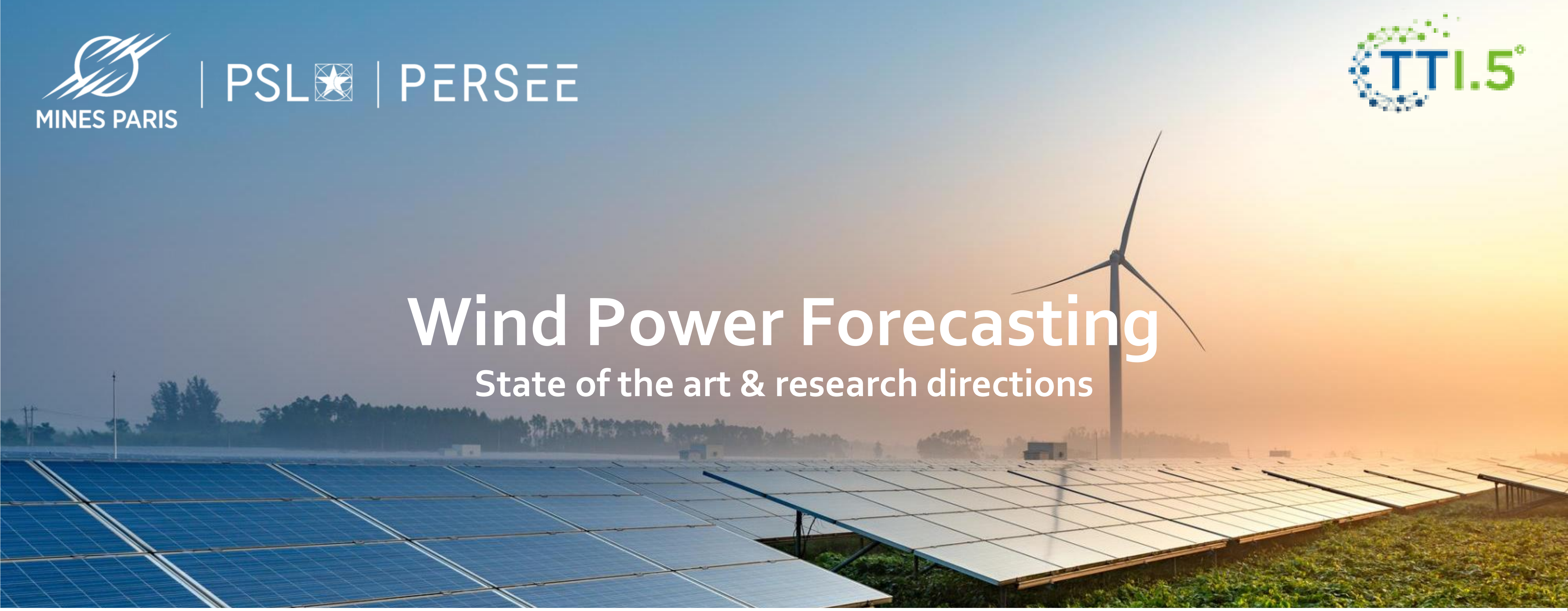


# Wind Power Forecasting

## State of the art & research directions

**Georges Kariniotakis**

Prof., Head of RES & Smart Energy Systems Group,

Mines Paris - PSL, Centre PERSEE

georges.kariniotakis@minesparis.psl.eu

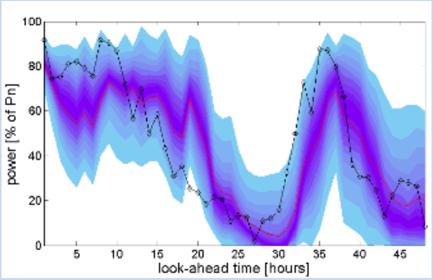
# RES & ENERGY SYSTEMS GROUP (ERSEI)

MINES PARIS | PSL | PERSEE

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

**3 RESEARCH AXES:**

| Forecasting for energy & electricity markets | Energy systems management & control | Energy systems planning & future markets design |
| --- | --- | --- |




# RESEARCH ON ENERGY FORECASTING



## WIND, SOLAR POWER FORECASTING & APPLICATIONS

- Since 1990
- Coordination of the 4 major EU projects (Anemos, Anemos.plus, Safewind, Smart4RES) and PEPR TASE project Fine4CAST
- Multiple projects: Micrigrids, More Microgrids, NiceGrid/Grid4EU, Sensible…

FINE4CAST | SafeWind | Smart4RES | ANEMOS | ANEMOS.plus

## ELECTRICITY DEMAND, EVs CHARGING DEMAND

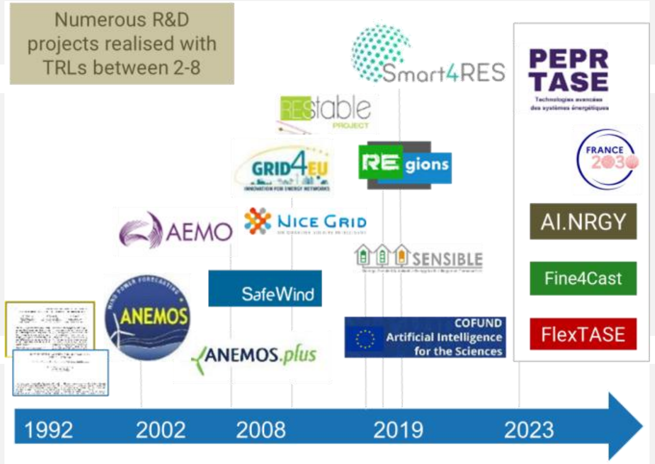
- From smart-home to national scale
- Projects: Care, More-Care, More-Microgrids, Sensible, Fine4CAST…

## DYNAMIC LINE RATING

- Value of DLR for power systems

## MARKET QUANTITIES

- Day-ahead, intraday prices, ancillary service prices, volumes….
- Projects: Restable, Regions, Smart4RES…



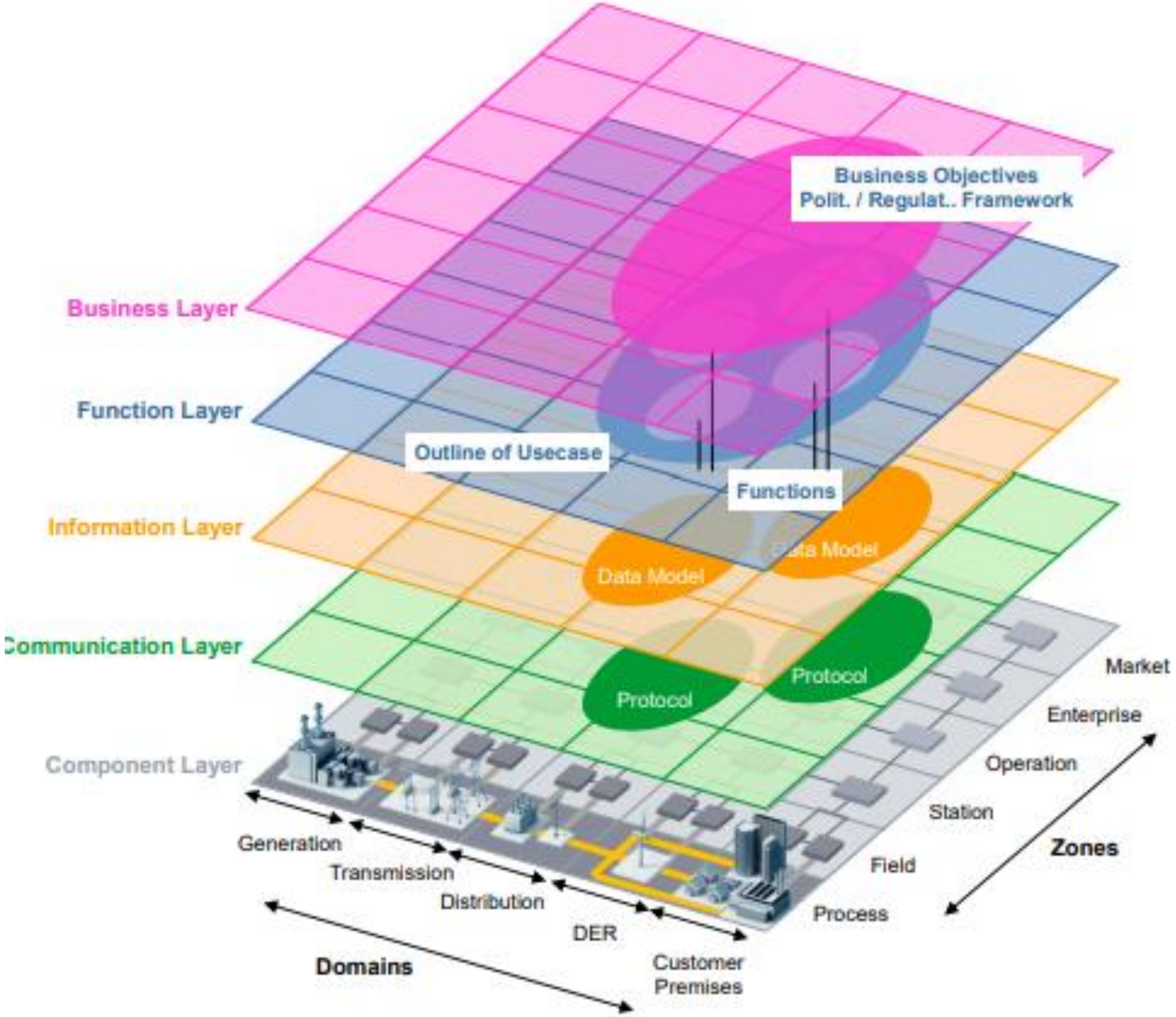
# OUTLINE

1. Context
2. State of the art in wind power forecasting
3. Research directions
4. Future challenges

# Evolution of power systems in the context of energy transition

## Challenges:

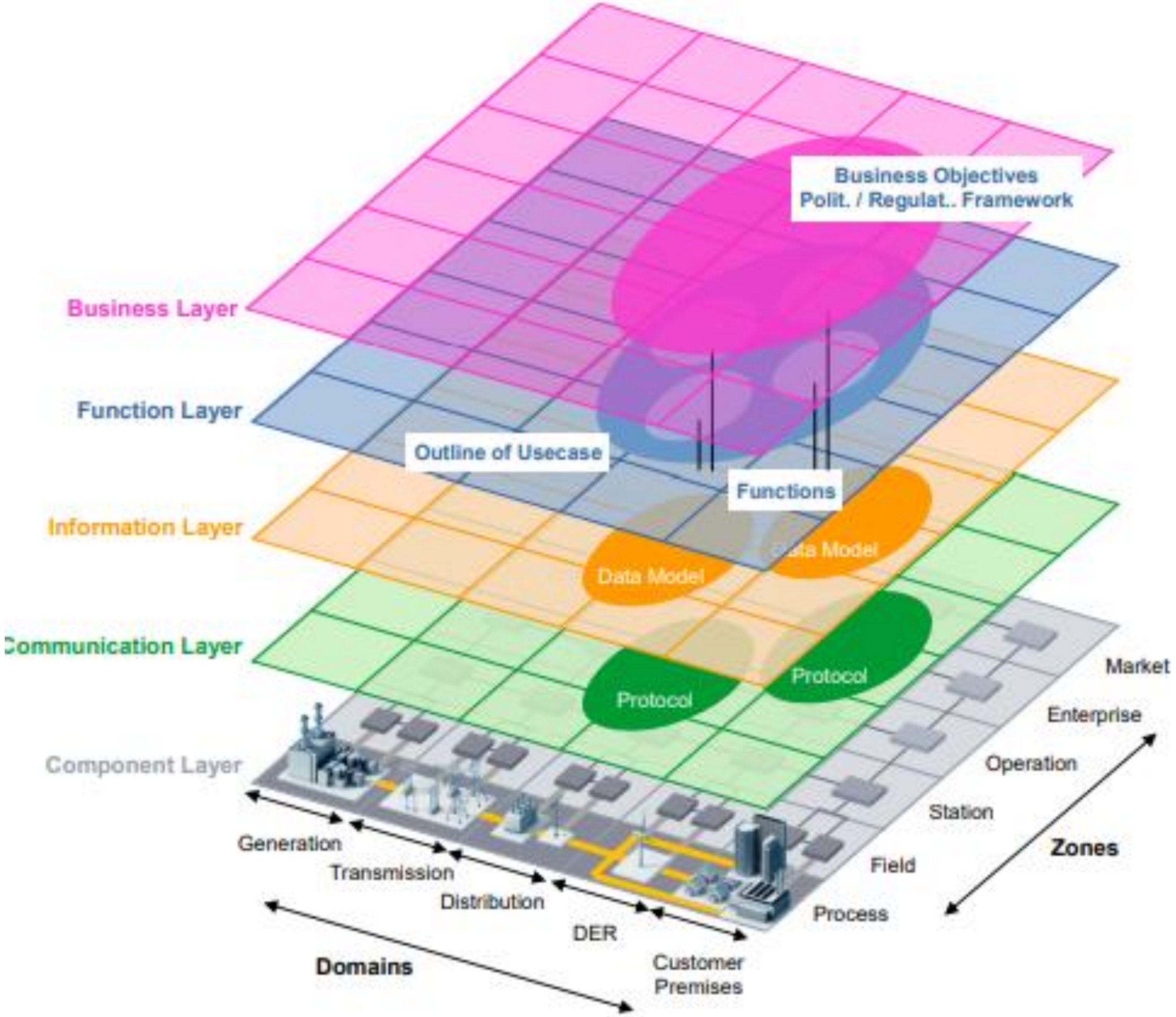
- Integration of **distributed sources**: renewables **(RES),** storage, demand response, P2X, X2P and other options.
- Evolution towards **highly complex & interacting energy systems** (system of systems)
- **Information sources multiply** : higher observability is an opportunity for more informed operational decisions.
- Need of an **efficient & resilient « intelligent layer »** for the secure and economic management of power systems.



# Evolution of power systems in the context of energy transition

## 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/storage, H2…)
- Trading of RES/virtual power plants  to markets
- Dynamic security assessment,
- Alarm management
- Control of assets
- Predictive maintenance
- End of life estimation
- ….

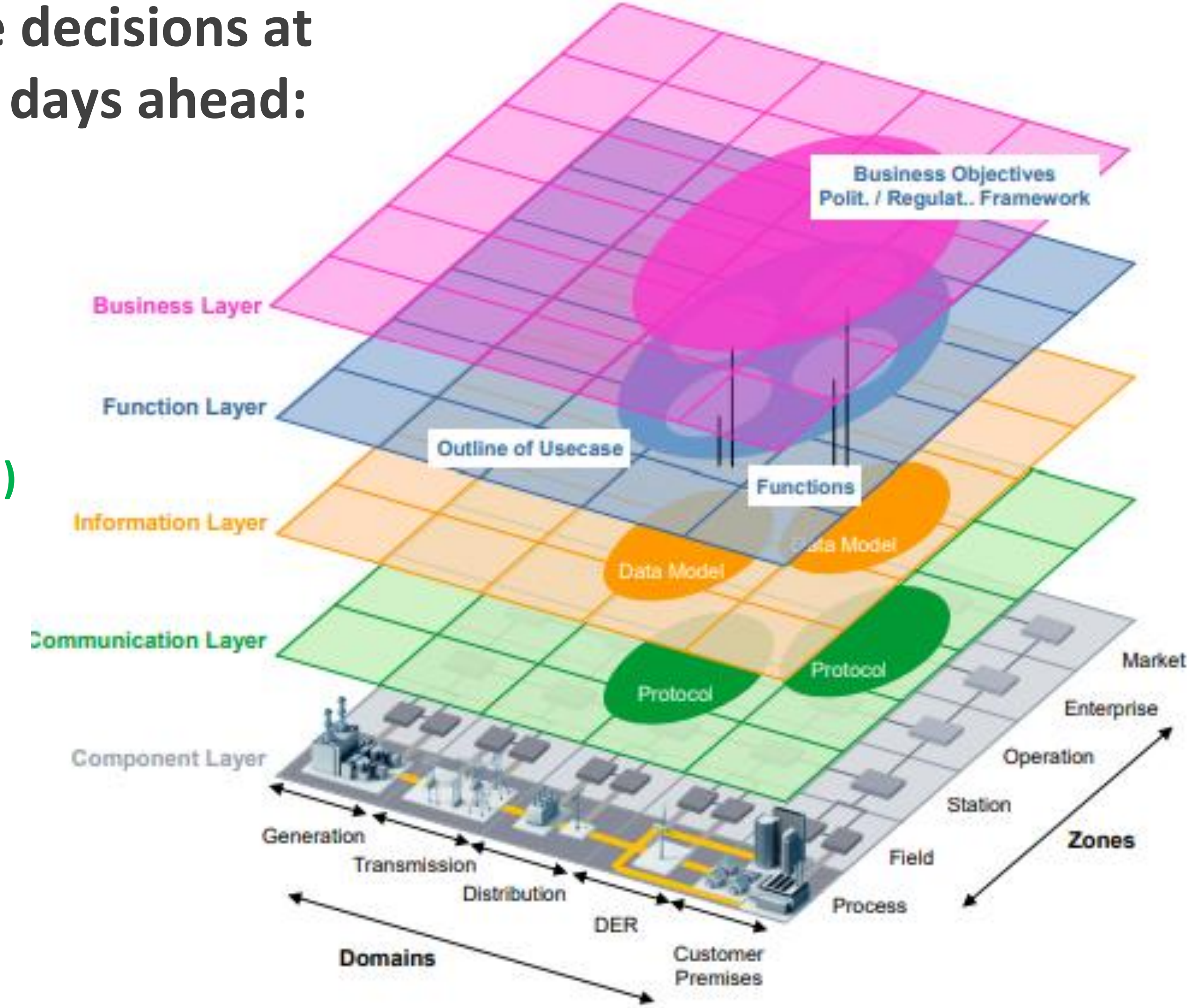


# Evolution of power systems in the context of energy transition

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

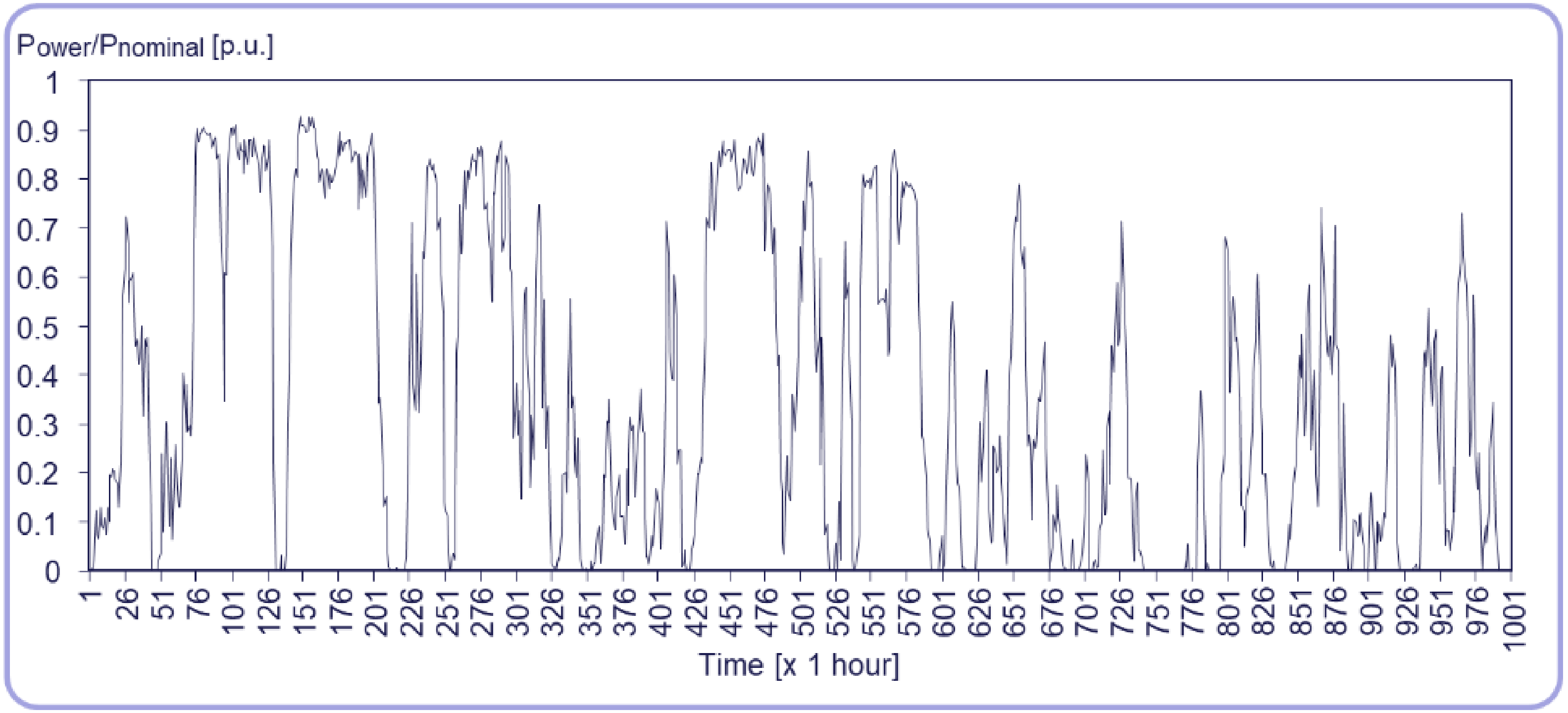
Related to RES integration:

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



# RES Integration in electricity grids and markets

- The weather dependency of variable Renewable Energy Sources (RES), mainly wind & solar production, brings challenges to operators (variability/uncertainties)

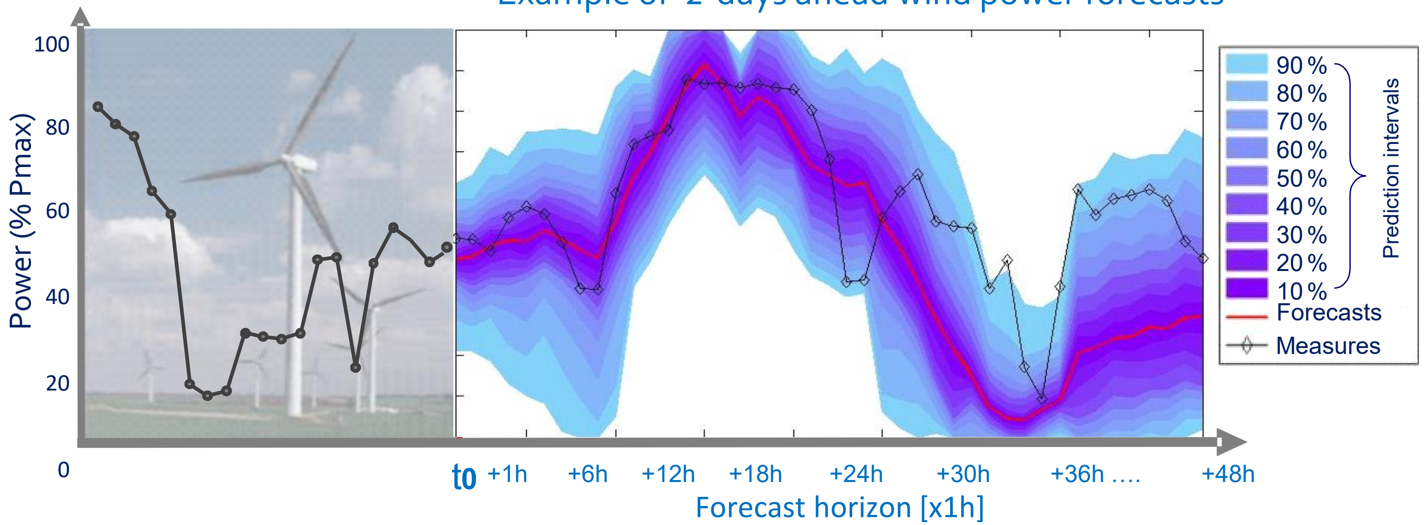



**Example of hourly variability of the production of a wind farm**

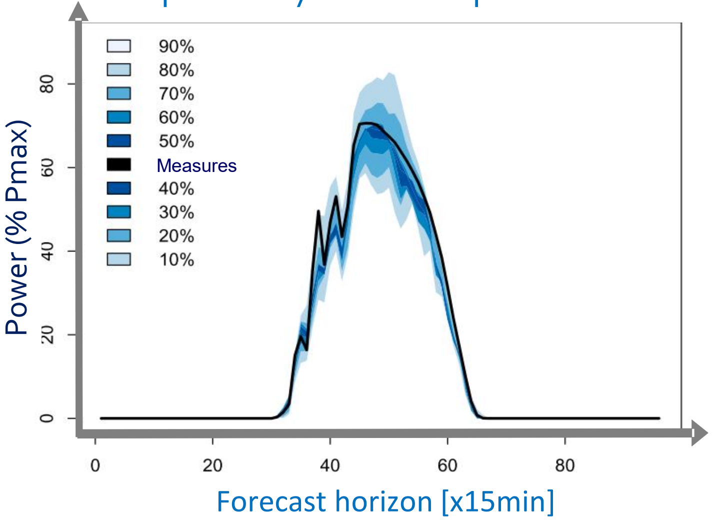
# The role of short-term RES forecasting

- Short-term (minutes-days ahead) forecasts of renewable generation (wind, solar) are necessary for a secure and economic operation of power systems.
- First solutions proposed in the literature in 1985.

Example of 2-days ahead wind power forecasts

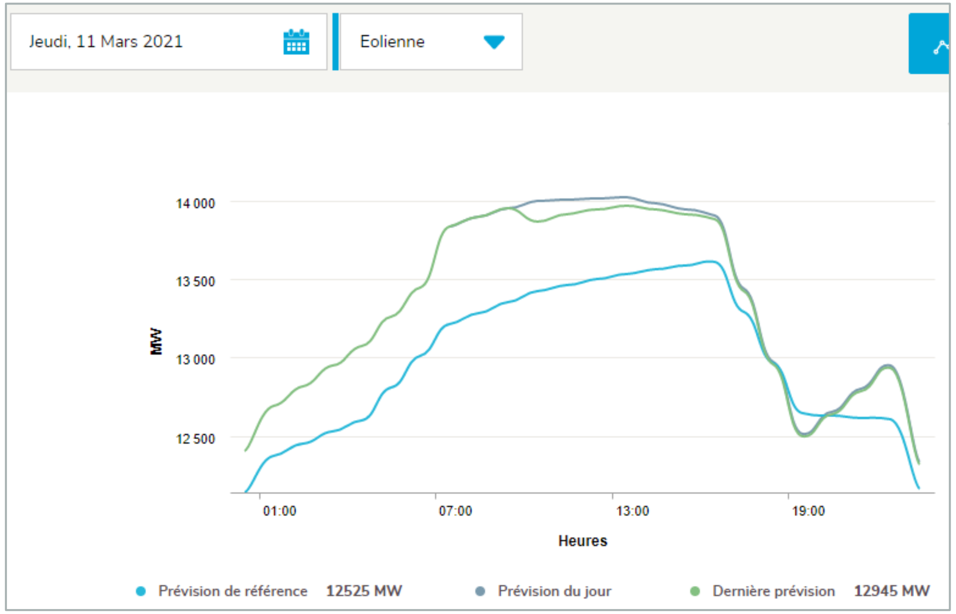



Example of day ahead PV power forecasts



# The role of short-term RES forecasting

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



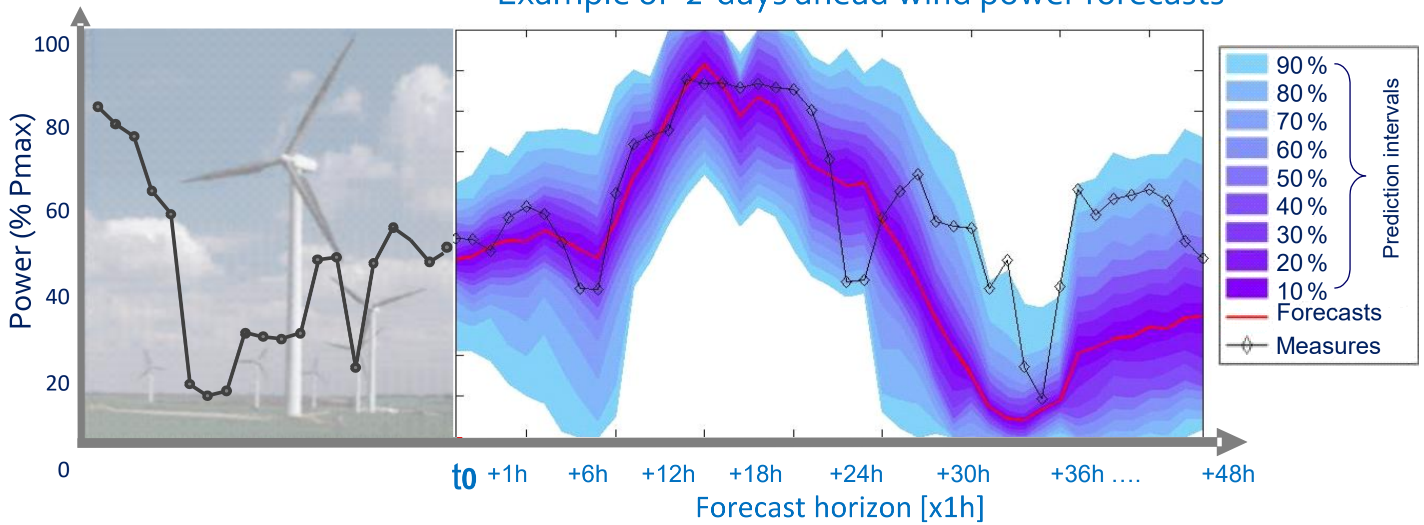

Example of wind power forecasts used by RTE (national scale)

# The role of short-term RES forecasting

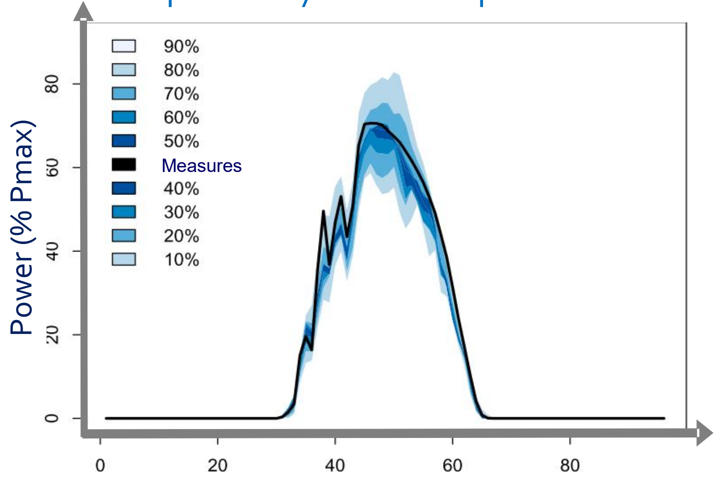
## Despite this apparent maturity:

- 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



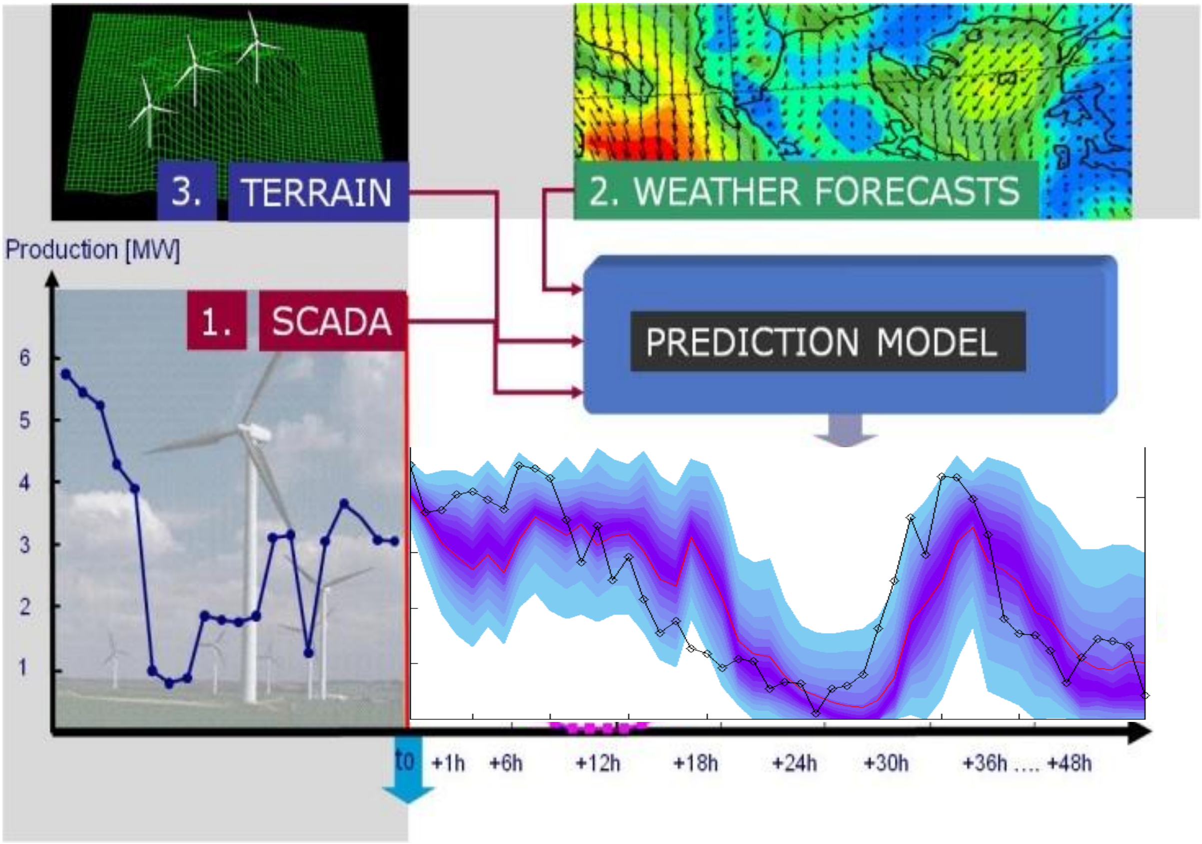

Example of day ahead PV power forecasts



# OUTLINE

1. Context
2. **State of the Art in wind power forecasting**
3. Research directions
4. Future challenges

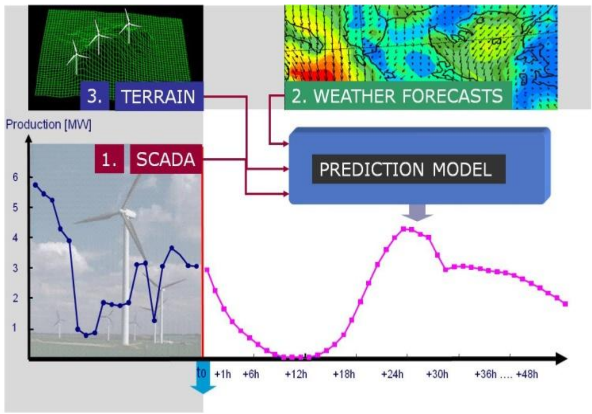
# The general principle of wind power forecasting

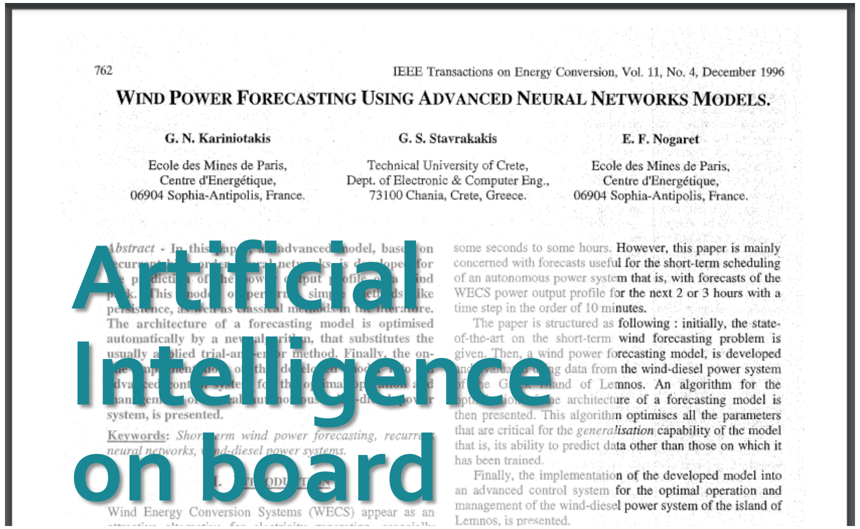


# The history of wind power forecasting

MINES PARIS | PSL | PERSEE

"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. Then, a wind power forecasting model is developed ... data from the wind-diesel power system ... and of Lemnos. An algorithm for 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.

1985 1990 2000 2010 2020

- First purely time series methods on WPF

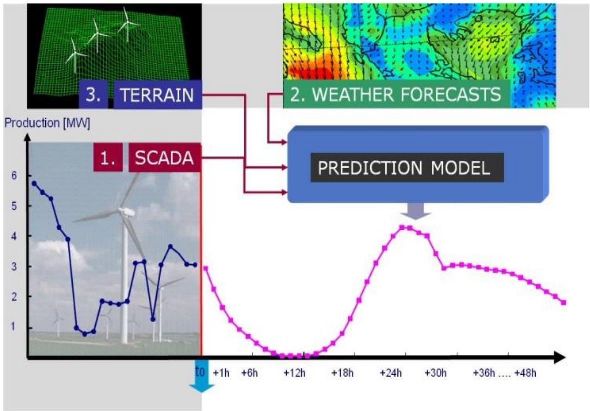
- Statistical / time-series approaches
- Physical modelling
- First AI-based approaches
- NWPs considered as input
- Empiric/hybrid implementations into operational forecast tools

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

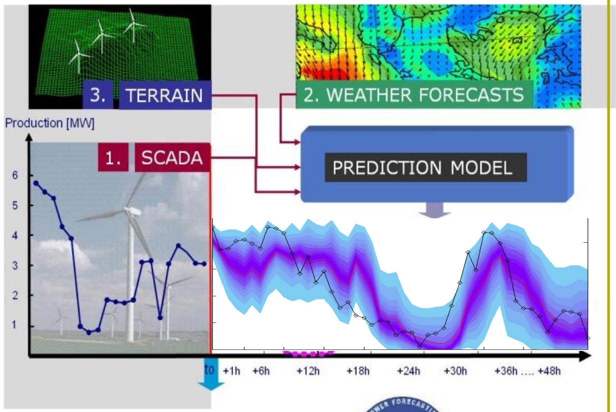
[2002-2006] ANEMOS (FP5), http://www.anemos-project.eu/
[2008-2011] ANEMOS.plus (FP6), http://www.anemos-plus-project.eu/
[2008-2012] SAFEWIND (FP7), http://www.safewind.eu/
[2019-2023] Smart4RES (H2020), http://www.smart4res.eu/

# The history of RES forecasting

"Deterministic" (spot) view

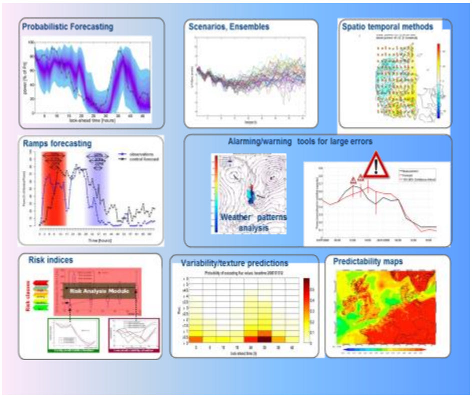



Probabilistic view




ANEMOS

Probabilistic & special situations




ANEMOS.plus SafeWind

Smart4RES

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

- 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

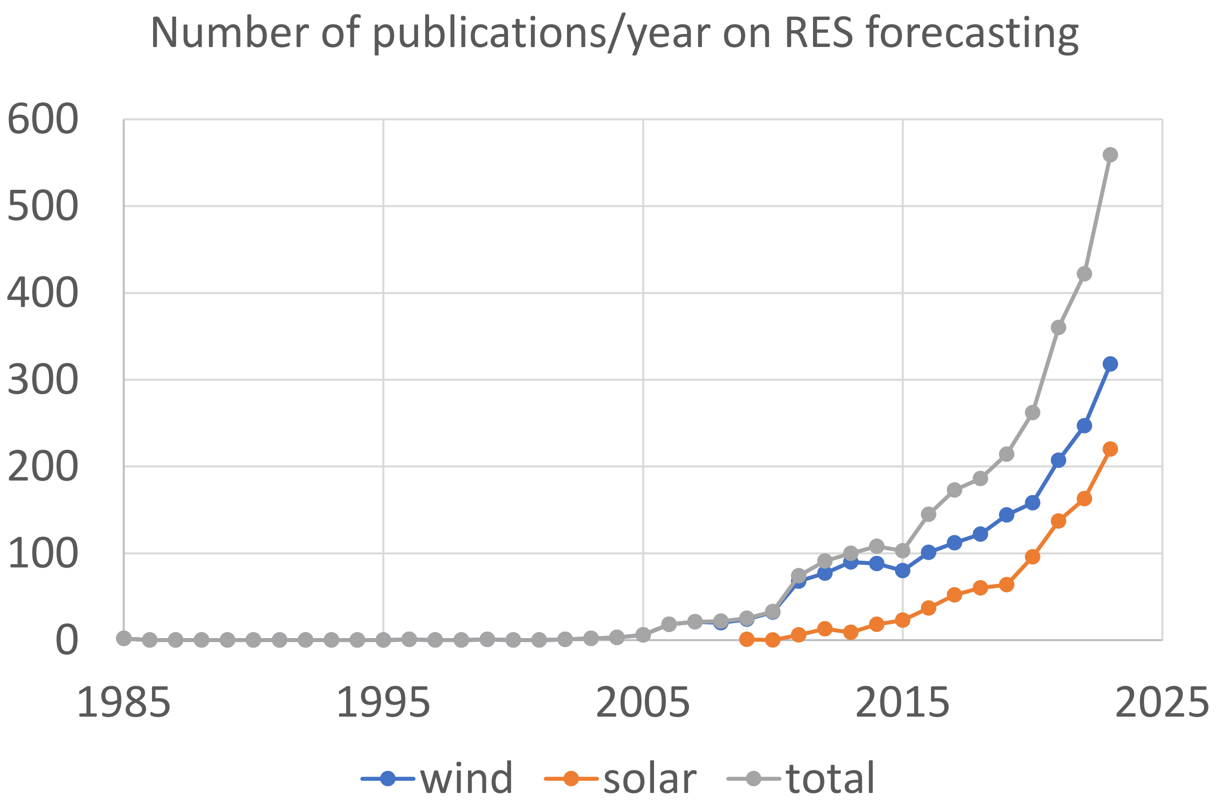
- Dedicated NWPs for RES
- Direct probabilistic predictions
- Ramps forecasting
- Scenarios, Enesembles,
- Risk indices
- Large errors warning/alarming
- Spatiotemporal forecasting
- Variability forecasting
- Predictability maps

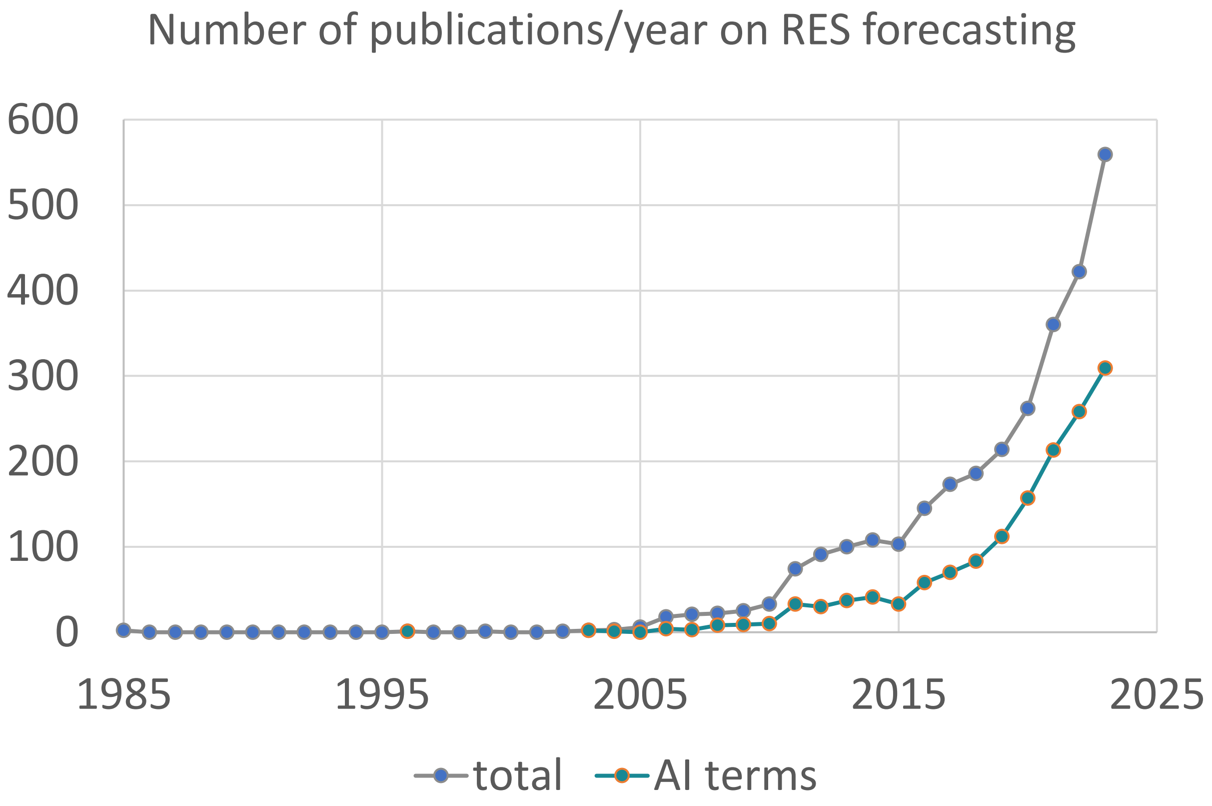
- Seamless forecasting
- Ultra high resolution (LES)
- Advanced NWPs
- Prescriptive analytics
- Extremes
- Data sharing/Data markets
- New forecasting products
- Resilience in forecasting
- Optimal use in applications

**[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

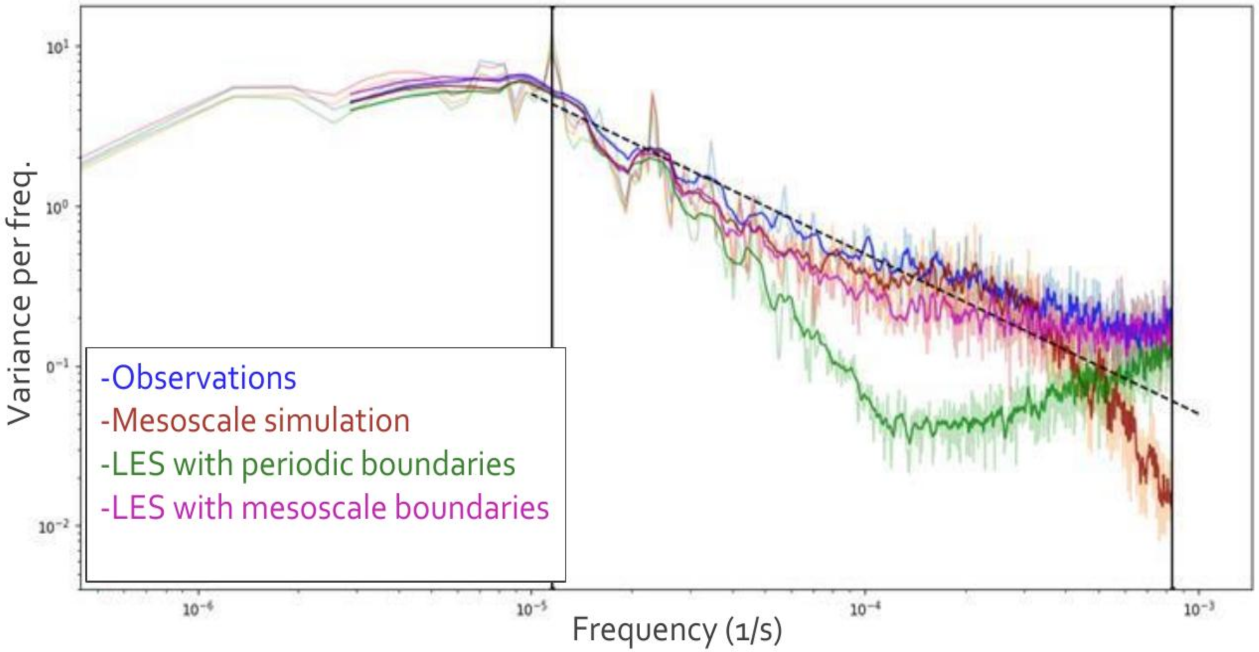


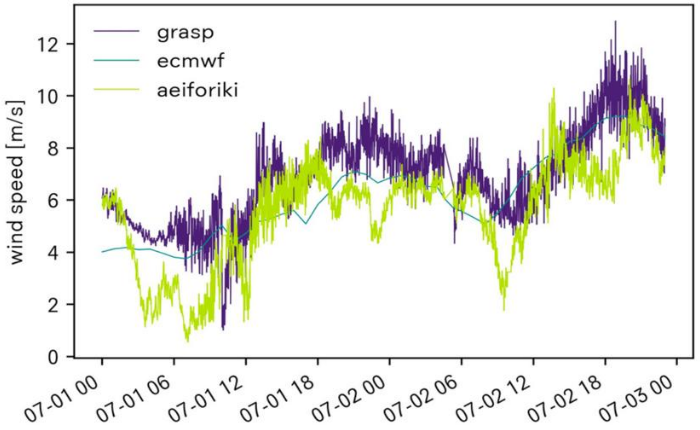
# OUTLINE

# Improved weather modelling and forecasting

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



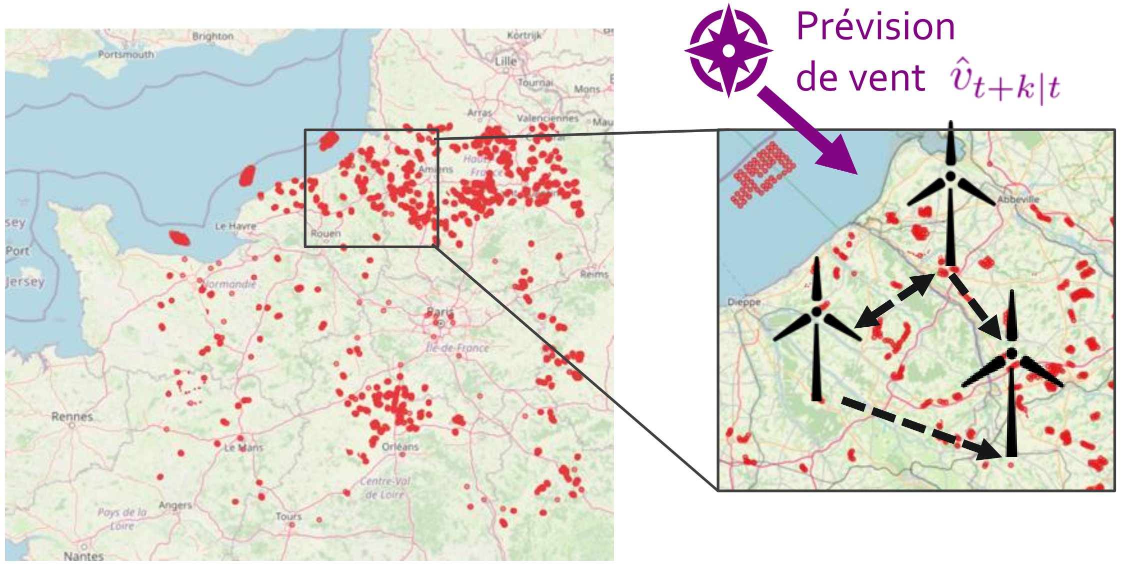

*Energy spectra for observed wind and for different simulations*

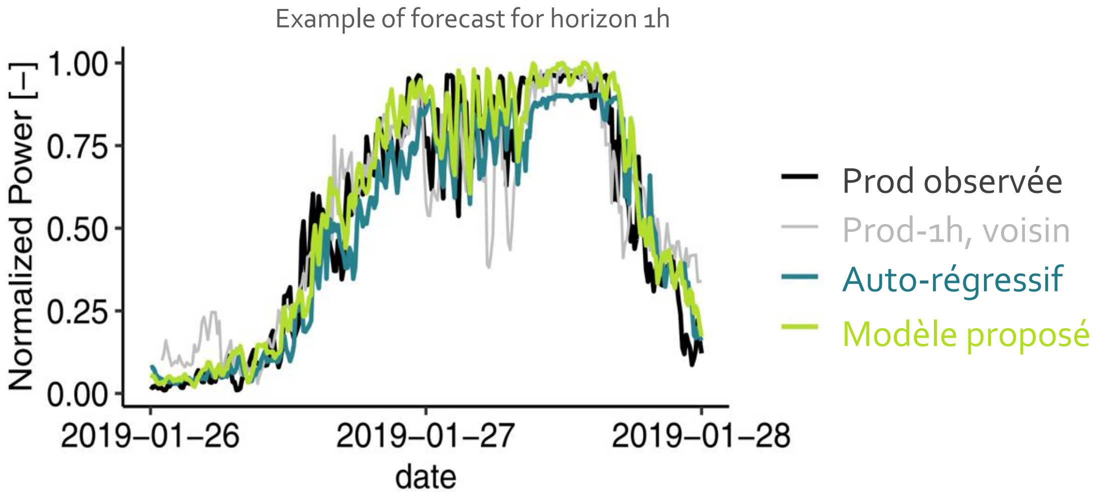



**Average improvement of 9 % for MAE of wind speed for 7 sites** (KPI 1.1)

# Spatiotemporal forecasting

- Use the measurements from neighbour wind farms as sensors to model spatio-temporal correlation and propagation of weather phenomena.
- Example: study for RTE for 600+ wind farms in France for horizons $t + 3\ h$ .
  - Conditional regression to predicted wind conditions and regularisation (lasso)



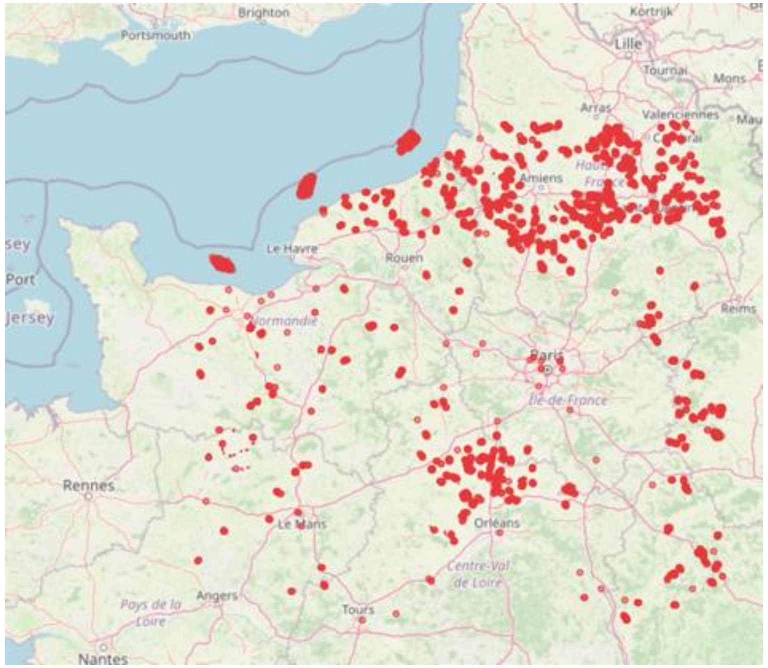

**RMSE error reduction between 4%-10% vs reference.**

Simon Camal, Robin Girard, Maxime Fortin, Augustin Touron, Laurent Dubus. A conditional and regularized approach for large-scale spatiotemporal wind power forecasting. Sustainable Energy Technologies and Assessments, 2024, 65, pp.103743.

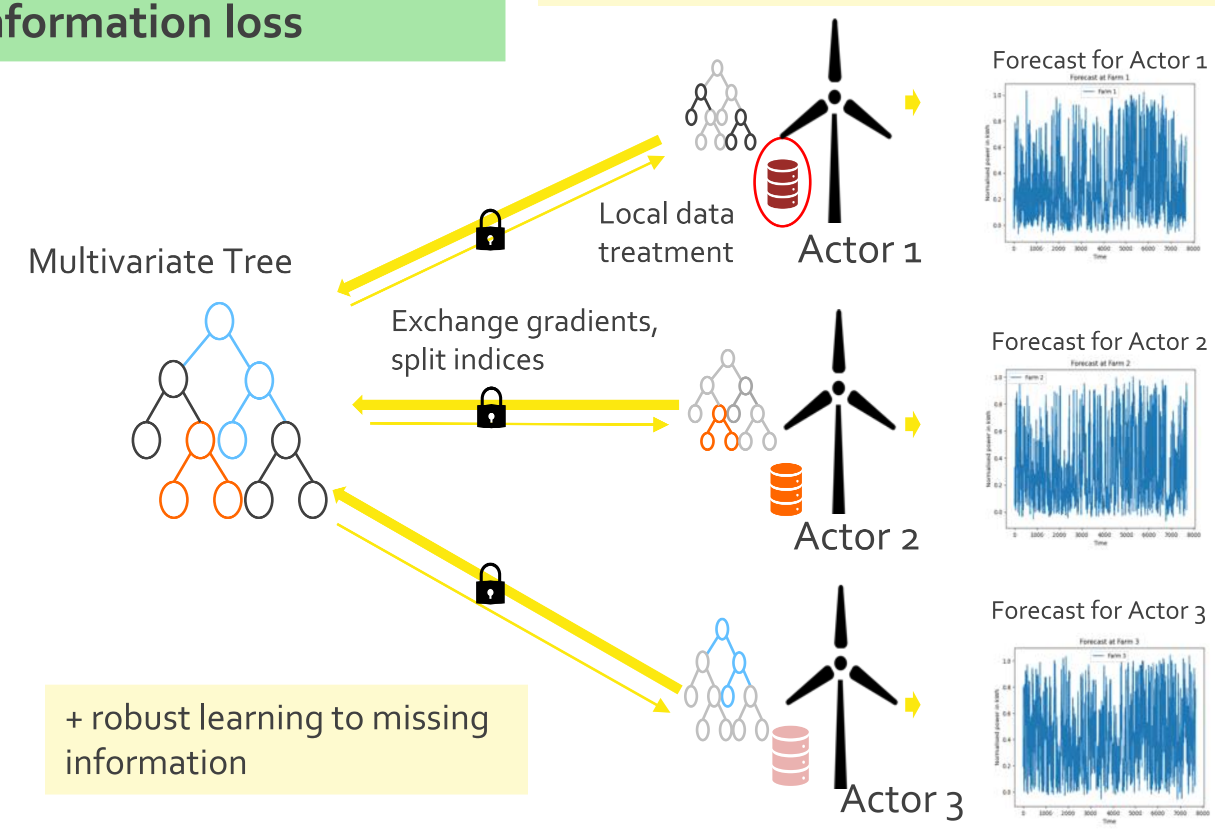
# Privacy-preserving data sharing for wind power forecasting

- Data might belong to different owners and have privacy/confidentiality constraints

**Federated Learning**, state of the art:
- Homomorphic encryption -> **computational intensive**
- Differential privacy -> **noise, thus information loss**




**Federated Trees with Secret Sharing**




Lukas Stippel, Simon Camal, Georges Kariniotakis. Multivariate Federated Tree-based Forecasting Combining Resilience and Privacy: Application to Distributed Energy Resources. Electric Power Systems Research, inPress, 234, pp.110730

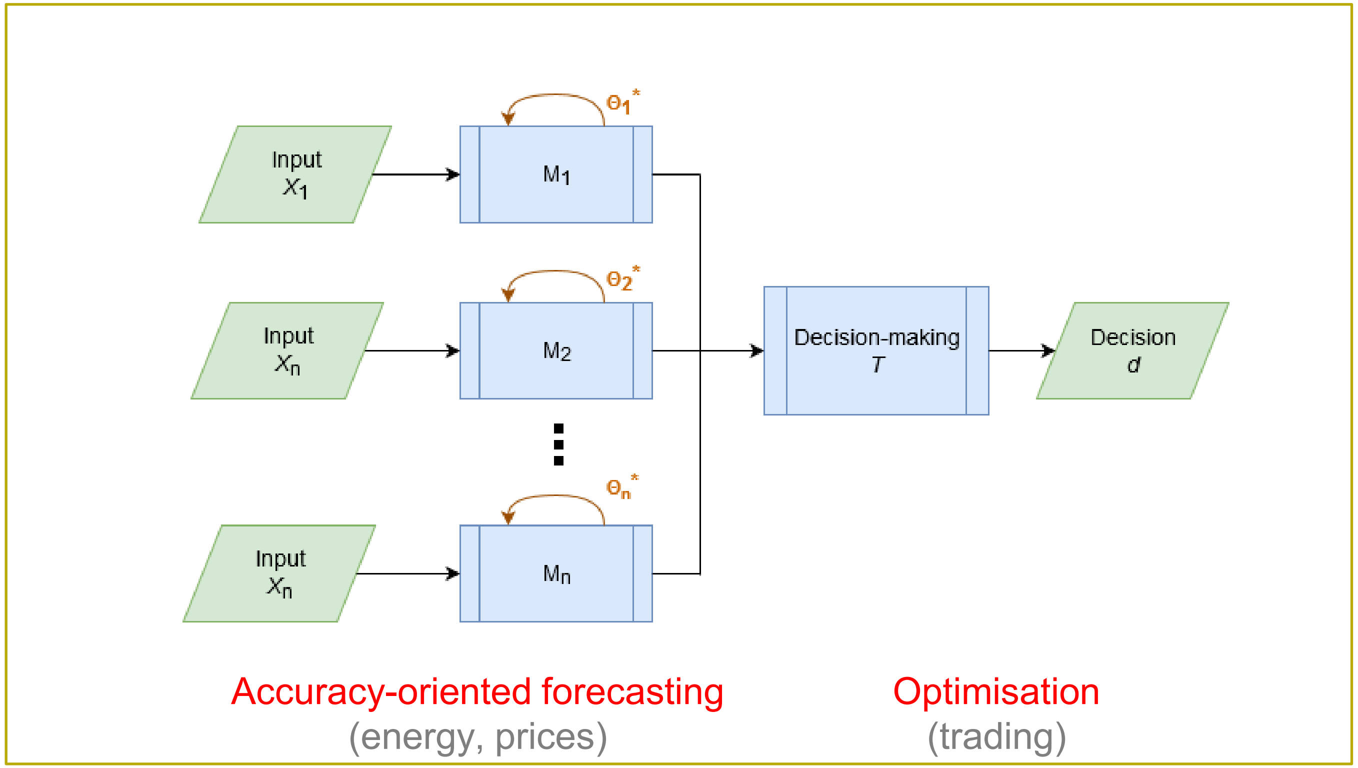
# Value-oriented forecasting

**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)

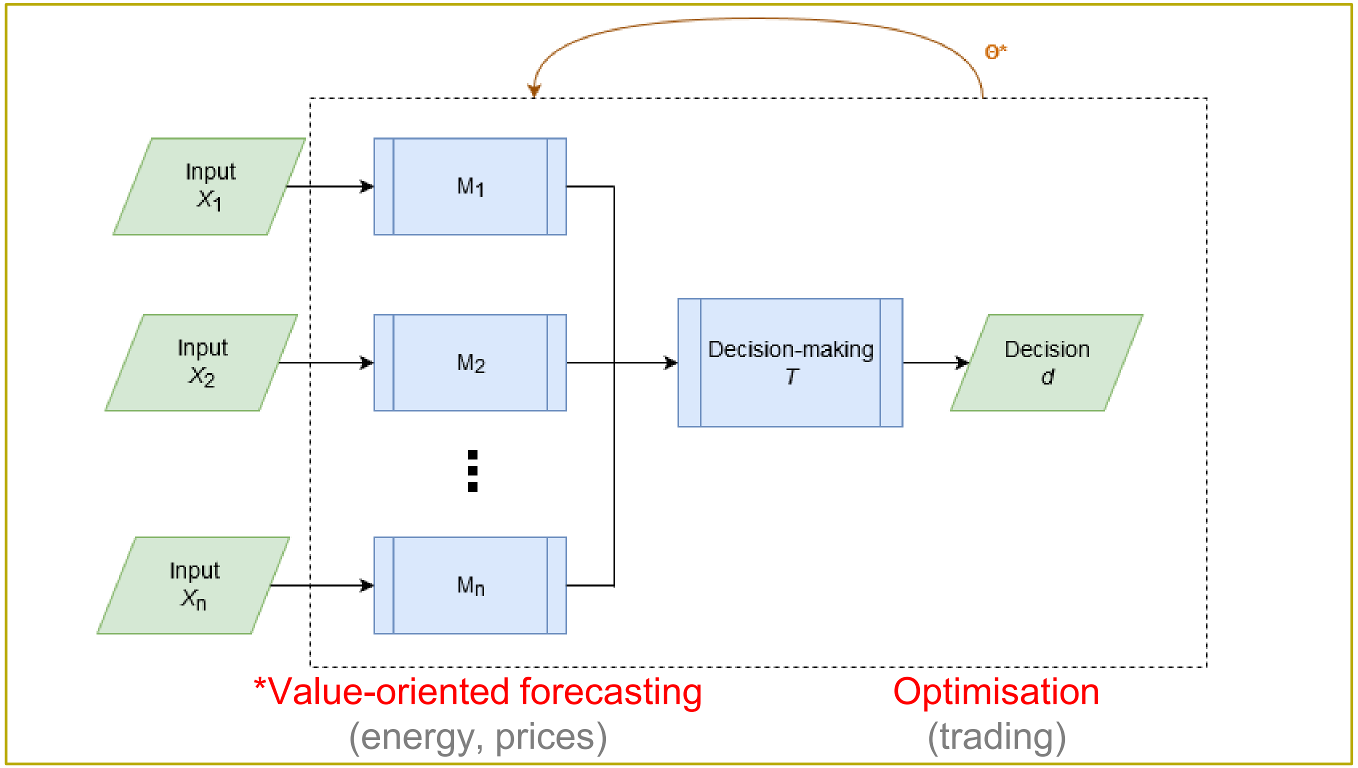
**Forecast** DA/ID energy market quantities (prices, imbalances) (3)

**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)

Decision-Focused Learning

Data on RES, storage, markets

**Forecast** aggregated RES production (1)

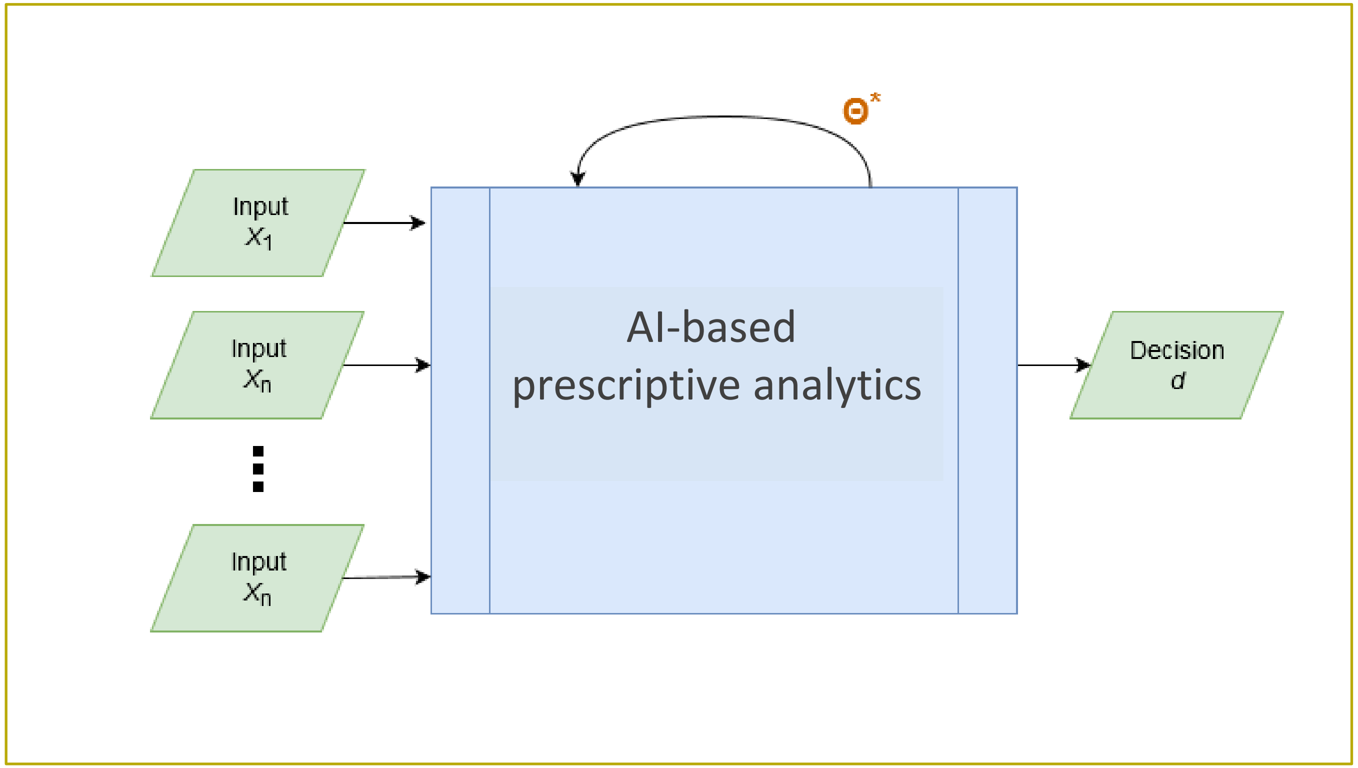
**Forecast** DA/ID energy market quantities (prices, imbalances) (3)

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

Stochastic optimisation for trading decisions (1)

Bids on energy + AS markets

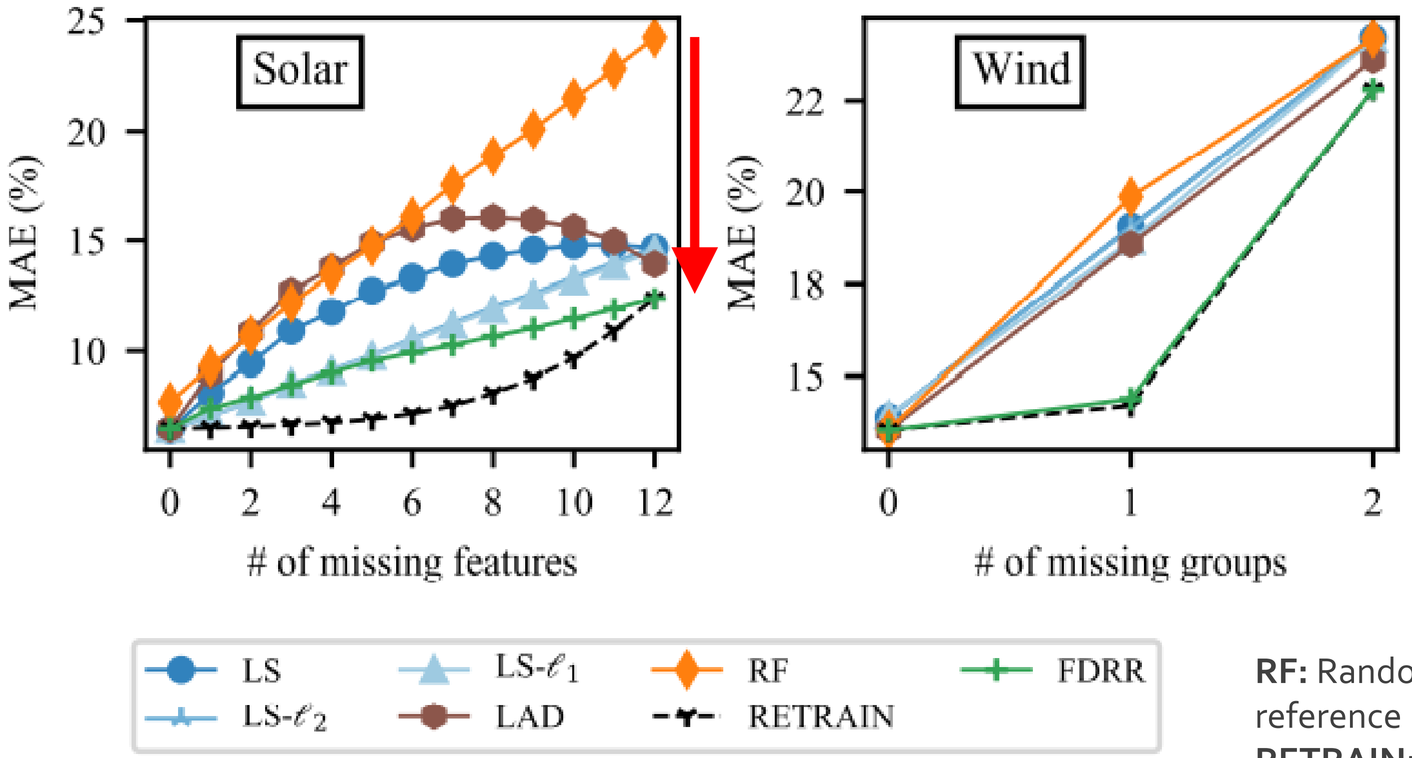
**JOINT FORECASTING & OPTIMISATION**




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.

# Resilient RES forecasting

- **Objective:** develop a forecasting approach that is robust against missing data at operational environment.
  - Combination of time series **forecasting** and **robust optimization**
  - 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.

# Interpretable AI for energy forecasting & decision making

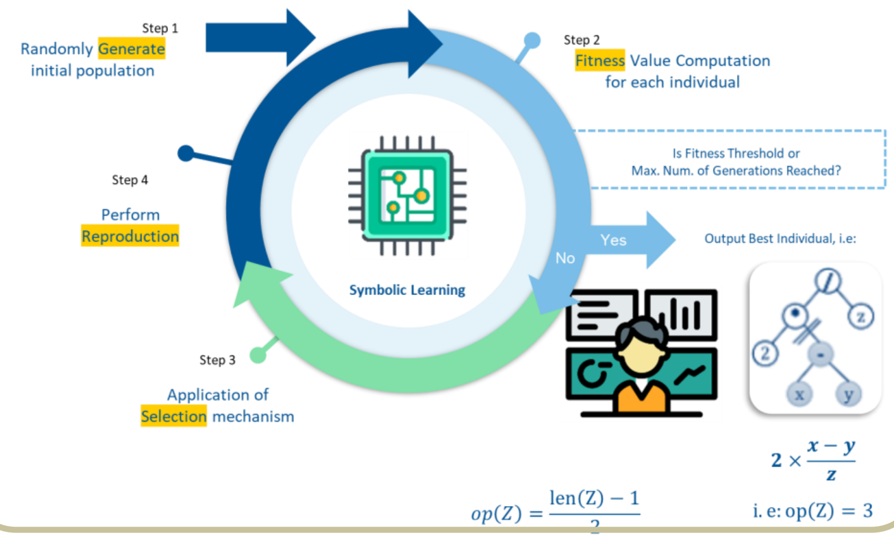
- **Goal: Develop a wind power trading approach which is interpretable by design**

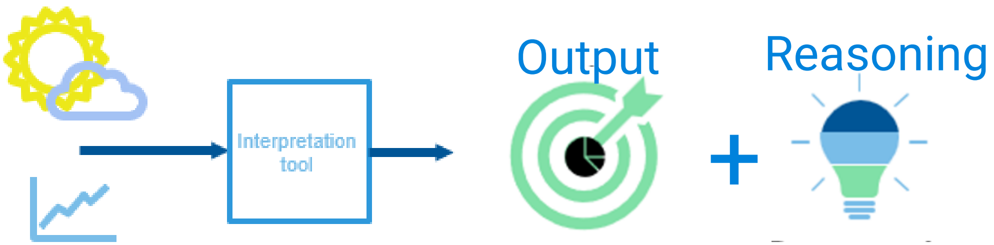
## Symbolic regression

### Start with a library of symbolic variables

$w_{speed}$ $w_{speed}^2$ $w_{speed}^3$ $Temp$ $TCC$

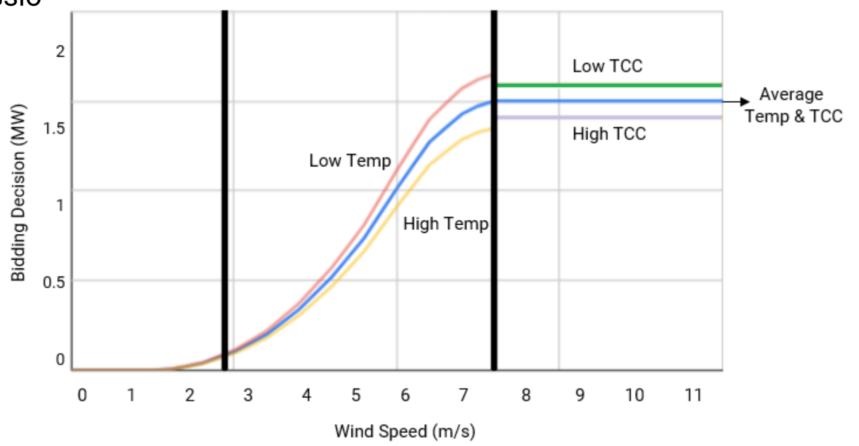
### Symbolic learning




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

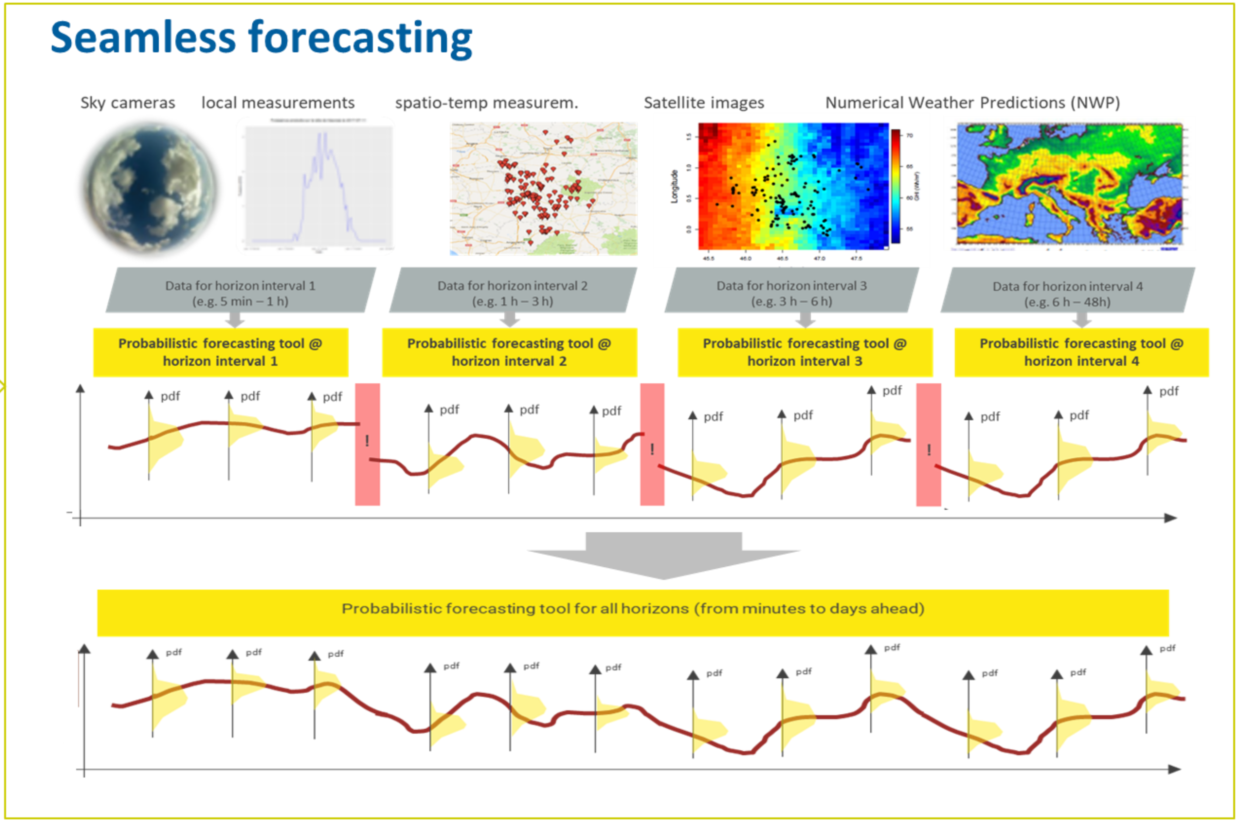
$Temp \in [271K, 311K]$
$TCC \in [0, 1]$



# Seamless forecasting

- Methods that satisfy multiple properties by design.

- HIGHER MODELLING ACCURACY
- RESILIENCE
- SIMPLICITY
- ROBUSTNESS
- VALUE MAXIMISATION
- TRUSTWORTHY AI




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.

# OUTLINE

1. AI in modern power systems
2. State of the Art in RES forecasting
3. Highlight results from the Smart4RES project
4. **Conclusions**

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

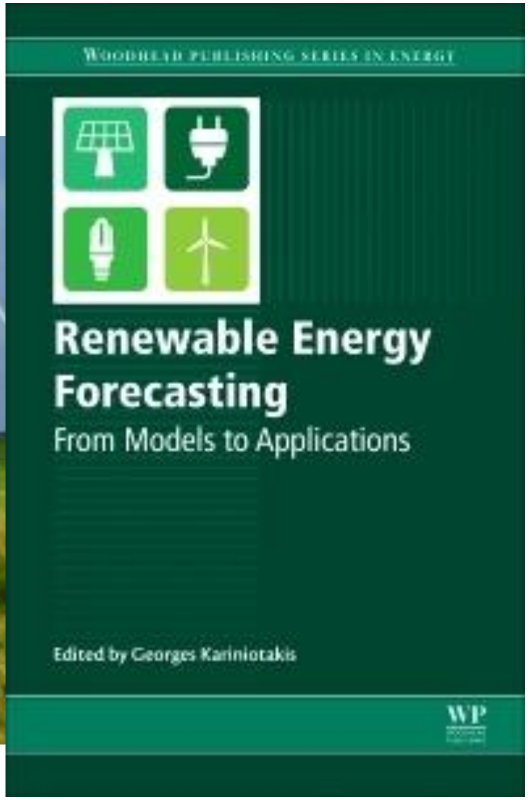
1. Research towards RES-dedicated weather forecast products (i.e. higher temporal resolution and frequency of updates for classical NWPs, focus on specific variables sensitive for energy applications)
2. Ultra high spatio-temporal resolution modelling of weather variables (i.e. Large Eddy Simulations).
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.


# Thank you for your attention




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

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

https://www.smart4res.eu/

https://www.pepr-tase.fr/projet/fine4cast/