

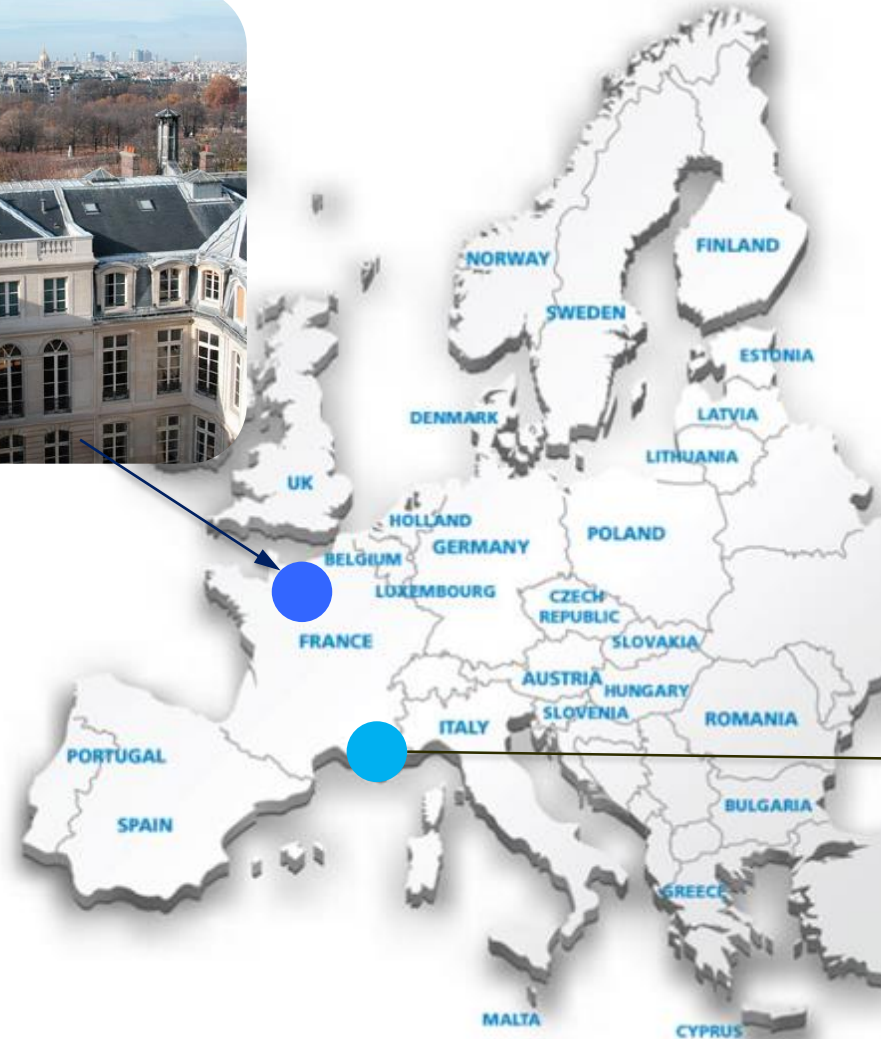
# Advances in RES forecasting and challenges for the future.

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Coordinator of Smart4RES  
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One of the 18  
research centers  
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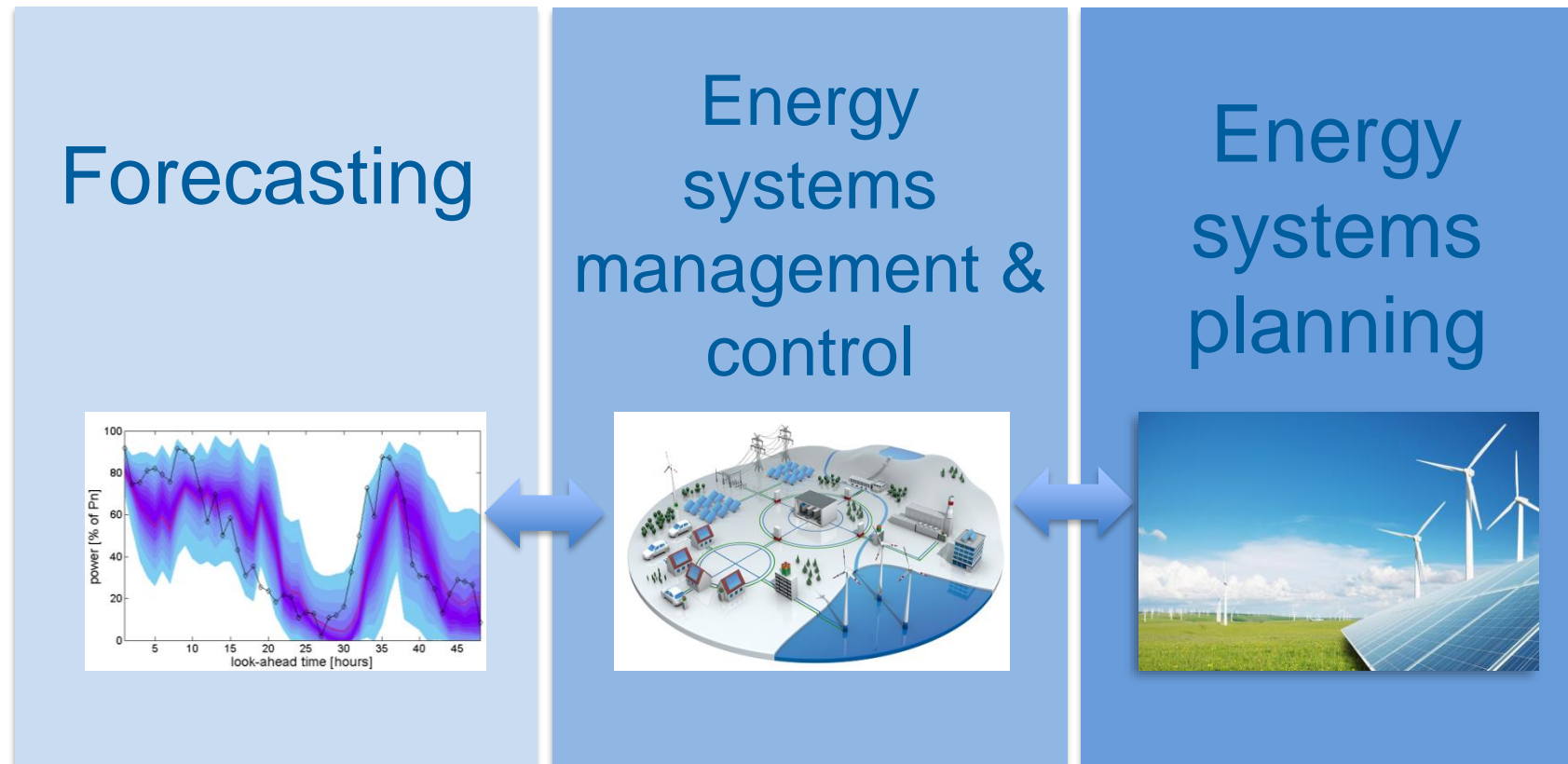
**Centre PERSEE**  
Centre for Processes,  
Renewable Energies and  
Energy Systems

*Mines Paris @ Sophia Antipolis*



**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.

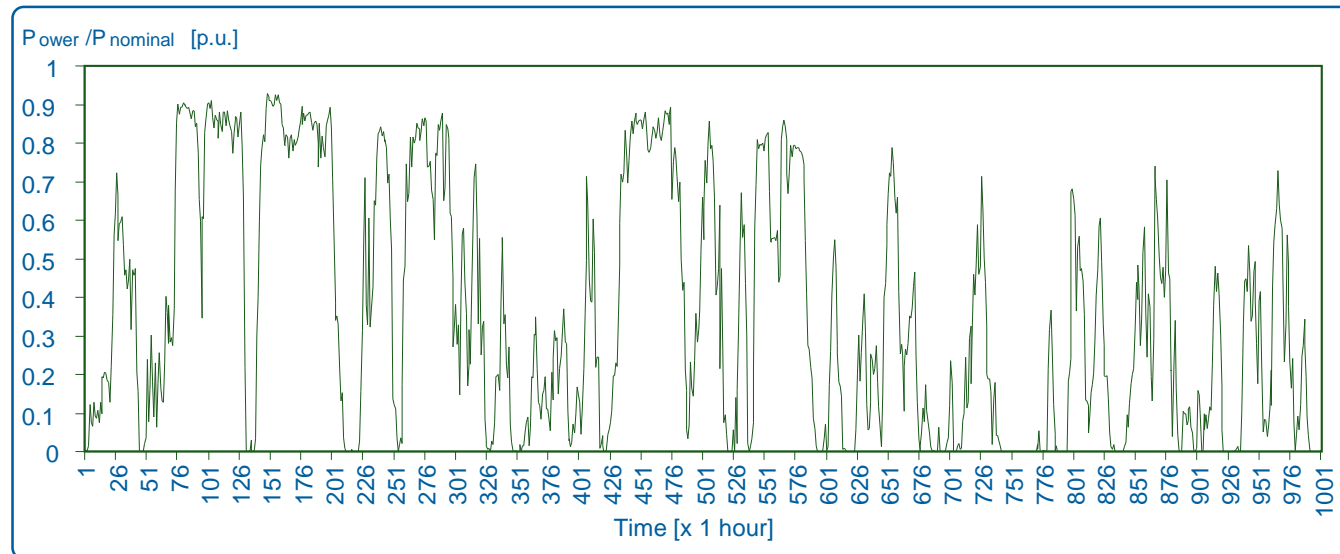
## 3 RESEARCH AXES:



## OUTLINE

1. Context
2. Evolution of the State of the Art in RES forecasting
3. Recent research advances - Smart4RES project
4. A selection of highlight results
5. Future research directions

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

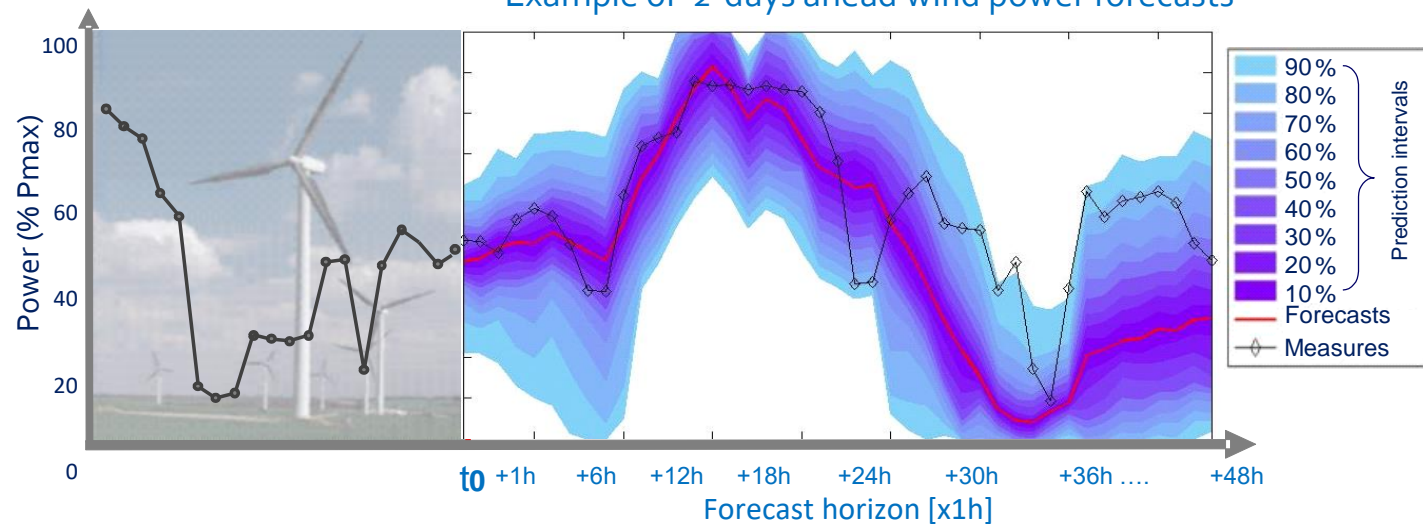


Example of hourly wind farm production over a month

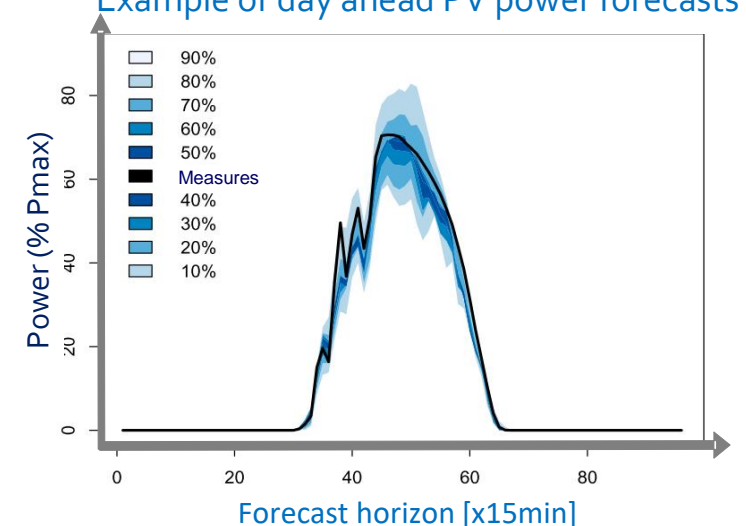


- Short-term (minutes-days ahead) forecasts of renewable generation (wind, solar) (RES) are necessary for a secure and economic operation of power systems.
- Forecasting solutions are used operationally by all stakeholders.
- However, large forecast errors may occur with a high financial/technical impact.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

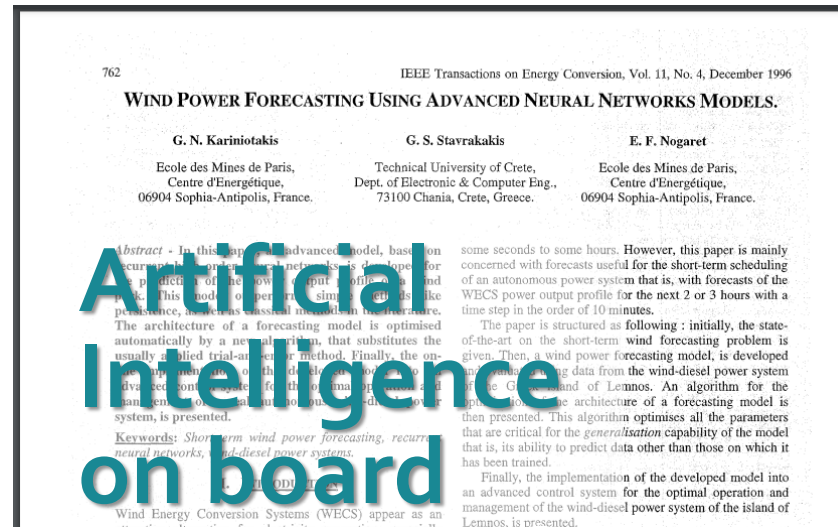
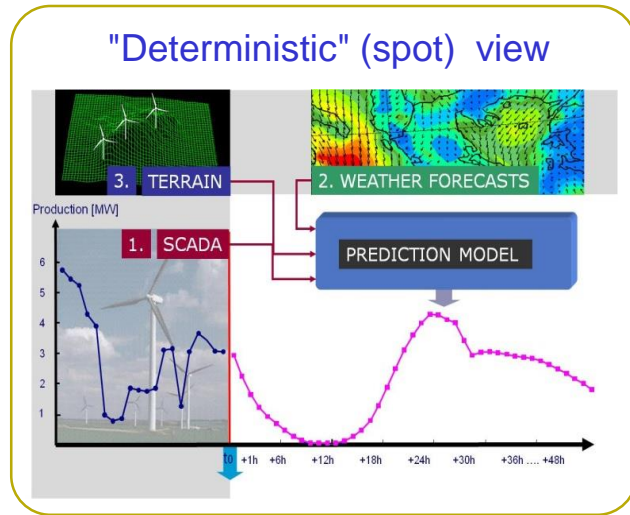
Example of 2-days ahead wind power forecasts



Example of day ahead PV power forecasts



# The history of RES forecasting



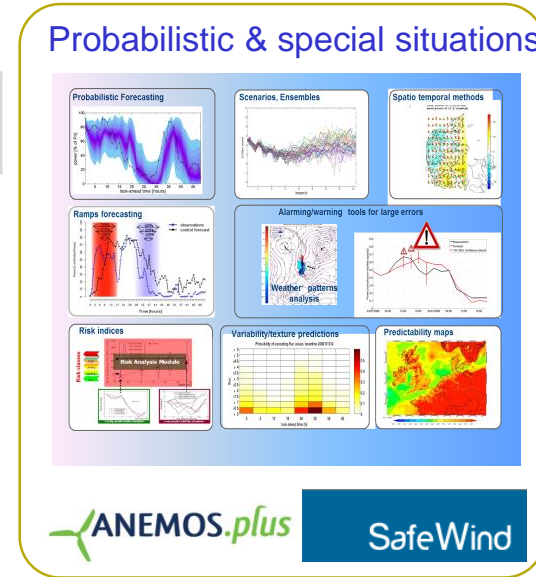
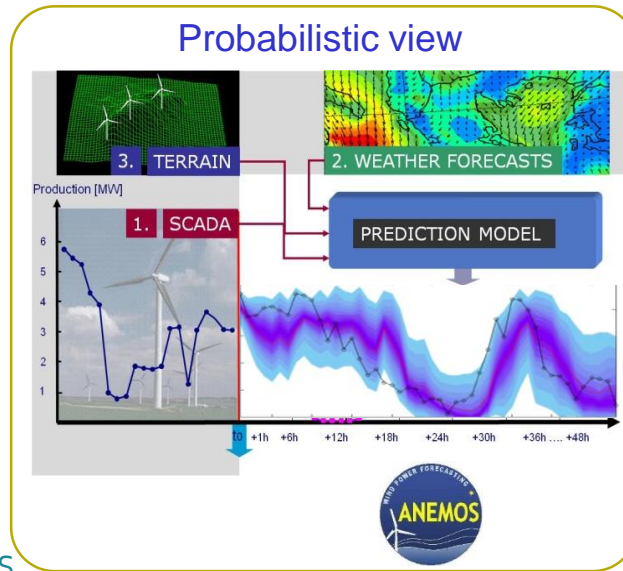
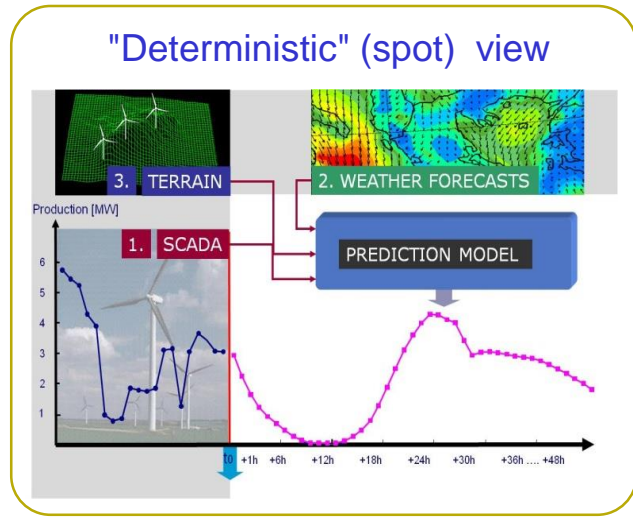
❖ (1996) 1<sup>st</sup> journal paper ever with AI applied in RES



- First purely time series methods on WPF

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

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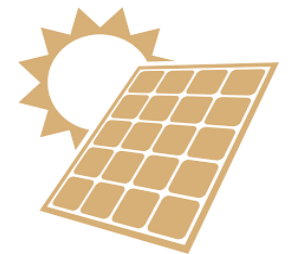


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- 1st benchmarking (Anemos competition)
- Physical modelling
- Statistical models, AI, Data mining,...
- Combination of models
- First probabilistic approaches/ensembles
- Upscaling
- Evaluation standardisation/protocol
- International collaboration

- Dedicated NWP's for RES
- Direct probabilistic predictions
- Ramps forecasting
- Scenarios, Ensembles,
- Risk indices
- Large errors warning/alarming
- Spatiotemporal forecasting
- Variability forecasting
- Predictability maps



[2002-2006] ANEMOS (FP5), <http://www.anemos-project.eu/>

[2008-2011] ANEMOS.plus (FP6), <http://www.anemos-plus-project.eu/>

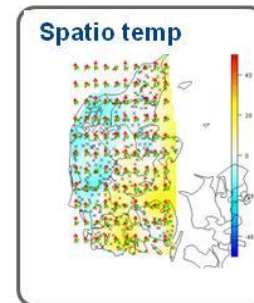
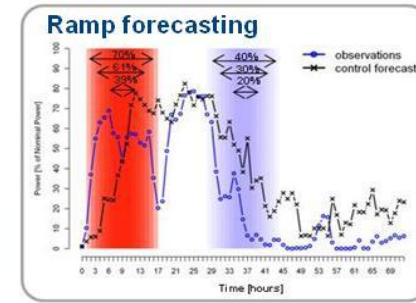
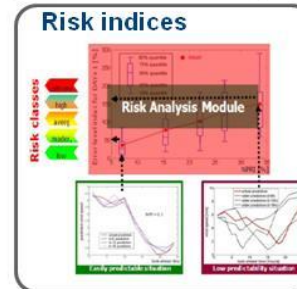
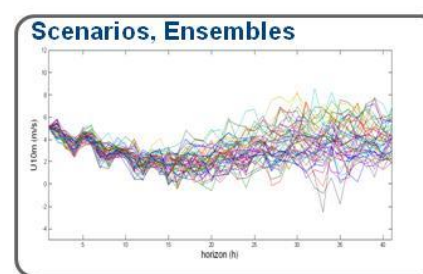
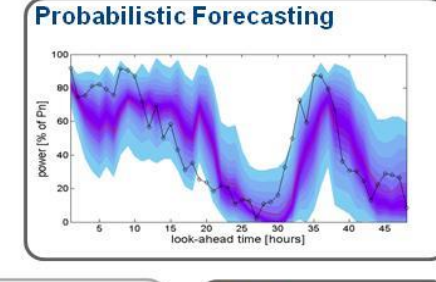
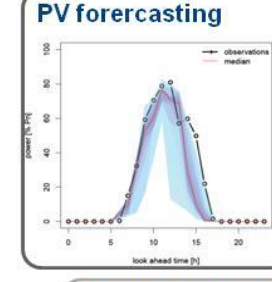
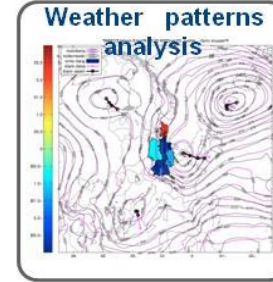
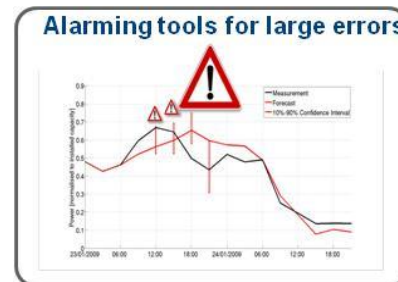
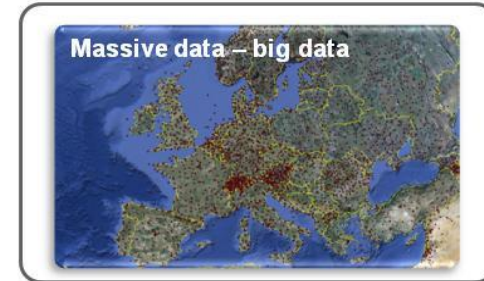
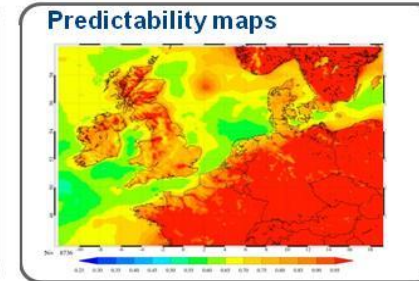
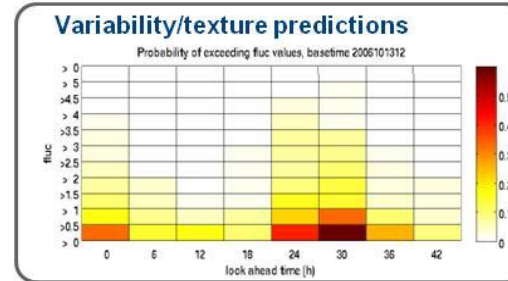
[2008-2012] SAFEWIND (FP7), <http://www.safewind.eu/>

[2019-2023] Smart4RES (H2020), <http://www.smart4res.eu/>



# 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



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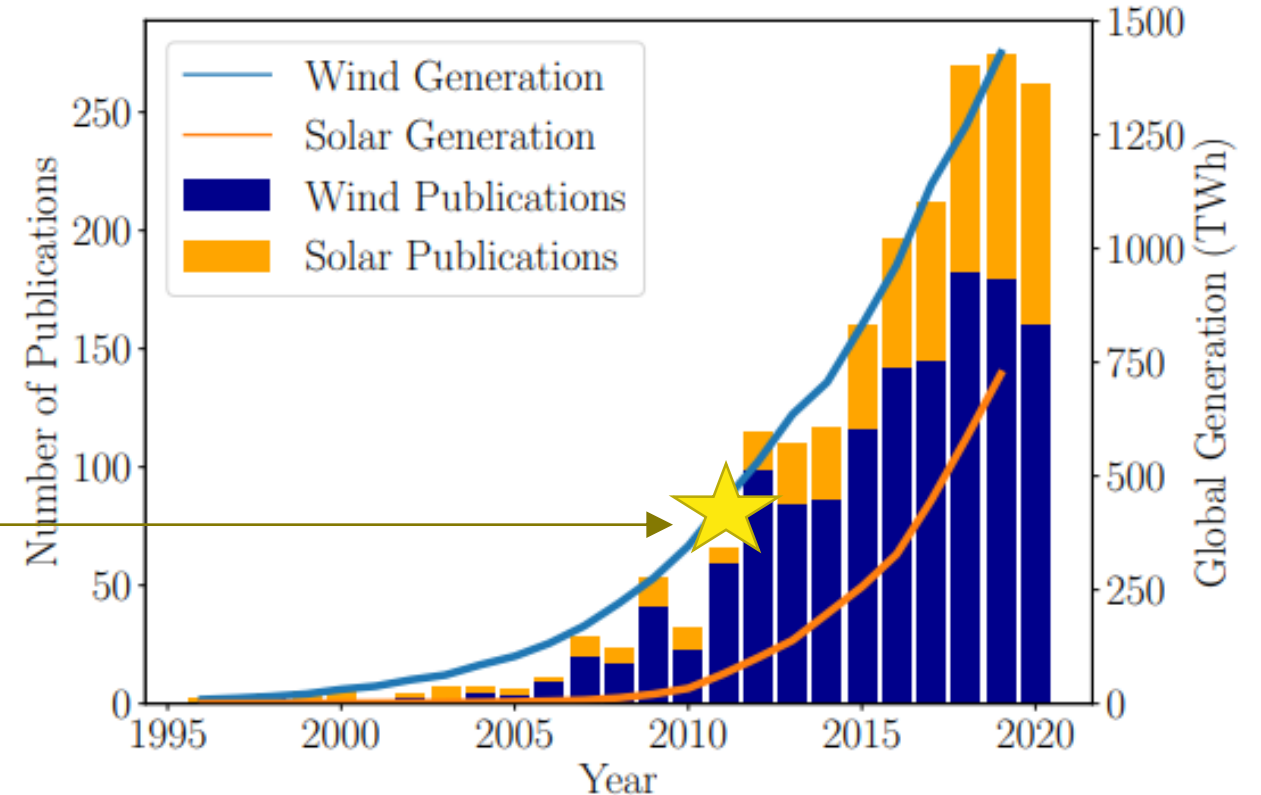


Figure 2.1: Forecasting publications broken down by wind and solar as a stacked bar chart, also plotted with global energy generation through time. Generation data provided under CC BY 4.0, Hannah Ritchie & Max Roser, [ourworldindata.org/renewable-energy](https://ourworldindata.org/renewable-energy).

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

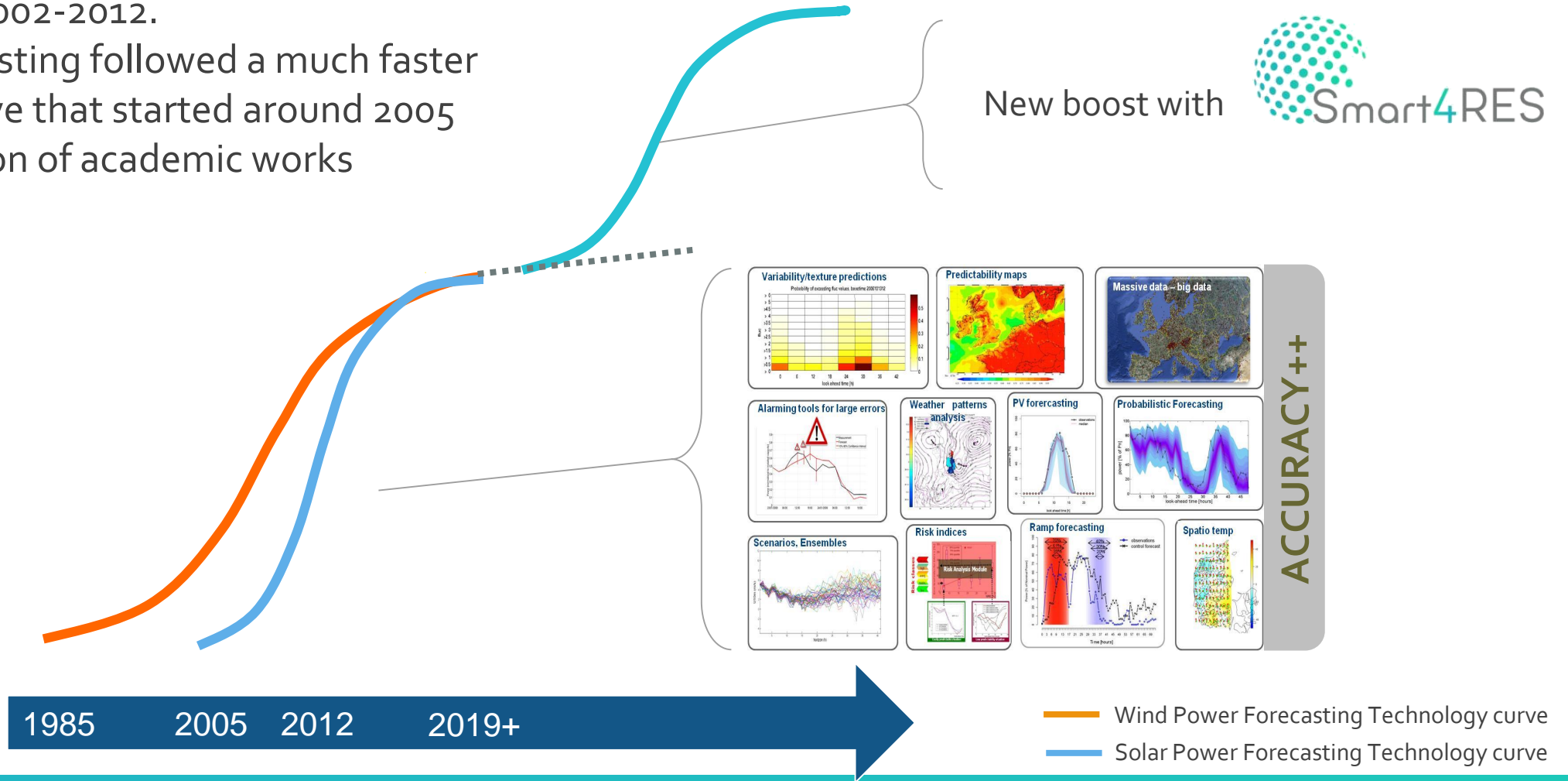


250 publications at conferences and journals

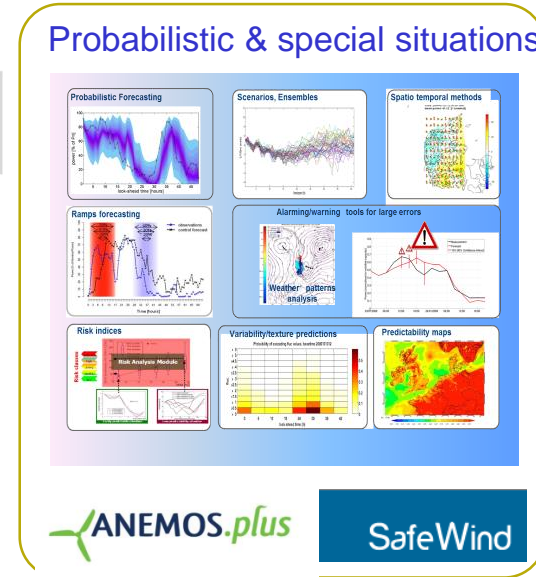
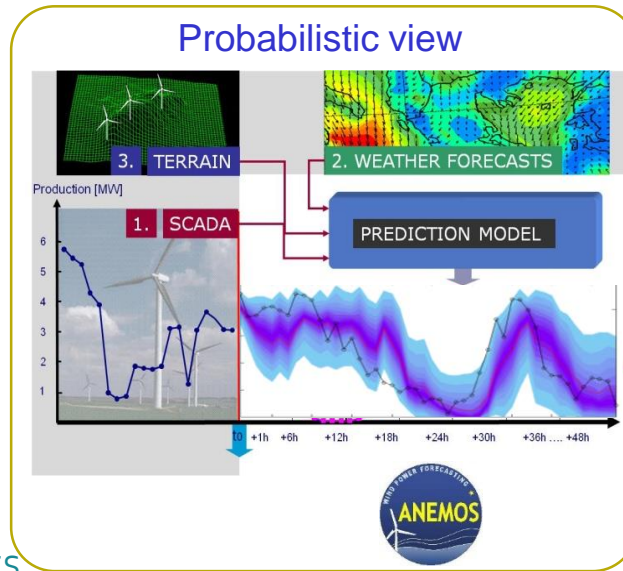
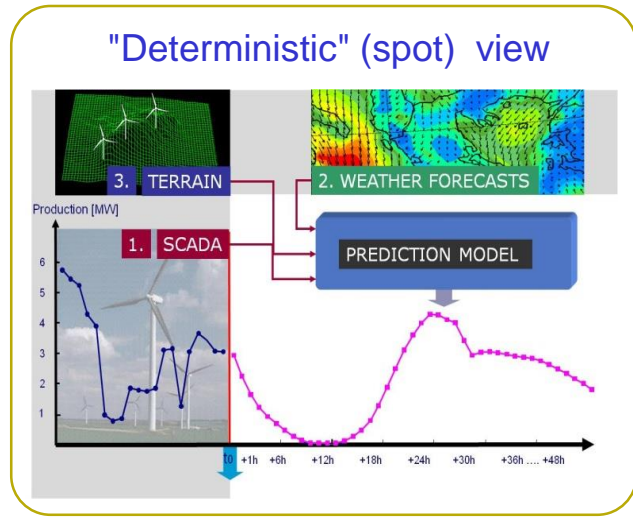
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New boost with



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- Mapping of state of the art
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- Seamless forecasting
- Ultra high resolution (LES)
- Advanced NWP's
- Prescriptive analytics
- Extremes
- Data sharing/Data markets
- New forecasting products
- Resilience in forecasting
- Optimal use in applications

[2002-2006] ANEMOS (FP5), <http://www.anemos-project.eu/>  
 [2008-2011] ANEMOS.plus (FP6), <http://www.anemos-plus-project.eu/>

[2008-2012] SAFEWIND (FP7), <http://www.safewind.eu/>  
 [2019-2023] Smart4RES (H2020), <http://www.smart4res.eu/>



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2. Evolution of the State of the Art in RES forecasting
3. **Recent research advances - Smart4RES project**
4. A selection of highlight results
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# The Smart4RES project in a nutshell



## ■ A multi-disciplinary consortium

**7 countries**

**13 partners**

End-users

Industry

Research

Universities

Meteorologists

Funds: H2020 program

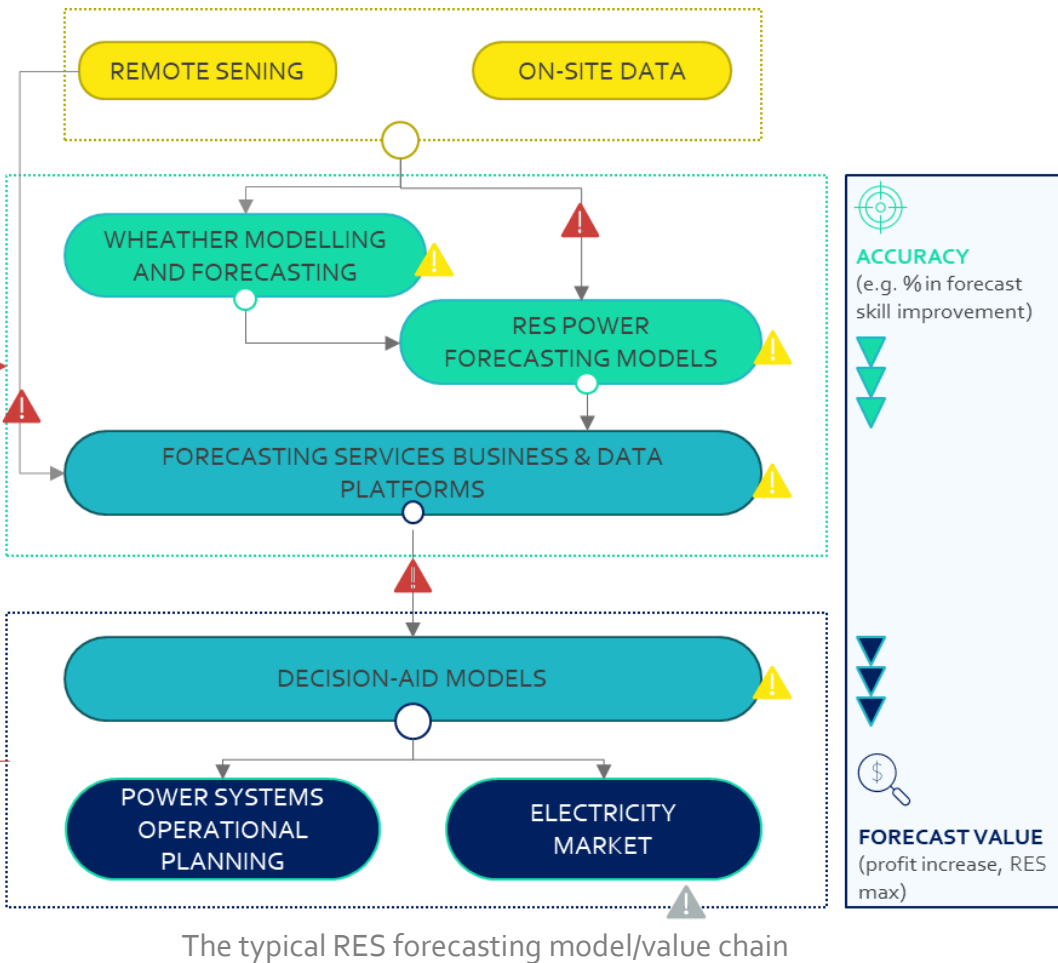
Budget: 4 M€

Duration: 3.5 years

**11/2019-4/2023**



# The Smart4RES project in a nutshell



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

## Objectives (& take aways)

- 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



**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 situations
- Optimisation tools to manage uncertainties

**ROBUSTNESS**

**SUBOPTIMALITY**

- Value-oriented vs accuracy-oriented forecasting
- Privacy/confidentiality preserving data sharing & data markets

**VALUE MAXIMISATION**



## OUTLINE

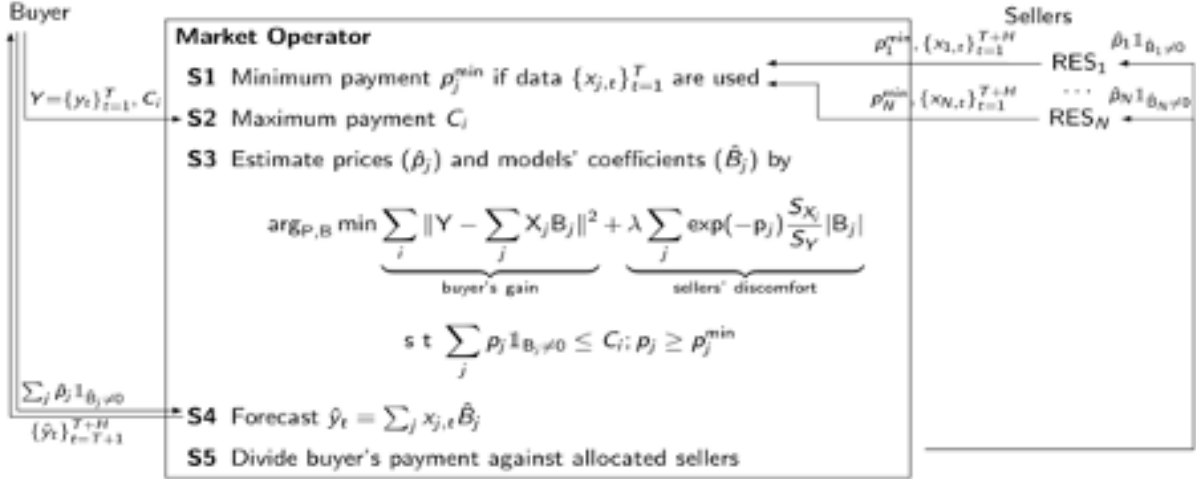
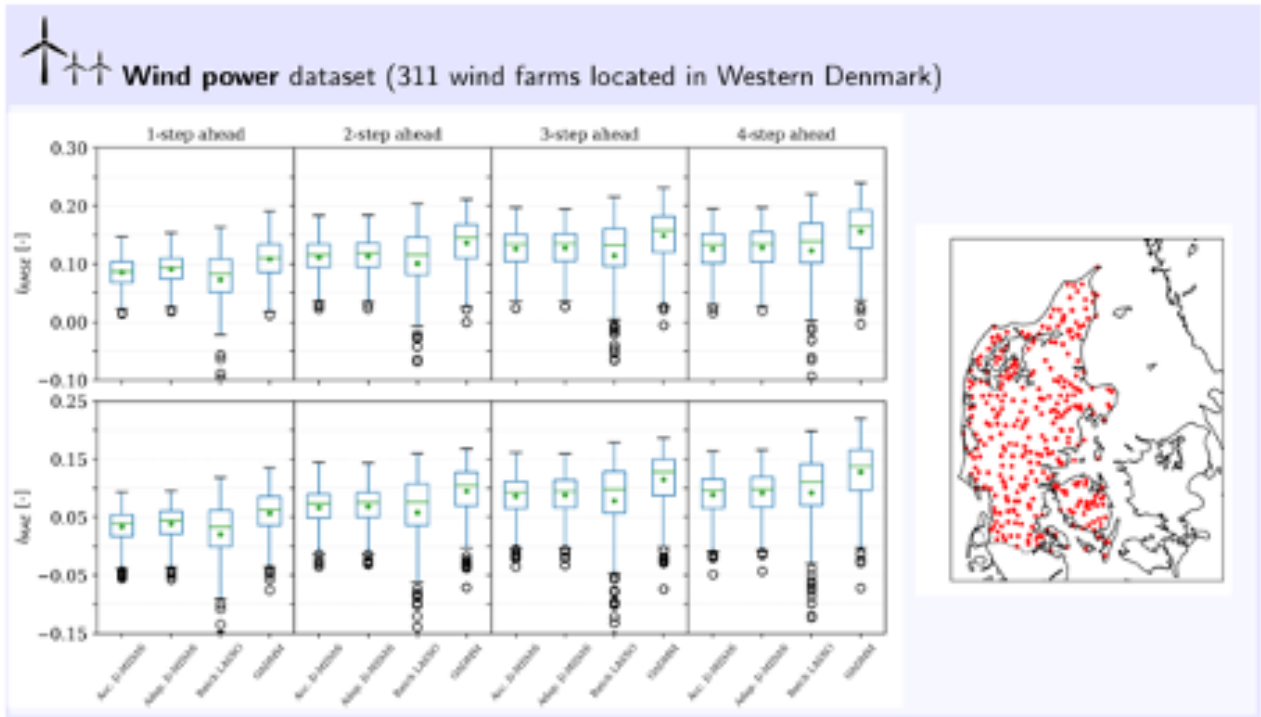
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# Collaborative forecasting, data sharing and data markets



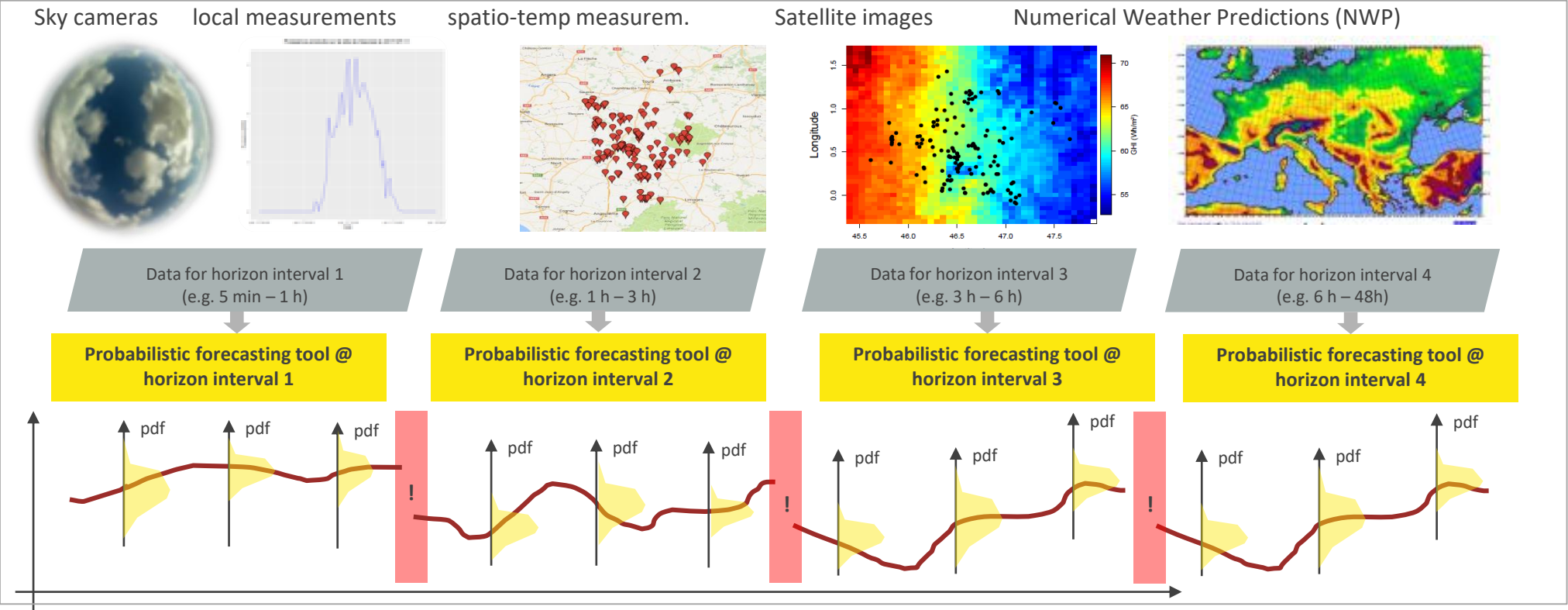
- Cutting-edge collaborative and distributed learning approaches that set a new standard within the field of renewable energy forecasting (INESC, DTU)
  - Data sharing while respecting confidentiality and privacy constraints.

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



# 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

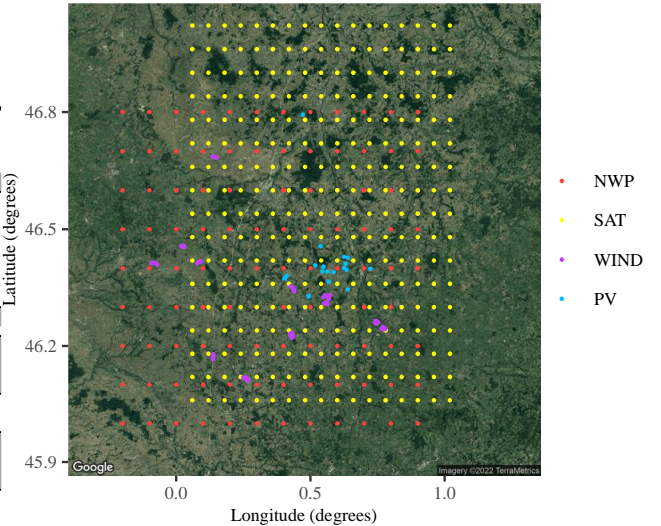
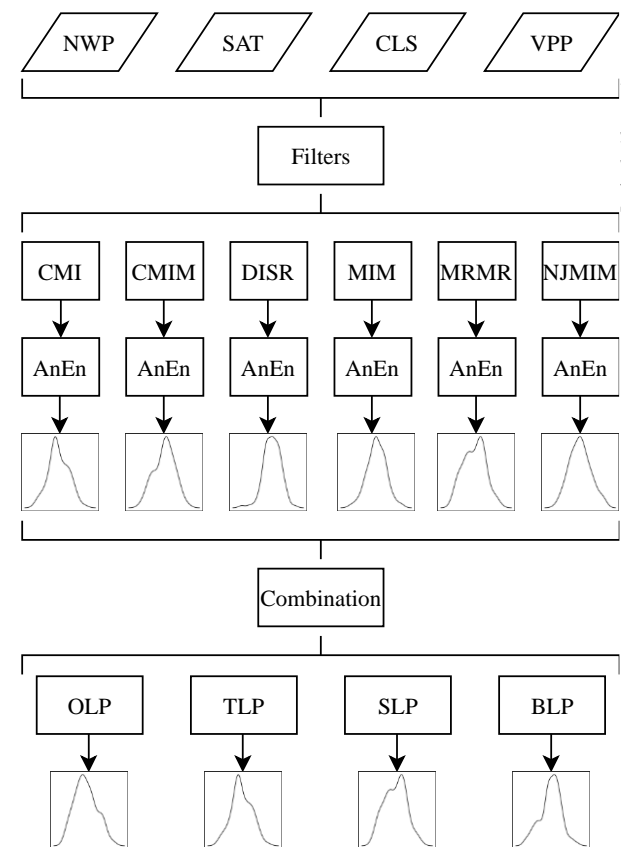
**Idea:** Use filters to automatically select and weigh features, and forecast combination to mitigate uncertainty caused by feature selection

## 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

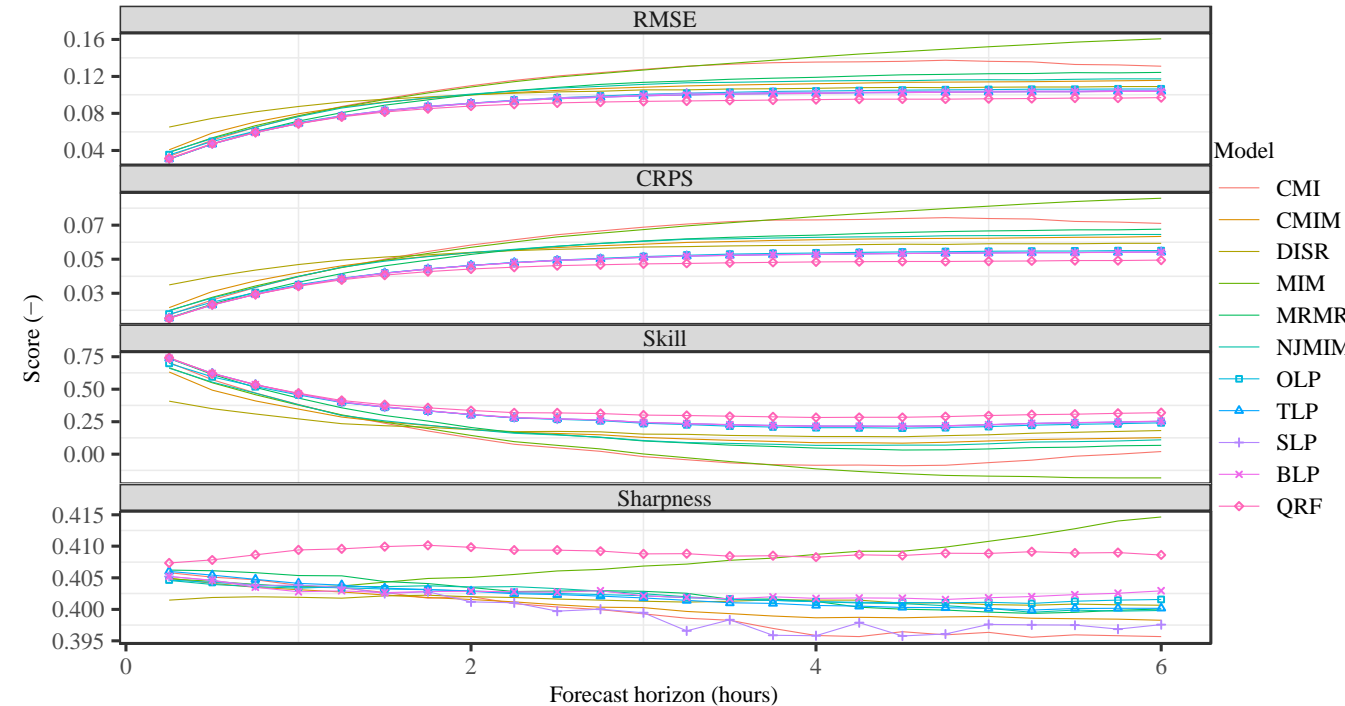




# Seamless RES forecasting with enhanced feature selection

## ■ Evaluation & results

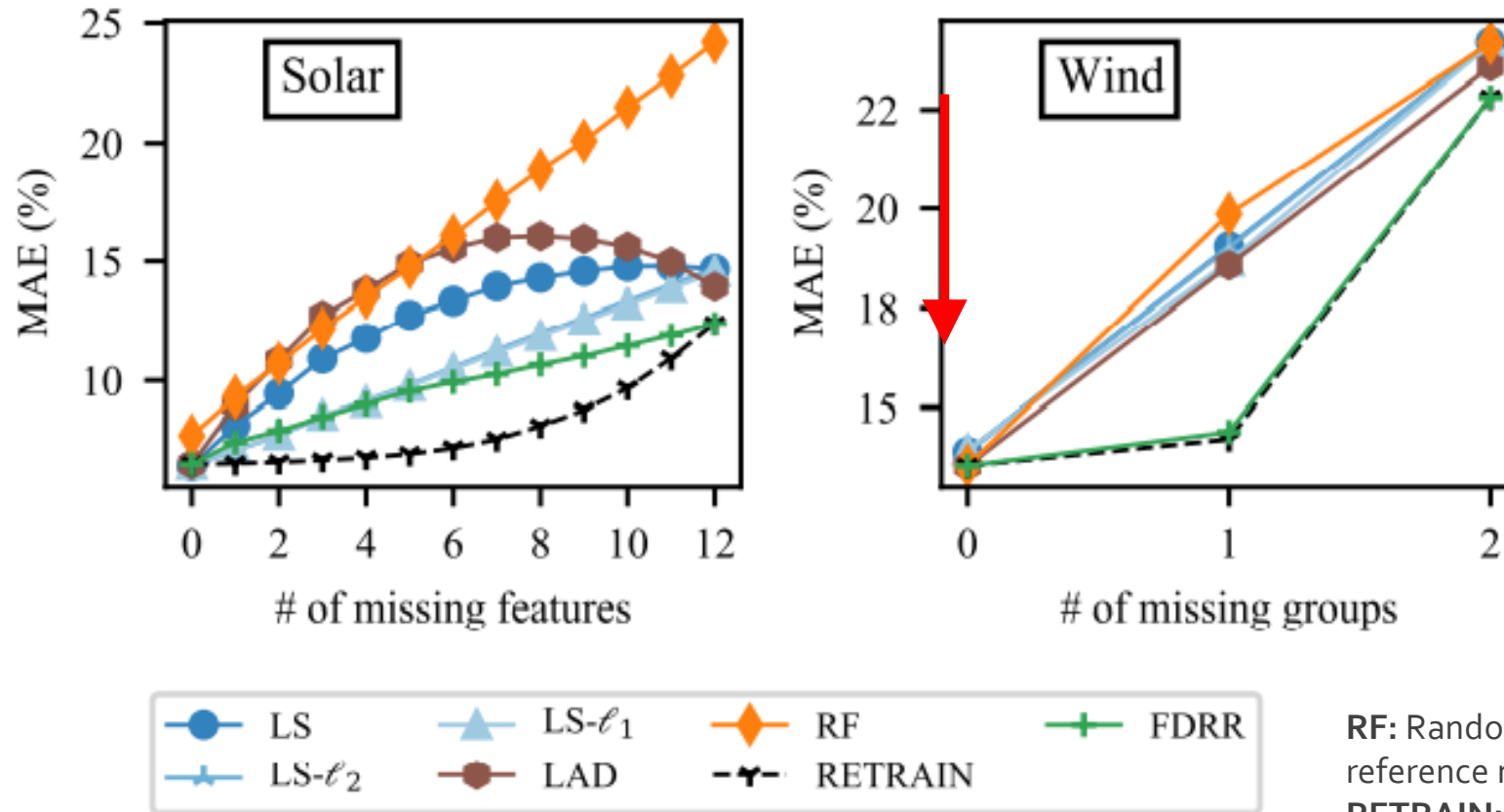
- Quantitative analysis for the period 2020-01-01 until 2020-09-30
- Comparison of:
  - Vanilla analog ensemble (AnEn) that uses all features
  - The 6 filter methods feeding data to an AnEn model
  - The 4 forecast combination methods that combine the 6 different forecasts
- The filter methods significantly 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  $\Gamma$  features are missing (MINES Paris).

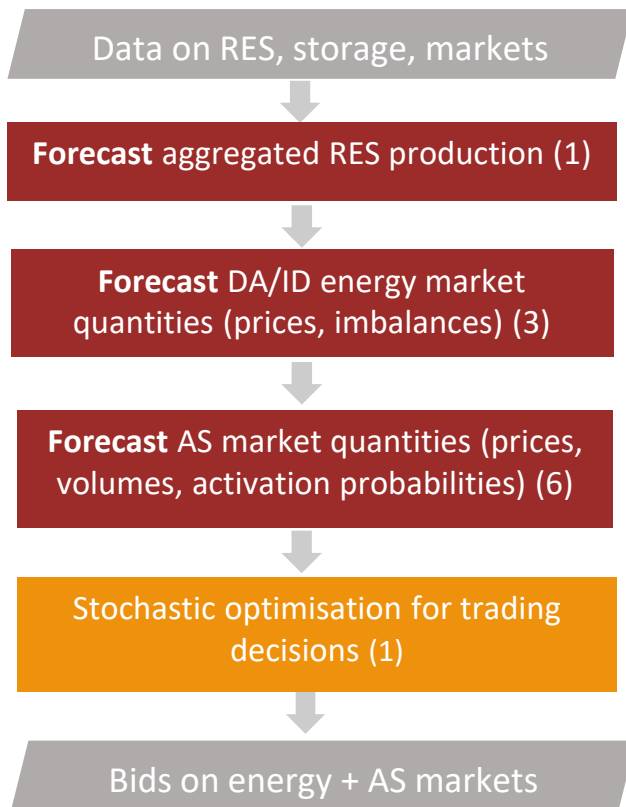


RF: Random Forest approach commonly used as advanced reference model.

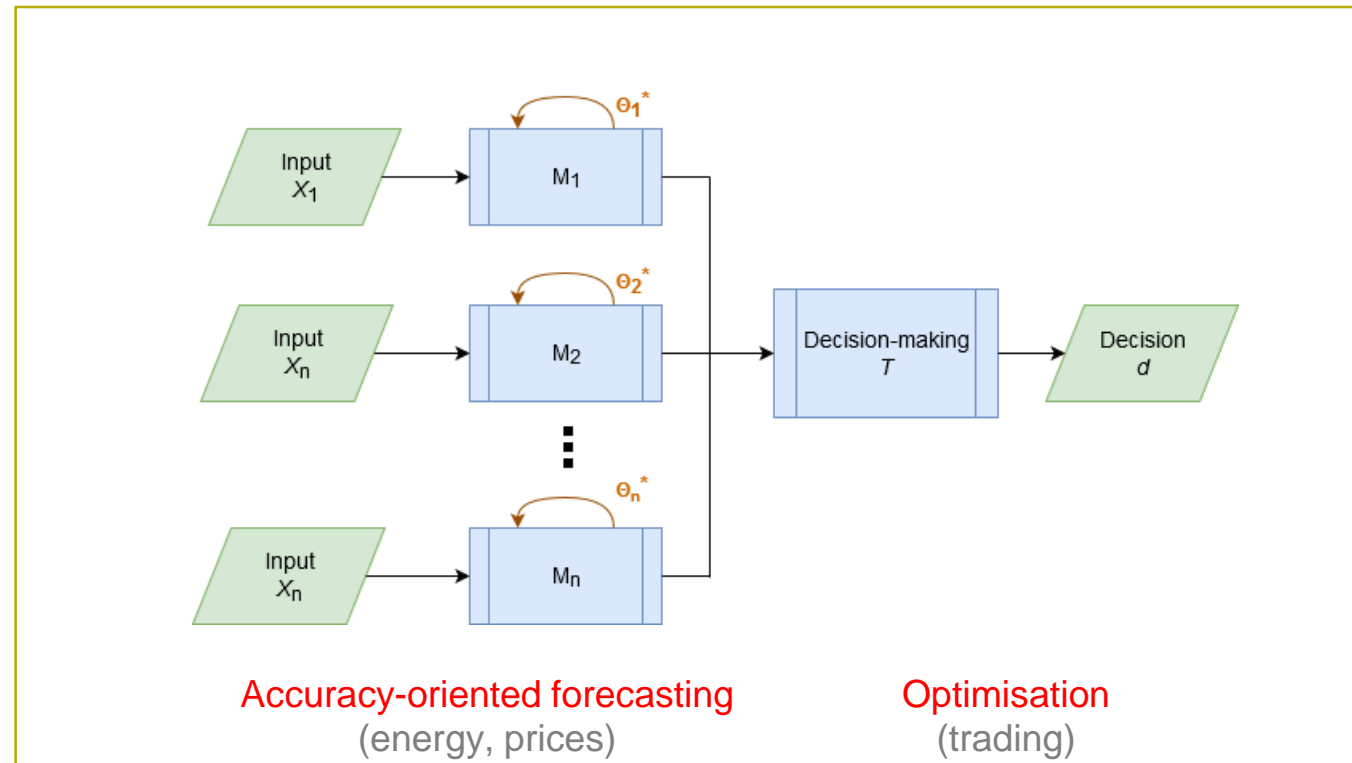
RETRAIN: retrained models with missing features.

# 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)

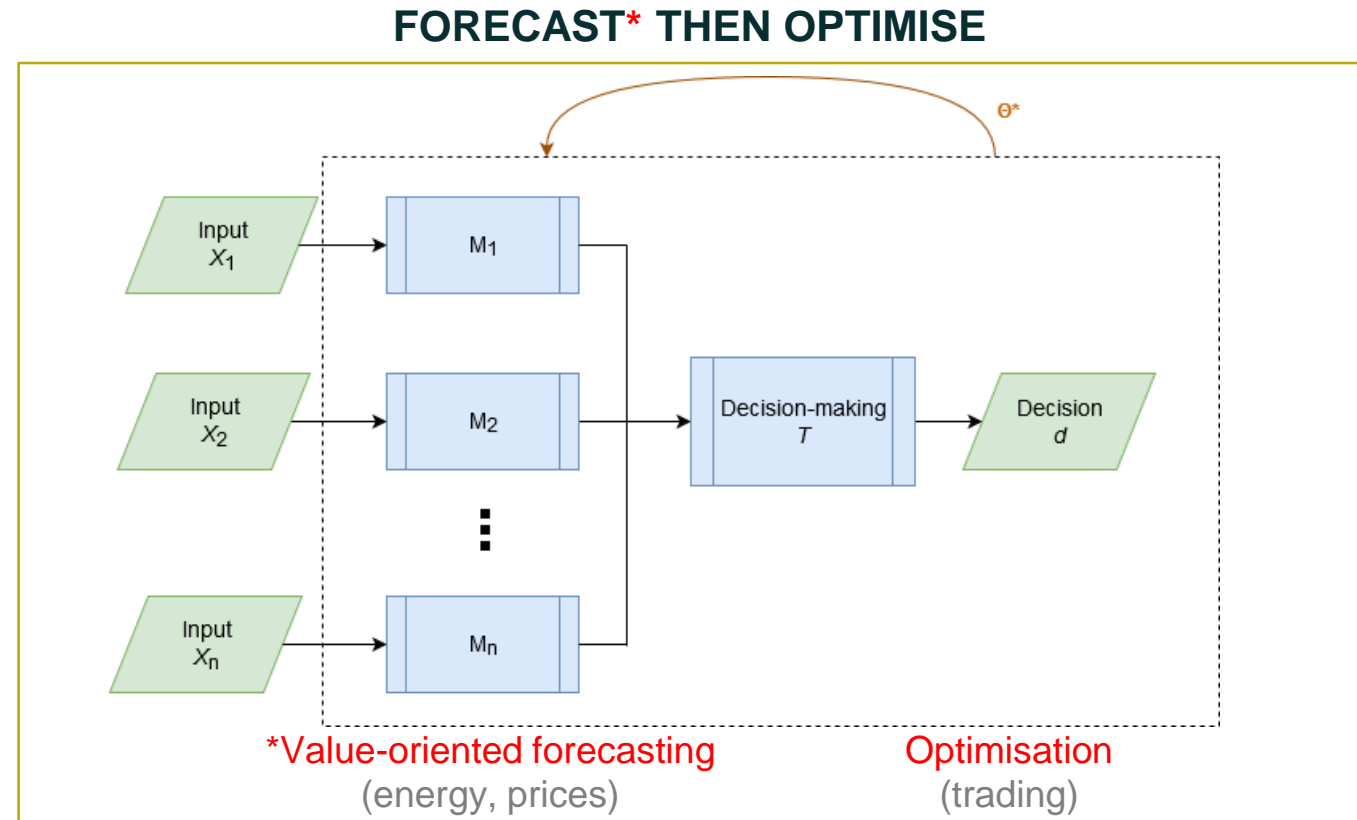
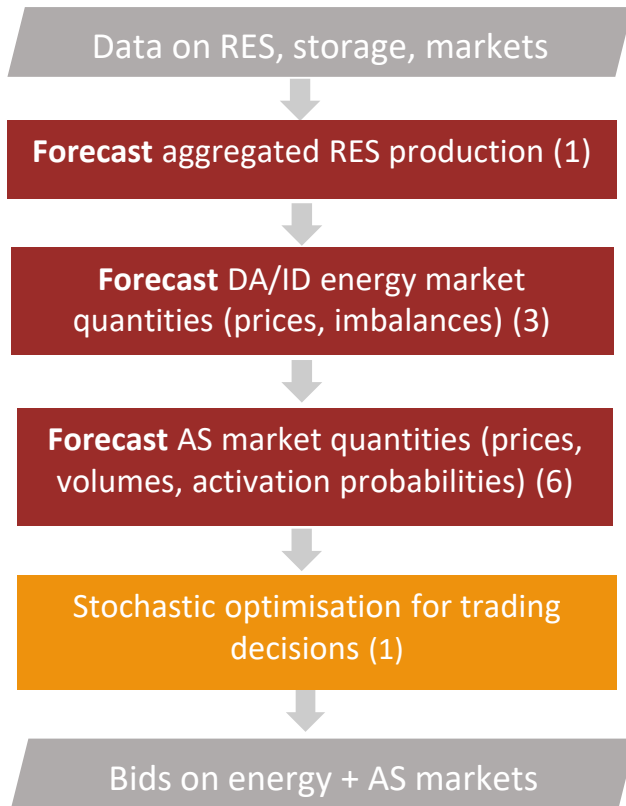


The classic approach:  
**FORECAST THEN OPTIMISE**



# Value-oriented forecasting

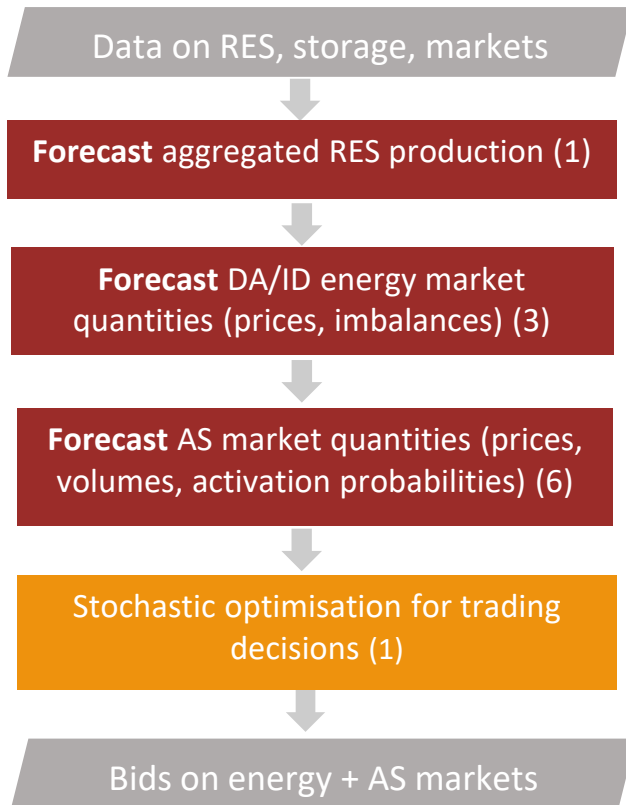
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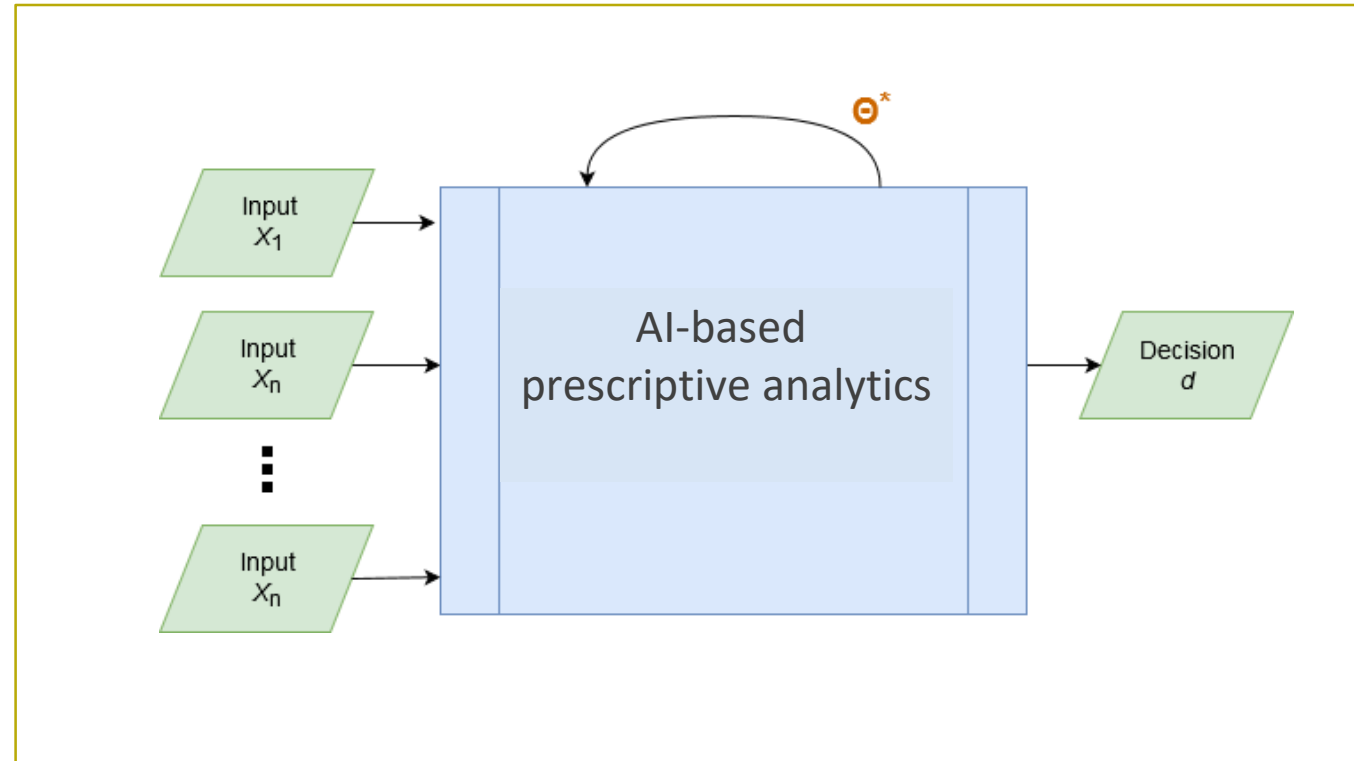


# Value-oriented forecasting

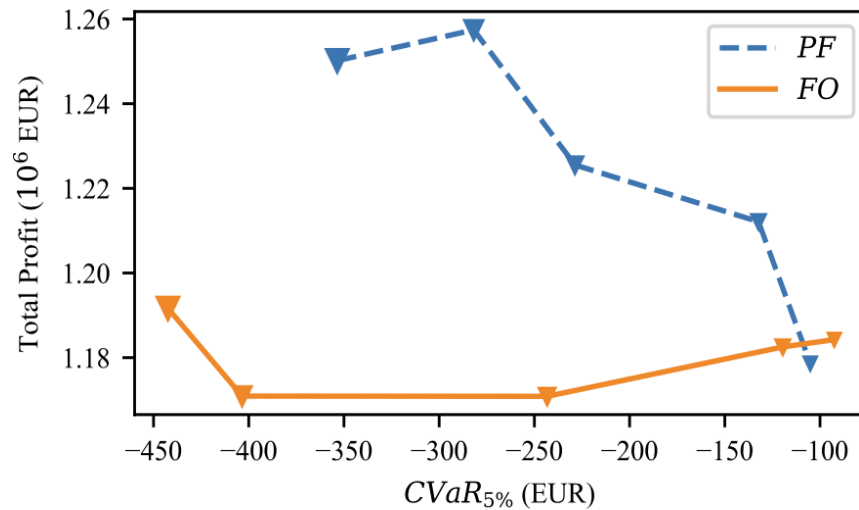
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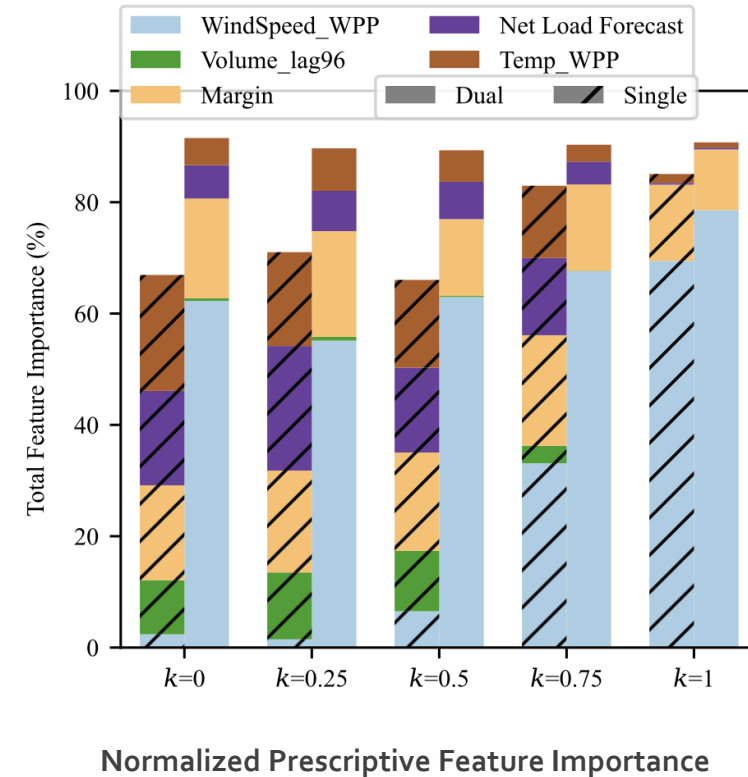
## JOINT FORECASTING & OPTIMISATION



- 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.





**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

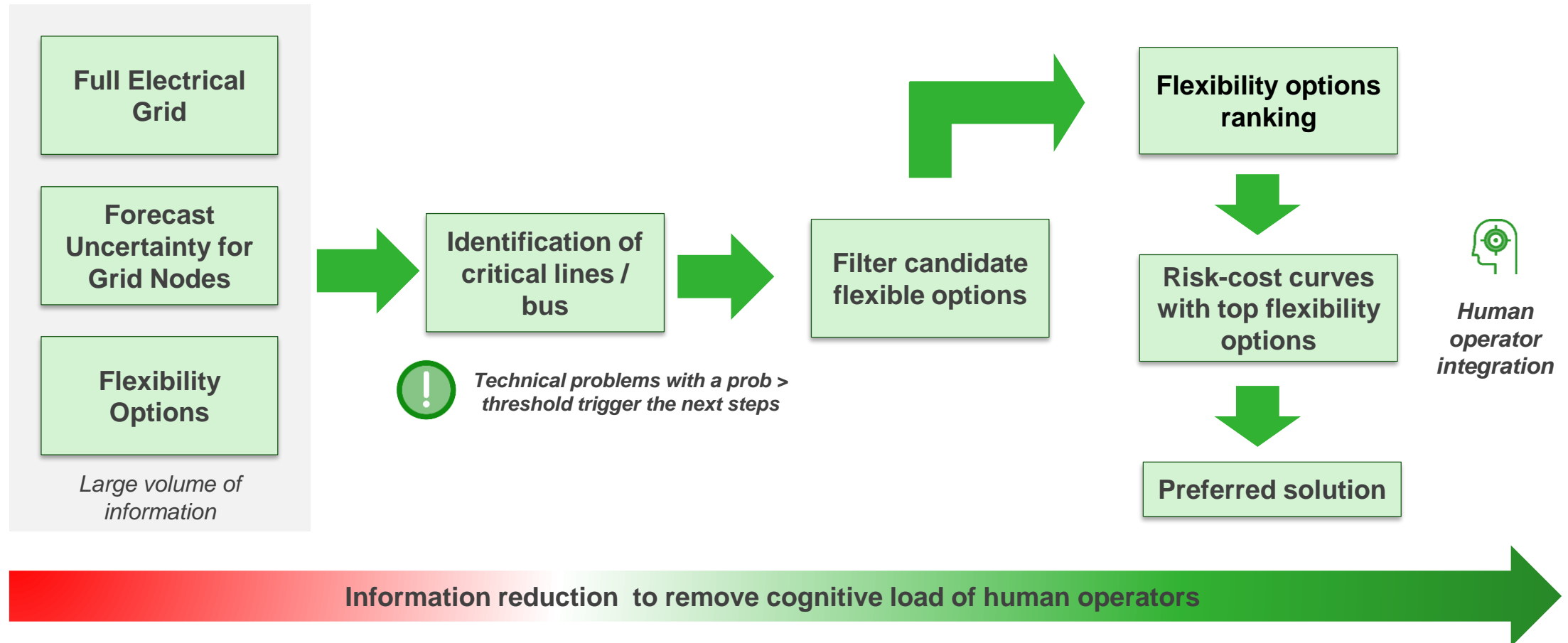
- (1) Provide interpretable control actions for flexibility “booking” under forecasting uncertainty
- (2) Hierarchical load and flexibility forecasting in electrical grids



## 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

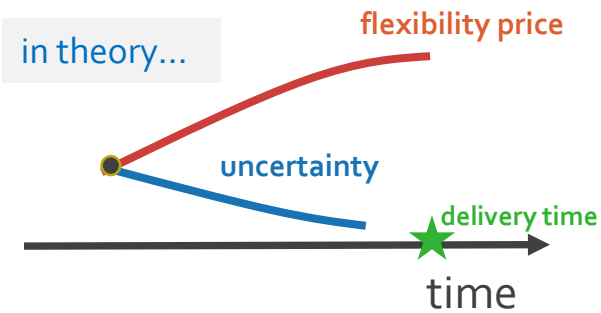


**Publication:** R.J. Bessa, F. Moaidi, J. Viana, J.R. Andrade, "Uncertainty-aware procurement of flexibilities for electrical grid operational planning," under review in IEEE Transactions on Sustainable Energy, 2023.

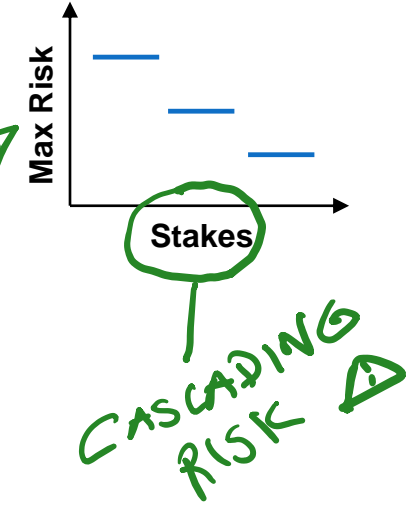
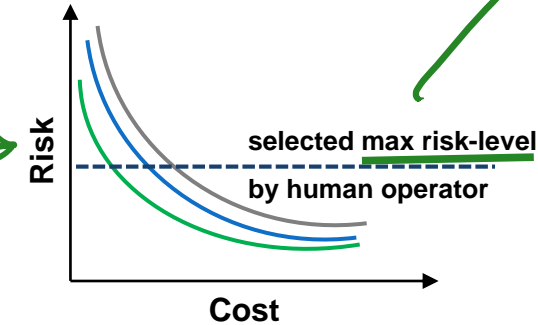
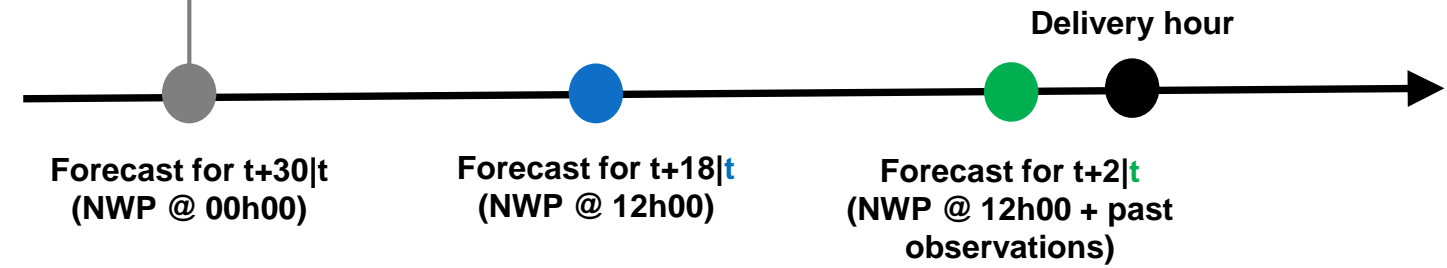
# Forecasting in TSO/DSO control rooms



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?



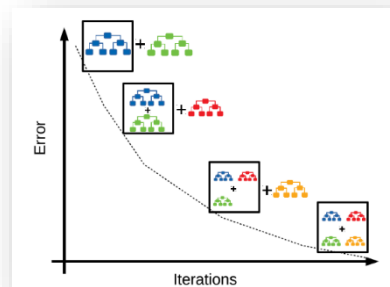
- At decision time  $t$  generates
- Forecast for t+30|t
  - Meta-forecast for t+30|t+12
  - Meta-forecast for t+30|t+28



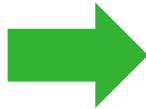


# Meta-forecasting concept and models

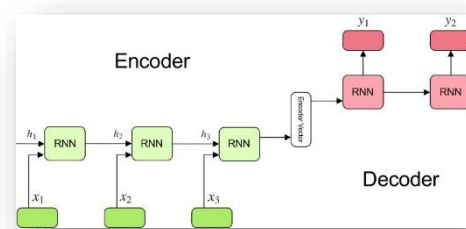
## Gradient Boosting Trees (GBT)



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



## 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%

## 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 ( $\gamma$ )

## Profiles of different decision/makers

Decision-making approach	Stakes ( $\rho$ ) range		
	$0 \leq \rho \leq a^*$	$a < \rho \leq 7$	$7 < \rho \leq 10$
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 ( $\gamma$ ) 20% lower than DM A

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# 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 NWP.

# 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. Explore the potential of the digital twins approach (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



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## 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/>



<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)

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### 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)

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### 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)



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