Wind Forecasting

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P R D C®

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Outline

- Introduction
- Intermittency
- Challenges for High Renewable Integration
- Wind Forecast Methods
- Wind Power Forecast (WPF) - Tools

Introduction: Wind Power

Region	COUNTRY	End 2011	New 2012	End of 2012
Asia	**China**	**62,364**	**13,200**	**75,564**
	India	**16,084**	**2,336**	**19,052***
	Japan	2,536	88	2,614
Europe	**Germany**	**29,071**	**2,439**	**31,332**
	Spain	**21,674**	**1,122**	**22,796**
	UK	6,556	1,897	8,445
	Italy	6,878	1,273	8,144
	France**	6,792	404	7,196
	Portugal	4,379	145	4,525
	Denmark	3,956	217	4,162
	Sweden	2,899	846	3,745
North America	**USA**	**46,929**	**13,124**	**60,007**
	Canada	5,265	935	6,200
	Mexico	569	801	1,370
Pacific Region	Australia	2,226	358	2,584
	New Zealand	623	-	623

States	Installed Capacity (MW)
Tamil Nadu	7162
Gujarat	3175
Maharashtra	3022
Rajasthan	2685
Karnataka	2135

** by 31st March 2013*

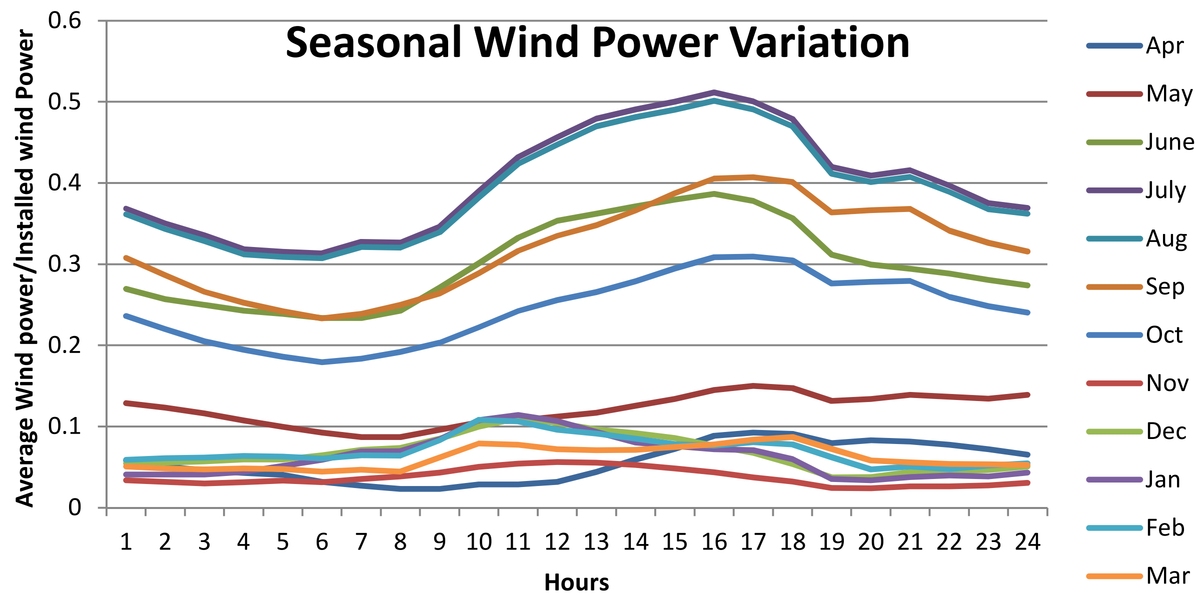
Introduction: Solar Power

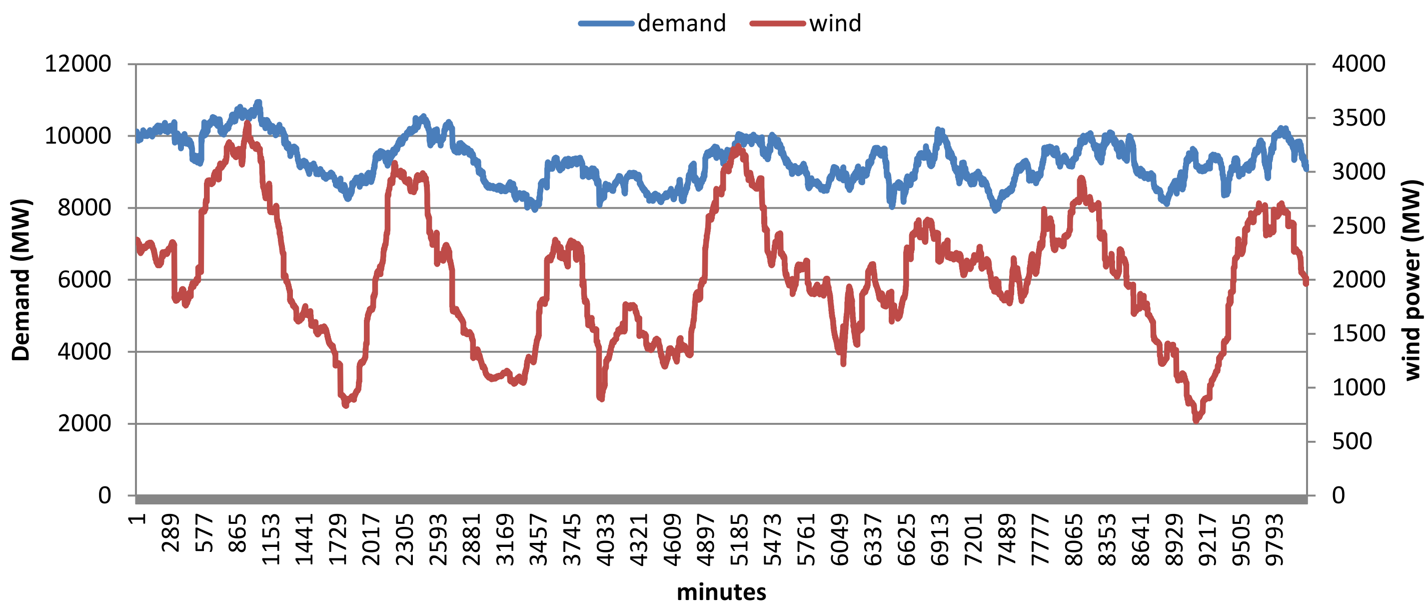
Region	Installed capacity in MW (by end of 2012)
Germany	32,509
Italy	16,987
China	8,043
United States	7,665
Japan	6,704
France	3,843
Australia	2,291
UK	1,831
India	1,440

States	Installed Capacity (MW)
Gujarat	824.09
Rajasthan	442.25
Maharashtra	34.5
Andhra Pradesh	23.15
Tamil Nadu	17.055
Jharkhand	16
Karnataka	14

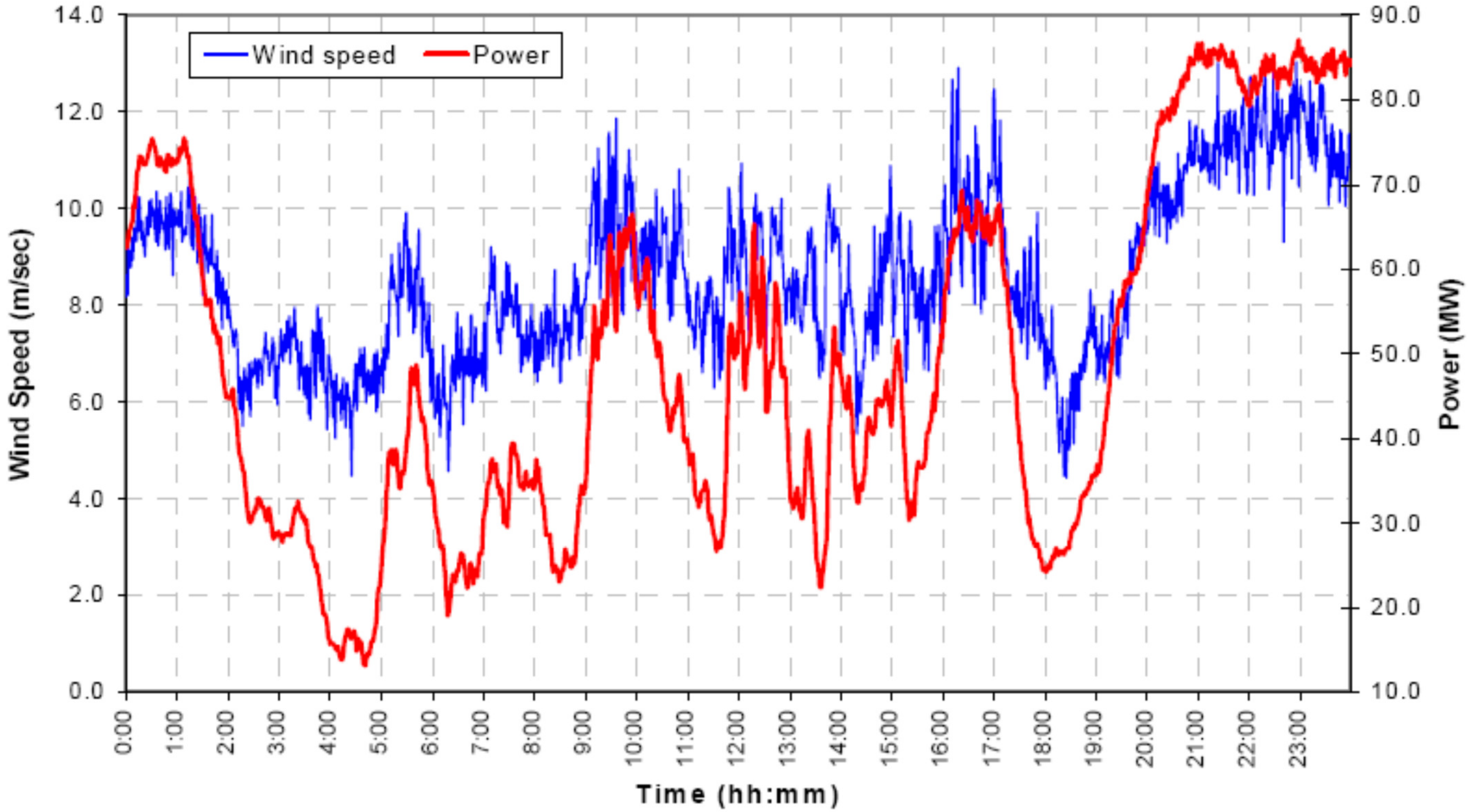
Intermittency

Wind Data Analysis

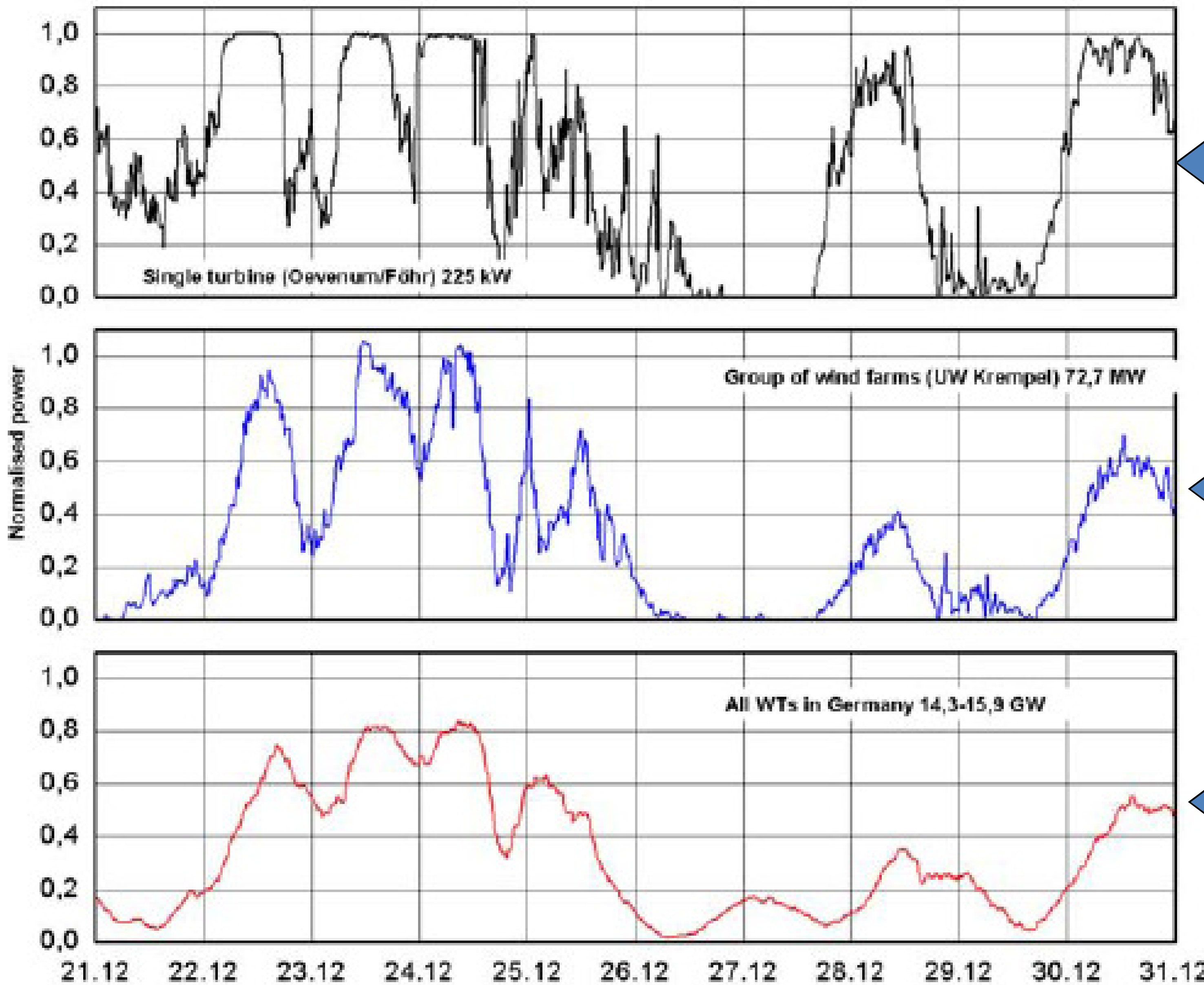




Variation of Wind speed and power Output



Wind output for single m/c., wind farm (72.7) and All wind farms (15900MW)



Variance
>80%

Variance
<40%

Variance
<10%

State Transition Rates with 1-Second Power Data

	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
10%	0.999	8E-04	0	0	0	0	0	0	0	0
20%	0.002	0.997	0.002	0	0	0	0	0	0	0
30%	0	0.002	0.996	0.002	0	0	0	0	0	0
40%	0	0	0.003	0.995	0.003	0	0	0	0	0
50%	0	0	0	0.003	0.993	0.004	0	0	0	0
60%	0	0	0	0	0.005	0.989	0.006	0	0	0
70%	0	0	0	0	0	0.007	0.986	0.007	0	0
80%	0	0	0	0	0	0	0.008	0.979	0.012	0
90%	0	0	0	0	0	0	0	0.01	0.976	0.014
100%	0	0	0	0	0	0	0	0	0.01	0.99

State Transition Rates with 1-Minute Average Power Data

	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
10%	0.9928	0.0072	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
20%	0.0140	0.9679	0.0181	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30%	0.0	0.0212	0.9560	0.0228	0.0	0.0	0.0	0.0	0.0	0.0
40%	0.0	0.0	0.0318	0.9385	0.0296	0.0001	0.0	0.0	0.0	0.0
50%	0.0	0.0	0.0	0.0374	0.9297	0.0328	0.0001	0.0	0.0	0.0
60%	0.0	0.0	0.0	0.0	0.0405	0.9187	0.0408	0.0	0.0	0.0
70%	0.0	0.0	0.0	0.0	0.0	0.0435	0.9161	0.0403	0.0001	0.0
80%	0.0	0.0	0.0	0.0	0.0	0.0001	0.0459	0.9076	0.0464	0.0
90%	0.0	0.0	0.0	0.0	0.0	0.0	0.0001	0.0359	0.9376	0.0265
100%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0191	0.9809

State Transition Rates with Hourly Average Power Data

	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
10%	0.857	0.12	0.017	0.004	0.002	0.0005	0	0	0	0
20%	0.22	0.495	0.198	0.07	0.012	0.0026	0.0018	0.003	0	0
30%	0.045	0.242	0.425	0.209	0.046	0.0228	0.0089	0.002	0	0
40%	0.005	0.08	0.276	0.344	0.177	0.0764	0.0306	0.009	0.0013	0
50%	0.003	0.013	0.132	0.211	0.317	0.1805	0.0959	0.031	0.013	0.003
60%	0	0.009	0.03	0.103	0.24	0.3132	0.1833	0.089	0.0249	0.007
70%	0	0.004	0.008	0.044	0.103	0.2447	0.2849	0.224	0.0803	0.008
80%	0	0	0.007	0.005	0.035	0.0726	0.2341	0.359	0.2523	0.035
90%	0	0	0	0.003	0.013	0.0217	0.0562	0.18	0.6066	0.12
100%	0	0	0	0	0	0.0028	0.0028	0.021	0.1487	0.824

Challenges: Forecasting & Scheduling

- The important challenges include scheduling, system control and dispatch; Reactive power supply and voltage control; Regulation and frequency response reserve; Energy imbalance service; operating synchronized reserve and supplemental reserve.
- Incorporation of Wind Power Forecasting (WPF) in real time power system day-to-day operational planning.
- A survey of grid operators worldwide** found near unanimous agreement that integrating a significant amount of wind will largely depend on the accuracy of wind power forecast.

*** Lawrence E. Jones, Strategies and Decision Support Systems for Integrating Variable Energy Resources in Control Centers for Reliable Grid Operations (Washington, DC: Alstrom Grid, Inc., 2011),*

Challenges: Forecasting & Scheduling

- The world wide figures of day-ahead hourly load forecast errors are typically in the range of 1% to 3%.
- Wind forecasts typically have errors in the range of 15% to 20% mean absolute error (MAE) for a single wind plant.
- Even with available forecasts, large-scale wind integration studies have demonstrated that using day-ahead wind power forecasts for unit commitment can dramatically improve system operation by reducing overall operating costs, reducing unserved energy, and reducing wind curtailment, while maintaining required levels of system reliability.

Wind Power Forecasting

Wind Forecasting & Its Applications

- With the increasing penetration of wind power, wind power forecasting (WPF) is an important tool to help efficiently address wind integration challenge, and significant efforts have been invested in developing more accurate wind power forecasts.
- WPF Applications
  - Allocation of reserves based on the expected wind power feed.
  - Optimization of the scheduling of conventional power plants by functions such as economic dispatch etc.
  - Optimization of the value of the produced electricity in the market. Such predictions are required by different types of end-users (utilities, TSOs, etc.) and for different functions such as unit commitment, economic dispatch, dynamic security assessment, participation in the electricity market, etc.
  - Additionally, even longer time scales (7 days) would be interesting for the maintenance planning of large power plant components, wind turbines or transmission lines.

WPF: Time Horizons

Time Horizons	GENCOs	SO
Very Short-term (up to 9 hrs)	Intraday market Real-time market	Ancillary services management Balancing resources Unit commitment Economic dispatch Congestion management
Short-term (up to 72 hrs)	Day-ahead market Maintenance planning of wind farms Wind farm and storage device coordination	Maintenance planning of network lines Congestion management Day-ahead reserve setting Unit commitment & economic dispatch
Medium-term (up to 7 days)	Maintenance planning of wind farms Maintenance planning of conventional generation	Maintenance planning of network lines

Forecast Terminology

Long term Forecast
Upto 2 weeks

↓

Medium term Forecast
12 to 72 hours

↓

Short term Forecast
1 to 12 hours

↓

Nowcasting
Less than an hour

Wind Forecasting Methods

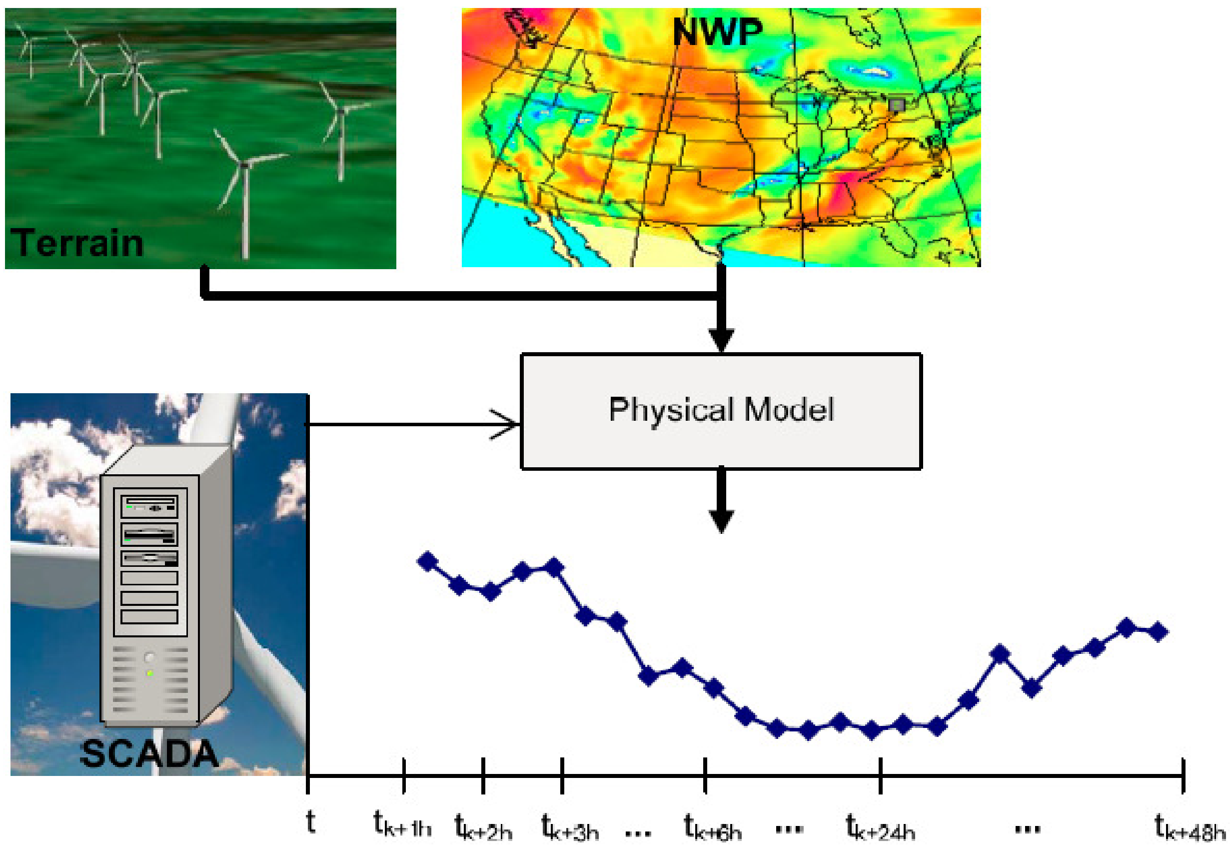
- Physical approach
  - It focuses on the description of the wind flow around and inside the wind farm, in addition to using the manufacturer's power curve in order to propose an estimation of the wind power output.
  - It consists of several sub models, which together deliver the translation from the NWP forecast at a certain grid point and model level, to power forecast at the considered site and at turbine hub height.

Wind Forecasting Methods

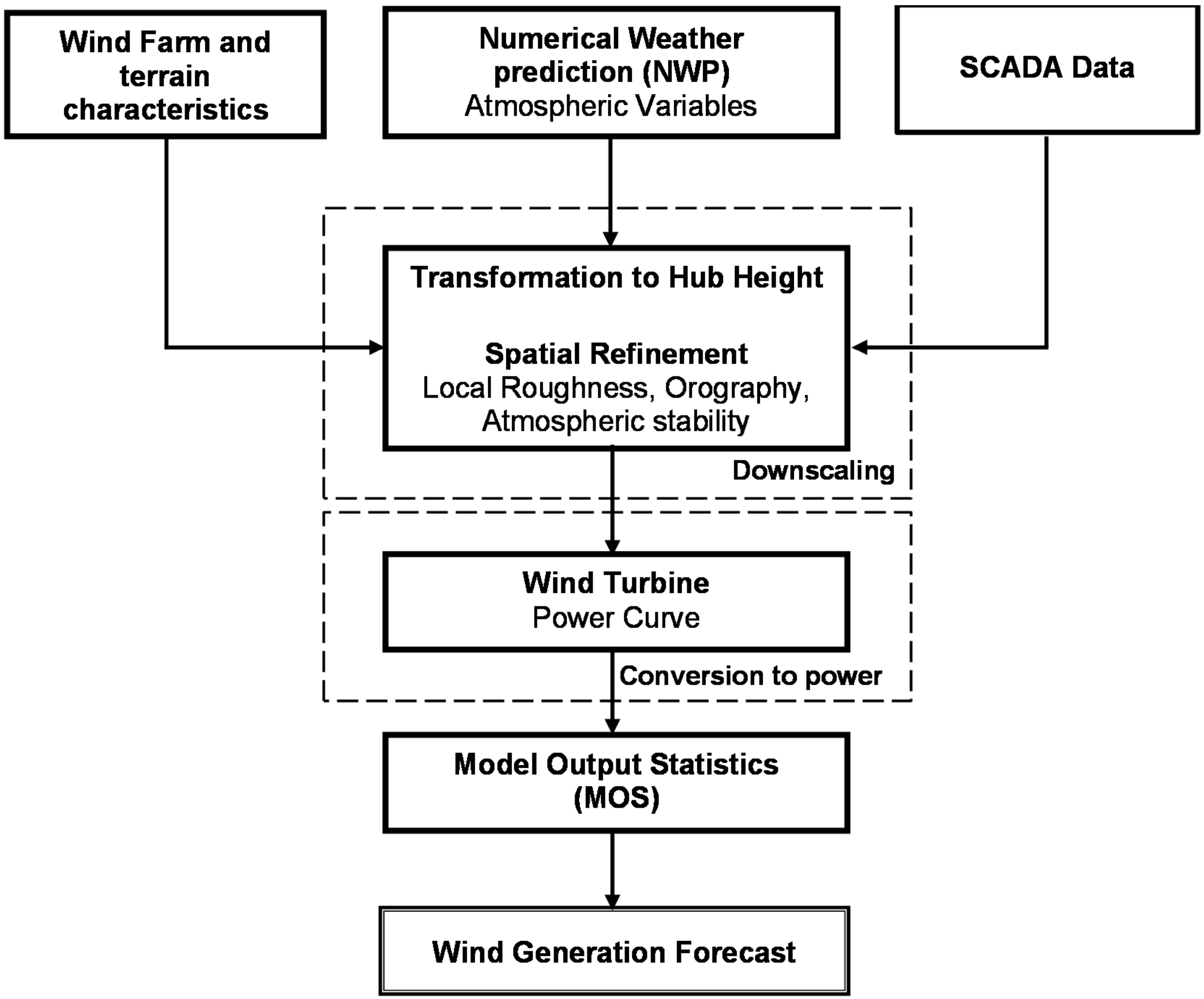
- Statistical approach
  - It consists of emulating the relation between meteorological predictions, historical measurements and generation output through statistical models whose parameters have to be estimated from data, without taking any physical phenomena into account.
- Hybrid approach
  - There are some WPF systems that combine the two approaches in order to join the advantages of both approaches and thus improve the forecasts.

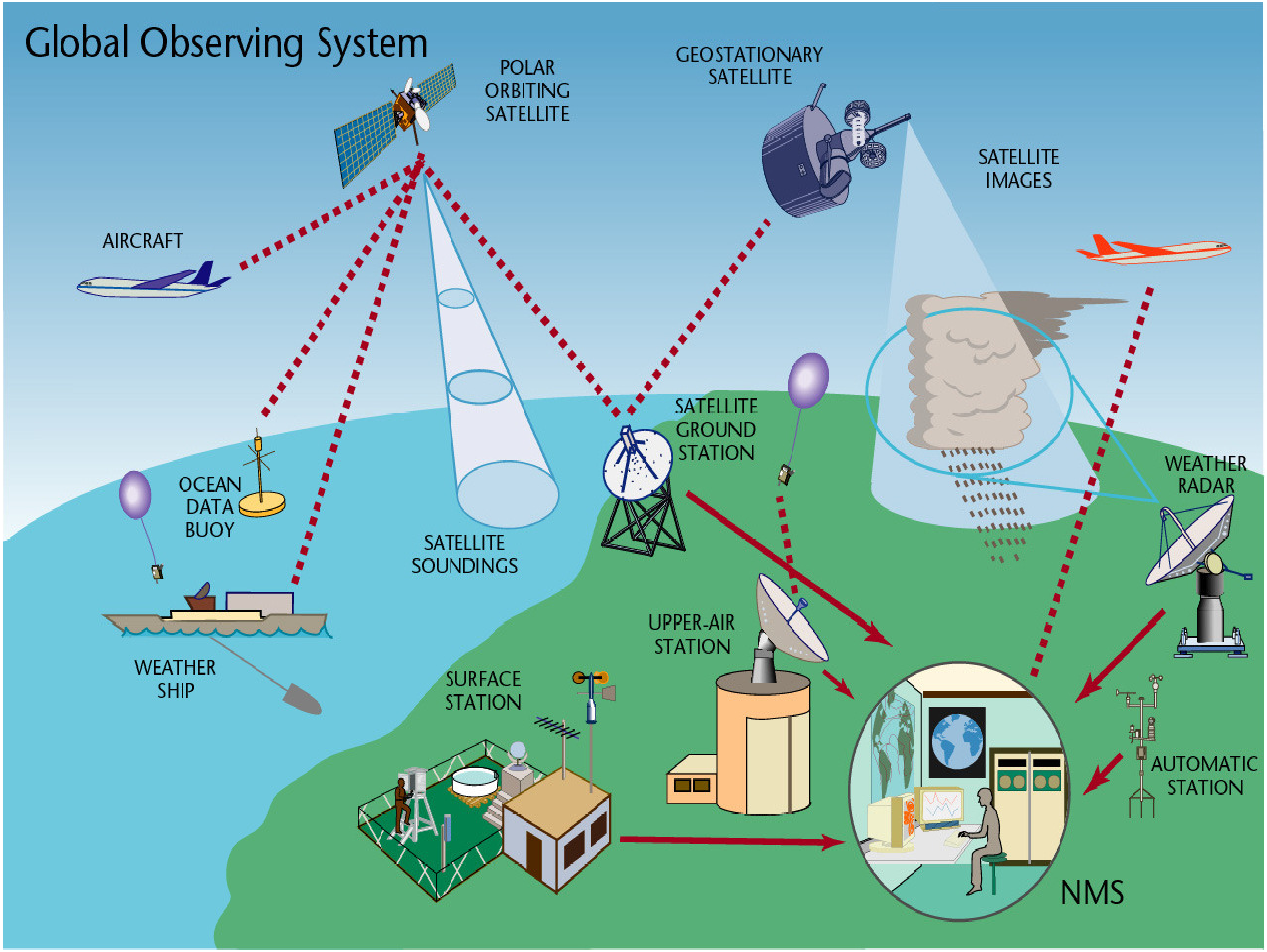
Physical Approach

- The two main steps are downscaling and conversion to power.

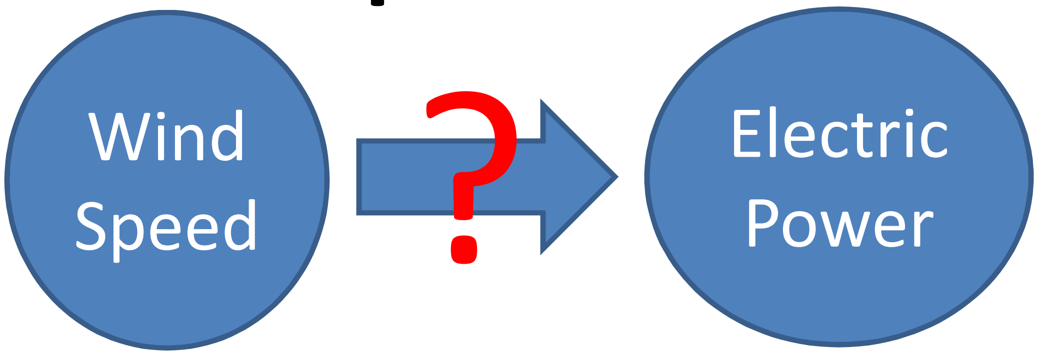


Physical Approach



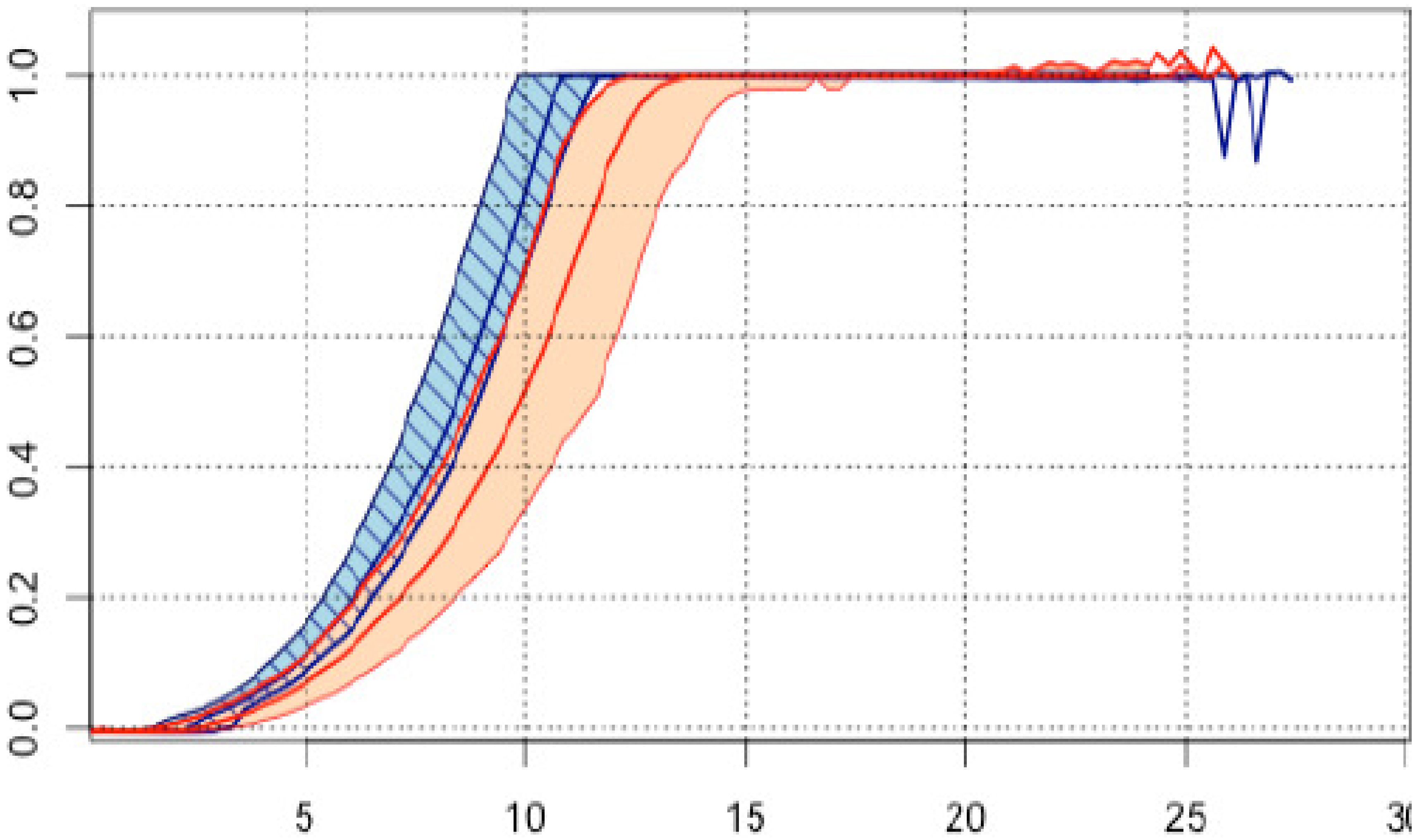

Global Observing System
POLAR ORBITING SATELLITE
GEOSTATIONARY SATELLITE
SATELLITE IMAGES
AIRCRAFT
SATELLITE GROUND STATION
OCEAN DATA BUOY
SATELLITE SOUNDINGS
WEATHER RADAR
UPPER-AIR STATION
WEATHER SHIP
SURFACE STATION
AUTOMATIC STATION
NMS

Wind Speed to Power



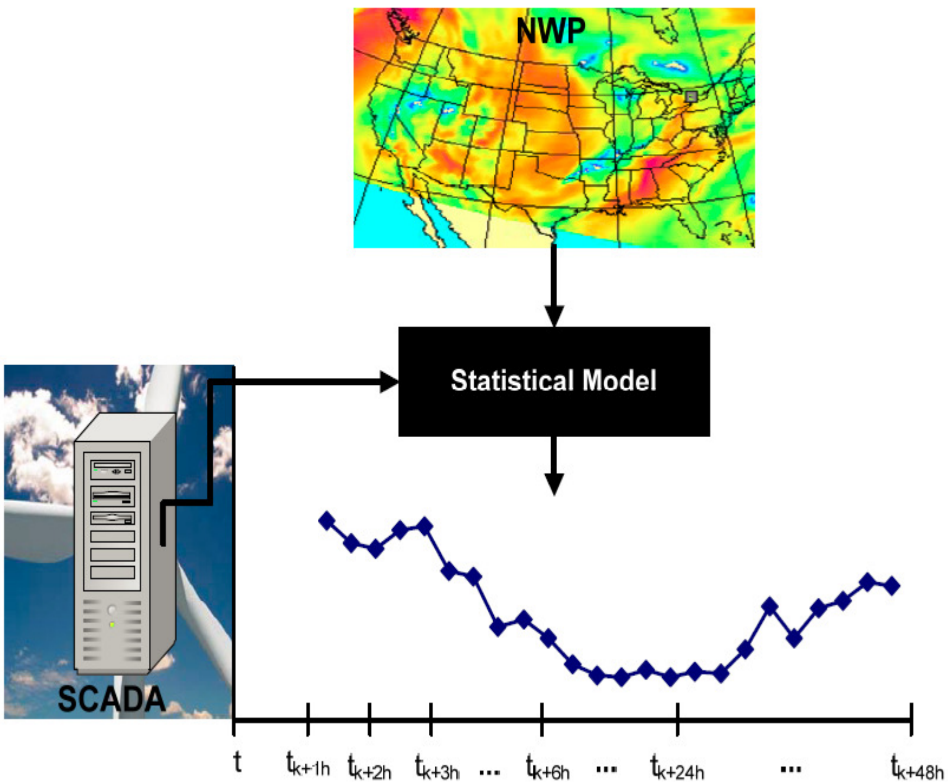
- Formulating wind generation from Wind speed
  - Wind speed interpolated to site from Meso Scale Forecast
  - Gross production estimate from turbine power curve
  - Subtract wind farm losses
    - Wake Losses – strong direction dependence
    - Availability losses
    - Environmental losses

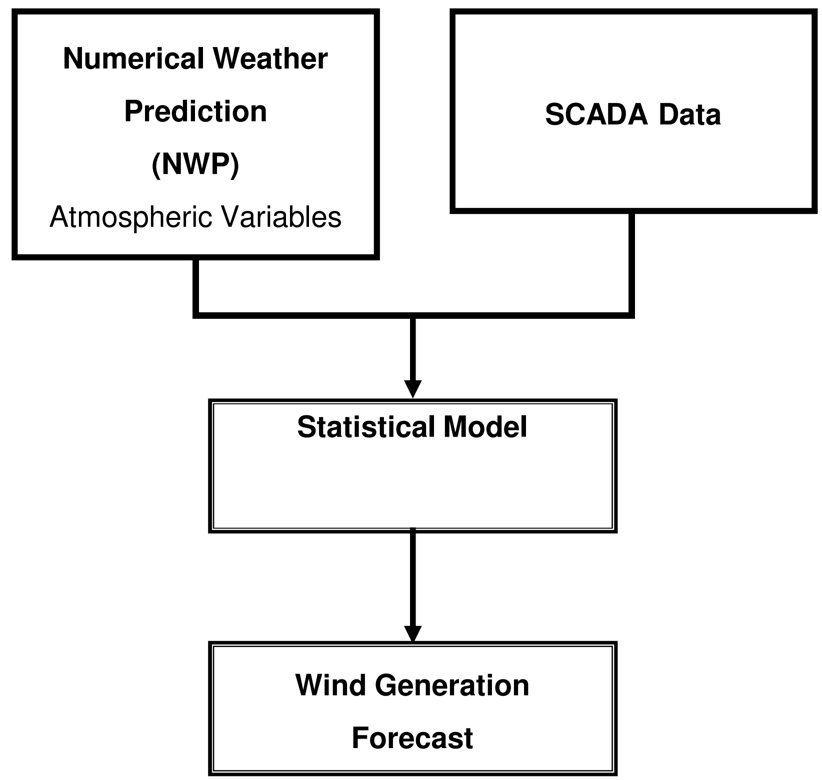
Wind Power Curve



Statistical Approach

Statistical block is able to combine inputs such as NWPs of the speed, direction, temperature, etc., of various model levels, together with on-line measurements, such as wind power, speed, direction, and others.





Statistical Approach

- Persistence Models: Persistence wind speed or wind power forecasting assumes that the wind (speed and direction) or power at a certain future time will be the same as it is when the forecast is made, which can be formulated as $p_{t+\Delta t} = p_t$.
- The very short-term forecasting approach consists of statistical models based on the time series approach, such as the Kalman Filters, Auto-Regressive Moving Average (ARMA), Auto- Regressive with Exogenous Input (ARX), and Box-Jenkins forecasting methods.
- The statistical models only take inputs like past values from the forecasted variable (e.g., wind speed, wind generation). At the same time, they can also use other explanatory or independent variables (e.g., wind direction, temperature), which can reduce the forecast error.
- For time horizons greater than 6 hours, NWPs would be used as inputs.

Statistical Approach

- ✓ From the statistical point of view, these models can be called univariate/ multivariate models. The univariate model only considers past values of wind power generation p.

$$p_{t+\Delta t} = f(p_t, p_{t-1}, \dots \dots, p_{t-n}) + e_t \quad \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (1)$$

where, e_t is white noise and f is a generic function that can be linear or nonlinear.

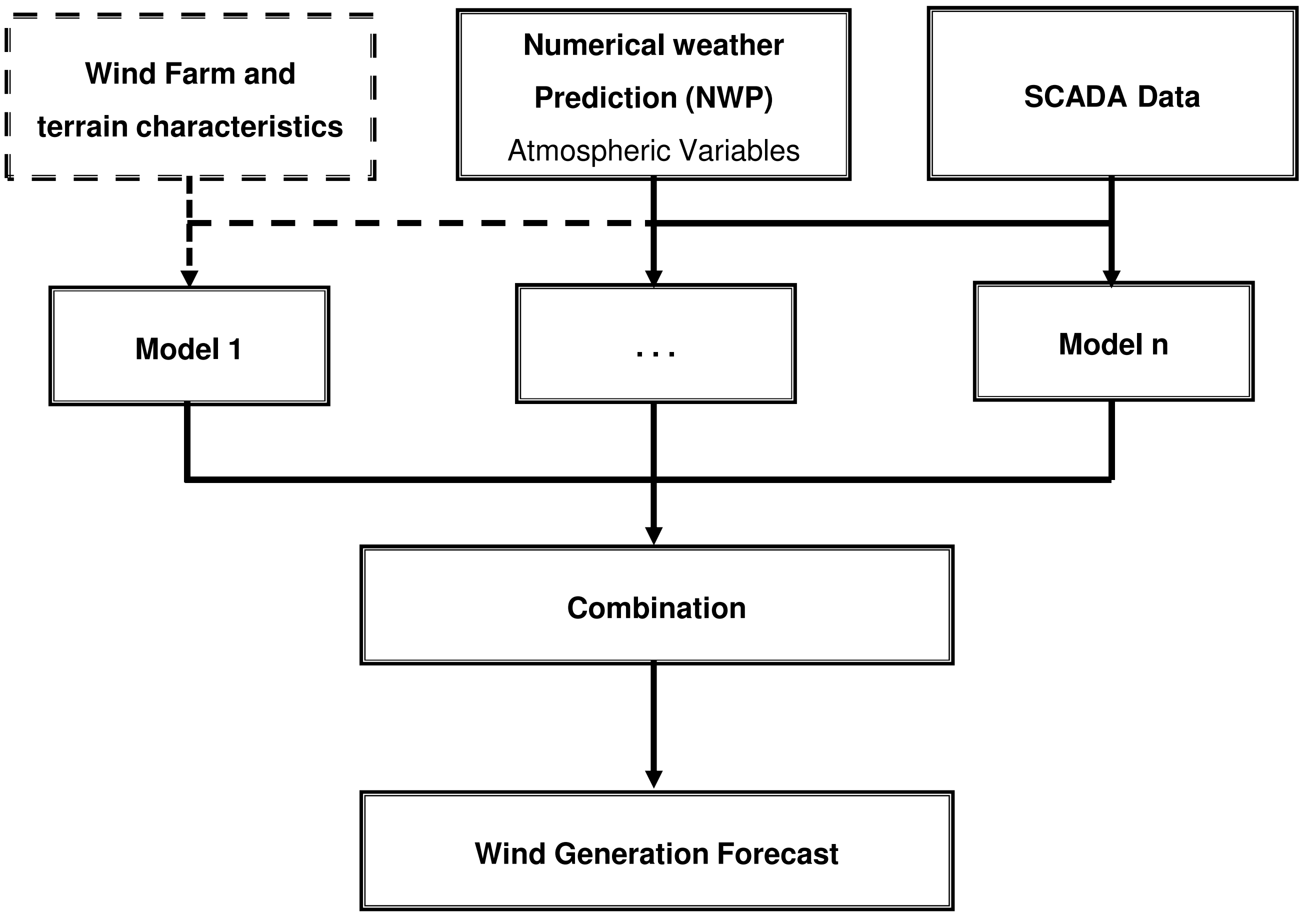
- ✓ The multivariate models not only use past values of that variable, but also past or present values of other variables. These past values (e.g., on-site meteorological data, active generation) are measured by the wind farm's SCADA system.

The multivariate model can be expressed as,

$$p_{t+\Delta t} = f(p_t, p_{t-1}, \dots \dots, p_{t-n}, \qquad x_t, x_{t-1}, \dots \dots, x_{t-n}) + e_t \quad \dots \dots \dots \dots (2)$$

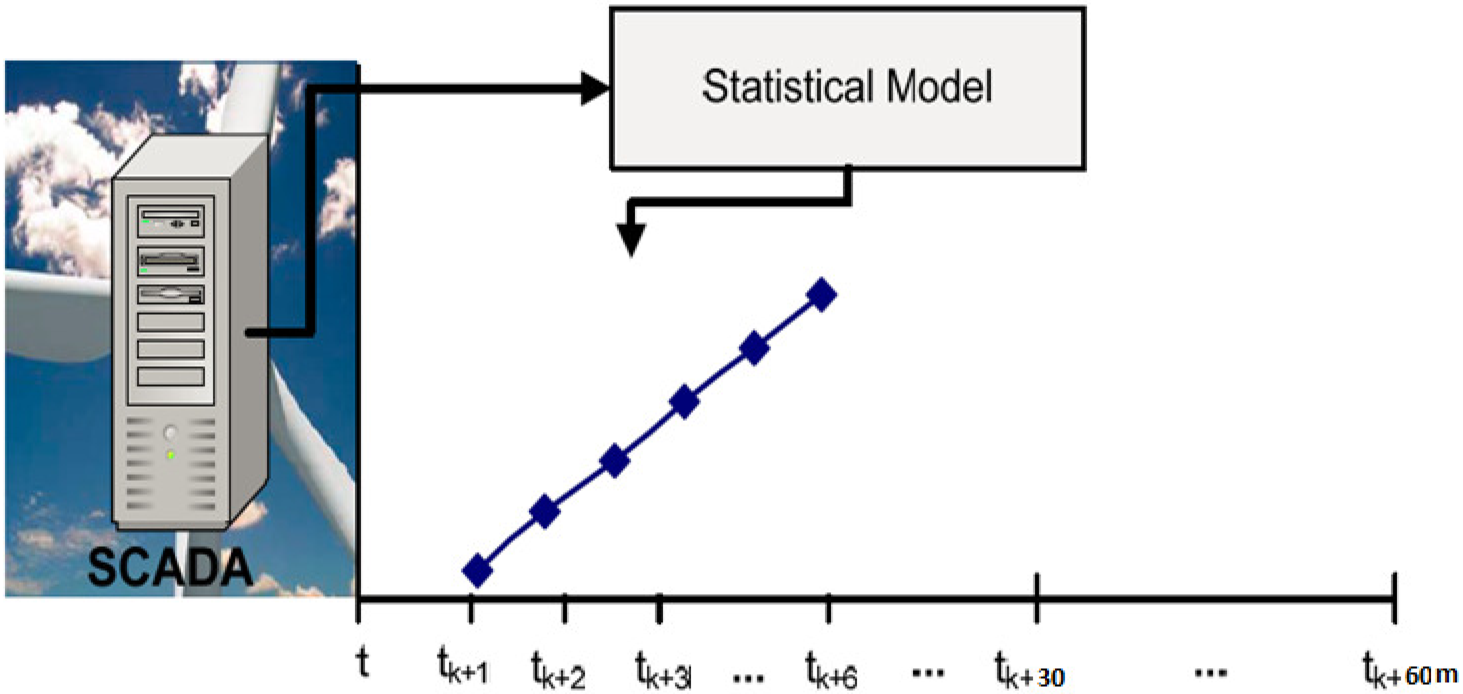
Hybrid Approach

The hybrid model benefits from the high accuracy of the time series models in short-time horizons and also from the high levels of accuracy of the physical models for horizons between 6 and 72 hours.



Wind Forecasting Methods: Nowcasting

- ✓ **Nowcasting structure**



- ✓ The alternative to using these models depends on the purpose of the forecasts, and so a trade-off between NWP costs and the utility of the forecast should be measured. *As an example, if the WPFs are inputs to a unit commitment or dispatch algorithm for horizons ranging from 10 min. to 1 hour, the use of very-short forecasts is enough and no additional costs with NWP are necessary.*

Wind Forecasting Methods: Short term

- The main feature that distinguishes the approaches has to do with the way predictions of meteorological variables are converted to predictions of wind power generation through the power curve.
- WPF with Numerical Weather Prediction
    - Physical Approach
    - Statistical Approach
    - Hybrid Approach
    - Regional Forecasting (Upscaling)

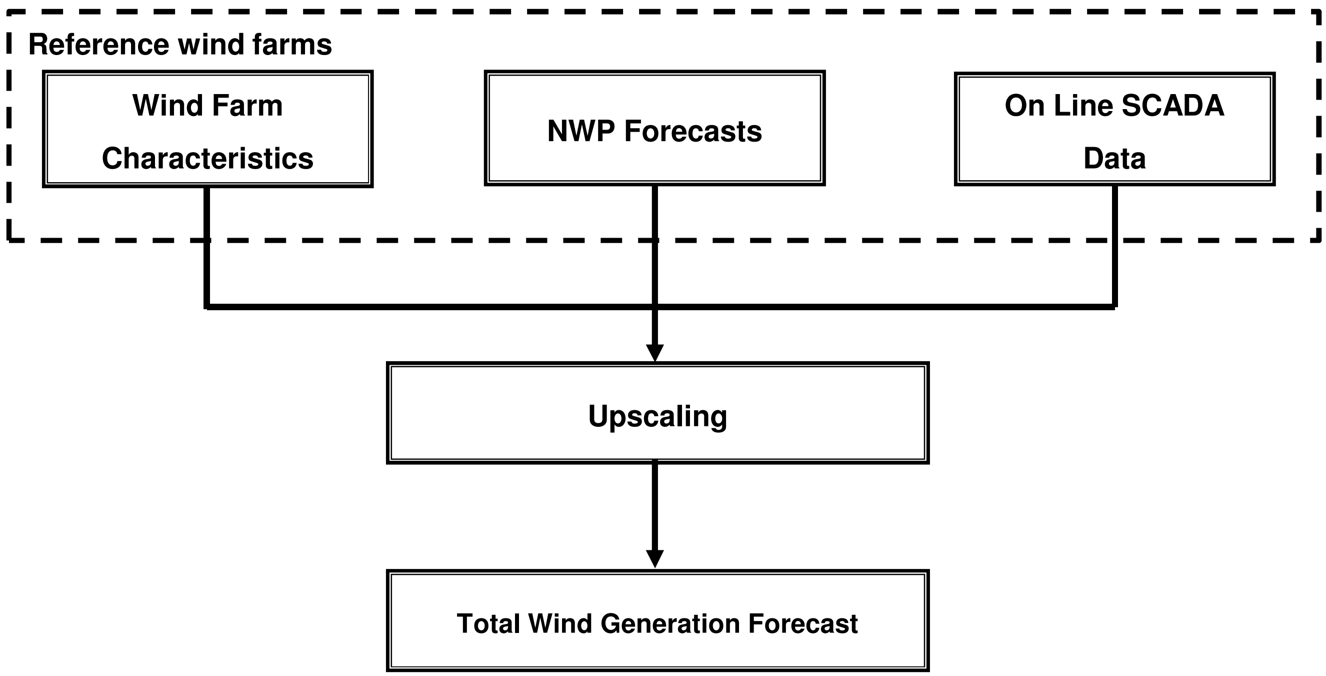
Regional Forecasting (Upscaling)

- The on-line information measured by the SCADA systems is not available because it is only mandatory to install the system in large wind farms.
- It would not possible to have NWP predictions for all wind farms under its control area because that involves high computational effort and costs.
- To overcome this problem, upscaling approaches have been developed to forecast multiple wind farms in an area or region/state wind generation from a sample of reference wind farms.
- Further, the aggregation of wind farms appears to reduce the forecast error as a result of spatial smoothing effects.
- Methods in Regional Forecasting;
  - Direct Upscaling
  - Cascaded Approach
  - Cluster or Sub regions Approach

➢ Regional Forecasting (Upscaling): *Direct Upscaling*

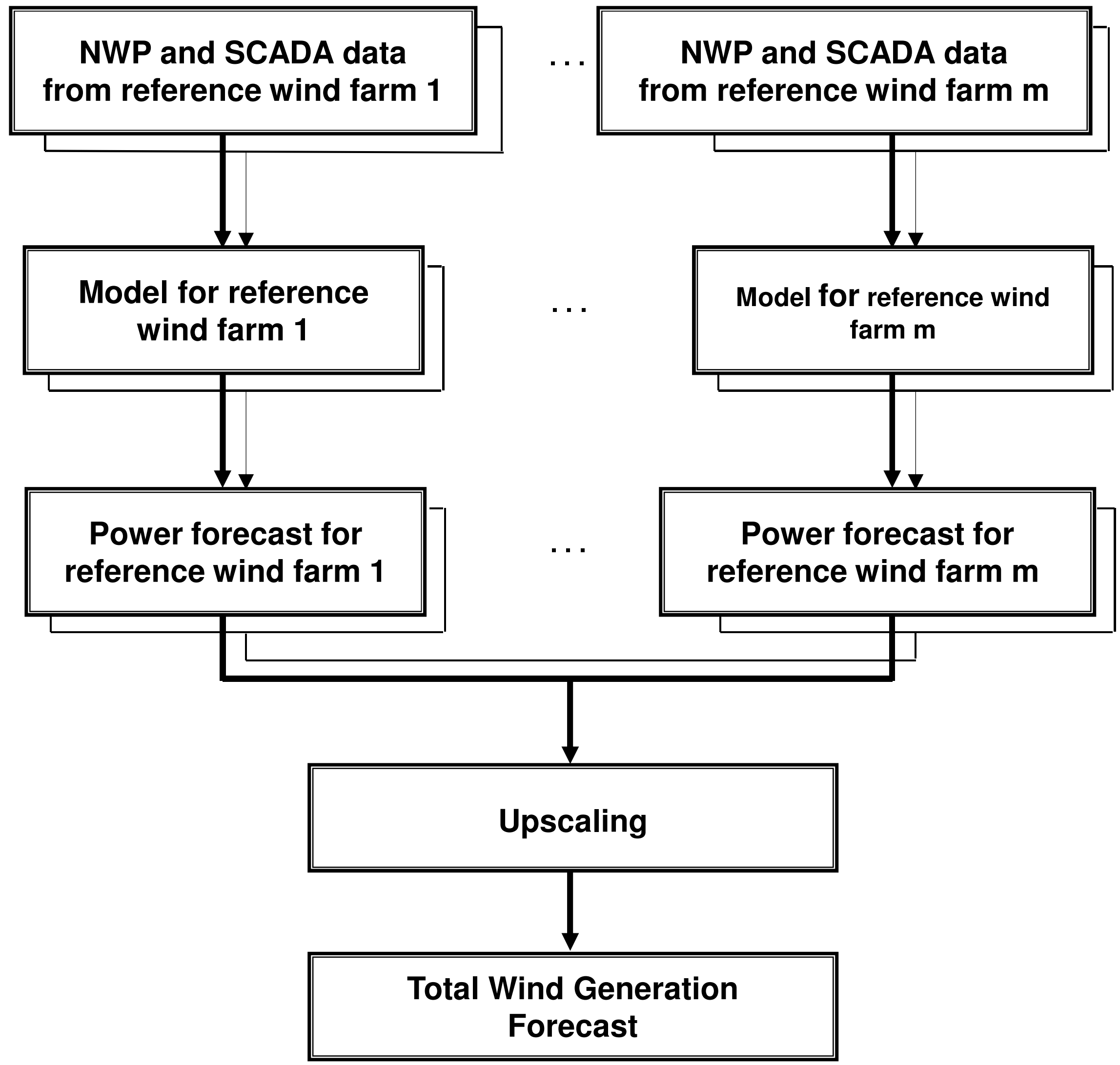
- ✓ The upscaling model is designed and trained to provide forecasts for the regional wind power directly by using input from these reference wind farms.

- ✓ The main difficulty with this approach is that the function has to be updated if new wind farms are added to the system.



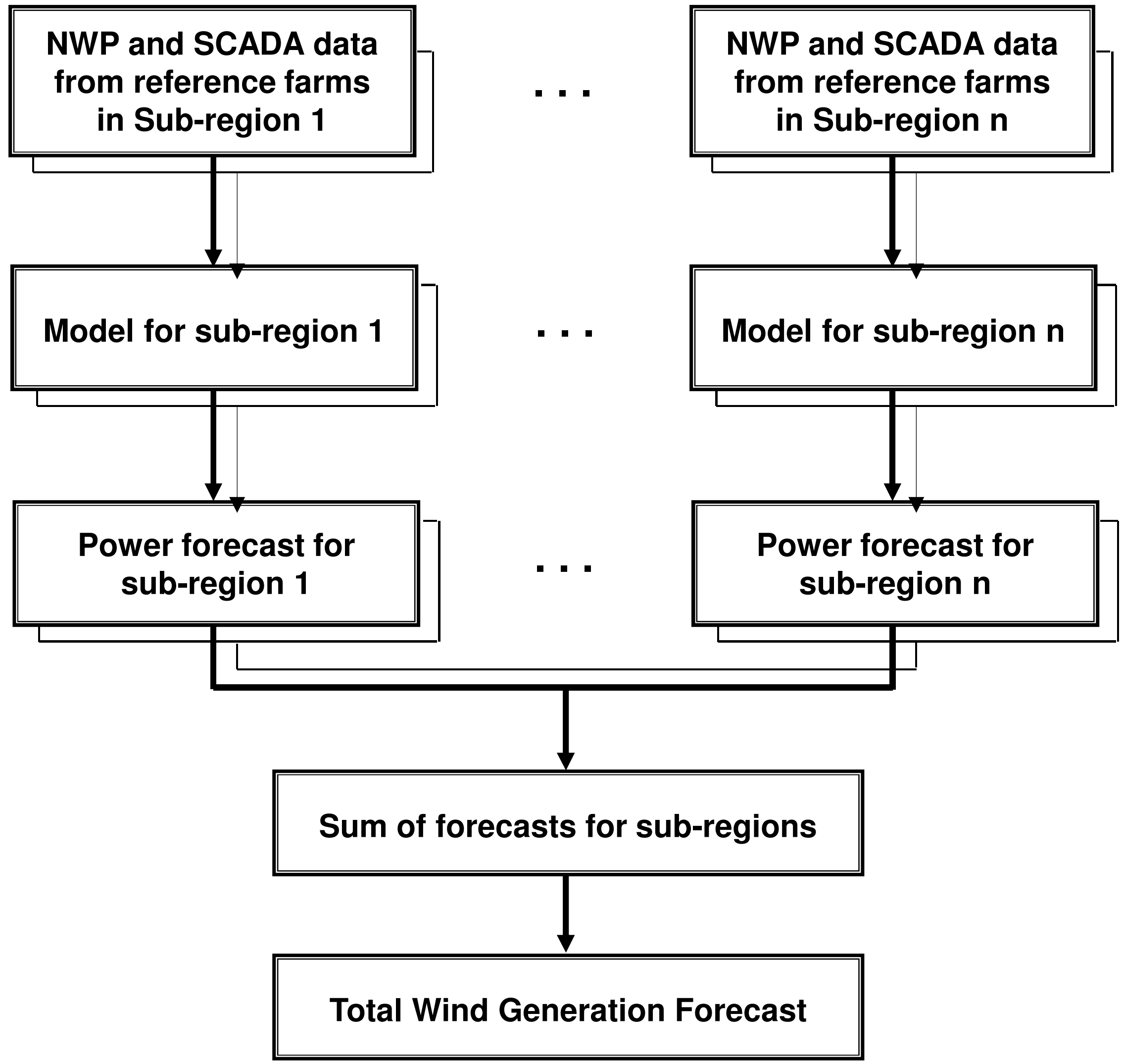
Regional Forecasting (Upscaling): *Cascaded Approach*

- ✓ The cascaded approach is the one that is mainly used today for upscaling. It considers two forecasting stages: first, the generation of the reference wind farms is estimated, and then the sum is extrapolated to the total region/State generation



Regional Forecasting (Upscaling): *Cluster or Sub regions Approach*

✓ This approach is based on aggregating wind farms into clusters that contain neighboring wind farms or wind farms belonging to the same sub region.



EVALUATION OF WIND POWER FORECASTS

- Evaluation of the quality of forecasting methods is conducted by comparing wind power predictions made at a certain time directly with the actual corresponding observations.
- The quality of forecasting methods will be quantified in terms of their statistical performance.
- As far as wind power forecasting is concerned, the prediction error observed at a given time $t+k$ for a prediction made at time origin e_{t+k}, is defined as the difference between the value of wind power that is effectively measured at $t+k, P_{t+k}$ and the value of wind power at $t+k$ that was originally predicted at $t, \widehat{P}_{t+k}$

$$e_{t+k} = P_{t+k} - \widehat{P}_{t+k}$$

EVALUATION OF WIND POWER FORECASTS

- It is often convenient to use the normalized prediction error e, which can be obtained by dividing the prediction error by the wind installed capacity P_{inst},

$$e_{t+k} = \frac{P_{t+k} -, \widehat{P}_{t+k}}{P_{inst}}$$

- The usefulness of normalizing prediction errors creates the possibility of obtaining results that can be compared from one wind farm to another, regardless of their rated capacity.
- This produces results that do not depend on wind farm sizes.

EVALUATION OF WIND POWER FORECASTS

- ✓ A common error measure to identify the contribution of both positive and negative errors to a forecasting method's lack of accuracy is the Mean Square Error (MSE), which consists of the average of the squared errors over the test set:

$$MSE_k = \frac{1}{N}\sum_{t=1}^{N} e_{t+k}^2$$

- ✓ Besides the MSE, there are two other basic criteria to illustrate a model's performance: the Mean Absolute Error (MAE) and the Root Mean Square Error, or RMSE.

The MAE is:

$$MAE_k = \frac{1}{N}\sum_{t=1}^{N} |e_{t+k}|$$

The RMSE corresponds to the square root of the MSE:

$$RMSE_k = \sqrt{MSE_k}$$

- ✓ The MAE and RMSE, divided by the installed capacity or the average production of the wind farm, are called NMAE (Normalized Mean Absolute Error) and NRMSE (Normalized Root Mean Square Error).

RECENT TRENDS IN WPF – UNCERTAINTY ESTIMATION

- Short-term forecasting tools that are widely in use provide single-valued point (or spot) forecasts.
- The main drawback of point forecasts is that no information is provided on the dispersion of observations around the predicted value.
- The uncertainty estimation in wind power forecasting is a complex subject that depends on several factors that influence the wind power forecast uncertainty:
  - NWP forecasts partially contribute to the forecasting error,
  - The nonlinearity of the power curve - the different W2P models, may lead to significant differences between WPF systems; and
  - the type of terrain (flat, complex, offshore, etc.) affects the forecasting error.
- Recent research efforts have focused on associating uncertainty estimates with point forecasts, taking into account the form of
  - probabilistic forecasts,
  - risk indices,

RECENT TRENDS IN WPF – UNCERTAINTY ESTIMATION

✓ **Probabilistic forecasting** consists of estimating the future uncertainty of wind power that can be expressed as a probability measure. The forecasted power output from wind farms is described by using random variables, which may be expressed with Probability density functions (pdfs).

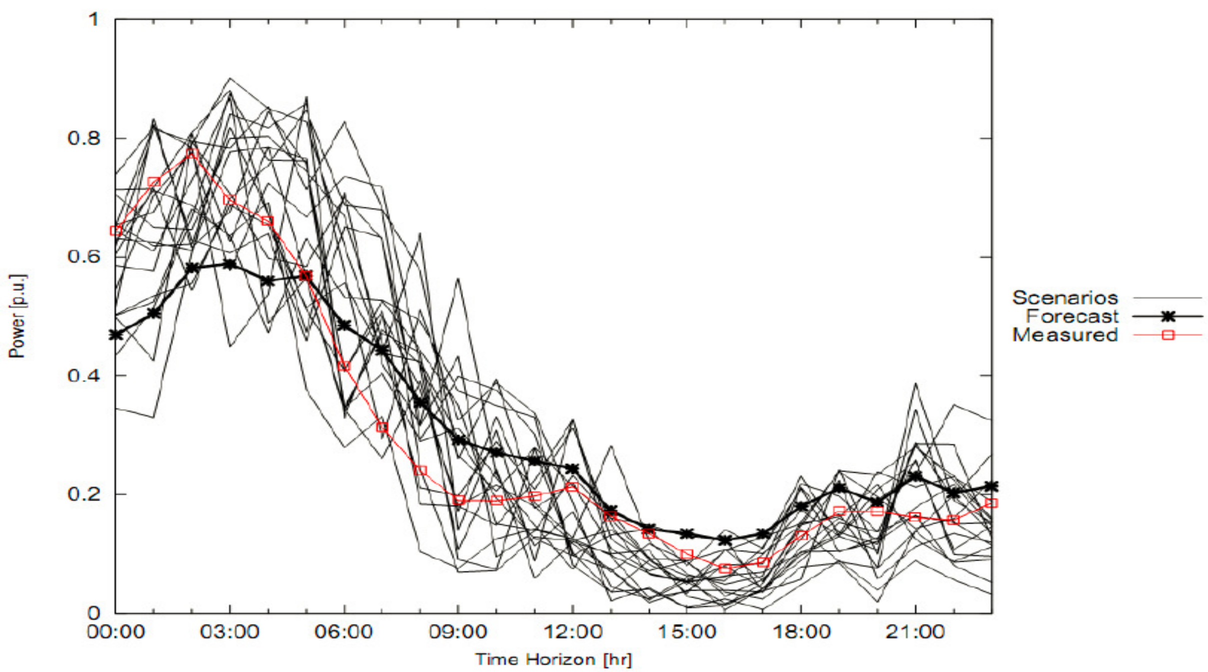


Fig : Scenarios of Wind Generation (20 scenarios)

RECENT TRENDS IN WPF – UNCERTAINTY ESTIMATION

✓ Risk Indices or Skill Forecasting

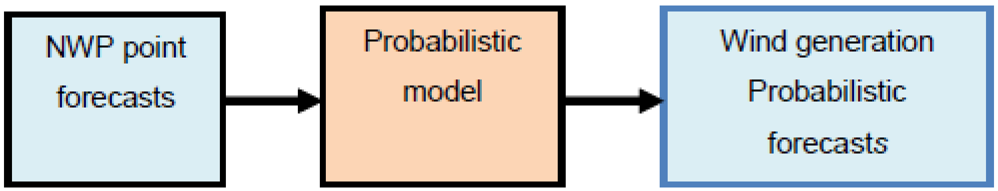
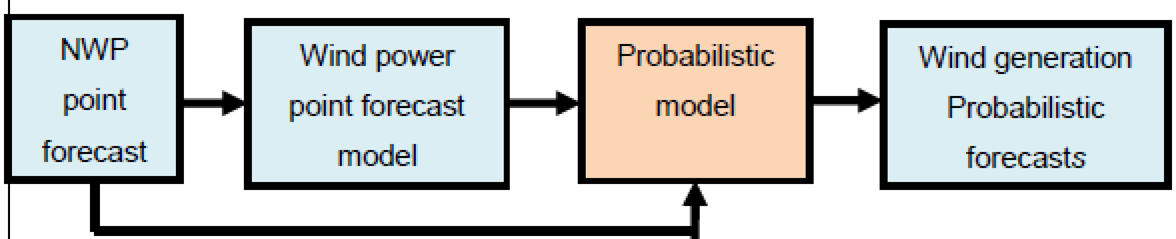
- ✓ Two risk indices (or skill forecasts) were proposed in the literature:
- The Meteo-Risk Index (MRI), which reflects the spread of the available NWP ensemble at a given time; and
- The Normalized Prediction Risk Index (NPRI), which reflects the spread of an ensemble of wind power forecasts for a single look-ahead time or over a forecast period.

These risk indices are not directly related to a forecasting method.

- ✓ From these risk indices, it is possible to understand how accurate or not the wind power forecast error is expected to be. For instance, if the MRI is low, the model is expected to be accurate. Therefore, it will be acceptable for the forecast to present small uncertainty intervals.

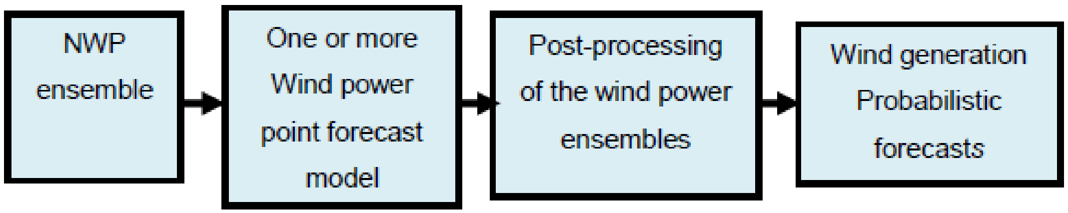
RECENT TRENDS IN WPF – UNCERTAINTY ESTIMATION

✓ Different Approaches for Uncertainty Estimation

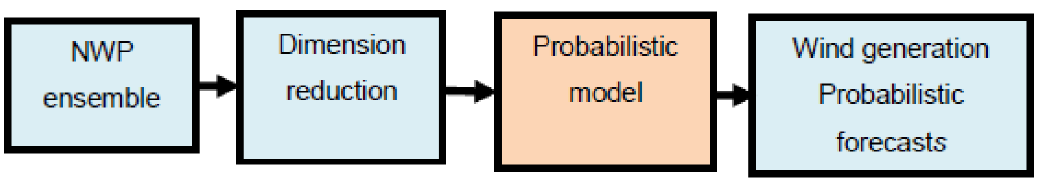
Approaches	Description
	In the NWP point forecast approach, either the NWP forecast error is used as input or the wind power uncertainty is directly computed from the NWP points forecast (e.g., local quantile regression).
	The power output point approach consists of forecasting uncertainty based on the WPF errors and NWP point forecasts. The probabilistic model is placed after the model that produces wind power forecasts (e.g., adapted resampling).

RECENT TRENDS IN WPF – UNCERTAINTY ESTIMATION

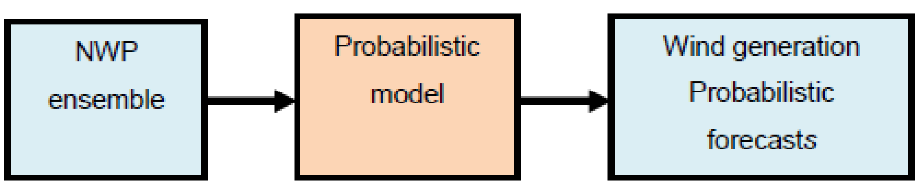
✓ Different Approaches for Uncertainty Estimation



In the filtering approach, wind NWP ensembles are converted into power ensembles. In which each ensemble member uses a single or different point forecasting model. It is also necessary to calibrate the power output ensembles with post-processing methods.



The dimension reduction approach consists of reducing the input dimensionality and then feeding the reduced inputs to a probabilistic model. The dimension can also be reduced to the ensemble mean and variance.



The direct approach consists of feeding the wind ensemble NWPs directly into a probabilistic model;

WPF: Europe

Prediktor: (Physical)

✓ A **physical** WPF system developed in Risø National Laboratory (Denmark)

✓ The model includes four main components :

(i) wind speed and direction data from an NWP model;
(ii) correction for height;
(iii) correction for local effects (roughness and orography);
(iv) wind power curve modeling, including wake effects.

✓ Prediktor achieved a mean annual MAE of 14.2% and 22.3% at the Altamont and San Gorgonio plants, respectively, for a period of one year.

WPF: Europe

Previento: (Physical)

- ✓ A **physical** model that uses NWP predictions as inputs was developed at the University of Oldenburg, and is currently being distributed by **Energy & Meteo Systems GmbH (EMSYS).**

- ✓ It is based on the same principle as Prediktor regarding the refining of NWP predictions of wind speed and direction. The upscaling algorithm is based on the correlation between the representative wind farm generations and the total production computed in past measurements.

- ✓ The power forecast Normalized Root Mean Square Error (**NRMSE**) for the entire country (**Germany**) is about **6% of the installed capacity.**

WPF: Europe

LocalPred and RegioPred: (Hybrid)

- ✓ LocalPred and RegioPred are two tools developed by CENER, the Spanish National Renewable Energy Center, in collaboration with the Spanish Research Center for Energy, Environment, and Technology (CIEMAT).

- ✓ The models have been operating since **2002** and running on-line since June 2003 at different wind farms in **Spain**.

- ✓ The RegioPred is a regional forecast model that is based on the single wind farm prediction model LocalPred. The regional forecast can be carried out by adding each single wind farm forecast or selected reference wind farms using cluster analysis.

- ✓ For very-short-term forecasts (i.e., up to 10 hours ahead), the system uses **autoregressive techniques (statistical model)**.

WPF: Europe

The WPPT System: (Statistical)

- ✓ The Wind Power Prediction Tool (WPPT) has been developed by the Institute for Informatics and Mathematical Modelling (IMM) of the Technical University of Denmark (DTU).

- ✓ WPPT is a forecasting system that is capable of forecasting for a single wind farm, for a group of wind farms, or for a wide region (e.g., the western part of Denmark).

- ✓ The model can successfully forecast for time horizons of up to 48 hours, depending on the forecast time horizon of the NWP model. The resolution is typically 30 min.

- ✓ The model is currently operating in Eltra/Energinet.dk (SO for the western part of Denmark), Elsam (combined heat and power (CHP) and wind farm owner in the western part of Denmark), Elkraft (SO for the eastern part of Denmark), and E2 (CHP and wind farm owner in the eastern part of Denmark).

WPF: Europe

The ARMINES Wind Power Prediction System (AWPPS): (Statistical, Fuzzy-NN)

- ✓ The AWPPS integrates:

  Short-term models (statistical), Longer-term models (fuzzy neural networks), Combined forecasts, Upscaling prediction model, Uncertainty estimation

- ✓ In Ireland, it was shown that using a power curve derived from HIRLAM wind and measured power can improve the forecast RMSE by nearly 20% in comparison to the manufacturer’s power curve

- ✓ Currently, the MORE-CARE system [24] is installed in Crete, managed by the Public Power Corporation of Greece (PPC). In Portugal, the MORECARE system is managed by EEM (Empresa de Electricidade da Madeira) and provides forecasts for the production of wind farms on the island of Madeira.

WPF: Europe

GH (Garrad Hassan) Forecaster: (Hybrid)

- ✓ It has been developed by Garrad Hassan and Partners Ltd, and its commercial operation in Europe has proved to be successful, especially for wind farms in complex terrains.

- ✓ The GH Forecaster is a forecast system that is used to forecast wind farm power outputs using multi-parameter statistical regression techniques.

- ✓ Although the GH Forecaster's power models can introduce significant errors in the predications, those errors can be reduced to an Mean Absolute Error (MAE) of 2% of the rated power.

WPF: USA

eWind: (hybrid)

- ✓ eWind is a U.S. model developed by AWS Truewind
- ✓ The model takes the following as inputs: grid point output from regional-scale and global-scale NWP models; measurement data from several meteorological sensors; high-resolution geophysical data (terrain height, roughness, etc.); and meteorological and power generation data from the wind farms. The forecast horizon is 48 hours.
- ✓ The following statistical tools are used: screening multiple linear regressions (SMLRs), neural networks, Support vector Machines (SVM), fuzzy logic clustering (FLC), and Principal Component Analysis (PCA)

WPF: USA

PowerSight:

- ✓ PowerSight is a WPF system developed by the 3TIER Environmental Forecast Group in cooperation with the University of Washington.
- ✓ They are providing (by 2009) operational forecasts for more than 6,000 MW of installed wind energy in the United States.
- ✓ The input data to this model is global weather data from the NCEP GFS model, as well as regional weather and high resolution surface data along with SCADA measurement and historical data.
- ✓ The typical accuracy of the day-ahead model is an Normalized Mean Absolute Error (NMAE) of between 11% and 14% of installed capacity, an Normalized Root Mean Square Error (NRMSE) of between 15% and 20%, and an improvement of 40% to 60% when compared with persistence.

WPF: China

- ✓ China Electric Power Research Institute (CEPRI) is the first wind power forecasting research organization in China.

- ✓ It has developed wind power forecasting model based on statistical methods such as artificial neural network, support vector machine, and so on.

- ✓ CEPRI developed the hybrid approach which combines the statistical method and physical method effectively.

- ✓ The first WPF system with independent intellectual property rights in China was successfully developed by CEPRI in November 2008 and put into operation in Jilin Power Dispatching Center.

WPF-Overview

Program	Program Developer	Methods	Country	Operational Since
Prediktor	RISO National Laboratory	Physical	Spin, Denmark, Ireland, Germany, USA	1994
WPPT	IMM, Technical University of Denmark	Statistical	Denmark (East & West)	1994
Previento	University of Oldenburg and Energy & Meteo System	Physical	Germany	2002
AWPPS (More-Care)	Armines/Ecole des Mines de Paris	Statistical, Fuzzy-ANN	Ireland, Greece, Portugal	1998, 2002
Sipreolico	University of Carlos III, Madrid; Red Electra de Espana	Statistical	4 GW, Spain	2002
Local Pred-RegioPred	CENER	Physical	Spain	2001
GH Forecaster	Garrad Hassan	Physical & Statistical	Spain, Ireland, UK, USA, Australia	2004
eWind	TrueWind (USA)	Physical & Statistical	Spain, USA	1998
WPFS	CEPRI	Physical & Statistical	China	2009

Observations

- Numerical Weather Prediction gives global weather forecasts with 6 hour intervals
- This would be interpolated to the wind farm site and wind speeds are determined. The interpolation is
  - Spatial &
  - Temporal
- Based on past data the conversion between wind farm wind speed and power .
- Forecast needs to be corrected using data from immediate past (SCADA).
- Dynamic process and needs to be “TRAINED”
- Indian Monsoon based wind system takes longer to train
- Need to develop close co-ordination with Met Dept. with a particular focus on local weather stations

Questions?

Thank you