“Les réseaux intelligents d’eau, de gaz et d’électricité. Technologies, enjeux et applications”, ASPROM, Paris, 1-2 avril 2015

Énergies renouvelables météo-dépendantes.

Le rôle de la prévision court-terme

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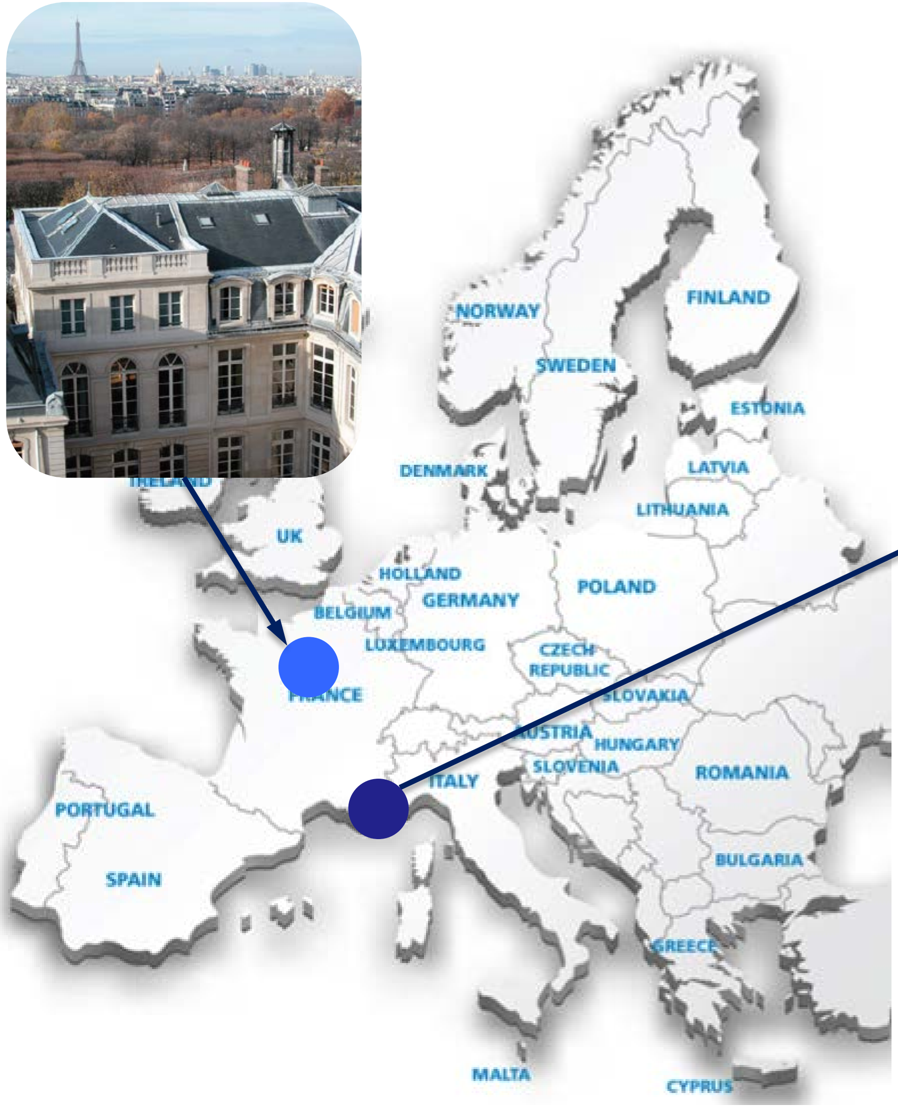

PERSEE: Centre for Processes, Renewable Energies and Energy Systems.

- *Renewable Energies & Smartgrids.*
- *Sustainable technologies & processes*
- *Materials for energy*

MINES ParisTech @ Sophia Antipolis

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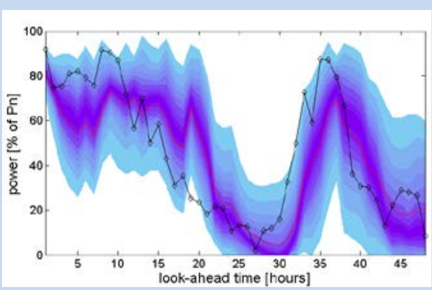
- **Research axis « Renewable energies & smartgrids »:** Development of methods and tools to facilitate the integration of distributed generation and renewable energies (RES) into power systems and electricity markets.

3 Research themes

RES forecasting

- ***Wind***
- ***Solar***



Multi energy hybrid systems

- ***Dimensioning/ design***
- ***Optimal operation and management***

Smart grids

- ***Modelling/simulation***
- ***Predictive management***
- ***Planning***
- ***RES integration into electricity markets***

Towards a weather dependent power system?

- In 2007 the European Council sets new targets for renewables, **20-20-20 by 2020** for EU-27.

  ✓ **-20%** GHG emissions /1990 or more,

  ✓ **+20%** renewables in final energy consumption,

  ✓ **-20%** primary energy (energy efficiency).

- These translate to ambitious targets for wind and solar energy :

  ✓ **230 GW** for wind energy. Capable of covering 14-18% of the EU-27 electricity demand (109 GW in 2012) [EWEA].

  ✓ **150 GWp** for **PV** is [EREC] (350 GWp [EPIA]).

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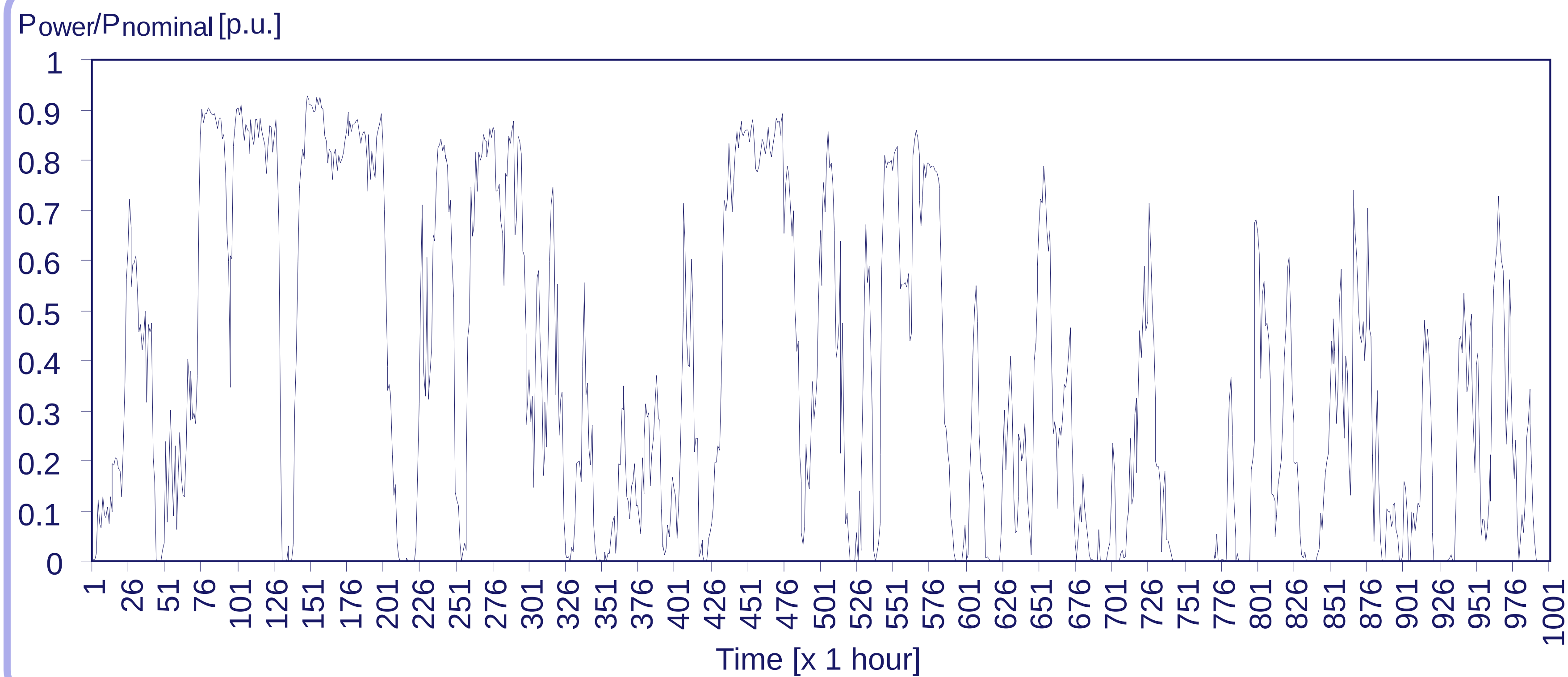
Renewable energy sources (RES) variability

- Both wind and PV generation are **highly variable** due to their dependence on the weather conditions.
- Example of the production of a **wind farm** (1 month period, complex terrain):



Renewable energy sources (RES) variability

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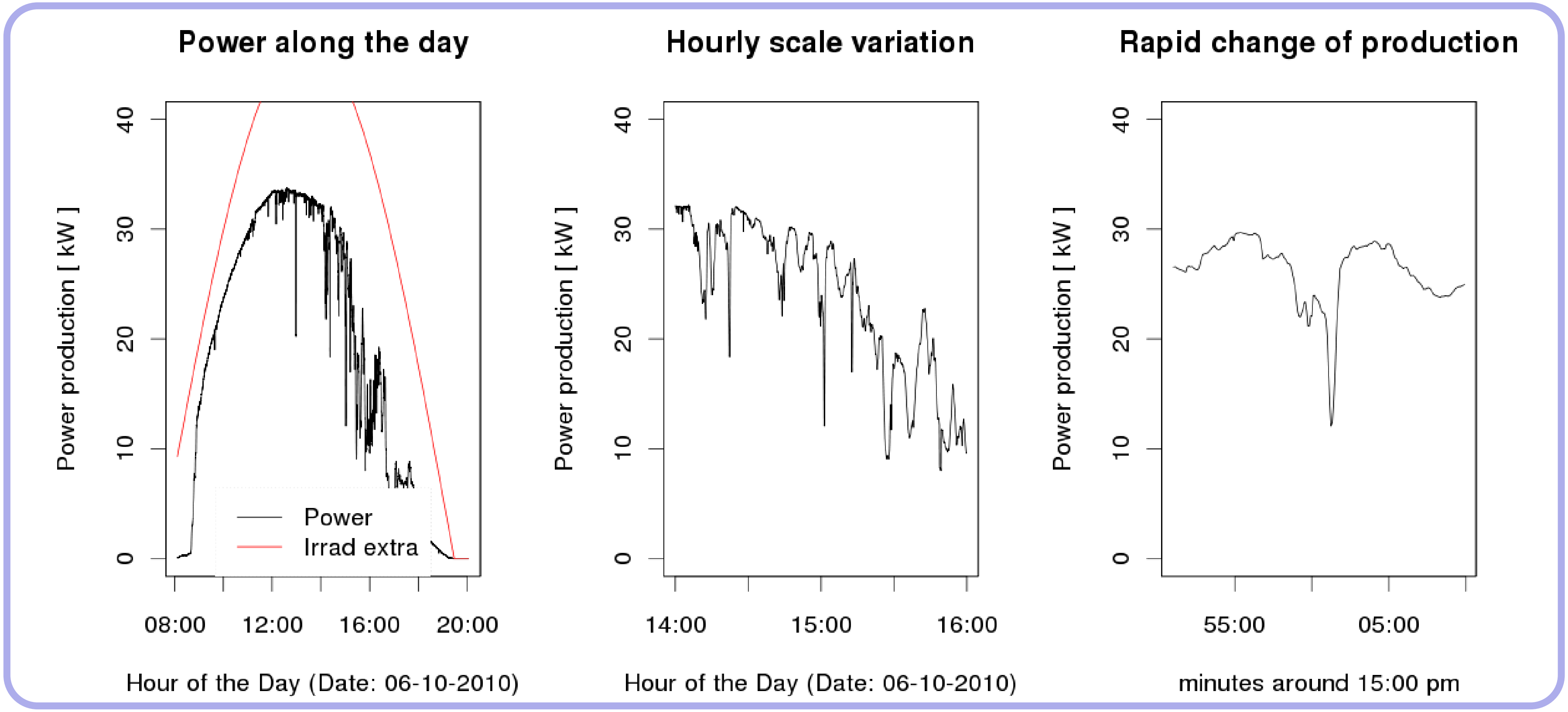


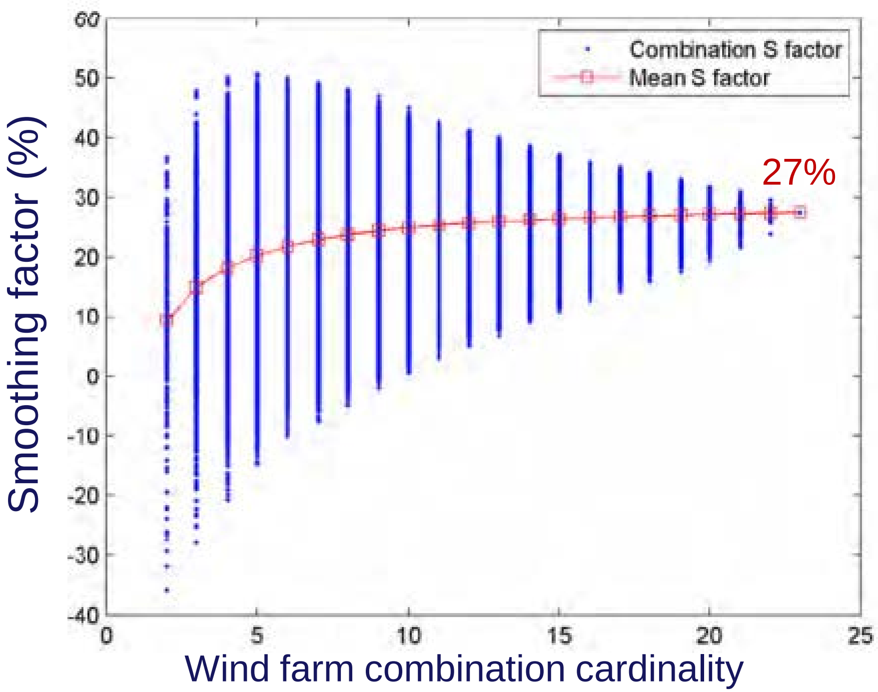
Renewable energy sources (RES) variability

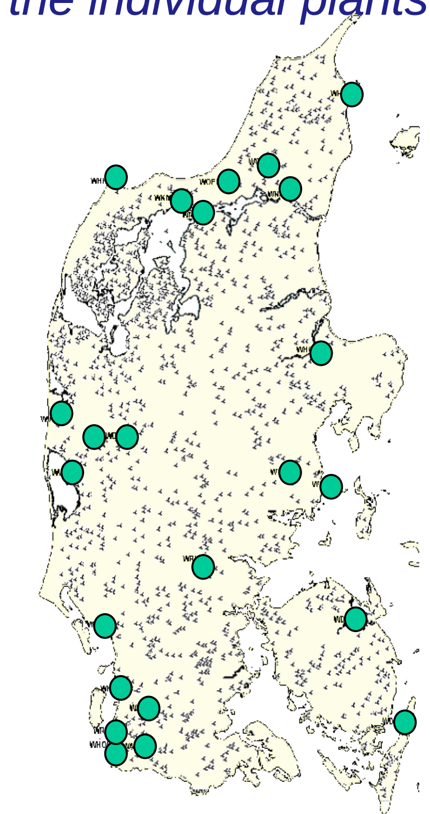
- The geographical distribution of RES plants brings a **smoothing effect**

- Smoothing factor: $$S = 1 - \frac{\frac{V\left(\sum_{i=1}^{N} P_i^{wf}\right)}{\left(\sum_{i=1}^{N} P_{inst,i}^{wf}\right)^2} -}{\frac{1}{N}\sum_{i=1}^{n} \frac{V\left(P_i^{wf}\right)}{\left(P_{inst,i}^{wf}\right)^2}}$$

Quantifies the reduction in the variance of the sum compared to the individual plants.

- **Example:** Denmark (23 Wind farms)





Challenges in managing the power system

- **Maximise the use of RES generation**, while **maintaing a secure** and **economic** power system operation.

- **RES penetration (t)** = $\dfrac{\text{RES production (MW) at time t}}{\text{Total demand (MW) at time t}}$ *

- **Necessity for advanced power system management tools for** power systems with high RES penetration.

* Different definitions exist for other purposes.

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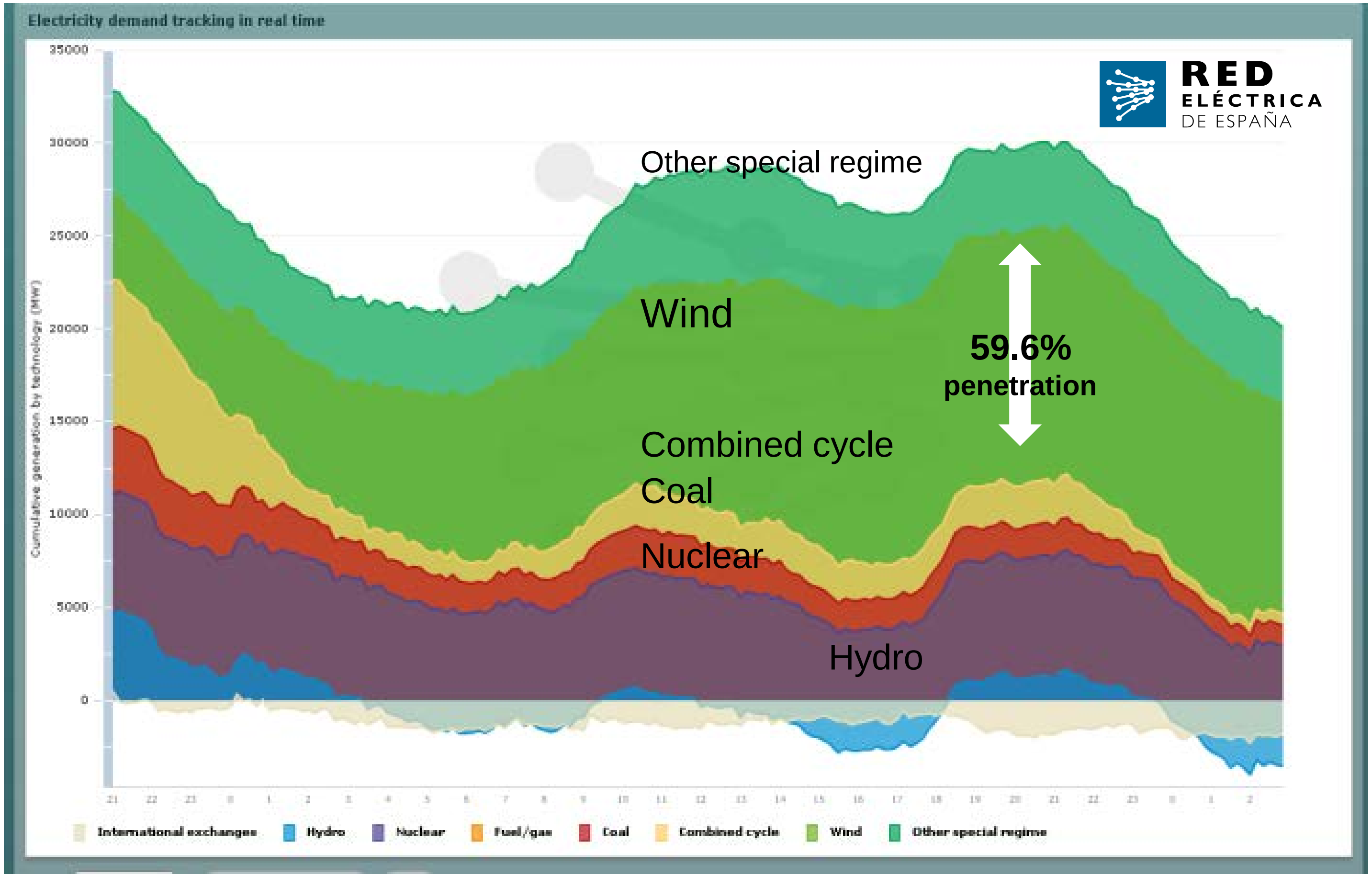
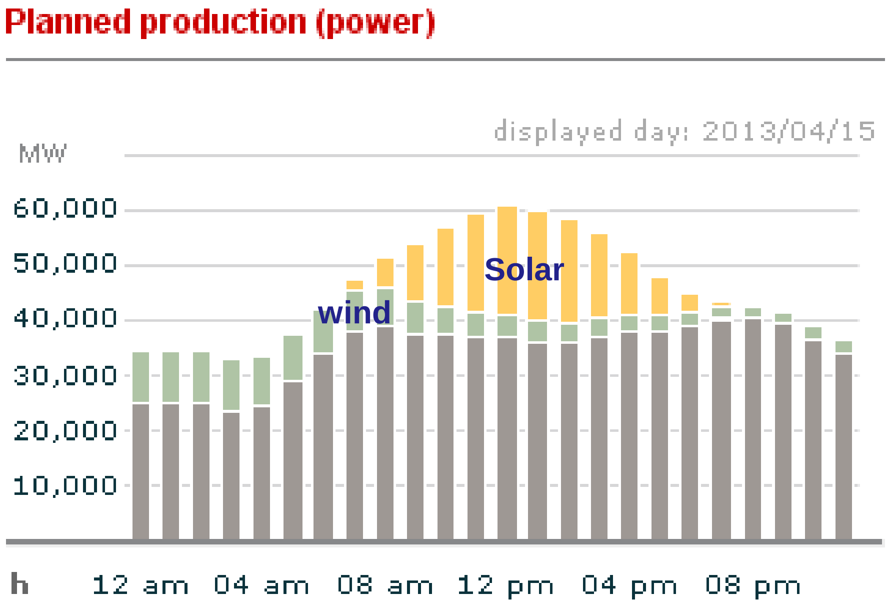
Examples of high RES penetration (Spain)

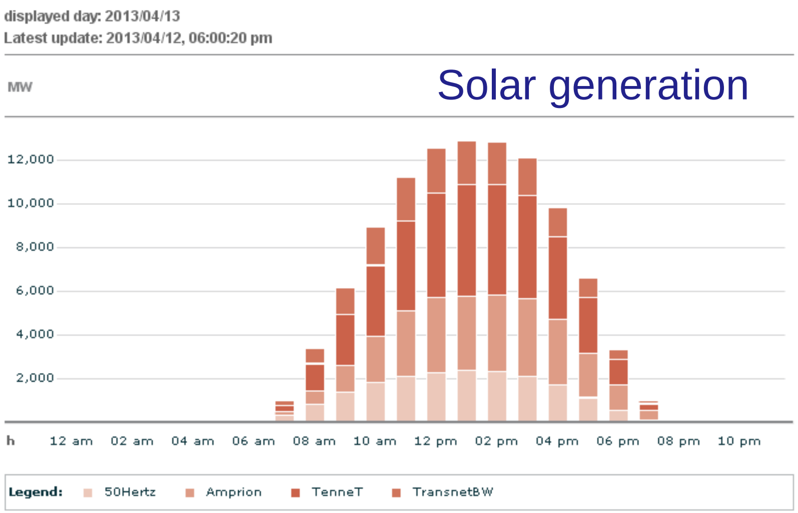
- **59.6% max** hourly penetration level (11/6/2011)

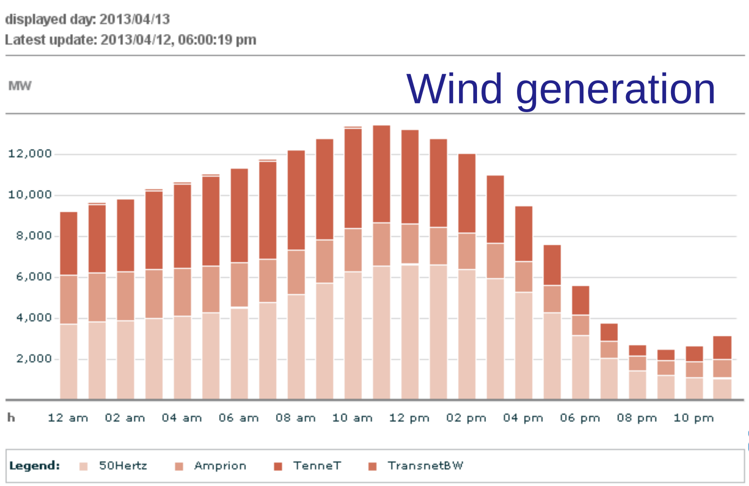


Examples of high RES penetration (Germany)

- **40% max** hourly penetration (2013/04/15)

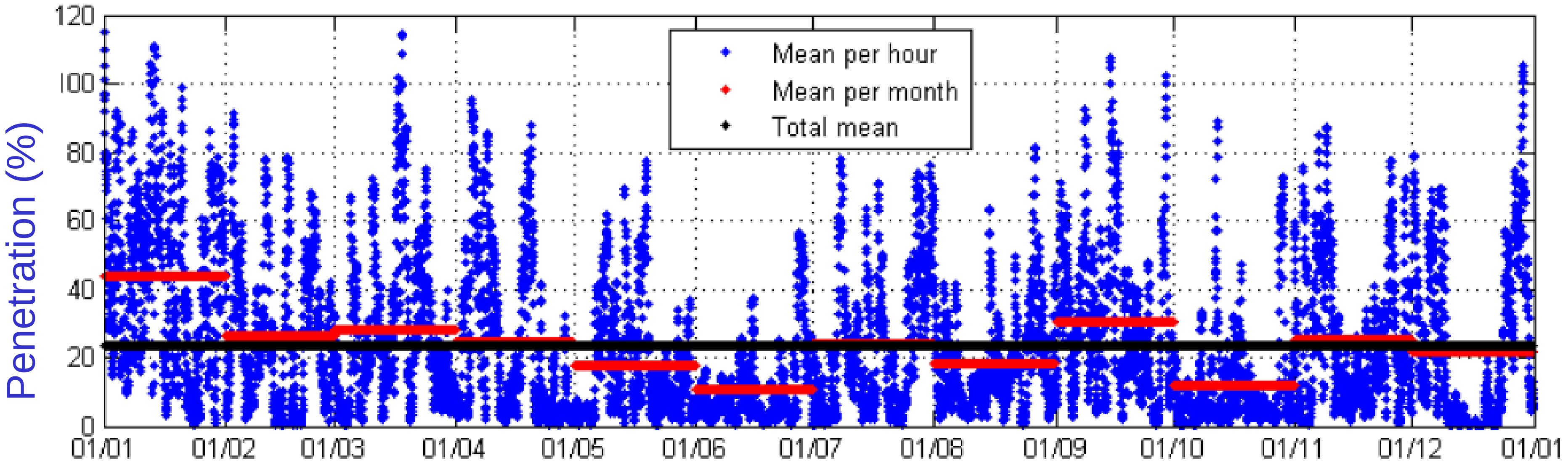






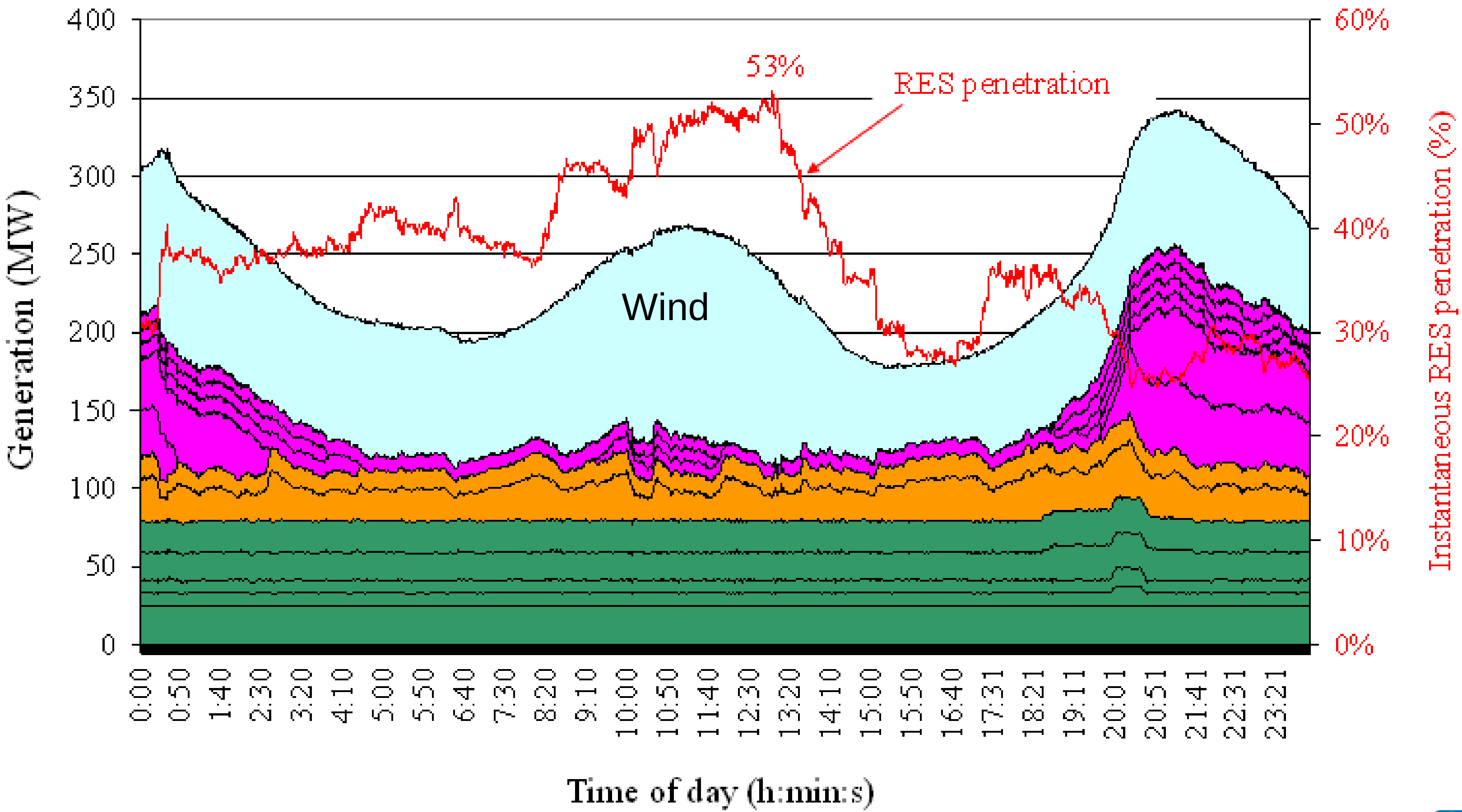
Examples of high RES penetration (Denmark)

- **100% max** hourly penetration level in Denmark (DK1 area) in **2007**



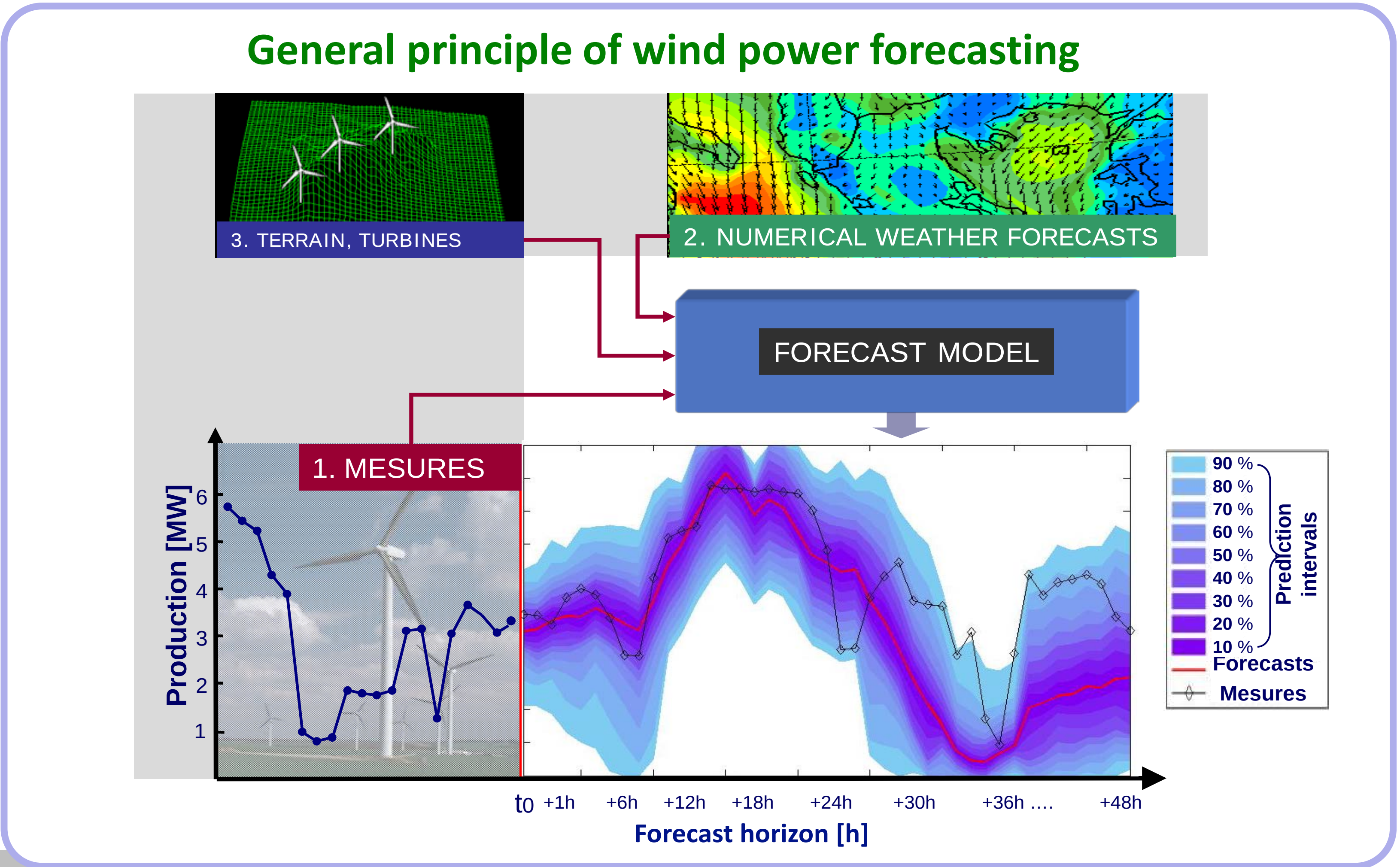
Examples of high RES penetration (island of Crete)

- **53% max** penetration level in the island of Crete, Greece (4/4/2012).



Short-term forecasts of RES generation

- **Accurate forecasts of RES generation** contribute to operate the power system in a secure and economic way



Overview of the end-user needs

- Forecasts of the RES generation for the near future (hours, days) and estimations of the uncertainty are needed for:

TSO, DSOs

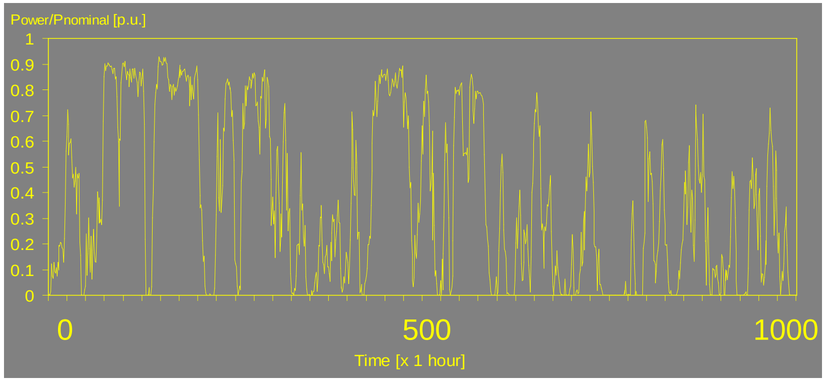
- **Economic dispatch (**set points to conventional units and wind farms**)**
- **Scheduling/Unit commitment of the power system generators**.
- **Planning reserves to compensate wind fluctuations.**
- **Congestion management**
- **Planning the use of energy (hydro) storage.**
- **Planning power exchanges/flows/maintenance with interconnections.**

IPPs, etc

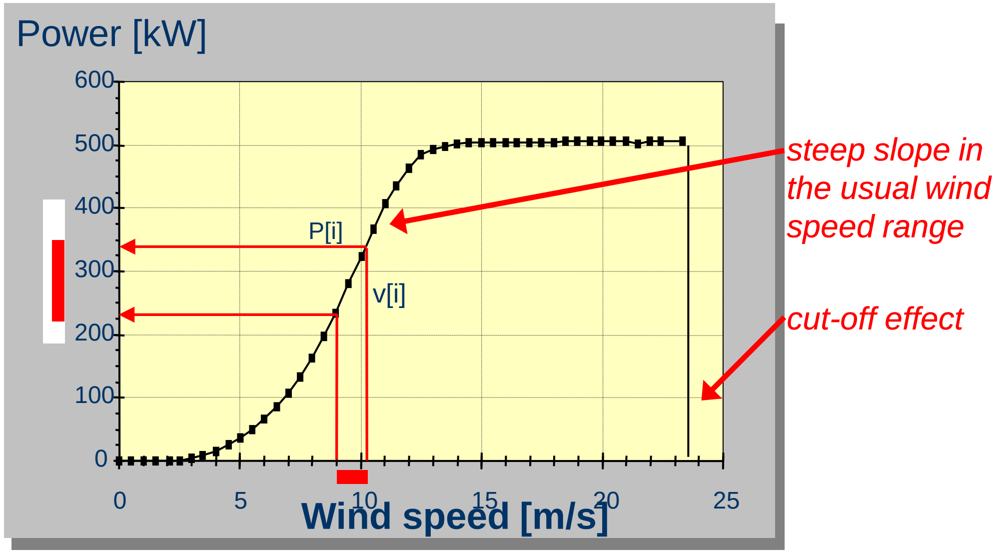
- **Planning maintenance of the wind farms for the next days (offshore).**
- **Making bids in an electricity market**
- **etc.**

A complex problem…

- Forecasting wind power is a complex problem. Some of the reasons:



Wind is highly variable by nature… (example: wind production of a wind farm during a month)

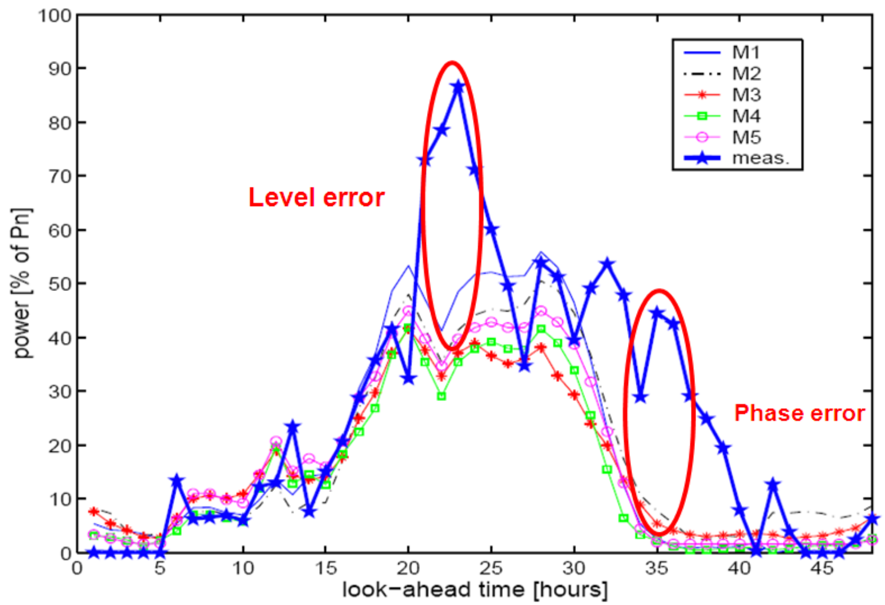


The wind turbine characteristic curve introduces important non-linearities.

The forecasts performance

- **The accuracy depends on :**
  - The quality of weather forecasts
  - The forecast horizon
  - The season, the climatic conditions
  - The terrain complexity (for wind)
  - The type of input and models
  - The level of production
  - The level of aggregation

- **Two important types of errors :**
  - **Phase** errors
  - **Level** errors

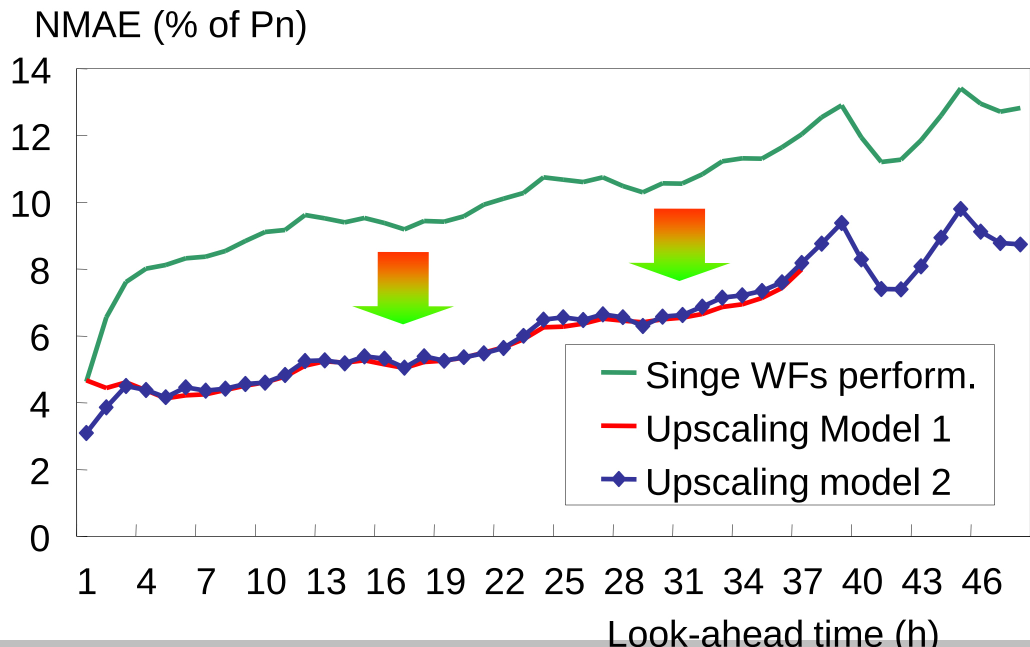


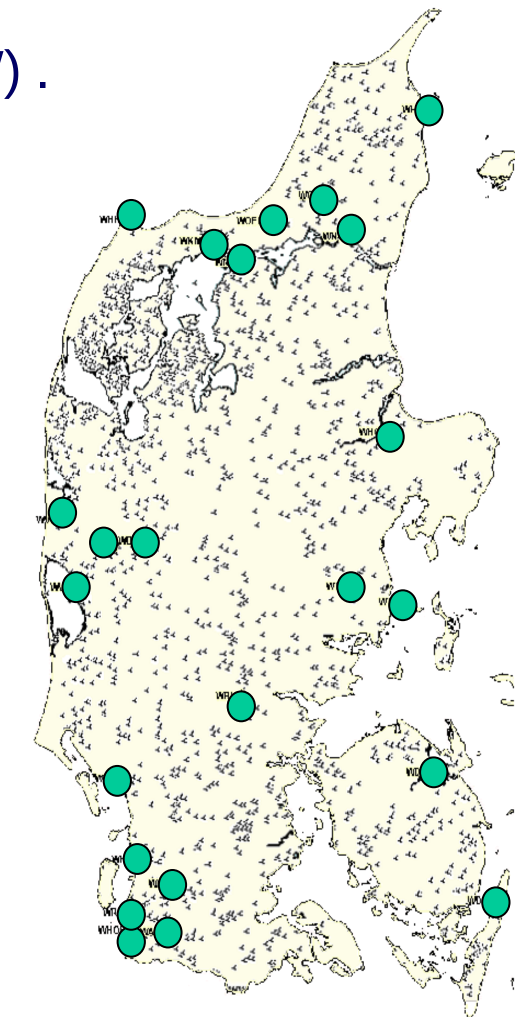
Factors affecting accuracy: Spatial smoothing effect

Example :

Prediction of 2200 MW in Jutland area in DK

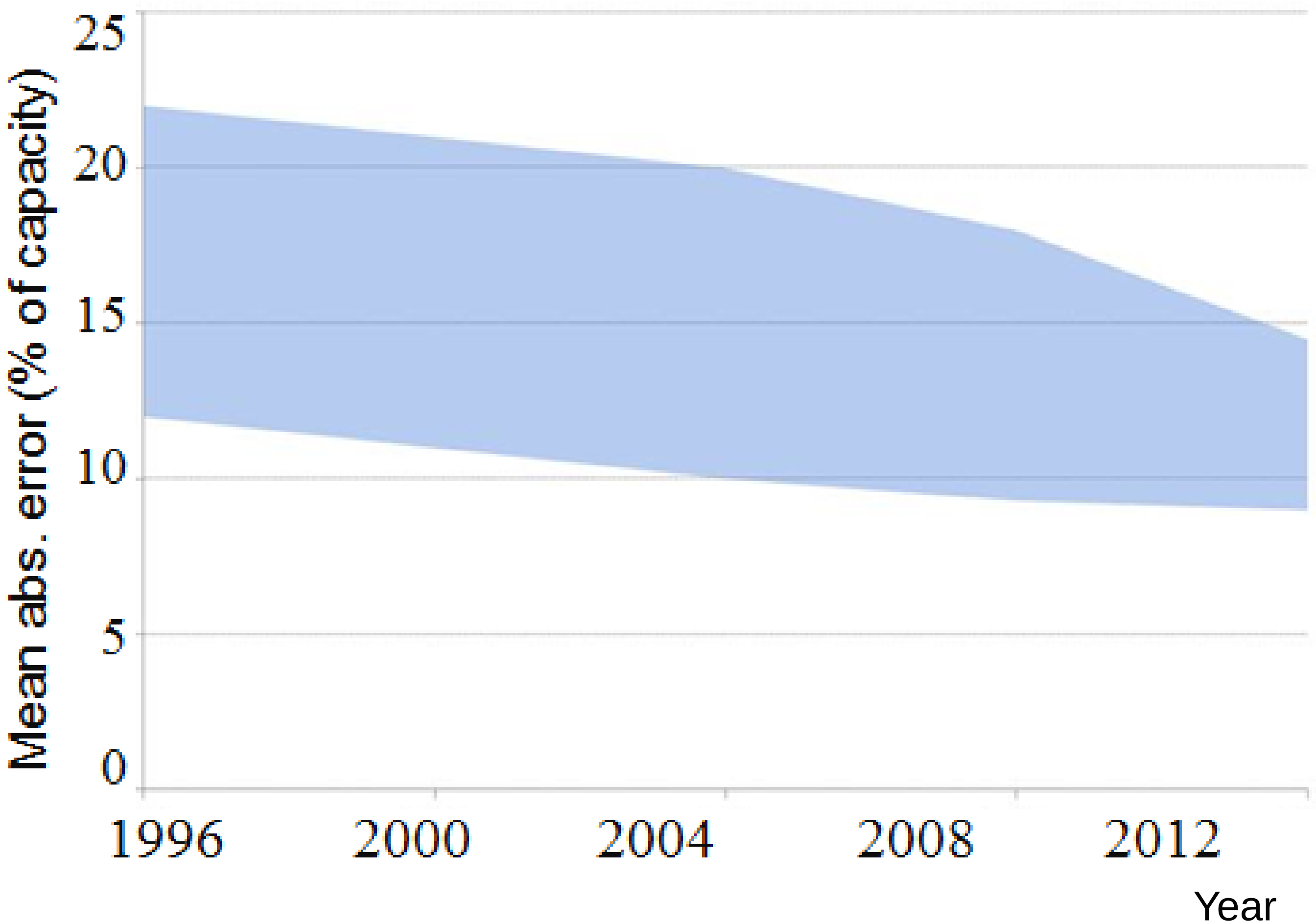
- SCADA measurements only from 23 WFs (~200 MW) .
- Differenced measurements of the total production.
- Prediction of 23 WFs output
- Then upscale to the total area.





Evolution of forecasts performance through time

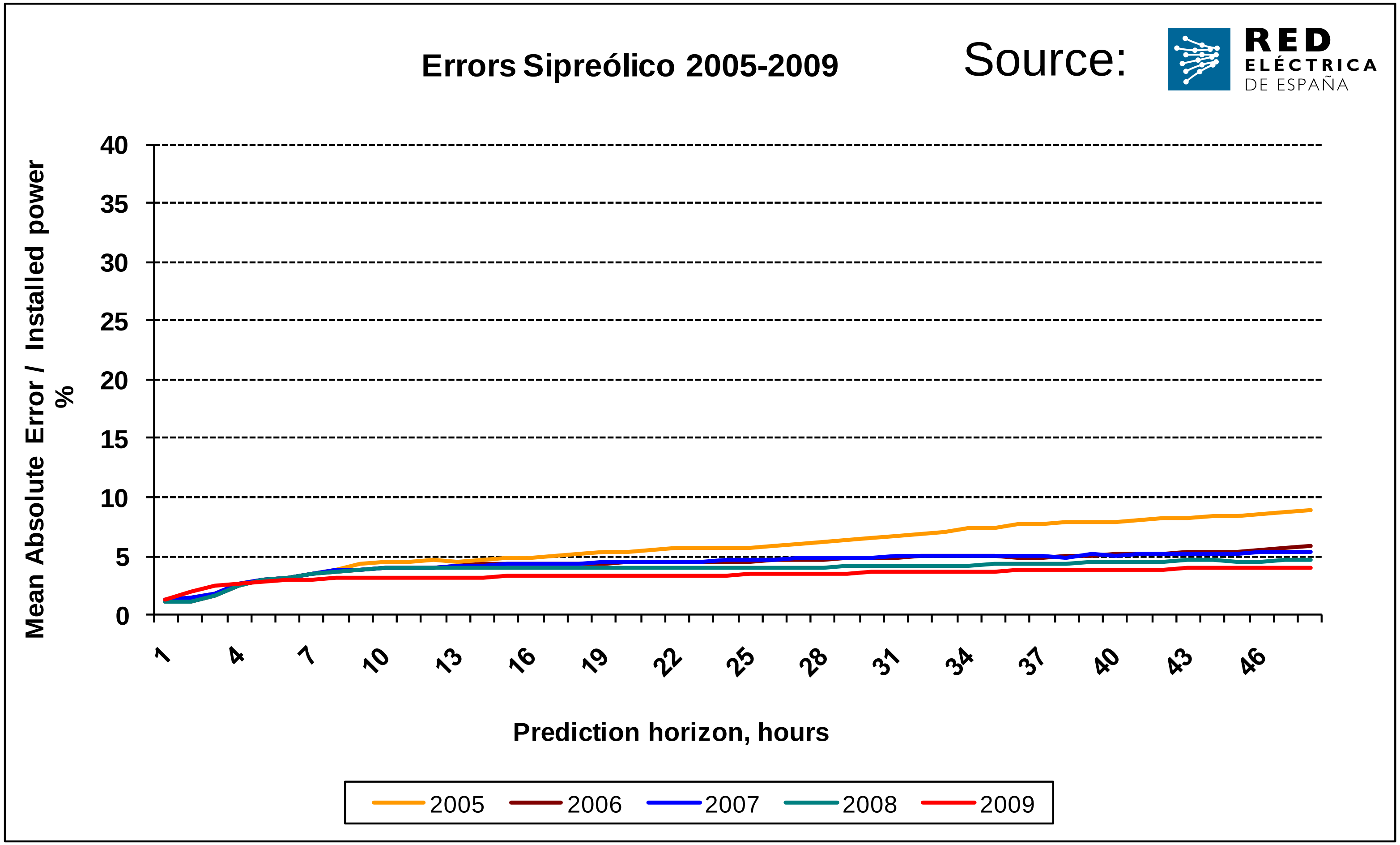
Evolution for the case of single wind farms



Source: GL Garrad Hassan, EWEA 2012

Evolution of performance through time (Spain)

- NMAE* performance between **1%-4.5%** (1h-48h). **<4%** for 24h.
- Progressive improvement between 2005 and 2009



NMAE: Normalised Mean Absolute Error (percentage of Installed Capacity)

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Evolution of performance through time (Germany)

- **Wind forecasting:**
  - **"3.7%** NRMSE* for day ahead delivered at 8 am the day before (2011) (time step 15 min, 96 predictions).
  - **2.1 %** NRMSE* for rolling 2 hour ahead forecast (so for intraday trading) (jan until nov 2011) (evaluated by a German TSO)"

- **PV forecasting:**
  - **4.17 %** RMSE (only sunshine hours, so without night values) for day ahead delivered at 8 am the day before (3-10/2011)
  - **2.85 %** RMSE (only sunshine hours, so without night values) for rolling 2 hours ahead forecast (3-10/2011)"

Source : energy & meteo systems

(*) NRMSE – Normalised Root Mean Square Error (as a function of installed capacity

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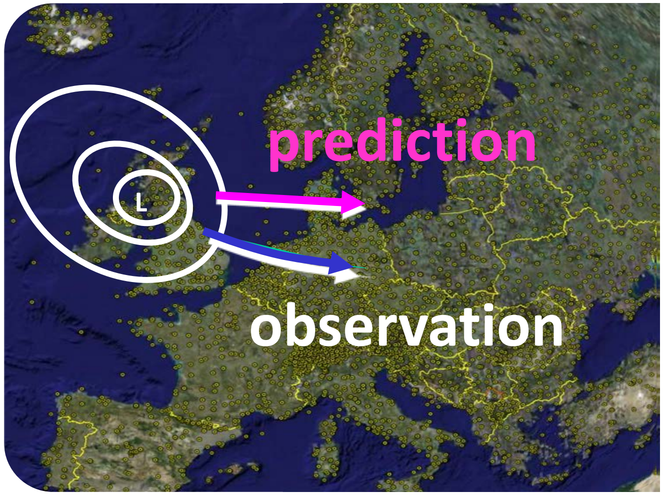
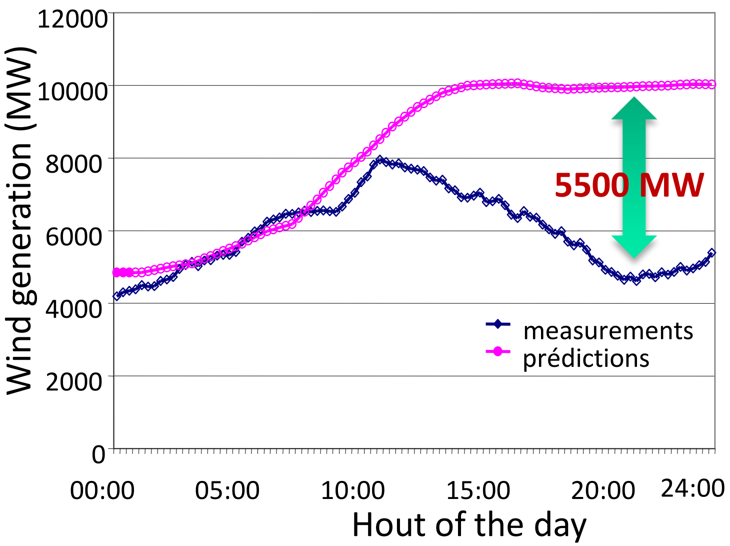
Overview of the state of the art

- The actual wind power forecasting technology is quite **mature**
- However, in some situations large forecast errors may have an **important impact** on the power system operation
- Intensive R&D: 3 large EU projects (**Anemos, Anemos.plus, SafeWind**)



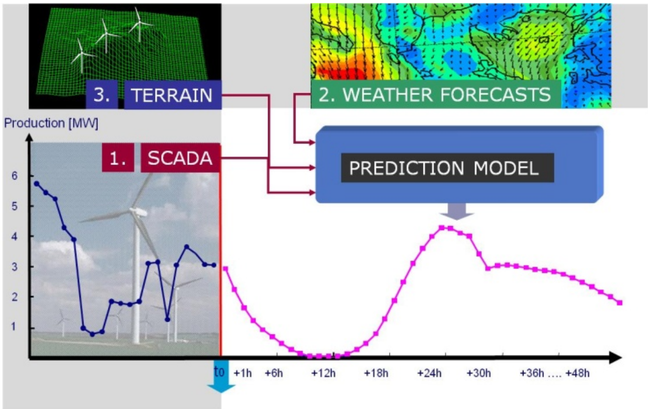


Forecast of total wind generation in Germany*: Path of low-pressure system was different than predicted resulting to a maximum error of 5500 MW

(*) Source: SafeWind project

Overview of the state of the art

"Deterministic" (spot) approaches



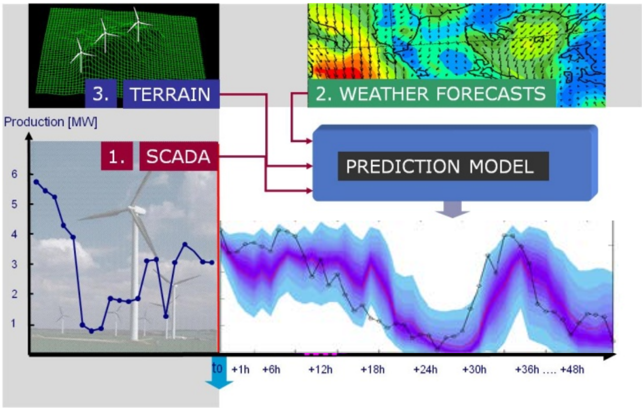
1990 2002

- Statistical/time-series approaches
- Artificial intelligence
- Physical modelling
- Empiric/hybrid implementations into operational forecast tool

Overview of the 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

1990 2002 Anemos

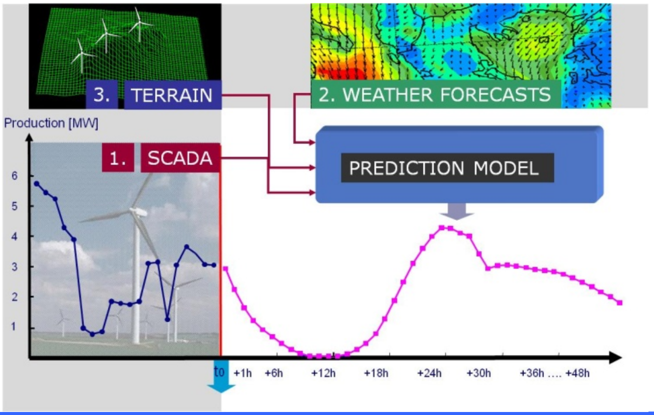


Probabilistic view

Overview of the state of the art

THE STATE OF THE ART

"Deterministic" (spot) approaches



New generation of tools

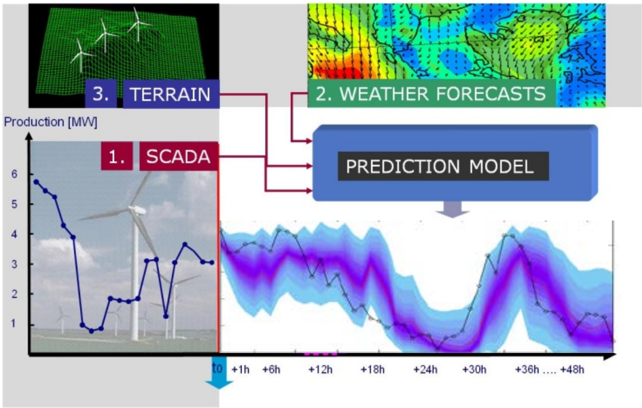
Diversified predicted information

Portfolio of products

1990

2002 Anemos

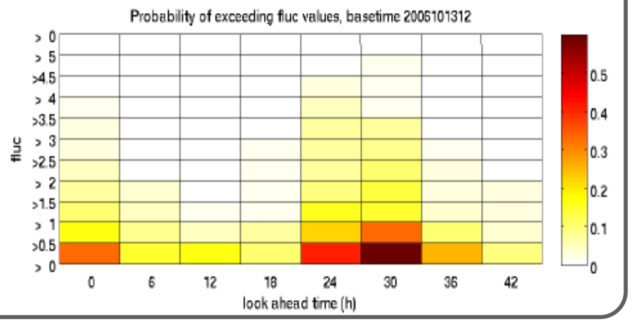
2008 SafeWind, Anemos.plus



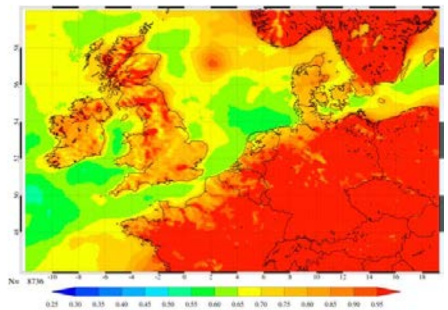
Probabilistic view

Overview of the state of the art

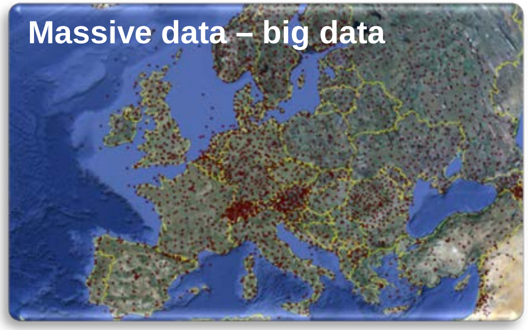
Variability/texture predictions



Predictability maps

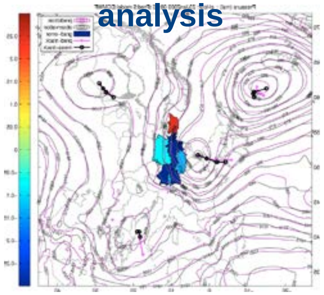


Massive data – big data

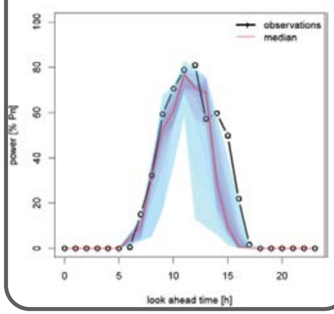


Alarming tools for large errors

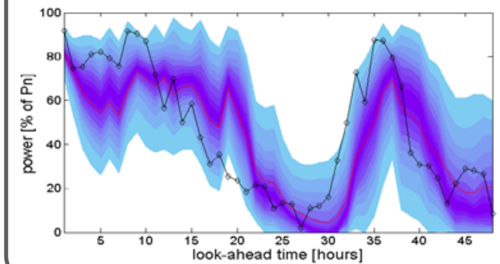
Weather patterns analysis



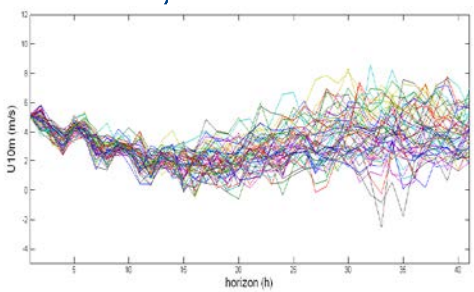
PV forecasting



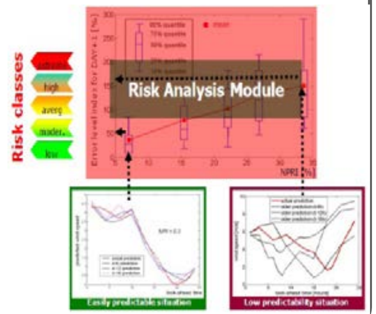
Probabilistic Forecasting



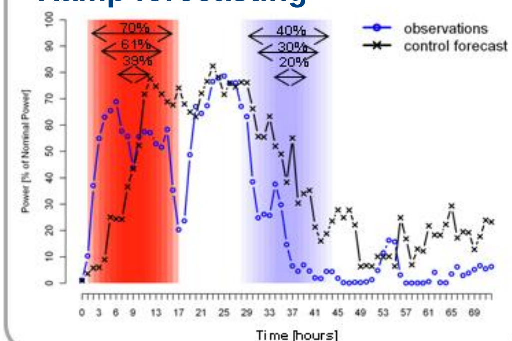
Scenarios, Ensembles



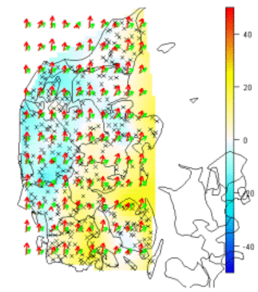
Risk indices



Ramp forecasting



Spatio temp



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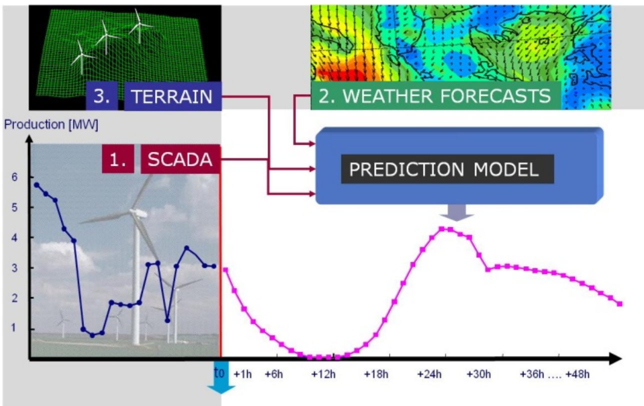
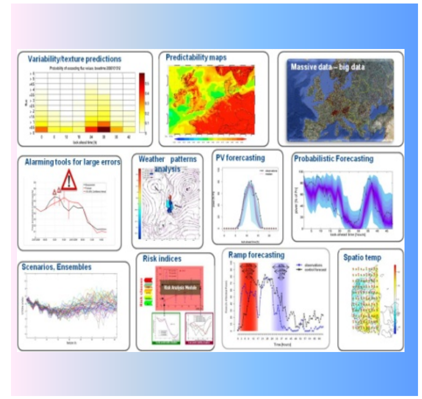
Perspectives

THE STATE OF THE ART

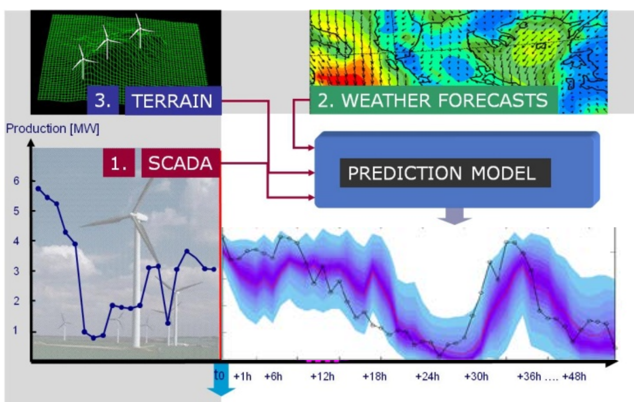
"Deterministic" (spot) approaches



New generation of tools



1990 — 2002 Anemos — 2008 SafeWind, Anemos.plus — 2015



Probabilistic view

On going research

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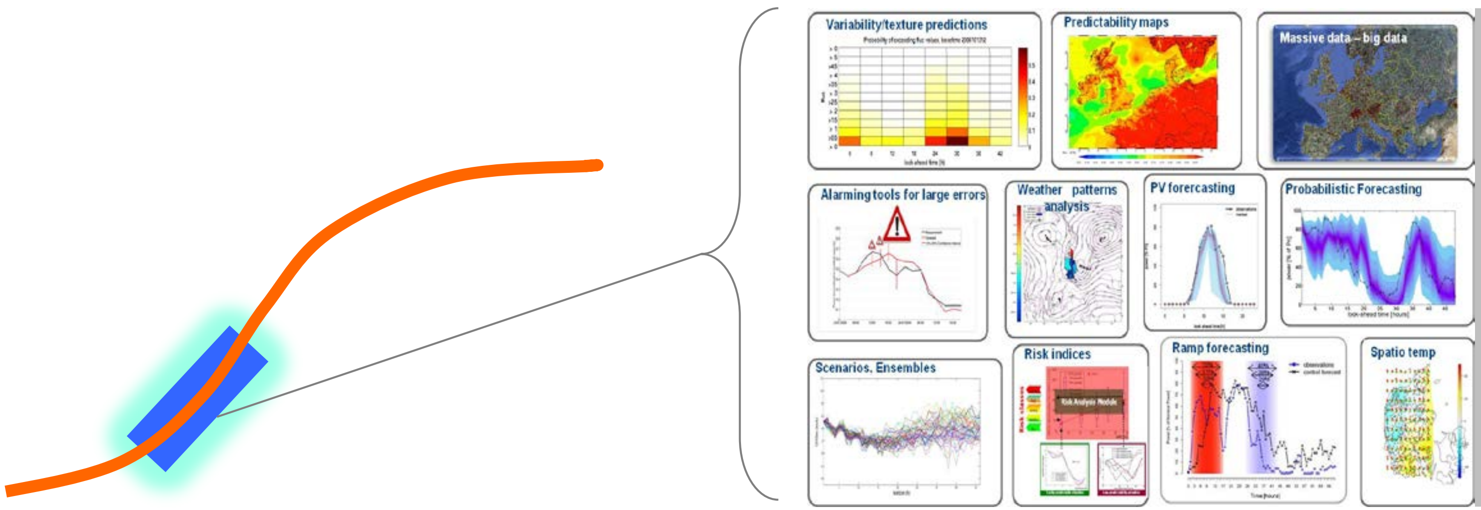
Perspectives



R&D for further improvement of wind predictability

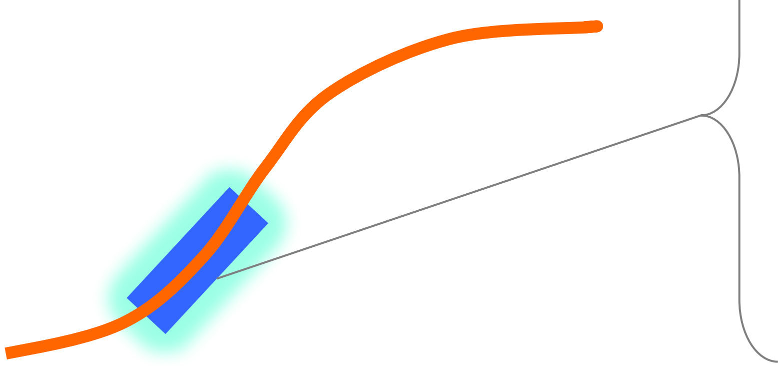
ACCURACY++

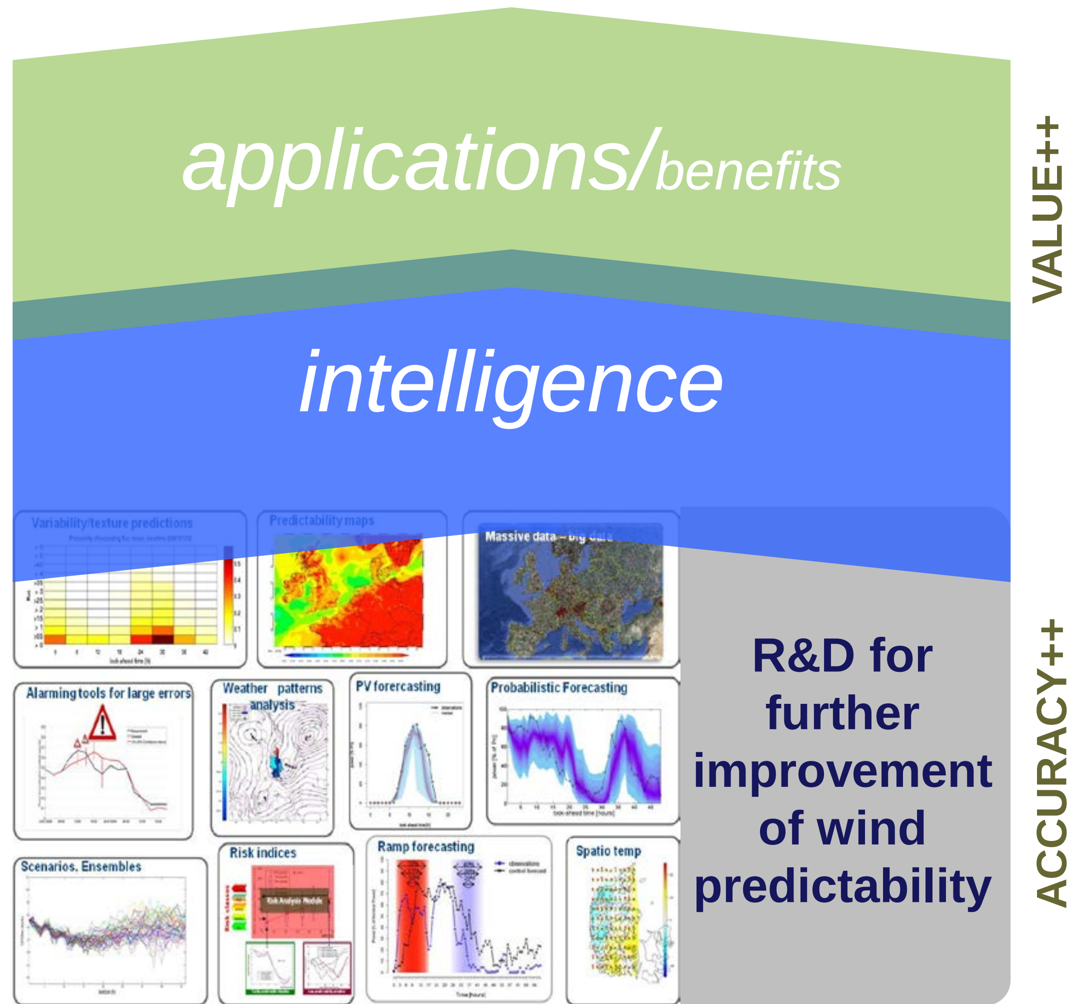
Perspectives

Développent of an

"intelligent" layer

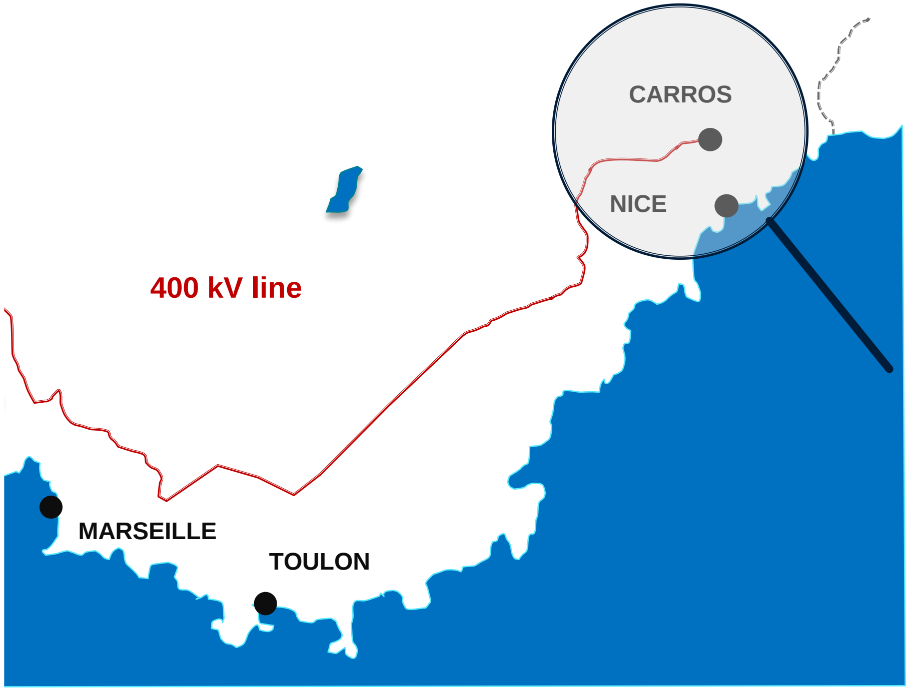
able to use the most relevant information and prediction products in a situation-dependent way, for optimising **decision making** under uncertainty in different applications





Developments on PV forecasting

- The Nice Grid demonstrator : Location & key figures



10 500
Inhabitants in Carros

2 300
Smart meters Linky

2,5 MWp
Solar PV capacity

1 300 kW
Storage power

30 M€
Overall budget

3,5 MW
Peak demand reduction

11
Companies involved in peak reduction

8
Public lightning sites involved

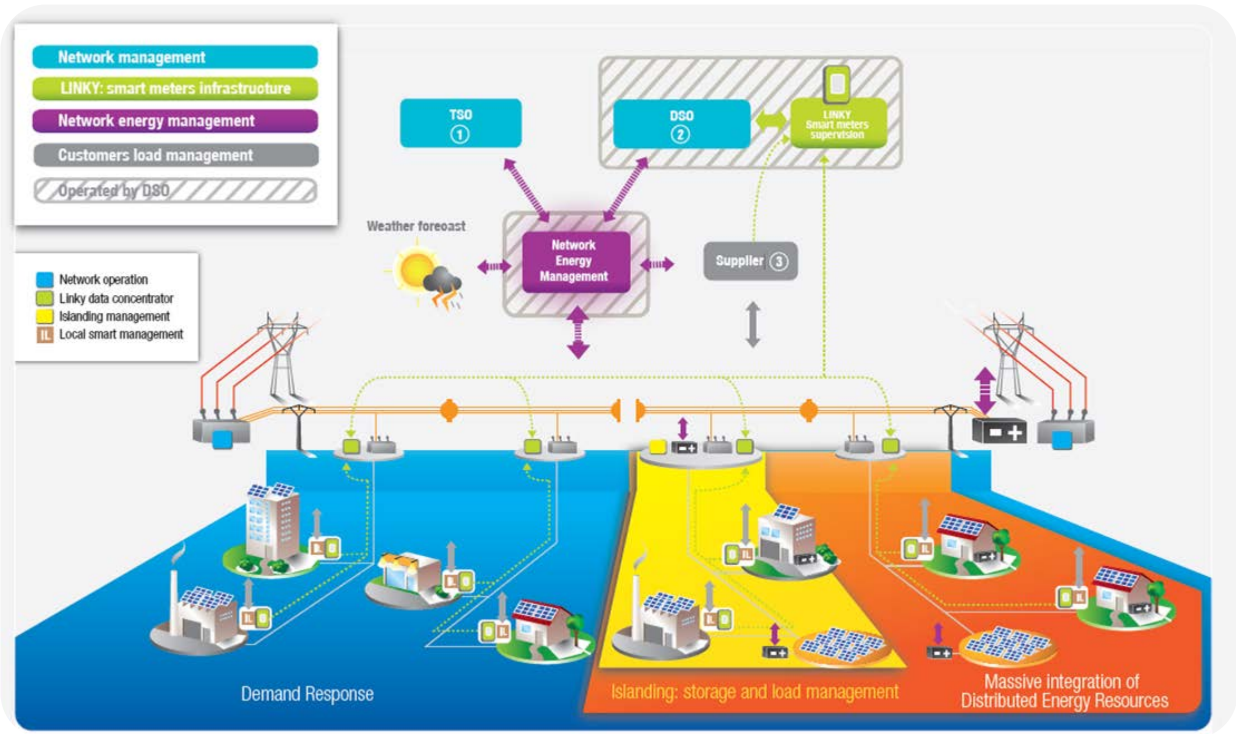
Overview of the demonstrator

- **4 OBJECTIVES**
  - **Increase MV/LV PV integration thanks to a "Network Energy Manager"**
  - **Study and model small customer response**
  - **Operate an LV microgrid on an Islanding mode**
  - **Study the business model**

- **4 USE CASES**
  - **Optimize massive PV integration in the distribution grid**
  - **Test islanding within a low voltage area**
  - **Test 3,5 MW load shedding within the area city of Carros**
  - **Incentivize prosumer behavior**

Overview of the demonstrator

- Energy management:
  - A combination of “centralised” and “decentralised” decision making.
  - A “centralised” approach based on a “local market” principle for flexibilities is implemented for the DSO (NEM-Network Energy Manager)
  - Actors like aggregators take decisions locally and interact with the NEM



The « intelligence » layer

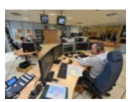
FLEXIBILITY DEMAND

TRANSMISSION SYSTEM OPERATOR LOAD SHEDDING REQUEST

Rte

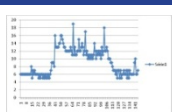
DISTRIBUTION SYSTEM OPERATOR LOAD SHEDDING REQUEST

eRDF ÉLECTRICITÉ RÉSEAU DISTRIBUTION FRANCE



CONSUMPTION FORECASTS D+1

EDF lab



PRODUCTION FORECASTS D+1

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OPTIMIZATION AND MANAGEMENT

eRDF ÉLECTRICITÉ RÉSEAU DISTRIBUTION FRANCE

NETWORK ENERGY MANAGER (NEM)

ALSTOM

FLEXIBILITY BIDS

B2B AGGREGATOR

COMPANIES & PUBLIC LIGHTNING

NetSeenergy GROUPE EDF

B2C AGGREGATOR

HOUSEHOLDS

edelia GROUPE EDF

NETWORK BATTERY AGGREGATOR (NBA)

GRID STORAGE ASSETS

eRDF ÉLECTRICITÉ RÉSEAU DISTRIBUTION FRANCE

36

PV forecasting

- Objective:
  - ✓ Generate **probabilistic** forecasts of the power production of all PV installations (on roofs and grid connected).
- Results:
  - ✓ Advanced statistical methods were developped and implemented into an operational module running at ERDF's production environnent

Historical PV generation
(training)

Surface solar radiation forecasts

Models:
- piecewise linear
- KDE

Forecasts for D and D+1 delivered to NEM at ~06:00 for
- **50+ PV plants**
- **between 2-200kWc**

Flowchart of the implemented operational software module

PV forecasting

- Objective:
  - ✓ Generate **probabilistic** forecasts of the power production of all PV installations (on roofs and grid connected).
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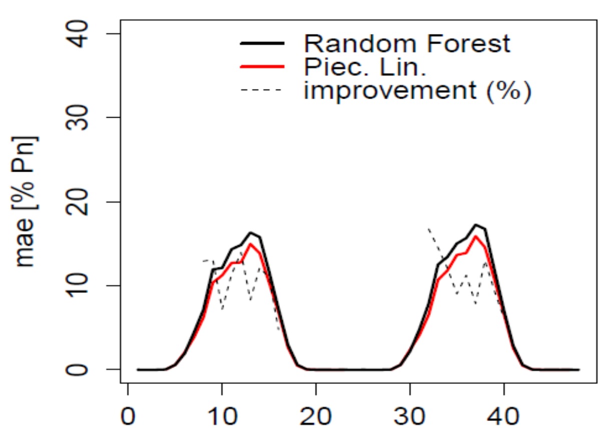
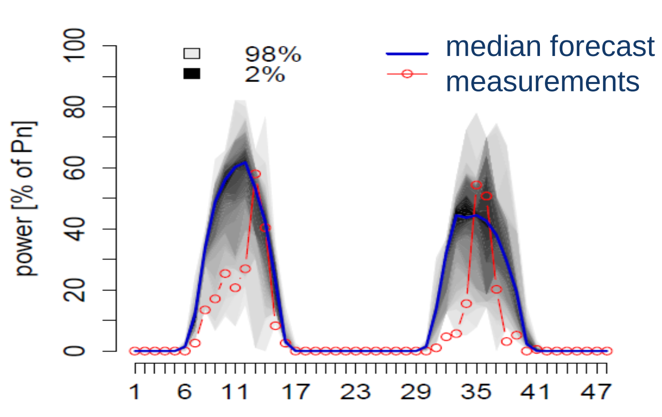
  - ✓ Advanced statistical methods were developped and implemented into an operational module running at ERDF's production environnent



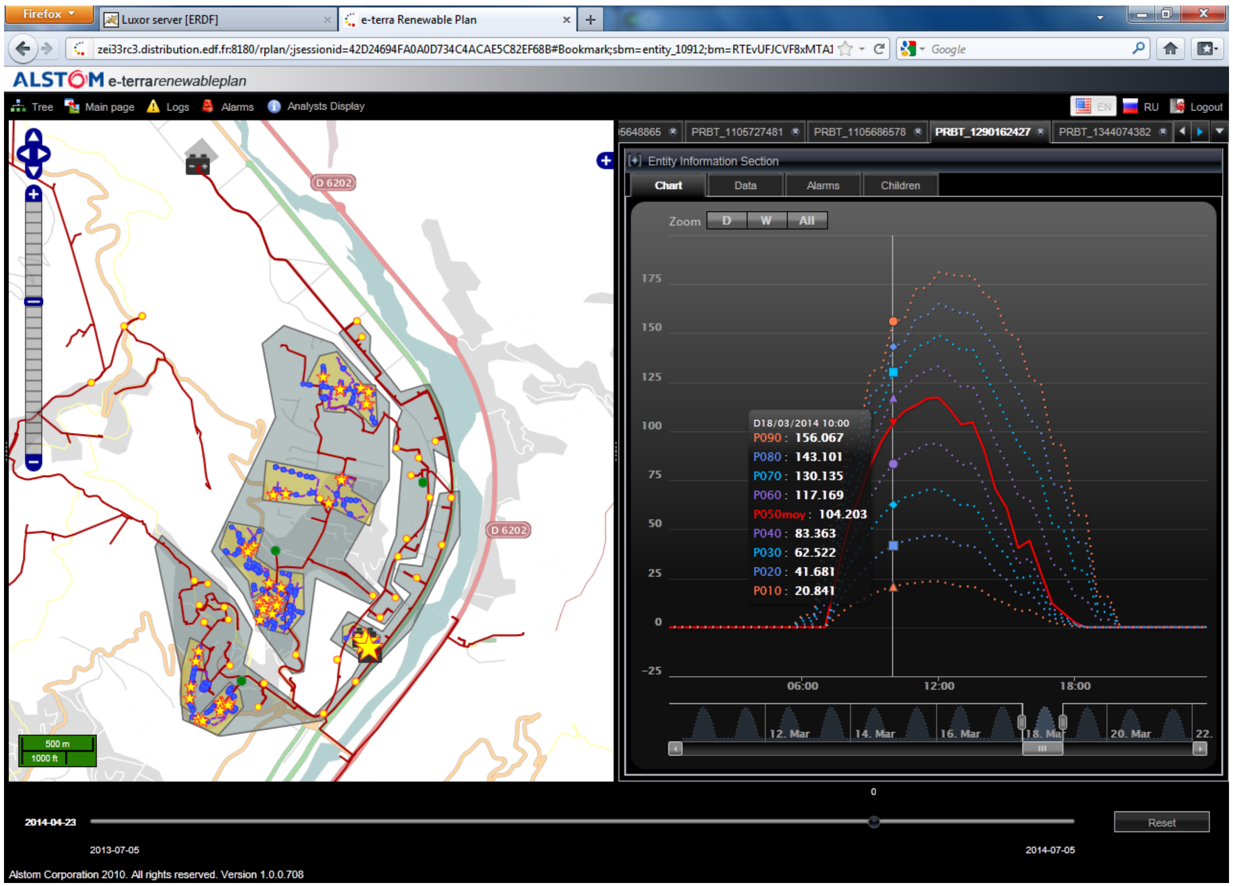
Mean Abs. Error performance of 2-day ahead forecasts of a large PV plant



Example of a 2-day head forecast of a large PV plant

PV forecasting

- Integration of forecasts in the NEM:



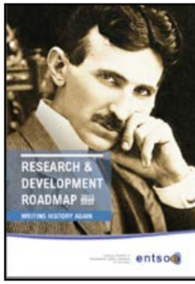
Conclusions

- Evolution to a more and more **weather-dependent power system**

- Continuous R&D effort needed to improve RES predictability.
  - R&D on probabilistic power system management tools required.

- RES forecasting is identified as a research priority within different research agendas (TPWind, Smartgrids, ENTSOE, IEA, EERA, ADEME, a.o.)

- Carrying out this research at EU level has proven a major driver for developing European **leadership** and **excellence** in the field.



Merci pour votre attention

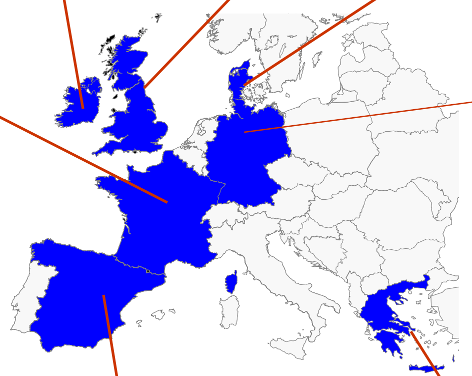
Short-term wind power forecasting

Coordination of 3 major EU projects (2002-2012)

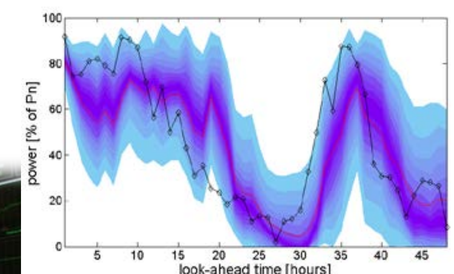
SafeWind

SEVENTH FRAMEWORK PROGRAMME

9 pays, 23 partenaires, 2008-2012
Budget: 5.6 Mio€
Coordinator: ARMINES – MINES ParisTech



INTERNATIONAL, INDIA

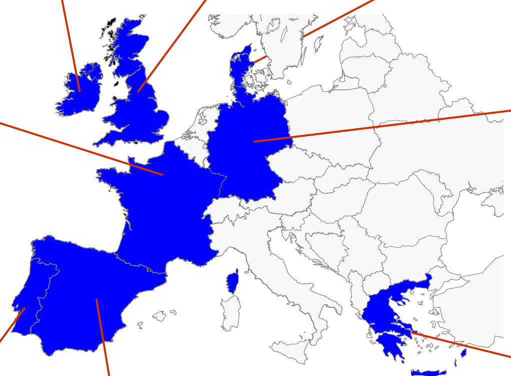


www.safewind.eu

Short-term wind power forecasting

Coordination of 3 major EU projects (2002-2012)

8 countries, 22 partners,
2008-2011
Budget: 5.7 Mio€
Coordinator : ARMINES - MINES ParisTech



www.anemos-plus.eu

7 countries, 23 partners,
2002-2006
Budget: 4.5 Mio€
Coordinator: ARMINES – MINES ParisTech

www.anemos-project.eu