

Session ERE3.8/HS5.6: Harnessing the resources offered by sun, wind and water: control and

# Application of stochastic methods for wind speed forecasting and wind turbines design at the area of Thessaly, Greece.

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The poster can be downloaded at: http://www.itia.ntua.gr/en/docinfo/1535/

#### "The answer my friend is blowin' in the wind" from Bob Dylan's song released in 1962

Several methods exist for estimating the statistical properties of wind speed, most of them being deterministic or probabilistic, disregarding though its long-term behaviour. Here, we focus on the stochastic nature of wind. After analyzing several historical timeseries at the area of interest (AoI) in Thessaly (Greece), we show that a Hurst-Kolmogorov (HK) behaviour is apparent. Thus, disregarding the latter could lead to unrealistic predictions and wind load situations, causing some impact on the energy production and management. Moreover, we construct a stochastic model capable of preserving the HK behaviour and we produce synthetic timeseries using a Monte-Carlo approach to estimate the future wind loads in the AoI. Finally, we identify the appropriate types of wind turbines for the AoI (based on the IEC-61400 standards) and propose several industrial solutions.

1. Abstract - Introduction

9. Stochastic structure (cont.)

**--**·10% n

Figure 5: Larissa, Note that we fit the model up

1.E+00 1.E+01 1.E+02 1.E+03 1.E+04 1.E+05 1.E+0

# 5. Cyclostationarity (cont.) Figure 2: (a) within-day fluctuation of hourly mean wind speed (w) for each month; (b) cyclostationary model fitting for months 2 (Feb.), 5 (May), 8 (Aug.) and 11 (Nov.); and (c) monthly fluctuation of cyclostationary model coefficients. All correspond to the Larissa station (HNMS).

We estimate the empirical climacogram (from hourly to climatic scale) for

the long timeseries of NOA and then, we fit an HK model to the apparent

to 10% of *n* (following the rule of thumb, cf. [5]). by high uncertainty).

long-term behaviour:

 $\gamma(m) = \frac{1}{m^{2-2H}}$ 

We calculate that the best fit,

for scales up to 10% n, is for  $\lambda$ 

 $\approx 45 \text{ m}^2/\text{s}^2$  and  $H \approx 0.7$  (Hurst

coefficient, ranging from 0 to

1), with correlation coefficient

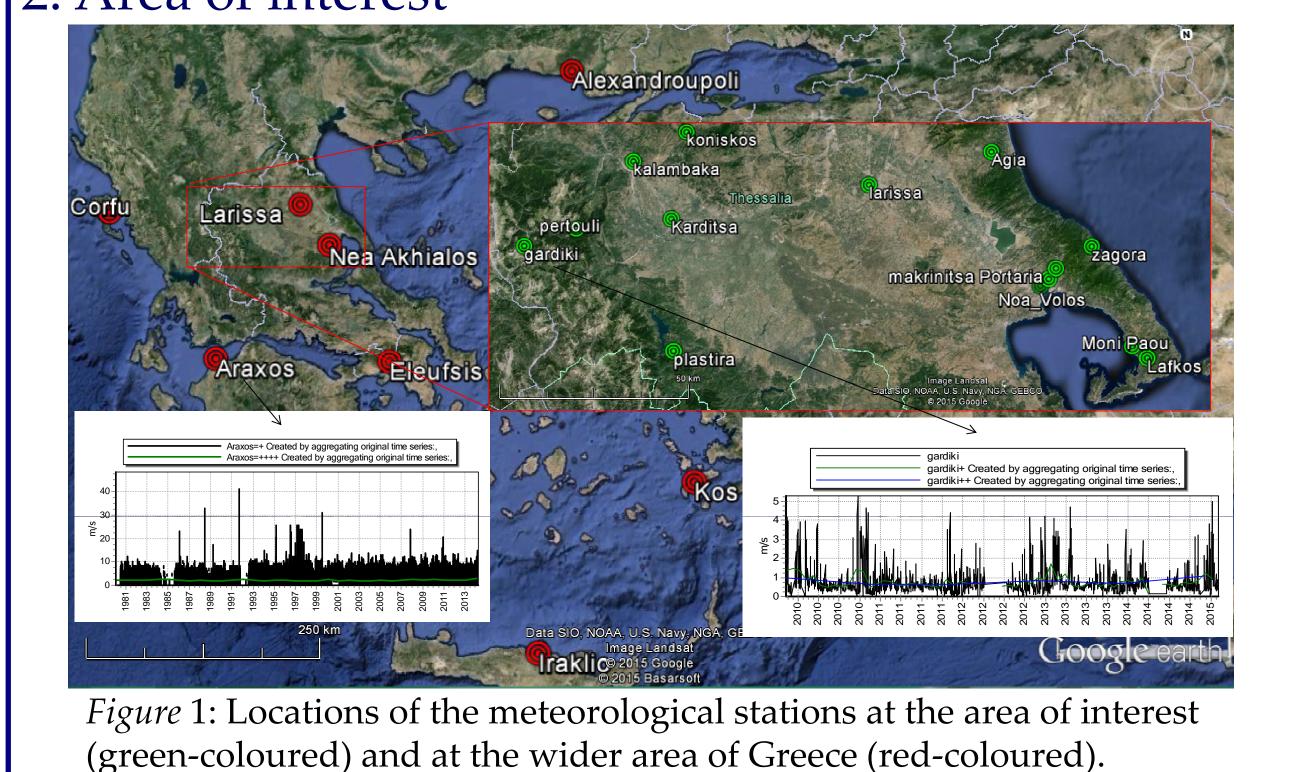
empirical variance's deviation

from the power-law model at

latter scales, is characterized

of  $R^2 \approx 95\%$  (note that the

### 2. Area of interest



### 6. Probability functions

For the marginal distribution functions of w, we check the Normal, Gamma and Weibull (cf. [3]), using maximum likelihood algorithms for the parameters' estimation (neglecting the low w part). For the Larissa station the minimum error corresponds to the Gamma function (with k=4.829 and  $\theta=0.758$ ), while for most other stations is the Normal one.

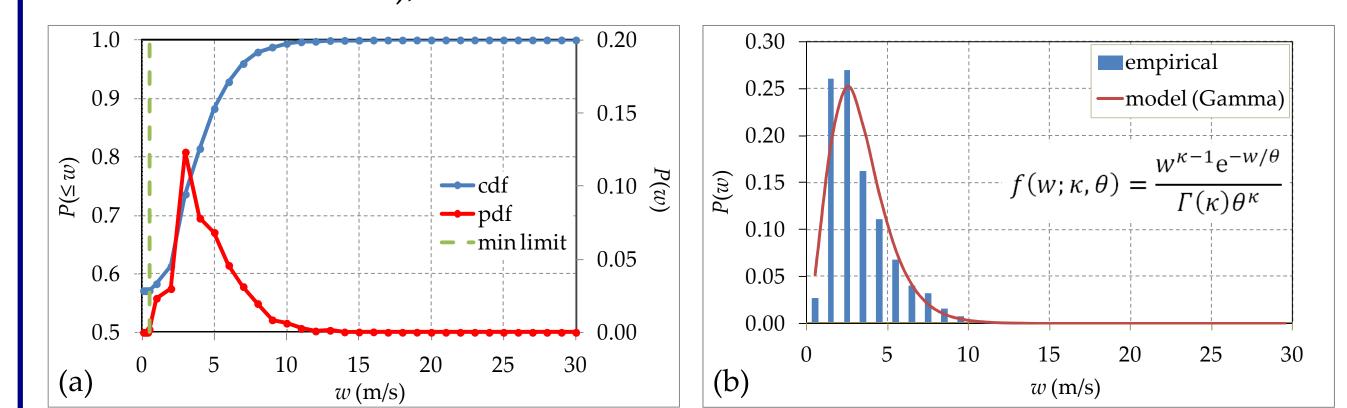


Figure 3: (a) Empirical cumulative and probability density functions of wind speed (with low value limit); and (b) fitting of the Gamma function for the Larissa station.

## 10. Stochastic generation of hourly wind speed

For the wind turbines installation we choose the area near the Plastira station, which exhibits the larger hourly mean wind speed, i.e. 11.782 m/s (calculated by multiplying the daily mean with 4.458, which is the ratio of the mean values of the HNMS and NOA stations of Larissa).

We can then produce an hourly wind speed timeseries by preserving the cyclostationary-deterministic model of Larissa station (which is the nearest one with a long period and an hourly time-step), the desired distribution function and the HK stochastic process (following [5]).

We finally categorize the wind turbine generator into class II, based on the IEC-61400 standards (cf. [6]) and for an annual average wind speed greater than 10 m/s as well as for a reference one approx. 33 m/s (estimated from the wind gust distribution function of the Larissa station). A possible industrial solution for the wind turbine is the ENERCON E-82 (e.g. [1]).

### 3. Marginal characteristics

Table 1: General characteristics of stations over the AoI To test the wind and allover Greece for wind speed and gust. potential over the AoI (cf. [1]), we choose to analyze 16 stations from NOA (meteo.gr). Due to the minimum daily scale and the small number of Nea Akhialos HNMS 22.800 39.217 years with available data, we also analyze 8 stations from allover Greece from HNMS (noaa.gov), which are in an hourly scale and include up to 75 years of measurements.

#### 7. Probability function (cont.)

For the marginal distribution functions of wind gust  $(w_{\sigma})$ , we check the General Extreme Value (GEV), Burr and Generalized Gamma (cf. [4]), using again the method of maximum likelihood. For the Larissa station the minimum error corresponds to the Burr function (with a=12.125, c=9.865 and l=0.831), while for most other stations is the GEV one.

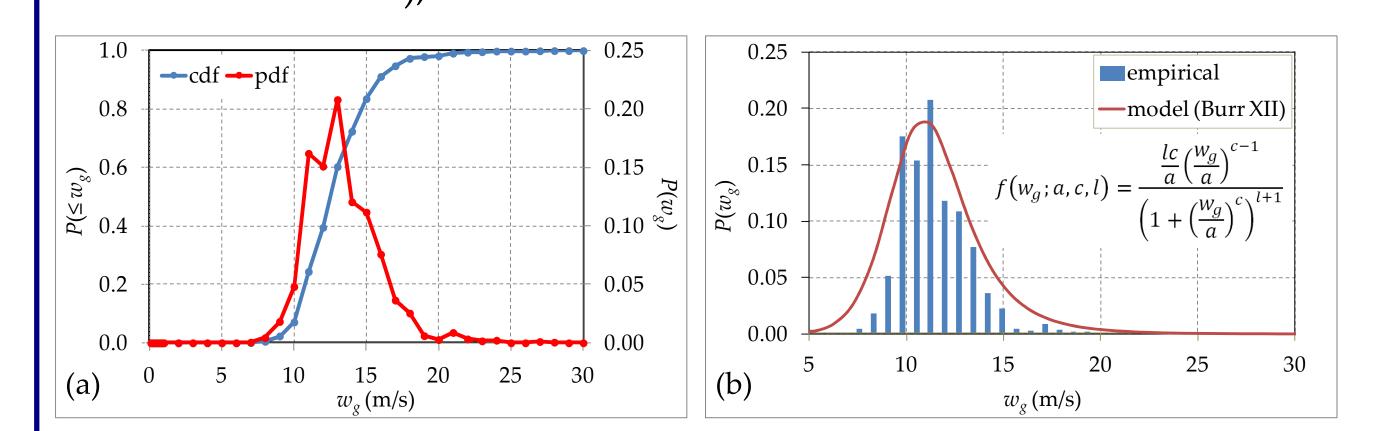


Figure 4: (a) Empirical cumulative and probability density functions of wind gust; and (b) fitting of the Burr function for the Larissa station.

11. Energy production forecasting Furthermore, we can estimate the hourly energy production (denoted E) based on the turbine's power curve (a time-window of the first month of

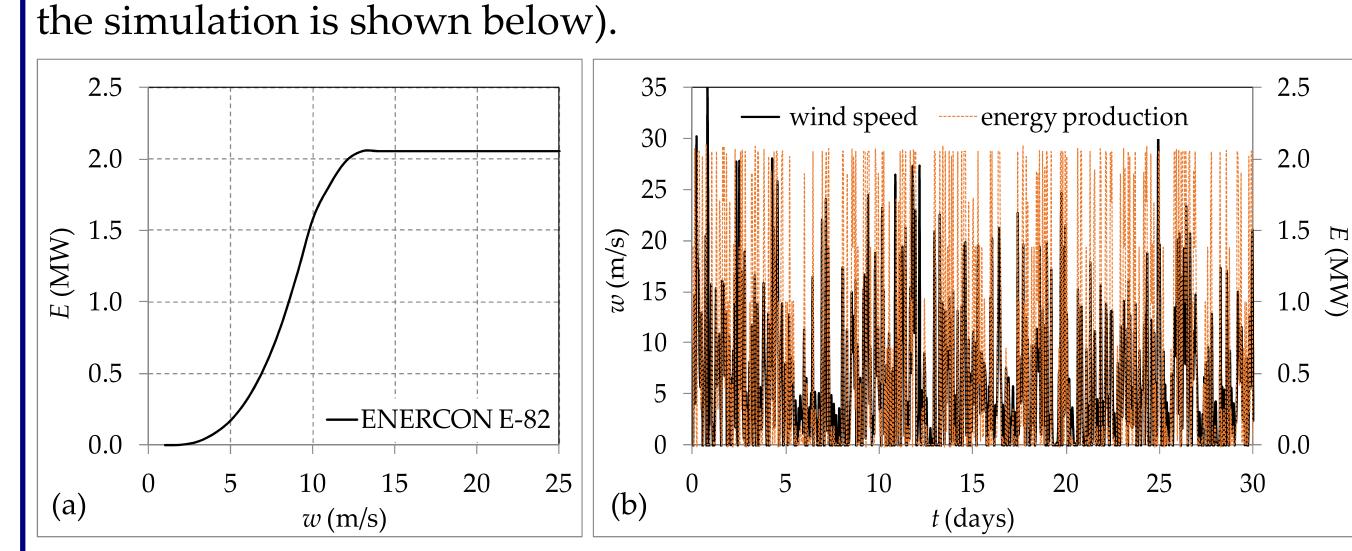


Figure 6: (a) wind turbine power curve (enercon.de) and (b) one month wind speed forecasting and the corresponding energy production from the wind turbine.

### 4. Cyclostationarity

The wind process (like any other hydrometeorological process) includes two cyclostationarities, one seasonal and one daily (cf. [2]). We apply a simple model of double periodicity (described by the equations below) to catch simultaneously both of them using nine dimensionless coefficients:

$$\mu_{\rm c}(t) = A(t) e^{-\cos(2\pi(t+B(t))/24)} + C(t)/\mu_{\rm h}$$
 (1)

$$A(t) = a_{\rm A} \cos \left( 2\pi \frac{(t + b_{\rm A})}{12 * 24 * 30.5} \right) + c_{\rm A}/\mu_{\rm h}$$
 (2)

$$B(t) = a_{\rm B} \cos \left( 2\pi \frac{(t + b_{\rm B})}{12 * 24 * 30.5} \right) + c_{\rm B}/\mu_{\rm h}$$
 (3)

$$f(t) = a_{\rm C} \cos\left(2\pi \frac{(t+b_{\rm C})}{12*24*30.5}\right) + c_{\rm C}/\mu_{\rm h}$$
 (4)

where t denotes time in hours;  $a_A$ ,  $a_B$ ,  $a_C$  are dimensionless coefficients;  $b_A$ ,  $b_B$ ,  $b_C$  are in time units;  $c_A$ ,  $c_B$  and  $c_C$  are in m/s; and  $\mu_h$  is the hourly mean of the process.

### 8. Stochastic structure

We investigate the structure of the wind process with the climacogram (i.e. variance of the averaged process versus averaging time scale). This choice is based on the analysis of [5], where the aforementioned stochastic tool resulted (for all the examined processes, e.g. Markov, HK and combinations thereof) in a smaller statistical uncertainty (i.e. meansquared error) for the majority of scales, in comparison to the power spectrum and autocovariance. In the equations below, we show its definition and expected value of its classical estimator:

$$\gamma(m) \coloneqq \operatorname{Var}\left[\int_0^m \underline{w}(\xi) d\xi\right]/m^2$$

where the underlined symbols denote random variables, m (in units of time) and k

Table 2: Model

coefficients for

station (HNMS).

*a* | 0.463 | 0.736 | -0.144

*b* |-1.107 |-6.558 |-6.776

0.323 | 1.039 | -1.619

A B C

the Larissa

(dimensionless) are the scales of the continuous and discrete-time process,  $\Delta$  is the sampling time interval and n is the total number of observations.

#### 12. Conclusions

We present a methodology for constructing a wind process and energy production model on an hourly time-scale, essential for the energy management of renewable sources. This model can preserve both daily and seasonal periodicity as well as the distribution function and stochastic structure of the process. Additionally, we apply the model to the area of Thessaly (Greece) and we propose an industrial wind-turbine solution based on the IEC-61400 standards classification.

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