Statistical simulation of wind speed in Athens, Greece based on Weibull and ARMA models

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***Abstract*—** Wind Speed simulation and modeling is essential in the field of wind power estimation and a useful tool in air pollution management and control applications. This study is focused on the simulation of the hourly wind speed sequences of a single station. Under this framework, the Weibull distribution and the autoregressive-moving average ARMA models are employed. The Weibull distribution is fitted to the monthly frequency wind speed distributions. For each month of the year a single ARMA model is trained according to the Box – Jenkins methodology. The ARMA models are assessed for their ability to reproduce successfully the main statistical figures of the observed time series. The goodness of fit tests along with the limited percentage error on the observed mean wind speed and standard deviation imply the usefulness of the simulation scheme in generating synthetic wind speed time series for the site under study. ARMA models are found superior in simulating the frequency distributions of wind speed.

***Keywords*—**ARMA models, Time series, Wind speed, Weibull distribution

I. Introduction

THE increasingly rising interest in estimating wind power and wind energy potential at a given site, highlights the importance of the statistical simulation of wind speed observations. Early simulations were limited to the distribution fitting of a theoretical probability function like Weibull, Rayleigh or Lognormal to the observed frequency distributions of wind speed [1]-[16]. A detailed review of the probability functions used in wind energy analysis is presented in [17]. Wind speed has a highly auto-correlated nature and the Box-Jenkins methodology [18] is suitable for simulating and forecasting wind speed observations in a specific site [19]-[23] and is proposed and used operationally for simulation and short-term wind speed and power forecasting in wind farms [24]-[27]. In this work, for each month, the Weibull distribution is fitted to the observed frequencies of the wind speed and subsequently a stochastic ARMA model is trained to generate synthetic time series for each month. The linear ARMA models give comparable results with artificial intelligence statistical methods like the neural networks [28]-[31], and are chosen in this study to assess the ability of statistical models to simulate wind speed data solely based on the autocorrelation of the time series.

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II. Experimental Data

The study is focused at the metropolitan Athens in Greece and a ten yearly, from January 1993 to December 2002, hourly averaged wind speed time series at the National Observatory of Athens (NOA) is used. The meteorological station of NOA (Fig. 1) is situated in the center of the Athens basin, 9.5km away from the Saronic shoreline, surrounded by mountains in North and East. The wind field in metropolitan Athens is influenced by complex sea-land breeze circulation cells and by katabatic flows from the surrounding mountains.

Fig. 1 Area of study and location of NOA meteorological station

Wind speed measurements are obtained from a three-cup rotor anemometer, with threshold level 0.2m/s, which is placed at 10m above ground. Wind speed observations are recorded every 10 seconds, averaged initially over ten minutes and then over one hour, to generate the hourly averaged wind speed time series.

The main monthly statistical features of the time series (mean wind speed, median, variance, kurtosis and skewness) are presented in Table 1. It is observed that the mean monthly wind speed exhibits two maxima, one in July, which is attributed to the etesian winds and one during the cold period of the year. The mean monthly wind speed frequency distributions have common distribution patterns and they are right-skewed.

Table 1 Monthly wind speed descriptive statistics

Month	Mean	Median	Variance	Kurtosis	Skewness
Jan	3.318	2.60	5.756	1.477	1.269
Feb	3.537	2.80	6.431	0.854	1.140
Mar	3.781	3.20	6.714	1.662	1.206
Apr	3.026	2.50	3.914	0.681	0.972
May	3.323	2.90	4.906	0.808	0.986
Jun	3.595	3.20	5.261	0.791	0.899
Jul	3.743	3.40	5.862	0.401	0.846
Aug	3.672	3.20	5.564	-0.254	0.723
Sep	3.127	2.50	4.465	1.000	1.117
Oct	3.141.	2.40	5.476	1.347	1.317
Nov	3,338	2.50	6.321	1.518	1.320
Dec	3.401	2.70	6.106	1.540	1.257

III. Weibull Distribution Modeling

Initially the Weibull distribution is fitted to the frequency distributions of the wind speed observations. The Weibull distribution family of curves is a special case of Pearson Type III distributions and is formulated by the probability density function f(u):

$$f(u) = \frac{k}{c}\left(\frac{u}{c}\right)^{k-1} \exp\left[-\left(\frac{u}{c}\right)^{k}\right] \tag{1}$$

where k is the dimensionless shape factor, c the scale parameter in m/sec and u the wind speed in m/sec. The mean wind speed and the variance σ^2, in terms of k and c may be calculated using the gamma function Γ, from the following expressions:

$$\bar{u} = c\Gamma\left(1+\frac{1}{k}\right) \tag{2}$$

$$\sigma^2 = c^2\left[\Gamma\left(1+\frac{2}{k}\right) - \Gamma^2\left(1+\frac{1}{k}\right)\right] \tag{3}$$

Several methods are proposed to determine the shape and scale parameters of the Weibull distribution function [32]-[34]. In this study the linear regression methodology is adopted and the parameter values of the fitted Weibull distributions are presented in Table 2. The values of k are close to 1, ranging from 1.2380 to 1.4238. This fact implies the high variability of the wind field at metropolitan Athens. The goodness of fit of the Weibull distribution to the frequency distributions of the observed data is assessed by the correlation coefficient (R^2) and the Root Mean Square Error (RMSE). The observed and the theoretical values of the mean wind speed and variance are compared by calculating their relative % errors (Table 2). The high correlation coefficient values, ranging from 0.866 to 0.922, along with the low RMSE and % errors, verify that the Weibull distribution fits the data reasonably well.

IV. Autoregressive Moving Average ARMA(P,Q) Modeling

Autoregressive – Moving Average ARMA(p,q) models are a group of linear stochastic models which are classified in three categories. The purely autoregressive AR(p) models, the moving average MA(q) models and the mixed ARMA(p,q) models, which are a combination of the autoregressive and moving average processes. At a particular time, the value of the time series in an ARMA(p,q) process is generated by the equation:

$$x_t = \delta + \varphi_1 x_{t-1} + \phi_2 x_{t-2} + \ldots\ldots + \phi_p x_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \\ - \theta_2 \varepsilon_{t-2} - \ldots\ldots - \theta_q \varepsilon_{t-q} \tag{4}$$

where δ, $\varphi_1, \varphi_2, \ldots, \varphi_p$, $\theta_1, \theta_2, \ldots, \theta_q$ are the parameters of the mixed ARMA(p,q) model. A three phase methodology framework is proposed by Box and Jenkins [18], which constitutes the identification of a possible ARMA(p,q) model, its parameter estimation phase and its diagnostic checking procedure.

Table 2: Goodness of fit and Weibull distribution parameters

Month	k	c (m/s)	R^2	RMSE	% error on $\bar{u}$	% error on σ^2
January	1.2681	3.0719	0.898	0.00063	14.05%	10.88%
February	1.3003	3.2763	0.903	0.00055	14.45%	14.37%
March	1.3228	3.6019	0.922	0.00036	12.32%	4.66%
April	1.3494	2.7452	0.866	0.00657	16.80%	9.14%
May	1.3380	3.0039	0.903	0.00067	16.96%	11.55%
June	1.3965	3.3425	0.914	0.00047	15.22%	7.08%
July	1.3916	3.4786	0.900	0.00053	15.22%	8.99%
August	1.4238	3.3406	0.885	0.00066	17.29%	15.86%
September	1.3488	2.8810	0.882	0.03239	15.49%	12.20%
October	1.2420	2.8731	0.870	0.00095	14.68%	13.97%
November	1.2666	3.1240	0.874	0.00076	13.10%	15.85%
December	1.2380	3.1154	0.901	0.00060	14.49%	8.59%

A. Transformation and Standardization

The application of ARMA models requires the modeled data to be stationary and normally distributed. As it is already proved, wind speed is distributed according to the Weibull distribution. Furthermore, wind speed time series are non-stationary, exhibiting seasonal and diurnal variations (Fig. 2).

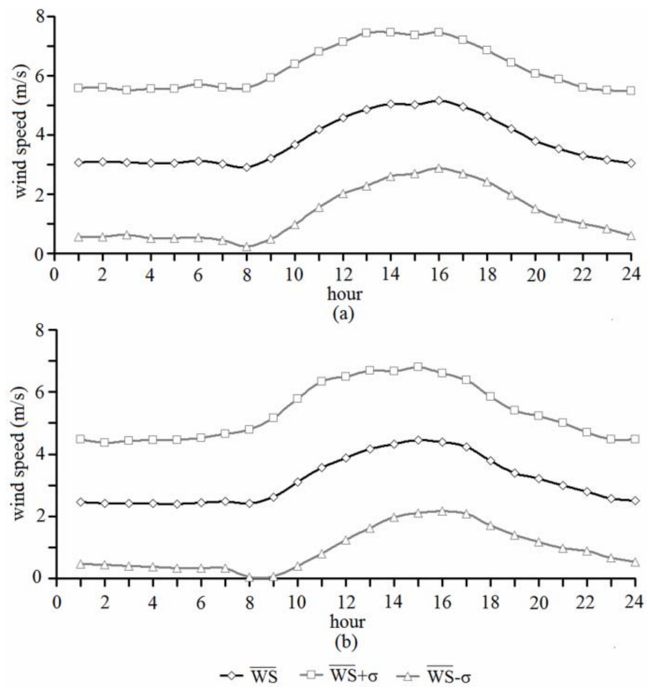

Fig. 2 Diurnal patterns of the hourly mean wind speed and standard deviation for March (a) and October (b)

Wind speed time series can be transformed to a normally distributed variable by raising each observation to an appropriate index x. The most efficient method determining the index x, is the skewness method [35], which evaluates the symmetry of the distribution, by using the formula:

$$S_k(x) = \frac{1}{Y \cdot M \cdot D} \sum_{y=1}^{Y} \sum_{d=1}^{M} \sum_{h=1}^{D} \left(\frac{WS^x(h,d,m,y) - \overline{WS^x}(m)}{\sigma'(m)} \right) \quad (5)$$

The method requires iterative calculation and the selected value of index x results to a symmetric distribution (i.e. $S_k = 0$). By the end of this step, the observed time series WS have been transformed to a normally distributed transformed variable WS'.

Seasonal non-stationarity is adequately removed by choosing a monthly scale for the stochastic modeling and standardization is required to remove diurnal non-stationarity [36] The standardization is performed to the WS' using the formulas [37]:

$$WS'^*(h,d,m,y) = \frac{WS'(h,d,m,y) - \overline{WS'}(h,m)}{\sigma'(h,m)} \quad (6)$$

where $\overline{WS'}(h,m)$ the expected mean value of hour h for the month m of WS' and $\sigma'^2(h,m)$ the variance of hour h for the month m, given by the formulas:

$$\overline{WS'}(h,m) = \frac{1}{YM} \sum_{y=1}^{Y} \sum_{d=1}^{M} WS'(h,d,m,y) \quad (7)$$

$$\sigma'^2(h,m) = \frac{1}{YM} \sum_{y=1}^{Y} \sum_{d=1}^{M} \left[WS'(h,d,m,y) - \overline{WS'}(h,m) \right]^2 \quad (8)$$

The observed hourly wind speed data have been transformed and standardized to a dimensionless and normally distributed variable. The normality check of WS'* is illustrated in Fig. 3.

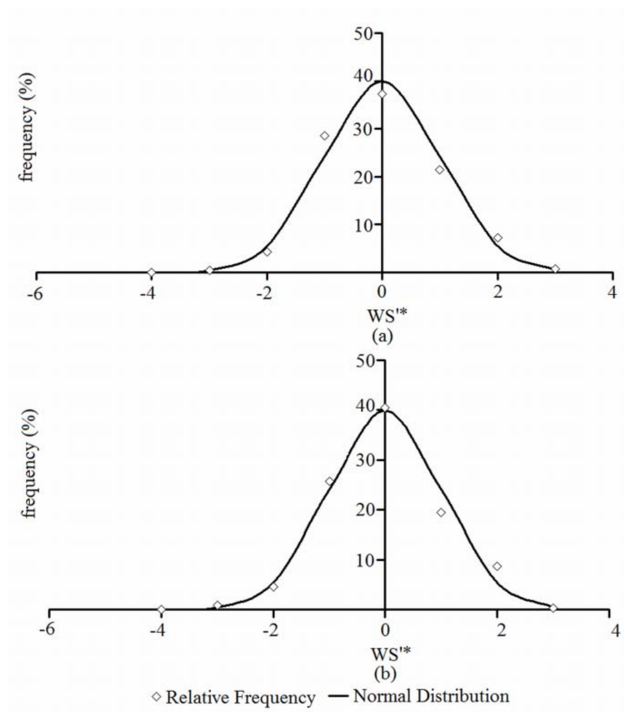

Fig 3 Normality check for the transformed and standardized wind speed for March (a) and October (b)

B. Identification Phase

The order of the autoregressive process p and the order q of the moving average process, are estimated during the identification phase. The analysis of the autocorrelation (ACF) and the partial autocorrelation (PACF) functions give an initial estimation of the stochastic process that generated the observed data. For a pure autoregressive model AR(p), the ACF gradually decreases to zero, while the PACF is zero after p lags. For a pure moving average process MA(q), the ACF is zero after q lags and the PACF is decreases geometrically after q lags. For a mixed process ARMA(p,q) the ACF decreases exponentially after lag p and is zero after q lags.

For each month, the correlograms (ACF and PACF) of WS'* have the same features, exhibiting a slow exponential decrease (Fig. 4). Furthermore, after the second or third lag, the partial autocorrelation functions are close to zero, implying that the data may be modeled by a low order ARMA(p,q) process.

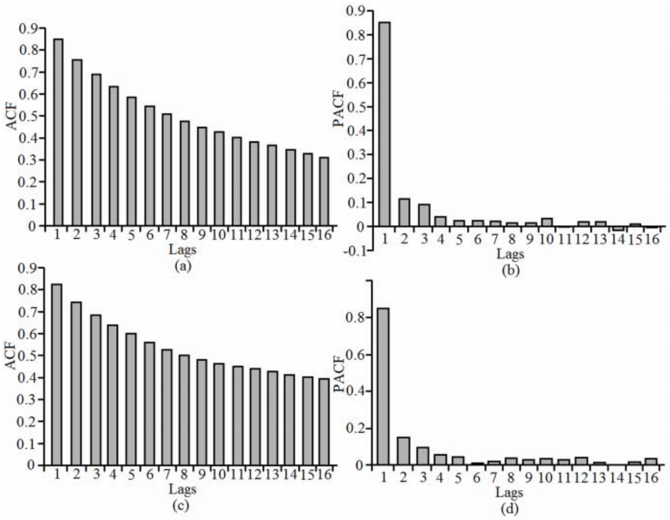

Fig. 4 Autocorrelation and partial autocorrelation functions for the transformed and standardized variable for March (a&b) and October (c&d)

For the selection of the appropriate class of the ARMA models the Bayesian Information Criterion (BIC) is employed. The BIC criterion considers the principle of parsimony, which is essential according to the Box – Jenkins methodology, and responds to the following expression:

$$BIC = (DMY)\ln\left(\sigma_e^2\right) + T\ln(DMY) \tag{9}$$

where D the number of observations in a day, M the number of days in a given month, Y the number of years of the observations, σ_e^2 the variance of the residuals and T the total number of the parameters estimated, equal to the order of the ARMA model T=p+q. The BIC criterion is employed to the suggested group of models from the visual analysis of the correlograms. The selected model during the identification phase is the one that minimizes the BIC criterion. An ARMA(2,1) model is proposed for each month except April, October and November where an ARMA(2,2) is selected. .

C. *Parameter Estimation Phase*

Once the provisional values of p and q have been identified, the model coefficients δ, φ_i and θ_i along with the variance of the residuals σ_e^2 can be estimated. Table 3 illustrates the proposed model and the estimated values of the parameters. The stationarity and the invertibility of each model, based on these parameters, are checked. For an ARMA(2,1) model, the following conditions must be fulfilled respectively [18]:

$$\begin{array}{ll} \phi_1 + \phi_2 < 1 & \\ \phi_2 - \phi_1 < 1 & -1 < \theta_1 < 1 \\ -1 < \phi_2 < 1 & \end{array} \tag{10}$$

The stationarity and the invertibility of an ARMA(2,2) model are ensured when the estimated parameters satisfy the following conditions:

$$\begin{array}{ll} \phi_1 + \phi_2 < 1 & \theta_1 + \theta_2 < 1 \\ \phi_2 - \phi_1 < 1 & \theta_2 - \theta_1 < 1 \\ -1 < \phi_2 < 1 & -1 < \theta_2 < 1 \end{array} \tag{11}$$

All proposed models were found to be stationary and invertible.

D. *Diagnostic Checking Phase*

The objective of the diagnostic checking phase is to reveal any lack of fit of the proposed models and diagnose its cause. If the fitted model is adequate then the autocorrelations of the residuals should be uncorrelated and normally distributed and thus their autocorrelations coefficients $r_k(\varepsilon)$ have to be random and close to zero. 'Portmanteau Lack-of-Fit' test, assesses weather a group of autocorrelations of a time series are random. For this study the first 15 autocorrelations of the residuals are used and the Box-Pierce statistic is calculated:

$$Q = N\sum_{k=1}^{K} r_k^2(\varepsilon) \tag{12}$$

where N is the number of observations, K the number of the first studied autocorrelations and $r_k(\varepsilon)$ the residuals autocorrelations.

Table 3 ARMA(p,q) model coefficients

Month	Model	Δ	φ_1	φ_2	θ_1	θ_2	σ_e^2
January	ARMA(2,1)	0.0179	1.34710	-0.38310	0.61965		0.24775
February	ARMA(2,1)	-0.0002	1.43760	-0.46619	0.70069		0.25835
March	ARMA(2,1)	0.0008	1.44046	-0.47070	0.70345		0.27098
April	ARMA(2,2)	-0.0054	1.72837	-0.73222	1.04146	-0.08454	0.36771
May	ARMA(2,1)	-0.00150	1.54192	-0.56135	0.81950		0.31995
June	ARMA(2,1)	-0.0302	1.67530	-0.68082	0.92773		0.31040
July	ARMA(2,1)	0.0120	1.63033	-0.63769	0.90658		0.31479
August	ARMA(2,1)	0.00310	1.60970	-0.61840	0.90007		0.33662
September	ARMA(2,1)	-0.00530	1.50437	-0.52133	0.82960		0.34016
October	ARMA(2,2)	-0.00172	1.69544	-0.70250	1.00313	-0.10057	0.26526
November	ARMA(2,2)	-0.00413	1.64020	-0.65467	0.96817	-0.12613	0.27094
December	ARMA(2,1)	0.00355	1.34329	-0.37881	0.62379		0.25099

The hypothesis of randomness is accepted when the Q-statistic follows the chi-square distribution, with K –(p+q) degrees of freedom. The results of the 'Portmanteau Lack-of-Fit' test are presented in Table 4.

Table 4 Q statistic values for each month and x^2 critical values

Month	Q – statistic	x^2 critical value
January	16,472	27,587
February	19,426	27,587
March	18,265	27,587
April	25,571	26,296
May	26,226	27,587
June	27,394	27,587
July	22,067	27,587
August	16,085	27,587
September	26,099	27,587
October	26,204	26,296
November	26,114	26,296
December	17,090	27,587

The computed Q values for each month were found to be lower than the critical values of the x^2 distribution, indicating that the proposed models is accepted at a significance level of 5%. Some researchers [37],[38] follow an alternative method for the diagnosing checking of the models. Their approach is based on the study of the autocorrelations of the residuals for a given number of lags, stating that if the $r_k^2(\varepsilon)$ are uncorrelated then the 95% of the $r_k^2(\varepsilon)$ should be within the $\pm 2/\sqrt{N}$ boundaries. The first 20 autocorrelations of the residuals are calculated for each month and presented in the Fig. 5 along $\pm 2/\sqrt{N}$ error boundaries.

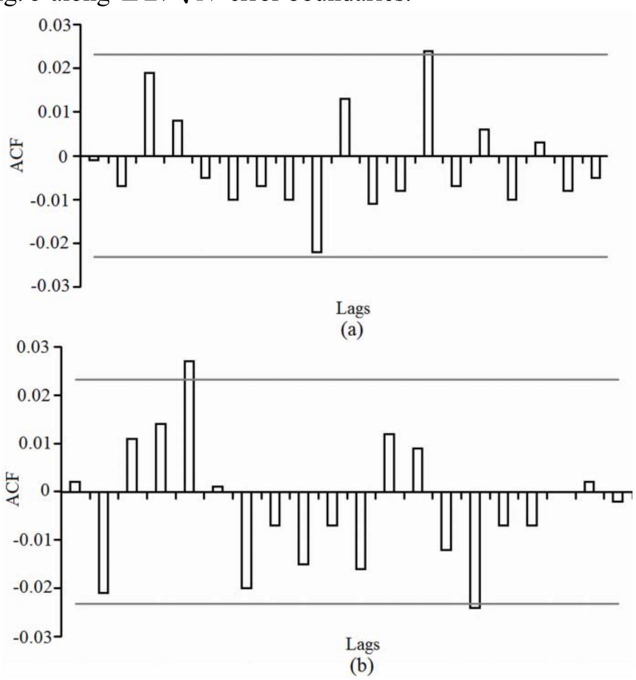

Fig 5 Autocorrelation function of the residuals for March (a) and October (b)

Both diagnostic checking techniques lead to the same findings, proving that the proposed models are adequate for the simulation of the wind speed.

V. Simulation Results

In order to check the validity of the ARMA models, the synthetic time series are compared with the observed wind speeds for each month of the year. In Fig. 8 the time series are illustrated for 2002, while in Fig. 6, the observed and the synthetic time series are compared with the scatter diagram for the complete 10-year study period. The overall correlation coefficient is high (R = 0.91) while for high wind speeds, both figures illustrate that the models underestimate the observed wind speeds.

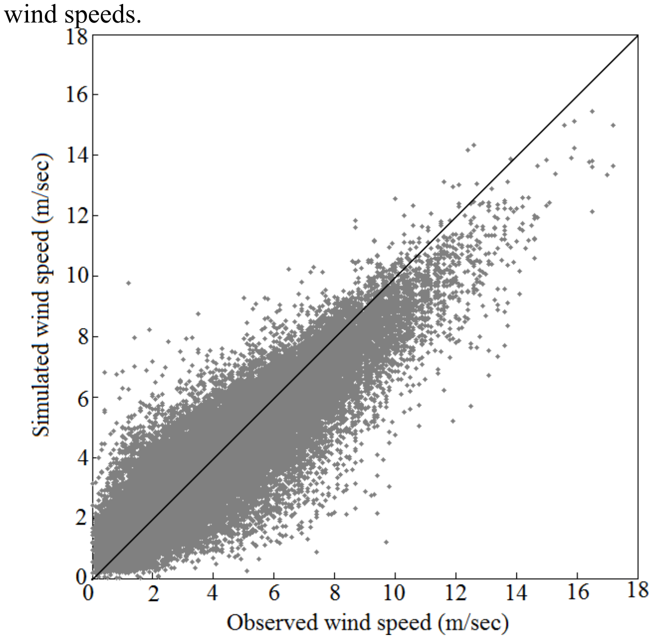

Fig 6 Comparison of the observed and simulated wind speed for the complete time series

The most important statistical feature of a time series is its autocorrelation. A statistical model reproduces accurately the time series values when the autocorrelation coefficients of the observed and simulated time series are similar. In our case, for both time series the first 8 autocorrelation coefficients were calculated and compared for each month. Fig 7 illustrates the comparison for March and October. For all months, a slight overestimation for the estimated autocorrelation coefficients is observed.

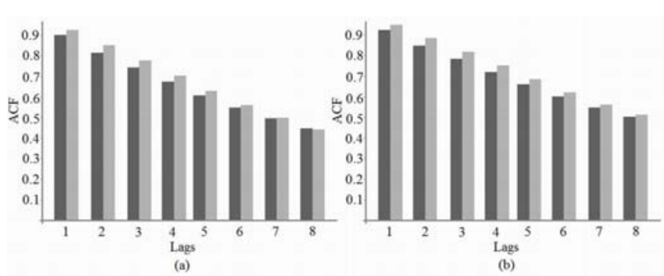

Fig 7 Comparison of the observed and simulated autocorrelation functions for the first 8 lags for March (a) and October (b)

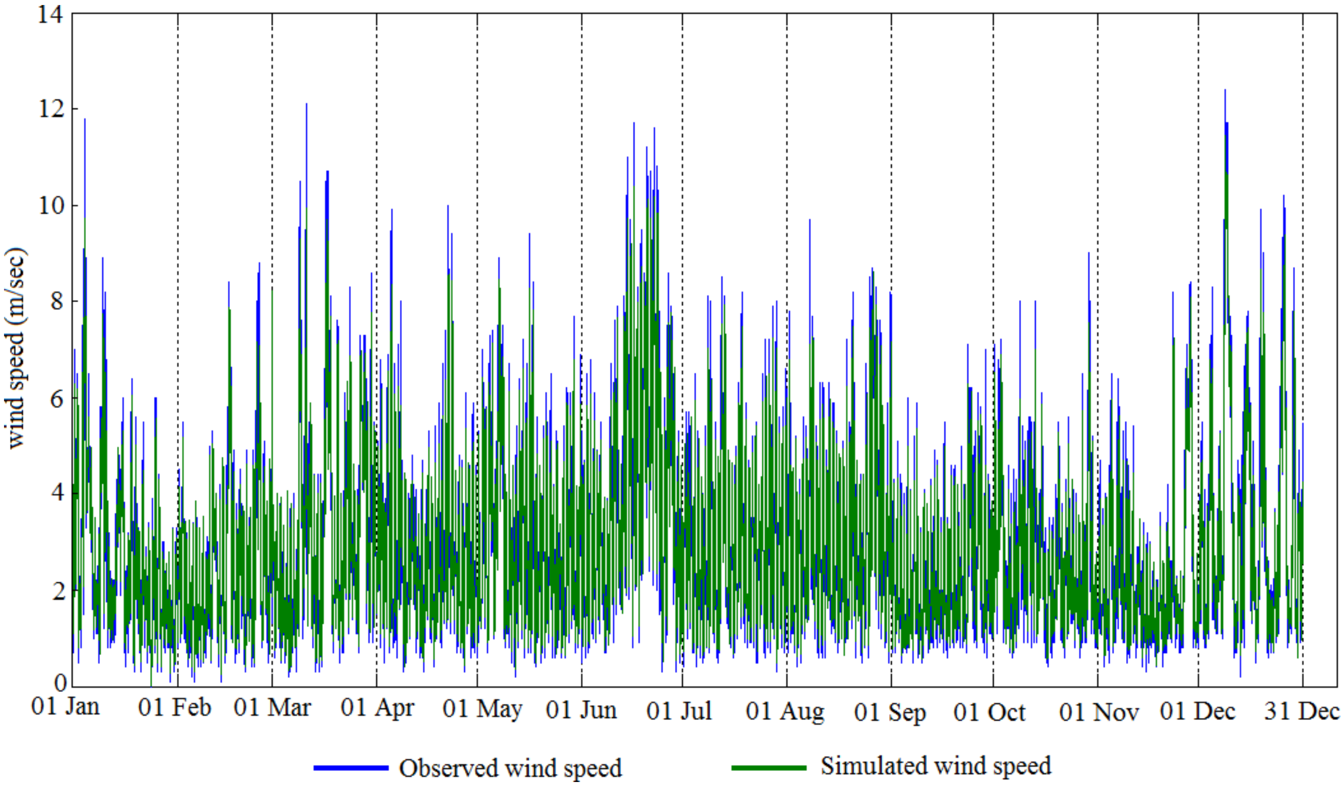

Fig 8 Comparison of the observed and simulated time series for 2002

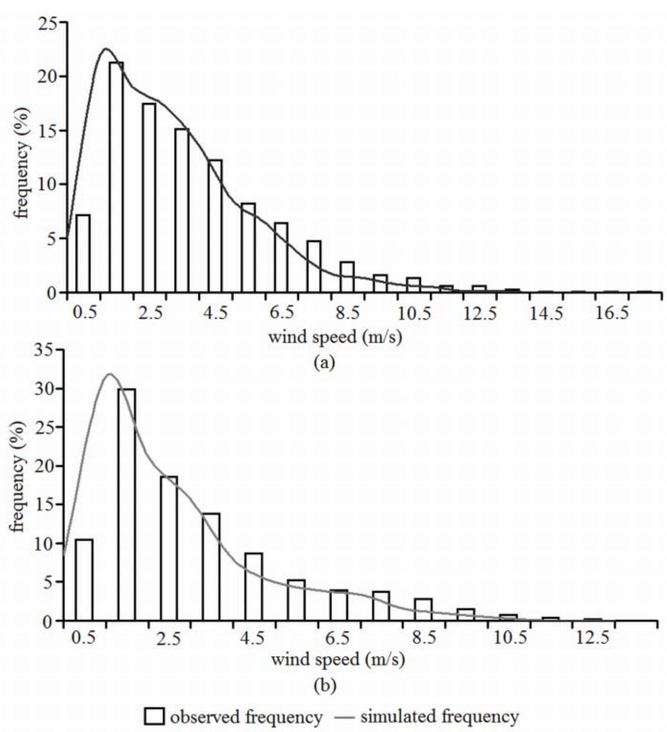

Fig 9 Observed and simulated frequency distributions for March (a) and October (b)

Furthermore, the comparison of the main statistical characteristics (Table 5), proves the ability of the ARMA models to generate and reproduce accurately the wind speed at the National Observatory of Athens. The comparison is based on the mean monthly wind speed, its standard deviation and on the two first autocorrelation coefficients. The percentage errors for each of the above statistical figures are calculated from the following expression:

$$error(\%) = \frac{(Obs - Sim)}{Obs} \cdot 100 \qquad (13)$$

Limited errors are observed for all statistical figures except for the standard deviation. Furthermore, the lower mean monthly wind speed percentage errors are observed for the summer months and the higher during autumn.

The comparison of the frequency distributions of the observed and the synthetic time series (Fig. 9) prove that the fit of the ARMA models to actual data is very promising. This is important especially for the lower wind speeds, where the Weibull distribution is incapable of simulating the observed distribution frequencies.

Table 5 Comparison of the observed and simulated main statistical figures along with the % errors on the monthly mean, standard deviation and the first and second autocorrelation coefficients.

Month		$\bar{u}$	σ^2	r_1	r_2	$\bar{u}$ error	σ^2error	$r_1$error	$r_2$error
January	Obs	3.318	5.756	0.916	0.844	3.986	25.010	2.620	4.265
	Sim	3.186	4.316	0.940	0.880				
February	Obs	3.537	6.431	0.915	0.833	4.042	25.042	2.186	3.721
	Sim	3.394	4.820	0.935	0.864				
March	Obs	3.781	6.714	0.900	0.815	3.682	26.022	2.889	4.417
	Sim	3.642	4.967	0.926	0.851				
April	Obs	3.026	3.914	0.872	0.746	3.724	28.081	4.128	6.032
	Sim	2.913	2.815	0.908	0.791				
May	Obs	3.323	4.906	0.893	0.785	3.049	23.882	3.024	4.968
	Sim	3.221	3.734	0.920	0.824				
June	Obs	3.595	5.261	0.897	0.782	2.535	21.416	2.341	4.348
	Sim	3.504	4.134	0.918	0.816				
July	Obs	3.743	5.862	0.899	0.786	2.563	20.883	2.781	5.089
	Sim	3.647	4.638	0.924	0.826				
August	Obs	3.672	5.564	0.892	0.777	2.844	21.850	3.139	5.534
	Sim	3.567	4.348	0.920	0.820				
September	Obs	3.127	4.465	0.900	0.798	3.863	26.150	3.333	5.764
	Sim	3.006	3.297	0.930	0.844				
October	Obs	3.141	5.476	0.920	0.845	4.580	24.582	2.826	4.142
	Sim	2.997	4.130	0.946	0.880				
November	Obs	3.338	6.321	0.918	0.846	4.753	27.209	3.050	4.374
	Sim	3.180	4.601	0.946	0.883				
December	Obs	3.401	6.106	0.917	0.843	4.234	25.617	2.617	4.389
	Sim	3.257	4.542	0.941	0.880				

VI. CONCLUSION

In this study a theoretical distribution function and a stochastic modeling approach are employed for the simulation of the hourly wind speed observations at a single station in metropolitan Athens. Weibull distribution, which is the most frequently used distribution in wind speed statistical analysis, is found to model satisfactory the observed relative frequency distributions of wind speed for each month. Although high correlation coefficient values and low RMSE errors are found for each month, the Weibull distribution does not model effectively the low wind speeds and does not take into account the autocorrelation feature of wind.

The analysis of the statistical characteristics of the time series, based on the autocorrelation and the partial autocorrelation functions, imply that the simulation should be based on a low order ARMA process. The Box – Jenkins methodology is employed and the time series are transformed and standardized, generating a dimensionless and normal distributed variable. A different ARMA model is trained for each month and an ARMA(2,1) is proposed for each month except April, October and November where an ARMA(2,2) is selected. The comparison of the observed and simulated time series proves the ability of the model to generate the wind speed at the NOA station. The synthetic time series follow closely the observed wind speed. The comparison is based on the monthly mean wind speed and standard deviation and their relative errors. Furthermore the synthetic time series are proved to reproduce accurately the autocorrelation dependence, which is the most important feature in wind speed time series. A slight overestimation of no statistical significance is observed for the first eight autocorrelation coefficients.

The fit of the ARMA model to the frequency distributions of the observed data is superior compared to Weibull models, especially for low wind speeds. ARMA models are found capable in generating synthetic time series with identical statistical characteristics with the measured data.

These stochastic models may be used as a weather wind speed generators of one month sequences that represent the actual statistical characteristics of the 10 years time series of wind speed data for each month. The simulation can be especially useful in generating missing wind speed data for the National Observatory of Athens and in air pollution modeling and control. Furthermore, such a simulation is important in energy conversion studies in wind energy applications.

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