Artificial intelligence & energy transition: a few stories about energy prosumer communities

Journée scientifique de RISEGrid @ CentraleSupelec

November 30th, 2017

Raphaël Fonteneau @R_Fonteneau

Joint work with D. Ernst, V. François-Lavet, D. Marulli, F. Olivier, D. Taralla
The Smart (Micro) Grids Lab
University of Liège - Belgium

20 researchers developing algorithmic solutions for solving research questions in the fields of microgrids, smartgrids, globalgrids & energy prosumer communities.
Happy to be back to Supelec :) 

Supelec 2007 (Gif 2004-06, Rennes 2006-07)

*Ingénierie des Systèmes Automatisés*


*Contributions to Batch Mode Reinforcement Learning*

Inria Lille - Nord Europe - 2012-2013

*Analysing the exploration/exploitation dilemma*

Back to ULiège - 2013 - …

*Conciliating reinforcement learning with the energy transition*
A few words about energy prosumer communities

Tentative definition:

« Consumers/Prosumers that organise themselves in order to optimize how they produce and consume energy in order to achieve an objective. »

Many types of energy prosumer communities:

• Physical communities, e.g. people living under the same low-voltage feeder,

• Mobile communities, e.g. people owning EV, able to adapt how and where they charge / discharge their EV,

• Hybridation of these two types of communities.
Outline

New control challenge within energy prosumer communities

Deep reinforcement learning solutions for energy microgrids
First story

Foreseeing New Control Challenges in Electricity Prosumer Communities
The physical prosumer community
Modeling

\( N \) prosumers dynamically interacting with each other over a time horizon \( T \):

\[
\forall (i, j) \in \{1, \ldots, N\}^2, \forall t \in \{0, \ldots, T - 1\}, \quad \theta_t^{(i \rightarrow j)} = \theta_t^{(j \leftarrow i)}
\]

with the convention that \( \theta_t^{(i \rightarrow i)} = 0, \theta_t^{(i \leftarrow i)} = 0 \forall i, t. \)

\[
\forall t, i, \quad P_{P,t}^{(i)} = L_{P,t}^{(i)} + D_{P,t}^{(i)} + S_{P,t}^{(i)}
\]

\[
\forall t, i, \quad D_{P,t}^{(i)} = \sum_{j=1}^{N} (\theta_t^{(i \rightarrow j)} - \theta_t^{(i \leftarrow j)}) + \delta D_{P,t}^{(i)}
\]

where \( \delta D_{P,t}^{(i)} \) is the difference between the power injected into the distribution network and the sum of active power exchanges between the members of the community.
Modeling

Conservation of reactive power at the prosumer’s location

\[ \forall t, i, \quad P_{Q,t}^{(i)} = L_{Q,t}^{(i)} + D_{Q,t}^{(i)} \]

Other power-related constraints:

\[ \forall t, i, \quad P_{P,t}^{(i)} \leq P_{P,t}^{(i),\text{max}} \]
\[ \forall t, i, \quad |P_{Q,t}^{(i)}| \leq P_{Q}^{(i),\text{max}} \left( P_{P,t}^{(i)} \right) \]
\[ \forall t, i, \quad |S_{t}^{(i)}| \leq S^{(i),\text{max}} \left( \lambda_{t}^{(i)} \right) \]
\[ \forall t, i, \quad 0 \leq \lambda_{t}^{(i)} \leq \lambda^{(i),\text{max}} \]
Modeling

Network voltage

\[ \forall t, i, \quad |D_{P,t}^{(i)}| \leq D_{P}^{(i),\text{max}} \left( P_{P,t}^{(i)}, P_{Q,t}^{(i)}, L_{P,t}^{(i)}, L_{Q,t}^{(i)}, S_{t}^{(i)}, D_{P,t}^{(j \neq i)}, D_{Q,t}^{(j \neq i)} \right) \]

\[ \forall t, i, \quad |D_{Q,t}^{(i)}| \leq D_{Q}^{(i),\text{max}} \left( P_{P,t}^{(i)}, P_{Q,t}^{(i)}, L_{P,t}^{(i)}, L_{Q,t}^{(i)}, S_{t}^{(i)}, D_{P,t}^{(j \neq i)}, D_{Q,t}^{(j \neq i)} \right) \]
Modeling

Losses « at the root of the community » :

\[ \forall t \quad \Lambda_{P,t}^{(c)} = D_{P,t}^{(c)} - \sum_{i=1}^{N} D_{P,t}^{(i)} \]

\[ \forall t \quad \Lambda_{Q,t}^{(c)} = D_{Q,t}^{(c)} - \sum_{i=1}^{N} D_{Q,t}^{(i)} \]

where \( D_{P,t}^{(c)} \) (resp. \( D_{Q,t}^{(c)} \)) is the active (resp. reactive) power measured at the root of the community.
Modeling

Costs and revenues

\[ c_t^{(i)} = \Delta \left( \max \left( -\delta D_t^{(i)} , 0 \right) P r_t^{(D \rightarrow i)} \right) \]

\[ + \sum_{j=1}^{N} \max \left( \theta_t^{(i \leftarrow j)} , 0 \right) P r_t^{(j \rightarrow i)} \right) \]

\[ r_t^{(i)} = \Delta \left( \max \left( \delta D_t^{(i)} , 0 \right) P r_t^{(i \rightarrow D)} \right) \]

\[ + \sum_{j=1}^{N} \max \left( \theta_t^{(j \leftarrow i)} , 0 \right) P r_t^{(j \rightarrow i)} \right) \]
Modeling

State and prices vector

\[ \Xi_t = \begin{pmatrix} P_{P,t}^{(1)} & P_{Q,t}^{(1)} \\ P_{P,t}^{(1), \max} & P_{Q,t}^{(1), \max} \\ \vdots & \vdots \\ P_{P,t}^{(N)} & P_{Q,t}^{(N)} \\ P_{P,t}^{(N), \max} & P_{Q,t}^{(N), \max} \\ S_t^{(1)} & \lambda_t^{(1)} \\ \vdots & \vdots \\ S_t^{(N)} & \lambda_t^{(N)} \\ L_{P,t}^{(1)} & L_{Q,t}^{(1)} \\ \vdots & \vdots \\ L_{P,t}^{(N)} & L_{Q,t}^{(N)} \\ D_{P,t}^{(1)} & D_{Q,t}^{(1)} \\ \vdots & \vdots \\ D_{P,t}^{(N)} & D_{Q,t}^{(N)} \end{pmatrix}, \quad \Phi_t = \begin{pmatrix} P_{r_t}^{(D \rightarrow 1)} \\ P_{r_t}^{(1 \rightarrow D)} \\ \vdots \\ P_{r_t}^{(D \rightarrow N)} \\ P_{r_t}^{(N \rightarrow D)} \\ P_{r_t}^{(1 \rightarrow 2)} \\ \vdots \\ P_{r_t}^{(1 \rightarrow N)} \\ P_{r_t}^{(N \rightarrow 1)} \\ \vdots \\ P_{r_t}^{(N-1 \rightarrow N)} \\ P_{r_t}^{(N \rightarrow N-1)} \end{pmatrix} \]

\[ \Theta_t^\to = \begin{pmatrix} \theta_t^{(i \rightarrow j)} \end{pmatrix}_{i,j}, \quad \Theta_t^\leftarrow = \begin{pmatrix} \theta_t^{(i \leftarrow j)} \end{pmatrix}_{i,j} \]

\[ \Xi_{t+1} = F(\Xi_t, \Phi_t, \Theta_t^\to, \Theta_t^\leftarrow, \ldots, \Xi_0, \Phi_0, \Theta_0^\to, \Theta_0^\leftarrow, \omega_t) \]

\[ \omega_t \sim P_t(\cdot) \]
Controlling the prosumers community

Need for an optimisation criterion

Local production:
\[
\max_{t \in \{0, \ldots, T-1\}, i \in \{1, \ldots, N\}} \mathbb{E} \left[ \sum_{t=0}^{T-1} \sum_{i=1}^{N} P_{P,t}^{(i)} \right]
\]

Taking losses into account:
\[
\max_{t \in \{0, \ldots, T-1\}, i \in \{1, \ldots, N\}} \mathbb{E} \left[ \sum_{t=0}^{T-1} \sum_{i=1}^{N} P_{P,t}^{(i)} - \Lambda_{P,t}^{(c)} \right]
\]

Revenues minus costs:
\[
\max_{t \in \{0, \ldots, T-1\}, i \in \{1, \ldots, N\}} \mathbb{E} \left[ \sum_{t=0}^{T-1} \sum_{i=1}^{N} r_{t}^{(i)} - c_{t}^{(i)} \right]
\]
Centralised control without storage (P)

Optimising PV production

---

**Figure 2.5**: Illustration of the PV production of the 3 last houses of the low-voltage feeder over 24 hours.

**Figure 3**: Illustration of the voltage potential over 24 hours.
Centralised control with storage

A centralised strategy

- We use the forward backward sweep optimal power flow strategy proposed in [Fortenbacher et al.]
- We obtain both a sizing and centralised planning strategy, for a given load and solar irradiance scenario

Why going decentralised?

Technical challenges for building centralised strategies

1. Information gathering

2. Need for a centralised controller for processing information

3. Concretising computational results into applied actions
Learning a decentralised strategy

We propose a data-driven, « learning approach »:

1. Built a set of centralised solutions

2. Generate learning (input, output) samples, where the input is made from local indicators, and the output is a decision that should be applied locally

3. Learn a strategy from the samples
   • Imitative learning
Building a set of data

First, generate scenarios: a solar irradiance scenarios, a set of load scenarios (for each prosumer).

Then, solve the pairs {solar irradiance, load profiles} (using, for instance, a forward backward sweep power flow approach)

\[
\Xi_{0}^{*}, \ldots, \Xi_{T-1}^{*}
\]

From this time series of data, one can extract a series of local data, i.e. relative to one single prosumer (i):

\[
\Xi_{t}^{(i),*} = \begin{pmatrix}
P_{P,t}^{(i),*} & P_{Q,t}^{(i),*} \\
P_{P,t}^{(i),\text{max}} & P_{Q,t}^{(i),\text{max}} \\
S_{t}^{(i),*} & \lambda_{t}^{(i),*} \\
L_{P,t}^{(i)} & L_{Q,t}^{(i)} \\
D_{P,t}^{(i),*} & D_{Q,t}^{(i),*}
\end{pmatrix}
\]
Learning from data - Imitative learning

We propose to use a machine learning approach

- Machine learning is about extracting pattern from data
- From the sample of data we learn a mapping state -> action

Here, we adopt a slightly indirect approach by learning 4 different regressors:

- Active power
- Reactive power
- Charging battery
- Discharging the battery
1st regressor: learning active power production

Data set: \[ \mathcal{L}^P = \left\{ \left( \text{in}_{i,t}^P, \text{out}_{i,t}^P \right) \right\}_{i=1, t=0}^{i=N, t=T-1} \]

\[ \text{in}_{i,t}^P = \]

\[ \left( i, |\bar{V}_t^{(i)}|, \text{arg}(\bar{V}_t^{(i)}), \phi_t, \lambda_t^{(i)}, L_{P,t}^{(i)}, P_{P,t}^{(i), max} \right) \]

\[ \text{out}_{i,t}^P = P_{P,t}^{(i),*} \]

- \( i \): id number of the bus
- \( |\bar{V}_t^{(i)}| \): magnitude of the voltage at bus \( i \) at time step \( t \)
- \( \text{arg}(\bar{V}_t^{(i)}) \): phase of the voltage at bus \( i \) at time step \( t \)
- \( \phi_t \): electricity price at time step \( t \), considered as being unique in the whole feeder
- \( \lambda_t^{(i)} \): level of charge of the storage of bus \( i \) at time step \( t \)
- \( L_{P,t}^{(i)} \): load consumption at bus \( i \) at time step \( t \)
- \( P_{P,t}^{(i), max} \): maximal production potential at bus \( i \) at time step \( t \)
2nd regressor: learning reactive power production

Data set:

\[ \mathcal{L}^Q = \left\{ \left( \text{in}^i_t, \text{out}^i_t \right) \right\}_{i=1,t=0}^{i=N,t=T-1} \]

\[ \text{in}^i_t = \text{in}_P^i \]

\[ \text{out}^i_t = \text{P}_{Q,t}^{(i),*} \]
3rd regressor: learning how to charge the battery

Data set:

\[ \mathcal{L}^C = \left\{ \left( in_{C}^{i,t}, out_{C}^{i,t} \right) \right\}_{i=1,t=0}^{i=N,t=T-1} \]

\[ in_{C}^{i,t} = in_{P}^{i,t} \]

\[ out_{C}^{i,t} = \max \left( S_{t}^{(i),*}, 0 \right) \]
4th regressor: learning how to draw power from the battery

Data set: \[
\mathcal{L}^D = \left\{ \left( in_{D}^{i,t}, out_{D}^{i,t} \right) \right\}_{i=1, t=0}^{i=N, t=T-1}
\]

\[
in_{D}^{i,t} = in_{P}^{i,t}
\]

\[
out_{D}^{i,t} = \max \left( -S_t^{(i),*}, 0 \right)
\]
Then, post processing & evaluating solutions

Post-processing solutions

-> Ensure physical constraints are satisfied

• For the active and reactive power production levels, ensure that the production levels are compatible with production bounds, for each prosumer i

• For the power injected into / drawn from the battery, ensure that both maximal charging/discharging powers and of the level of charge evolution are feasible

Generating other scenarios to try the learned strategy

-> Evaluate the performance of learned policies in other environments
Test case

The number of buses is 15

The number of prosumers is 14

The number of branches is 14

$\Delta t$ is 1h

The time horizon $T$ is 8760

The line resistance $R_{d1} = R_{d2} = \ldots = R_{dL}$ is 0.025 $\Omega$

The line reactance $X_{d1} = X_{d2} = \ldots = X_{dL}$ is 0.005 $\Omega$

The nominal voltage of the network is 400 V

The maximum admissible voltage $v^{max}$ is 1.10 $pu$

The minimum admissible voltage $v^{min}$ is 0.90 $pu$
CHAPTER 5. CASE STUDY

Test case: prosumers characteristics

- The maximum admissible voltage $v_{\text{max}}$ is 1.10 pu;
- The minimum admissible voltage $v_{\text{min}}$ is 0.90 pu;
- For the feeder, $P_{\text{max}}$, $P_{\text{min}}$, $Q_{\text{max}}$, $Q_{\text{min}}$, $t_{\text{pot}}$, $0 = 1 \text{ MW}, -1 \text{ MW}, 1 \text{ MW}, -1 \text{ MW}$

Each prosumer inside the community is defined by an identification number (its position along the network), the number of occupants of the associated dwelling, the PV and storage installed capacity. These information are resumed in Table 5.1.

<table>
<thead>
<tr>
<th>Id</th>
<th>Number of occupants</th>
<th>PV installed capacity $kW_p$</th>
<th>Storage installed capacity $kWh$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>3</td>
<td>3.5</td>
<td>5</td>
</tr>
<tr>
<td>7</td>
<td>3</td>
<td>3.5</td>
<td>5</td>
</tr>
<tr>
<td>8</td>
<td>3</td>
<td>3.5</td>
<td>5</td>
</tr>
<tr>
<td>9</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>10</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>11</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>12</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>13</td>
<td>5</td>
<td>7</td>
<td>8</td>
</tr>
<tr>
<td>14</td>
<td>5</td>
<td>7</td>
<td>8</td>
</tr>
</tbody>
</table>

Table 5.1: Dwellings characteristic inside the community

All the values are then converted in the per unit system.

5.2 Test scenarios

To create a complete scenario that can be used to test the control schemes, we need, after defining the characteristic of the test network, to specify the load profiles, maximal production potentials and electricity prices over the entire period of time. Three different scenarios, named $S_1$, $S_2$, and $S_3$, are generated as follows.
Test scenarios

Load profiles are generated using the model provided in:


3 scenarios solar production + electricity prices
Learning scenarios

We generate two additional price scenarios, S4 and S5.

The FBS-OPF algorithm is run on these two scenarios.

The resulting outputs of the FBS-OPF are used to generate learning sets for the regressors.
Results

Overall costs (objective function)

<table>
<thead>
<tr>
<th>Scenario</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
</tr>
</thead>
<tbody>
<tr>
<td>FBS-OPF algorithm</td>
<td>1105.54 €</td>
<td>2121.16 €</td>
<td>1837.80 €</td>
</tr>
<tr>
<td>SL algorithm</td>
<td>2711.44 €</td>
<td>7832.43 €</td>
<td>5123.09 €</td>
</tr>
<tr>
<td>RT algorithm</td>
<td>5143.32 €</td>
<td>6501.94 €</td>
<td>5807.77 €</td>
</tr>
</tbody>
</table>

Energy outlook:

<table>
<thead>
<tr>
<th>Scenario</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
</tr>
</thead>
<tbody>
<tr>
<td>FBS-OPF algorithm</td>
<td>7.01%</td>
<td>11.20%</td>
<td>9.69%</td>
</tr>
<tr>
<td>SL algorithm</td>
<td>11.13%</td>
<td>32.78%</td>
<td>14.80%</td>
</tr>
<tr>
<td>RT algorithm</td>
<td>11.91%</td>
<td>13.46%</td>
<td>15.12%</td>
</tr>
</tbody>
</table>
Second story

Deep reinforcement learning solutions for energy microgrids management
Operating storage devices in microgrids

The context: imagine a microgrid (MG) featuring photovoltaic (PV) panels, with both short and long term storage devices.

The problem: how to optimally active the storage devices so that to minimise the operating costs of the MG?
(Deep) Reinforcement Learning (RL)

Ingredients

1) An agent evolving within an environment

2) A reward function, assessing the immediate quality of decision

3) A capacity of interacting with the environment
(Deep) Reinforcement Learning (RL) 
More formally...

Markov Decision Process 
\[ M = (S, A, T, R) \]
\[ S = \{ s^{(1)}, \ldots, s^{(n_s)} \} \quad A = \{ a^{(1)}, \ldots, a^{(n_A)} \} \]
\[ T(s_t, a_t, s_{t+1}) = P(s_{t+1} | s_t, a_t) \quad r_t = R(s_t, a_t, s_{t+1}) \]

Policy: \[ \pi : S \rightarrow A \]

\[ \forall s \in S, \quad J^\pi(s) = \mathbb{E} \left[ \sum_{t=0}^{\infty} \gamma^t R(s_t, \pi(s_t), s_{t+1}) | s_0 = s \right] \]
\[ \gamma \in [0, 1) \]
(Deep) Reinforcement Learning (RL)  
More formally…

Searching for optimality: \( \forall s \in S, \quad J^{\pi^*}(s) \geq J^{\pi}(s) \)

Solving (or approximating) the Bellman equation:

\[
\forall s \in S,
J^*(s) = \max_{a \in A} \sum_{s' \in S} T(s, a, s') \left( R(s, a, s') + \gamma J^*(s') \right)
\]

Theoretically, one may just to behave optimally with respect to the optimal state-action value function:

\[
\forall (s, a) \in S \times A,
Q^* : S \times A \rightarrow \mathbb{R} \quad Q^*(s, a) = \sum_{s' \in S} T(s, a, s') \left[ R(s, a, s') + \gamma J^*(s') \right]
\]

In practice: partial observability, too many states / dimensions…
Formalising a RL problem

\[ s_t = [c_{t-hc}, \ldots, c_{t-1}, \phi_{t-hp}, \ldots, \phi_{t-1}, s^MG_t] \]

- **State**: \[ s_t = [c_{t-hc}, \ldots, c_{t-1}, \phi_{t-hp}, \ldots, \phi_{t-1}, s^MG_t, \zeta_s] \]

\[ s_t = [c_{t-hc}, \ldots, c_{t-1}, \phi_{t-hp}, \ldots, \phi_{t-1}, s^MG_t, \zeta_s, \rho_{24}, \rho_{48}] \]

- **Action**: \[ a_t = [a^{H2}_t, a^B_t] \in A_t \quad \forall t \in T: A_t = \left(\left[-\zeta^B s^B_t, \frac{x^B - s^B_t}{\eta^B}\right]\right) \times \left([-\zeta^{H2} s^{H2}_t, \infty \cap [0, x^{H2}]]\right) \]

- **Battery dynamics**: \[ s^{B}_{t+1} = s^B_t + \eta^B a^B_t \text{ if } a^B_t \geq 0 \text{ and } s^{B}_{t+1} = s^B_t + \frac{a^B_t}{\zeta^B} \text{ otherwise.} \]

- **Hydrogen dynamics**: \[ s^{H2}_{t+1} = s^{H2}_t + \eta^{H2} a^{H2}_t \text{ if } a^{H2}_t \geq 0 \text{ and } s^{H2}_{t+1} = s^{H2}_t + \frac{a^{H2}_t}{s^{H2}_t} \text{ otherwise.} \]

- **Reward function**: \[ r_t = r(a_t, d_t) = r^{H2}(a_t, d_t) + r^-(a_t, d_t) \]

\[ r^-(a_t, d_t) = k\delta_t \text{ when } \delta_t < 0 \]

\[ r^{H2}(a_t, d_t) = k^{H2} a^{H2}_t \]
Using a deep neural network to approximate the value function

Approximating a state-action value function using a deep neural network.

![Diagram of Neural Network Architecture]

4.1 Neural network architecture

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 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.

4.2 Splitting times series to avoid overfitting

We consider the case where the agent is provided with two years of actual past realizations of $(c_t)$ and $(t_t)$. In order to avoid overfitting, these past realizations are split into a training environment ($y = 1$) and a validation environment ($y = 2$). The training environment is used to train the policy while the validation environment is used at each epoch to estimate how well the policy performs on the undiscounted objective $M_y$ and selects the final NN. The final NN is then used in a test environment ($y = 3$) to provide an independent estimation on how well the policy performs.
Results

(a) Typical policy during summer

(b) Typical policy during winter

(a) Operational revenue

(b) LEC
V. François-Lavet open source project: the DeeR framework

DeeR (Deep Reinforcement) is a python library to train an agent how to behave in a given environment so as to maximise a cumulative sum of rewards:

https://github.com/VinF/deer
As a conclusion…
(Ongoing) next steps

Many, many problems to (re)think regarding energy prosumer communities

We are currently working on the integration of (distributed) reinforcement learning approaches for agents to cooperate within a community

Also, we are investigating how to take into account 3 phase unbalanced load problems...
References

[1] Towards the minimization of the levelized energy costs of microgrids using both long-term and short-term storage devices
V. François-Lavet, Q. Gemine, D. Ernst, R. Fonteneau
Smart Grid: Networking, Data Management, and Business Models, 295-319, 2016

V. François-Lavet, D. Taralla, D. Ernst, R. Fonteneau
European Workshop on Reinforcement Learning (EWRL), 2016

A. Dubois, A. Wehenkel, R. Fonteneau, F. Olivier, D. Ernst
International Conference on Agents and Artificial Intelligence (ICAART), 2017

F. Olivier, D. Ernst, R. Fonteneau
Congrès International des Réseaux Electriques de Distribution (CIRED), 2017

[5] Foreseeing New Control Challenges in Electricity Prosumer Communities
F. Olivier, D. Marulli, D. Ernst, R. Fonteneau
10th Bulk Power Systems Dynamics and Control Symposium (IREP), 2017

M. Glavic, R. Fonteneau, D. Ernst
The 20th World Congress of the International Federation of Automatic Control (IFAC), 2017