The 2016 World Congress on
Advances in Civil, Environmental, and Materials Research (ACEM16)
Jeju Island, Korea, August 28-September 1, 2016

A Method of Short-term Wind Speed Forecasting Based on Generalized Autoregressive Conditional Heteroscedasticity Model

Yan Jiang[1)],*Guoqing HUANG[2)], Xinyan PENG[3)] and Yongle LI[4)]

[1), 2, 3), 4)]Research Center for Wind Engineering, Southwest Jiaotong University, Chengdu 610031,China

ABSTRACT

In order to improve the safety of train operation, a short-term wind speed forecasting method is proposed based on a linear recursive autoregressive integrated moving average (ARIMA) algorithm and a non-linear recursive generalized auto-regressive conditionally heteroscedastic (GARCH) algorithm (ARIMA-GARCH). Firstly, the non-stationarity embedded in the original wind speed data is pre-processed to eliminate its effect on the model. Then, a linear recursive ARIMA algorithm is employed to predict wind speed. Finally, a non-linear recursive forecasting model is proposed based on the GARCH algorithm. Numerical example based on wind samples from field measurements shows that the proposed approach has a higher prediction accuracy. The new method explains the non-linear characteristics (heteroscedasticity) of wind speed time series and improves the prediction accuracy compared with the usual ARIMA approach.

1. Introduction

One of the major influences on the train running safety, comfort and stability is strong crosswind. High speed train derails and capsizes due to strong crosswind. Yuan and Zhou et al. (2008) shows that the overturning force not only is related to the crosswind speed, but also the speed of the train. When high speed train meets a strong crosswind speed, limiting the run speed or stopping the operation can reduce the force effect on the train as well as the risk of train overturning.

In recent decades, the research on wind speed prediction is extensive and includes a number of contributions on various aspects: the linear model includes auto-regressive moving average model (ARMA), ARIMA model (Kamal L and Jafri Y Z, 1997) and empirical mode decomposition of difference auto-regressive moving average model (EMD-ARIMA) (Liu Hui et al., 2015); the nonlinear model includes support vector machine (SVM) (Qi Shuangbin et al., 2009), kalman filtering method (Bossanyi E A,

[1),3)]Graduate Student
[2),4)]Professor, mail: [2)]ghuang1001@gmail.com

1985) and neural network (Kariniotakis G N et al, 1996) and so on. Although these models have been widely used, the forecast effect needs improvement for short-term wind speed prediction. Studies have shown that short-term wind speed has the characteristics of nonlinear and non-stationary. However, linear model is only suitable for stationary or simple nonstationary linear time series prediction, which has been studied extensively. For the strong nonlinear and non-stationary characteristics of short-term wind speed time series, it is important to develop a new method for wind speed prediction.

In this paper, the time series method is used for high speed railway short-term wind speed prediction. Firstly, the non-stationarity embedded in the original wind speed data is pre-processed to eliminate its effect on the following model. Then, a linear recursive ARIMA algorithm is employed to predict wind speed. Finally, a non-linear recursive forecasting model is proposed based on the GARCH algorithm. The results of two kinds of model prediction are compared and the conclusions are received.

2. System model

In this study, the stability of the decomposed wind speed will be all checked by Run Sequence Method (RSM) (Liu Hui et al., 2015), a non-parametric statistical test, which is used to check the stability of a group of time series data.

2.1 Autoregressive Integrated Moving Average (ARIMA) model

The equations of the ARIMA (p, d, q) are defined as follows:

$$\phi(B) \cdot (1-B)^d \cdot X(t) = \theta(B) \cdot a(t) \tag{1}$$

where:

$$B = X(t-1) / X(t) \tag{2}$$

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 \cdots - \phi_{p-1} B^{p-1} - \phi_p B^p \tag{3}$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 \cdots - \theta_{q-1} B^{q-1} - \theta_q B^q \tag{4}$$

where $X(t), (t = 1, 2, 3, \cdots)$ is the wind speed time series; $a(t), (t = 1, 2, 3, \cdots)$ is the random error series assumed to be a white process with a mean of zero and equal variance; $\phi_i (i = 1, 2, 3, \cdots p)$ is the parameter of autoregressive part, and $\theta_j (j = 1, 2, 3, \cdots q)$ is the parameter of the moving average part; B is the backward shift operator; p, d, q are the order of the autoregressive part, the order of the difference computation operator and the order of the moving average part in the ARIMA model, respectively.

2.2 Generalized Auto-Regressive Conditionally Heteroscedastic (GARCH) model

The GARCH model was introduced by Boollerslev in 1986, which has shown to be successful in estimating and predicting volatility changes (Bollerslev T, 1986), i.e., the assumption of $a(t)$ in ARIMA model is not reasonable. If $X(t)$ follows a GARCH model, it can be expressed as:

$$\begin{aligned} X(t) &= \phi_1 X(t-1) + \cdots + \phi_p X(t-p) \\ &\quad + a(t) + \theta_1 a(t-1) + \cdots + \theta_q a(t-q) \end{aligned} \tag{5}$$

$$a(t) = \sqrt{h_t} \cdot e_t \tag{6}$$

$$h_t = \beta_0 + \sum_{j=1}^{m} \beta_j a_{t-j}^2 + \sum_{j=1}^{n} \alpha_j h_{t-j} \tag{7}$$

where the equation (5) can be derived by ARIMA model; $a(t),(t=1,2,3,\cdots)$ is the random error series; $\{e_t\}$ is independent and identically normally distributed zero mean unit variance stochastic variable; $\beta_j > 0(j=0,1,\cdots m)$, $\alpha_j > 0(j=1,\cdots n)$ and $\sum_{j=1}^{m} \beta_j + \sum_{j=1}^{n} \alpha_j < 1$.

*2.3 Estimation Standard for forecasting result**s***

Four error indexes are employed to estimate the accuracy performance of all the involved forecasting models, including the Mean Absolute Error (MAE), Mean Relative Percentage Error (MRPE), Root Mean Square Error (RMSE) and Root Mean Square Relative Error (RMSRE).

$$\begin{aligned} \mathrm{MAE} &= \frac{1}{n_{\mathrm{te}}} \sum_{i=1}^{n_{\mathrm{te}}} \left| x_i - \overline{x_i} \right| \\ \mathrm{MRPE} &= \frac{1}{n_{\mathrm{te}}} \sum_{i=1}^{n_{\mathrm{te}}} \left| \frac{x_i - \overline{x_i}}{x_i} \right| \times 100\% \end{aligned} \tag{8}$$

$$\begin{aligned} \mathrm{RMSE} &= \sqrt{\frac{1}{n_{\mathrm{te}}} \sum_{i=1}^{n_{\mathrm{te}}} \left(x_i - \overline{x_i} \right)^2} \\ \mathrm{RMSRE} &= \sqrt{\frac{1}{n_{\mathrm{te}}} \sum_{i=1}^{n_{\mathrm{te}}} \left(\frac{x_i - \overline{x_i}}{x_i} \right)^2} \end{aligned} \tag{9}$$

where n_{te} is the number of the terms in the x_i series, x_i is the measured wind time series, $\overline{x_i}$ is the forecasted wind speed time series.

3. Experimental results and analysis

3.1 Original wind speed data

A group of real wind speed series measured by wind speed stations (sampling interval is 3 s) is adopted to demonstrate the forecasting performance of the proposed ARIMA-GARCH model. According to response time of railway dispatching system and the response time of the train, a comprehensive estimate of wind speed forecasting schedules at least more than 2 min in advance. In order to reduce the predictive step and improve the predictive accuracy, the original wind speed data should be pre-processed (the sample interval adopts 24 s). They are named $\{X_{1\mathrm{t}}\}$ series and $\{X_{2\mathrm{t}}\}$ series, as show in Figs. 1 and 2. The 1st-225th ones of $\{X_{2\mathrm{t}}\}$ series are used to establish the forecasting models and the 226st-300th ones are utilized to check the built models.

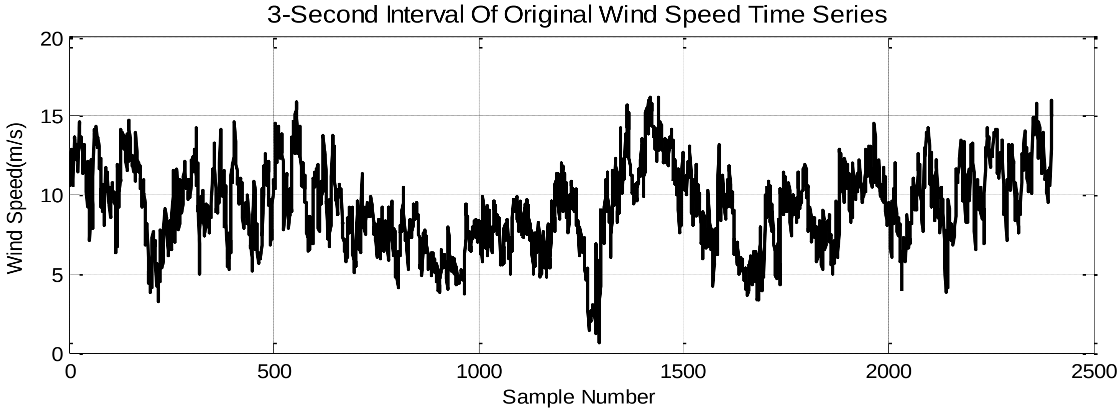

Fig.1 Original wind speed time series $\{X_{1t}\}$

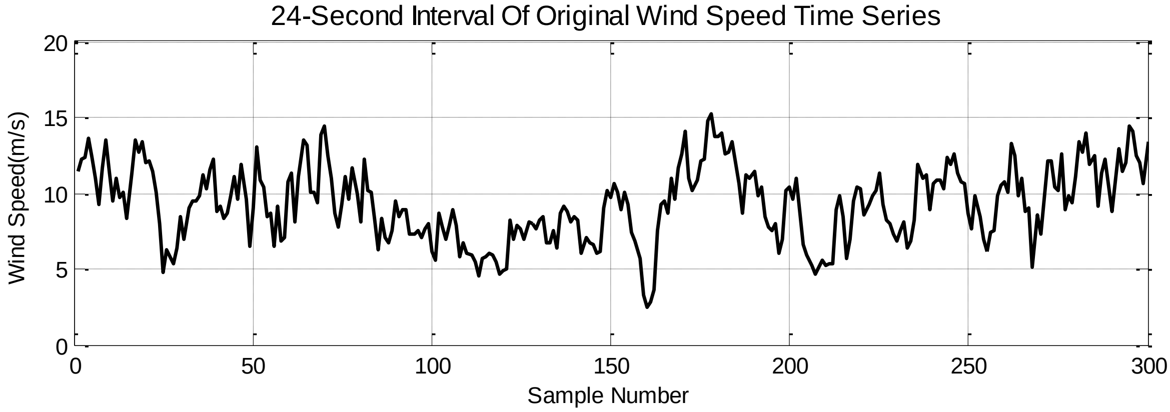

Fig.2 Original wind speed time series $\{X_{2t}\}$

3.2 Test on the two methods

In this study, two methods are selected to forecast the wind speed in order to protect the safety of the running trains. Figs. 3-5 show the prediction results of the 226st-300th wind speed series $\{X_{2t}\}$ by different forecasting methods. The assessments of the accuracy for these predictions are given in Tables 1-3, respectively.

From Tables 1-3, it can be observed that: (a) the numerical example based on wind speed samples from field measurements shows that the proposed approach has a higher prediction accuracy; (b) with increasing of the prediction step, the prediction accuracy reduces gradually. (c) comparing the proposed GARCH model with the ARIMA model, the former has improved the accuracy performance of the latter obviously. The improved accuracy percentages of MAE indexes from one-step to six-step are 16.15%, 17.35% and 11.54%, respectively. The improved accuracy percentages of MRPE indexes from one-step to six-step are 16.93%, 17.13% and 11.88%, respectively. The improved accuracy percentages of RMSE indexes from one-step to six-step are 11.26%, 15.14% and 8.09%, respectively. The improved accuracy percentages of RMSRE indexes from one-step to six-step are 12.39%, 14.81% and 8.58%, respectively. The reason of this improving phenomenon is that the GARCH model explains parts of the non-linear characteristics (heteroscedasticity) of wind speed time series.

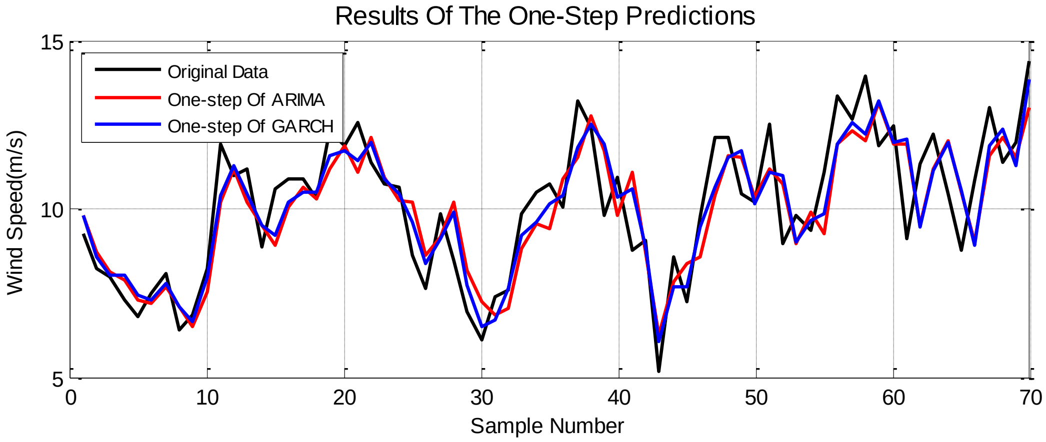

Fig.3 Results of the one-step predictions for the original wind speed time series {X_{2t}} by the ARIMA and the GARCH

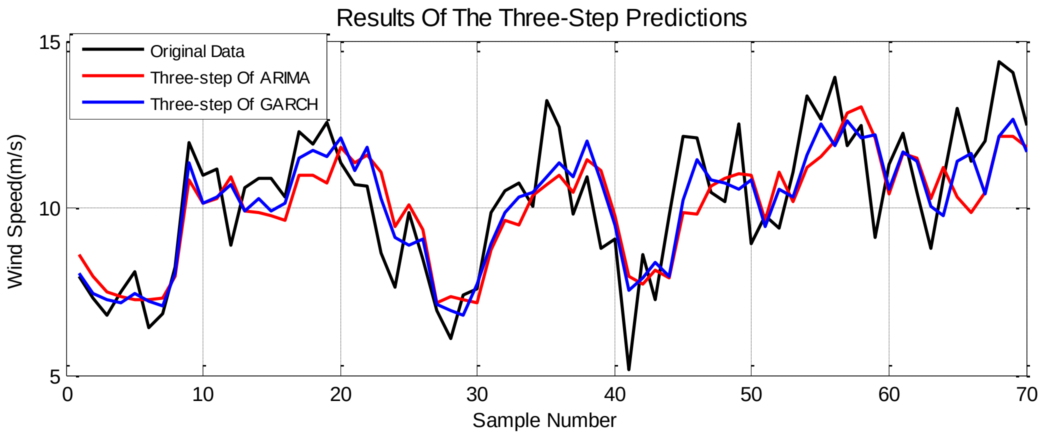

Fig.4 Results of the three-step predictions for the original wind speed time series {X_{2t}} by the ARIMA and the GARCH

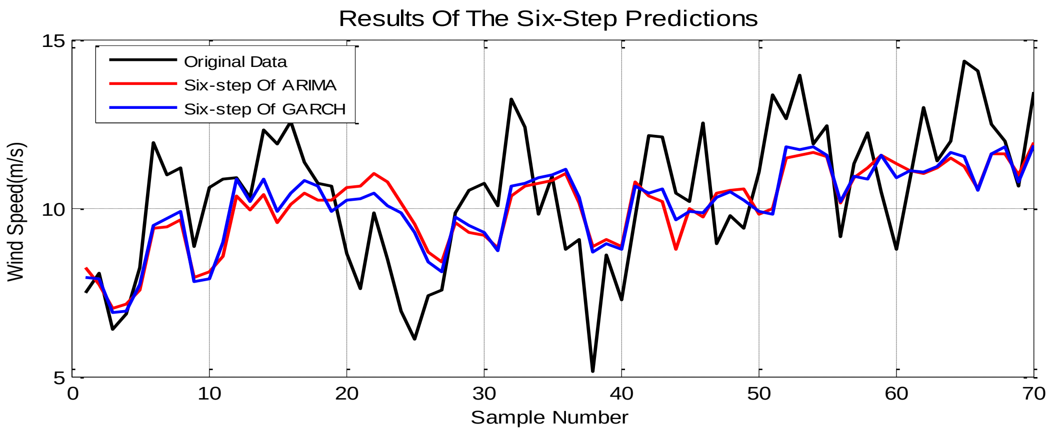

Fig.5 Results of the six-step predictions for the original wind speed time series {X_{2t}} by the ARIMA and the GARCH

Tab.1 Analysis of the one-step wind speed predictions given in Fig. 3

Error Types	ARIMA	GARCH	Difference	Improvement
MAE	0.997	0.836	0.161	16.15%
MRPE	10.16%	8.44%	1.72%	16.93%
RMSE	1.163	1.032	0.131	11.26%
RMSRE	11.93%	10.45%	1.48%	12.39%

Tab.2 Analysis of the three-step wind speed predictions given in Fig. 4

Error Types	ARIMA	GARCH	Difference	Improvement
MAE	1.153	0.953	0.200	17.35%
MRPE	11.62%	9.63%	1.99%	17.13%
RMSE	1.361	1.155	0.206	15.14%
RMSRE	14.38%	12.25%	2.13%	14.81%

Tab.3 Analysis of the six-step wind speed predictions given in Fig. 5

Error Types	ARIMA	GARCH	Difference	Improvement
MAE	1.438	1.272	0.166	11.54%
MRPE	14.65%	12.91%	1.74%	11.88%
RMSE	1.730	1.590	0.140	8.09%
RMSRE	19.12%	17.48%	1.64%	8.58%

4. Conclusions

In this study, a GARCH method is proposed to forecast the multi-step wind speed. The numerical example based on wind speed samples from field measurements validates that: (a) for the non-linear characteristics (heteroscedasticity) of wind speed time series, the proposed GARCH method has a higher prediction accuracy, and with increasing of the prediction step, the prediction accuracy reduces gradually; (b) compared to the ARIMA model, the GARCH model improves all forecasting accuracy considerably; it can provide a new feasible method for high speed train wind speed prediction; (c) GARCH model can only explain parts of the non-linear characteristics (heteroscedasticity) of wind speed time series, so it is critical to explain all the non-linear characteristics of wind speed time series in the future work.

REFERENCES

[1] Yuan X X, Zhou D, Lu Z J, Aerodynamics forces acting on a box car running on Qinghai-Tibet railway under strong cross-wind. Journal of Railway Science and Engineering[J]. 2008, (2):75-78.

[2] KAMAL L, JAFRI Y Z. Time series models to simulate and forecast hourly averaged wind speed in Quetta, Pakistan[J]. Solar Energy, 1997, 61(1): 23-32.

[3] Liu H, Tian H Q, Li Y F. An EMD-recursive ARIMA method to predict wind speed for railway strong wind warning system[J]. Journal of Wind Engineering and Industrial Aerodynamics, 2015, 141: 27-38.

[4] Qi S B, Wang W Q, Zhang X Y, Wind Speed and Wind Power Prediction Based on SVM. East China Electric Power[J] . 2009, 37(9): 1600-1603.

[5] Bossanyi E A. Short-term wind prediction using Kalman filters[J]. Wind Engineering, 1985, 9(1): 1-8

[6] Kariniotakis G N, Stavrakakis G S, Nogaret E F. Wind power forecasting using advanced neural networks models[J]. Energy conversion, IEEE transactions on, 1996, 11(4): 762-767.

[7] Bollerslev T. Generalized autoregressive conditional heteroskedasticity[J]. Journal of Econometrics, 1986, 31(3):307–327.