Optimal Capacity Design and Operation of Energy Hub Systems

Ian A. Hiskens

Vennema Professor of Engineering

Professor, Electrical Engineering and Computer Science

University of Michigan, Ann Arbor

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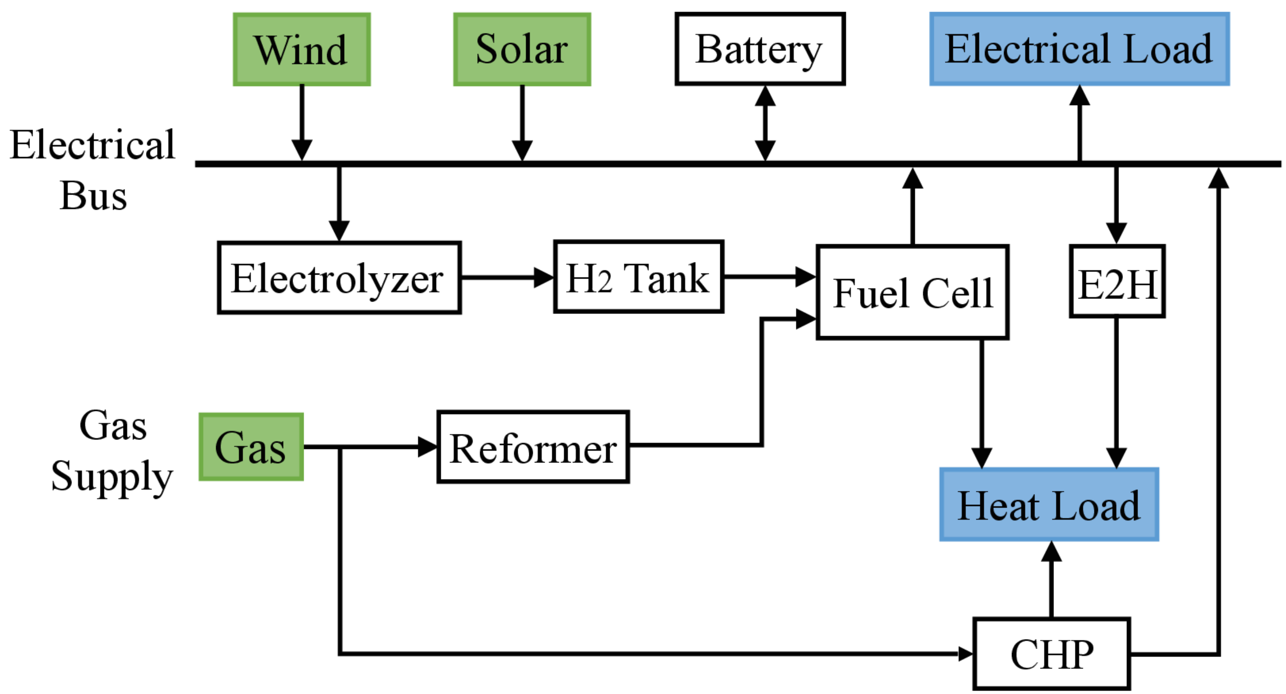
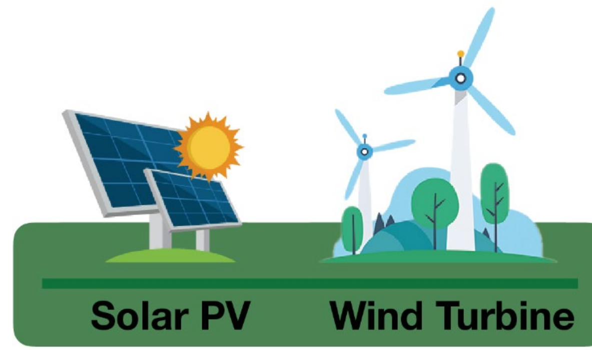
Energy hubs

- No electricity grid connection.
- Gas supply (possibly from local storage tank).
- Renewable sources (wind, solar PV).
- Battery and hydrogen storage.
- Electrical and heat load.



Objective

- Determine the minimum cost energy-hub capacity design while ensuring electrical and heat loads are satisfied with high probability.
  - Taking into account uncertainty in renewable generation (wind and solar) and loads, and flexibility in storage.
  - Wind generation: $\tilde{\mathbf{p}}_{\mathrm{w}} = \overline{p}_{\mathrm{w}} \cdot \tilde{\mathbf{p}}_{\mathrm{w}}^{0}$
    where $\tilde{\mathbf{p}}_{\mathrm{w}}^{0}$ is a normalized random scenario,
    $\overline{p}_{\mathrm{w}}$ is the wind turbine capacity.
  - Similarly for solar PV.
  - Load $\tilde{\mathbf{p}}_{\mathrm{d}}$ is not normalized.



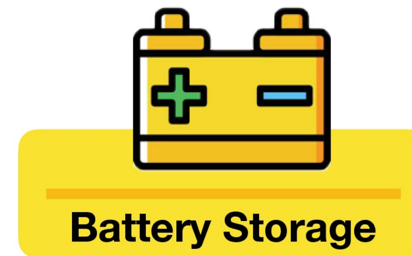
- Capacity design can be formulated as a chance-constrained problem:

$$\min_{x \in \mathcal{X} \subseteq \mathbb{R}^{n_x}} \quad J(x)$$
$$\text{subject to} \quad \Pr\Big(\max_{j=1,\ldots,m} g_j(x,\delta) \leq 0 | \delta \in \Delta\Big) \geq 1-\epsilon$$

  - $\delta \in \Delta \subseteq \mathbb{R}^{n_\delta}$ are the random variables: renewable generation and load.
  - $x \in \mathcal{X} \subseteq \mathbb{R}^{n_x}$ are the decision variables: component capacities.
  - ϵ is a pre-defined maximal probability of violation.

Chance-constrained optimization

- Uncertainty in generation and load results in stochastic constraints:
  - Power balance/sufficiency.
  - Battery charging/discharging (through a control policy that is dependent upon the stochastic variables).



- There are also a variety of deterministic constraints and non-negativity constraints.
- The objective function is composed of the net present cost of all the devices that form the energy hub.

- This is a difficult problem to solve due to non-convexity.
  - Integer variables describe battery charging/discharging complementarity.

Robust reformulation

- The chance-constrained problem can be solved through a robust reformulation.
- This reformulation is based on a new chance-constrained problem:

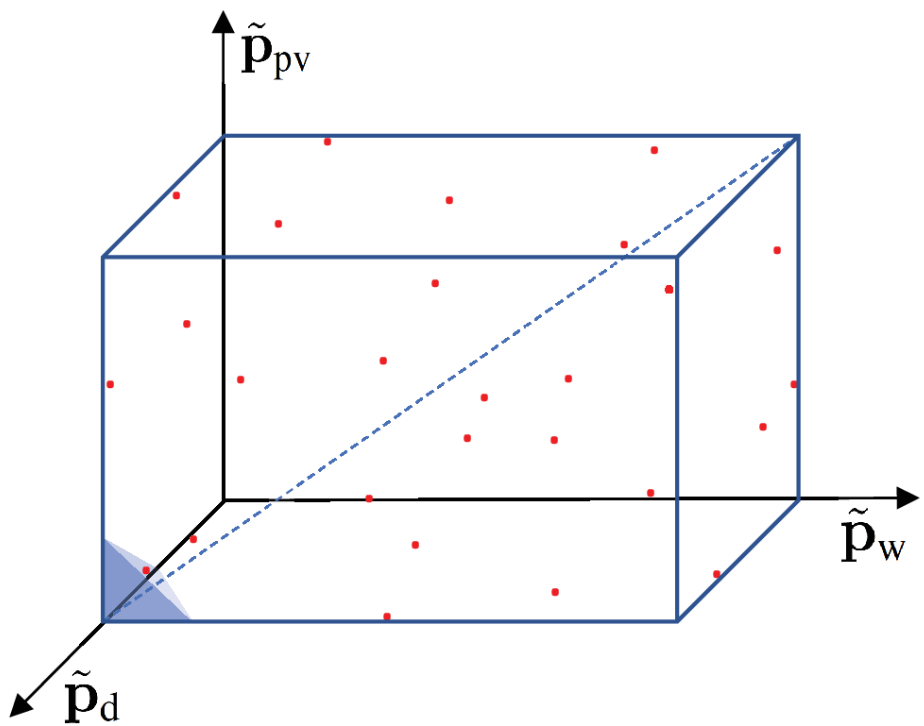
$$\min \ ||\overline{\xi} - \underline{\xi}||_1$$
$$\text{subject to } \Pr\left(\delta \in [\underline{\xi}, \overline{\xi}] \middle| \delta \in \Delta \subseteq \mathbb{R}^{3T}\right) \geq 1 - \epsilon$$

  which is used to construct a hyper-rectangular robust set $B^* = [\underline{\xi}^*, \overline{\xi}^*]$ for the random vector.
  - This new problem is solved using a scenario approach.
- A robust counterpart of the original chance-constrained problem confines the random vector to $B^* \subset \Delta$.

- This can, however, give quite conservative results.

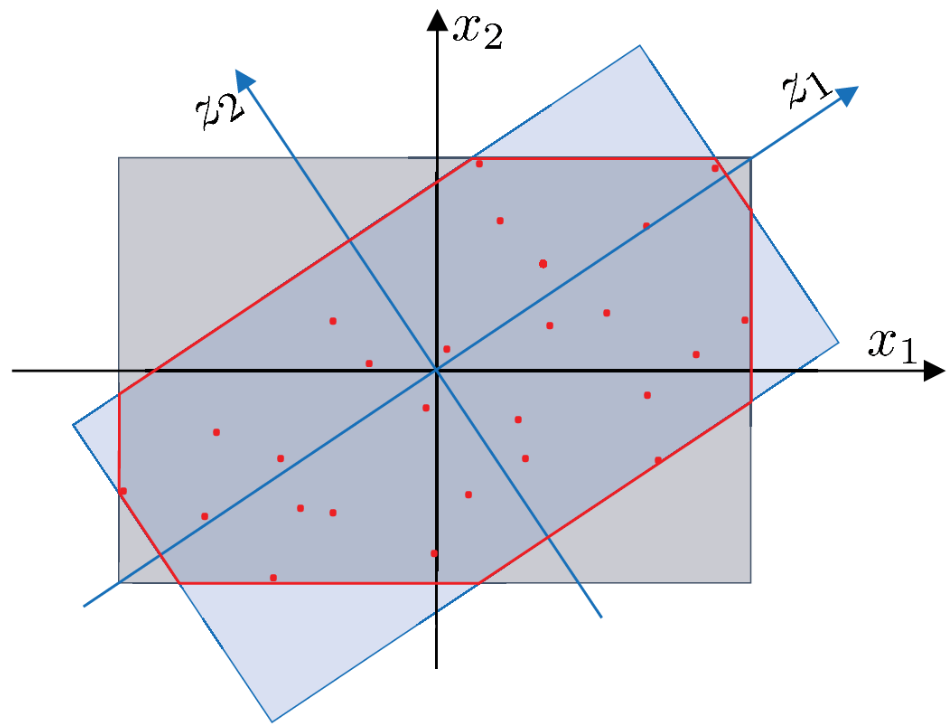
Robust set reshaping: cutting

- The process of constructing the hyper-rectangle can capture highly unlikely possibilities.
  - Example: low renewable generation plus high load all day.
- Introduce hyperplanes to trim the unrealistic corners of the hyper-rectangle.



Robust set reshaping: PCA

- Principal component analysis provides a coordinate transformation.
- Introduce two hyperplanes for each principal component.
- The intersection of the original and new hyper-rectangles gives a much smaller (polytopic) robust set.
- All the data points are still enclosed.
- Less conservative.

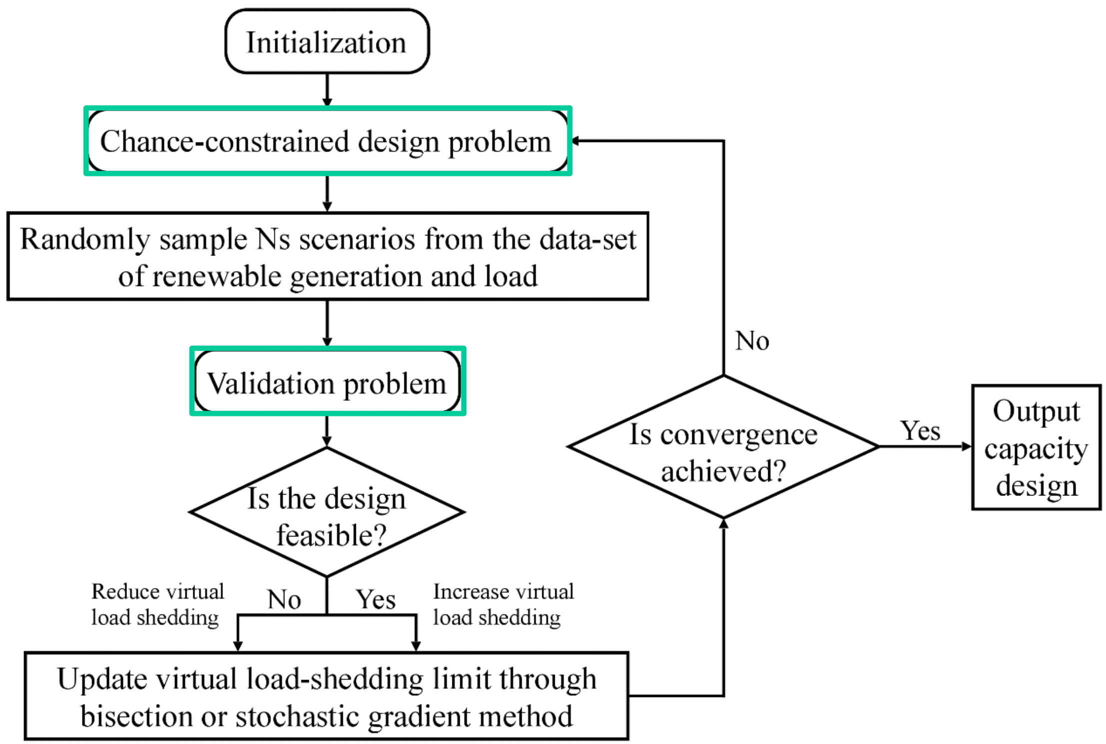


Tractable linear program

- Battery dispatch is governed by an affine control policy.
- This enables the charge/discharge complementarity condition to be reformulated.
- The result is a robust linear program (LP) with polytopic uncertainty set.
- It can be converted to a regular LP by taking the dual.
  - **Computationally tractable problem.**
- The solution may, however, still be quite conservative.

Iterative design method

- An iterative method is used to address conservativeness of the chance-constrained problem.
- The (scalar) maximum load shedding parameter $\hat{r}^{\mathrm{e}}_{\mathrm{sh}}$ is used to bridge between the chance-constrained and validation sub-problems.
- Bisection and stochastic gradient algorithms have been implemented.



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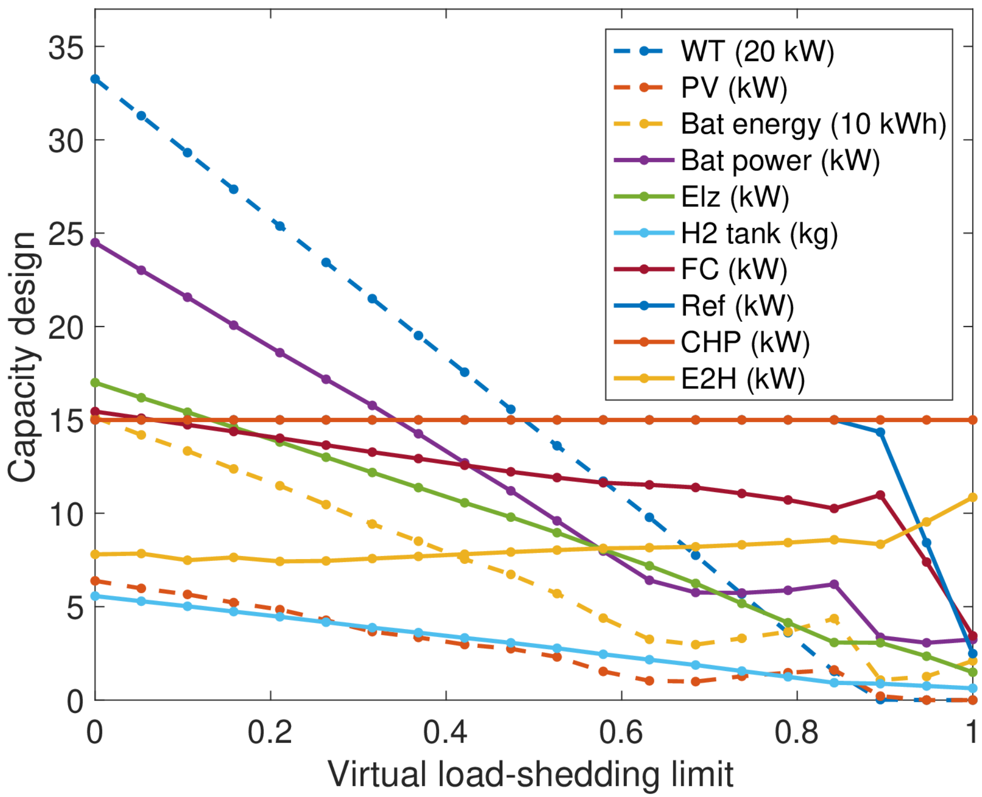
Parameterization of the CC problem

- Load shedding $\hat{r}_{\mathrm{sh}}^{\mathrm{e}}$ parameterizes the chance-constrained problem.
  - Decreasing $\hat{r}_{\mathrm{sh}}^{\mathrm{e}}$ tightens the problem, increases design conservativeness.
  - Increasing $\hat{r}_{\mathrm{sh}}^{\mathrm{e}}$ relaxes the problem, decreases design conservativeness.



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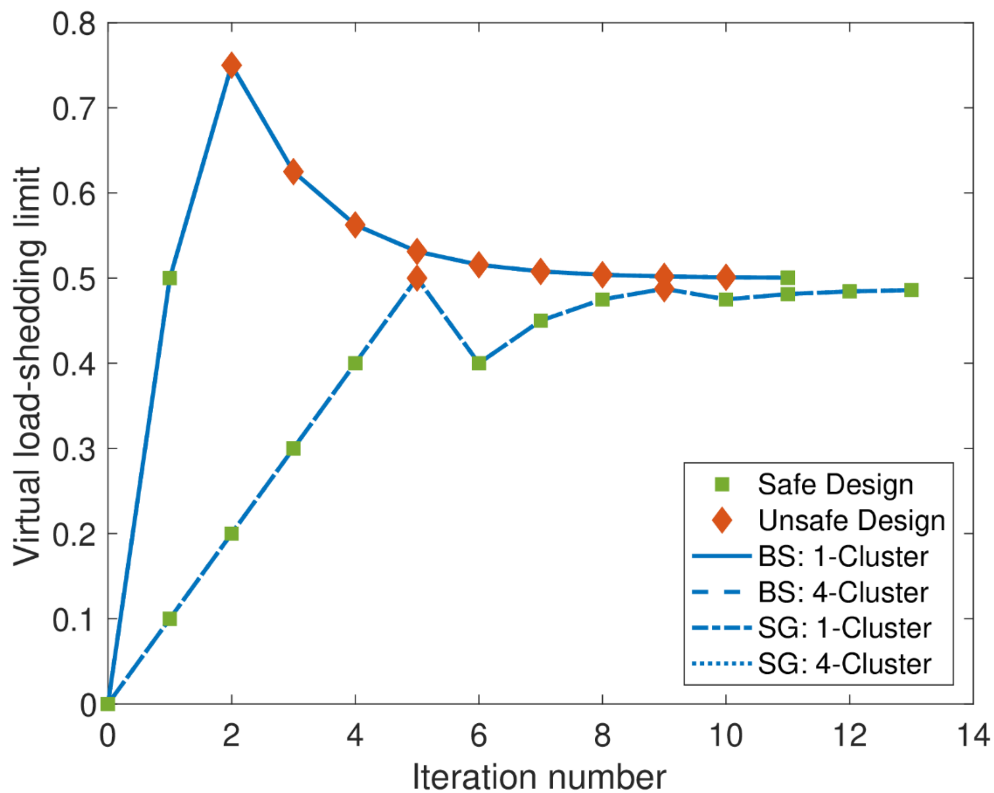
Convergence

Optimal Design

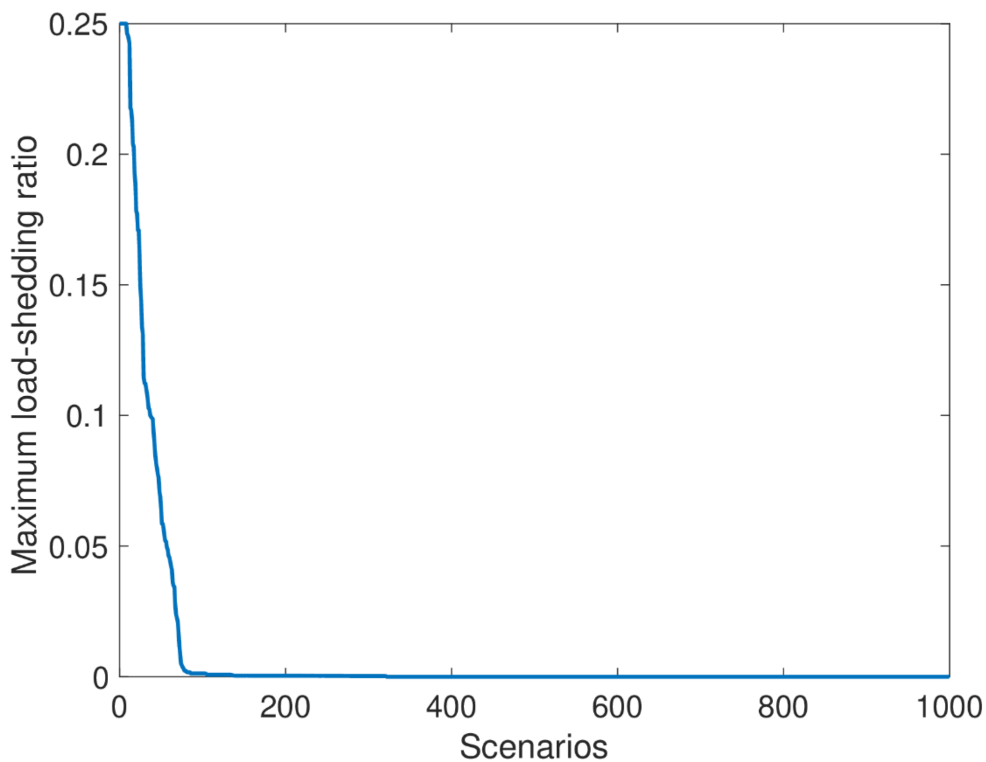
$\overline{p}_{\mathrm{w}}(\mathrm{kW})$	291.31
$\overline{p}_{\mathrm{pv}}(\mathrm{kW})$	2.56
$\overline{p}_{\mathrm{b}}(\mathrm{kW})$	10.42
$\overline{e}_{\mathrm{b}}\ (\mathrm{kWh})$	62.47
$\overline{p}_{\mathrm{elz}}(\mathrm{kW})$	9.38
$\overline{m}_{\mathrm{h_2}}(\mathrm{kg})$	2.92
$\overline{p}_{\mathrm{fc}}(\mathrm{kW})$	12.06
$\overline{p}_{\mathrm{rfm}}(\mathrm{kW})$	15.00
$\overline{p}_{\mathrm{chp}}(\mathrm{kW})$	15.00
$\overline{p}_{\mathrm{e2h}}(\mathrm{kW})$	7.98
$\hat{r}^{\mathrm{e}}_{\mathrm{sh}}(\mathrm{kW})$	0.5005
Cost (Million)	\$1.39

Design peak load is 100kW



Actual load shedding outcome

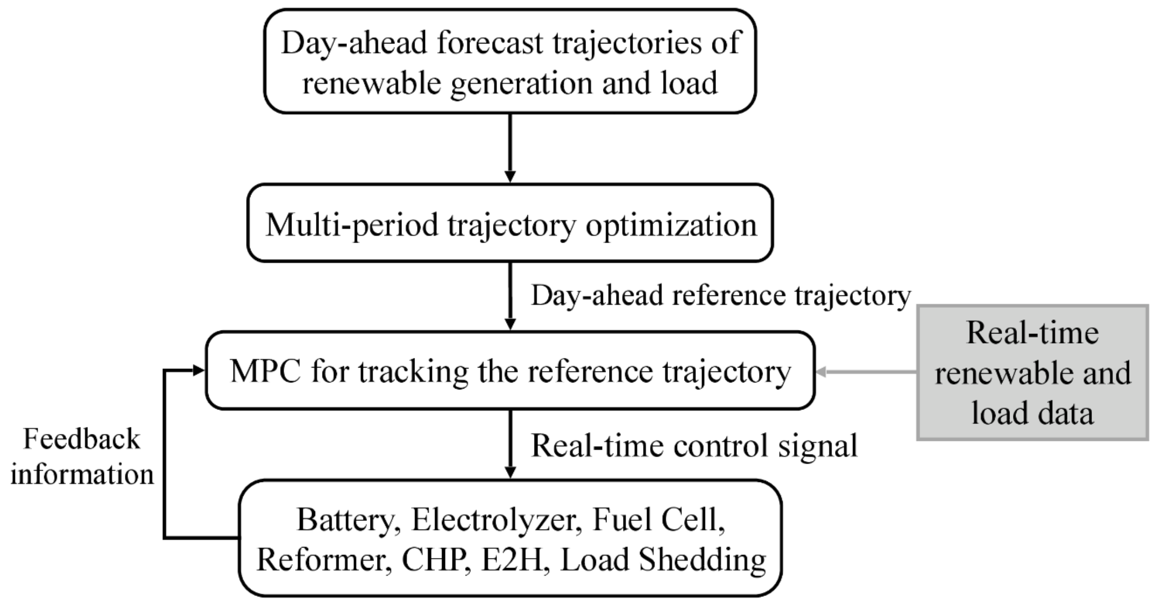
- The validation phase ensures feasibility of 100 of the 1000 scenarios.
  - Ensures the true load shedding limit (25% for our example) is not exceeded.
- *A posteriori* evaluation of all 1000 scenarios indicated that 7 failed to satisfy the load-shedding limit.
  - This corresponds to an upper bound on the violation probability of $\epsilon = 2\,\%$.



Energy hub operation

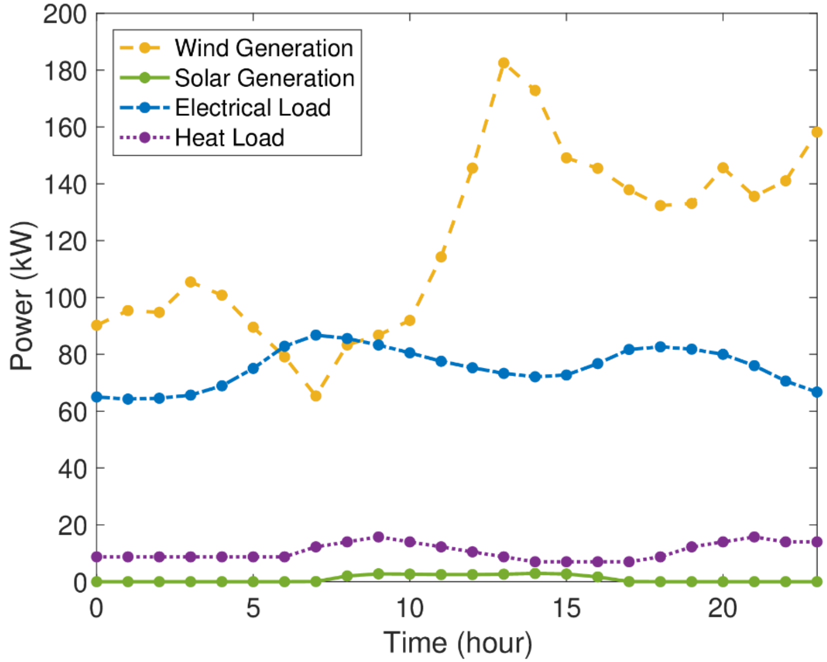
- A two-level operating scheme has been adopted.
  - Upper level: day-ahead optimal scheduling.
  - Lower level: real-time model predictive control (MPC).
- Real-time realizations of renewable generation and load differ from their day-ahead forecast.
  - MPC seeks to track the reference trajectories for battery state of charge and hydrogen storage provided by the day-ahead schedule, while minimizing load shedding.

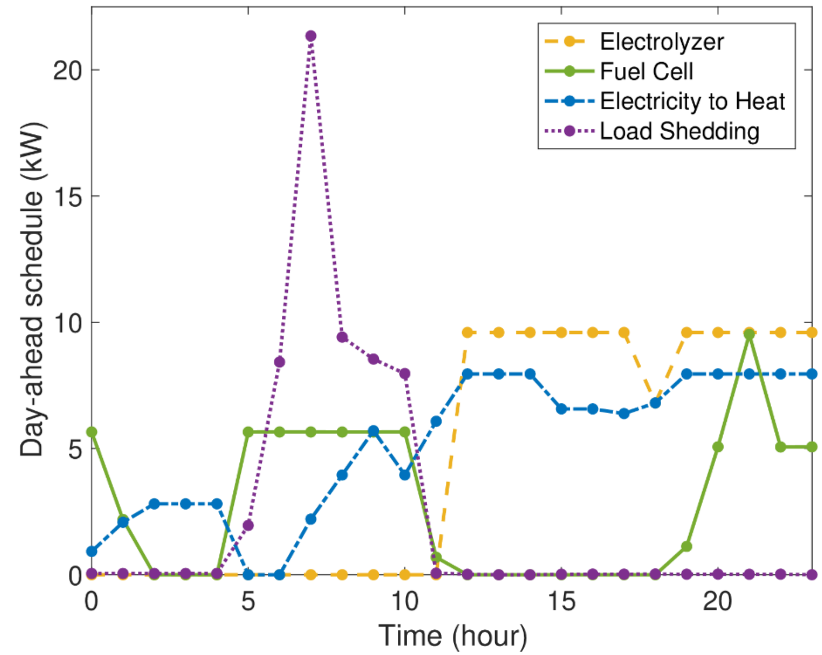
This two-level operating strategy has been extended to networked energy hubs.

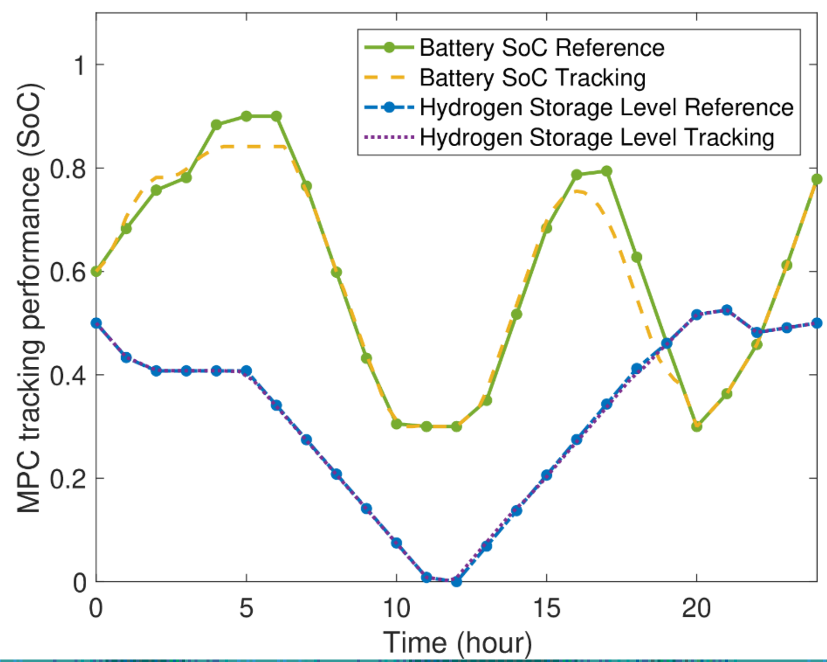


Example

Renewable generation and load (scenario)







Conclusions

- Energy hubs incorporate multiple energy carriers.
  - Example: electricity, gas, heat, hydrogen.
  - They form the building blocks for community-based energy grids.
- Capacity design of autonomous energy hubs must take into account the stochasticity of renewable generation and load.
  - This results in a chance-constrained optimization problem.
- An affine policy for battery dispatch allows a robust reformulation of the chance-constrained problem to be expressed as a tractable linear program.
  - This may give quite conservative results.
- Conservativeness can be addressed through iteration between the robust problem and a validation problem.
- Economic operation of an autonomous energy hub can be achieved using a two-level control structure.
- This two-level operating strategy extends to networks of energy hubs.