Forecasting of Renewable Power Generations

By

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Present and Future Power System

Present Power System
- Heavily Relying on Fossil Fuels
- Generation follows load
- Limited ICT use

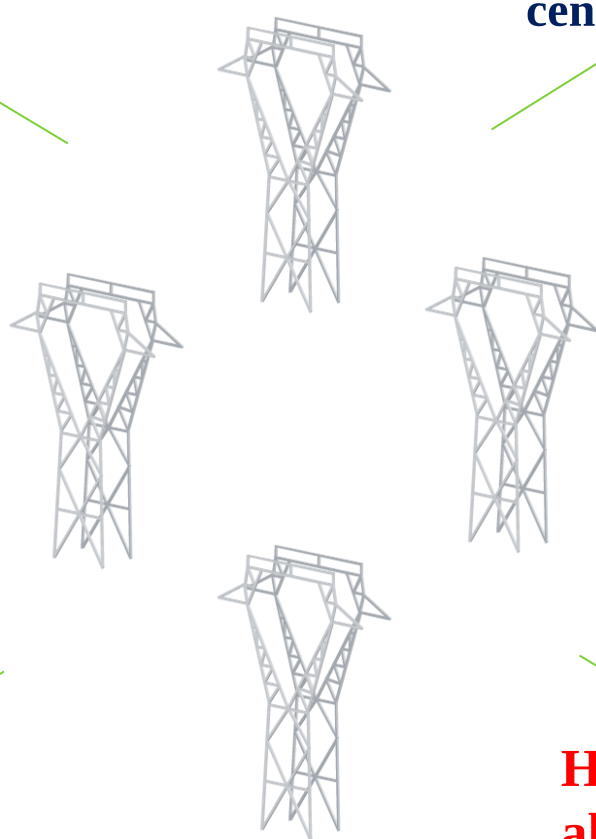
Future Power System
- More use of RES, clean coal, nuclear power
- Load follows Generation
- More ICT & Smart meter use
- More competition

SMART GRID

Future Grid – Smart(er) Grid

Wide area monitoring and control systems

Coordinated, full energy management and full integration of DG with large central power generation



Extensive small, distributed generation close to end user

Secure, reliable and green power supply

Customer driven value added services

Harmonized legal framework allowing cross border power trading

Smart Grid Advantages

Operational Efficiency

Reduced Onsite Premise Presence / Field Work Required
Shorter Outage Durations
Optimized Transformer Operation
Standards & Construction
Improved Network Operations
Reduce Integration & IT maintenance cost
Condition-based Asset Maintenance / Inspections

Energy Efficiency

Reduced Energy Losses

Active/Passive Demand-side Management

Smart Grid

Customer Satisfaction

Enable Customer Self-Service / Reduce Call Center Inquiries

Improved Revenue Collection

Environmental Impact

Reduced Greenhouse Gas Emissions

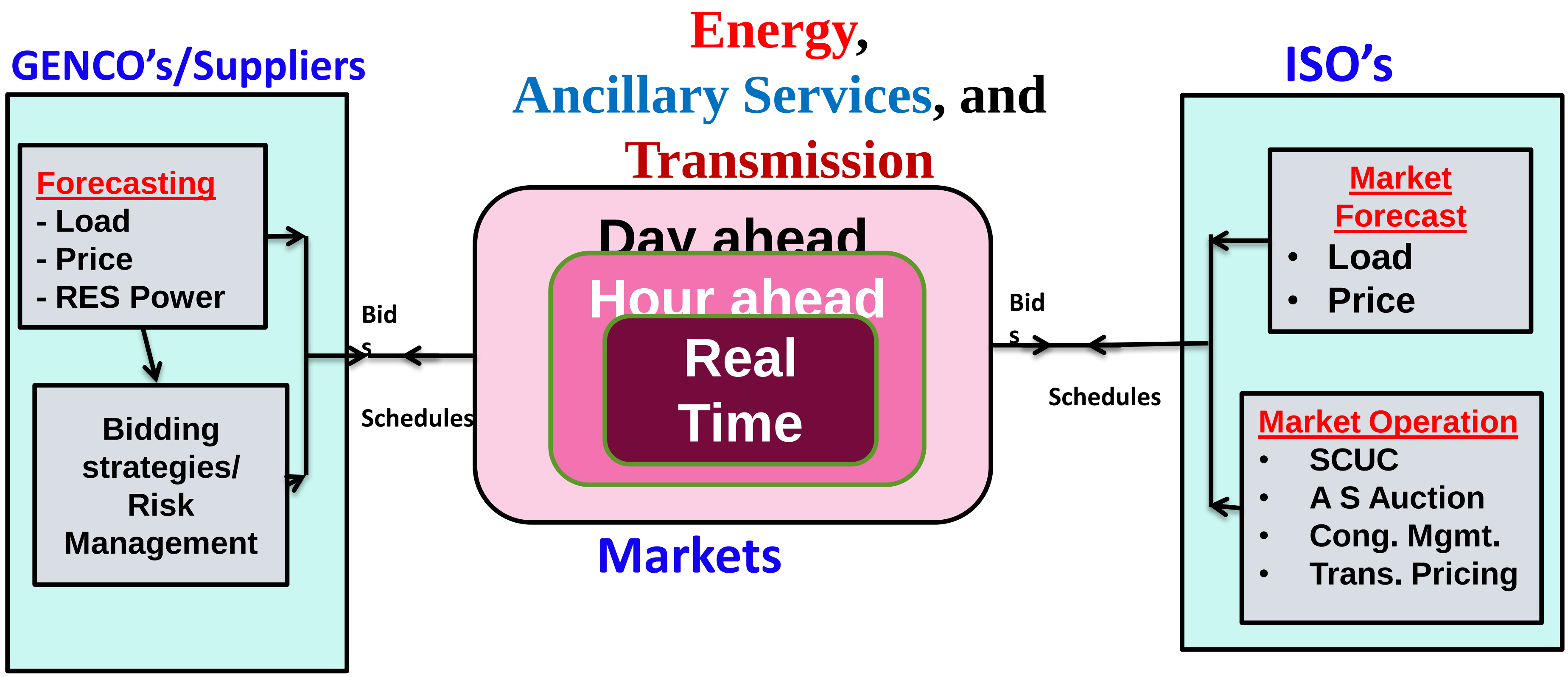
Delayed Generation & Transmission Capital Investments

Challenges in Smart Grid Implementation

- Increase in system Operational Complexity
- More business oriented attitude
- Large Data Handling
- Information Security
- Cost-effecting implementation (including ICT)
- Requirement of Accurate Forecasting approaches
- Utilization of Demand Response
- Redesigning of electricity market structure
- Fast analysis tools
- Integration of renewable energy sources
- Power Quality and Many more…

Role of Forecasting in Electric Power System

Electricity Market Operation



Necessity in Market Operation

1. **Load Forecasting**
2. **Price Forecasting**
3. **Operating Reserve Margin Forecasting**
4. **Wind/Solar Forecasting**

Planning and Operational problems due to uncertainity in Renewable energy

Planning Problems:

Due to uncertainty, unlike conventional generators, RES(wind, solar) power generation cannot be included into ELD and UC problems.

Operational:

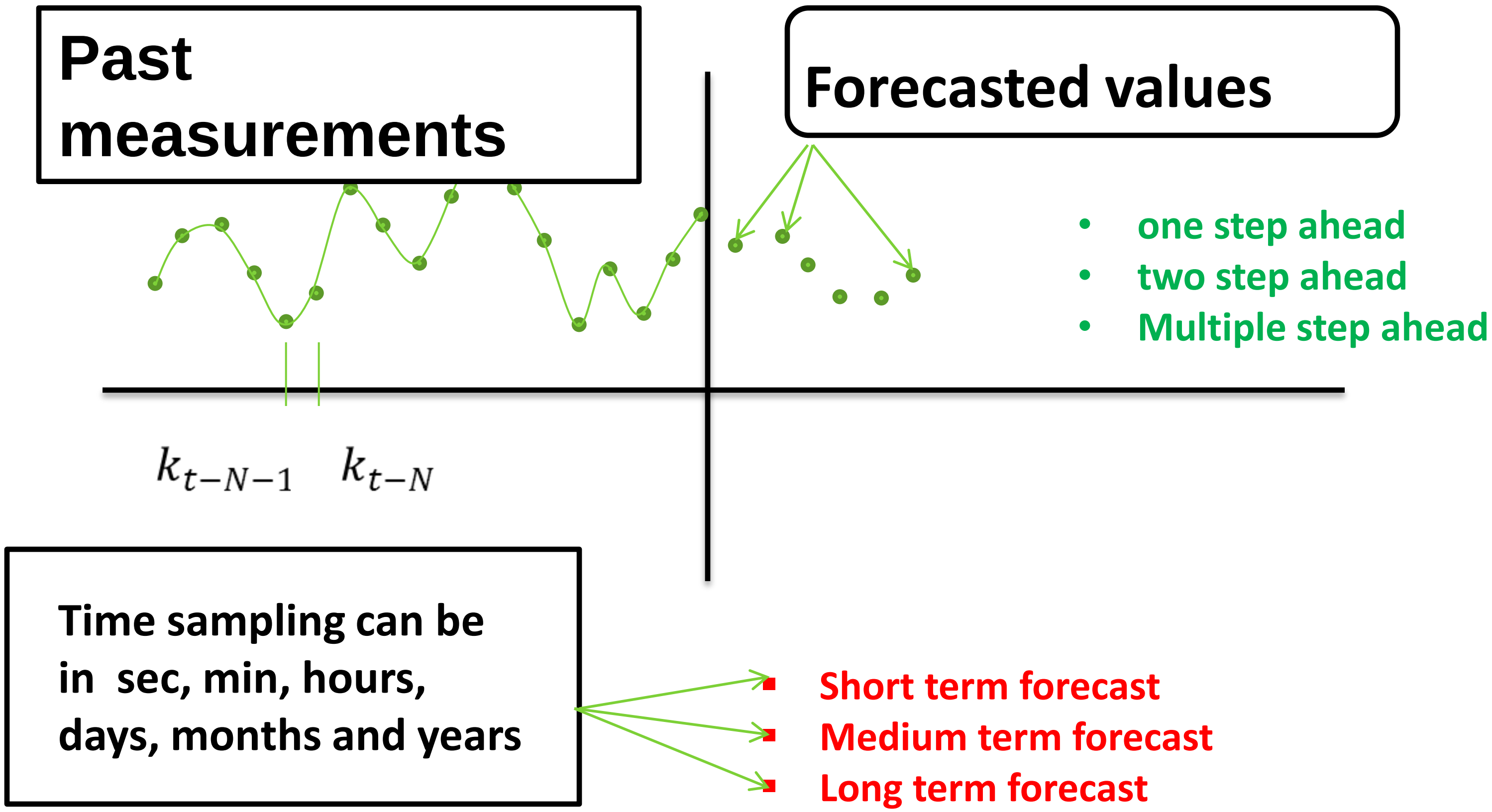
Frequency control, Voltage control, Power Quality, Ancillary services provision.

RES power producer point of view:

Bidding in day ahead, adjustment and settling Electricity Markets to maximize profits/minimize their imbalance costs.

Basic Definition of Forecasting

Forecasting is a problem of determining the future values of a time series from current and past values.



Factors Influencing the Forecast variable

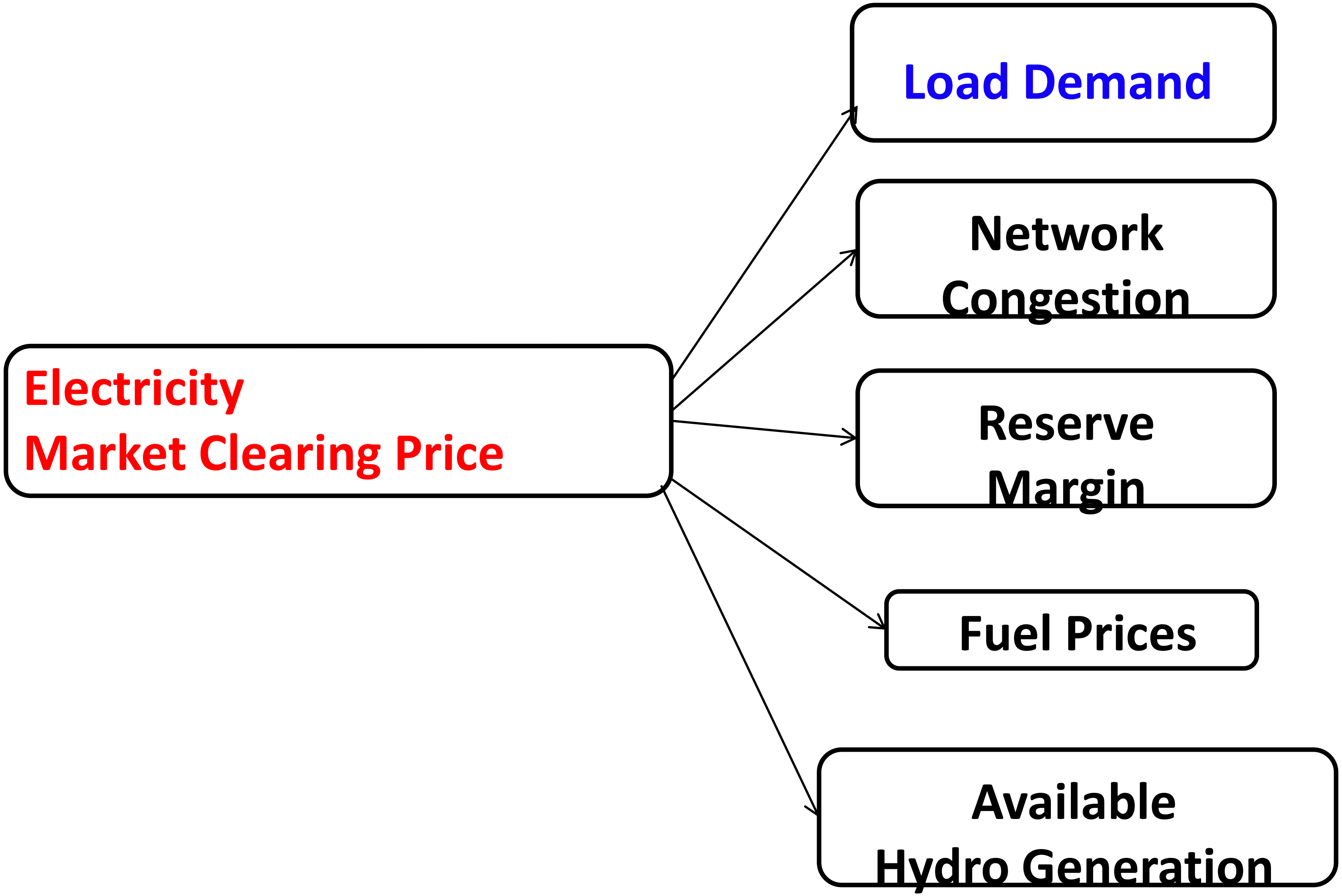
Load Demand

Time Factor
- Hour in a day
- Day of the Week
- Holiday

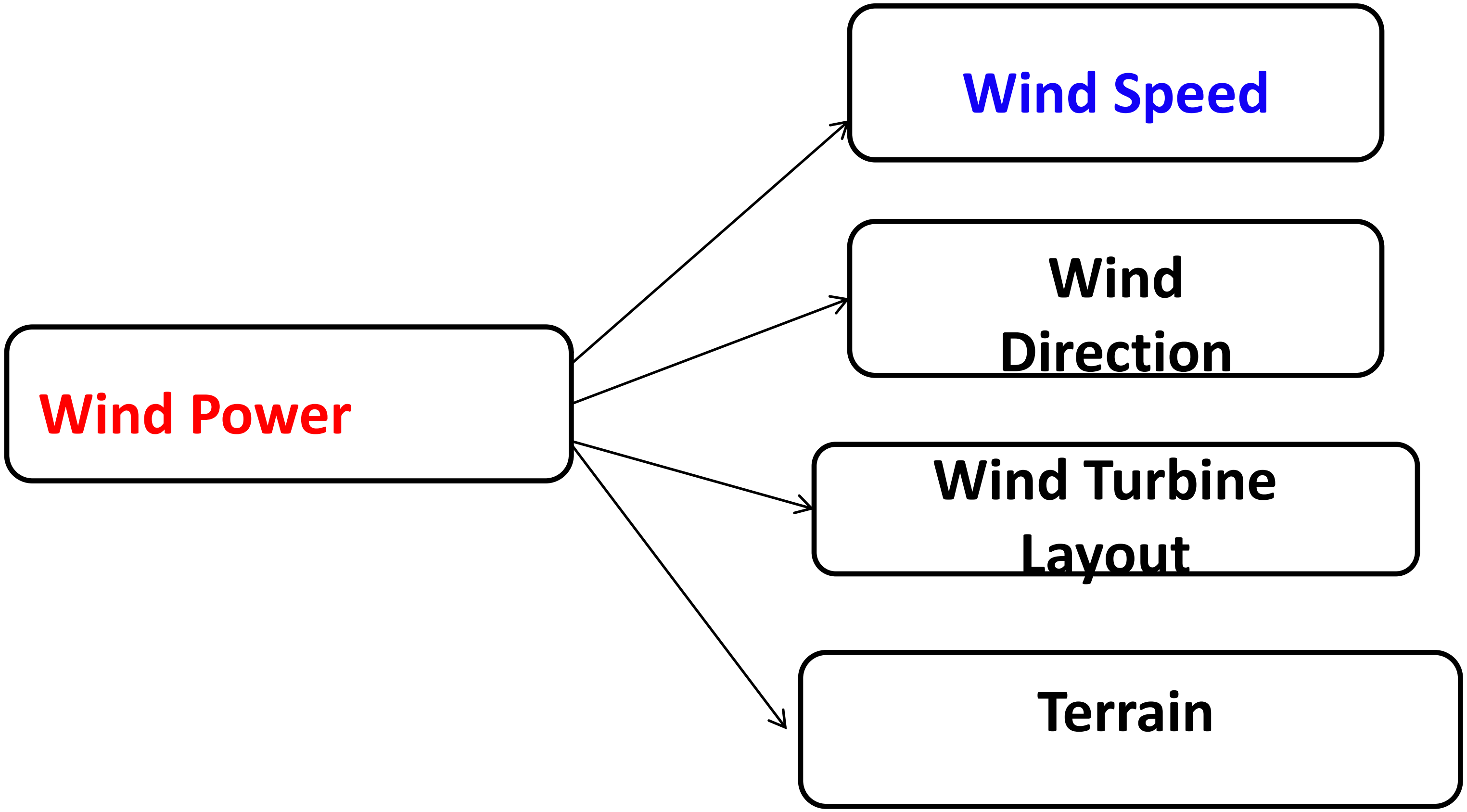
Type of Customer
- Domestic loads
- Commercial loads
- Industrial loads

Weather Parameters
- Temperature
- Humidity
- Sky cover
- Sun shine
- Wind Speed

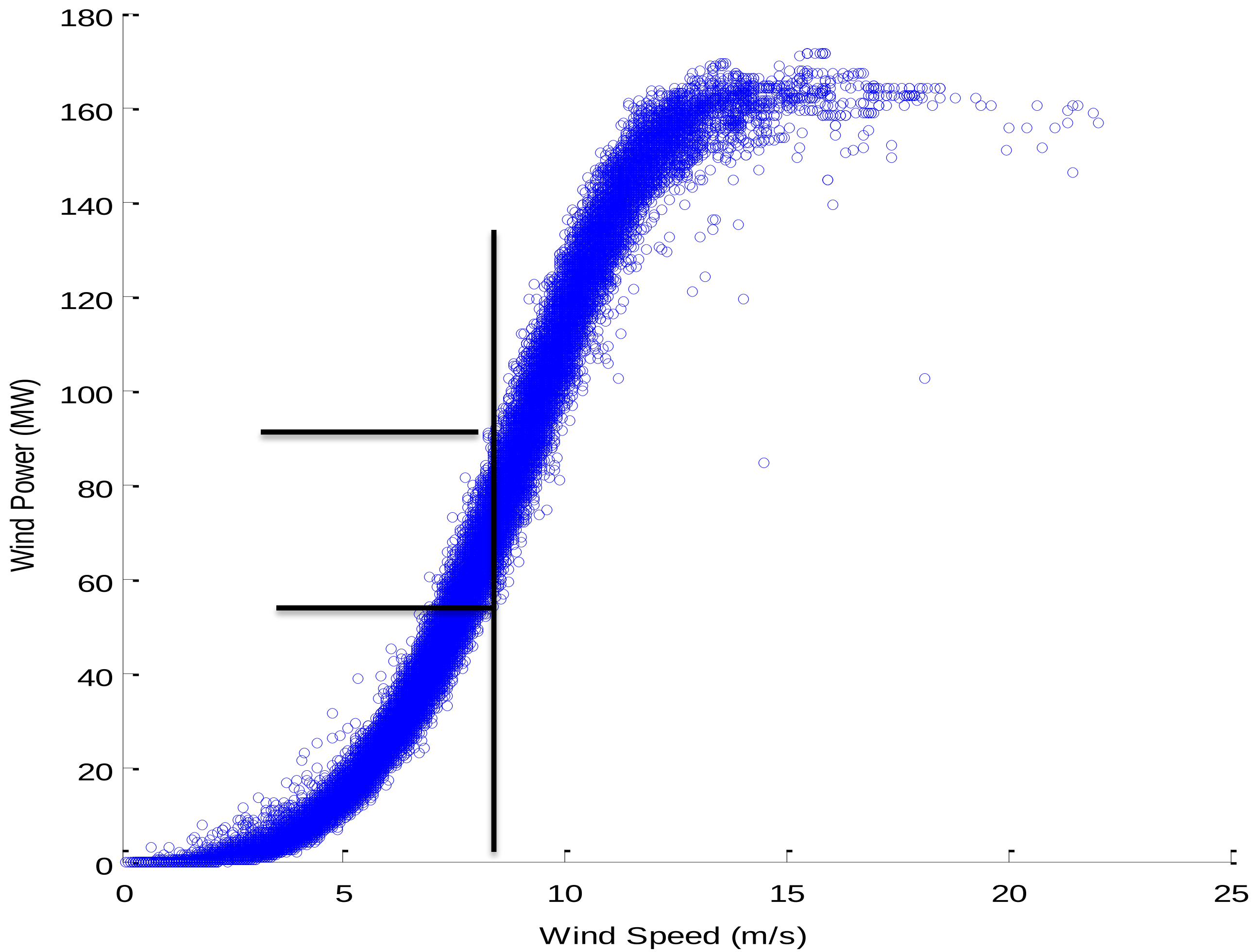
Factors Influencing Electricity Market Price



Factors Influencing Wind Power Generation



Wind Speed vs. Wind Power scatter plot



Forecasting Approaches

Linear Regression Models : **(AR, ARMA, ARIMA, GARCH, etc.)**

The forecast value is linearly dependent on the past historical values of the time series

- **Time Series Modeling – Maximum Likelyhood Estimation, Least Square Estimation Methods are used for Parameter Estimation.**
- **State Space Modeling- Kalman Filtering Techniques used**

Limitations of Linear Regression Models

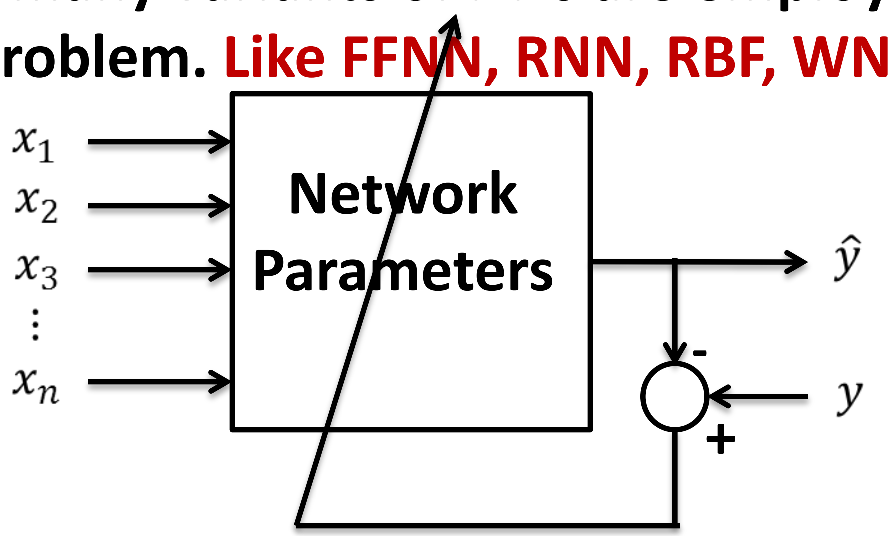
1. **As they are linear models, they cannot capture the non-linear relation between the independent and dependent variable.**
2. **The forecasting error increases rapidly with the increase in look-ahead time.**
3. **The model parameters have to be updated very frequently.**

Forecasting Approaches .....contd

Non-Linear Regression models:

$$X_t = F(X_{t-1}, X_{t-2}, X_{t-3}, \cdots, u_t, u_{t-1}, u_{t-2}, \cdots) + \varepsilon_t$$

Artificial Neural Networks (ANN) are well established in function approximation, many variants of NNs are employed in the field of forecasting problem. Like FFNN, RNN, RBF, WNN.



Back-Propagation Algorithm, Evolutionary based Optimization methods like GA, PSO are also applied for network training.

Input variables are selected using ACF and PACF.

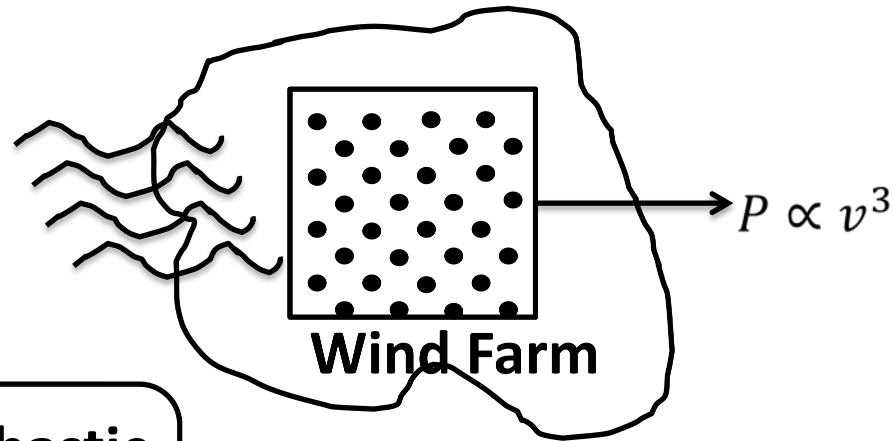
Other Methods..

- **Fuzzy Logic**
- **Adaptive Neuro-Fuzzy Inference System (ANFIS)**
- **Data Mining techniques like clustering and Support Vector Machines (SVM) based classification and Regression models.**
- **Wavelet pre-filtering based ANN and Fuzzy models.**

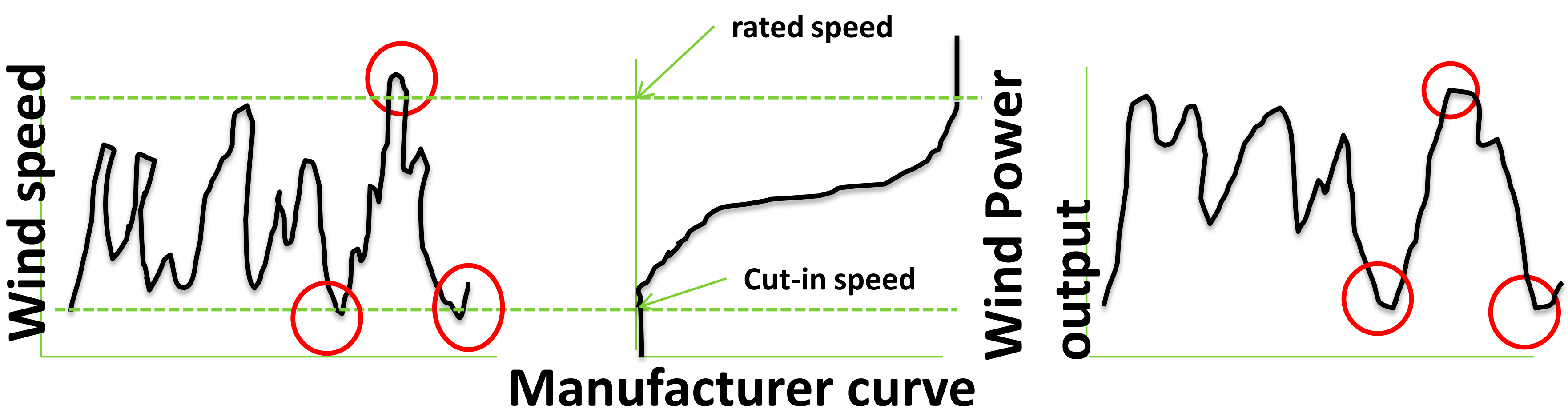
Wind Power Forecasting

Wind Power Forecast

Wind Speed



highly stochastic
random
non-stationary.



Wind Power Forecasting: Approaches

1) Physical Models

- **The idea is to transform the wind speed forecasts, of NWP model, on a coarse numerical grid to the onsite conditions at the location of the wind form.**
- **Detailed physical description of lower atmosphere by considering factors like :surface roughness and its changes, scaling of the local wind speed within wind forms, wind form layouts and turbine power curves.**
- **The first physical wind power prediction model, *Prediktor*, developed at National Laboratory, Risø, Denmark, is based on the local refinement of wind speed prediction of the NWP system HIRLAM.**

Examples of Physical Model [1]

PREDICTION MODEL	DEVELOPER	OPERATIONAL STATUS	OPERATIONAL SINCE
Prediktor	National Laboratory, Risø, Denmark.	Spain, Denmark, Ireland, Germany, (US)	1993
Previento	University of Oldenburg, Germany. (Later with) Energy & Meteo system	US & European countries.	- 2004
LocalPred	CENER	La Muela, Soria, Alaiz	2001
HIRPOM (HIRlam POwer prediction Model)	University College Cork, Ireland & Danish Meteorological Institute	Denmark	2001

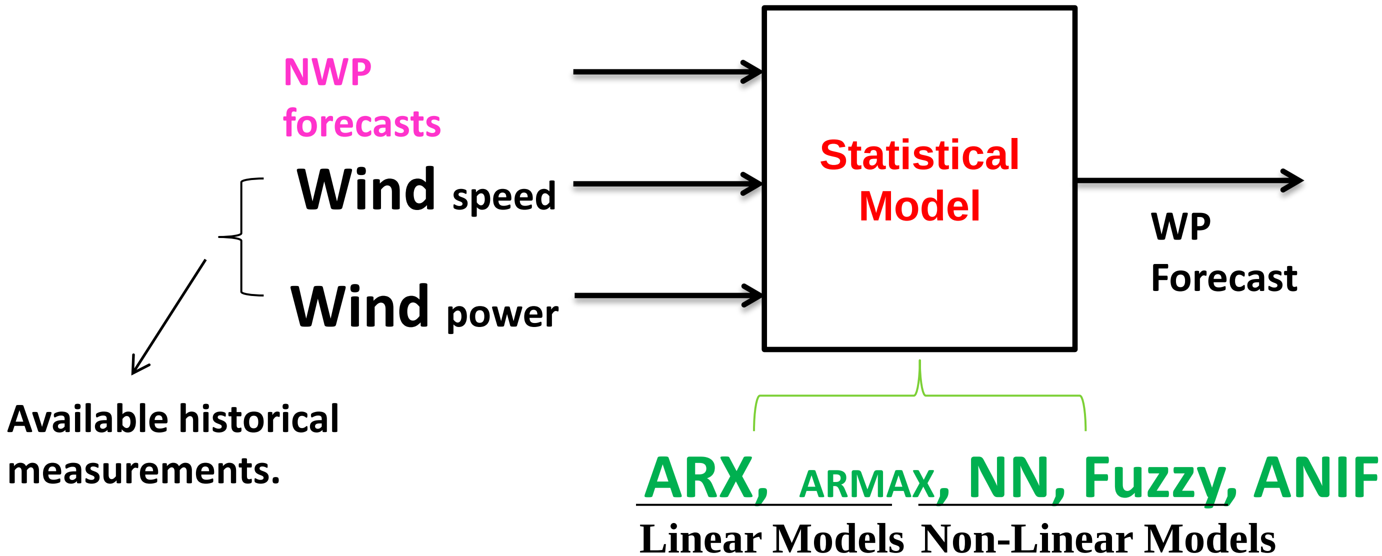
- They are complex mathematical models.
- More time for execution
- They are site-dependent and not Plug and Play models

[1] G. Giebel, L. Landberg, G. Kariniotakis, and R. Brownsword, "State-of-the-art on methods and software tools for short-term prediction of wind energy production," in *Proc. Eur. Wind Energy Conf. and Exhibition (EWEC)*, Madrid, Spain, 2003.

Wind Power Forecasting: Approaches Contd

2) Statistical Models

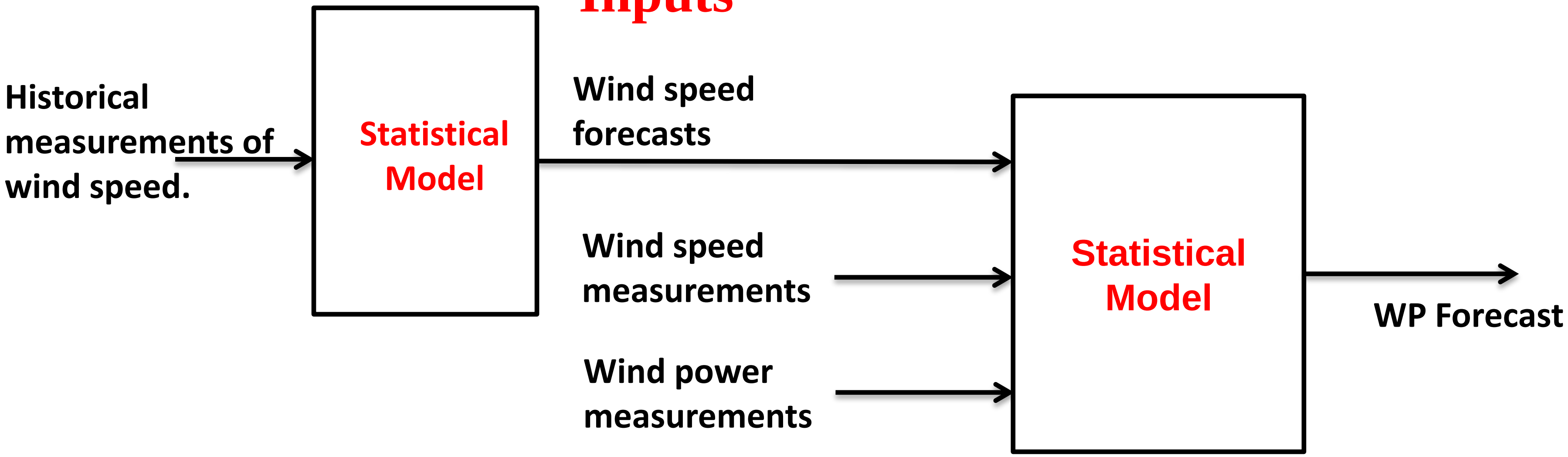
i) with NWP inputs
ii) without NWP inputs



- **Statistical systems require no mathematical modeling**
- **Have very high accuracy in very short term forecasting**
- **They are not site dependent**

Two stage approach for Wind Power Forecast

Without NWP Inputs



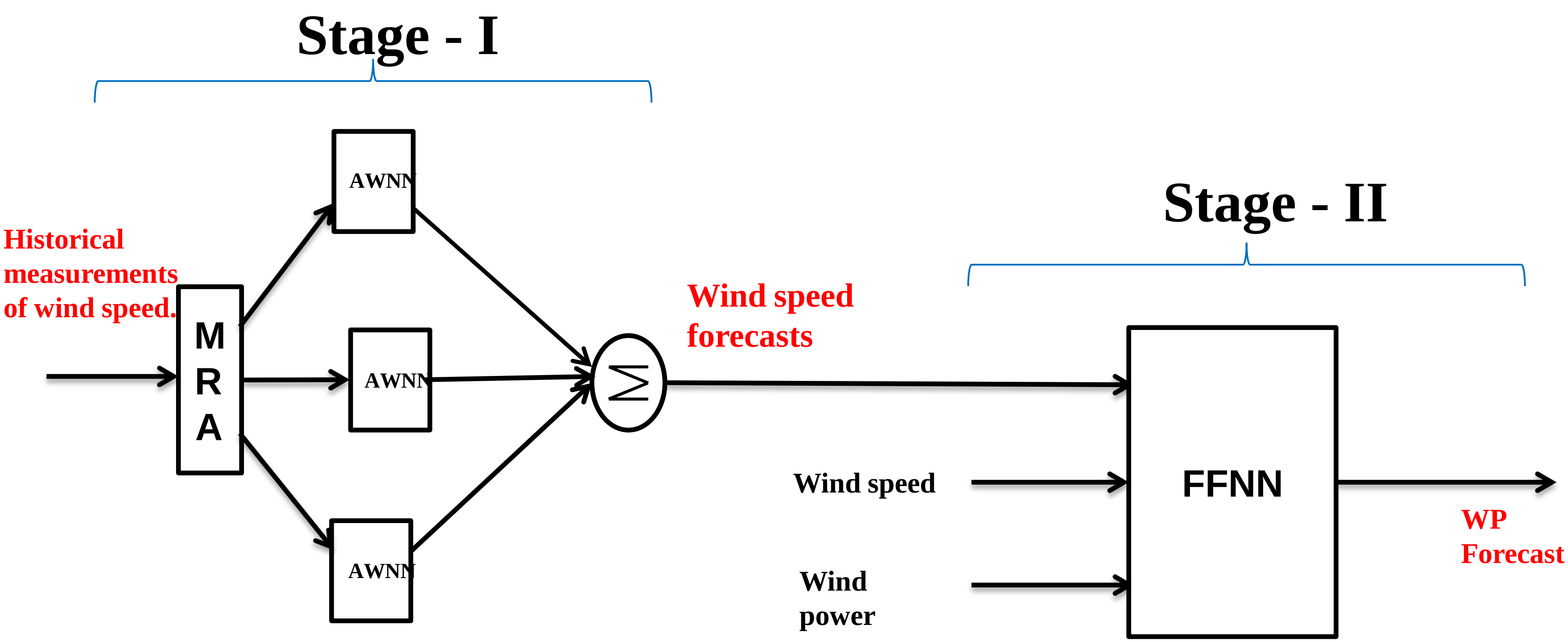
- **Statistical models with NWP inputs are capable of forecasting up to 72 h and models taking purely measured values of wind speed and power can forecast up to 24 h.**

Examples of Statistical Models [1]

PREDICTION MODEL	DEVELOPER	OPERATIONAL STATUS	OPERATIONAL SINCE
WPPT (Time Series)	IMM (Informatics and Mathematical Modelling); University of Copenhagen	Denmark (E & W)	1994
AWPPS (Fuzzy-ANN)	Armines/Ecole des Mines de Paris	Ireland, Crete, Madeira	2002
AWPT (ANN based)	ISET (Institut für Solare Energieversorgungstechnik)	Germany	
SIPREÓLICO (Time Serie & ANN Models)	University Carlos III, Madrid Red Eléctrica de España	Spain	2002

A Two-stage approach for Wind Power Forecast

- **The model uses only historical measurements of wind speed (locally and/or near by sites) and wind power output values.**



Benchmark Models

Forecasting up to 30 h ahead is carried and compared with benchmark models (persistence and new-reference models).

Persistence Model:

Also called as naive predictor, the most common benchmark model, which states that future wind production remains the same as the last measured value of the power;

$$\hat{P}(t+k|t) = P(t).$$

Drawback: forecast error increases rapidly with the increase in look-ahead time

New Reference Model: $\hat{P}(t+k|t) = a_k P(t) + (1-a_k)\bar{P}(t)$

The constant a_k is defined as the correlation coefficient between $P(t)$ and $P(t+k)$.

Measure of Errors

If error is given as; $e(t+k|t) = P(t+k) - \hat{P}(t+k|t).$

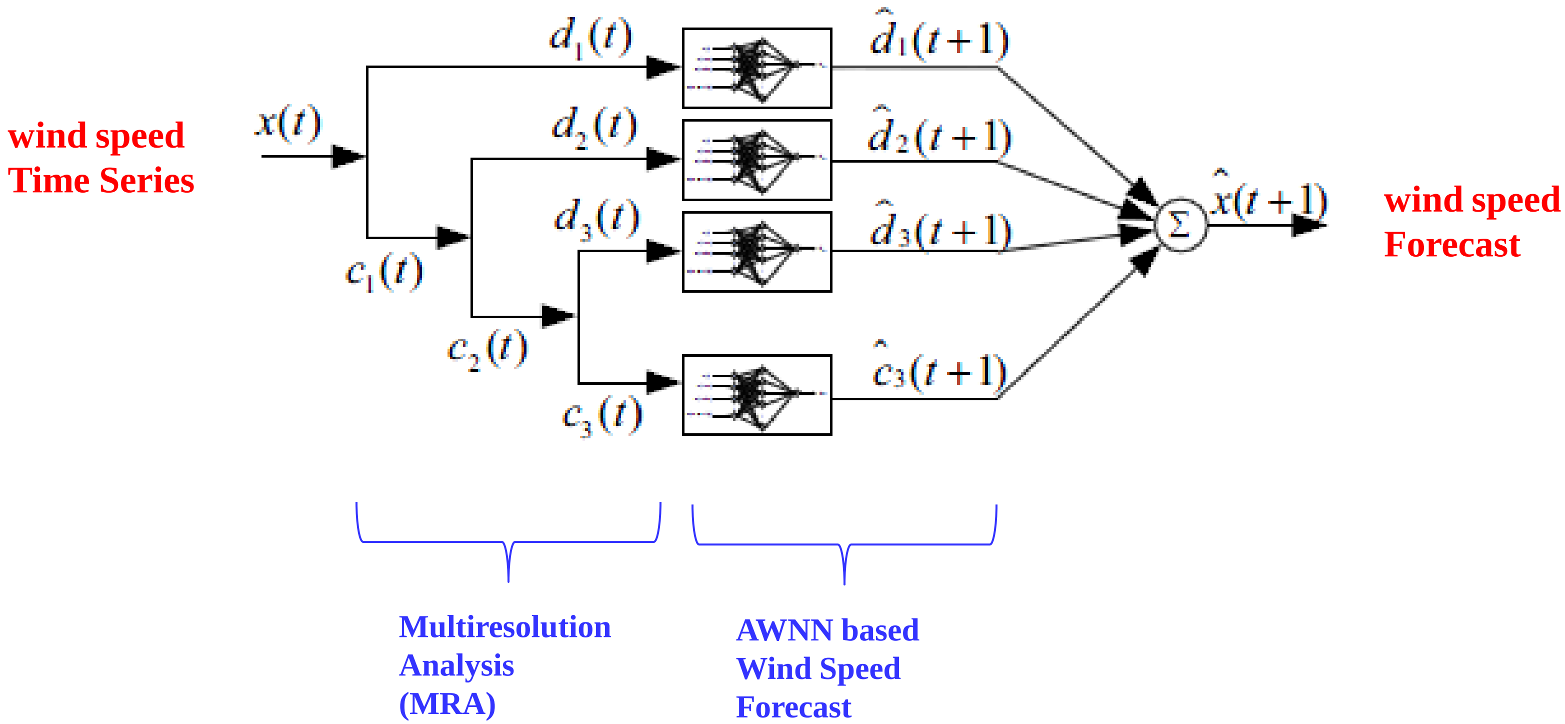
Then, $$BIAS(k) = \bar{e}_k = \frac{1}{N}\sum_{t=1}^{N} e(t+k|t)$$

$$MAE(k) = \frac{1}{N}\sum_{t=1}^{N} |e(t+k|t)|$$

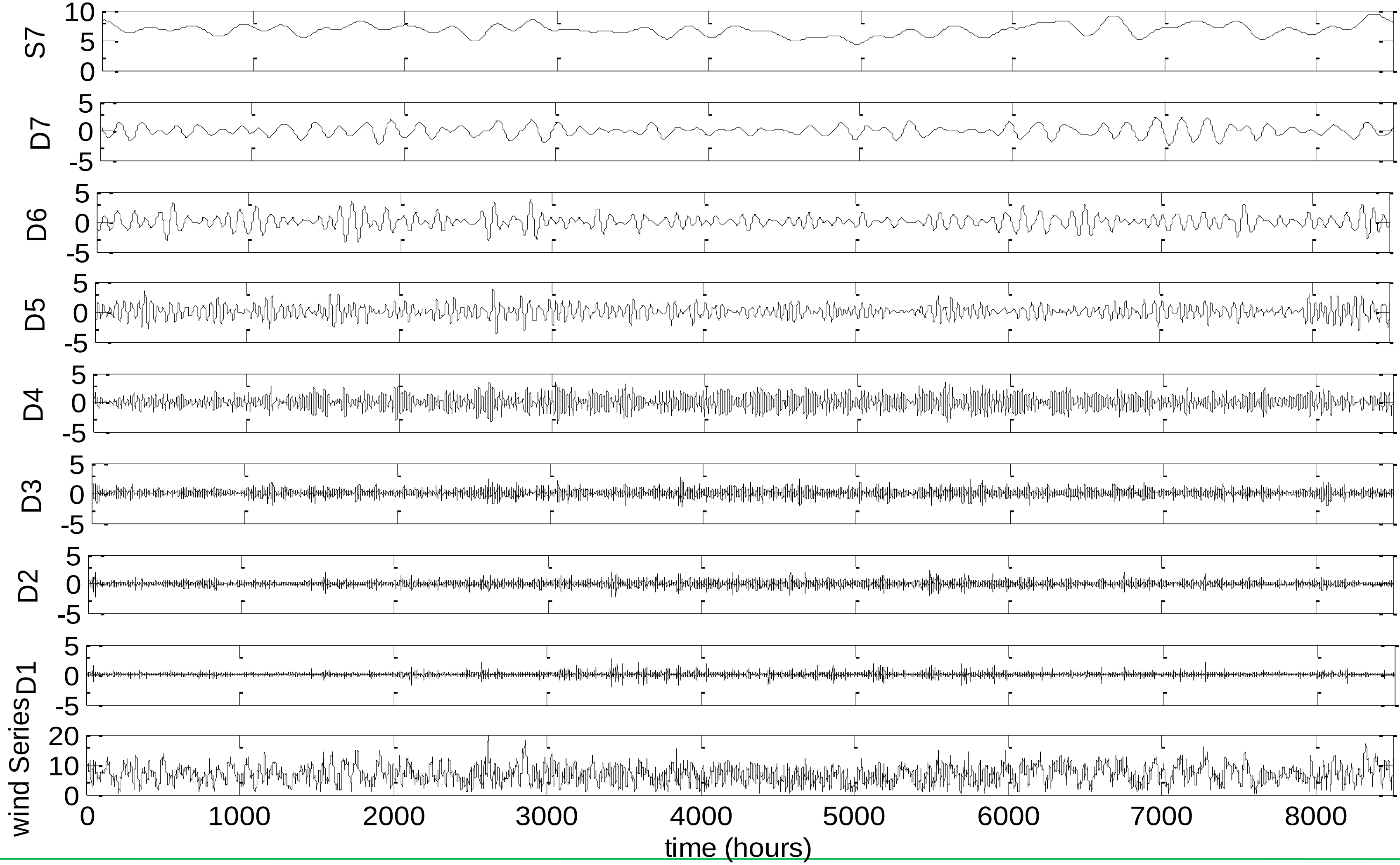
$$RMSE(k) = \left[\frac{1}{N}\sum_{t=1}^{N} e^2(t+k|t)\right]^{1/2}$$

Schematic Block Diagram for Wind Speed Forecasting

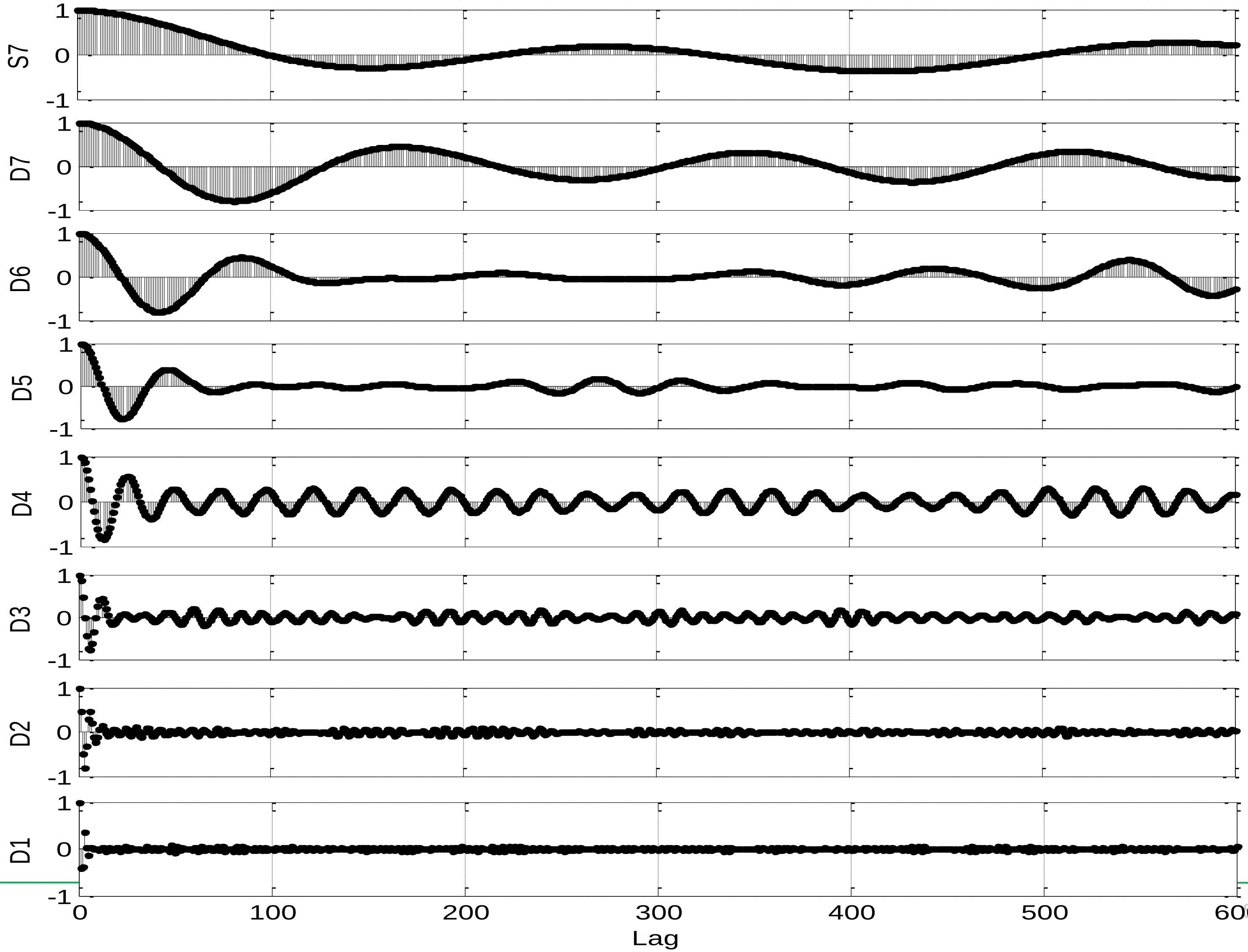
Stage -I



MRA of Wind Time Series using LA-8 Wavelet



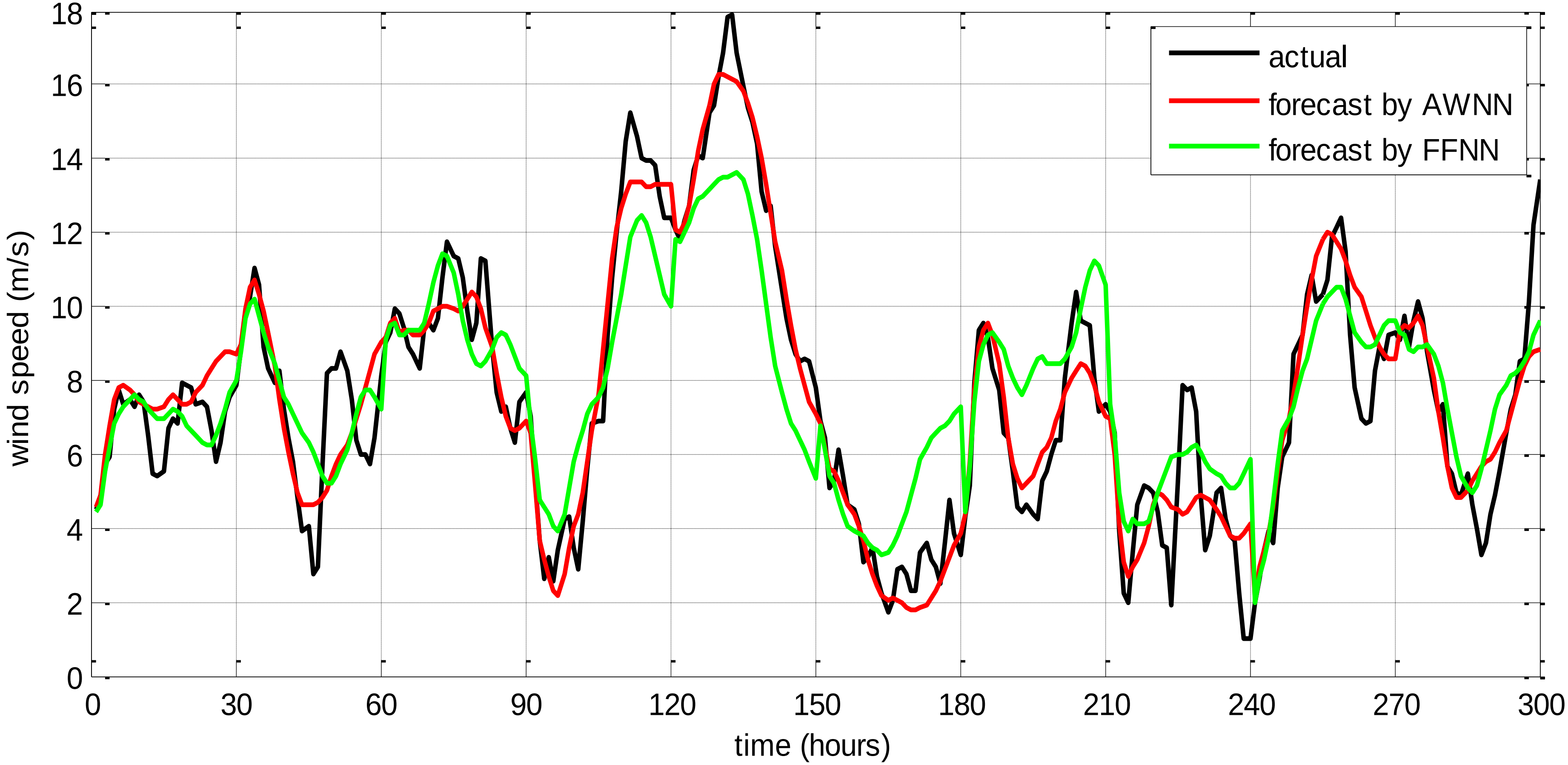
Auto-Correlation Analysis of Decomposed Wind Speed Time Series for Network Input selection



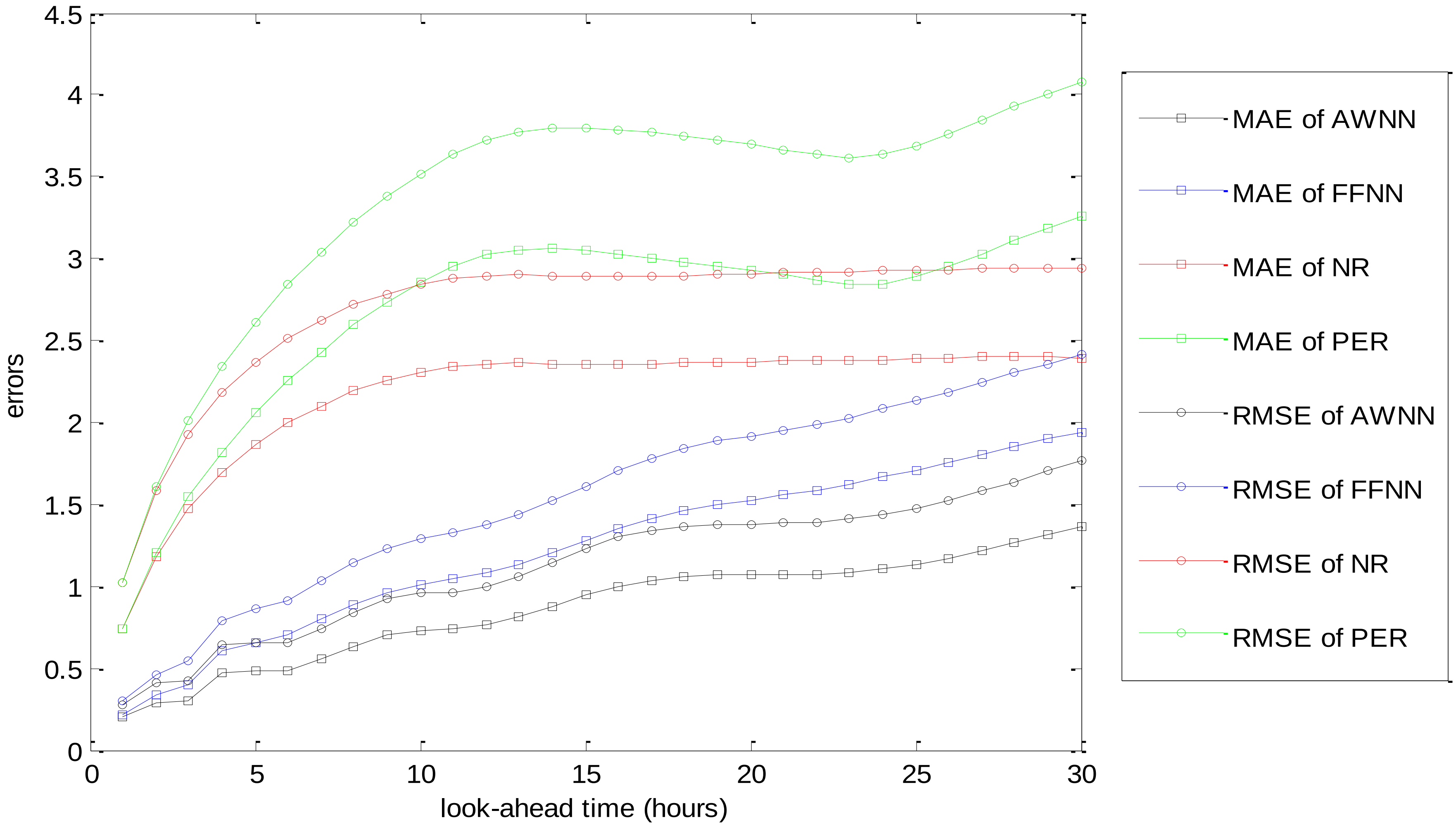
Network Architectures and Input Lag Hours used

Decomposed Signal	Input Lag-hours	Network Architecture	
		AWNN	FFNN
S7	1-14,157-159,285-287	20-2-1	20-3-1
D7	1-12,76-83,167-169	19-2-1	19-3-1
D6	1-10,41-44,84-86	17-2-1	17-3-1
D5	1-6,21-23,44-47	13-2-1	13-3-1
D4	1-3,11-13,23-25,48,72	11-2-1	11-3-1
D3	1,2,5,6,12,60,72	7-2-1	7-3-1
D2	3,6,9,15	4-2-1	4-3-1
D1	1,2,5,22	4-2-1	4-3-1

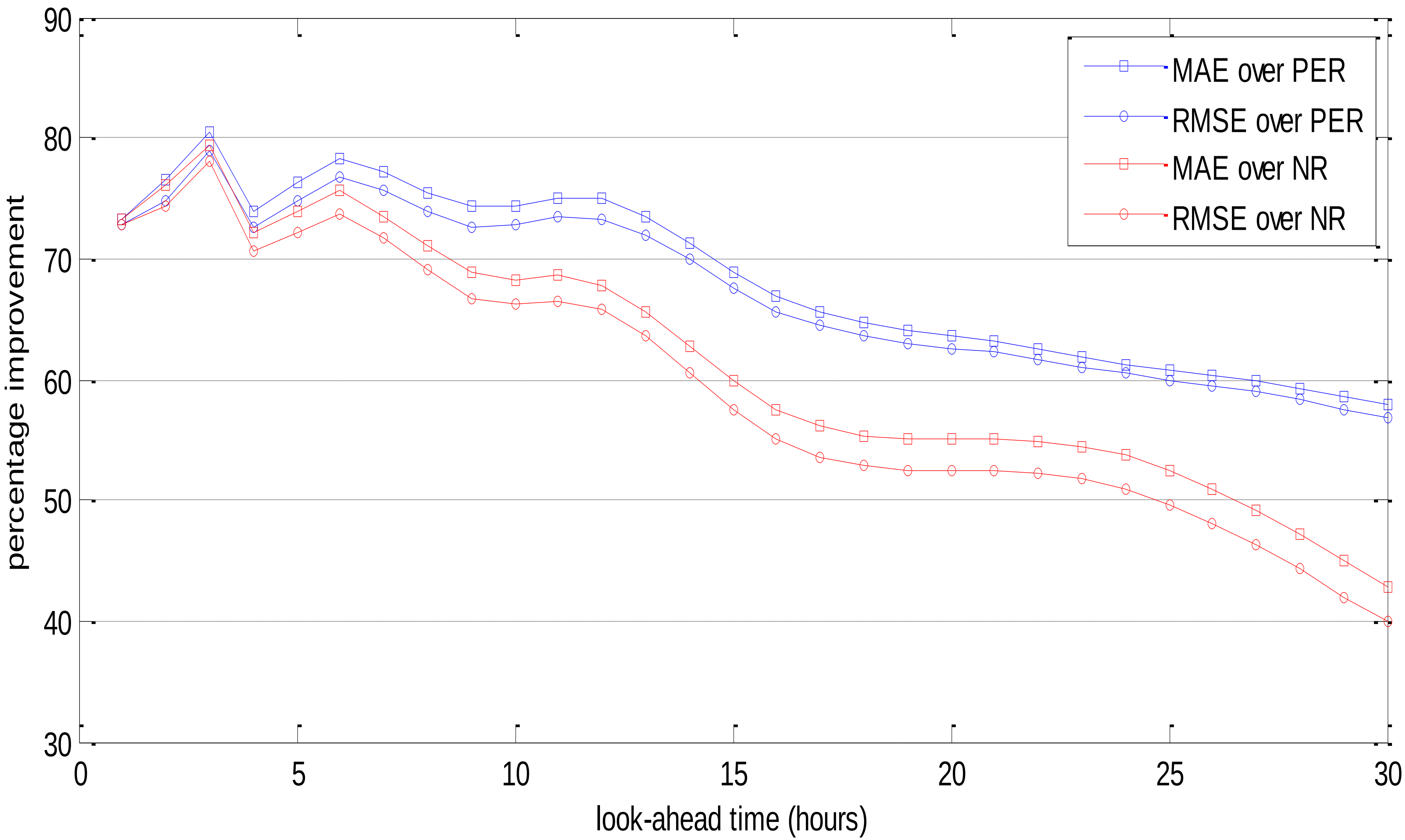
30-hours ahead Wind Speed Forecast



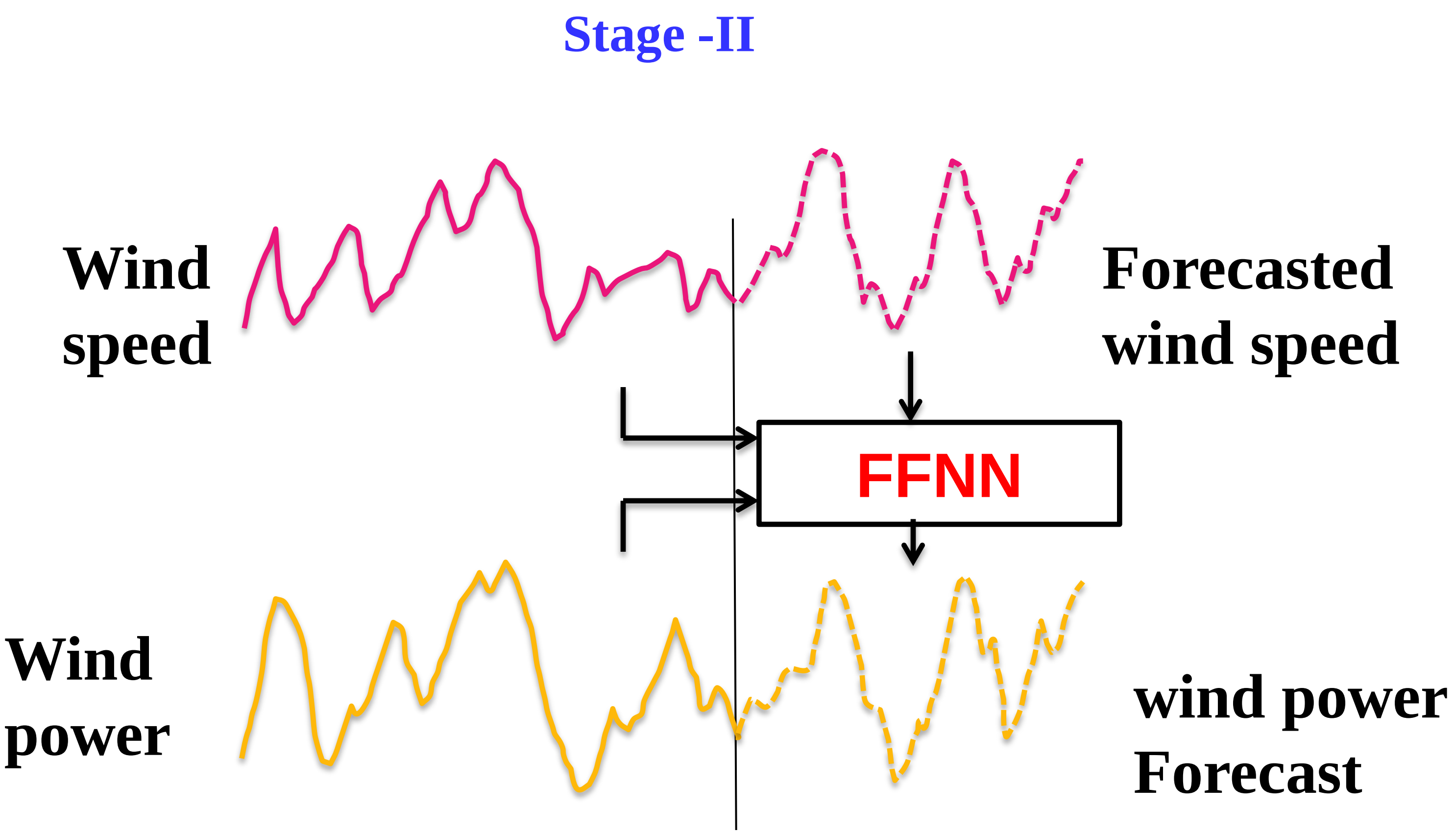
Comparative Performance



Percentage Improvement



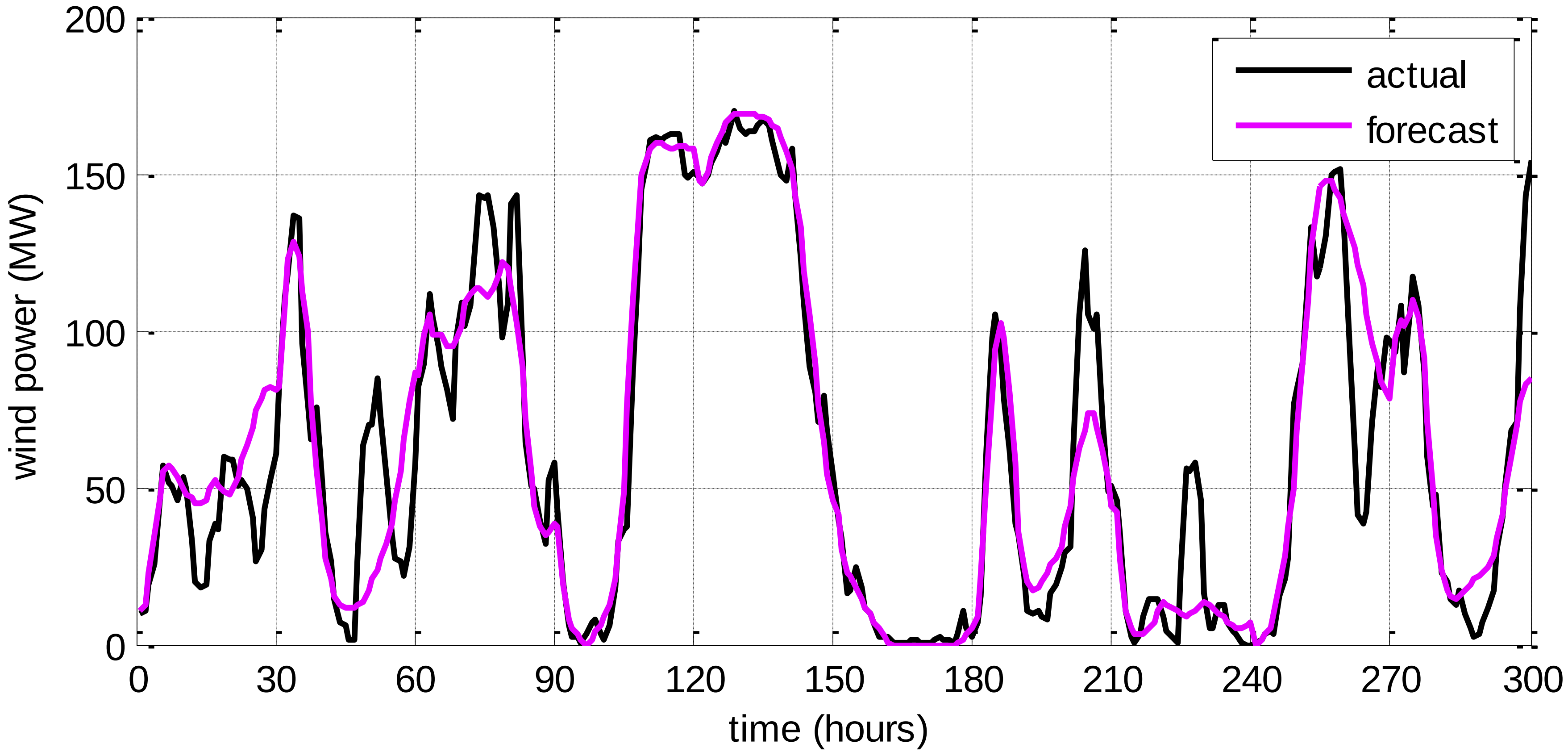
Wind speed to Wind Power Transformation



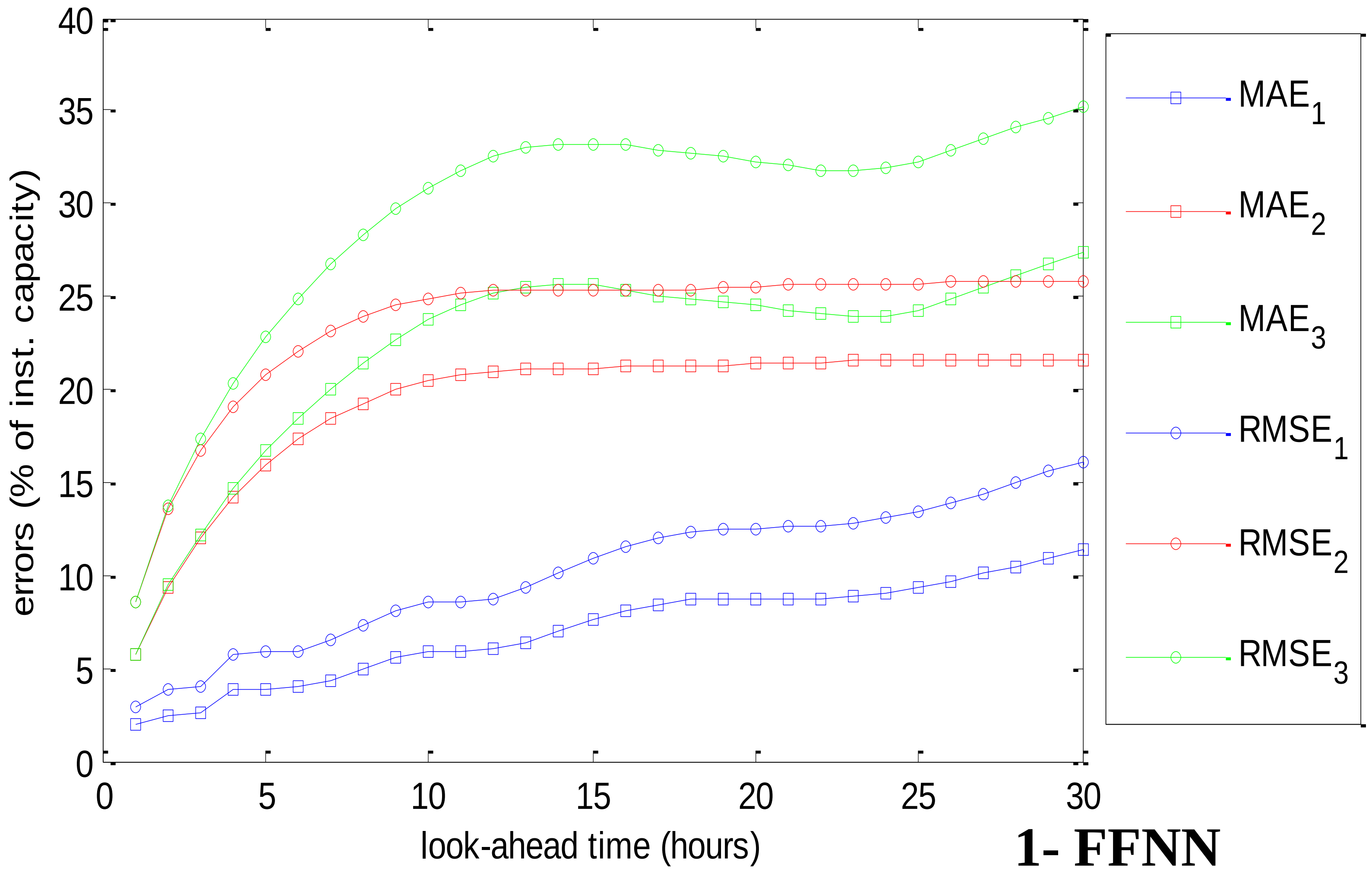
FFNN Inputs:

wind speed {0, 1, 2} lag hours and from
wind power series {1, 2, 3, 4, 5, 6} lag hours.

30-hours ahead Wind Power Forecast



Comparative Performance

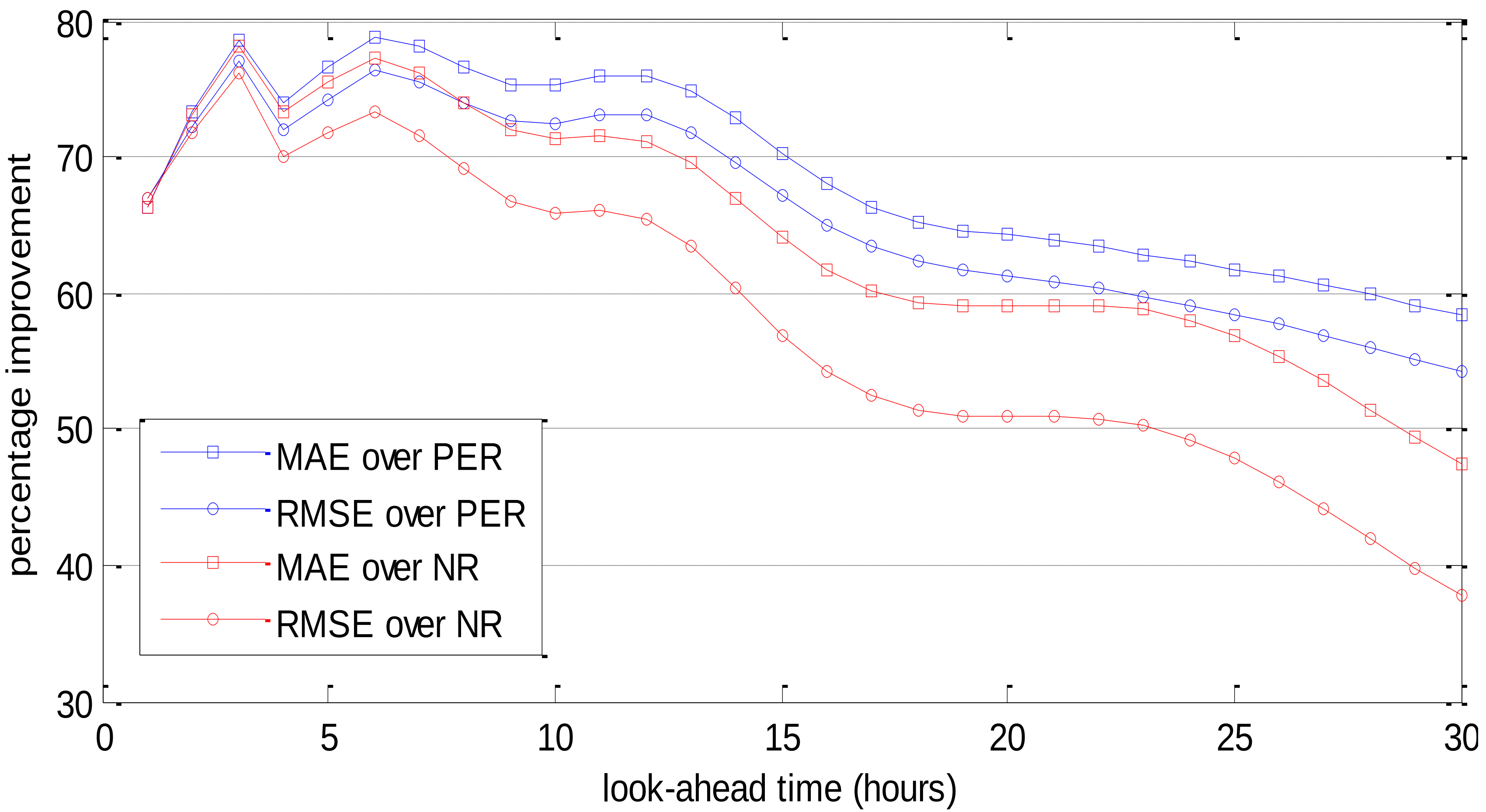


1- FFNN

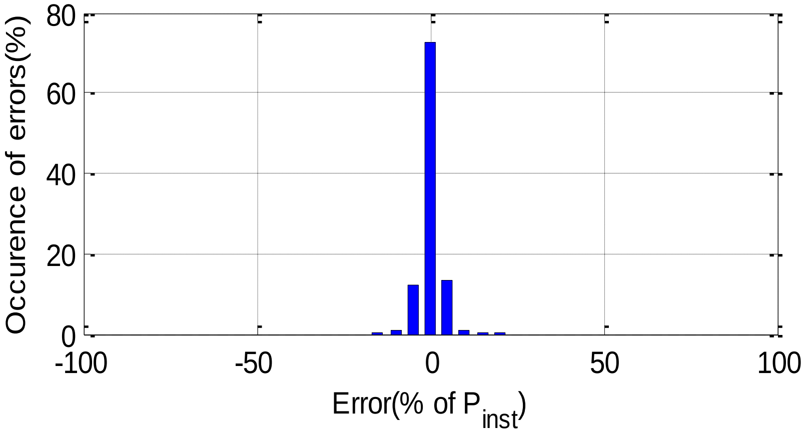
2-New-Reference

3-Persistence

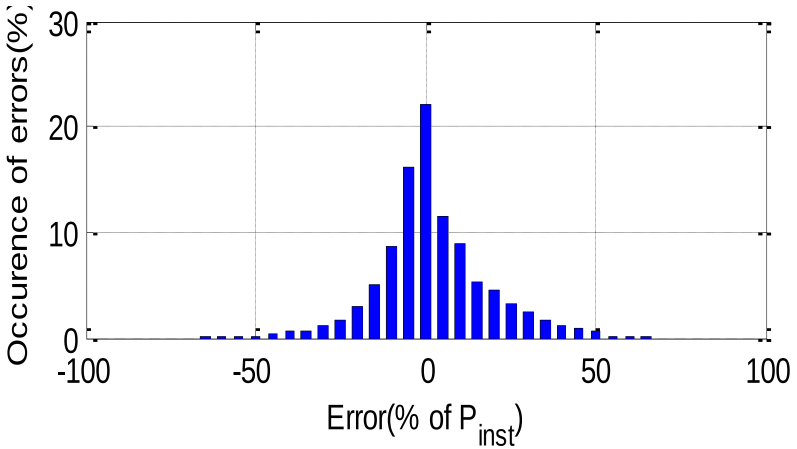
Percentage Improvement



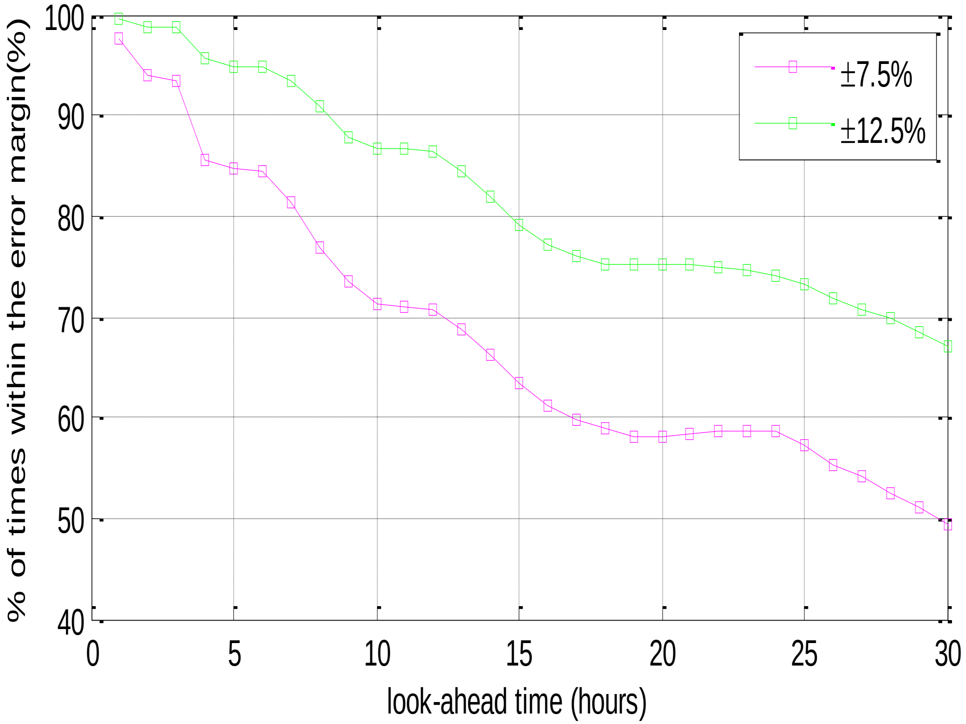
Error Distributions and Forecasting Ability



1-hr ahead forecast error distributions



30th -hr ahead forecast error distributions



Summary

- **Hourly forecast of wind power, up to 30h ahead, is carried out in two stages.**
- **In stage-I, multiresolution analysis of wind speed is carried and the decomposed signals are forecasted using AWNN.**
- **In stage-II, a Feed Forward Neural Network is used for non-linear mapping between the obtained wind speed forecasts and wind power outputs.**
- **The forecasting results when compared, shows that the proposed method has an average improvement of 67% over Persistence and 60% over New-Reference benchmark model.**


THANK YOU