Reinforcement learning for microgrid management

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Delta project
Inria Lille
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Agenda

- Introduction to smart microgrid management
- Example of reinforcement learning for microgrid operation
- Workplan

Introduction

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A bit about my background

I apply optimization and machine learning to power systems

PhD: EDF's generation assets scheduling

Management and design of European Day-Ahead market algorithm (Euphemia)

Active management of distribution networks and hosting capacity computation (GREDOR project coordination)

Microgrids

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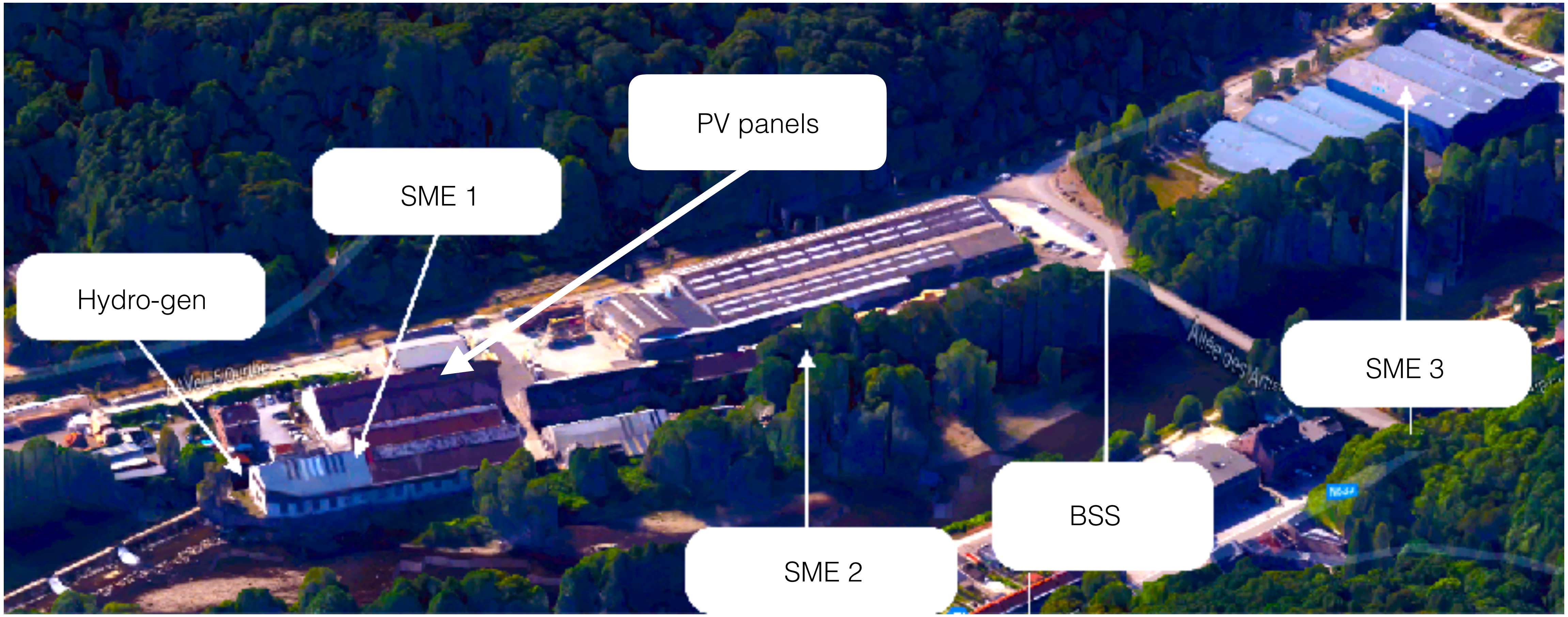
A microgrid example



With the support of the Wallon Government, in collaboration with Nethys, CE+T, Sirris, MeryTherm, SPI

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A (grid-tied) microgrid offers many value creation mechanisms

Function	Description	BSS*
Energy markets	Decide on the price your are willing to pay/sell	++
Ancillary services	Sell services to the grid	++
Peak reduction	Through local and community optimization	++
UPS functionality	Operate in islanded mode	++
Efficiency	Through optimized load and generation management	

*BSS: Battery Storage System

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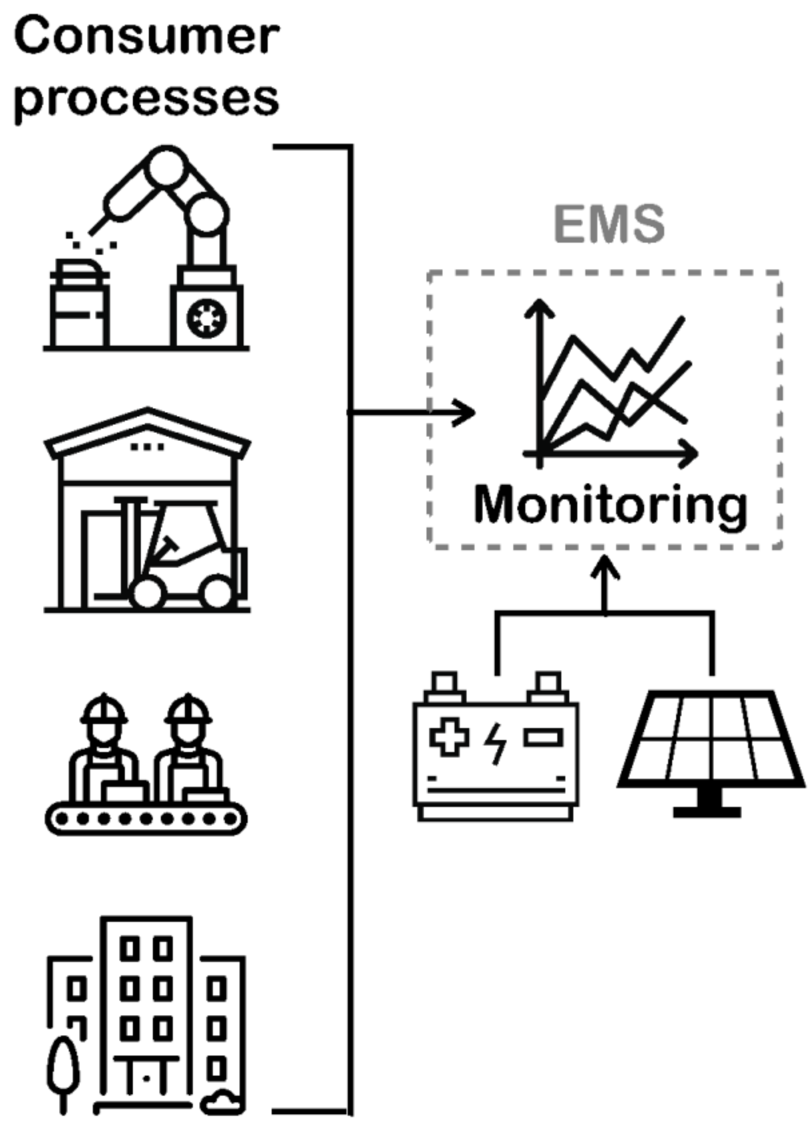
Advantages for the public grid

Function	Description	BSS*
Peak reduction / flow management	Momentarily set constraints to the microgrid	++
Voltage support	Reactive power flexibility of battery storage and PV	++
Phase balancing	Using storage DC buffer	++
Power factor correction	Flexibility of inverters	++
Frequency support	Primary or secondary reserve	++

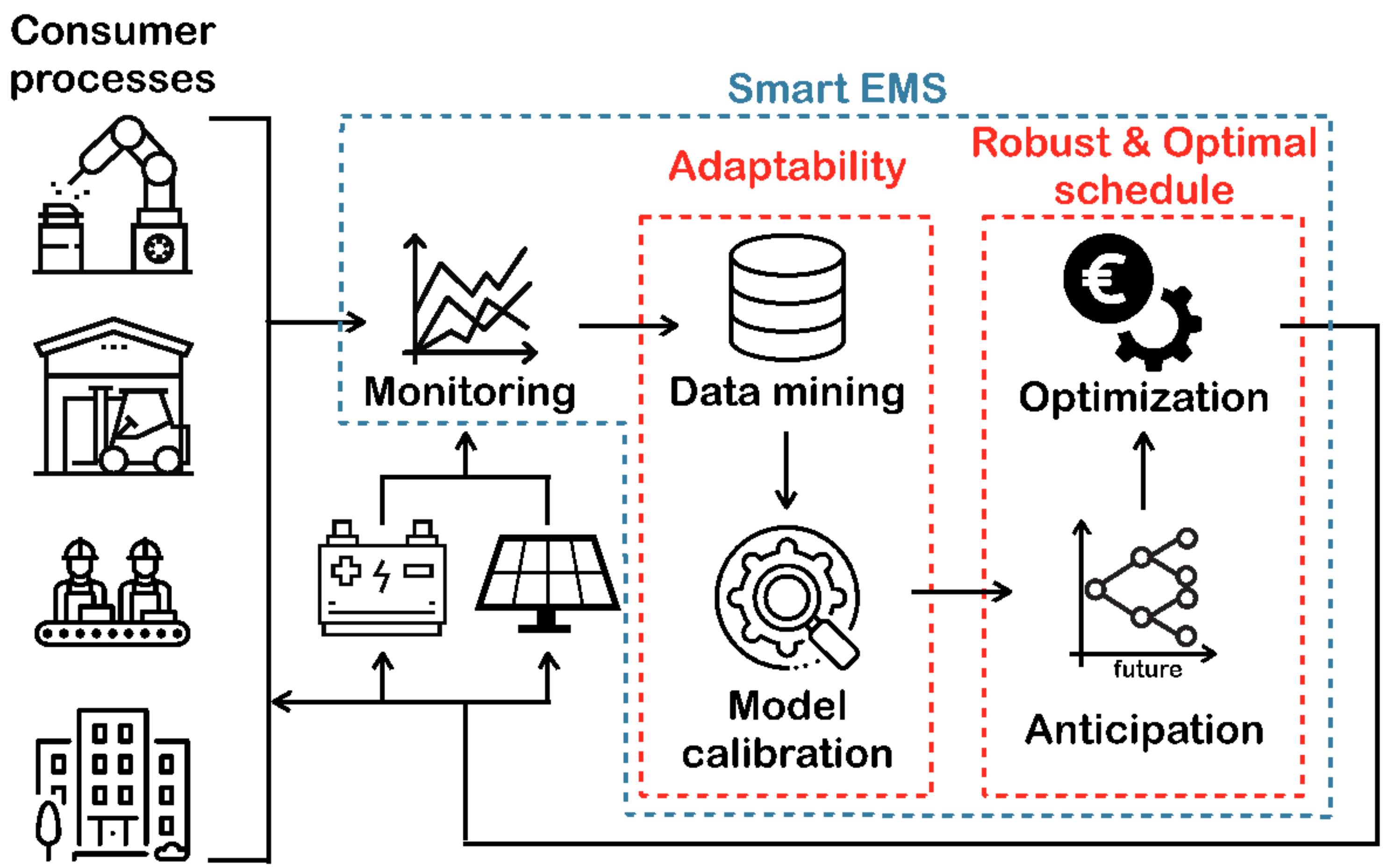
*BSS: Battery Storage System

A **standard** energy management system



- Energy monitoring
- Fixed rules for storage operation

A **smart** microgrid energy management system …



- exploits data to make the microgrid flexible, robust, and extract the maximum of value!
- has a community management feature

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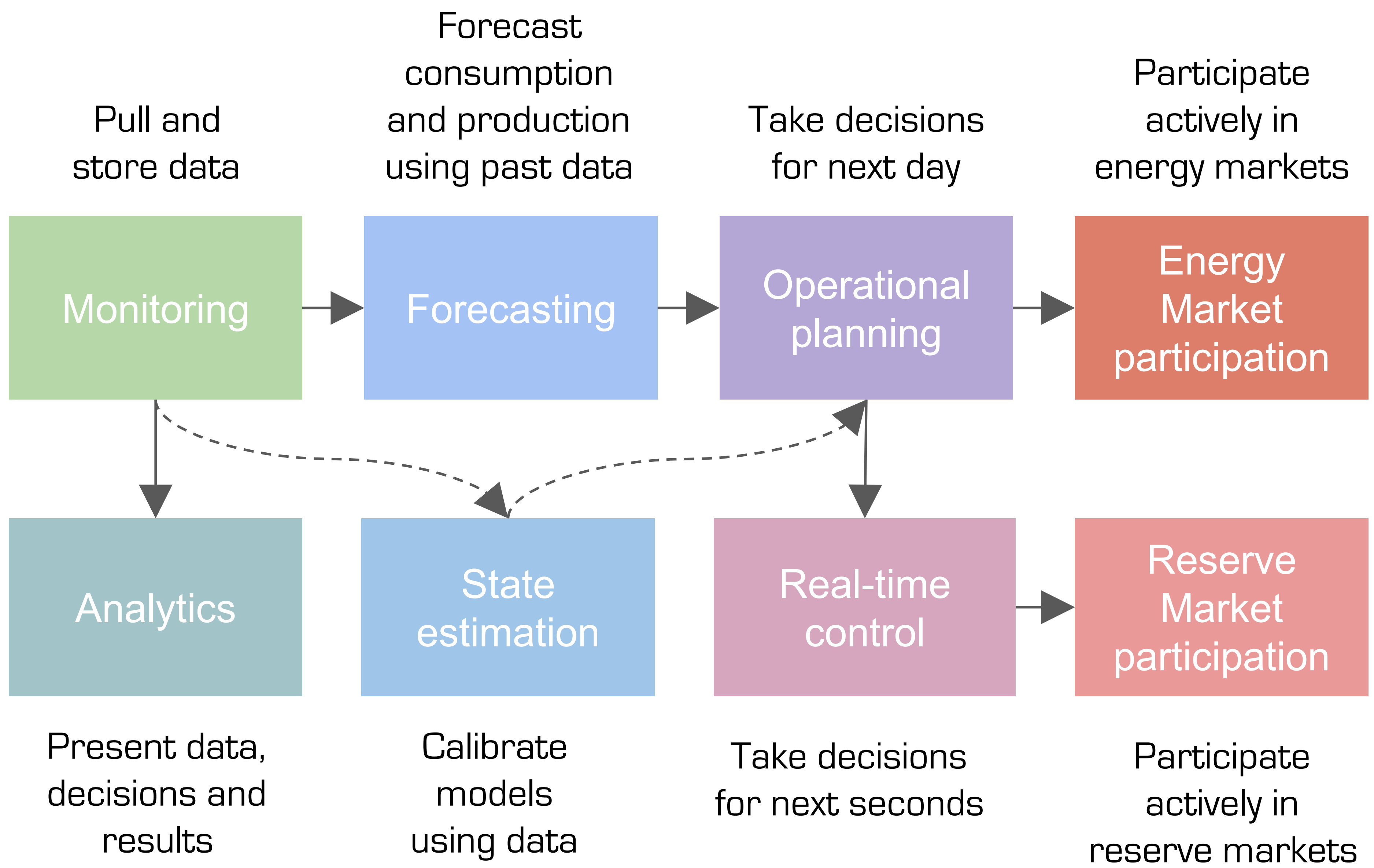
Functional modules that exploit data



Arrows indicate a dependency between functional modules, not a flow of information!

A combination of AI methods

Discipline	Description
Machine learning	Deep neural nets for forecasting
Stochastic optimization	Mixed Integer Programming formulations of operational planning problems
Reinforcement learning	Autocalibration of operational policies
Model Predictive control	For real-time battery management problem

Operational planning

- Optimize operation by anticipating on the evolution of load, generation and prices, taking into account the technical constraints of the microgrid

- Typically with an horizon of one day

- Important to plan the operation of storage systems, and other devices having a highly "time-coupled" behavior such as flexible loads, or steerable generators

- Islanded mode: take preventive decisions to maintain the power to critical loads as long as possible.

Take decisions for next day

Operational planning

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Real-time control

- Grid-tied mode:
  - implements operational planning decisions
  - corrects the error and dispatches among flexibility sources
  - manages storage systems to limit their degradation
- Islanded mode:
  - monitors and dispatches flexibility sources to maintain system frequency
  - Dispatch of hybrid energy storage systems

Real-time control

Take decisions for next seconds

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Advanced energy/ancillary services market participation

- Optimal bidding in day-ahead market using anticipated load, generation, and prices.
- Adjust energy exchanges in intra-day market to match changes in load, generation, and prices.
- Exploit balancing opportunities by reacting to TSO's signals.
- Provide remunerated flexibility margins that the TSO can activate for balancing purposes.

Participate actively in energy markets

Energy Market participation

Reserve Market participation

Participate actively in reserve markets

Reinforcement learning for microgrid operation

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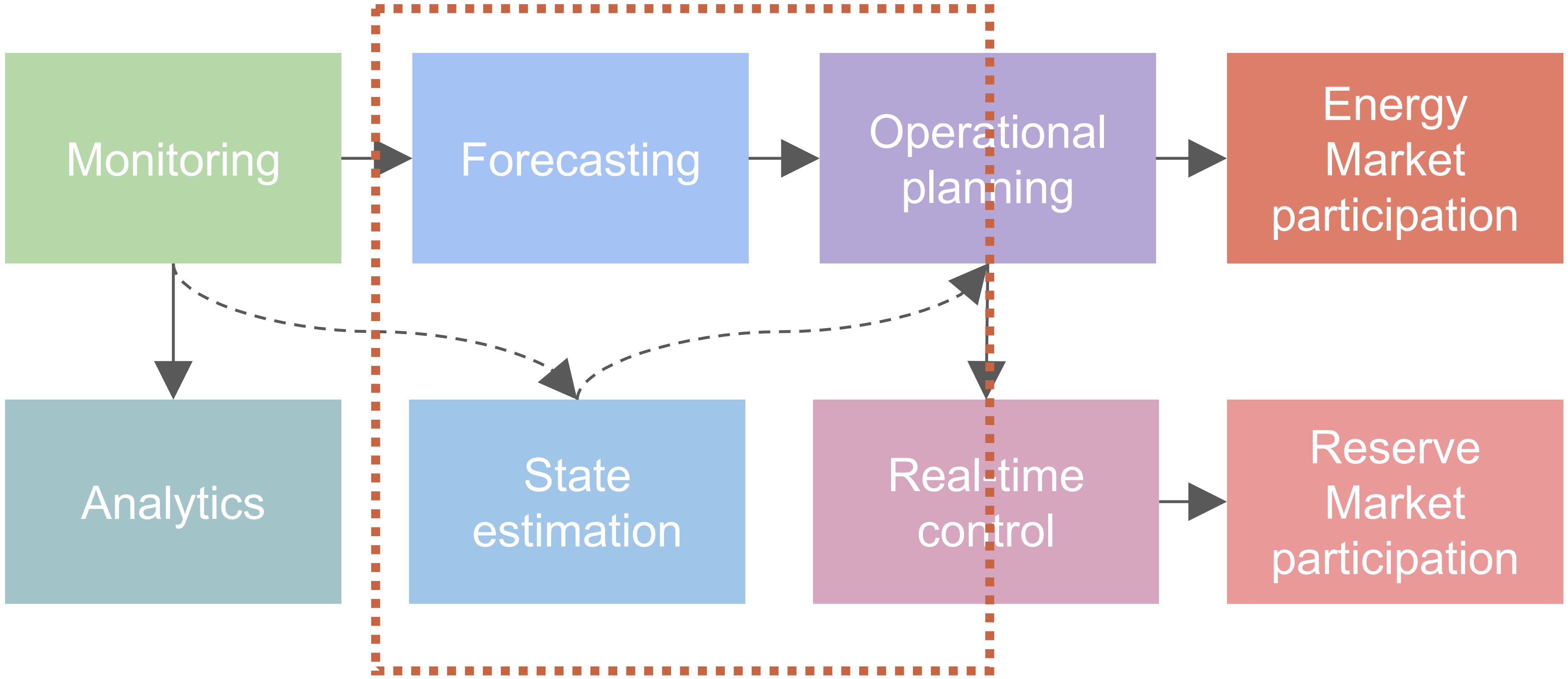
What's the point?



Merge these blocks

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Example of application of reinforcement learning

Deep Reinforcement Learning Solutions for Energy Microgrids Management

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François-Lavet, Vincent, et al. "Deep reinforcement learning solutions for energy microgrids management." European Workshop on Reinforcement Learning. 2016.

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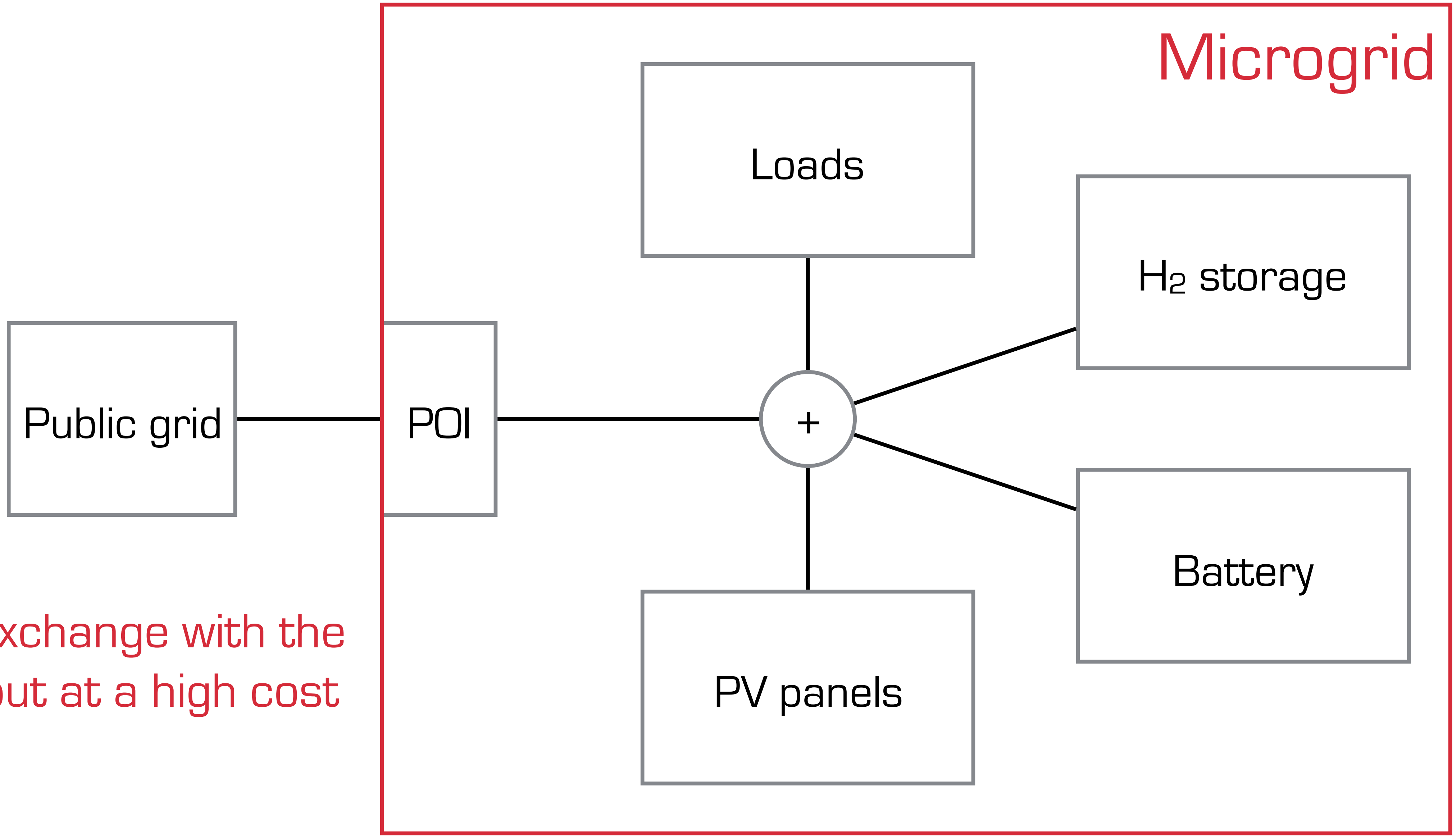
Use case: MG tries to work in high autonomy



Can exchange with the grid but at a high cost

POI: Point of interconnection, also called point of common coupling (PCC)

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Assumptions

- We assume that we have access to:
  - an accurate simulator of the dynamics of a microgrid
  - time series describing past load and production profiles, which are realizations of some unknown stochastic processes

François-Lavet, Vincent, et al. "Deep reinforcement learning solutions for energy microgrids management." European Workshop on Reinforcement Learning. 2016.

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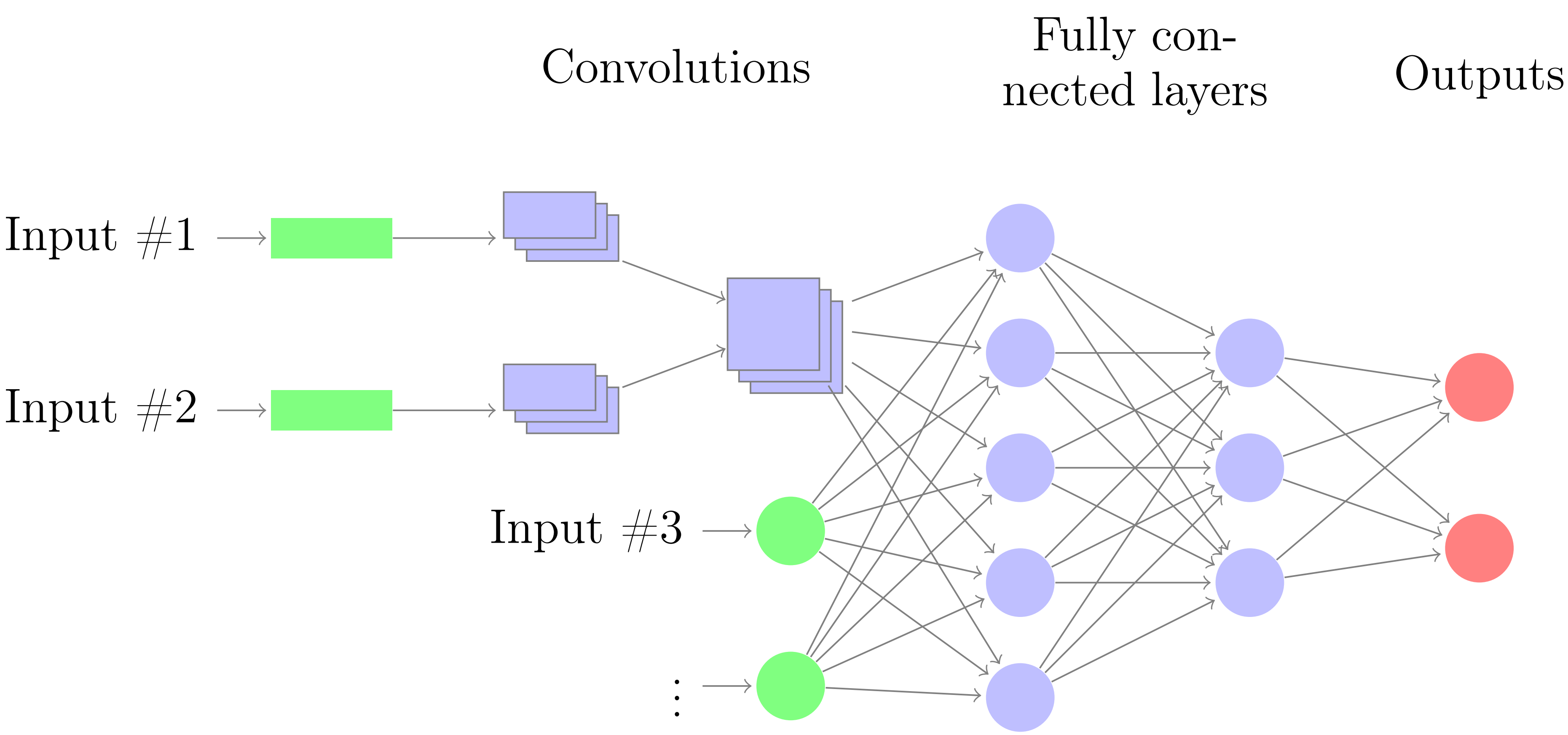
Architecture of the deep neural net for learning the state-action value function Q(s,a)



Time series of consumption, etc.

Convolutional layers to extract meaningful features from time series

Value of decision to store in a given state of the microgrid

François-Lavet, Vincent, et al. "Deep reinforcement learning solutions for energy microgrids management." European Workshop on Reinforcement Learning. 2016.

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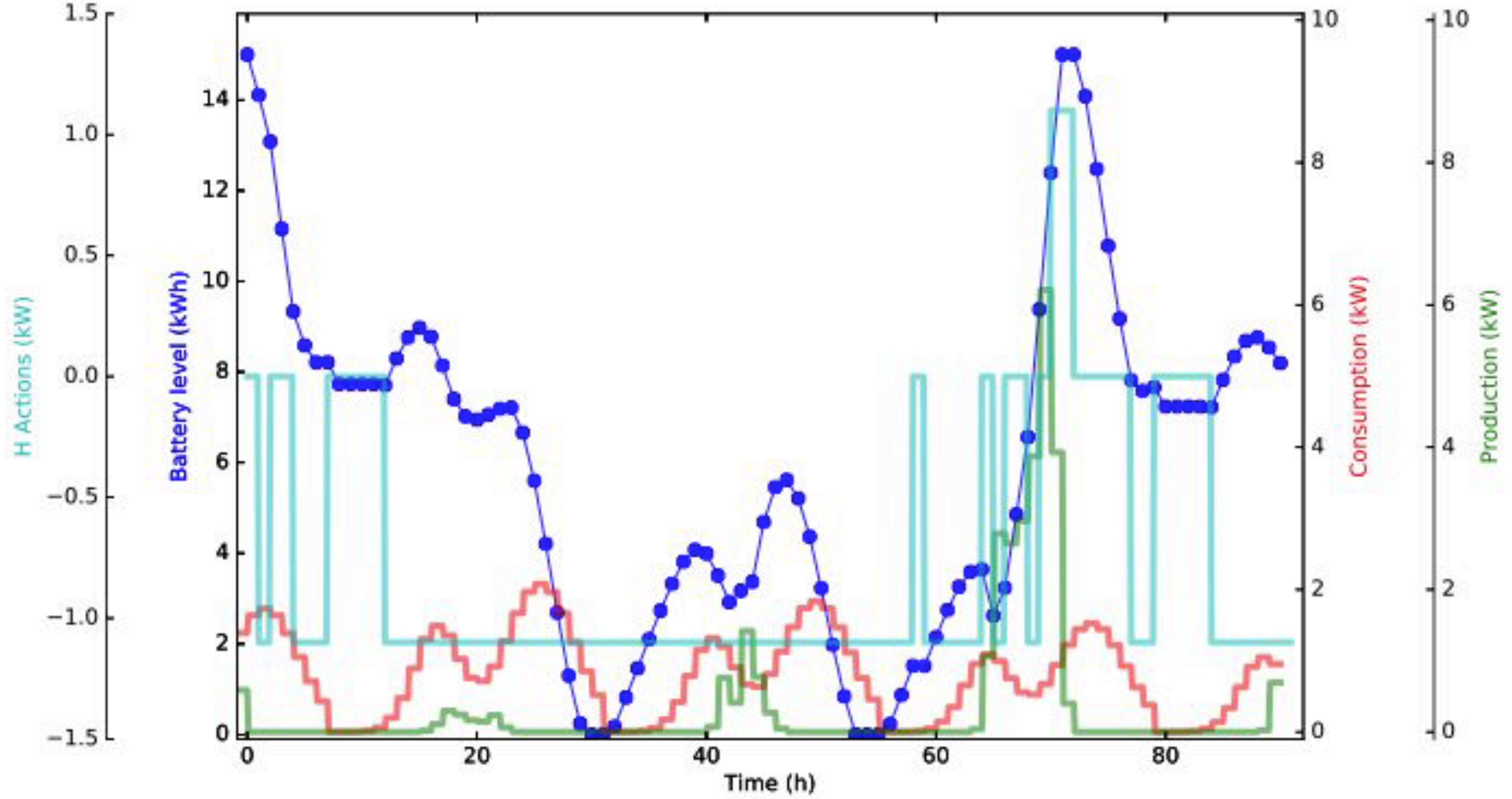
Results: minimal information



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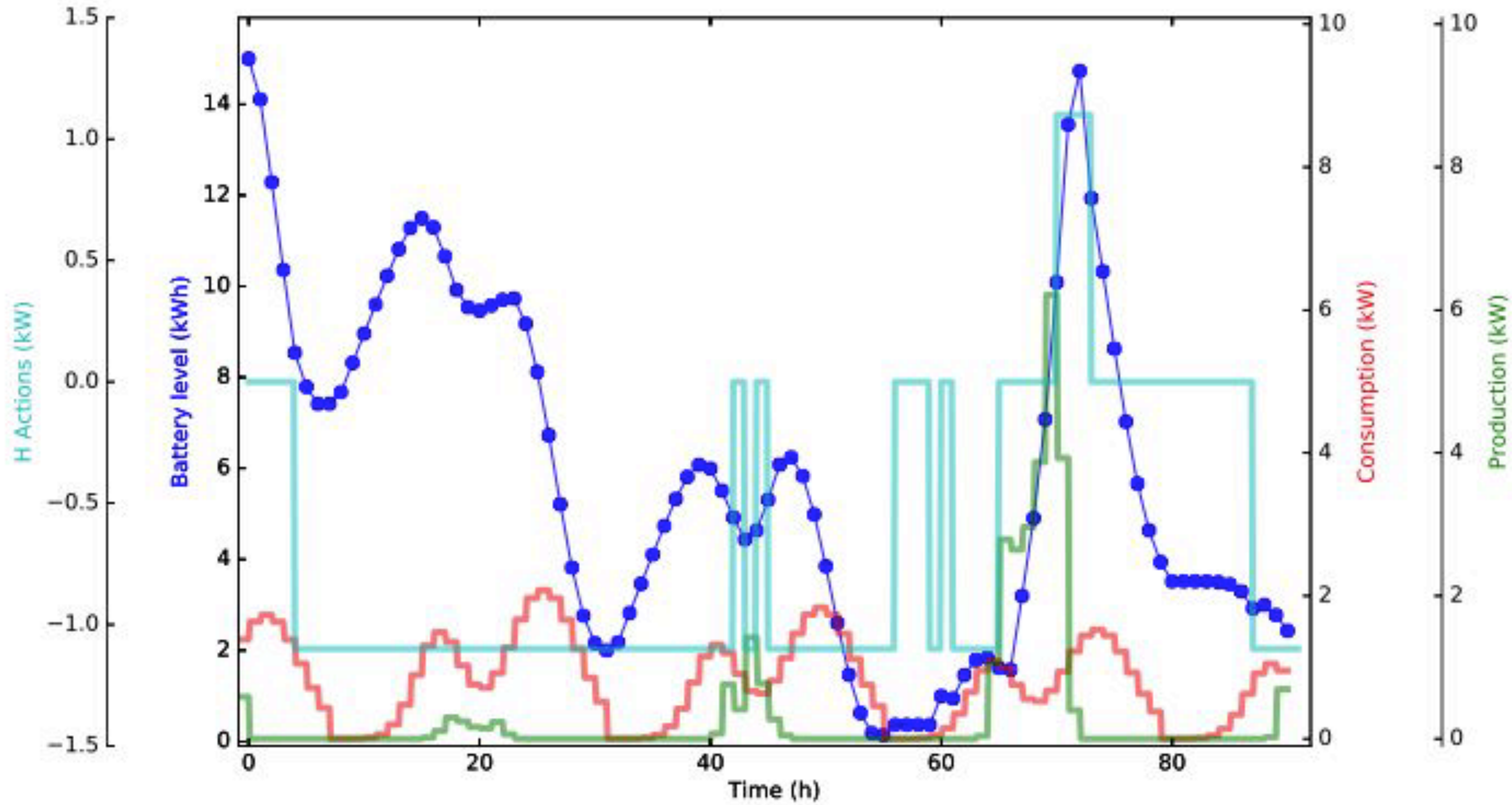
Results: with average PV production forecast



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Problem Statement

Goal: off-grid Microgrid management

Control actions:

- Storages
- Generation

Continuous and high dimensional space, with linear constraints

Reduce the action space to:

- on | off decisions for the generators
- idle | charge | discharge decisions for the storages

Define meta-actions

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Test case

Storage decisions: **idle | charge | discharge**

Meta-actions:

- Charge if there is excess
- Discharge if there is deficit
- Generator covers the rest at a cost
- Curtail the excess otherwise

DQN for a day of data ($\Delta t = 1$h)

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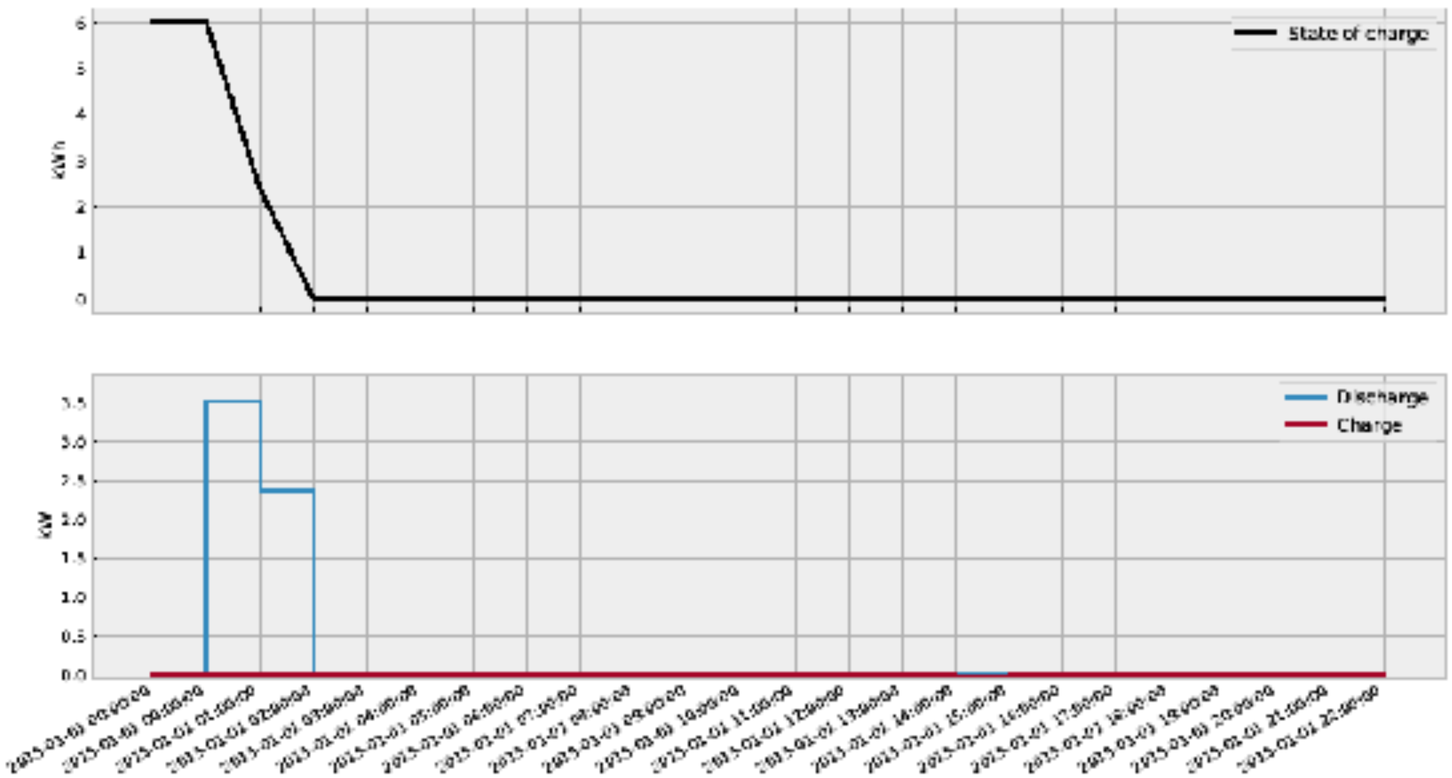
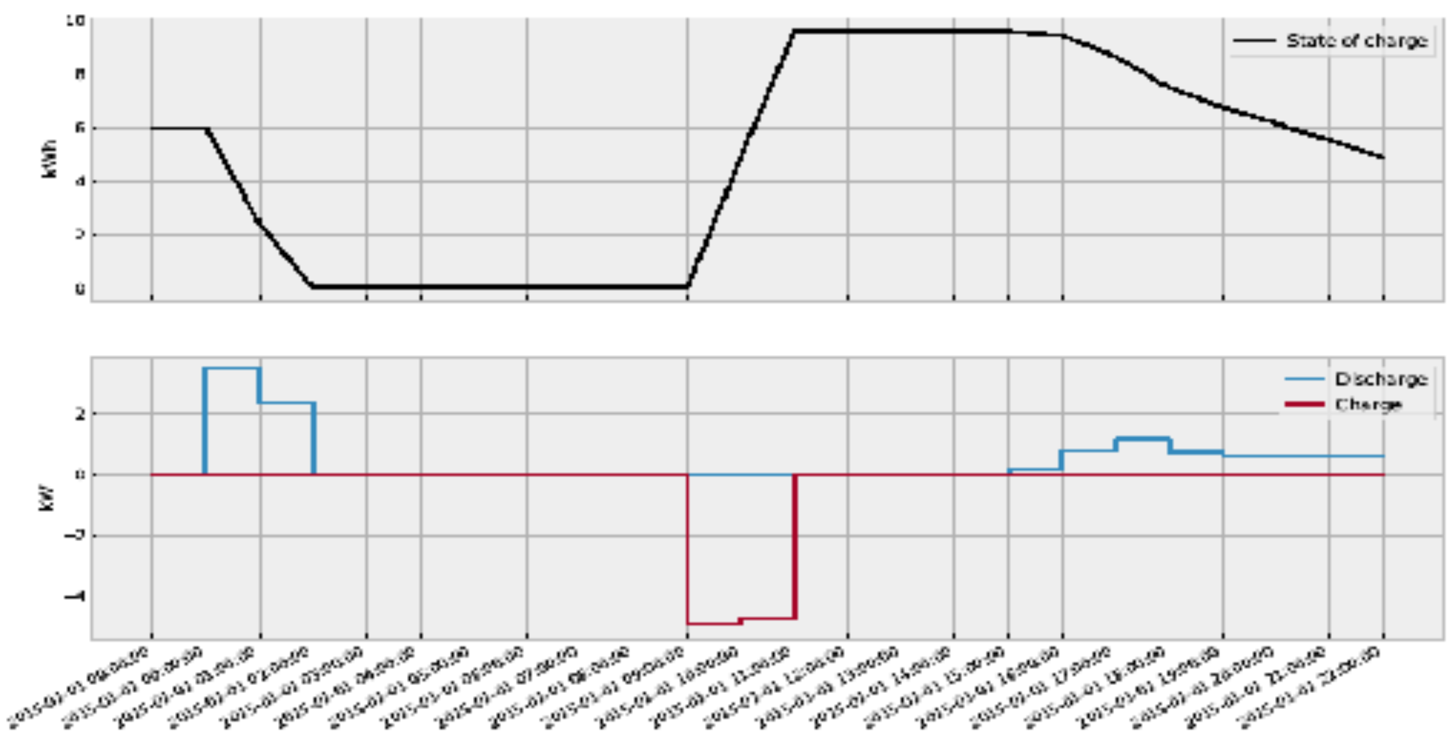
Preliminary results



Total costs: 5.5 $10^2$$



Total costs: 4.3 $10^2$$

Conclusions

- Learning is achieved
- Most of the time one action is preferable while the rest two have similar value
- One day only for train and test so no idea about generalization
- Open discussion for possibilities to model differently

Microgrid benchmark development plan

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1. Add genset device

- Not energy-constrained
- Costly
- minimum stable generation
- non-linear efficiency
- Should be used when no renewable generation, and sometimes preventively to charge the battery if peak consumption is anticipated

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2. Make system multi-objective

- Minimize operation cost (current objective)
- Maximize service level or served demand (reliability)

3. Release a stable version of the simulator

- With current features
    - only storage and genset management
    - multi-objective
    - no price arbitrage
- Provide benchmarks with several storage systems having different properties (e.g. Lithium, H2, flow-battery)
    - Different efficiencies, power/energy ratio, capacities
- Document, further test before release, etc.

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4. Make system evolve over time

- New actions : device is added
- Degradations of components, replacements
  - Modification of the transition function
- … To be discussed depending on what you want to highlight

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5. Add grid interaction options

- Can buy / sell to the grid and price evolves with time
- Peak consumption penalty
- …

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6. Integrate electrical network model

- Import features from ANM benchmark
  - electrical grid model
- means
  - system is more constrained (voltage range, thermal limits)
  - new actions may be necessary (generation curtailment, load shedding, reactive power production)

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Development plan (6 months)

		2018												2019												
		Oct.				Nov.				Dec.				Jan.					Feb.				March			
		41	42	43	44	45	46	47	48	49	50	51	52	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Add genset																									
2	Multi-objective																									
3	Release first version						1.0																			
4	System evolution											2.0														
5	Grid interaction																			3.0						
6	Network model																									(API change) 4

How to make the environment evolve over its lifetime

- What is a change of the environment
  - Change in action space : a new battery is available
  - Change in transition function / params (e.g. degradation)
  - Change in transition function / constraints (e.g. grid config)
  - How is evolution discovered by agent -> Is system partially observable

Contact

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