Advance Dispatching and real-time forecasts of active & reactive load

ETIP SNET - South Eastern Region Workshop

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Overview

- Advance Dispatching: real-time adequacy assessment
- LoadForecast: real-time P&Q predictions
- LoadForecast: prediction errors

Few words about Terna

- the sixth Transmission System Operator (TSO) in the world
- the owner of the National High Voltage Transmission Grid
- responsible for the transmission and dispatching of the electricity all over the Country

Grid
- ~ 72,300$_{Km}$ of electric lines
- 25 interconnections (NTC ~ 9.2$_{GW}$)
- 841 substations

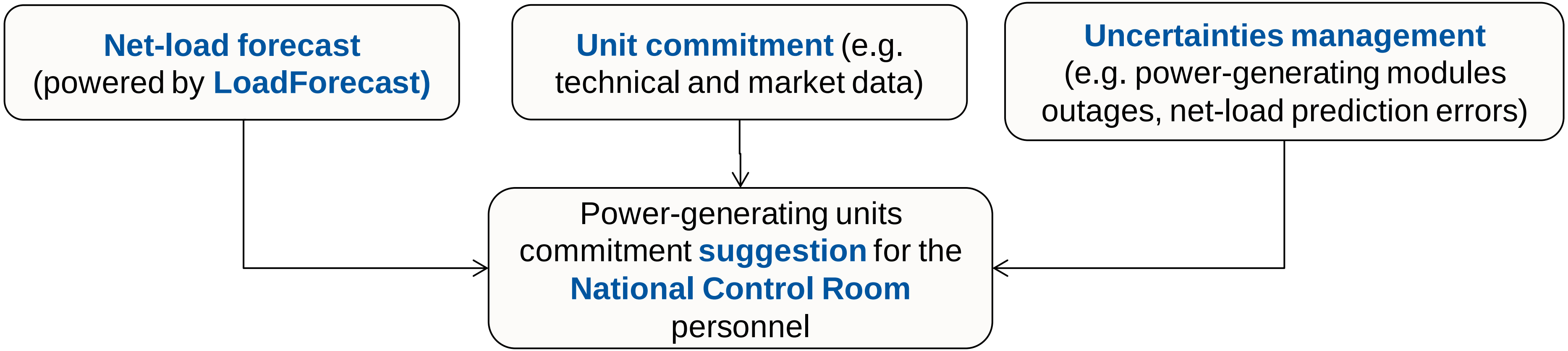
Demand
- 315$_{TWh}$ energy demand (2015)
- 59.3$_{GW}$ highest peak of demand (21st July 2015)

Generation Asset 3
- 75$_{GW}$ Conventional (gas, coal, oil, hydro pumping)
- 46$_{GW}$ RES (PV, wind, hydro, biomass, geothermal)

Electricity Market
- 62% Conventional (gas, coal, oil, hydro pumping)
- 38% RES (PV, wind, hydro, biomass, geothermal)

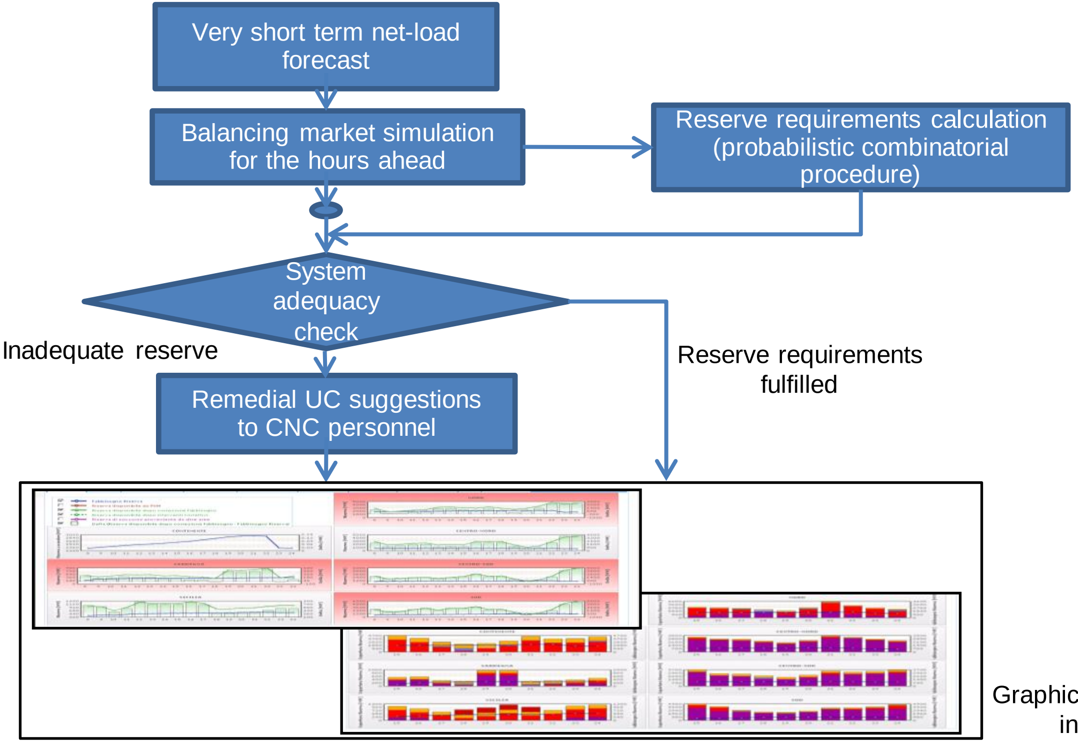
Advance Dispatching – Key points[1]

- Real time application for the italian TSO’s National Control Room
- Very short-term net-load forecasts powered by LoadForecast platform (Artificial Neural Networks algorithms, ANN)
- Real time power-generating modules’ adequacy assessment and remedial commitment proposals through optimization programming



[1] Simplified workflow

Advance Dispatching – Workflow[1]



Graphical display on interface

Data

- Technical
  - ✓Plant's data (size, gradients, operation time, etc.)
  - ✓Hydroelectric energetic constraints
  - ✓etc.
- System
  - ✓ Wind production forecast
  - ✓ Grid data (power exchange limitation between areas, clusters limitation)
  - ✓ etc.
- Market
  - ✓Producer's offers
- Uncertainties
  - ✓ On load and eolic production forecast
  - ✓ Power plants probability of outage

[1] Simplified workflow

Advance Dispatching – Spatial model

Optimization applies at national level with the respect of the italian market zone structure.

HV levels managed for each market zone:

- for Continental Italy: main grid (380 and 220 kV)
- for the main islands (Sardinia and Sicily): 380-220-150 kV

HV grid model configuration might be easily changed, adjusting load prediction provision consequently.

Advance Dispatching – Unit commitmet optimization[1]

- Overall dispatching costs minimization
- Power balancing adopting **zonal net-load** predictions by **LoadForecast**
- **Italian market zone** model
- **Energy constraints** for hydro powerplants
- **Tertiary reserve dimensioning** meeting requirements for each zone
- **Sharing of tertiary reserve** margins between market zones

Mixed-Integer Linear Programming algorithms deployed, in order to manage at the same time:

- Linear objective function
- Bounds and linear constraints

e.g. P profile within Pmin and Pmax

- Restrictions on some components of vector x of unknowns to have integer values

e.g. unit operational mode: on [1] or off [0]

Tertiary reserve dimensioning through **integral convolution** between:

- Net-load prediction uncertainty
- Power-generating modules outage probability

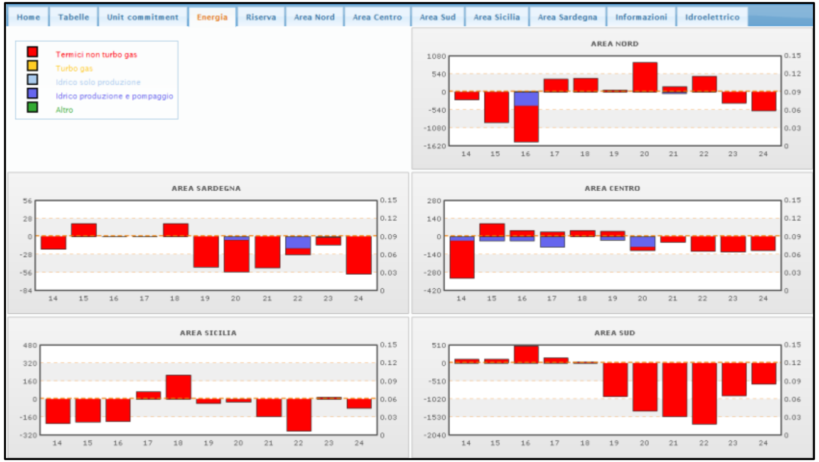
and adopting a **dimensioning rule** with the aim of reducing the probability of **unsufficient tertiary reserve** equal or less to **predetermined values**

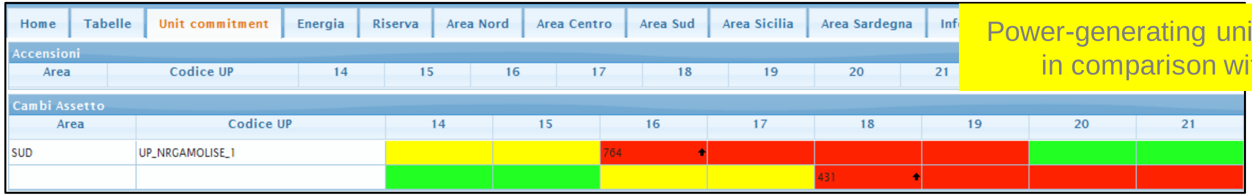
[1] Simplified representation

Advance Dispatching – Graphic displays[1]

Trend of zonal total energy balanced for each type of generators

Zonal total upward tertiary reserve margins in comparison with dimensioning requirements





Power-generating unit commitment proposal in comparison with market outcome

[1] A display selection is presented

Real Time Electric Load Forecasting (LFOR)
Data Mining Techniques on Distributed Computing

Special thanks to eng. Felice Tuosto (felice.tuosto@eng.it)

LoadForecast – Real time electric load forecasting

Automatic and real-time predictions

Aim:

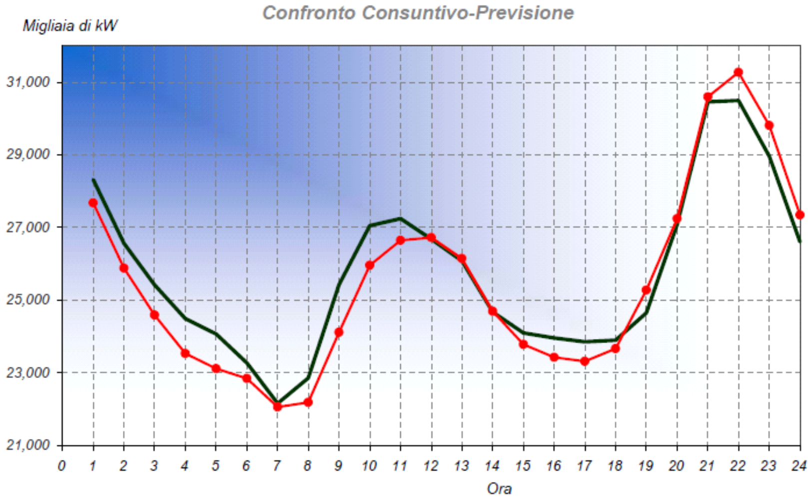
- To estimate the electric load along a future time horizon on the basis of the available information (actual system state, its history and correlated exogenous variables)

Features:

- Real time - very short term forecasting (Ts=15min) of the **zonal active power** (6 forecasts within 5min)
- Real time - very short term forecasting (Ts=15min) of the **nodal active and reactive power** (up to 500 forecasts within 5min)
- Real time - very short term forecasting (Ts=15min) of the **significant weather variables** (6 forecasts within 5min)
- Real time **errors** estimation

EMS key users:

- **ORPF/OPF** (Optimal Reactive/Active Power Flow) [1]
- **AD** (Advance Dispatching)



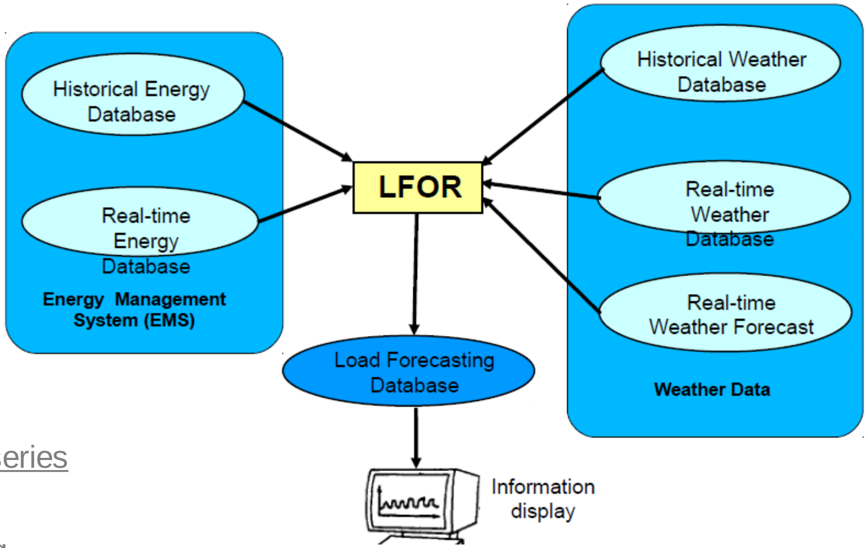
- *Italian load demand (red curve) predicted one day in advance*
- *Real-time load demand (green curve) calculated from actual measures*

[1] integration in progress

LoadForecast – Technology and solutions

Technology

- Core implemented in **Python/C++**
- Use of scientific and advanced custom libraries and **Data Mining** tools



Models deployed

- **Statistical** (e.g. time series AR, MA, ARMA)
- **Machine learning** (e.g. Artificial neural network, Gradient Boosting Trees, custom Hybrid Models)

Historical load is used as input for model prediction

➢the most recent available load

➢the load of yesterday (in a range of same hours), the same day of the last week and the same hours for last 1÷3 weeks and few years

➢ a GradientBoostingTree model is used for best features selection

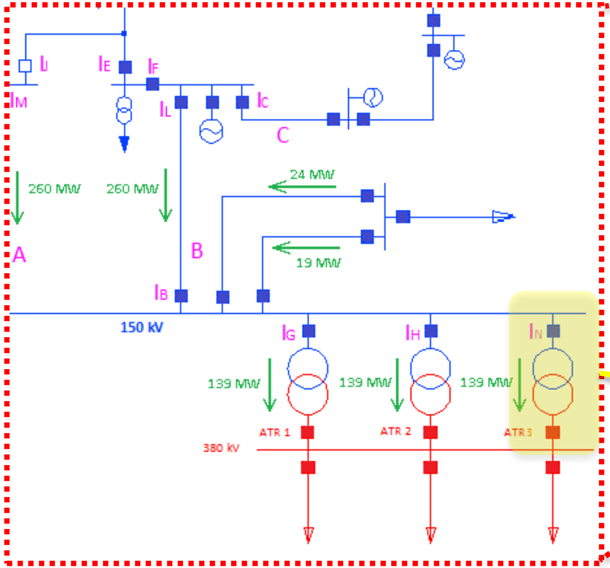
➢ a clustering model is used for input selection (hierarchical cluster)

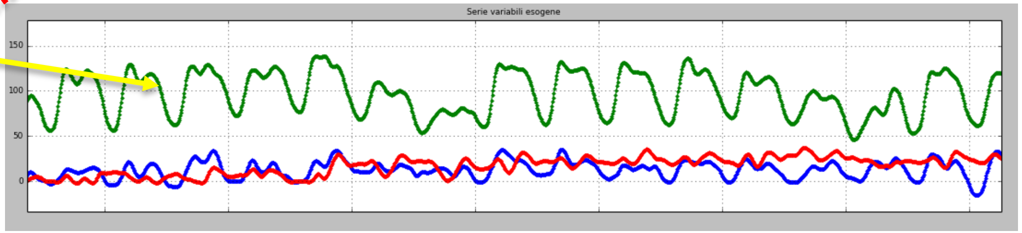
LoadForecast - ADAPTIVE-Hybrid models:

- adaptivity granted by online and recursive learning stage for each new prediction (managing its own calibration)

LoadForecast – Spatial classification

- Zonal (e.g. italian market zones for AD)
- Nodal (for ORPF/OPF)





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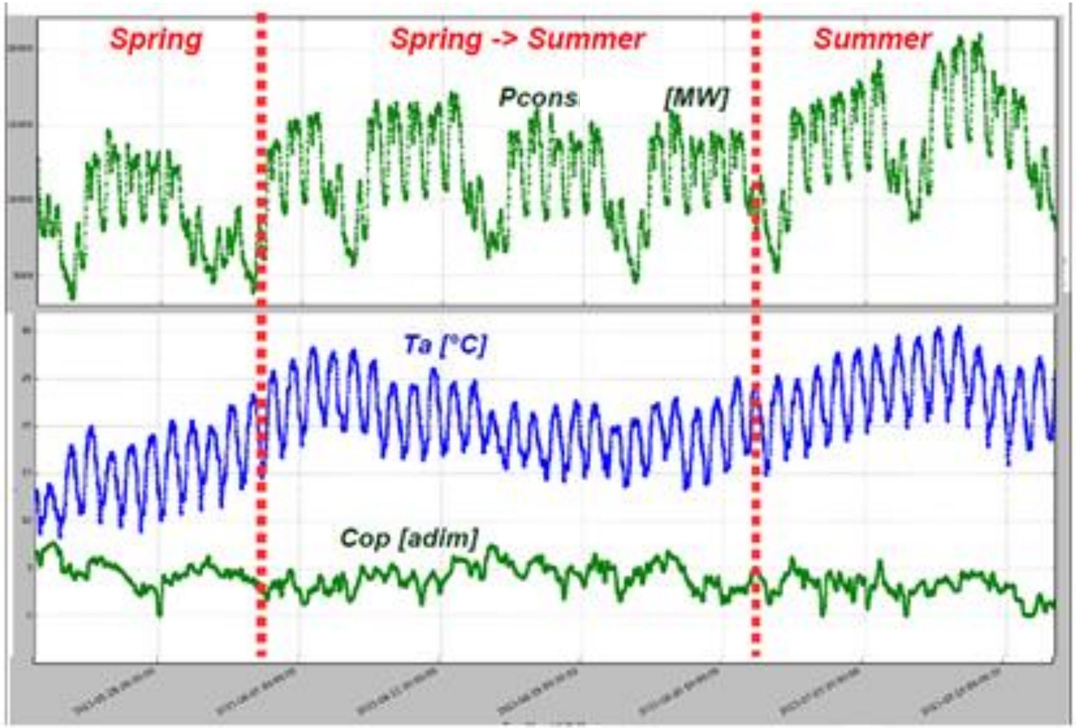
LoadForecast – Cross-correlation & weather forecasts



Active power zonal load time series (**autocorrelation**)

Exogenous weather variables time series (**cross-correlation**):

- Environmental temperature [°C]
- Cloud cover [pu]

LoadForecast – Models selection

A system and its dynamics (e.g. zonal net-load) could not be considered as either completely linear or completely non-linear: a hybrid approach grants the best fitting.

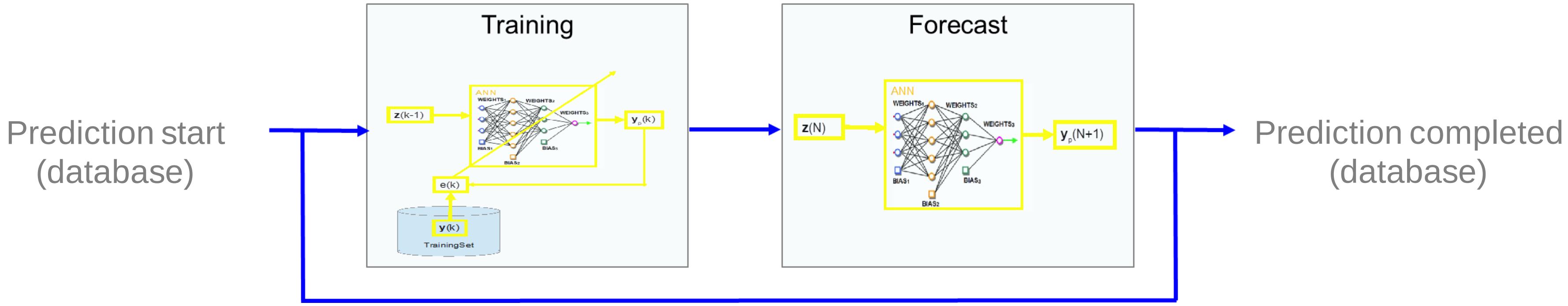
LoadForecast integrates statistics (SM) and artificial intelligence methods (ANN):

- SMs good when relationships are linear and there are many redundant features
- SMs take only the most relevant and linear features => training time is very low
- ANNs use the results of SM model (features/linearity/errors) to reduce errors and training time
- ANNs capture nonlinearities and similar days

The **Hybrid Model** (HM) is understandable (no black-box models): **fully adaptable** and **robust** to time series **changes.** HMs' accuracy can not be lower than those by single models

[1] integration in progress

LoadForecast - Hybrid models



HybridModel = Statistic algorithm + ANN algorithm

Statistic algorithm	ANN algorithm
Linearities catched	Nonlinearities catched
Robust	SMs errors mitigated
Short training times	Redundancy (in case of SMs failure)

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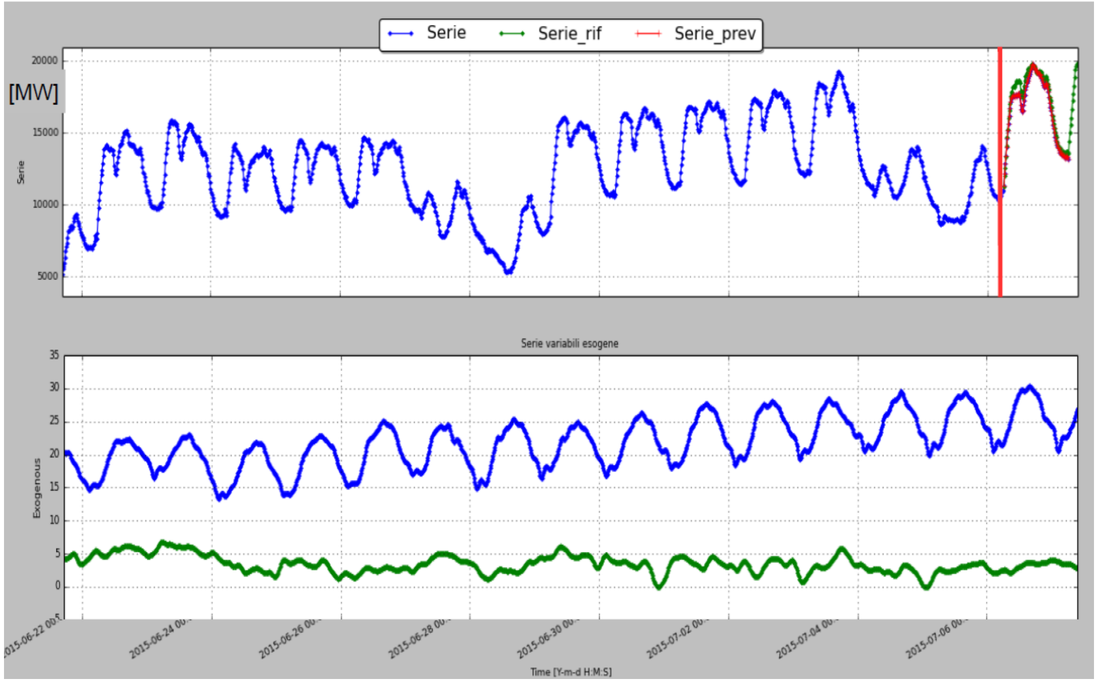
Zonal

LoadForecast – Zonal P prediction

horizon=24h Tcamp=15min



P prediction

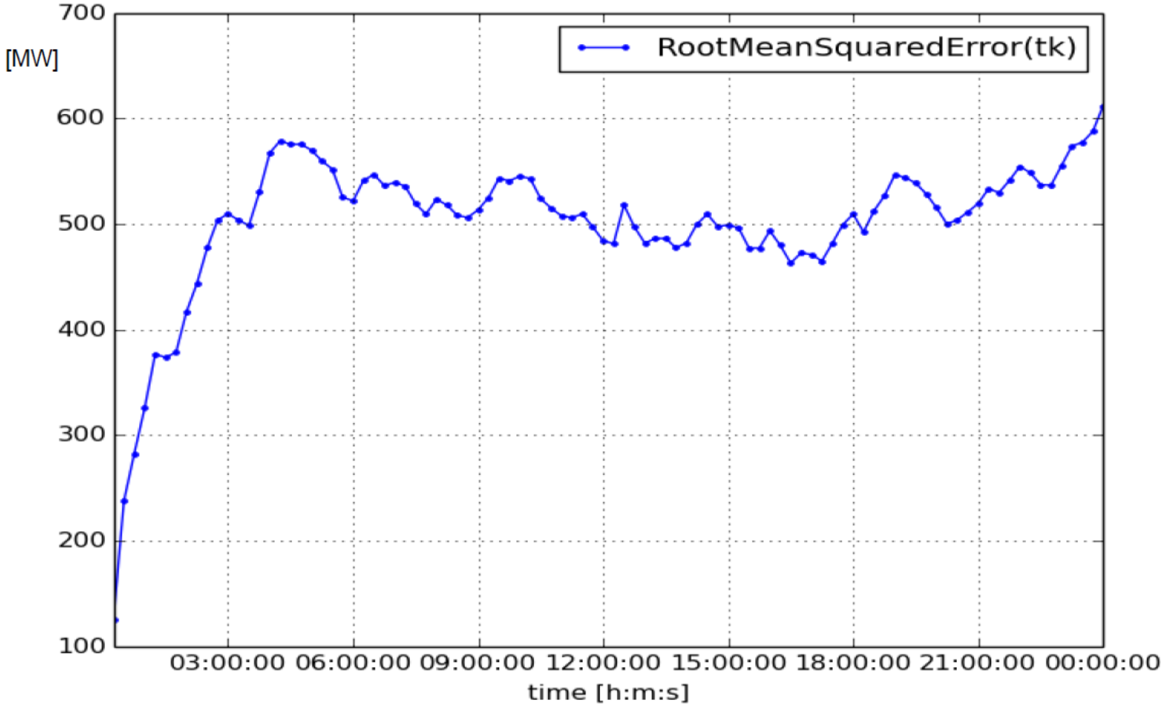
P Actual measurements

Environmental temperature

Cloud cover

Zonal

LoadForecast – Zonal P prediction[1]



Root Mean Squared Error

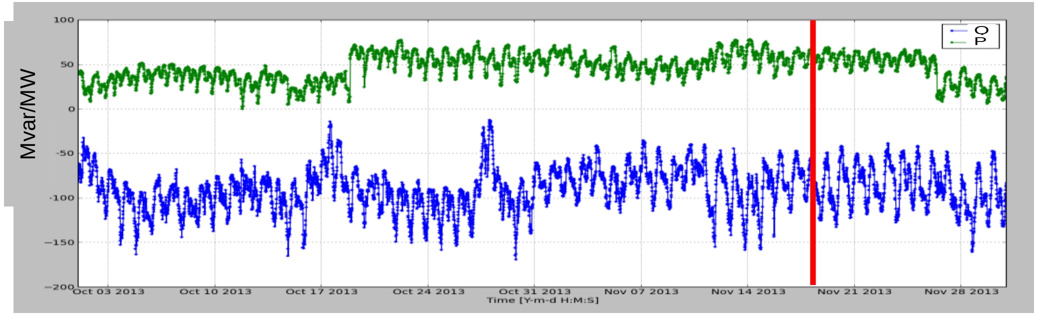
- RMS error increases as prediction is further away
- RMS error saturation within +6 hours prediction-ahead
- No bias error (accuracy)

[1] this analysis has no general validity

Nodal

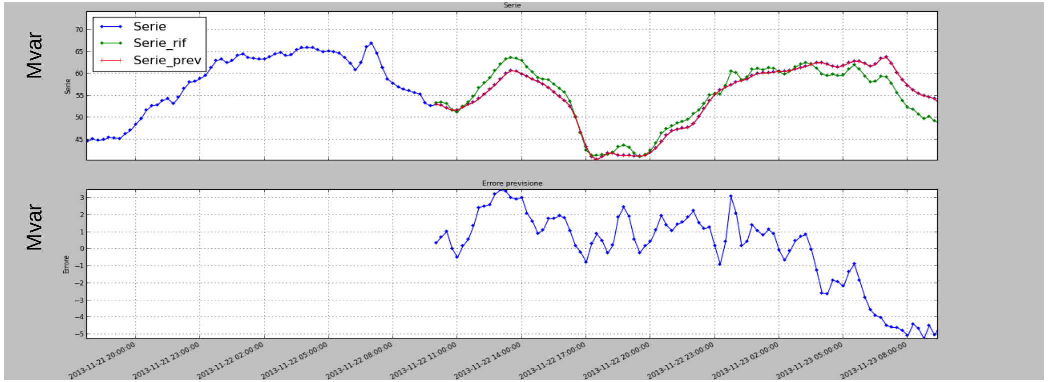
LoadForecast – Nodal Q prediction

Autotransformer 380/150 kV



Q [Mvar]

P [MW]



Q prediction vs. measures

Prediction Error

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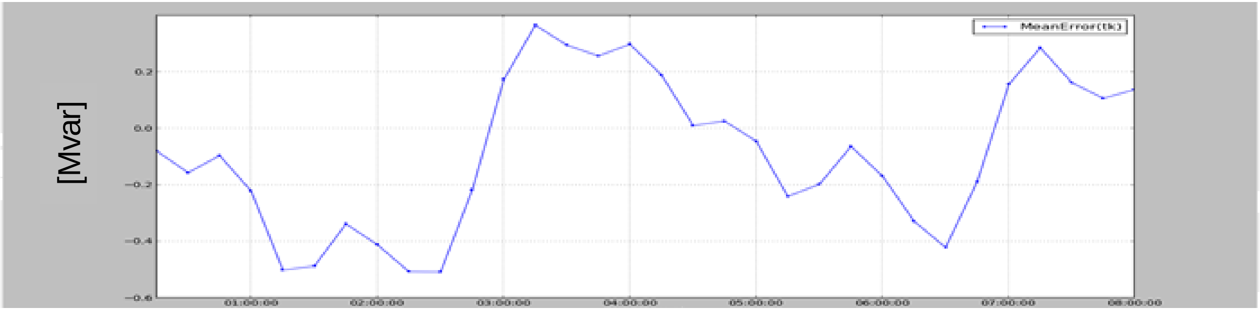
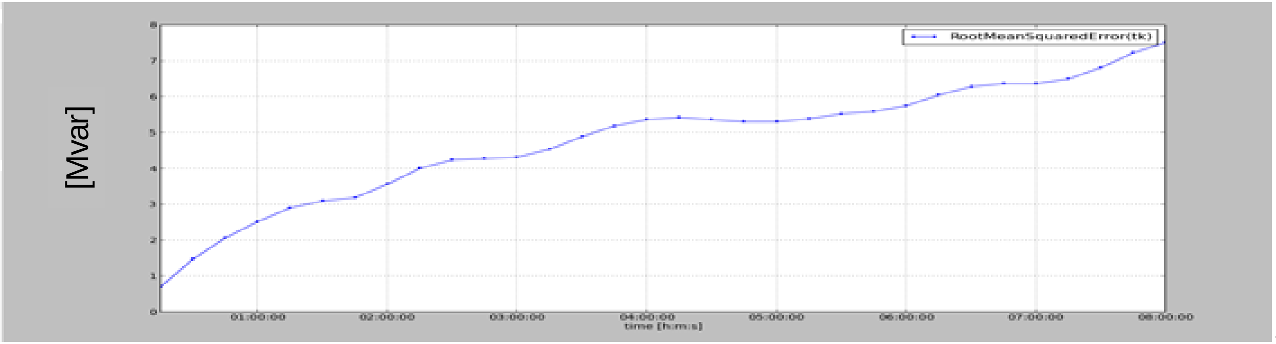
Nodal

LoadForecast – Nodal Q prediction

Autotransformer 380/150 kV



Mean error [Mvar]



RMS error [Mvar]

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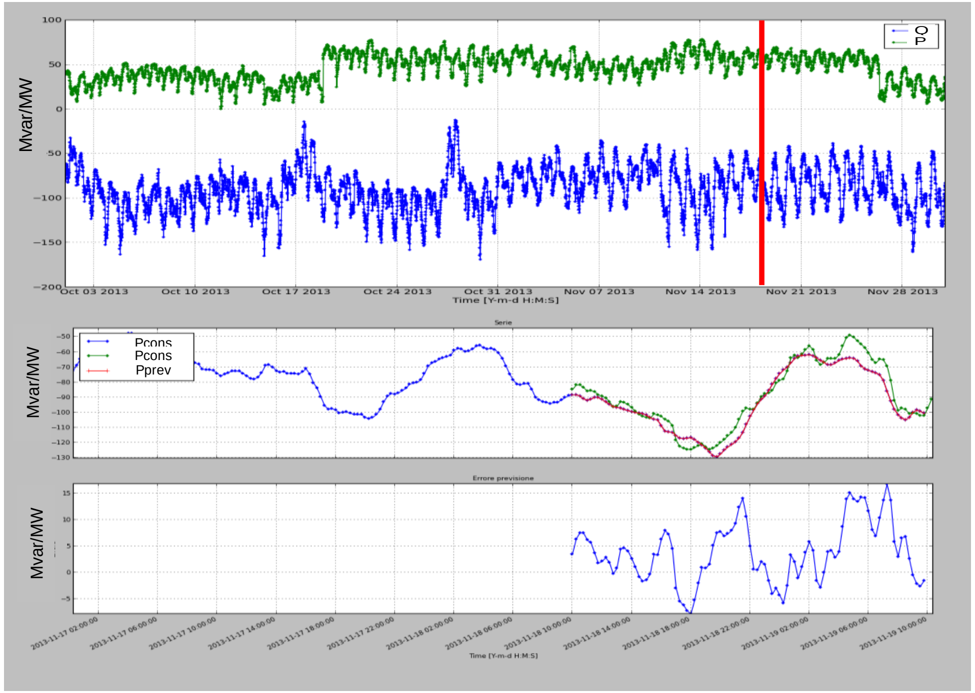
LoadForecast – Nodal P prediction



Autotransformer 380/150 kV

Q [Mvar]

P [MW]

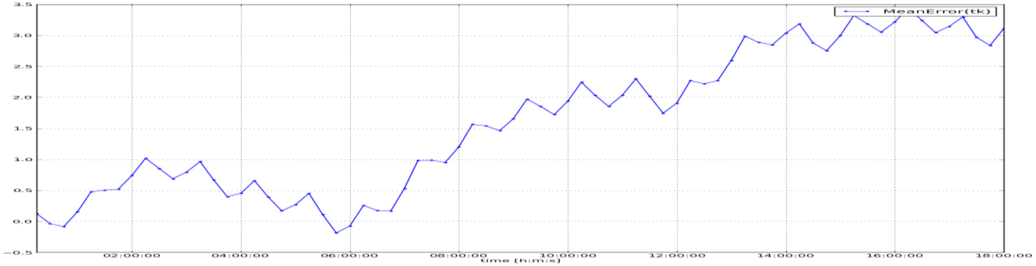
P prediction vs. measures

Prediction Error

LoadForecast – Nodal P prediction

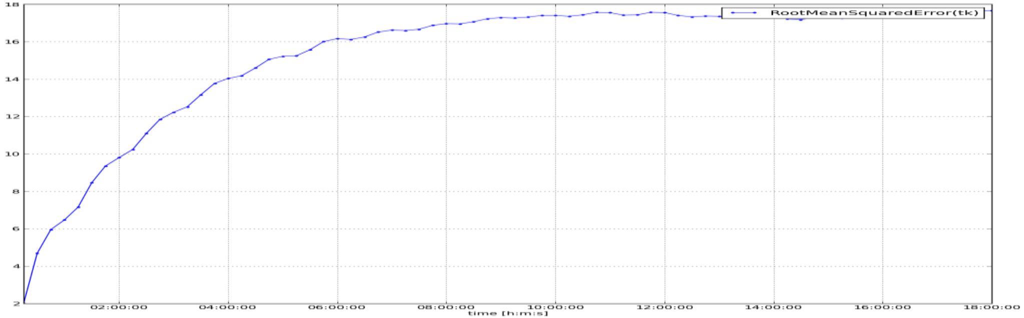
Autotransformer 380/150 kV

MW



Mean error [MW]

MW



RMS error [MW]

Nodal

P LoadForecast – Operational performances[1]

Total number of **real-time** P nodal forecasts operated in parallel:

≈ 400 real-time forecasts in less than 5 minutes

Nodal

P nodal LoadForecast – Operational prediction accuracy[1]

Standard EMS[2] active power forecast vs LoadForecast P (LFOR-P)

Substation 1

- **Transformer 1** 380-150 kV (250 MVA)
- **Transformer 2** 380-150 kV (250 MVA)

Features:
- RES (wind) generation
- Medium-low ACF values

Low recursion P series

Substation 2

- **Transformer C** 380-150 kV (250 MVA)
- **Transformer D** 380-150 kV (250 MVA)
- **Transformer E** 380-150 kV (250 MVA)

Features:
- Civil load
- Medium-high ACF values

Medium-high recursion P series

[1] 15 days time interval statistics (seasonality: mid of June); **this analysis has no general validity**

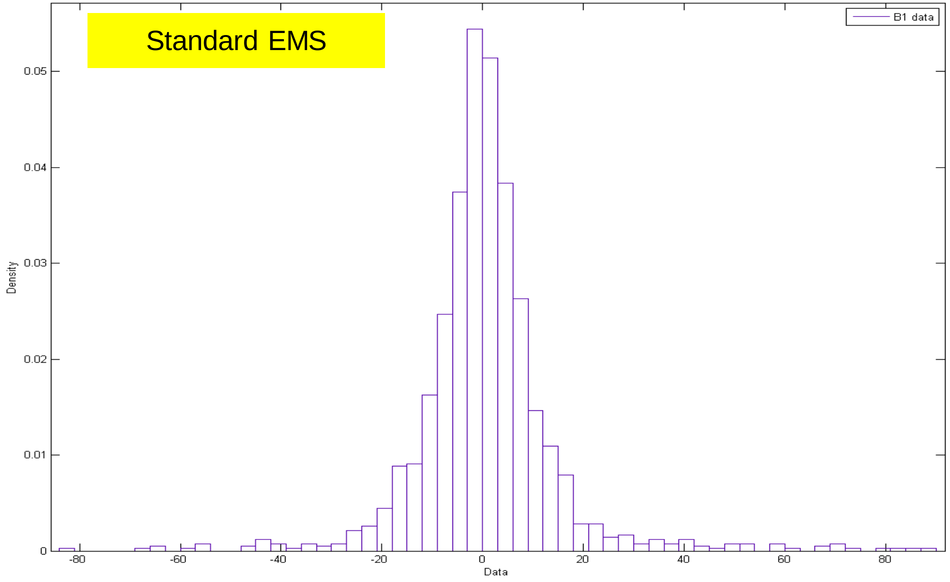
[2] Energy Management System

Nodal

P nodal LoadForecast – Precision & Bias prediction errors

Substation 1 - Transformer 1 380-150 kV (250 MVA)

Low recursion P series



+15' ahead prediction errors[1]

[MW]	Standard EMS	LFOR-P
Mean	0.5	-0.28
StandardDeviation	14.0	7.05

[1] prediction error cumputed as (forecast – actual values)

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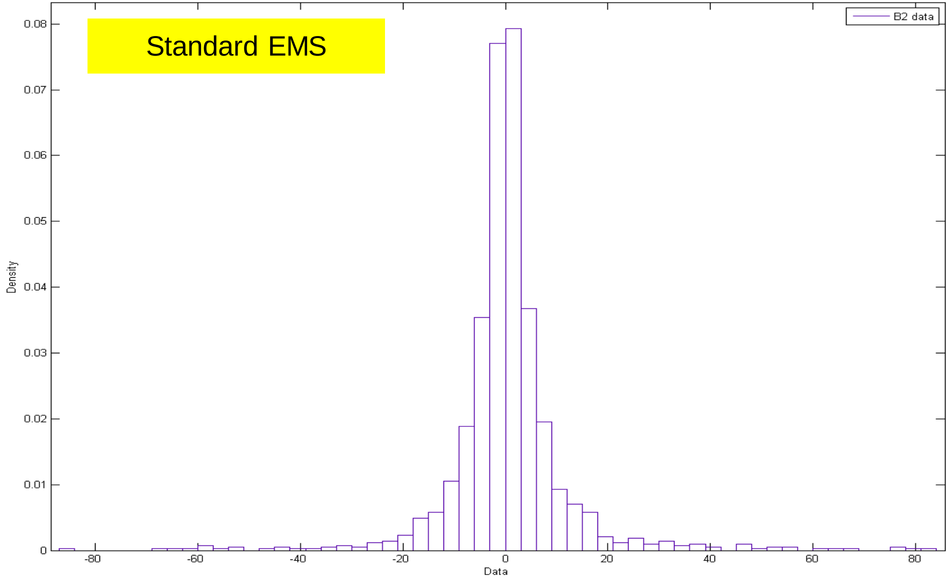
Nodal

P nodal LoadForecast – Precision & Bias prediction errors

Substation 1 - Transformer 2 380-150 kV (250 MVA)

Low recursion P series



+15’ ahead prediction errors[1]

[MW]	Standard EMS	LFOR-P
Mean	0.4	-0.13
StandardDeviation	12.0	5.37

[1] prediction error cumputed as (forecast – actual values)

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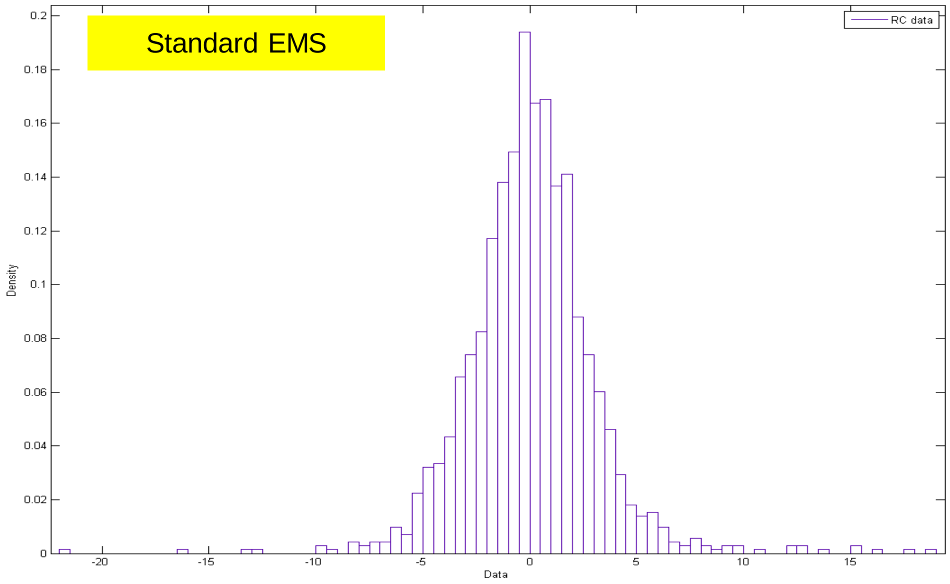
Nodal

P nodal LoadForecast – Precision & Bias prediction errors

Substation 2 - Transformer C 380-150 kV (250 MVA)

Medium-high recursion P series



+15' ahead prediction errors[1]

[MW]	Standard EMS	LFOR-P
Mean	0.1	-0.08
StandardDeviation	3.0	1.63

[1] prediction error cumputed as (forecast – actual values)

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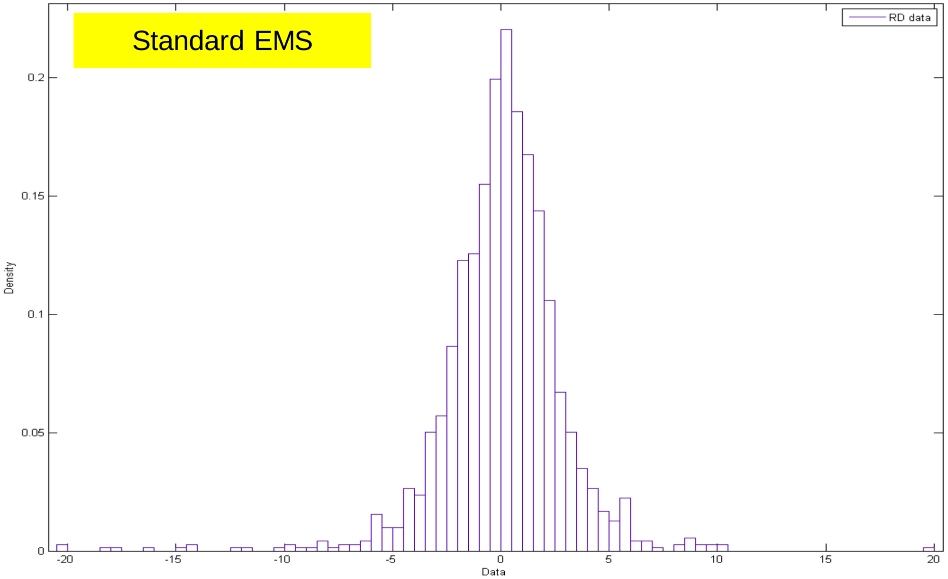
Nodal

P nodal LoadForecast – Precision & Bias prediction errors

Substation 2 - Transformer D 380-150 kV (250 MVA)

Medium-high recursion P series



+15' ahead prediction errors[1]

[MW]	Standard EMS	LFOR-P
Mean	0.1	-0.04
StandardDeviation	2.9	1.45

[1] prediction error cumputed as (forecast – actual values)

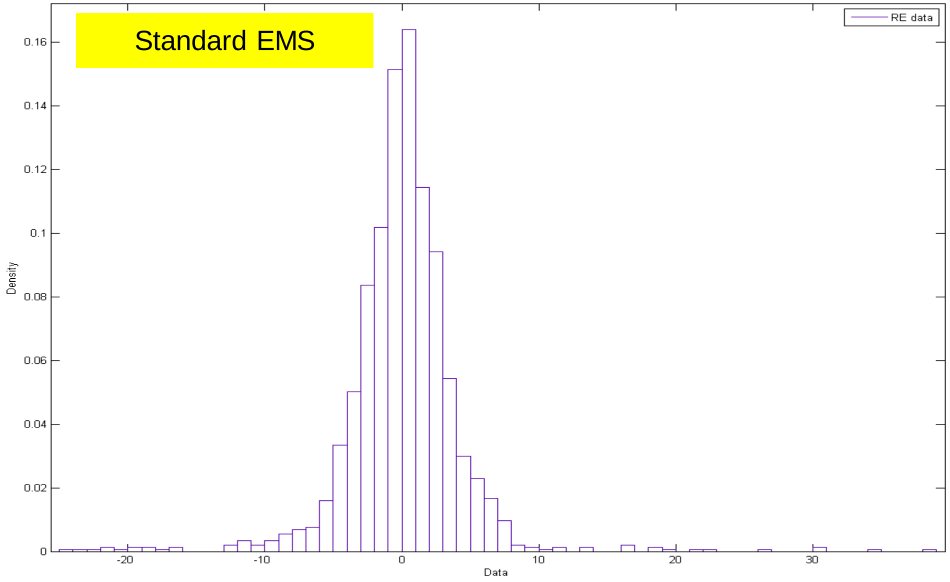
Nodal

P nodal LoadForecast – Precision & Bias prediction errors

Substation 2 - Transformer E 380-150 kV (250 MVA)

Medium-high recursion P series

Standard EMS



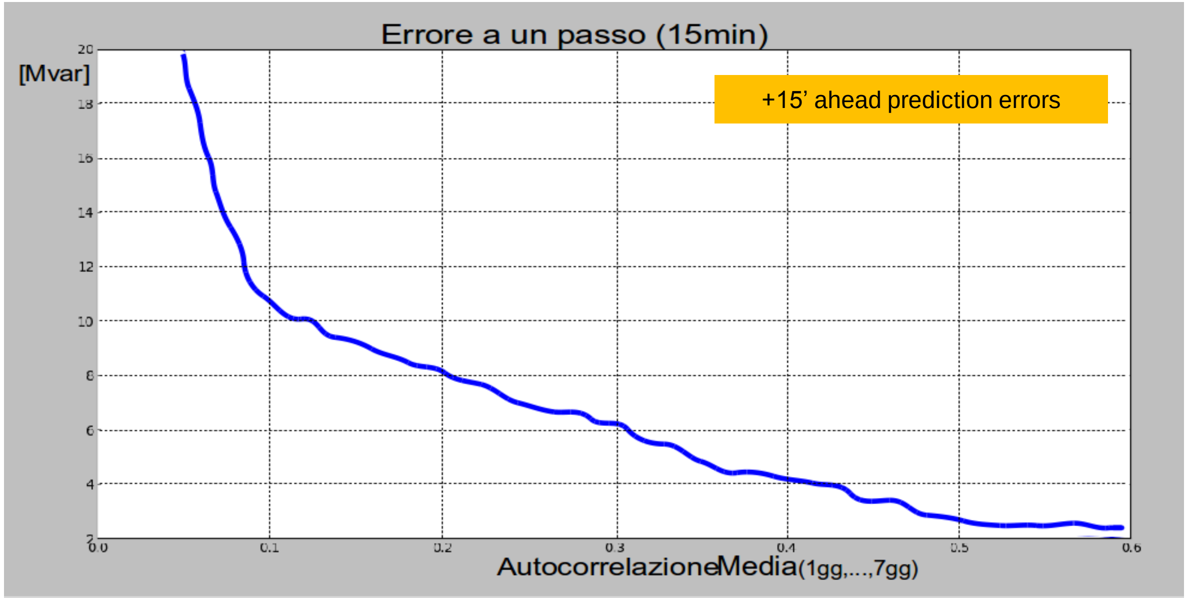
+15' ahead prediction errors[1]

[MW]	Standard EMS	LFOR-P
Mean	0.1	-0.02
StandardDeviation	4.4	2.02

[1] prediction error cumputed as (forecast – actual values)

Nodal

Nodal (P or Q) LoadForecast – Precision vs Autocorrelation



- Similar performances between P and Q series (mainly depending on ACF values)
- Root mean squared errors more than double from medium to low ACF values
- No bias error (independently from ACF)

Conclusions

- **Advance Dispatching** (AD) might be a suitable tool for supporting real-time control in order to manage the **transition** from **energy** to **balancing markets**, granting load balancing and adequacy with the aim of minimizing overall system costs

- **Reserve dimensiong might be run in real-time**, managing effective and updated **fleet**'s **outage** probability as well as **load** prediction **errors** (e.g. depending on daily pattern load phase such as steep ramps)

- Adopting **integral convolution** between load prediction errors and fleet outage probabilities **enhances** real-time **adequacy assessment**, **passing** a dimensioning approach based on **deterministic evaluations** only (e.g. reference incident coverage)

- Adopting an exogenous load forecast provision (e.g. powered by LoadForecast), **AD** may **apply** at **different spatial levels** simply changing its configuration

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Conclusions

- **LoadForecast** (LFOR) might be a suitable tool for real-time load prediction, granting high performance standards in terms of reliability, execution times and computational resource consumption (where deployed on commercial enterprise servers)

- **Hybrid model** (main prediction by linear algorithms, refinements prediction by ANN ones) grants redundancy and to catch load nonlinearities whilst achieving highest accuracy standards

- **Data Mining** techniques and **distributed computing** might represent a direct way for predicting nodal active and reactive loads (in addition to zonal load), where issues related to **load high variability** as well as **large number** of **nodes** forecasted must be tackled

- LFOR predictions are proving to achieve **no bias error** (accuracy) and a **gaussian error distribution** (precision): in comparison with standard nodal EMS forecasts (nodal P for +15' ahead) **errors halved**

- Forecast precision deeply depends on **ACF values**: if ACF moves from **medium-high** to **low recursion values** then the **errors** more than double

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Thanks!

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