

Market Design for Energy Resource Allocation

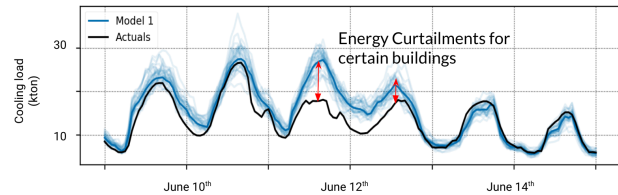
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Introduction and Motivation

During heat waves there is a severe misallocation of energy resources, with a large discrepancy between demand and supply on days two and three of the heat



Comparison between actual served demands (black) and true demands (blue) during a heat wave in June 2019

Building Heterogeneity and stochasticity in weather conditions add additional layers of complexity:

1. Cost function may differ by building
2. Weather conditions and individual building demands are uncertain

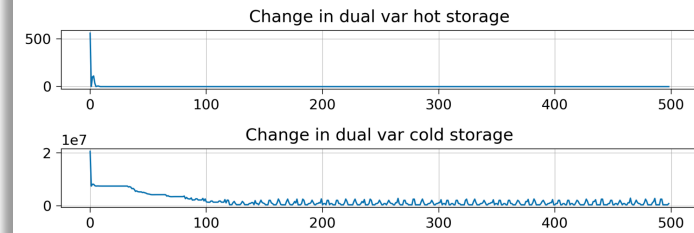
Deterministic Centralized Optimization

The deterministic centralized optimization problem optimally allocates energy between buildings

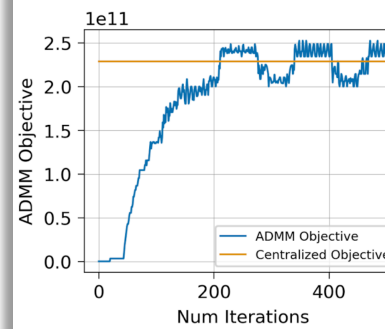
$$\begin{aligned} \min \quad & \sum_{t=1}^{T-1} \pi_{e,t} (\|D_{t,CEP}\|_1 + \pi_{g,t} g_t) \delta_t + \sum_{t=1}^{T-2} \pi_z \cdot (Z_t \odot Z_t) \\ & + \sum_{b \in \mathcal{B}} \left(\pi_{u,b} \sum_{t=1}^{T-1} U_{t,b} \odot U_{t,b} + \pi_{c,b} \sum_{t=1}^{T-1} C_{t,b} \odot C_{t,b} + \sum_{t=1}^{T-1} \pi_{e,t,b} D_{E,t,b} \right) \\ & + \sum_{j \in \mathcal{M}} \pi_{p,j} \max_{t:m(t)=j} \frac{\|D_{t,CEP}\|_1 + \sum_{b \in \mathcal{B}} D_{E,t,b}}{\delta_t} \\ \text{s.t.} \quad & S_{t+1} = S_t + \eta_E D_{t,CEP} - \eta_D \sum_{b \in \mathcal{B}} D_{t,b}, \quad t = 1 \cdots T-1, \\ & S_1 = S_i, \quad S_T = S_f, \\ & S_t \in [0, \bar{S}], \quad t = 1 \cdots T, \\ & g_t = \eta_g \text{boiler} P_{\text{boiler},t}, \\ & \eta_E D_{t,CEP} \leq \bar{q}, \\ & D_{t,b} = \bar{D}_{t,b} - U_{t,b} - C_{t,b}, \forall b \in \mathcal{B}, t \\ & C_{t,b} \leq \bar{C}_{t,b} (1 - y_{t,b}), \quad y_{t,b} \in \{0, 1\}^3, \forall b \in \mathcal{B}, t \\ & U_{t,b} = \bar{D}_{t,b} y_{t,b}, \quad y_{t,b} \in \{0, 1\}^3, \forall b \in \mathcal{B}, t \\ & Z_t \geq \bar{D}_{t,CEP} - D_{t+1,CEP}, \quad t = 1 \cdots T-2, \\ & Z_t \geq \bar{D}_{t+1,CEP} - D_{t,CEP}, \quad t = 1 \cdots T-2, \\ & E_{t,CEP}, D_{t,b}, U_{t,b}, C_{t,b}, Z_t \geq 0, \quad t = 1 \cdots T-1. \end{aligned}$$

- Cost at CEP
- Cost to buildings
- Demand Charge
- Storage Constraints
- Capacity Constraints
- Demand Constraints
- Wear and Tear Constraints

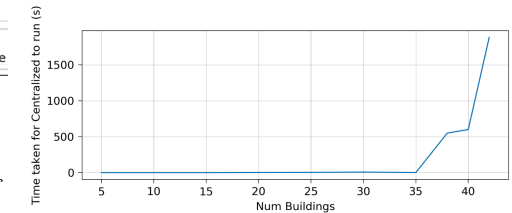
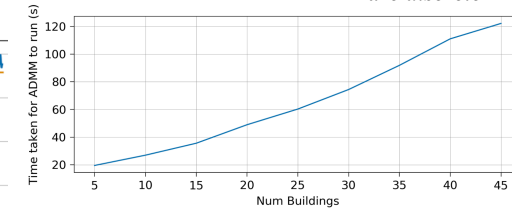
Results of Applying ADMM



1. Violation of Storage Constraints with the number of iterations as expected since ADMM is not guaranteed to converge when the decision variables are discrete



2. Change in the objective of the ADMM solution with the number of iterations as compared to the fixed centralized objective. Numerical experiments suggest "near" convergence despite binary decisions



3. Running time of the centralized and ADMM problems as the number of buildings is increased. The runtime of the centralized problem "blows up" as the number of buildings is increased

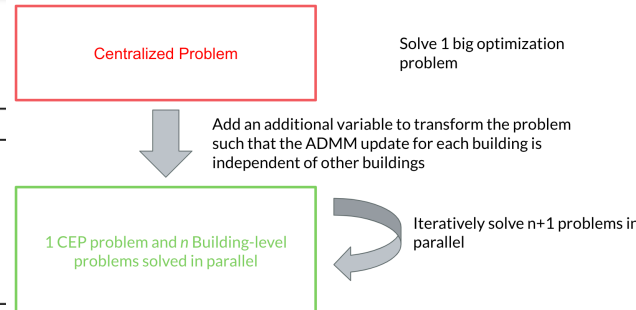
ADMM for Distributed Optimization

Runtime of Centralized Optimization problem scales with the number of buildings and time periods, which is computationally intensive
ADMM unlocks the scale-up to city scale settings while providing a market interpretation

$$\begin{aligned} \min_{\mathbf{x} \in \mathcal{X}, \mathbf{y} \in \mathcal{Y}} \quad & h(\mathbf{x}, \mathbf{y}) = f(\mathbf{x}) + g(\mathbf{y}) \\ \text{s.t.} \quad & \mathbf{Ax} + \mathbf{By} = \mathbf{c} \\ \mathcal{L}_\beta(\mathbf{x}, \mathbf{y}) = & f(\mathbf{x}) + g(\mathbf{y}) + \lambda^T (\mathbf{Ax} + \mathbf{By} - \mathbf{c}) \\ & + \frac{\beta}{2} \|\mathbf{Ax} + \mathbf{By} - \mathbf{c}\|^2 \end{aligned}$$

Algorithm 1: Two Block ADMM

Input : Initial dual multiplier $\lambda^{(0)}$, and initial vector $\mathbf{y}^{(0)}$
for $k = 0, 1, 2, \dots$ **do**
 $\mathbf{x}^{(k+1)} = \arg \min_{\mathbf{x} \in \mathcal{X}} \mathcal{L}_\beta(\mathbf{x}, \mathbf{y}^{(k)})$;
 $\mathbf{y}^{(k+1)} = \arg \min_{\mathbf{y} \in \mathcal{Y}} \mathcal{L}_\beta(\mathbf{x}^{(k+1)}, \mathbf{y})$;
 $\lambda^{(k+1)} \leftarrow \lambda^{(k)} - \beta (\mathbf{Ax}^{(k+1)} + \mathbf{By}^{(k+1)} - \mathbf{c})$;
end



Future Work

1. Incorporate stochastic uncertainties to inform energy allocation decisions
2. Investigate fairness notions in the objective to ensure that all buildings get a certain proportion of requested demand
3. Distributed implementation through market prices in the stochastic setting