hybrid AR-KF model, completely, for wind speed forecasting, and compared the performance with other methods. They combined an ARIMA with KF model in order to initialize the state equation for a KF. Tatinati and Veluvolu (2013) 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. The hybrid ARIMA-KF model was also reviewed with many other methods for wind speed and wind power forecasting by bibliographical survey in (Jung and Broadwater, 2014). In this study, AR and ARIMA models have been reviewed as one of important method to obtain the best initial parameters for the KF that was regarded for handling the stochastic uncertainty and improve wind speed forecasting accuracy. AR and ARIMA models are used with the KF model just for constructing the structure of the state-space equation.

Several studies investigated finding one method that can handle the nonlinearity and the stochastic uncertainty problems jointly in the time series datasets for more enhancement of the accuracy of forecasting. Some of these studies have combined the KF model to handle stochastic uncertainty, with another approach, such as support vector regression (SVR) or support vector machines (SVM) which handle the nonlinearity of wind speed. SHEN and PEI (2011) accomplished a comprehensive study by using a hybrid method combine the extended Kalman filter (EKF) with SVR to improve the accuracy of modelling and forecasting. Tatinati and Veluvolu (2013) proposed several approaches for short term wind speed forecasting such as a the KF model based on AR, a least squares version of 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 (2014) integrated unscented Kalman filter (UKF) with 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.

By following comparable methodologies of the previous recent studies, a new hybrid KF-ANN model will be reviewed as one of important method in this study based on an ARIMA model to further improve the forecasting accuracy of wind speed. ANN and KF will be useful for handling nonlinearity and stochastic uncertainty problems jointly in the wind speed datasets.

3. Summary and Conclusions

In this section, the conclusions of the forecasting results of the proposed wind speed forecasting methods are presented alongside an accelerated review of these methods.

3.1 Speed Forecasting Methods

ARIMA model that is a classical method was reviewed for forecasting and for assisting to construct the structure of other methods. Although ARIMA is preferable for time series forecasting for many types of time series data, it is unable to identify the nonlinearity and the uncertainty of wind speed data and these are the main reasons for inaccurate forecasting. Many modified forecasting methods were also reviewed to improve the forecasting and handle the different problems for modelling and forecasting process.

An ANN approach was employed in review to handle the nonlinear nature of wind speed data. A hybrid ARIMA–ANN model was reviewed as developed method to improve and enhance the accuracy of wind speed forecasting.

A new hybrid KF-ANN model was also proposed based on an ARIMA model to further enhance the forecasting accuracy of wind speed. It depended on both ANN and KF to handle the nonlinearity and the stochastic uncertainty jointly associated with wind speed data.

In conclusion, the hybrid ARIMA-ANN and hybrid KF-ANN models will outperform all other studied methods. Therefore, the wind speed data with nonlinearity and uncertainty characteristics can be forecasted more accurately using the hybrid KF-ANN and ARIMA-ANN models.

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