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Stochastic Optimization for Generation Scheduling in a Local Energy Community under Renewable Energy Uncertainty

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Part 1 Introduction: Context, objectives and methods

1.1 Context : High penetration ratio of renewable energy sources (RESs) in local energy communities

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□ Energy and Climate Change

Decarbonization and sustainable development

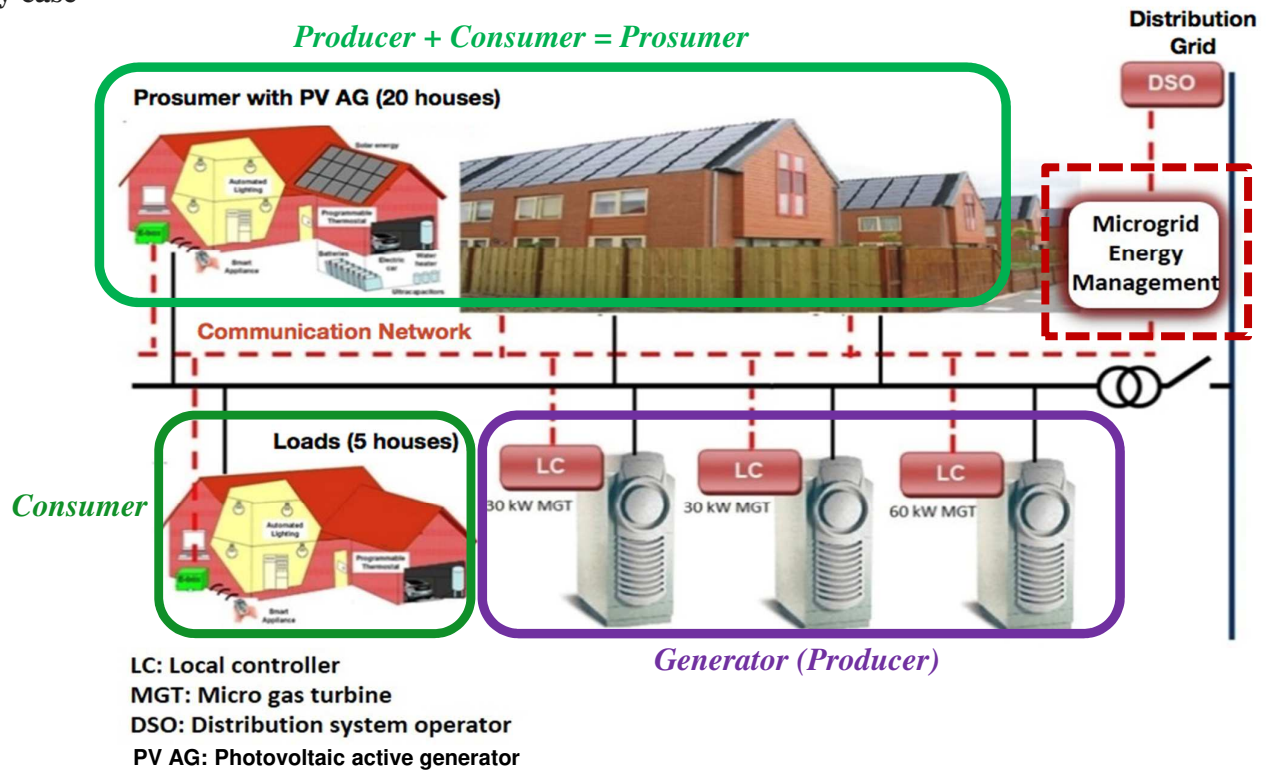
- Increase energy efficiency
 - Reduce power flow transmission losses in a large electrical system
 - Cost saving by reducing agents in commercial and operational transactions
- Reduce environmental impact
 - Substitution by carbon free generation



Local RES based electrical production for local consumption

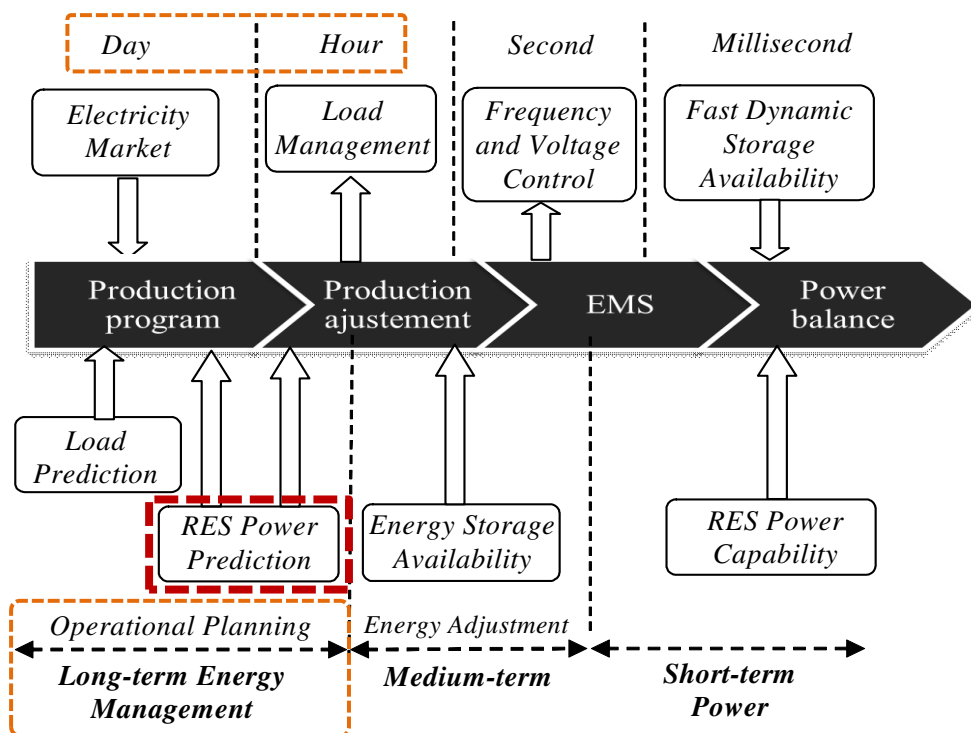
- Decarbonization, decentralization and democratization of the electricity generation and management.
- Emerging of Local Energy Communities (related also with islanded networks and microgrids).
- Increasing the participation of RES in the electrical system, introduces **uncertainties** and problems.
 - Local energy balancing
 - Reliability and operational power reserve
 - Economic costs and CO2 abatement
- How to **integrate RES into operational planning, anticipation and flexibility** in energy management systems?
- Needs for numerical methods that handle **RES uncertainty** in modelling and optimization.

Study case



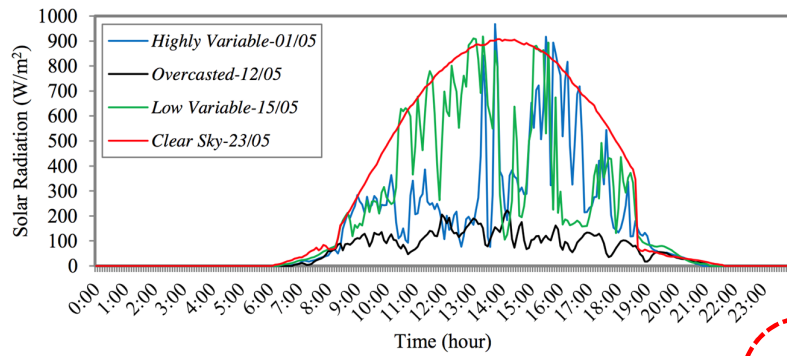
- Micro Gas Turbines are considered to study impacts of RES on existing generation in electrical systems
- Out of the scope : business plan, socio-economic issues and transaction markets

Organization of a Microgrid supervision in different time scales

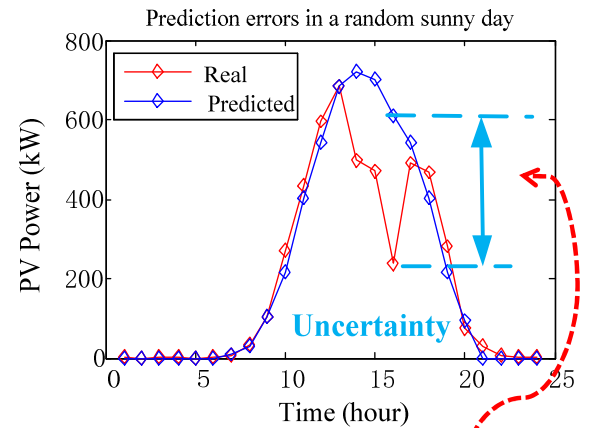


- Focus on day-ahead load and RES predictions, uncertainty analysis, and optimization of the network operation.

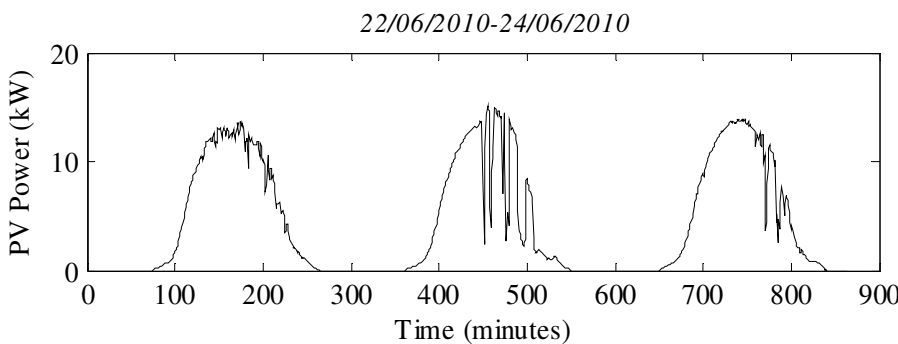
Solar energy...



Different conditions of irradiance caused by cloudy variations



Uncertainty caused by forecasting errors



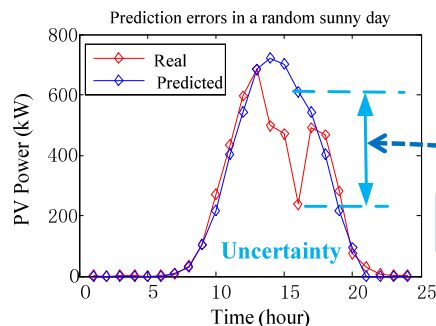
PV generation is intermittent but predictable

Unfortunately with errors !

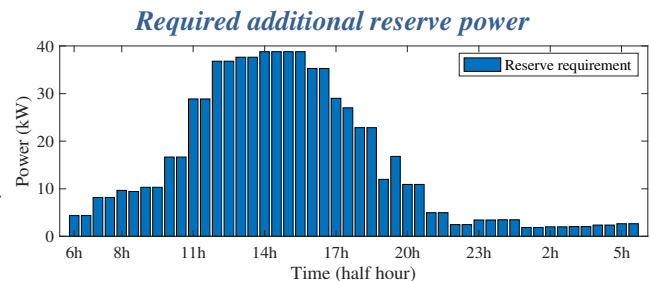
To deal with this **variable uncertainty**, **additional reserve power** should be considered (as insurance to against the sudden loss of generation and / or unexpected increase of the demand).

How **to schedule** the reserve power? How **to dispatch** reserve power on available flexibilities (generators, ...)?

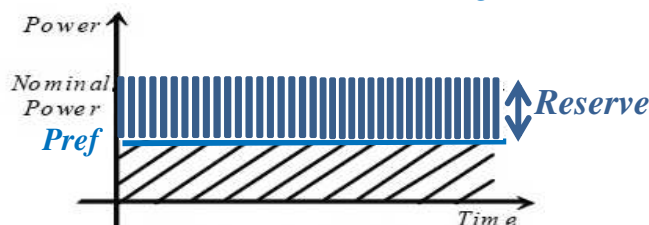
Non-dispatchable renewable energy source



Uncertainty caused by forecasting errors

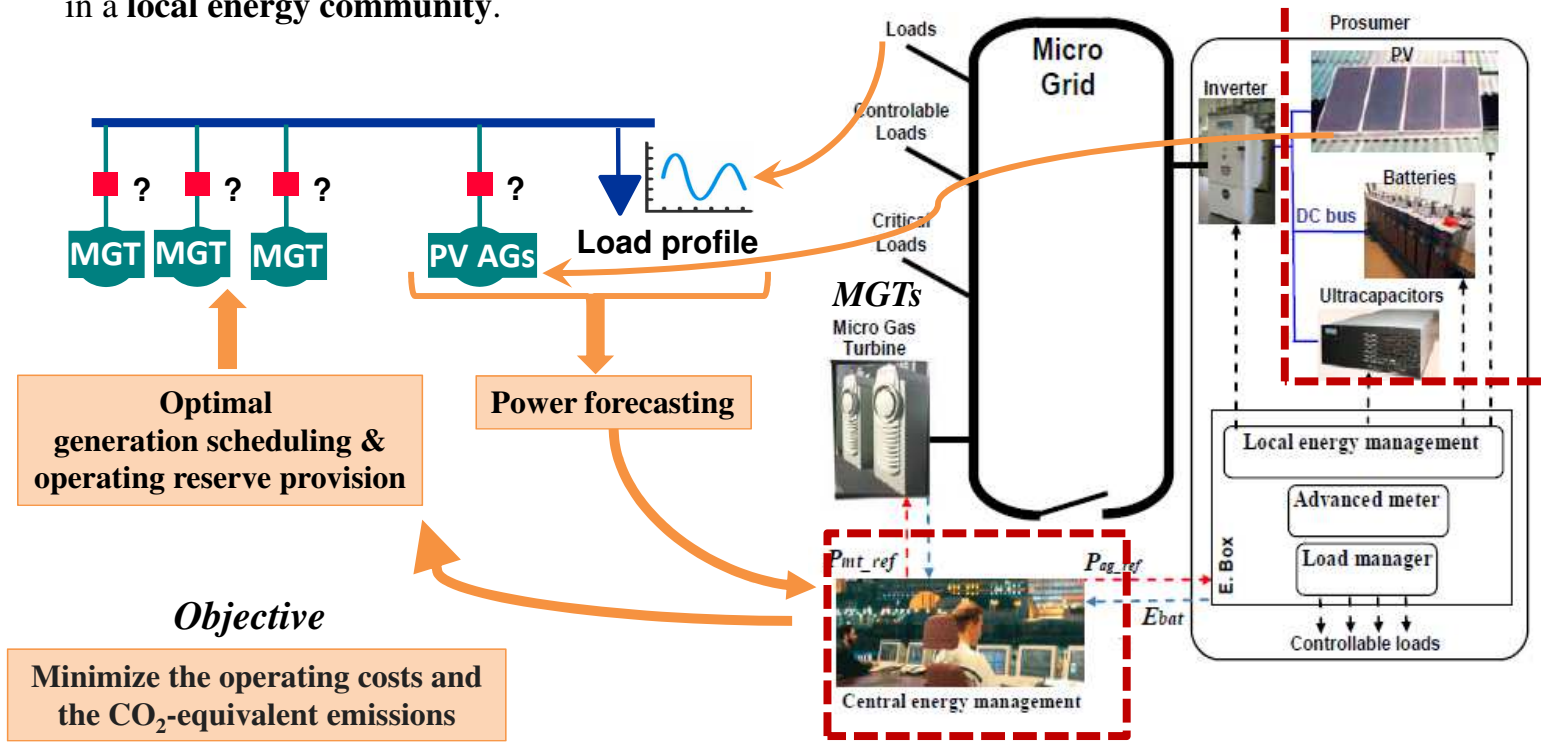


Reserve allocation on a conventional generator



First, we consider the reserve is only provided by MGTs **already in service** (operating below their rated power), or by offline MGTs **with a fast start-up**.

Day-ahead optimal **generation scheduling** including the **operating reserve (OR)** provision under stochastic characteristics of **photovoltaic (PV)** renewable energy in a **local energy community**.



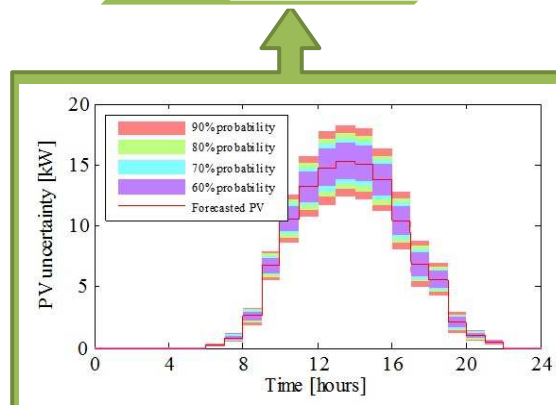
PhD thesis of Hristiyan KANCHEV (L2EP), Jan 2014

Deterministic optimization of the generation scheduling for an urban microgrid.



PhD thesis of Xingyu YAN (L2EP), May 2017

Energy management under uncertainty: Deterministic optimization, uncertainty analysis of past PV forecast, quantification and allocation of power reserve.



1) Impacts of uncertainty onto objectives (operational costs and carbon emissions)

-> Propagation of uncertainty with persistent assumption

Uncertainty modelling with pdf of past data
 Probabilistic-Based Deterministic Optimization



Uncertainty propagation analysis with probabilistic methods

2) Consideration of future uncertainties

-> Integration of uncertainty in the solution search

Uncertainty modelling with future probable scenarios
 Multi-Objective Stochastic Optimization



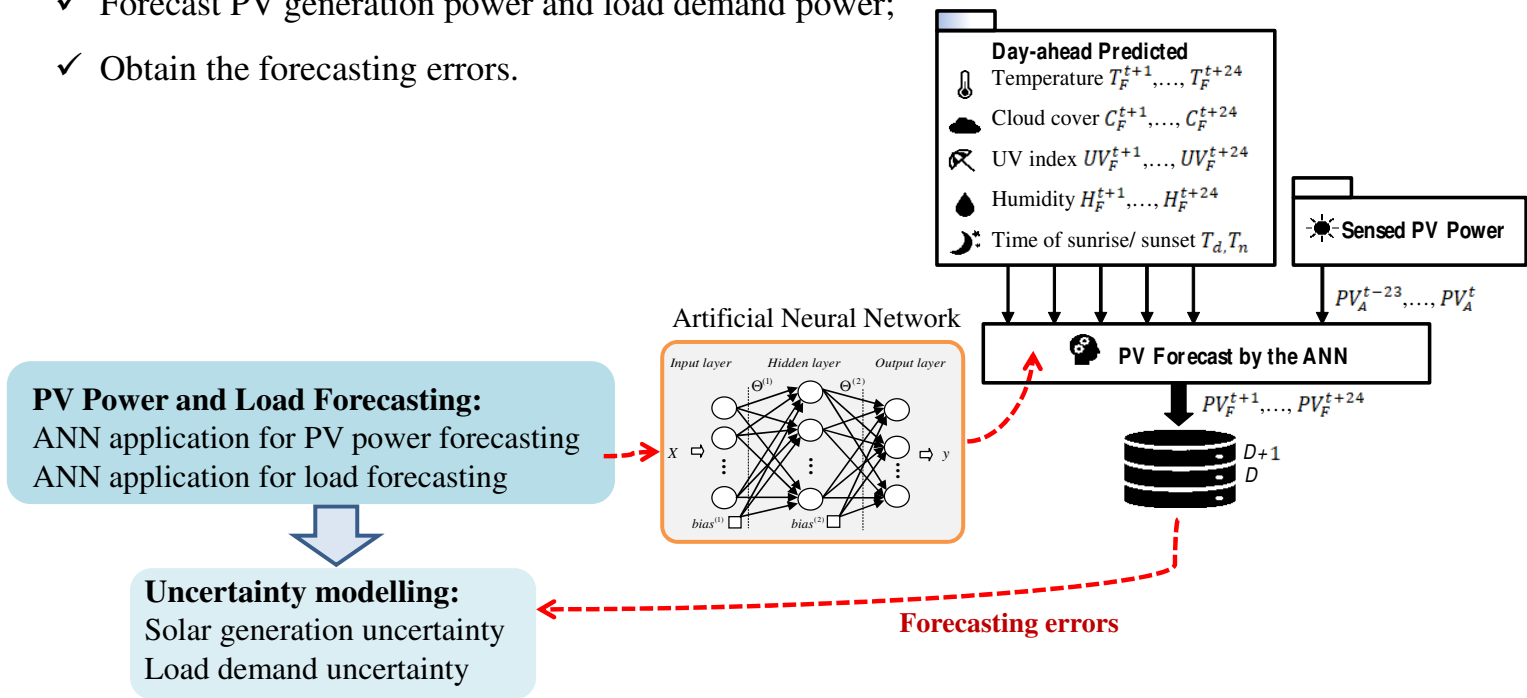
Scenario-based stochastic optimization approach

- Chance-constrained optimization
- Robust optimization with uncertainty set

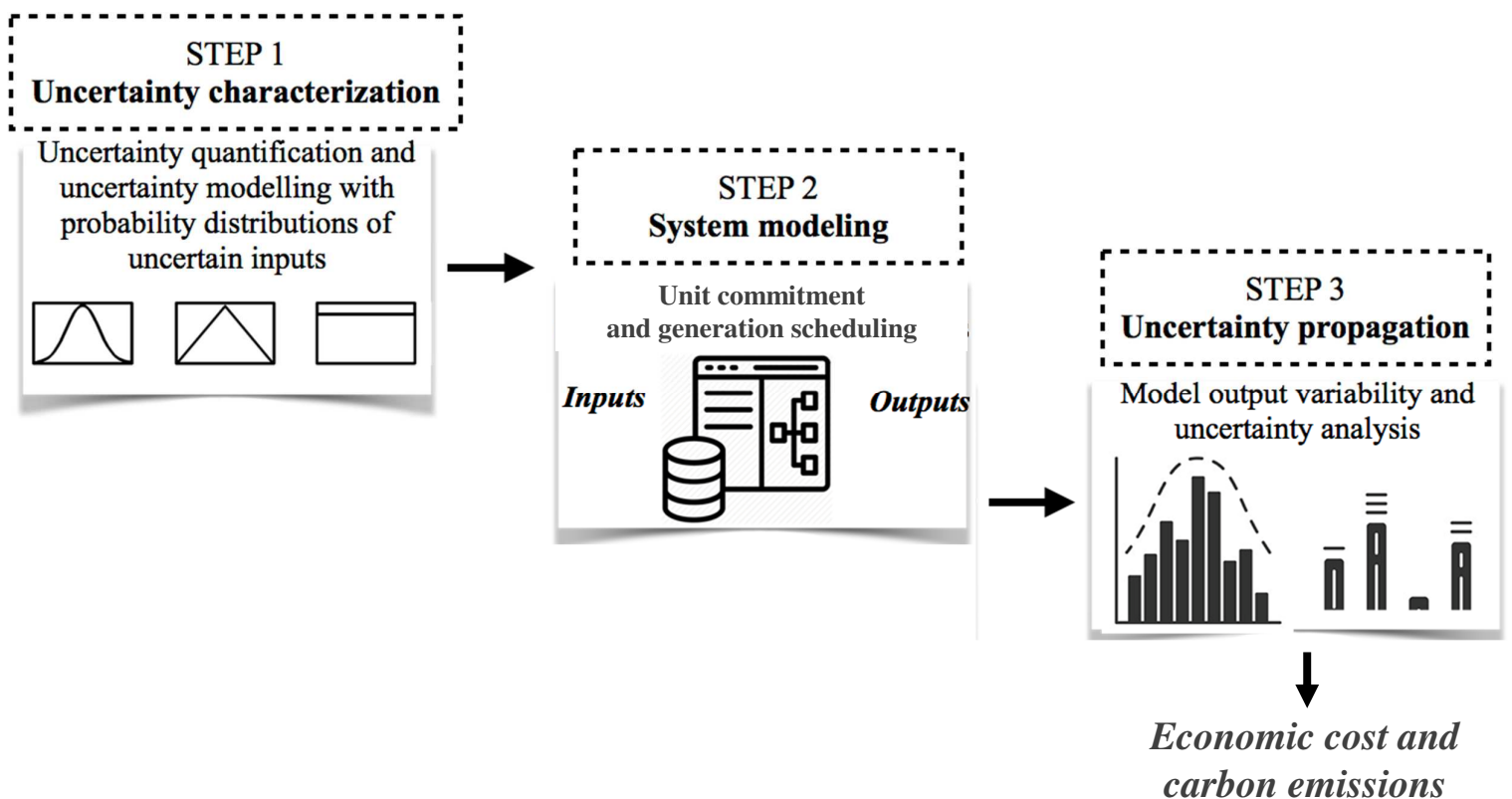
- Part 2 • Uncertainty analysis from forecasting
- Part 3 • Deterministic unit commitment under uncertainty
- Part 4 • Anticipating uncertainty with a scenario-based stochastic optimization
- Part 5 • Participation of storage for operating reserve provision
- Part 6 • Microgrid Central Energy Management System interface design

To build a database of forecasting errors, we consider artificial neural network (ANN) to:

- ✓ Forecast PV generation power and load demand power;
- ✓ Obtain the forecasting errors.



Impact of uncertainty onto criteria : economic cost and carbon emissions ?



- Part 2 • Uncertainty analysis from forecasting
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Part 3 Deterministic unit commitment under uncertainty

3.1 Methodology

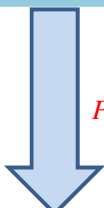
Uncertainty representation:
PV Power and Load Forecasting Errors



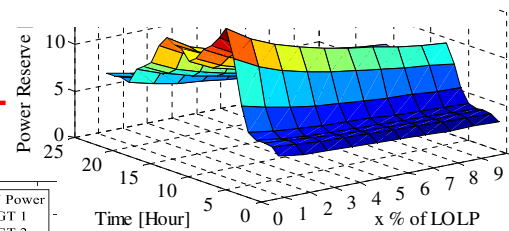
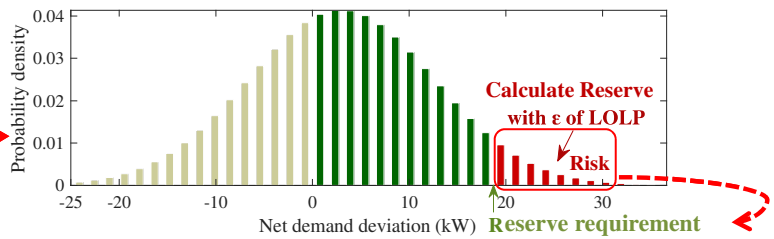
Operating Reserve Quantification:
Risk assessment by Loss of Load probability (LOLP)



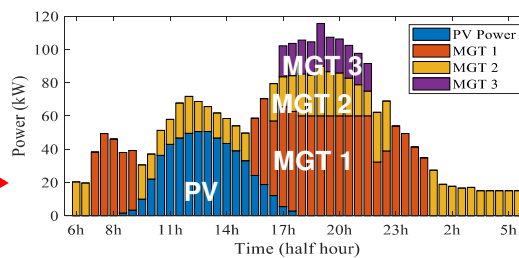
Day-ahead Generation Scheduling
with Dynamic Programming /
Mixed-integer linear programming



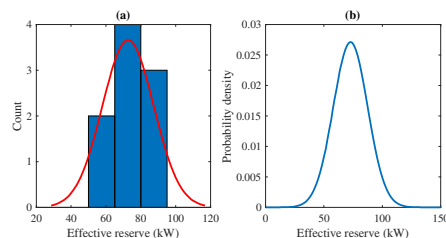
Uncertainty propagation Analysis
regarding PV generation



Operating reserve power profile

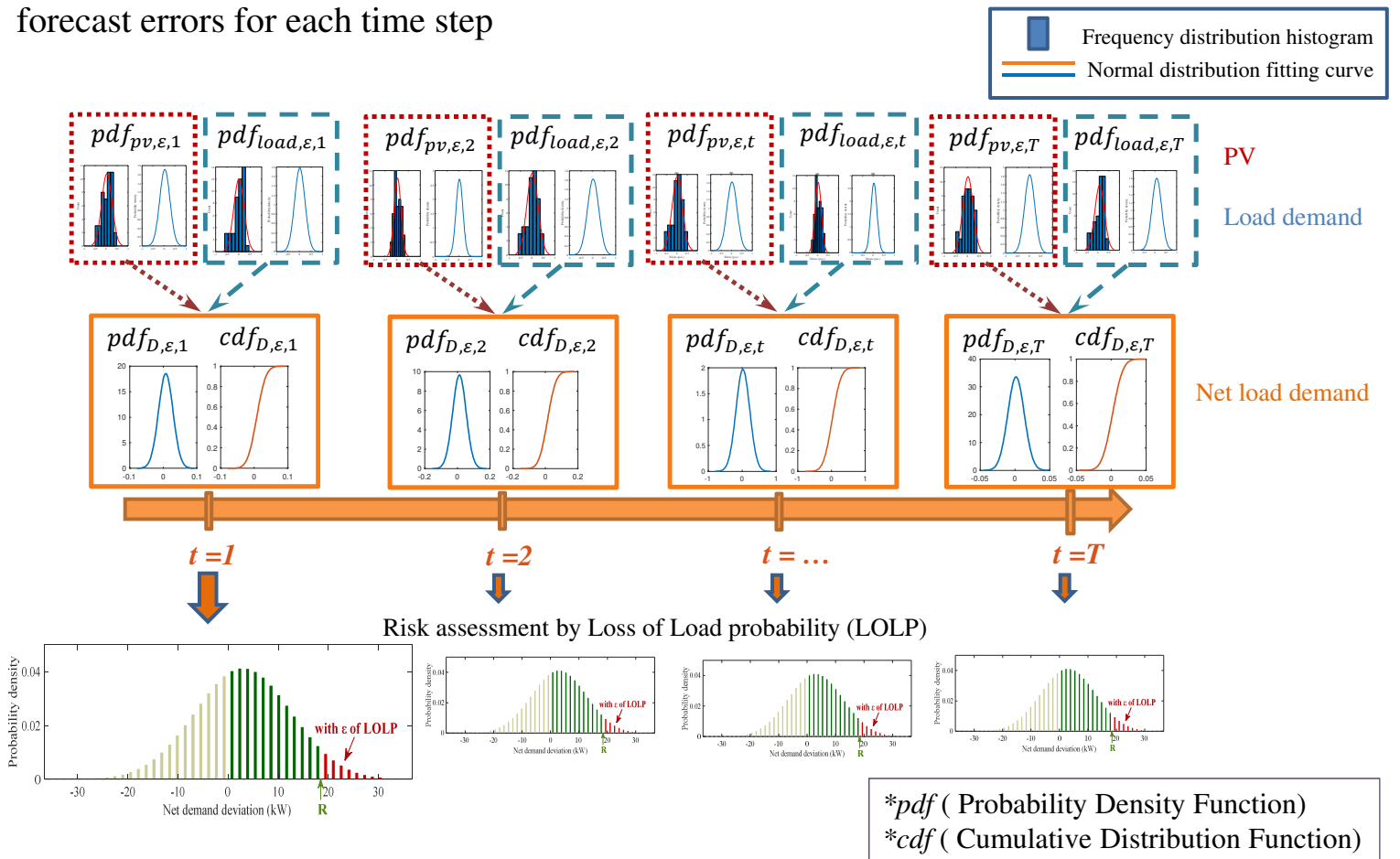


Planning of MGTs



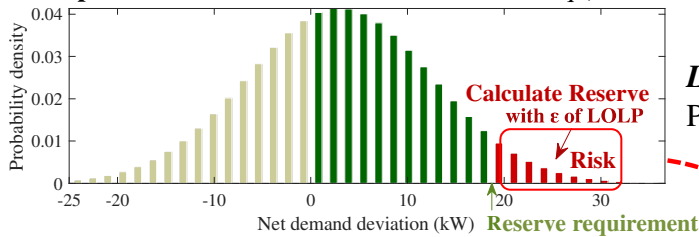
We are going to detail each step...

3.2 Reserve quantification from probabilistic analysis of forecast errors for each time step



3.3 Reserve quantification from probabilistic analysis with forecast errors

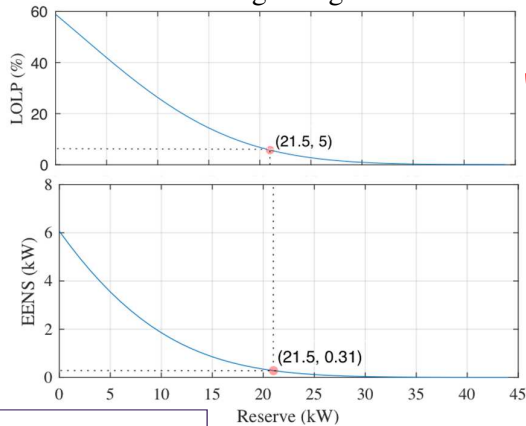
Example : Reserve at 11:00 in Villeneuve d'Ascq (Lille, France) the 23th of June, 2020:



LOLP (Loss of Load Probability):

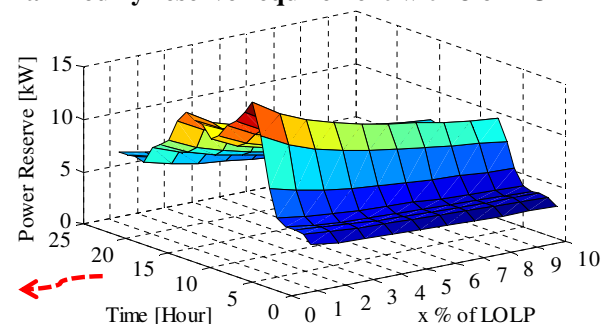
Probability that load will exceed the available power generation.

Risk characteristic regarding reserve at 11:00



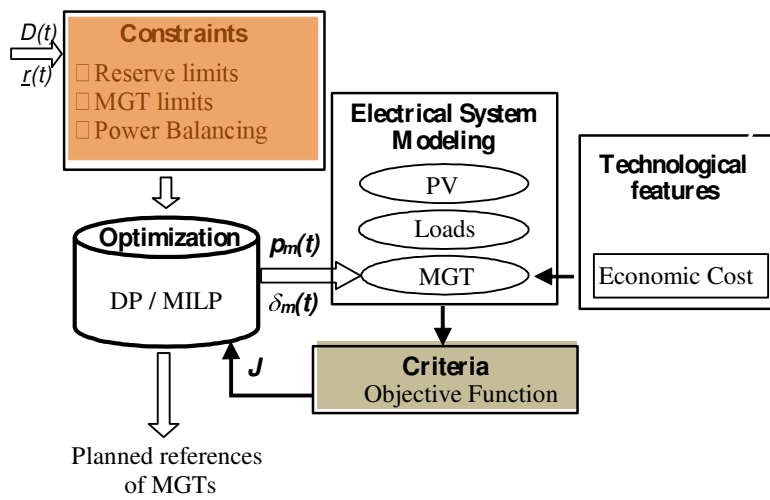
*EENS (Expected Energy Not Served)

Half-hourly reserve requirement with ϵ of LOLP



Reserve power is obtained at each time step for tomorrow!

Optimization framework



$m \in \mathcal{M}$ Set of conventional generators
 $t \in \mathcal{T}$ Set of time steps.
 $p_m(t)$ M decision variables

DP: Dynamic programming
 MILP: Mixed Integer Linear Programming

Constraints

Power balancing constraint

$$\sum_{m=1}^M p_m(t) = D(t)$$

net load demand = (Load demand forecast - PV production forecast)
 $p_m(t)$: power generated by MGT m at time step t

Reserve constraint

$$\sum_{m=1}^M p_m(t) = D(t) + r(t)$$

maximum available power of MGT m at time step t
 $r(t)$: reserve power

Generation limits constraint

State of the MGT m at time step t

$$p_m \delta_m(t) \leq p_m(t) \leq \bar{p}_m \delta_m(t)$$

minimum/maximum power generation limits of MGT m

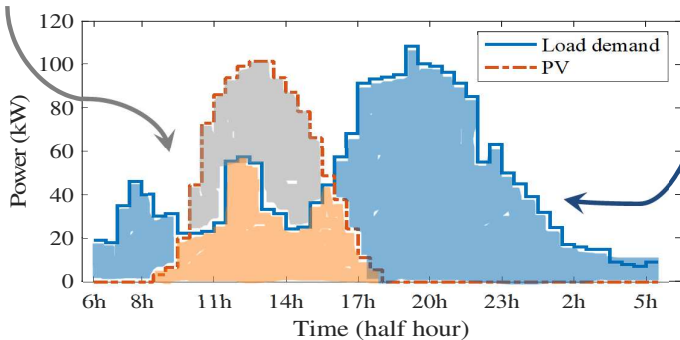
Criteria of optimization (J)

$$J = \min \sum_{t=1}^T \sum_{m=1}^M c_m(p_m(t)) + c_m^S s_m(t)$$

fuel cost of producing $p_m(t)$ startup/shutdown penalties

PV power profile

Load profile



- ❑ Forecasted daily PV energy is 539 kWh
- ❑ Forecasted daily load demand energy is 1082 kWh
- ❑ The PV self-consumption rate is about 50% $(\frac{\text{orange}}{\text{orange} + \text{grey}})$
- ❑ The PV self-production rate is about 25% $(\frac{\text{orange}}{\text{orange} + \text{blue}})$

- ❑ Without energy management and optimization during the day, a part of the available PV energy will not be consumed locally and will be lost (when power supply > Load demand).
 -> Hence the PV self-consumption rate and the PV self-production rate will decrease.
- ❑ The unused PV power (when the irradiance is high), can be valued by:
 - providing reserve power (scheduled PV limitation or PV curtailment), or
 - being saved in a storage (charging mode) in order to be used later (through a discharging mode),

3.7 Generation scheduling by considering N-1 criterion

- ❑ The classical *N-1* criterion for the reserve quantification is implemented as following :
 - 1) PV AGs are not seen as reliable generators;
 - 2) Planning of MGTs commitment is calculated without considering PV generation
 - 3) For all committed MGTs, power references are reduced in case of PV production

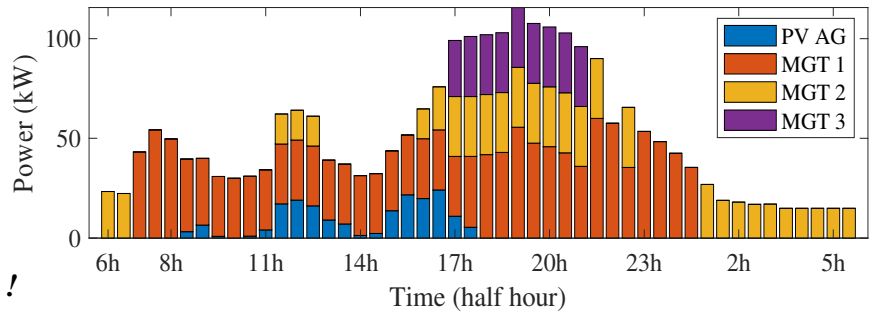
If the minimum power limit of committed MGTs is achieved, the PV production is curtailed (or limited)

- ❑ Deterministic generation planning

PV self-consumption rate = 17%

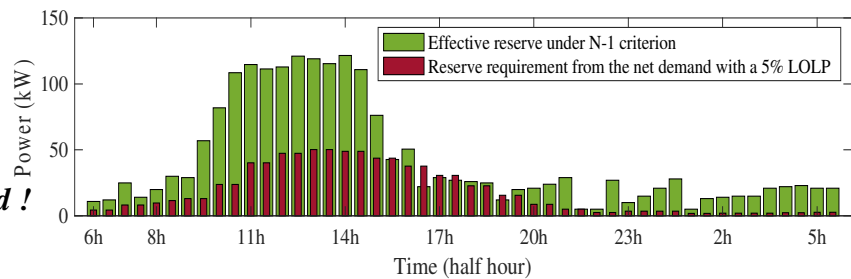
PV self-production rate = 9%

A significant part of PV generation is curtailed !



- ❑ Obtained effective reserve

Too much unnecessary effective reserve is provided !



3.6 Generation Scheduling by considering probabilistic reserve provision

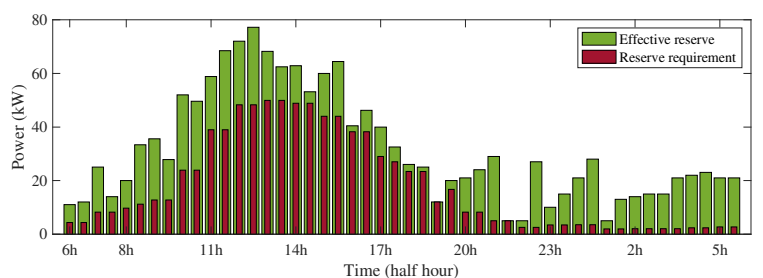
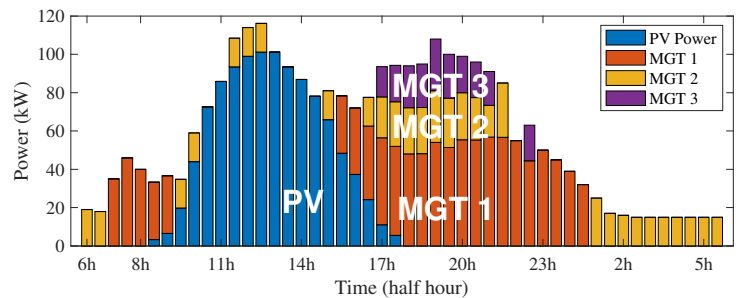
- ❑ Optimization method --- Dynamic programming (DP)

- ❑ Deterministic generation planning

PV self-consumption rate = 50%

PV self-production rate = 25%

- ❑ Obtained effective reserve with a LOLP $\leq 5\%$



- ❑ Cost variation domain

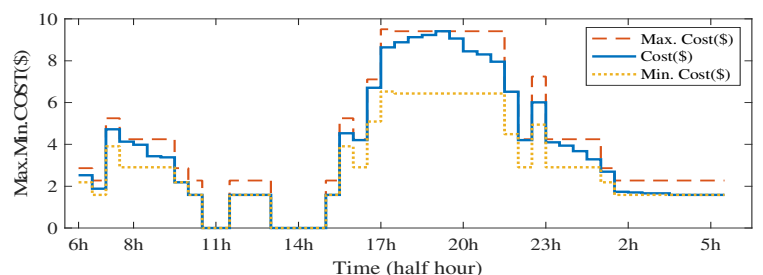
- Cost with exact forecasted data

- Cost in case of upper bound:

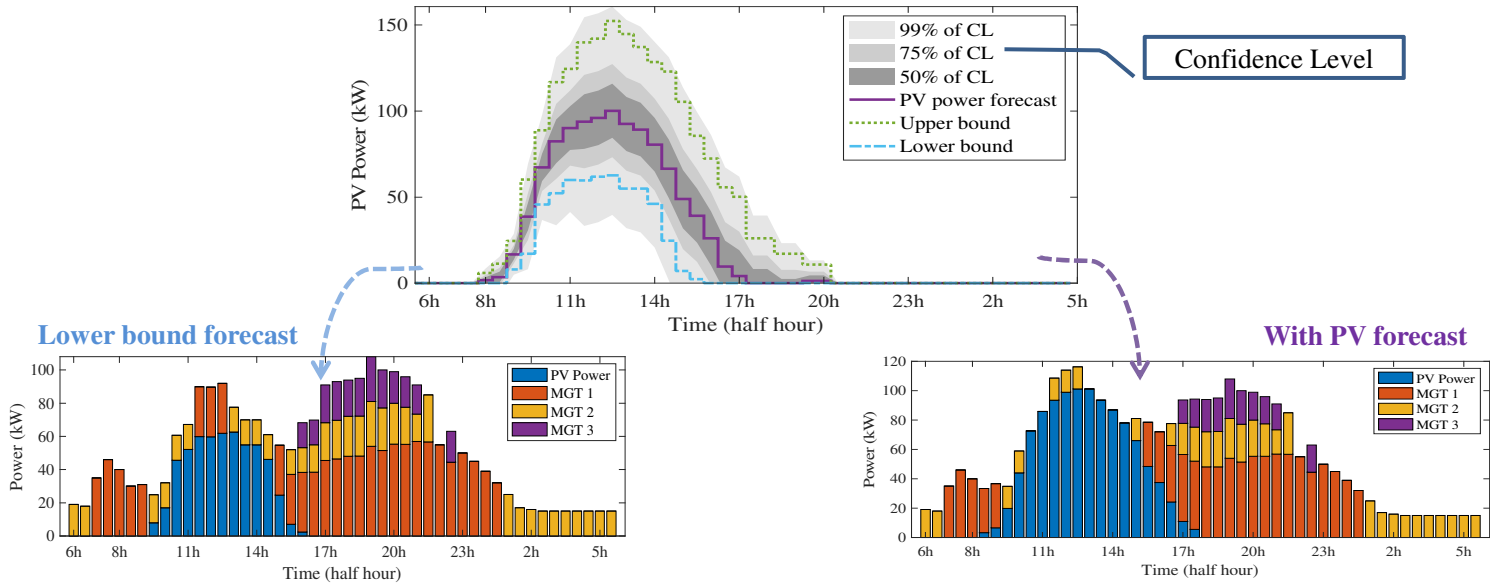
PV is less, OR is delivered

- Cost in case of lower bound:

PV is more, no delivered OR



3.8 Impact of uncertainty in Dynamic Programming Optimization



Impact of uncertainty onto cost and reserve

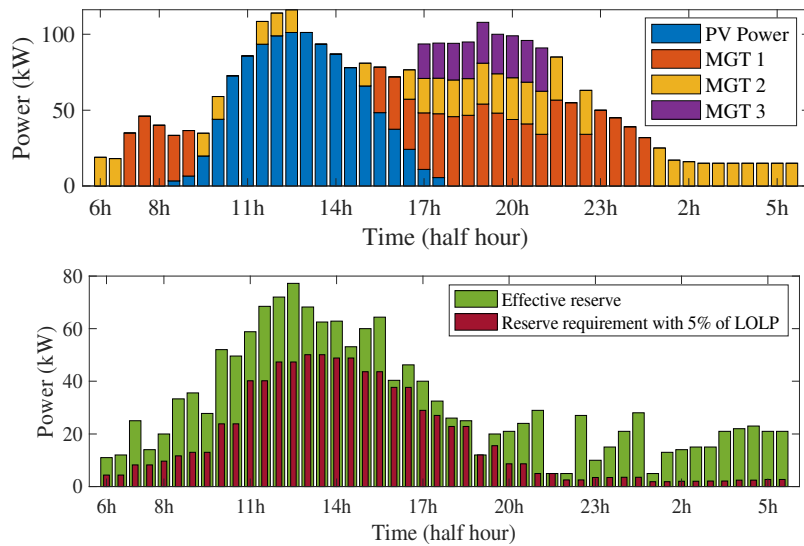
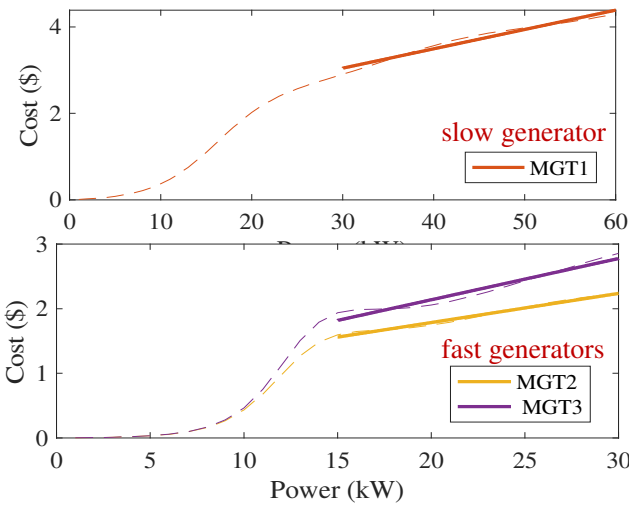
variation domain

| Scenarios | Daily Net Demand (kWh) | Daily PV (kWh) | Daily Reserve (kWh) | | Daily Cost (\$) | | |
|----------------|------------------------|----------------|-------------------------------|---------------------------------|-----------------------|------|-------------------------|
| | | | Positive OR (up power margin) | Negative OR (down power margin) | Max. Cost (up margin) | Cost | Min. Cost (down margin) |
| PV lower bound | 1230 | 279 | 712 | 490 | 236 | 211 | 164 |
| PV predicted | 1017 | 539 | 763 | 401 | 202 | 179 | 141 |
| PV upper bound | 833 | 938 | 842 | 336 | 176 | 159 | 128 |

3.9 From Dynamic Programming to Mixed-Integer Linear Programming

- To reduce the computational time, we simplify models of nonlinear MGTs' characteristics.
- Optimization method --- Mixed-integer linear programming (MILP)

Linearized operational cost functions of generators:



Comparison of DP and MILP

| | DP | MILP |
|-------------------------------|-----------|--------|
| Objective Function Type | Quadratic | Linear |
| Computational Time (s) | 4.39 | 2.53 |
| Optimal operational cost (\$) | 179 | 180 |

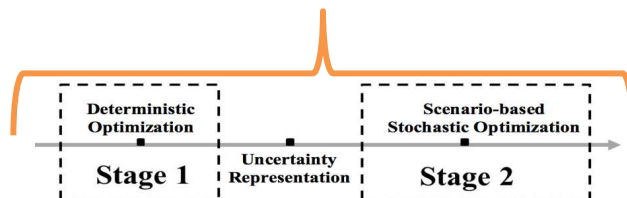
---> Acceptable errors

- Part 2 • **Uncertainty analysis from forecasting**
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Part 4 Anticipating uncertainty with a scenario-based stochastic optimization

4.1 Evolution: From deterministic to stochastic optimization

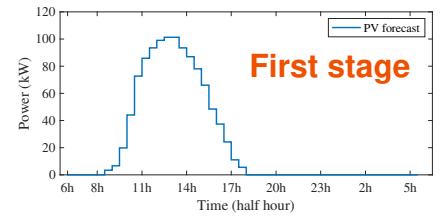
Probabilistic-Method for Risk Based Quantification of the reserve



| | Stage 1 | Stage 2 |
|-------------------------------|-------------------------------------------|---------------------------------------------------------------------------------|
| Uncertainty modelling | Historical forecasting errors | Possible future scenarios |
| Commitment decision | Slow generators Fast generators | Fast generators (flexible) to erase probable uncertainty if necessary |
| Reserve quantification | By considering forecasting errors | By anticipating different scenarios |
| Reserve dispatching | MGTs and PV AGs (limitation) | Only fast MGTs and PV AGs |

4.3 Uncertainty represented by scenarios

Prediction



Using the past and the future to handle the uncertainties

Knowledge from the past

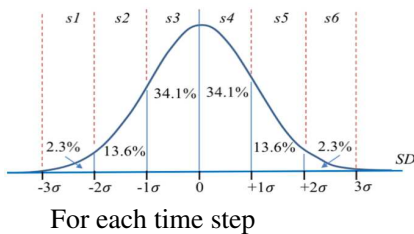
Consider the possible future

Past Build probable scenarios Present Impact of scenarios Future

Certain of what happened

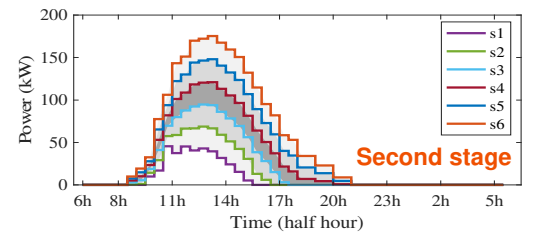
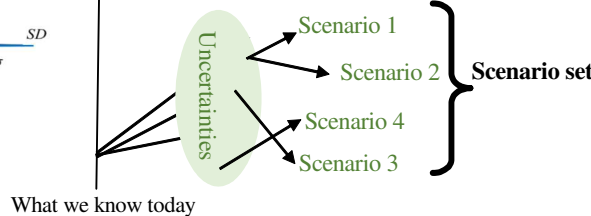
Uncertain
it has not happened yet

Build probable scenarios



| Scenario s_ω | s1 | s2 | s3 | s4 | s5 | s6 |
|--------------------------|------|-------|-------|-------|-------|------|
| Probability π_ω | 2.3% | 13.6% | 34.1% | 34.1% | 13.6% | 2.3% |

Foresight



4.4 Mathematical formulation of scenario-based optimization

Multi-objective: Operational cost and CO₂-equivalent emission cost

$$\min_{\Delta, p, r} \sum_{\omega=1}^{\Omega} \pi_{\omega} \sum_{t=1}^T \sum_{m=1}^M \{ \delta_{m,\omega}(t) [\alpha_c c_m(p_{m,\omega}(t)) + \alpha_{ce} c_{em}(p_{m,\omega}(t))] + u_{m,\omega}(t) [c_m^u + c_{em}^u] + d_{m,\omega}(t) [c_m^d + c_{em}^d] \}$$

s.t.

Parameters for unit normalization

start-up penalties

shutdown penalties

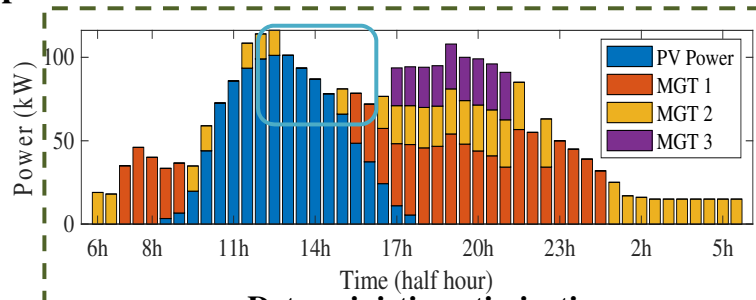
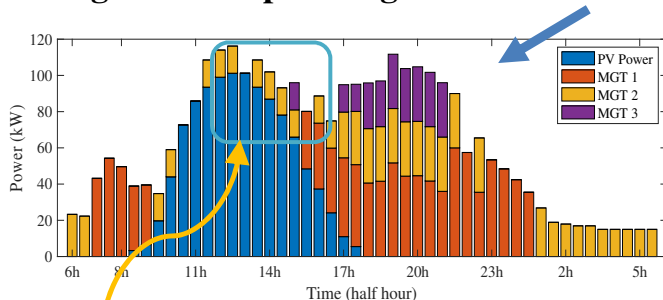
Net demand constraint,

Reserve constraint,

Generator constraint, and the commitment of slow generators in stage 2 should be same as in stage 1

- $m \in \mathcal{M}$ Set of conventional generators
- $t \in \mathcal{T}$ Set of time steps.
- $\omega \in \mathcal{W}$ Set of scenarios.
- π_{ω} Probability of occurrence of scenario ω .
- c_m, c_{em} Operational / Emission cost function
- $(\Delta, p, r) \in \mathcal{F}$ Set of feasible solutions.
- $\delta_{m,\omega}(t)$ Commitment of generator m with scenario ω at time step t .
- $p_{m,\omega}(t)$ The power generation set point of generator m with scenario ω at time step t .
- α_c, α_{ce} Parameters for normalization

Results of generation planning under stochastic optimization



Higher security level by considering uncertainty under different net demand scenarios.

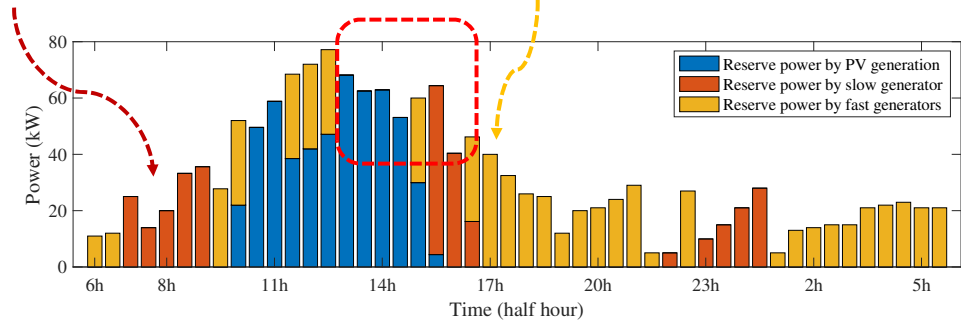
4.5 Obtained effective reserve from slow and fast generators (with a LOLP $\leq 5\%$)

- Fast generators : response time less than one time step (1-30 minutes).
- In the second stage, they are used as flexible generators to handle the possible future uncertainty.

Obtained effective reserve in first stage:

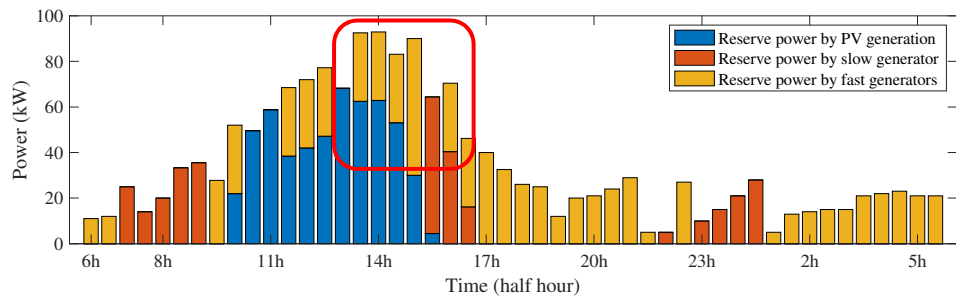
From slow generators

From fast generators



Obtained effective reserve in second stage:

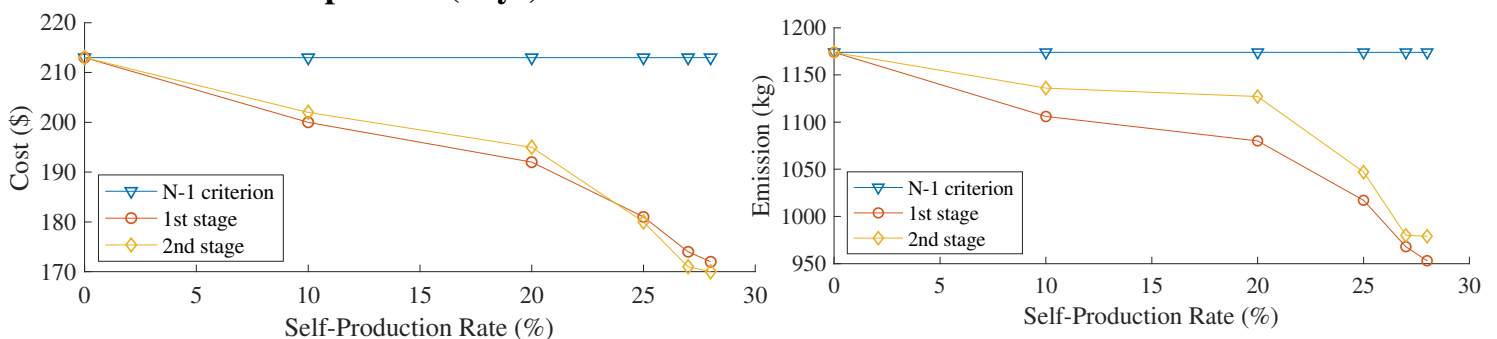
More effective reserve is provided by fast generators in second stage



4.6 Day-ahead operational planning results comparison

| | Deterministic Optimization | | | |
|-----------------------------------|----------------------------|----------------------|---------------|----------------------|
| | Without Criterion | | N-1 Criterion | |
| | Cost (\$) | CO ₂ (kg) | Cost (\$) | CO ₂ (kg) |
| Multi-objective (cost & emission) | 149 | 832 | 213 | 1174 |
| Mono-objective (cost) | 147 | 868 | 211 | 1221 |
| Mono-objective (emission) | 157 | 818 | 220 | 1164 |
| Reserve requirement (kWh) | \ | | \ | |
| Effective reserve (kWh) | 403 | | 554 | |

Extension to other profiles (days)



Part 2

- **Uncertainty analysis from forecasting**

Part 3

- **Deterministic unit commitment under uncertainty**

Part 4

- **Anticipating uncertainty with a scenario-based stochastic optimization**

Part 5

- **Participation of storage for operating reserve provision**

Part 6

- **Microgrid Central Energy Management System interface design**

Part 5 Participation of storage for operating reserve provision

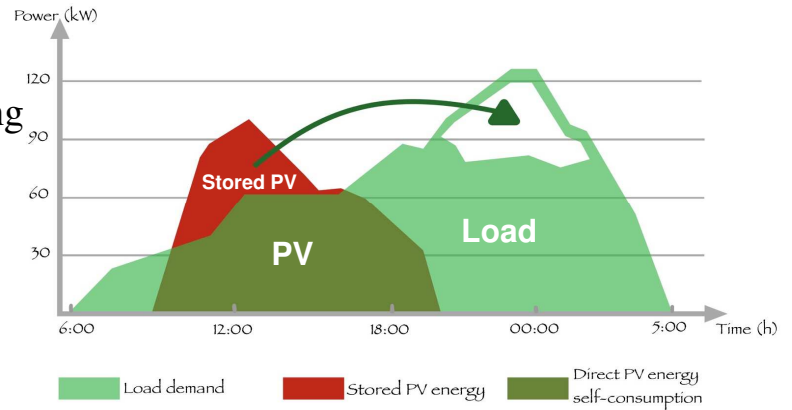
5.2 Deal with uncertainties--- Storage

30

- ❑ Multiple storage applications exist
- ❑ The main idea is to save the PV curtailed energy
- ❑ The stored energy can then be used for various energy services
- ❑ Two applications are explored
 - ❑ Use of the stored energy to supply the load demand later
“Renewable energy time-shift “
 - ❑ Use of the stored energy to provide “clean” power reserve
“Clean technology for the power reserve provision“
- ❑ Quantify the reduction of the CO₂-equivalent emission and operating costs

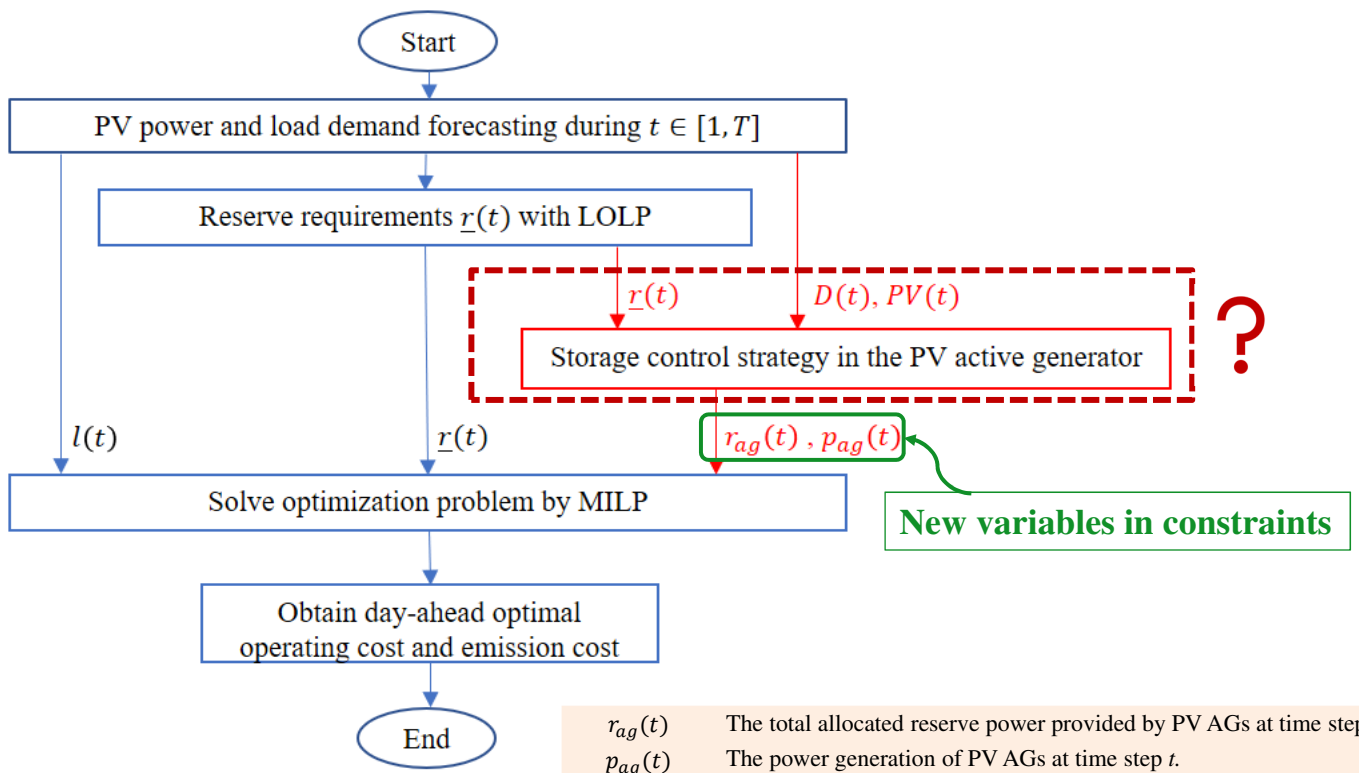
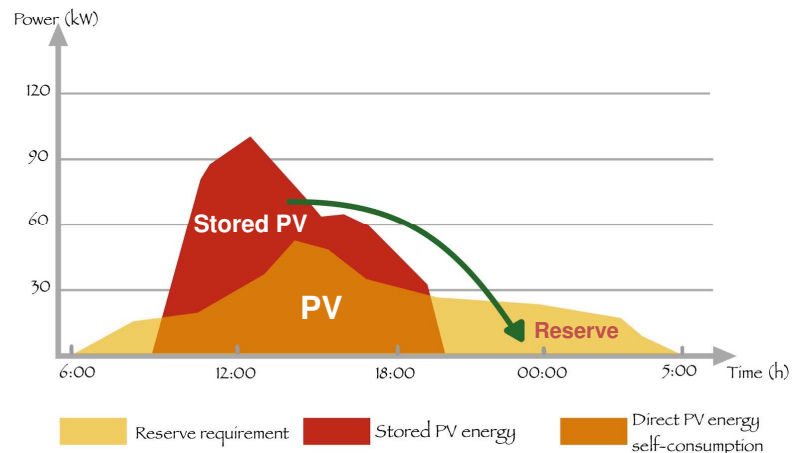
Storage application 1:

Renewable energy time-shift by maximizing solar energy self-consumption rate.



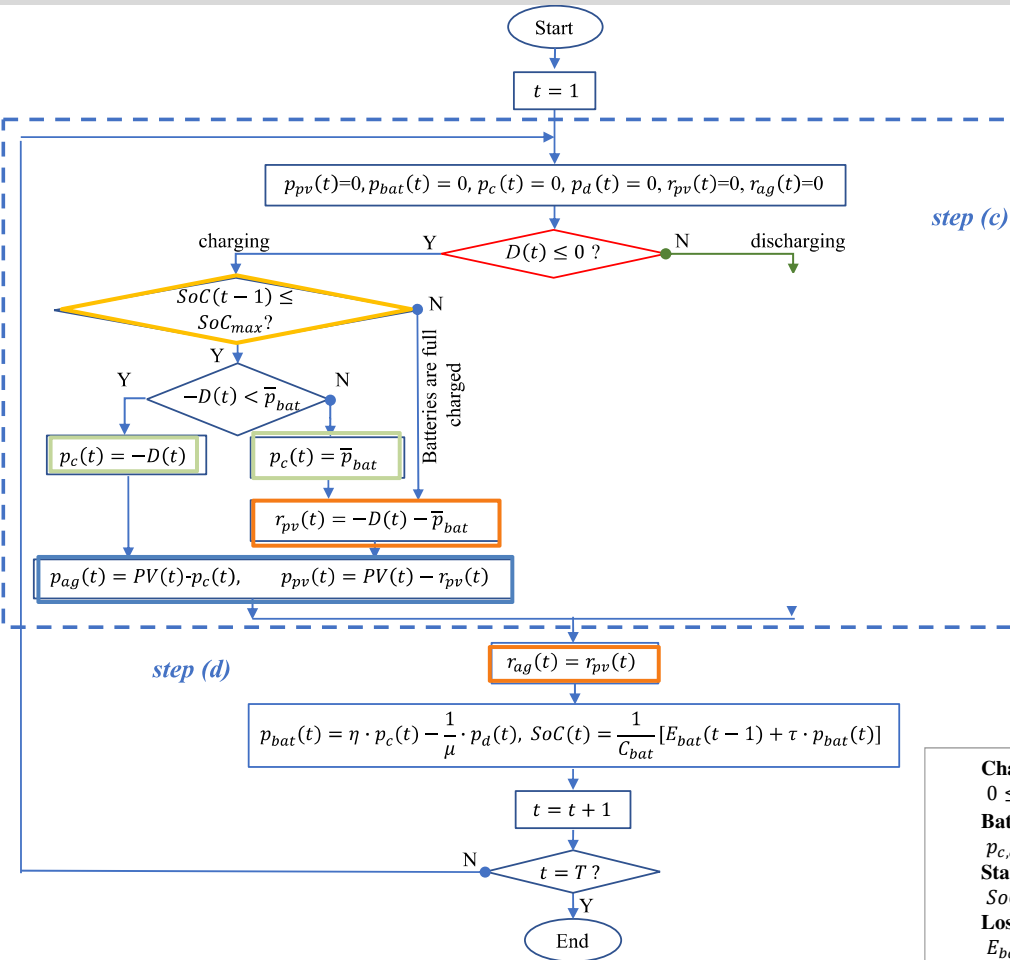
Storage application 2:

Clean technology to provide power reserve



- ❑ The storage control strategy impacts directly the operational planning of MGTs
- ❑ Implementation of the control strategy : use case, control of the SoC and rated values, ...

Saving the PV power surplus



Charging or discharging at time step t ?

Check the state of charge (SoC)

Calculate the charging power

Direct PV power surplus for reserve provision

Calculate the power exchanged with PV AG

Charge and discharge power limits :

$$0 \leq p_{c,\omega}(t) \leq \bar{p}_{bat}, 0 \leq p_{d,\omega}(t) \leq \bar{p}_{bat}$$

Batteries cannot be charged and discharged at the same time:

$$p_{c,\omega}(t) \cdot p_{d,\omega}(t) \leq 0, \forall t \in \mathcal{T}$$

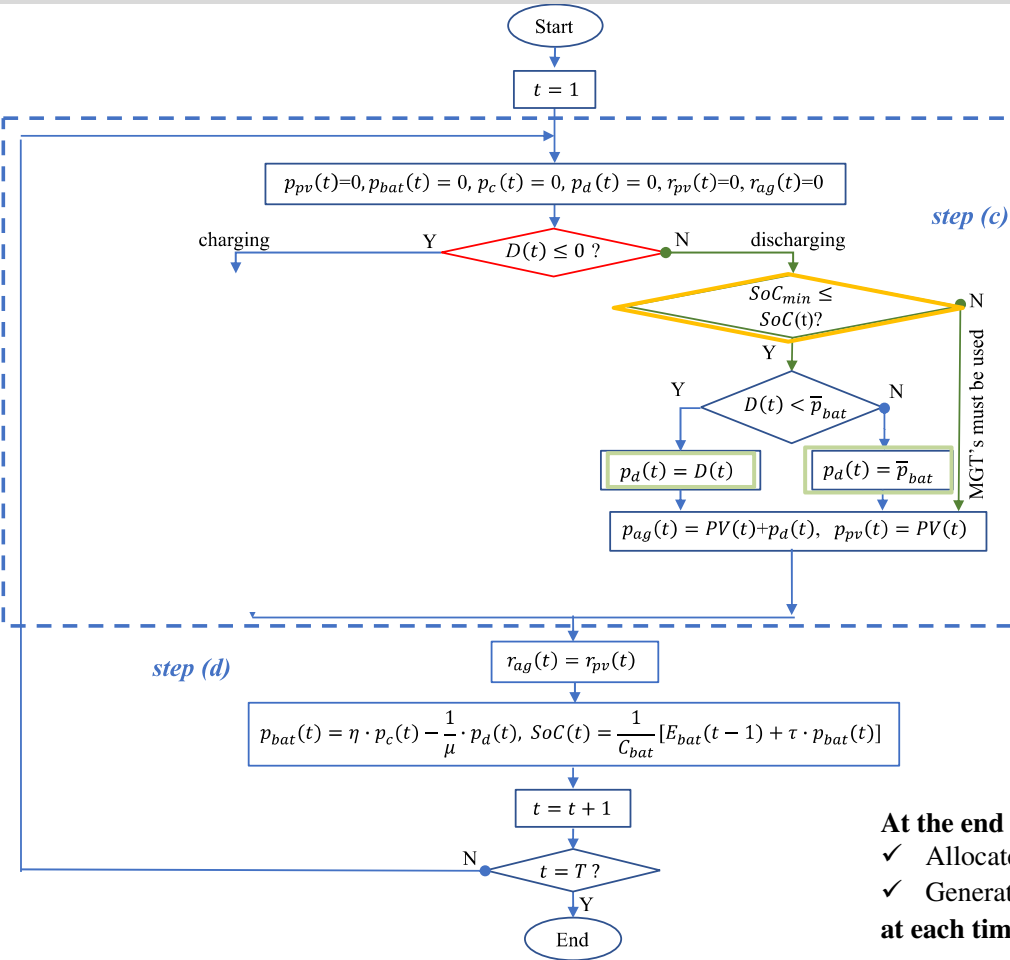
State of charge (SoC) of batteries in a certain interval :

$$SoC_{min} \leq SoC_{\omega}(t) \leq SoC_{max}$$

Losses during charging and discharging :

$$E_{bat,\omega}(\tau) = E_{bat}(0) + \sum_{t=1}^{\tau} \eta \cdot p_{c,\omega}(t) + \sum_{t=1}^{\tau} 1/\mu \cdot p_{d,\omega}(t)$$

Discharging for load supply



Check the SoC

Calculate the discharging power

At the end of ESS control strategy, we know:

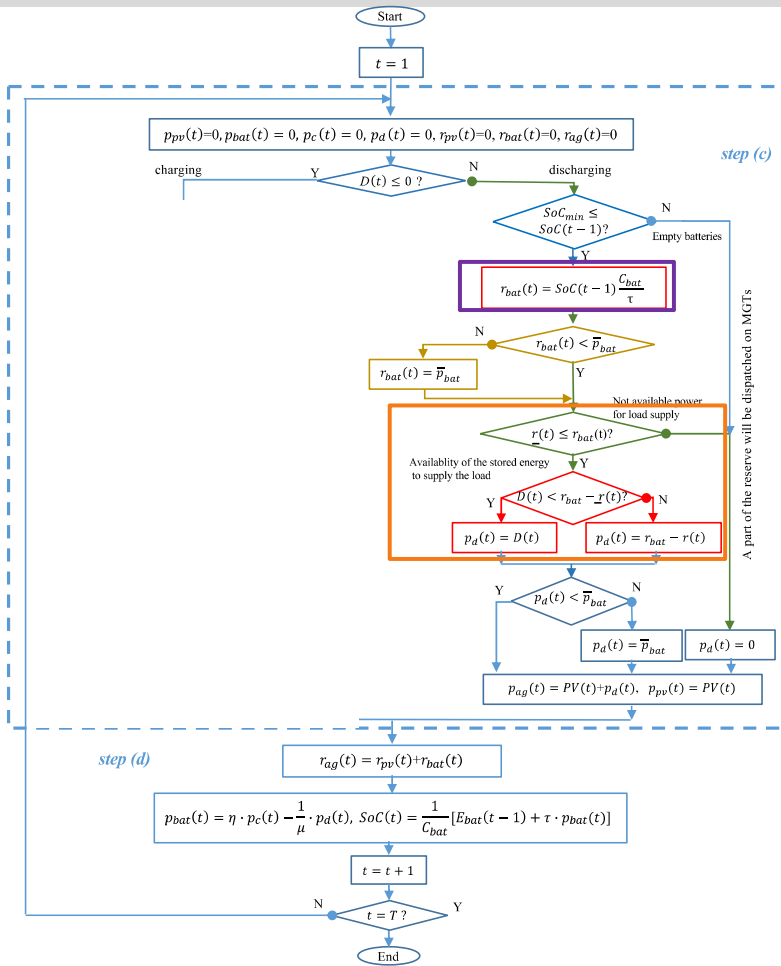
✓ Allocated reserve power provided by PV AGs $r_{ag}(t)$

✓ Generated power of PV AGs $p_{ag}(t)$

at each time step !

5.4.3 ESS control strategy 2 : Reserve provision

Another control strategy
Discharging for power reserve

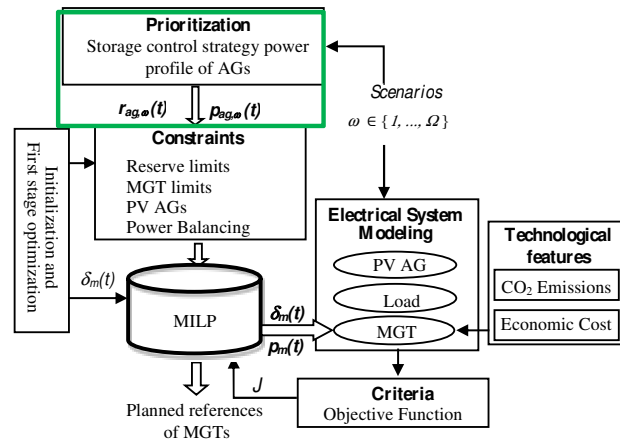


How much stored energy for reserve provision

After reserve provision,
what is the availability of stored energy to supply the load?

5.5 Mathematical formulation of scenario-based optimization with storage

Optimization framework



Multi-objective: Operational cost and CO₂-equivalent emission cost

$$\min_{\Delta, p, r} \sum_{\omega=1}^{\Omega} \pi_{\omega} \sum_{t=1}^T \sum_{m=1}^M \{ \delta_{m,\omega}(t) [\alpha_c c_m^u(p_{m,\omega}(t)) + \alpha_{ce} c_m^e(p_{m,\omega}(t))] + u_{m,\omega}(t) [c_m^u + ce_m^u] + d_{m,\omega}(t) [c_m^d + ce_m^d] \}$$

s.t.

(New variables are added in constraints because of the participation of storage)

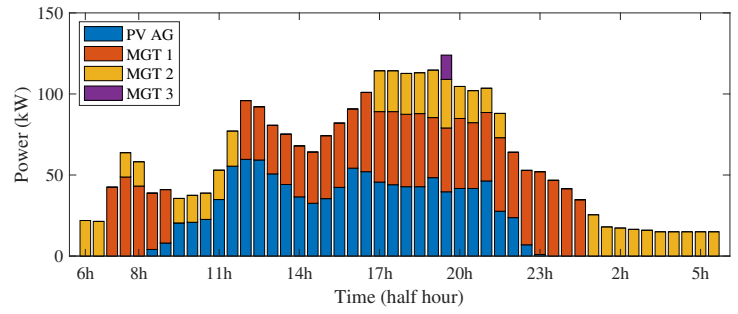
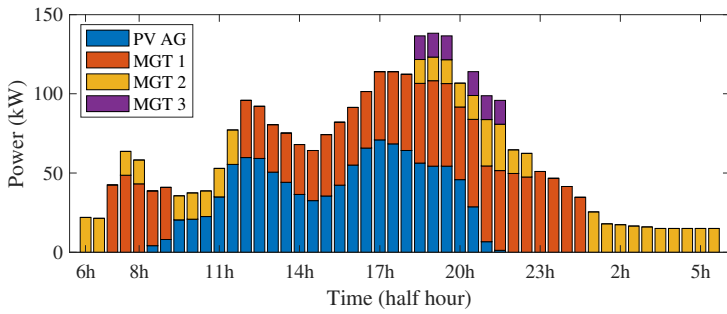
Reserve constraint: $r_{mgt,\omega}(t) = \underline{r}_{\omega}(t) - r_{ag,\omega}(t)$ → total allocated reserve power provided by PV AGs

Net demand constraint: $\sum_{m=1}^M p_{m,\omega}(t) = l_{\omega}(t) - \sum_{a=1}^A p_{ag,\omega}(t) + r_{mgt,\omega}(t)$ → power generation of PV AGs

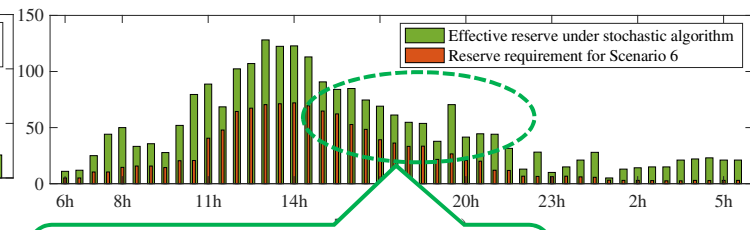
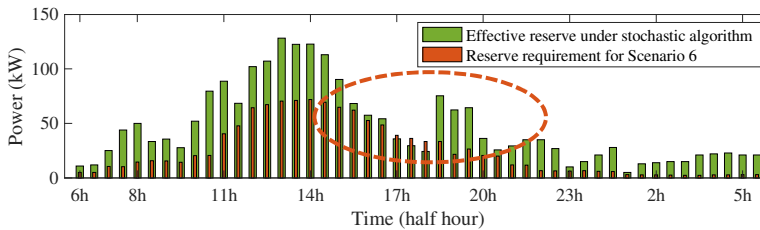
Generator constraint: $\underline{p}_m \delta_{m,\omega}(t) \leq p_{m,\omega}(t) \leq \bar{p}_m \delta_{m,\omega}(t)$, and commitment of slow generator keep unchange

Storage control strategy 1: Renewable energy time-shift

Storage control strategy 2: Reserve provision



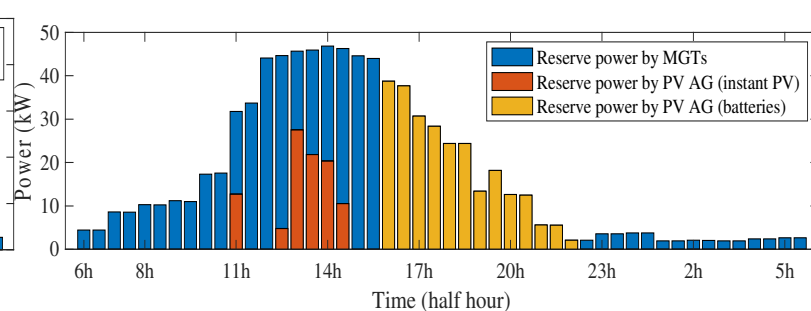
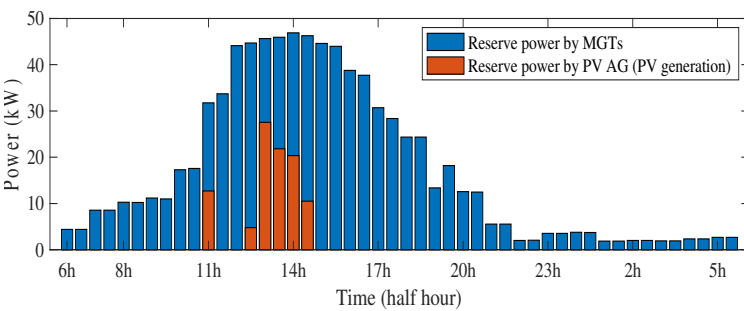
Under WORST CASE (scenario 6): Reserve requirement and obtained effective reserve with a LOLP ≤ 5%



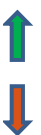
More reasonable reserve provision
Higher security level

Storage control strategy 1: Renewables energy time-shift

Storage control strategy 2: Reserve provision

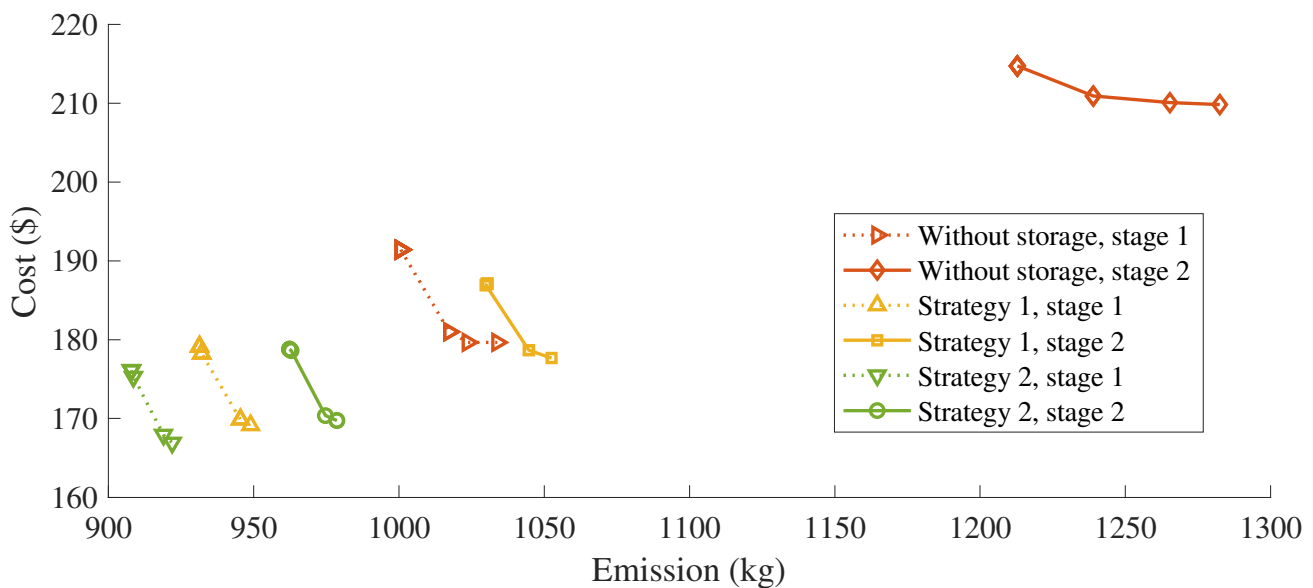


| Storage control strategy | Scenario | | |
|--------------------------|----------------------------|---------------|-------|
| | S 1 | | |
| Strategy 1 | Reserve energy from PV AGs | PV limitation | 0 |
| | | Batteries | 0 |
| | Reserve energy from MGTs | | 151.2 |
| Strategy 2 | Reserve energy from PV AGs | PV limitation | 0 |
| | | Batteries | 51.1 |
| | Reserve energy from MGTs | | 100.2 |



| Storage control strategy | Objective | Scenario-based Stochastic Optimization | | | |
|--------------------------|-----------------------------------|----------------------------------------|---------------------------|-------------------------------------------|---------------------------------------|
| | | Fuel Cost (€) | CO ₂ Cost (kg) | Possibility of risk under worst-case (S6) | Possibility of risk under S4 |
| No storage | Multi-objective (cost & emission) | 211 | 1239 | ≤16.7% of time steps | ≤2.1% of time steps |
| | Mono-objective (cost) | 209 | 1283 | ≤3.6% of daily reserve energy deficit | ≤0.2% of daily reserve energy deficit |
| | Mono-objective (emission) | 215 | 1213 | (21.2 kWh / 591.5 kWh) | (0.7 kWh / 411.7 kWh) |

Pareto-optimal fronts: CO₂ equivalent emission vs. operational cost



- Part 2 • **Uncertainty analysis from forecasting**
- Part 3 • **Deterministic unit commitment under uncertainty**
- Part 4 • **Anticipating uncertainty with a scenario-based stochastic optimization**
- Part 5 • **Participation of storage for operating reserve provision**
- Part 6 • **Microgrid Central Energy Management System interface design**

Part 6 Microgrid central energy management system interface design

6.1 Four main interfaces in the presented energy management system (EMS)

Generation scheduling using probabilistic & stochastic strategies in a MG including PV active generator

Microgrid Integration of a Prosumer and Micro Gas Turbines (MGTs)

LC: Local controller
MGT: Micro gas turbine
DSO: Distribution system operator

Microgrid Management
Data Collection, Uncertainty Analysis, PV Power and Load Forecast

Uncertainty analysis

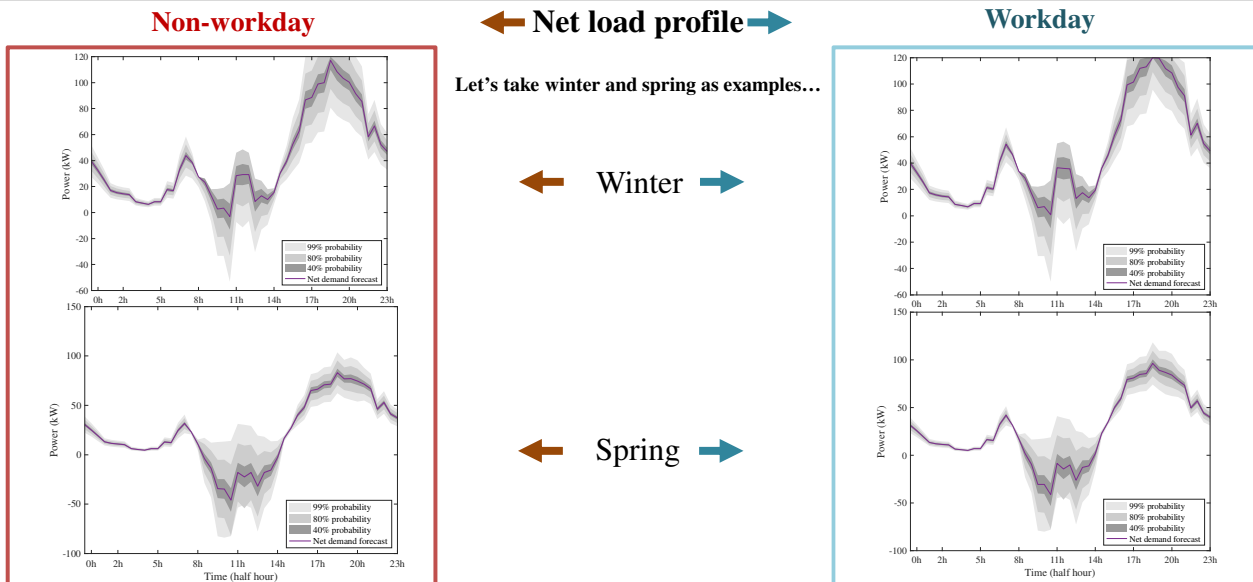
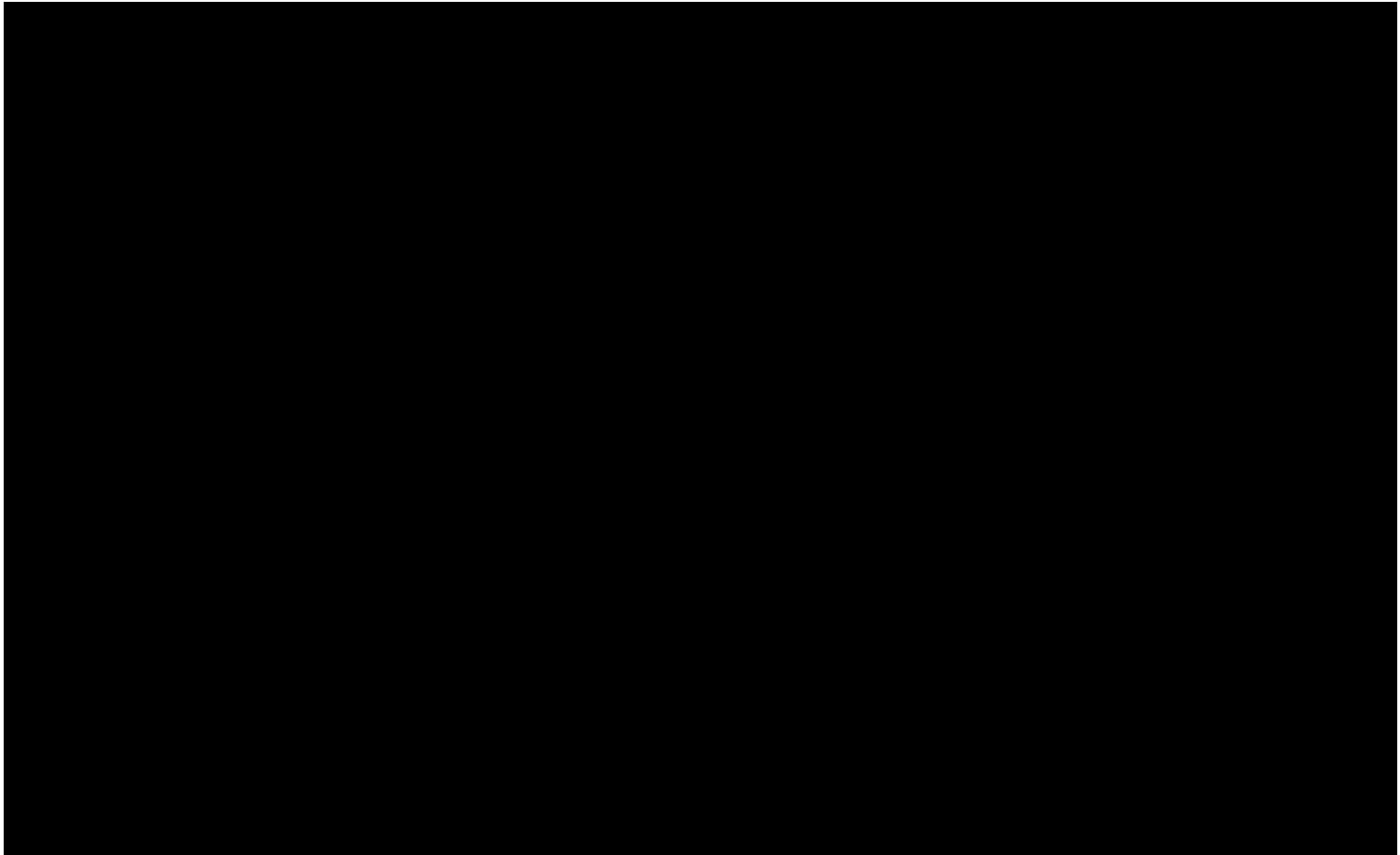
Uncertainty Assessment for OR Quantification

OR Quantification

Day-ahead Optimization Planning

Deterministic algorithm **Stochastic algorithm**

Stochastic algorithm



Let's take winter and spring as examples...

| Seasons | Spring | | Summer | | Autumn | | Winter | |
|----------------------------------------------------------|--------|-----|--------|-----|--------|----|--------|----|
| | n | w | n | w | n | w | n | w |
| Workdays/ non-workdays (w / n) | | | | | | | | |
| Mean value of renewable energy surplus (kWh) | 129 | 98 | 113 | 82 | 9 | 9 | 2 | 0 |
| Renewable energy surplus within 40% of probability (kWh) | 179 | 146 | 158 | 126 | 22 | 26 | 11 | 6 |
| Renewable energy surplus within 80% of probability (kWh) | 278 | 246 | 250 | 217 | 59 | 83 | 45 | 36 |

Sizing of battery:

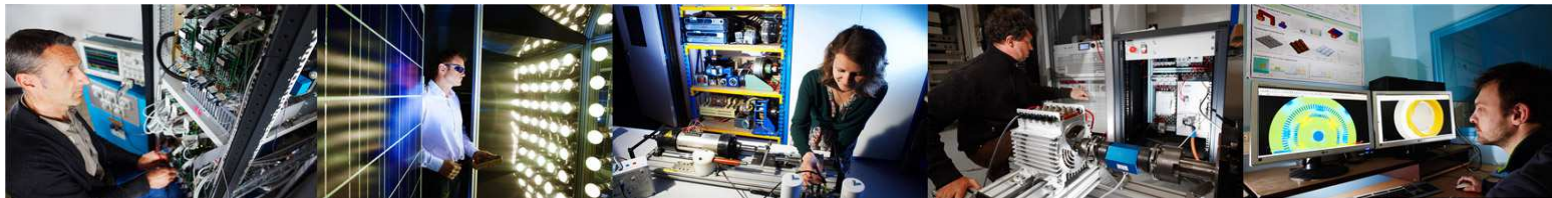
280 kWh of capacity → 350 kWh of storage size (considering a 20% of minimum allowable state of charge)

□ Conclusion

- A scientific method to **build scenarios and anticipate uncertainties.**
- Minimization of **CO₂ equivalent emissions and operational costs.**
- **Impact analysis** of stochastic optimization **on operating reserve.**
- Use of **storage as energy flexibility** for **both power balancing and reserve provision.**
- **Inclusion of storage control strategies** into the stochastic optimization.

□ Perspective

- Impact of seasonal factor on generation scheduling.
- Investigation on both CAPEX and OPEX of storage.
- Sensitivity analysis.



Thank you for your attention!

Publication:

Journals:

WEN Xin, ABBES Dhaker, FRANCOIS Bruno, "Modelling of Photovoltaic Power Uncertainties for Impact Analysis on Generation Scheduling and Cost of an Urban Micro Grid", Mathematics and Computers in Simulation, 04/2020. ISSN 0378-4754, <https://doi.org/10.1016/j.matcom.2020.02.023>.

Conferences:

WEN Xin, ABBES Dhaker, FRANCOIS Bruno, "Day-Ahead Generation Planning and Power Reserve Allocation with Flexible Storage Strategy", International Conference on Electricity Distribution CIRED 2020, 22-23 September 2020, Berlin, 09/2020.

WEN Xin, ABBES Dhaker, FRANCOIS Bruno, "Impact of Photovoltaic Power Uncertainties on Generation Scheduling and Cost of an Urban Micro Grid", 13th international conference of IMACS TC1 Committee (ELECTRIMACS). 20-23 mai 2019. Salerne, Italie, 05/2019.

YAN Xingyu, WEN Xin, FRANCOIS Bruno, ABBES Dhaker, "Management of distributed operating power reserve in an urban microgrid beyond DSO risk decision", International Conference on Electricity Distribution CIRED 2018, 7-8 June 2018, Lubjana, Slovenia, 06/2018.

