Fault Tolerant MPC Design for Reliable Microgrid Energy Management

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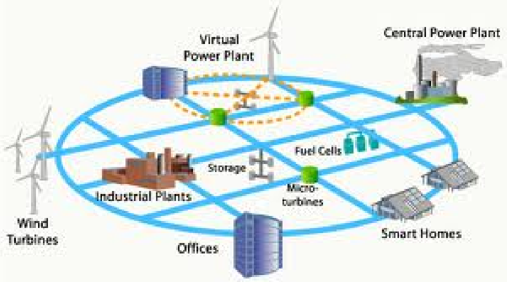
Outline

1. Motivation
2. Microgrid energy management optimization-based control problem
3. Simulation results and comparison
4. Undergoing work
5. Summary

Control of Complex Energy Systems under Vulnerabilities and Risks



Control Theory for Complex Energy Dynamical Systems

Objectives

- Complex energy dynamical systems (description & management)
- Constraint handling (internal and external influences)
- Stability & robustness (under perturbations)
- Detection and tolerance to fault events (active fault tolerant schemes)
- Centralized vs. distributed vs. decentralized control

Different approaches

- Agent-based modeling approach Weidlich and Veit (2008)
- Reinforcement learning algorithms Katiraei and Iravani (2006)
- Robust optimization Conejo et al. (2005, 2006)
- Constrained optimization-based control approaches Hooshmand et al. (2012), Parisio and Glielmo (2011), Negenborn et al. (2009), Zervas et al. (2008)

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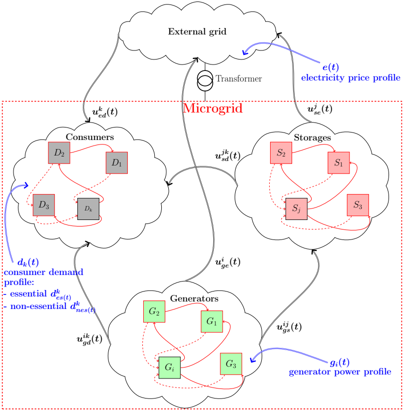
Microgrid energy management control problem formulation

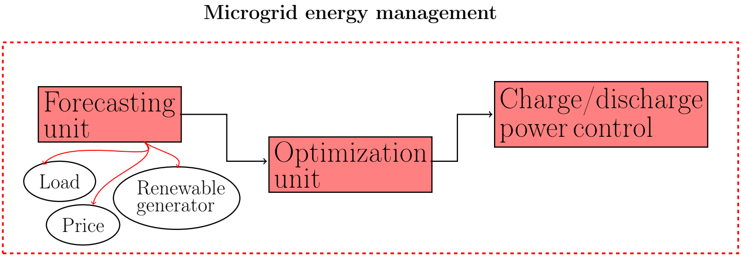


Goal: Provide an efficient management/scheduling of the microgrid system:

- minimize the energy costs (minimize buying, maximize selling);
- strengthen the microgrid system (cover essential demands at all time, handle fault events and power generation variations);
- minimize wear and tear (especially for the storage component).

Solution: Design a centralized predictive controller which takes into account constraints, uncertainties, failures and power profiles within the microgrid.

Microgrid energy management control problem formulation



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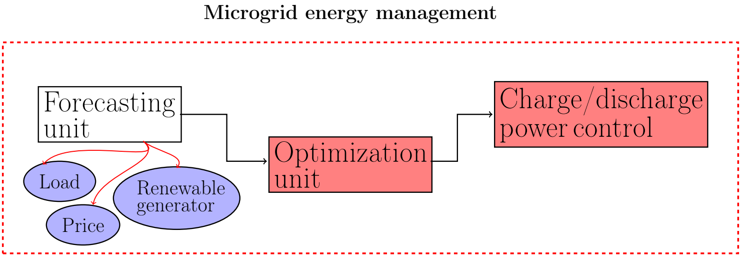

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Dynamic models of the microgrid components

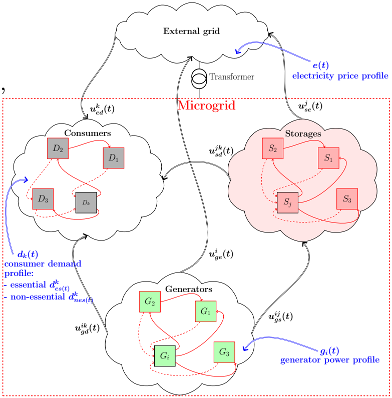
Consider the dynamic model of the electrical storage units S_j:

$$x_j(t+1) = (1-\sigma_j)x_j(t) + \sum_{M_{gs}(i,j)\neq 0} u_{gs}^{ij}(t) - \sum_{M_{sd}(i,j)\neq 0} u_{sd}^{jk}(t) - \sum_{M_{se}(j,k)\neq 0} u_{se}^{j}(t) + w_j(t),$$

with the *mixed-integer conditions*:

$$\begin{cases} 0 \leq u_{gs}^{ij}(t) \leq M\alpha_j(t), & \forall i \text{ with } M_{gs}(i,j) \neq 0, \\ 0 \leq u_{sd}^{jk}(t) \leq M(1-\alpha_j(t)), & \forall k \text{ with } M_{sd}(j,k) \neq 0, \\ 0 \leq u_{se}^{j}(t) \leq M(1-\alpha_j(t)), & \text{if } \exists j \text{ with } M_{se}(j) \neq 0, \end{cases}$$

- $x_j(t) \in \mathbb{R}$ represents the amount of energy stored in S_j at time step t;
- $\sigma_j \in \mathbb{R}^+$ is the hourly self-discharge decay;
- $w_j(t) \in \mathbb{W} \subset \mathbb{R}$ are additive disturbances affecting the level of battery charge;
- $\alpha_j(t) \in \{0,1\}$ are the auxiliary binary variables which govern the mode switching;
- $M \in \mathbb{R}$ is an appropriately chosen constant;
- $M_{ab} \in \mathbb{R}^{N_a \times N_b}$ adjacency matrix describing the links among components.



Dynamic models of the microgrid components

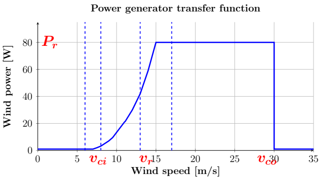
Consider the dynamic model of the electrical storage units S_j:

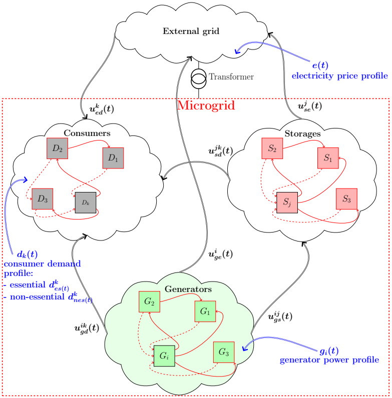
$$x_j(t+1) = (1-\sigma_j)x_j(t) + \sum_{M_{gs}(i,j)\neq 0} u_{gs}^{ij}(t) - \sum_{M_{sd}(i,j)\neq 0} u_{sd}^{jk}(t) - \sum_{M_{se}(j,k)\neq 0} u_{se}^{j}(t) + w_j(t),$$

Consider the dynamic model of the power generators G_i:

$$g_i(t+1) = f(g_i(t), v_i(t)),$$

which can be approximated with the power curve transformation Justus et al. (1976):





Constraints description within the microgrid system

At least the essential demand has to be supplied to the users:

$$d_{es}^k(t) < \sum_{M_{gd}(i,k)\neq 0} u_{gd}^{ik}(t) + \sum_{M_{sd}(j,k)\neq 0} u_{sd}^{jk}(t) + \sum_{M_{ed}(k)\neq 0} u_{ed}^{k}(t) \leq d_{es}^k(t) + d_{nes}^k(t).$$

Magnitude and variation bounds on the quantity of stored energy:

$$B_{min}^j \leq x_j(t) \leq B_{max}^j,$$

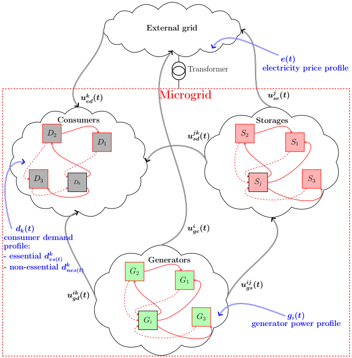
$$V_{min}^j \leq \Delta x_j(t) \leq V_{max}^j.$$

Physical limits on the energy transfer:

$$\mathbf{0} \leq \mathbf{u}(t) \leq \bar{\mathbf{u}},$$

$$\mathbf{u} = \begin{bmatrix} u_{gs}^{ij} & u_{gd}^{ik} & u_{ge}^{i} & u_{sd}^{jk} & u_{se}^{j} & u_{ed}^{k} \end{bmatrix}^T \in \mathbb{R}^{N_u}.$$

$$\bar{\mathbf{u}} = \begin{bmatrix} \bar{u}_{gs}^{ij} & \bar{u}_{gd}^{ik} & \bar{u}_{ge}^{i} & \bar{u}_{sd}^{jk} & \bar{u}_{se}^{j} & \bar{u}_{ed}^{k} \end{bmatrix}^T \in \mathbb{R}^{N_u}.$$



Limitations on the generator power outputs:

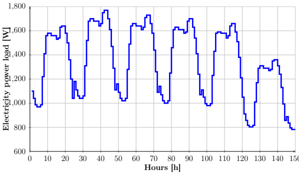
$$0 \leq \sum_{M_{gs}(i,j)\neq 0} u_{gs}^{ij}(t) + \sum_{M_{gd}(i,k)\neq 0} u_{gd}^{ik}(t) + \sum_{M_{ge}(i)\neq 0} u_{ge}^{i}(t) \leq g_i(t).$$

Reference profiles

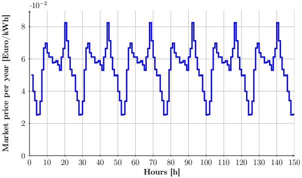
Real numerical data for power system reliability evaluation studies Grigg et al. (1999):

- Consider the nominal reference profiles:

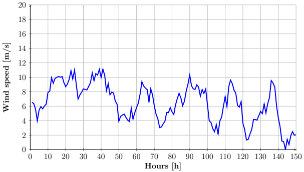
Consumer load profile $d(t)$



Electricity price profile $e(t)$

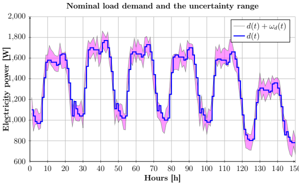


Wind speed profile $v(t)$



- Consider the real reference profiles affected by bounded disturbances:

$d(t) + \omega_d(t)$



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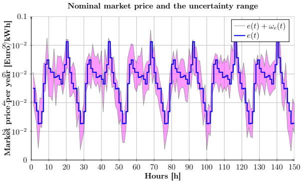

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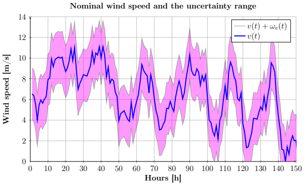

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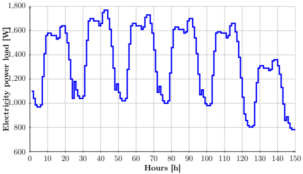

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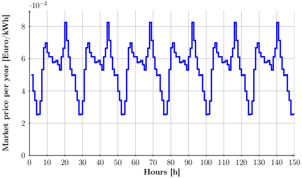

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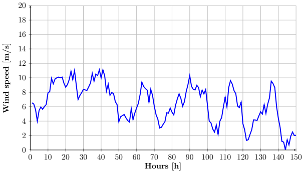

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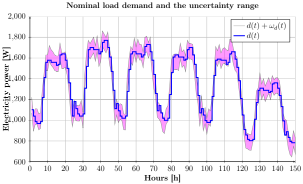

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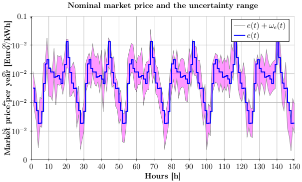
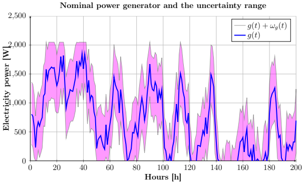


$g(t) + \omega_g(t)$



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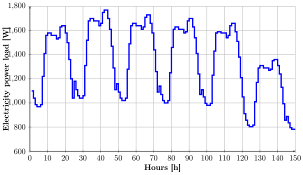

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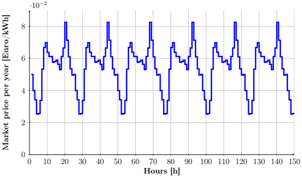

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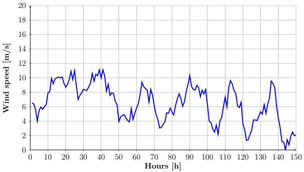

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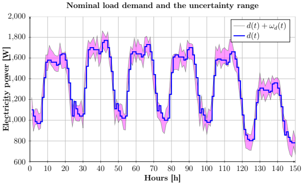

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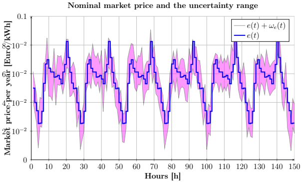

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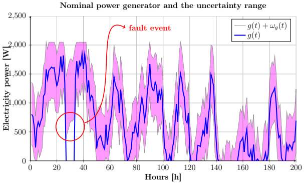
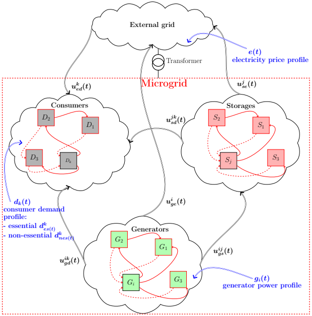


Microgrid costs



Penalize for the wear and tear cost of the storage:

$$C_s(t) = \sum_{j=1}^{N_s} (\alpha_j(t) - \alpha_j(t-1))$$

Penalize the difference between provided load and required demand:

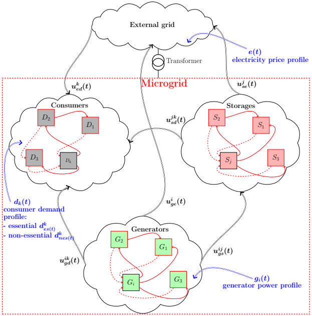
$$C_d(t) = \sum_{k=1}^{N_d} d_k(t) - \left(\sum_{M_{sd}(j,k)\neq 0} u^{jk}_{sd}(t) + \sum_{M_{gd}(i,k)\neq 0} u^{ik}_{gd}(t) + \sum_{M_{ed}(k)\neq 0} u^{k}_{ed}(t) \right)$$

Penalize buying and encourage selling electrical power:

$$C_e(t) = e(t) \cdot \left(\sum_{M_{ed}(k)\neq 0} u^{k}_{ed}(t) - \sum_{M_{ge}(i)\neq 0} u^{i}_{ge}(t) - \sum_{M_{se}(j)\neq 0} u^{j}_{se}(t) \right)$$

I. Prodan and E. Zio, (MSC'14, IJEPES'14)

Microgrid costs



Penalize for the discharging cost of the storage:

$$C_s(t) = \sum_{j=1}^{N_s} \alpha_j(t)$$

Penalize the difference between provided load and required demand:

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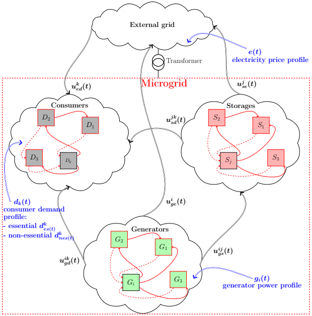

Penalize for the charging cost of the storage:

$$C_s(t) = \sum_{j=1}^{N_s} (1 - \alpha_j(t))$$

Penalize the difference between provided load and required demand:

$$C_d(t) = \sum_{k=1}^{N_d} d_k(t) - \left(\sum_{M_{sd}(j,k)\neq 0} u^{jk}_{sd}(t) + \sum_{M_{gd}(i,k)\neq 0} u^{ik}_{gd}(t) + \sum_{M_{ed}(k)\neq 0} u^{k}_{ed}(t) \right)$$

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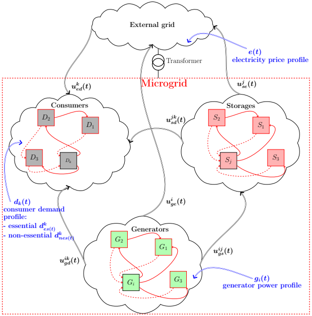

Penalize for the wear and tear cost of the storage:

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Penalize the difference between provided load and required demand:

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Constrained MILP control problem

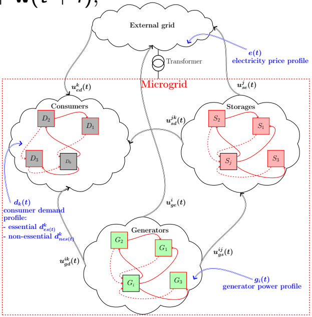
Construct an optimal control sequence $\mathbf{u} = \{u(k), u(k+1), \cdots, u(k+N_p-1)\}$ over a *finite* constrained receding horizon, with $\mathbf{u} = \begin{bmatrix} u_{gs}^{ij} & u_{gd}^{ik} & u_{ge}^{i} & u_{sd}^{jk} & u_{se}^{j} & u_{ed}^{k} \end{bmatrix} \in \mathbb{R}^{N_u}$ and $\alpha = \begin{bmatrix} \alpha_j \end{bmatrix} \in \{0,1\}^{N_s}$ the decision binary variables:

$$u^* = \arg \min_{u(t), u(t+1), \cdots, u(t+N_p-1), \alpha} \sum_{l=0}^{N_p-1} \gamma_e C_e(t+l) + \gamma_d C_d(t+l) + \gamma_b C_s(t+l),$$

subject to the set of constraints:

$$\begin{cases} \mathbf{x}(t+l+1) = \mathbf{A}\mathbf{x}(t+l) + \mathbf{B}_{ch}\mathbf{u}(t+l) + \mathbf{B}_{disch}\mathbf{u}(t+l) + \mathbf{w}(t+l), \\ \mathbf{0} \le \mathbf{B}_{ch}\mathbf{u}(t+l) \le M\alpha(t+l), \\ \mathbf{0} \le \mathbf{B}_{disch}\mathbf{u}(t+l) \le M(\mathbf{1} - \alpha(t+l)), \\ \mathbf{B}_{min} \le \mathbf{x}(t+l) \le \mathbf{B}_{max}, \\ \mathbf{V}_{min} \le \Delta\mathbf{x}(t+l) \le \mathbf{V}_{max}, \\ \mathbf{0} \le \mathbf{G}\mathbf{u}(t+l) \le \mathbf{g}(t+l), \\ \mathbf{d}_{es}(t+l) \le \mathbf{D}\mathbf{u}(t+l) \le \mathbf{d}_{es}(t+l) + \mathbf{d}_{nes}(t+l), \\ \mathbf{0} \le \mathbf{u}(t+l) \le \bar{\mathbf{u}}. \end{cases}$$

for $l = 0, \ldots, N_p - 1$.



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$$C(t+l) = (e(t+l)\mathbf{F} - \mathbf{D})\,\mathbf{u}(t+l) + \mathbf{1}^T\left(\mathbf{d}_{es}(t+l) + \mathbf{d}_{nes}(t+l)\right) + \mathbf{H}\Delta\alpha(t+l),$$

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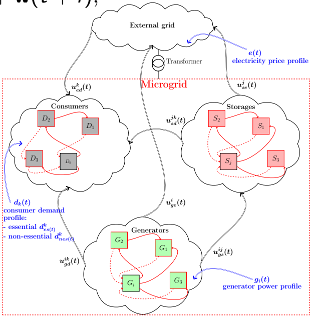
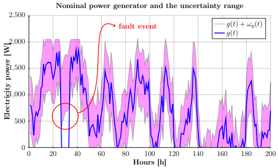


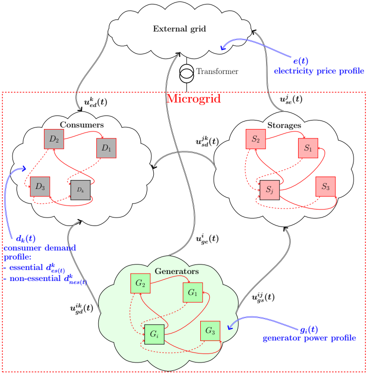
Fault tolerant control strategies

Total output failure i.e., some of the generators may fail to provide power:

$$0 \leq \mathbf{G}\mathbf{u}(t) \leq \mathbf{B}_f \mathbf{g}(t),$$

where $\mathbf{B}_f = \mathrm{diag}(\{0, 1\}^{N_g})$ characterizes the generators functioning.



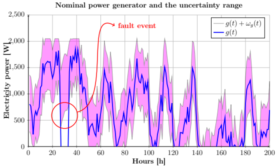


Fault tolerant control strategies

Total output failure i.e., some of the generators may fail to provide power:

$$0 \leq \mathbf{G}\mathbf{u}(t) \leq \mathbf{B}_f \mathbf{g}(t),$$

where $\mathbf{B}_f = \mathrm{diag}(\{0, 1\}^{N_g})$ characterizes the generators functioning.



Consider the following restrictive assumptions:

- the microgrid fulfills only the essential demands;
- the remaining healthy generators do not sell power to the external grid ($u^i_{ge}(t) = 0$);
- the external grid gives the maximum amount of power to the user ($u^k_{ed}(t) = \overline{u}^k_{ed}$).

I. Prodan, F. Stoican, E. Zio, (Energy'15)

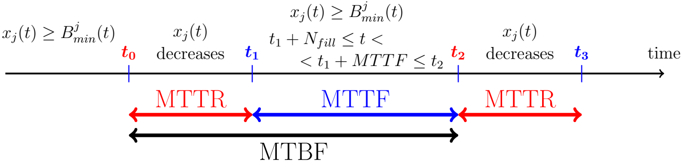
Fault tolerant control strategies - electrical storage capacity bounds

The FTC scheme implements an adaptive control which modifies minimal storage bounds B_{min} w.r.t. the fault events:

- healthy functioning (fault tolerance and cost minimization ensured):

$$\mathbf{B}_{h,min} = \min_{\mathbf{B}_{h,min}} \mathbf{B}_{min}\mathbf{1}^T,$$

$$\text{s.t} \begin{cases} \sum\limits_{M_{sd}(j,k)\neq 0} B^j_{min}(t) \geq \sum\limits_{\tau=t}^{t+MTTR_i-1} \max\left[0, d^k_{es}(\tau) - \overline{u}^k_{ed} - \sum\limits_{M_{gd}(i,k)\neq 0, \mathbf{B}_f(i,i)\neq 0} u^{ik}_{gd}(\tau)\right], \\ \sum\limits_{k=1}^{N_d} u^{ik}_{gd}(\tau) = g_i(\tau), \quad \mathbf{B}_f(i,i) \neq 0, \quad \tau = t \dots t + MTTR_i - 1, \\ \mathbf{0} \leq \mathbf{B_{min}} \leq \mathbf{B_{max}}, \qquad \text{where } \mathbf{B}_{h,min} = \left[B^1_{h,min} \dots B^{N_s}_{h,min}\right]. \end{cases}$$



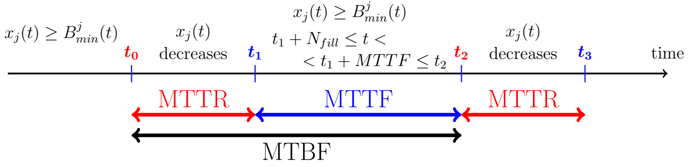
Fault tolerant control strategies - electrical storage capacity bounds

The FTC scheme implements an adaptive control which modifies minimal storage bounds B_{min} w.r.t. the fault events:

- faulty functioning (essential demands satisfied, degraded performance):

  $\mathbf{B}_{f,min} = \mathbf{0}$.

  Enforce only $\mathbf{B}_{min} = (1 - DoD)\mathbf{B}_{max}$ for the interval $MTTR$.



Fault tolerant control strategies - electrical storage capacity bounds

The FTC scheme implements an adaptive control which modifies minimal storage bounds B_{min} w.r.t. the fault events:

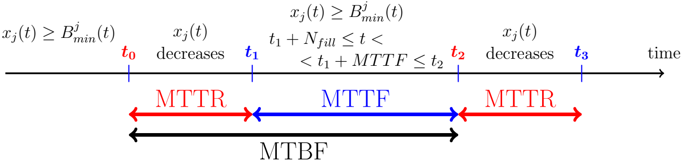
- "nominal after fault" functioning (gradual increase of storage bounds towards the safe values):

$$\mathbf{B}_{r,min}(\tau) = \mathbf{B}_{min}(t_1) + \frac{\tau - t_1}{N_{fill}}(\mathbf{B}_{h,min}(t_1 + N_{fill}) - \mathbf{B}_{min}(t_1)),$$

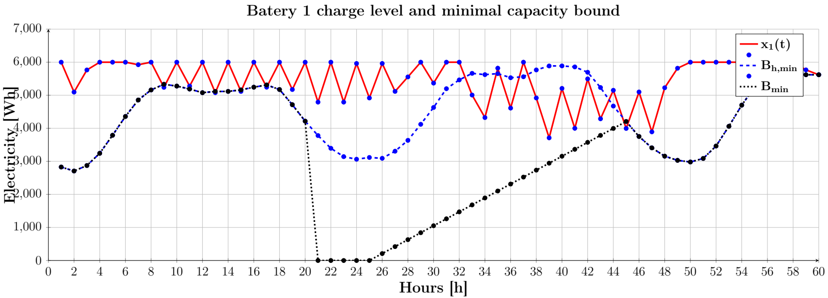
where N_{fill} represents a feasible recharging interval obtained by solving a minimal time problem:

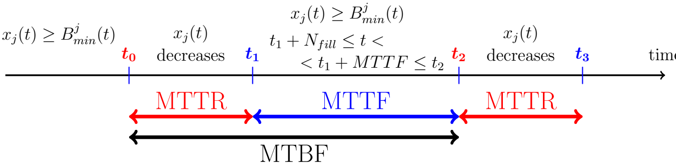
$$N_{fill} = \min\ \tau$$

$$\text{s.t} \begin{cases} \mathbf{x}(t_1+\tau) \geq \mathbf{B}_{h,min}(t_1+\tau),\ \forall j = 1,\ldots,N_s, \\ \text{dynamical model of the microgrid system and} \\ \text{physical constraints are verified for } \ t = t_1,\ldots,t_1+\tau. \end{cases}$$



Fault tolerant control strategies - example

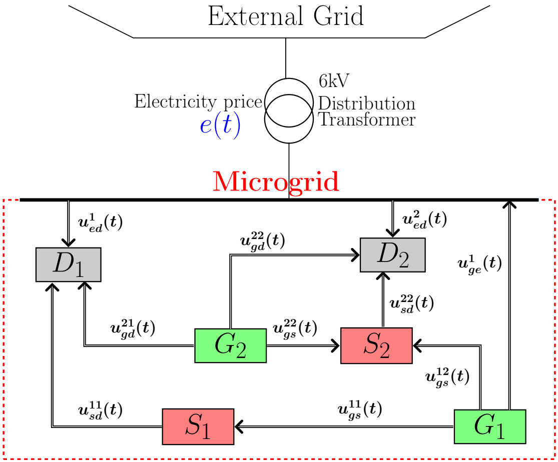




Outline

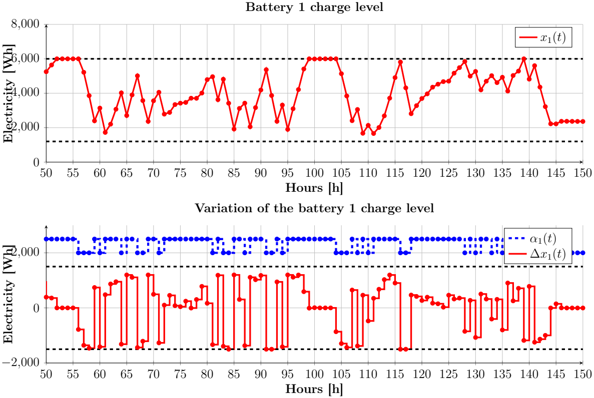
Simulation results

Consider the microgrid system with numerical data of a test system (IEEE RTS–96) developed for bulk power system reliability evaluation studies Grigg et al. (1999).



Simulation results

Battery load and power signals are shown along the simulation horizon (i.e., 100 hours) for pre-known consumer, electricity price, generator power profiles and $N_p = 5$:



- Battery load and charge constraints are verified.

$$\sigma = 13 \cdot 10^{-4}, \qquad B^1_{min} = 12 \cdot 10^2 \ [Wh], \qquad V^1_{min} = -1.5 \cdot 10^3 \ [Wh],$$

$$M = 9 \cdot 10^3, \qquad B^1_{max} = 6 \cdot 10^3 \ [Wh], \qquad V^1_{max} = 1.5 \cdot 10^3 \ [Wh].$$

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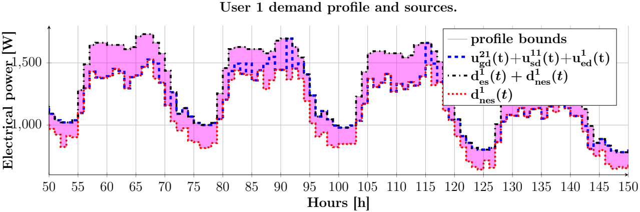
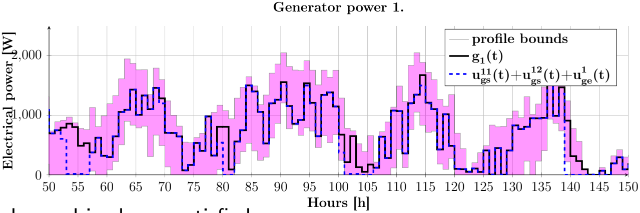
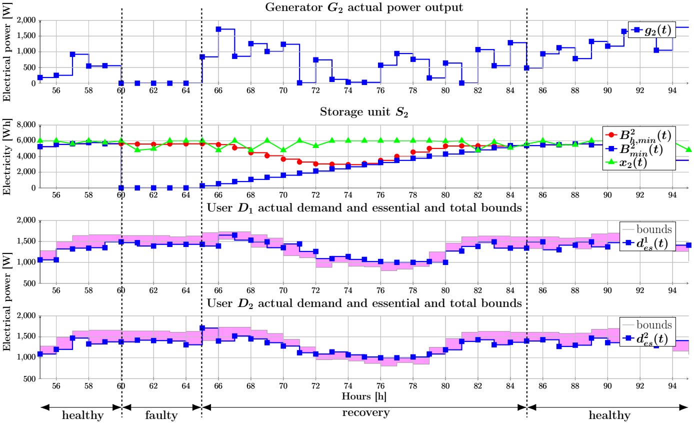




- Consumer demand is always satisfied.
- Generator power stays within a tube around the nominal curve.

Simulation results

Battery load and power signals are shown along the simulation horizon (i.e., 100 hours) for pre-known consumer, electricity price, generator power profiles and $N_p = 5$:



- Storage values and minimal bound for the first storage unit under a fault event affecting the second generator, G_2 during the interval [60, 65] hours.
  $MTTF = 5$ hours, $N_{fill} = MTTR = 20$ hours.

Comparison results

Compare the proposed MPC algorithm with a reinforcement learning algorithm on medium-term (2 steps-ahead) scenarios as in Kuznetsova et al. (2013):

$$V_0 = \frac{\sum_{t=0}^{s_{max}} b_c(t)}{\sum_{t=0}^{s_{max}} d(t)} \qquad V_1 = \frac{\sum_{t=0}^{s_{max}} g_b(t)}{\sum_{t=0}^{s_{max}} g(t)} \qquad E = \left(\sum_{t=0}^{s_{max}} d(t) - \sum_{t=0}^{s_{max}} b_c(t) \right) e(t)$$

Values of the performance indicators over a year long simulation

Values of the performance indicators obtained in (Kuznetsova et al., 2013) with a reinforcement learning algorithm					
V_0		V_1		E	
Minimal	Maximal	Minimal	Maximal	Minimal	Maximal
0.102	0.109	0.176	0.186	$2.863 \cdot 10^7$	$2.890 \cdot 10^7$
Values of the performance indicators obtained with the proposed MPC algorithm					
0.196		0.389		$1.807 \cdot 10^6$	

Advantages of the MPC algorithm

- Performs noticeably better in what regards the criteria V_0, V_1, E.
- Has a variable prediction horizon which allows for increasingly optimal input values.
- It is relatively easy to add constraints regardless of their nature (convex or non-convex).

Comparison results

Compare the proposed MPC algorithm with a reinforcement learning algorithm on medium-term (2 steps-ahead) scenarios as in Kuznetsova et al. (2013):

$V_0 \rightarrow$ ratio of the cumulative power taken from the battery to the yearly cumulative load.

$V_1 \rightarrow$ ratio of the yearly cumulative power taken from the wind generator to the yearly cumulative available wind power output.

$E \rightarrow$ cumulative annual expenses for power purchases from the external grid.

Values of the performance indicators over a year long simulation

Values of the performance indicators obtained in (Kuznetsova et al., 2013) with a reinforcement learning algorithm					
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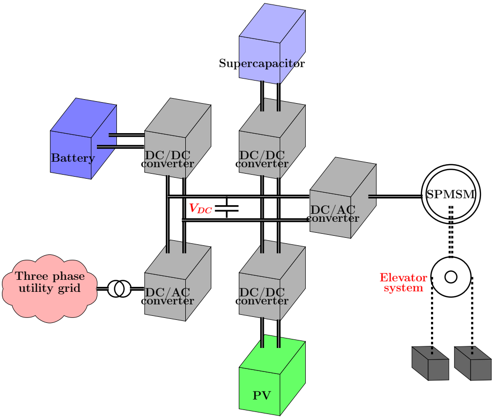
Outline

Undergoing work

Extension of the proposed optimization-based control approach for DC microgrid elevator system T.H. Pham, I. Prodan, L. Lefèvre (ICSTCC'15).



Solution: Load balancing DC microgrid elevator system using a coherent combination between

- port-Hamiltonian approach for physical system modeling,
- differential flatness for profiles generation,
- predictive control for taking into account constraints, optimization costs and reference profiles.

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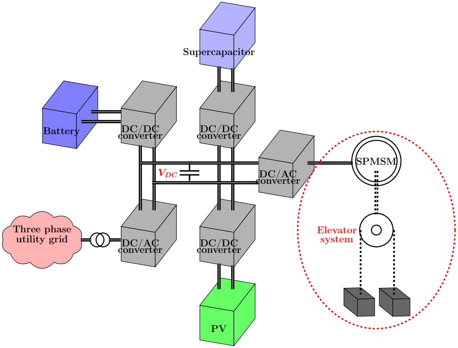
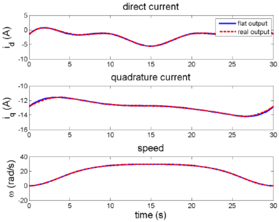


- provide a speed profile for the elevator system so that the dissipated energy is minimized.



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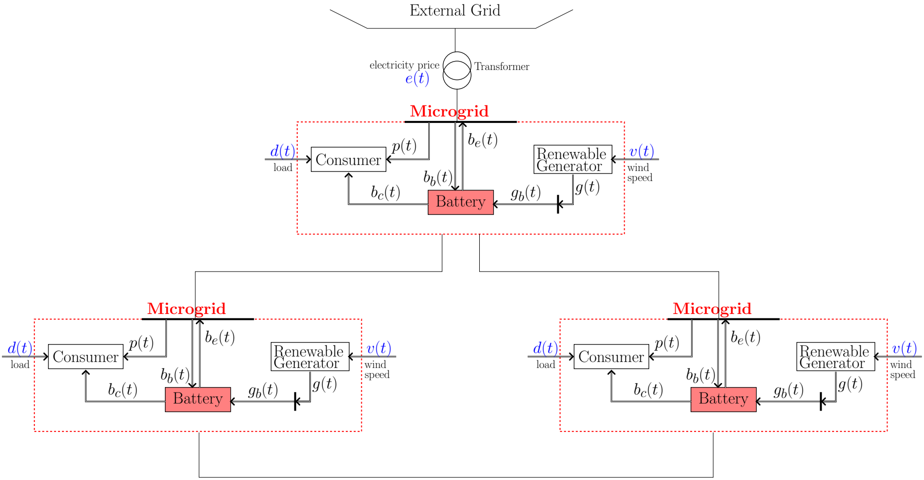
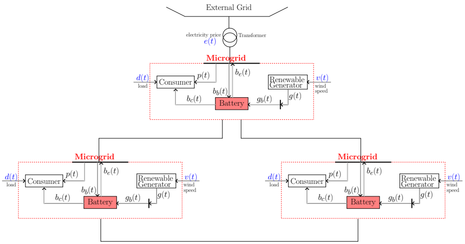
Undergoing work

What are the challenges in the design, control and management of interconnected microgrid energy systems?



Interconnected microgrid systems

Goal: Ensure load balancing within the global energy system.



Open issues

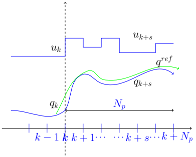
- take into account transmission costs;
- analyze the importance of the dependency links between the systems;
- integrate mixed-integer techniques to efficiently describe on/off states and operating modes of different components added to the grid;
- develop efficient decentralized, distributed and/or hierarchical strategies which will establish optimal operation of electrical storage units;
- account for slow and fast time scale behavior when formulating the dynamic scheduling problem;
- study and design fault tolerant control strategies which take into account the topology of the system.

Outline

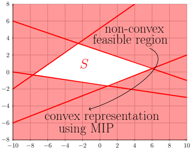
Summary

- Model Predictive Control and fault tolerant design for reliable microgrid energy management.
- Mixed-integer Linear Programming for electrical storage scheduling.
- Essential and non-essential user demand satisfaction.
- Constraint and control reconfiguration for fault mitigation.

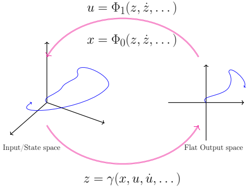
Model Predictive Control (MPC)
Rawlings and Mayne (2011)



Mixed-Integer Programming (MIP)
Jünger et al. (2009)



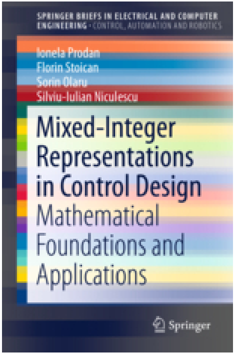
Flatness for profile generation
Fliess et al. (1995)



Summary

SpringerBriefs in Control, Automation and Robotics (2016)

I. Prodan, F. Stoican, S. Olaru, S.-I. Niculescu: Mixed-Integer Representations in Control Design. Mathematical Foundations and Applications.
http://www.springer.com/in/book/9783319269931



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