

Optimization and machine learning for smart-microgrids

overview

About the Montefiore Institute

Electrical Engineering and Computer Science
department of the University



Engineering
degrees in
electronics,
power systems,
computer
science, data
science

In the power systems group:

- Challenge power system design and regulation
- New management of security in power systems (Garpur project)
- Global-grid concept
- Micro-grid concept (grid-tied)

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

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

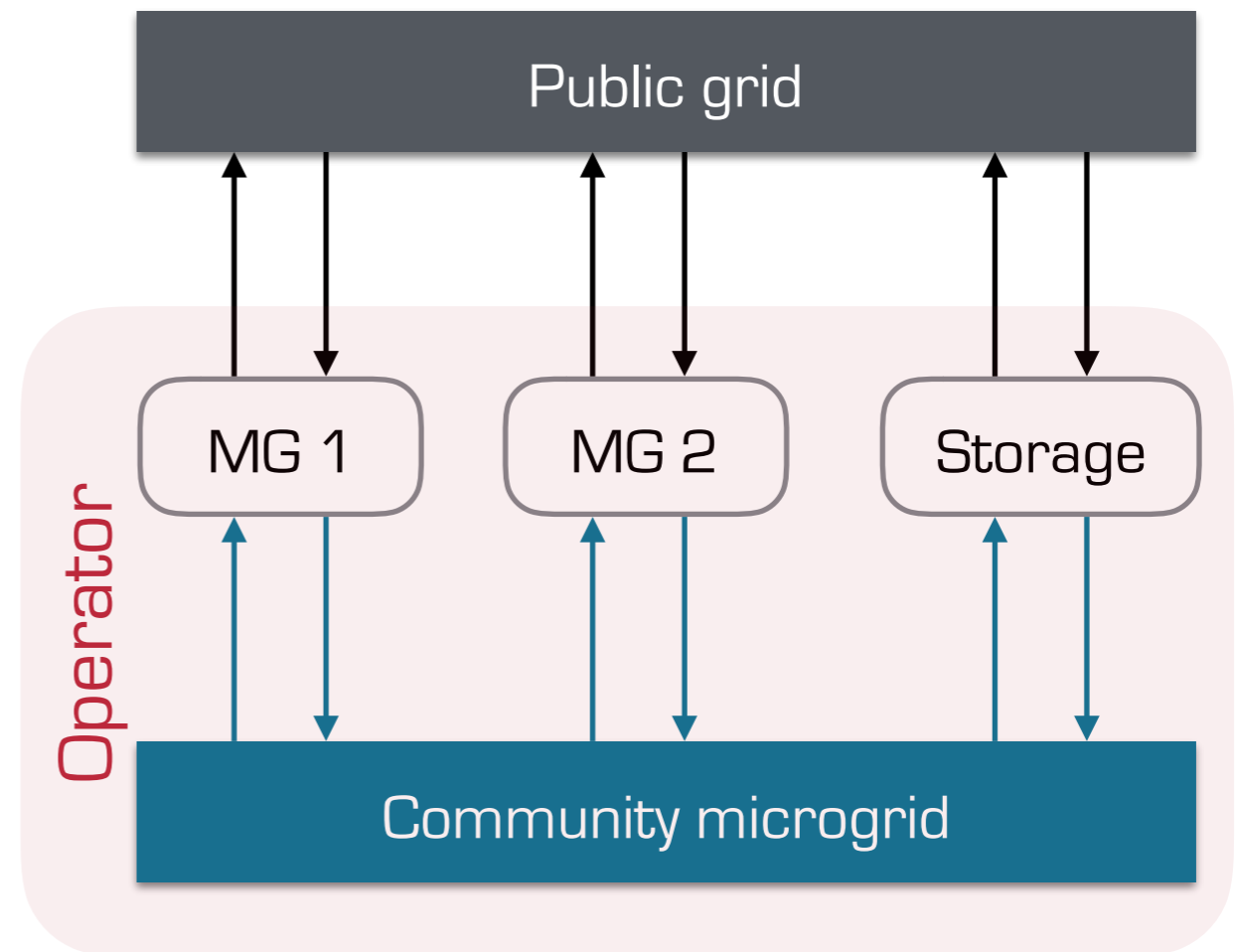
Function	Description	BSS *
Energy markets	Decide on the price your are willing to pay/sell	++
Ancillary services	Sell services to the grid	++
Peak reduction	Through local and community optimization	++
UPS functionality	Operate in islanded mode	++
Efficiency	Through optimized load and generation management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

* BSS: Battery Storage System

A few definitions

Single-user microgrid: loads, generation, storage, a network, a connection to the grid

Community microgrid: a group of single-user microgrids + a microgrid operator



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	++

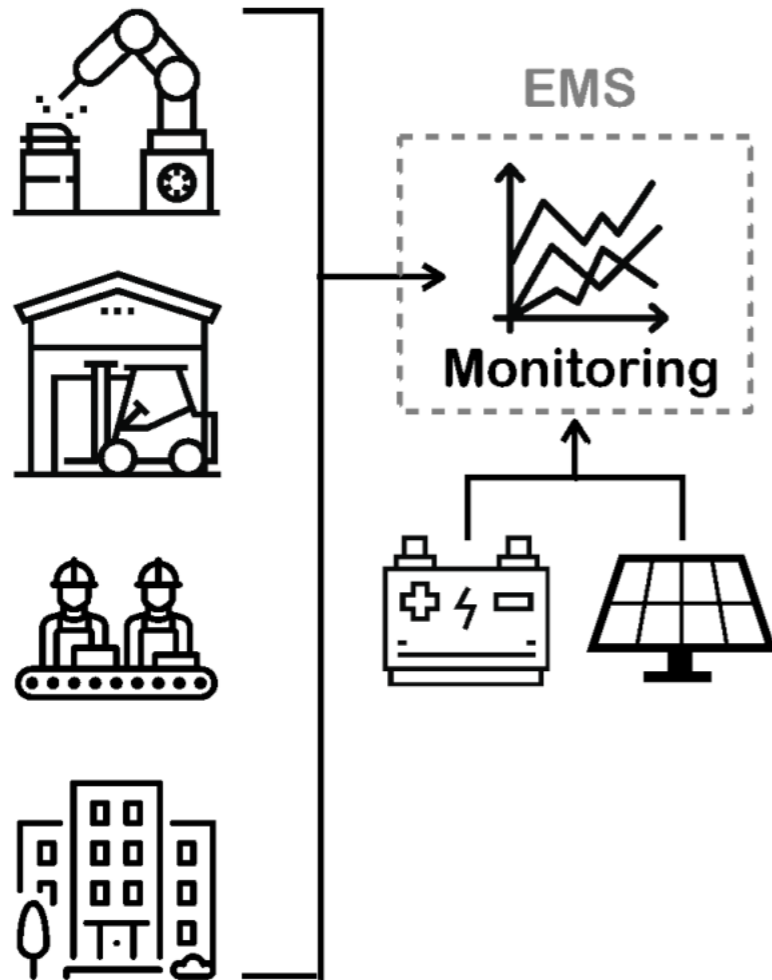
* BSS: Battery Storage System

“These advantages can be offered only by a **smart** microgrid energy management system”

- The Smart(micro)grids Team -

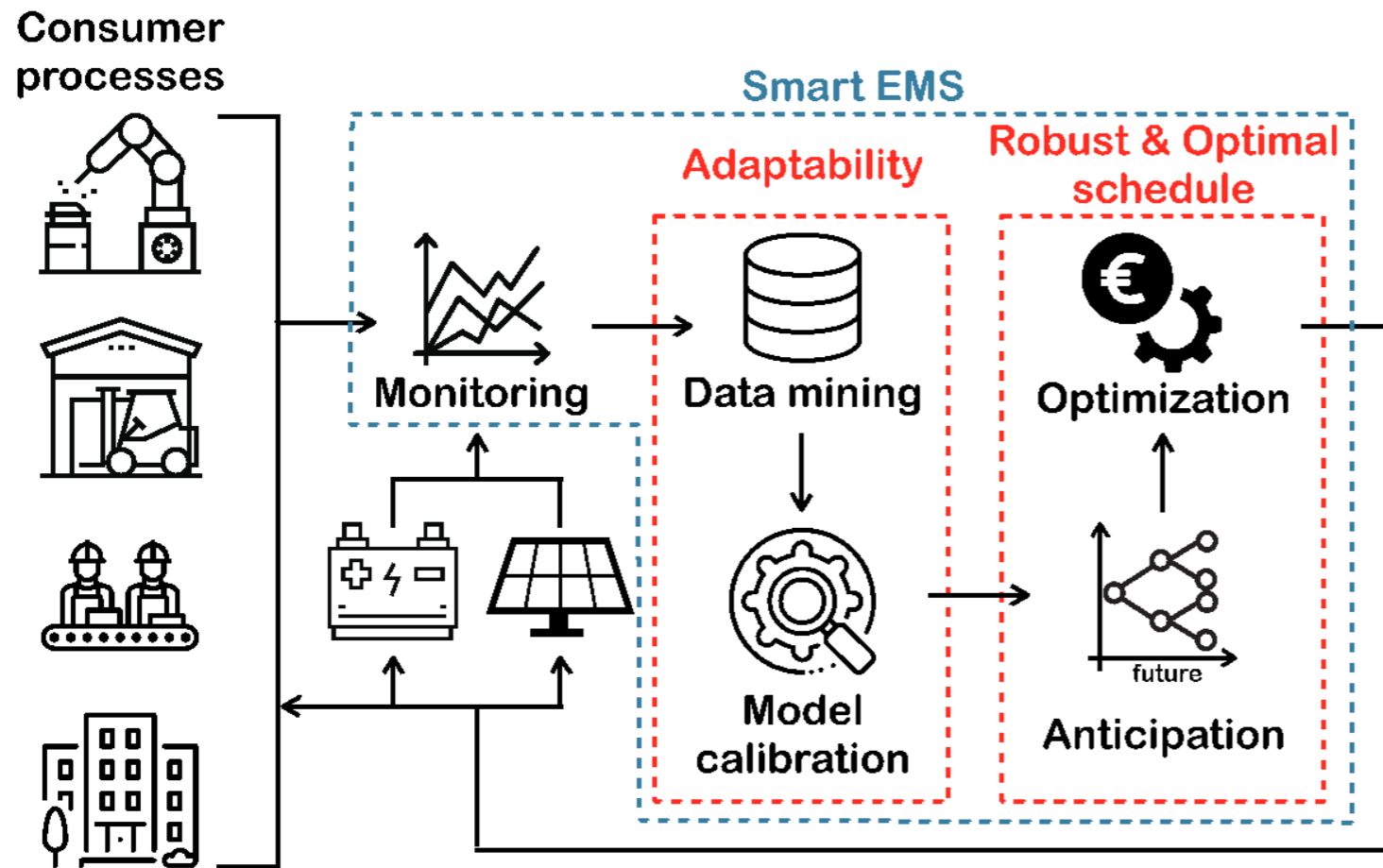
A standard energy management system

Consumer processes



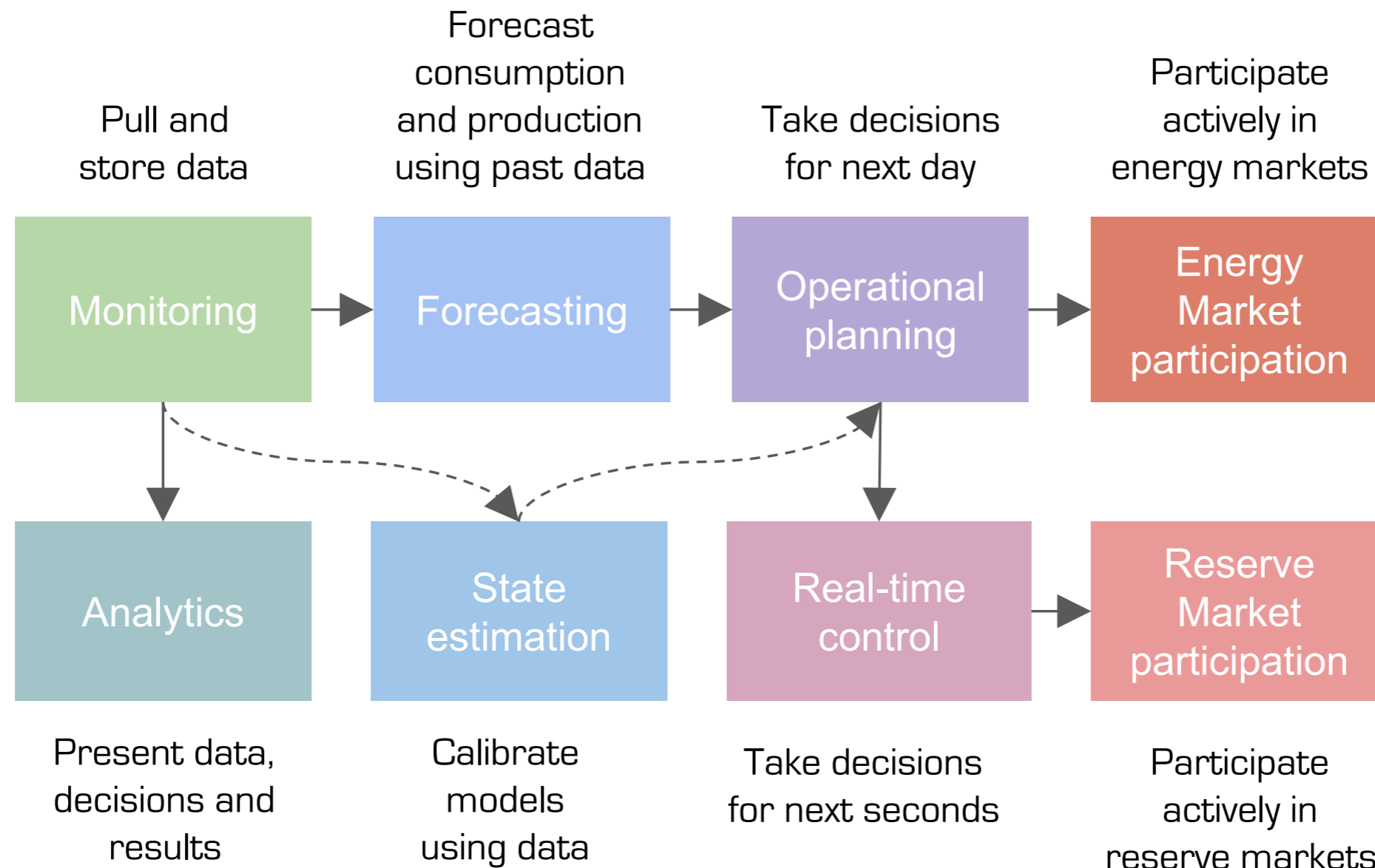
- Energy monitoring
- Fixed rules for storage operation

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

Functional modules that exploit data



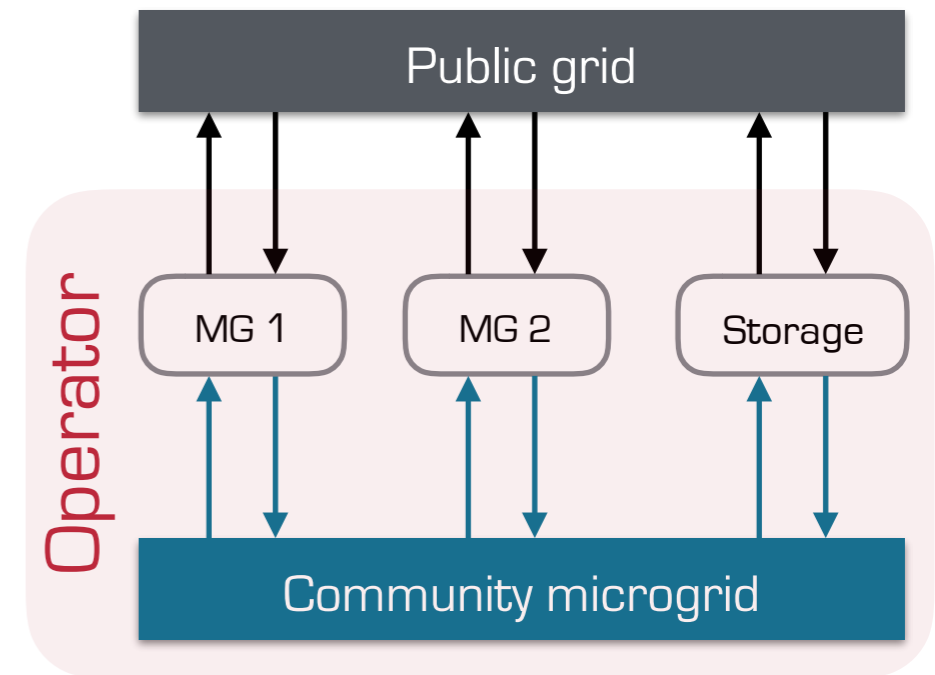
Arrows indicate a dependency between functional modules, not a flow of information!

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

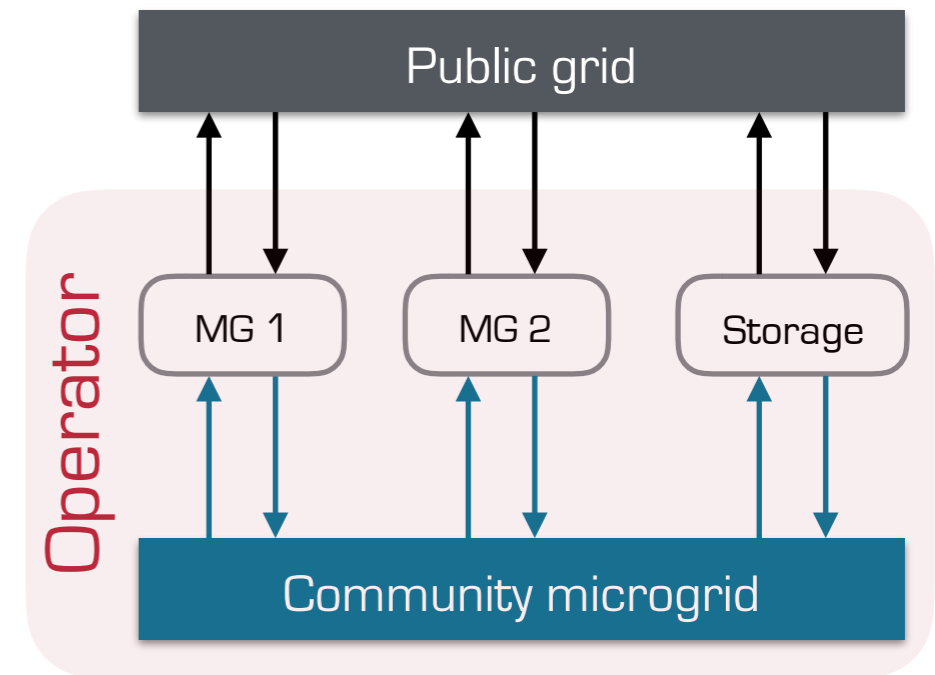
Community management (1/2)

- Each member of the community can decide, at every moment, either to connect to the public grid or to the community microgrid
 - ♦ This is not physical, this is accounting
 - ♦ Members have their own retailer
- Each member only sees data pertaining to his activities, plus information for the community



Community management (2/2)

- Members see what would be their optimal profit if they were not part of the community (selfish profit)
 - ✦ Community always makes at least the same profit as the sum of selfish profits
 - ✦ Fairness achieved through an “a priori” repartition rule



Should soon have a paper on the proposed method

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

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.

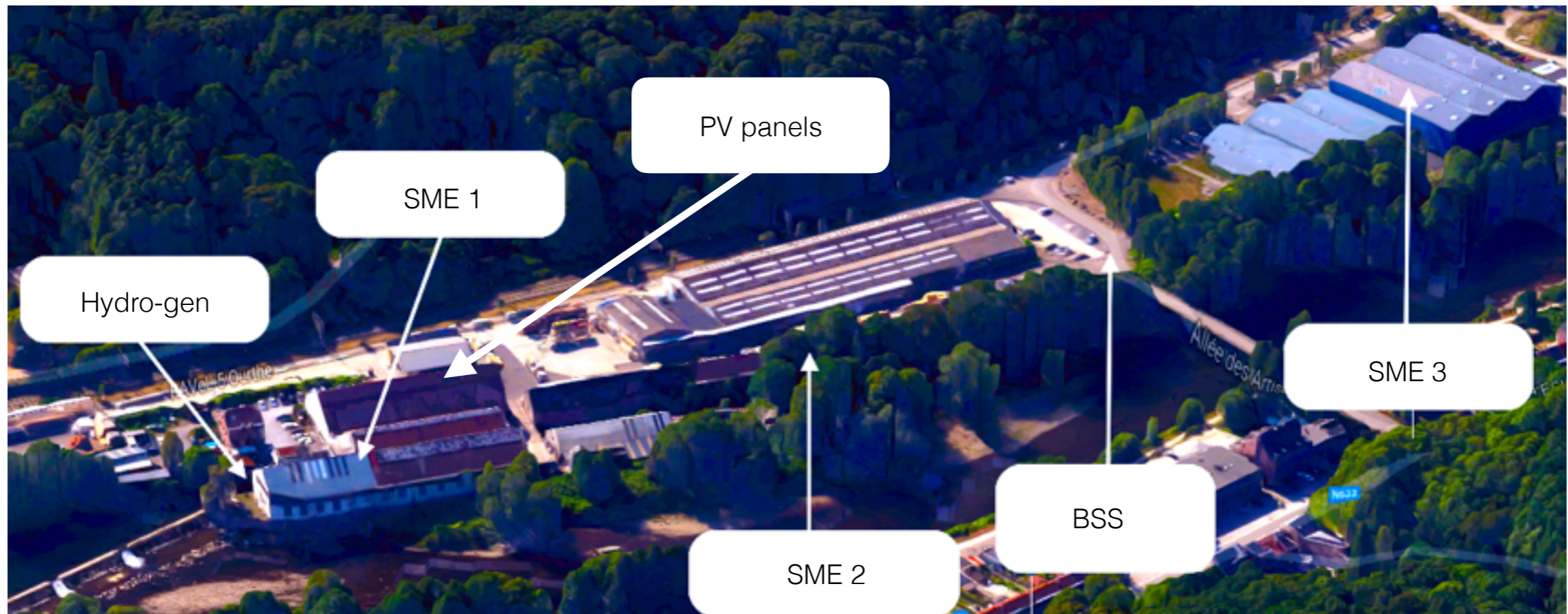
Participate actively in energy markets

Energy Market participation

Reserve Market participation

Participate actively in reserve markets

We are applying these concepts to a pilot project



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

Example of application of machine learning

Deep Reinforcement Learning Solutions for Energy Microgrids Management

Vincent François-Lavet
David Taralla
Damien Ernst
Raphael Fonteneau

V.FRANCOIS@ULG.AC.BE

DTARALLA@ULG.AC.BE

DERNST@ULG.AC.BE

RAPHAEL.FONTENEAU@ULG.AC.BE

Department of Electrical Engineering and Computer Science, University of Liege, Belgium

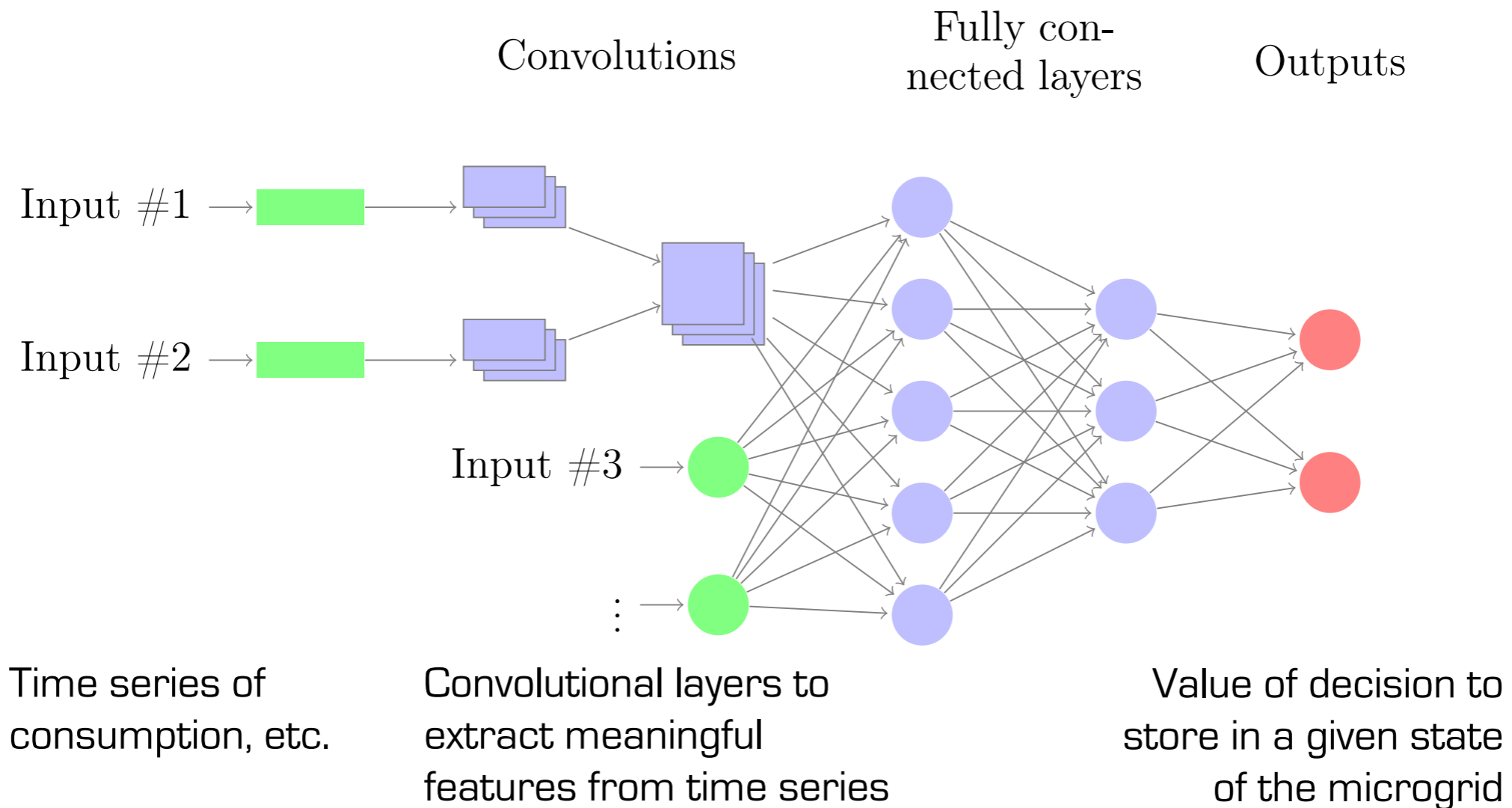
François-Lavet, Vincent, et al. "Deep reinforcement learning solutions for energy microgrids management." European Workshop on Reinforcement Learning. 2016.

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

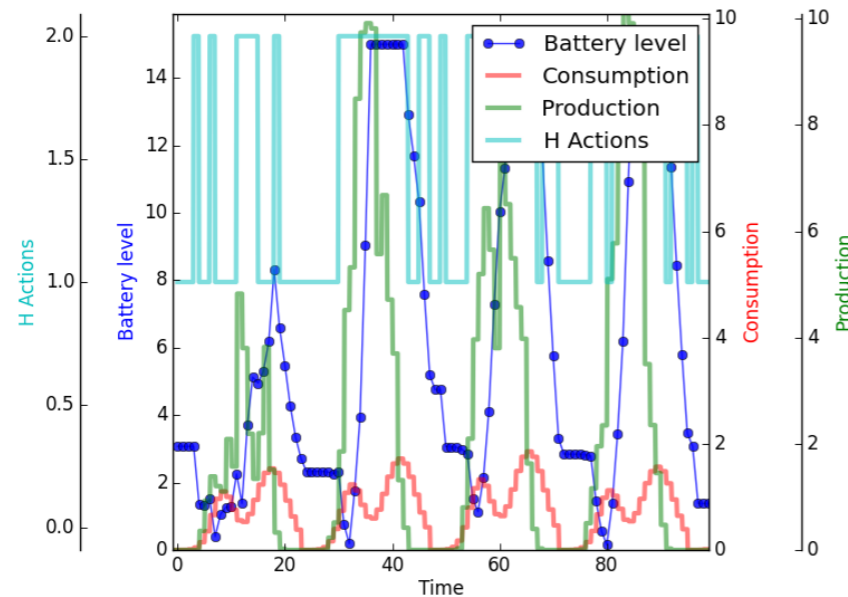
François-Lavet, Vincent, et al. "Deep reinforcement learning solutions for energy microgrids management." European Workshop on Reinforcement Learning. 2016.

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

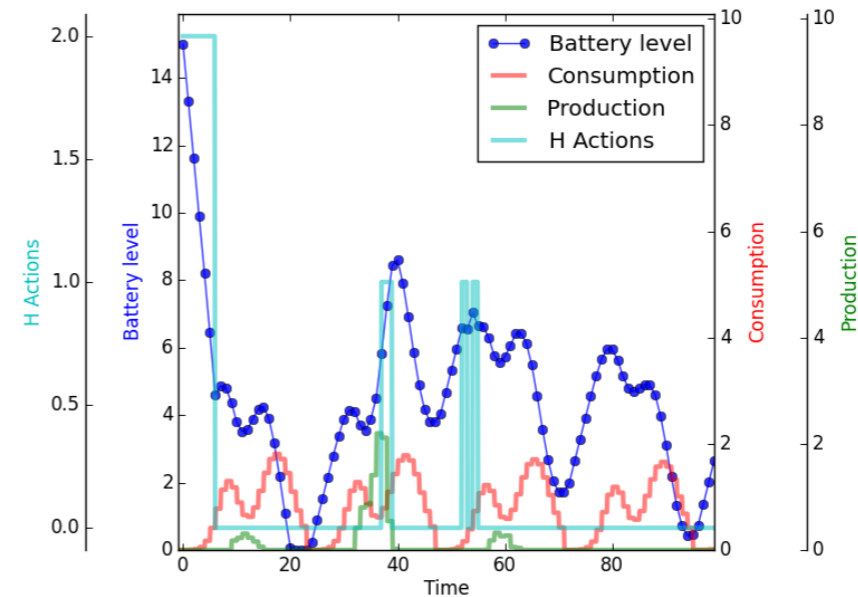


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Example results (long term + short term storage)



(a) Typical policy during summer



(b) Typical policy during winter

Figure 2: Computed policy with minimal information available to the agent. $H\ action = 0$ means discharging the hydrogen reserve at maximum rate; $H\ action = 1$ means doing nothing with the hydrogen reserve; $H\ action = 2$ means building up the hydrogen reserve at maximum rate.

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

Other flavors of learning

- **Transfer learning:** can we reuse a deep neural network on another microgrid?
- **Imitative learning:** Learn from “optimal” trajectories => optimize offline, learn, apply learned strategy online

We are also developing a microgrid laboratory



Contact

Pr. **Bertrand Cornélusse**

Smart microgrids – Montefiore Institute – Chaire Nethys

Electrical engineering and computer science department



Allée de la découverte 10, B-4000 Liège (Belgium)



+32 (0)477 32 42 75



bertrand.cornelusse@ulg.ac.be