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HS3.3/ERE6: Stochastic modelling and real-time control of complex environmental systems

Empirical metric for uncertainty assessment of wind forecasting models in terms of power production and economic efficiency

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Setting the wind energy forecasting problem

- As made for almost all renewable energy sources, aeolic energy is driven by **highly uncertain and thus unpredictable wind processes**.
- Since the generation of aeolic energy is **nonlinear transformation of wind speed** through the **power curve** of the turbine, **the errors in meteorological predictions have different impacts on wind power forecasts.**
- For quite a large range of wind speed values, the wind power production is either **zero or constant**, thus **independent of the individual wind velocity value**.
- Taking advantage of this interesting feature, the methodology being developed aims to **assess the performance of wind forecasting models**, with focus to output accuracy, i.e. energy production, instead of input, i.e. wind speed.
- In particular, the methodology consists of four key stages:
  - **Statistical and stochastic assessment** of wind process;
  - Quantification of **wind forecasting uncertainty** using typical error metrics;
  - Contrasting of errors in wind forecasting with errors to derived energy production (**transformation of input to output errors**);
  - Development of **overall performance measure** accounting for the **economic footprint** of wind errors to energy predictions.
- For our analyses we consider the operation a commercial 900 MW wind turbine in **Ikaria island**, Aegean sea, Greece, driven with hourly wind speed data (7 years).

Our methodology in a nutshell

Input data: Hourly time series of wind speed, commercial wind turbine with given power curve

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Statistical analysis for various time scales and simulation of wind energy production

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Wind speed forecasting using simple models with **a priori known uncertainties** and **evaluation** of wind and energy errors via a number of typical statistical metrics

↓

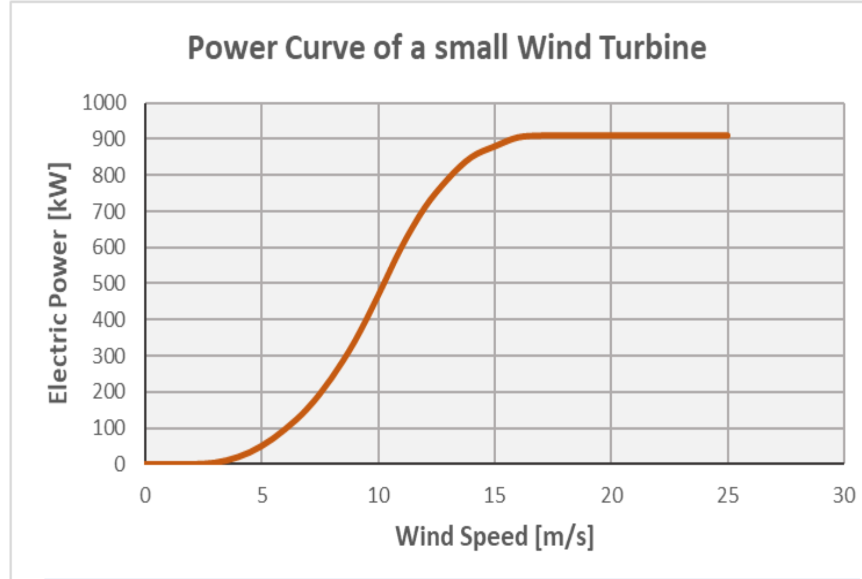
Pseudo-economic evaluation of forecasting models through a newly developed empirical index

↓

Combination of different approaches towards establishing a **generic protocol for assessing wind forecasting models** both in terms of power production and economic efficiency (*preliminary outcomes shown h*ere).

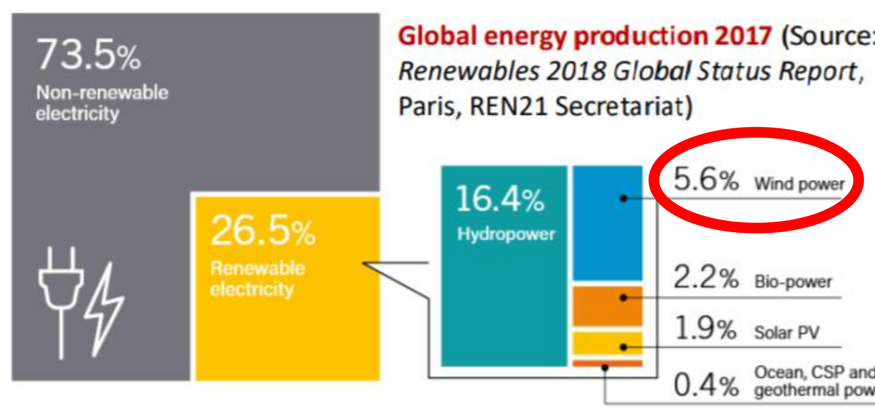
Brief overview of wind energy production

- Aeolic (wind) energy is renewable, as driven by the **kinetic energy of wind**.
- The efficiency of an ideal wind turbine is bounded to a theoretical upper value (**Betz limit**), which equals 16/27.
- The actual efficiency of a real-world turbine is expressed by the **power curve**, which is provided by the manufacturer.
- Wind turbines operate within a range of **feasible wind speed values**, typically from 3.5 to 25.0 m/s (cut-off limit is set for safety); for relatively large wind speed values, the turbine produces an almost constant energy, i.e. the **nominal power**.



Wind energy is nonlinear transformation of wind speed, through the power curve of each specific turbine.

<u>Wind Power Capacity Statistics (year 2018)</u>
Worldwide: 600 GW (53.9 GW added in 2018)
China: 221 GW
EU-28: 189 GW (sharing 14% of electricity demand)
Greece: 2.84 GW (9% of demand)
Highest share: Denmark (41%)

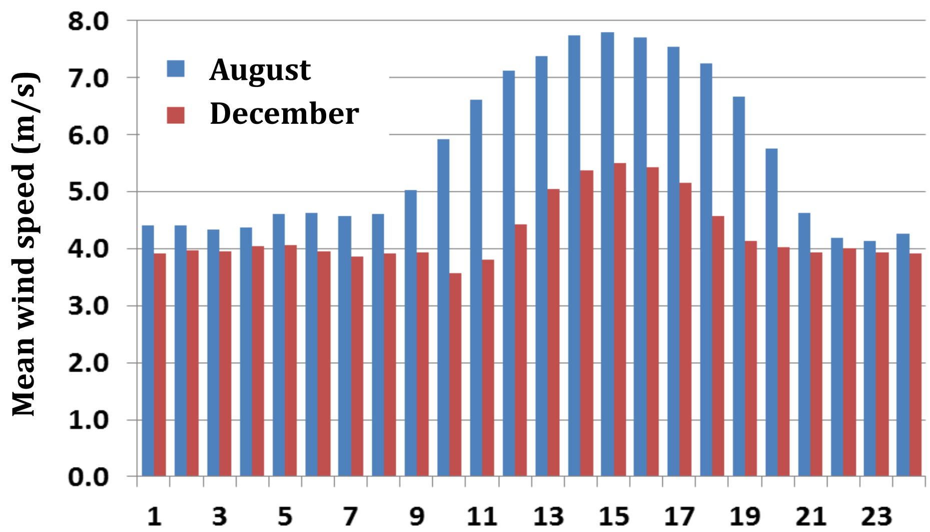


Global energy production 2017 (Source: *Renewables 2018 Global Status Report*, Paris, REN21 Secretariat)

From wind process peculiarities to forecasting challenges

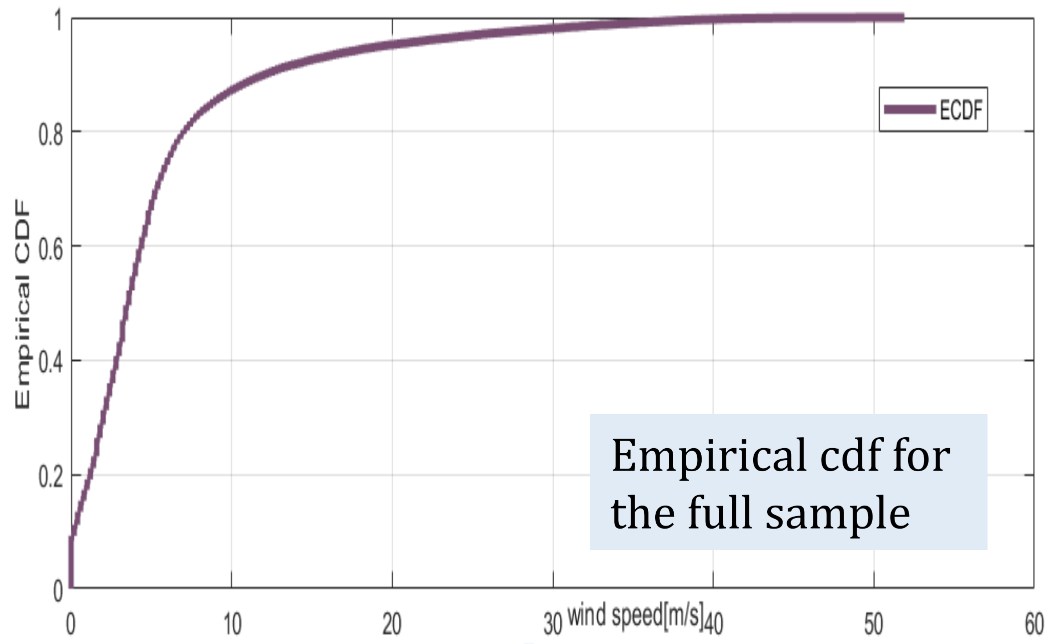
- The wind speed process is governed by **irregular fluctuations** across all scales, and the common peculiarities of all hydrometeorological processes (non-Gaussian behavior, strong asymmetries at fine time scales, long-term persistence, auto-dependencies, etc.);
- Additional feature is its **double periodicity**, as result of deterministic **intra-daily and seasonal** cycles.
- While wind forecasting is by definition a very challenging task, even more challenging is the investigation of **its effects to energy forecasts**, induced by the nonlinear transformation through the power curve of wind turbines.
- **Are the existing evaluation measures for wind forecasting representative enough in terms of energy?**

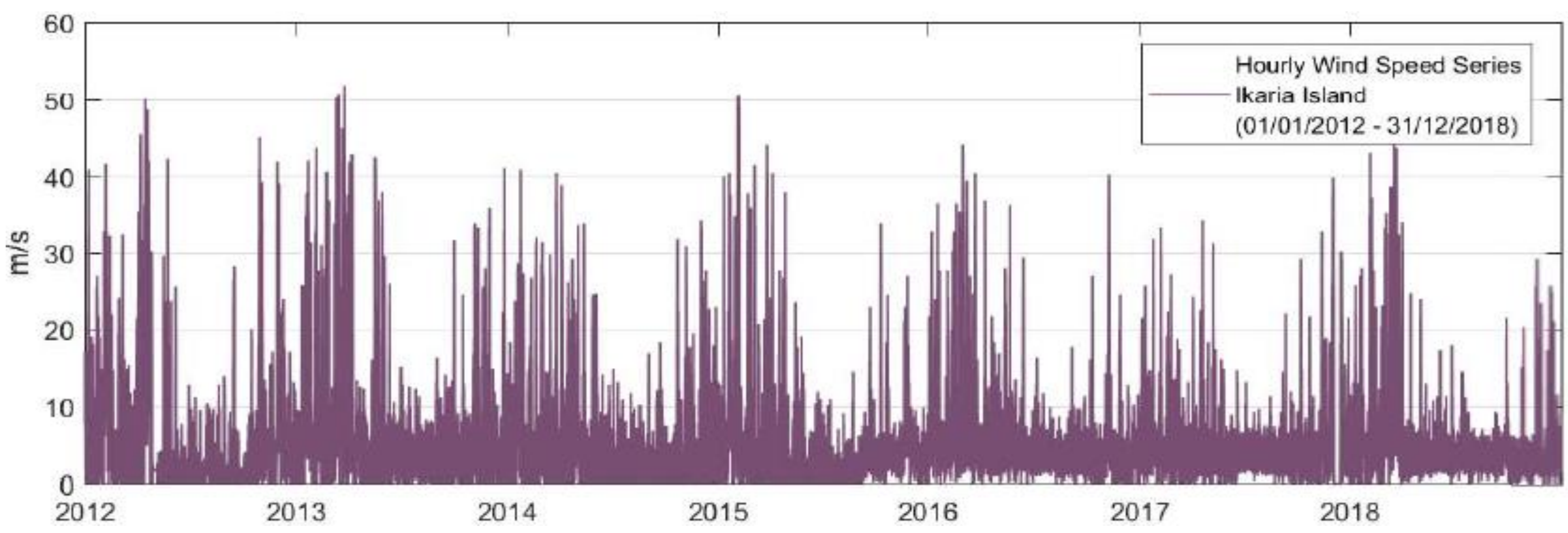
The double periodicity of wind processes, indicated by contrasting average hourly speed data from Ikaria island across the daily time scale (24 values), and across seasons (two characteristic months are shown, i.e. August and December)



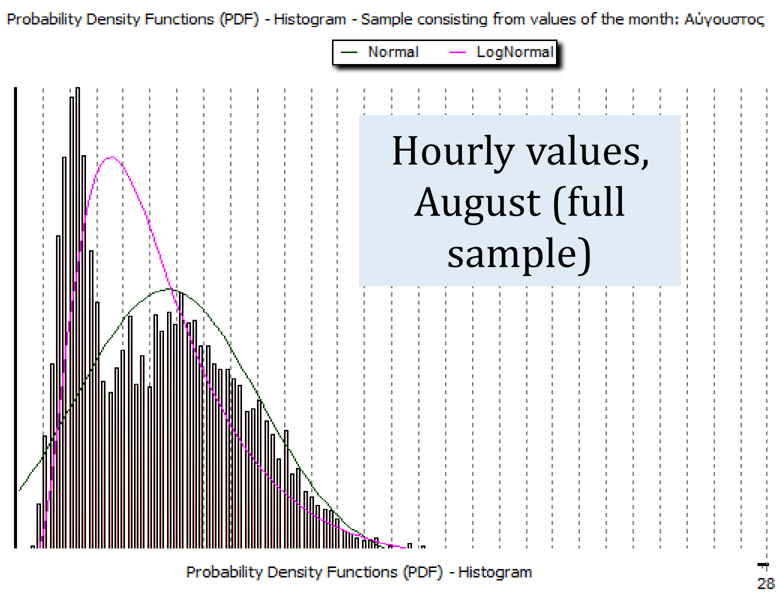
Case study data

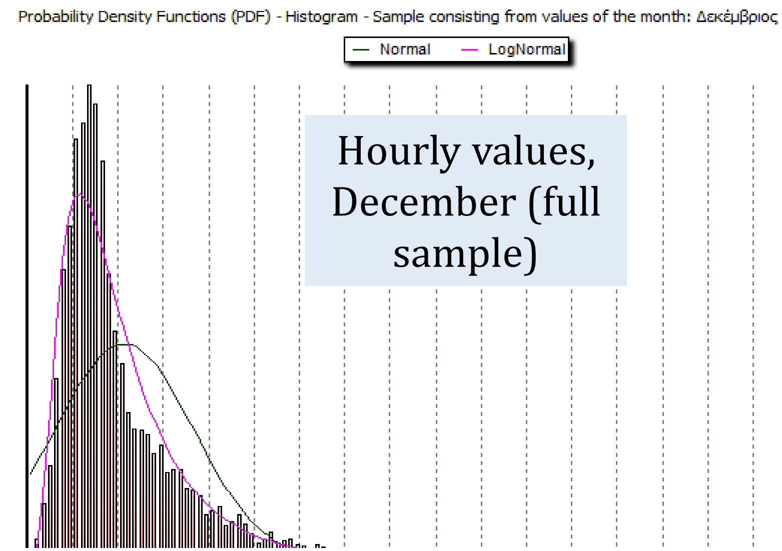
- Raw ten-minute timeseries from Ikaria island, from 2012 to 2019;
- Aggregation of 10-min data to hourly time scale;
- Wind turbine VESTAS 900 kW, with known power curve;
- Adjustment of wind speed data to the elevation of the hub (logarithmic law);

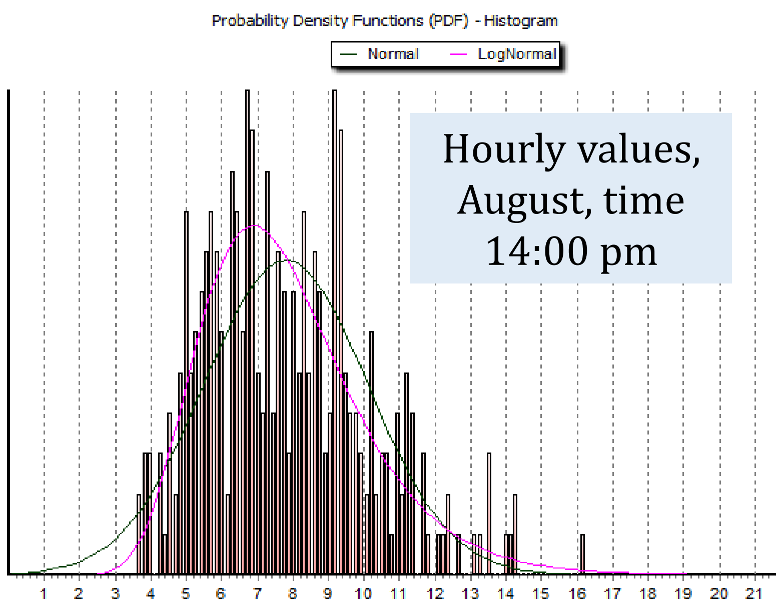


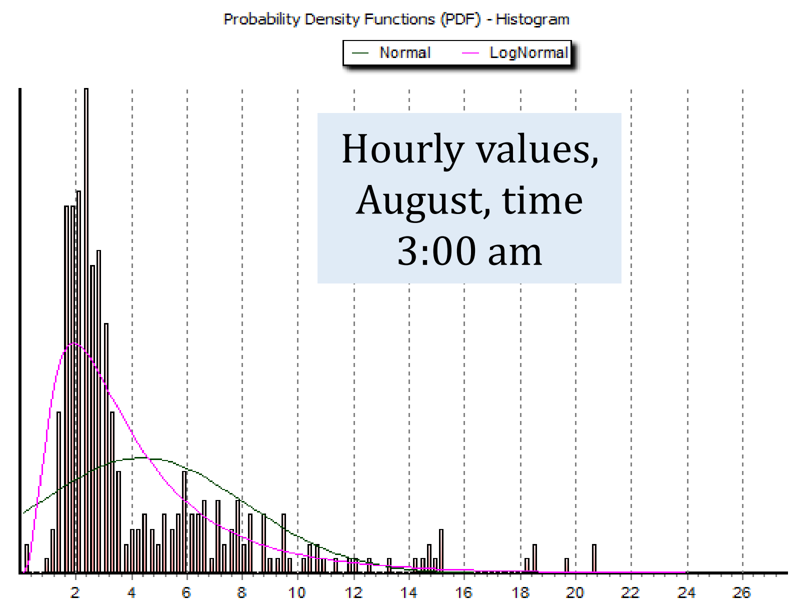


Statistical analysis of hourly wind data







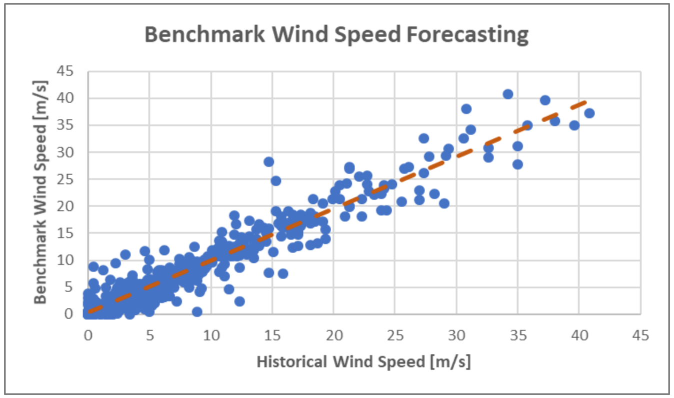


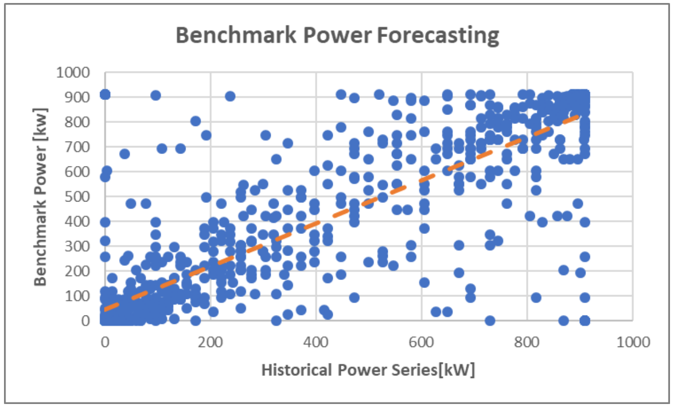
Wind forecasting models (for testing purposes only!)

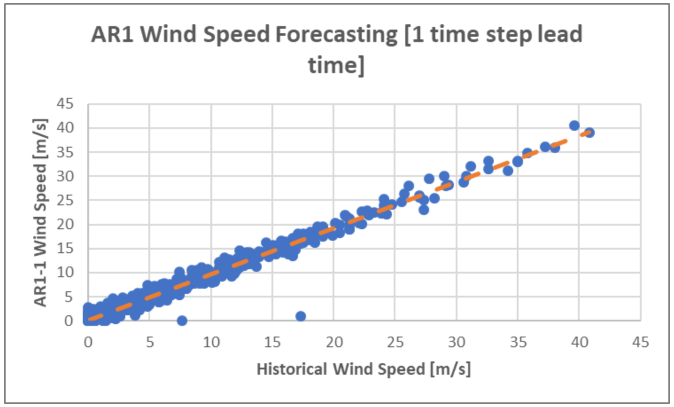
- For the purpose of developing and testing the empirical performance metrics, we employed simple wind forecasting models that enable us to know in advance the structure of the error and the uncertainty they contain.
- The models used are:
  - **Last-known-value forecasting model**, that considers the previous hourly observation as predictor of the wind speed value of the current time step (hour $t = 0$);
  - **First-order autoregressive stochastic model AR(1)**, employed with lead times one and two hours (the model accuracy is expected to decrease with time lag, following the autocorrelation structure of wind);
  - **Whatever model**, simply derived by adding to actual (observed) data a normal (version A) and a uniform (version B) error, with known statistical properties, e.g. m=0, s=1;
- By aware that none of the above approaches are operational. Ongoing research will provide further analyses using more sophisticated forecasting schemes (stochastic, copulas, machine learning, analogues, etc.).

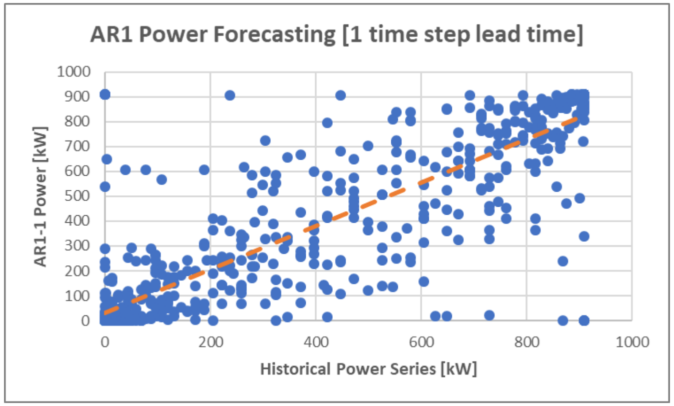
> ➢ *The last-known-value forecasting model model will be next used as **benchmark** for the evaluation approach using the proposed performance index*

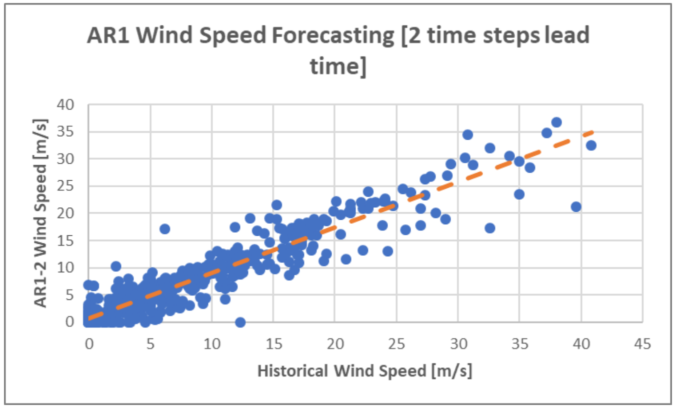
Predictive capacity in wind and energy terms (1)

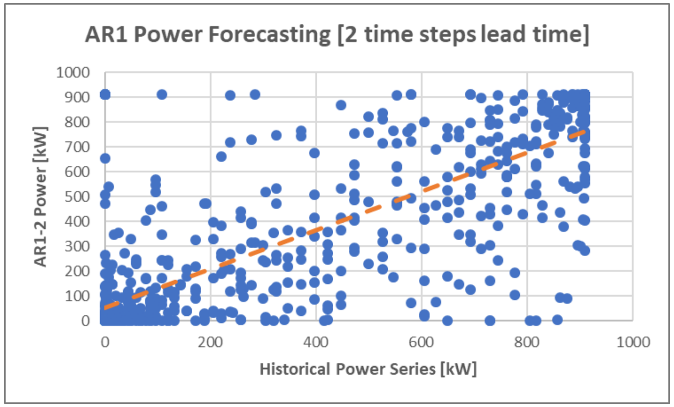




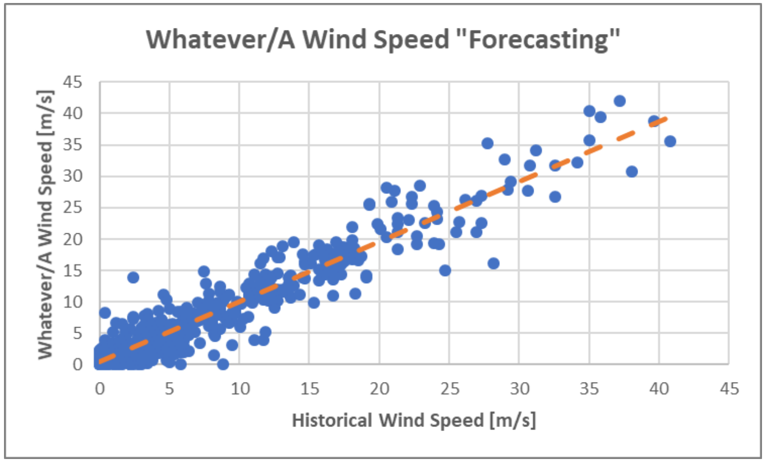


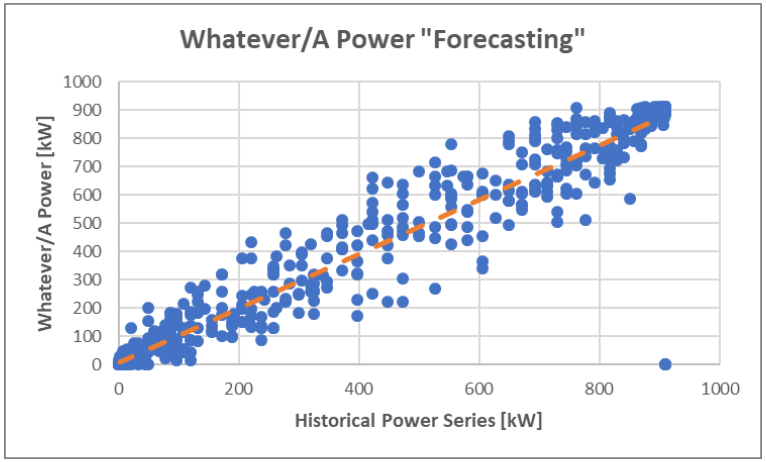


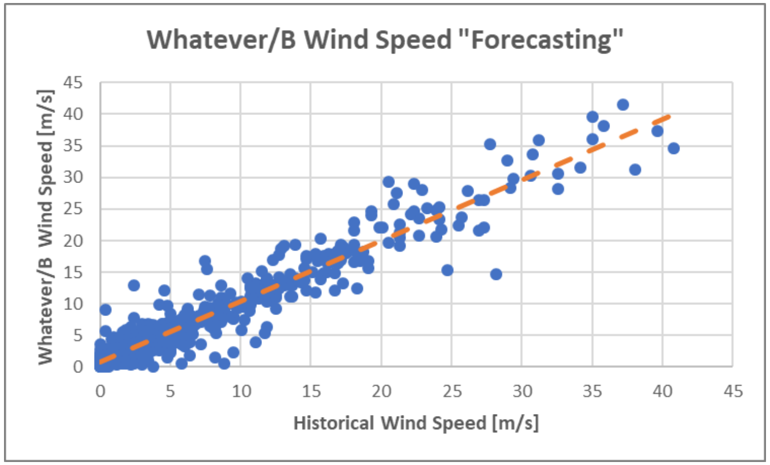


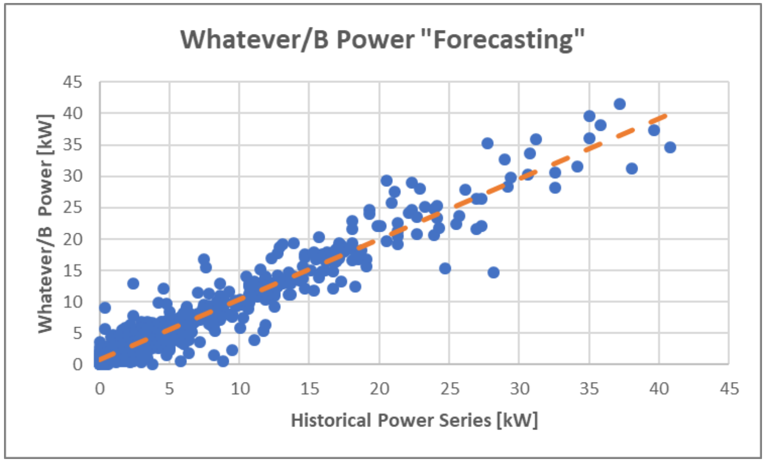


Predictive capacity in wind and energy terms (2)



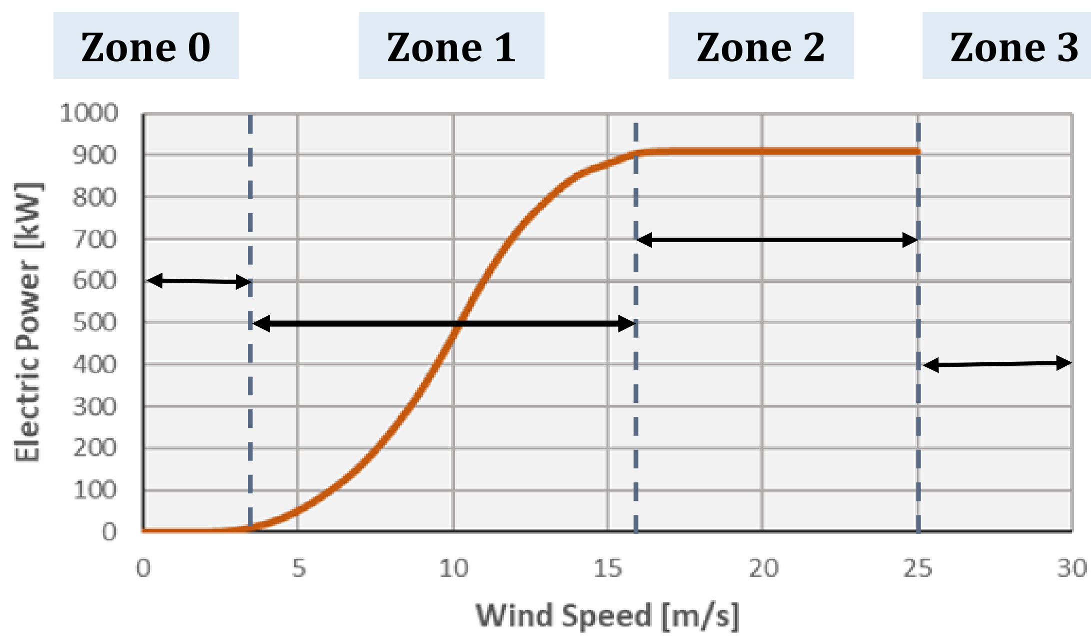






Further challenges induced by the power curve

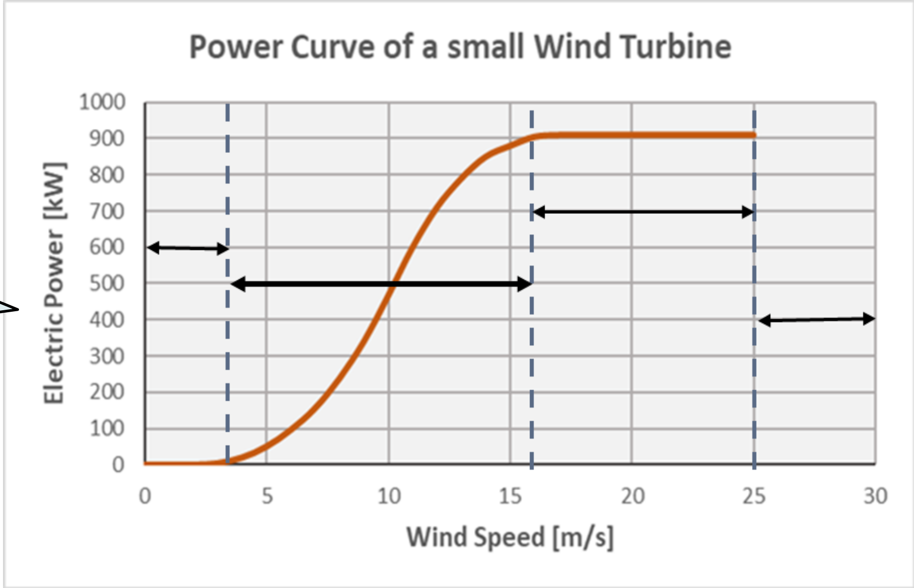
- Our analyses so far reveal that even for good wind forecasts there are significant errors in power forecasts, especially in the range of high wind speed values.
- This feature is easily interpreted if we consider the **irregular shape of the wind turbine power curve**, which can be classified into **four characteristic zones**:
  - Zone 0: low wind speed → no power production;
  - Zone 1: medium wind speed → nonlinear transformation of wind velocity;
  - Zone 2: high wind speed → constant power production;
  - Zone 3: extreme wind speed → wind turbines stop operating;
- The most uncertain area is near the cut-off point, where a minor deviation in wind speed may result in grand losses in energy production. In this respect, **a slight error in wind forecasting will dramatically effect in power forecasting (all or nothing!)**.



From wind value forecasting to power-zone forecasting

- Provided that for zones 0, 2 and 3 the wind power production **is either zero or constant, thus independent of the individual wind velocity value**, a relatively small error in wind forecast may ensure a perfect forecast of power production.
- In this respect, **it suffices to predict the power zone**, and not the wind value.
- Regarding zone 2, the power production is a non-linear transformation of the wind velocity, therefore the forecasting accuracy depends on the applied model.
- The classification of the power curve into four zones allows for expressing the forecasting problem in **discrete** terms, thus assessing the **transition probabilities** across all combinations of zones (4×4 matrix).

How does the zone classification impact forecasting outcomes?



Transition probabilities

HISTORICAL DATA TRANSITION PROBABILITIES				
ZONE	0	1	2	3
0	80,90%	19,10%	0,00%	0,00%
1	11,95%	86,56%	1,44%	0,05%
2	0,00%	24,27%	63,89%	11,84%
3	0,00%	1,21%	12,71%	86,08%

BENCHMARK TRANSITION PROBABILITIES				
ZONE	0	1	2	3
0	80,90%	19,10%	0,00%	0,00%
1	11,95%	86,56%	1,44%	0,05%
2	0,00%	24,27%	63,89%	11,84%
3	0,00%	1,21%	12,71%	86,08%

AR1[Lead Time 1] TRANSITION PROBABILITIES				
ZONE	0	1	2	3
0	73,27%	26,70%	0,02%	0,01%
1	17,82%	80,61%	1,52%	0,05%
2	0,05%	26,04%	61,77%	12,14%
3	0,06%	1,65%	13,17%	85,13%

AR1 [Lead Time 2] Model TRANSITION PROBABILITIES				
ZONE	0	1	2	3
0	78,44%	21,50%	0,05%	0,01%
1	15,20%	83,66%	1,01%	0,13%
2	0,31%	18,53%	72,36%	8,80%
3	0,07%	2,02%	12,28%	85,63%

Whatever/A TRANSITION PROBABILITIES				
ZONE	0	1	2	3
0	73,12%	26,87%	0,01%	0,00%
1	17,17%	81,21%	1,56%	0,06%
2	0,10%	26,29%	60,16%	13,46%
3	0,00%	1,40%	14,12%	84,48%

Whatever/B TRANSITION PROBABILITIES				
ZONE	0	1	2	3
0	77,13%	22,87%	0,00%	0,00%
1	10,82%	87,78%	1,35%	0,05%
2	0,05%	24,38%	63,27%	12,31%
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Transition probabilities

HISTORICAL DATA TRANSITION PROBABILITIES				
ZONE	0	1	2	3
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ZONE	0	1	2	3
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2	0,00%	24,27%	63,89%	11,84%
3	0,00%	1,21%	12,71%	86,08%

Identical transition probabilities ... though, 84% accurate zone prediction and 51% accurate power!

AR1[Lead Time 1] TRANSITION PROBA				
ZONE	0	1	2	
0	73,27%	26,70%	0,02%	0,01%
1	17,82%	80,61%	1,52%	0,05%
2	0,05%	26,04%	61,77%	12,14%
3	0,06%	1,65%	13,17%	85,13%

RANSITION PROBABILITIES				
		1	2	3
0	78,44%	21,50%	0,05%	0,01%
1	15,20%	83,66%	1,01%	0,13%
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Transition probabilities

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1	11,95%	86,56%	1,44%	0,05%
2	0,00%	24,27%	63,89%	11,84%
[illegible]	[illegible]	[illegible]	[illegible]	86,08%

Increased transition probability from Zone 2 to Zone 3, leading to significant deviations in the forecasting output.

AR1[Lead Time 1] TRANSITION PROBABILITIES				
ZONE	0	1	2	3
0	73,27%	26,70%	0,02%	0,01%
1	17,82%	80,61%	1,52%	0,05%
2	0,05%	26,04%	61,77%	12,14%
3	0,06%	1,65%	13,17%	85,13%

[illegible]OBABILITIES				
[illegible]	0	1	2	3
0	78,44%	21,50%	0,05%	0,01%
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ZONE	0	1	2	3
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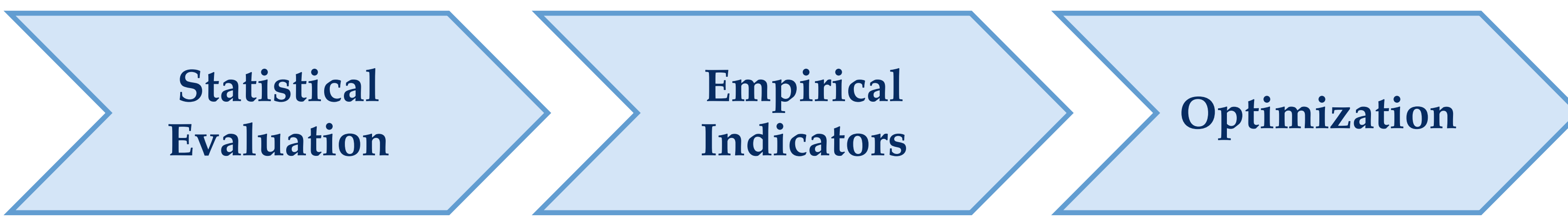
3	0,00%	1,29%	12,56%	86,15%

Impacts of power curve to forecasting outputs

- The wind power curve's shape in Zones "0" and "2" offers a considerable advantage in terms of forecasting accuracy for a significant range of wind speed values.
- On the other hand, the fluctuations between Zones "2" and "3" introduced pronounced predictive uncertainty, thus resulting to energy deficits and/or surpluses during prosperous periods of high wind speed.

<u>Key research idea:</u> Taking advantage of the shape of power curve in Zones 0 and 2 and by accounting for the fluctuations between Zones 2 and 3, we can provide a **robust forecasting model evaluation approach in terms of energy production and economic efficiency**.



Statistical evaluation of forecasting models using everyday goodness-of-fitting metrics (there are too many ….)

- In order to evaluate the forecasting models, several statistical measures were applied in both wind and power production outputs for each model.
- Particularly, **13 typical goodness-of-fitting metrics** that are generally employed within hydrological evaluations were applied to investigate the performance of each model in terms of accuracy and sensitivity.

Wind Forecasting Statistical Performance Measures													
	nRMSE	***BIAS***	***pBIAS***	***rSR***	***rSD***	***NSE***	***mNSE***	***rNSE***	***d***	***md***	***cp***	***Pr***	***R2***
Benchmark	*3,72*	*0,00*	*0,00*	*0,29*	*1,00*	*0,92*	*0,71*	*0,92*	*0,98*	*1,00*	*0,00*	*0,96*	*0,92*
AR1 -1	*4,10*	*0,02*	*-2,25*	*0,32*	*0,97*	*0,90*	*0,66*	*0,90*	*0,97*	*0,99*	*-0,22*	*0,95*	*0,90*
AR1-2	*5,65*	*0,06*	*-6,39*	*0,44*	*0,93*	*0,80*	*0,53*	*0,80*	*0,95*	*0,96*	*-1,31*	*0,90*	*0,81*
Whatever/A	*1,83*	*-0,01*	*1,07*	*0,14*	*1,00*	*0,98*	*0,82*	*0,98*	*0,99*	*1,01*	*0,76*	*0,99*	*0,98*
Whatever/B	*1,11*	*-0,09*	*9,33*	*0,09*	*1,00*	*0,99*	*0,88*	*0,99*	*1,00*	*1,06*	*0,91*	*1,00*	*1,00*

Power Forecasting Statistical Performance Measures													
	nRMSE	**BIAS**	**pBIAS**	**rSR**	**rSD**	**NSE**	**mNSE**	**rNSE**	**d**	**md**	**cp**	**Pr**	**R2**
Benchmark	*14,51*	*0,00*	*0,00*	*0,55*	*1,00*	*0,69*	*0,69*	*0,69*	*0,92*	*1,00*	*0,00*	*0,85*	*0,72*
AR1 -1	*14,38*	*0,01*	*-12,27*	*0,55*	*0,99*	*0,70*	*0,68*	*0,70*	*0,92*	*1,00*	*0,02*	*0,85*	*0,72*
AR1-2	*18,97*	*0,03*	*-2,64*	*0,72*	*0,98*	*0,48*	*0,54*	*0,48*	*0,85*	*0,99*	*-0,71*	*0,73*	*0,54*
Whatever/A	*6,86*	*-0,01*	*2,75*	*0,26*	*1,00*	*0,93*	*0,86*	*0,93*	*0,98*	*1,01*	*0,78*	*0,97*	*0,93*
Whatever/B	*5,47*	*-0,11*	*10,79*	*0,21*	*1,02*	*0,96*	*0,90*	*0,96*	*0,99*	*1,04*	*0,86*	*0,98*	*0,96*

And now what?

- Different evaluation outcomes depending on the applied measure…
- Many different metrics may result to confusing and contrasting conclusions.
- Forecasting accuracy always leads to desired power and economic efficiency...? No, if we don’t take into account the **power curve impact** to the forecasting output.

Empirical pseudo-economic index for wind power

- When we deal with wind energy production, instead of evaluating the wind and energy forecast by applying statistical comparison measures, it is proposed to analyze the **simulated energy data per se**, relying on empirical indicators.
- In this respect, we propose an overall index that derives from a simple yet effective **pricing procedure, inspired from hydroelectric energy assessment**.
- Key assumption is to consider **actual energy as demand** and assign **economical goals** based on **comparisons with predicted energy**.
- For each time step, the forecasted energy is evaluated depending on whether the energy pseudo-demand is met or not. In particular:
  - Each time step takes a unit score, for each kWh meeting the demand.
  - For each kWh of surplus, the score increases by 30%.
  - For each kWh of deficit, the score decreases by 800%.
- In order to express a **dimensionless index**, the outcome score is compared to a reference score of a benchmark model or to the absolute score of historical data.
- This **unique and representative performance metric** can be used for direct evaluation of any forecast in terms of energy production and economic efficiency.

Results for Ikaria

Model	*Index*
Benchmark	-0,82166
AR1-1	-0,89353
AR1-2	-1,65102
Whatever/A	0,047456
Whatever/B	0,0106

Ideas for further research

- Accounting for the pseudo-economical index a **sensitivity analysis** regarding the score values is necessary, as well as for the selection of the benchmark model.
- More indexes can be produced combining statistical and empirical methods for a **broader investigation of the forecasting performance**.
- Such indexes may be combined in the forecasting modelling process, thus developing an **optimized approach of the wind speed forecasting** in terms of power production and economic efficiency.
- Application in various case studies will provide further data for the optimization of the proposed indexes and methodologies.