Coordination of operational planning and real-time optimization in microgrids

Jonathan Dumas, Selmane Dakir, Clément Liu, Bertrand Cornélusse

Department of electrical engineering and computer science ULiège, Liège, Belgium
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Microgrid hierarchical control

Fig. 1 Hierarchical control architecture.

[1] Fei, G. A. O., et al. "Primary and secondary control in DC microgrids: a review." Journal of Modern Power Systems and Clean Energy 7.2 (2019): 227-242.
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Literature: two-layer approach

Schedule layer:
- economical operation scheme;
- 24 hours ahead, 15 min resolution.

Dispatch layer:
- Computes set points based on the schedule and the microgrid status;
- 15 min ahead, resolution of a few seconds.

How interact the schedule and dispatch layers?

Two-layer approach intensively studied:

[2] Jiang, Quanyuan, Meidong Xue, and Guangchao Geng. "Energy management of microgrid in grid-connected and stand-alone modes." IEEE transactions on power systems 28.3 (2013): 3380-3389.
[3] Wu, Xiong, Xiuli Wang, and Chong Qu. "A hierarchical framework for generation scheduling of microgrids." IEEE Transactions on Power Delivery 29.6 (2014): 2448-2457.
[4] Sachs, Julia, and Oliver Sawodny. "A two-stage model predictive control strategy for economic diesel-PV-battery island microgrid operation in rural areas." IEEE Transactions on Sustainable Energy 7.3 (2016): 903-913.
[5] Cominesi, Stefano Raimondi, et al. "A two-layer stochastic model predictive control scheme for microgrids." IEEE Transactions on Control Systems Technology 26.1 (2017): 1-13.
[6] Ju, Chengquan, et al. "A two-layer energy management system for microgrids with hybrid energy storage considering degradation costs." IEEE Transactions on Smart Grid 9.6 (2017): 6047-6057.
[7] Solanki, Bharatkumar V., Claudio A. Cañizares, and Kankar Bhattacharya. "Practical energy management systems for isolated microgrids." IEEE Transactions on Smart Grid 10.5 (2018): 4762-4775.
Summary

1. Problem formulation
2. Proposed method
3. Case study description
4. Numerical results
5. Conclusions & perspectives
Abstract problem formulation

\[
a^*_\mathcal{T}(t) = \arg \min_{t' \in \mathcal{T}(t)} \sum_{t' \in \mathcal{T}(t)} c(a_{t'}, s_{t'}, \hat{\omega}_t)
\]

\[\text{s.t. } \forall t' \in \mathcal{T}(t), \ s_{t'+\Delta t'} = f(a_{t'}, s_{t'}, \hat{\omega}_t, \Delta t'), \]

\[s_{t'} \in S_t'\]

\[a_t = (a_t^m, a_t^d) \quad \text{Actions set: market related (m) and set points to the devices (d).}\]

\[s_t = (s_t^m, s_t^d) \quad \text{Microgrid state: related to the market (m) and devices (d).}\]

\[c \quad \text{Cost function.}\]

\[f \quad \text{Transition function of the system.}\]

\[\hat{\omega}_t \quad \text{Uncertainty.}\]

This problem is very difficult to solve since the evolution of the system is uncertain, actions have long-term consequences, and are both discrete and continuous.
Summary

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Proposed method: two-layers with a value function

\[ c(a_t, s_t, w_t) = c^m(a_t^m, s_t, w_t) + c^d(a_t^d, s_t, \omega_t) \]

Planner Controller

Two-layers approach with a **value function** to **propagate information** from operational planning to real-time optimization.

**Fig. 2 Hierarchical control procedure illustration.**
Proposed method: two-layers with a value function

Operational planner:

\[
\mathbf{a}^m_{\hat{\mathcal{M}}(t)} = \arg\min_{\mathbf{a}^m(t)} \sum_{t' \in \hat{\mathcal{M}}(t)} c^m(a^m_{t'}, s_{t'}, \hat{\omega}_{t'})
\]  
\textbf{s.t.} \forall t' \in \hat{\mathcal{M}}(t), s_{t'+\Delta t} = f^m(a^m_{t'}, s_{t'}, \hat{\omega}_{t'}, \Delta t) 
\]

Real-time controller:

\[
\mathbf{a}^d_{\tau(t)} = \arg\min_{\mathbf{a}^d(t)} c^d(a^d_{t}, s_{t}, \hat{\omega}_{t}) + v_{\tau(t)}(s_{\tau(t)})
\]  
\textbf{s.t.} s_{\tau(t)} = f^d(a^d_{t}, s_{t}, \hat{\omega}_{t}, \tau(t) - t) 
\]

Value function at the end of the first market period.
Proposed method: objective function of the operational planner

Operational planner:

\[
J^{OP}_{\mathcal{T}^m(t)} = \sum_{t' \in \mathcal{T}^m(t)} \left( C^{OP}_{t'} + D^{OP}_{t'} \right) \quad (4) \quad \text{Immediate and delayed costs.}
\]

\[
C^{OP}_{t'} = \left( \sum_{d \in \mathcal{D}^{she}} \Delta \pi_{d,t'}^{she} C_{d,t'}^{she} a_{d,t'}^{she} + \sum_{d \in \mathcal{D}^{ste}} \Delta \pi_{d,t'}^{ste} C_{d,t'}^{ste} a_{d,t'}^{ste} + \sum_{d \in \mathcal{D}^{nst}} \Delta \pi_{d,t'}^{nst} C_{d,t'}^{nst} a_{d,t'}^{nst} \right) \quad \text{shed demand} \quad \text{steered generation} \quad \text{non steered generation}
\]

\[
+ \sum_{d \in \mathcal{D}^{sto}} \Delta \gamma_{d}^{sto} \left( \bar{P}_d \eta_d^{cha} a_{d,t'}^{cha} + \frac{P_d}{\eta_d^{dis}} a_{d,t'}^{dis} \right) \quad \text{storage fee}
\]

\[
- \pi_{t'}^{e_{gri}} + \pi_{t'}^{i_{gri}} \right) \quad \text{selling/purchasing energy to/from the grid}
\]

\[
D^{OP}_{t'} = \pi^p \delta p_{t'} - \pi^s_{OP} r_{t'}^{sym} \quad \text{peak cost and symmetric reserve}
\]
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Proposed method: objective function of the real-time controller

Real-time controller:

\[ J_t^{RTO} = C_t^{RTO} + D_t^{RTO} + v_{\tau(t)}(s_{\tau(t)}) \]  (5)

Immediate, delayed costs, and value function.

Value function = cost-to-go at the end of the ongoing market period as a function of the state of charge.

Evaluated by solving (4) for several states of charge = parametrization by changing the RHS -> provide cuts.

Cut 1 to 3:

- \( s_{\tau(t)} = s_1 \) \([\mu_1]\) \( \rightarrow v_{\tau(t)}(s) \geq v_{\tau(t)}(s_1) + \mu_1^T s \)
- \( s_{\tau(t)} = s_2 \) \([\mu_2]\) \( \rightarrow v_{\tau(t)}(s) \geq v_{\tau(t)}(s_2) + \mu_2^T s \)
- \( s_{\tau(t)} = s_3 \) \([\mu_3]\) \( \rightarrow v_{\tau(t)}(s) \geq v_{\tau(t)}(s_3) + \mu_3^T s \)

Fig. 3 Value function approximation illustration.
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MiRIS case study

Fig. 3 PV and consumption on June 12, 2019.

MiRIS microgrid located at the John Cockerill Group’s international headquarters in Seraing, Belgium.

https://johncockerill.com/fr/energy-2/stockage-denergie/

27 days of data (measurements and point forecasts) available on the Kaggle platform:

https://www.kaggle.com/jonathandumas/liege-microgrid-open-data
# MiRIS case study: managing the peak penalty

**Table I: Case study parameters.**

| Case | PV<sub>p</sub> | PV | PV<sub>max</sub> | PV<sub>min</sub> | PV<sub>std</sub> |
|------|---------------|----|-----------------|-----------------|-----------------|
| 1    | 400           | 61 | 256             | 0               | 72              |
| 2    | 875           | 133| 561             | 0               | 157             |
| 3    | 1750          | 267| 1122            | 0               | 314             |

| Case | \(C_p\) | \(\bar{C}\) | \(C_{max}\) | \(C_{min}\) | \(C_{std}\) |
|------|---------|------------|-------------|-------------|-------------|
| 1-3  | 1000    | 153        | 390         | 68          | 72          |

| Case | \(S_p\) | \(\bar{S}, S\) | \(P, \bar{P}\) | \(\eta^{cha}, \eta^{dis}\) | \(S^{init}\) |
|------|---------|-----------------|-----------------|-----------------|-------------|
| 1-3  | 1350    | 1350, 0         | 1350, 1350      | 0.95, 0.95      | 100         |

| Case | \(p_h, \pi^p\) | \(I^{cap}\) | \(E^{cap}\) | \(\pi^d, \pi^i\) | \(\pi^e\) |
|------|----------------|-------------|-------------|-----------------|-------------|
| 1-3  | 150, 40        | 1500        | 1500        | 0.2, 0.12       | 0.035       |

**Peak penalty** if import > 150 kW paid at 40 euros / kW
Day/night import prices: 200/120 euros MWh.
Single export price 35 euros /MWh.
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Numerical results: RTO-OP vs RBC

**Planner (OP):**
- 24 hours ahead;
- 15 min resolution;
- run on a quarterly basis.

**Controller (RTO):**
- 15 min ahead;
- run on a one minute basis.

RTO-OP is compared to a Rule Based Controller (RBC).
Numerical results: RTO-OP vs RBC

PV and consumption weather based point forecasts for OP use Recurrent Neural Network (RNN) and Gradient Boosting Regression (GBR) techniques.

The weather forecasts provided by the Laboratory of Climatology of the university of Liège, based on the MAR regional climate model.
Numerical results: peak management

Table II: Results without symmetric reserve.

| Case   | $c_E$ (k euros) | $c_p$ (k euros) | $c_t$ (k euros) | $\Delta_p$ (kW) |
|--------|----------------|----------------|----------------|-----------------|
| RBC    | 10.13          | 6.68           | 16.81          | 167             |
| RTO-OP$^{RNN}$ | 10.37         | 3.62           | 13.99          | 91              |
| RTO-OP$^{GBR}$ | 10.25           | 5.27           | 15.53          | 132             |
| RTO-OP* | 10.24          | 0.99           | 11.23          | 25              |

| Case   | $c_E$ (k euros) | $c_p$ (k euros) | $c_t$ (k euros) | $\Delta_p$ (kW) |
|--------|----------------|----------------|----------------|-----------------|
| RBC    | 3.19           | 4.85           | 8.04           | 121             |
| RTO-OP$^{RNN}$ | 4.78          | 2.87           | 7.65           | 72              |
| RTO-OP$^{GBR}$ | 4.30           | 4.90           | 9.2            | 123             |
| RTO-OP* | 4.06           | 0              | 4.06           | 0               |

| Case   | $c_E$ (k euros) | $c_p$ (k euros) | $c_t$ (k euros) | $\Delta_p$ (kW) |
|--------|----------------|----------------|----------------|-----------------|
| RBC    | -2.13          | 4.12           | 1.99           | 105             |
| RTO-OP$^{RNN}$ | -1.66         | 4.12           | 2.46           | 105             |
| RTO-OP$^{GBR}$ | -1.67          | 4.23           | 2.56           | 106             |
| RTO-OP* | -1.90          | 0              | 0              | 0               |

$RTO-OP^*$ = perfect forecasts

RTO-OP is still a long way to manage the peak as $RTO-OP^*$ due to the forecasting errors.

RTO-OP optimizes PV-storage usage, and thus requires less installed PV capacity for a given demand level than RBC.
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Numerical results: peak management with symmetric reserve

Fig. 5 Case 3 SOC comparison for RTO-OP (RNN) with and without symmetric reserve.

RTO-OP tends to maintain a storage level that allows to better cope with forecast error.
There is an **economic trade-off** to reach to **manage the peak** and the **reserve** simultaneously depending on the valorization or not on the market of the symmetric reserve.
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Conclusions & extensions

The value function computed by the operational planner based on PV and consumption forecasts allows to cope with the forecasting uncertainties.

The approach is tested in the MiRIS microgrid case study with PV and consumption data monitored on site.

The results demonstrate the efficiency of this method to manage the peak in comparison with a Rule Based Controller.

Extension to a stochastic/robust formulation to deal with probabilistic forecasts.

Extension to a community by considering several entities inside the microgrid.
Annex: Point forecasting methodology

Inputs:
- PV production / Load historical data
- Weather forecast from the laboratory of climatology of Liège.

Outputs:
- PV production / load **24 ahead hours** with **15 min** resolution

The point forecasts are computed on a quarterly basis using a **Long Short Term Memory** (LSTM) with the keras python library [8] and a **Gradient Boosting Regression** (GBR) with the scikit-learn python library [9].

The forecasting process is implemented using a **rolling forecast methodology**. The Learning Set (LS) is **refreshed every six hours** and limited to **the week preceding the forecasts**.

[8] F. Chollet et al., “Keras,” https://keras.io, 2015.
[9] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vander- plas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duch- esnay, “Scikit-learn: Machine learning in Python,” Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.
Annex: Point forecasting results

Fig. 4 PV forecast scores for GBR (top) and RNN (bottom).