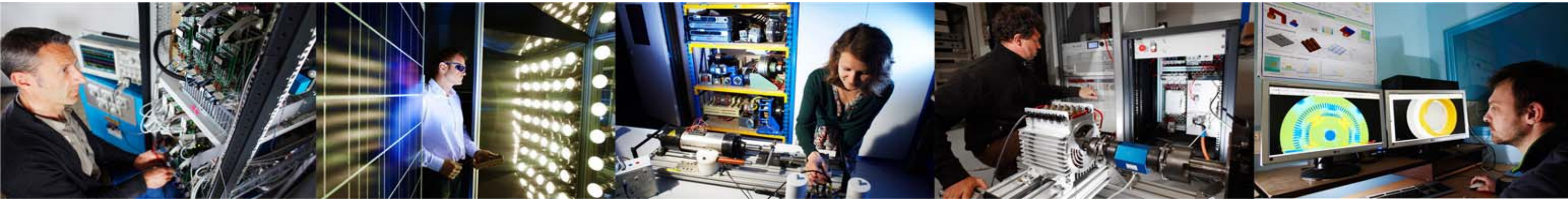

PhD thesis defense

Thursday, May 18, 2017

Energy management under uncertainty:

Application to the day-ahead planning and power reserve allocation of an urban microgrid with active photovoltaic (PV) generators and storages

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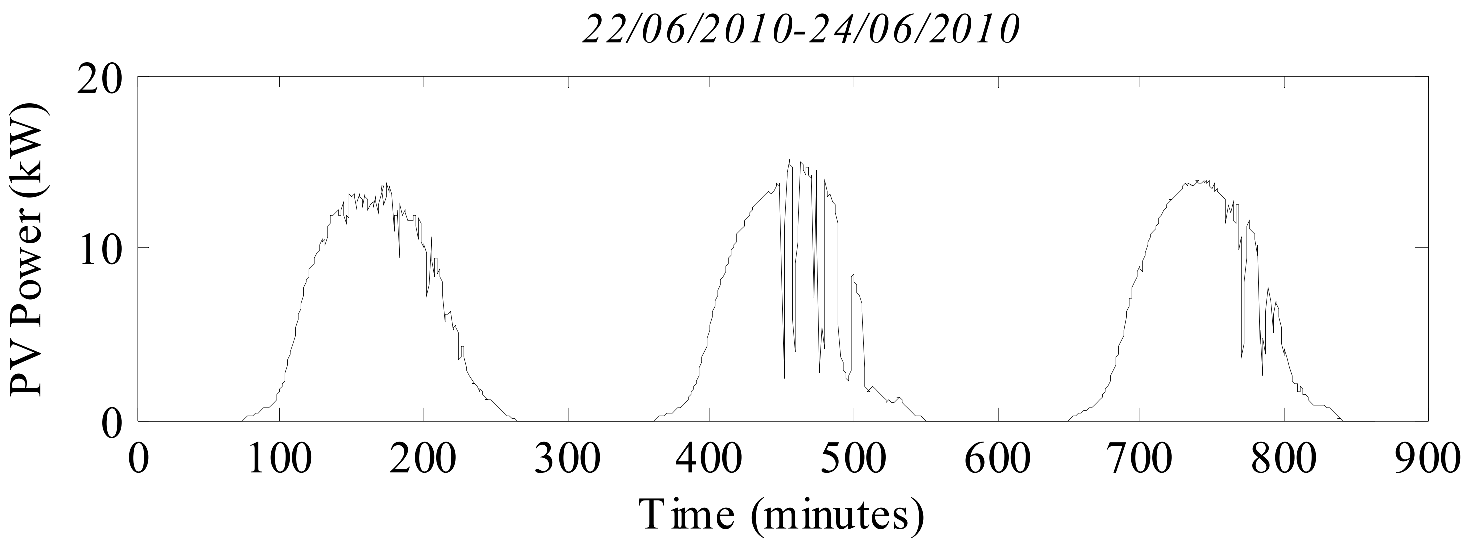
I.1 Problem: Variability of RES

- Wind and photovoltaic (PV) power production are highly **intermittent** due to the influence of meteorological conditions on the primary energy resource.



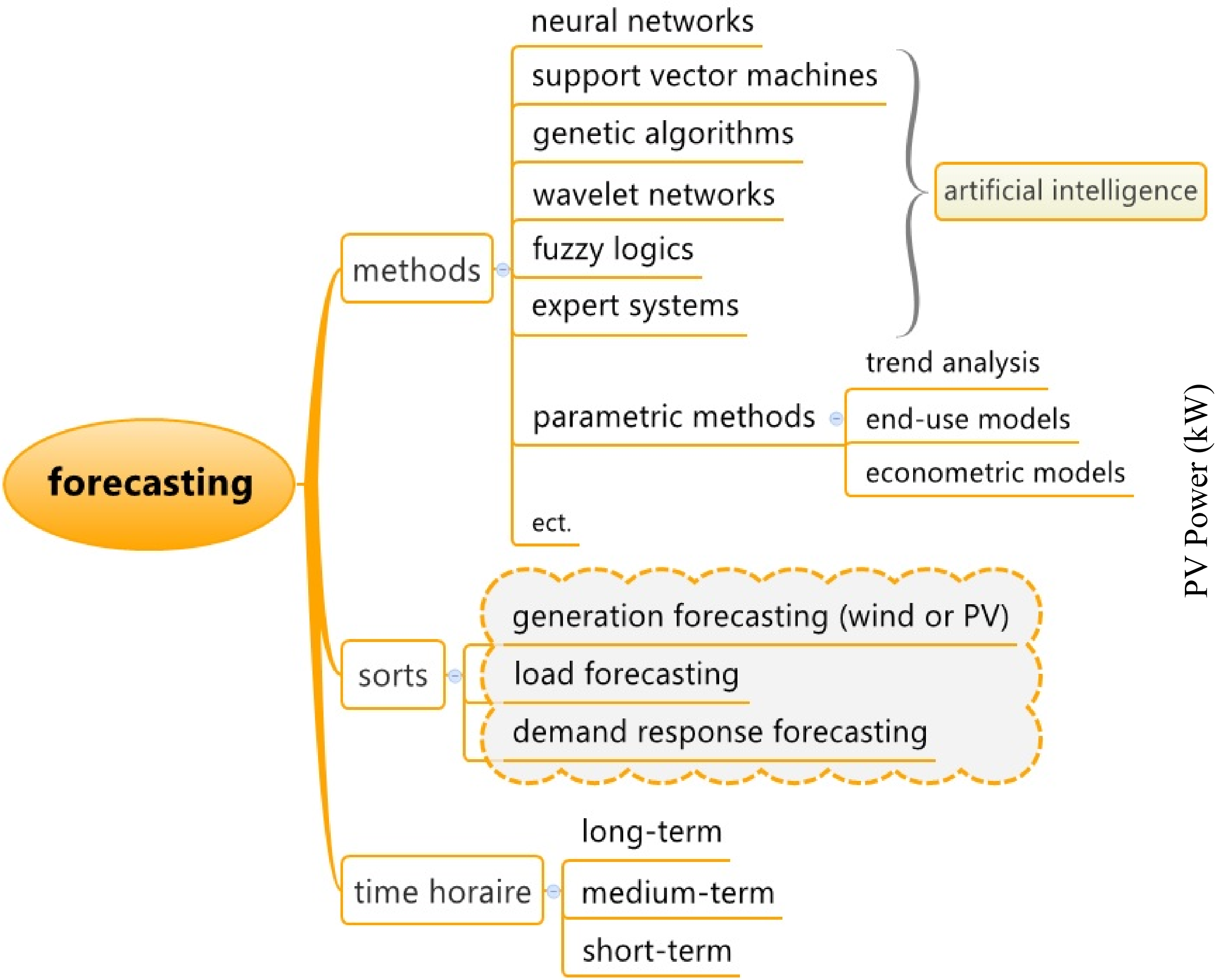
- Operate the power system in a **secure and economic way.**

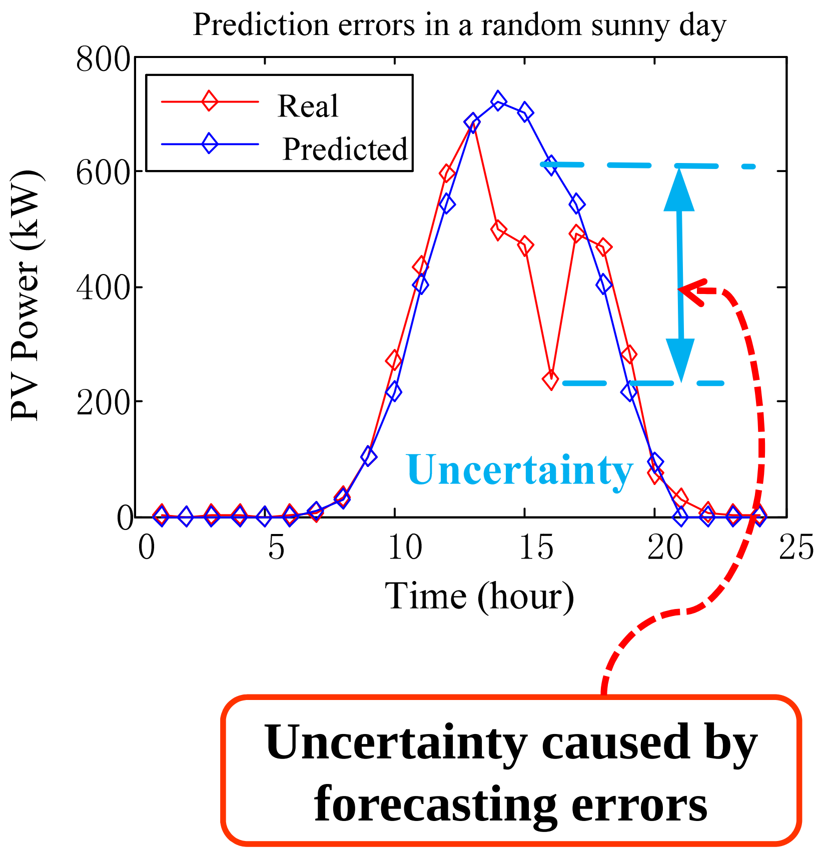
- **Accurate forecasts of renewable energy generation** are useful for
  - **Producers**: Making bids in electricity markets, Planning maintenance of wind farms, etc.;
  - **Grid operators:** Economic dispatch, planning power reserve, planning power exchanges with interconnections and other stakeholders, etc.

RES: renewable energy sources

I.1 Problem: Prediction Errors

- Intermittent RES energy production is predictable thanks to weather and statistical tools.
- **However, forecasting errors can not be eliminated even with the best forecasting tools.**

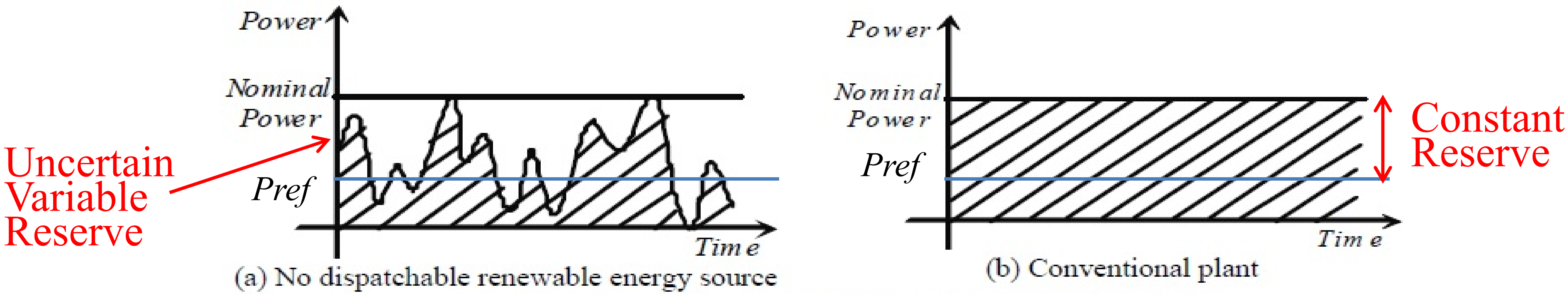




I.1 Problem: Power Reserve to Cover the Uncertainty

- To cover the risk of an unexpected RES generation losses or load increasing, **operating reserve (OR)** is scheduled one day ahead.

- Today the consumption/production balancing and OR provision are performed by conventional generators.



Pref is given by the system operators (power dispatch)

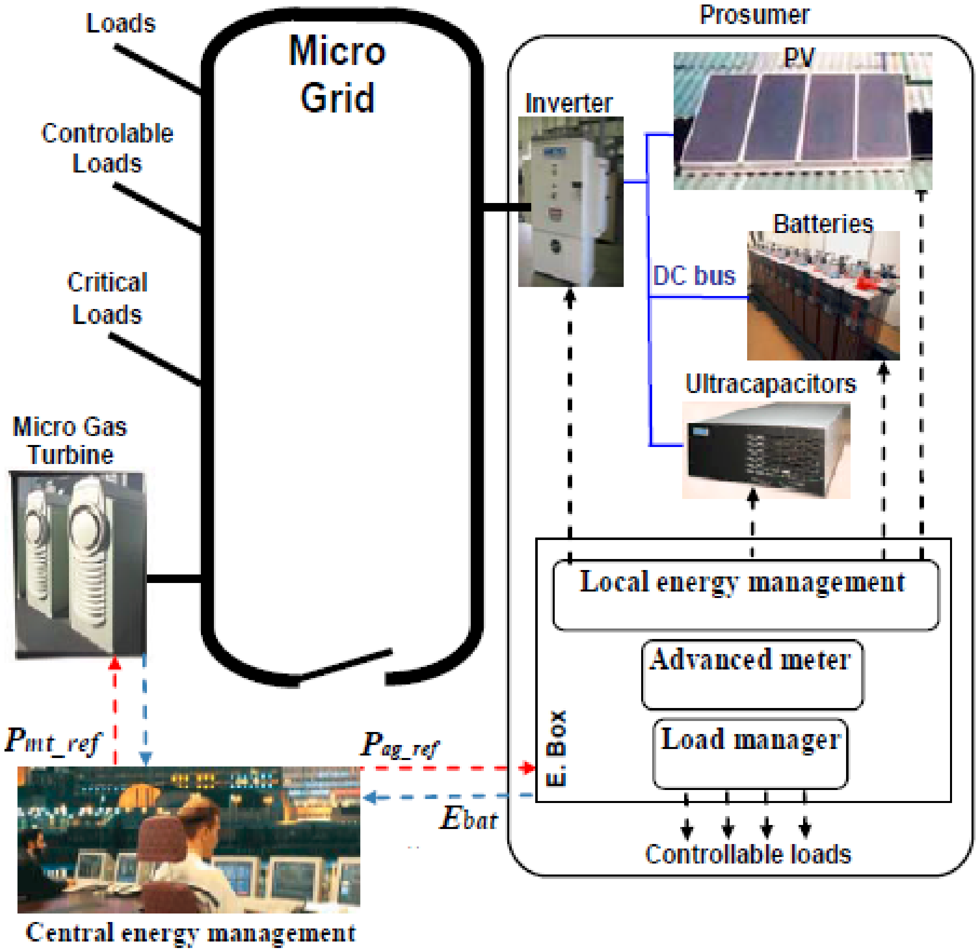
- Massive RES generators increase the system **uncertainty of power production** and so the difficulties to maintain the system security level.

- **To cover the risk:** Additional OR is needed !

How much ? How to provide it ?

I.2 Applied method

❑ Microgrid: From a **centralized network** to a **decentralized network**.



❑ Distributed generators (DG)

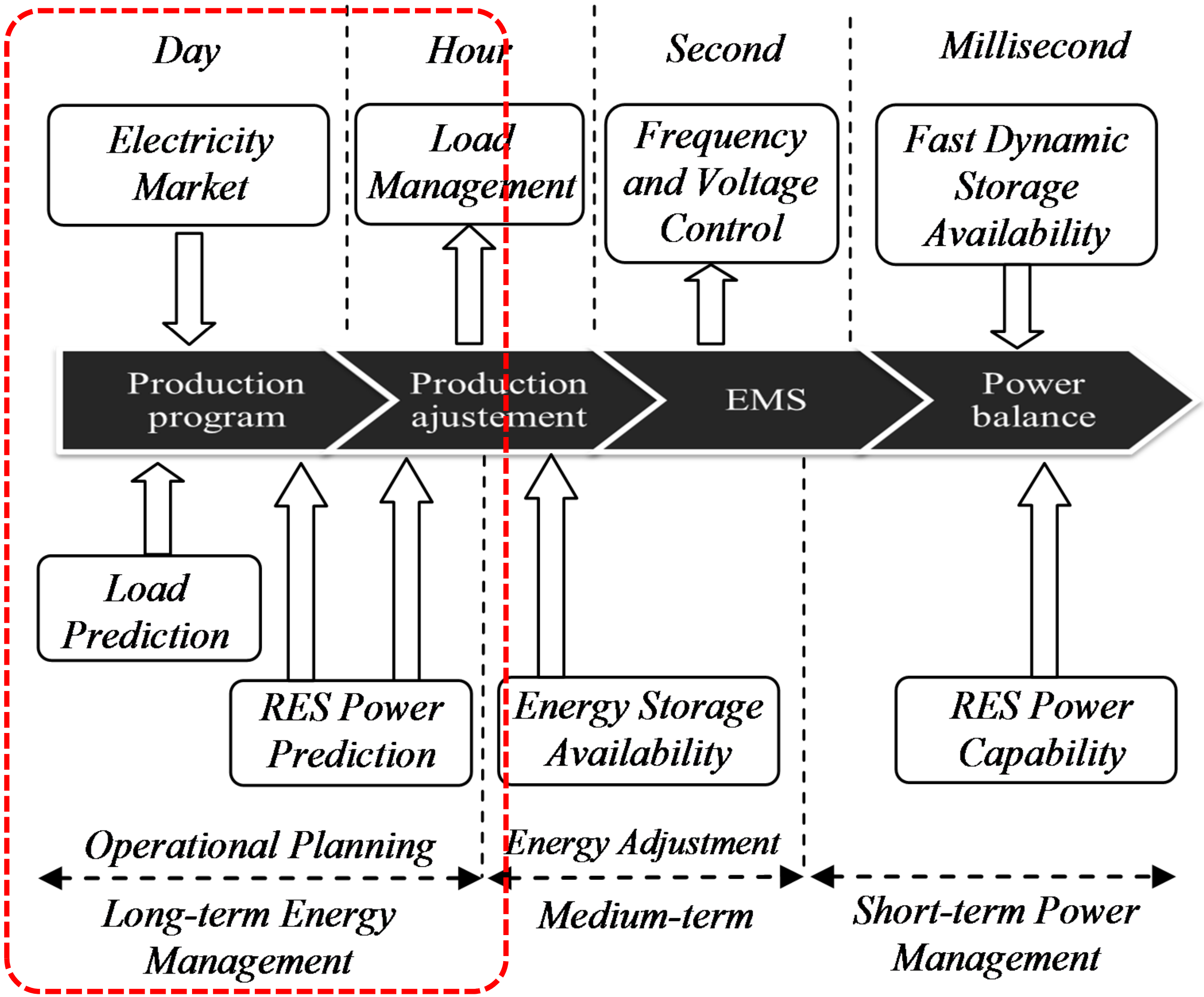
- **MGTs:** constant power sources, with controlled power output;
- **PV AGs:** can provide ancillary services thanks to storage devices.

❑ Uncertainty challenges of RES integration into the Microgrid ?

- ***Active PV Generators (PV AGs)***: with an additional storage system (batteries and super-capacitors);
- ***MGTs:*** *Micro gas-turbines.*

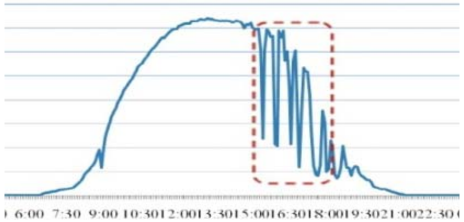
I.3 General Organization of Energy Management System (EMS)

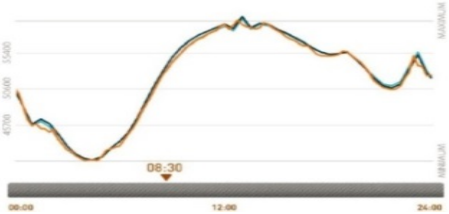
- Microgrid supervision can be analyzed in different timing scales and functions.



- Focuses on day-ahead optimization of the network operation.

I.4 Goals and Methods for the Study Case





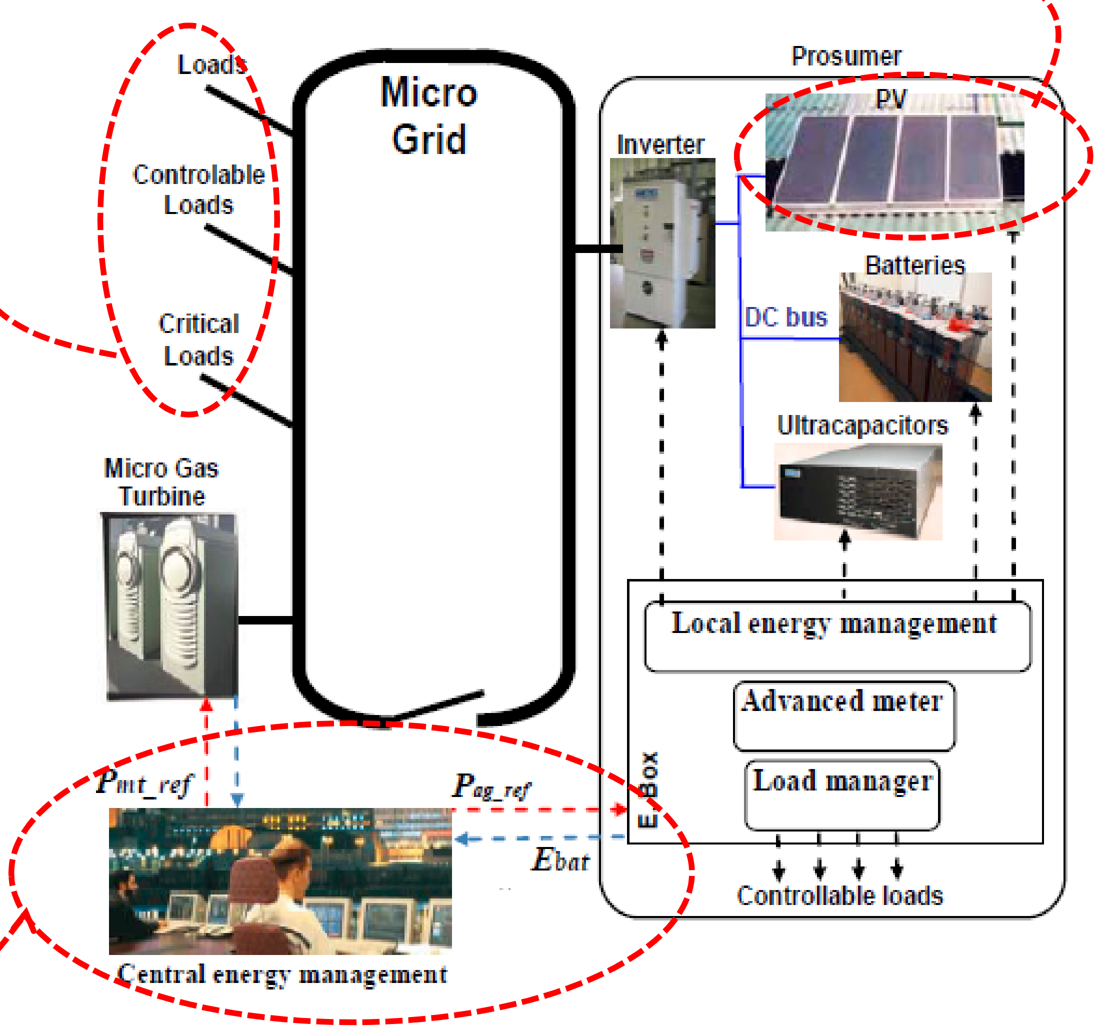
Predictive Analysis for Uncertainty: PV power and load forecasting

Operating Reserve Quantification: Loss of load probability (LOLP)

OR Dispatching Strategies on Generators

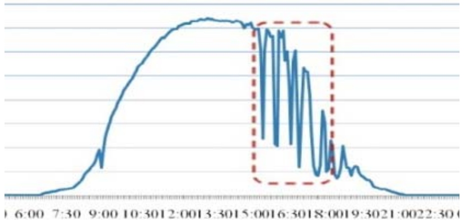
Day-ahead Optimization Planning: Unit commitment problem with dynamic programming

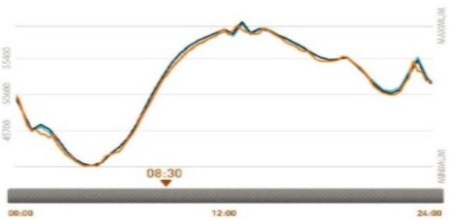
A User-friendly EMS and Operational Supervisor



- ***Active PV Generators (PV AGs)***: with an additional storage system (batteries and super-capacitors);
- ***MGTs:*** *Micro gas-turbines.*

Roadmap: Part II





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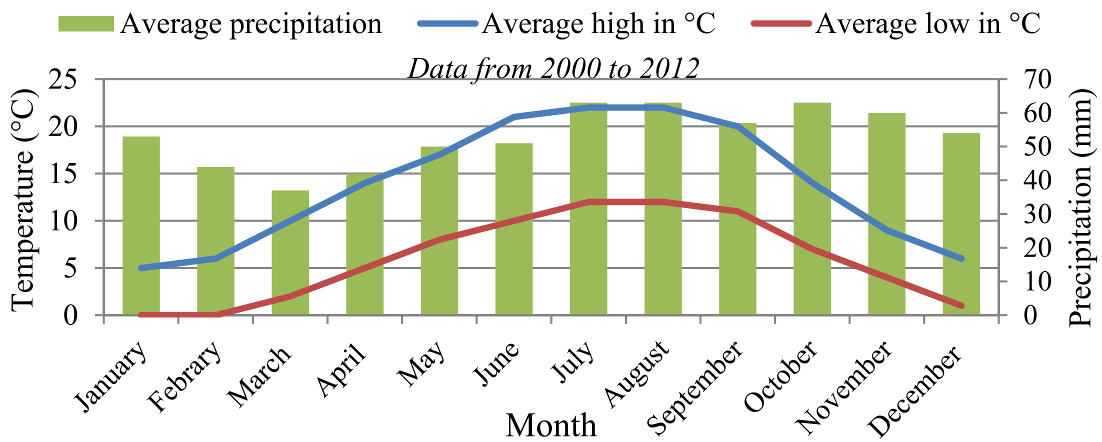
II.1 Data Management and Predictive Analysis (1)

❑ Data collecting for database building

- PV data collecting: (*Sunways*) three PV inverters (3 kW each), Centrale de Lille

- Load data collecting (www.rte-france.com)

- Meteorological data collecting (www.wunderground.com)

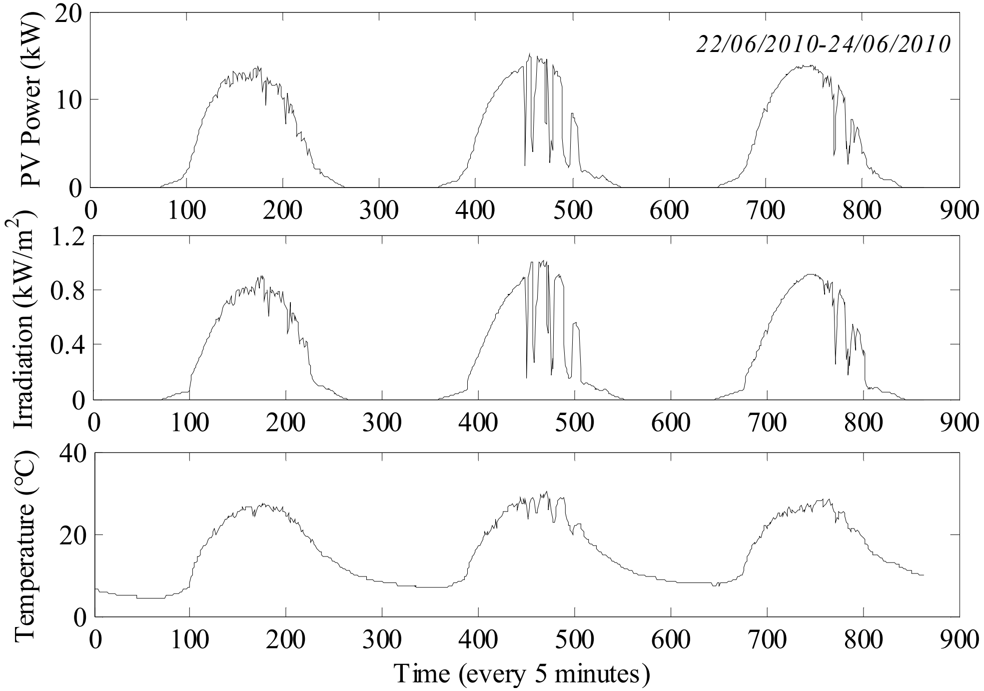


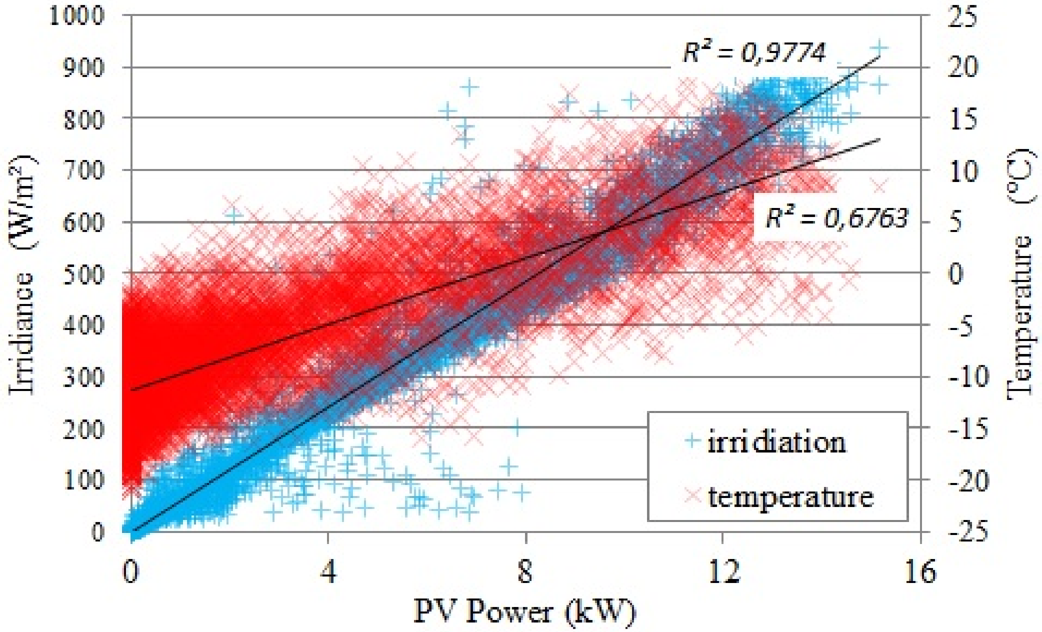
II.1 Data Management and Predictive Analysis (2)

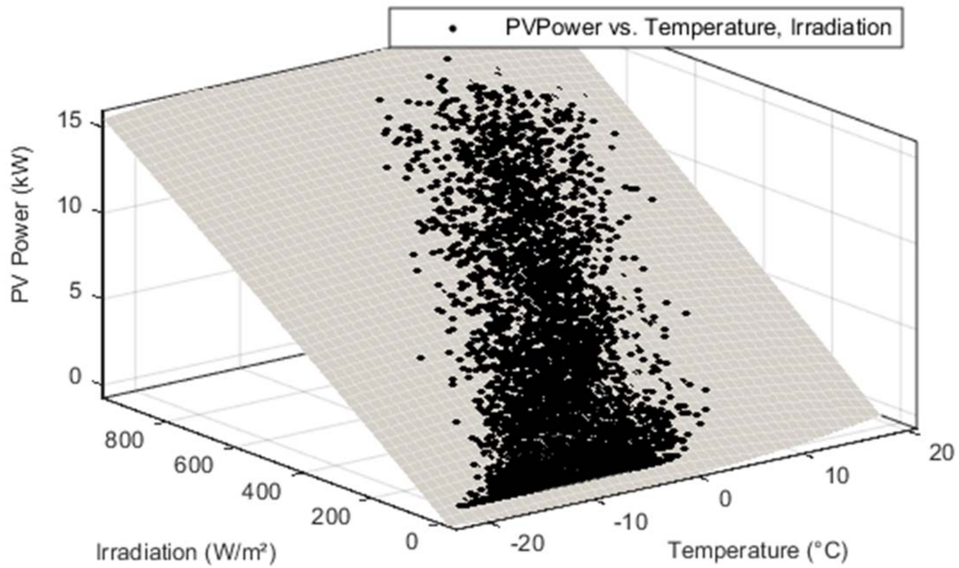
Data mining and predictive analysis (PV power)

- Mathematical Modeling of PV Generator

$$PV_P(t) = \eta_{pv}(t)\, A_{pv}\, \underline{I_r(t)}\,(1 - 0.0035(\underline{T(t)} - 25))$$



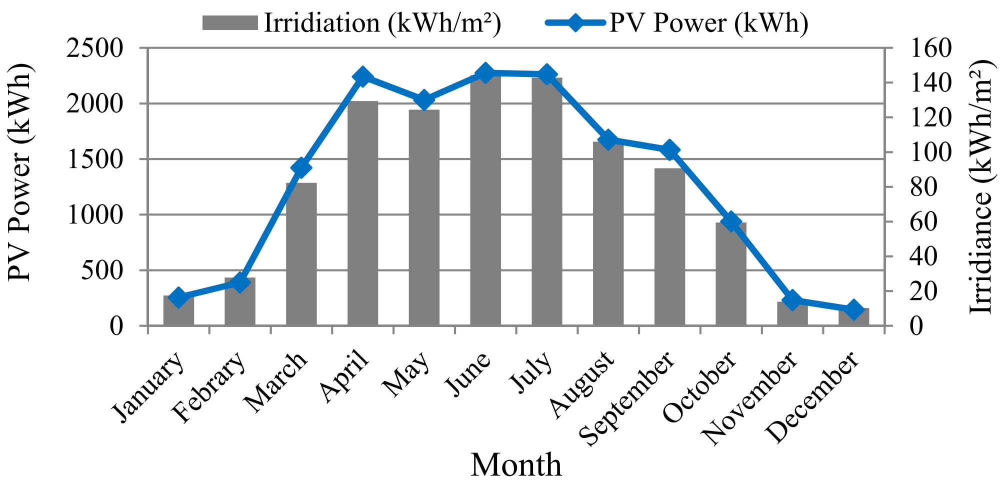


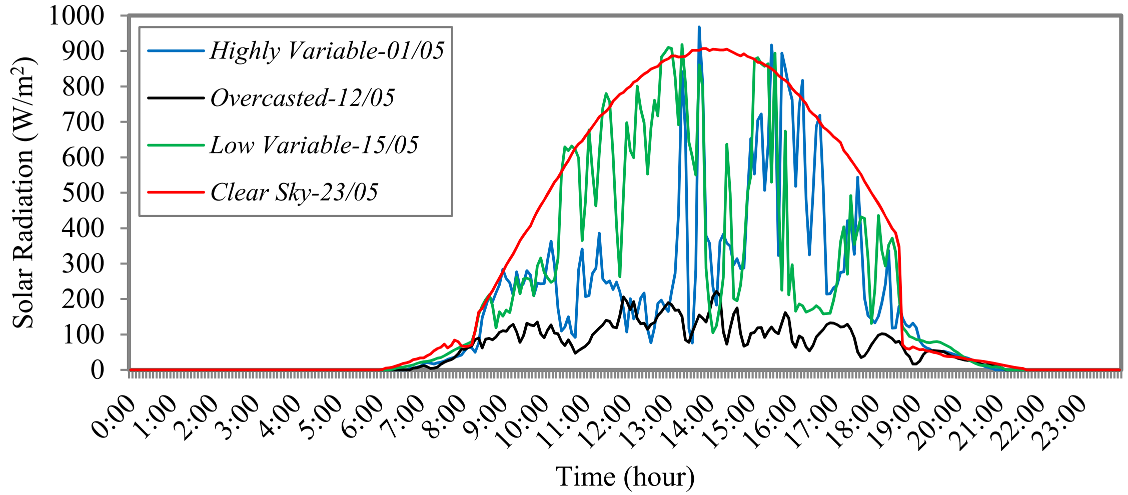


R^2 is used to determine how closely the irradiance and the temperature fit PV power.

II.2 PV Power variability quantification

- PV power and irradiance in 2010

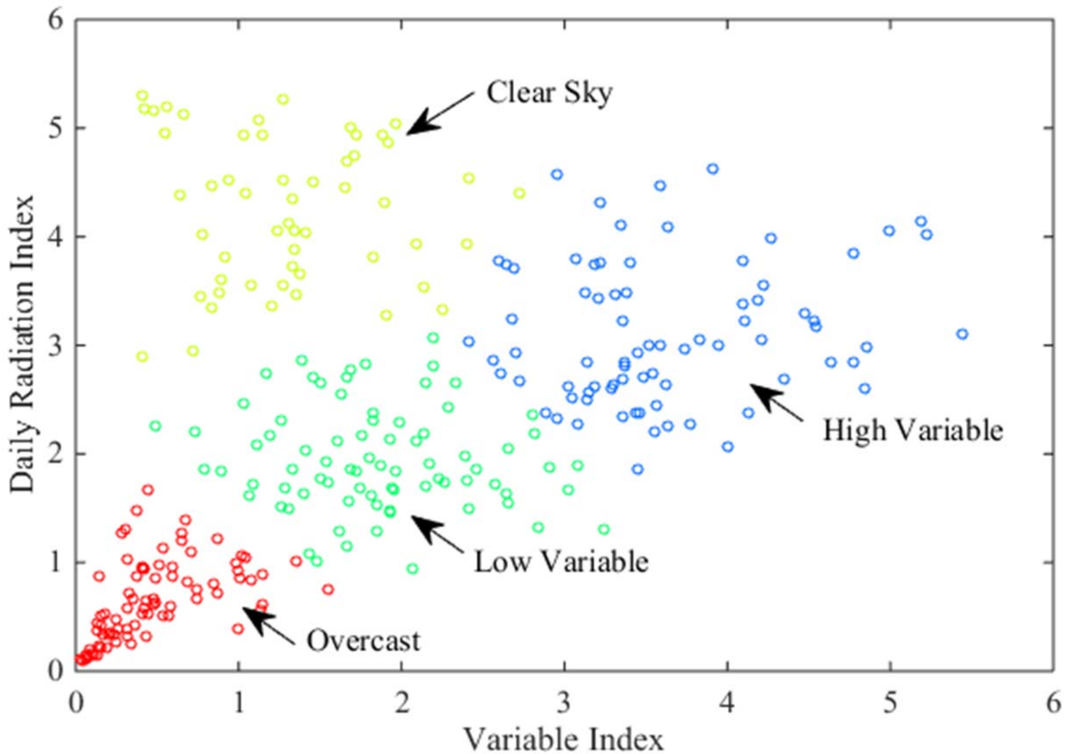




- Variable Index (VI) and Radiation Index (RI)

$$VI = \frac{\sqrt{\frac{1}{N-2}\sum_{k=2}^{N}\left[2\times SR_{k-1} - (SR_k + SR_{k-2})\right]^2}}{I_{SC}}$$

$$RI = \frac{1}{12}\frac{\sum_{k=2}^{N} SR_k}{I_{SC}}$$

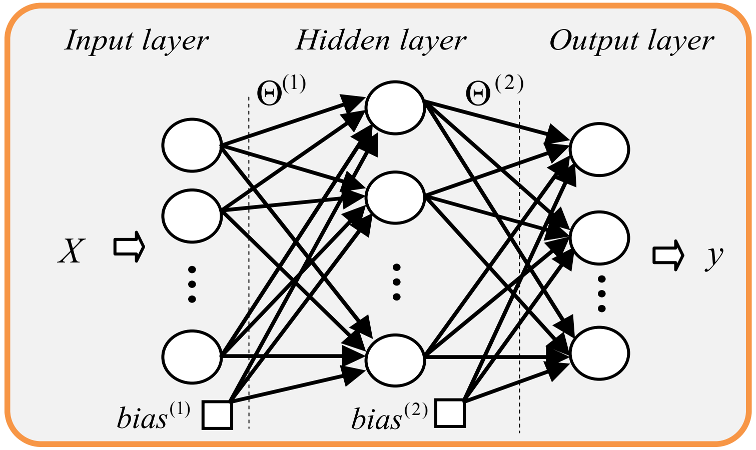


VI: *calculates PV power variability*
RI: *calculates daily solar radiation*
SR_k: *solar radiation during 5 minutes scale*

II.3 PV Power and Load Forecasting with ANN (1)

Forecasting with Artificial Neural Networks (ANN)

- A three-layer ANN



- Data description: PV power and Load forecasting databases

- Data normalization

$$f:\bar{x}\to x=\frac{x_i-x_{\min}}{x_{\max}-x_{\min}}$$

- Error Computing Method

$$nRMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\tilde{y}_k-y_k)^2}$$

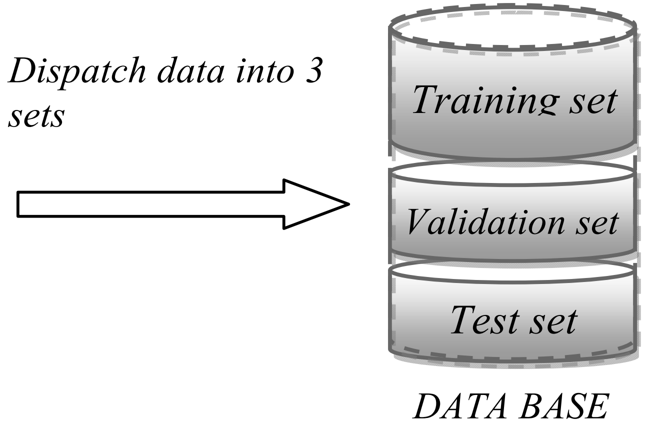
$$nMAE=\frac{1}{n}\sum_{i=1}^{n}\left|\tilde{y}_k-y_k\right|$$

nRMSE: *normalized Root Mean Square Error*
nMAE: *the normalized Mean Absolute Error*

PV forecast database

PV power data
- ***PV power output***
- *AC voltage*
- *DC voltage*

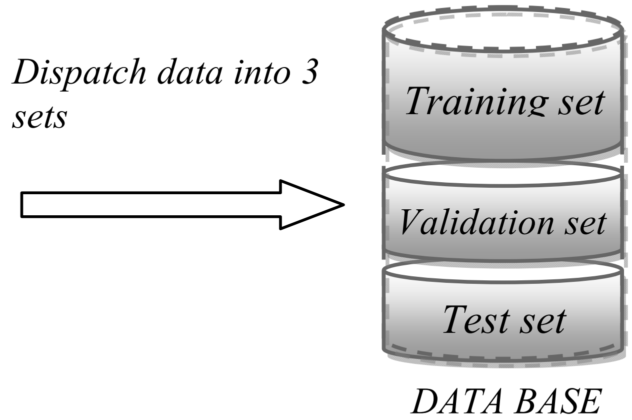
Meteorological data
- ***Solar irradiation***
- *Humidity*
- *Air pressure*
- *Wind speed*
- ***Temperature***



Load forecast database

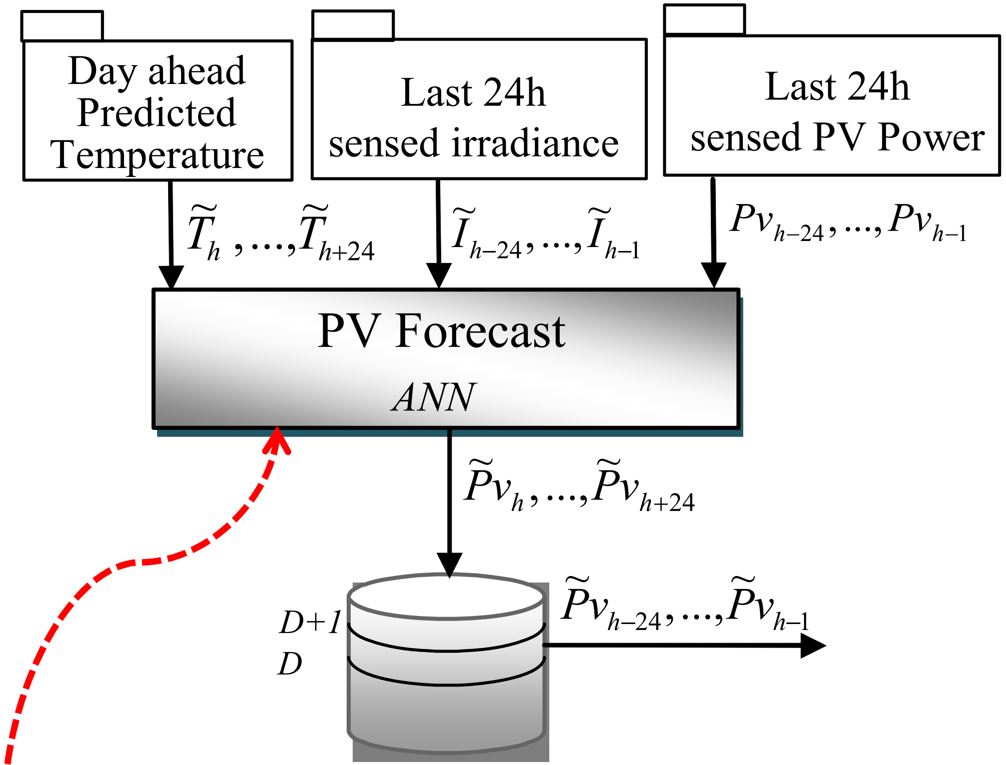
Load demand data
- ***Historical load data***

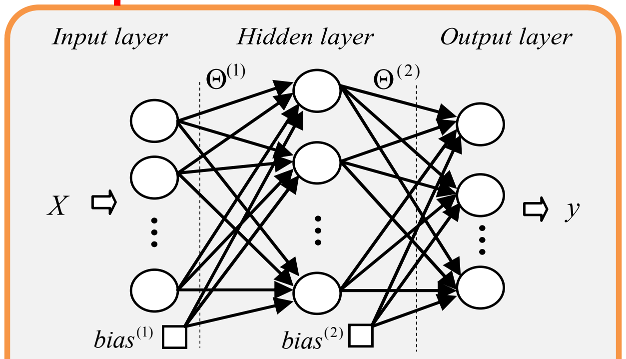
Meteorological data
- *Solar irradiation*
- *Humidity*
- *Air pressure*
- *Wind speed*
- ***Temperature***



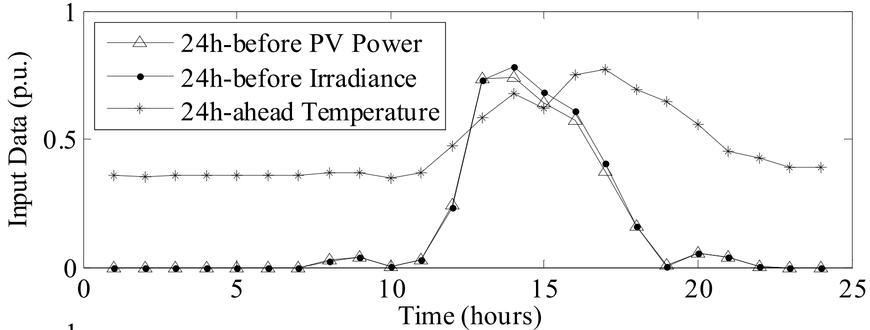
II.3 PV Power and Load Forecasting with ANN (2)

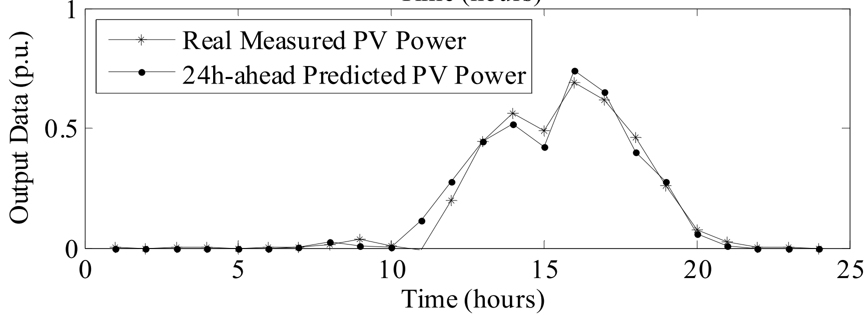
❑ PV Power Forecasting with ANN





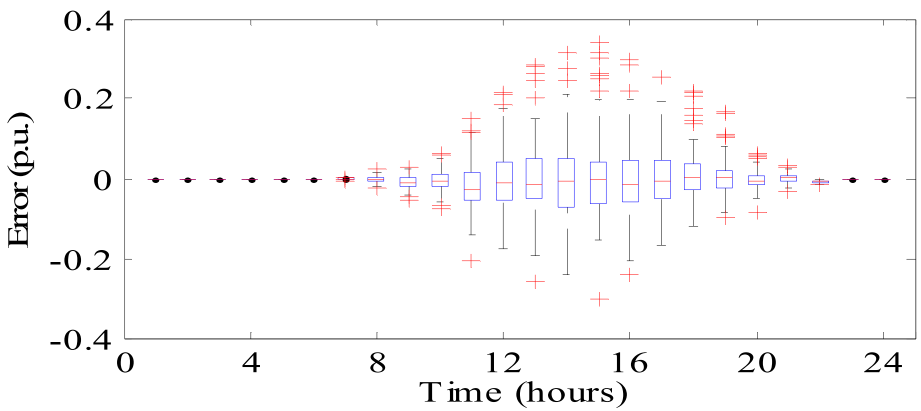
A three-layer ANN





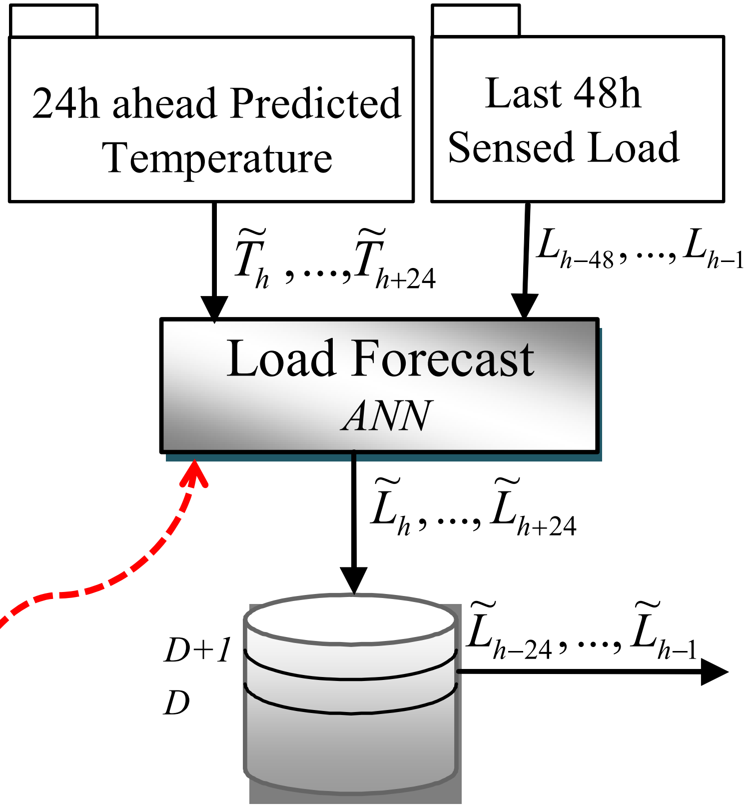
Errors of the PV power forecasting with ANN.

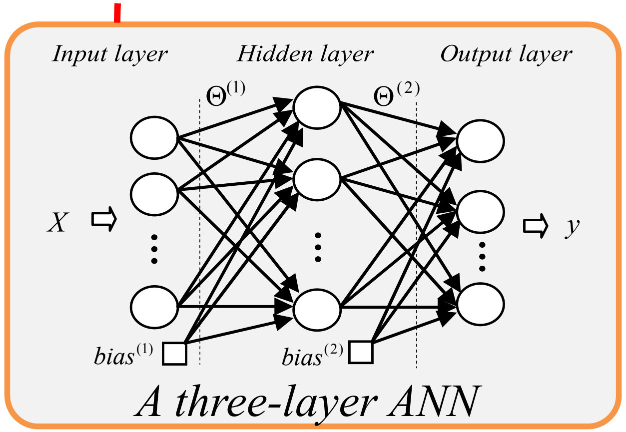
	nRMSE [%]	nMAE [%]
Training Set	6.09	3.69
Validation Set	5.58	3.13
Test Set	5.95	3.12



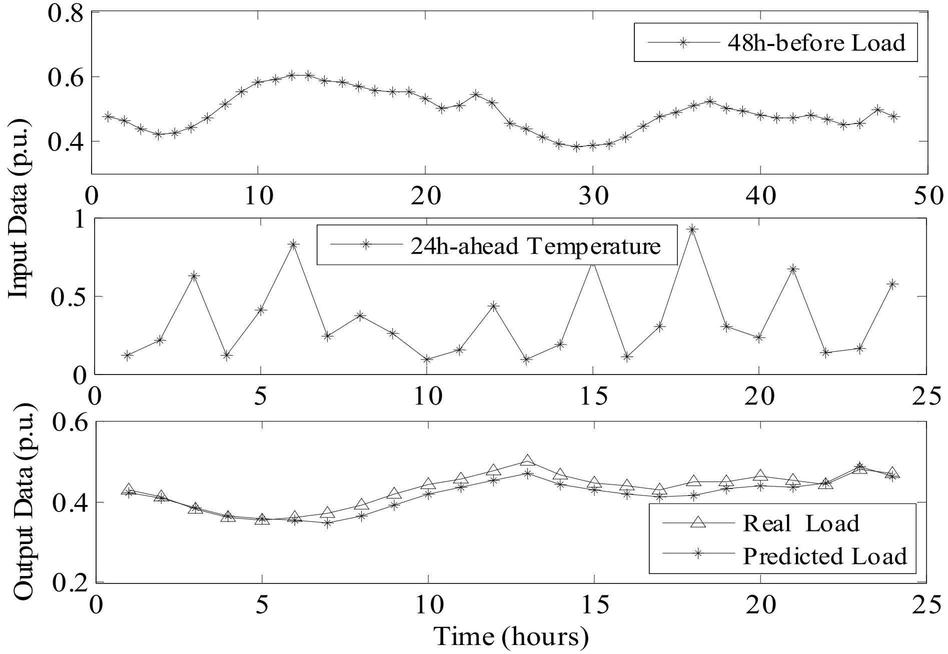
II.3 PV Power and Load Forecasting with ANN (3)

❑ Load Forecasting with ANN



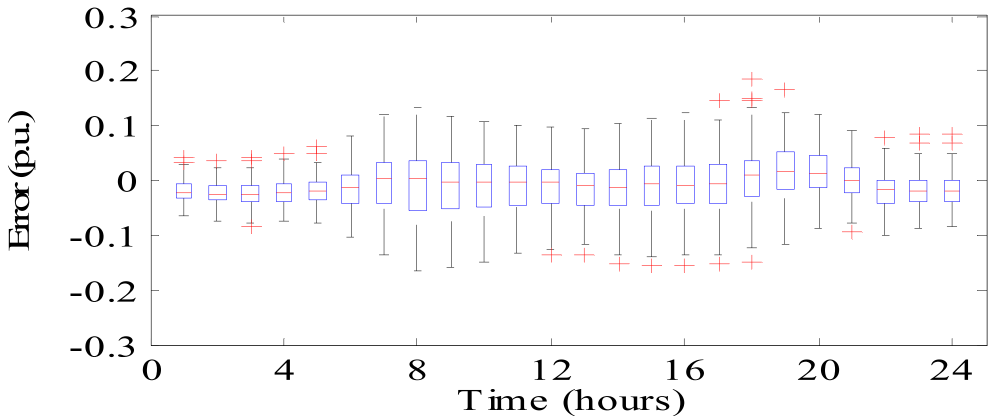


A three-layer ANN

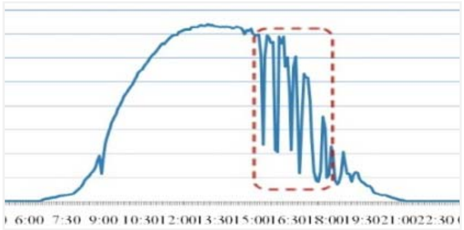


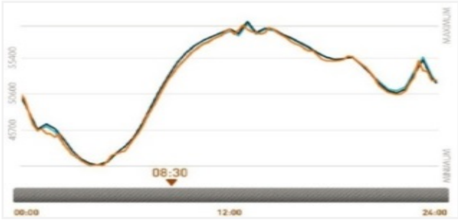
Errors of the Load forecasting with ANN.

	nRMSE [%]	nMAE [%]
Training Set	3.18	2. 45
Validation Set	3.57	2.76
Test Set	3.67	2.84



Roadmap: Part III





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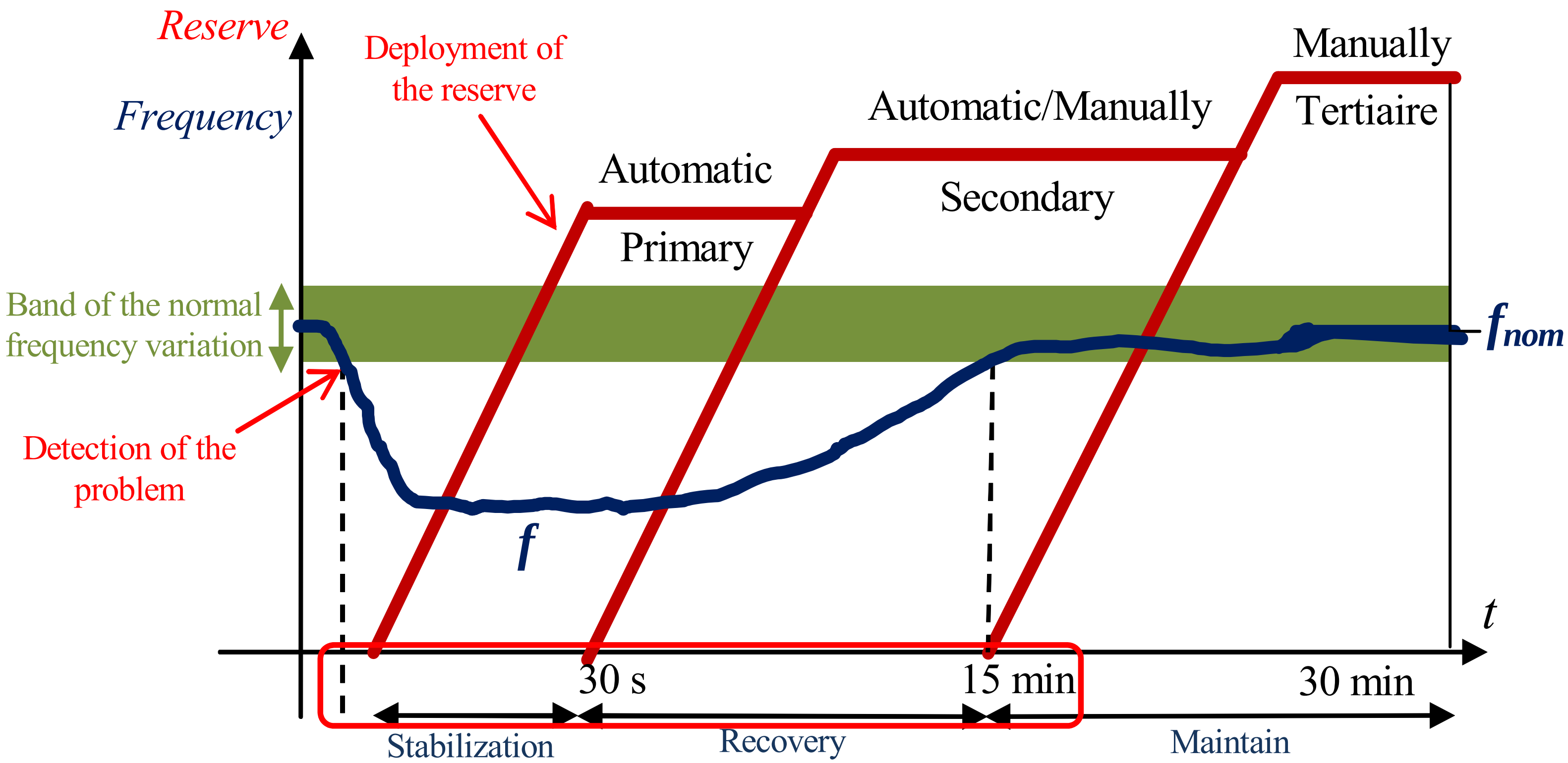
III.1 Calculation of OR by considering RES uncertainties (1)

- Frequency control and energy balancing



Deploying of the primary, secondary and tertiary regulation of frequency.

In this thesis, the OR is defined as the real power that can be called on instantaneously for the imbalance between power generation and load demand (*Primary and secondary reserve*).

III.1 Calculation of OR by considering RES uncertainties (2)

- The OR must be precisely quantified in order to **maintain a specified level of system security with a minimum cost**.

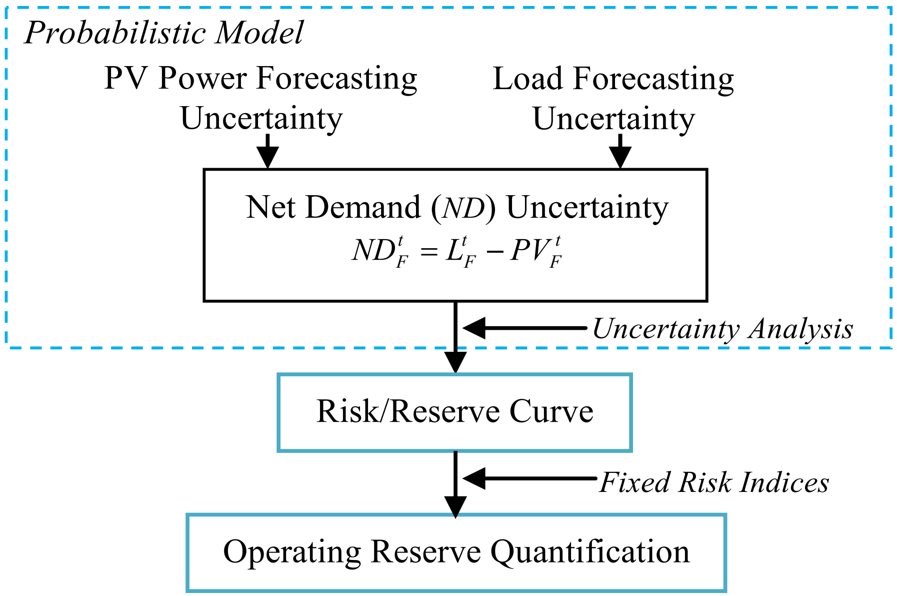
- Most conventional utilities have adopted deterministic criteria by considering only two sources of uncertainty:
  - the **possibility of multiple large generators failing**: low probability but high impact;
  - and **load forecast errors:** often but usually relatively small.

- Deterministic methods **do not match the stochastic nature** of the OR quantification problem.

- **Probabilistic methods** are adapted to the **stochastic characteristics** of RES based generators and loads. They can set a certain security level.

III.1 Calculation of OR by considering RES uncertainties (3)

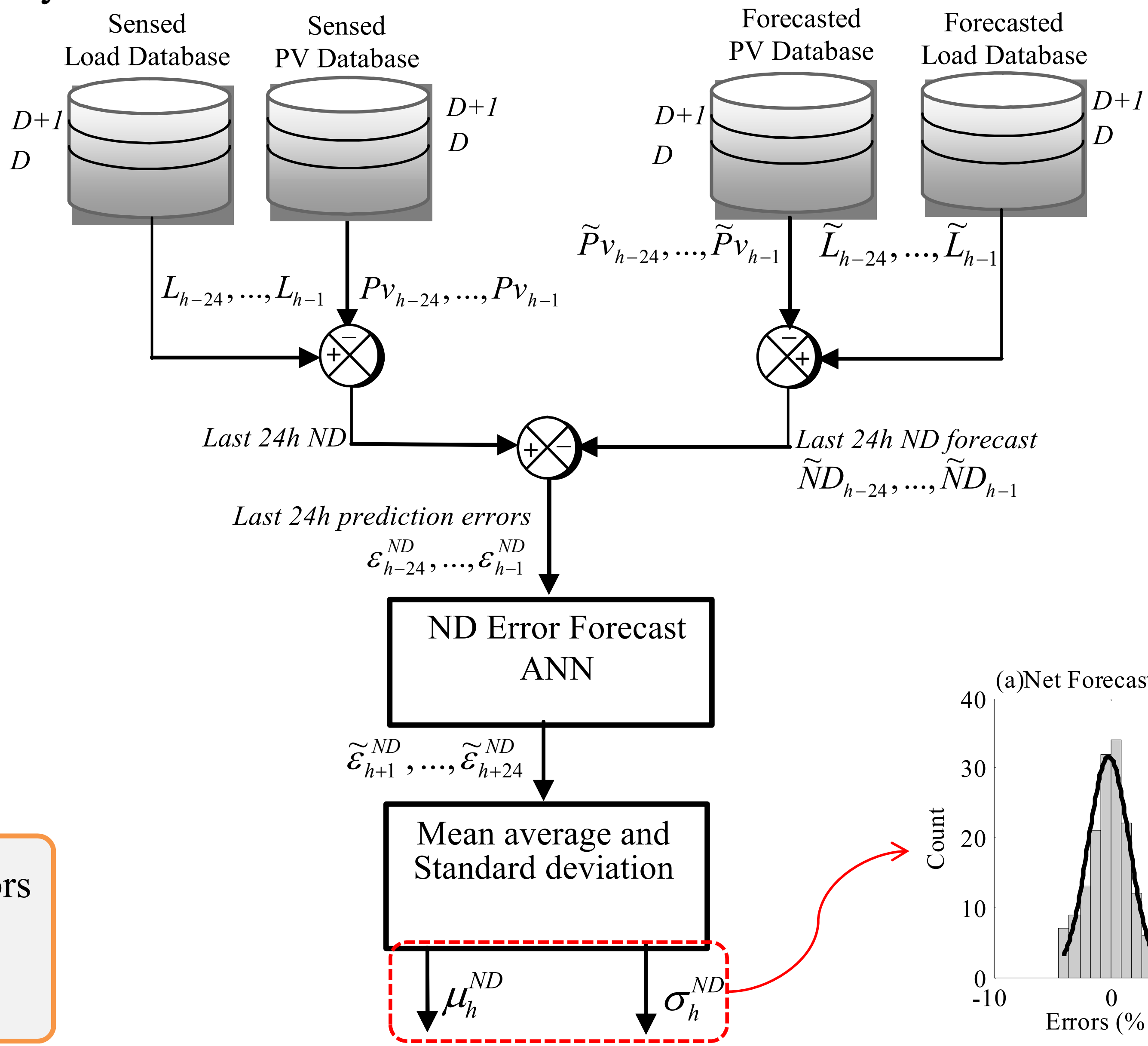
- Decisions made under uncertainty must be informed by **probabilistic information** in order to **correctly quantify the risk**.
- Recent examples of probabilistic methods:
  - ***Eastern Wind Integration and Transmission Study (EWITS):*** focused on the operational impacts of various wind penetrations. Load variability and wind power variability are considered independent [1].
  - ***Western Wind and Solar Integration Study (WWSIS):*** discussed the OR requirement that dynamically relied on both the load and wind penetration levels [1].
  - ***Other probabilistic methods***
- **General Scheme for OR quantification**

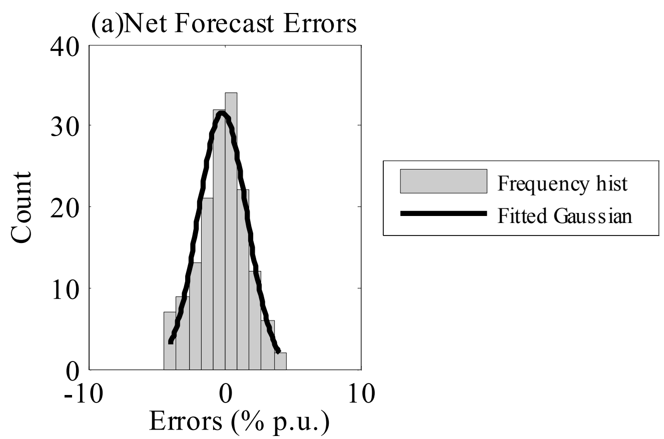


[1]: L. E. Jones, Renewable energy integration: practical management of variability, uncertainty, and flexibility in power grids: Academic Press, 2014.

III.2 Net Demand (ND) Uncertainty Analysis (1)

- The real ND is composed of the forecasted ND and an error: $ND_h = \widetilde{ND}_h + \boxed{\varepsilon_h^{ND}}$
- **First Method:** Day-ahead Net Demand Errors Forecast

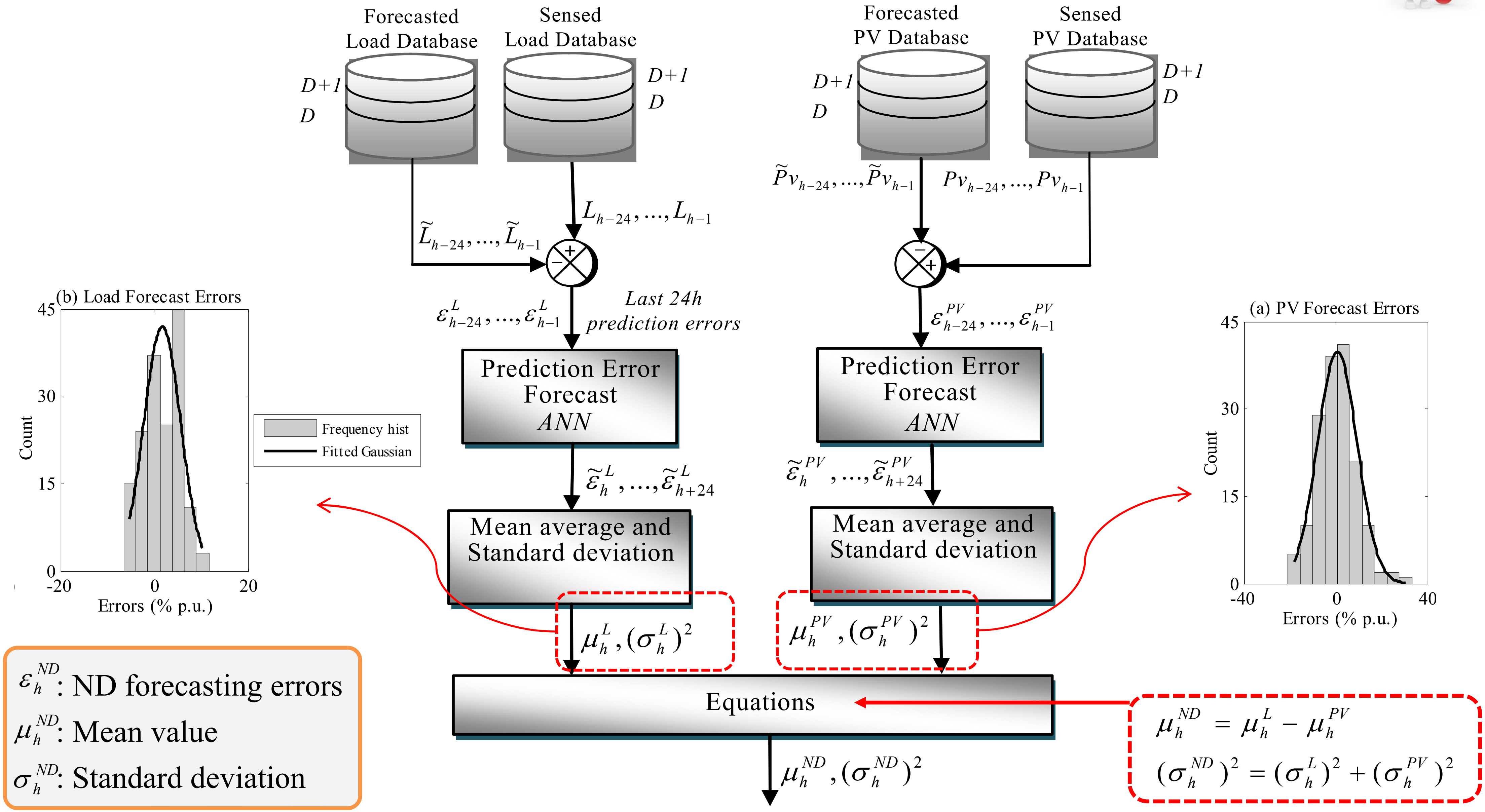




ε_h^{ND}: ND forecasting errors
μ_h^{ND}: Mean value
σ_h^{ND}: Standard deviation

III.2 Net Demand (ND) Uncertainty Analysis (2)

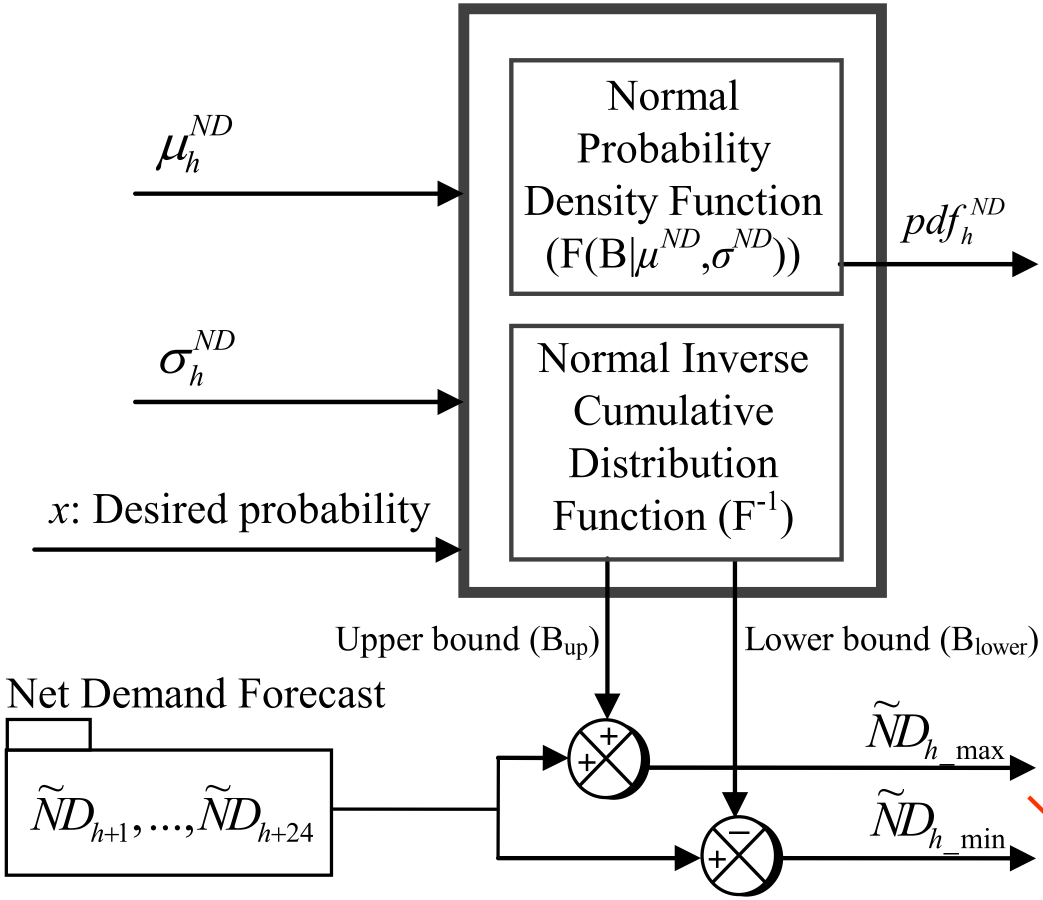
- The real ND is composed of the forecasted ND and an error: $ND_h = \widetilde{N}D_h + \varepsilon_h^{ND}$
- **Second Method**: Calculation from the PV Power and the Load Forecast Errors Estimation.

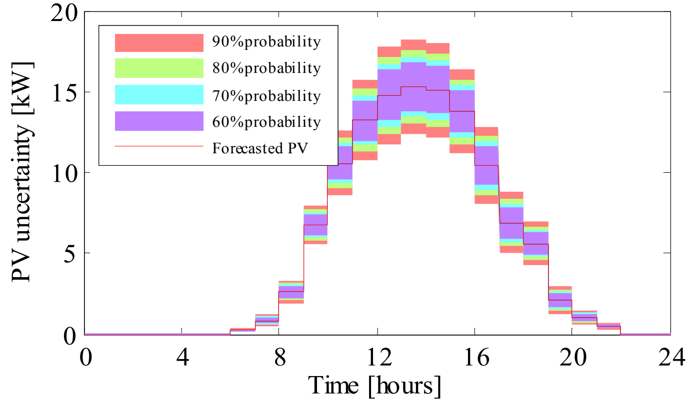


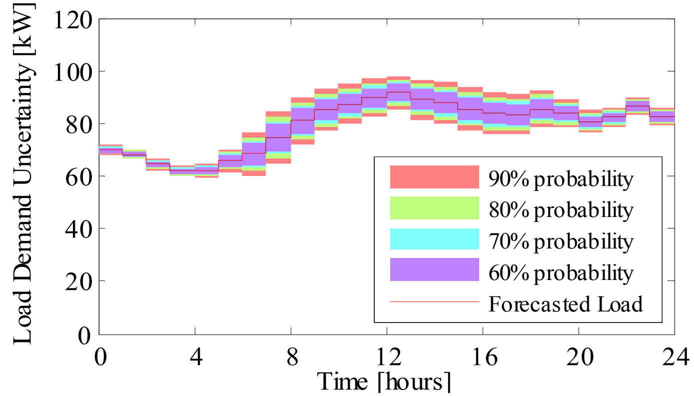
ε_h^{ND}: ND forecasting errors
μ_h^{ND}: Mean value
σ_h^{ND}: Standard deviation

III.3 Uncertainty Assessment

- Hourly ND uncertainty assessment

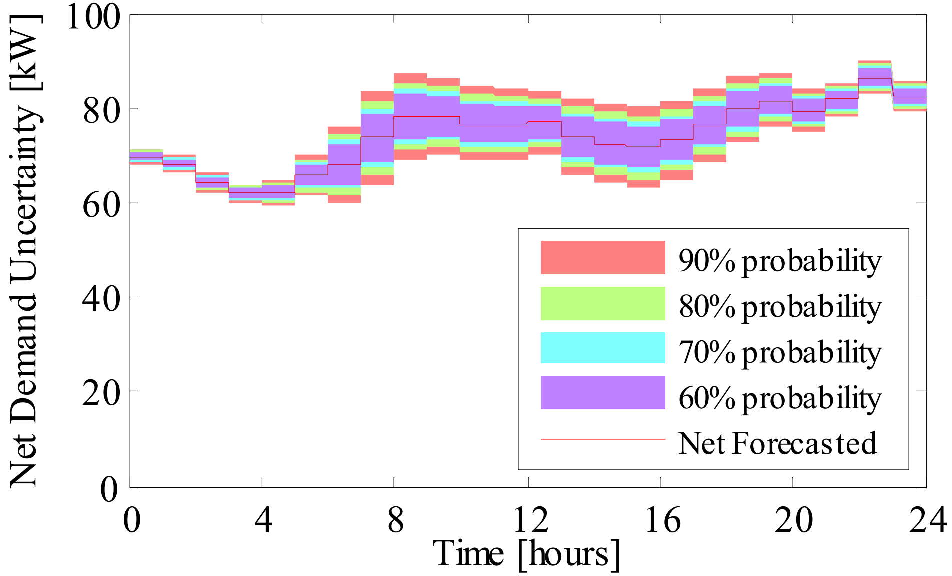






Bound margin: $B = F^{-1}(x|\mu_h^{ND},\sigma_h^{ND}) = \{B : F(B|\mu_h^{ND},\sigma_h^{ND}) = x\}$

Probability: $x = F(B|\mu_h^{ND},\sigma_h^{ND}) = \dfrac{1}{\sigma_h^{ND}\sqrt{2\pi}}\int_{-\infty}^{B} e^{\frac{-(\tau-\mu_h^{ND})^2}{2(\sigma_h^{ND})^2}}\, d\tau$



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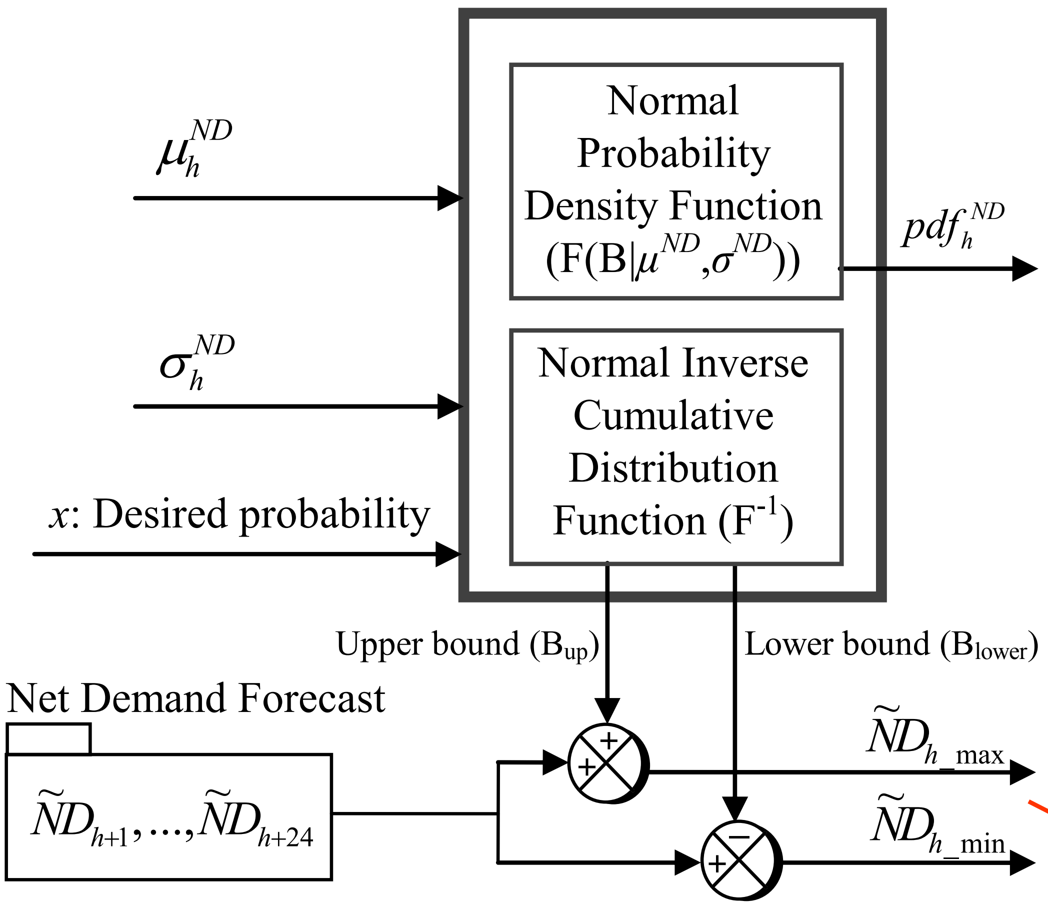
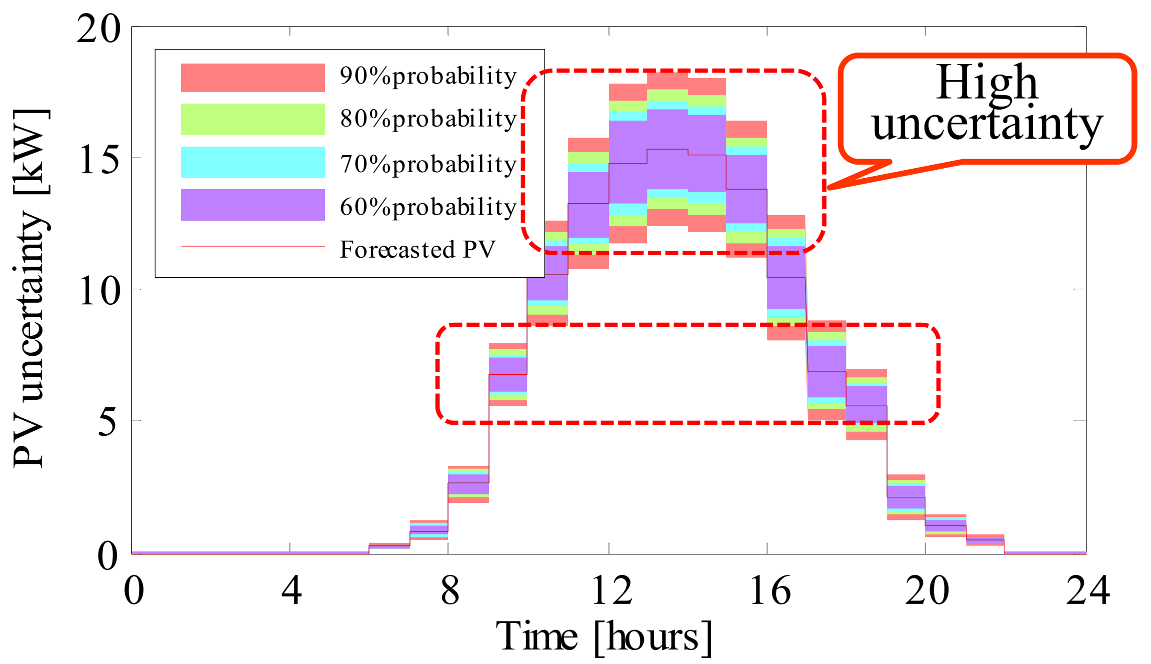
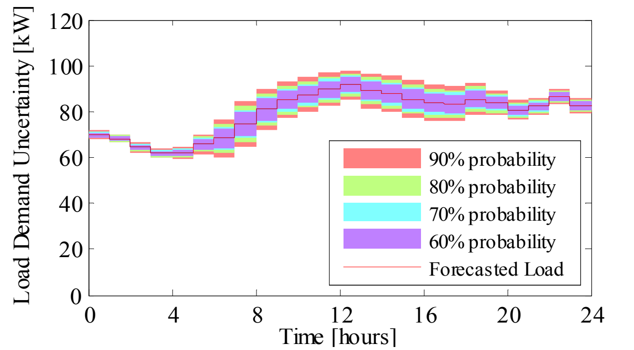
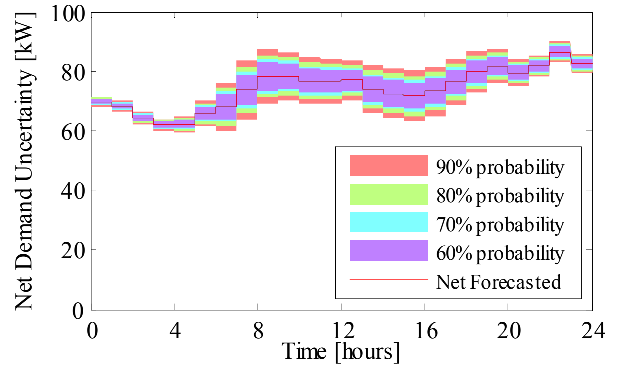
- Hourly ND uncertainty assessment









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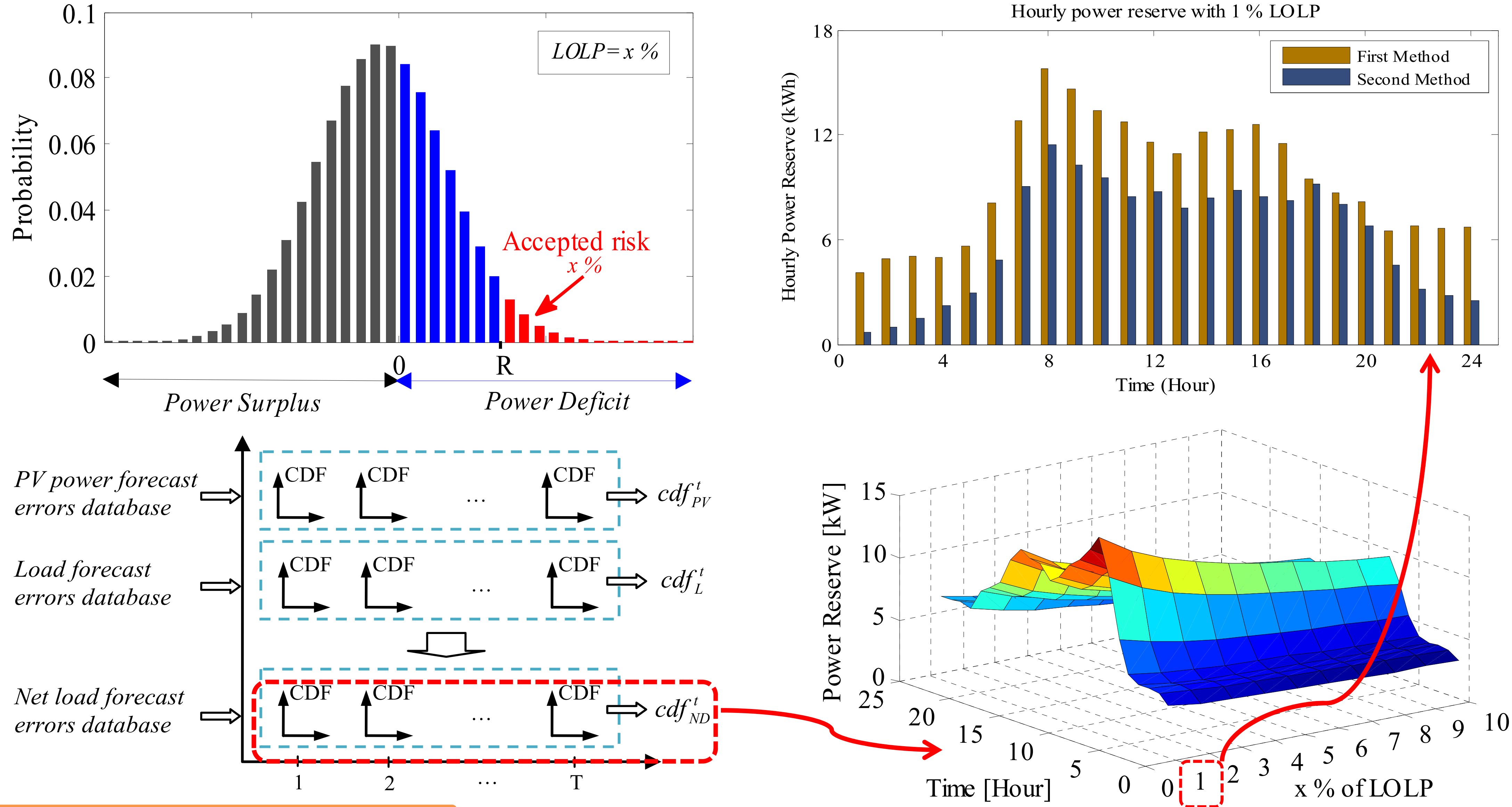
Probability: $x = F(B|\mu_h^{ND},\sigma_h^{ND}) = \dfrac{1}{\sigma_h^{ND}\sqrt{2\pi}}\displaystyle\int_{-\infty}^{B} e^{\frac{-(\tau-\mu_h^{ND})^2}{2(\sigma_h^{ND})^2}}\, d\tau$

III.4 OR Quantification

❑ Power reserve quantification

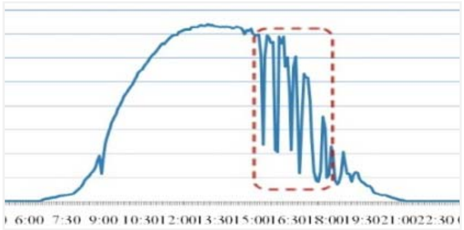
LOLP represents the probability that load exceeds PV power.

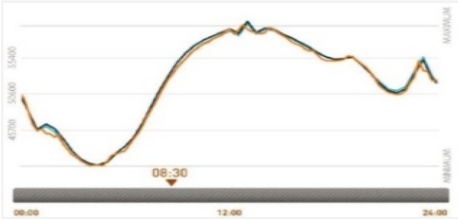
$$LOLP_h = prob(L_h - P_h > 0) = \int_{PR}^{+\infty} pdf(\tau)\mathrm{d}\tau$$



CDF: cumulative distribution function

Roadmap : Part IV





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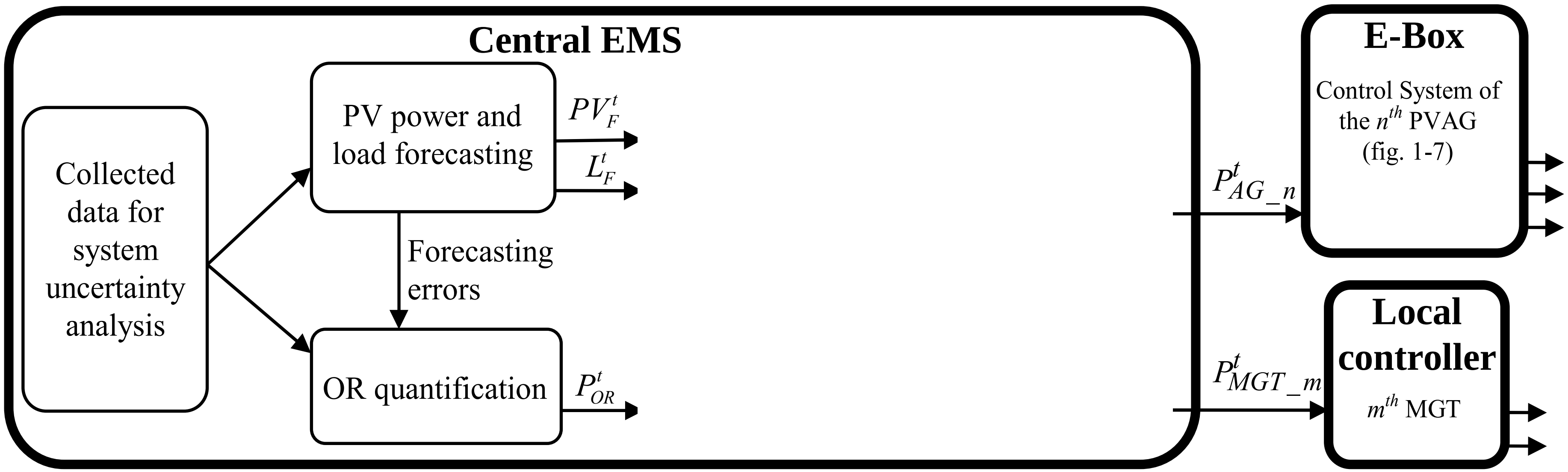
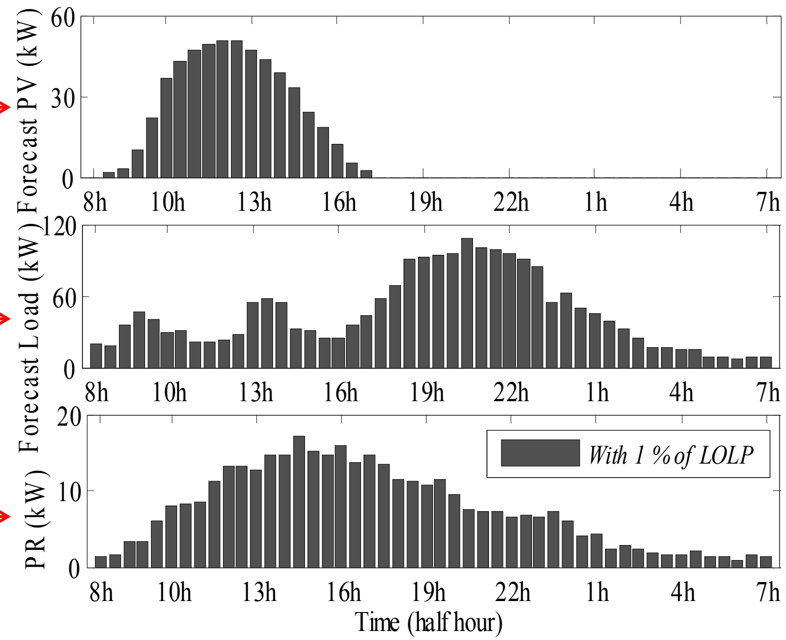
IV.1 Optimal OR Dispatching Strategies

- The flowchart of the energy management



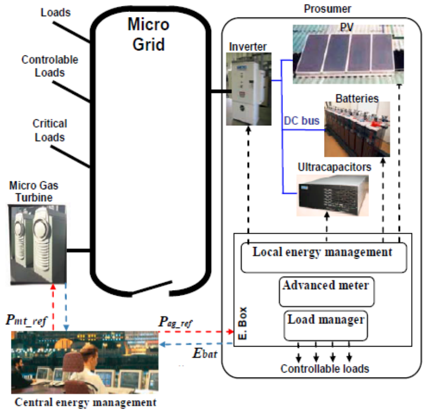
- Forecasted PV, load and OR quantification

- Day-ahead PV power forecasting
- Day-ahead load forecasting
- Statistic OR quantification



- **One Day-ahead OR dispatching**

IV.2 Non-linear Constraints



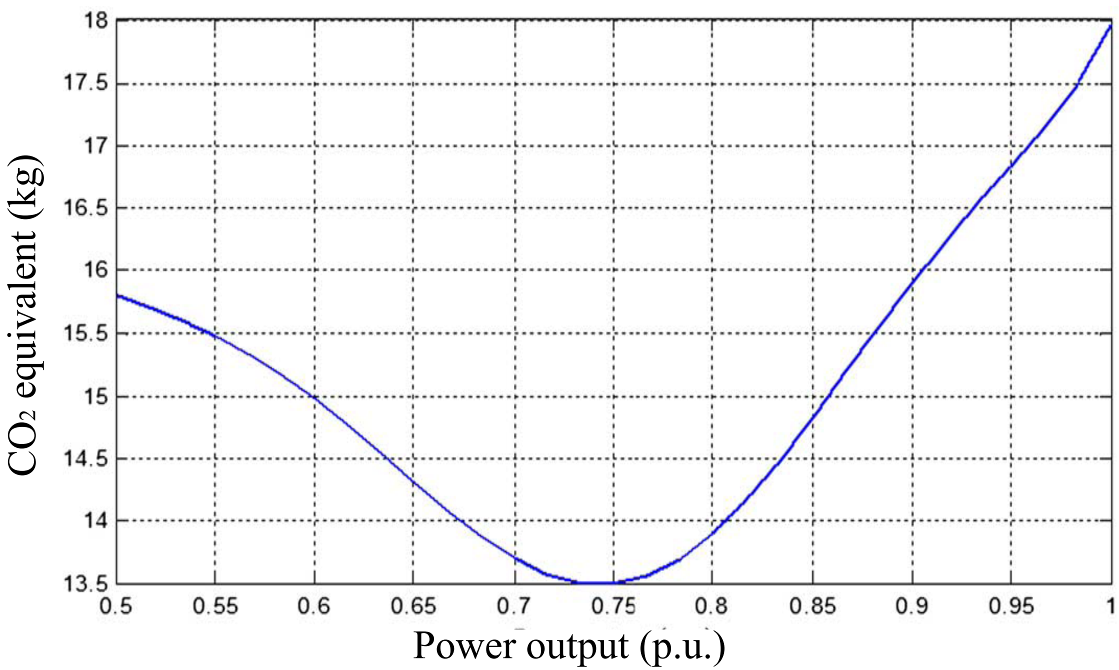
- Security: OR assessment with ***x* % of LOLP**;

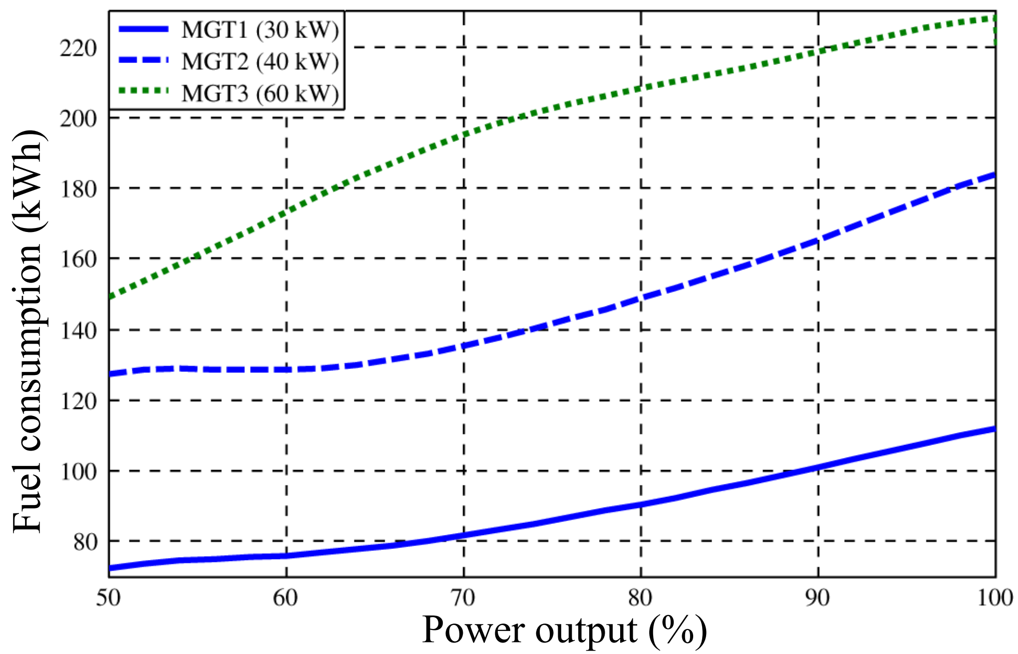
Load and OR

- Power balancing: $\psi(t) = \boxed{P_L(t) + P_{res}(t)} - \boxed{\sum_{n=1}^{N} P_{AG\_n}(t) - \sum_{i=1}^{M} (\delta_i(t) \bullet P_{MGT\_i}(t))} = 0$

- Maximization of RES usage: considering the battery capacity limitation (more PV power, larger battery storage !)

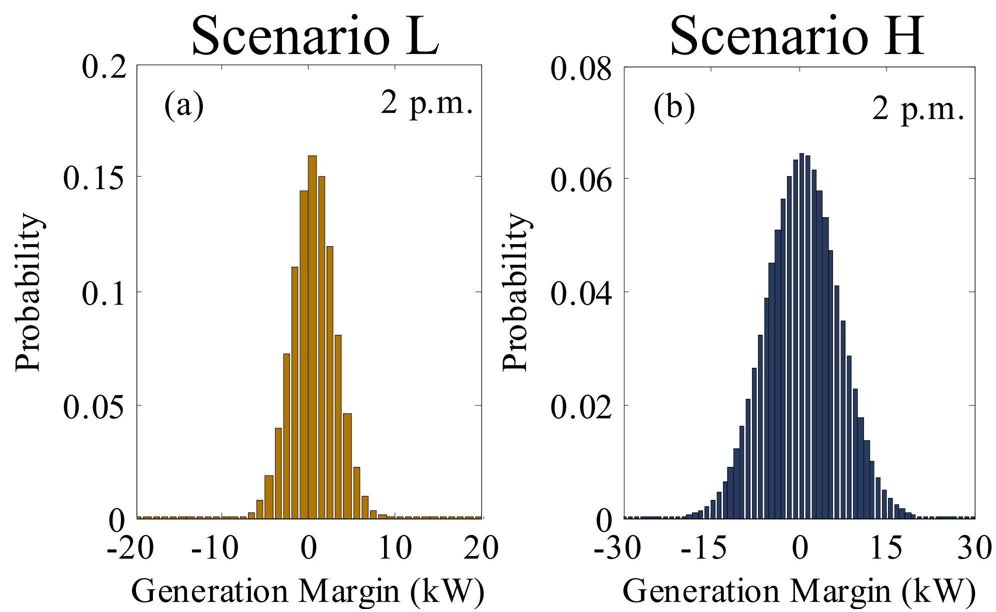
- Non-linear characteristic of MGTs: $50\% P_{M\_\max\_i}(t) \le P_{M\_i}(t) \le 100\% P_{M\_\max\_i}(t)$





IV.3 Management Strategy of OR Dispatching

- Two considered scenarios



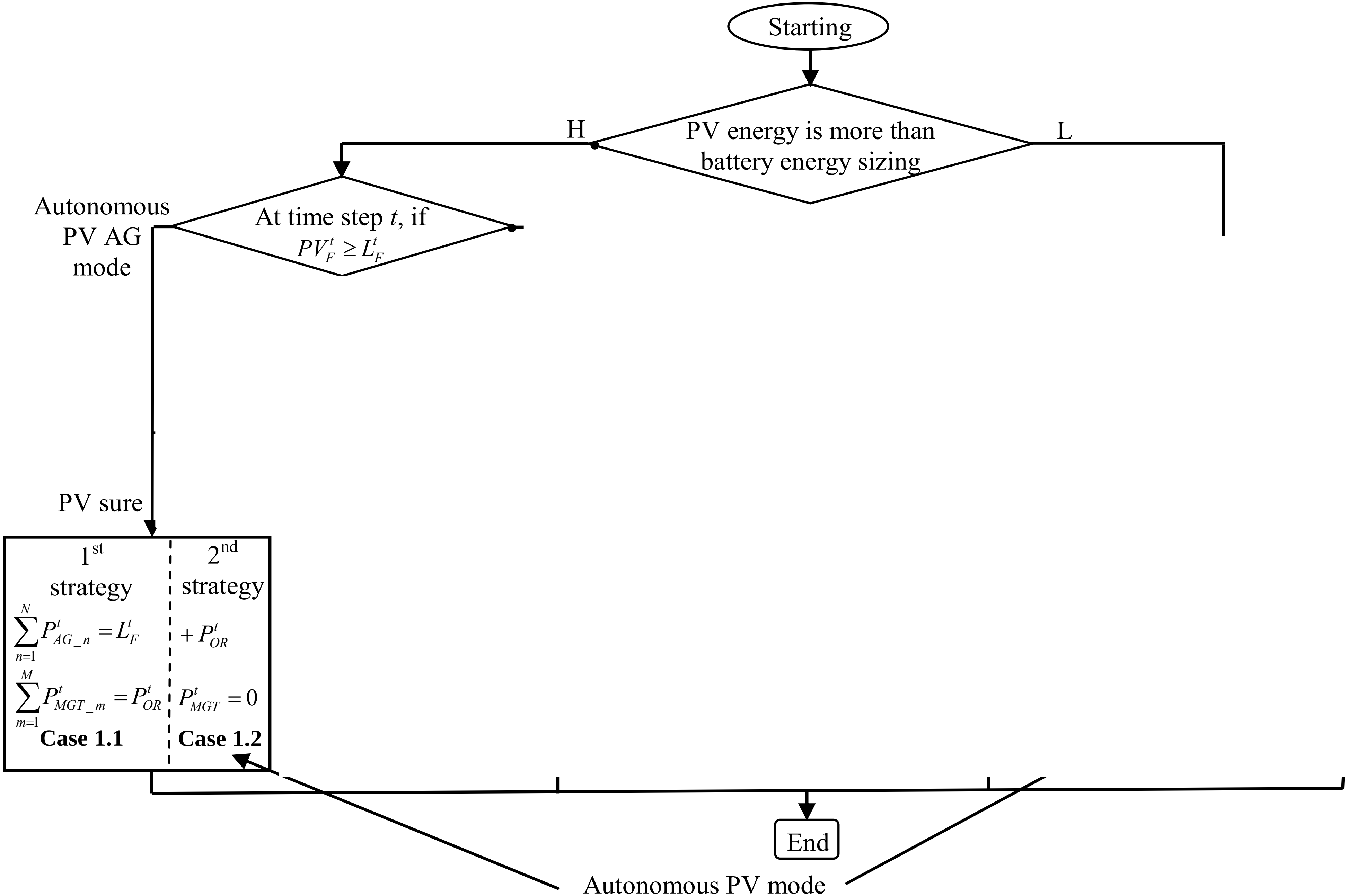
- Pre-processing of the uncertainty by energy management of batteries

	According to	PV energy during the day	Uncertainty from
Scenario H	$\sum \tau * PV_F^t > \sum E_{Bat\_i}^{max}$	Used	PV power and load forecasting

- OR quantification for the electrical system

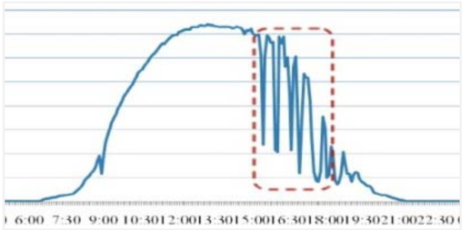
- OR dispatching strategies according to power sources:
- First strategy: OR on three **MGTs only**
- Second strategy: OR on three MGTs **and PV AGs including batteries**

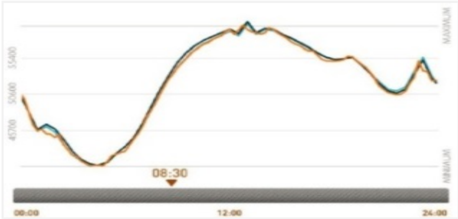
IV.4 OR Dispatching Strategies



More details can be found: *X. Yan, D. Abbes, B. Francois, and Hassan Bevrani "Day-ahead Optimal Operational and Reserve Power Dispatching in a PV-based Urban Microgrid," EPE 2016, ECCE Europe, Karlsruhe/ Germany.*

Roadmap : Part V





Predictive Analysis for Uncertainty: PV power and load forecasting

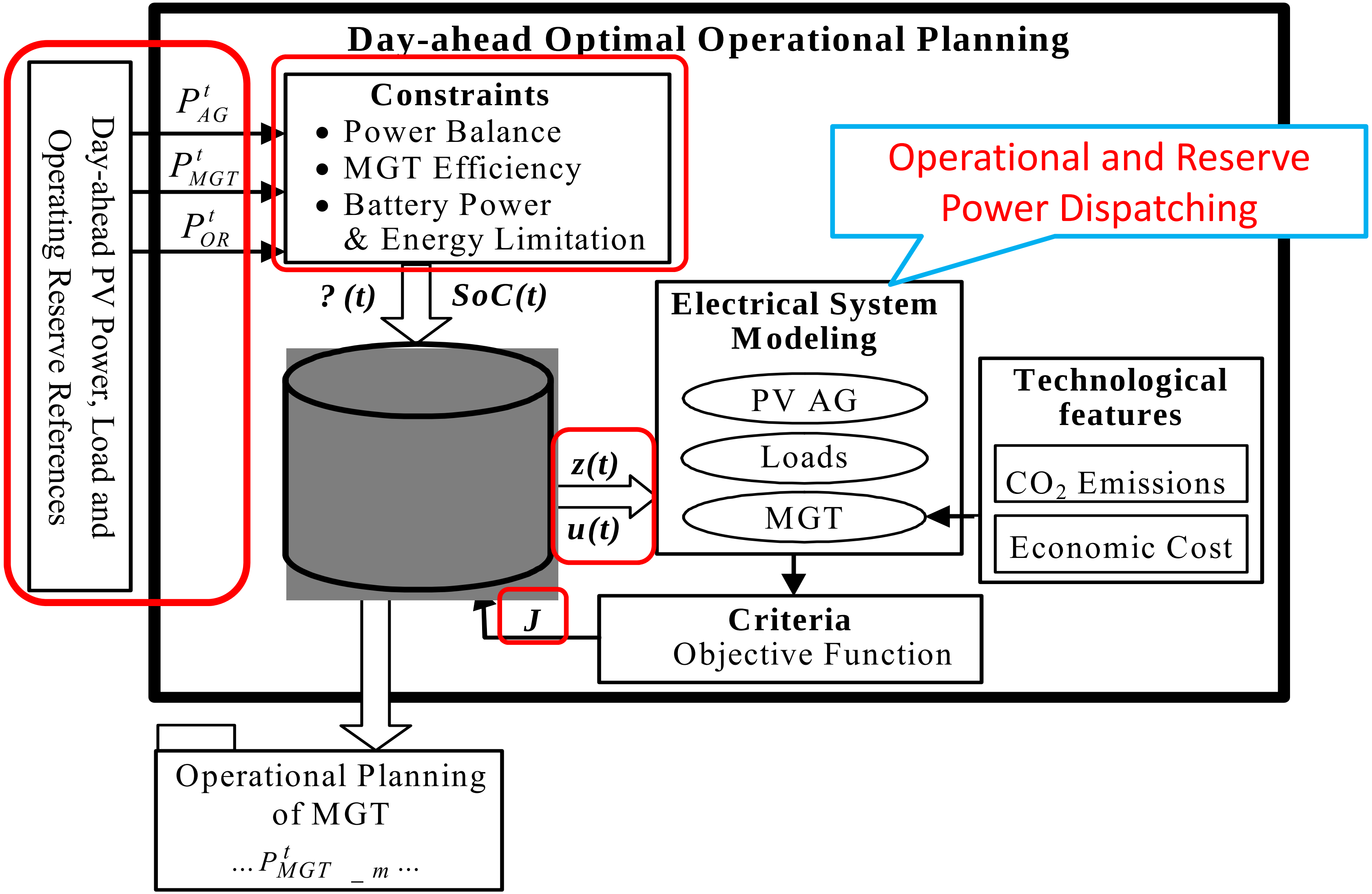
Operating Reserve Quantification: Loss of load probability (LOLP)

OR Dispatching Strategies on Generators

Day-ahead Optimal Planning: Unit commitment problem with dynamic programming

A User-friendly EMS and Operational Supervisor

V.1 Day-ahead Optimal OR Planning on MGTs



- Focus on the design of the microgrid central EMS.
- Unit commitment (UC) problem with dynamic programming (DP) is developed in order to reduce the economic cost and CO_2 equivalent emissions.

V.2 Unit Commitment (UC) Problem

- UC Problem: is an operation scheduling function.
- Problem: optimal operation of a cluster of MGTs (three in our case)

$$x(\mathrm{t}) = \left[P_{MGT\_1}(t), P_{MGT\_2}(t), \ldots, P_{MGT\_i}(t)\right]$$

$$u(\mathrm{t}) = \left[\delta_1(t), \delta_2(t), \ldots, \delta_i(t)\right]$$

Number of states	Generators states
1	$\delta_1=1; \delta_2=1; \delta_3=1$
2	$\delta_1=1; \delta_2=1; \delta_3=0$
3	$\delta_1=1; \delta_2=0; \delta_3=1$
4	$\delta_1=1; \delta_2=0; \delta_3=0$
5	$\delta_1=0; \delta_2=1; \delta_3=1$
6	$\delta_1=0; \delta_2=1; \delta_3=0$
7	$\delta_1=0; \delta_2=0; \delta_3=1$
8	$\delta_1=0; \delta_2=0; \delta_3=0$

MGT1(30kW)

MGT2(30kW)

MGT3(60kW)

Three MGTs with different characteristics

V.3 Optimization Goals

- Economic criteria: minimize the total fuel cost;

Fuel cost *Start/stop penalty*

$$J_{C\_i}^{t} = \boxed{\delta_i^t \times C_{M\_i}^{t}} + \boxed{C_{P\_i}^{Cost}(\delta_i^{t+1}, \delta_i^t)}$$

$$J_{\text{Cost}} = \sum_{\text{t}=1}^{T} \sum_{i=1}^{M} J_{C\_i}^{t}$$

- Environmental criteria: minimize the equivalent CO_2 emission;

$$J_{CO2\_i}^{t} = \delta_i^t \times CO2_{M\_i}^{t} + C_{P\_i}^{CO2}(\delta_i^{t+1}, \delta_i^t)$$

$$J_{\text{CO2}} = \sum_{\text{t}=1}^{T} \sum_{i=1}^{M} J_{CO2\_i}^{t}$$

- Best compromise criteria: make a compromise of economic and environmental criteria.

$$J_{BC\_i}^{t} = \boxed{\gamma}(\delta_i^t \times C_{M\_i}^{t} + C_{P\_i}^{Cost}(\delta_i^{t+1}, \delta_i^t)) + (1-\gamma)(\delta_i^t \times CO2_{M\_i}^{t} + C_{P\_i}^{CO2}(\delta_i^{t+1}, \delta_i^t))$$

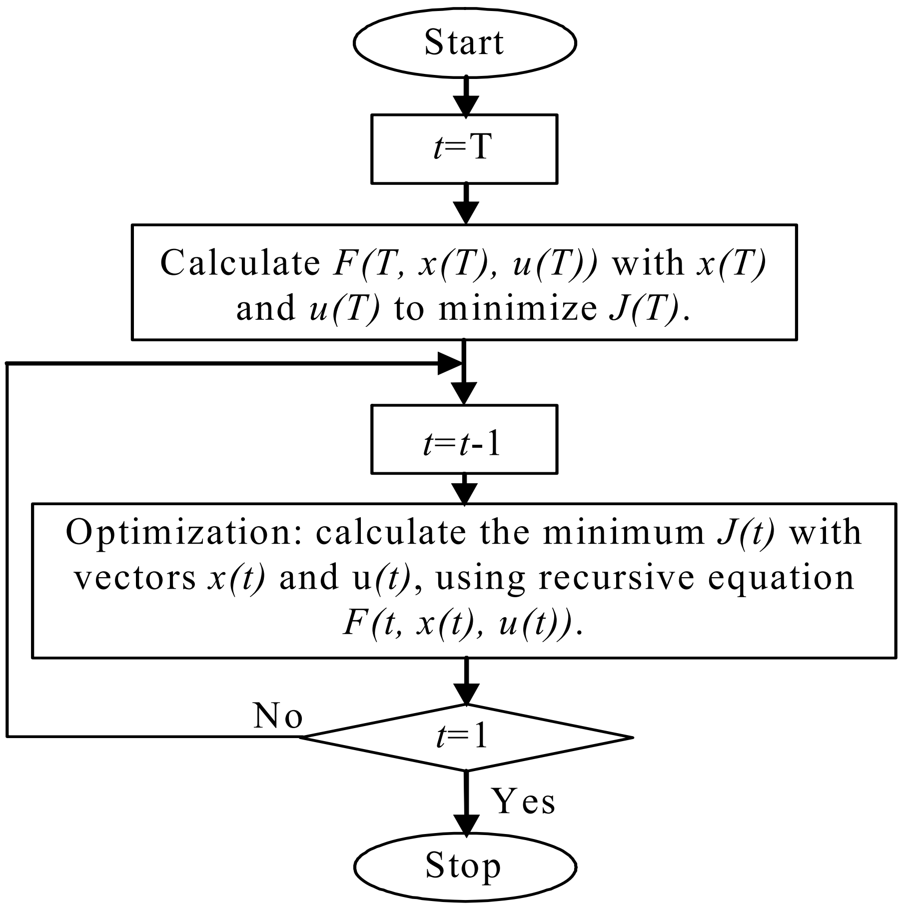
the proportion rate, from 0 to 1

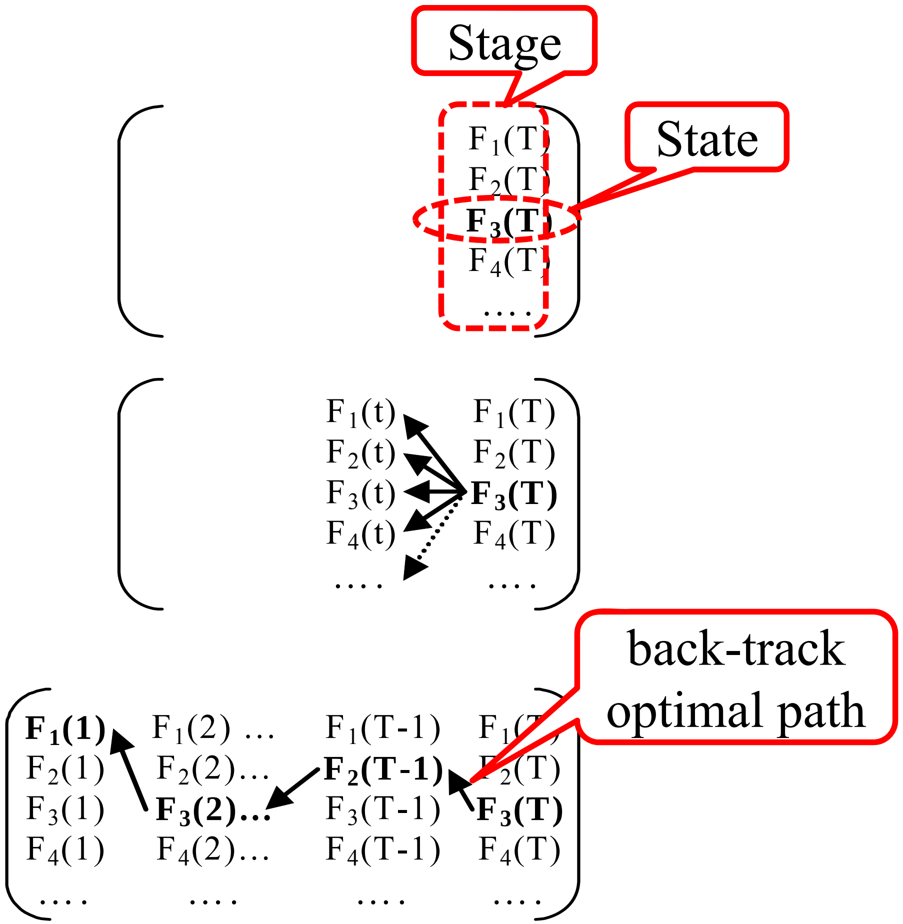
$$J_{\text{BC}} = \sum_{\text{t}=1}^{T} \sum_{i=1}^{M} J_{BC\_i}^{t}$$

M: the number of MGTs;
T: the number of operational steps.

V.3 Dynamic Programming (DP)

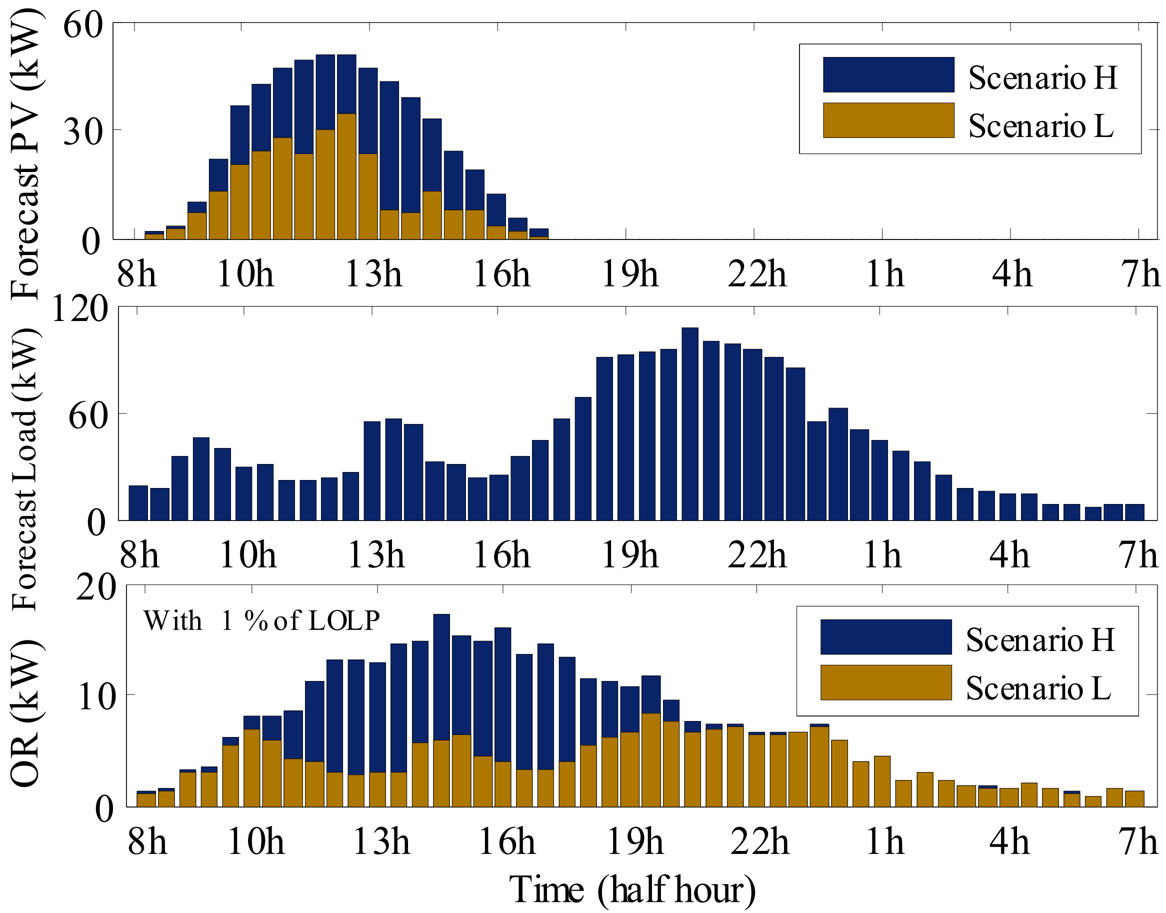
- DP: *Systematically evaluates a large number of possible decisions in a multi-step problem considering the "transition costs".*
- Multistage decision process formulation with backward recursion:
  - An evaluation of all possible configurations in each time step (**Stages** and **States**);
  - A “back-track” operation from the end back to the beginning (**Recursive Optimization**).





V.4 Case Study and Simulation Results (1)

- In this case: rated load (110 kW), rated PV power (55 kW) and the OR (with 1 % of LOLP) coming from the net demand uncertainty assessment.



- Scenario H, sunny day, 269.5 kWh;
- Scenario L, cloudy day, 128.4 kWh;
- The total battery capacity (150 kWh).

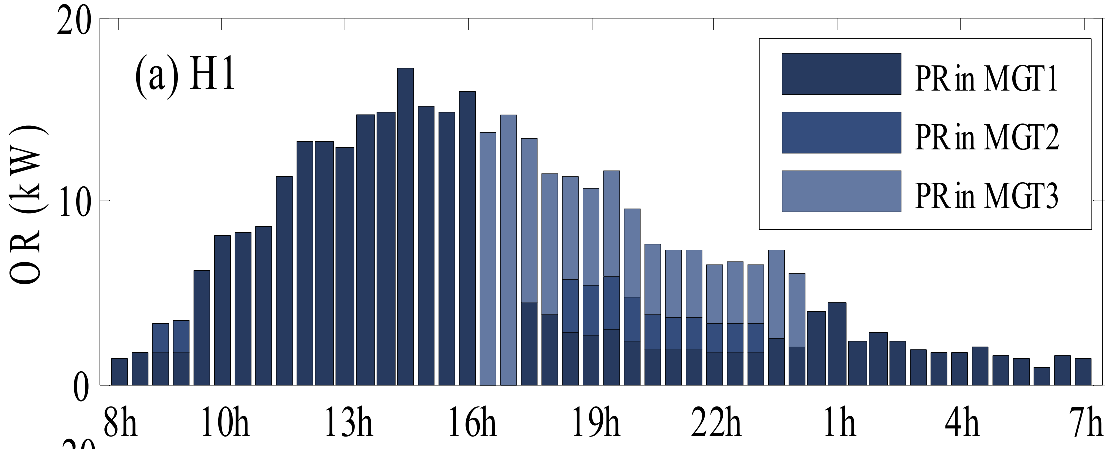
- The daily load is 1082 kWh.

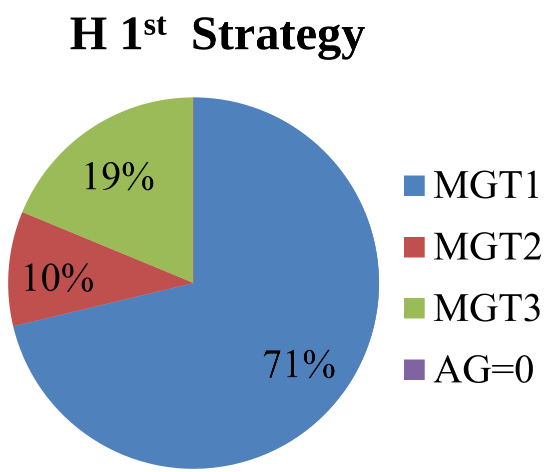
- OR calculation with two scenarios.

V.4 Case Study and Simulation Results (2)

- Day-ahead Operational Planning Results.

Scenarios	Optimization Criteria	Cost (€)	Pollution (kg)	OR on AG (%)	$E_{bat-Max}$ (kWh)
H **1st strategy: Only MGTs**	None	173	1224	0	78.6
	Environmental	169	1141	0	78.6
	Economic	**167**	**1167**	**0**	**78.6**
	Best compromise	171	1156	0	78.6





V.4 Case Study and Simulation Results (2)

- Day-ahead Operational Planning Results.

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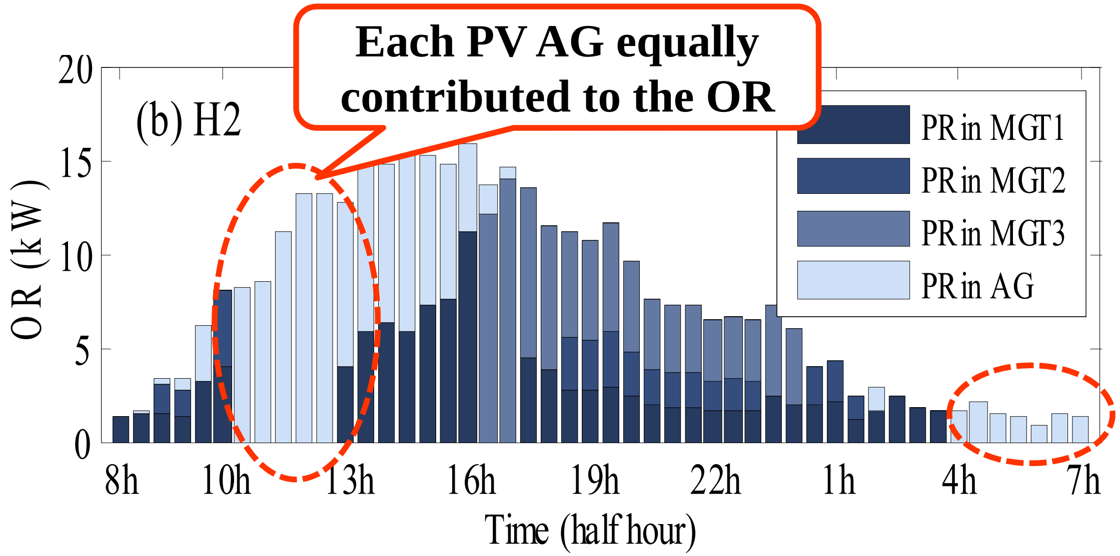
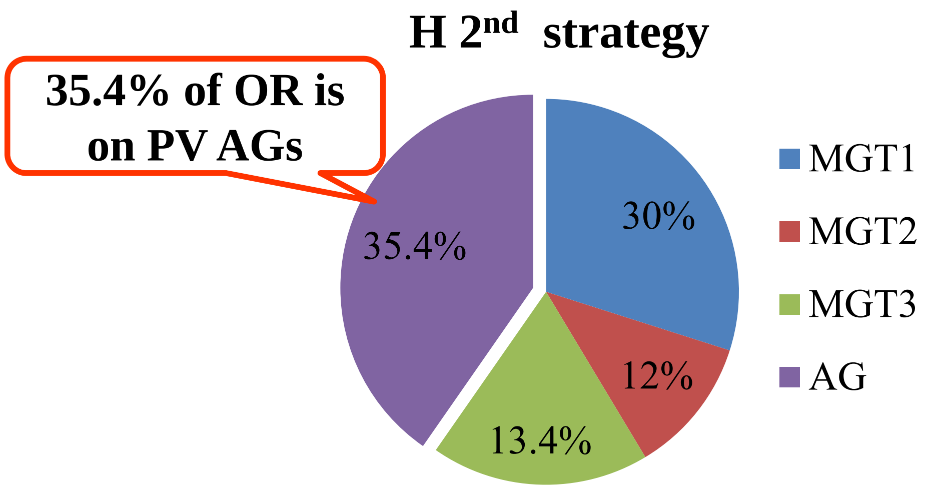
H 1st strategy: Only MGTs	None	173	1224	0	78.6
	Environmental	169	1141	0	78.6
	Economic	**167**	**1167**	**0**	**78.6**
	Best compromise	171	1156	0	78.6
H 2nd strategy: MGTs and AGs	None	173	1027	35.4	52.7
	Environmental	171	937	35.4	52.7
	Economic	**168**	**976**	**35.4**	**52.7**
	Best compromise	170	952	35.4	52.7





V.4 Case Study and Simulation Results (2)

- Day-ahead Operational Planning Results.

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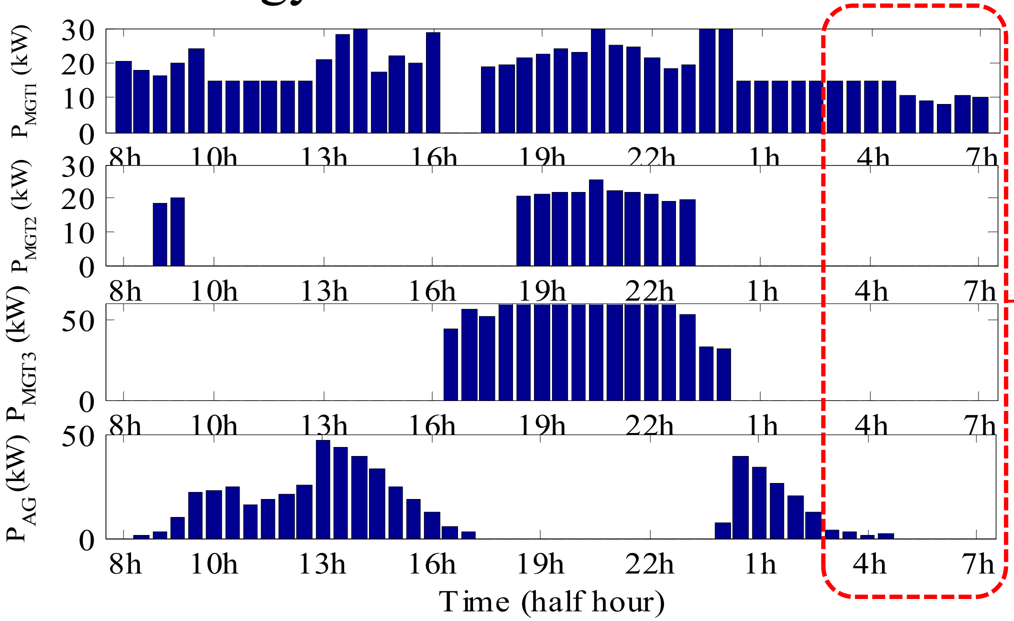
	Environmental	171	937	35.4	52.7
	Economic	**168**	**976**	**35.4**	**52.7**
	Best compromise	170	952	35.4	52.7
L 1st strategy	None	[illegible]	1290	[illegible]	**132.4**
	Environmental	182	1181	0	**132.4**
	Economic	**180**	**1245**	**0**	**132.4**
	Best compromise	183	1195	0	**132.4**
L 2nd strategy	None	188	1119	11.8	**132.4**
	Environmental	184	993	11.8	**132.4**
	Economic	**181**	**1063**	**11.8**	**132.4**
	Best compromise	185	1006	11.8	**132.4**

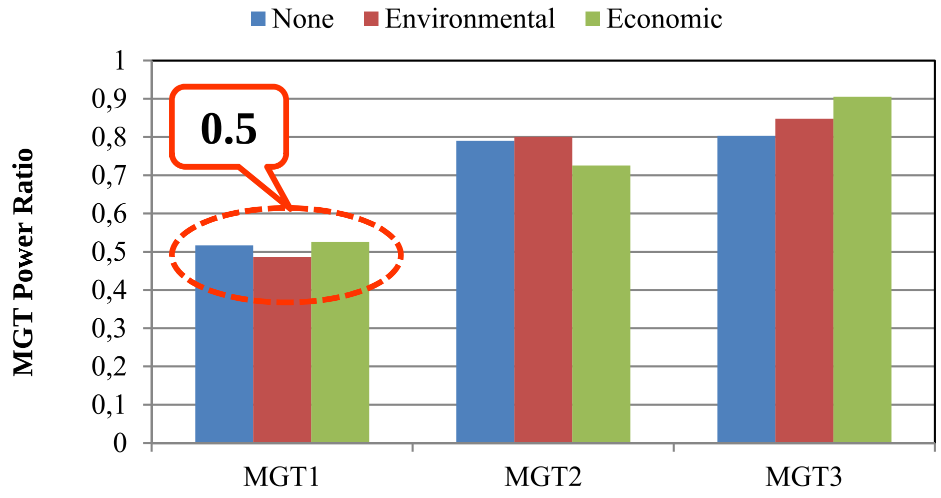
Cost and pollution are increased

Battery size is larger

V.4 Results (3): MGTs Load Ratio

- H 1st Strategy: OR on MGTs

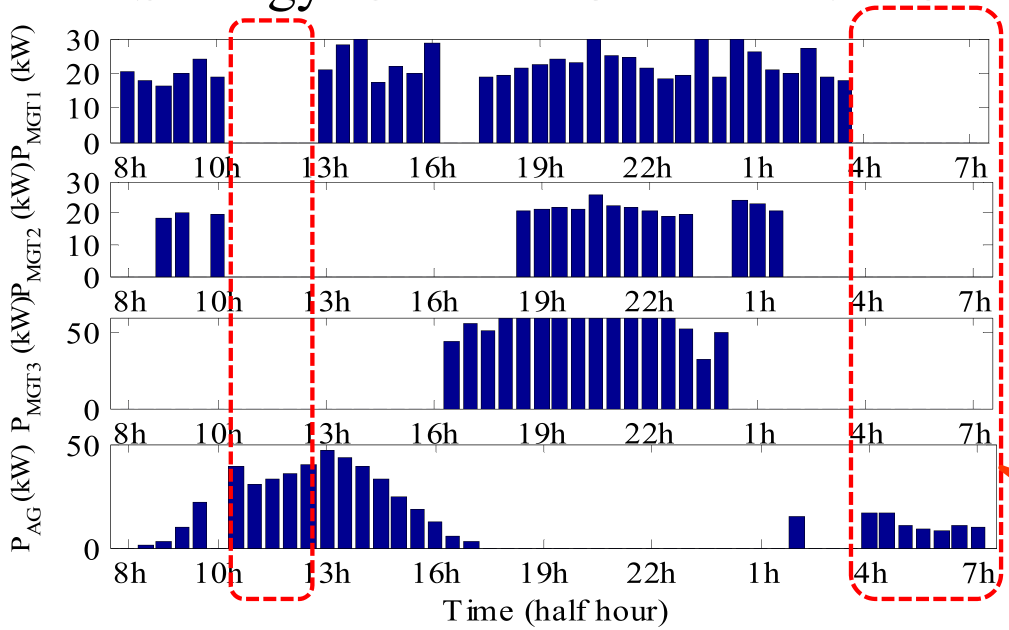




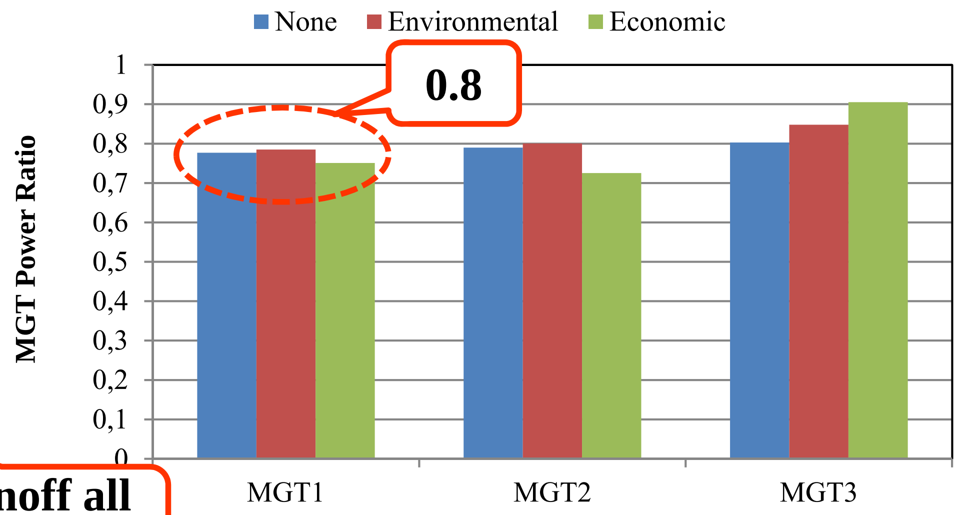
MGT Power Ratio with Strategy 1

Better use of MGTs in their higher efficiency operation domain.

- H 2nd Strategy: OR on MGTs and PV AGs



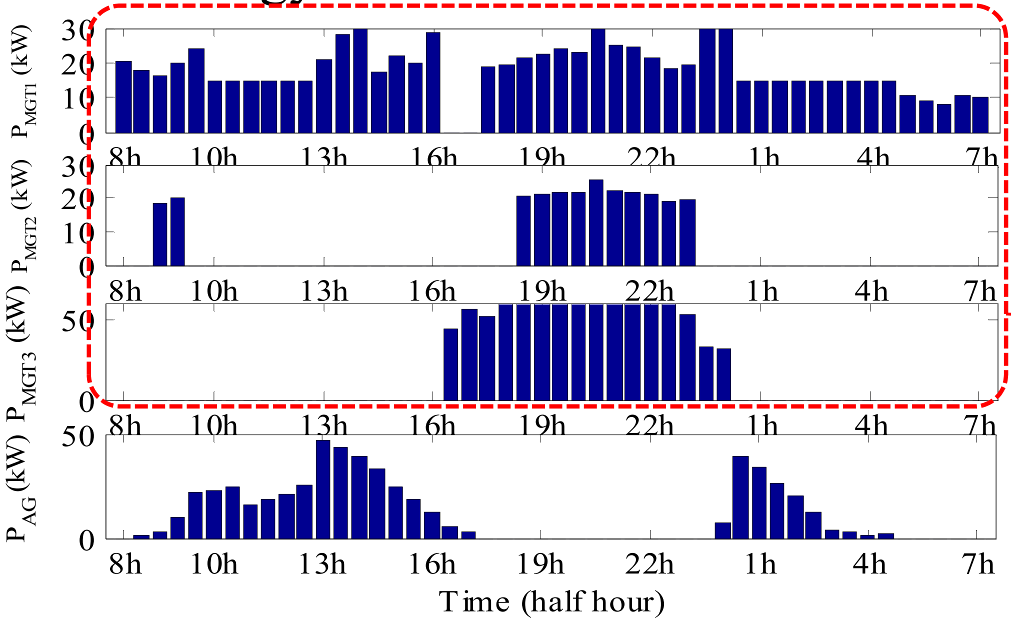
Turnoff all the MGTs



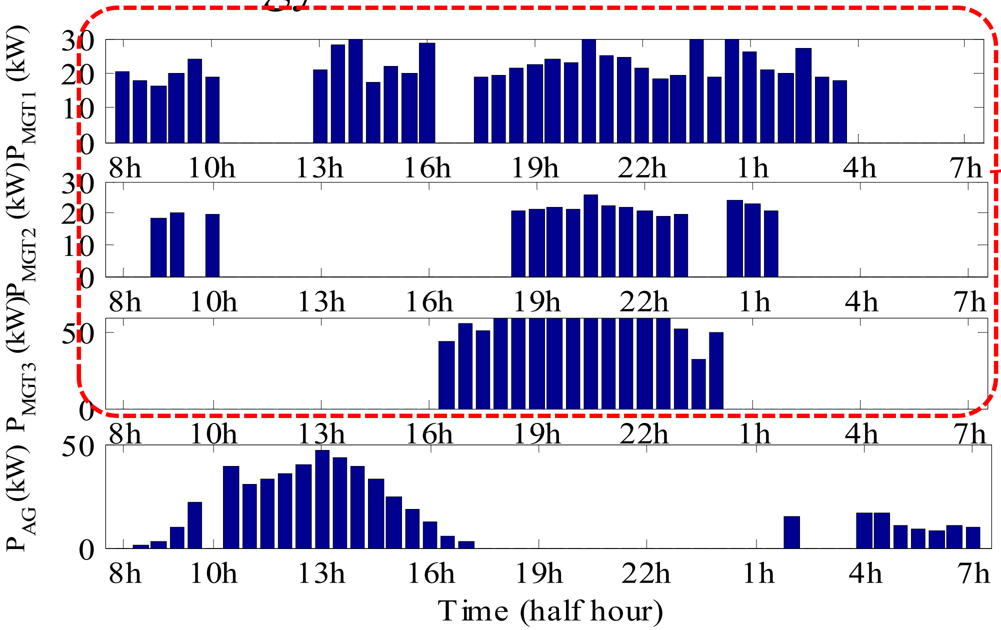
MGT Power Ratio with Strategy 2

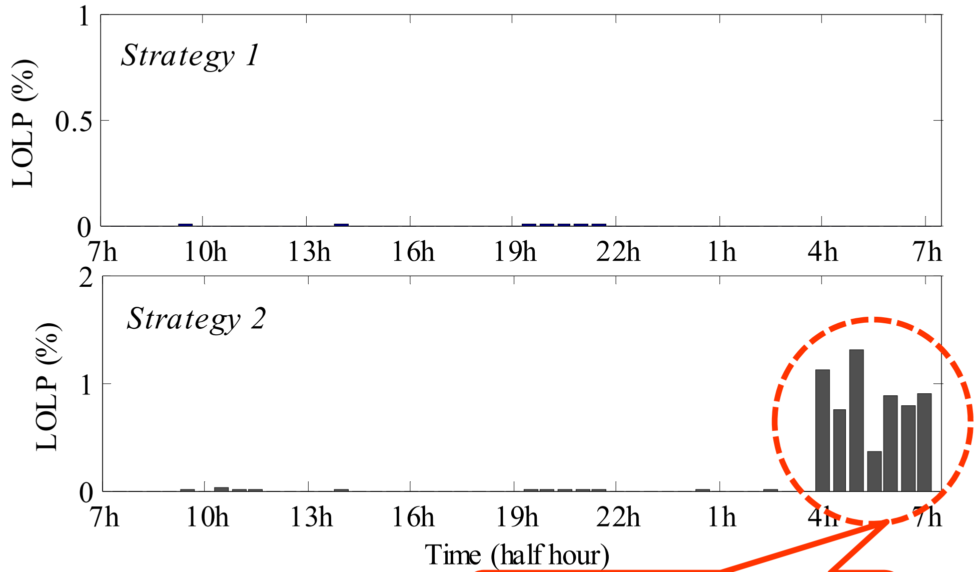
V.4 Results (3): Obtained system security

- H 1st Strategy: OR on MGTs



- H 2nd Strategy: OR on MGTs and PV AGs

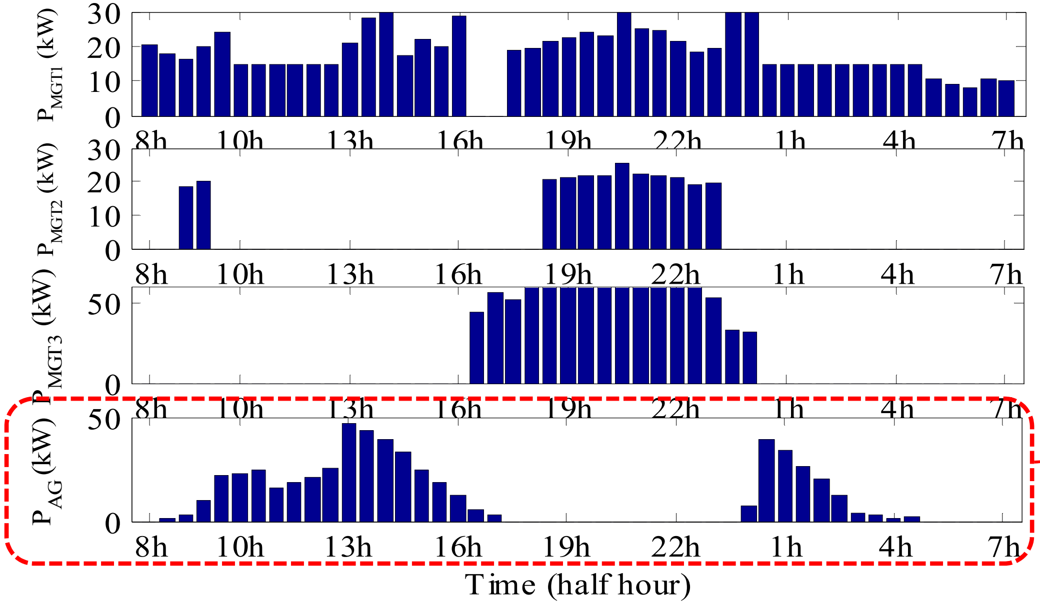


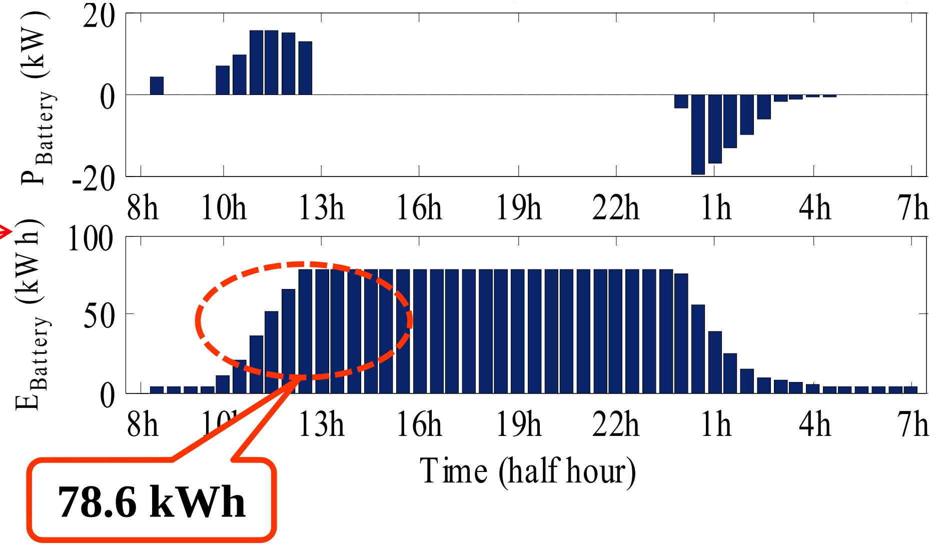


This is the risk we need to face with.

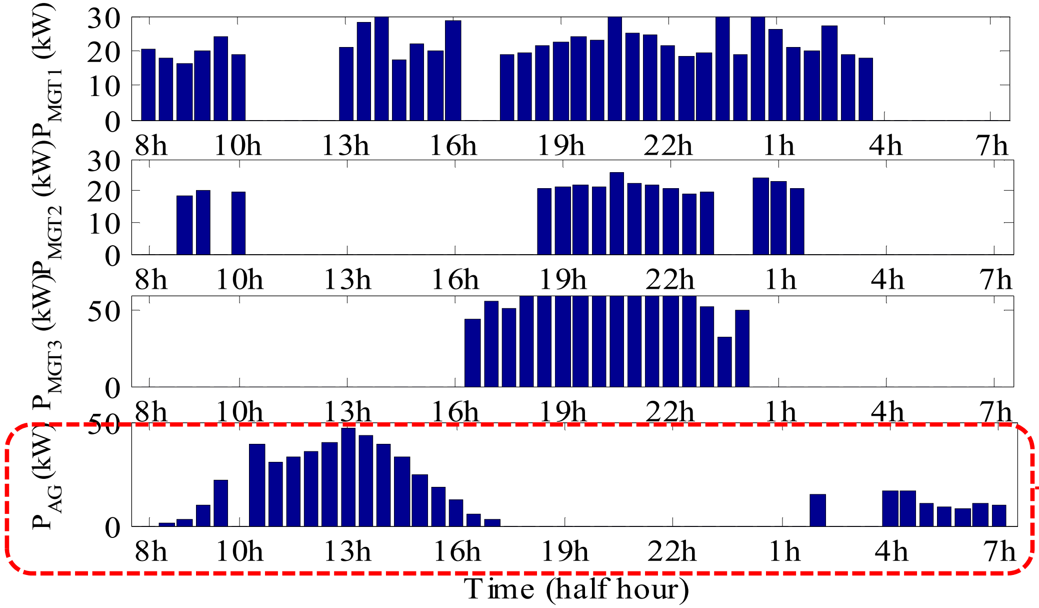
V.4 Results (4): Battery State of Charge

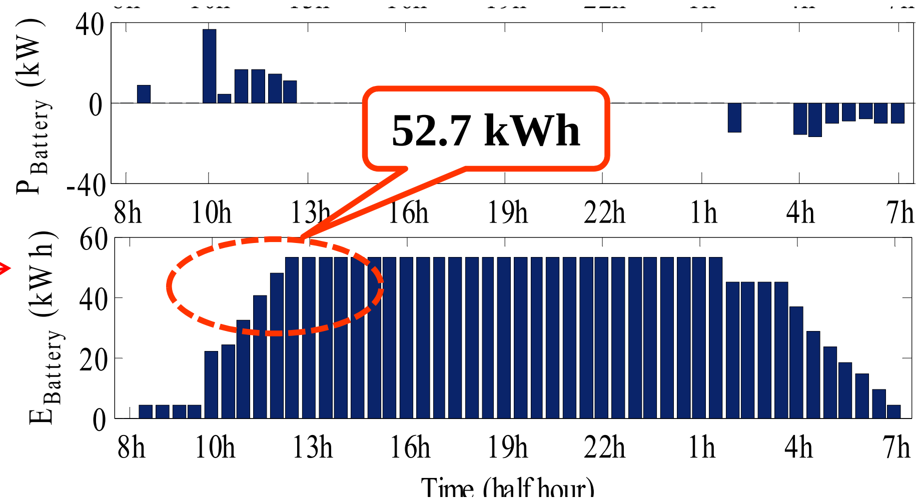
- H 1st Strategy: OR on MGTs



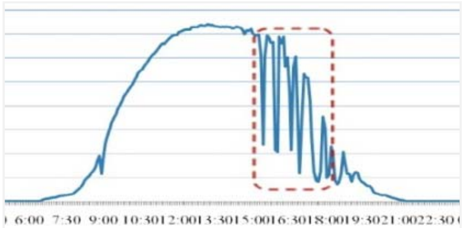


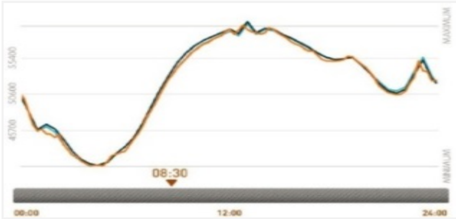
- H 2nd Strategy: OR on MGTs and PV AGs





Roadmap : Part VI





Predictive Analysis for Uncertainty:
PV power and load forecasting

Operating Reserve Quantification:
Loss of load probability (LOLP)

OR Dispatching Strategies on Generators

Day-ahead Optimal Planning:
Unit commitment problem with dynamic programming

A User-friendly EMS and Operational Supervisor

VI.1 Application

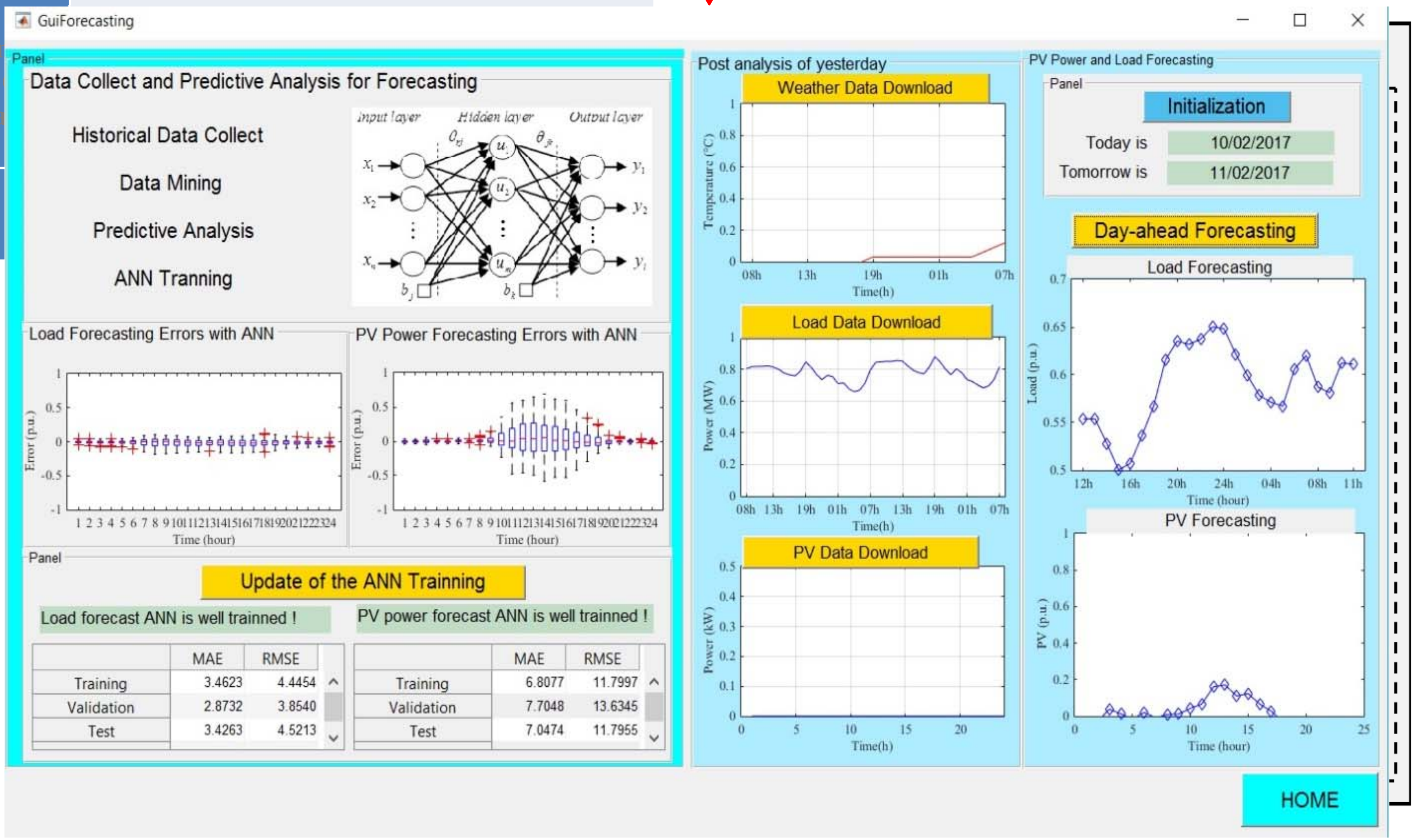
- **Objective:** to provide a complete set of user-friendly GUI to properly model uncertainties and optimal manage the details of PV AGs, loads, and MGTs one day-ahead.

VI.2 Microgrid EMS Supervisor Frame Design

Main Interfaces	Individual Modules
Data Collect and System Uncertainty Analysis	• Historical Data Collect for ANN Training • Day-ahead Data Download: Weather Information, Load, and PV Power Data • PV Power and Load Demand Forecast by Using Well Trained ANN
System Uncertainties Assessment and OR Power Quantification	• PV Power Uncertainty • Load Demand Uncertainty • Net Demand Uncertainty • OR Quantification
Operational and OR Dispatching	• Dispatching Strategies • PV AGs and MGTs Power References

VI.2 Development software

Main Interfaces	Individual Modules
Data Collect and System Uncertainty Analysis	• Historical Data Collect for ANN Training • Day-ahead Data Download: Weather Information, Load, and PV Power Data • PV Power and Load Demand Forecast by Using Well Trained ANN
System Uncertai Assessment and Power Quantifica	
Operational and Dispatching	



VI. A User-friendly EMS and Operational Supervisor

VI.2 Microgrid EMS Supervisor Frame Design

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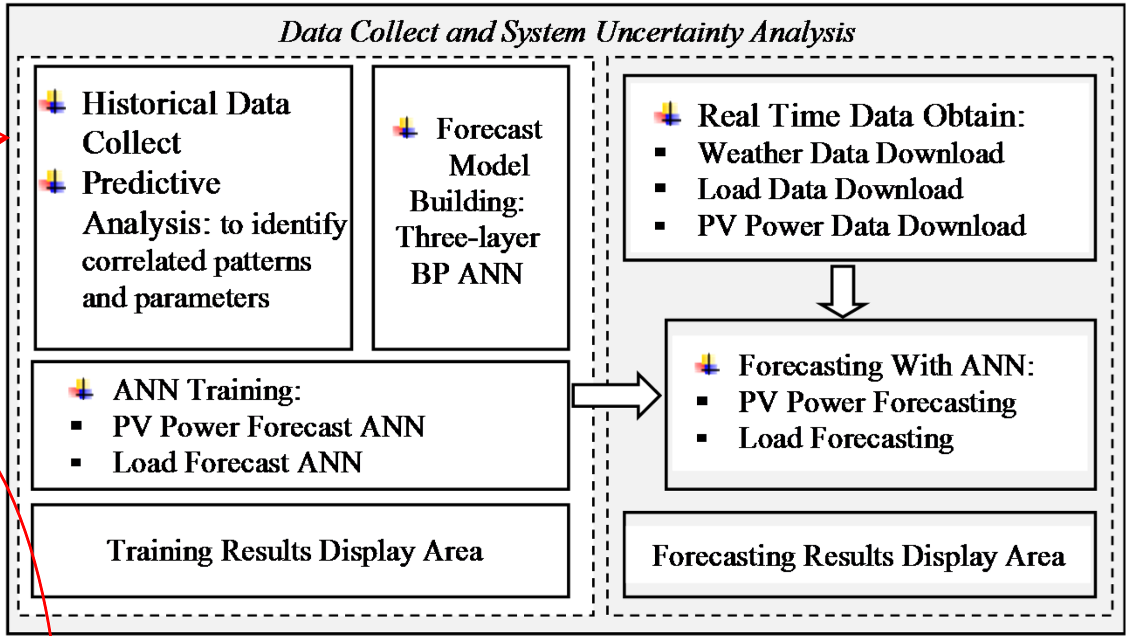
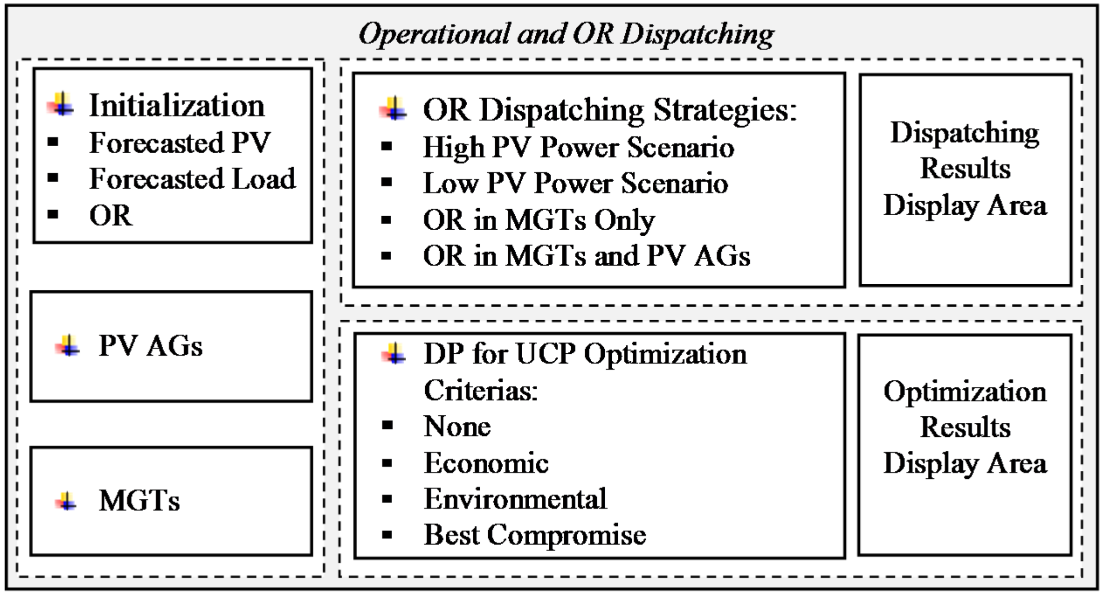
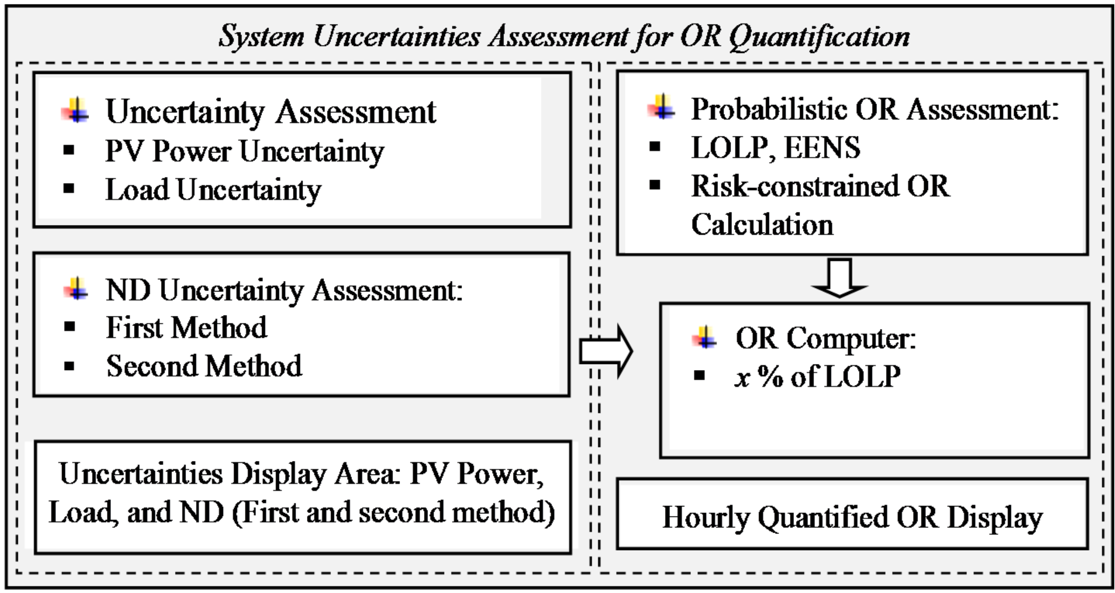




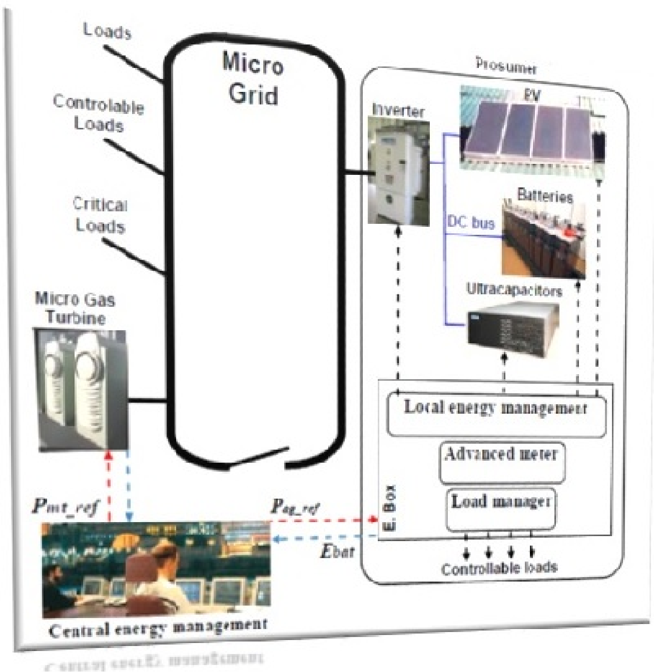


VI.3 Demonstration

MCEMS

Microgrid

Probabilistic Power Reserve Quantification and Dispatching Strategies in a Microgrid Including Active PV Generators

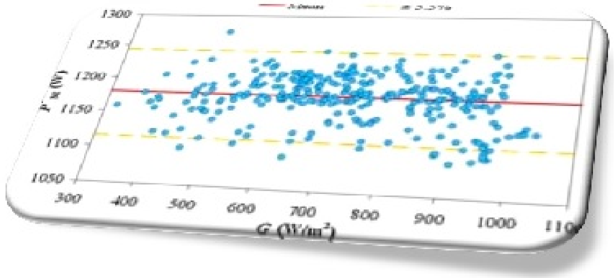


Microgrid integration of a prosumer and micro gas turbines (MGTs)

Microgrid Management

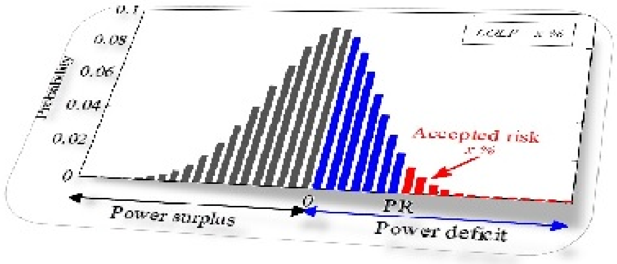
Data Collection, Uncertainty Analysis, PV Power and Load Forecast

Uncertainty Analysis



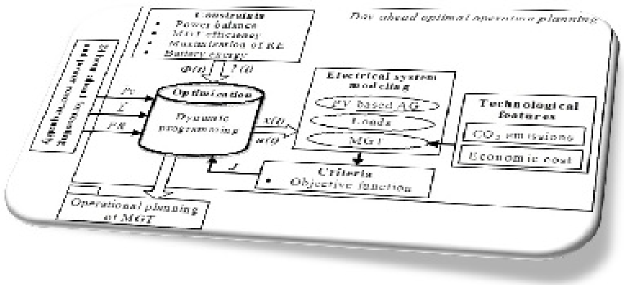
Uncertainty Assessment for OR Quantification

OR Quantification



Day-ahead Optimization Planning

Planning

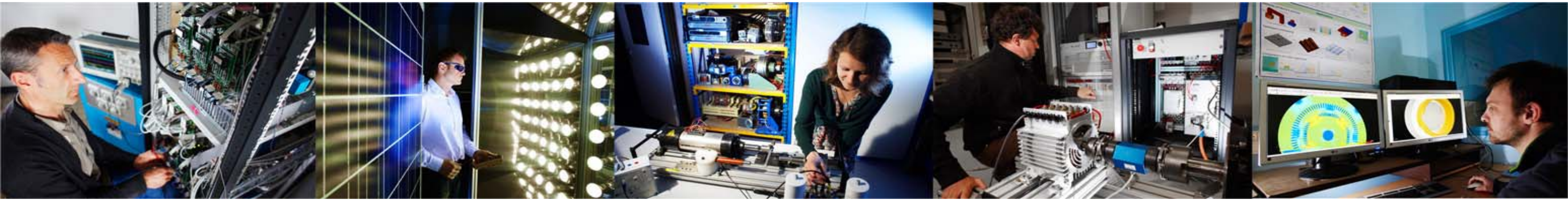


Contributions

- PV power variability and load demand variability are analyzed;
- A probabilistic method for the OR calculation is proposed (with two different kinds of ND uncertainty assessment methods);
- The dynamic joint operational and OR dispatching strategies are developed;
- Day-ahead operational and OR planning with DP is proposed by considering different optimization strategies;
- A User-friendly EMS and Operational Supervisor is developed.

Prospectives

- “Big data” for distributed RES uncertainty analysis, prediction for more then one day and with multiple time steps, and intraday adjustment;
- Optimization method to improve the battery efficiency and its lifespan;
- Considering load shedding;
- How the uncertainties are propagated in the electrical system.



Related Publications (https://www.researchgate.net/profile/Xingyu_Yan)

1. X. Yan, B. Francois, and D. Abbes, "*Uncertainty Analysis for Power Reserve Quantification in an Urban Microgrid Including PV Generators*", Elsevier, *Renewable Energy*, Vol (106), June 2017, pp. 288–297. (Accepted 9 January, 2017)
2. X. Yan, B. Francois, and D. Abbes, "Operating Reserve Quantification and Day-ahead Optimal Dispatching of a Microgrid with Active PV Generators," Elsevier, Sustainable Energy, Grids and Networks, ***under review***.

3. X. Yan, B. Francois, and D. Abbes, "Solar radiation forecasting using artificial neural network for local power reserve," in Electrical Sciences and Technologies in Maghreb (CISTEM), 2014 International Conference, pp. 1-6.
4. X. Yan, B. Francois, and D. Abbes, "Operating power reserve quantification through PV generation uncertainty analysis of a microgrid," in PowerTech, 2015 IEEE Eindhoven, 2015, pp. 1-6.
5. Yan, X., Abbes, D., Francois, B. and Bevrani, H., 2016, October. Day-ahead optimal operational and reserve power dispatching in a PV-based urban microgrid. In *Power Electronics and Applications (EPE'16 ECCE Europe), 2016 18th European Conference on* (pp. 1-10). IEEE.

Thank you for your attention !

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