Smart4RES

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Renewable Energy Forecasting – State of the art, highlight results of Smart4RES and future directions.

Georges Kariniotakis

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MINES PARIS PSL PERSEE

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 864337

MINES PARIS – Centre PERSEE

One of the 18 research centers of MINES Paris

Centre PERSEE
Centre for Processes, Renewable Energies and Energy Systems

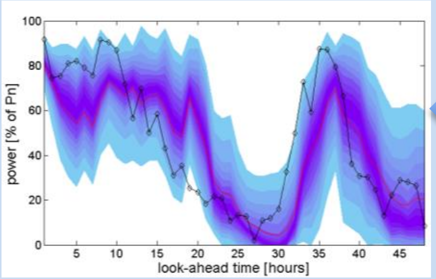
MINES Paris @ Sophia Antipolis

MINES PARIS – Centre PERSEE

OBJECTIVE: Development of methods and tools to facilitate the **integration** of renewables and other new technologies into power systems and electricity markets for the decarbonization of the energy sector.

3 RESEARCH AXES:

Forecasting



Energy systems management & control

Energy systems planning

MINES PARIS – Centre PERSEE

OBJECTIVE: Development of methods and tools to facilitate the **integration** of renewables and other new technologies into power systems and electricity markets for the decarbonization of the energy sector.

3 RESEARCH AXES:

Forecasting	Energy systems management & control	Energy systems planning

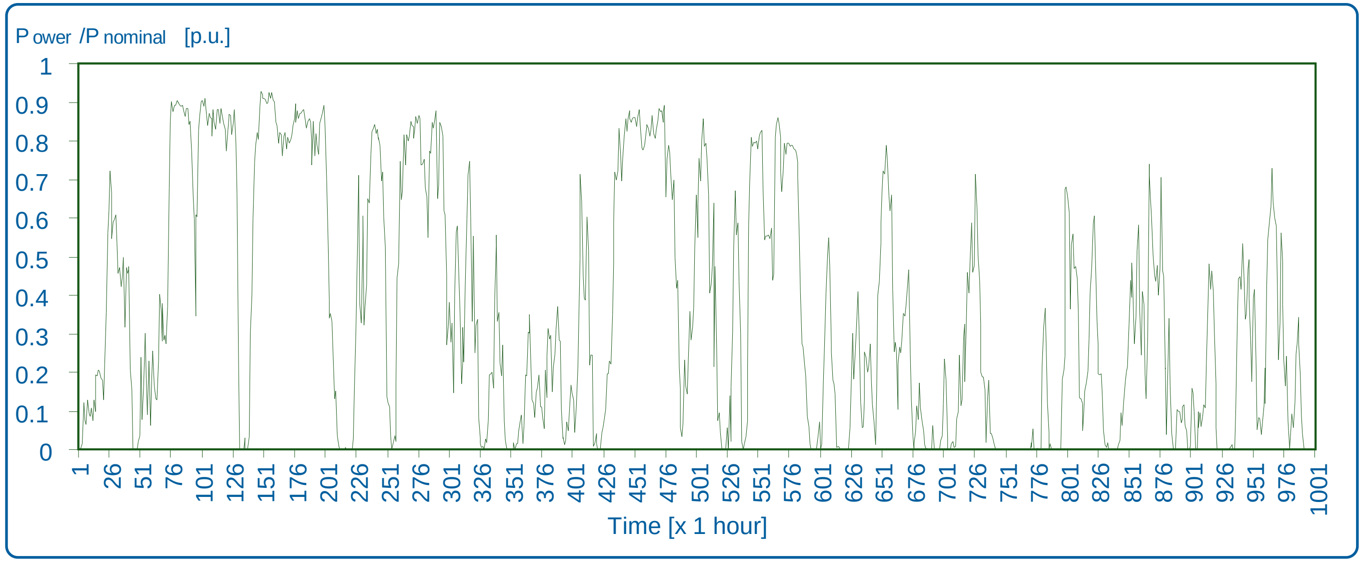
We have **5 PhD positions** open currently in these areas:
Contact me for more info

OUTLINE

1. Context
2. Evolution of the State of the Art in RES forecasting
3. The Smart4RES project
4. Highlight results
5. Future research directions

Context

- Short-term (minutes-days ahead) forecasts of renewable generation (wind, solar) (RES) are necessary for a secure and economic operation of power systems.

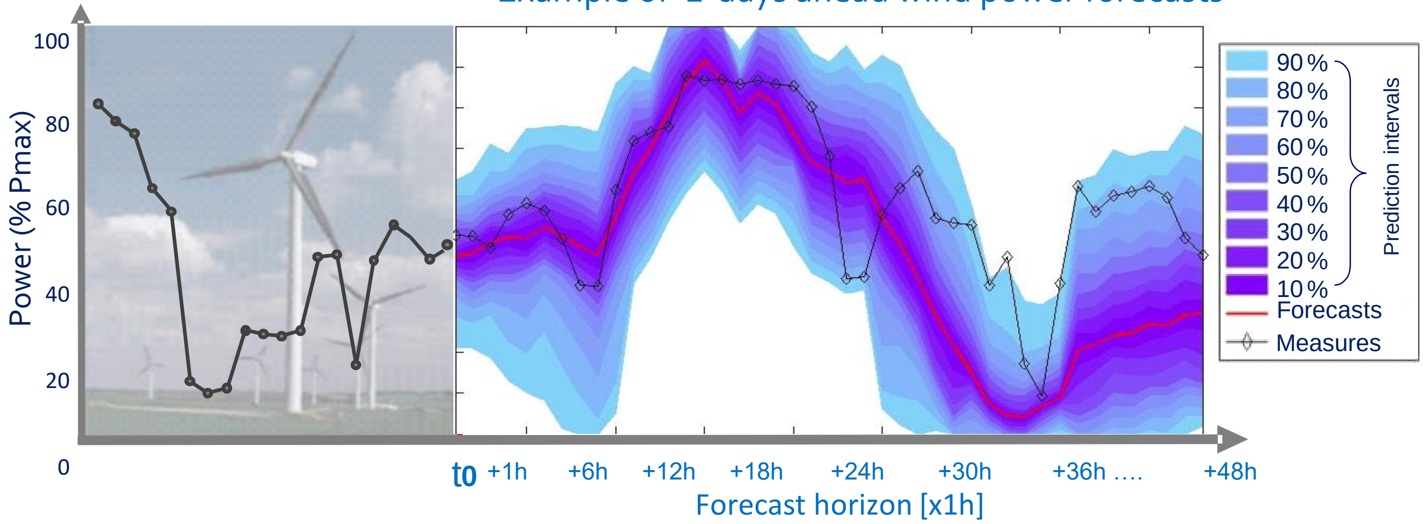


Example of hourly wind farm production over a month

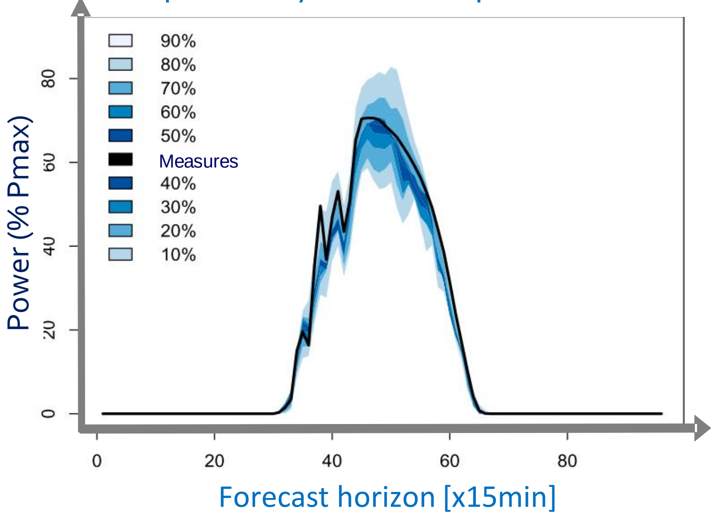
Context

- Short-term (minutes-days ahead) forecasts of renewable generation (wind, solar) (RES) are necessary for a secure and economic operation of power systems.
- Forecasting solutions are used operationally by all stakeholders.
- However, large forecast errors may occur with a high financial/technical impact.
- Improving forecasting accuracy has been a continuous requirement by end users.

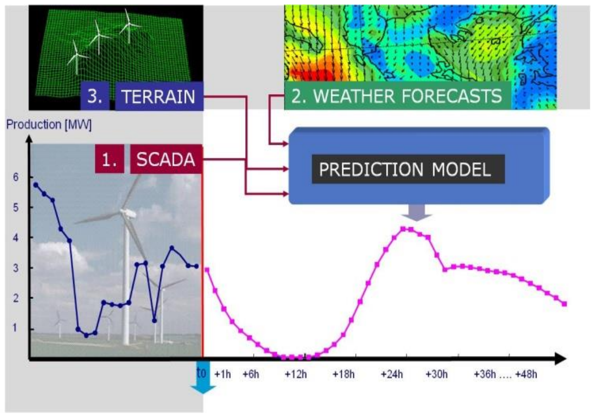
Example of 2-days ahead wind power forecasts

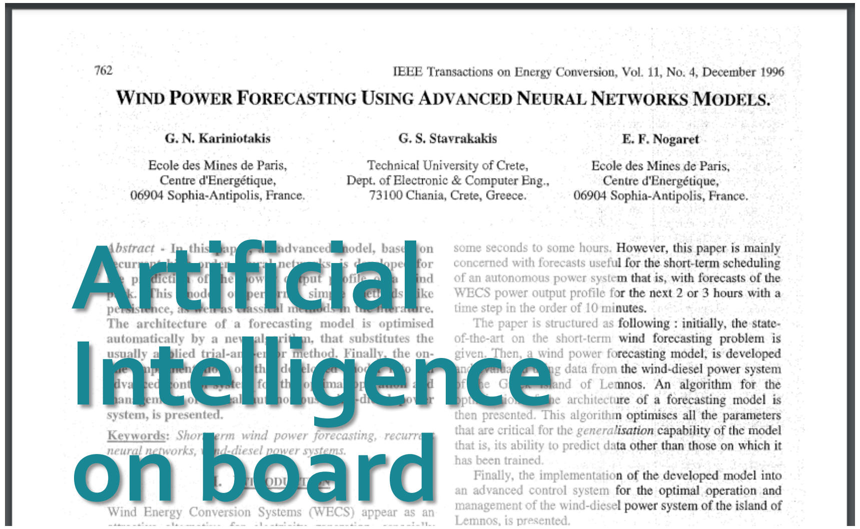


Example of day ahead PV power forecasts



The history of RES forecasting





762 IEEE Transactions on Energy Conversion, Vol. 11, No. 4, December 1996

WIND POWER FORECASTING USING ADVANCED NEURAL NETWORKS MODELS.

G. N. Kariniotakis
Ecole des Mines de Paris,
Centre d'Energétique,
06904 Sophia-Antipolis, France.

G. S. Stavrakakis
Technical University of Crete,
Dept. of Electronic & Computer Eng.,
73100 Chania, Crete, Greece.

E. F. Nogaret
Ecole des Mines de Paris,
Centre d'Energétique,
06904 Sophia-Antipolis, France.

some seconds to some hours. However, this paper is mainly concerned with forecasts useful for the short-term scheduling of an autonomous power system that is, with forecasts of the WECS power output profile for the next 2 or 3 hours with a time step in the order of 10 minutes.

The paper is structured as following : initially, the state-of-the-art on the short-term wind forecasting problem is given. Then, a wind power forecasting model, is developed and evaluated using data from the wind-diesel power system of the Greek island of Lemnos. An algorithm for the optimisation of the architecture of a forecasting model is then presented. This algorithm optimises all the parameters that are critical for the *generalisation* capability of the model that is, its ability to predict data other than those on which it has been trained.

Finally, the implementation of the developed model into an advanced control system for the optimal operation and management of the wind-diesel power system of the island of Lemnos, is presented.

❖ (1996) 1st journal paper ever with AI applied in RES

1985 1990 2000 2010 2020

- First purely time series methods on WPF

- Statistical / time-series approaches
- Physical modelling
- First AI-based approaches
- NWPs considered as input
- Empiric/hybrid implementations into operational forecast tools

[2002-2006] ANEMOS (FP5), http://www.anemos-project.eu/
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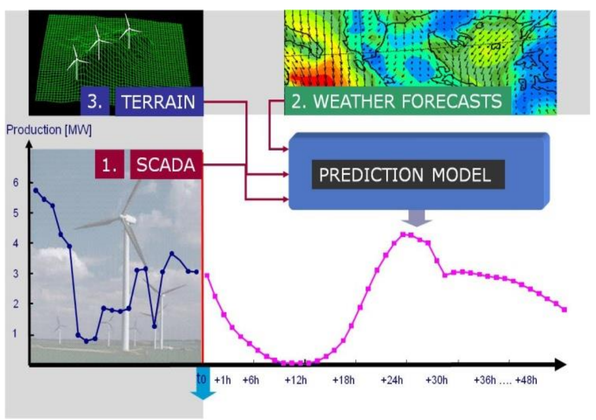
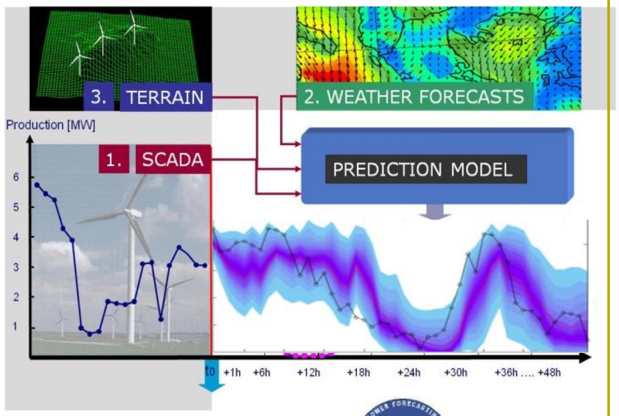
[2019-2023] Smart4RES (H2020), http://www.smart4res.eu/

The history of RES forecasting

"Deterministic" (spot) view



Probabilistic view



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- 1st benchmarking (Anemos competition)
- Physical modelling
- Statistical models, AI, Data mining,…
- Combination of models
- First probabilistic approaches/ensembles
- Upscaling
- Evaluation standardisation/protocol
- International collaboration

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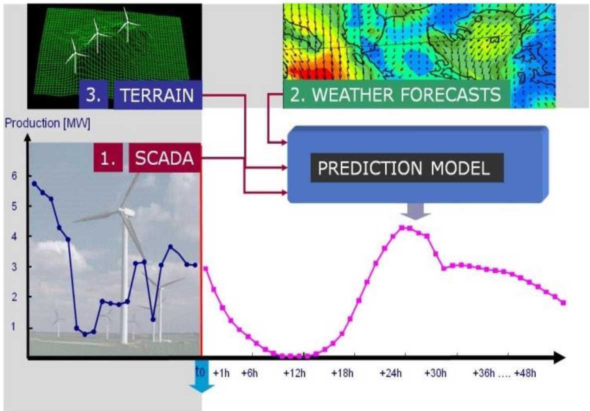

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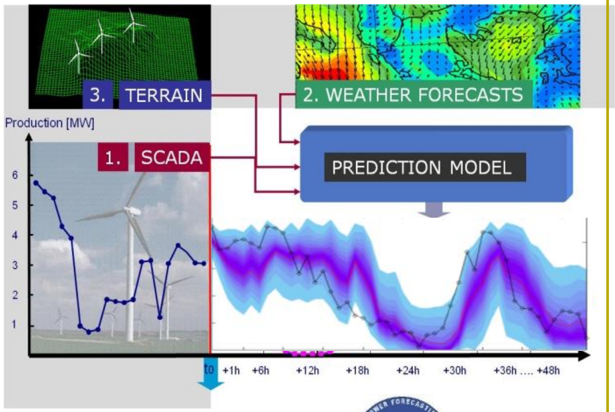
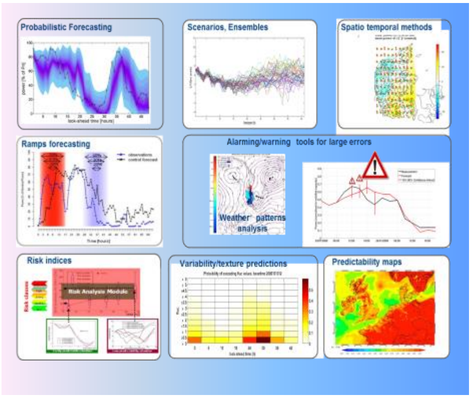


Probabilistic & special situations



ANEMOS.plus SafeWind

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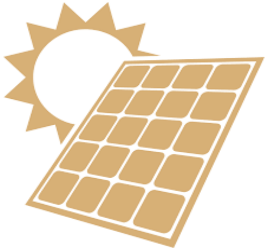
- Dedicated NWPs for RES
- Direct probabilistic predictions
- Ramps forecasting
- Scenarios, Enesembles,
- Risk indices
- Large errors warning/alarming
- Spatiotemporal forecasting
- Variability forecasting
- Predictability maps



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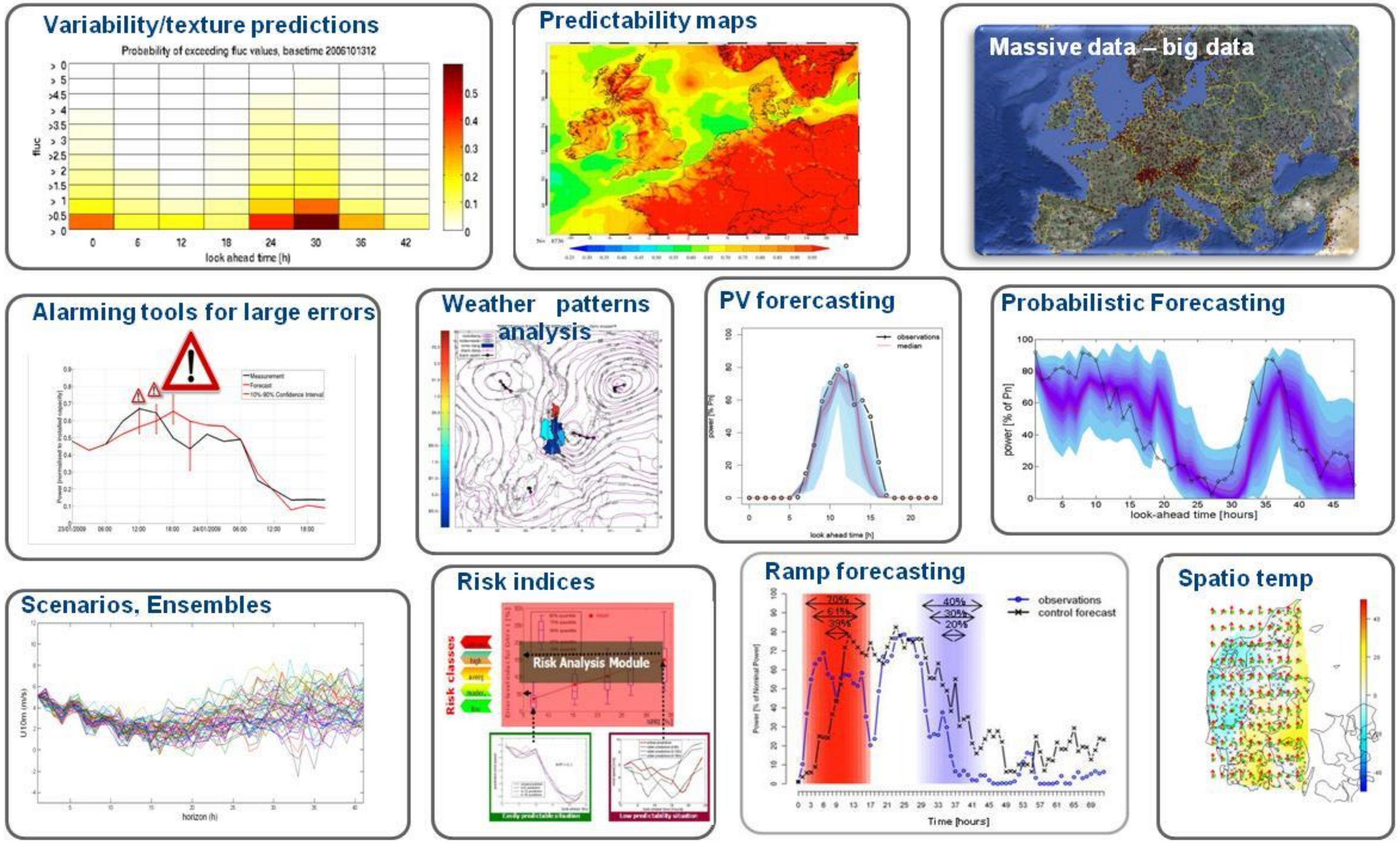
The history of RES forecasting

- Major developments in wind forecasting in the period 2002-2012.
- Solar forecasting followed a much faster learning curve that started around 2005



The history of RES forecasting

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- Multiplication of academic works

ANEMOS.plus
ANEMOS
SafeWind

250 publications at conferences and journals

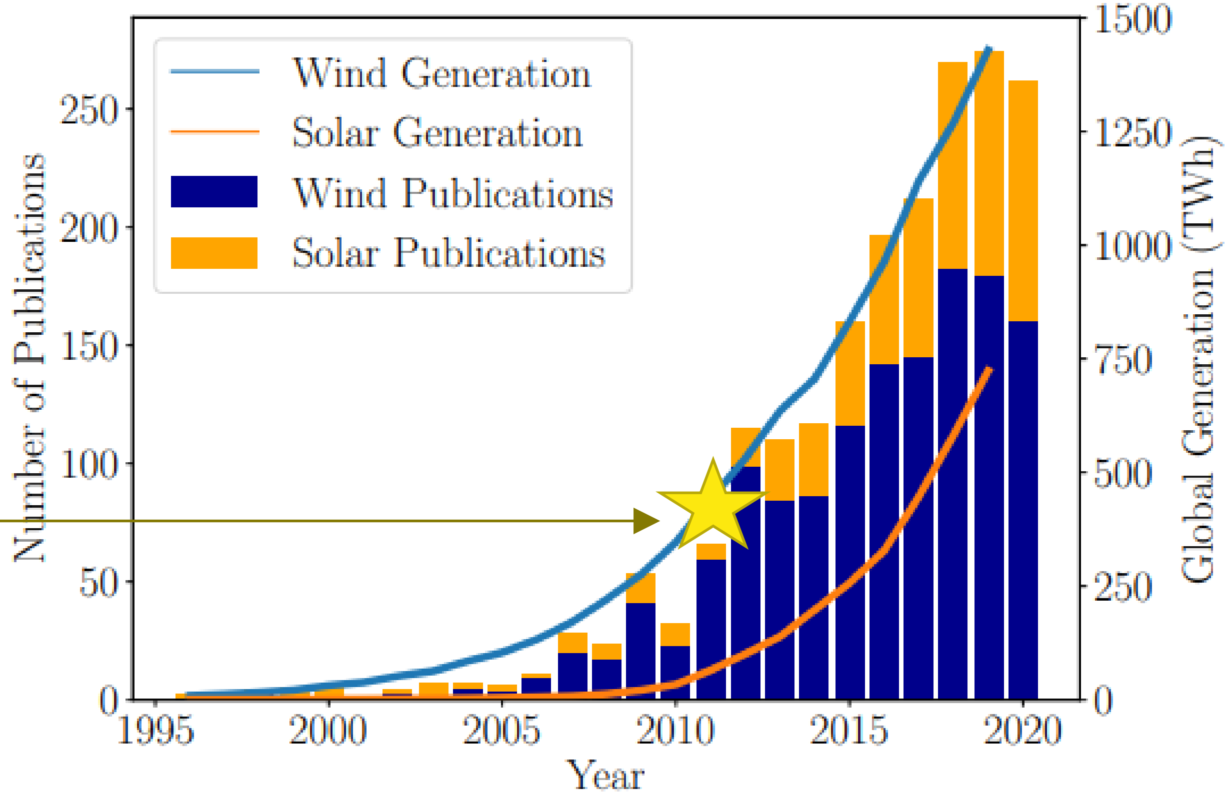

Figure 2.1: Forecasting publications broken down by wind and solar as a stacked bar chart, also plotted with global energy generation through time. Generation data provided under CC BY 4.0, Hannah Ritchie & Max Roser, ourworldindata.org/renewable-energy.

SOURCE: PhD thesis Rosemary Tawn , Strathclyde University, 2022.

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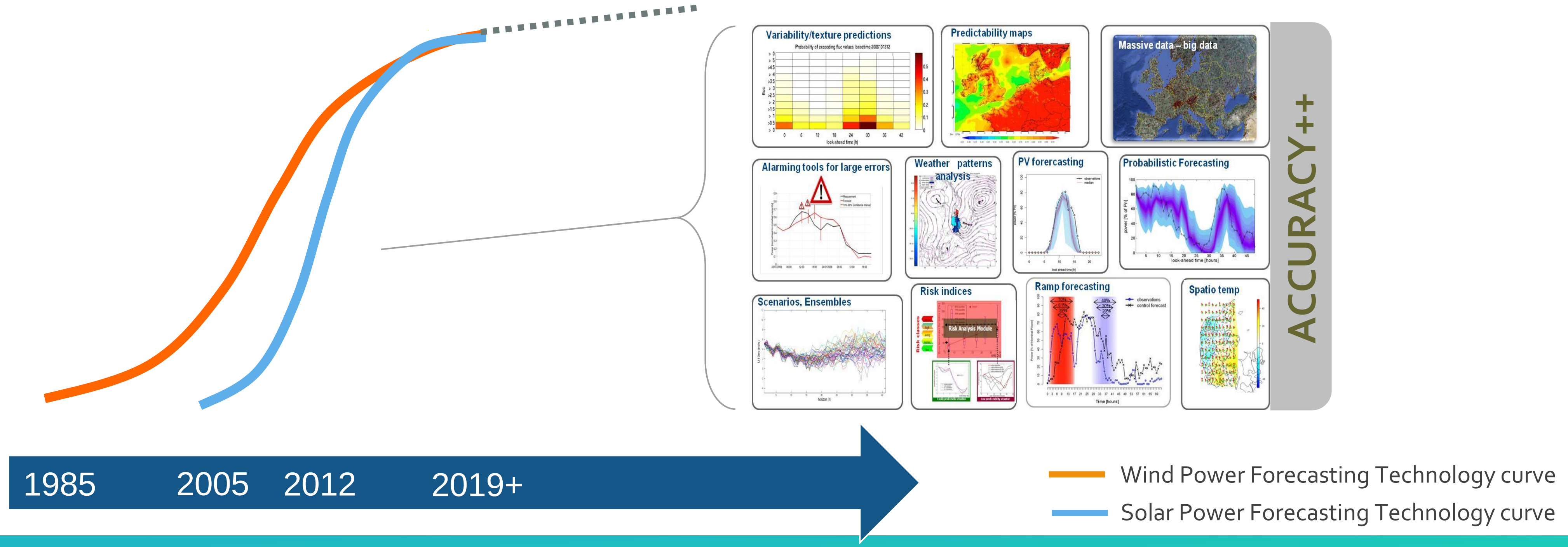

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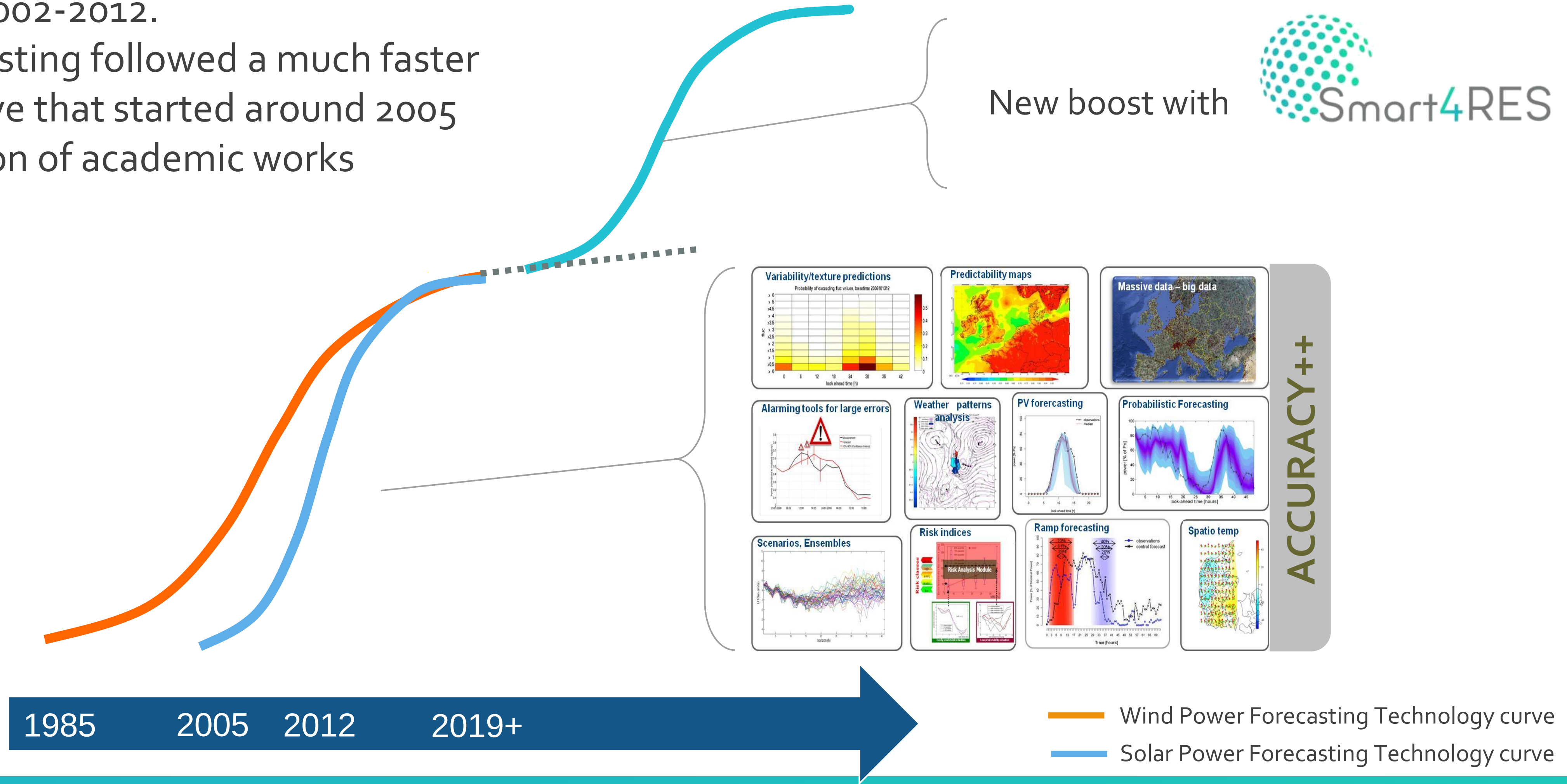

The history of RES forecasting

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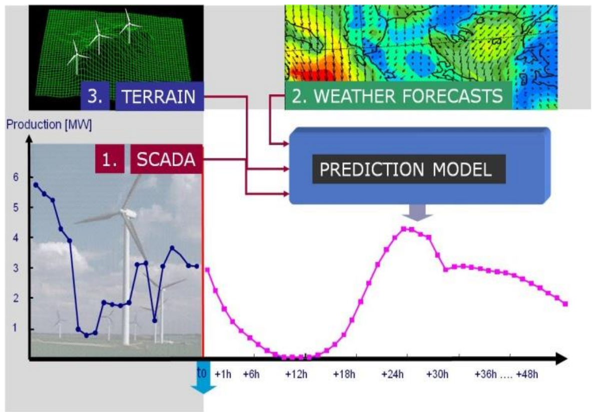
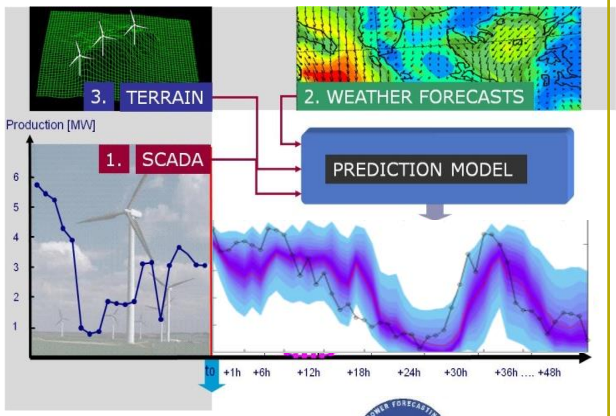


Probabilistic view



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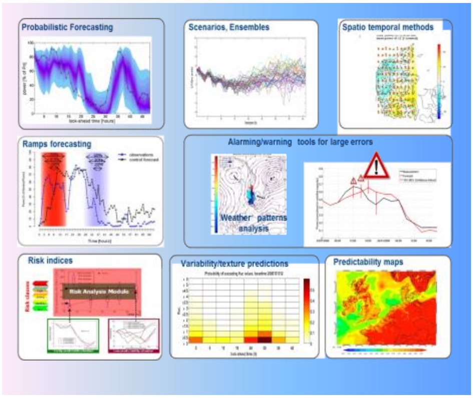

ANEMOS.plus SafeWind

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- Mapping of state of the art
- 1st benchmarking (Anemos competition)
- Physical modelling
- Statistical models, AI, Data mining,...
- Combination of models
- First probabilistic approaches/ensembles
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- Dedicated NWPs for RES
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- Ramps forecasting
- Scenarios, Enesembles,
- Risk indices
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- Variability forecasting
- Predictability maps

- Seamless forecasting
- Ultra high resolution (LES)
- Advanced NWPs
- Prescriptive analytics
- Extremes
- Data sharing/Data markets
- New forecasting products
- Resilience in forecasting
- Optimal use in applications

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OUTLINE

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3. **The Smart4RES project**
4. Highlight results
5. Future research directions

The Smart4RES project in a nutshell

Smart4RES

- **A multi-disciplinary consortium**

7 countries
13 partners

End-users
Industry
Research
Universities
Meteorologists

Funds: H2020 program
Budget: 4 M€
Duration: 3.5 years

11/2019-4/2023

France: MINES PARIS, PSL, ARMINES, METEO FRANCE, Dowel innovation

Germany: energy & meteo systems, DLR

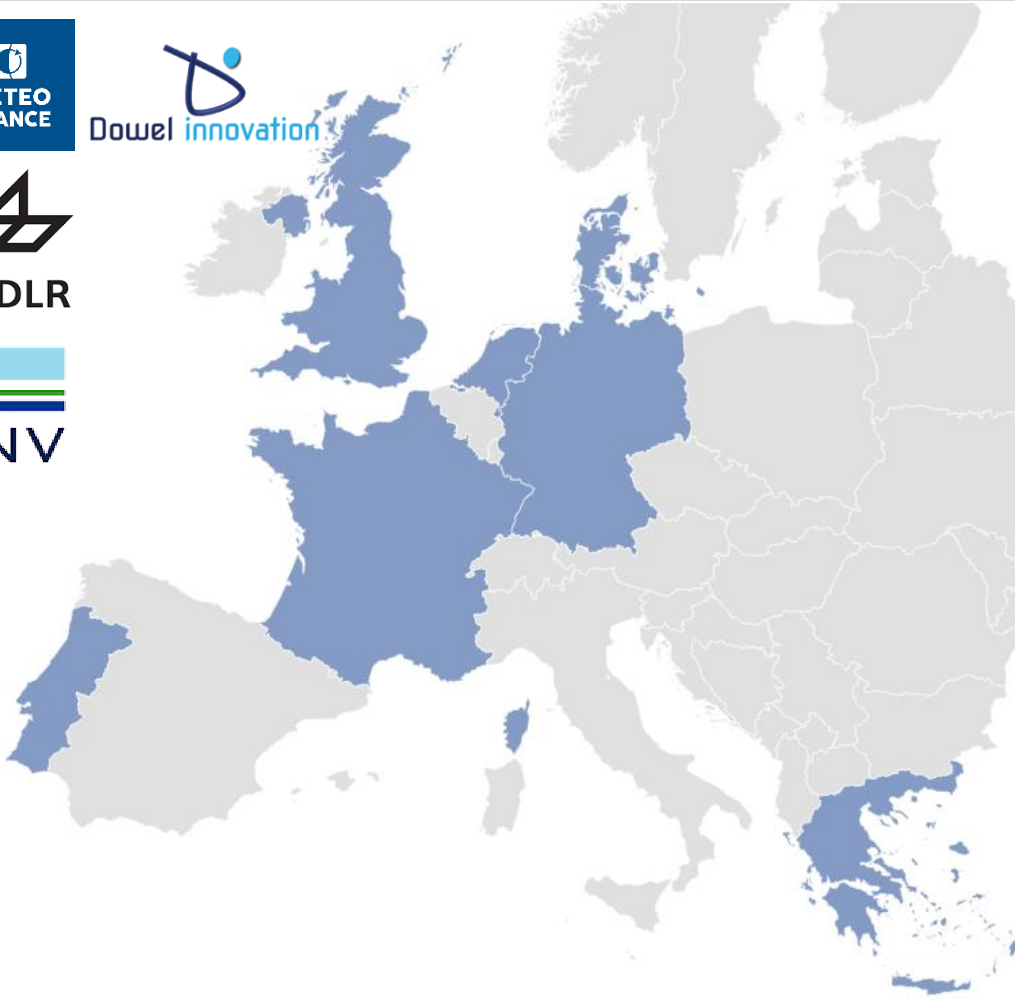
Netherlands: whiffle precision weather forecasting, DNV

Denmark: DTU

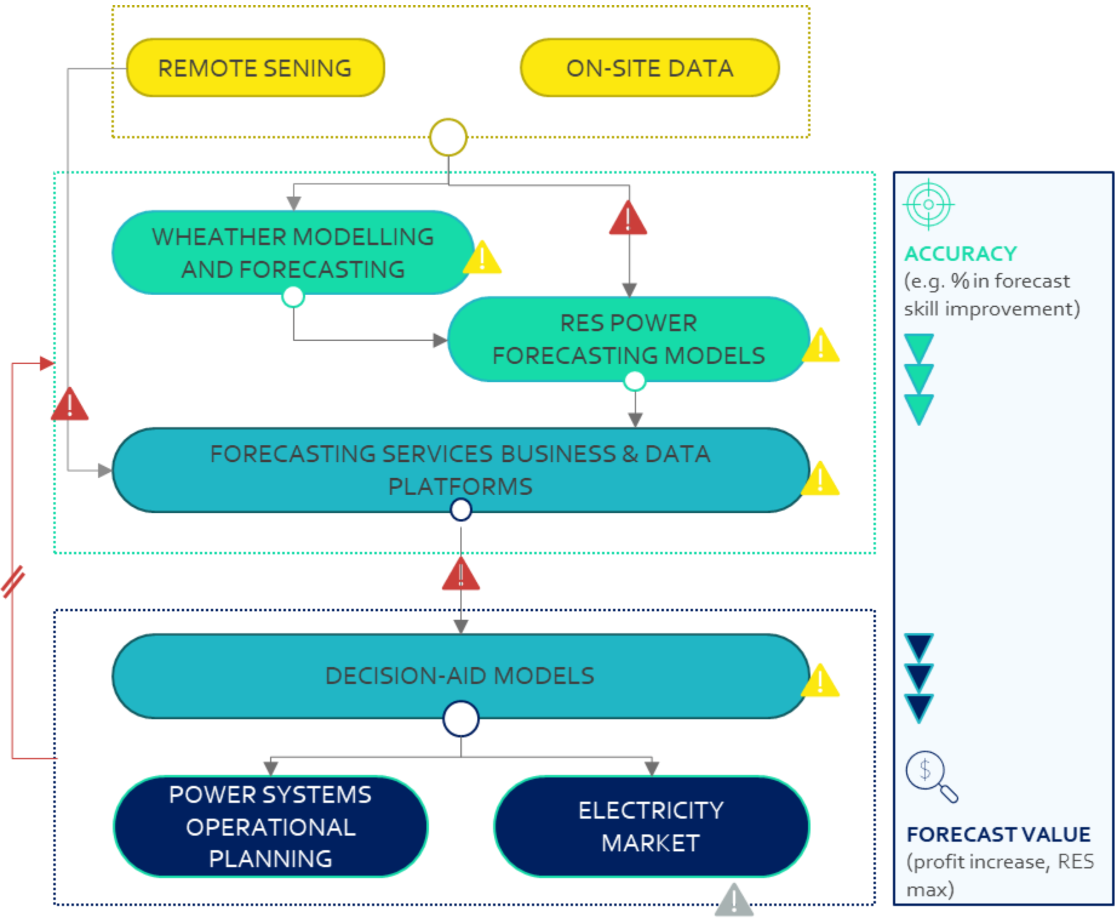
UK: Imperial College London

Portugal: INESCTEC, NEW by EDP & CTG

Greece: ΕΠΙΣΕΥ ICCS, HEDNO HELLENIC ELECTRICITY DISTRIBUTION NETWORK OPERATOR S.A.



The Smart4RES project in a nutshell



The typical RES forecasting model/value chain

<u>Project vision:</u> Achieve outstanding improvement in RES predictability through a **holistic approach,** that covers the whole model and value chain related to RES forecasting

<u>Objectives (& take aways)</u>

- Methods to extract the value out of data through data sharing and data market concepts
- Advanced weather modelling & forecasting adapted to the energy sector
- New RES forecasting tools which, by design, are not only optimized to maximize accuracy, but also other properties, like simplicity, resilience, robustness, value in applications.
- A new generation of AI-based tools to simplify decision making of operators like meta-forecasting and prescriptive analytics .

Challenges & Smart4RES solutions and impacts

Challenge	Smart4RES solutions	Impact
REDUCED KNOWLEDGE OF THE PHYSICAL SYSTEM	• Ultra/high resolution modeling of weather conditions • Weather forecasts adapted to the energy sector • Modelling based on multiple sources of data	HIGHER MODELLING ACCURACY
VULNERABILITY	• Solutions that permit operators to take optimal decisions under situations with lacking information	RESILIENCE
COMPLEXITY	• Convergence of the technology through seamless solutions • Joint forecasting and optimisation prescriptive approach • Reduction of information for human operators	SIMPLICITY
UNCERTAINTIES	• Reduce uncertainties especially in extreme siituations • Optimisation tools to manage uncertainties	ROBUSTNESS
SUBOPTIMALITY	• Value-oriented vs accuracy-oriented forecasting • Privacy/confidentiality preserving data sharing & data markets	VALUE MAXIMISATION

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1. Context
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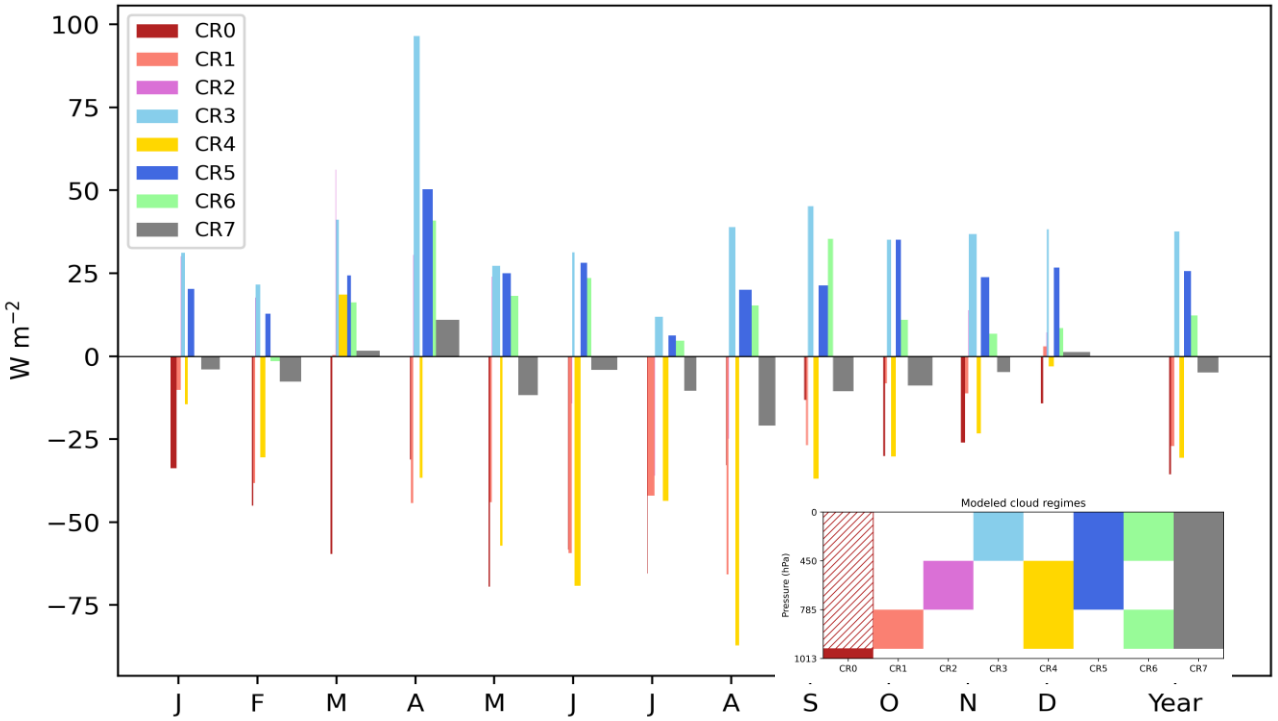
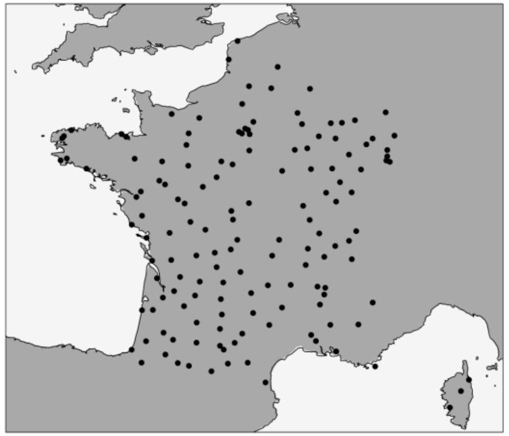
3. The Smart4RES project
4. **Highlight results**
5. Future research directions

Improved weather modelling and forecasting

- Evaluation of AROME solar radiation (1 year of hourly forecasts, 168 pyranometers)
- Identified large error compensations (high clouds too transparent and low clouds too opaque)



Monthly (and annual) SWD (short-wave radiation downward) bias for various AROME cloud regimes

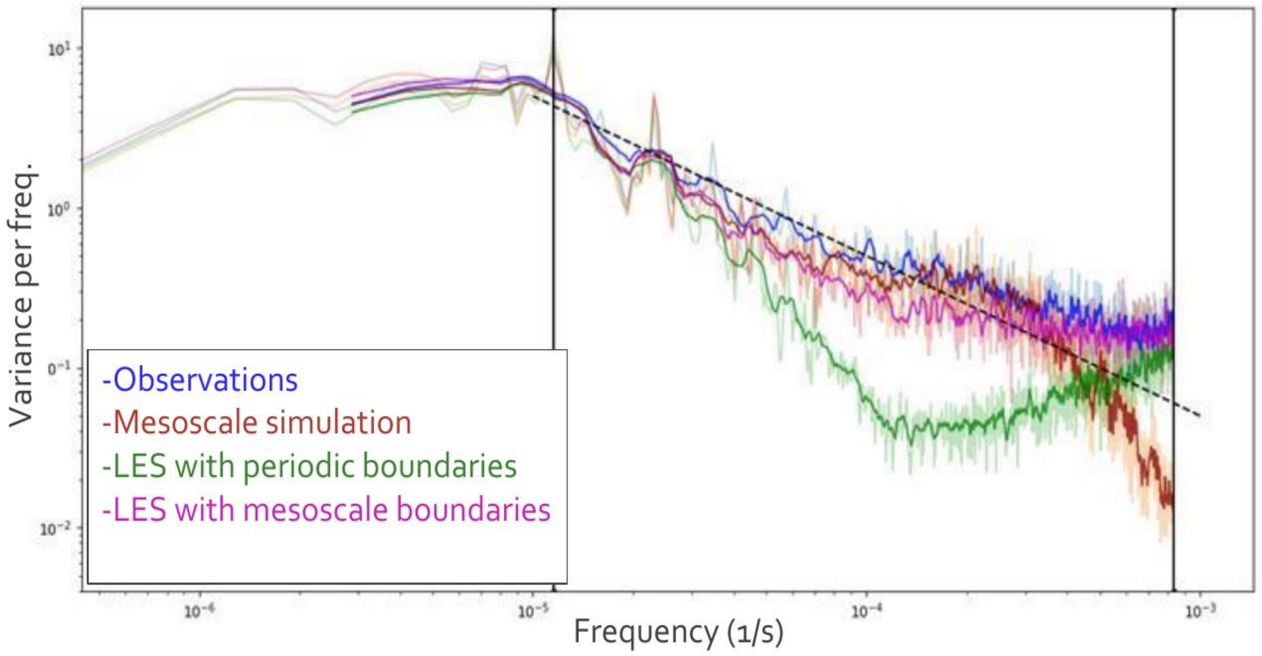


Pyranometers used

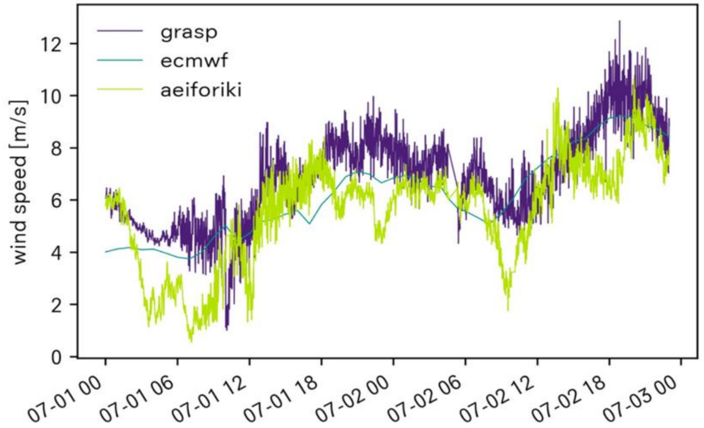
Model deficiencies identified, now to be tackled

Improved weather modelling and forecasting

- Refined LES simulations thanks to improved physics and realistic boundary conditions
- Small scale fluctuations correctly captured by LES (resol. 50 m, 30 sec).



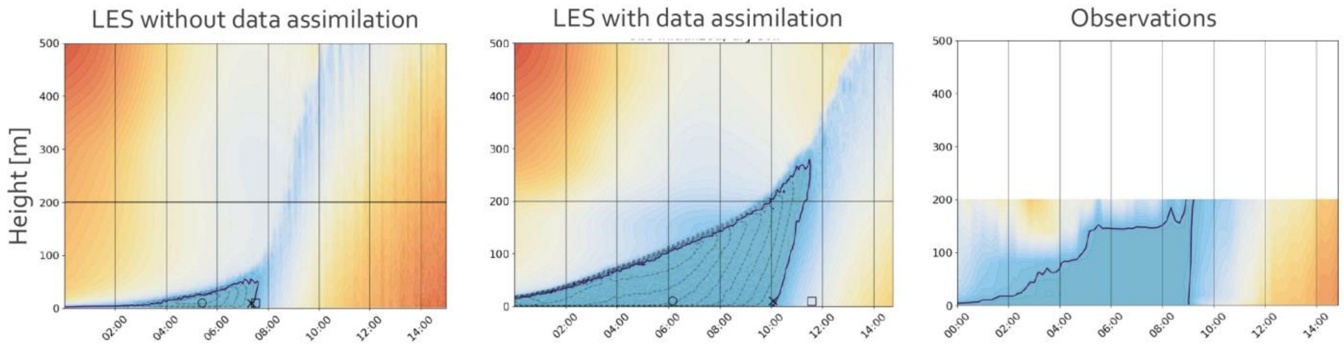
Energy spectra for observed wind and for different simulations



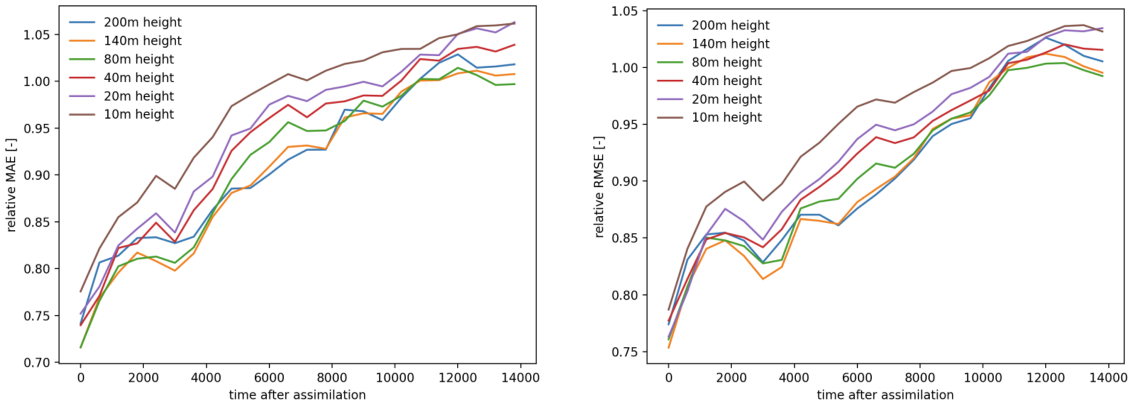
Average improvement of 9 % for MAE of wind speed for 7 sites (KPI 1.1)

Improved weather modelling and forecasting

- LES simulations can be initialized or updated with local observations via data assimilation
- Very promising approach to improve fog formation and wind speed forecasts



Comparison of LES (or 1D?) forecasts of a fog event at Cabauw initilized with ECMWF analysis (left) or with local observations (center). Observations are shown in the right panel.



(a) Mean absolute error statistics

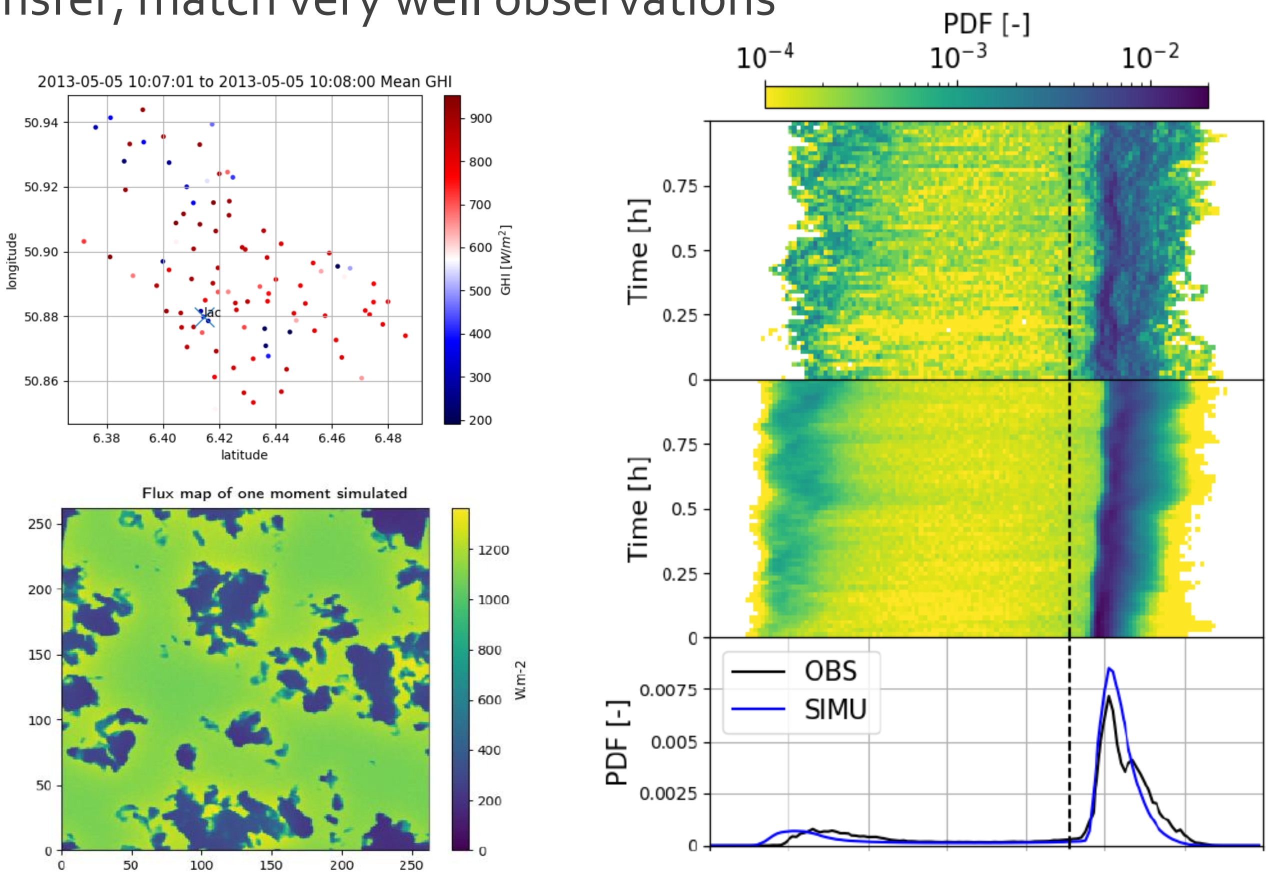
(b) Root mean square error statistics

Relative errors of a wind forecast with and without data assimilation for the Cabauw mast

Data assimilation of local observations **greatly improves LES forecasts.** Improvements better than **10 % in MAE and RMSE** for the first hour

Improved weather modelling and forecasting

- Solar radiation fields simulated combining i) cloud fields simulated by LES and ii) 3D radiative transfer, match very well observations

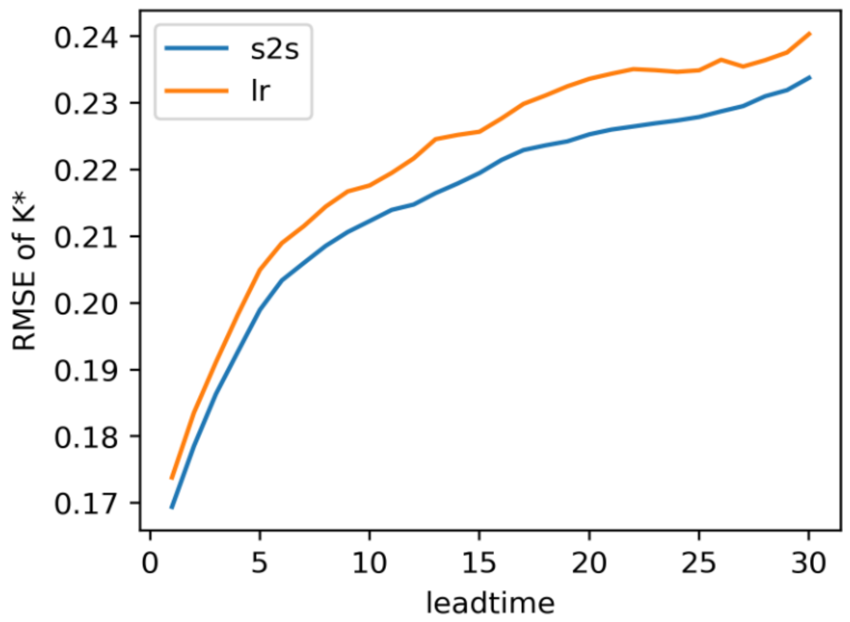


Snapshot of SWD measured by HOPE pyranometers network and simulated, and comparison of the distributions along one hour

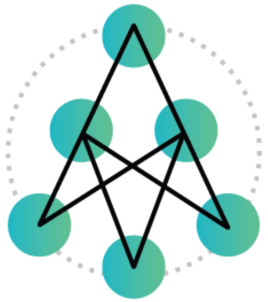
LES could simulate the impact of individual clouds on solar farms

Improved weather modelling and forecasting

- Use of a long short-term memory (LSTM) network to combine ASI and satellite forecasts of solar radiation
- This strategy outperforms the linear regression approach



RMSE of clear sky index (K) for the linear regression based combination (lr) and the LSTM (s2s) approaches*

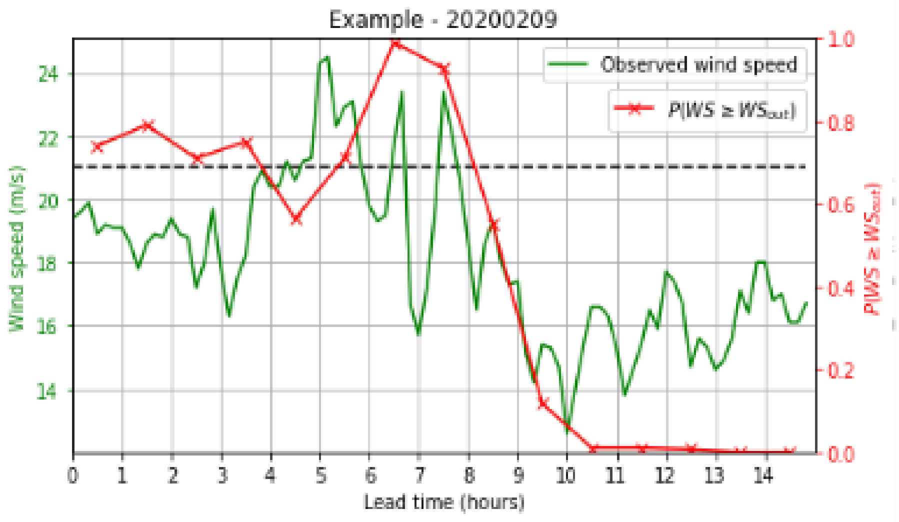


RMSE reduction of 2-5 % for very short-term solar radiation forecasts when using an LSTM instead of a simple linear regression

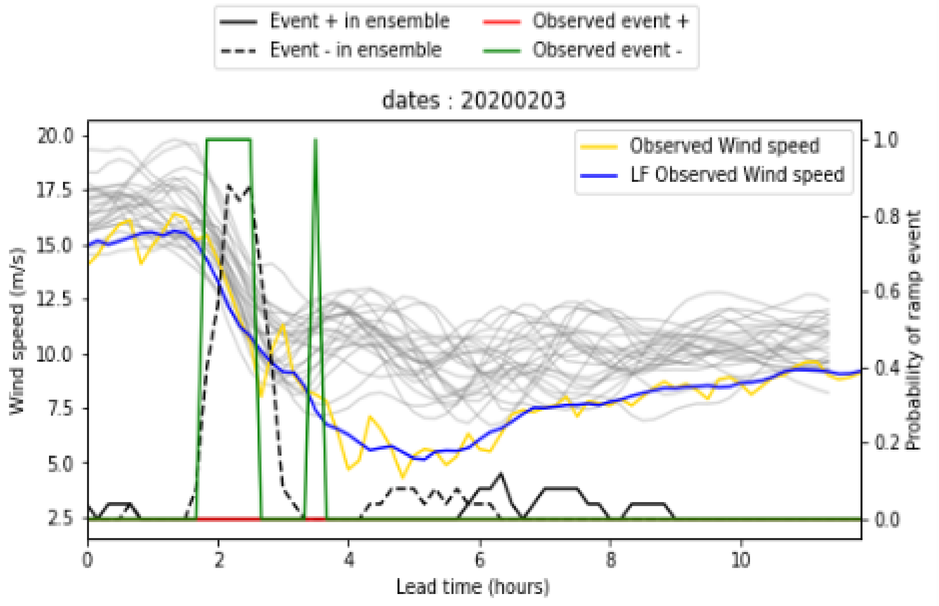
Improved weather modelling and forecasting

- Generation of high resolution ensembles (1km - 5min, MeteoFrance)

  Derive different types of products, i.e.:
  - Pseudo-deterministic Numerical Weather Predictions
  - Forecasts for extreme situations (cut-out, ramps…).
  - Applied to wind speed and direction at hub height (121 wind farms)



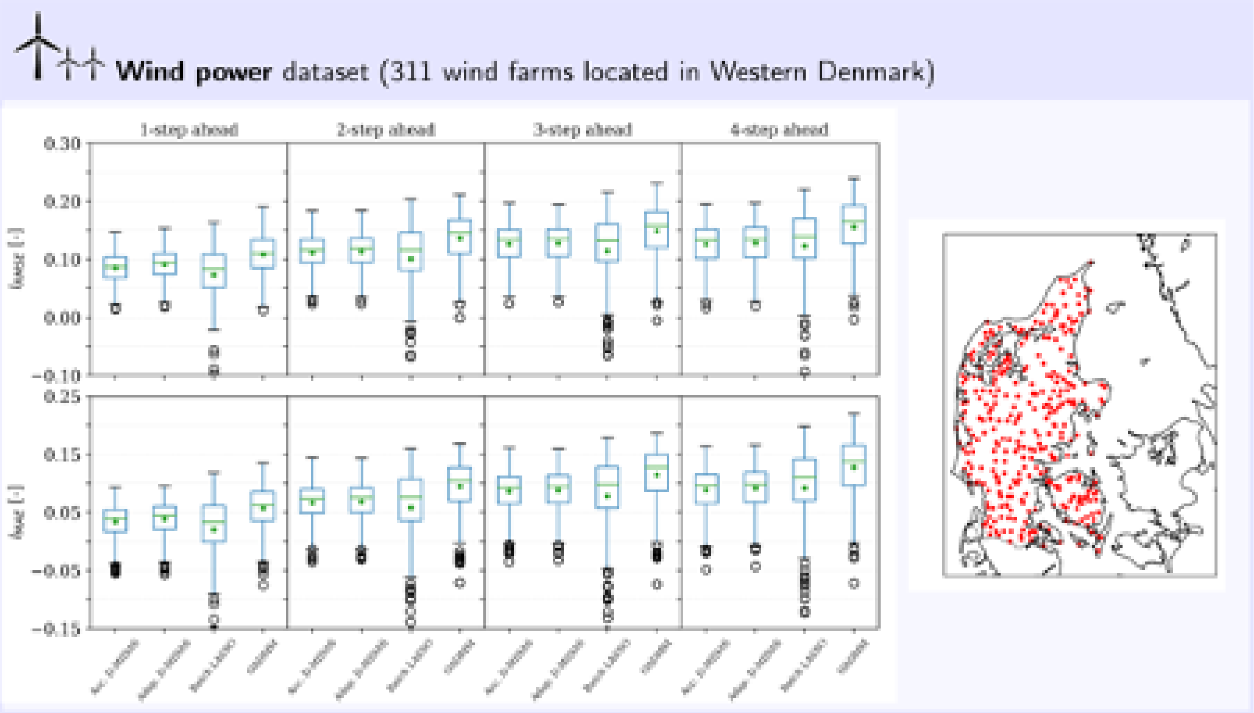
Cut-out probability



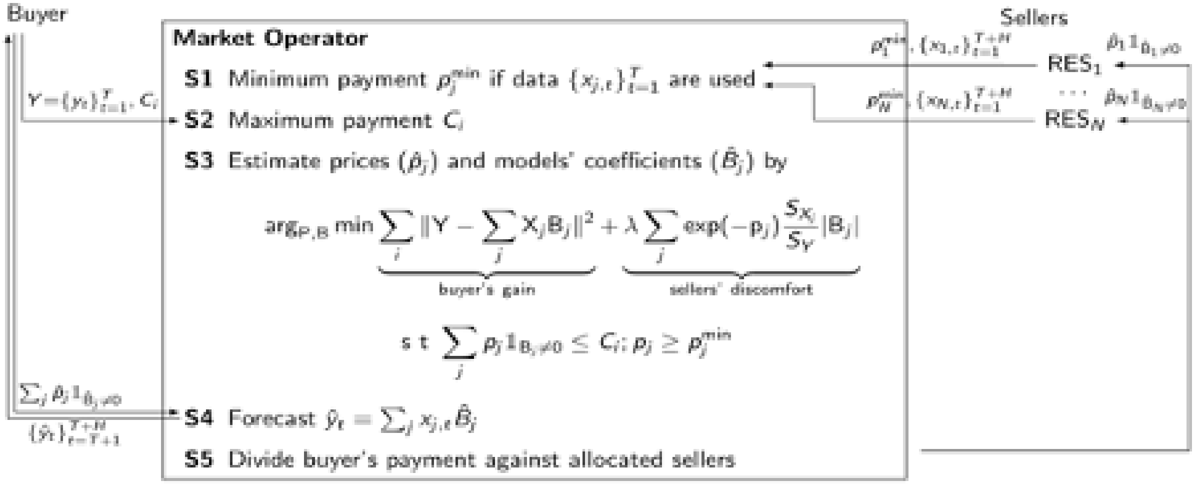
Ramp probability

Collaborative forecasting, data sharing and data markets

- Cutting-edge collaborative and distributed learning approaches that set a new standard within the field of renewable energy forecasting (INESC, DTU)
  - Data sharing while respecting confidentiality and privacy constraints.



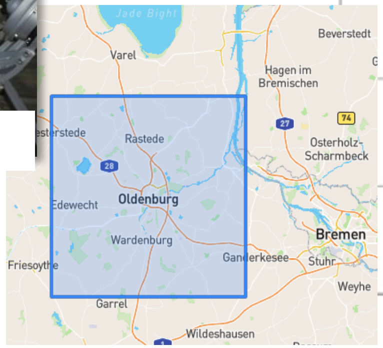
- First-even proposal of a data market for energy applications, relying on several methodological and application-related developments (INESC, DTU)

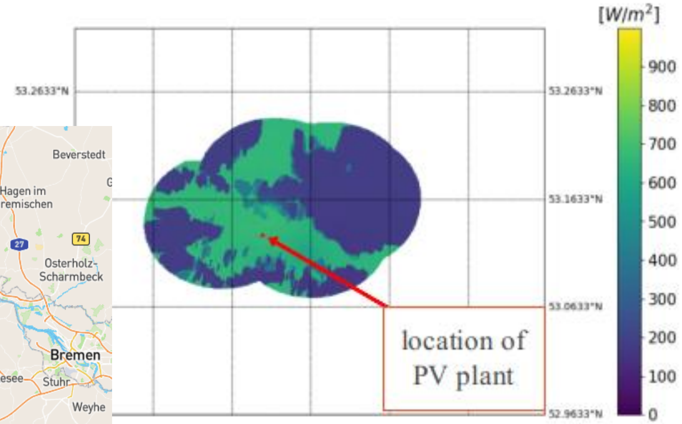


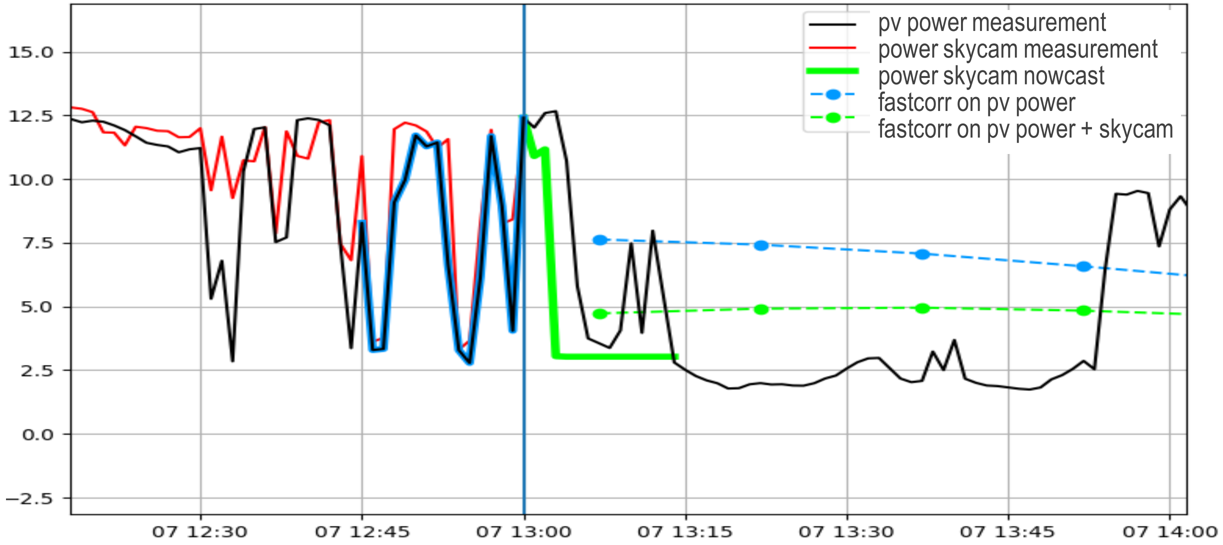
Using SkyImager data for PV forecasting

Idea: Use SkyImager data (DLR) to improve minute-ahead PV forecast

- **Data**
  - SkyImager data from Eye2Sky SkyCam network in Northwestern Germany (DLR)
  - Irradiance maps and nowcasts
- **Method**
  - Derive power at location of PV plant from irradiance maps (calibration with measurements)
  - Creating SkyImager nowcast from irradiance maps
  - Combining SkyImager nowcast with short-term forecast based on PV data

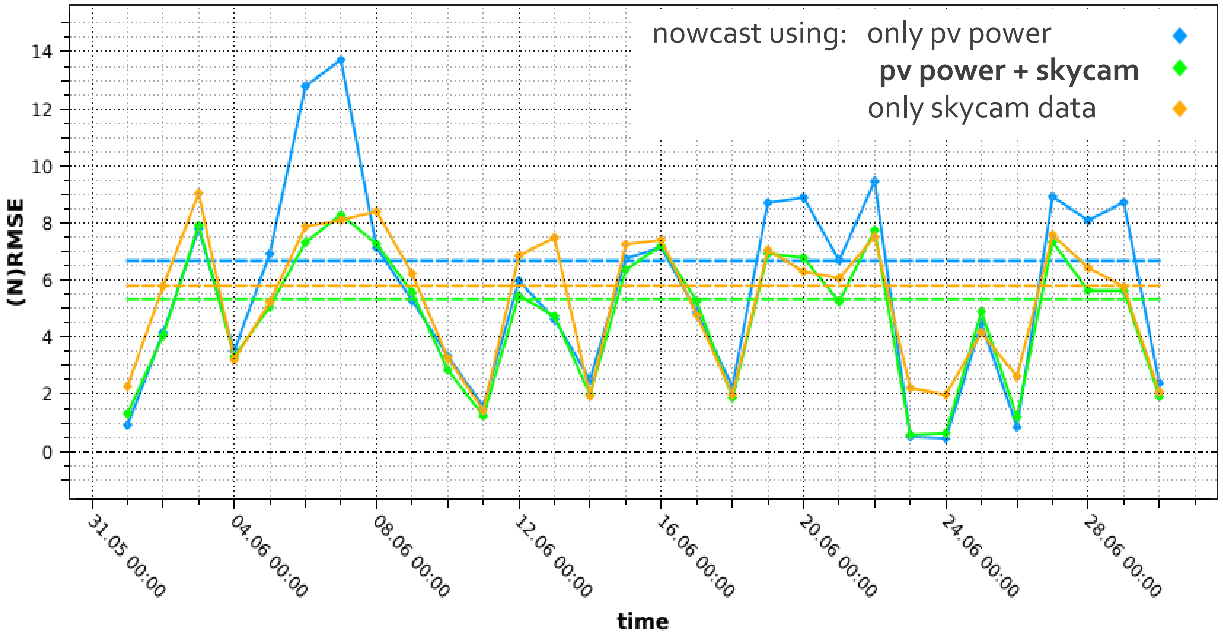






Using SkyImager data for PV forecasting

- **Evaluation & results**
  - Qualitative and quantitative analysis for three periods in 2020: Mar, Jun, Nov
  - Comparison of:
    - Operational EMSYS forecast (using PV power data)
    - SkyImager nowcast
    - Combination of SkyImager nowcast with EMSYS forecast based on PV data

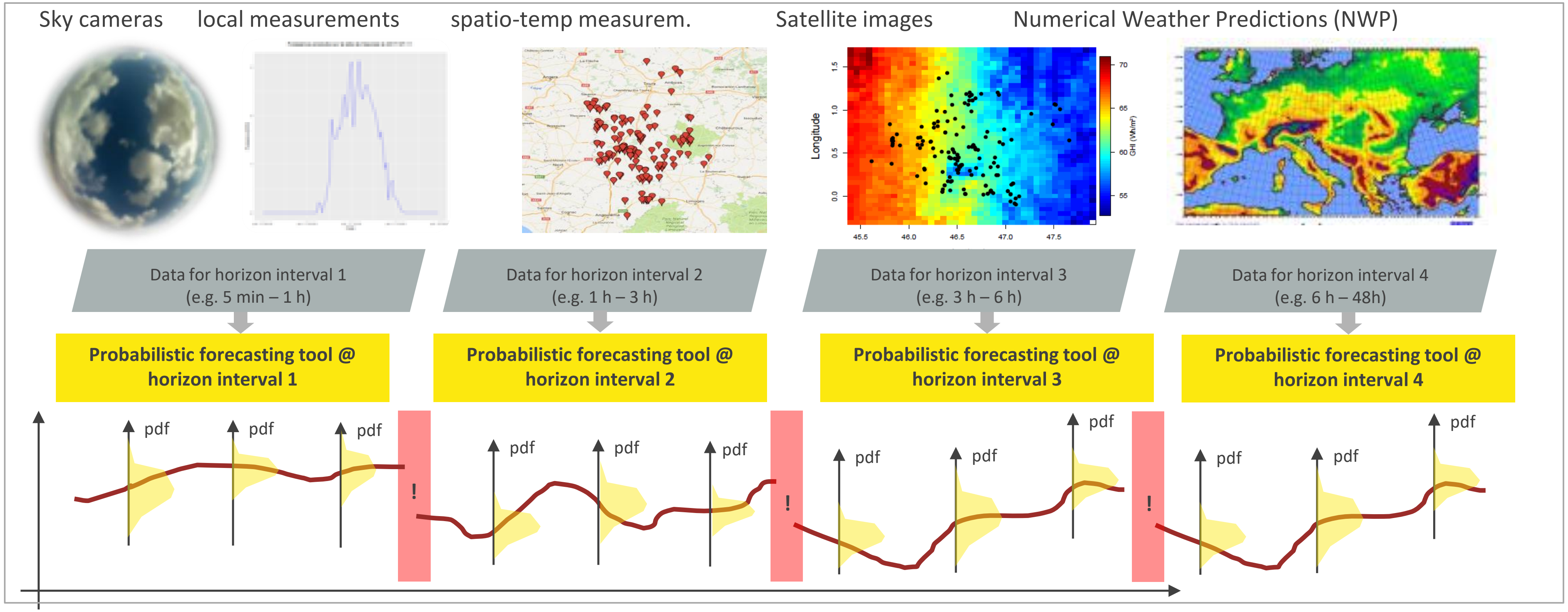


- SkyImager nowcast is significantly better than state-of-the-art forecast
- SkyImager + EMSYS forecast combined yields further improvement
- Strong improvement of the 15-min ahead forecast on days with broken clouds: **on average 20% RMSE reduction, on some days up to 40%**

20% RMSE improvement compared to operational EMSYS forecast

Seamless RES forecasting

- **Objective:** develop a single probabilistic model able to cover all time frames, all available data input and applicable to all technologies (wind/solar/combinations…). Have at least same level of performance as existing dedicated models.

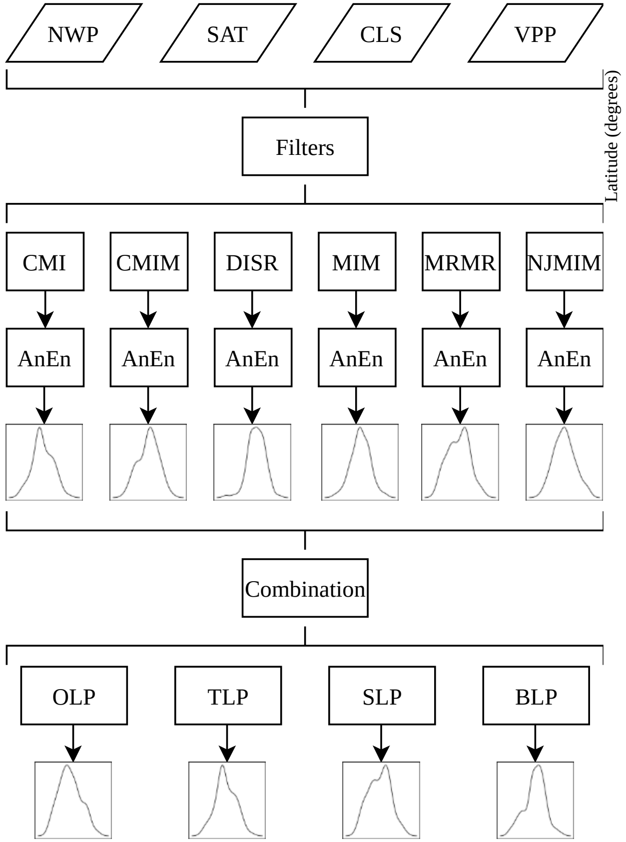


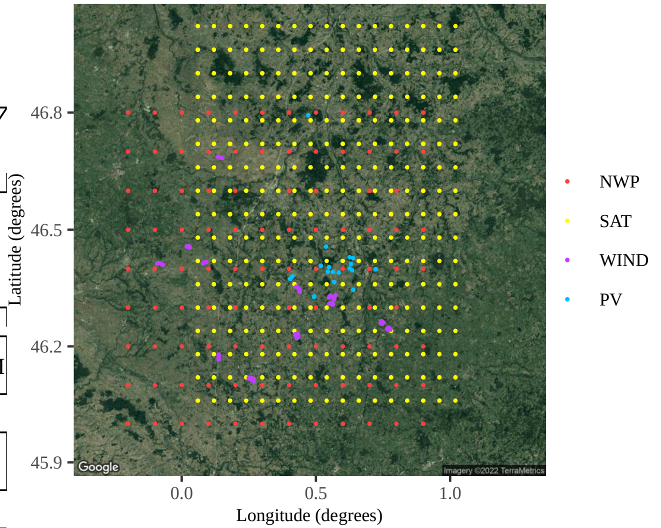
The usual RES forecasting consists in separate models for different time frames

Seamless RES forecasting with enhanced feature selection

Idea: Use filters to automatically select and weigh features, and forecast combination to mitigate uncertainty caused by feature selection

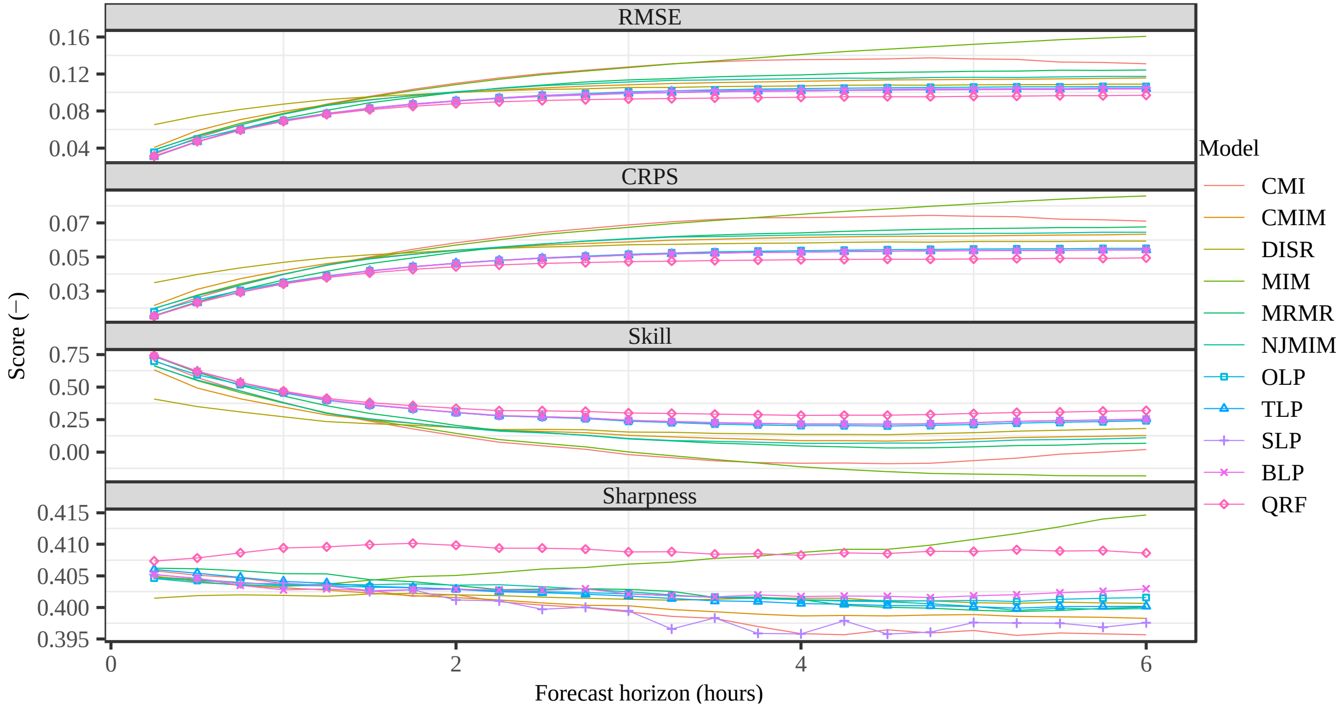
- **Data**
  - 20 PV systems and 60 wind turbines
  - Satellite derived irradiance maps with 289 pixels
  - NWP forecasts at 108 grid points
- **Method**
  - Apply 6 filters to score the available features
  - Normalize the scores to dynamically weigh the features
  - Optimally combine the probabilistic forecasts with linear and nonlinear methods





Seamless RES forecasting with enhanced feature selection

- **Evaluation & results**
  - Quantitative analysis for the period 2020-01-01 until 2020-09-30
  - Comparison of:
    - Vanilla analog ensemble (AnEn) that uses all features
    - The 6 filter methods feeding data to an AnEn model
    - The 4 forecast combination methods that combine the 6 different forecasts

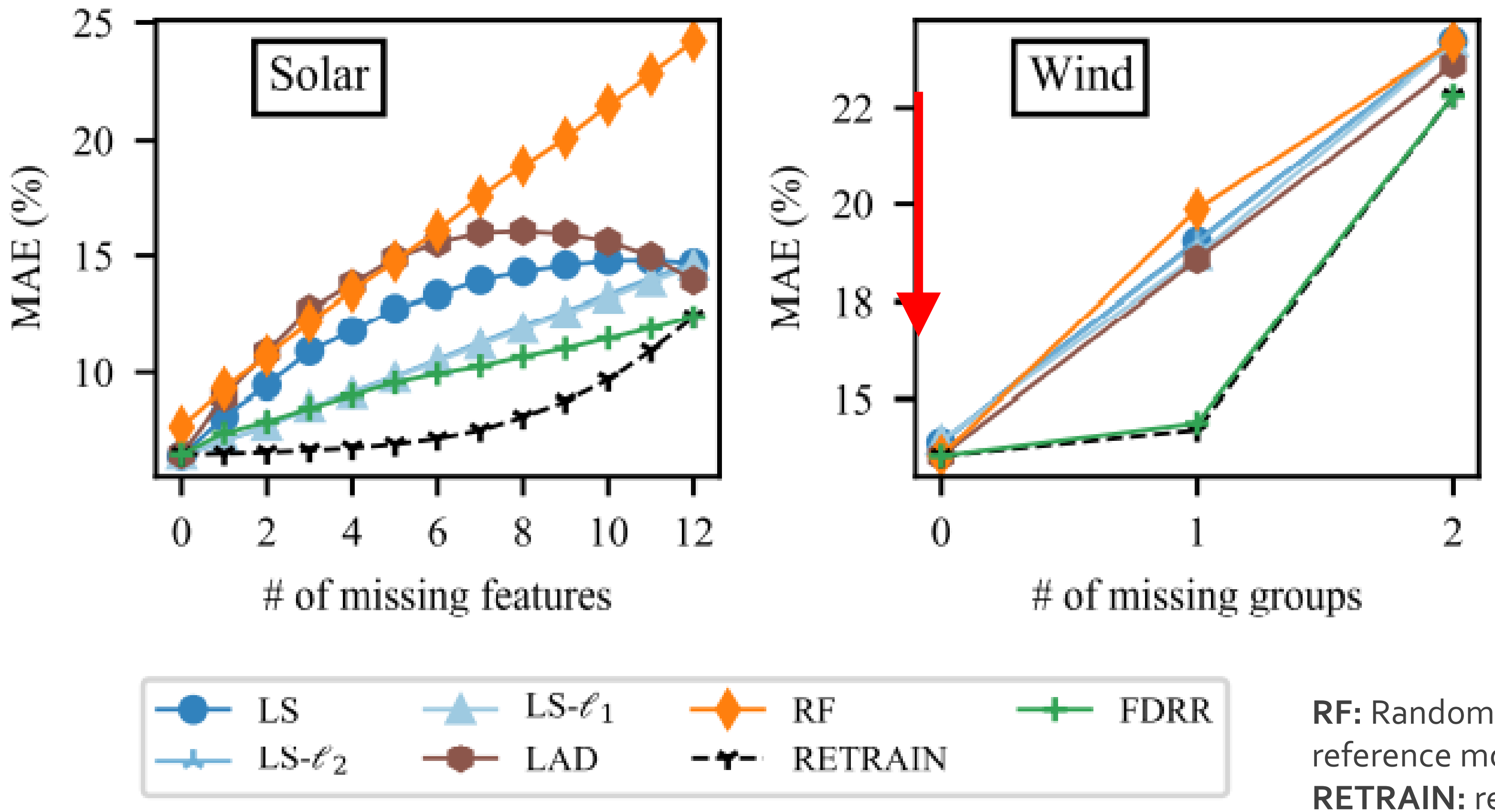


  - The filter methods significantly lower the computational effort (90%) and improve the accuracy between 6% - 16% on average
  - Forecast combination improves probabilistic combination and thereby accuracy with 16% - 31% on average

16% CRPS improvement compared to vanilla analog ensemble model

Resilient RES forecasting

- **Objective:** develop a forecasting approach that is robust against missing data at operational environment.
  - Feature-deletion robust regression (FDRR) minimizes the worst-case loss when Γ features are missing (MINES Paris).



RF: Random Forest approach commonly used as advanced reference model.
RETRAIN: retrained models with missing features.

Akylas Stratigakos, Panagiotis Andrianesis, Andrea Michiorri, Georges Kariniotakis. Towards Resilient Energy Forecasting: A Robust Optimization Approach. 2022. Submitted to IEEE Transactions on SmartGrid, ⟨hal-03792191⟩

Value-oriented forecasting

Example Use-Case: Optimisation of VPP participation in day-ahead (DA) + Intraday (ID) + Ancillary Service (AS) markets:
(in parenthesis the number of models: 11 in total)

Data on RES, storage, markets

Forecast aggregated RES production (1)

Forecast DA/ID energy market quantities (prices, imbalances) (3)

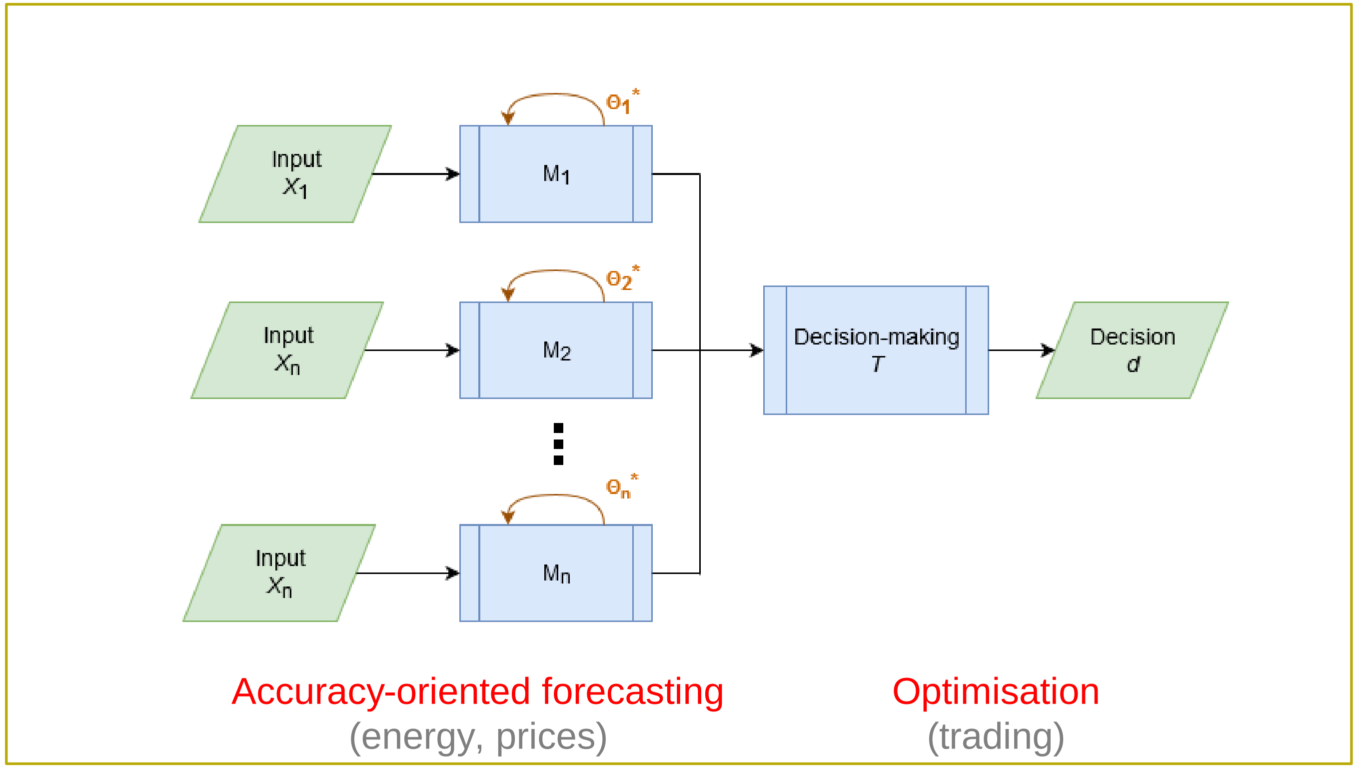
Forecast AS market quantities (prices, volumes, activation probabilities) (6)

Stochastic optimisation for trading decisions (1)

Bids on energy + AS markets

The classic approach:

FORECAST THEN OPTIMISE



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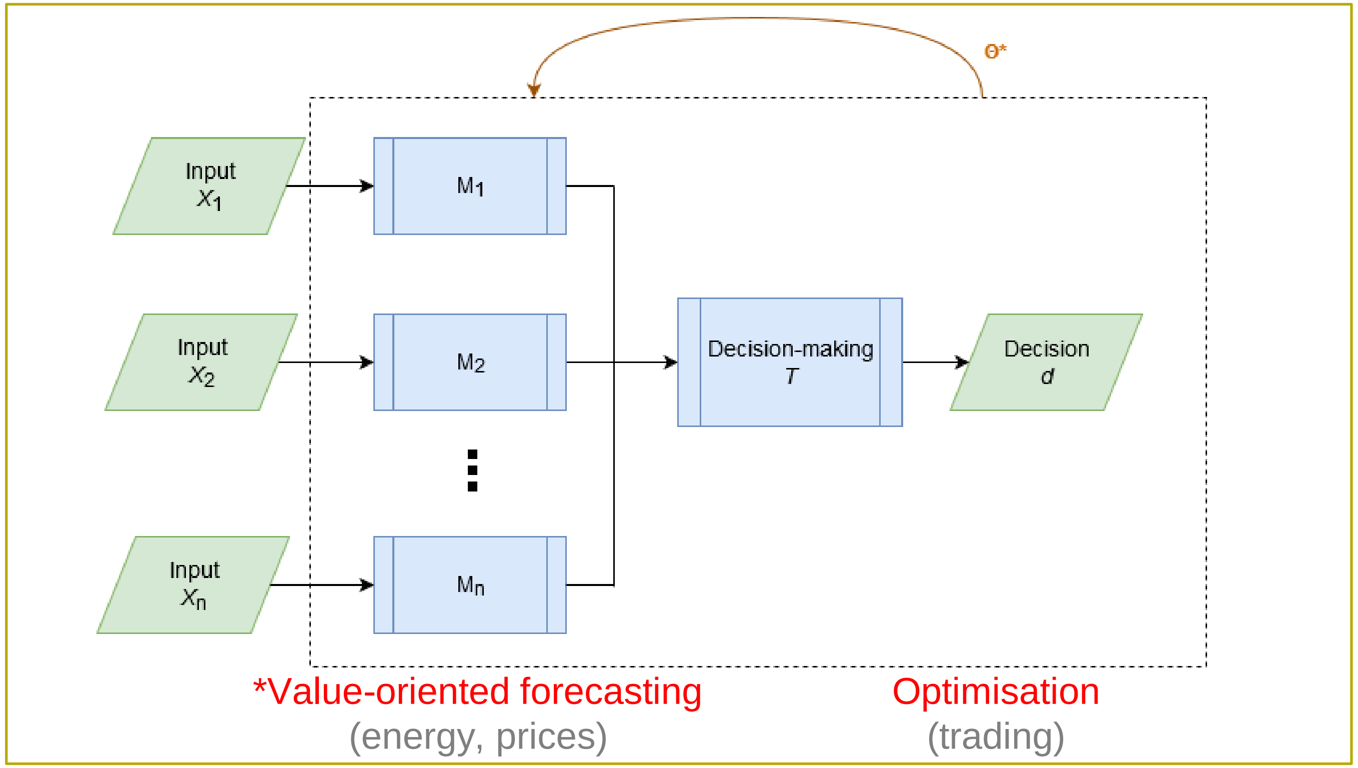
FORECAST* THEN OPTIMISE



T. Carriere, G. Kariniotakis. An Integrated Approach for Value-oriented Energy Forecasting and Data-driven Decision-making. Application to Renewable Energy Trading. *IEEE Transactions on Smart Grid*, ⟨10.1109/TSG.2019.2914379⟩. ⟨hal-02124851⟩

Value-oriented forecasting

Smart4RES

Example Use-Case: Optimisation of VPP participation in day-ahead (DA) + Intraday (ID) + Ancillary Service (AS) markets:
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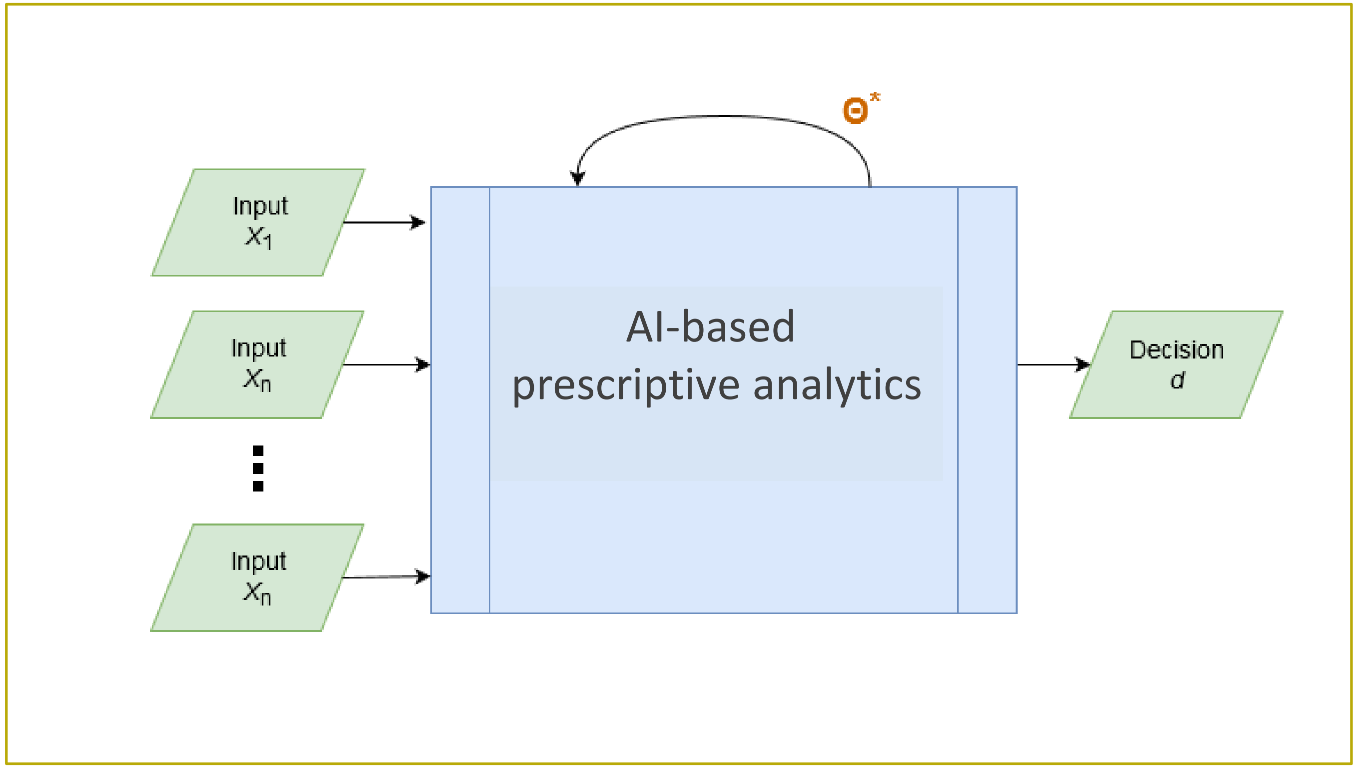
Bids on energy + AS markets

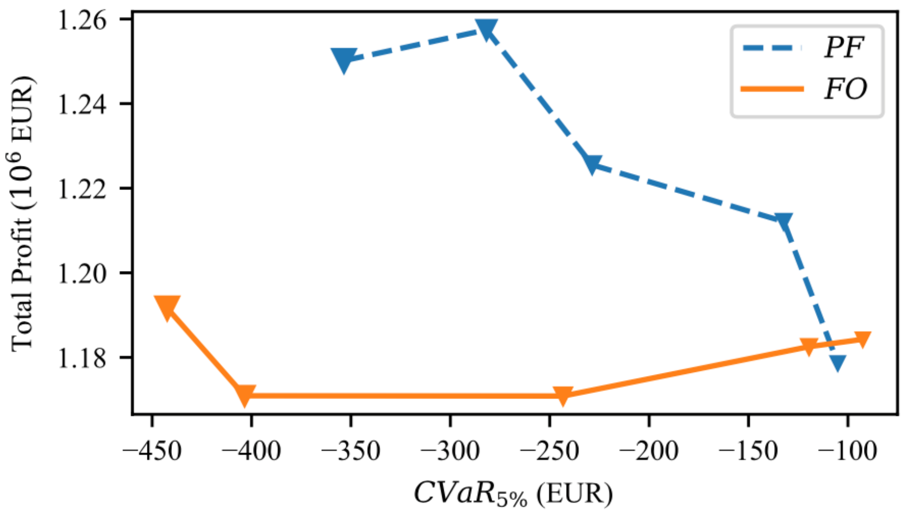
JOINT FORECASTING & OPTIMISATION



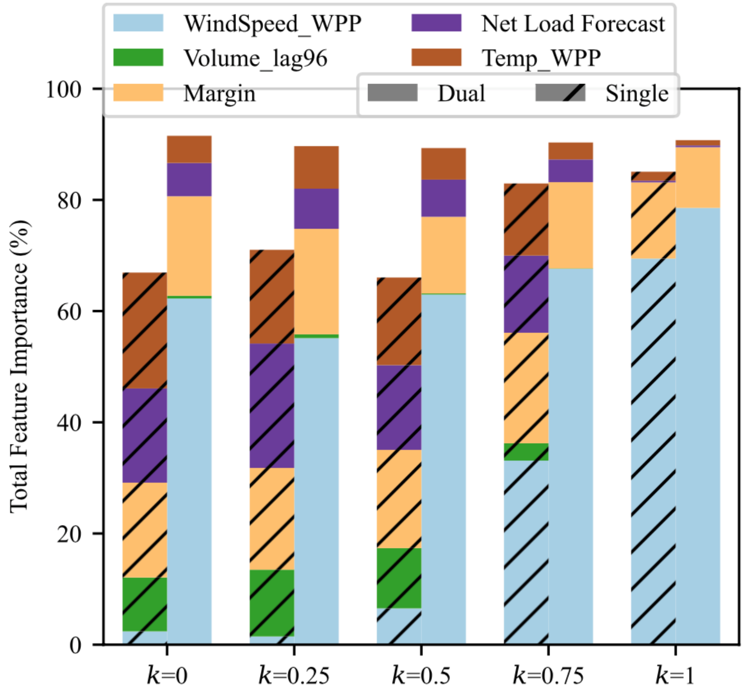
A. C. Stratigakos, S. Camal, A. Michiorri and G. Kariniotakis, "Prescriptive Trees for Integrated Forecasting and Optimization Applied in Trading of Renewable Energy," in *IEEE Transactions on Power Systems*, doi: 10.1109/TPWRS.2022.3152667.

Value-oriented forecasting

- **Prescriptive trees for integrated forecasting and optimization applied in RES trading**
  - Illustrative results
  - Proposed method Prescriptive Forest (PF), benchmarked against the standard Forecast-then-Optimize (FO) modeling approach



Risk-reward trade-off against the standard FO.



Normalized Prescriptive Feature Importance

Forecasting in TSO/DSO control rooms

Integrate RES forecasting in control rooms for managing technical constraints (voltage, congestion), **postpone investments** and promote a better use of the assets **under high-RES integration**

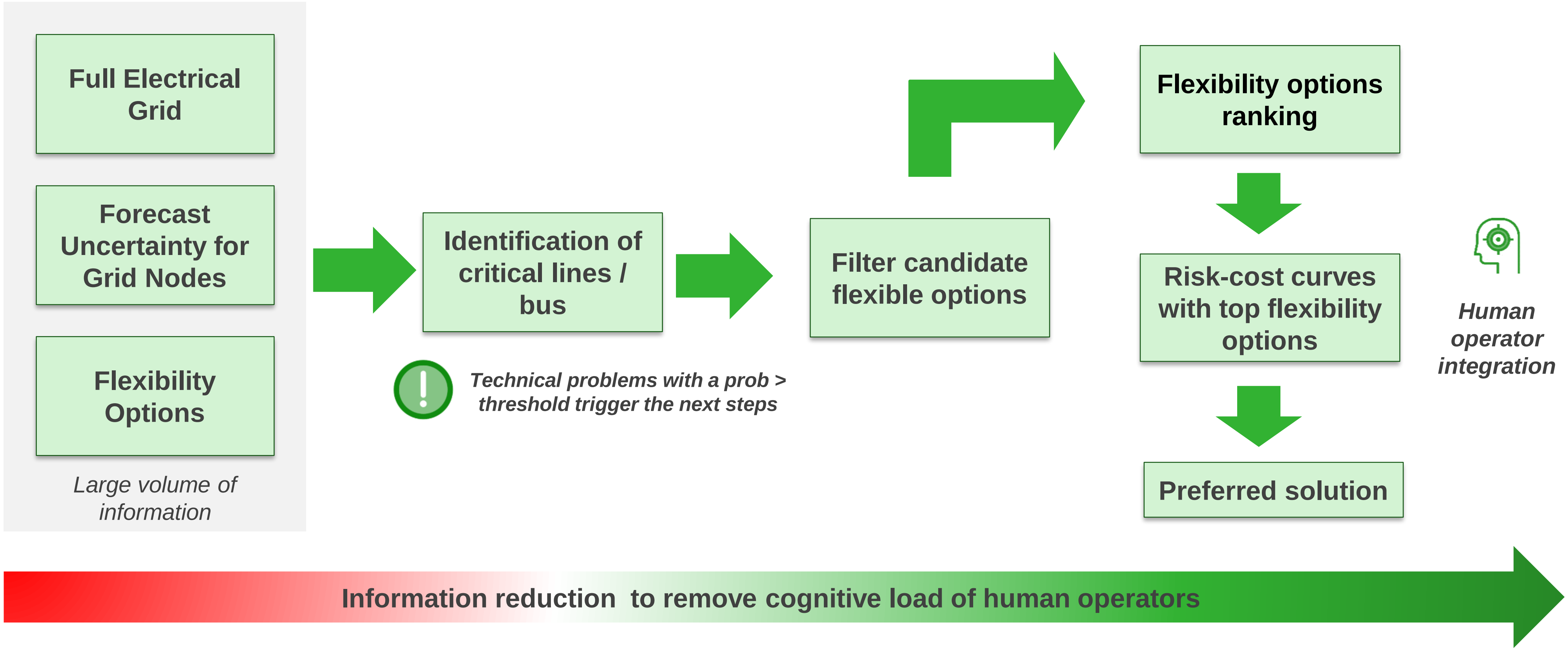
Research challenges

(1) Provide interpretable control actions for flexibility "booking" under forecasting uncertainty
(2) Hierarchical load and flexibility forecasting in electrical grids

Key outcomes

(1) Predictive multi-criteria decision-making strategies for human operators in control centers
(2) Using reconciled forecasts in an optimal power flow problem and identification of flexibility map at the interface between TSO and DSO

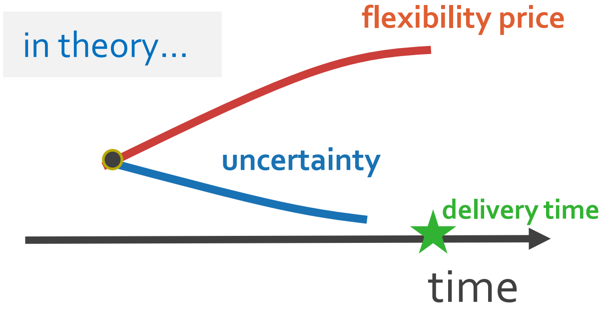
Forecasting in TSO/DSO control rooms

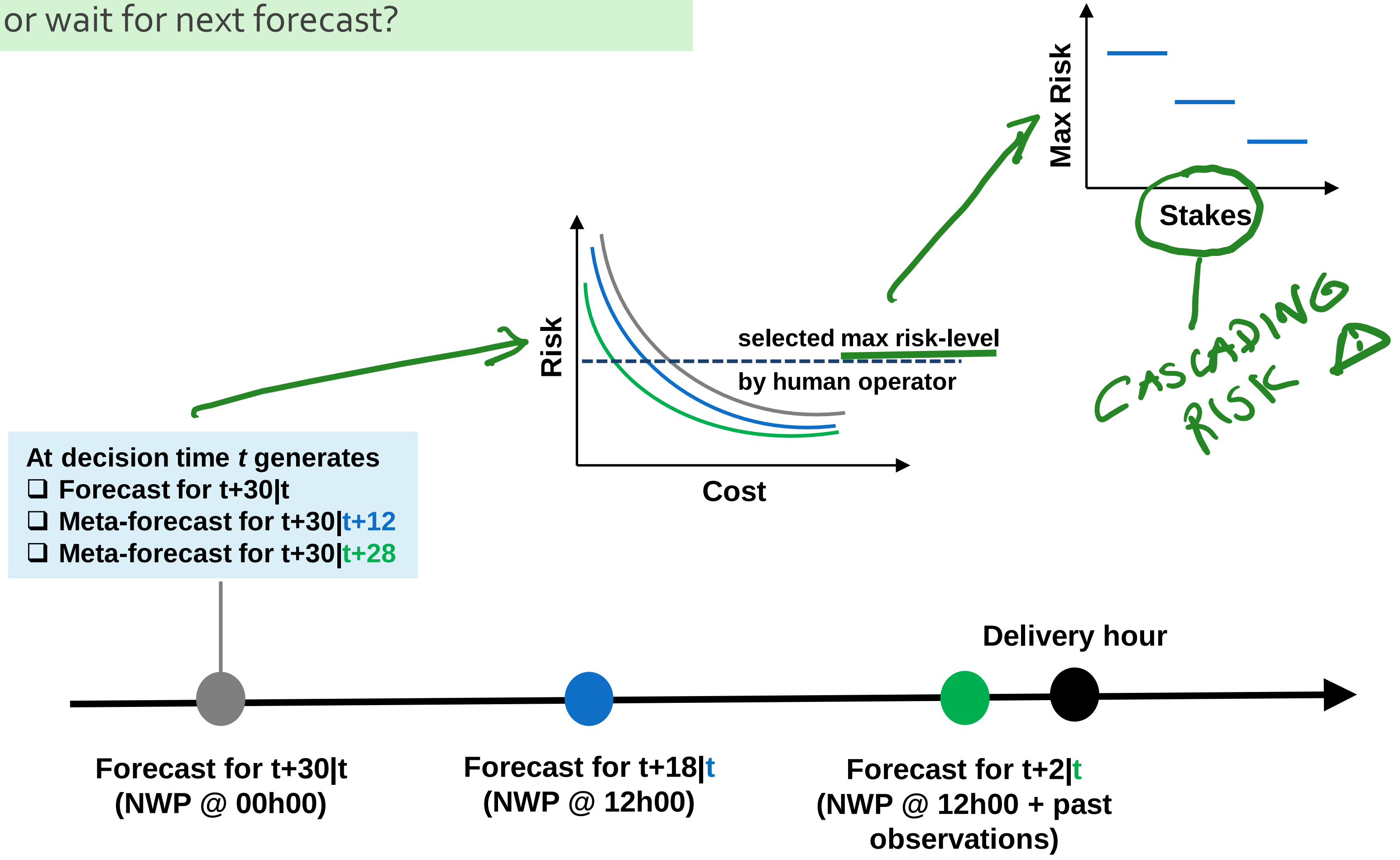


Publication: R.J. Bessa, F. Moaidi, J. Viana, J.R. Andrade, "Uncertainty-aware procurement of flexibilities for electrical grid operational planning," under review in IEEE Transactions on Sustainable Energy, 2023.

Forecasting in TSO/DSO control rooms

Probability of a congestion forecasted with NWP for day D+1 (lead time: t+30)
> Decide now ("reserve" a flexibility option) or wait for next forecast?

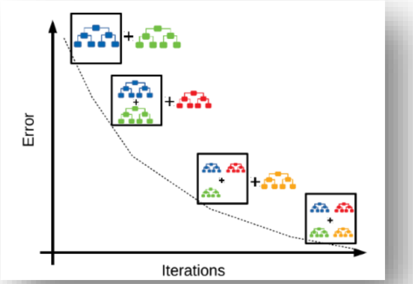




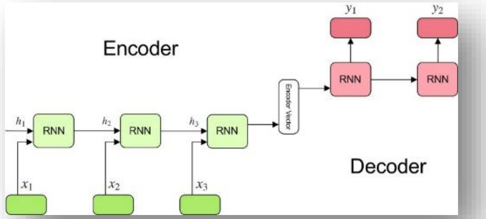
Meta-forecasting concept and models

Forecasted generated with 00h00 NWP
+
Features characterizing level uncertainty (IQR, forecasted quantiles, stdev.)

Gradient Boosting Trees (GBT)



ED-ANN



baseline** model: **forecast does not change

- ❑ MAE improvement (**meta-forecast with NWP @ 12h00**) between 13% and 26%
- ❑ MAE improvement (**meta-forecast for t+2|t**) between 16% and 31%

Forecasting in TSO/DSO control rooms

KEY RESULTS

- ❑ **Time-to-decide (T2D) approach outperforms deterministic strategies**
  - e.g., F3-score 0.85 (T2D) vs 0.37 (deterministic)
- ❑ **T2D outperforms a decision-now strategy** (operator decides to reserve flexibility at the lowest availability cost)
  - Improves in 30% the cost-loss matrix performance metric (γ)

Profiles of different decision/makers

	Stakes (ρ) range		
Decision-making approach	$0 \leq \rho \leq a^*$	$a < \rho \leq 7$	$7 < \rho \leq 10$
DM A: Maximum risk threshold	10	6	3
DM B: Maximum risk threshold	20	15	10
DM C: Maximum risk threshold	25	20	20
DM D: Risk-cost trade-off	30	50	70

- ❑ Different **decision-maker profiles lead to distinct results**
  - ❑ e.g., F3-score 0.85 (DM A) vs 0.77 (DM C)
  - ❑ DM D has a cost-loss matrix performance metric (γ) 20% lower than DM A

OUTLINE

1. Context
2. Evolution of the State of the Art in RES forecasting
3. The Smart4RES project
4. Highlight results
5. **Future research directions**

Recommendations for future research directions (1/2)

With order of priority following a pool at the WindEuropeTechnology Workshop – Lyon, 1-2 June 2023:

1. Better forecasting of extreme situations (ramps, fog, snow, icing, lightnings,...)
2. Improve seasonal forecasting and associated uncertainty
3. Advanced techniques for combination of multiple sources of data for RES forecasting.
4. Promote knowledge sharing and open code and data to be able to verify academic contributions.
5. Research towards RES-dedicated weather forecast products.
6. Ultra high spatio-temporal resolution modelling of weather variables (i.e. Large Eddy Simulations).
7. Higher temporal resolution and frequency of updates for classical NWPs.

Recommendations for future research directions (2/2)

With order of priority following a pool at the WindEuropeTechnology Workshop – Lyon, 1-2 June 2023:

8. Forecasting RES production under external constraints (curtailments due to congestions, AS provision, noise, birds…).
9. Go beyond "accuracy-oriented" RES forecasting to "value-oriented" forecasting.
10. Towards digital twins of the weather system (i.e. Destination Earth).
11. End-to-end interpretable AI-based approaches, like prescriptive analytics, to simplify the classic model chain "Forecast then Optimise" to "Joint Forecasting and Optimisation".
12. Work towards standardisation of RES forecasting products.
13. Develop tools to compile heterogenous forecast information (scenarios, ramps etc) to simplify decision making by operators.
14. Collaborative forecasting based on privacy/confidentiality preserving data sharing.

KEY TAKE AWAYS

Smart4RES addresses the whole model and value chain of RES forecasting from data, advanced weather modelling down to applications.

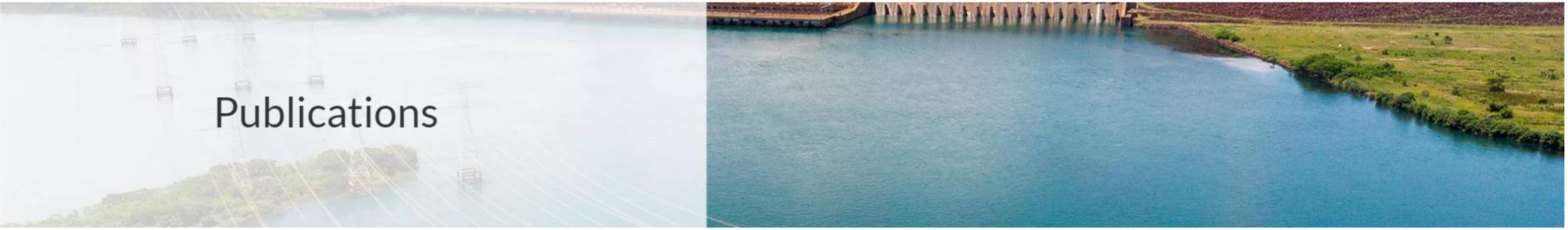
A next generation of RES forecasting tools are proposed which, by design, are not only optimized to maximize accuracy but also other properties like simplicity, resilience, robustness, value in applications.

Further research is needed in the field of RES forecasting to meet the challenges in energy systems of the future with very high RES penetrations

45+ publications and conference papers

Smart4RES

Contact



Home » Publications

Download Smart4RES publications and other scientific communications

2023

- Lindberg O, Lingfors D, Arnqvist J, van der Meer D, Munkhammar J. Day-ahead probabilistic forecasting at a co-located wind and solar power park in Sweden: Trading and forecast verification. *Advances in Applied Energy*. 2023 https://doi.org/10.1016/j.adapen.2022.100120.
  Download the pre-proof.

https://www.smart4res.eu/publications/

Smart4RES final conference presentations (14/4/23)

https://www.smart4res.eu/workshop-and-webinar/

Smart4RES Final Conference

Session 1: General overview

- Keynote speech 'EU's research and innovation priorities on renewable energy', M. Soede (DG Research and Innovation,European Commission)
- Evolution of the state of the art and The Smart4RES project in a nutshell, G. Kariniotakis (MINES Paris)

Download the presentation
Watch the recording

Session 2: Advances in Weather Modelling

- RES-dedicated weather forecasting models, Q. Libois (Météo France)
- High-resolution weather models – Large Eddy Simulation (LES): the future, R. Verzijlbergh (Whiffle)
- Improvement of solar forecasting through the use of multi-source observations, J. Lecaza (DLR)

Download the presentation
Watch the recording

Session 3: Next Generation RES Forecasting

- Improved RES models in particular weather conditions, M. Lange (EMSYS)
- Data driven methods for minute-scale wind power and structural load forecasts using Lidars, T. Göçmen (DTU)
- How to simplify RES forecasting using a seamless approach, D. van der Meer (MINES Paris)

Smart4RES

THANK YOU !

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France

Germany

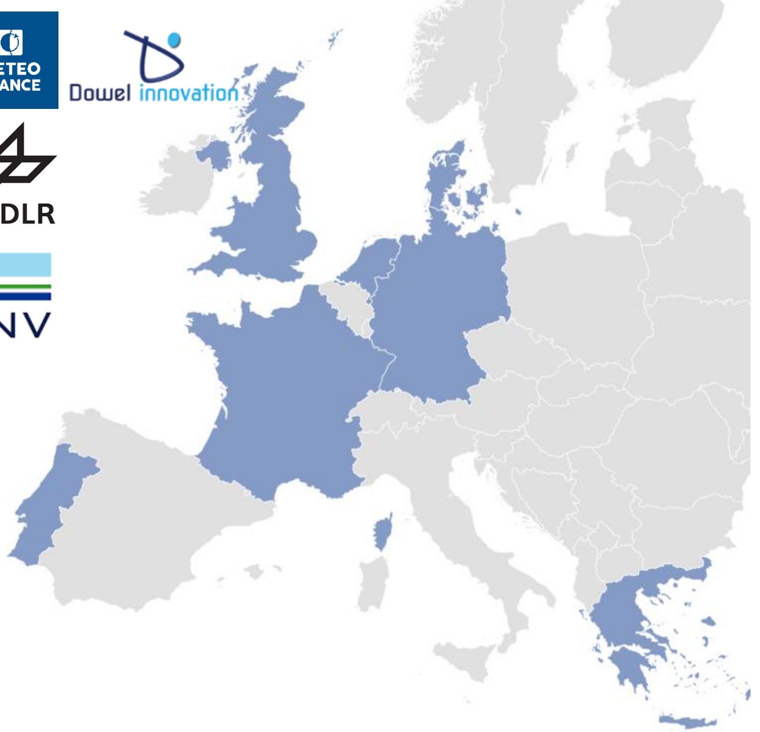
Netherlands

Denmark

UK

Portugal

Greece



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