MPC formulation

Pareto frontier vs. cost function

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Considered formulations

Formulation #1: Pareto frontier

- Multi-objective
- Discrete search domain
- Policy selection based on the objective priority list (possibly time-varying)
- Post-optimization normalization

Formulation #2: Cost function

- Cost function with normalized objectives
- Soft constraints
- Possibly discrete search domain

Both formulations are being tested in a simulated environment:

- **Emulation:** currently EnergyPlus, also Modelica in the future
- **Control:** currently gray-box, also black-box in the future

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Formulation #1: Pareto frontier and policy selection

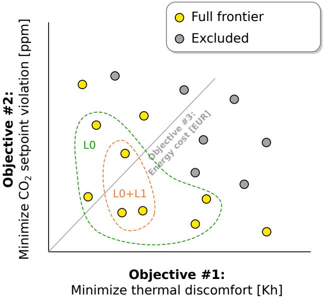
Priority levels:

L0	Objective #1, Objective #2	**Post-optimization** normalization required (does not affect frontier)
L1	Objective #3	Objectives at different levels do not have to be normalized
L2	Objective #4	
L3		

Recursive policy selection:

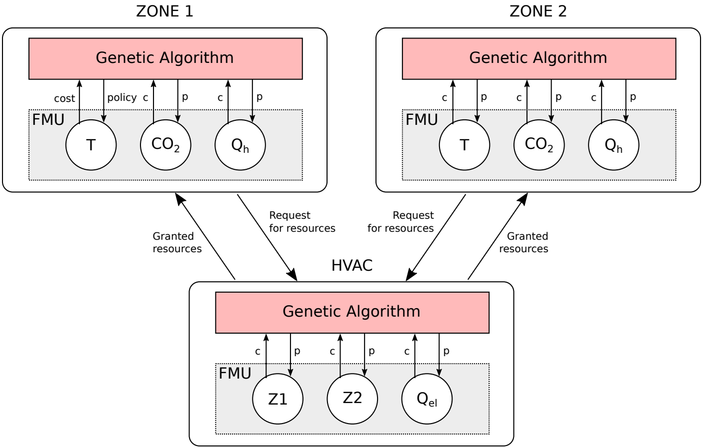
1. Select L0 frontier (subset of the full frontier)
2. Select L0+L1 frontier (subset of L0)
3. Select L0+L1+L2 frontier (subset of L0+L1)
4. ...
5. One or more policies left (equally optimal solutions)

Pareto frontier:



NOTE: No need to compare units of objectives at different levels

Formulation #1: Distributed optimization



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Formulation #1: Exemplary results

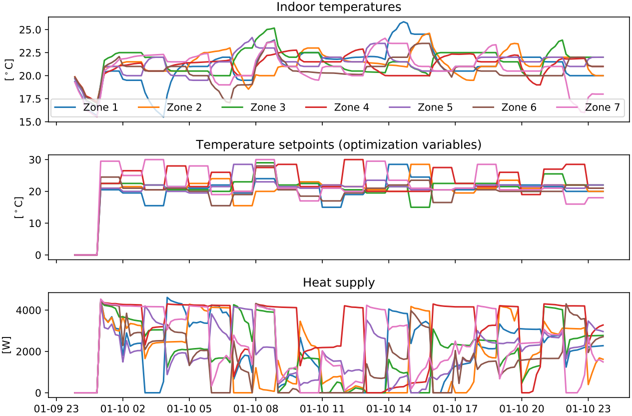

Figure: Experiment with distributed optimization of 7 zones (EnergyPlus emulation, Modelica control models)

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Formulation #2: Cost function

Simple cost function including thermal comfort and energy price:

$$\min_{q_0,\ldots,q_N} J = \sum_{i=0}^{N} |q_i P_i \Delta t_i| + \sum_{i=0}^{N} \max\left\{T_{h,i} - T_{z,i}; 0\right\} \Delta t_i D + \sum_{i=0}^{N} \max\left\{T_{z,i} - T_{c,i}; 0\right\} \Delta t_i D$$

s.t.

$$q_{max,i} > q_i > q_{min,i} \qquad \text{(parameter bounds)}$$

where:

N	number of control steps
q_i	heat supply at step i
P_i	energy price at step i
Δt_i	time step i size
$T_{z,i}$	zone temperature at step i
$T_{h,i}$	heating setpoint at step i
$T_{c,i}$	cooling setpoint at step i
D	discomfort scaling factor

Difficulty

How to include other objectives?
E.g. indoor air quality?

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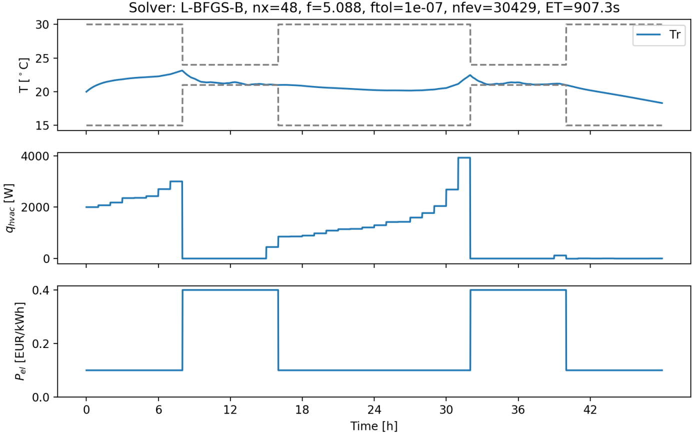

Figure: Optimal control solved using L-BFGS-B (SciPy)

Formulation #2: Solver comparison

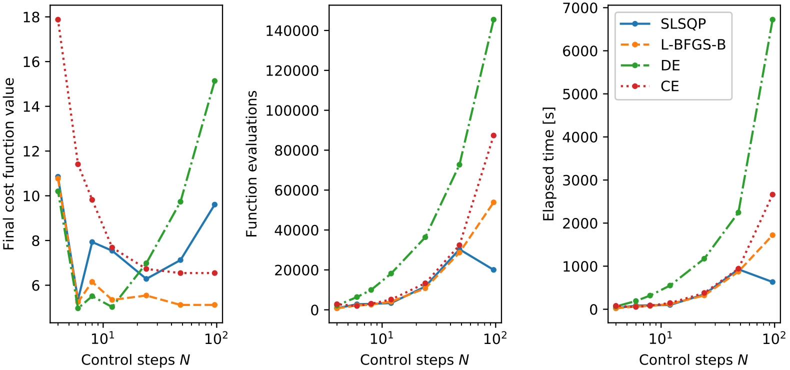

Figure: Comparison of solvers in terms of robustness and scalability: SLSQP – sequential least squares, L-BFGS-B – limited memory BFGS, DE – differential evolution, CE – cross entropy optimization

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References

1. Sørensen, J. C., & Jørgensen, B. N. (2017). An extensible component-based multi-objective evolutionary algorithm framework. In Proceedings of the 6th International Conference on Software and Computer Applications (pp. 191-197). ACM.
2. Clausen, Anders, et al. (2017). Agent-Based Integration of Complex and Heterogeneous Distributed Energy Resources in Virtual Power Plants. International Conference on Practical Applications of Agents and Multi-Agent Systems. Springer, Cham, 2017.

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