Optimization and machine learning for smart-microgrids

overview
About the Montefiore Institute

Electrical Engineering and Computer Science department of the University

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

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

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

- 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

- Monitoring: Pull and store data
- Forecasting: Forecast consumption and production using past data
- Operational planning: Take decisions for next day
- Energy Market participation: Participate actively in energy markets
- Analytics: Present data, decisions and results
- State estimation: Calibrate models using data
- Real-time control: Take decisions for next seconds
- Reserve Market participation: Participate actively in reserve markets

Arrows indicate a dependency between functional modules, not a flow of information!
A combination of AI methods

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

Participate actively in reserve markets

Reserve Market participation
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
Abstract
This paper addresses the problem of efficiently operating the storage devices in an electricity microgrid featuring photovoltaic (PV) panels with both short- and long-term storage capacities. The problem of optimally activating the storage devices is formulated as a sequential decision making problem under uncertainty where, at every time-step, the uncertainty comes from the lack of knowledge about future electricity consumption and weather dependent PV production. This paper proposes to address this problem using deep reinforcement learning. To this purpose, a specific deep learning architecture has been designed in order to extract knowledge from past consumption and production time series as well as any available forecasts. The approach is empirically illustrated in the case of a residential customer located in Belgium.

1. Introduction
An electricity microgrid is an energy system consisting of local electricity generation, local loads (or energy consumption) and storage capacities. In this paper, we consider microgrids that are provided with different types of storage devices in order to be able to address both short- and long-term fluctuations of electricity production using photovoltaic (PV) panels (typically, batteries for short-term fluctuations, and hydrogen/fuel cells for long-term fluctuations). Distinguishing short- from long-term storage is mainly a question of cost: batteries are currently too expensive to be used for addressing seasonal variations. Energy microgrids face a dual stochastic-deterministic structure: one of the main challenge to meet when operating microgrids is to find storage strategies capable of handling uncertainties related to future electricity production and consumption; besides this, microgrids also have the characteristics that their dynamics deterministically reacts to storage management actions.

In this paper, we propose to design a storage management strategy which exploits this characteristic. We assume that we have access to: (i) an accurate simulator of the (deterministic) dynamics of a microgrid and (ii) time series describing past load and production profiles, which are realizations of some unknown stochastic processes. In this context, we propose to design a deep Reinforcement Learning (RL) agent (Mnih et al. (2015)) for approximating the optimal strategy through interaction with the environment. The deep RL algorithm proposed in this paper has been specifically designed to the setting which is original in the sense that the environment is partly described with a deterministic simulator (from which we can generate as much data as necessary), and partly with a limited batch of real data.

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

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

We propose a Neural Network (NN) architecture where the inputs are provided by the state vector, and where each separate output represents the Q-values for each discretized action. Possible actions $a$ are whether to charge or discharge the hydrogen storage device with the assumption that the batteries handle at best the current demand (avoid any value of loss load whenever possible). We consider three discretized actions: (i) discharge at full rate the hydrogen storage, (ii) keep it idle or (iii) charge it at full rate.

The NN processes time series thanks to a set of convolutions with 16 filters of $2 \times 1$ with stride 1 followed by a convolution with 16 filters of $2 \times 2$ with stride 1. The output of the convolutions as well as the other inputs are then followed by two fully connected layers with 50 and 20 neurons and the output layer. The activation function used is the Rectified Linear Unit (ReLU) except for the output layer where no activation function is used.

Example results (long term + short term storage)

4.3 Training
By starting with a random Q-network, we perform at each time step the update given in Eq. 1 and, in the meantime, we fill up a replay memory with all observations, actions and rewards using an agent that follows an $\varepsilon$-greedy policy $\pi(s) = \max_a Q(s, a; \theta_k)$ is selected with a probability $\frac{1}{\varepsilon}$, and a random action (with uniform probability over actions) is selected with probability $\varepsilon$. We use a decreasing value of $\varepsilon$ over time. During the validation and test phases, the policy $\pi(s) = \max_a Q(s, a; \theta_k)$ is applied (with $\varepsilon = 0$). As discussed in François-Lavet et al. (2015), we use an increasing discount factor along with a decreasing learning rate through the learning epochs so as to enhance learning performance.

4.4 Results and discussions
We consider a robust microgrid sizing provided by François-Lavet et al. (2016). The size of the battery is $x_B = 15 \text{ kWh}$, the instantaneous power of the hydrogen storage is $x_{H_2} = 1.1 \text{ kW}$ and the peak power generation of the PV installation is $x_{PV} = 12 \text{ kW}$. We first run the base case with minimal information available. The selected policy is based on the best validation score. The typical behaviour of the policy is illustrated in Figure 2 (test data).

Since the microgrid has no information about the future, it builds up (during the night) as sufficient reserve in the short-term storage device so as to be able to face the next day consumption without suffering too much loss load. It also avoids wasting energy (when the short term storage is full) by storing in the long-term storage device whenever possible.

![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.](image)

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
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