OSPREY

On the fly sensitivity analysis for a discrete event model

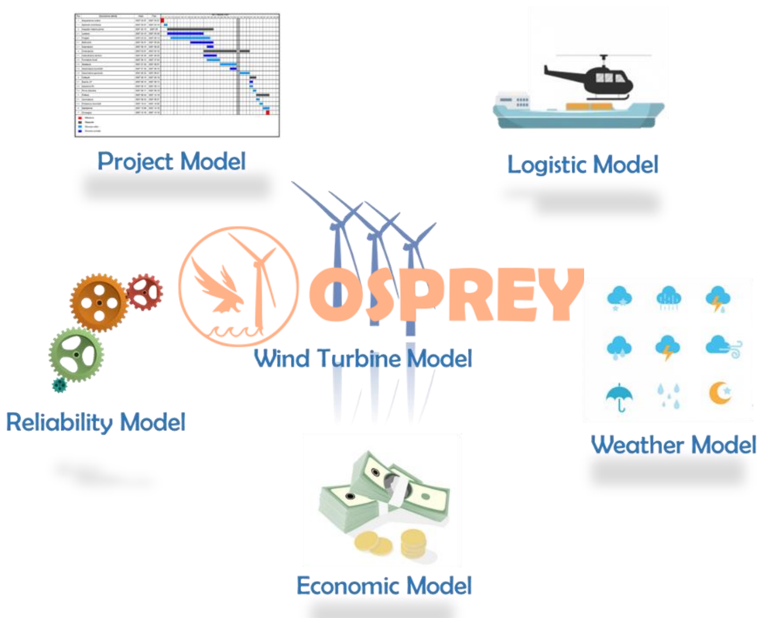
EDF R&D
Département PRISME

CHANGER L'ÉNERGIE ENSEMBLE

1

OSPREY

OSPREY – GENERAL ARCHITECTURE



The core of OSPREY is the wind turbine model, describing how the wind turbine farm is functioning.

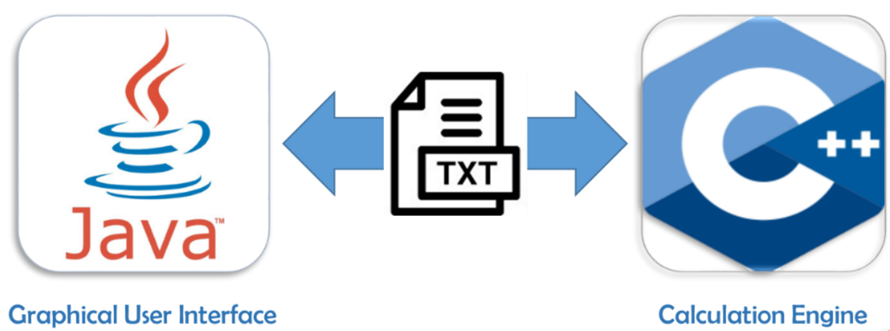
This model is linked with various models describing the economic-technical environment the farm is operated in.

Some models use the expertize of EDF R&D that has been developed in the past for other power generation types.

Some models (weather, project) are new developments.

Modular structure of the software making it flexible and easy to maintain.

Java and C++ languages facilitate the distribution of the tool.

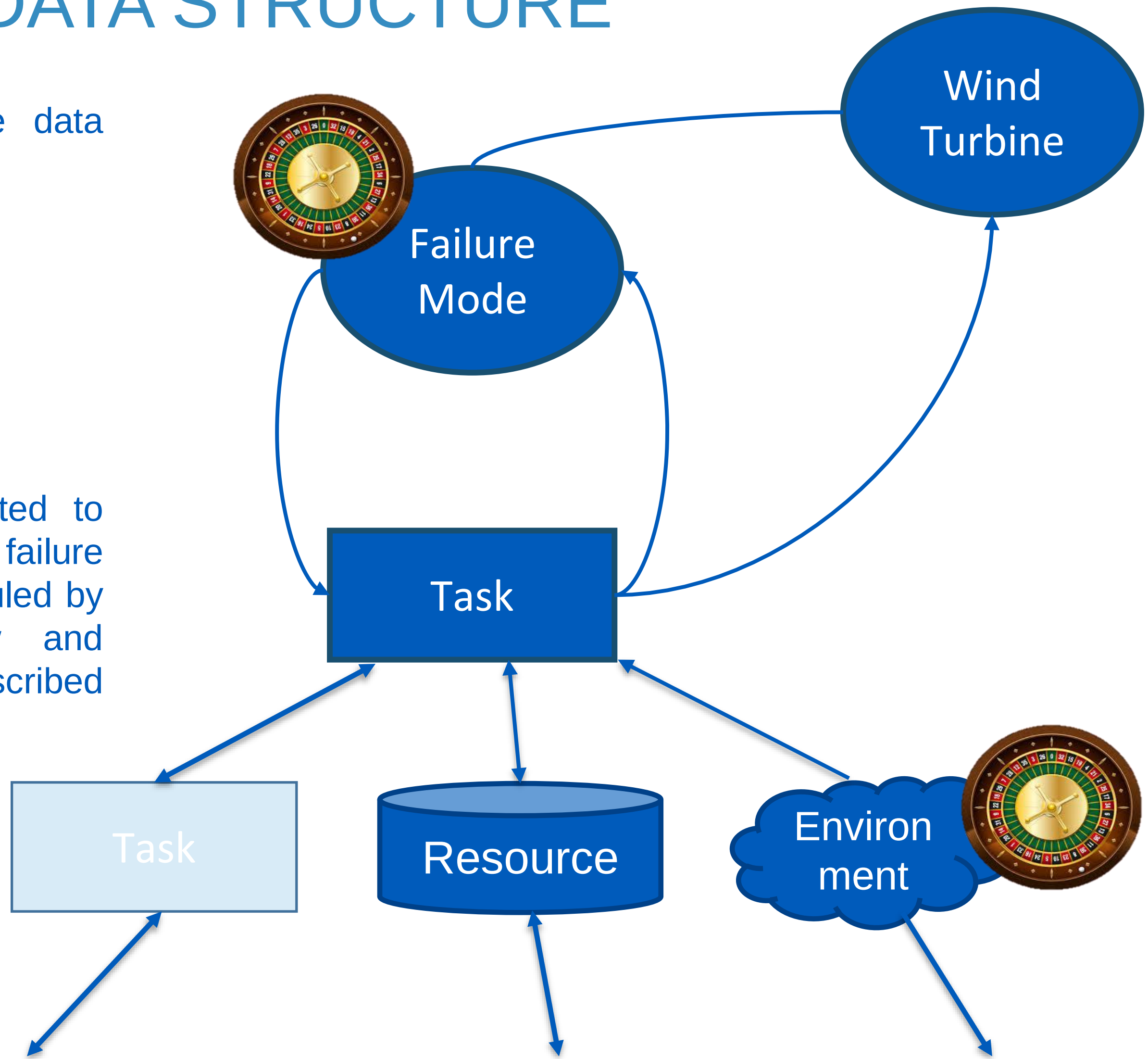


OSPREY – DATA STRUCTURE

The main objects in the data structure of OSPREY are:

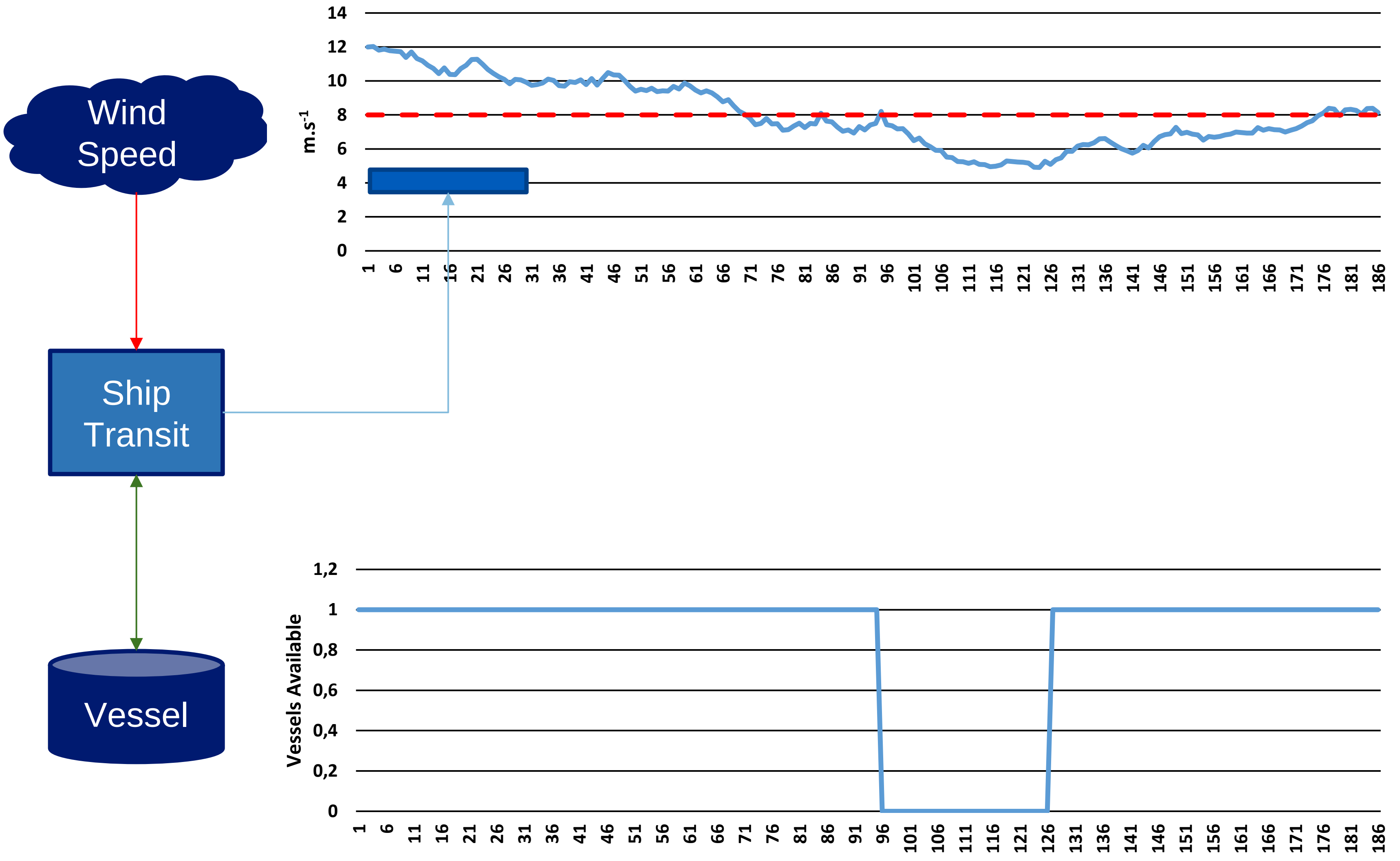
1. Wind Turbine
2. Failure Mode
3. Task
4. Resource
5. Environment

Two of them are subjected to some uncertainties: the failure modes with failure dates ruled by stochastic reliability law and environment conditions described by stochastic time series.

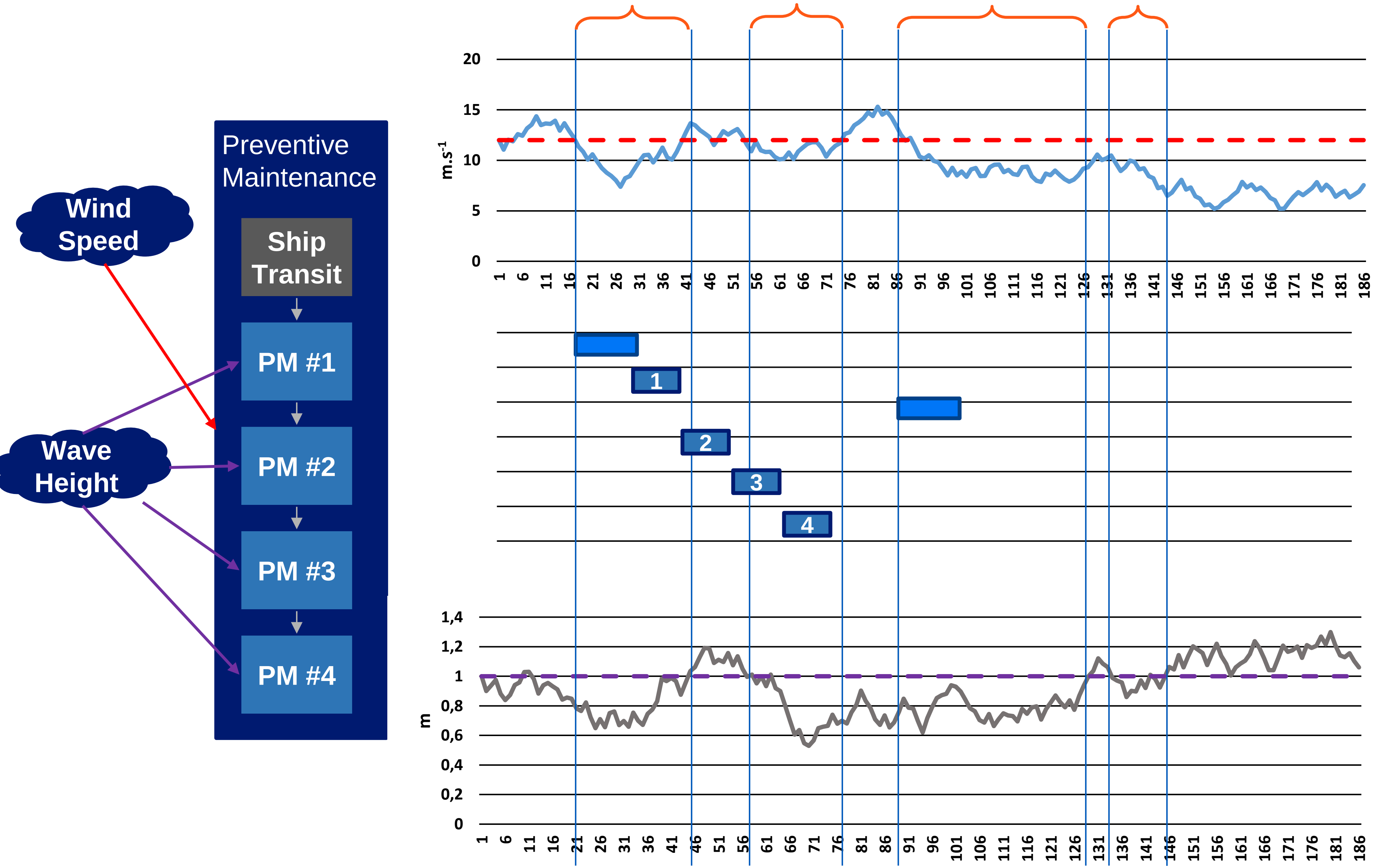


A Monte-Carlo simulation algorithm is implemented to simulate several possible lives of the farm and give to the user not only mean values but also risk indicators.

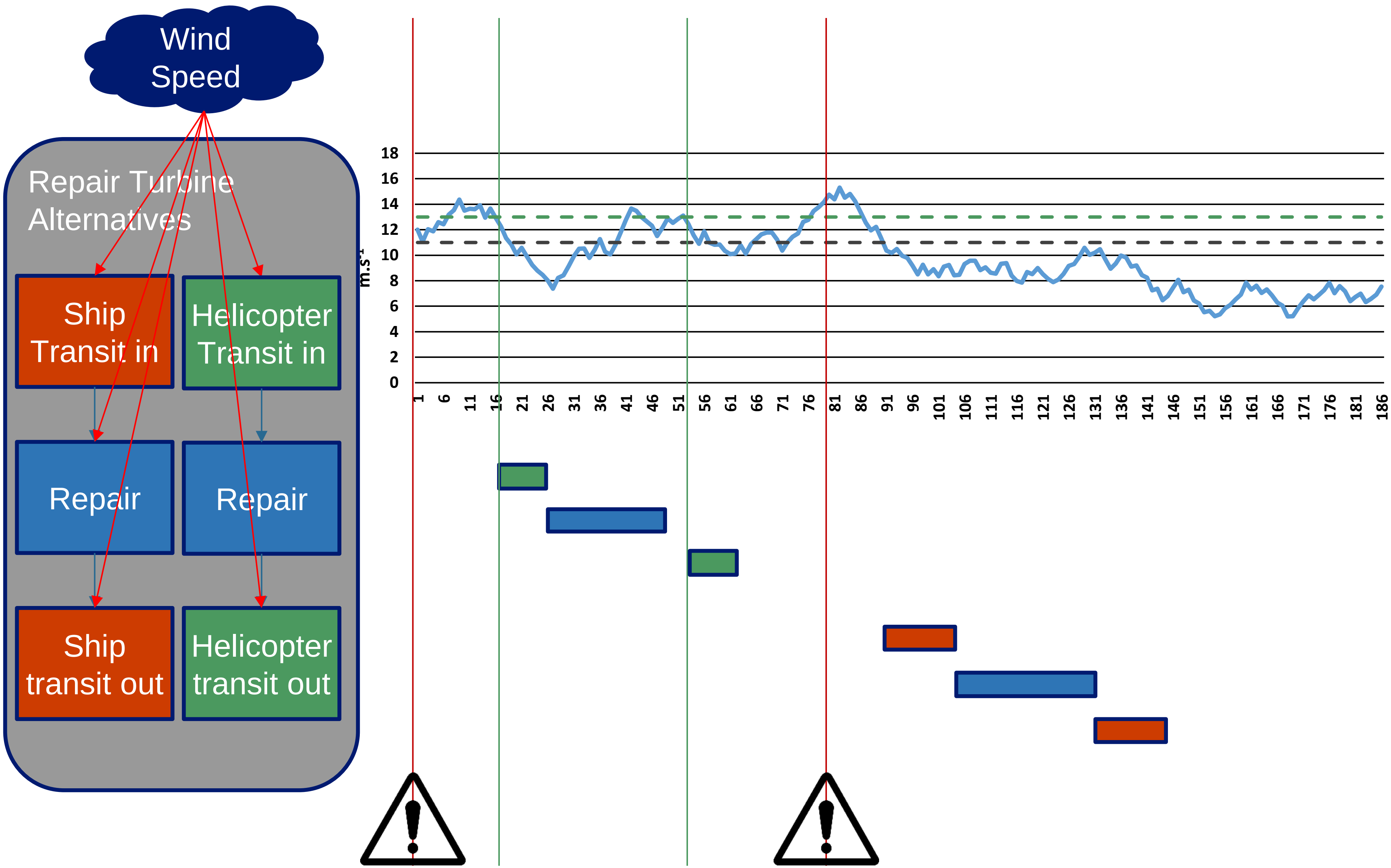
PROJECT MODEL – SIMPLE TASK



PROJECT MODEL – MACRO TASK

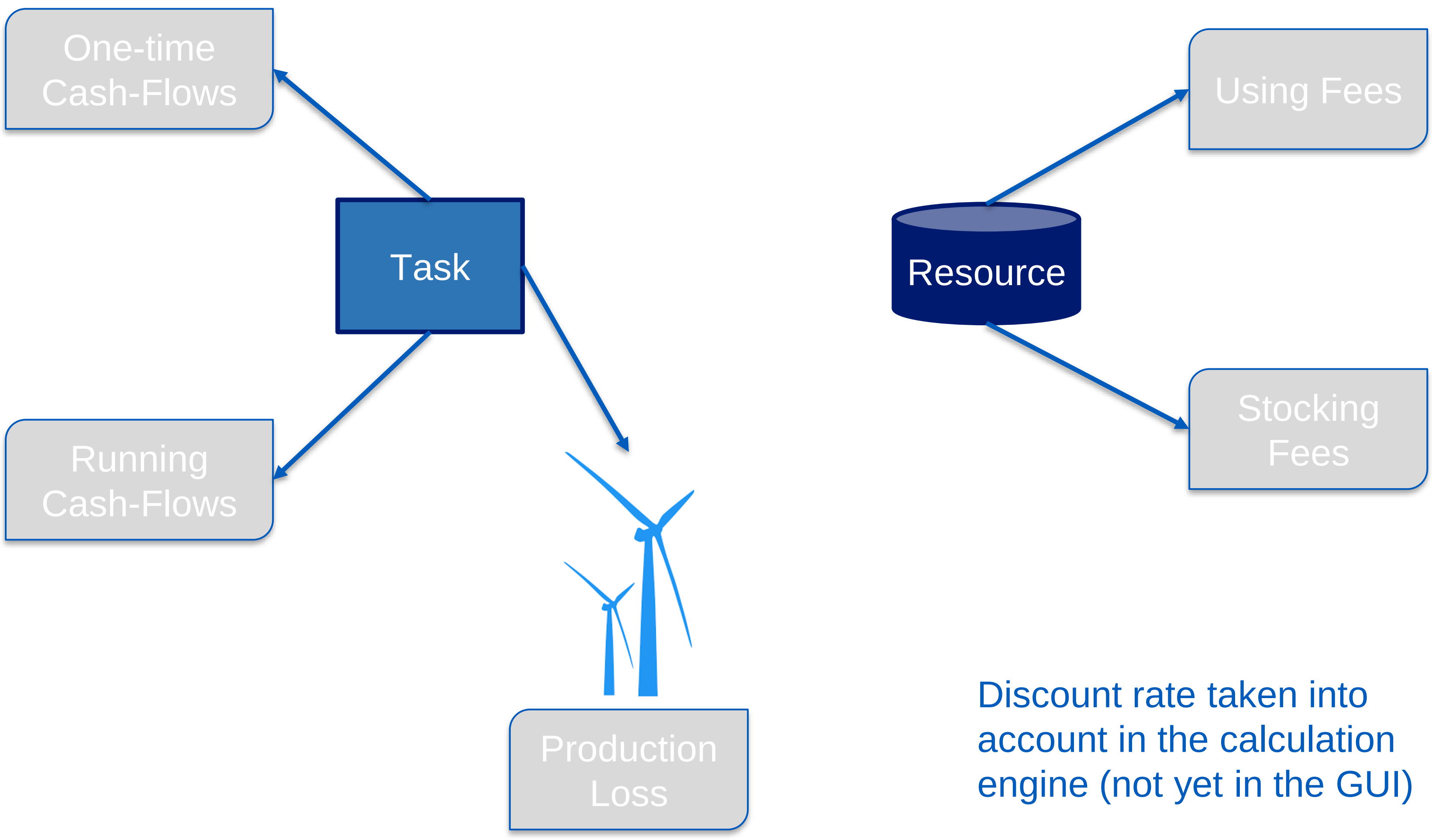


PROJECT MODEL – ALTERNATIVE TASKS



OSPREY – ECONOMIC MODEL

Tasks and resources generates cash-flows with different types and values. These cash-flows are summed up to give global economic indicators.



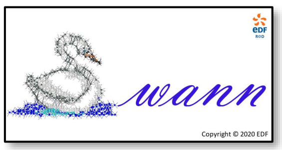
Discount rate taken into account in the calculation engine (not yet in the GUI)

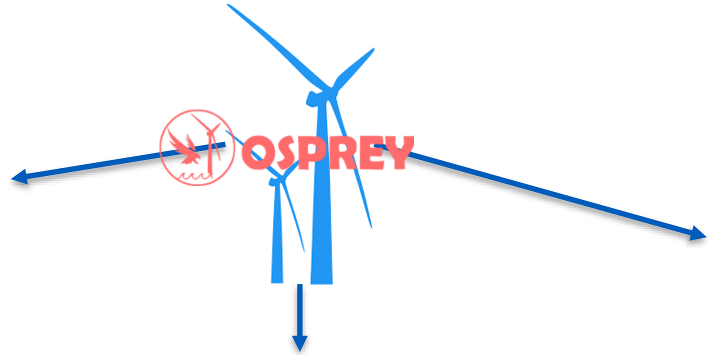
OSPREY – WEATHER MODEL

OSPREY can take into account several types of weather models

Built-in stochastic Auto-Regressive models:

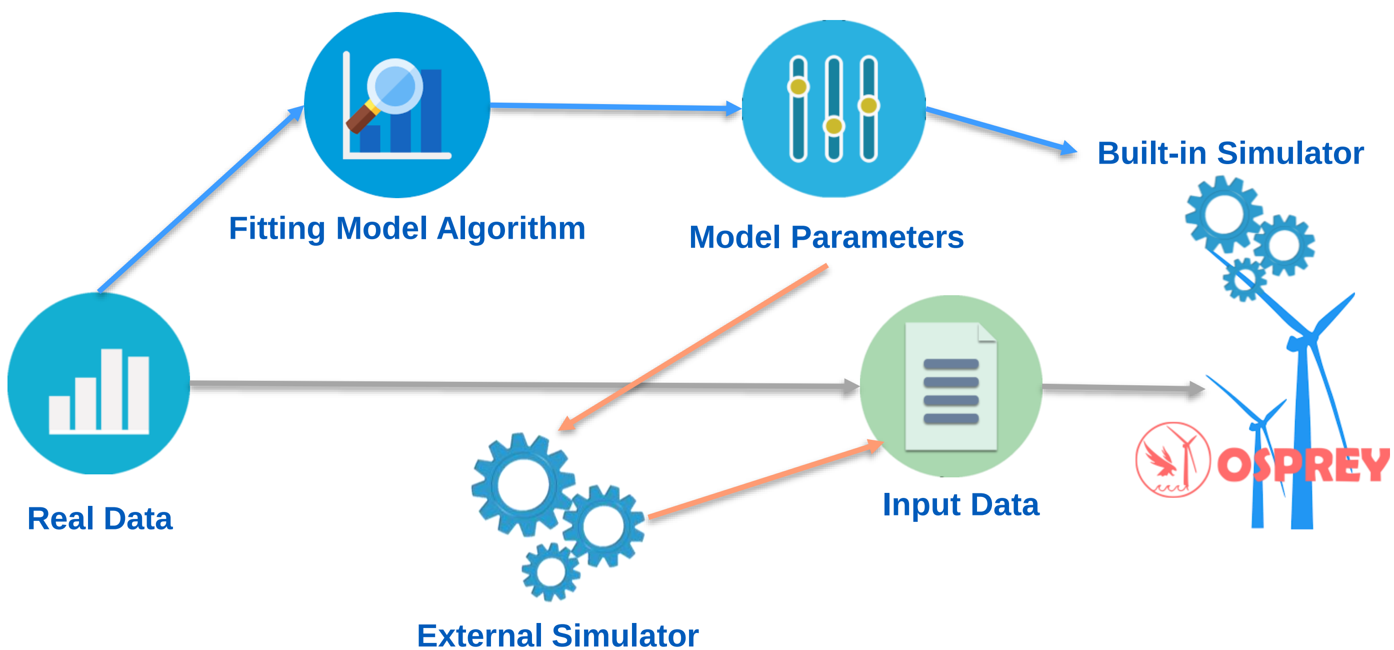
- SWANN: model using Artificial Neural Network (done)



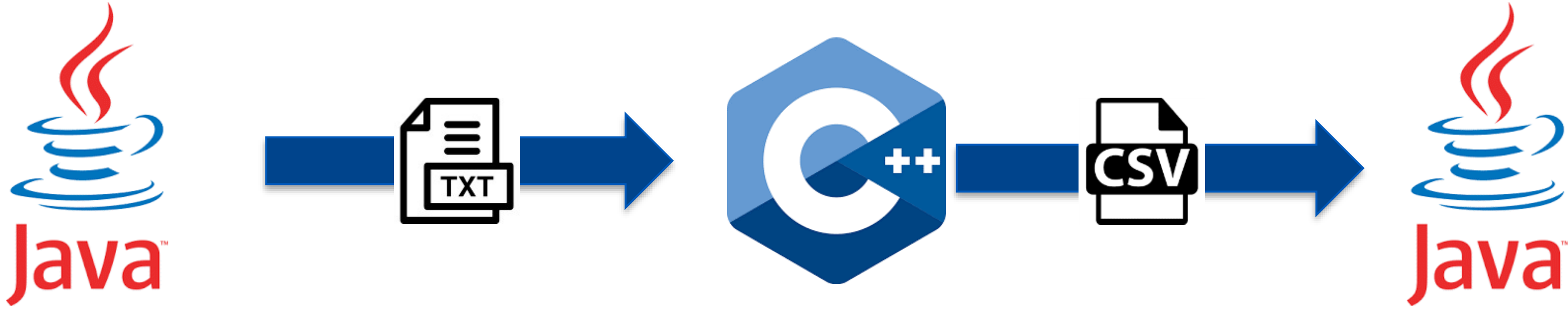


Deterministic data, cyclic or not (text files) for time of the day, tides, day-light…

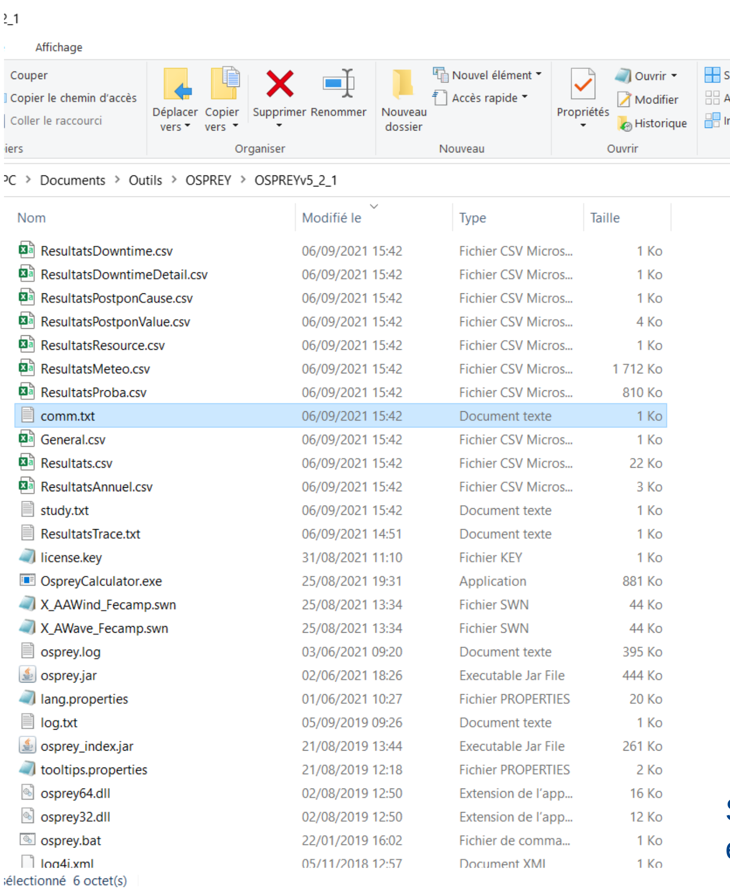
Randomized external data (bootstrap)



DISTRIBUTED “PACKAGE”



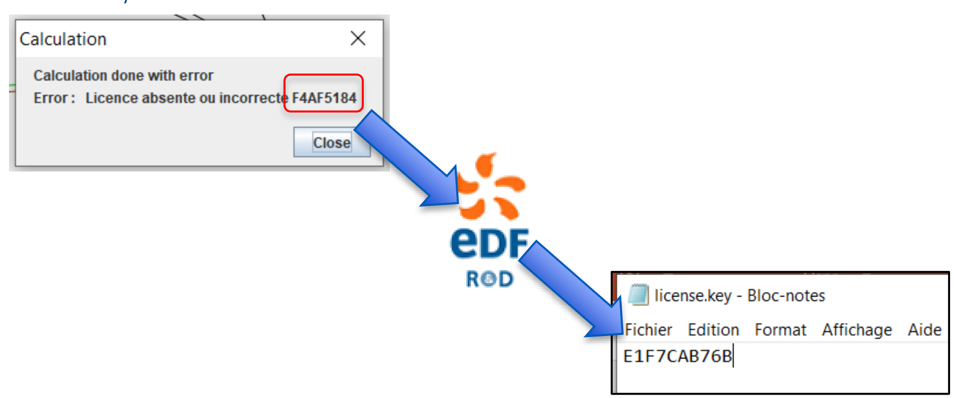
Graphical User Interface **Calculation Engine** **Graphical User Interface**



A folder containing all GUI files:

1. osprey.jar (GUI launcher)
2. lang.properties (editable text file with all GUI labels)
3. Calculation engine OspreyCalculator.exe
4. A license key file license.key

The interface is free to use without a valid license, it will be needed to run simulations

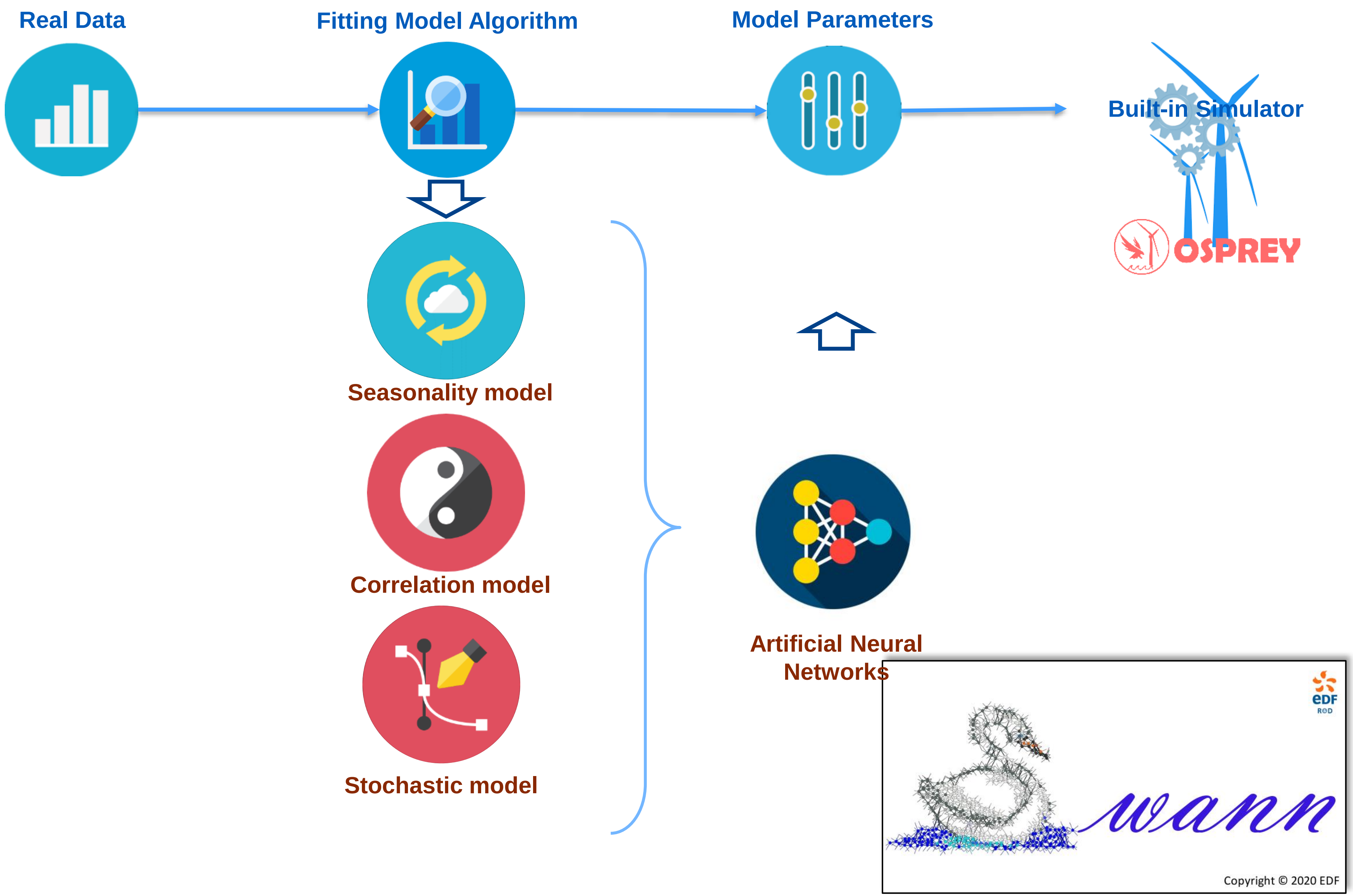


Send the Id number to EDF R&D and then edit the license.key file to enter the correct key that will be sent back

2

SWANN

SWANN



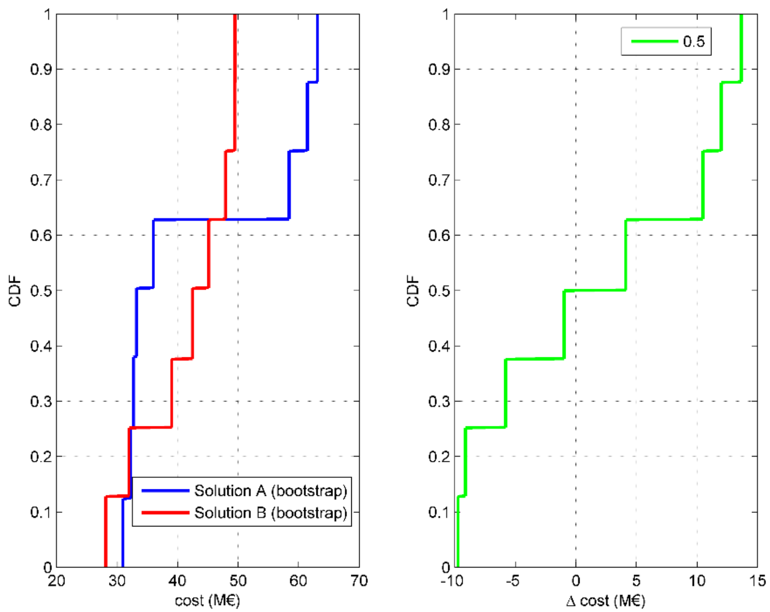
Real Data
Fitting Model Algorithm
Model Parameters
Built-in Simulator
OSPREY
Seasonality model
Correlation model
Stochastic model
Artificial Neural Networks
wann
eDF R&D
Copyright © 2020 EDF

SWANN

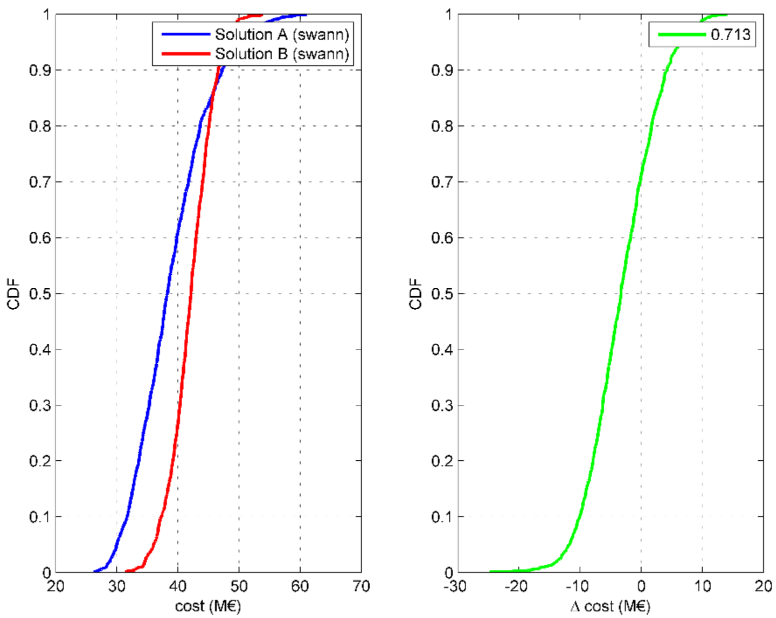
SWANN stands for **S**tochastic **W**eather Emulator using **A**rtificial **N**eural **N**etwork

Stochastic weather generator is important for Asset Management because observed data don’t provide enough data to asses risk indicators

Bootstrap



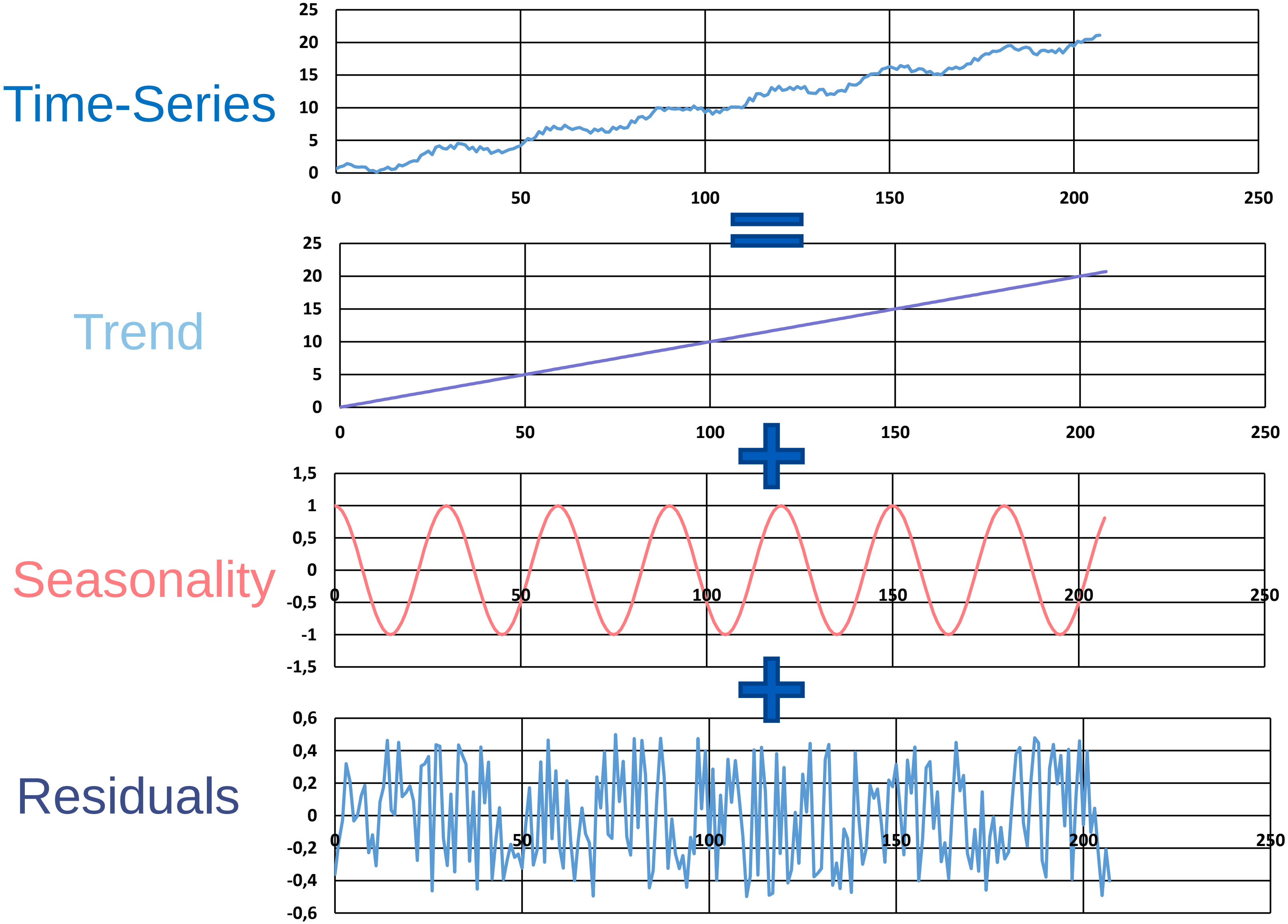
Swann



	Mean (M€)	Median (M€)
Solution A	43,4	33,2
Solution B	41,6	42,4

	Mean (M€)	Median (M€)
Solution A	38,9	38,2
Solution B	42,1	42,1

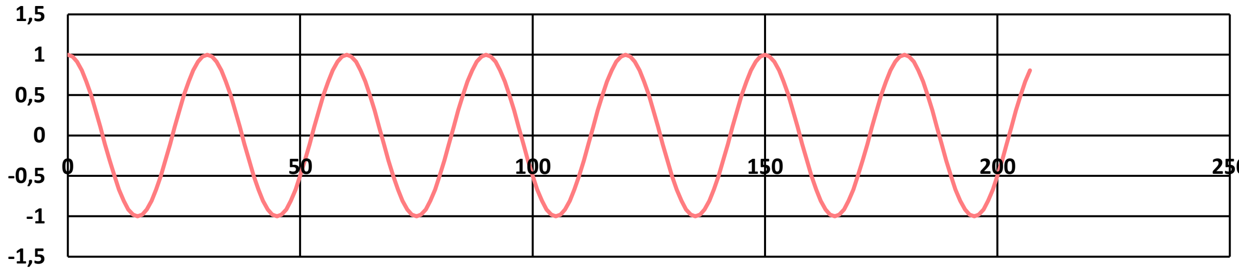
TIME SERIES

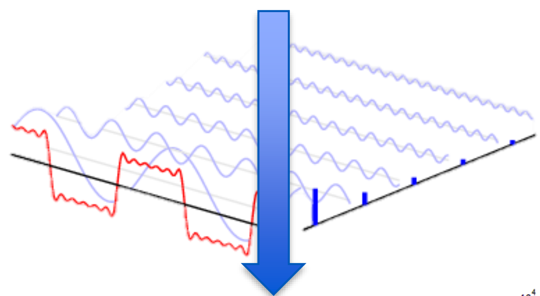


Time-Series
Trend
Seasonality
Residuals
25
20
15
10
5
0
0
50
100
150
200
250
1,5
1
0,5
0
-0,5
-1
-1,5
0,6
0,4
0,2
0
-0,2
-0,4
-0,6

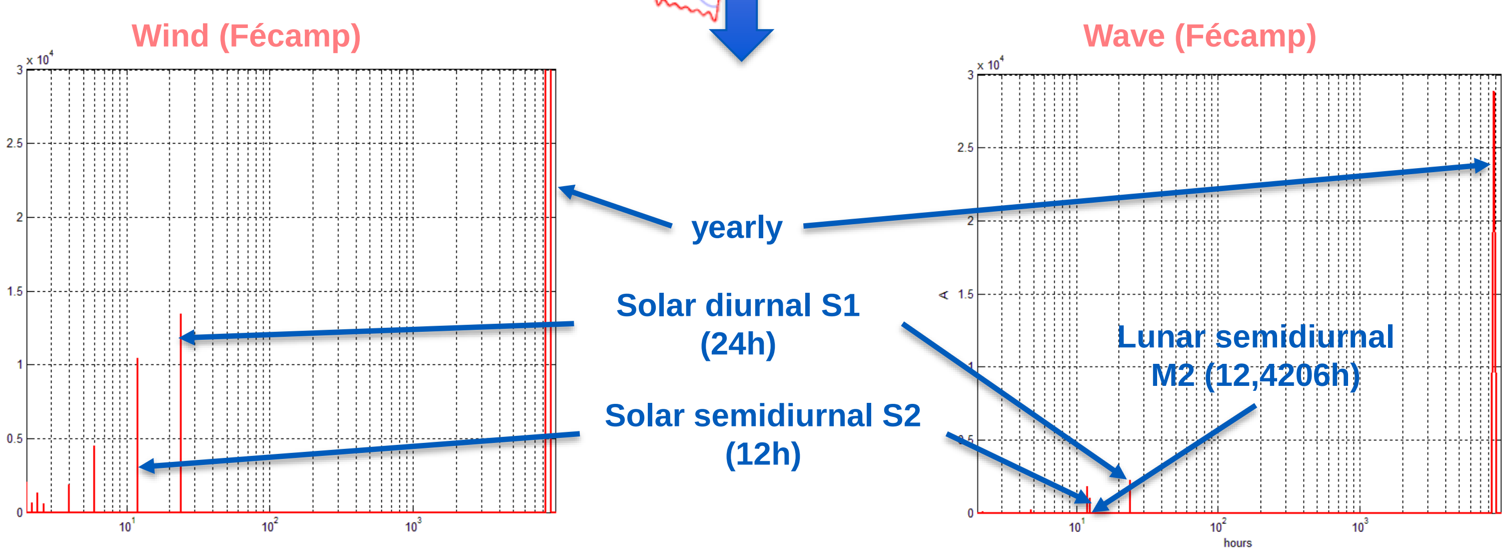
SEASONNALITY

In the case of metocean data, seasonality is the deterministic sum of harmonic constituents (like tides)



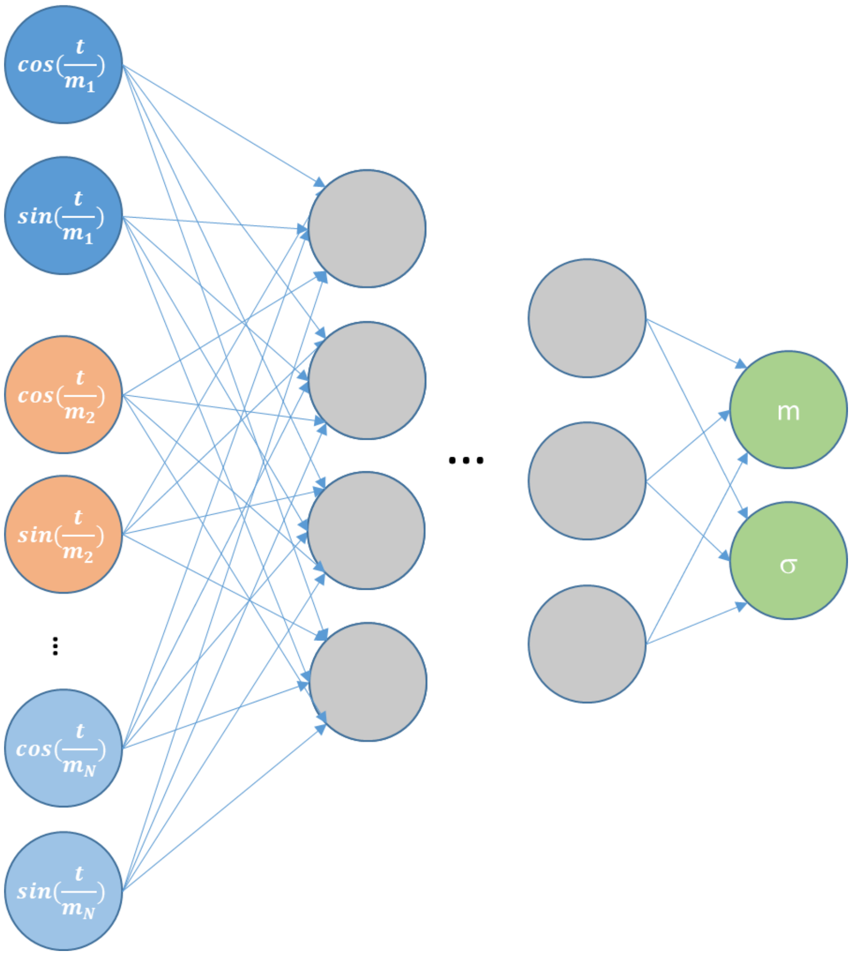


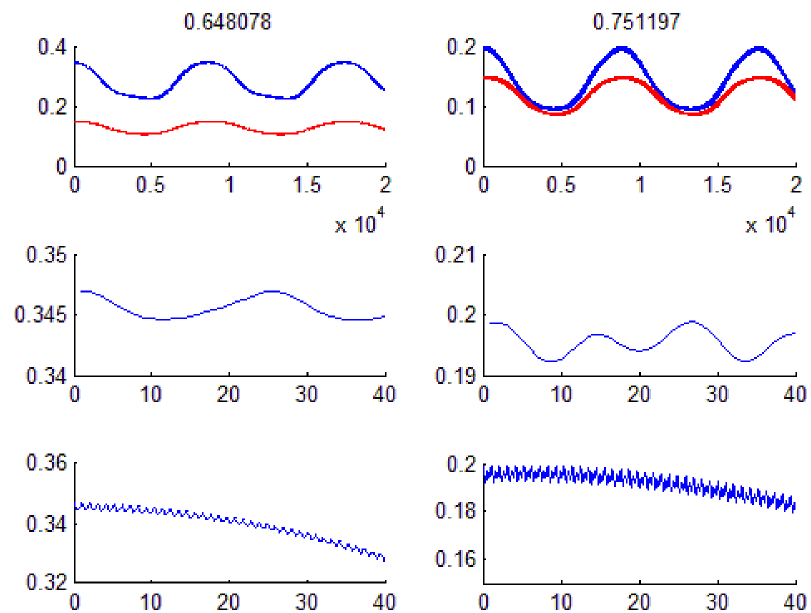
Fourier Analysis



SEASONNALITY

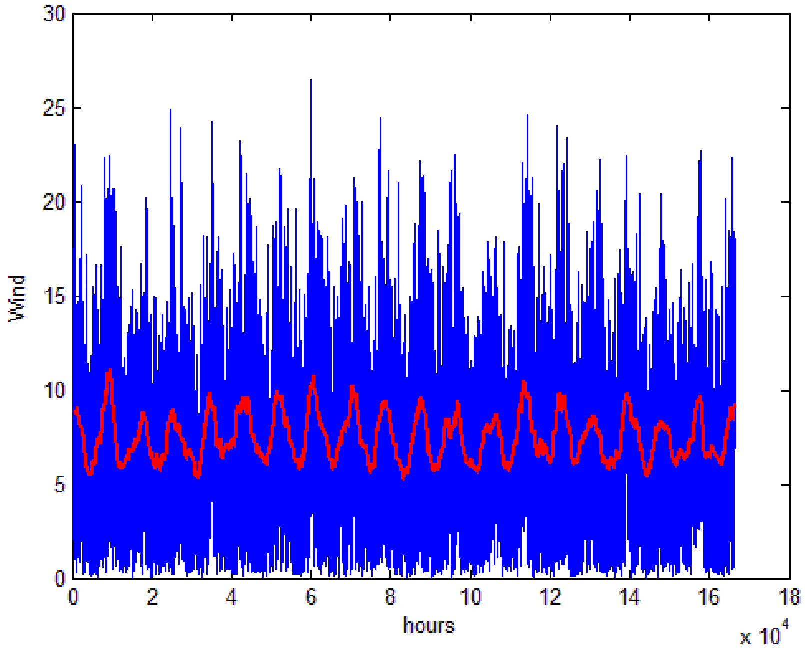
Once the constituents are selected, the global harmonic of average and standard deviation of seasonality are interpolated with an ANN

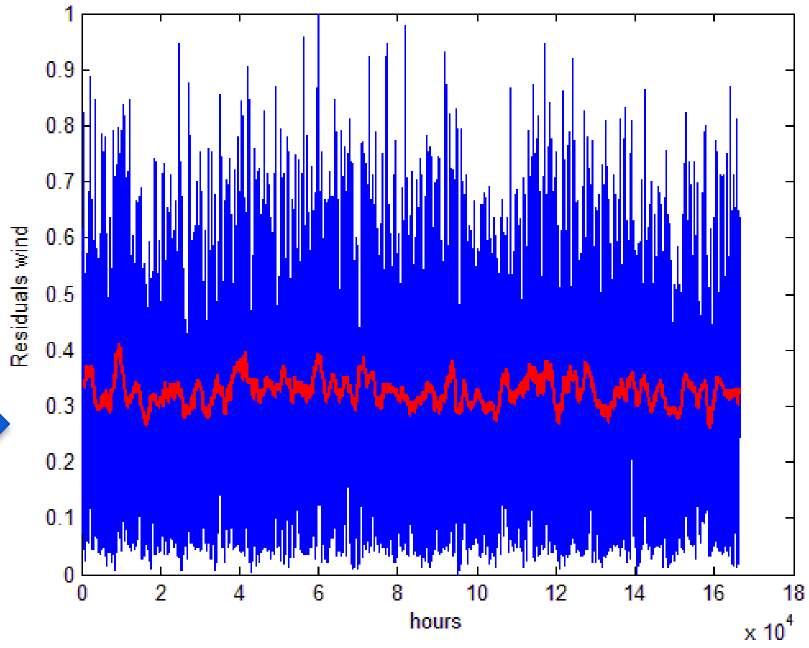




RESIDUALS

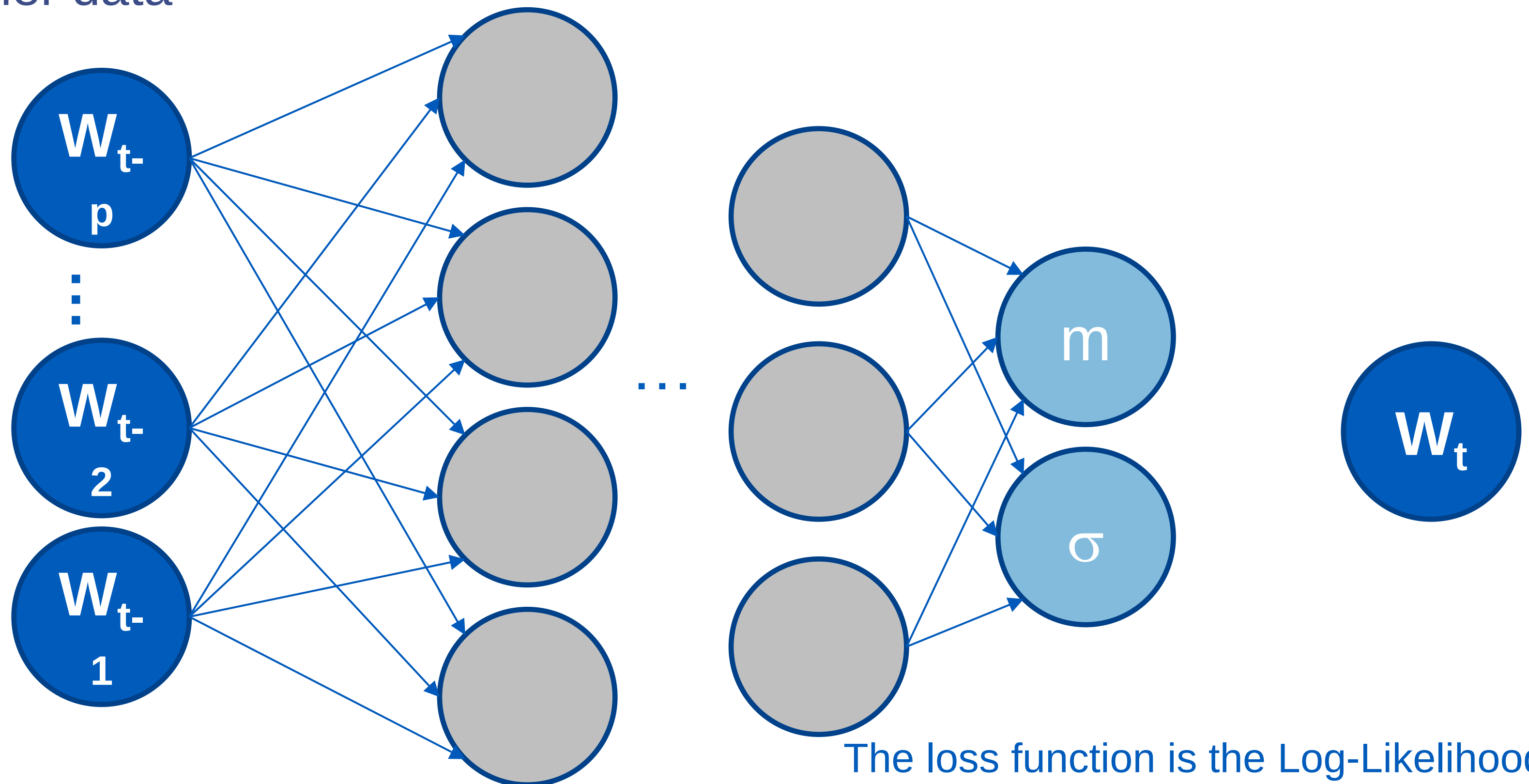
Once the seasonality is taken out we are left with stochastic residuals. The resulting time series is supposed to be stationary





RESIDUALS

For stochastic weather generators, residuals may be modelled with a stochastic process (AutoRegressive, Moving-Average…)
A generic model can use a Neural Network trained on past observed weather data



p is the time lag of the model. The wind speed depends only on the p previous wind speeds

The loss function is the Log-Likelihood function given the obervation at time step t. For a Gaussian:

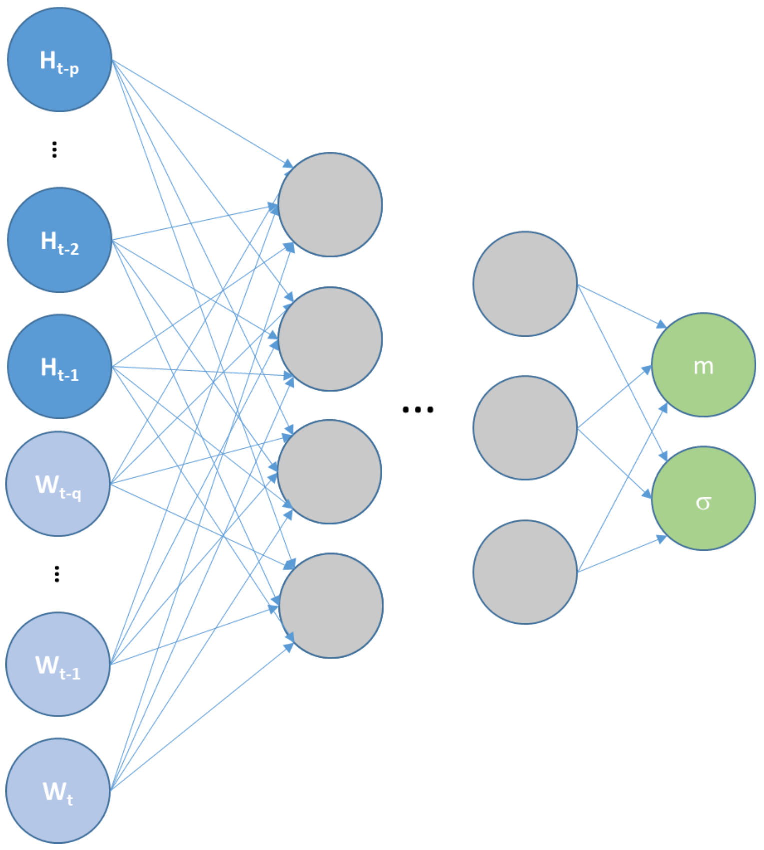
$$L = -\frac{\ln(2\cdot\pi)}{2} - \ln(\sigma) - \frac{(W_t - m)^2}{2\cdot\sigma^2}$$

CORRELATION

Different possible methods to take into account the correlation between several data (wind speed Vs wave height for example):

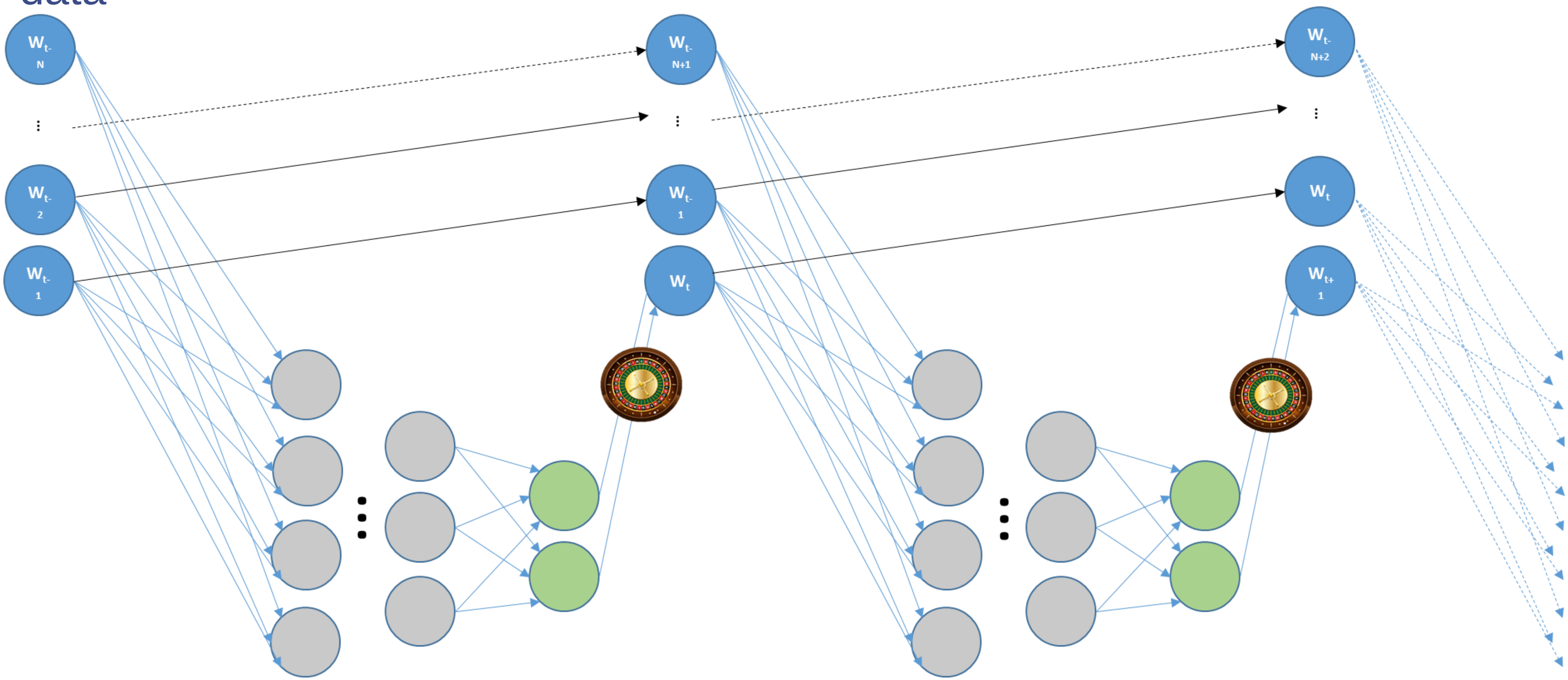
- Rigorous models like Copulas
- **Simplified iterative correlation**

One variable at time step t will depend
on its p previous values
&
q previous values for correlated
variables with a higher rank
&
q-1 previous values and the current
value for correlated variables with a
lower rank



SIMULATION

Time series are simulated iteratively based on the models fitted on observed data

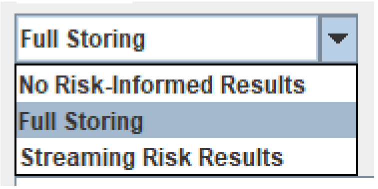


At each time step random values are created based on the output of the network. These values being used as inputs for the next time step.

Once the residuals are generated, data is “reseasoned” using the seasonality models

3 Simulation

RISK RESULTS

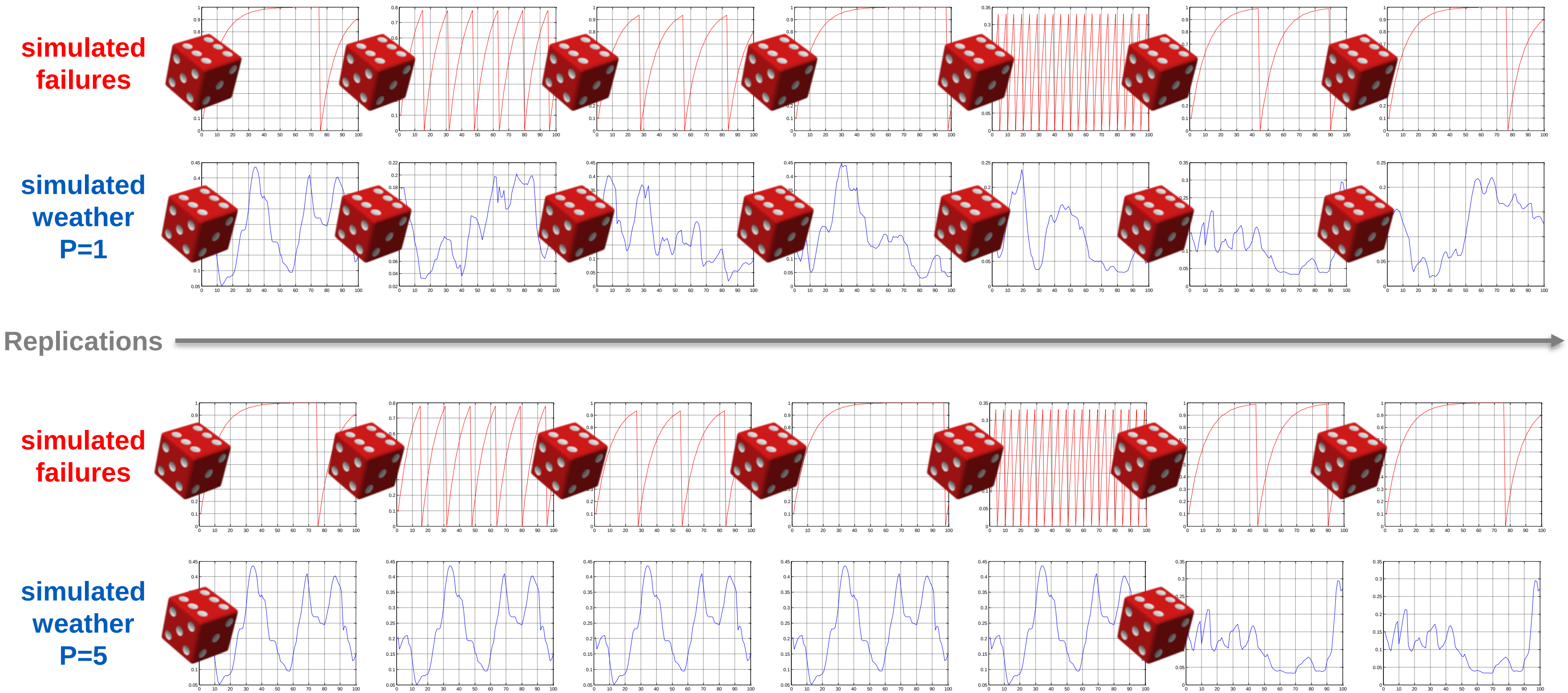


- <u>Full storing</u>: classic method used in past version of OSPREY. All replications output are stored and quantiles are calculated in posttreatment.
  - Pros: convergence to the exact quantile function is known. Possibility to replay a quantile.
  - Cons: large results files (storage issues but moreover exporting times issues)

- <u>Streaming Risk Results:</u> based on Robbins-Monro algorithm, the quantiles approximations are updated at each replication without storing any values.
  - Pros: no i/o time issues for the result files are smaller
  - Cons: convergence is not measurable (no confidence interval or convergence speed is known). Impossible to “replay” a given quantile.

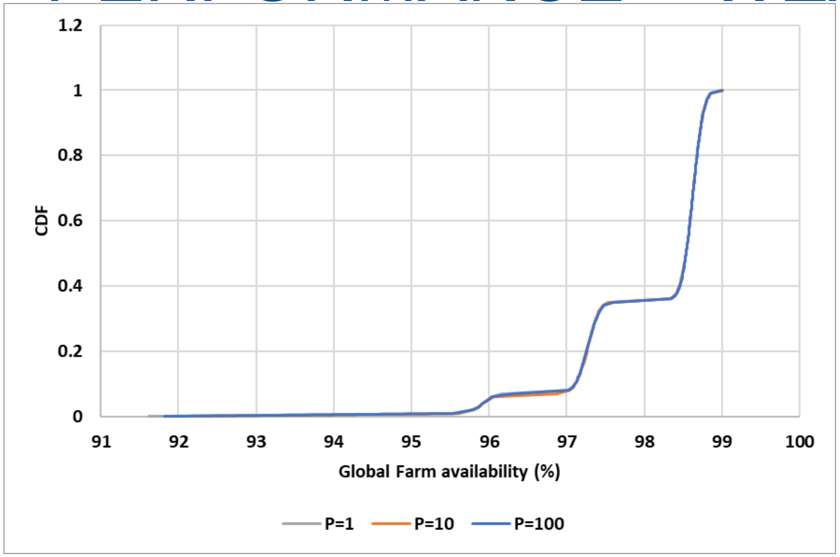
- <u>No Risk-Informed Results</u>: no quantiles evaluation
  - Pros: fast calculations
  - Cons: no probabilistic results at all

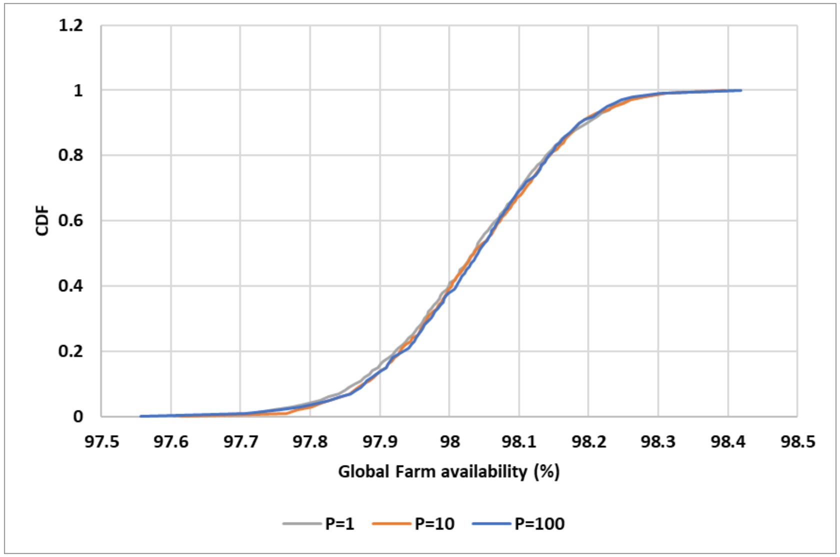
WEATHER DATA SIMULATION



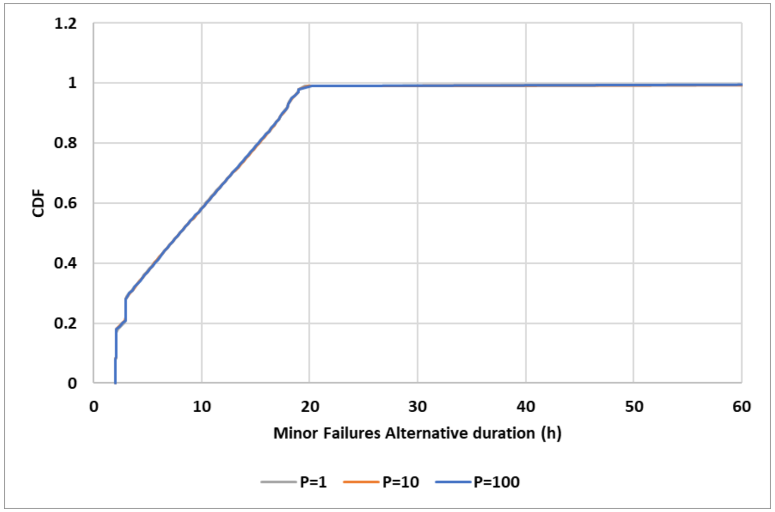
Increasing the period for weather data initialization P shortens the calculations with a potential loss of convergence

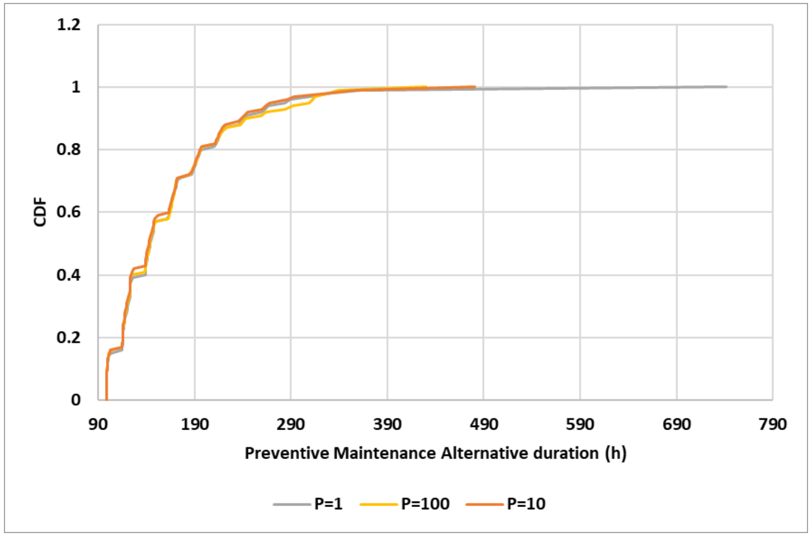
PERFORMANCE – WEATHER SIMULATION





Limited impact on availability results





Only significant impact is visible for “deterministic” events. For other events the stochasticity of occurrence times is sufficient

ROBBINS-MONRO ALGORITHM

The algorithm was described by Robbins and Monro in 1951[1]

The chosen implementation is the based on the works of Bertrand Iooss[2]:

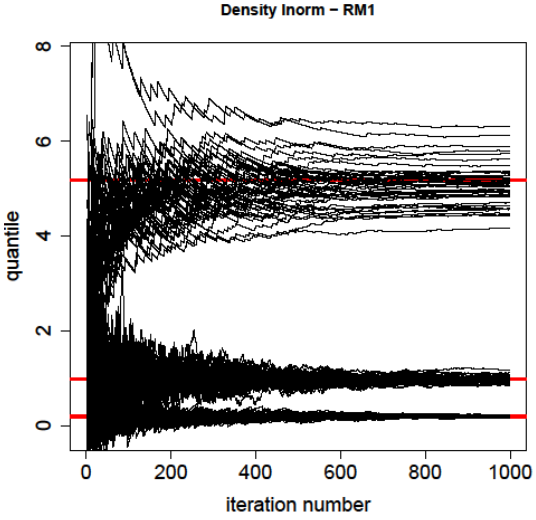
1. Application of the algorithm to quantiles approximation through an iterative "on-the-fly" formula:

$$q_\alpha(n+1) = q_\alpha(n) - \frac{C}{n^\gamma}\left(\mathbf{1}_{Y_{n+1} \leq q_\alpha(n)} - \alpha\right)$$

2. Dynamic evolution of C and γ parameters

$$\gamma(n) = 0.5 + 0.5\,\frac{n-1}{N-1}$$

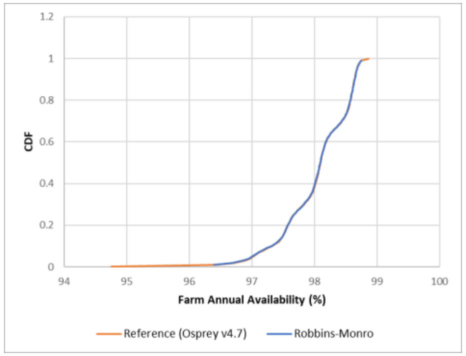
$$C(n) = \left|q_{\alpha_{max}}(n-1) - q_{\alpha_{min}}(n-1)\right|$$

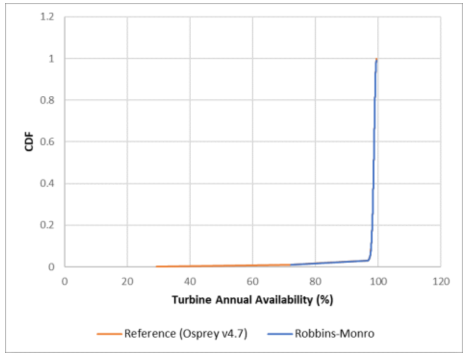


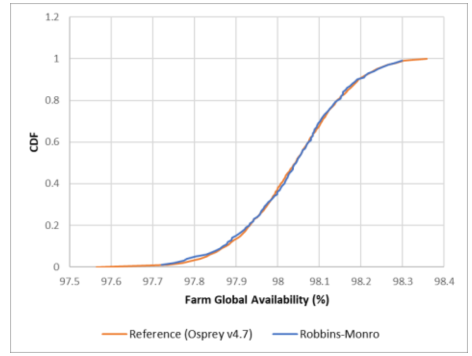
[1]Robbins, H.; Monro, S. (1951). "A Stochastic Approximation Method". The Annals of Mathematical Statistics. 22 (3): 400.

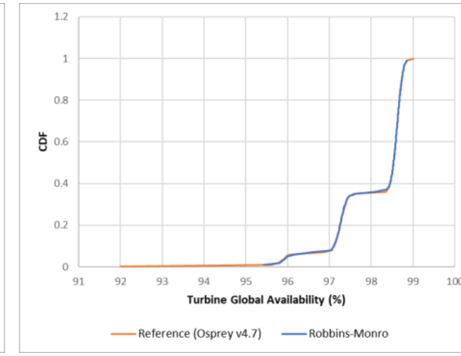
[2]Iooss, B. "Robust tuning of Robbins-Monro algorithm for quantile estimation in iterative uncertainty quantification". ESREL 2020.

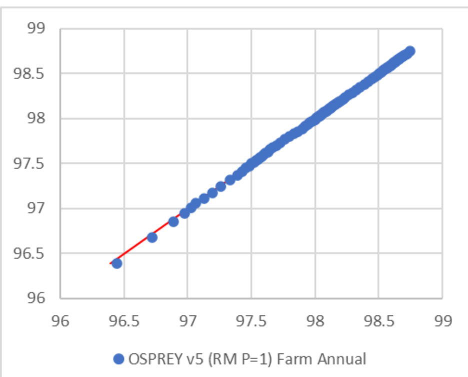
PERFORMANCE – QUANTILES EVALUATION (1/2)

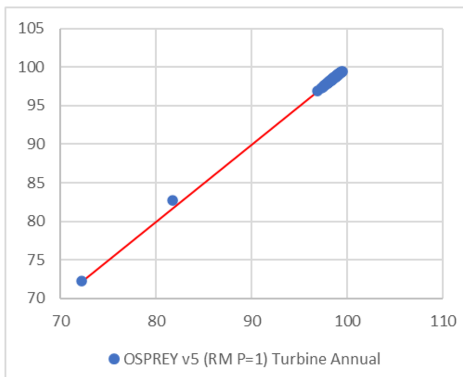


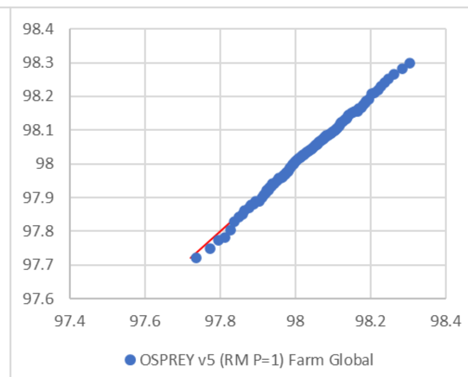


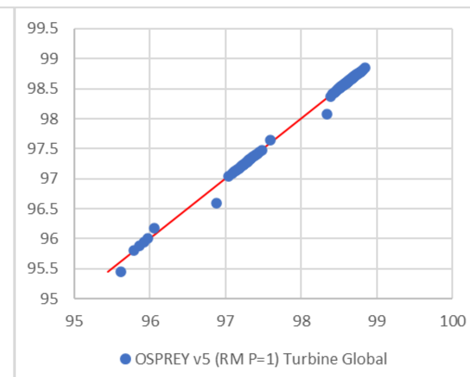








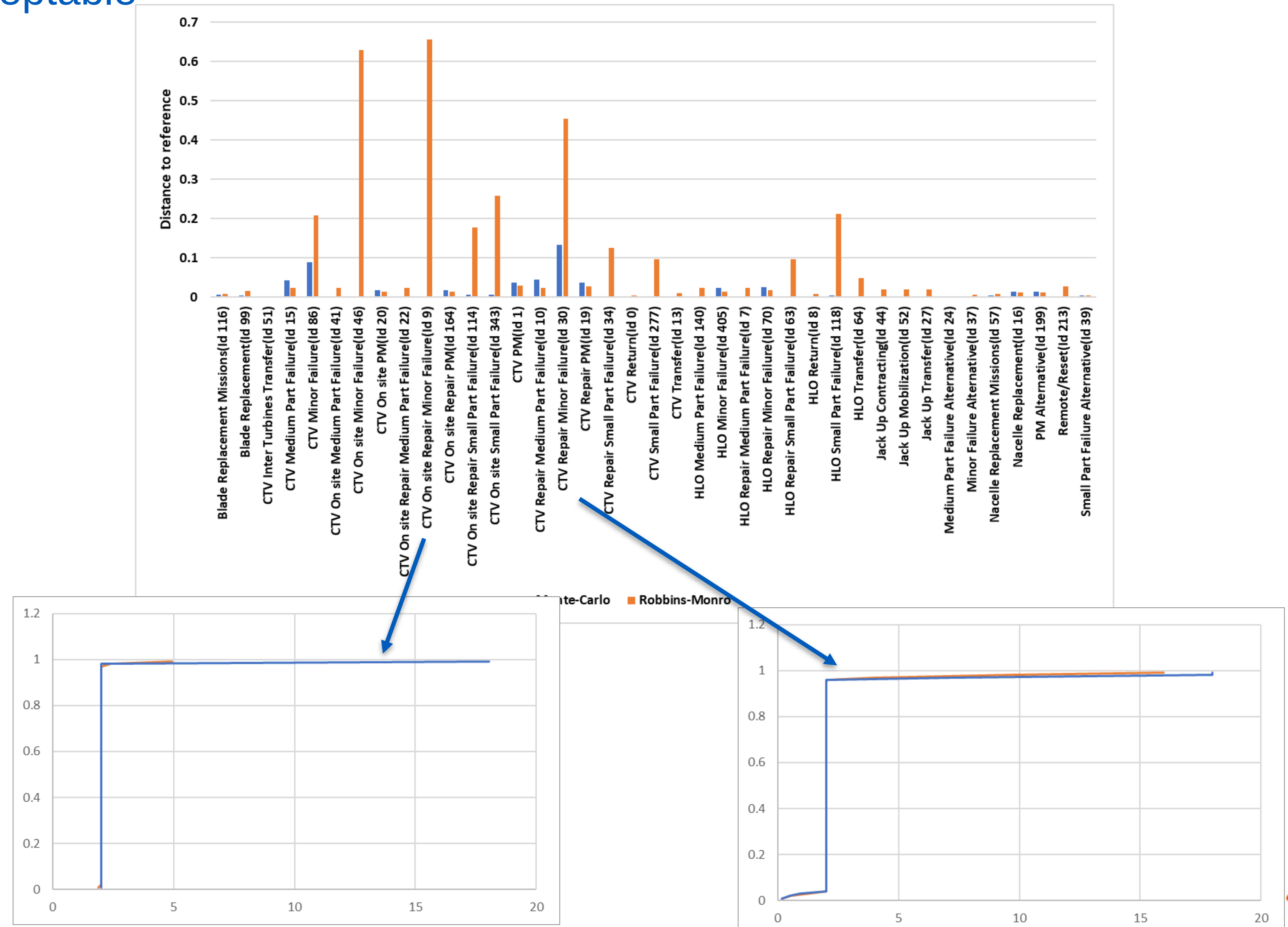




Good performance on the availability indicators

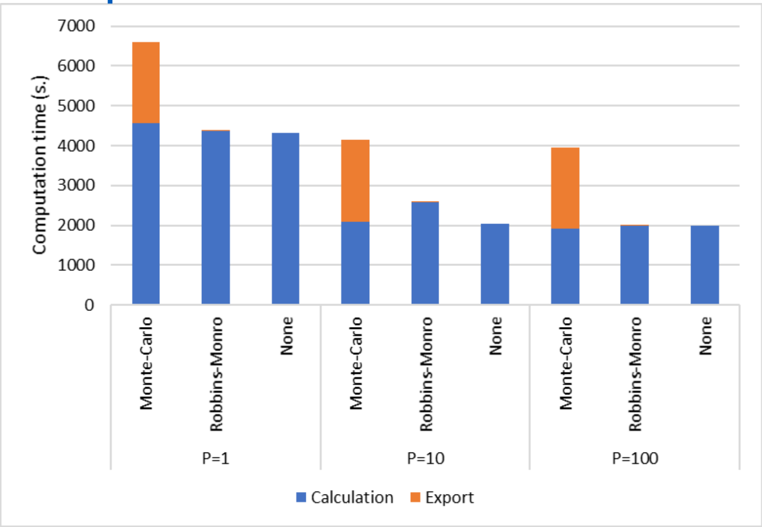
PERFORMANCE – QUANTILES EVALUATION (2/2)

On task durations, poor performance on extreme quantiles, but globally acceptable

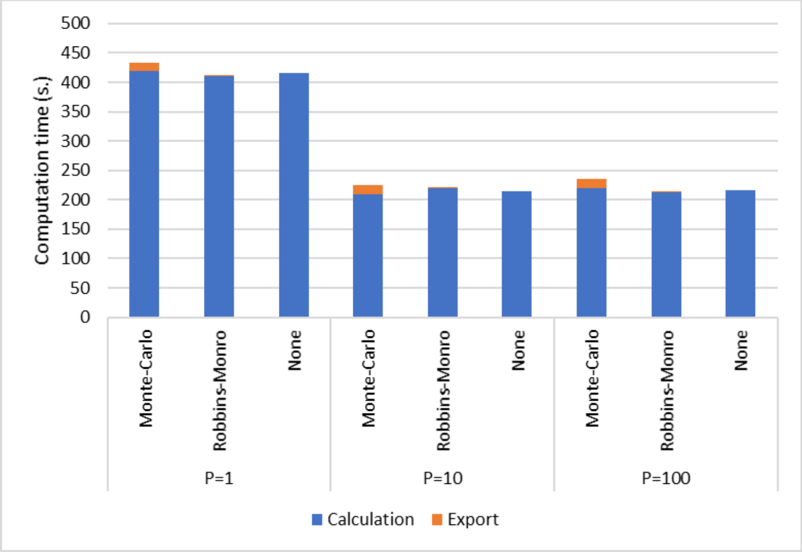


PERFORMANCE – CALCULATION TIME

1000 replications, 4 threads



100 replications, 4 threads



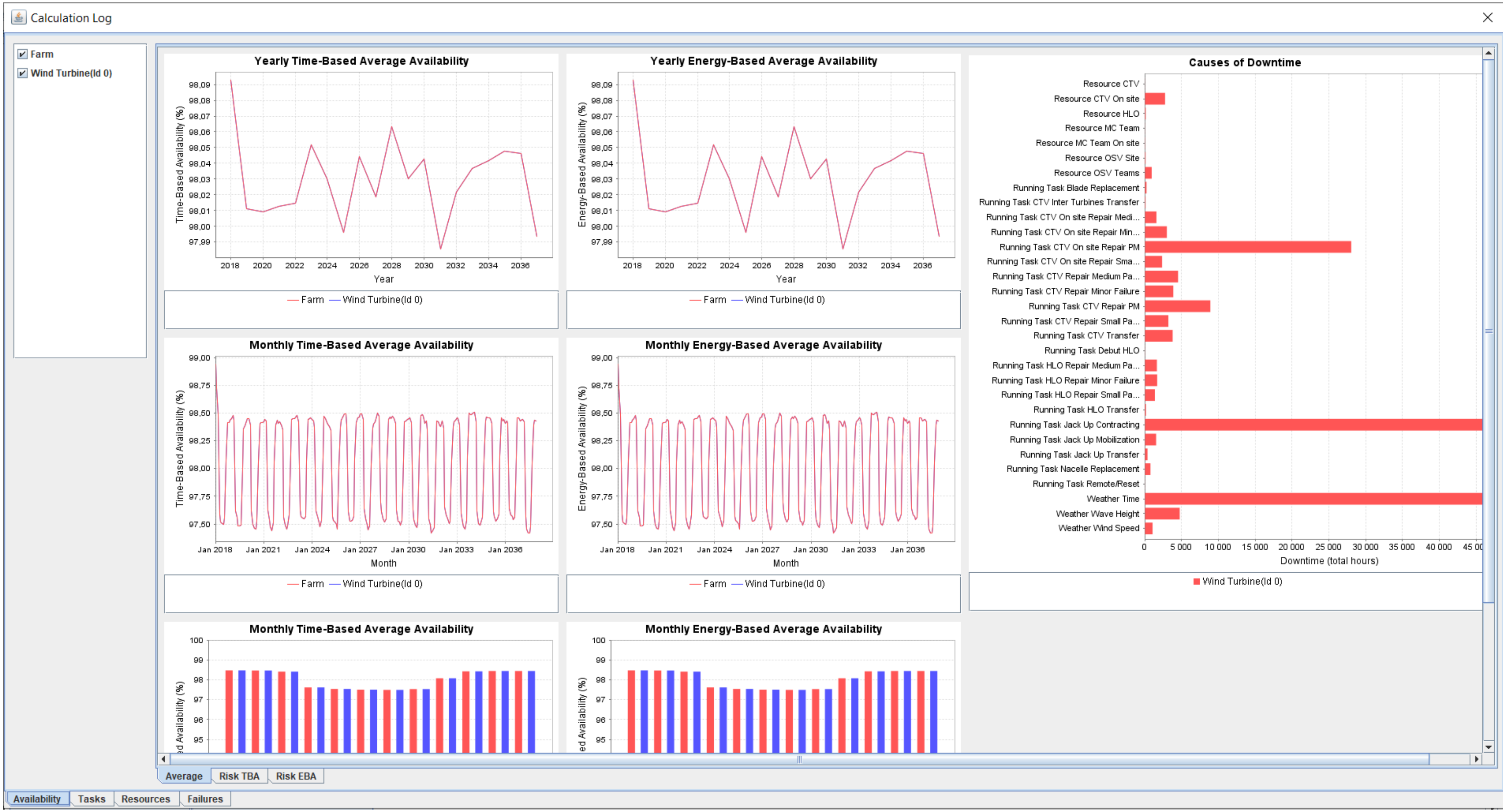
Increasing the initialization period for weather simulation speeds up the calculation up to P=10 then converge

Export results are almost instantaneous for Robbins-Monro risk results (independent from the number of replications)

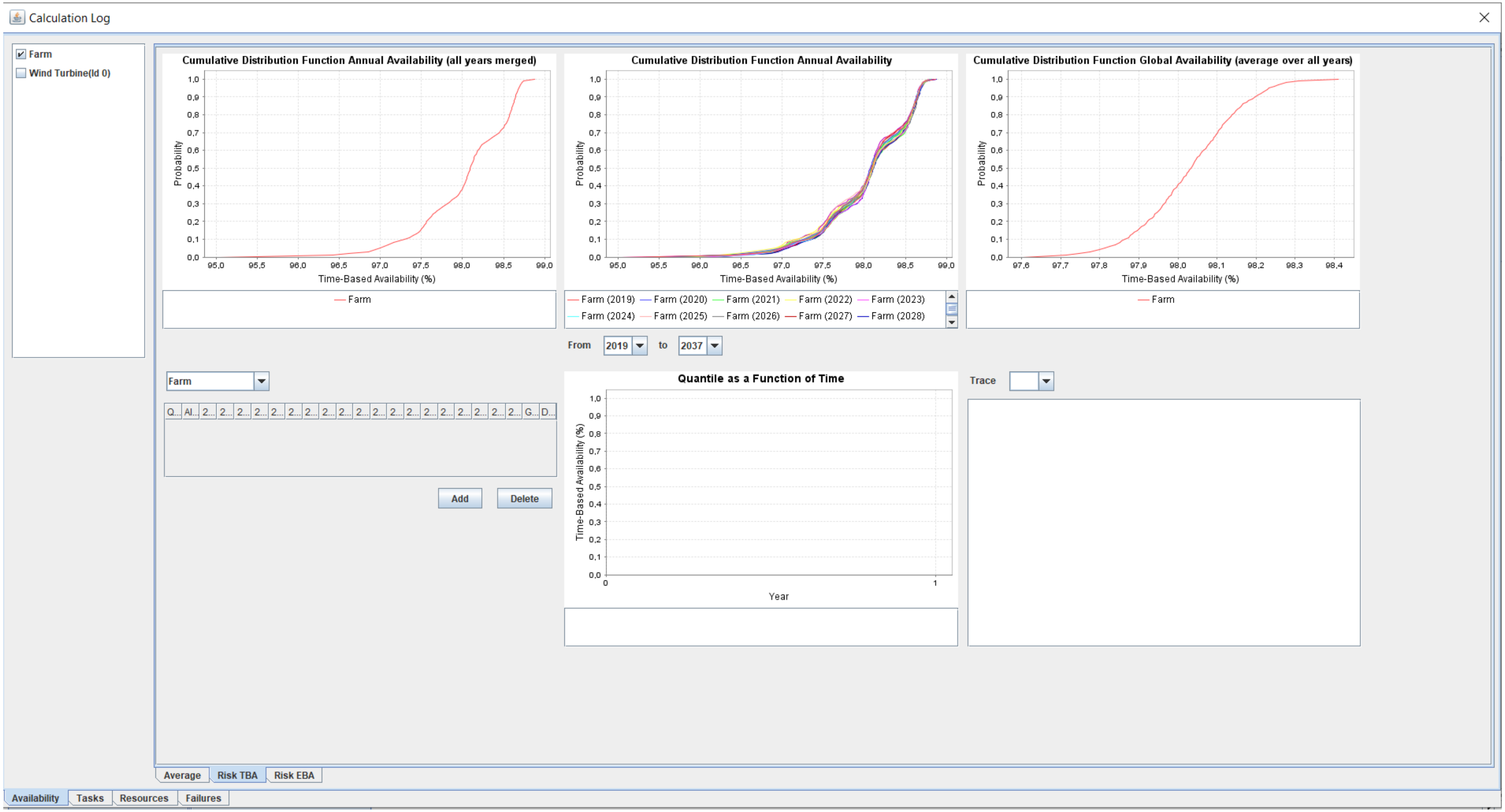
4

Results

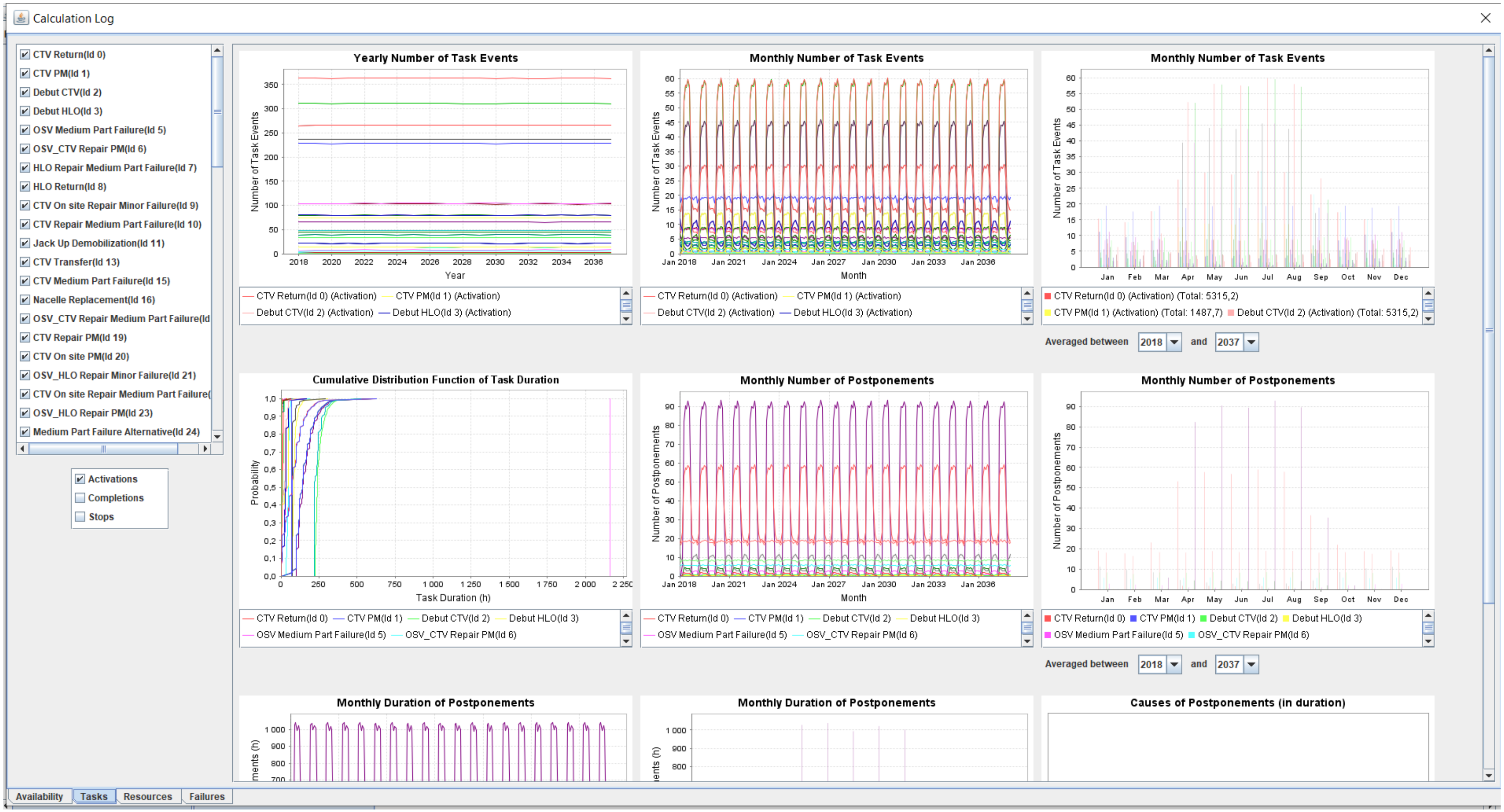
AVAILABILITY CALCULATIONS - AVERAGE



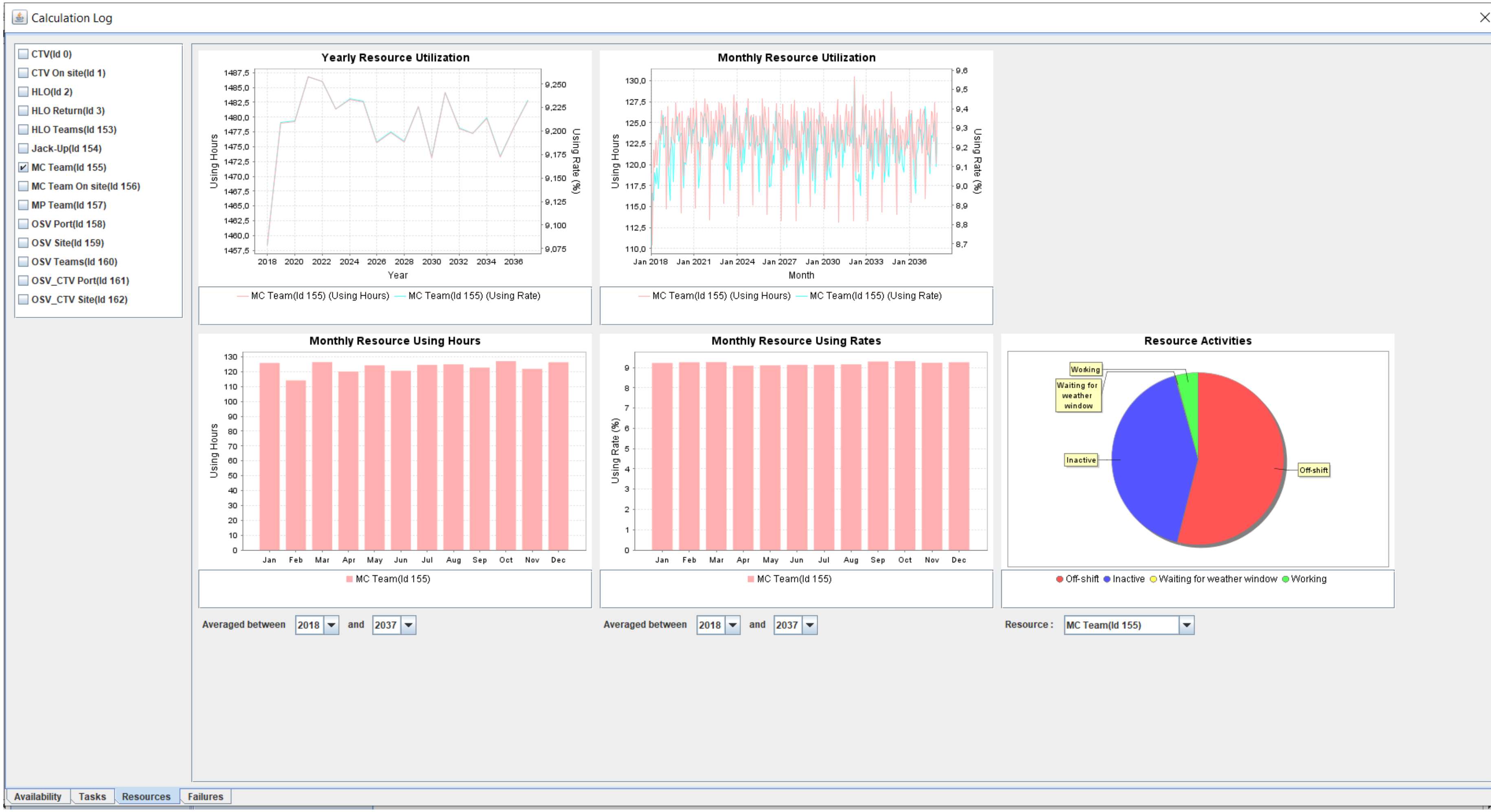
AVAILABILITY CALCULATIONS - RISK



TASKS CALCULATIONS



TASKS RESSOURCES



5

Sensitivity Analysis

SENSITIVY ANALYSIS

In addition with the variants generator implemented in the previous version, the sensitivity analysis features enables a deeper analysis of the impacts of variables uncertainties on Quantity of Interest.

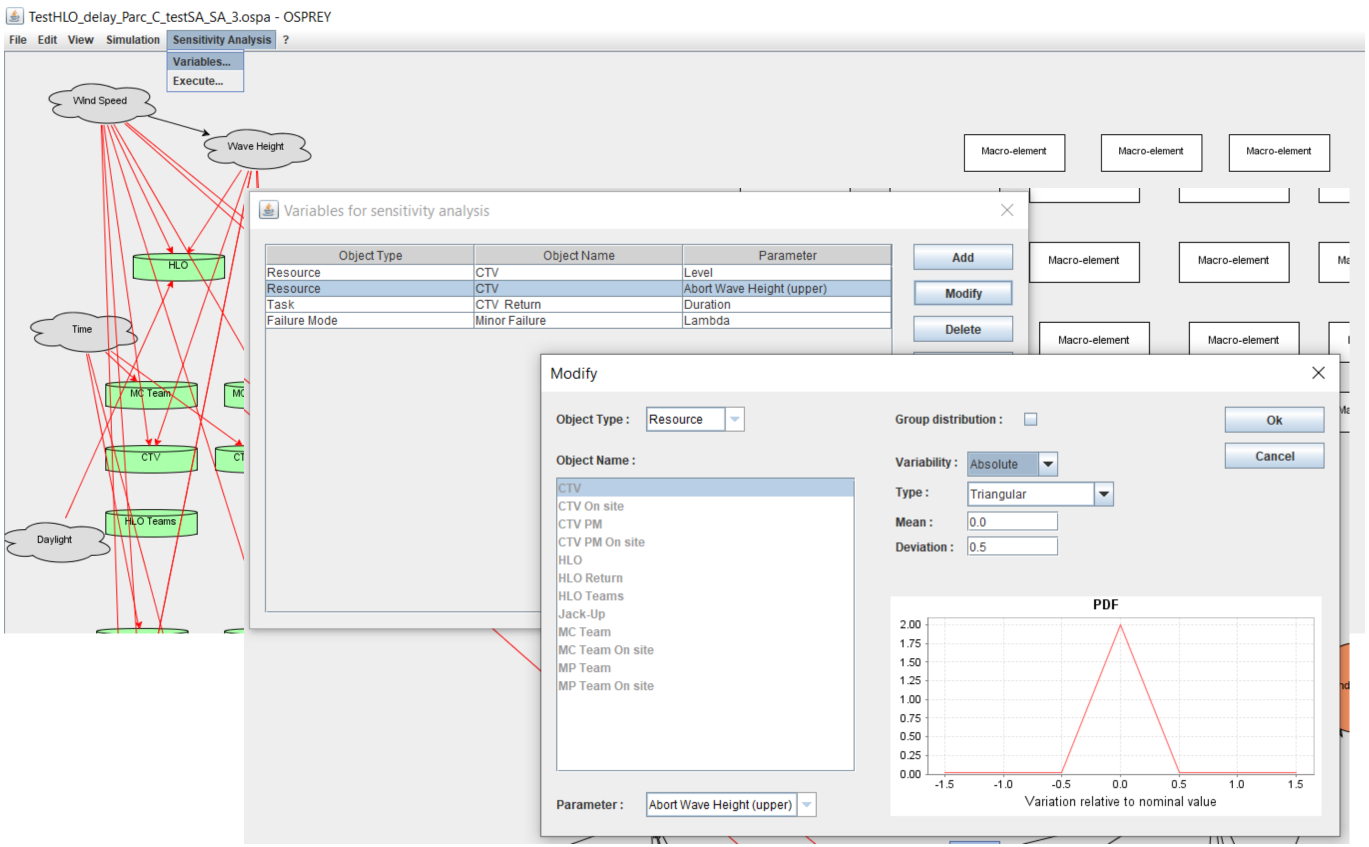
Osprey v6.0 QoI:

- Mean and quantiles of a farm availability
- Mean and quantiles of a task duration

Variables are the same available for variants generation in OSPREY previous version:

Variable Type	Parameters
Resource	Level All weather limits
Task	Duration All weather limits
Failure Mode (if not User Defined)	All parameters

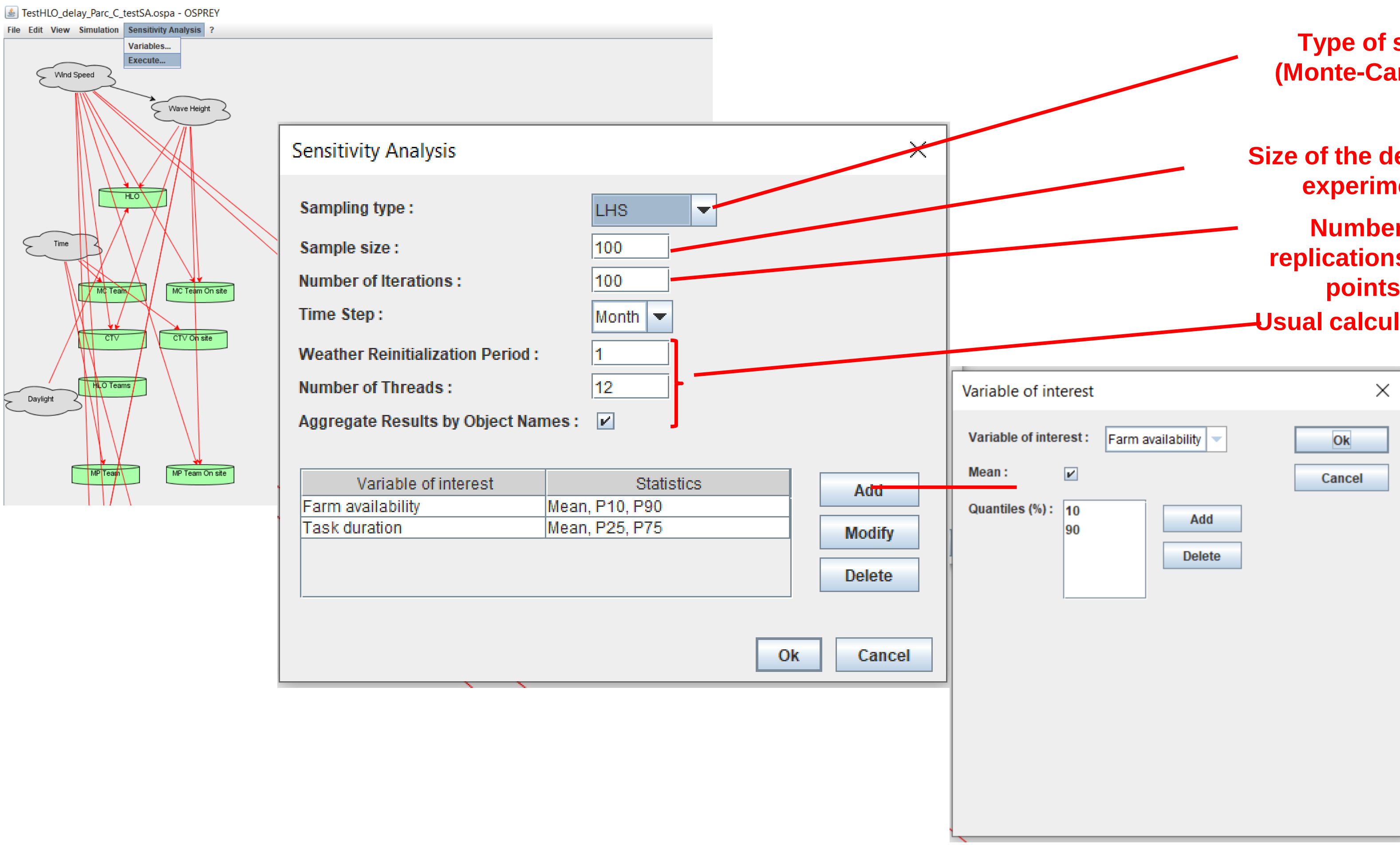
GUI UNCERTAINTIES PARAMETERS



Variations of the variables are always differences with the nominal values

They can be defined in absolute values or percentage

GUI QUANTITIES OF INTEREST PARAMETERS



Type of sampling (Monte-Carlo or LHS)

Size of the design of experiment

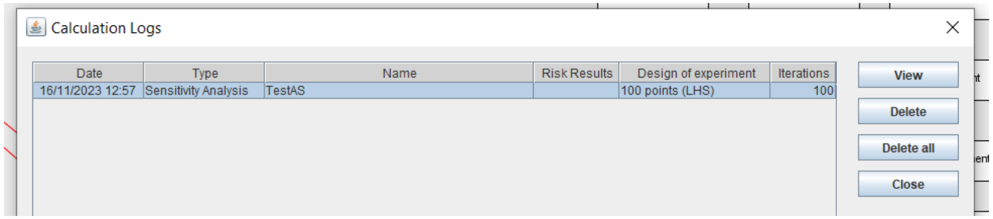
Number of OSPREY replications for each of the points in the DoE

Usual calculation parameters

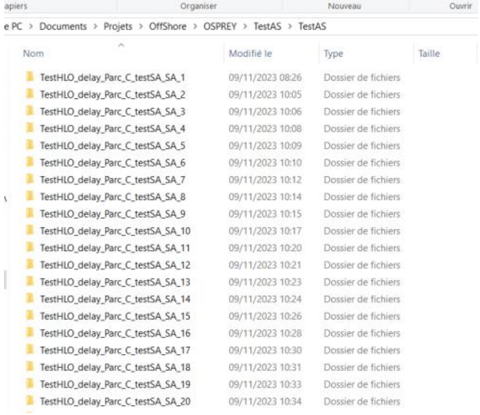
Definition of the Quantities of Interest

GUI SENSITIVITY ANALYSIS CALCULATIONS

Results of the calculations are saved in the OSPREY calculation log of the study file



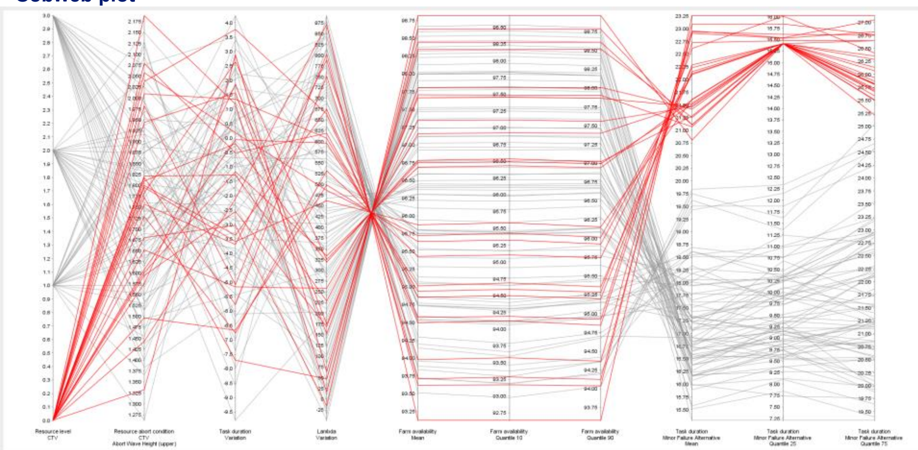
Individual study files are created for each point of the DoE and stored in a directory with the same architecture than the variants generation feature



GRAPHICAL ANALYSIS

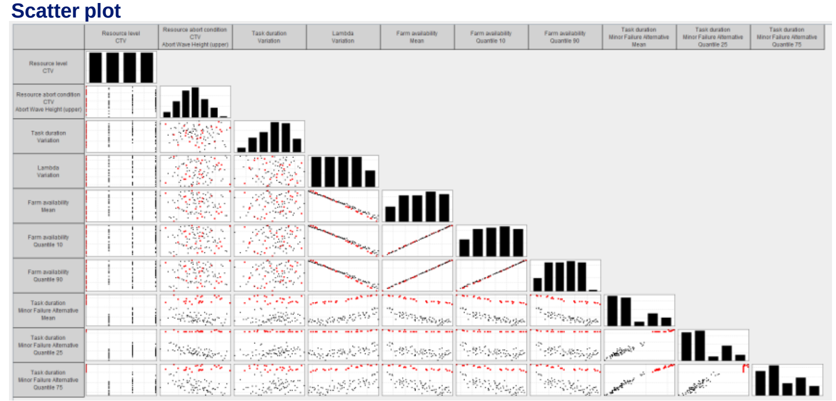
Once the variables and QoI are defined OSPREY runs the calculation and provides synthetic output to help users analyse the impact of uncertainties on key indicators of a model:

Cobweb plot



Possibility to select runs in a specific range of variables and/or quantities of interest values, appearing in red in the graphs

Scatter plot



Correlation matrix

	Resource level CTV	Resource abort condition CTV Abort Wave Height (upper)	Task duration Variation	Lambda Variation	Farm availability Mean	Farm availability Quantile 10	Farm availability Quantile 90	Task duration Minor Failure Alternative Mean	Task duration Minor Failure Alternative Quantile 25	Task duration Minor Failure Alternative Quantile 75
Resource level CTV		-0.042	-0.031	-0.014	0.034	0.026	0.041	-0.499	-0.438	-0.504
Resource abort condition CTV Abort Wave Height (upper)	-0.042		-0.101	0.045	-0.019	-0.020	-0.023	-0.168	-0.335	-0.229
Task duration Variation	-0.031	-0.101		-0.091	0.082	0.083	0.084	0.073	0.160	0.098
Lambda Variation	-0.014	0.045	-0.091		-0.993	-0.994	-0.993	0.498	0.338	0.443
Farm availability Mean	0.034	-0.019	0.082	-0.993		1.000	1.000	-0.543	-0.400	-0.493
Farm availability Quantile 10	0.026	-0.020	0.083	-0.994	1.000		0.999	-0.537	-0.394	-0.487
Farm availability Quantile 90	0.041	-0.023	0.084	-0.993	1.000	0.999		-0.544	-0.400	-0.494
Task duration Minor Failure Alternative Mean	-0.499	-0.168	0.073	0.498	-0.543	-0.537	-0.544		0.933	0.984
Task duration Minor Failure Alternative Quantile 25	-0.438	-0.335	0.160	0.338	-0.400	-0.394	-0.400	0.933		0.944
Task duration Minor Failure Alternative Quantile 75	-0.504	-0.229	0.098	0.443	-0.493	-0.487	-0.494	0.984	0.944	

6

Needs

SENSITIVITY ANALYSIS

Need for sensitivity analysis indicators for discrete events models (HSIC has been implemented in a similar EDF tool, named VME)

Variables could be real, discrete or even “functional” (weather time-series)

Outputs are stochastic and potentially multimodal, sensitivity analysis could be done on the probabilistic distribution or on a given statistic (mean, quantile…)

Simulation times can be moderately high (up to a minute for a single replication of the Monte-Carlo algorithm)

Tackling the problem on a complete model could be a challenge, possibility to build a smaller dedicated model