

# Control of microgrids integrating renewable energy and hybrid storage

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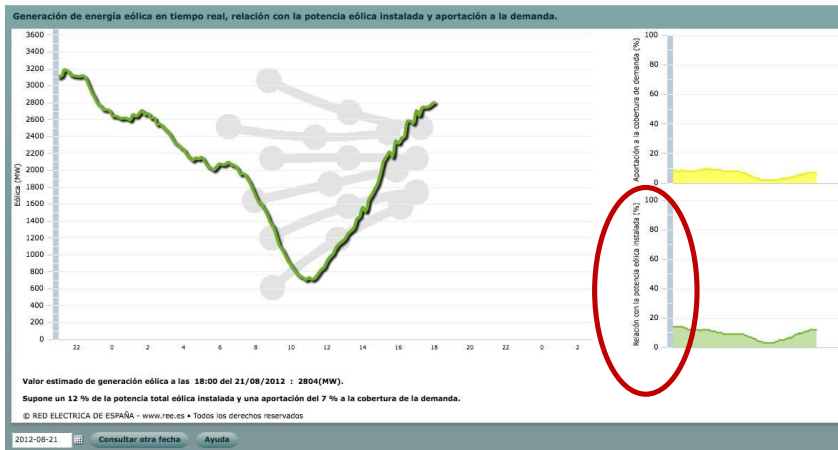
*With the collaboration of Paulo Mendes, Luis Valverde,  
Félix García-Torres and Pablo Velarde*



- Energy Management in microgrids with **renewable sources** (solar, wind) and **hybrid storage (H<sub>2</sub>)**
- Control issues in Model Predictive Control framework
- Control objectives: durability, economic profit, etc.
- Consideration of Disturbances
- Electric Vehicles
- Interconnection of microgrids
- Illustrated on a demonstration microgrid

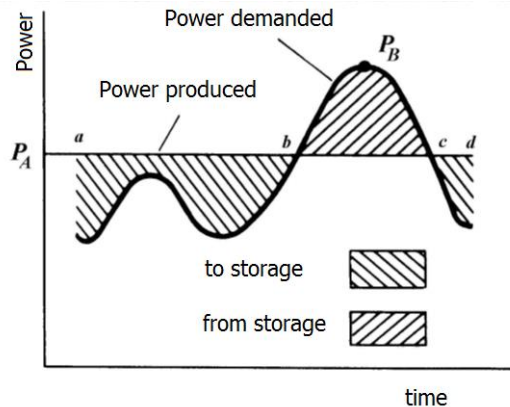
## 1. Introduction

2. Energy Management in Microgrids
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5. Integration of Electric Vehicles
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Solar/Wind energy generation:

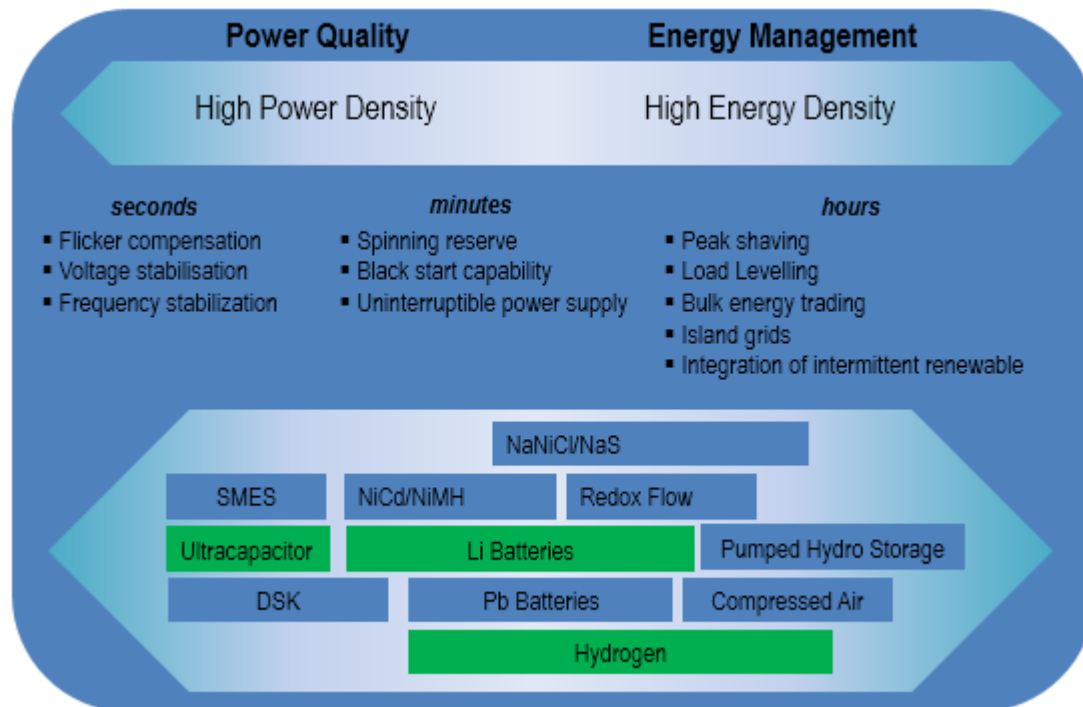
- Highly time-varying
- Differs from the installed



**Energy storage** must become an integral element of the renewable adoption strategy

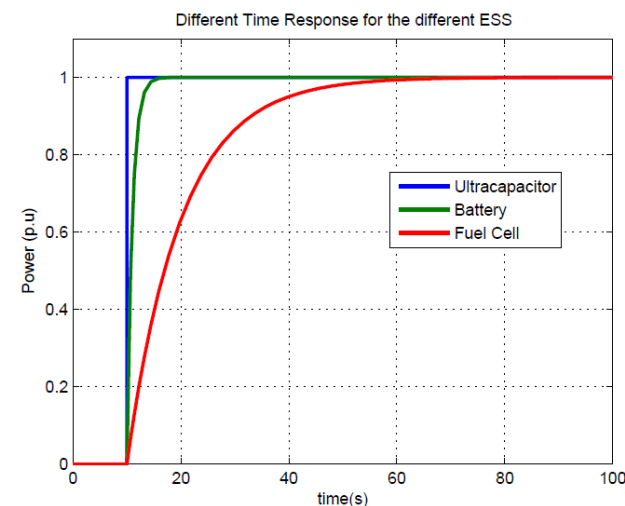
Storage allows a non-dispatchable generator (RES) to be **dispatchable**

Storage must be operated in an optimal way



Different dynamics-Complementary

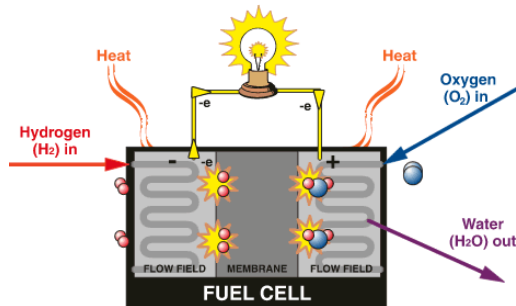
Cover a range of time scales



Need for  
hybridization:  
**Management**

# Hydrogen-based Energy Systems (HBES)

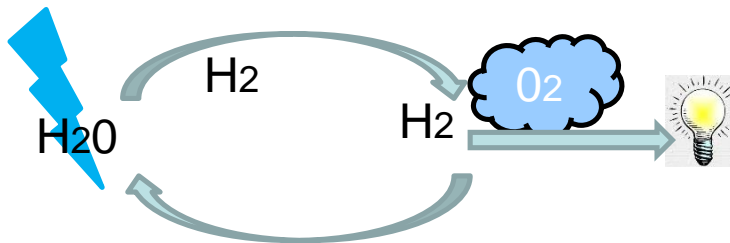
Hydrogen can be an option: **high energy density** and **high power density**



Also for FCHVs: Toyota Mirai



 **“The Green Hydrogen Cycle”**



**Distributed and mobile storage**

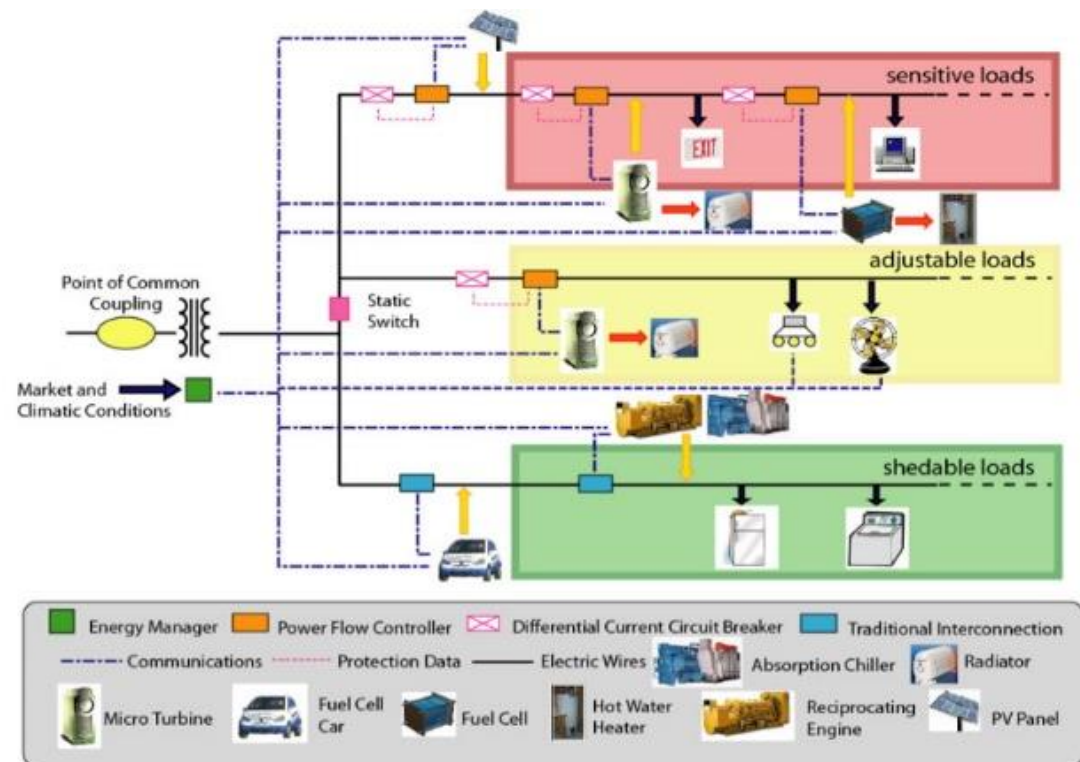
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Main objective: supply the energy demanded by the loads using DGs and DS in an efficient and reliable way. Both in normal conditions and in contingency, independently of the main grid

- Supply and demand **balancing**
- Power **quality**: avoid variations as harmonic distortion or sudden events as interruptions or even voltage dips.
- In isolated mode: **Voltage** and **frequency** management
- Economic benefit

Adjust the **manipulated units** in the proper way (generators, storage and loads)

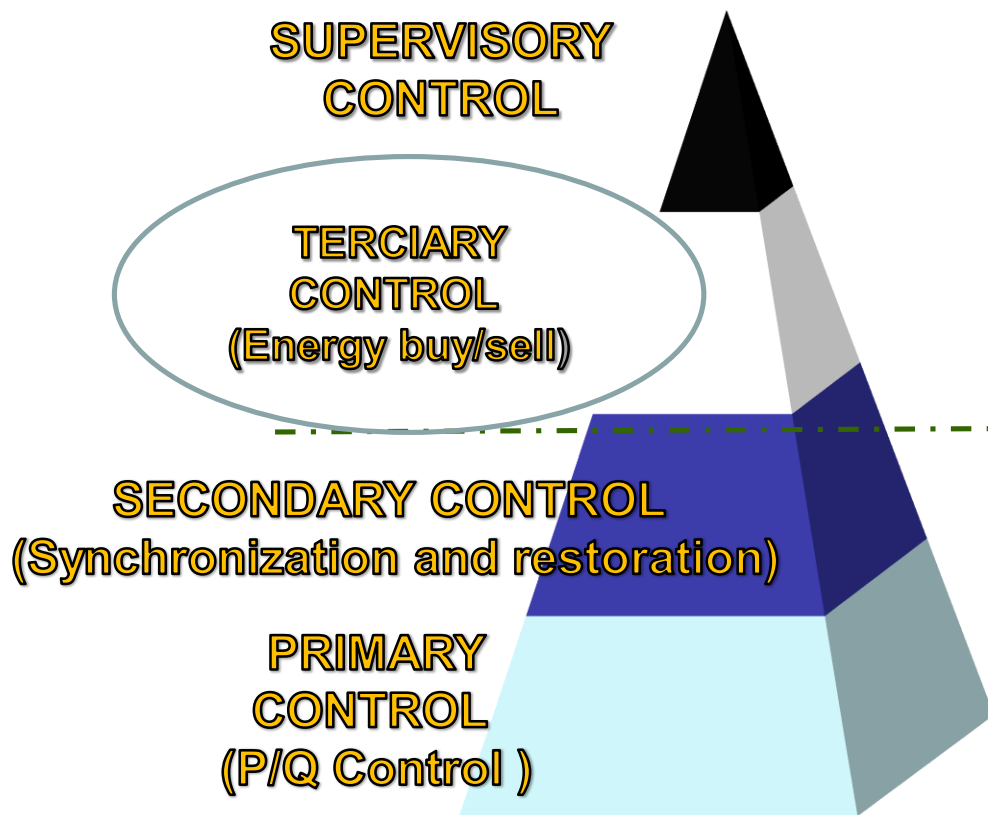


F Katiraei, R Iravani, N Hatziargyriou, A Dimeas. Microgrids management. IEEE power and energy magazine 6 (3), 2008.

Bidram, A., Lewis, F. L., Davoudi, A. Distributed control systems for small-scale power networks. IEEE Control Systems Magazine 34 (6), 56–77. 2014.

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## Energy management

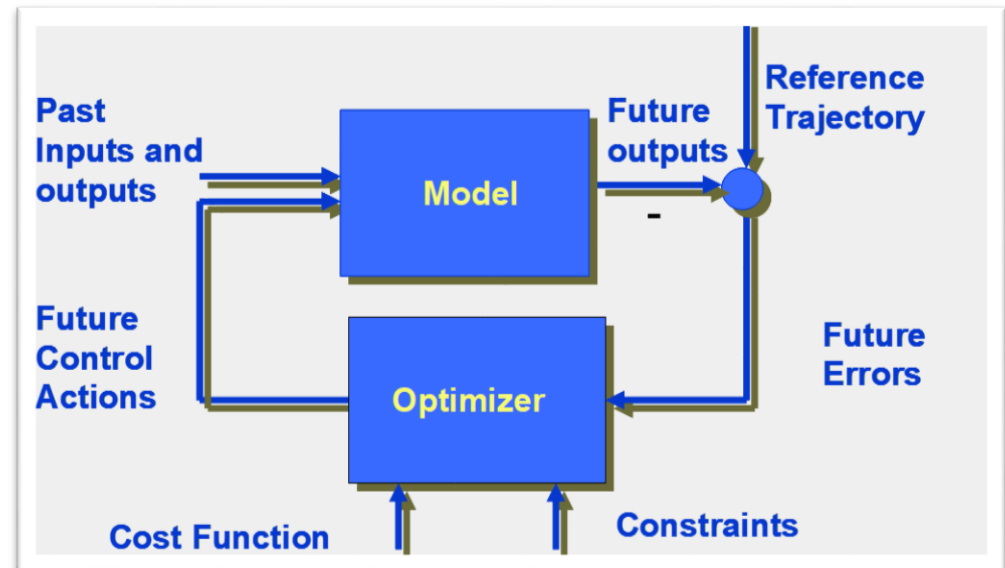
- Hysteresis (Ulleberg, 2003), (Ghosh, 2003), (Ipsakis, 2008)
- GA (Dufo-López, 2007)
- Fuzzy (Bilodeau, 2006), (Stewart, 2009)
- MPC (Korpäs, 2007) (Del Real, 2007), (Valverde, 2013), (De Angelis, 2013), (García, 2015)

## Power Quality

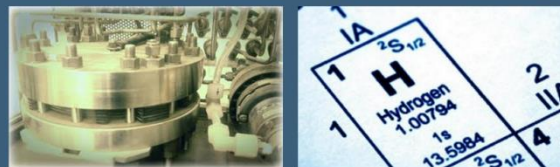
- Droop Control (Vázquez 2009), (Vadak 2011)
- $H_\infty$  (Zhong 2006)
- MPC (Rodríguez 2007)

The use of MPC technique allows to **maximize** the economical benefit of the microgrid, **minimizing** the degradation causes of each storage system, fulfilling **constraints** (operational or imposed)

Optimization over a future receding horizon using a dynamic model of the plant



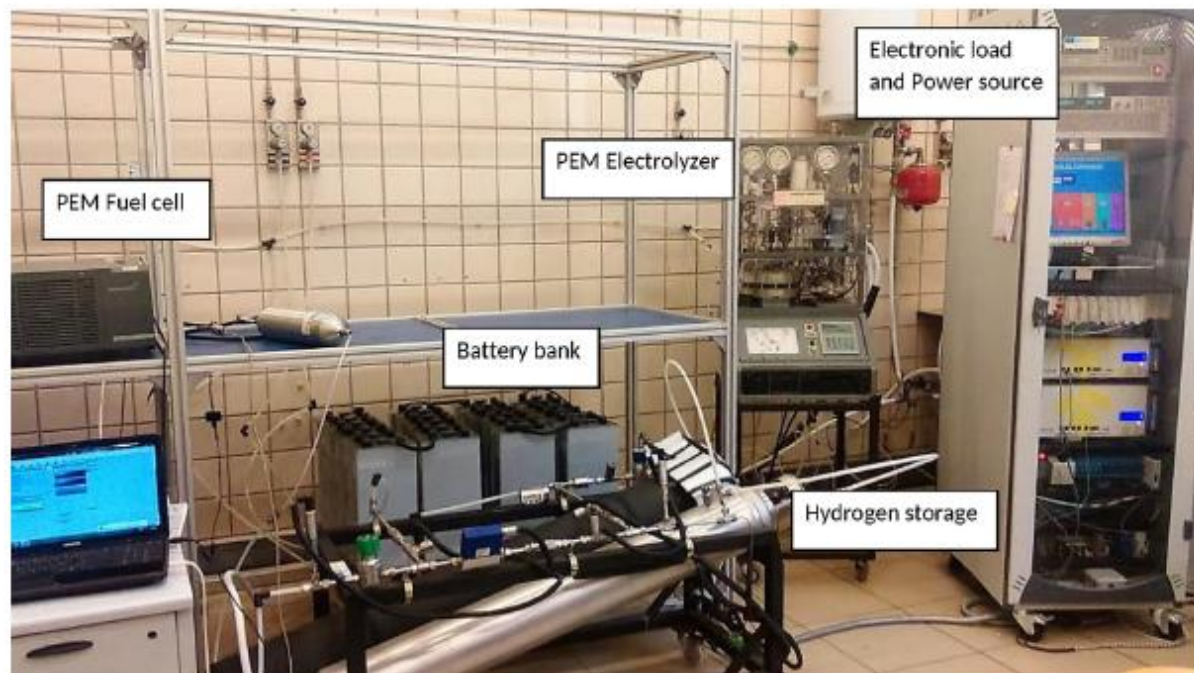
HYLAB (Hydrogen and control research Lab)

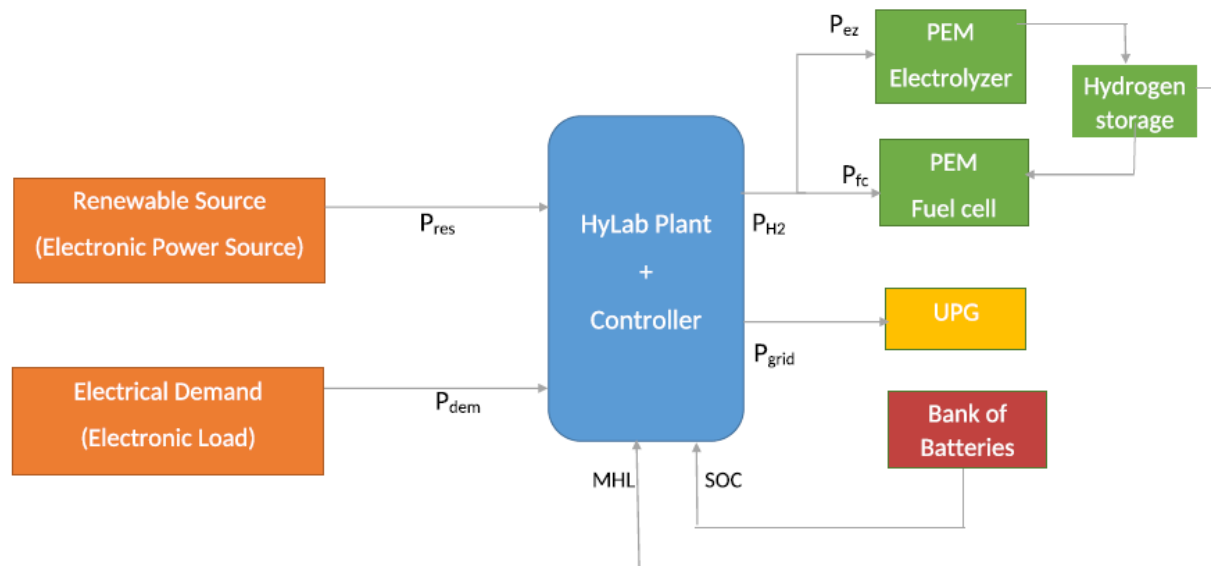


<https://sites.google.com/site/laboratorioh2/>



## DC microgrid. Seville





Disturbances

Power in the battery bank:

$$P_{bat} = P_{gen} - P_{dem} + P_{fc} - P_{ez} + P_{grid} + P_{net}$$

Must be 0 to  
balance power



**MPC States:**  
Battery SOC  
Metal Hydride Level

**MPC:**  
Constraints  
Cost function  
minimization

**MPC outputs (MVs):**  
FC Power  
ELZ Power  
Grid Power

The behavior of the MPC is defined by the **cost function**

(Objective)

**3 weighted objectives**

- ☐ Power balance with prioritization
- ☐ Protect equipment from intensive use
- ☐ Keep storage levels (H2 and electricity)

The first group of weighting factors controls priority (based on costs)

$$J = \sum_{k=1}^{Nu} \alpha_1 P_{fc(t+k)}^2 + \alpha_2 P_{ez(t+k)}^2 + \alpha_3 P_{grid(t+k)}^2 + \alpha_4 P_{net(t+k)}^2 +$$

$$+ \beta_1 \Delta P_{fc(t+k)}^2 + \beta_2 \Delta P_{ez(t+k)}^2 + \beta_3 \Delta P_{grid(t+k)}^2 + \beta_4 \Delta P_{net(t+k)}^2 +$$

$$+ \sum_{k=1}^N \gamma_1 (SOC_{(t+k)} - SOC_{ref})^2 + \gamma_2 (MHL_{(t+k)} - MHL_{ref})^2$$

The second group ( $\beta$ ) is set to protect the equipment from intensive use (soft constraints)

The  $\gamma$  group penalizes the error in reference tracking in order to give flexibility to the plant operation

Different set of parameters for different objectives (or operating conditions: sunny, cloudy, etc.)

**Constraints:** power and power rates limits. Storage limits

$$P_{ez,min} = 100W \leq P_{ez} \leq 900W = P_{ez,max}$$

$$P_{fc,min} = 100W \leq P_{fc} \leq 900W = P_{fc,max}$$

$$P_{grid,min} = -2500kW \leq P_{grid} \leq 6kW = P_{grid,max}$$

$$P_{net,min} = -2500 W \leq P_{net} \leq 6 kW = P_{net,max}$$

$$\Delta P_{fc,min} = -20 W / s \leq \Delta P_{fc} \leq 20 W / s = \Delta P_{fc,max}$$

$$\Delta P_{fc,min} = -20 W / s \leq \Delta P_{fc} \leq 20 W / s = \Delta P_{fc,max}$$

$$\Delta P_{net,min} = -2500 W / s \leq \Delta P_{net} \leq 6000 W / s = \Delta P_{net,max}$$

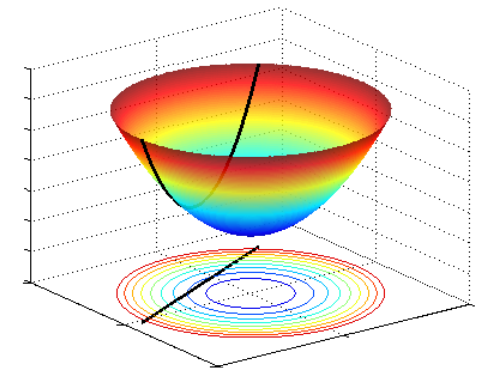
$$\Delta P_{grid,min} = -1000 W / s \leq \Delta P_{grid} \leq 1000 W / s = \Delta P_{grid,max}$$

$$SOC_{min} = 40 \% \leq SOC \leq 75 \% = SOC_{max}$$

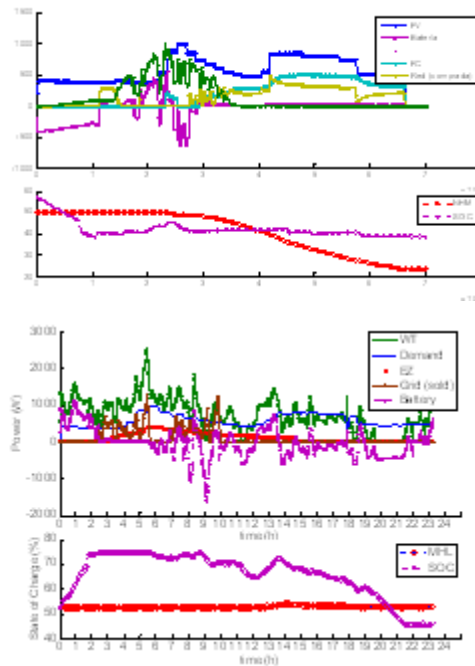
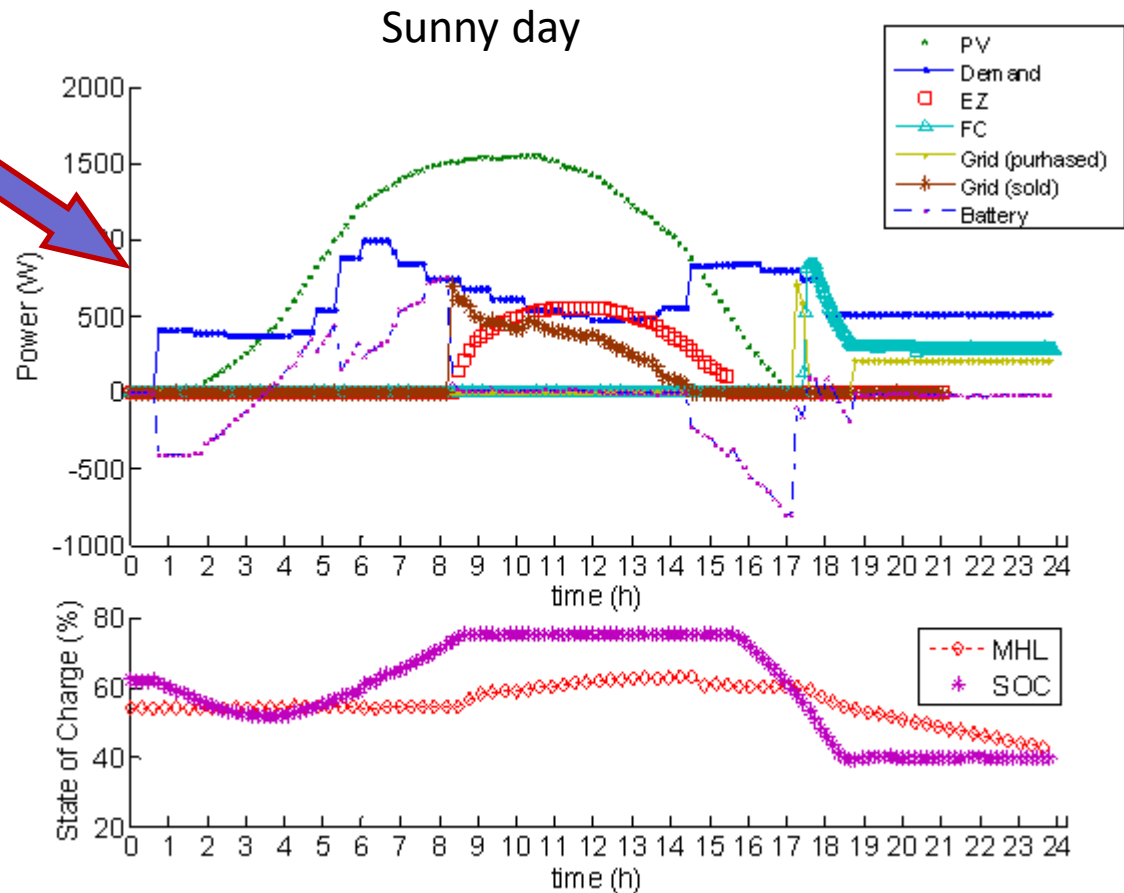
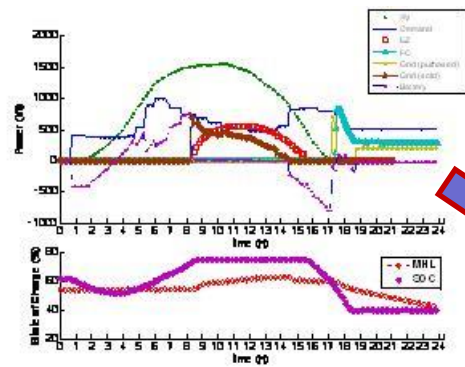
$$MHL_{min} = 10 \% \leq MHL \leq 90 \% = MHL_{max}$$

Matlab/Simulink → PLC  
Real-Time control

Quadratic cost  
function+ linear  
constraints: Quadratic  
Programming (QP)









Improved performance over heuristic control (HB): Fewer start-up/shut downs, smooth power references to units. But

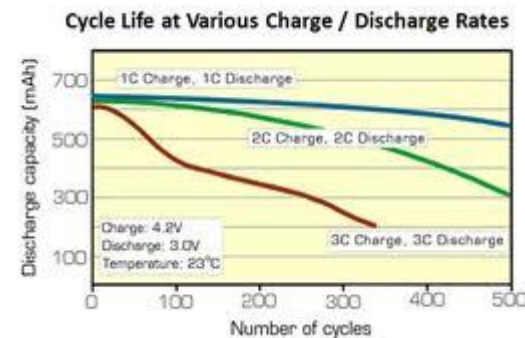
### Issues not addressed:

- **Durability** of storage devices. Facilitated by constraints (smooth operation), but not imposed
- Different **efficiencies** for charge/discharge
- Forecast of demand/generation (RES). **Uncertainties**
- Different **prices** sale/purchase (quantify). Market

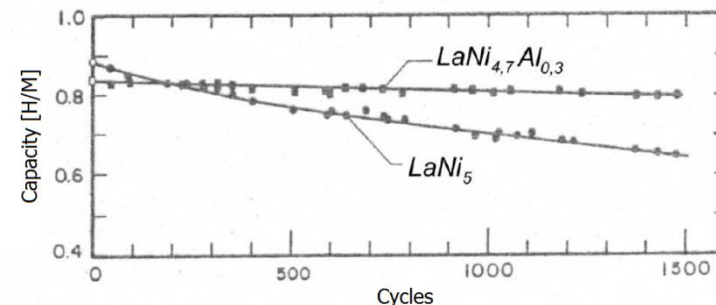
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- Durability is an important issue in ESS
- Batteries: Manufacturers of batteries quantify the life of this ESS as a function of the number of the charge and discharge cycles.  
Ultracapacitor: similar.
- Can be included in the cost function:

$$J_{bat} = \sum_{h_i=1}^{24} \left( \frac{CC_{bat}}{2 \cdot Cycles_{bat}} P_{bat,ch}(h_i) \cdot T_s \cdot \eta_{bat,ch} \right. \\ \left. + Cost_{degr,ch} \cdot P_{bat,ch}^2(h_i) \right. \\ \left. + \frac{CC_{bat}}{2 \cdot Cycles_{bat}} \frac{P_{bat,dis}(h_i) \cdot T_s}{\eta_{dis,bat}} \right. \\ \left. + Cost_{degr,dis} \cdot P_{bat,dis}^2(h_i) \right)$$



Metal hydride storage



Energy Storage System	Degradation Issues
Ultracapacitors	Overcharge, Undercharge
Batteries	Overcharge, Undercharge High stress current ratio AC Current Ripple
Electrolyzer	Fluctuations of current Start/Stop Cycles
Fuel Cell	Fluctuations of current Start/Stop Cycles

- Manufacturers of ELZ and FC give the life expression of this kind of systems as a function of the number of working hours. **Start-up and shut-down cycles** and **fluctuating load** conditions can affect seriously to these devices.
- Logical** variables included: on/off states ( $\delta$ ), and transitions: startup and shutdown states ( $\sigma$ )

$$\sigma_j^{on}(t_k) = \max(\delta_j(t_k) - \delta_j(t_{k-1}), 0)|_{j=elz,fc}$$

$$\sigma_j^{off}(t_k) = \max(\delta_j(t_{k-1}) - \delta_j(t_k), 0)|_{j=elz,fc}$$

$$J_{elz}(h_i) = \left( \frac{CC_{elz}}{Hours_{elz}} + Cost_{o\&m,elz} \right) \delta_{elz}(h_i) +$$

$$Cost_{startup,elz} \cdot \sigma_{elz}^{on}(h_i) + Cost_{shutdown,elz} \cdot \sigma_{elz}^{off}(h_i)$$

$$+ Cost_{degr,elz} \cdot \vartheta_{elz}^2(h_i)$$

$$J_{fc}(h_i) = \left( \frac{CC_{fc}}{Hours_{fc}} + Cost_{o\&m,fc} \right) \delta_{fc}(h_i) +$$

$$Cost_{startup,fc} \cdot \sigma_{fc}^{on}(h_i) + Cost_{shutdown,fc} \cdot \sigma_{fc}^{off}(h_i)$$

$$+ Cost_{degr,fc} \cdot \vartheta_{fc}^2(h_i)$$

Mixed Integer  
Quadratic  
Program **MIQP**

- To manage the purchase and sale of energy to the external network **different prices** for sale and purchase are used.
- Use different weights for the same variable ( $P_{\text{network}}$ ) depending on the situation.
- To make this possible a new variable is defined

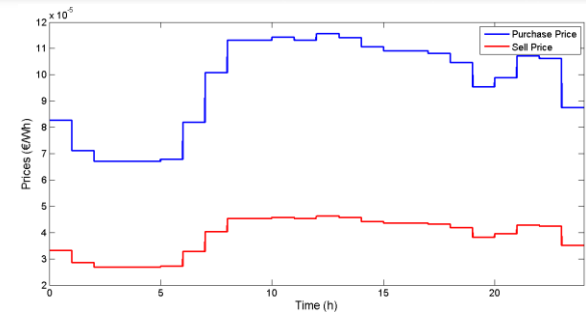
$$z_{\text{Network}}(k) = P_{\text{Network}}(k) \delta_{\text{Network}}(k)$$

$$[\delta_{\text{Network}} = 1] \leftrightarrow [P_{\text{Network}} \geq 0] \quad \text{Purchase}$$

- Cost function:

$$J_{\text{local}1} = \sum_{l=0}^{N_p-1} \hat{P}_{\text{Network}}(k+l)^T Q_{\text{sale}} \hat{P}_{\text{Network}}(k+l) +$$

$$\hat{z}_{\text{Network}}(k+l)^T (Q_{\text{purchase}} - Q_{\text{sale}}) \hat{z}_{\text{Network}}(k+l) +$$

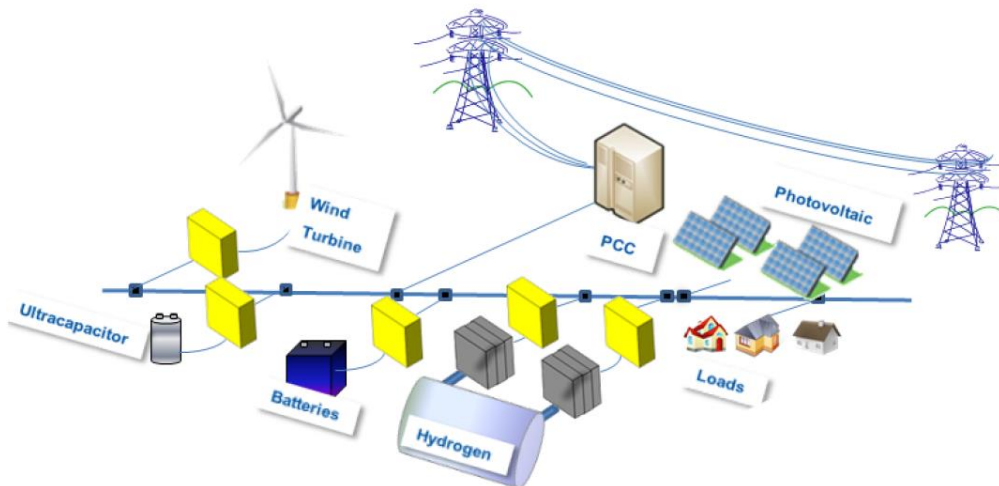


$$u = \begin{bmatrix} P_{\text{Solar}} \\ P_{\text{Network}} \\ P_{\text{aux}} \\ \hline P_B \\ P_{H2} \\ \hline \delta_{H2} \\ \boxed{\begin{matrix} \delta_{\text{Network}} \\ \hline z_{\text{Network}} \end{matrix}} \\ \hline z_{H2} \end{bmatrix}$$

New variables

MIQP

- Microgrid in the electricity market
- The microgrid operator can act as a conventional power plant (gas, coal, etc. ) and participate in the auction process
- **Optimal scheduling policy** linked to the time-varying price of energy. Microgrid's **non-dispatchable generation is converted into dispatchable using the ESS.**

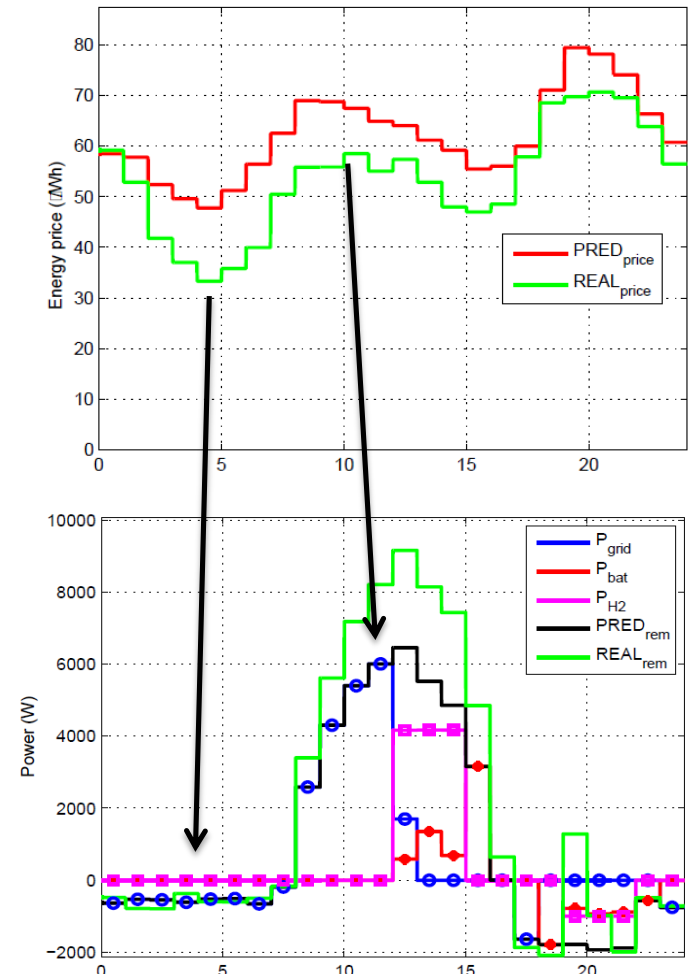
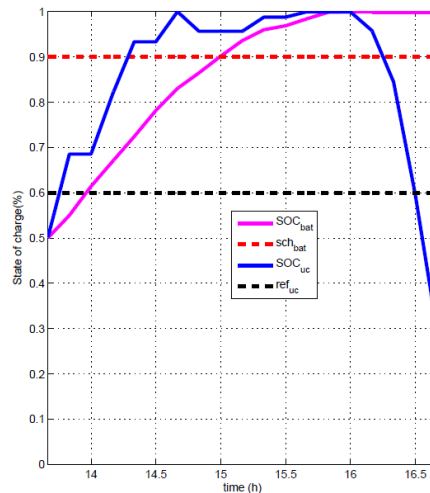


## Markets:

- Day-ahead
- Intraday
- Regulation services

- Daily market forecast
- Daily market controller schedule
- Purchase to the grid when price low. Sell when price high
- Constants setpoints to ELZ y FC to minimize degradation
- This will be recomputed.

(zoom)





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- MPC can be used to deal with the uncertainty in the energy demand and the renewable generation (disturbances)

$$x(k+1) = Ax(k) + Bu(k) + D\omega(k)$$

- Approaches:
  - Robust MPC: min-max (computationally heavy)
  - **Stochastic MPC**:
    - Multiple-scenario: **single control** sequence that takes into account different possible evolutions of the process disturbances and satisfies all their potential realizations with a certain probability
    - Tree-based: One control sequence per scenario. Possible evolutions of the disturbances can be confined to a tree (reduce the possibilities)
    - **Chance constraints**: uses an explicit **probabilistic modeling** of the system disturbances to calculate explicit bounds on the system constraint satisfaction.

- CC-MPC uses an **explicit probabilistic modeling** of the system disturbances to calculate **explicit bounds on the system constraint satisfaction**.
- Probabilistic constraints converted to **deterministic**
- Advantage: the **computational burden (on-line)** is not increased as in the scenario-based techniques.
- Assumption: disturbances are Gaussian random variables, which are modeled based on historical data, with a **known** cumulative distribution function (CDF).

$$\mathbb{P} \left[ G_{(m)} x(k+1) < g_{(m)} \right] > 1 - \delta_x$$

Risk of constraint violation

(state constraints)

Probabilistic constraints converted to deterministic

$$F_{G(m)D\omega(k)} \left( g_{(m)} - G_{(m)} (Ax(k) + Bu(k)) \right) > 1 - \delta_x$$



represents the cumulative distribution function of the random variable  $G D w(k)$ . Built based on historical data. **Drawback**

$$\min_{\{u(k), \dots, u(k+N-1)\}} \sum_{i=0}^{N-1} \mathbb{E}[J(x(k+i), u(k+i))],$$

subject to

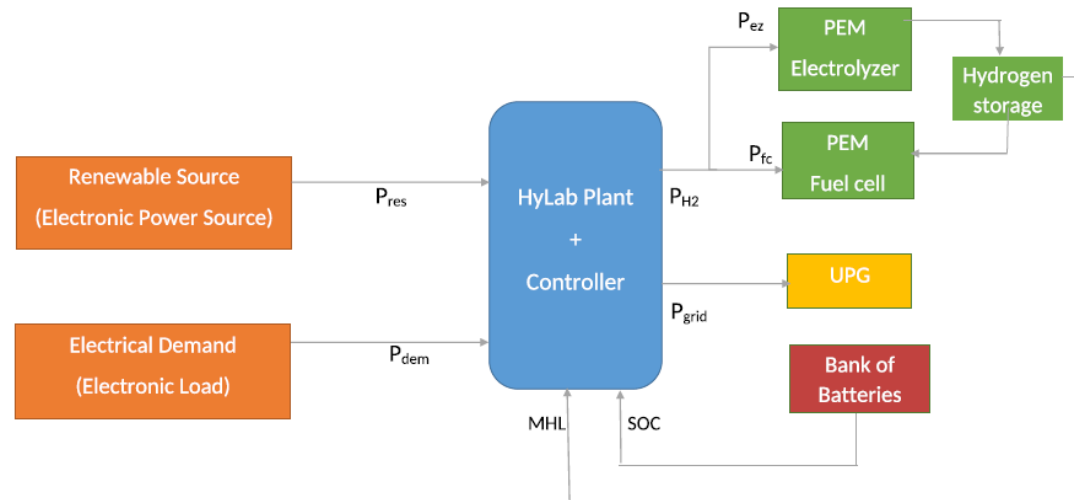
Chance constraint converted to deterministic

$$x(i+1) = Ax(i) + Bu(i) + D\omega(i),$$

$$G_{(m)} (Ax(k) + Bu(k)) < g_{(m)} - F_{G(m)D\omega(k)}^{-1} (1 - \delta_x)$$

- The system is subject to uncertainties in the power **generated** by the solar field, and the power **demanded** by the consumers
- Constraints on states and inputs
- Linearized model

$$x(k+1) = x(k) + \begin{bmatrix} 8.1360 & 5.958 \\ -15.2886 & 0 \end{bmatrix} u(k) + \begin{bmatrix} 5.958 \\ 0 \end{bmatrix} \omega(k).$$



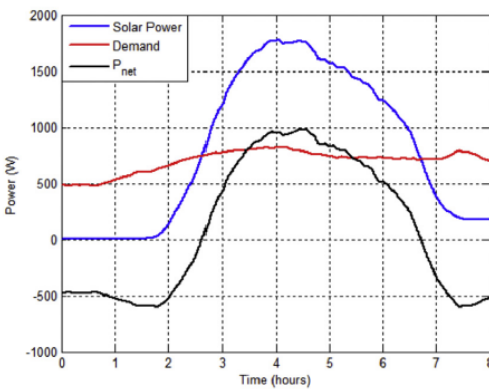
# Experimental results

Similar performance for the 3 methods

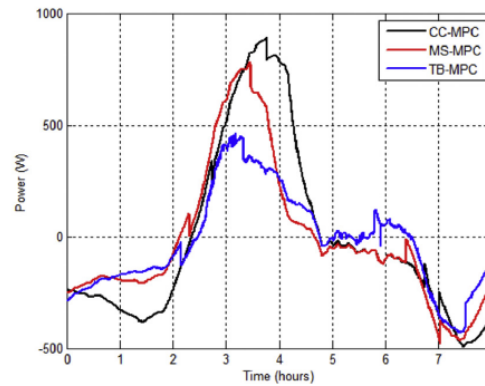
Controller	KPI <sub>1</sub> (cost units)	KPI <sub>2</sub> (s)
MS-MPC	$6.24 \times 10^{12}$	7.76
TB-MPC	$5.33 \times 10^{12}$	18.20
CC-MPC	$4.22 \times 10^{12}$	1.04
PF-MPC	$4.05 \times 10^{12}$	0.98

Deterministic MPC:  $3.9 \times 10^{13}$

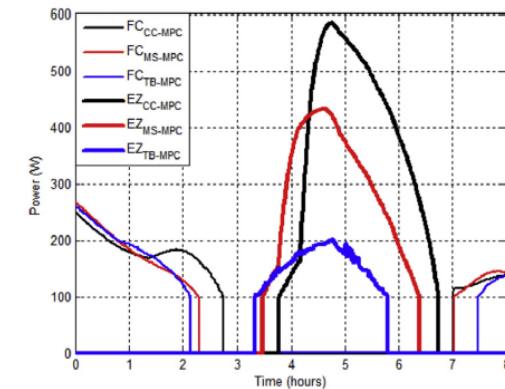
$T_s = 30$  s.  $N=5$ .



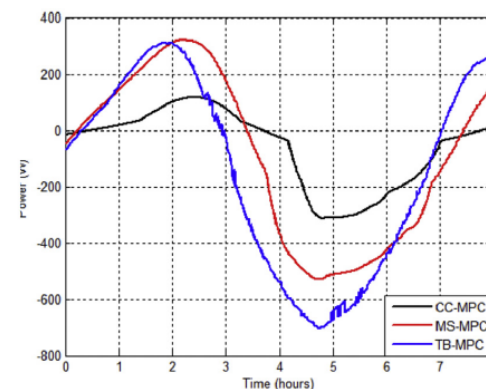
(a) Energy generated by solar panels  $P_{res}$ , demand of energy  $P_{dem}$ , and  $P_{net}$  corresponding to May 23, 2014.



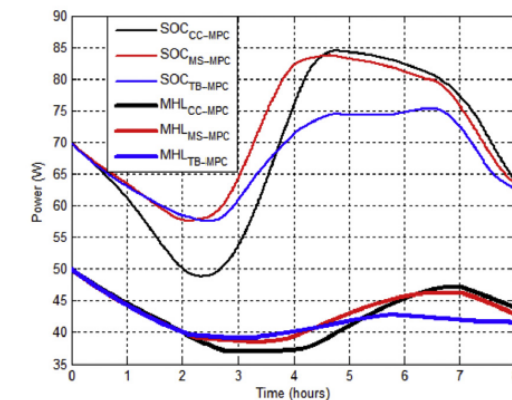
(b) Battery power.



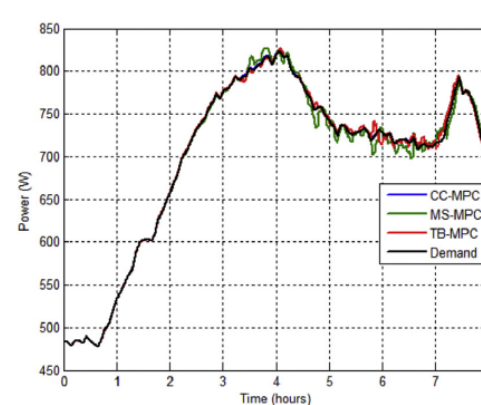
(c) Fuel cell power and Electrolyzer power.



(d) Grid power.



(e) Battery SOC and MHL.

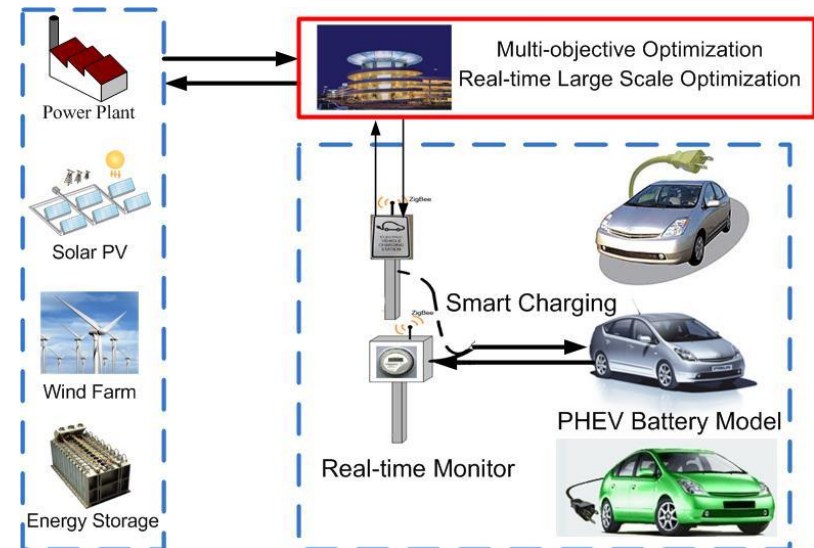


(f) Electric power provided by the microgrid compared with the consumer demand.

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- Microgrid management including EVs charge
- Vehicle to Grid (V2G): use EVs battery as storage while parking
- Selection of charge mode:
  - Slow: battery charged during parking time
  - Fast: charged in the final 30 minutes. Used as a buffer the rest of the time
- Selection of pickup time
- Optimization: constrained MPC (QP)

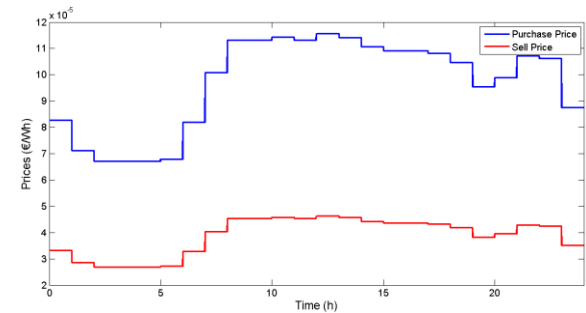


# MPC formulation

Objective function:

Minimize cost of energy purchased from the grid

$$J_2 = \sum_{l=0}^{N_p-1} \hat{P}_{DNO}(k+l)^T Q_{sale} \hat{P}_{DNO}(k+l) + \hat{z}_{DNO}(k+l)^T (Q_{purchase} - Q_{sale}) \hat{z}_{DNO}(k+l) + f_{sale} \hat{P}_{DNO}(k+l) + (f_{purchase} - f_{sale}) \hat{z}_{DNO}(k+l)$$



Logical (binary) variables: Different price buy/sell, EZ/FC interlocking, minimum times for switch on/off

$$J_{local2} = \sum_{l=0}^{N_p-1} (\hat{x}(k+l) - \hat{x}_{ref}(k+l))^T Q_x (\hat{x}(k+l) - \hat{x}_{ref}(k+l)) + (\hat{x}(k+N_p) - \hat{x}_{ref}(k+N_p))^T Q_{N_p} (\hat{x}(k+N_p) - \hat{x}_{ref}(k+N_p))$$



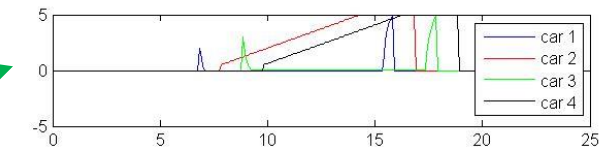
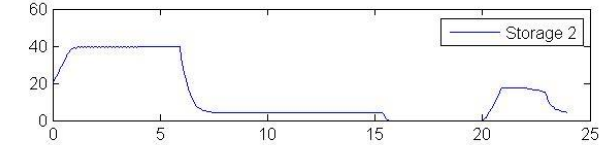
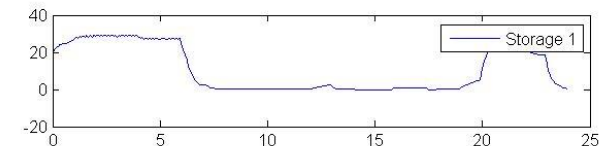
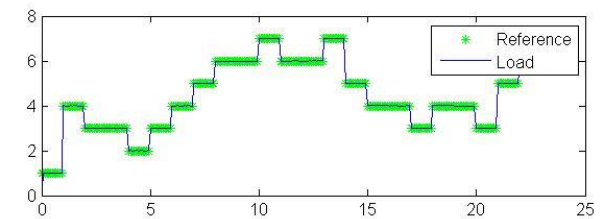
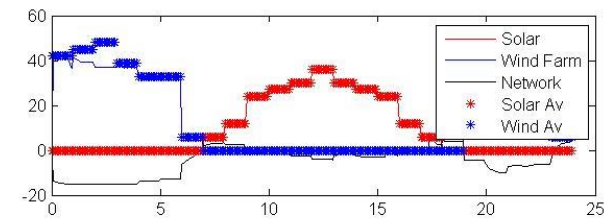
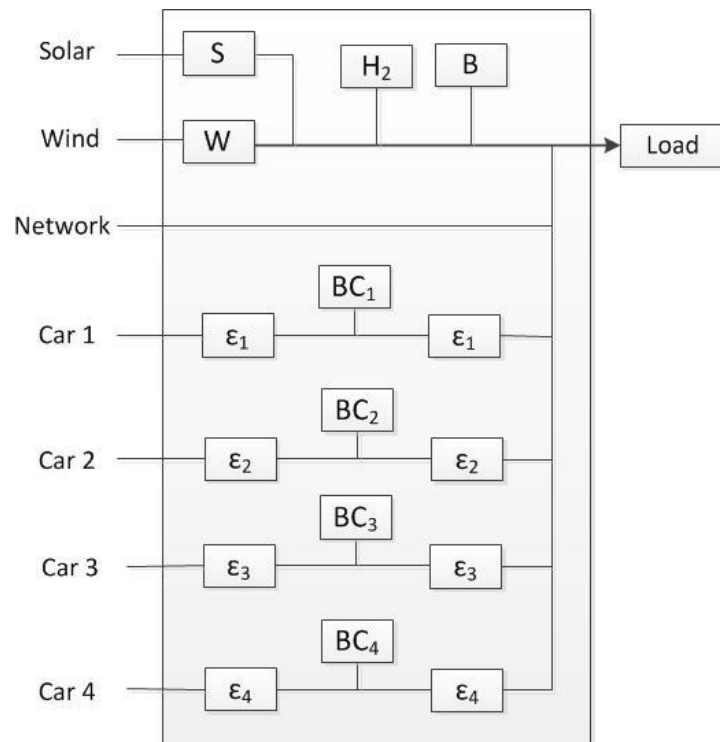
Guarantee that the vehicles' batteries will be fully charged **at the end of the charging time**

MIQP

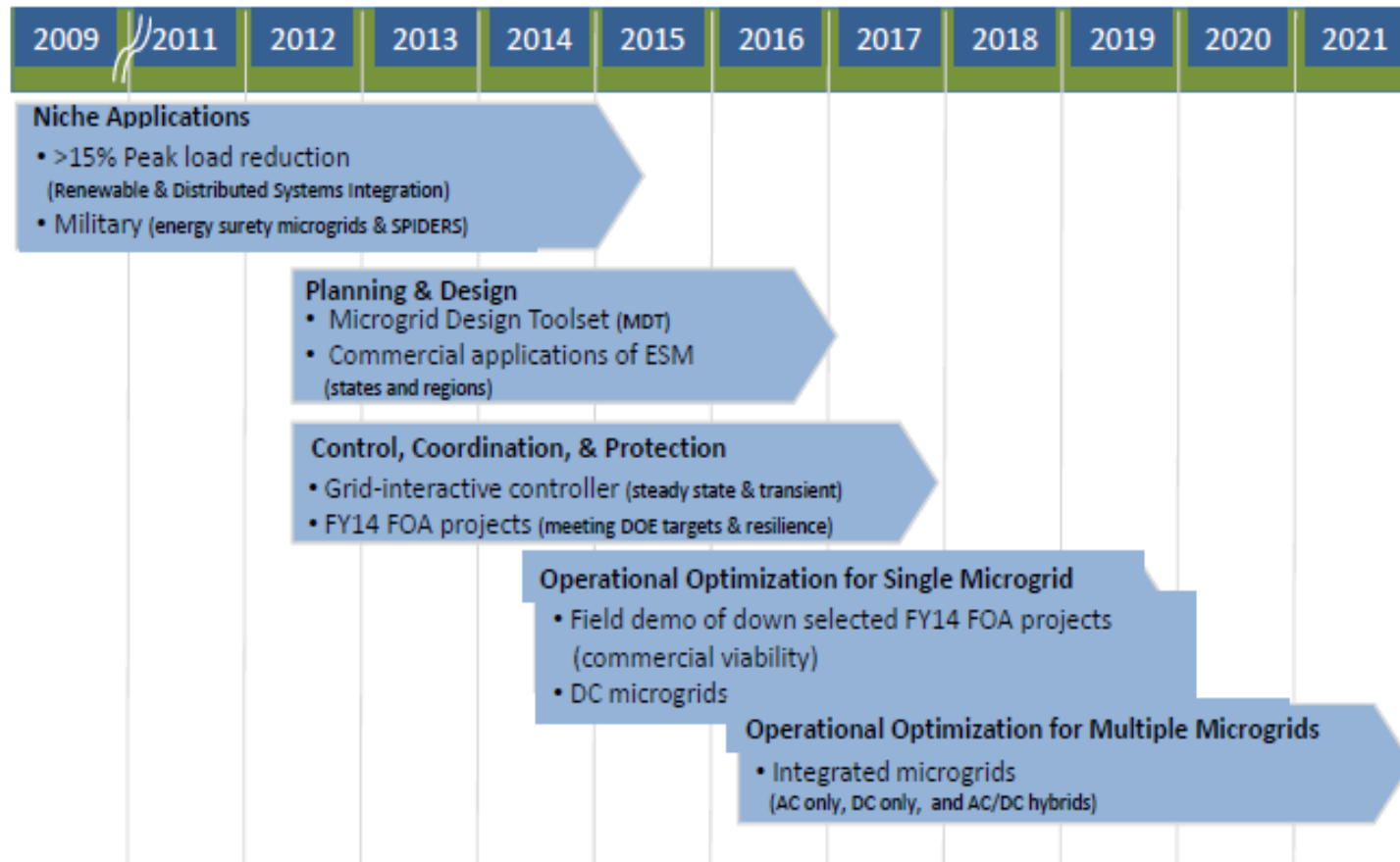
Z=1 buy

## Simulations with 4 EVs, 24 h

- Use all the available RES (and sell to the grid)
- Fulfill demand (loads and EVs)

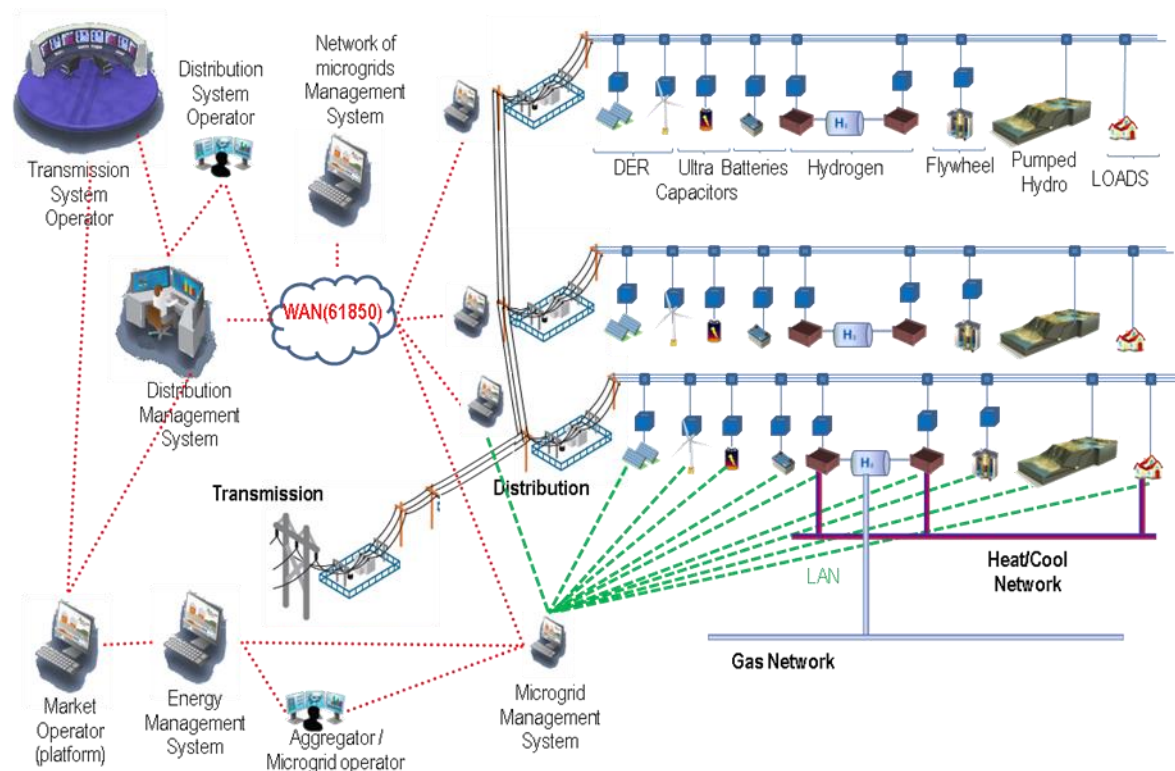


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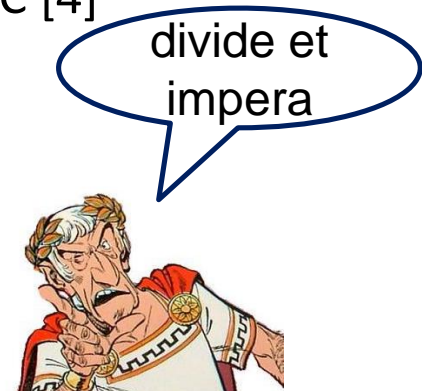


Source: US DOE

- Power flow no longer static and flowing one way from the substation transformers to the end users, but instead is **dynamic and flowing two ways**.
- Network of microgrids



- **Centralized** control has important **limitations** when considering very large and complex systems.
  - Prohibitive computational burden of a very large network,
  - Sharing of subnetwork models required. It is usually impossible
  - Number of generation and customer units involved exponentially increases the computational demand.
- Efficient centralized heuristic optimization algorithms to solve EED problems: Fuzzy, Neural Networks, simulated annealing, genetic algorithm, particle swarm optimization etc. [1][2][3] or centralized MPC [4]
- A **distributed** formulation can be adopted
  - to solve simpler optimization problems
  - taking advantages of the smart grid communications
  - Distributed scheme provides better scalability



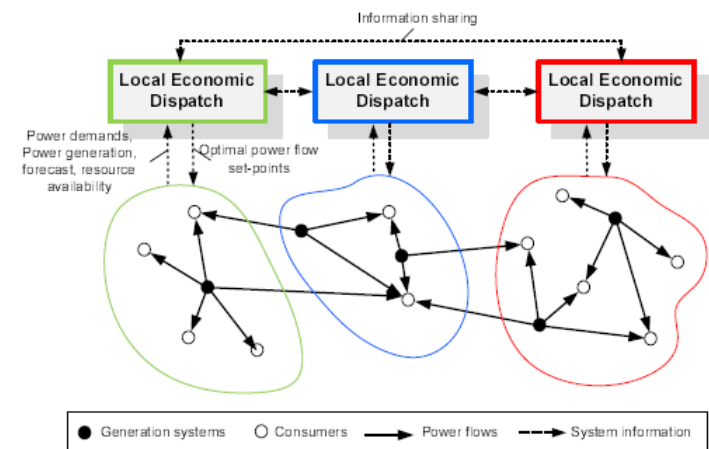
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- [1] Chen PH, Chang HC. Large-scale economic dispatch by genetic algorithm. 1995  
[2] Rajan CCA. A solution to the economic dispatch using EP based SA algorithm on large scale power system, 2010  
[3] Chaturvedi KT, Pandit M, Srivastava L. Modified neo-fuzzy neuron-based approach for economic and environmental optimal power dispatch., 2008  
[4] Arnold M, Andersson G. Investigating renewable infeed in residential areas applying model predictive control, 2010



- Distributed Control: control **responsibility shared by several agents**, each one solving the control problem of its subnetwork
- A distributed formulation is adopted to solve simpler optimization problems intercommunicated each other in **parallel** computation stations.
- **Overall network control** problem is the aggregation of all local control problems:

$$\begin{aligned} & \min_{\substack{\tilde{\mathbf{x}}_1(k+1) \dots \tilde{\mathbf{x}}_{n_N}(k+1) \\ \tilde{\mathbf{u}}_1(k) \dots \tilde{\mathbf{u}}_{n_N}(k) \\ \tilde{\mathbf{y}}_1(k) \dots \tilde{\mathbf{y}}_{n_N}(k)}}} \phi_{\text{local},i}(\tilde{\mathbf{x}}_i(k+1), \tilde{\mathbf{u}}_i(k), \tilde{\mathbf{y}}_i(k)) \end{aligned}$$

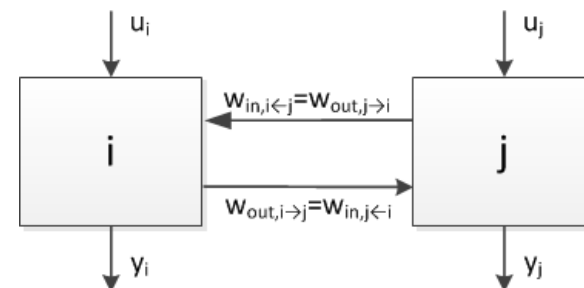
Notice that, in the case of a network of microgrids, a **centralized solution** may not exist: different owners.



Subject to local **dynamics**, interconnecting constraints and operational **constraints**

- Each control agent incorporates terms related to the **interconnecting** constraints

$$\begin{aligned} \mathbf{w}_{in,i \leftarrow j}(k) &= \mathbf{w}_{out,j \rightarrow i}(k) \\ \mathbf{w}_{out,i \rightarrow j}(k) &= \mathbf{w}_{in,j \leftarrow i}(k), \end{aligned}$$



- Distributed** objective function

$$\begin{aligned} \min \quad & J_{local,i}(\hat{x}_i(k+1), \hat{u}_i(k), \hat{y}_i(k)) + \\ & \hat{x}_i(k+1), \hat{u}_i(k), \hat{y}_i(k), \quad J_{inter,i}(\hat{w}_{in,i}(k), \hat{w}_{out,i}(k)) \\ & \hat{w}_{in,i}(k), \hat{w}_{out,i}(k) \end{aligned}$$

- The aggregation of the local solutions obtained through an iterative process at each sampling time  $k$  is **equivalent** to the optimal solution calculated in a centralized way [1] (convexity of the cost function and affinity of the model)
- Proof of **convergence** [2]

[1] R. Negenborn, B. D. Schutter, and H. Hellendoorn, "Multi-agent model predictive control of transportation networks," in *Proc. of IEEE ICNSC 2006*,

2] D. P. Bertsekas, *Constrained Optimization and Lagrange Multiplier Methods*, 1996.

- Augmented cost function

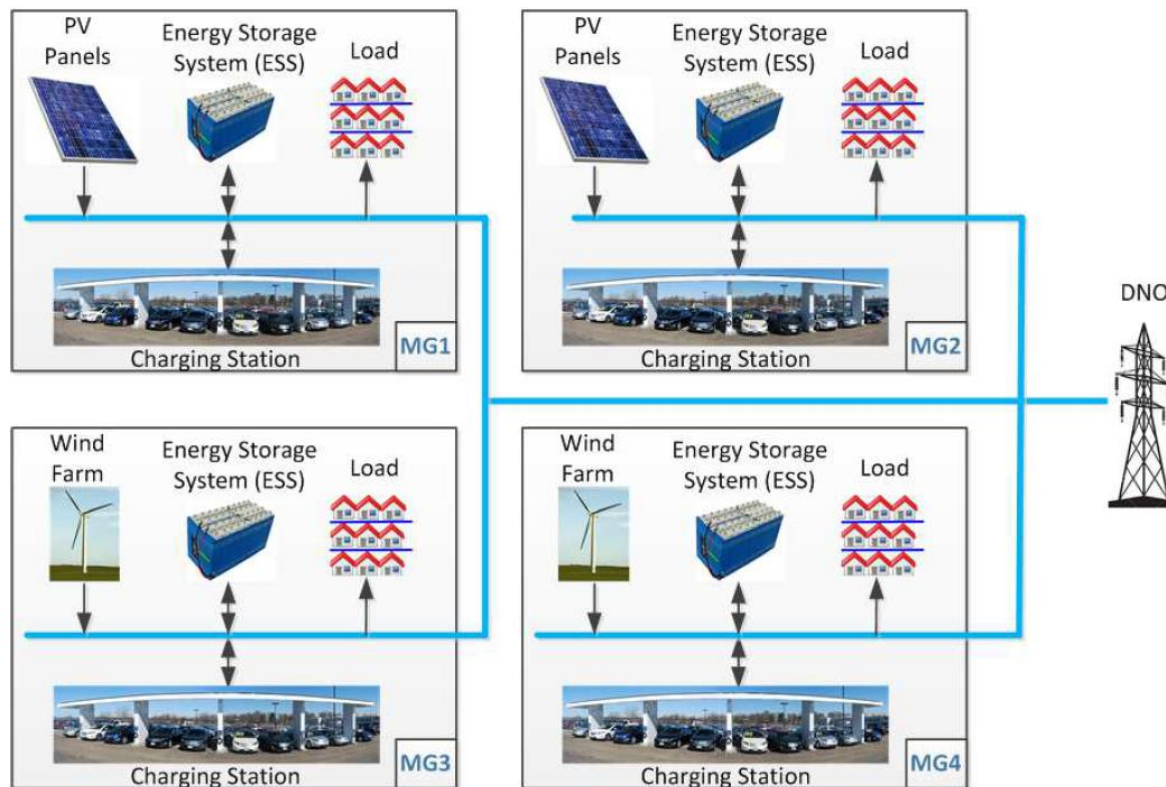
Lagrange multipliers

$$\begin{aligned} \phi_{aug}(\tilde{\mathbf{X}}(k+1), \tilde{\mathbf{U}}(k), \tilde{\mathbf{Y}}(k), \tilde{\mathbf{W}}_{in}(k), \tilde{\mathbf{W}}_{out}(k), \tilde{\Lambda}_{in}(k)) = \\ = \sum_{i=1}^{n_N} \left( \phi_{local,i}(\tilde{\mathbf{x}}_i(k+1), \tilde{\mathbf{u}}_i(k), \tilde{\mathbf{y}}_i(k)) \right. \\ \left. + \sum_{j \in \mathcal{N}_i} \tilde{\lambda}_{in,i,j}(k) (\tilde{\mathbf{w}}_{in,i \leftarrow j}(k) - \tilde{\mathbf{w}}_{out,j \rightarrow i}(k)) \right) \end{aligned}$$

- The optimal solution is found when the Lagrange multipliers do not change with respect to the last iteration

# Case study: aggregation of microgrids

- Microgrids with EV **charging stations**
- Each microgrid is composed by renewable energy sources and a V2G system to charge 10 EVs
- Maximize the **energy exchange among microgrids** to reduce the amount of energy purchased from the DNO.



- Microgrid has 12 binary variables related to the physical dynamics:
  - 1 for energy sell/purchase to DNO
  - 1 to battery bank
  - 10 related to electric vehicles
- Prediction horizon of  $N_p = 6$
- Total number of binary variables is 72.
- This way each microgrid has  $2^{72}$  possible instances to the local controller:

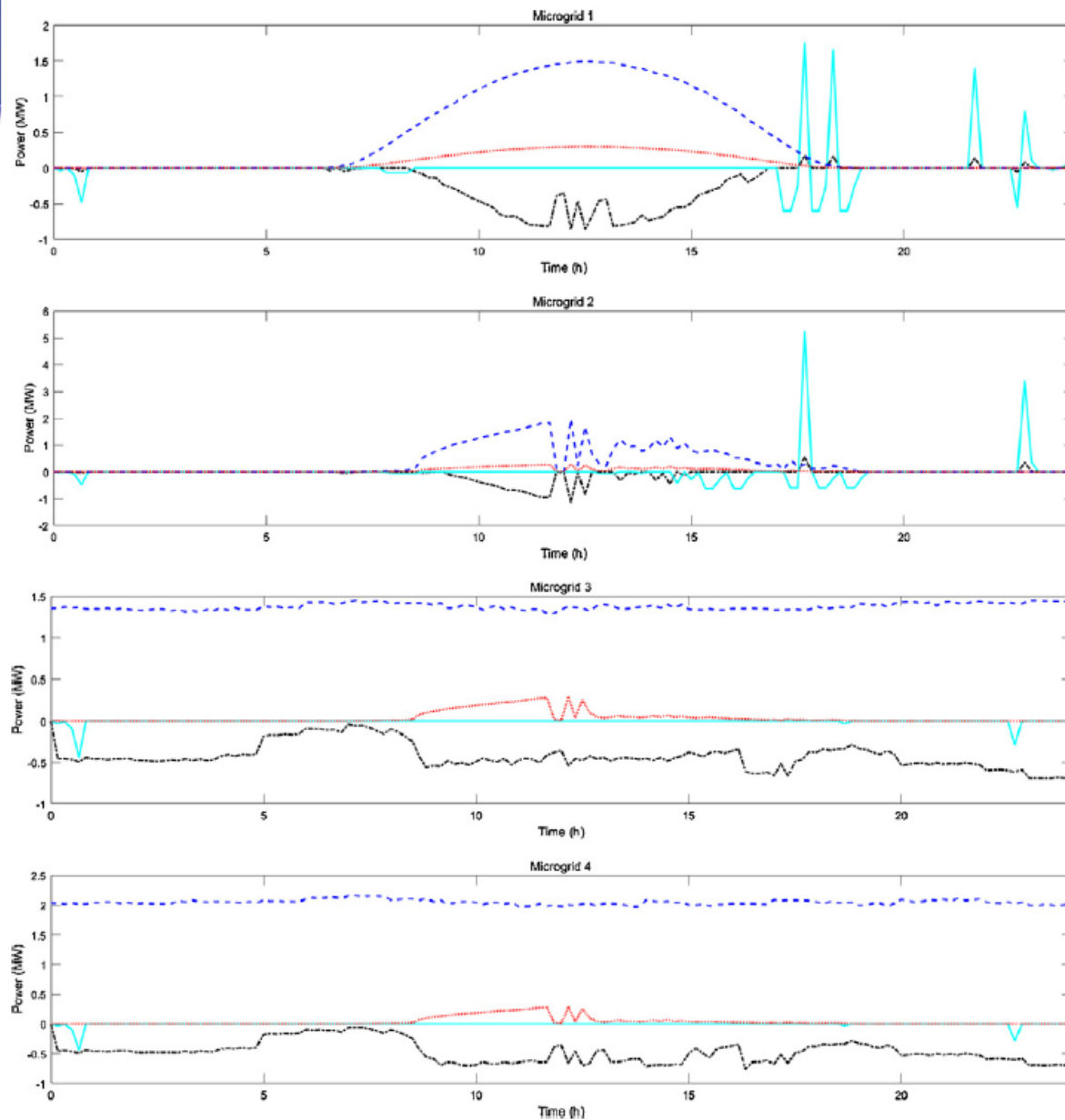
$\prod_{i=1}^4 2^{72}$  configurations for the binary variables in the global optimization problem.

CPLEX or suboptimal solutions

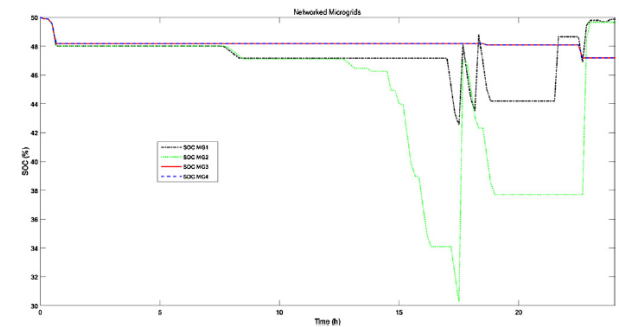
# Simulation Results

Energy management  
in each uG

Storage (SOC)



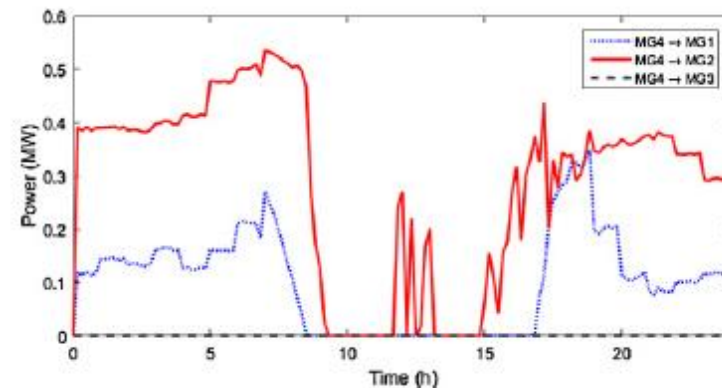
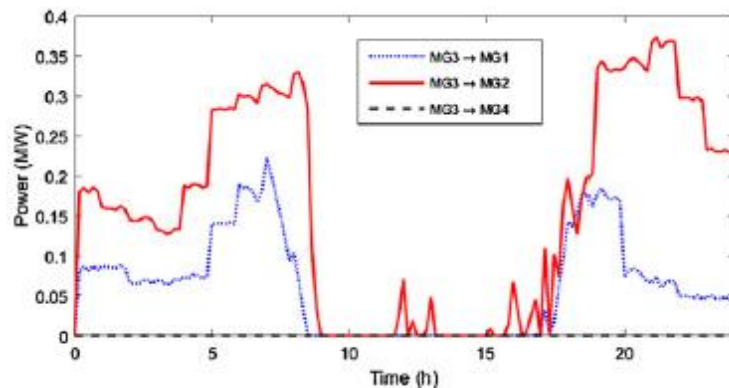
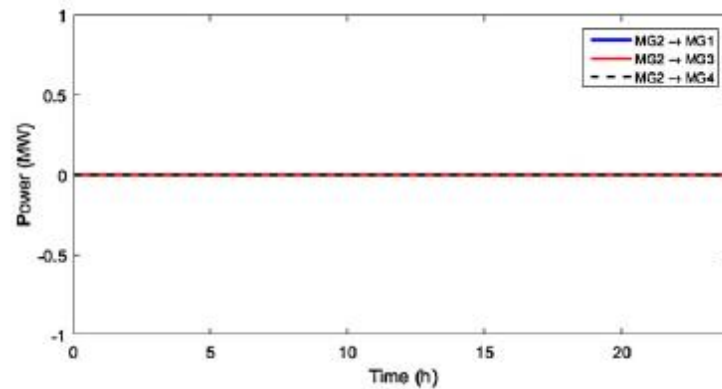
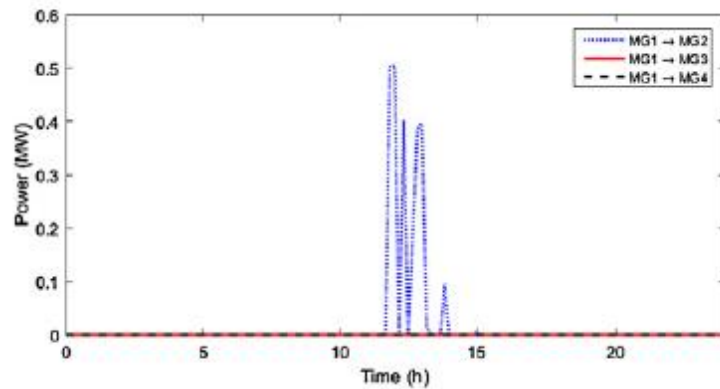
**Fig. 7.** Interconnected simulation energy sources. (blue (dash) – renewable energy sources, red (dot) – charging station photovoltaic source, black (dash-dot) – power exchanged with DNO, cyan (solid) – battery power). (For interpretation of the references to color in this figure legend, the reader is referred to the web version



# Energy exchange among microgrids

These exchanges reduce the energy purchased from the grid

Interconnection variables

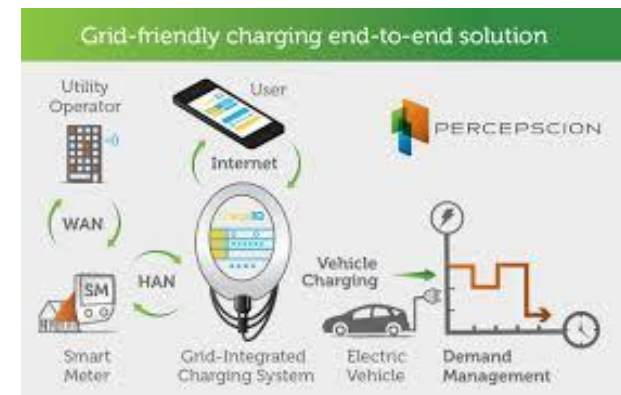




1. Introduction
2. Energy Management in Microgrids
3. Extended control objectives
4. Disturbances Management
5. Integration of Electric Vehicles
6. Networks of Microgrids
- 7. Concluding remarks**

- MPC: good candidate for microgrid control with hybrid storage ( $H_2$ )
- Outstanding features in smooth operation, lower cost, higher lifetime
- Changes in cost function, tuning parameters and logical constraints can help fulfil different objectives
- Non-dispatchable RES can be converted into dispatchable using the ESS and advanced control. Optimal economic schedule can be achieved (market)
- Stochastic disturbances can be included
- Centralized/Distributed approaches
- V2G included in microgrid management

- Dispatchable microgrids in the pool market
- Contribution of (up-to-now) non-dispatchable RES to frequency regulation (virtual inertia)
- Reconfiguration. Failures / Plug & Play
- Coupling/stability issues
- Networks of microgrids (SoS). Coalitional control (game theory)
- Microgrids for EVs: Distributed storage (electricity and H<sub>2</sub>). V2G. New business models
- Combination of several types of energy: electricity, gas, ethanol, H<sub>2</sub>, heat, etc.



# Control of microgrids integrating renewable energy and hybrid storage

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