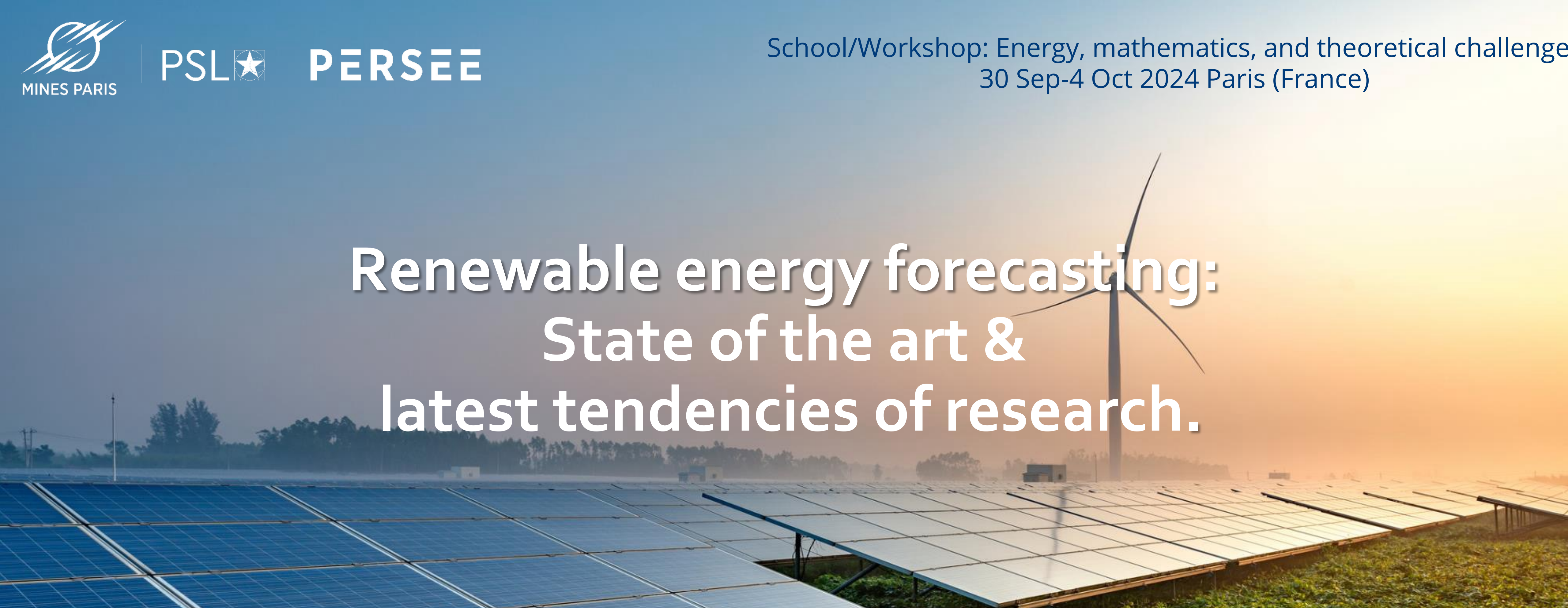


Renewable energy forecasting: State of the art & latest tendencies of research.

Georges Kariniotakis

Prof., Head of Renewable Energies & Smart Energy Systems Group,
Coordinator of Smart4RES project
Mines Paris - PSL, Centre PERSEE
georges.kariniotakis@minesparis.psl.eu

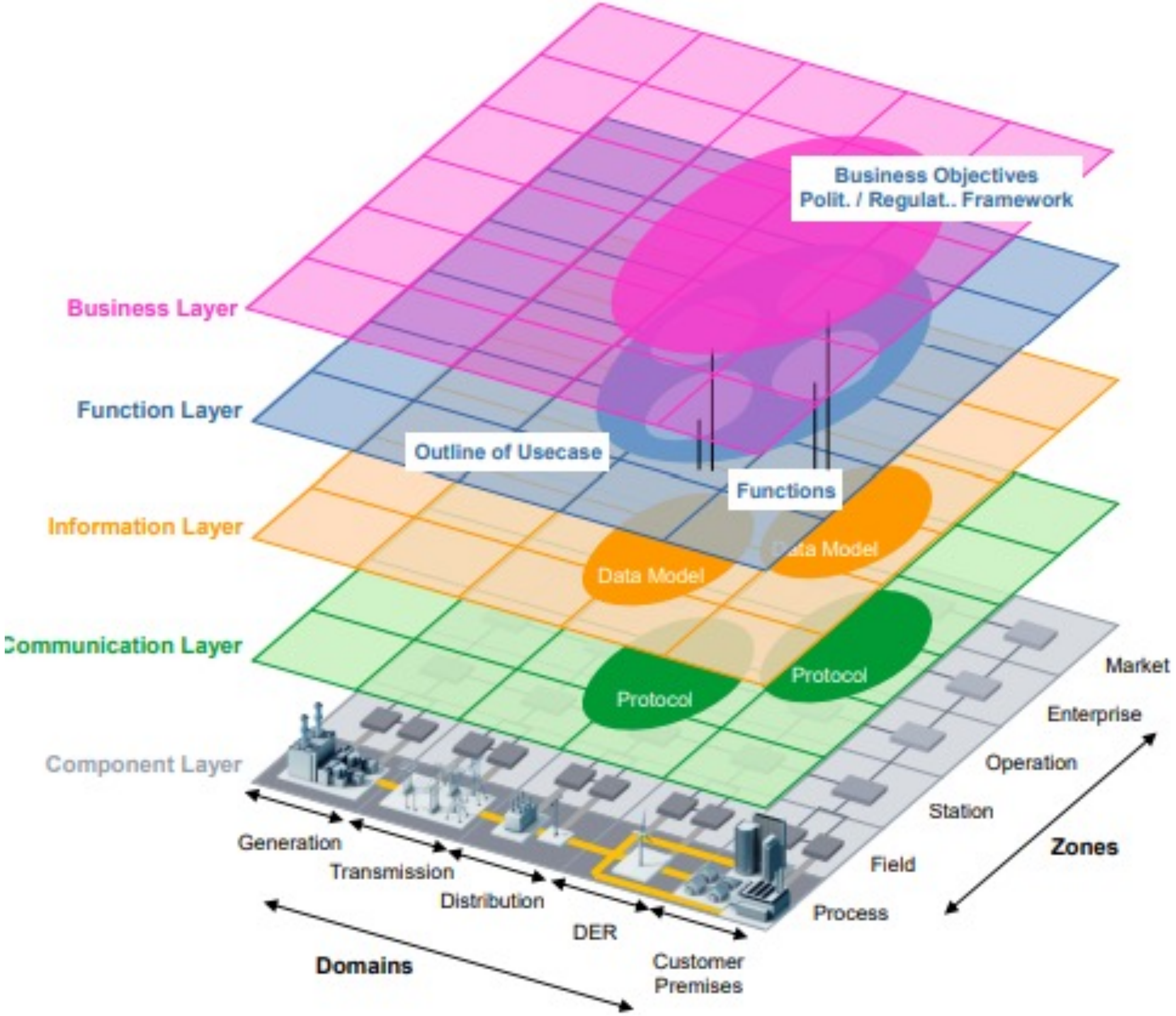
OUTLINE

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

Evolution of power systems in the context of energy transition

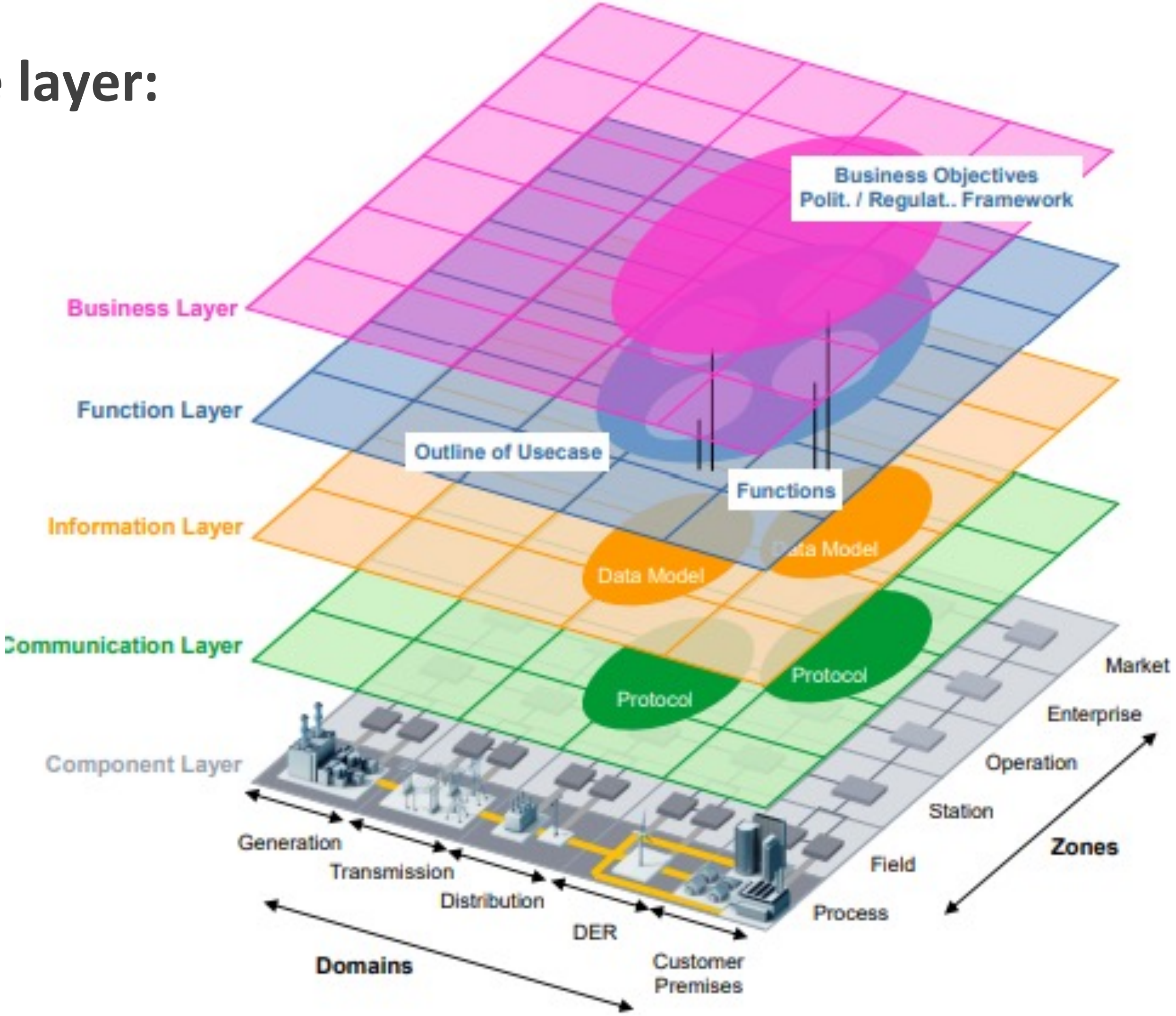
Challenges:

- Integration of **distributed sources**: renewables, storage, demand response, P2X, X2P and other options.
- **Information sources multiply** and increase the level of complexity in decisions
- Evolution towards **highly complex & interacting energy systems** (system of systems)
- Need of an **efficient « intelligent layer »** for the secure ans economic management of power systems.
- Moreover, this has to be **resilient** to extreme situations (i.e. due to climate change) and crisis



Example of functionalities of the intelligence layer:

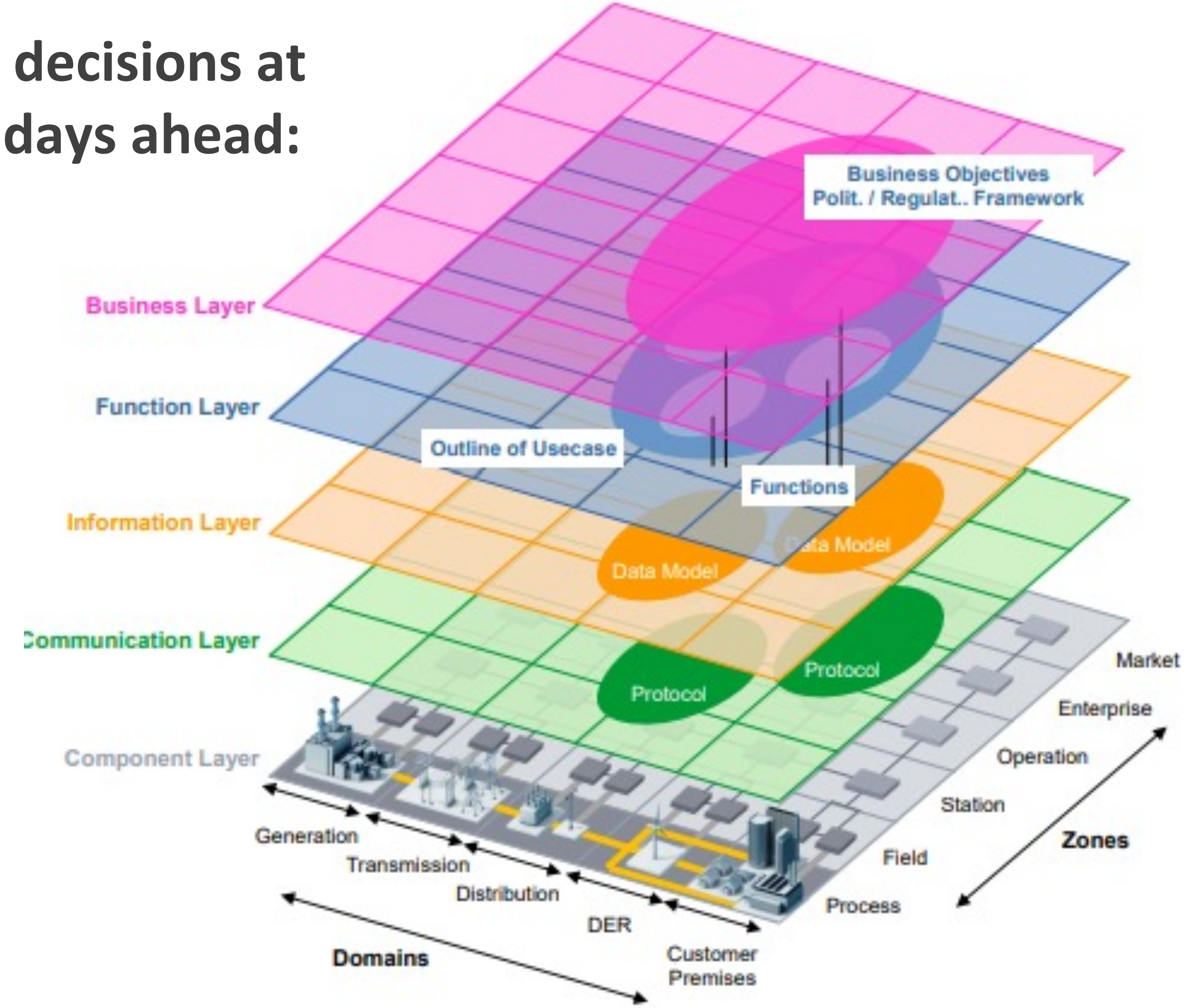
- Forecasting of demand, generation, DLR....
- Scheduling/Unit commitment
- Optimal allocation of reserves
- Congestion management
- Management of hybrid systems (RES + RES, H2...)
- Trading of RES/virtual power plants to markets
- Control of assets
- Predictive maintenance
- End of life estimation
- ....



Evolution of power systems in the context of energy transition

Focus on functionalities needed to optimise decisions at operational time scales of a few minutes to days ahead:

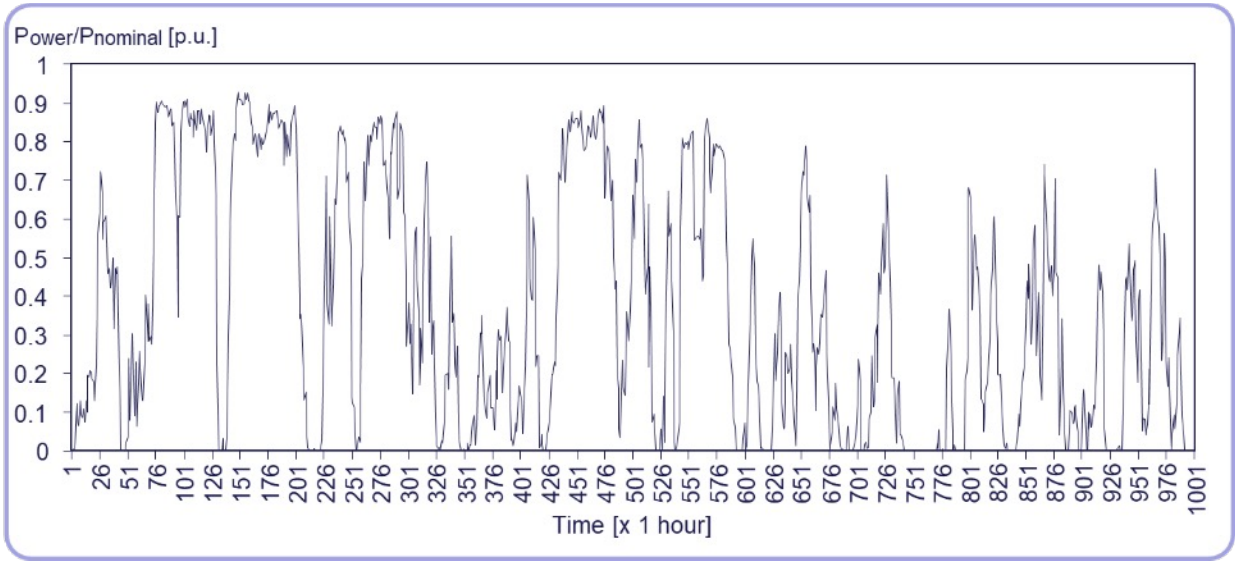
- **Forecasting of demand, generation, DLR....**
- **Scheduling/Unit commitment**
- **Optimal allocation of reserves**
- **Congestion management**
- **Management of hybrid systems (RES + RES, H2...)**
- **Trading of RES/virtual power plants to markets**
- Control of assets
- Predictive maintenance
- End of life estimation
- ....



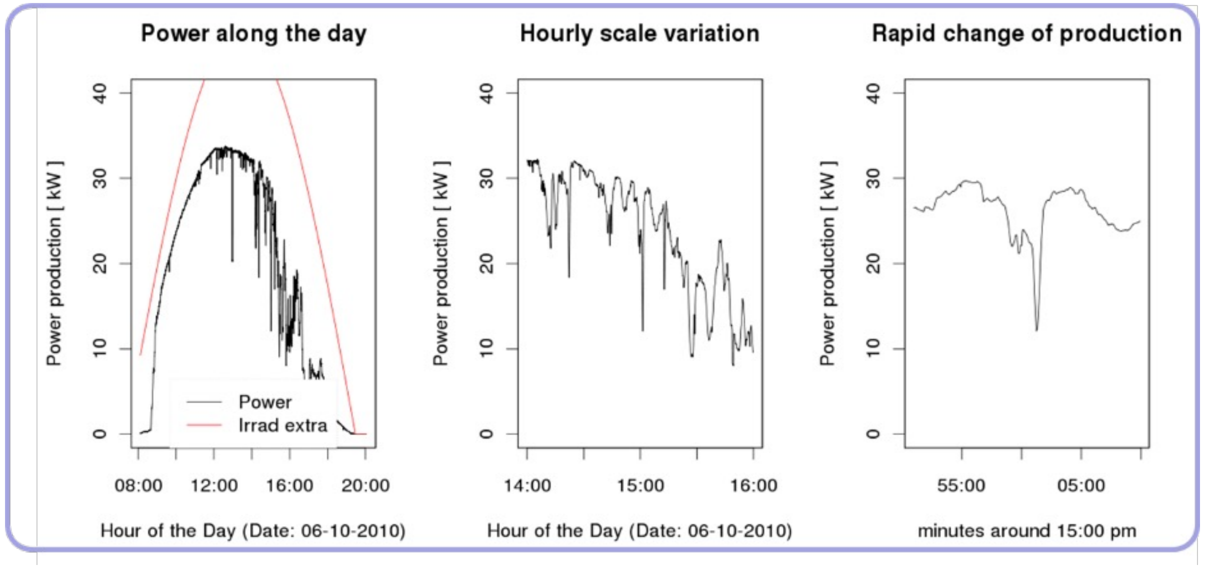
Integration of renewables in electricity grids and energy markets

- The weather dependency of wind & solar production brings challenges to operators (variability/uncertainties)

Examples of variability of RES production



Hourly power production of a wind farm

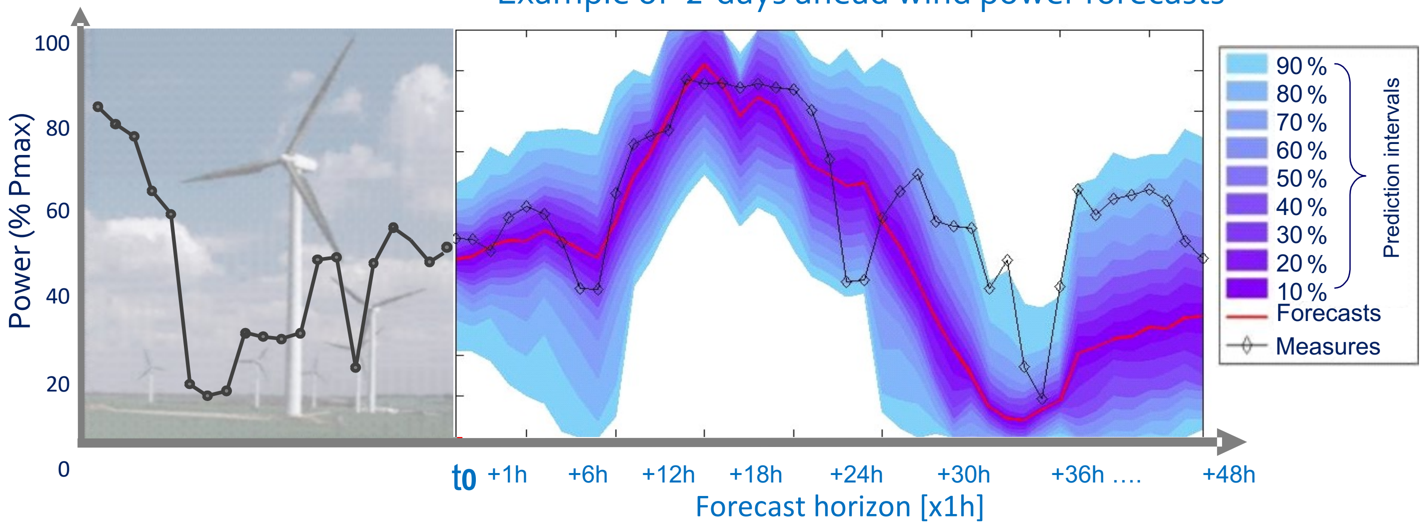


Power production of a photovoltaïc plant

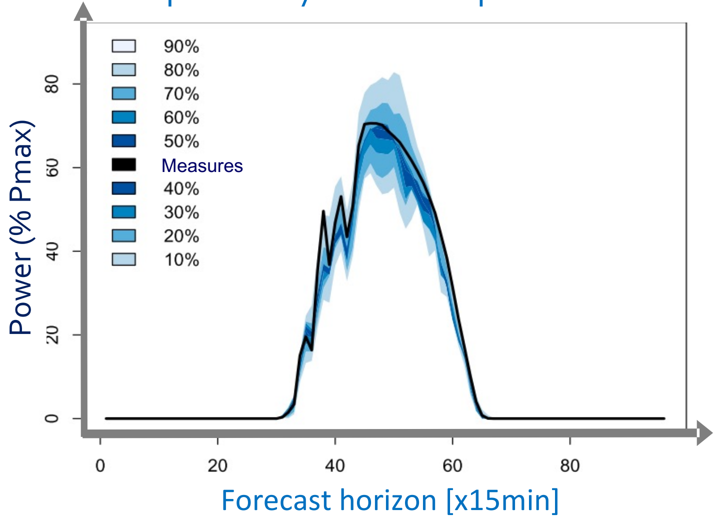
The role of short-term RES forecasting

- Short-term (minutes-days ahead) forecasts of renewable generation (wind, solar) (RES) are necessary for a secure and economic operation of power systems.
- First solutions proposed in the literature in 1985.
- Forecasting solutions are used operationally by stakeholders since early '90s.

Example of 2-days ahead wind power forecasts



Example of day ahead PV power forecasts

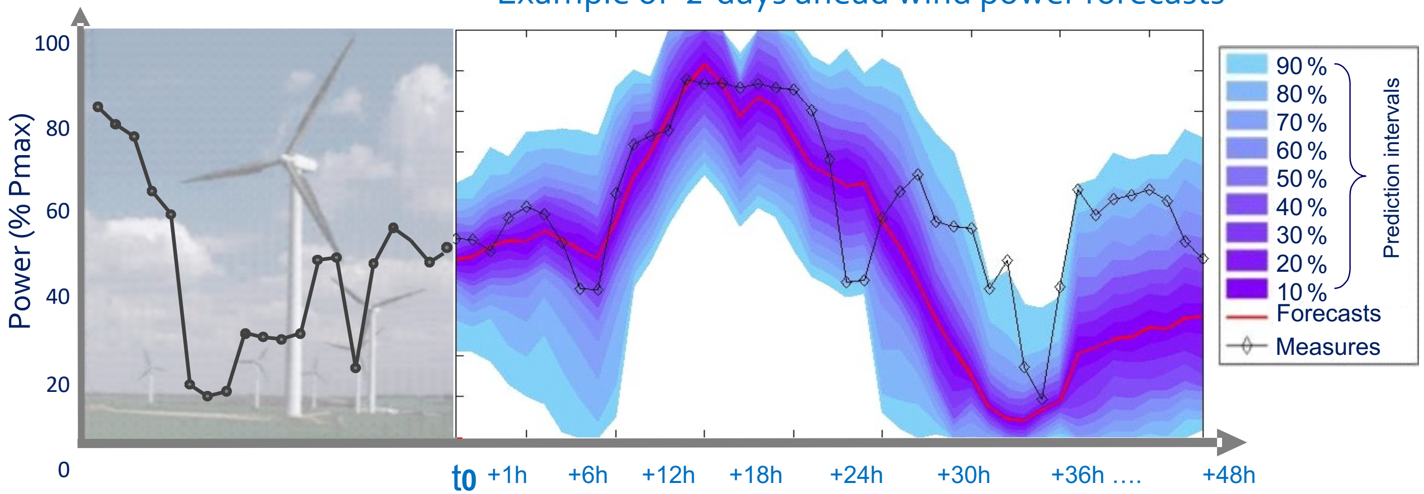


The role of short-term RES forecasting

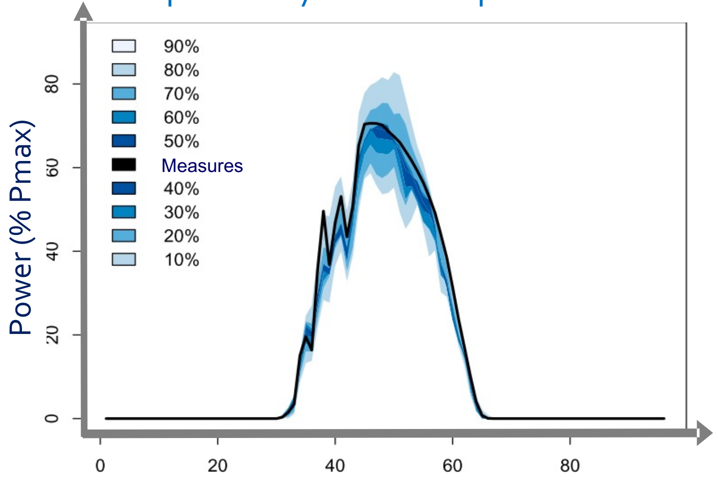
Despite this apparent maturity:

- Large forecast errors may occur with a high financial/technical impact.
- Improving **forecasting accuracy** has been a continuous requirement by end users.
- Requirements for **new forecasting products** continuously emerge

Example of 2-days ahead wind power forecasts

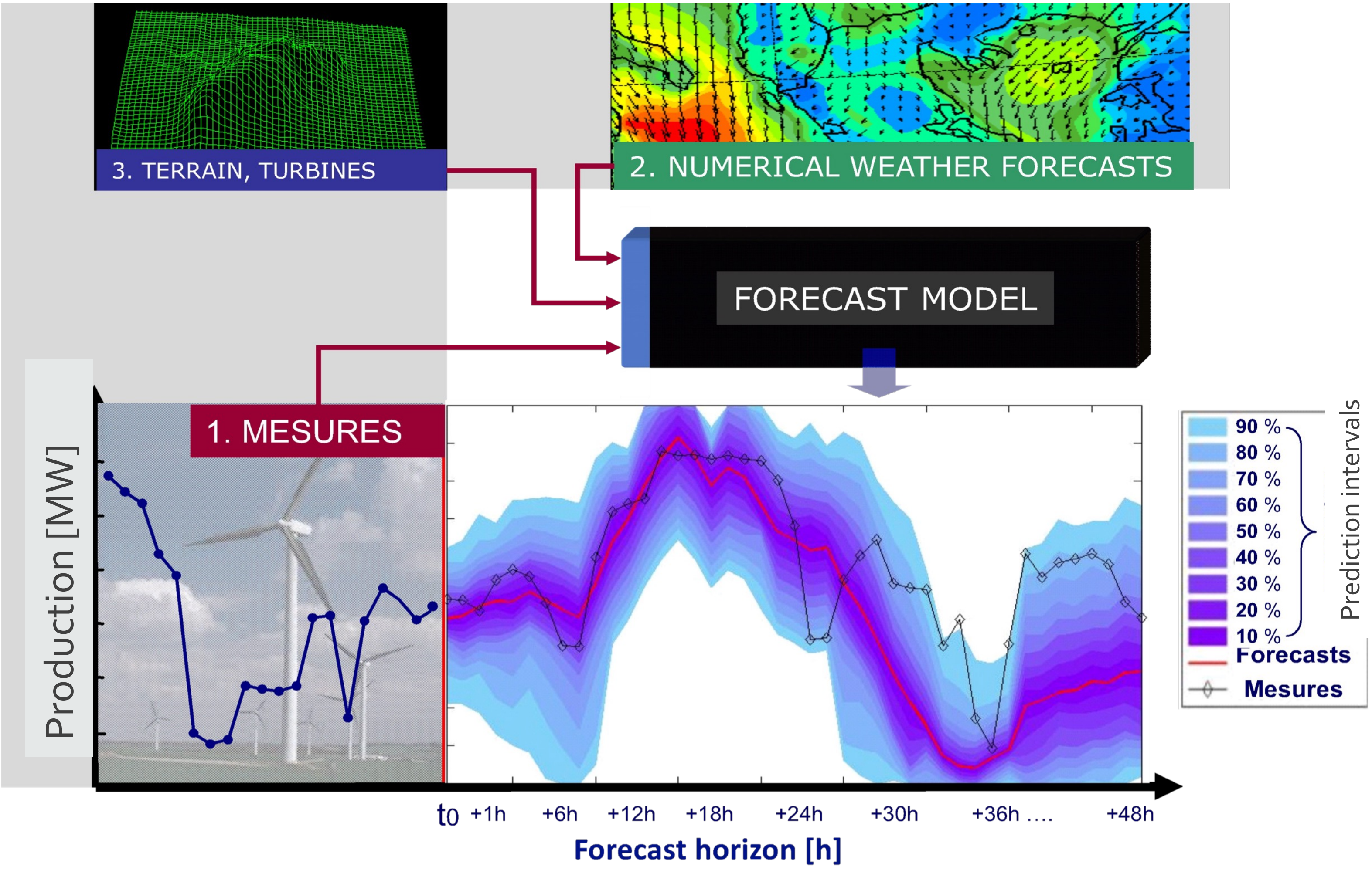


Example of day ahead PV power forecasts



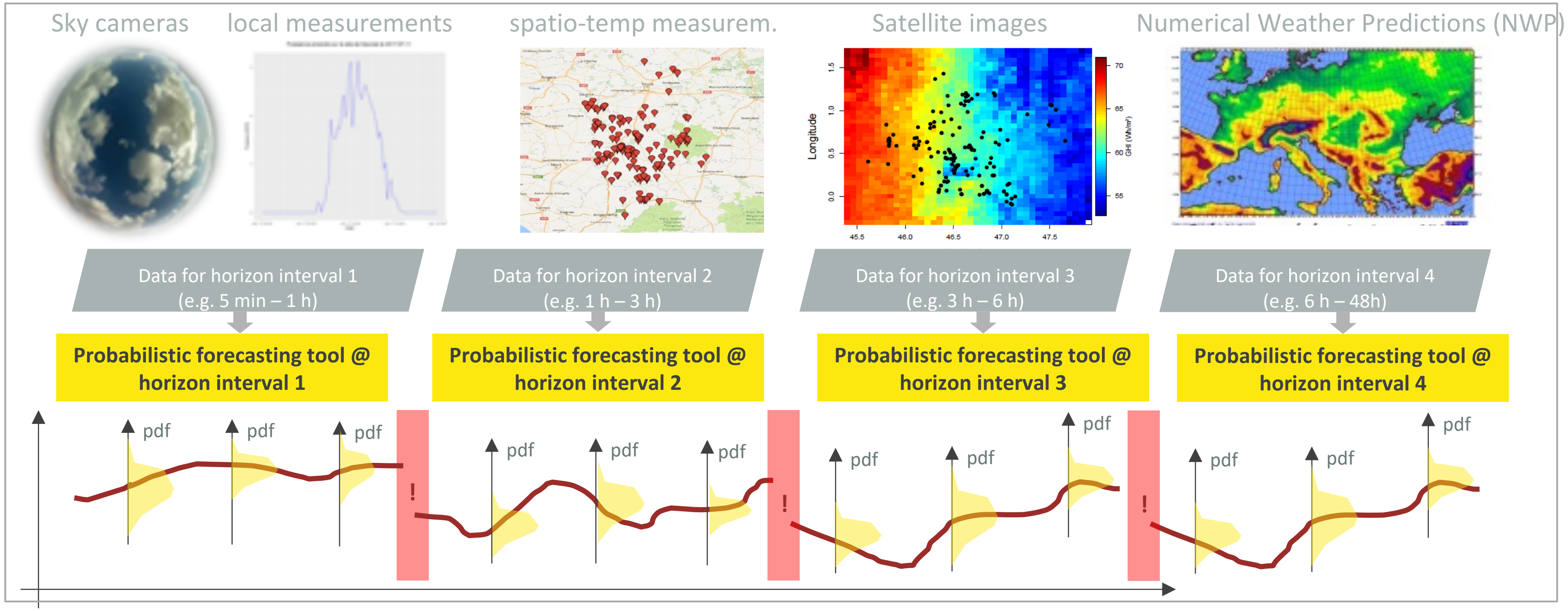
The general principle of RES forecasting

The case of wind power forecasting



The general principle of RES forecasting

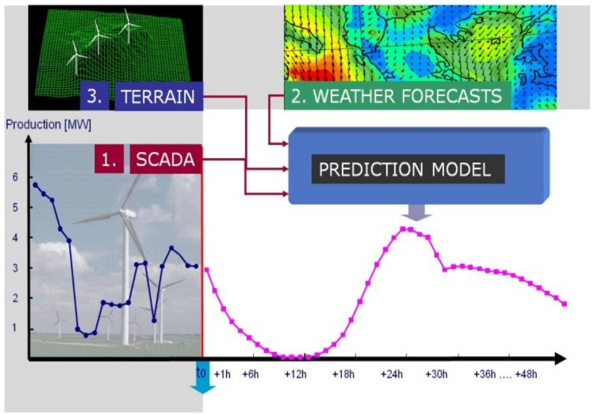
The case of PV power forecasting

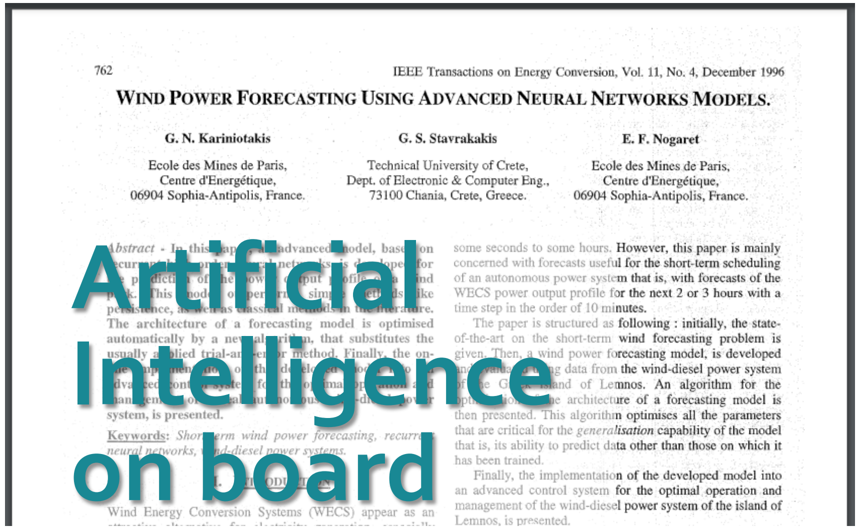


Multi-time scale
Power Forecast

The history of RES forecasting

"Deterministic" (spot) view




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. ... Lemnos. ... 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.

1985 1990 2000 2010 2020

- First purely time series methods on WPF

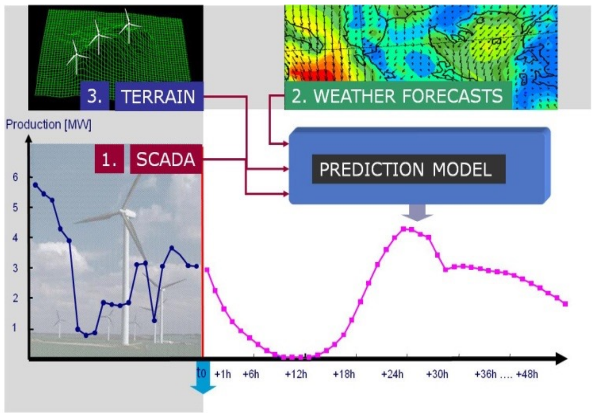
- Statistical / time-series approaches
- Physical modelling
- First AI-based approaches
- NWPs considered as input
- Empiric/hybrid implementations into operational forecast tools

- The **1st ever journal paper**, where IA was applied in the renewable energies field was published in 1996 (ANN for wind power forecasting).

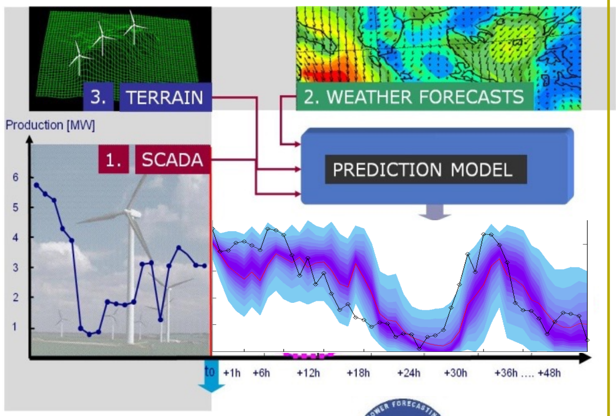
[2002-2006] ANEMOS (FP5), http://www.anemos-project.eu/
[2008-2011] ANEMOS.plus (FP6), http://www.anemos-plus-project.eu/
[2008-2012] SAFEWIND (FP7), http://www.safewind.eu/
[2019-2023] Smart4RES (H2020), http://www.smart4res.eu/

The history of RES forecasting

"Deterministic" (spot) view

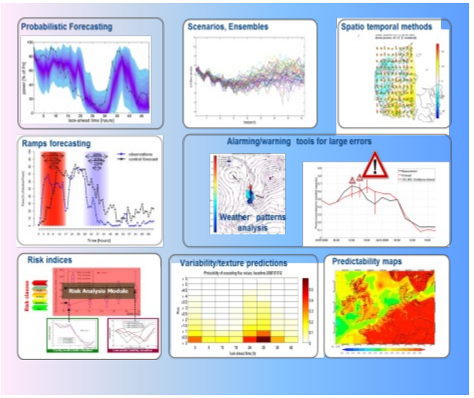


Probabilistic view



ANEMOS

Probabilistic & special situations



ANEMOS.plus SafeWind

1985 1990 2000 2010 2020

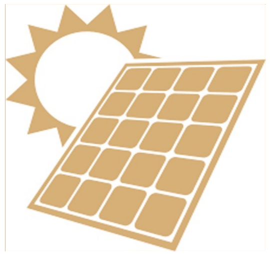
AWEFS

- 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

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

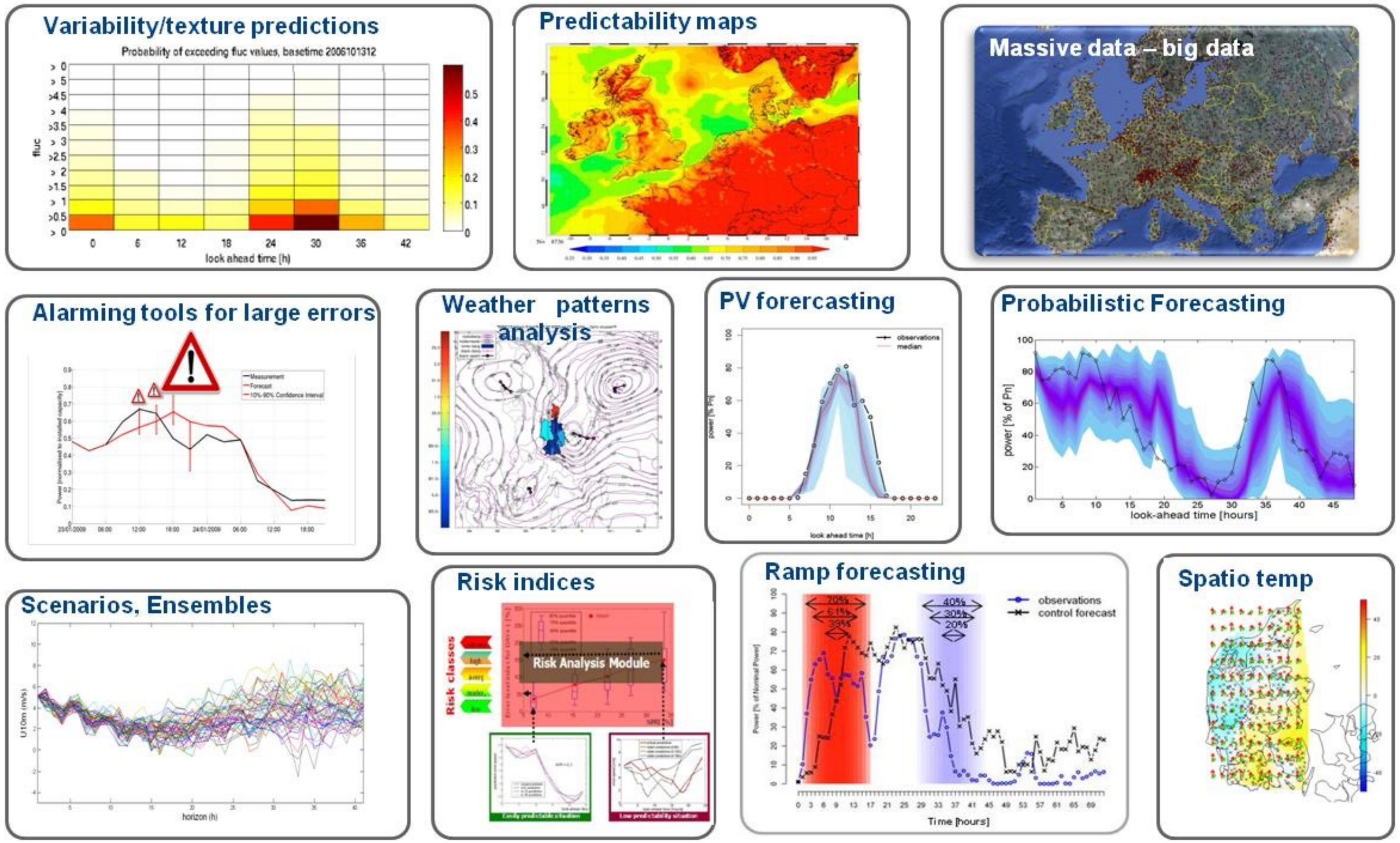
- Dedicated NWPs for RES
- Direct probabilistic predictions
- Ramps forecasting
- Scenarios, Enesembles,
- Risk indices
- Large errors warning/alarming
- Spatiotemporal forecasting
- Variability forecasting
- Predictability maps



[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

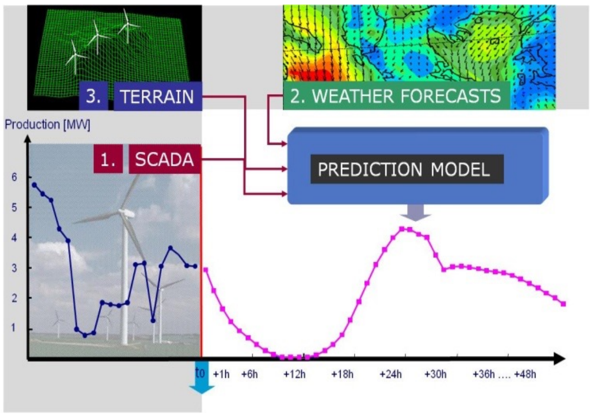
- Major developments in wind forecasting in the period 2002-2012.
- Solar forecasting followed a much faster learning curve that started around 2005



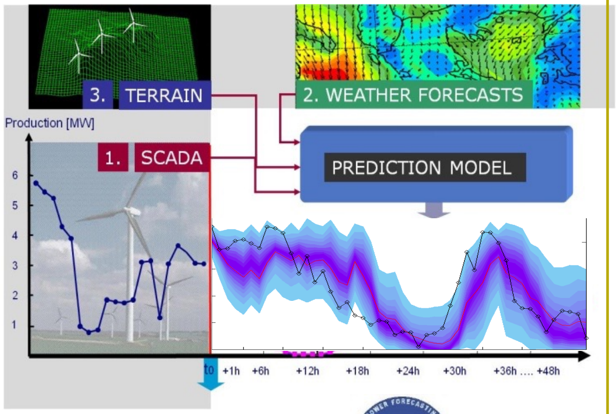
The history of RES forecasting

MINES PARIS | PSL | PERSEE

"Deterministic" (spot) view

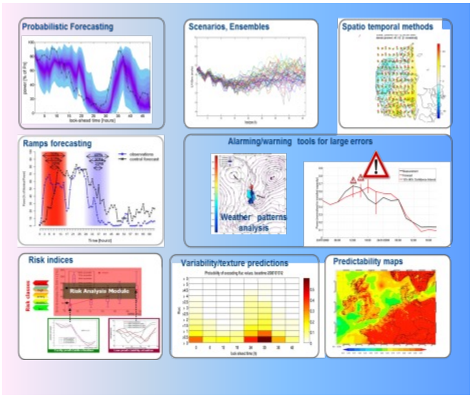


Probabilistic view



ANEMOS

Probabilistic & special situations



ANEMOS.plus | SafeWind

Smart4RES

1985 | 1990 | 2000 | 2010 | 2020

1985–1990
- First purely time series methods on WPF

1990–2000
- Statistical / time-series approaches
- Physical modelling
- First AI-based approaches
- NWPs considered as input
- Empiric/hybrid implementations into operational forecast tools

2000–2010
- Mapping of state of the art
- 1st benchmarking (Anemos competition)
- Physical modelling
- Statistical models, AI, Data mining,…
- Combination of models
- First probabilistic approaches/ensembles
- Upscaling
- Evaluation standardisation/protocol
- International collaboration

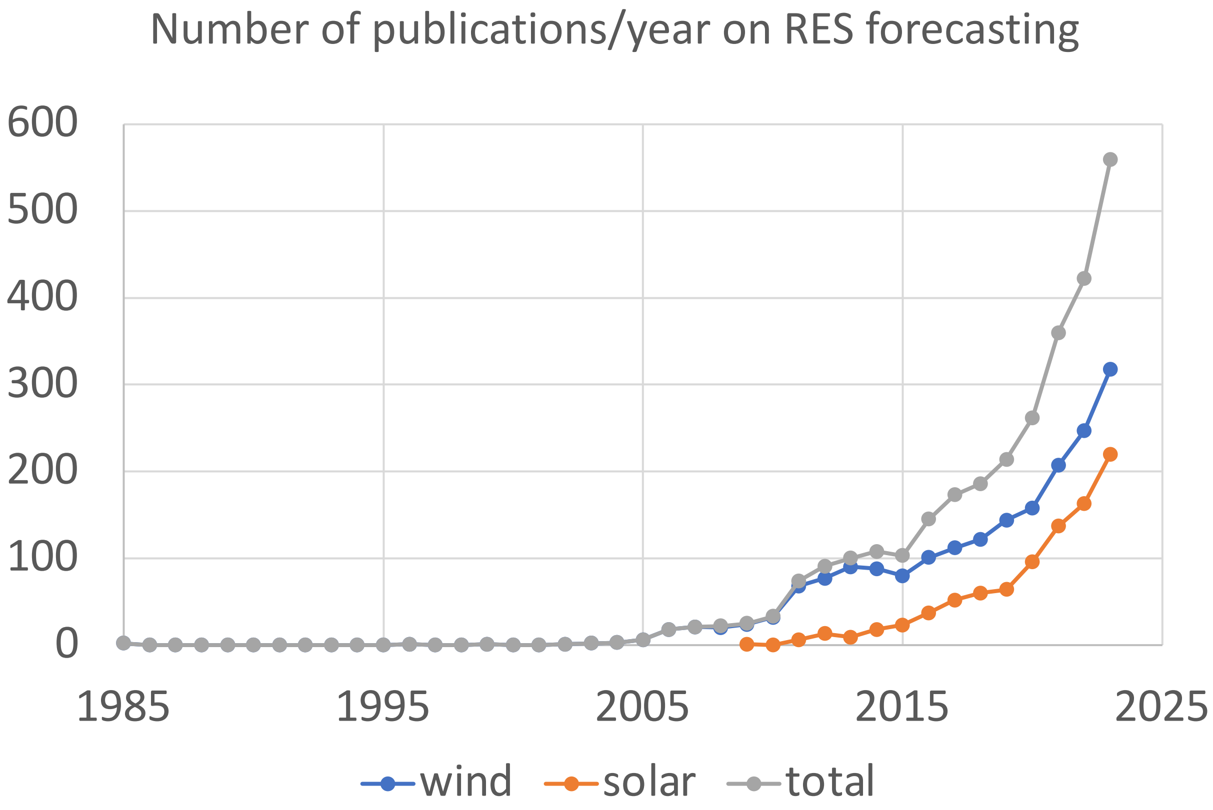
2010–2020
- Dedicated NWPs for RES
- Direct probabilistic predictions
- Ramps forecasting
- Scenarios, Enesembles,
- Risk indices
- Large errors warning/alarming
- Spatiotemporal forecasting
- Variability forecasting
- Predictability maps

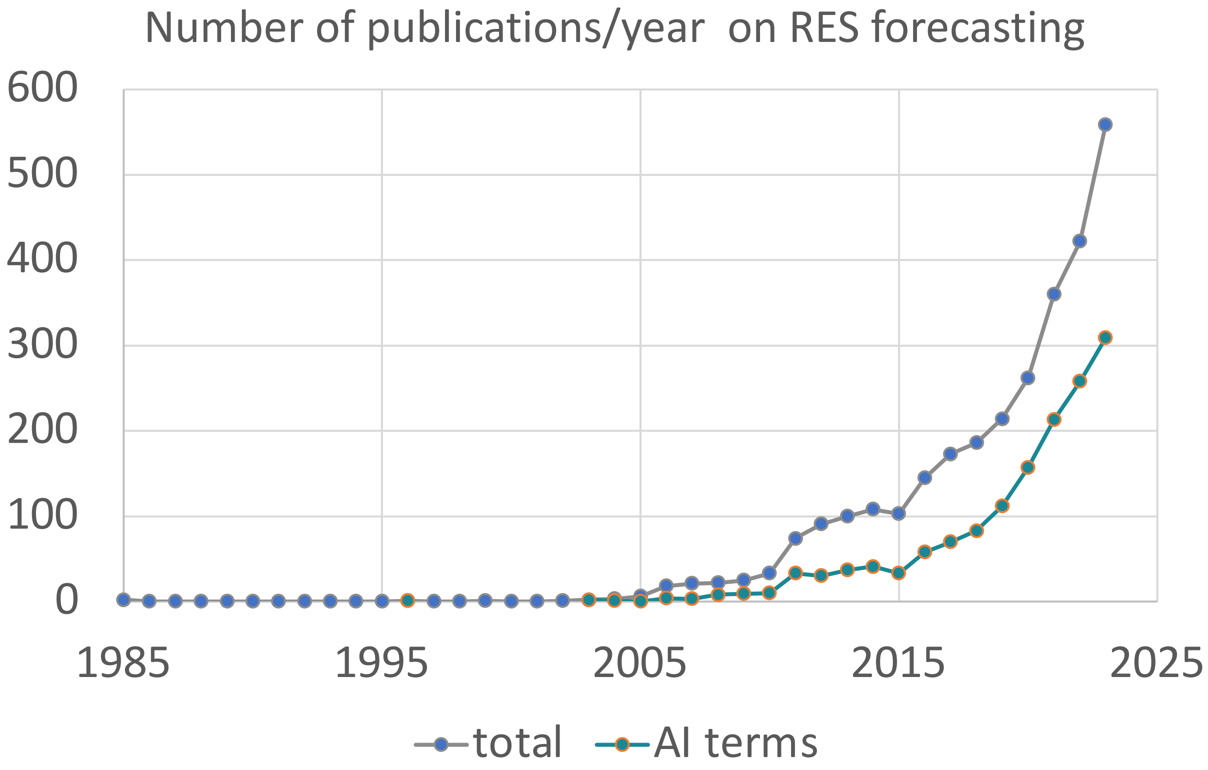
2020–
- Seamless forecasting
- Ultra high resolution (LES)
- Advanced NWPs
- Prescriptive analytics
- Extremes
- Data sharing/Data markets
- New forecasting products
- Resilience in forecasting
- Optimal use in applications

[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

- Bibliometric analysis on Scopus on Solar/wind energy/power forecasting and similar
- 2930 documents between 1985 and 2023





OUTLINE

The Smart4RES project in a nutshell

- **A multi-disciplinary consortium**

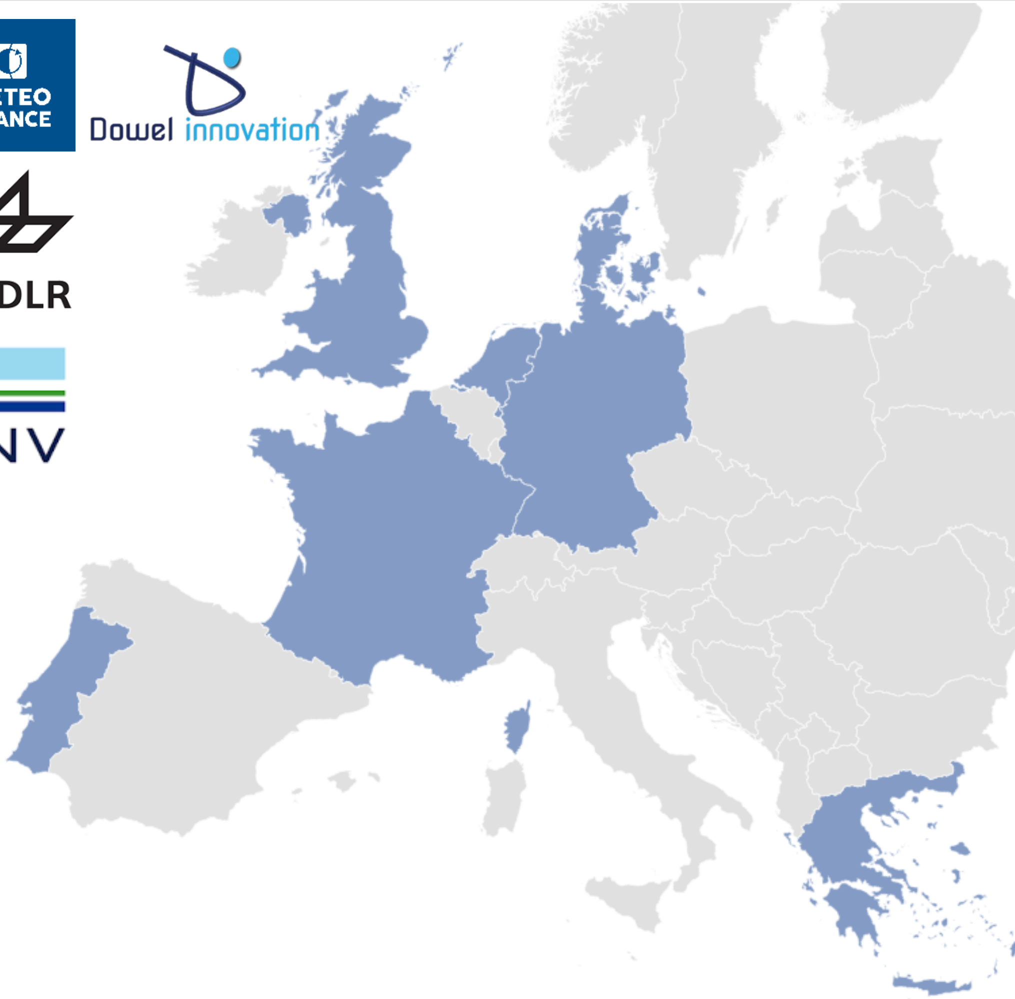
7 countries
13 partners

End-users
Industry
Research
Universities
Meteorologists

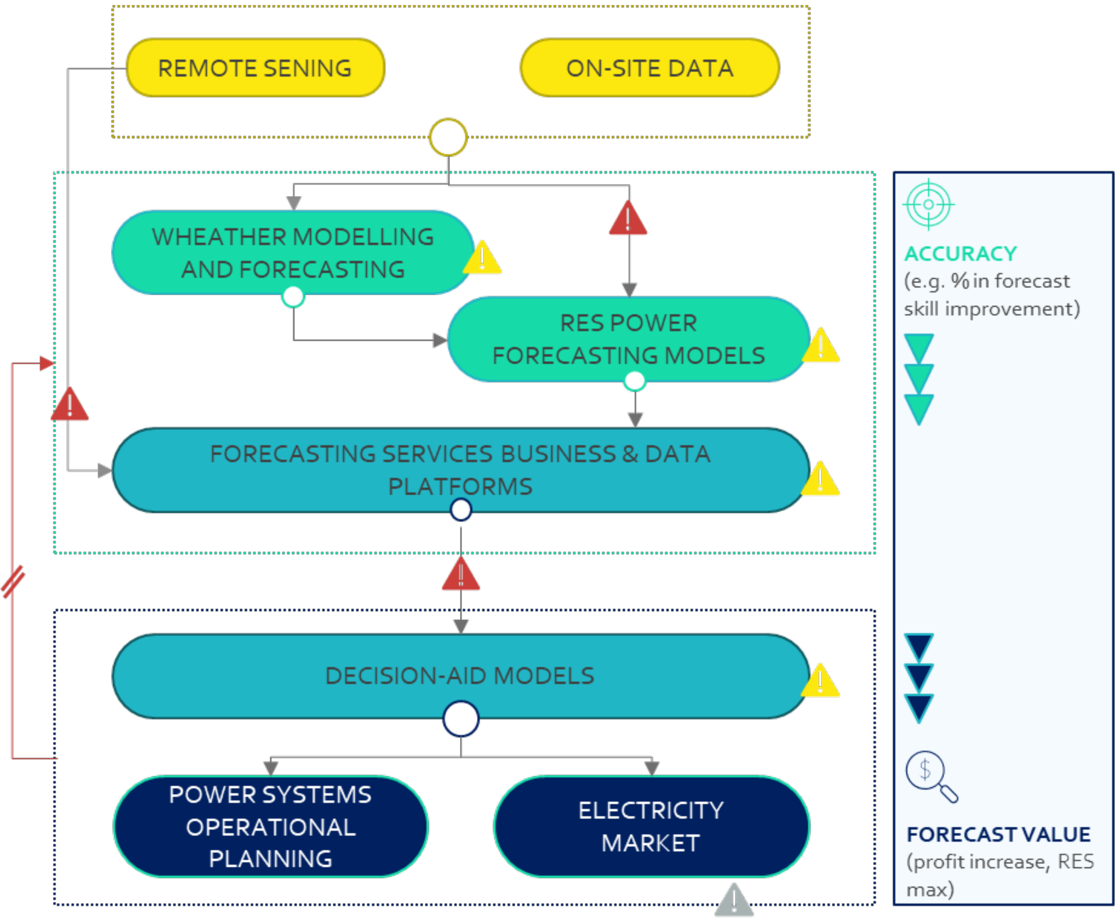
Funds: H2020 program
Budget: 4 M€
Duration: 3.5 years

2019-2023

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



The Smart4RES project in a nutshell



The typical RES forecasting model/value chain

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

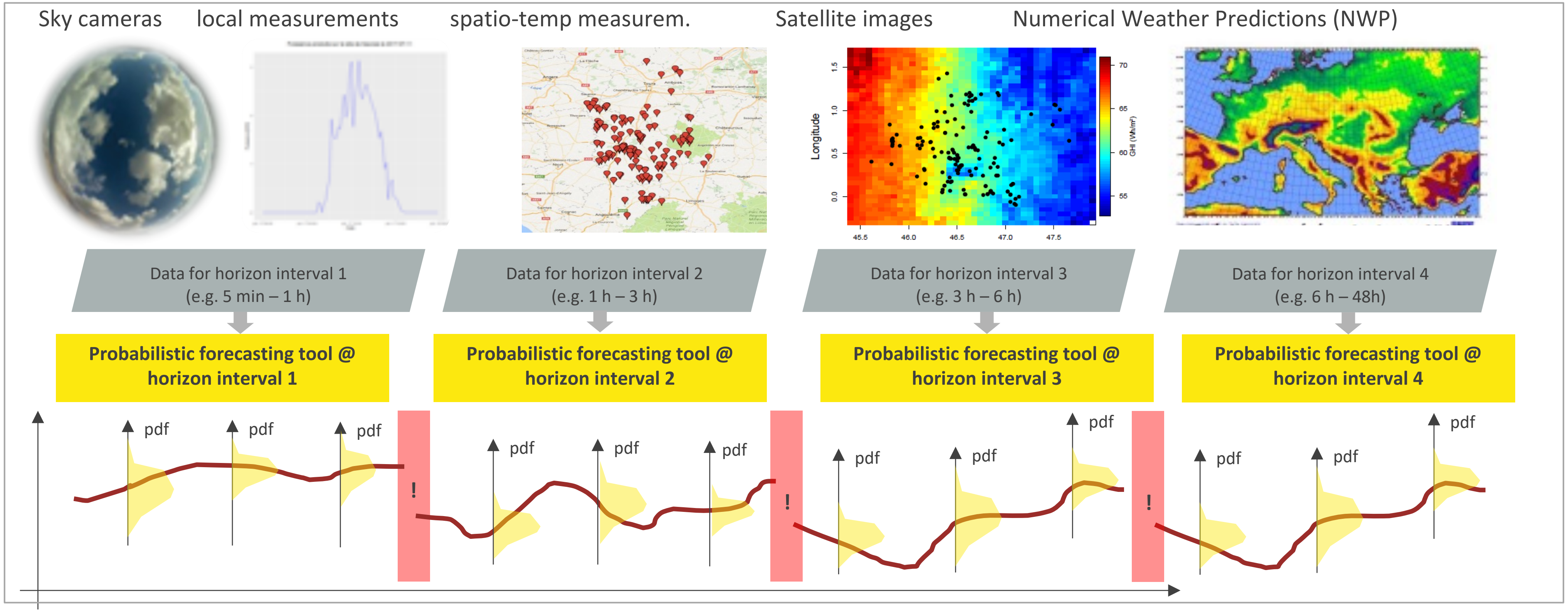
Challenge	Smart4RES solutions	Impact
REDUCED KNOWLEDGE OF THE PHYSICAL SYSTEM	• Ultra/high resolution modeling of weather conditions • Weather forecasts adapted to the energy sector • Modelling based on multiple sources of data	HIGHER MODELLING ACCURACY
VULNERABILITY	• Solutions that permit operators 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

MINES PARIS | PSL | PERSEE

OUTLINE

Seamless RES forecasting

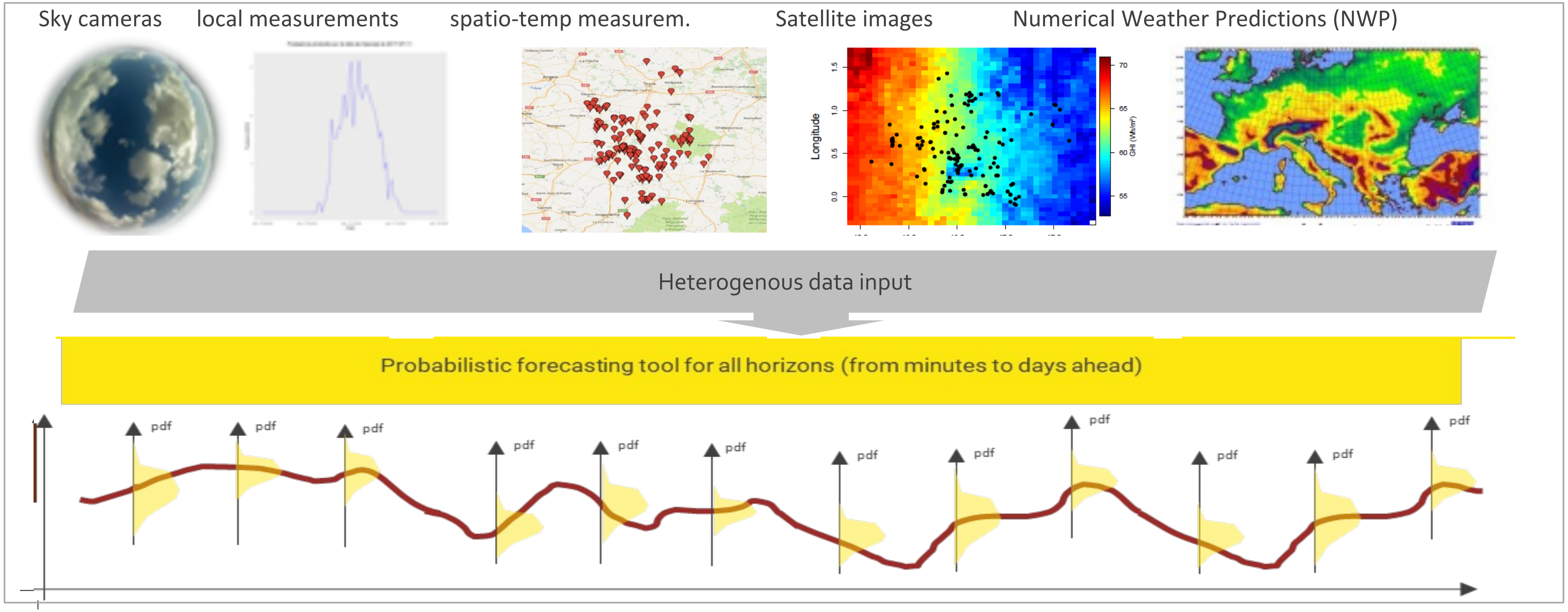
- **Objective:** develop a single probabilistic model able to cover all time frames, all available data input and applicable to all technologies (wind/solar/combinations…). Have at least same level of performance as existing dedicated models.



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

Seamless RES forecasting

- **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.



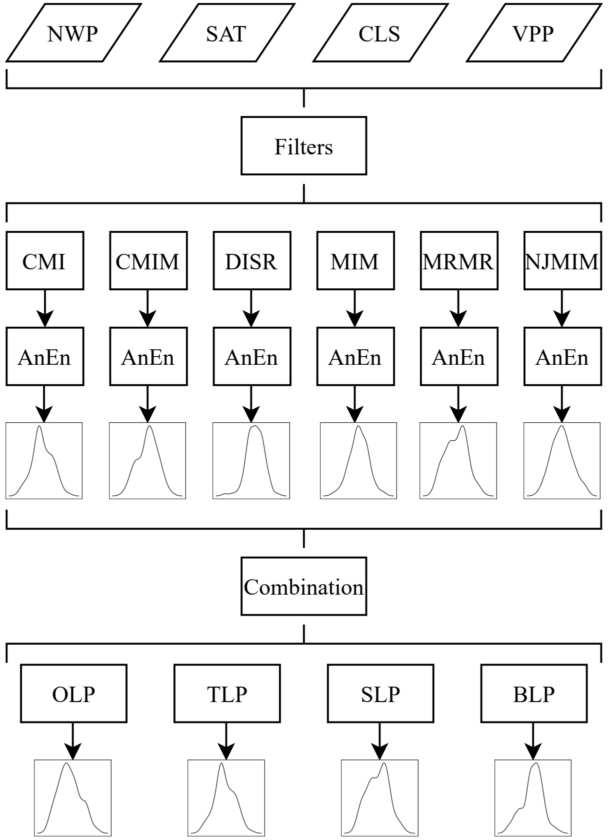
The usual RES forecasting consists in separate models for different time frames

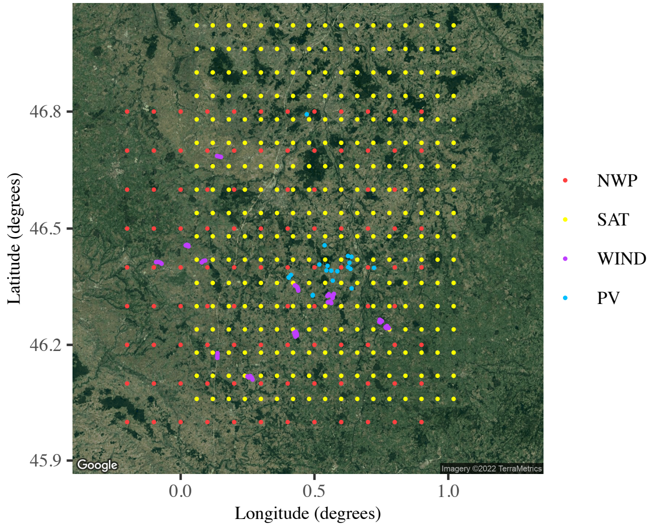
Dennis van der Meer, Pierre Pinson, Simon Camal, Georges Kariniotakis. CRPS-based online learning for nonlinear probabilistic forecast combination. *International Journal of Forecasting*, 2024, ⟨10.1016/j.ijforecast.2023.12.005⟩. ⟨hal-04408320⟩

Seamless RES forecasting with enhanced feature selection

<u>**Idea:**</u> **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

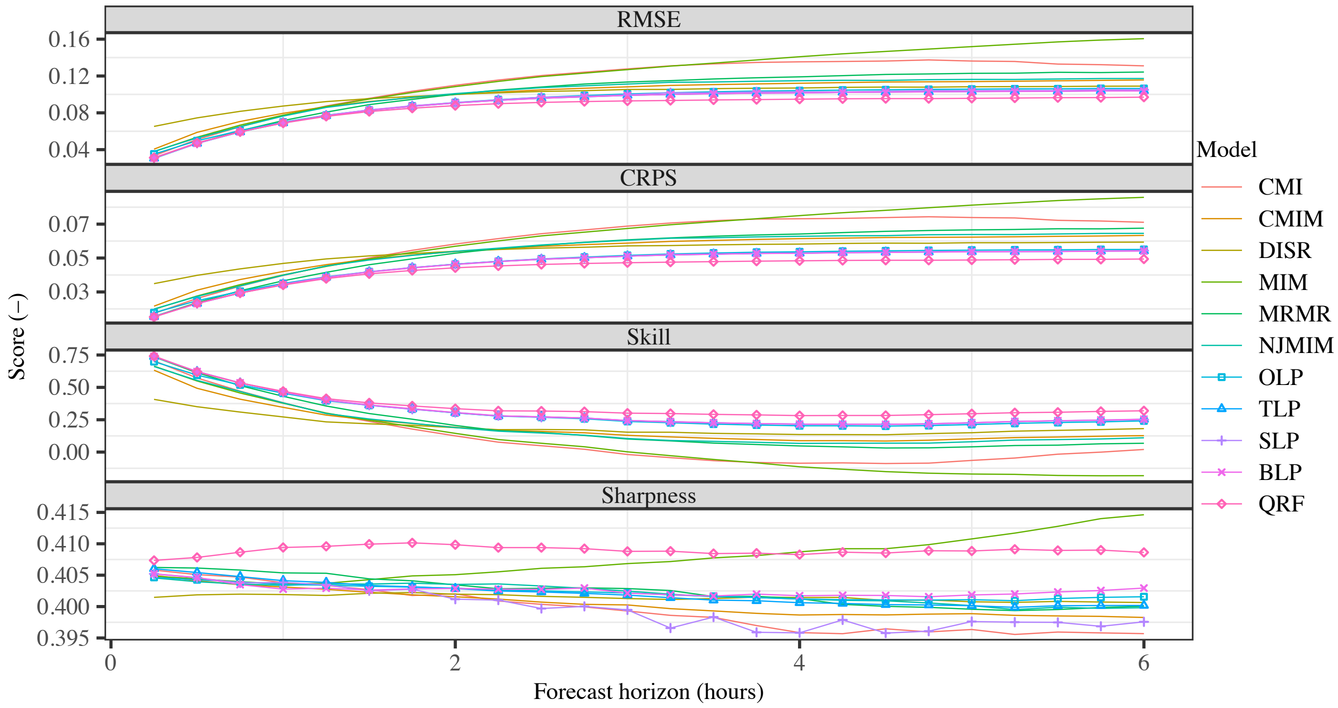




Dennis van der Meer, Pierre Pinson, Simon Camal, Georges Kariniotakis. CRPS-based online learning for nonlinear probabilistic forecast combination. *International Journal of Forecasting*, 2024, ⟨10.1016/j.ijforecast.2023.12.005⟩. ⟨hal-04408320⟩

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



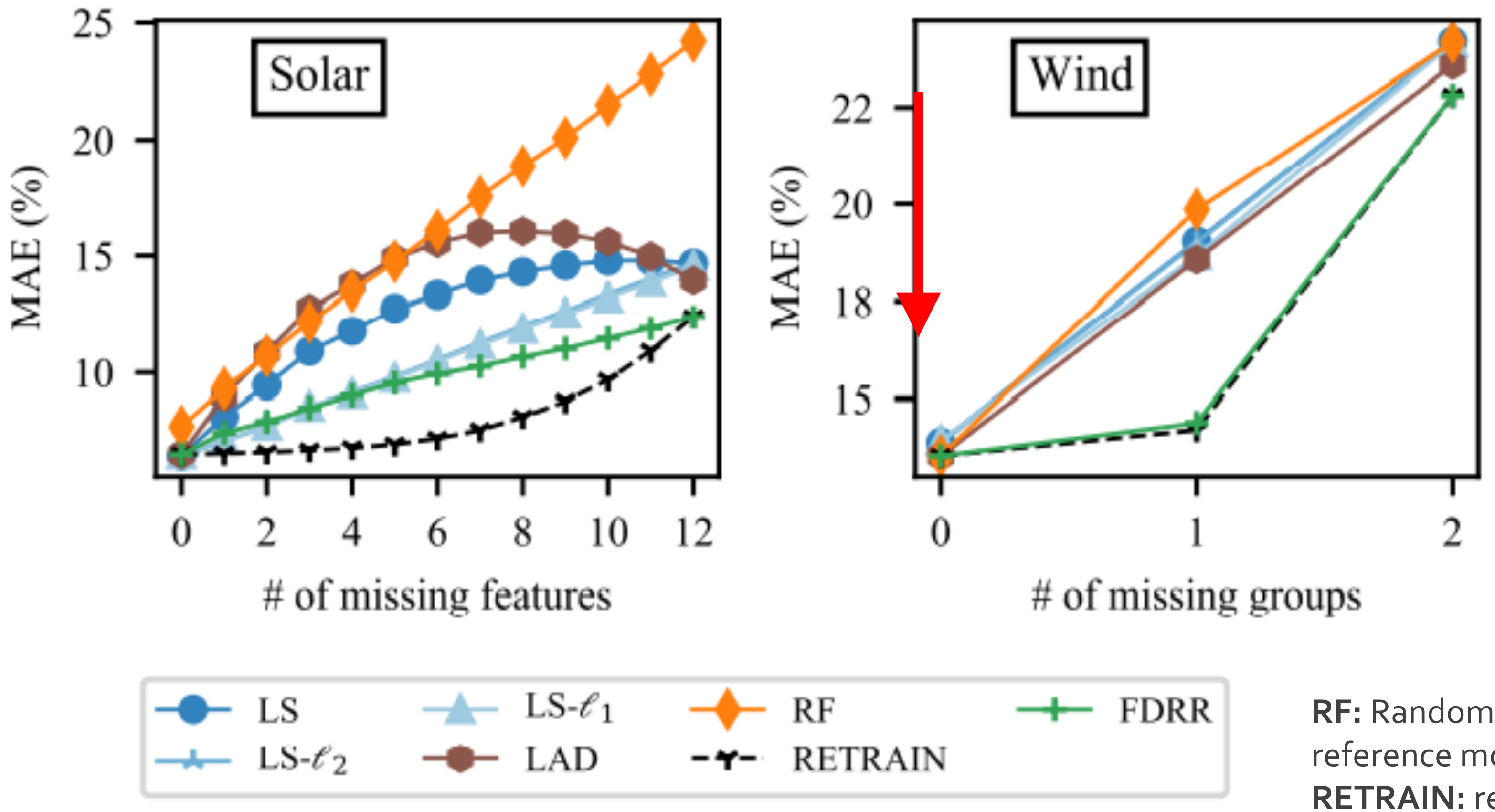
  - The filter methods significantly lower the computational effort (90%) and improve the accuracy between 6% - 16% on average
  - Forecast combination improves probabilistic combination and thereby accuracy with 16% - 31% on average

16% CRPS improvement compared to vanilla analog ensemble model

Dennis van der Meer, Pierre Pinson, Simon Camal, Georges Kariniotakis. CRPS-based online learning for nonlinear probabilistic forecast combination. *International Journal of Forecasting*, 2024, ⟨10.1016/j.ijforecast.2023.12.005⟩. ⟨hal-04408320⟩

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. IEEE Transactions on SmartGrid, preprint at: https://laas.hal.science/ENSMP_PERSEE/hal-03792191v2 , https://ieeexplore.ieee.org/document/10113854

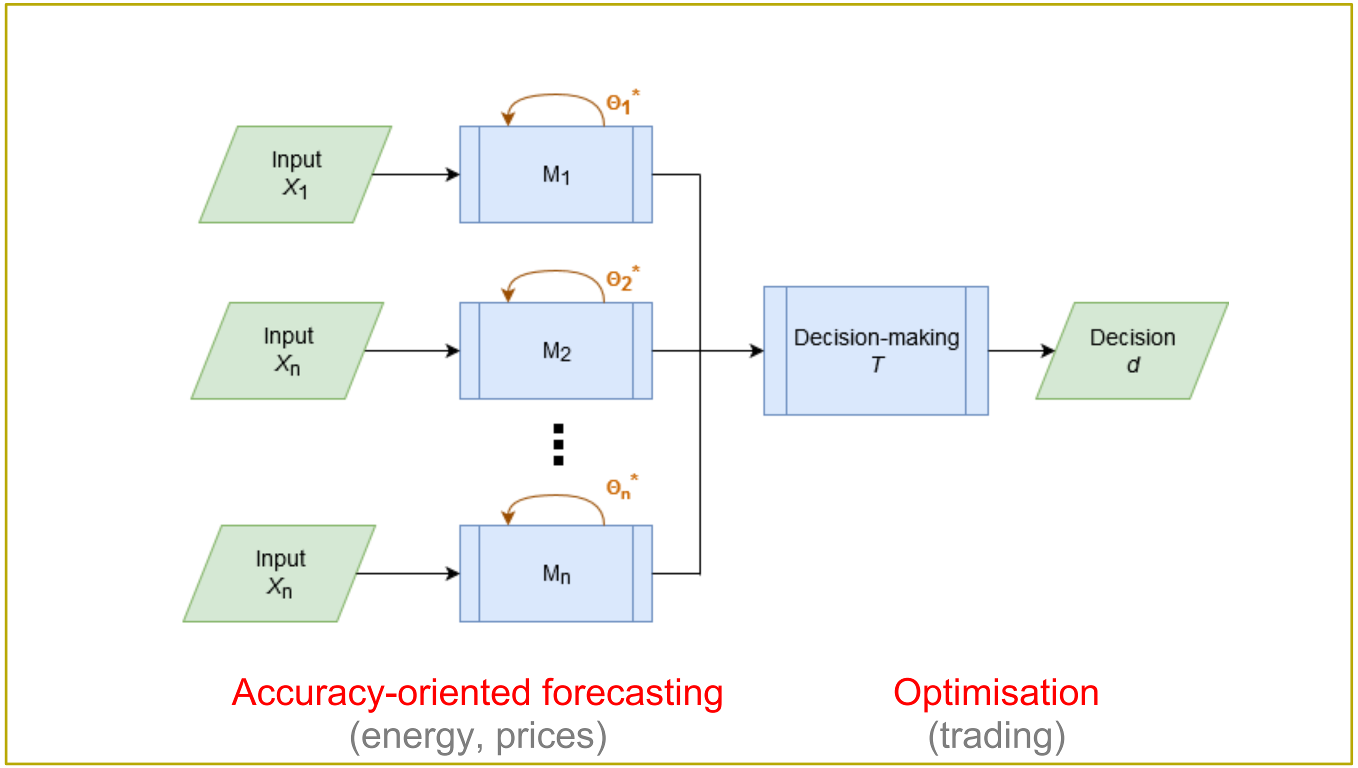
Value-oriented forecasting

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



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)

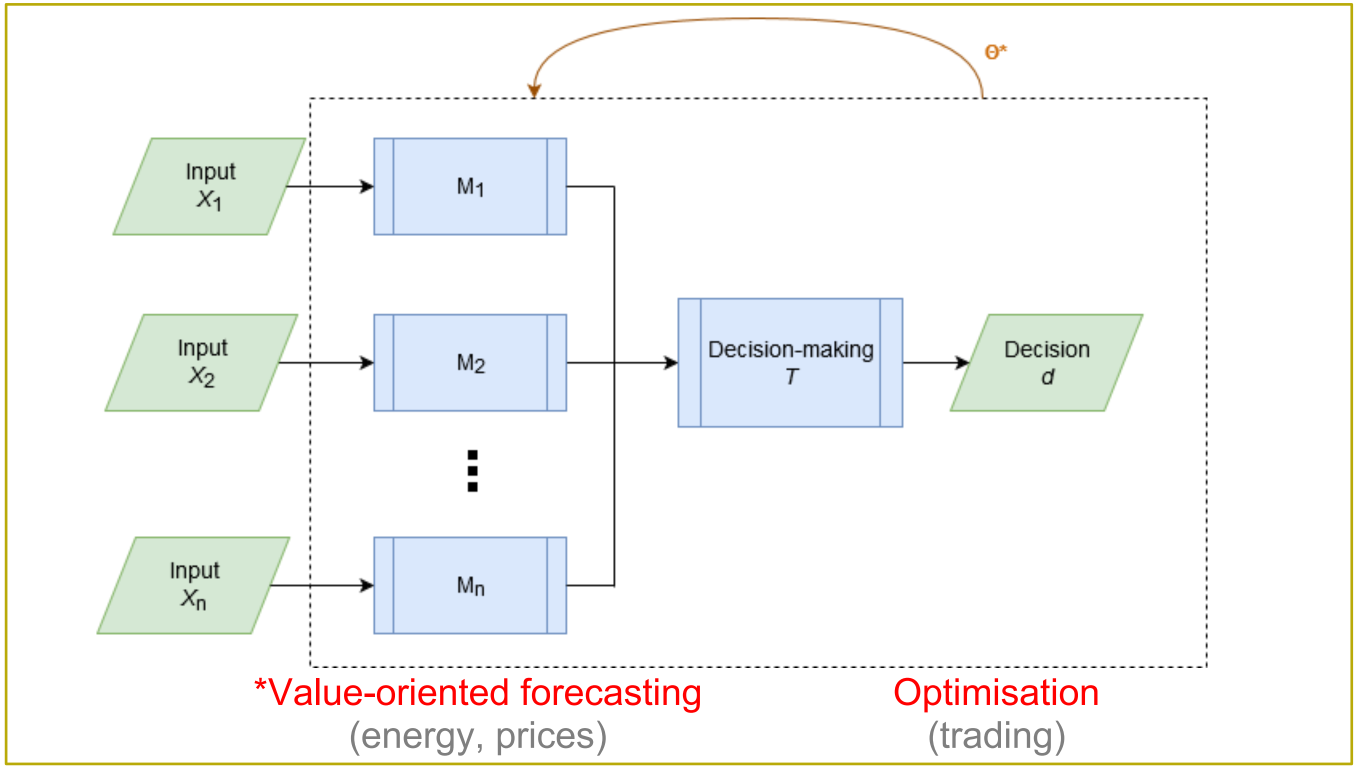
Forecast DA/ID energy market quantities (prices, imbalances) (3)

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

Stochastic optimisation for trading decisions (1)

Bids on energy + AS markets

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

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)

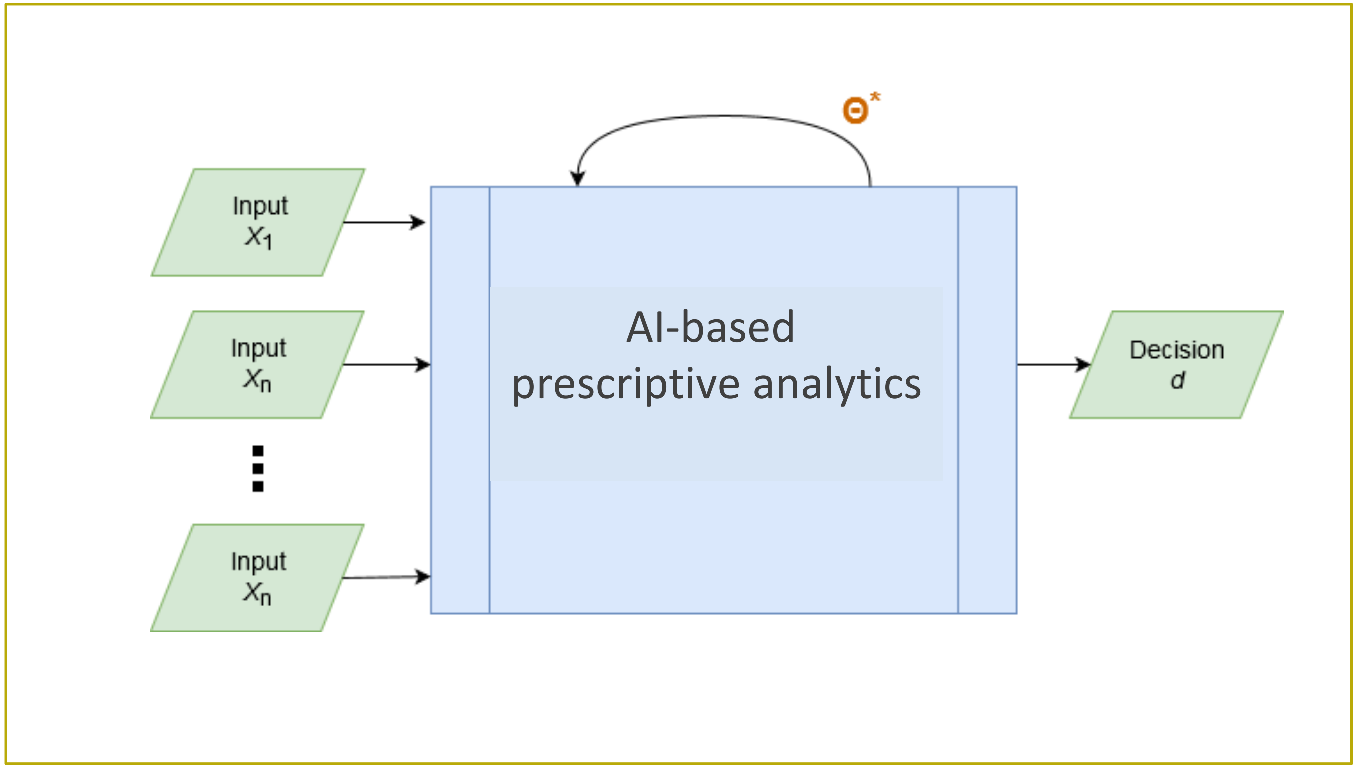
Forecast AS market quantities (prices, volumes, activation probabilities) (6)

Stochastic optimisation for trading decisions (1)

Bids on energy + AS markets

Decision-Oriented Learning

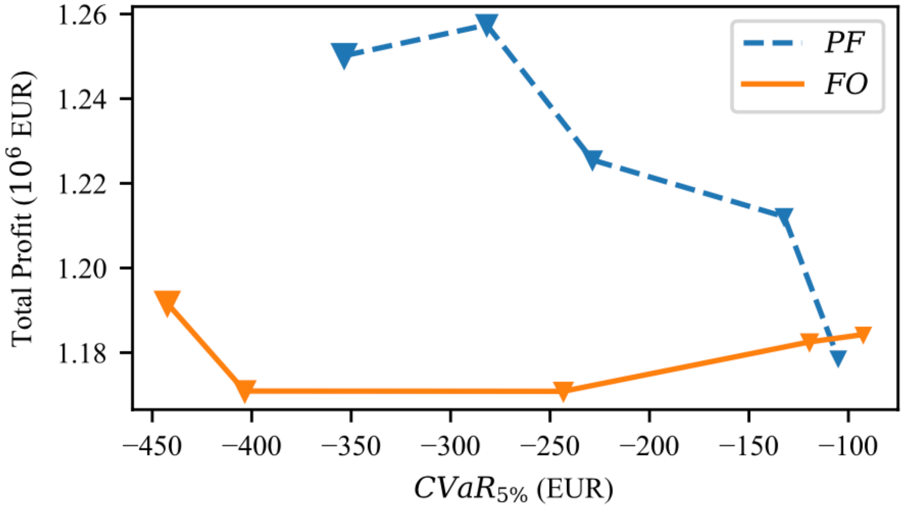
JOINT FORECASTING & OPTIMISATION



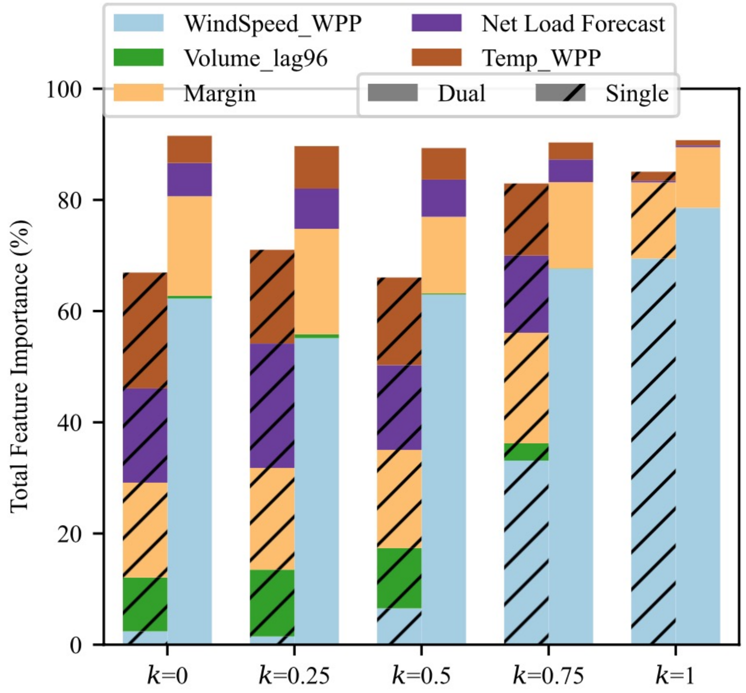
A. C. Stratigakos, S. Camal, A. Michiorri and G. Kariniotakis, "Prescriptive Trees for Integrated Forecasting and Optimization Applied in Trading of Renewable Energy," in *IEEE Transactions on Power Systems*, doi: 10.1109/TPWRS.2022.3152667.

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

Interpretable AI for energy forecasting & decision making

MINES PARIS | PSL | PERSEE

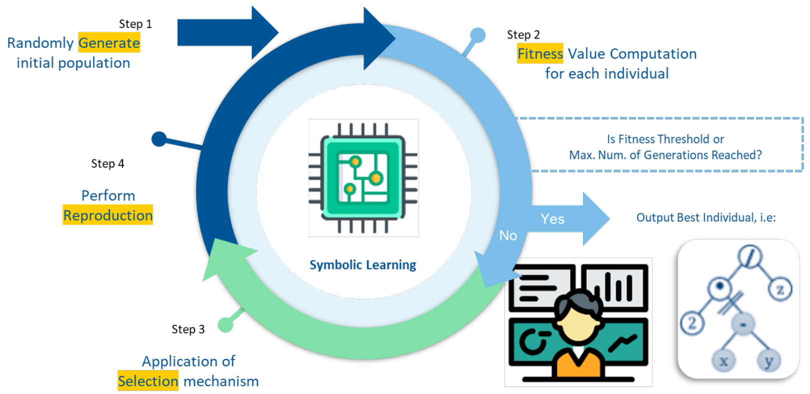
- **Goal: Develop a wind power trading approach which is interpretable by design**

Symbolic regression

Start with a library of symbolic variables

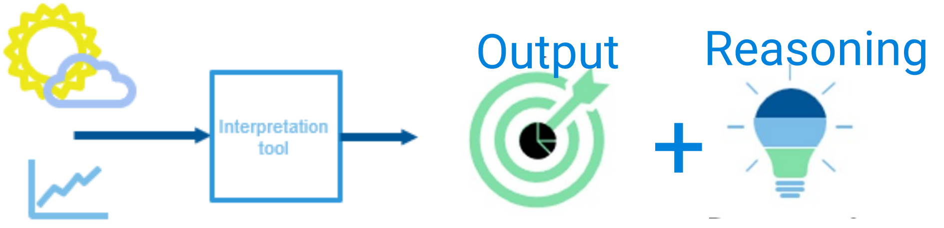
w_{speed} $\quad w^2_{speed}$ $\quad w^3_{speed}$ $\quad Temp$ $\quad TCC$

Symbolic learning



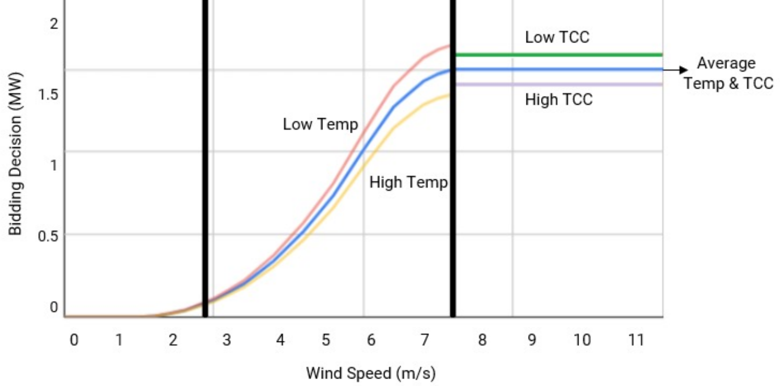
$2 \times \frac{x-y}{z}$

$op(Z) = \frac{\text{len}(Z)-1}{2}$ $\quad$ i. e: op(Z) = 3



	Low wind speed	Medium wind speed	High wind speed
Symbolic Expression	$0.04w^2_{speed}$	$-0.027 + \frac{0.87w^3_{speed}}{Temp}$	$\frac{1.77w_{speed}}{2TCC + w_{speed}}$

$Temp \in [271K, 311K]$
$TCC \in [0, 1]$

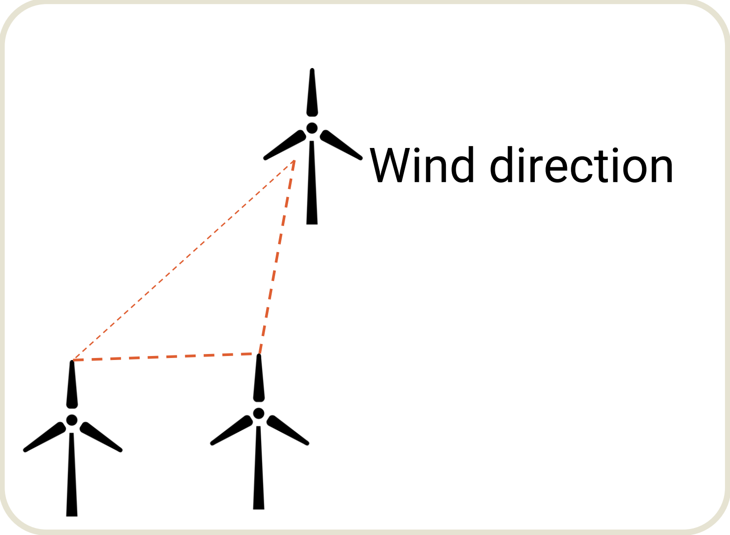


Privacy preserving data-sharing for forecasting

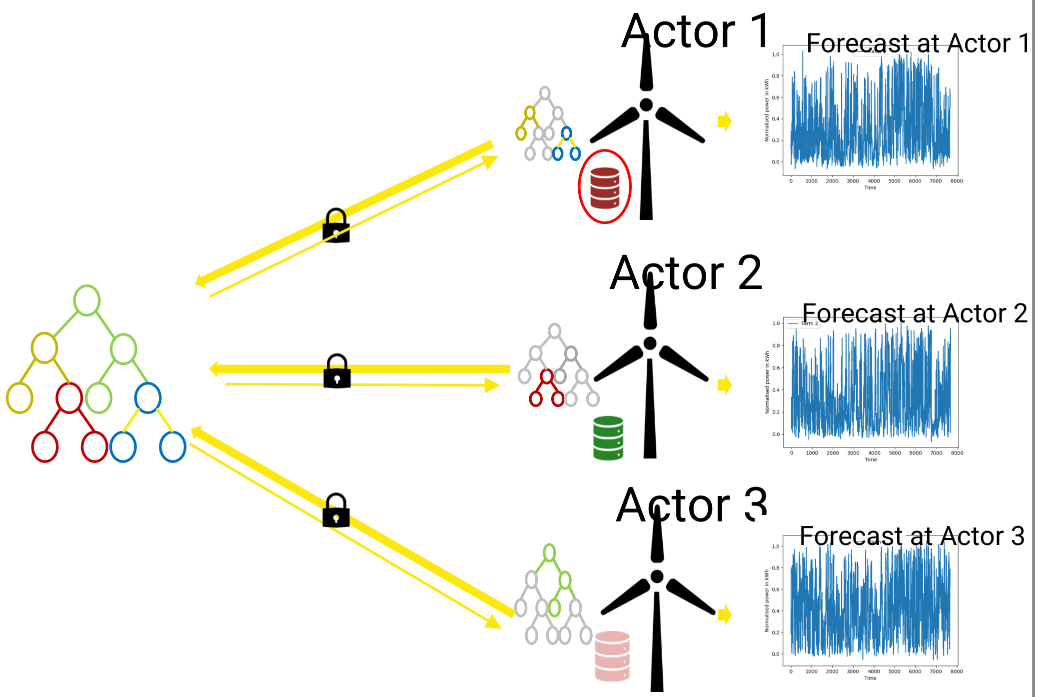
- **Goal: Extract information from spatially distributed data**
  - Correlations due to propagation of weather phenomena

⚠ Data might belong to different owners and has privacy and confidentiality constraints

RES Forecasting



1. Contractual Data-Sharing Framework
2. Communication
3. Encryption techniques
4. Collaborative AI Learning
5. Trust-> Verification/Accountability



MINES PARIS | PSL | PERSEE

OUTLINE

Challenges/Recommendations for future research directions (1/2)

MINES PARIS | PSL | PERSEE

1. Research towards RES-dedicated weather forecast products (i.e. higher temporal resolution and frequency of updates for classical NWPs, focus on specific variables sensitive for energy applications)
2. Ultra high spatio-temporal resolution modelling of weather variables (i.e. Large Eddy Simulations).
3. Improve seasonal forecasting and associated uncertainty
4. Better forecasting of extreme situations (ramps, fog, snow, icing, lightnings,...)
5. Advanced techniques for combination of multiple sources of data for RES forecasting.
6. Forecasting RES production under external constraints (curtailments due to congestions, AS provision, noise, birds...).

Challenges/Recommendations for future research directions (2/2)

8. Go beyond "accuracy-oriented" RES forecasting to "MultiProperty-oriented" forecasting by design.
   - If based on AI methods: they should be follow trustworthy AI principles.
   - Models need to be **resilient** (missing data, extemes, cyberattacks…), robust to uncertainties,

9. Mature privacy/confidentiality data sharing solutions for collaborative forecasting and optimization. Solutions like data markets for value sharing.
10. End-to-end interpretable AI-based approaches, like prescriptive analytics, to simplify (automatise?) the classic model chain "Forecast then Optimise" to "Joint Forecasting and Optimisation".
11. Need to develop **optimisation/decision-making tools** able to integrate **alternative forecasting products** (i.e. ramps forecasting, risk indices, scenarios…) to simplify decision making by operators.
12. Need to facilitate the **adoption of probabilistic decision-making by operators**.
13. Work towards standardisation of RES forecasting products.

- **Publication practices/criteria** should evolve to be able to bring added value to the society (use of open data, code submission for replicability check)..

Smart4RES

THANK YOU !

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

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

Germany — energy & meteo systems, DLR

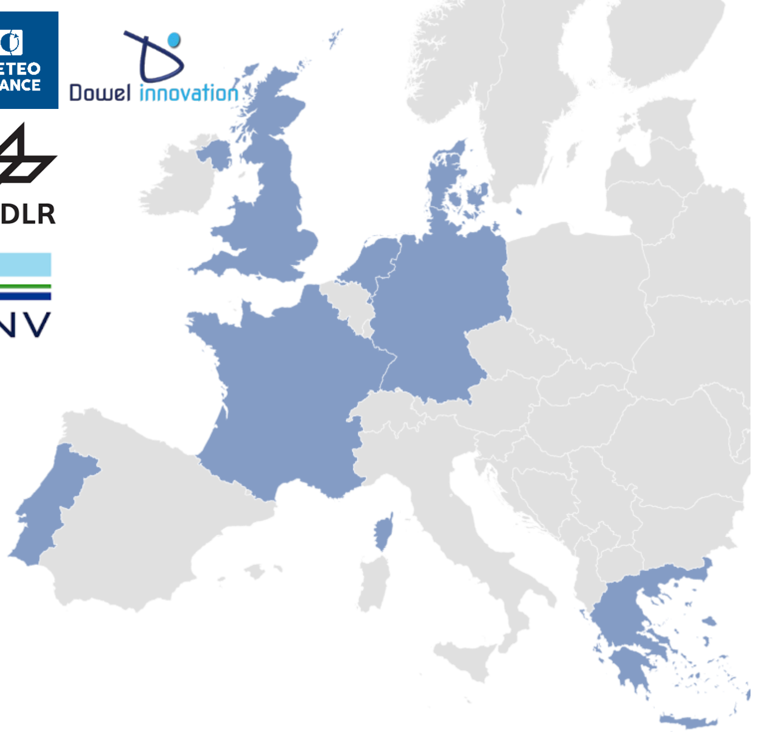
Netherlands — whiffle precision weather forecasting, DNV

Denmark — DTU

UK — Imperial College London

Portugal — INESCTEC, NEW by EDP & CTG

Greece — ΕΠΙΣΕΥ ICCS, HEDNO



(*) The Smart4RES team:

- Georges Kariniotakis, Simon Camal, Dennis van der Meer, Akylas Stratigakos; Fabrizio Sossan, **MINES Paris**, PSL, Centre PERSEE, France.
- Gregor Giebel, Tuhfe Göçmen, Pierre Pinson; **DTU**, Denmark.
- Ricardo Bessa; Carla Goncalves, **INESC TEC**, Portugal.
- Ivana Aleksovska, Bastien Alonzo, Marie Cassas, Quentin Libois, Laure Raynaud; **Meteo France**, France.
- Gerrit Deen, Daan Houf, Remco Verzijlbergh; **Whiffle**, The Netherlands.
- Matthias Lange, Björn Witha; **Energy and Meteo Systems**, Germany.
- Jorge Lezaca, Bijan Nouri, Stefan Wilbert; **DLR**, Germany.
- Maria Ines Marques, Manuel Silva; **EDP**, Portugal.
- Wouter De Boer, Marcel Eijgelaar, Ganesh Sauba; **DNV**, The Netherlands.
- John Karakitsios, Theodoros Konstantinou, Dimitrios Lagos, George Sideratos; **NTUA/ICCS**, Greece.
- Theodora Anastopoulou, Efrosini Korka, Christos Vitellas; **HEDNO**, Greece.
- Stephanie Petit; **Dowel Innovation**, France.

Smart4RES

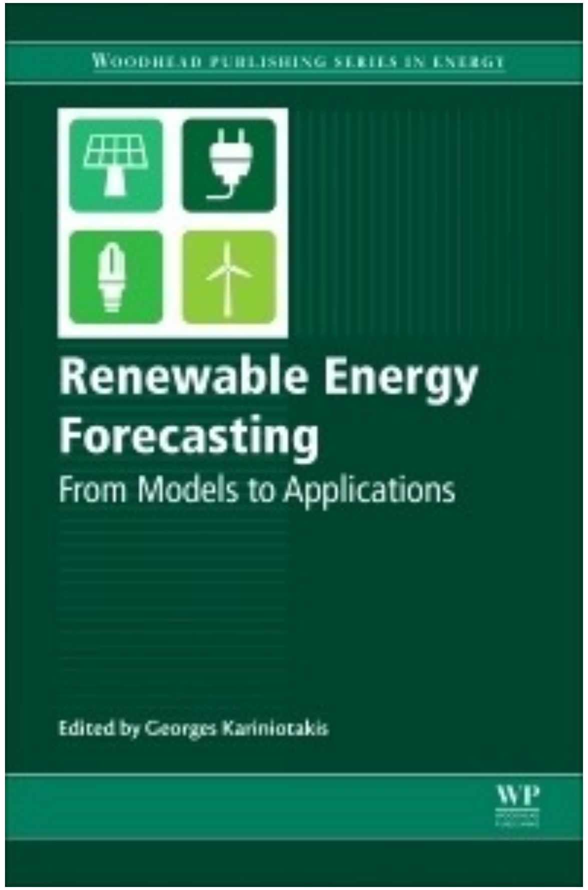
THANK YOU !

The Smart4RES project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 864337

georges.kariniotakis@minesparis.psl.eu

https://www.linkedin.com/in/george-kariniotakis-2a868912/

Publications: https://cv.archives-ouvertes.fr/georges-kariniotakis



Take aways

- Further evolutions of **weather forecasting** models needed (data assim., frequent updates…).

- AI is a game changer in weather forecasting. The first fully AI-based models emerge
  - **ECMWF model:** https://www.ecmwf.int/en/about/media-centre/aifs-blog
  - Encoder and decoder using attention-based graph neural networks.

Source ECMWF