Intelligent Web-Based Fuzzy and Grey Models for Hourly Wind Speed Forecast

Shun Jyh Wu and Shu Ling Lin

***Abstract*—**An intelligent web-based fuzzy model is developed for the forecast of hourly wind speed. The hourly wind speed of three meteorological stations in Taiwan are forecasted and compared. The selected sites of Taiwan meteorological stations are Lan-Yu, Tung-Chi-Tao, and Wuci, whose wind speeds are the highest among 25 areas during the period of 1971-2000. An intelligent time series model and GM(1,1) are developed and used to forecast the randomly distributed wind speed data. Hourly records of wind speed are first used to establish intelligent fuzzy linguistic functions, and then fuzzy relational matrix is developed to form the time series relationship. Effects of interval number are studied. For the same order of the intelligent fuzzy model, the model with higher interval number provides better prediction of the hourly wind speed with lower RMSE. On the other hand, GM(1,1) gives higher RMSE for all the three site. The present results demonstrate the benefits and the robustness of the intelligent model.

***Keywords*—**fuzzy logics, intelligent model, wind Speed, forecast.

I. Introduction

FOR the operation of usual power plants that are joined to the same power grid as those conversion systems, the prediction of the power output of wind turbines is noteworthy. Thus, the forecast of hourly average wind speed and in so doing the power output of wind farm is imperative [1-2]. For a large number of researchers, the modeling and forecast of the time series of hourly wind speed has been a vital subject. When the factors of the wind speed distribution were given, the Monte Carlo method was developed to make predictions. Time series obtained by the method showed the flaw of not considering the autocorrelation of the hourly wind velocities. On the other hand, Chou and Corotis [3] integrated the effects of autocorrelation, but the non-Gaussian nature of the wind speed distribution is not considered. Brown et al. [4] proposed a pure autoregressive model (AR) that included the characteristic of autocorrelation, and the non-Gaussian shape of the wind speed. Geerts [5] used an ARMA model for the 1-year time series one for forecasting wind speeds in a relatively short term. Torres et al. [6] developed the model for the forecast of hourly average wind speed by using ARMA models. A new prediction models uses regression techniques based on SVR, ARMA and ARIMA models, features include on-line measures and the corresponding on-time treatment, using algorithms based on time-series forecasting and wireless technology to transmit the signals [7].

Taiwan is encountered with many predicaments in energy exploitation. Since most fossil fuels are imported, the accessibility and price can be varied significantly. Also, the current energy policy tends to limit the development of nuclear power generation. Thus, the development and popularization of renewable energy resources become crucial at the current stage. Due to the meteorological features in Taiwan, wind energy shows the most potential among all renewable energy resources [8].

In order to evaluate the potential of wind energy, many statistical models have been developed and studied for different areas. In 1995, Jamil et al [9] proposed a model for evaluating wind characteristics, including wind energy density, in Iran. In 1999, Rosen et al [10] analyzed the wind potential energy of two locations in the coastal area of the Red Sea. Li [11] studied the feasibility of developing large scale offshore wind power. Chang et al [8] analyzed the wind characteristics and wind turbine characteristics in Taiwan based on a long-term measured data source of hourly mean wind speed at 25 meteorological sites across Taiwan. Most of the aforementioned studies are based on the wind speed distribution model of Weibull [12]. Recently, a study of wind turbine focused on a doubly-fed induction machine with an improved wind turbine has been simulated [13]. Furthermore, Shao et al. [14] find that the time-frequency analysis can be used to more precisely detect the fault characteristics of windings. Since the source data of wind characteristics are highly unpredictable and randomly distributed over a time span, this study attempts to deal with these data using the time series models.

A time series comes to pass when evaluations are recorded on a certain variable at consecutive points in time or when a certain variable is collected over an interval of time. For the forecasting of highly irregular time series, fuzzy time series models have been developed based on the analysis of linguistic variables [15]. Further extensions and applications show the robustness and reliability of the fuzzy forecasting models [16-21]. In 1993, Song and Chissom [22] developed the fuzzy time series using a first-order model with application to the forecast of enrollments at the University of Alabama. Due to the computational efforts and technical difficulties involved in Song and Chissom's model, Chen [23] simplified the calculation procedures of fuzzy time series model into a simple arithmetic operation. Tsai and Wu [24] developed the fuzzy time series model for the forecast of local regional data. Chen's method shows the simplicity and clarity of the computation. This approach provides an excellent tool for exploring the essence of modeling a fuzzy time series. On the other hand, Song and Chissom's approach gives a basis for the construction of computer code. On the other hand, the grey system analysis has been used for the prediction of linear motion guide [25]. A hybrid model combining grey prediction and rough set approach is developed to predict the failure firms based on past financial performance data [26], and applying grey group model to forecast the earning per share [27]. The results demonstrate that the grey model is a competitive and competent one in prospective analysis [28-29].

Though both approaches show significant potential in forecasting effectiveness, both methods cannot be disseminated quickly and widely due to the inherent technical barriers. In the recent years, the rapid advent of internet gives rise to lots of new applications. In order to take the advantages of wildly spreading internet and reducing the technical barriers of forecast system, this study developed a web-based forecasting system with application to the modeling of wind characteristics in Taiwan. In the web-based forecast system, entry web and four major frameworks are designed: source framework, model framework, output framework, and graphics framework.

This paper is organized as follows: in the next section, formulas of wind characteristics are introduced. Next, the major frameworks of the current intelligent system are defined. The model of intelligent time series is described and a general procedure presented. What follows is a discussion of the results. Finally, a brief concluded remark will be given.

II. Hypothesis and Methodology

The wind power per unit area of the wind stream at the speed V can be evaluated with

$$p(V) = 0.5 * \rho V^3 \tag{1}$$

Where ρ is the density of the air. Assume the wind turbine has a swept area of A, and then the total wind power is

$$P(V) = 0.5 * \rho V^3 A \tag{2}$$

Since wind source data are highly irregular, there are many probability density functions developed for the modeling of wind characteristics. Weibull distribution of wind speed is one of the widely used models [11]. Te probability density function is represented by

$$f(V) = k'(V*)^{k-1} e^{-(V*)^k} \tag{3}$$

Where $k' = \dfrac{k}{c}, V^* = \dfrac{V}{c}$, k is the shape parameter, c is the scale parameter, and V the wind speed. The cumulative distribution function then gives

$$g(V) = 1 - e^{-(V*)^k} \tag{4}$$

We can obtain the density function of the wind power as follows:

$$p = P / A = \int_0^\infty P(V) f(V) dV \tag{5}$$

$$\therefore p = 0.5 \rho c^3 \Gamma\left(\frac{k+3}{k}\right) \tag{6}$$

Where the Gamma function is used. Based on the wind power density, the wind energy is evaluated by multiplying it with the total operation hours T, that is:

$$e = \frac{E}{A} = p \cdot T = 0.5 \rho c^3 \Gamma\left(\frac{k+3}{k}\right) T \tag{7}$$

III. Intelligent Modeling

To establish the prediction model based on fuzzy logics, the definition of fuzzy time series model is introduced by following the concepts presented by [13-16]. The definition of fuzzy time series is first presented as follows.

A. Definition I. Fuzzy time series

Let $Y(t)(t = 0,1,2\cdots)$, a subset of R_1, be the universe of discourse on which fuzzy set $f_i(t)(i = 1,2\cdots)$ are defined. $F(t)$ is a collection of $f_1(t), f_2(t),....$, then $F(t)$ is called a fuzzy time series defined on $Y(t)$.

In definition I, $F(t)$ could be viewed as a linguistic variable. This represents for the major differences between fuzzy time series and traditional time series, whose values must be real numbers. Note that conventional time series models fail to work when its values are linguistic ones.

B. Definition II. First-order model of fuzzy time series

Suppose $F(t)$ is affected by $F(t-1)$ only, then the fuzzy relation can be expressed by $F(t) = F(t-1) \circ R(t, t-1)$, where $R(t, t-1)$ is the fuzzy relationship between $F(t-1)$ and $F(t)$. And the model $F(t) = F(t-1) \circ R(t, t-1)$ is called the first order model of $F(t)$.

C. Definition III. mth-order model of fuzzy time series

Suppose $F(t)$ is simultaneously caused by $F(t-1)$ and $F(t-2)$ and... $F(t-m)$, $(m > 1)$, then this relation can be expressed by the following equation:

$$F(t) = \left[F(t-1) \times F(T-2) \times \cdots \times F(t-m)\right] \circ Rand(t, t-m), \tag{8}$$

This is defined as the m-model of $F(t)$.

Note that the fuzzy relationship defined by $Rand(t, t-m)$ or $R(t, t-1)$ can be dependent or independent of time. For example, if $Rand(t, t-m)$ is independent of t, then $F(t)$ is called a time-invariant fuzzy time series; otherwise it is called a time-variant fuzzy time series. In case of time-invariant time series, the fuzzy relationship can be rewritten as:

$$R(t,t-1)=R \tag{9}$$

$$Rand(t,t-m)=Rand(m) \tag{10}$$

Where R contains only constant elements and $Rand(m)$ depends on m only.

For time-invariant time series, the forecasting model can be constructed by the following steps. Firstly, the historical data, which can be linguistic values, are collected and analyzed. Based on the collected data, we can determine the universes of discourse on which the fuzzy sets will be defined. Fuzzy sets on the universe of discourse based on the fuzzy historical data are then determined and fuzzy relationships using historical data are computed. The intelligent fuzzy forecasting model is constructed by the fuzzy relationships defined in the previous step. Finally, use the historical data at time t as inputs to the forecasting model and compute the output result at time $t+1$, which will be the forecasted values.

For developing grey forecast model, GM(1,1), the grey system is first defined as follows. A system which has none of information is defined as a black system, while a system which is full of information is called white. Thus, when the information of a system is either incomplete or undetermined, it is defined as grey system. The grey number in grey system represents a number with less complete information. The grey element represents an element with incomplete information. The grey relation is the relation with incomplete information.

Definition1. Let the set X be a vector space to apply grey relational analysis, and the vectors x, y are elements of X. First, the inner product of x and y and metric of vectors is defined as follows:

$$\langle x,y\rangle = \|x\|_{\xi}, \|y\|_{\xi} \cos\theta \tag{11}$$

Where $x, y \in R^n$, $x=(x_1, x_2, ..., x_n)^T$ (12)

$$\|x\|_{\xi} = \sqrt[\xi]{\sum_{i=1}^{n} x_i^{\xi}} \tag{13}$$

The X is content with the vector space axiom. Eq. (11) is satisfied with the inner product axiom[29]. To ompare the fuzzy time series model, the GM(1,1) model is developed based on the grey regeneration process. Further details are referred to [29].

IV. Empirical Results

The hourly wind speed of the meteorological stations are forecasted and compared. The selected three sites of Taiwan meteorological stations are Lan-Yu, Tung-Chi-Tao and Wuci, whose wind speeds are the highest among 25 areas during the period of 1971-2000. Table 1 shows the monthly wind speed of 25 Taiwan meteorological stations (Source: Taiwan Central Weather Bureau), ranking in the order of average wind speed during the indicated period. As the Table shows, the top four positions are Lan-Yu, Tung-Chi-Tao, Peng Gui Island and Wuci. Since the hourly wind speed of Peng Gui Island is not complete, we pick three sites, Lan-Yu, Tung-Chi-Tao, and Wuci, for further studies of hourly wind speed. Lan-Yu has an average wind speed of 9.0 m/s, while 8.2 m/s for Tung-Chi-Tao and 5.3 for Wuci site. For both sites, the hourly wind speed records at the day Sep 10, 2010 are used to establish randomly distributed time series and create the forecast model. The hourly wind speed of Lan-Yu is first used to explain the modeling processes of the forecasting system.

The model is constructed as follows: first, we define the universes of discourse U, on which the fuzzy sets will be defined. The minimum value $V_{\min}$ and maximum value $V_{\max}$ are generally defined and used to define the universe of discourse U. In this study, $V_{\min}=0$ and $V_{\max}=9$. The number of fuzzy partition then needs to be assigned. We use the number of intervals $N=10$, 20 and 30, and then divide the universe into N equal intervals. Let $u_1, u_2, \cdots u_N$ denotes N fuzzy intervals. Next, define fuzzy set based on the universe U. Let A_i be the linguistic variable of monthly mean values of wind speed. Let A_1 = (very very slow), A_2 = (very slow), A_3 = (slow), A_4 = (fair)… etc. We then transfer the historical data set into fuzzy set. In this practice, the equivalent fuzzy set to each mean wind speed will be found and the memberships of each record to A_i will be determined. Then we can construct the fuzzy relations based on historical and linguistic knowledge. Based on the relations established, we construct the fuzzy forecasting model. Denote $R(1)$ as the first fuzzy relational function, which can be written as

$$R(1)=Y(1)\times Y(2)$$

Where the elements of $R(1)$ is defined as

$$R_{ij}=\min\lfloor Y(1)_i, Y(2)_j \rfloor$$

In which $Y(1)_i$ represents the $i-th$ element of $Y(1)$, and $Y(2)_j$ for the $j-th$ elements of $Y(2)$. For all the historical knowledge, the fuzzy relational functions are found and repeated union operators are applied to obtain the model, that is

$$R = \text{Union of } R_i$$

Using the resulting model R, forecasted output data can be obtained as follows. As the relational function is determined, historical data can be used to obtained the predicted values by

$$A_i = A_{i-1} \circ R$$

Finally, we transform the output fuzzy set into forecasted data set. Seeing as the outputs are linguistic results, they need to be transformed into real numbers using defuzzification process. Fig. 1 shows the current predicted results along with the actual wind speed. As shown in this diagram, we apply both the first-order model with N=10 and the second-order models with N=30. Also, results of GM(1,1) model is obtained and plot in the same diagram. The results show that the wind speed fluctuates randomly from time to time. The second-order model gives better results than the first-order one. The GM(1,1) model here does not perform as satisfactorily as the intelligent fuzzy models. Fig.2 plots the prediction of hourly wind speed for the Tung-Chi-Tao site and Fig. 3 for the Wuci site. These evidences clearly show the benefits of the current fuzzy model. Overall root mean square errors (RMSE) are compared in Fig. 4 to 6 for each site. In these diagrams, the effects of interval number (N) are clearly shown. For the same order of the intelligent fuzzy model, the model with higher interval number provides better prediction of the hourly wind speed with lower RMSE. On the other hand, GM(1,1) gives higher RMSE for all the three site.

V. Conclusion

The forecast of hourly wind speed was conducted using an intelligent web-based model as well as GM(1,1). The hourly wind speed of the selected three sites of Taiwan meteorological stations were forecasted and compared. An intelligent time series model was developed and used to forecast the randomly distributed wind speed data. Both first- and second- order models were applied for the prediction and compared to the GM(1,1) model which is developed based on grey system theory. Results of wind speed forecast as well as root mean square errors were evaluated and compared to show the effectiveness and accuracy of the proposed model. As shown from the results, GM(1,1) gave higher RMSE for all the three site. On the other hand, second-order model provided better prediction than first-order ones. When we used more intervals, the RMSE decreased significantly. The present results demonstrate the benefits and the robustness of the intelligent model.

References

[1] H. M. Geerts, "Short range prediction of wind speeds: a system-theoretic approach (Published Conference Proceedings style)," in *Proc. of European Wind Energy Conference*, Hamburg, Germany, 1984, pp. 594 – 599.

[2] A. Sfestos, "A comparison of various forecasting techniques applied to mean hourly wind speed time series," *Renewable Energy*, vol. 21, pp. 23 – 35, 2000.

[3] K. C. Chou and R. B. Corotis, "Simulation of hourly wind speed and array wind power," *Solar Energy*, vol. 26, no. 3, pp. 199– 212, 1981.

[4] B. G. Brown, R. W. Katz, and A. H. Murphy, "Time series models to simulate and forecast wind speed and wind power," *Journal of Climate and Applied Meteorology*, vol. 23, pp. 1184– 1195, 1984.

[5] H. M. Geerts, "Short range prediction of wind speeds: a system-theoretic approach," in *Proc. of European Wind Energy Conference,* Hamburg, Germany, 1984, pp. 594– 599.

[6] J. L. Torres, A. Garcı´a, M. De Blas, and A. De Francisco, "Forecast of hourly average wind speed with ARMA models in Navarre (Spain)," *Solar Energy*, vol. 79, pp. 65–77, 2005.

[7] I. Fonseca, T. Farinha, and F. M. Barbosa, "On-condition maintenance of wind generators - from prediction algorithms to hardware for data acquisition and transmission," *WSEAS Trans. on Circuits and Systems*, vol. 7, no. 9, pp. 909-918, September 2008.

[8] T. J. Chang, Y. T. Wu, H. Y. Hsu, C. R. Chu, and C. M. Liao, "Assessment of wind characteristics and wind turbine characteristics in Taiwan," *Renewable energy*, vol. 28, pp 851—871, 2003.

[9] M. Jamil, S. Parsa, and M. Majidi, "Wind power statistics and an evaluation of wind energy density," *Renewable energy*, vol. 6, pp 623—628, 1995.

[10] K. R. Rosen, R. Van Buskirk, and K. Garbesi, "Wind energy potential of coastal Eritrea: an analysis of sparse wind data," *Solar energy*, vol. 66, pp 201—213, 1999.

[11] G. Li, "Feasibility of large scale offshore wind power for Hong Kong—a preliminary study," *Renewable Energy*, vol. 21, pp 387—402, 2000.

[12] M. R. Patel, *Wind and solar power system*. Florida, America: CRC press, 1999.

[13] H. K. Jafari, "Simulation of doubly-fed machine with improved wind turbine," *WSEAS Trans. on Circuits and Systems*, vol. 8, no. 2, 217-226, February 2009.

[14] Y. Shao, Z. Rao, and Z. Jin, "Online state diagnosis of transformer windings based on time-frequency analysis," *WSEAS Trans. On Circuits and Systems*, vol. 8, no. 2, 227-236, February 2009.

[15] L. A. Zadeh, "The concept of a linguistic variable and its application to approximate reasoning," Part 1-3, *Inform. Sci*, vol. 8, pp. 43-80; pp. 199-249; pp. 301-357, 1975.

[16] H. Q. Saremi and G. A. Montazer, "An application of type-2 fuzzy notions in website structures selection: Utilizing extended TOPSIS method," *WSEAS Trans. on Computers*, vol. 7, no. 1, pp. 8-15, January 2008.

[17] J. H. Cheng, C. M. Lee, and C. H. Tang," An application of fuzzy Delphi and fuzzy AHP on evaluating wafer supplier in semiconductor industry," *WSEAS Trans. on Information Science and Applications*, vol. 6, no. 5, pp. 756-767, May 2009.

[18] C. S. Reddy and K. Raju, "Improving the accuracy of effort estimation through fuzzy set combination of size and cost drivers," *WSEAS Trans. on Computers*, vol. 8, no. 6, pp. 926-936, June 2009.

[19] C. L. Tang, S. G. Wang, and W. Xu, "A kind of generalized fuzzy C-means clustering model and its applications in mining steel strip flatness signal," *WSEAS Trans. on Information Science and Applications*, vol. 6, no. 12, pp. 1913-1929, December 2009.

[20] M. Memmedli and O. Ozdemir, "An application of fuzzy time series to improve ISE forecasting," *WSEAS Trans. on Mathematics*, vol. 9, no. 1, , pp. 12-21, January 2010.

[21] M. B. Al-Zoubi, A. Al-Dahoud, and A. A. Yahya, "New outlier detection method based on fuzzy clustering," *WSEAS Trans. On Information Science and applications*, vol. 7, no. 5, pp. 681-690, May 2010.

[22] Q. Song and B. S. Chissom, "Forecasting enrollments with fuzzy time series: Part I," *Fuzzy Sets and Systems*, vol. 54, pp. 1-9, 1993.

[23] S. M. Chen, "Forecasting enrollments based on fuzzy time series," *Fuzzy Sets and Systems*, vol. 81, pp. 311-319, 1996.

[24] C. C. Tsai and S. J. Wu, "Forecasting local region data with fuzzy time series," *in Proc. of IEEE International Symposium on Industrial Electronics*, ISIE, vol. 1, 2001, pp122 -133.

[25] Y. F. Hsiao, Y. S. Tarng, and K. Y. Kung, "Comparison of the grey theory with neural network in the rigidity prediction of linear motion guide," *WSEAS Trans. on Applied and Theoretical Mechanics*, Vol.4, No.1, 2009, pp. 32-41.

[26] J. H. Cheng, H. P. Chen, and K. L. Cheng, "Business failure prediction model based on grey prediction and rough set theory," *WSEAS Trans. on Information Science and Applications*, Vol.6, No.2, 2009, pp. 329-339.

[27] Z. L. Chen, C. C. Chiu, and C. J. Lai, "Grey group model forecasting of quarterly accounting earnings," *WSEAS Trans. on Information Science and Applications,* Vol.6, No.2, 2009, pp. 329-339.

[28] K. L. Wen, *Grey systems: Modeling and prediction.* Tucson: Yang's Scientific Research Institute, 2004.

[29] K. L. Wen, S. K. Changchien, C. K. Yeh, C. W. Wang, and H. S. Lin, *Apply MATLAB in grey system theory*. Taipei: CHWA Publisher, 2006.

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Table 1 Monthly wind speed (m/s) of Taiwan meteorological stations
(Source: Taiwan Central Weather Bureau http://www.cwb.gov.tw/)

LOCATION	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
Lan-Yu	9.3	8.9	8.4	8.0	7.9	9.4	9.0	8.9	7.7	9.9	11.0	10.0	9.0
Tung-Chi-Tao	11.4	10.4	8.6	6.8	5.7	5.6	5.1	5.0	6.4	10.1	11.6	11.8	8.2
Peng Gui Island	8.7	8.5	7.7	6.9	6.5	6.6	7.2	7.1	7.2	8.4	9.1	8.9	7.7
Wuci	7.1	6.8	5.7	4.5	3.8	3.9	3.6	3.6	4.5	6.4	6.8	7.1	5.3
Yushan	6.4	6.2	5.8	5.4	4.7	5.1	4.8	4.4	4.3	4.2	4.8	5.7	5.2
Penghu	6.3	5.9	5.0	4.1	3.6	3.5	3.2	3.2	4.2	6.2	6.7	6.6	4.9
Anbu	3.9	3.8	3.6	3.2	3.1	3.0	3.4	3.8	4.1	4.3	4.4	4.0	3.7
Hengchun	4.3	4.0	3.5	3.2	2.7	2.6	2.8	2.6	2.8	4.4	5.1	4.9	3.6
Cheng Kung	4.2	4.0	3.6	3.2	2.9	2.8	2.8	2.8	3.4	4.5	4.9	4.5	3.6
Hsinchu	4.0	3.8	3.1	2.7	2.2	2.7	2.4	2.2	2.9	4.4	4.3	4.6	3.3
Keelung	3.6	3.5	3.1	2.6	2.3	2.4	2.7	2.9	3.2	3.7	3.9	3.7	3.1
Tainan	3.5	3.4	3.1	2.7	2.6	2.8	2.9	2.8	2.6	2.7	3.0	3.3	3.0
Taipei	2.9	2.9	2.9	2.8	2.7	2.2	2.4	2.6	3.0	3.6	3.6	3.2	2.9
Dawu	3.4	3.1	2.9	2.6	2.3	2.2	2.3	2.2	2.5	3.6	4.0	3.7	2.9
Su-ao	3.0	3.0	2.6	2.4	2.2	2.2	2.8	2.8	2.9	3.0	2.9	3.0	2.7
Tamshui	2.8	2.7	2.6	2.3	2.2	2.3	2.5	2.6	2.5	2.9	3.0	2.9	2.6
Kaohsiung	2.8	2.8	2.6	2.5	2.5	2.8	2.9	2.8	2.5	2.2	2.3	2.6	2.6
Chiayi	3.1	3.1	2.7	2.4	2.2	2.7	2.8	2.5	2.1	2.1	2.4	2.8	2.6
Bamboo Lake	3.2	3.2	2.6	2.0	1.8	1.5	1.4	1.6	2.1	2.9	3.2	3.2	2.4
Hualien	2.6	2.5	2.3	2.2	2.0	2.1	2.1	2.1	2.2	2.5	2.6	2.6	2.3
Taitung	2.3	2.2	2.1	2.0	1.8	1.8	1.9	1.9	2.0	2.4	2.5	2.3	2.1
Ilan	1.5	1.5	1.5	1.4	1.4	1.4	1.8	1.9	1.8	1.8	1.5	1.5	1.6
Taichung	1.8	1.8	1.7	1.5	1.3	1.5	1.5	1.5	1.4	1.6	1.7	1.7	1.6
Alishan	1.4	1.6	1.5	1.4	1.3	1.3	1.3	1.2	1.1	1.0	1.1	1.3	1.3
Sun Moon La	1.1	1.1	1.1	1.1	1.1	1.2	1.2	1.3	1.1	1.0	1.0	1.1	1.1

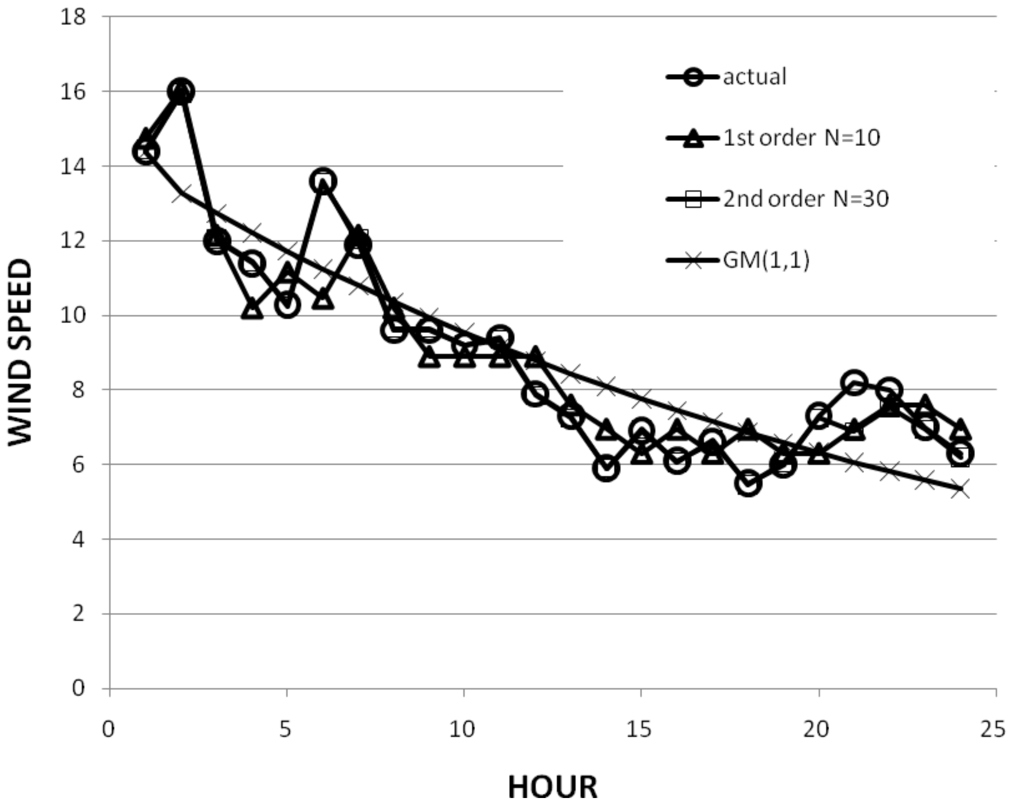

Fig. 1 The forecast of hourly wind power for Lan-Yu site

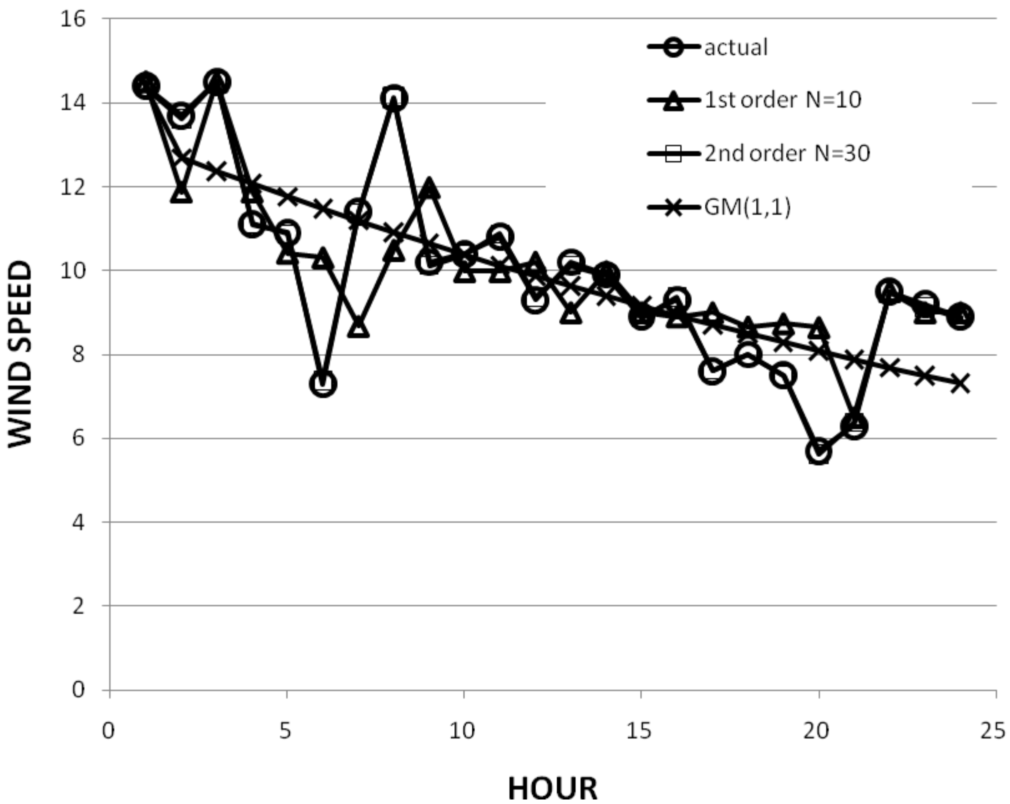

Fig. 2 The forecast of hourly wind power for Tung-Chi-Tao site

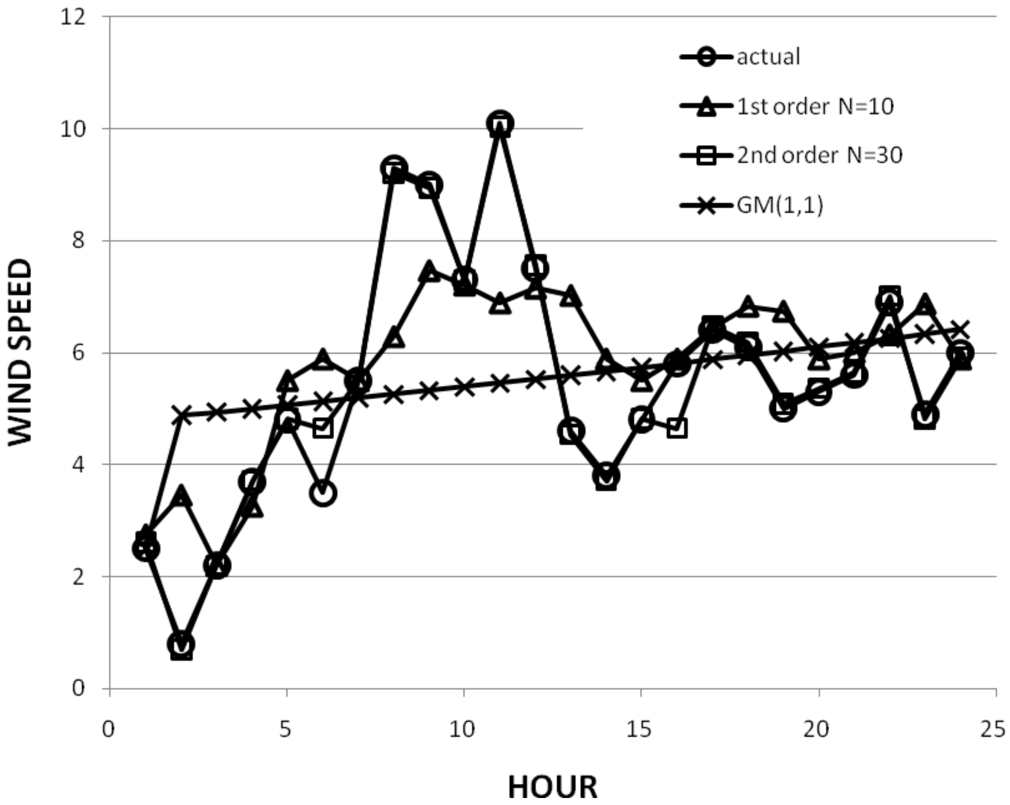

Fig. 3 The forecast of hourly wind power for Wuci site

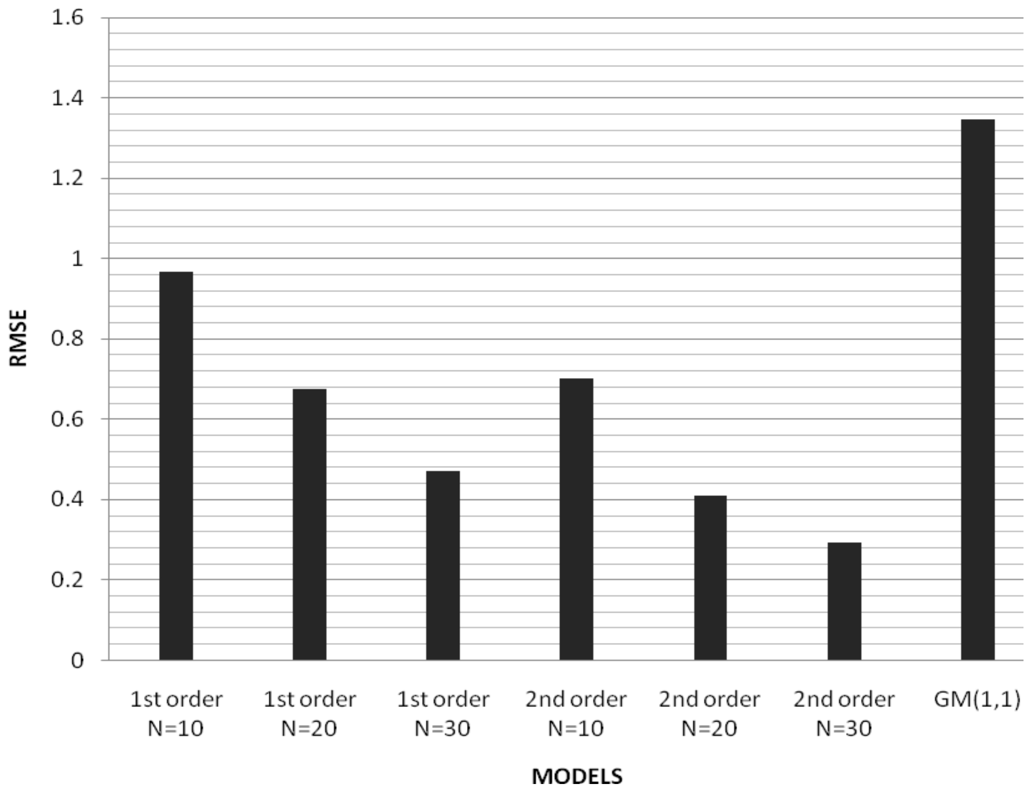

Fig. 4 The root mean square error of forecasting hourly wind power for Lan-Yu site

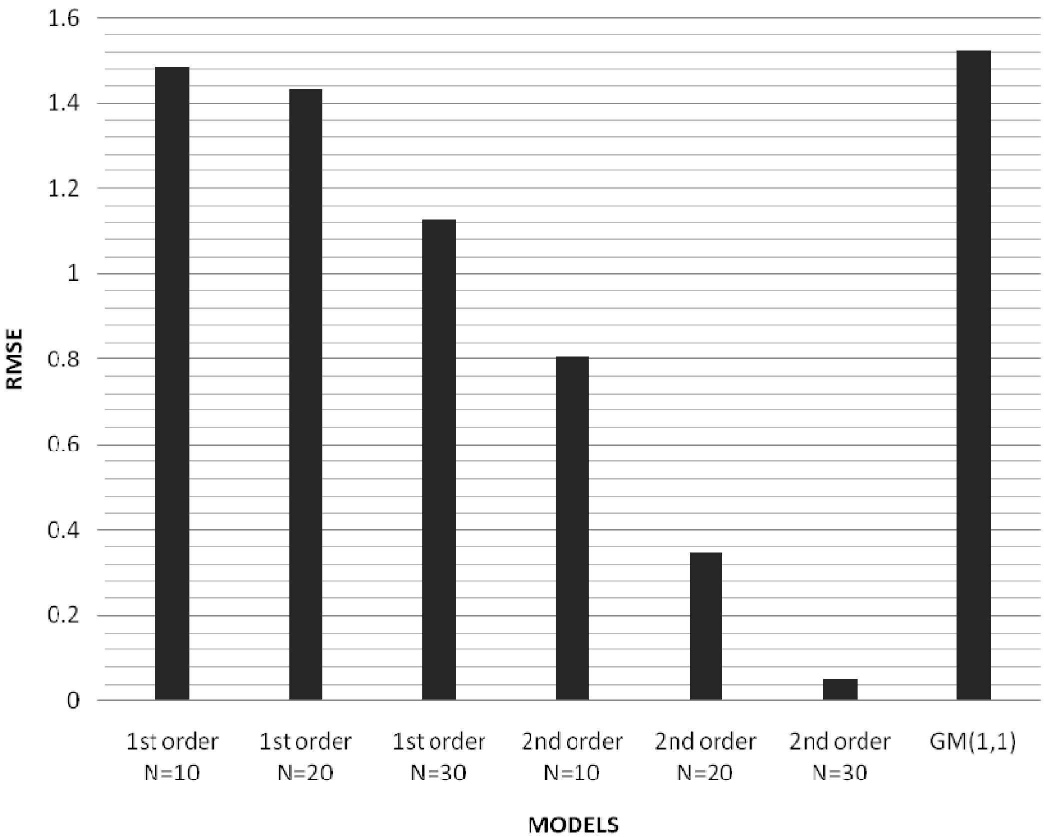

Fig. 5 The root mean square error of forecasting hourly wind power for Tung-Chi-Tao site

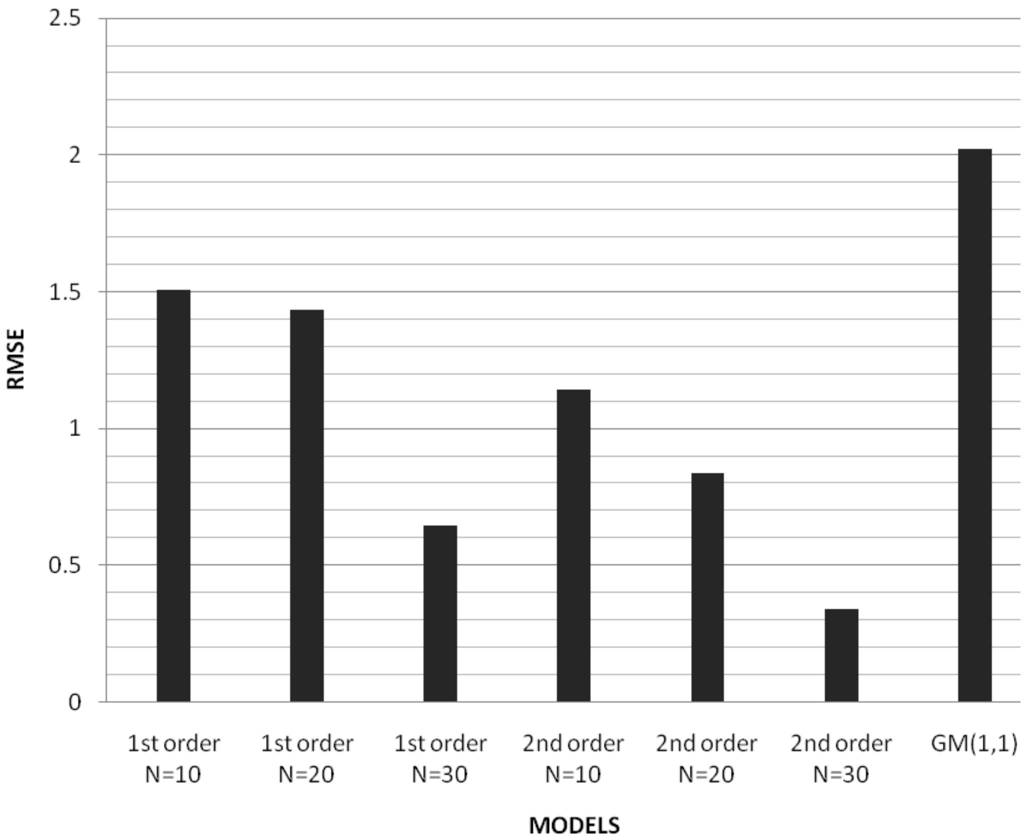

Fig. 6 The root mean square error of forecasting hourly wind power for Wuci site