# Advanced peak demand forecast and battery dispatch algorithms to integrate storage-based demand response with BAS


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## INTRODUCTION

- Up to **20%** of the total installed generation capacity in the United States is dedicated to meeting peak loads, but is in use only **5%** of the time.
- The building sector contributes up to **75%** of all electricity usage and is a significantly larger contributor, proportionately, to peak demand.
- **Demand-side management (DSM) techniques, together with the integration of effective energy storage** can play essential roles in increasing the efficiency and reliability of the grid system.
- **Mature technologies in large-scale CPS applications**, such as in modern commercial buildings that have building automation systems and electricity storage, can potentially enable more efficient grids and distributed generation.

## OBJECTIVE

We envision that, "***Demand peaks and associated grid stress, electricity unit cost, and carbon emissions can be effectively reduced, by investigating a novel CPS Demand-Side Management framework that integrates battery storage within an advanced Building Automation Systems***".

## APPROACH & INTELLECTUAL MERIT

To address this fundamental objective, we propose a novel Predictive **CPS-based Demand Side Management framework**

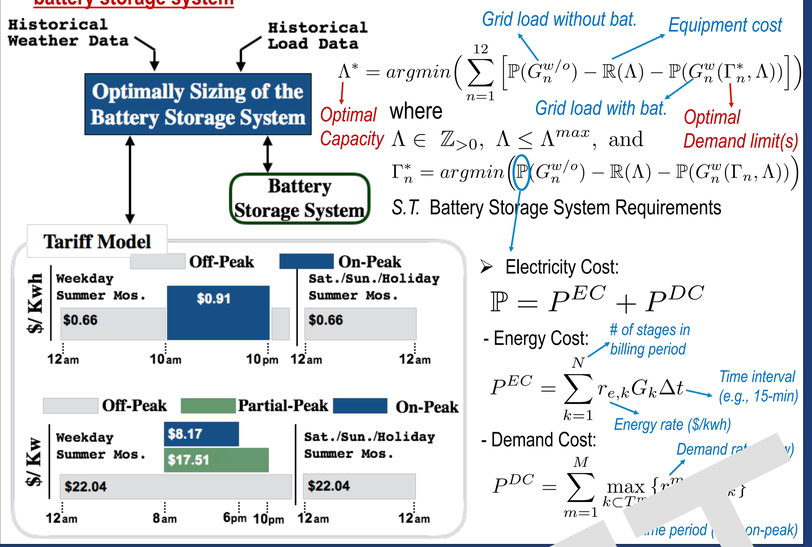
- Its transformative capability is derived from an integrative systems-of-systems approach, by formulating a bi-level optimization framework to concurrently optimize the daily temperature setpoints and dispatch strategy of the storage system.
- It utilizes intelligent technologies and advanced mixed-integer optimization to control the trade-off between energy consumption and cost vs. occupant's comfort level.
- It uses B-splines modeling (tuned by hourly temperature control points) to maximize the flexibility of the algorithm in representing different arbitrary trajectories in the real-time setpoint temperature.
- It minimizes the need for human interaction in building control.
- It mitigates the uncertainties in the return.
- It will use a powerful model selection approach to select the best statistical learning models to represent the next day's energy consumption (load profile).
- It will utilize the adaptive model refinement approach to increase the fidelity of statistical learning models when strategically updated data is available.

## SIGNIFICANCE & IMPACT

- Successful outcome of the proposed framework will **promote greater and informed adoption of related/upcoming green technologies (such RE generation, and EVs)** in large scale CPS applications.
- Successful CPS framework **can pass the ~30% barrier** in load profile reduction reached by commercially available BAS.
- Performance of the control framework will be calibrated to improve storage lifetime and cost of ownership

## PASSIVE DSM OPTIMIZATION

- The Passive DSM Optimzation conducts the size (or capacity) optimization of the battery storage system




$$\Lambda^* = argmin\Big(\sum_{n=1}^{12}\Big[\mathbb{P}(G_n^{w/o}) - \mathbb{R}(\Lambda) - \mathbb{P}(G_n^w(\Gamma_n^*, \Lambda))\Big]\Big)$$

Grid load without bat. · Equipment cost · Optimal Capacity · Grid load with bat. · Optimal Demand limit(s)

where $\Lambda \in \mathbb{Z}_{>0},\ \Lambda \leq \Lambda^{max}$, and

$$\Gamma_n^* = argmin\Big(\mathbb{P}(G_n^{w/o}) - \mathbb{R}(\Lambda) - \mathbb{P}(G_n^w(\Gamma_n, \Lambda))\Big)$$

*S.T.* Battery Storage System Requirements

➢ Electricity Cost:

$$\mathbb{P} = P^{EC} + P^{DC}$$

- Energy Cost: (# of stages in billing period; Time interval (e.g., 15-min); Energy rate ($/kwh))

$$P^{EC} = \sum_{k=1}^{N} r_{e,k} G_k \Delta t$$

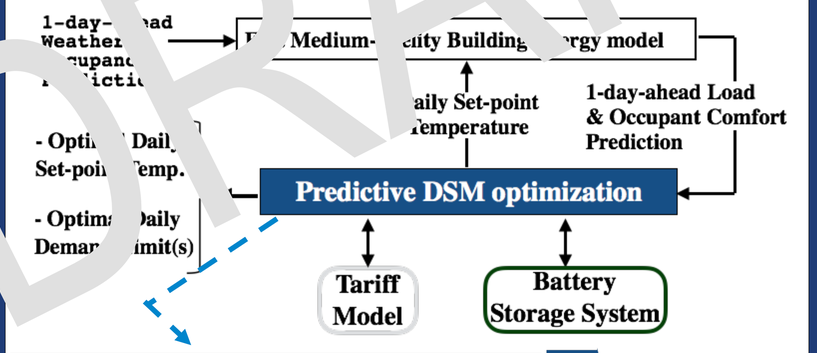
- Demand Cost: (Demand rate ($/kw); time period (on-peak))

$$P^{DC} = \sum_{m=1}^{M} \max_{k \subset T^m} \{r^m \quad \kappa\}$$

**OPTIMAL CAPACITY**

## REARL-TIME DSM OPTIMIZATION

- The Predictive DSM Optimization performs day-ahead electricity cost minimization to find the optimal strategy and the optimal setpoint temperature profile




**Predictive DSM Optimization Algorithm**

for $d = 1$ *to* $D$ **do** (# of day in billing period)

  **Result:** $X^*_{TEMP}$, (Optimal hourly temperature control points in d-th day)

  Initialize: ${}^dX^*_{TEMP} = X_{TEMP}$ based on ASHRAE Standard-55

  $Q^+_m = \max_{k \subset T^m}\{G_k\};\ k \in \mathbb{Z}_{>0}, and\ k \leq N^{d-1}$

  $Q^d_m = \max_{k \subset T^m}\{G_k({}^dX^*_{TEMP})\};\ k \in \mathbb{Z}_{>0}, and\ N^{d-1} \leq k \leq N^d$

  **if** $\exists m \mid Q^d_m > Q^+_m$ **then**

    $X^*_{TEMP} = argmin(\mathbb{H}(X_{TEMP}))$

    *subject to:* $X^{lb}_{TEMP} \leq X_{TEMP} \leq X^{ub}_{TEMP}$

    Occupancy Comfort Constraints

  **end**

**end**

(Estimated using modified version of Predictive Percentage of Dissatisfaction model)

Minimize: Energy Cost · Demand Cost · Loss of Comfort

➢ Lower level Optimization:

(Optimal capacity (estimated on Passive DSM Opt.))

$$\mathbb{H}(X_{TEMP}) = \max_{\Gamma_m}\Big[\mathbb{P}(G_k(X_{TEMP}, \Gamma_m, \Lambda^*))\Big];$$

*where*

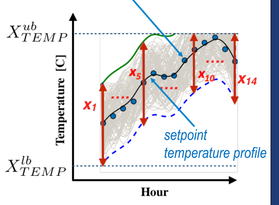
$m = 1, 2, ..., M,\ k \in \mathbb{Z}_{>0}$, and $k \leq N^{d-1}$

*subject to:* $\Gamma_m \leq Q^+_m$

Battery Storage System Requirements

(Daily demand limit(s); 0.05 <SoC < 0.95; Rate of charge/discharge = 1C)

(Hourly temperature control points used to train the setpoint temperature profile:)




➢ Daily ToU Tariff

$$\mathbb{P} = P^{EC} + P^{DC}$$

$$P^{EC} = \sum_{k=N^{d-1}}^{N^d} r_{e,k} G_k \Delta t$$

$$P^{DC} = \sum_{m=1}^{M} \max_{k \subset T^m}\{r^m_d \times G_k\};\ k \in \mathbb{Z}_{>0}, and\ N^{d-1} \leq k \leq N^d$$

## ACKNOWLEDGMENT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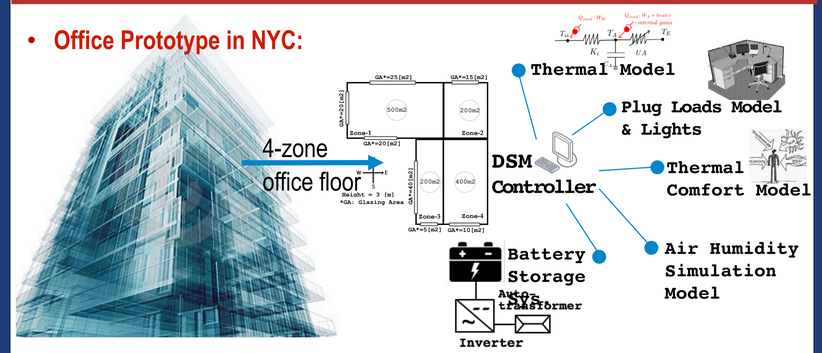
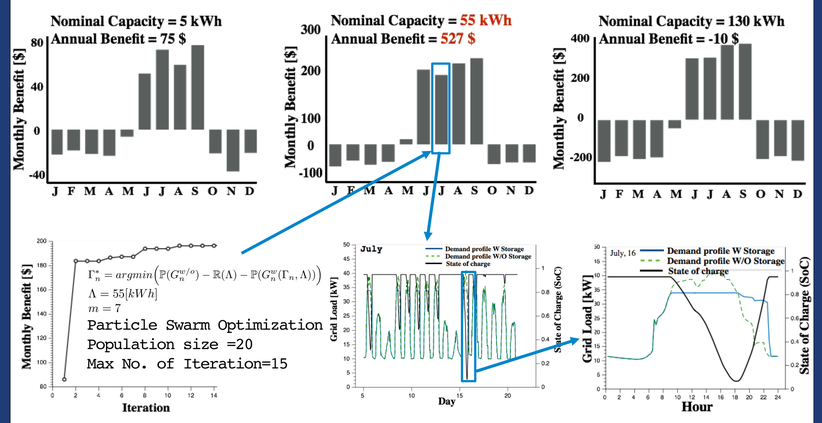
## CASE STUDY

- **Office Prototype in NYC:**




- **Optimal sizing of battery storage - Passive DSM optimization** (using 2012 weather data):




- **Real-time DSM Optimization using Predictive DSM** (on 2014 weather data):

➢ No DSM Action :

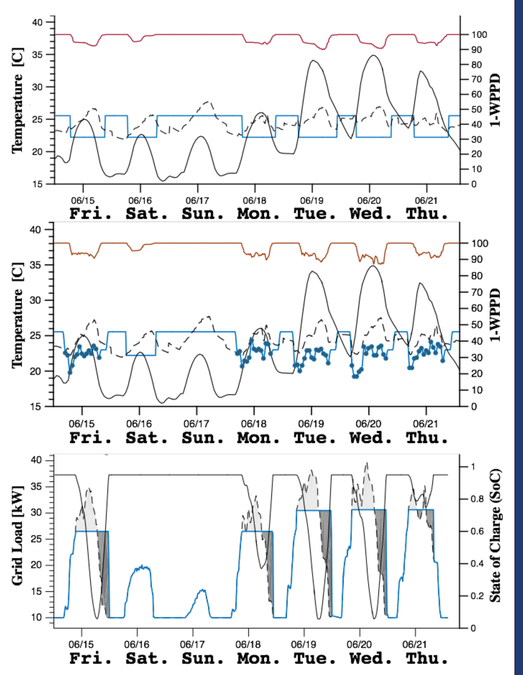
Setpoint Temperature based on ASHRAE Standard-55 · Occupant Comfort 1- Weighted Predicted Perce. of Dissatisfaction · Ambient Temperature · Mean Radiant Temperature

➢ Predictive DSM Optimization:

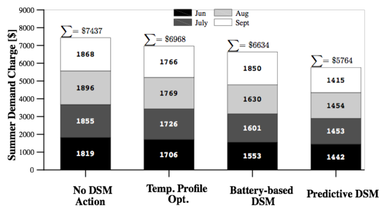
**Optimal** Control Temperature · **Optimal** Setpoint Temperature · Occupant Comfort 1- Weighted Predicted Perce. of Dissatisfaction · Ambient Temperature · Mean Radiant Temperature

➢ Predictive DR optimization in a peak week of Jun:

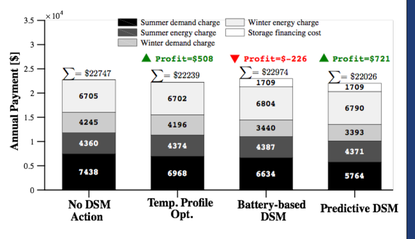
No DSM Action · Predictive DSM Optimization · State of Charge




➢ Breakdown of demand cost in summer months:




➢ Breakdown of total annual cost:




➢ Peak load reduction in summer months via Predictive DSM optimization: