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Coordination of operational planning and real-time optimization in microgrids

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Microgrid hierarchical control

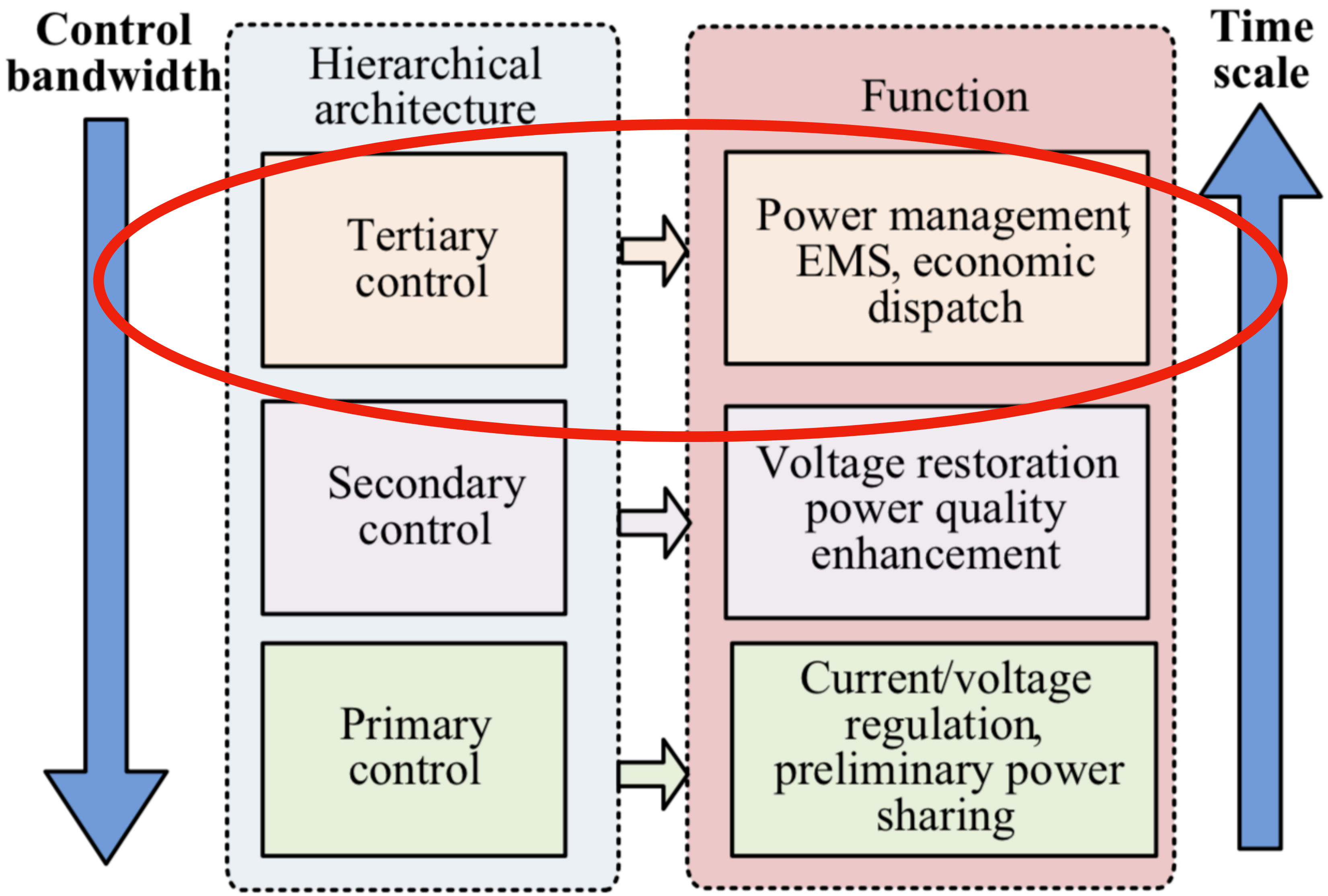

Fig. 1 Hierarchical control architecture.

[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

Abstract problem formulation

$$\mathbf{a}^{\star}_{\mathcal{T}_l(t)} = \arg\min \sum_{t' \in \mathcal{T}_l(t)} c(a_{t'}, s_{t'}, \hat{\omega}_{t'})$$

$$\textbf{s.t. } \forall t' \in \mathcal{T}_l(t),\ s_{t'+\Delta t'} = f(a_{t'}, s_{t'}, \hat{\omega}_{t'}, \Delta t'), \tag{1}$$

$$s_{t'} \in S'_t$$

$a_t = (a_t^m, a_t^d)$	Actions set: **market** related (**m**) and **set points** to the devices (**d**).
$s_t = (s_t^m, s_t^d)$	Microgrid state: related to the **market** (m) and **devices** (d).
c	Cost function.
f	Transition function of the system.
$\hat{\omega}_t$	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

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

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

$v_t(s)$

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

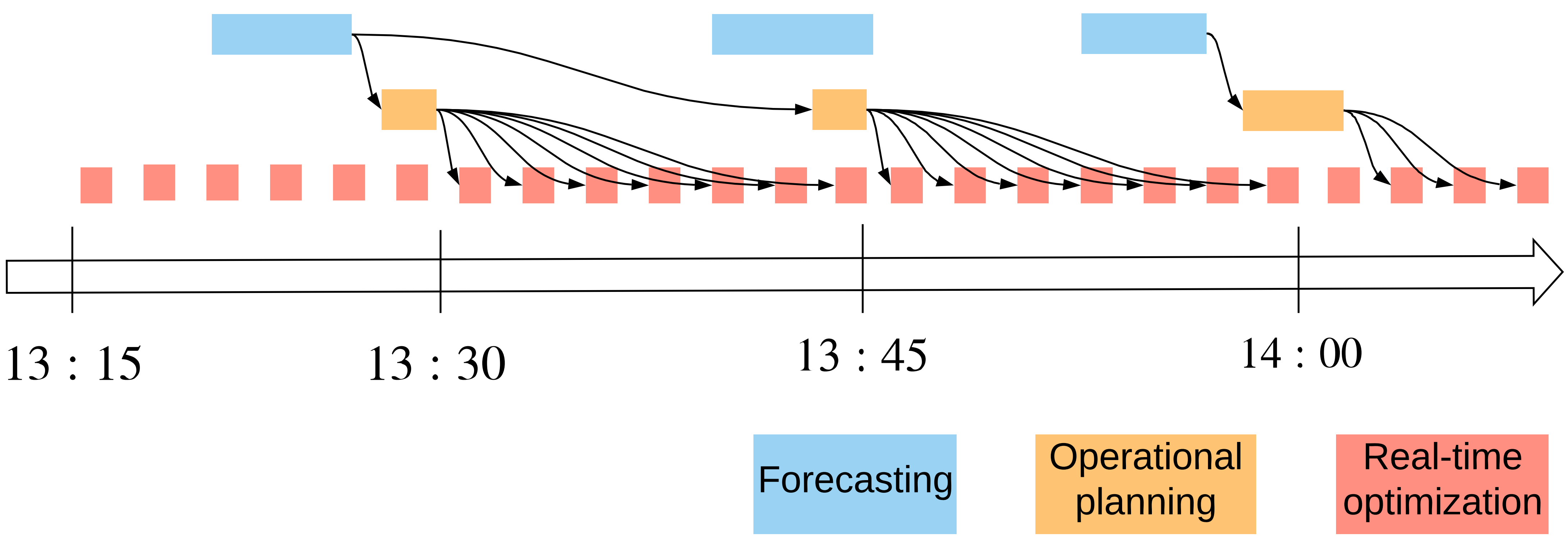


Fig. 2 Hierarchical control procedure illustration.

Proposed method: two-layers with a value function

Operational planner:

$$\mathbf{a}^{m,\star}_{\mathcal{T}^m_a(t)} = \arg\min \sum_{t' \in \mathcal{T}^m_a(t)} c^m(a^m_{t'}, s_{t'}, \hat{\omega}_{t'}) \tag{2}$$

s.t. $\forall t' \in \mathcal{T}^m_a(t),\ s_{t'+\Delta\tau} = f^m(a^m_{t'}, s_{t'}, \hat{\omega}_{t'}, \Delta\tau)$

$$s_{t'} \in S_{t'}$$

$v_t(s_{\tau(t)})$

Value function at the **end of the first** market period.

Real-time controller:

$$a^{d,\star}_t = \arg\min\ c^d(a^d_t, s_t, \hat{\omega}_t) + v_{\tau(t)}(s_{\tau(t)})$$

s.t. $s_{\tau(t)} = f^d(a^d_t, s_t, \hat{\omega}_t, \tau(t) - t) \quad (3)$

$$s_{\tau(t)} \in S_{\tau(t)}$$

Proposed method: objective function of the operational planner

Operational planner:

$$J^{OP}_{\mathcal{T}^m_a(t)} = \sum_{t' \in \mathcal{T}^m_a(t)} \left(C^{OP}_{t'} + D^{OP}_{t'} \right) \quad (4)$$

Immediate and **delayed** costs.

$$C^{OP}_{t'} = \Bigg(\sum_{d \in \mathcal{D}^{she}} \Delta_\tau \pi^{she}_{d,t'} C^{she}_{d,t'} a^{she}_{d,t'} + \sum_{d \in \mathcal{D}^{ste}} \Delta_\tau \pi^{ste}_{d,t'} C^{ste}_{d,t'} a^{ste}_{d,t'} + \sum_{d \in \mathcal{D}^{nst}} \Delta_\tau \pi^{nst}_{d,t'} C^{nst}_{d,t'} a^{nst}_{d,t'}$$

shed **demand** steered **generation** non steered **generation**

$$+ \sum_{d \in \mathcal{D}^{sto}} \Delta_\tau \gamma^{sto}_d \left(\overline{P}_d \eta^{cha}_d a^{cha}_{d,t'} + \frac{\underline{P}_d}{\eta^{dis}_d} a^{dis}_{d,t'} \right)$$

storage fee

$$- \pi^e_{t'} e^{gri}_{t'} + \pi^i_{t'} i^{gri}_{t'} \Bigg)$$

selling/purchasing energy to/from the grid

$$D^{OP}_{t'} = \pi^p \delta p_{t'} - \pi^s_{OP} r^{sym}_{t'}$$

peak cost and **symmetric reserve**

Proposed method: objective function of the real-time controller

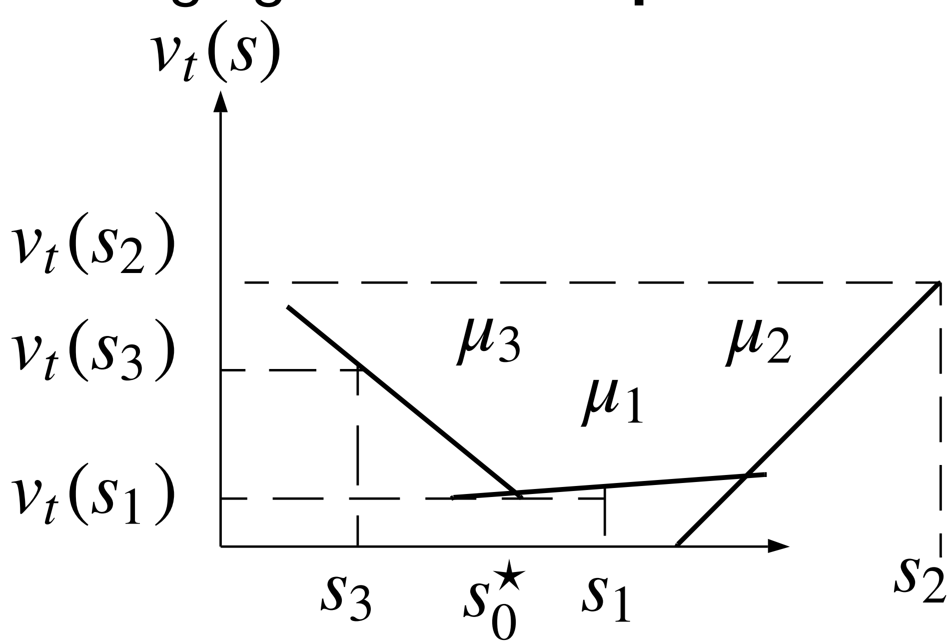
Real-time controller:

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

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:

$$s_{\tau(t)} = s_1 \quad [\mu_1] \quad \rightarrow v_{\tau(t)}(s) \geq v_{\tau(t)}(s_1) + \mu_1^T s$$

$$s_{\tau(t)} = s_2 \quad [\mu_2] \quad \rightarrow v_{\tau(t)}(s) \geq v_{\tau(t)}(s_2) + \mu_2^T s$$

$$s_{\tau(t)} = s_3 \quad [\mu_3] \quad \rightarrow v_{\tau(t)}(s) \geq v_{\tau(t)}(s_3) + \mu_3^T s$$

Fig. 3 Value function approximation illustration.

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MiRIS case study

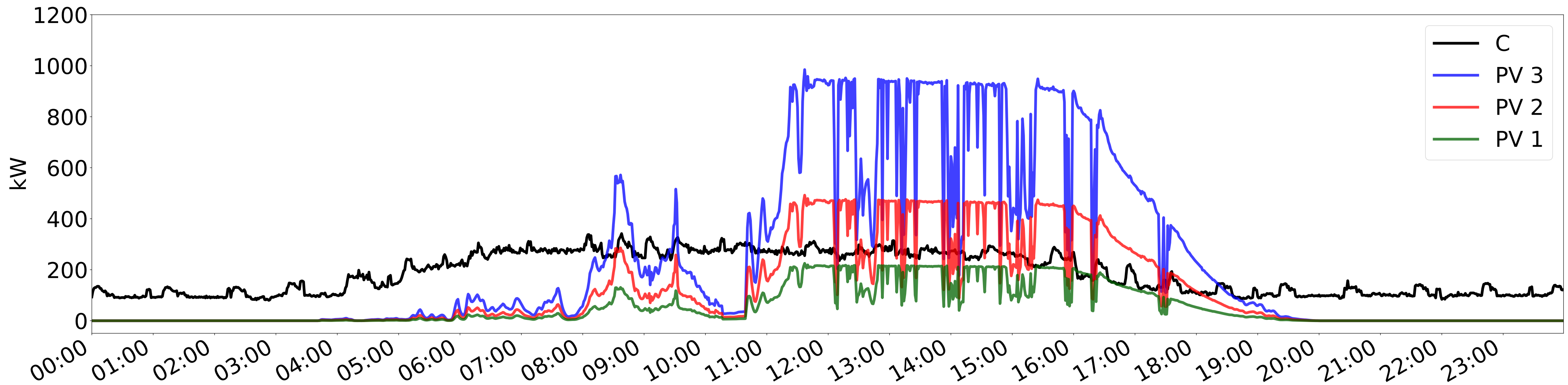

Fig. 3 PV and consumption on June 12, 2019.

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_p	$\overline{PV}$	PV_{max}	PV_{min}	PV_{std}
1	400	61	256	0	72
2	875	133	561	0	157
3	1750	267	1122	0	314
Case	C_p	$\overline{C}$	C_{max}	C_{min}	C_{std}
1 - 3	1000	153	390	68	72
Case	S_p	$\overline{S}$, $\underline{S}$	$\underline{P}$, $\overline{P}$	η^{cha}, η^{dis}	S^{init}
1 - 3	1350	1350, 0	1350, 1350	0.95, 0.95	100
Case	p_h, π^{p}	I^{cap}	E^{cap}	π^{i}_d, π^{i}_n	π^{e}
1 - 3	150, 40	1500	1500	0.2, 0.12	0.035

C = load
S = Battery

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).

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Numerical results: RTO-OP vs RBC

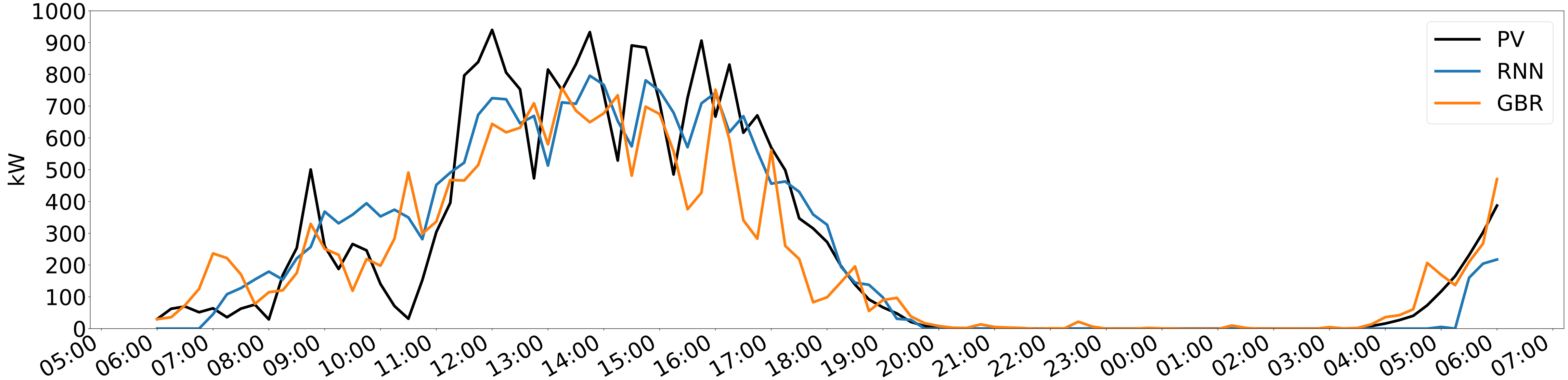

Fig. 4 Case 3 PV forecast on June 12, 2019, 06h00 UTC.

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.

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Numerical results: peak management

Table II: Results without symmetric reserve.

Case 1	c_E	c_p	c_t	Δ_p
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 2	c_E	c_p	c_t	Δ_p
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 3	c_E	c_p	c_t	Δ_p
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

c_E energy cost (k euros)

c_p peak cost (k euros)

$c_t = c_E + c_p$ total cost (k euros)

Δ_p peak power (kW)

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

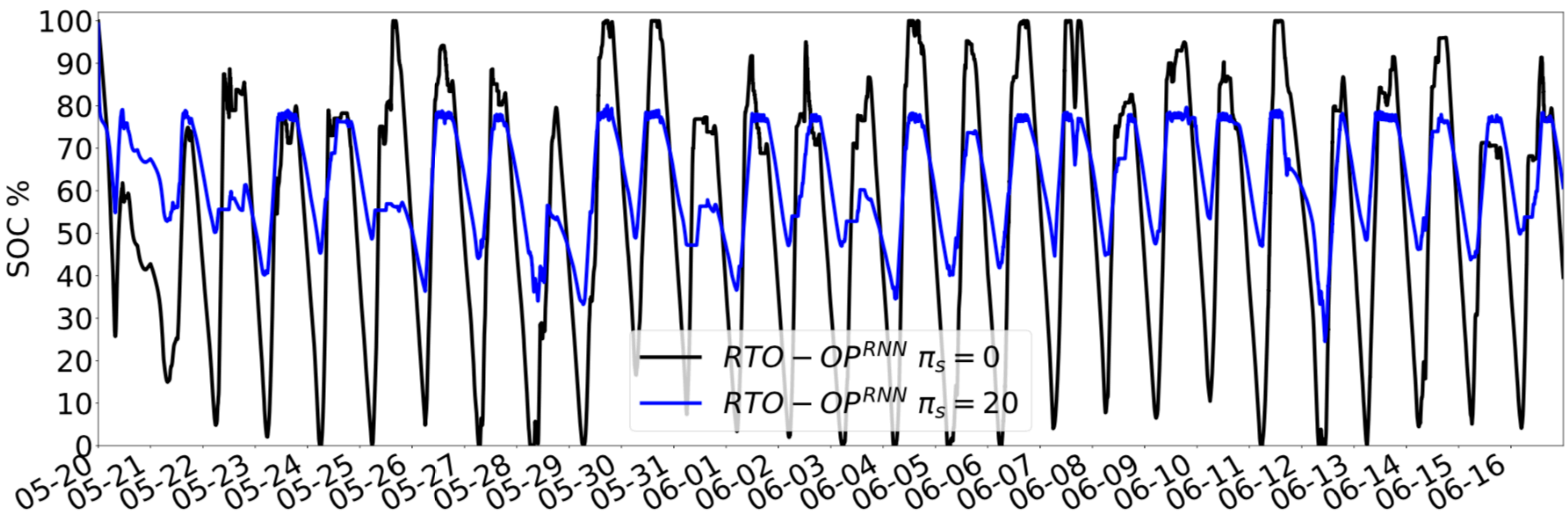

Fig. 5 Case 3 SOC comparison for RTO-OP (RNN) with and without symmetric reserve.

RTO-OP tends to **maintain a storage level** that allows to **better cope with forecast error.**

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Numerical results: peak management with symmetric reserve

Table III: Results with symmetric reserve for RTO-OP (RNN)

Case 1	c_E	c_p	c_t	Δ_p
$\pi^s = 20$	10.50	2.12	12.62	53
$\pi^s = 0$	10.37	3.62	13.99	91
Case 2	c_E	c_p	c_t	Δ_p
$\pi^s = 20$	5.33	0.04	5.37	1
$\pi^s = 0$	4.78	2.87	7.65	72
Case 3	c_E	c_p	c_t	Δ_p
$\pi^s = 20$	-0.04	0	-0.04	0
$\pi^s = 0$	-1.66	4.12	2.46	105

$c_t = c_E + c_p$

The peak power has decreased.

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.

Summary

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.

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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

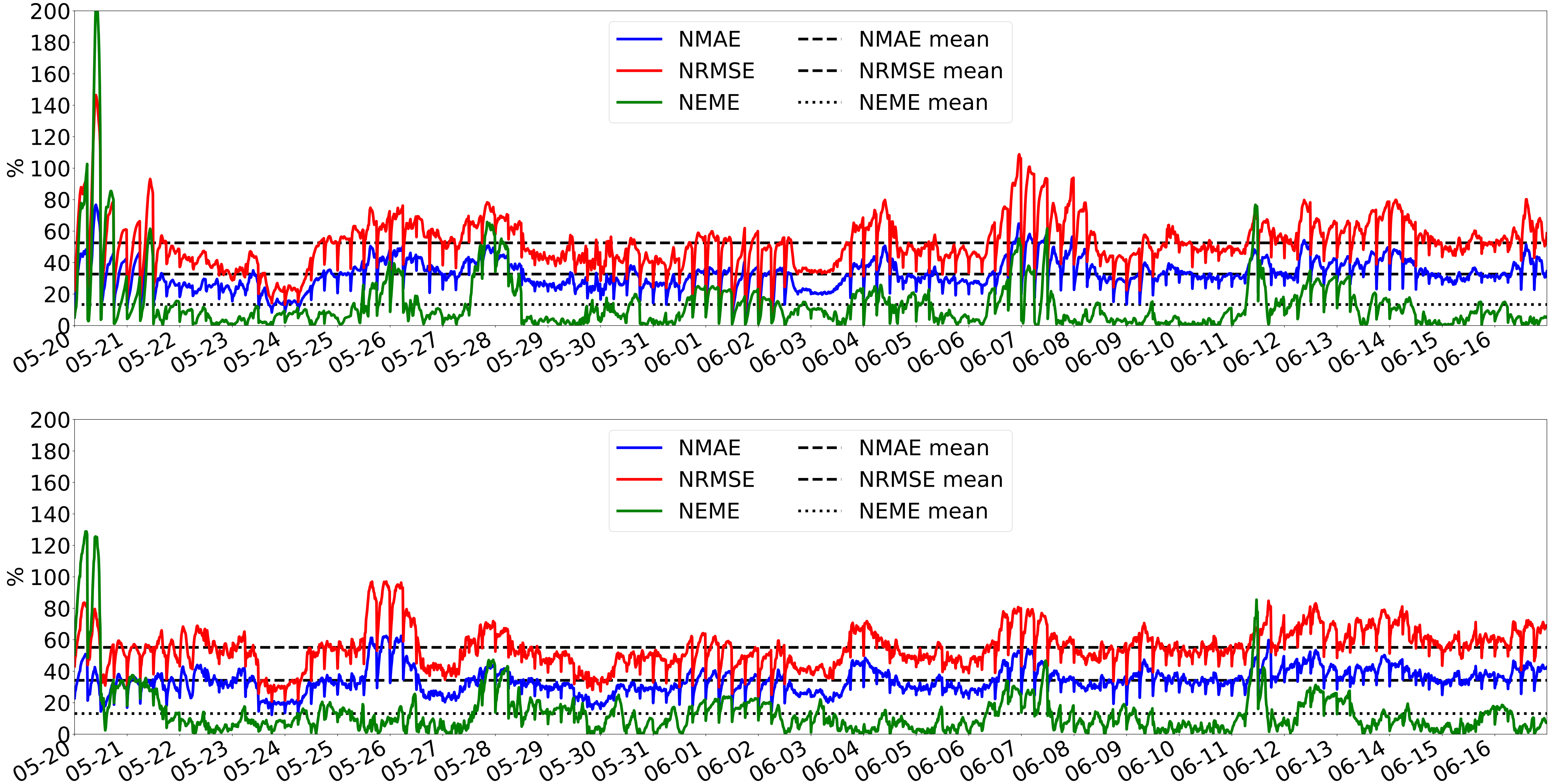

Fig. 4 PV forecast scores for GBR (top) and RNN (bottom).