PREDICTING RENEWABLE ENERGY GENERATION BY THE MEANS OF WEATHER-SCENARIOS, IOT SENSORS AND COMPLEX HPC INFRASTRUCTURE

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Concept and approach

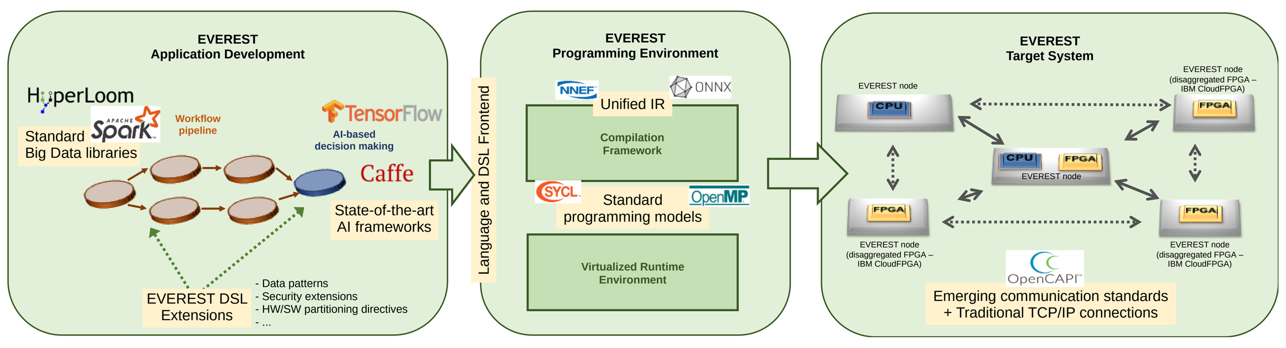
EVEREST focuses on **High Performance Big Data Analytics (HPDA) applications.**

- Future Big Data systems will be data-driven.
- Complex heterogeneous and reconfigurable architectures are difficult to program.

The EVEREST project aims at developing a holistic approach for co-designing computation and communication in a heterogeneous, distributed, scalable, and secure system for HPDA.

Main features:

- **data-driven design approach;**
- combination of **compiler transformations, high-level synthesis, and memory management;**
- efficient monitoring of the execution with a **virtualisation-based environment.**

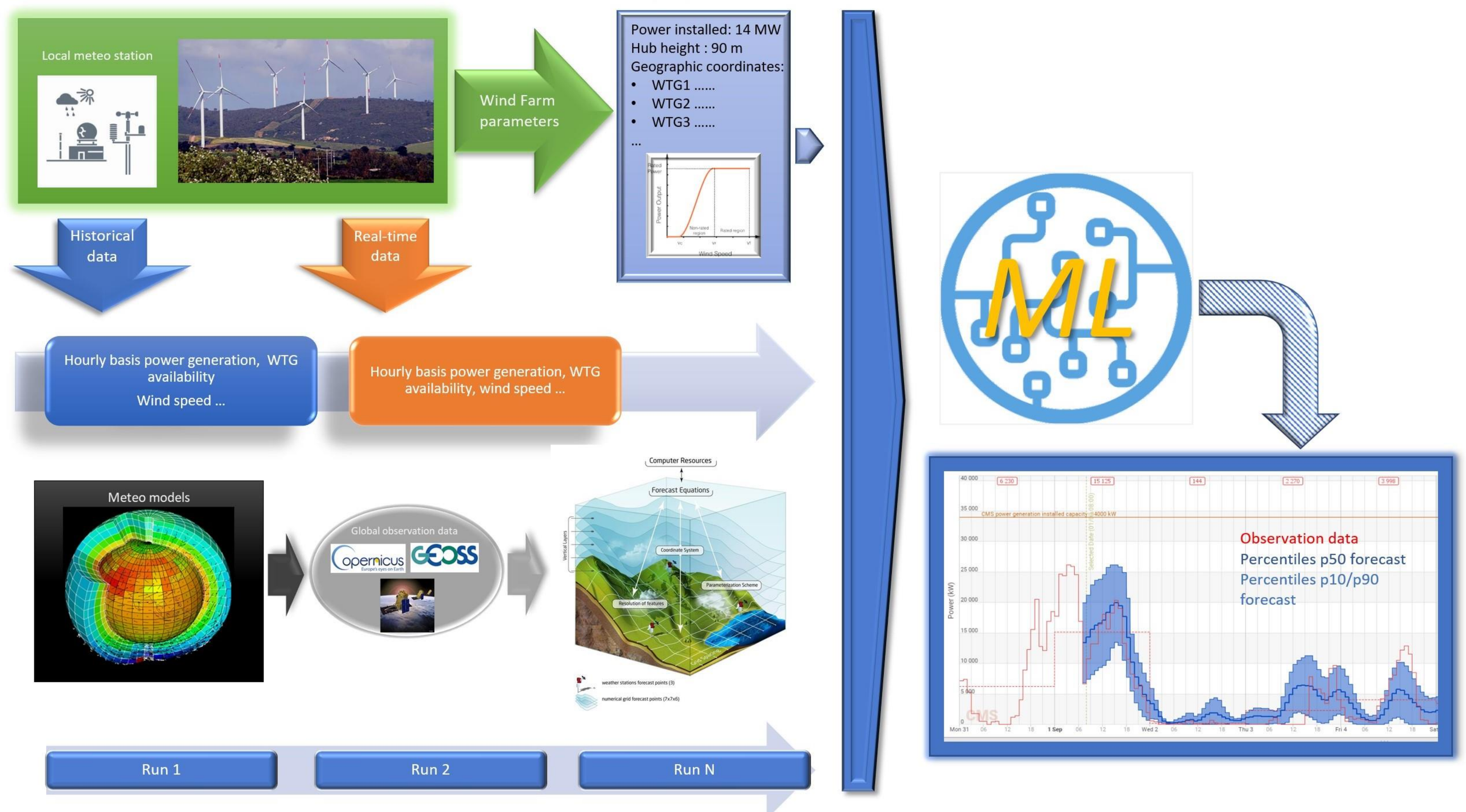


EVEREST proposes a **design environment** that combines state-of-the-art, stable programming models, and emerging communication standards with novel and **dedicated domain-specific extensions.** The EVEREST approach will be validated on three industrial use cases, one is related to **wind energy production**; the application is developed during the project lifetime.

Weather-based renewable-energy prediction

The use case combines deterministic **high resolution weather forecast** processed by WRF models (2,5 km grid) and improved by **global data assimilation,** with an application based on **Machine Learning (ML)** algorithms analysing **historical site specific datasets** to obtain **wind farms generation forecast.**

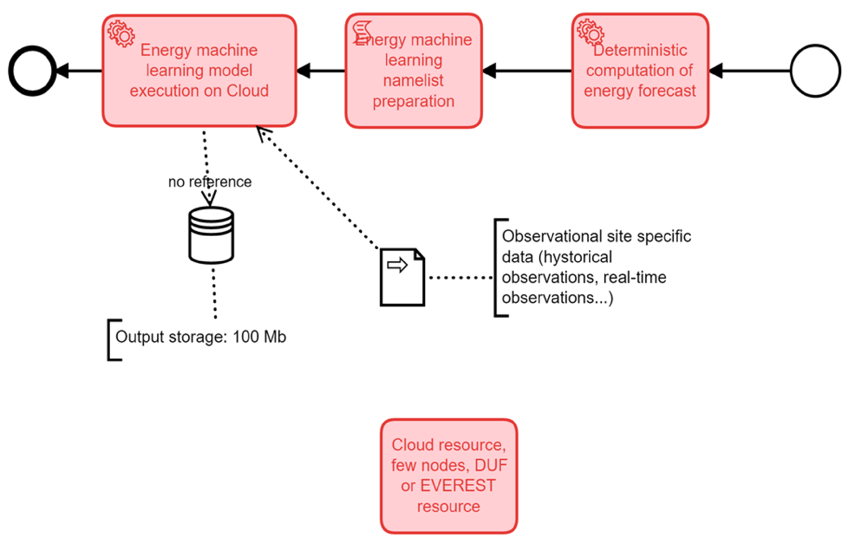
GOAL: achieve **better accuracy of forecast products** for the day-ahead energy market, intraday energy market, and next continuous energy trading market, **reducing imbalances costs.**



Meteorological Model

The production (and the prediction) of weather-based scenarios is provided as an EVEREST service for downstream applications.

The WRF model can be described as a computational and memory intensive model highly demanding for ICT resources.



WRF model configuration

WRF is a state-of-the-art numerical prediction model and encompasses physics schemes, numeric/dynamics options, initialisation routines, and a data assimilation package (WRFDA). The EVEREST design environment allows:

- to push forward data assimilation aspects to achieve augmented descriptions of the atmospheric state – used as initial conditions of the run;
- to improve model resolution in terms of spatial and temporal scale thus to better fit the geographical domain;
- to speed up performance figure of the WRF model by the means of the EVEREST FPGA-hardware to implement and test an ensemble prediction.

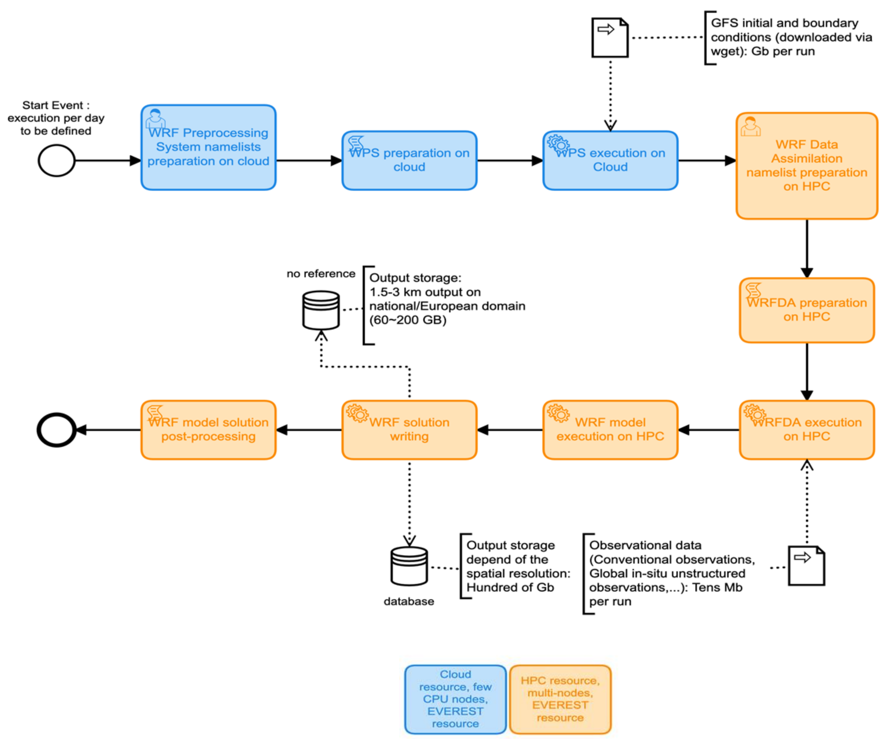
Wind farm data collection

Training, calibration and model validation need at least **one year of historical data:**

- historical hourly **power generation;**
- historical hourly **wind speed**, from local anemometer;
- historical hourly power **availability**, due to maintenance or failure of wind turbines;
- historical hourly power **curtailment by TSO.**

The specific datasets of **5 Wind Farms** will be used to validate the predictions.

Workflow implementation



Energy prediction: a ML approach

Selection of **algorithm Kernel-Ridge.**

The application is written in **Python, Pycharm** exploiting **Jupyter**; **Scikit-learn** modules are used for **kernel methods**; Keras and Tensorflow libraries for deep learning.

Validation path

State-of-the-art KPI have been selected to evaluate the accuracy of wind power generation. Continuous analysis of the results and experimentation of different strategies to better customise the workflow. Strong collaboration with CIMA to evaluate the possible improvements to the WRF parameters to better understand the physics behind the prediction.

First results on CALABRIA Wind Farm – 34 MW

Experiment ID	Description	Algorithm	Training filter	Training size	Training strategy	Validation strategy	MAE June	MAE July	Notes
1	**Baseline model**. Model trained using data relating to the WRF coordinate closest to the wind farm barycenter.	KernelRidge, kernel=rbf	None	198-228 fixed	rolling	gamma fixed=1.1 alpha fixed=1.0	2,74	3,01	**Choice of the coordinates on which to retrieve the input data.**
2	Model trained on the data of the 9 WRF coordinates that enclose the wind farm. Each coordinate was given equal weight (1/9).	KernelRidge, kernel=rbf	None	198-228 fixed	rolling	gamma fixed=1.1 alpha fixed=1.0	2,75	3,02	
3	Model trained on the data of the 9 WRF coordinates that enclose the wind farm. Each coordinate was given a different weight with respect to the distance from the barycenter of the wind farm.	KernelRidge, kernel=rbf	None	198-228 fixed	rolling	gamma fixed=1.1 alpha fixed=1.0	2,74	3,01	
4	Combination of 9 models, each trained on the data of one of the coordinates. The forecasts were weighted based on the distance of the coordinate from the barycenter of the wind farm.	KernelRidge, kernel=rbf	None	198-228 fixed	rolling	gamma fixed=1.1 alpha fixed=1.0	2,74	3,01	
5	As experiment 1, filtering the training data if they have wind speed>3m/s and wind production=0.	KernelRidge, kernel=rbf	cutin (>=3 m/s)	198-228 fixed	rolling	gamma fixed=1.1 alpha fixed=1.0	2,76	2,99	**Filters on training data samples.**
6	As experiment 1, filtering the training data that has wind speed>=(wind_speed_avg)*perc on the test day.	KernelRidge, kernel=rbf	wind speed (perc=0.5) dynamic	198-228 fixed	rolling	gamma fixed=1.1 alpha fixed=1.0	2,81	2,88	
7	As experiment 1, with both filters of experiments 5 and 6.	KernelRidge, kernel=rbf	cutin cutoff & wind speed (perc=0.5) dynamic	198-228 fixed	rolling	gamma fixed=1.1 alpha fixed=1.0	2,80	2,85	
8	As experiment 1, with increasing training strategy rather than rolling.	KernelRidge, kernel=rbf	None	198-228+	increasing	gamma fixed=1.1 alpha fixed=1.0	2,66	3,01	**Increasing training size strategy.**
9	As experiment 5, with increasing training strategy rather than rolling.	KernelRidge, kernel=rbf	cutin (>=3 m/s)	198-228+	increasing	gamma fixed=1.1 alpha fixed=1.0	2,68	2,98	
10	As experiment 6, with increasing training strategy rather than rolling.	KernelRidge, kernel=rbf	wind speed (perc=0.5) dynamic	198-228+	increasing	gamma fixed=1.1 alpha fixed=1.0	2,72	2,88	
11	As experiment 7, with increasing training strategy rather than rolling.	KernelRidge, kernel=rbf	cutin cutoff & wind speed (perc=0.5) dynamic	198-228+	increasing	gamma fixed=1.1 alpha fixed=1.0	2,71	2,84	
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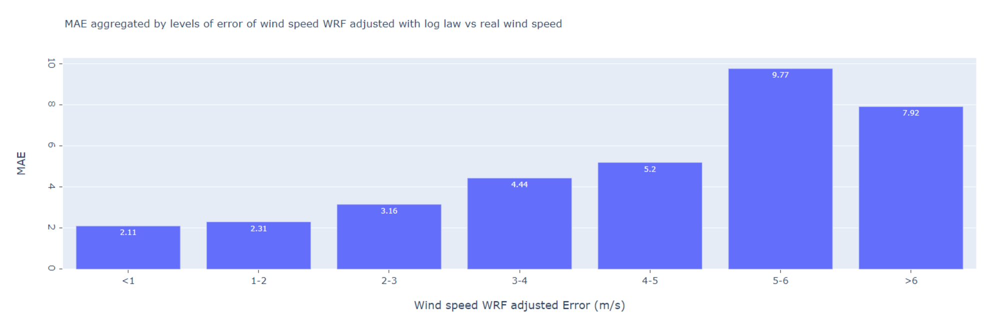

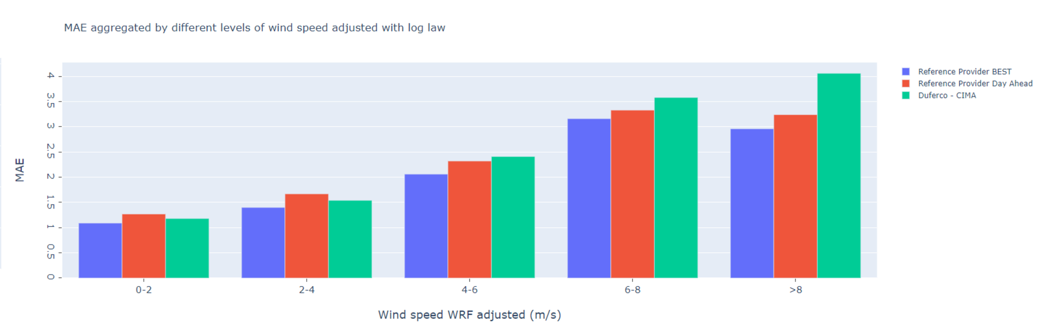

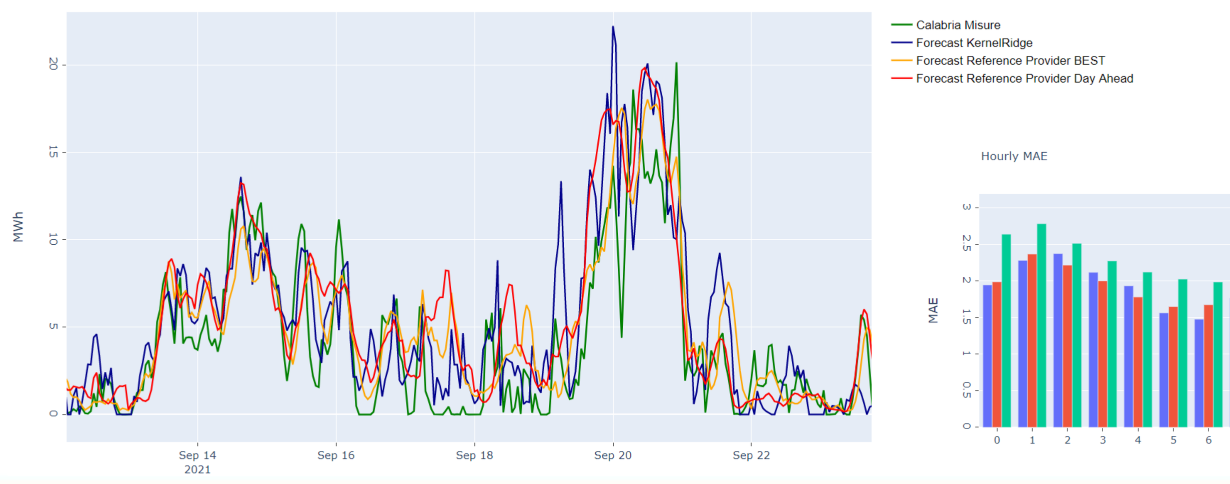

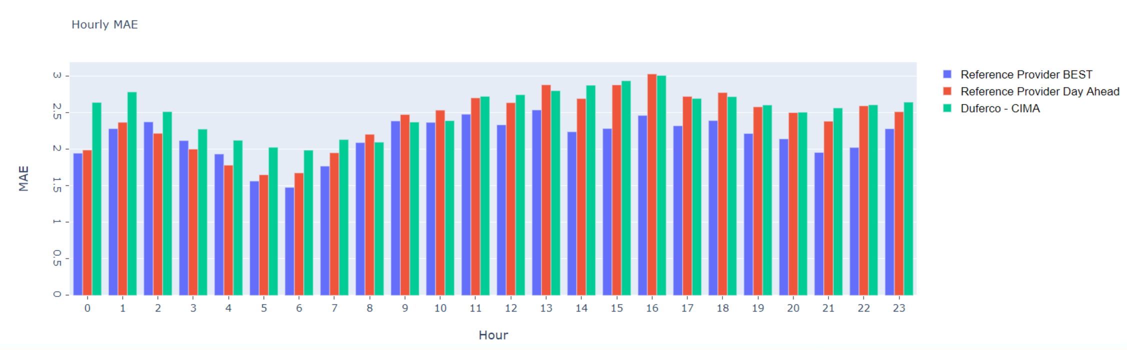

EVEREST
DESIGN ENVIRONMENT
FOR EXTREME-SCALE BIG DATA ANALYTICS
ON HETEROGENEOUS PLATFORMS

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