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ScienceDirect

Energy Procedia 97 (2016) 278 – 285

Energy Procedia

European Geosciences Union General Assembly 2016, EGU
Division Energy, Resources & Environment, ERE

Global investigation of double periodicity of hourly wind speed for stochastic simulation; application in Greece

Ilias Deligiannis, Panayiotis Dimitriadis* , Olympia Daskalou, Yiannis Dimakos and Demetris Koutsoyiannis

National Technical University of Athens, Heroon Polytechniou 9, Zografou 15780, Greece

Abstract

The wind process is considered an important hydrometeorological process and one of the basic resources of renewable energy. In this paper, we analyze the double periodicity of wind, i.e., daily and annual, for numerous wind stations with hourly data around the globe and we develop a four-parameter model. Additionally, we apply this model to several stations in Greece and we estimate their marginal characteristics and stochastic structure best described by an extended-Pareto marginal probability function and a Hurst-Kolmogorov process, respectively.

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Keywords: wind speed; double periodicity; marginal distribution; dependence strusture; stochastic simulation

1. Introduction

beware of the periodic double threat of the windmill maneuver,
dedicated to Bobby Fischer for the 1956 game of the century.

Several studies have been conducted for the stochastic simulation of hourly wind speed on the purpose of renewable energy simulation and management [1]. However, the double periodicity of wind [2,3] is often

* Corresponding author. Tel.: +302107722831; fax: +302107722831.
E-mail address: pandim@itia.ntua.gr

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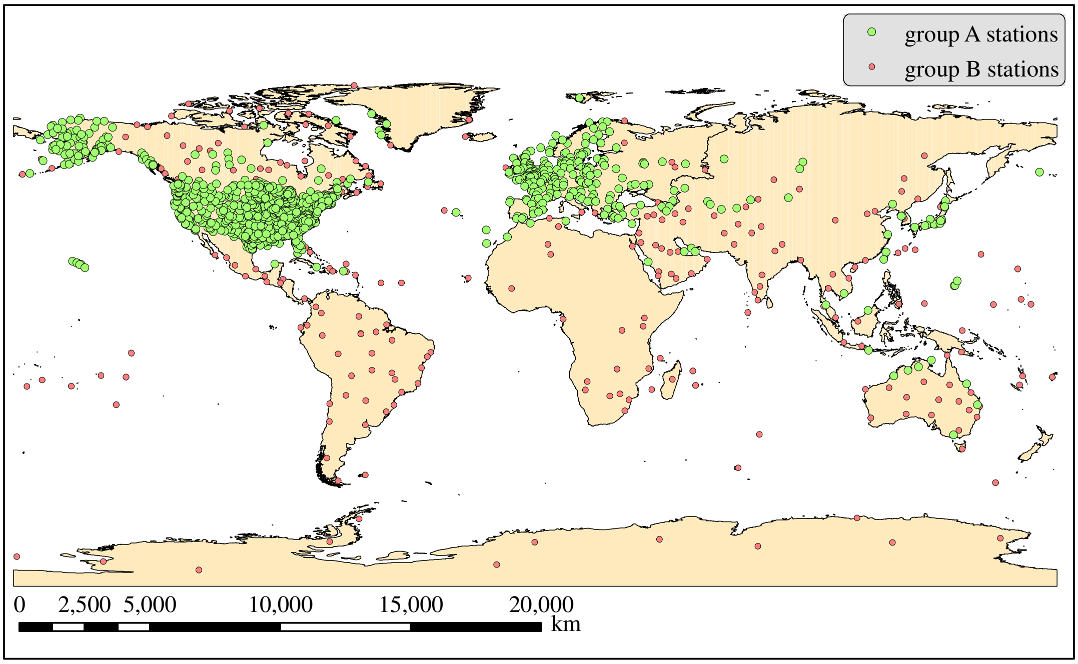
Peer-review under responsibility of the organizing committee of the General Assembly of the European Geosciences Union (EGU)
doi:10.1016/j.egypro.2016.10.001

overlooked with most models focusing solely on the annual cycle and therefore, neglecting the contribution of daily wind fluctuation in energy production and management. In this work, we present a methodology based on [3] for wind speed simulation that includes a deterministic model for the double periodicity of wind as well as a stochastic model for the probability and dependence structure of the process under a cyclostationary concept [4]. In section 2, we describe the former model and we compare the hourly-monthly mean wind profiles with the corresponding temperature ones in an attempt to provide a physical reasoning. We then test the double periodic model to approximately 2000 stations around the globe with high quality and large quantity of records and we show several statistical characteristics related to the model performance for each station and model parameter. Finally, in section 3 we estimate the parameters of the double cyclostationary model including the stochastic structure and marginal characteristics of the most credible stations in Greece.

2. Double periodicity of wind

2.1. Data

From the original database of more than 15000 land-based stations around the globe downloaded from noaa (www.ncdc.noaa.gov), we choose all stations that are still operational (7500) and we form two groups. The first group includes stations with at least 10^5 observations in total and at least one observation per hour (1600 stations). For the purpose of having as much as possible a uniform spatial distribution of stations around the globe, we add 250 stations located mostly at the Southern Hemisphere (group B). These stations have at least 1800 records per year corresponding to one measurement per 3 hours and for at least 10 months per year. In Map 1, we depict the selected stations for each group.



Map. 1. Spatial distribution of wind stations with hourly data.

2.2. Correlation between temperature and wind speed

The kinetic state of air molecules is related to both their velocity and thermal energy [5]. Therefore, wind speed and air temperature must have a strong correlation not only in microscale but also in macroscale, i.e. a difference in temperature causing a difference in air pressure and as a consequence, in wind speed, similarly to the lake stratification process. In Fig. 1, we estimate the correlation coefficient (denoted r) between hourly wind speed and temperature and we plot the monthly average correlation (r_{av}) for each station. It is notable that 90% of stations have $r_{av} > 0.65$ and 46% of stations have $r_{av} > 0.9$.

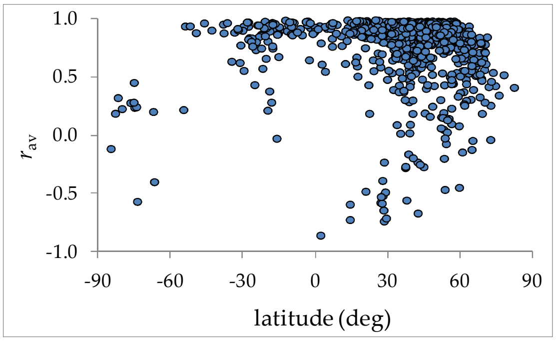


Fig. 1. Correlation coefficient between hourly-monthly mean wind speed and temperature.

2.3. Double periodic model

Several models exist for simulating the deterministic behaviour of hourly-monthly air temperature with the most popular ones to be a combination of periodical and exponential functions [6,7]. Since the correlation coefficient between wind speed and temperature is high enough, it is only reasonable to adopt similar models for describing the double periodicity of wind. Here, we expand the model presented in [3] for the hourly-monthly mean wind speed of the form $A(t)\ e^{B(t)} + C(t)$, where A, B and C are periodic functions describing the annual variability and with the exponential function corresponding to the daily variability of the process:

$$\mu_c = \left(\left(a_1 + a_2 \cos\left(2\pi \frac{t_m - a_m}{T_m} \right) \right) \exp\left(\cos\left(2\pi \frac{t_h - a_h}{T_h} \right) \right) + a_3 \cos\left(2\pi \frac{t_m - a_m}{T_m} \right) + a_4 \right) \mu_h \tag{1}$$

where μ_c (m/s) is the mean for the specific hour of the day and month of the year (24×12 different values in total); μ_h (m/s) is the overall mean of the process (one value); t_h is the continuous time in hours and t_m the continuous time in months; T_h = 24 h; T_m = 12 months; a_1, a_2, a_3 are dimensionless parameters; a_4 equals $1 - a_1 \int_0^{2\pi} \exp(\cos x) dx \approx 1 - 1.266 a_1$, in order to exactly preserve the mean of the process; a_m is a parameter depicting the month of maximum wind speed and varies from 0 to 12 months; and a_h is considered a coefficient depicting the hour of maximum wind speed varying from 0 h to 24 h (see at the end of section for justification).

The four parameters are calculated through the minimization of the average squared error between the observed and modeled values. Parameter a_1 is closely related to daily fluctuation of wind speed. Furthermore, we estimate the average of the daily velocity ratios, i.e., v_{max}/v_{min} in order to evaluate the temporal variation of wind speed. The monthly-average ratio v_{rh} describes the weighting factor of the temporal variation. We estimate that the 82% of stations have $v_{rh} > 1.5$ and 26% of stations have $v_{rh} > 2.5$.

Likewise, parameter a_2 is closely related to the annual periodicity of wind. To evaluate the monthly variation of annual wind speed, the ratio $v_{rm} = v_M/v_m$ is calculated, where v_M, v_m are the maximum and minimum monthly wind speed. This ratio is evaluated quite larger than unity for most stations indicating a significant annual variation, with 64% of stations having $v_{rm} > 1.5$.

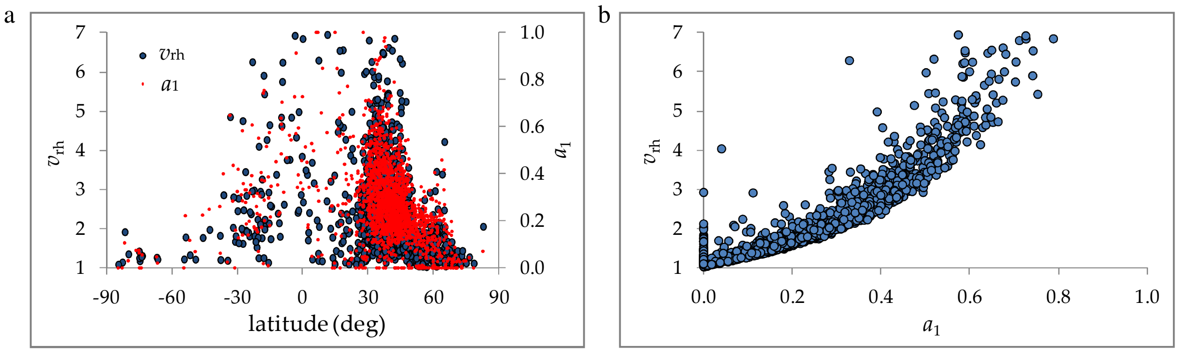


Fig. 2. Variation of (a) v_{rh} and a_1 with latitude and (b) v_{rh} with a_1.

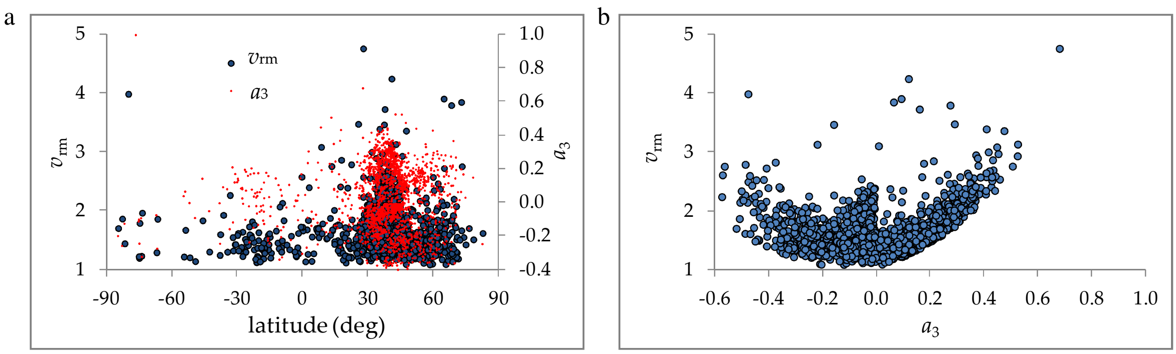


Fig. 3. Variation of (a) v_{rm} and a_3 with latitude and (b) v_{rm} with a_3.

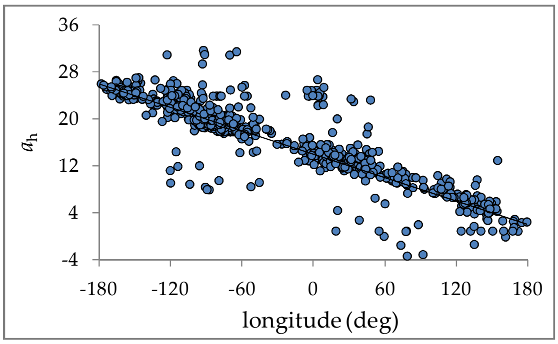


Fig. 4. Variation of a_h with longitude.

Parameter a_2 in combination with a_3 can capture the most commonly met profiles of wind speed (see Fig. 7 in section 3). There are three profiles exhibiting hourly-monthly means: (1) almost parallel to each other, i.e., $a_2 = 0$; (2) with similar low values and different peak values for each month, i.e., $a_3 = 0$; and (3) with similar peak values and different low values for each month, i.e., $a_2\, a_3 \neq 0$.

Coefficients a_h and parameter a_m determine the peak hour and month, respectively. The variation of a_h with longitude is linear with r^2 around 0.7, meaning that the maximum velocity seems to appear at the same approximately local hour (14h00) for all examined stations around the globe (all observations are recorded in Greenwich Time). As a result of this, a_{h} can be calculated as follows (note that if $a_{\mathrm{h}} > 24$ then $a_{\mathrm{h}} = a_{\mathrm{h}} - 24$:

$$a_{\mathrm{h}} = al + \beta \tag{2}$$

where $\alpha = 12/180$ h/deg; l is the longitude varying from –180 to +180 deg; $\beta = 14.2$ h.

2.4. Model performance from global analysis

Coefficient r and nrmse (abbreviation for the normalized root mean square error) between observed and modeled values are in most cases remarkably high and low, respectively. In Fig. 5, we plot the monthly average r and nrmse (denoted r_{av} and $\mathrm{nrmse}_{\mathrm{av}}$) and we observe that 90% of stations indicate $r_{\mathrm{av}} > 0.65$ and 75% of stations $r_{\mathrm{av}} > 0.9$. In addition, 34% of stations have $\mathrm{nrmse}_{\mathrm{av}} < 0.1$ and 90% of stations $\mathrm{nrmse}_{\mathrm{av}} < 0.2$.

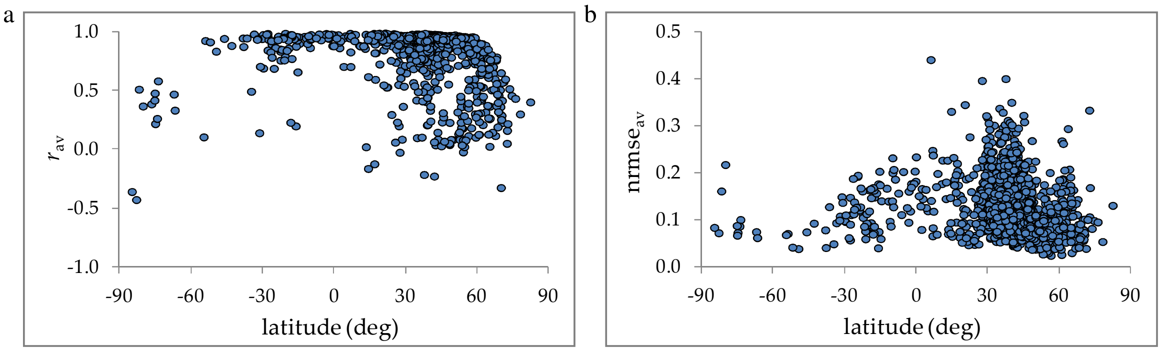


Fig. 5. Variation of (a) r_{av} with latitude and (b) $\mathrm{nrmse}_{\mathrm{av}}$ with latitude.

However, r can sometimes underestimate the goodness of fit, especially if v_{rh} is close to unity. In that case, nrmse is close to zero and a smooth hourly-monthly mean profile can be easily fitted. Reasonably, when both nrmse and v_{rh} have large values then so will r. In general, both r and nrmse show adequate results with 80% of stations having $r_{\mathrm{av}} > 0.7$ and $\mathrm{nrmse}_{\mathrm{av}} < 0.2$ (Fig. 6).

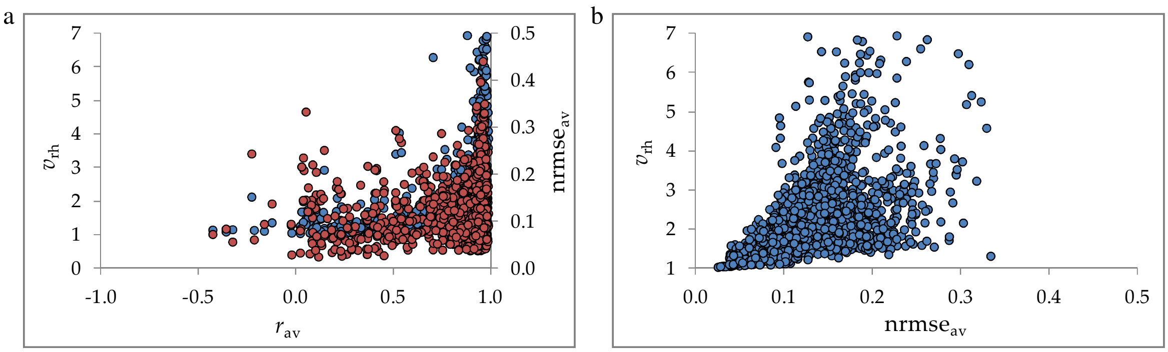


Fig. 6. Variation of (a) v_{rh} and $\mathrm{nrmse}_{\mathrm{av}}$ with r_{av} and (b) v_{rh} with $\mathrm{nrmse}_{\mathrm{av}}$.

3. Application

In this section, we apply the double periodic model to 17 stations of high quality and large quantity of records in Greece (Table 1-2 and Fig. 7). Additionally, we model the standard deviation of the process by a single periodic function corresponding solely to annual fluctuation since daily fluctuation is minimal for all stations:

$$\sigma_{\mathrm{c}} = \left(b\cos\left(2\pi \frac{t_{\mathrm{m}} - b_{\mathrm{m}}}{T_{\mathrm{m}}} \right) + 1 \right) \sigma_{\mathrm{h}} \tag{3}$$

where σ_{c} (m/s) is the standard deviation for each month, σ_{h} (m/s) is the hourly standard deviation of the process, b is a dimensionless parameter related to the magnitude of the monthly fluctuation and b_{m} is a coefficient depicting the month of maximum wind speed standard deviation and varying from 0 to 12 months.

Furthermore, we estimate the dependence structure of the wind process all over Greece by combining the climacogram (i.e., the variance of the mean process vs. scale, denoted as γ ($\mathrm{m}^2/\mathrm{s}^2$) and introduced in [8]) of the 17 stations (Fig. 8). The justification for the use of climacogram to estimate the stochastic structure of the process instead of the commonly used autocorrelation function or power spectrum can be seen in [9]. There, it is illustrated that the climacogram has always smaller statistical uncertainty from the other two stochastic tools for common processes such as Markov and Hurst-Kolmogorov (HK) as well as combinations thereof. In Fig. 8, we conclude that the wind process in Greece follows an HK process:

$$\gamma = \lambda / k^{2-2H} \tag{4}$$

where λ = 2 $\mathrm{m}^2/\mathrm{s}^2$ is the standardized variance of the discretized stationary process and H = 0.9 is the Hurst coefficient.

This behaviour is somehow expected based on the analysis of [10,11], where the HK behaviour is detected in an annual scale and in approximately 4000 stations around the globe. Also, we estimate the average marginal probability function for the standardized process and we fit a two-parameter extended Pareto-type cumulative probability function that shows good agreement with data in a global scale [12]:

$$F(v) = 1 - 1/\left(1 + (v/a_{\mathrm{p}})^2\right)^{\beta_{\mathrm{p}}} \tag{5}$$

with $\alpha_{\mathrm{p}} \approx 10$ and $\beta_{\mathrm{p}} \approx 8.5$.

Table 1. General characteristics of the 17 stations in Greece downloaded from noaa (www.ncdc.noaa.gov).

station name	longitude (deg)	latitude (deg)	elevation (m)	years of records	mean wind speed (m/s)	std wind speed (m/s)
Karpathos	27.13	35.42	20	17	7.6	4.1
Santorini	25.47	36.40	39	24	5.7	3.2
Syros	24.95	37.42	72	17	5.1	3.0
Samos	26.92	37.70	7	37	4.4	3.1
El. Venizelos	23.95	37.93	94	11	4.0	3.1
Chios	26.13	38.33	4	24	3.7	2.8
Limnos	25.23	39.92	4	38	4.4	3.5
Paros	25.13	37.02	36	11	5.5	3.3
Kavala	24.60	40.98	5	24	2.4	2.1
Meganisi	20.77	38.62	4	42	3.6	2.7
Zakynthos	20.88	37.75	5	24	2.5	2.6
Kos	27.07	36.78	129	81	4.8	2.6
N. Aghialos	22.80	39.22	15	62	3.3	2.3
Larissa	22.42	39.63	74	32	1.7	2.7
Aleksandroupoli	25.92	40.85	3	80	3.6	3.1
Herakleio	25.18	35.33	39	41	4.6	2.9
Araksos	21.42	38.15	12	17	2.6	2.1

Table 2. Estimation of the four parameters and the one coefficient of the hourly-monthly mean and standard deviation model for the 17 stations in Greece along with the model performance.

mean model (parameters)			mean model (coefficients)		r_{av}	nrmse$_{av}$	stdev model (parameter)	stdev model (coefficient)	r	nrmse$_{av}$
a_1	a_2	a_3	a_h (h)	a_m (months)			b	b_m (months)		
0.130	0.042	0.213	11.88	7.12	0.94	0.13	0.019	5.6	0.43	0.05
0.144	0.000	0.051	11.89	2.00	0.96	0.08	0.164	1.2	0.98	0.06
0.185	0.000	0.102	12.07	0.34	0.96	0.08	0.122	1.3	0.95	0.08
0.165	0.000	0.036	12.09	11.00	0.81	0.15	0.098	0.6	0.96	0.16
0.416	0.188	-0.163	12.51	6.94	0.95	0.13	0.106	0.2	0.79	0.12
0.291	0.064	-0.140	11.67	5.51	0.96	0.13	0.207	0.6	0.97	0.12
0.264	0.000	0.139	11.28	0.35	0.95	0.12	0.280	0.6	0.98	0.12
0.250	0.000	0.005	12.02	11.00	0.95	0.12	0.051	1.2	0.56	0.13
0.401	0.189	-0.306	12.44	6.67	0.96	0.12	0.210	1.1	0.98	0.07
0.305	0.000	0.060	13.73	1.80	0.66	0.22	0.217	1.2	0.99	0.10
0.477	0.220	-0.400	12.75	6.71	0.91	0.16	0.346	1.1	0.98	0.15
0.251	0.016	0.007	13.23	3.47	0.96	0.07	0.231	1.2	0.98	0.07
0.314	0.290	-0.318	13.23	6.45	0.80	0.12	0.145	1.8	0.97	0.10
0.674	0.489	-0.295	15.35	6.36	0.97	0.15	0.121	2.2	0.89	0.16
0.427	0.164	-0.323	12.27	6.50	0.97	0.11	0.270	0.7	0.99	0.10
0.171	0.119	-0.225	11.95	6.50	0.89	0.10	0.163	1.5	0.97	0.06
0.527	0.265	-0.496	13.74	6.95	0.97	0.11	0.244	1.1	0.96	0.13

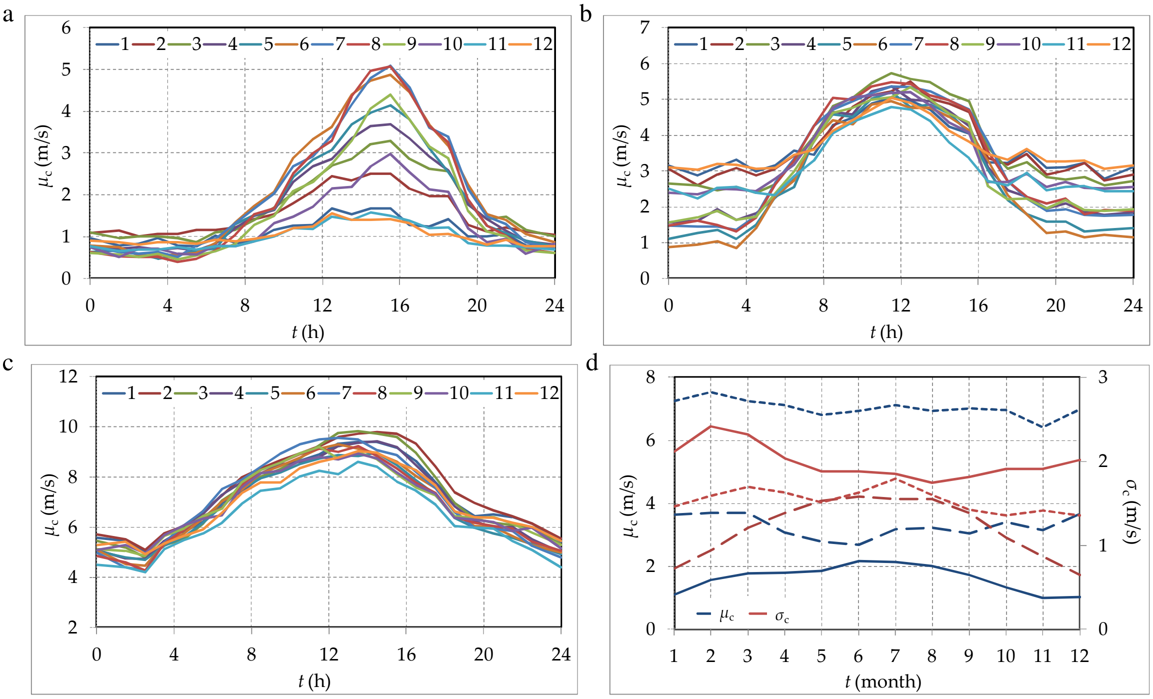


Fig. 7. Hourly-monthly mean velocities for the (a) Larissa, (b) Alexandroupoli and (c) Kos stations and monthly standard deviation of mean and standard deviation for Larissa (continuous line), Alexandroupoli (dashed line) and Kos (dot dashed line) stations.

Finally, we describe a methodology to produce synthetic hourly wind timeseries with double periodicity as well as preferable marginal characteristics and stochastic structure. Particularly, after we estimate the parameters for the hourly-monthly mean wind speed (Eq. 1), the parameters for the standard deviation (Eq. 3), the dependence structure of the process (Eq. 4) and the marginal probability function (Eq. 5), we can use the scheme described in [3] to produce hourly wind speed timeseries approximating the desired distribution and with the desired dependence structure generated by the sum of multiple Markov processes. The generation algorithm used in [3] is introduced in [9] and although it includes only two parameters, it is capable of generating any length of timeseries following an HK or various other processes. By applying this method we assume stationarity in autocorrelation rather than cyclostationarity. Although this assumption can be cruel for certain hydrometeorological processes, it can be applied as an approximation for the wind process, due to the small fluctuation of the autocorrelations of wind for the same lag in different months.

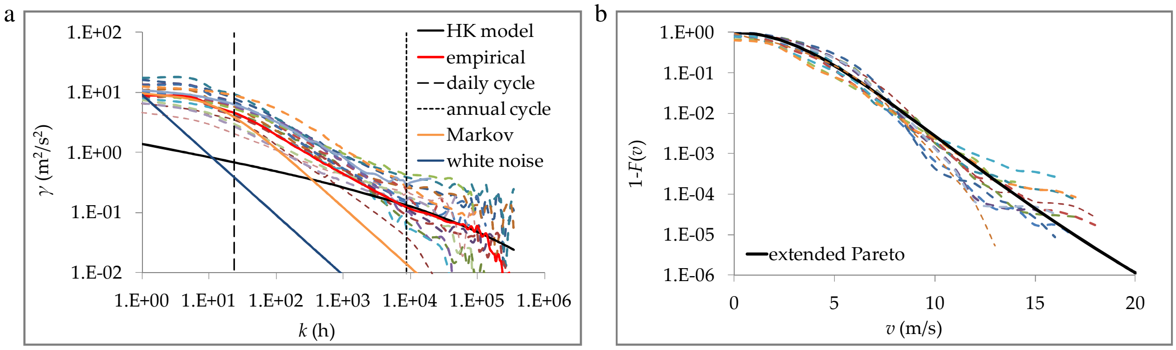


Fig. 8. (a) Climacograms for all stations, best fitted HK, Markov and white noise processes and model; (b) empirical tail functions for all stations and model.

4. Conclusions

In this paper, we investigate the double periodicity of wind and we present a model for the hourly-monthly mean comprising four parameters. We further test our model against approximately 2000 stations around the globe with 75% of stations having correlation coefficients with the observed values above 0.9. Finally, we apply our model to several stations in Greece by also suggesting a deterministic model for the hourly-monthly standard deviation and an HK stochastic model for the dependence structure with a Pareto-type marginal probability function, all showing excellent agreement with data.

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