AEE Webinar
Wednesday, January 22nd, 2020
2:00-3:00pm EDT

Predictive Demand Side Management Optimization

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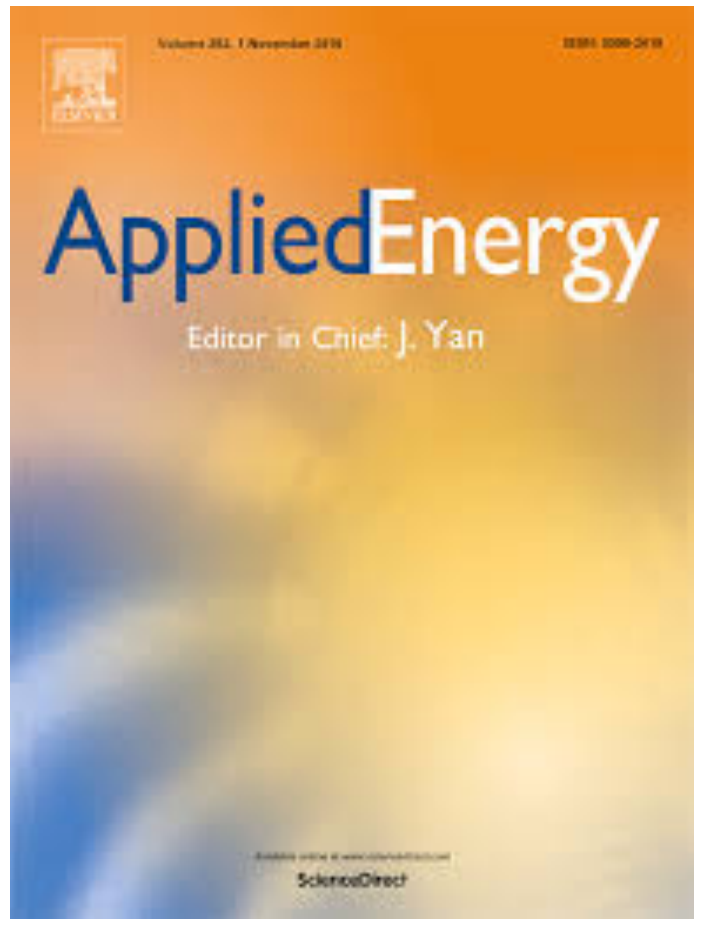

Published on Sept. 2019

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Space Utilization
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Anomaly Detection
System Optimization
VTN (ISO)
VEN (BLD)
kw
Demand Response

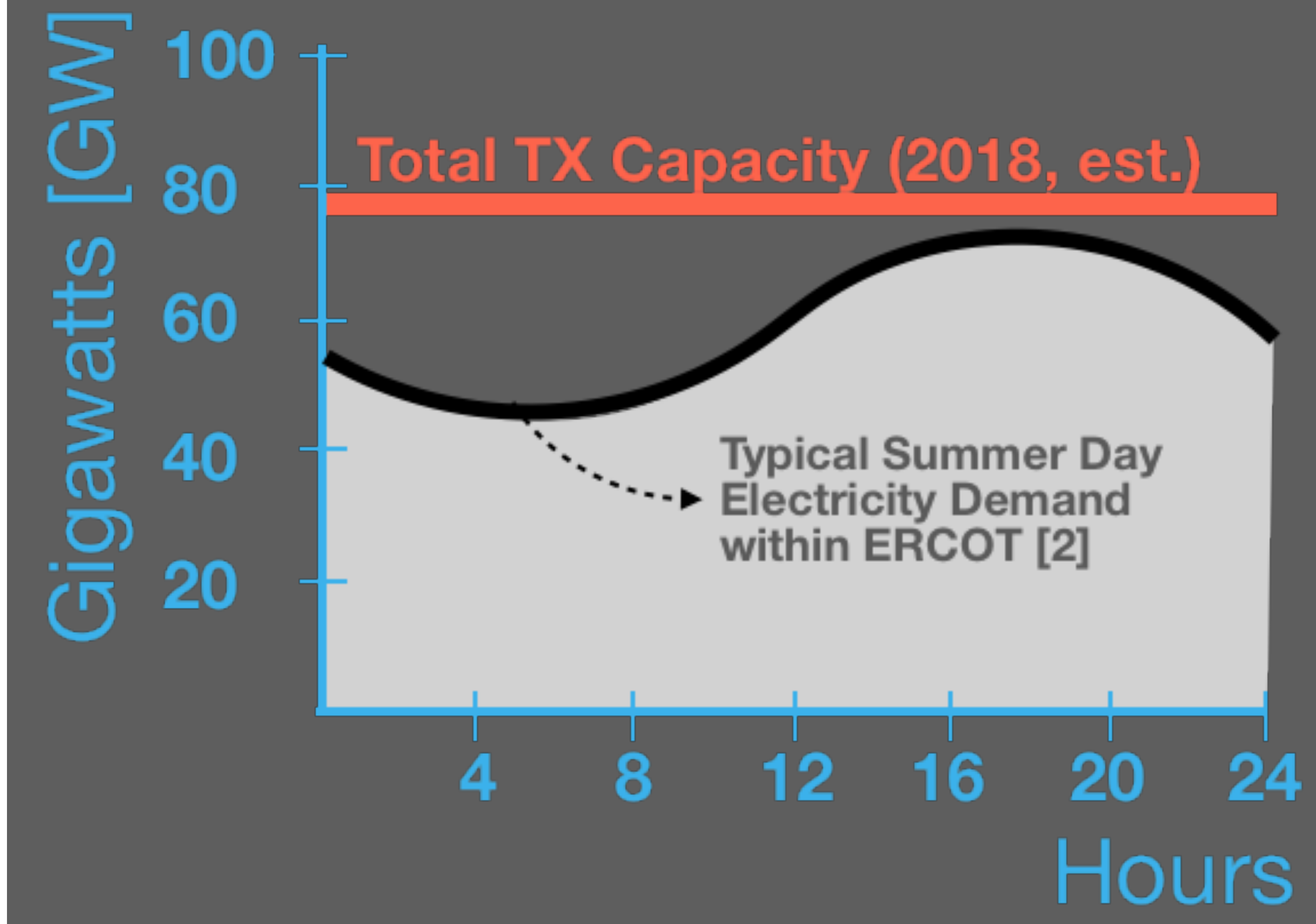
Outline

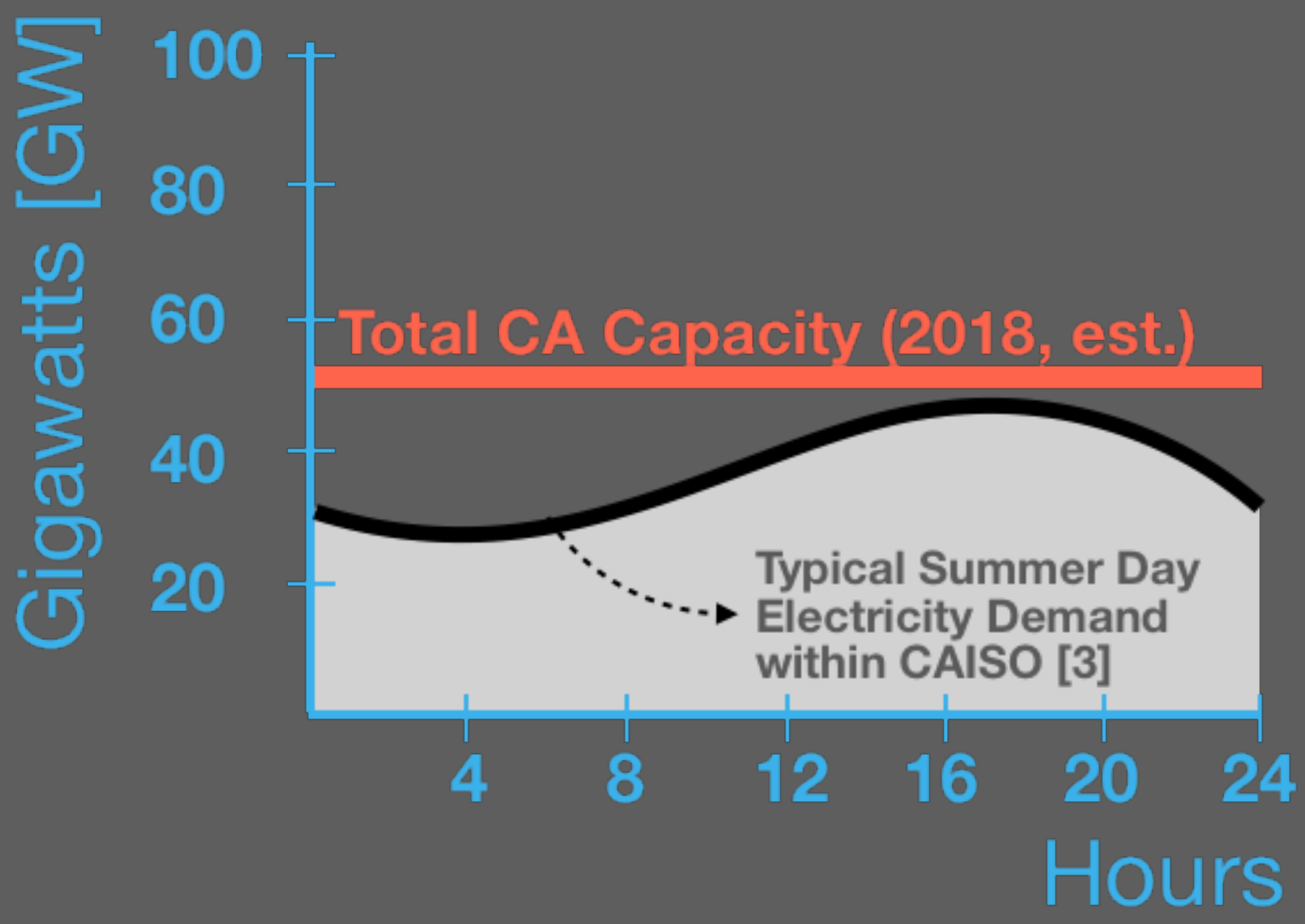
- Motivation
- Background and Literature
- Objectives
- Predictive Demand Side Management Opt.
- Results and Discussion
- Concluding Remarks

Motivation

- Demand load vs Capacity
- Building Sector Contribution
- Demand/Supply Management

Up to **20%** of the total installed electricity generation capacity in the United States is dedicated to meeting peak loads (defined as in use only **5%** of the time.





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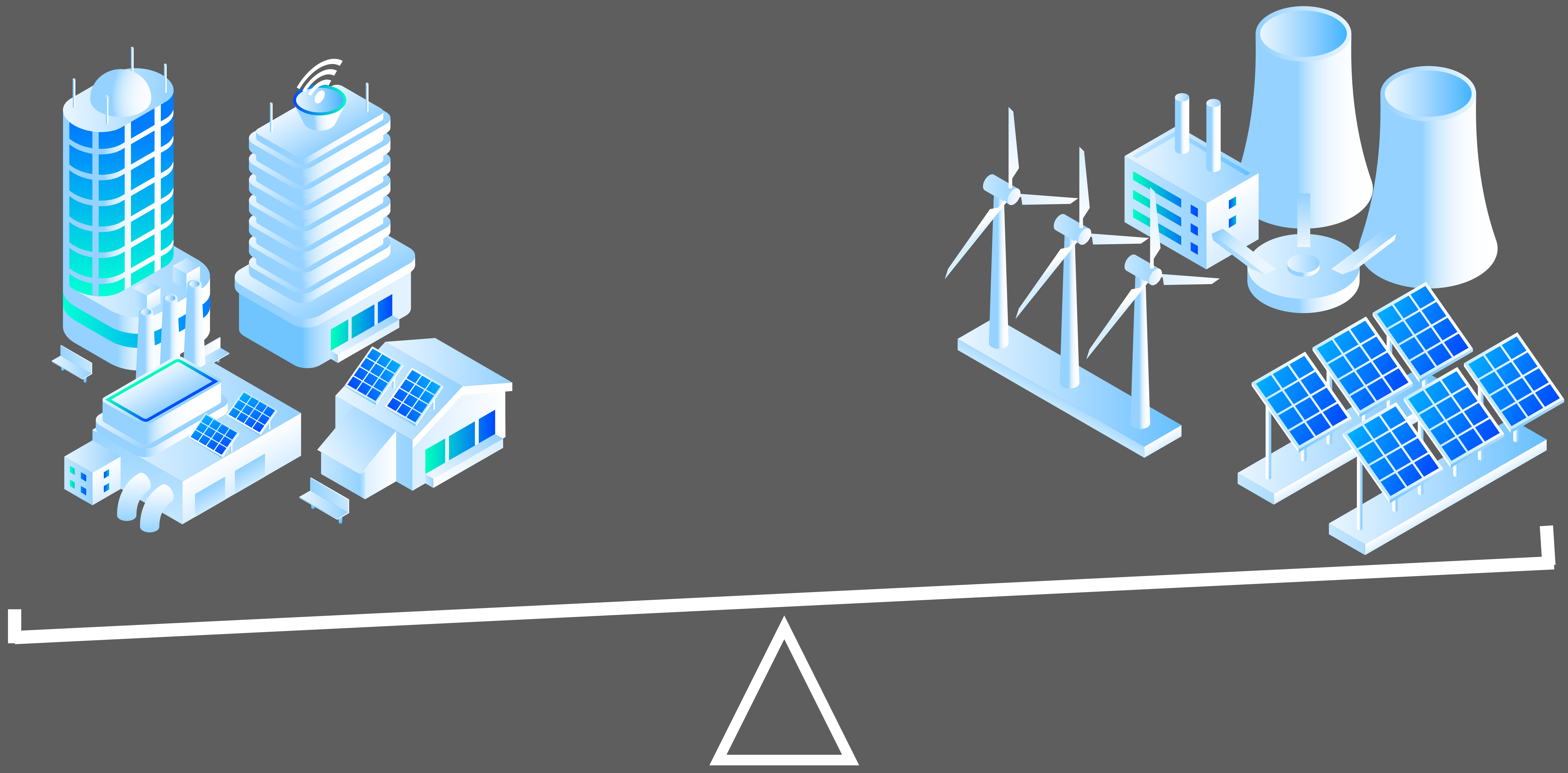
Motivation

- Demand load vs Capacity
- Demand/Supply Management
- Building Sector Contribution

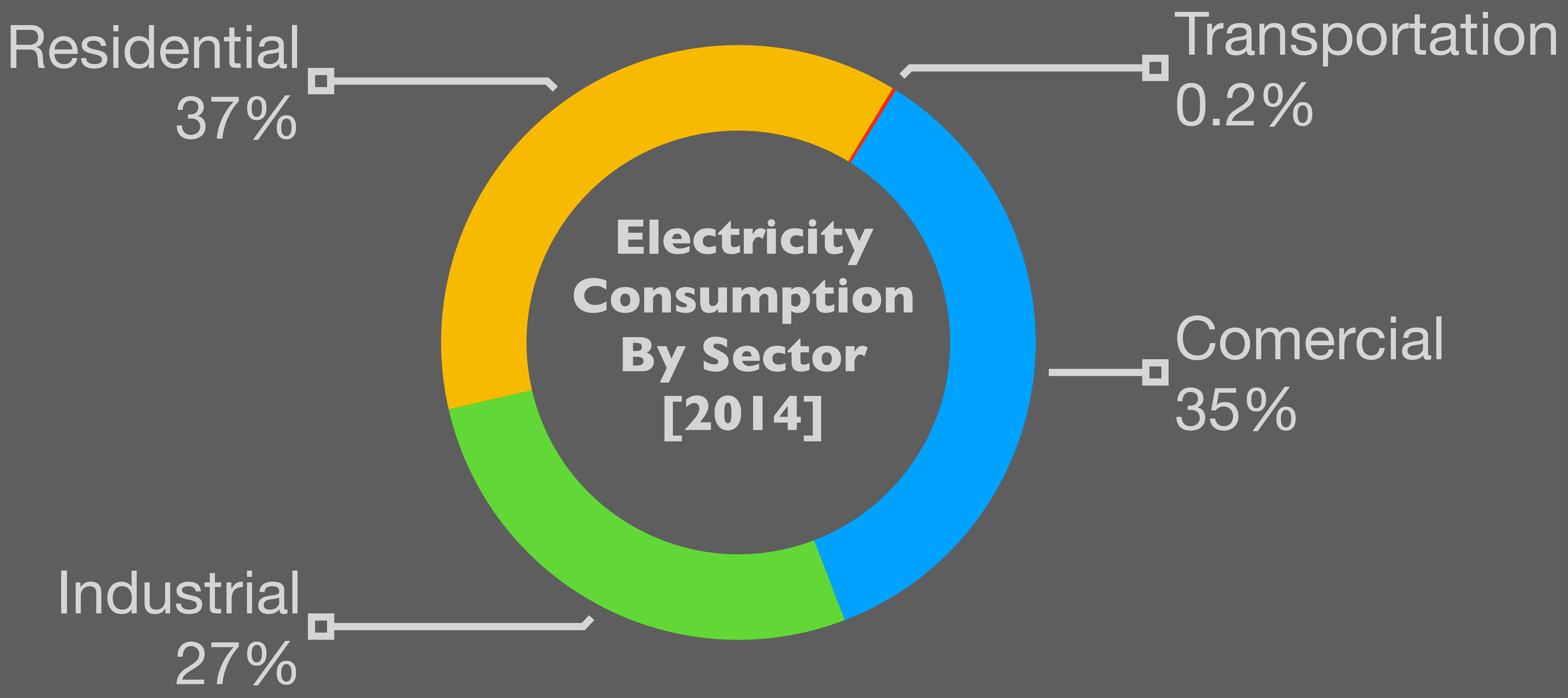
Demand and supply-side management techniques can play essential roles in smoothing peak demands and thus increasing the efficiency and reliability of the grid system.



Motivation

- Demand load vs Capacity
- Demand/Supply Management
- Building Sector Contribution

The building sector contributes up to **75%** of all electricity usage and is a significantly larger contributor, proportionately, to peak demand.

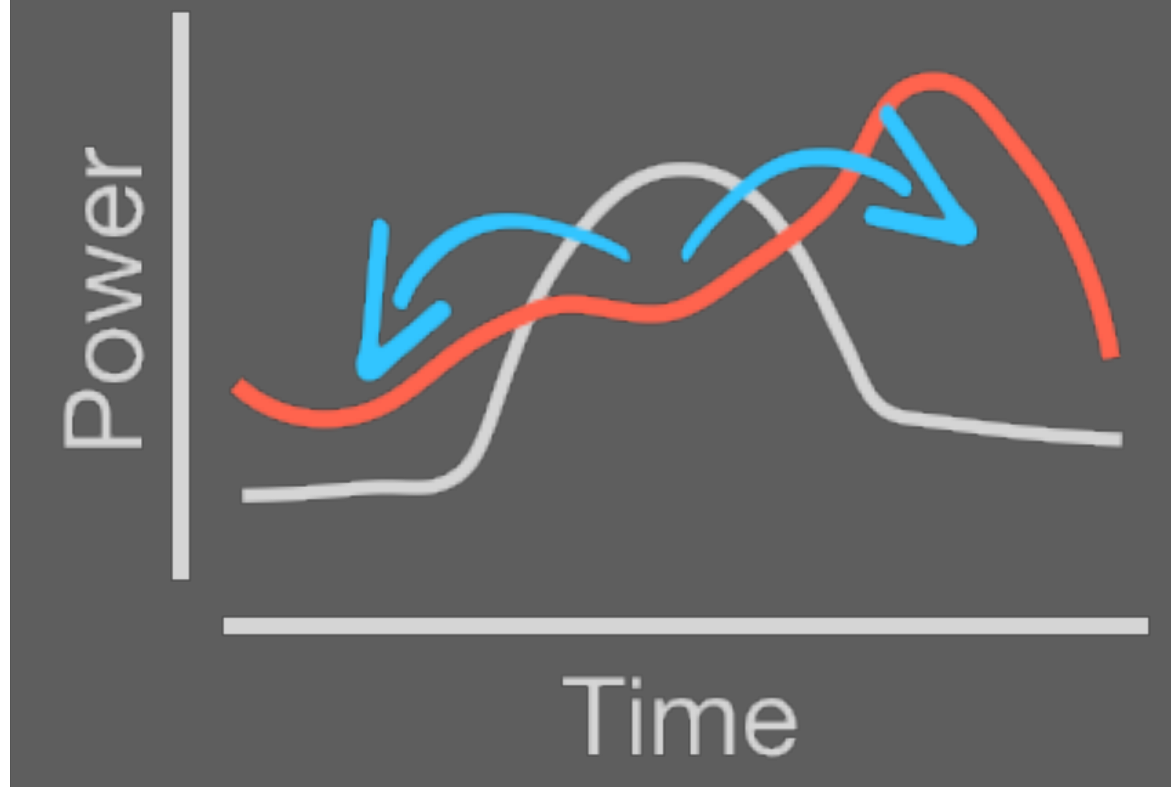


Background

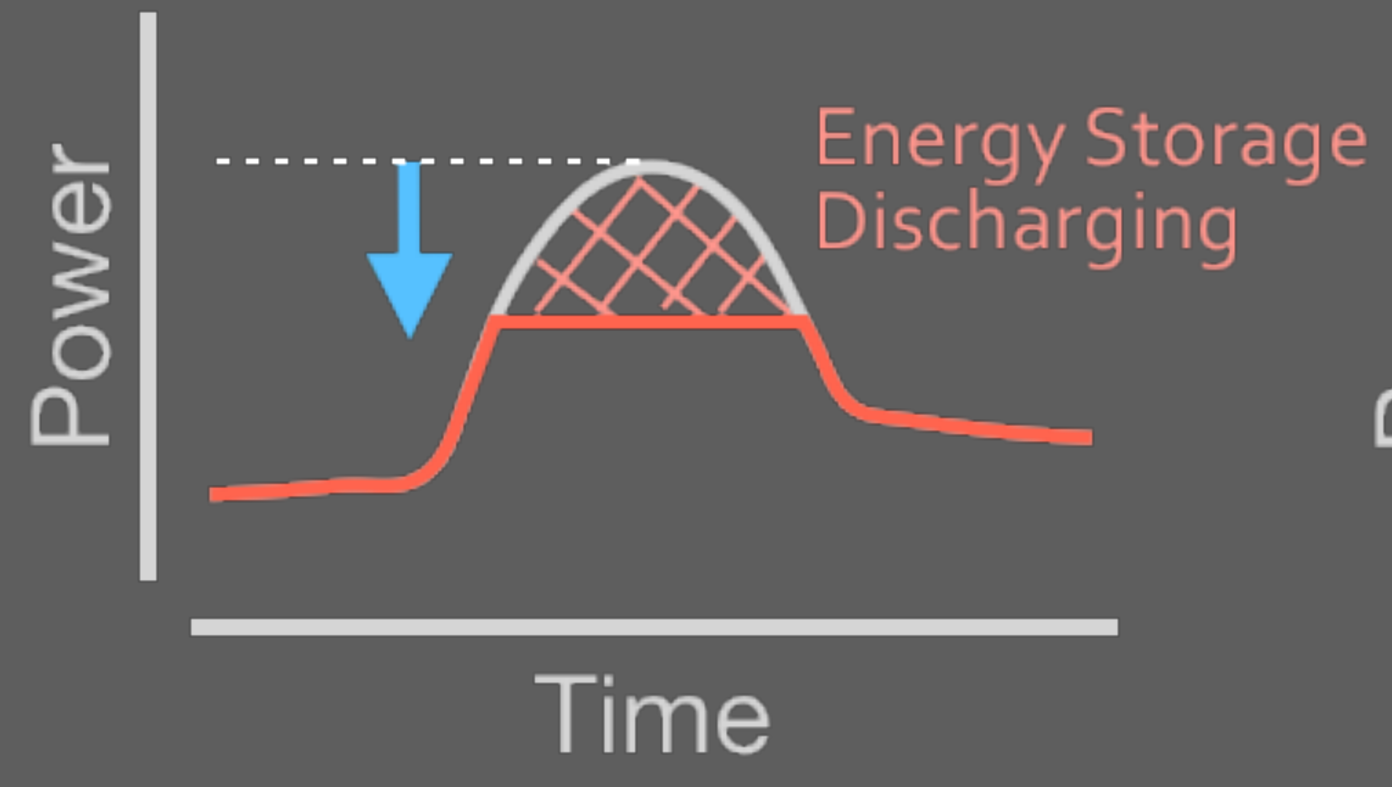
Demand Side Management (DSM)

"Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized"

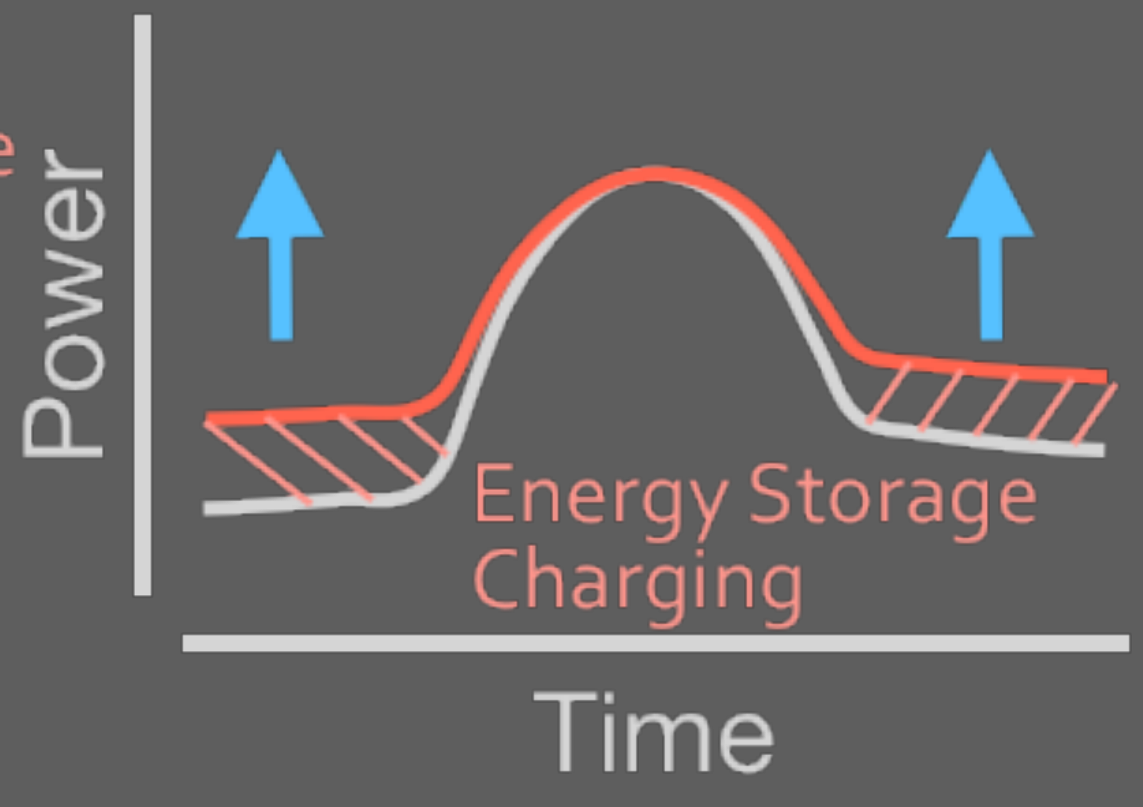
Load Shifting



Peak Shaving



Vally Filling



Background

DSM Technology

- Direct-load control
- Load-limiter technique
- Price-based techniques

Storage-based DSM

Direct-load Control Technique

Utility remotely controls customers' registered appliances/thermostats.

Background

DSM Technology

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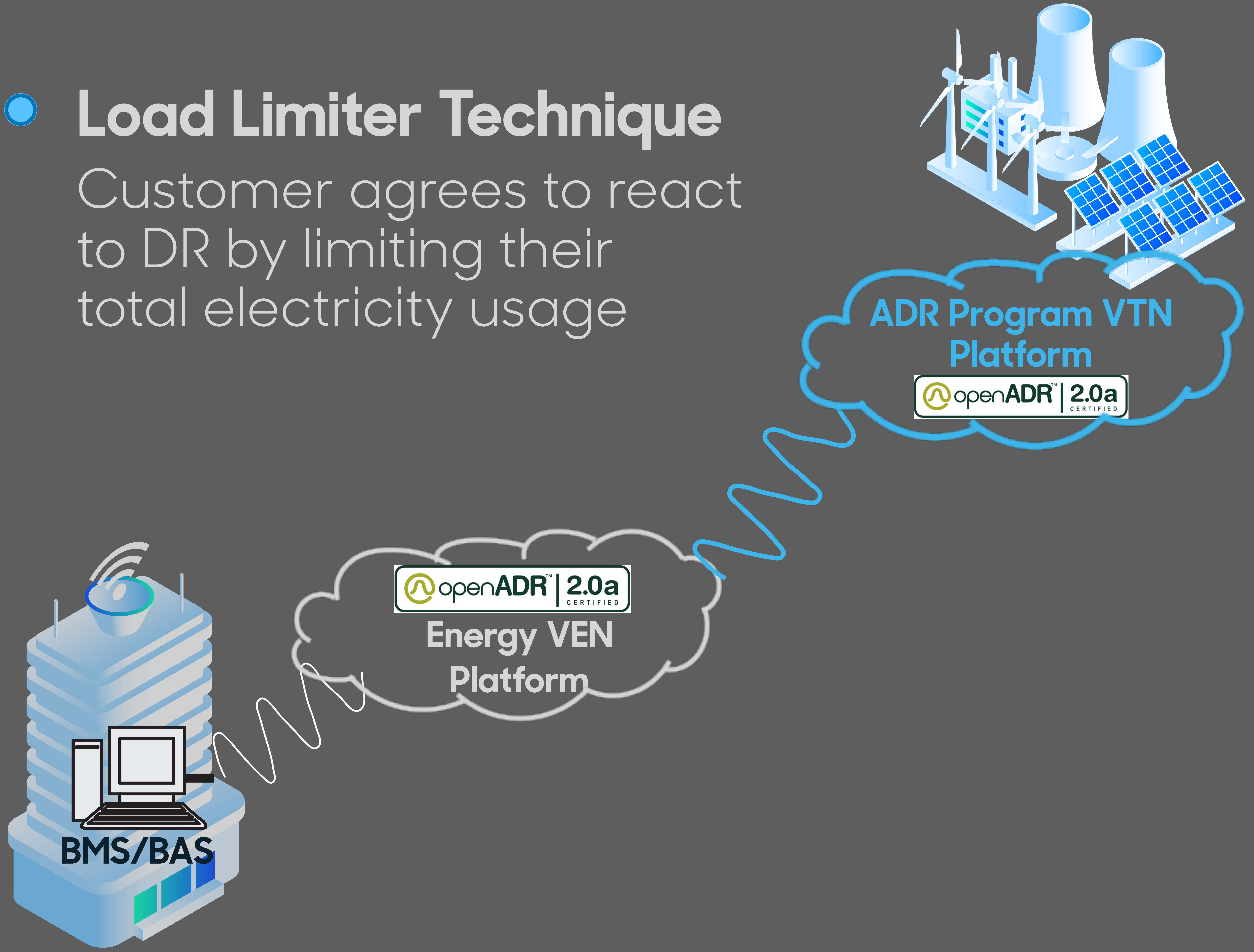
- Load-limiter technique
- Price-based techniques

Storage-based DSM

- **Load Limiter Technique**

  Customer agrees to react to DR by limiting their total electricity usage



Background

DSM Technology

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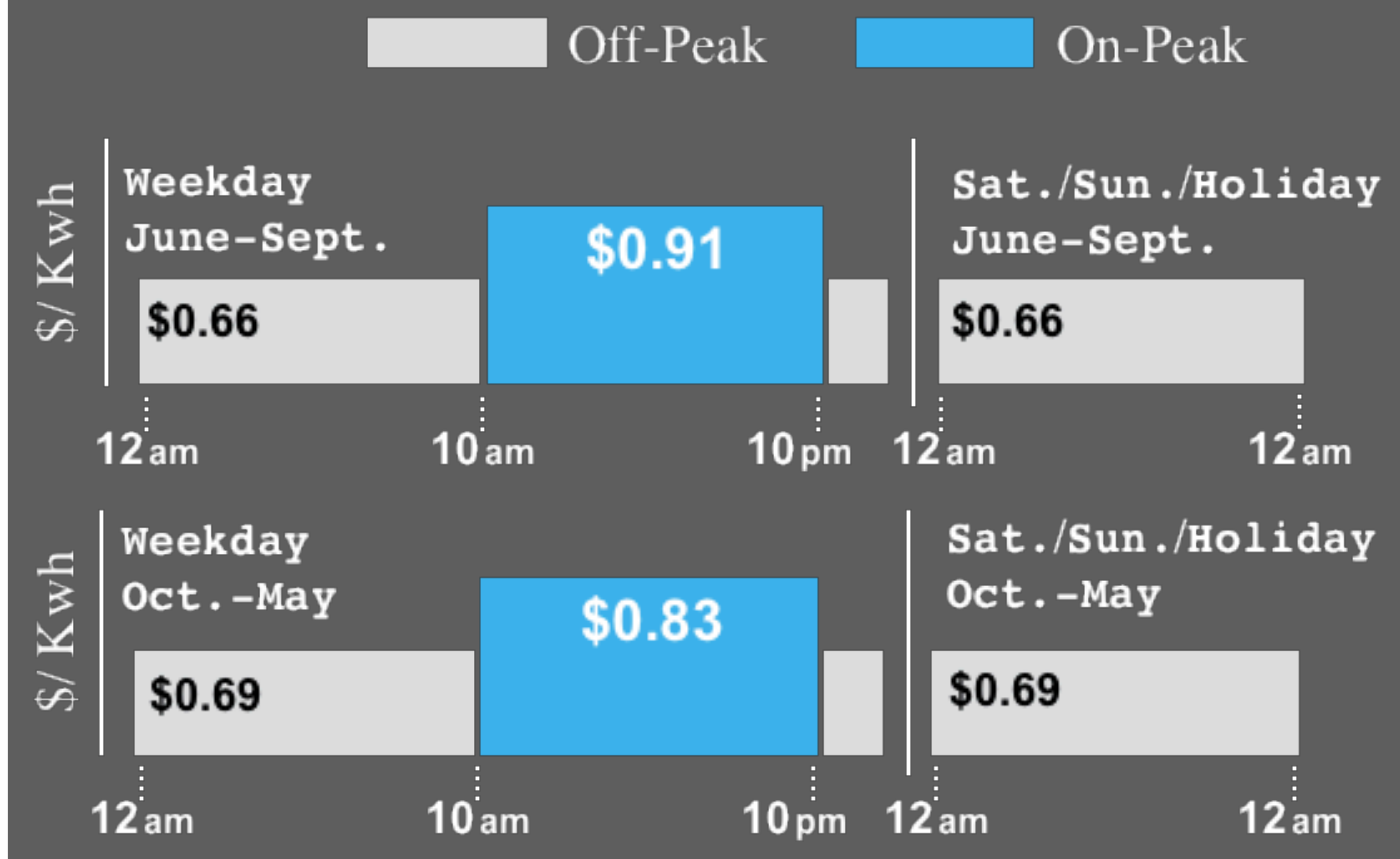
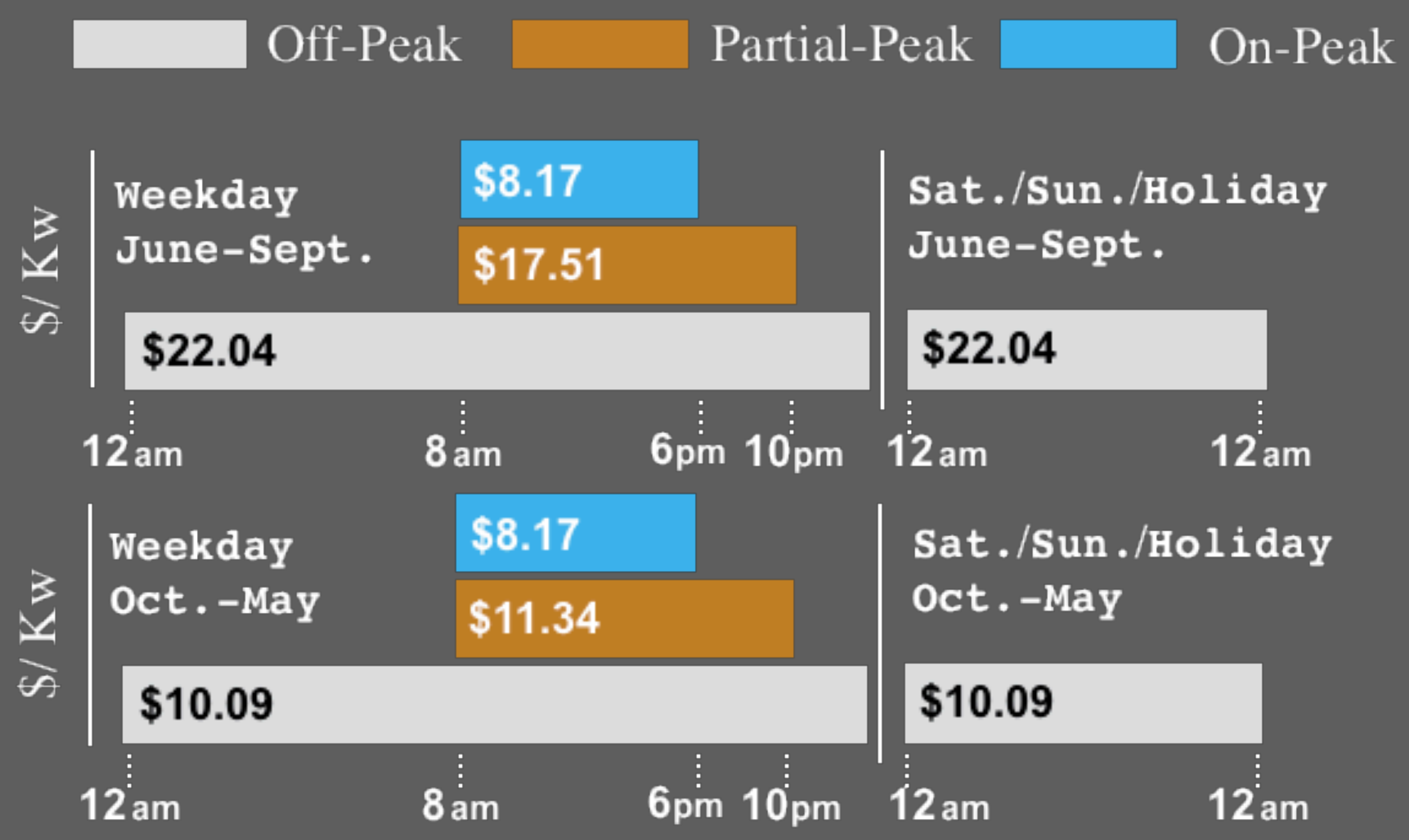
Storage-based DSM

- **Price-based Technique (e.g. ToU)**

  Electricity cost is set high at peak load time and low at off-peak time, to encourage customers to engage in load management.





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Background

DSM Technology

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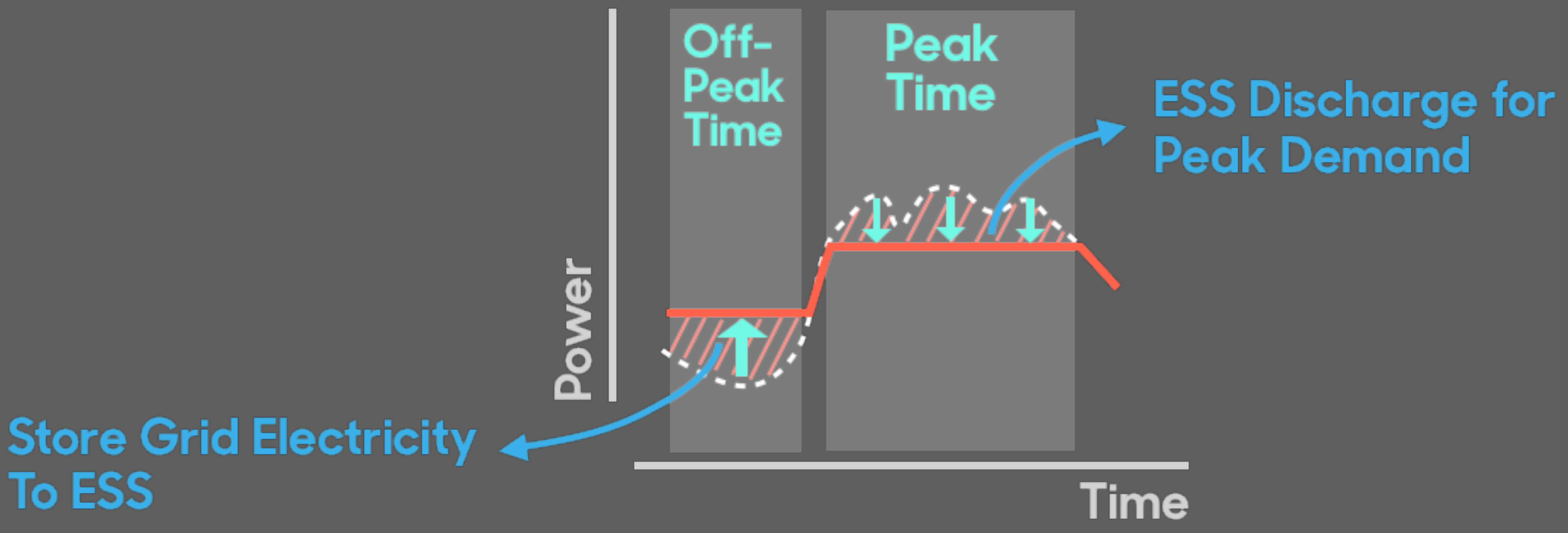
Storage-based DSM

DSM using Energy Storage Systems (ESS)

Applicability of DSM techniques has been improved by integrating ESS in a distributed fashion.

- Electricity cost variation
- Modern storage systems



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Literature

Storage-based DSM

- Stable et al. (2013) formulated the integration of electrical energy storage systems in commercial buildings as a mixed-integer linear program to minimize energy cost and CO2 emissions.
- Dufo-Lopez, (2015) formulated a new model to find the optimal nominal capacity of the electrical storage under a real-time pricing tariff.
- Zheng et al. (2015) demonstrated cost savings of different storage systems (flywheels, conventional, advanced and flow batteries) in a household with a ToU or peak-demand based New York City tariff structure through simulations.
- Wang et al. (2016) investigated the integration of stationary battery systems and electric vehicles in a commercial building by formulating a price-based DSM as a mixed-integer linear programming problem.

While there has been substantial research on optimizing the energy consumption and peak demand through MPC algorithms, a relatively limited number of them have focused on approaches for adjusting zone setpoint temperature

Objective

The primary objective of this study is to design a novel DSM framework based on particle swarm optimization algorithms that

- Minimize grid load peaks
- Minimize electricity cost,
- Quantify system payback time and
- Preserving occupant comfort.

Methodology

Passive DSM Optimization

- Capacity Optimization
- Dispatch Strategy
- Degradation

Real-time DSM Opt.

- Hierarchical opt. Formulation

Passive DSM Optimization

Conducting the size (i.e., nominal capacity) optimization of the battery storage by minimizing

Electricity Cost

Equipment Installation Cost

Financing Cost

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Methodology

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Passive DSM Optimization

Conducting the size (i.e., nominal capacity) optimization of the battery storage by minimizing

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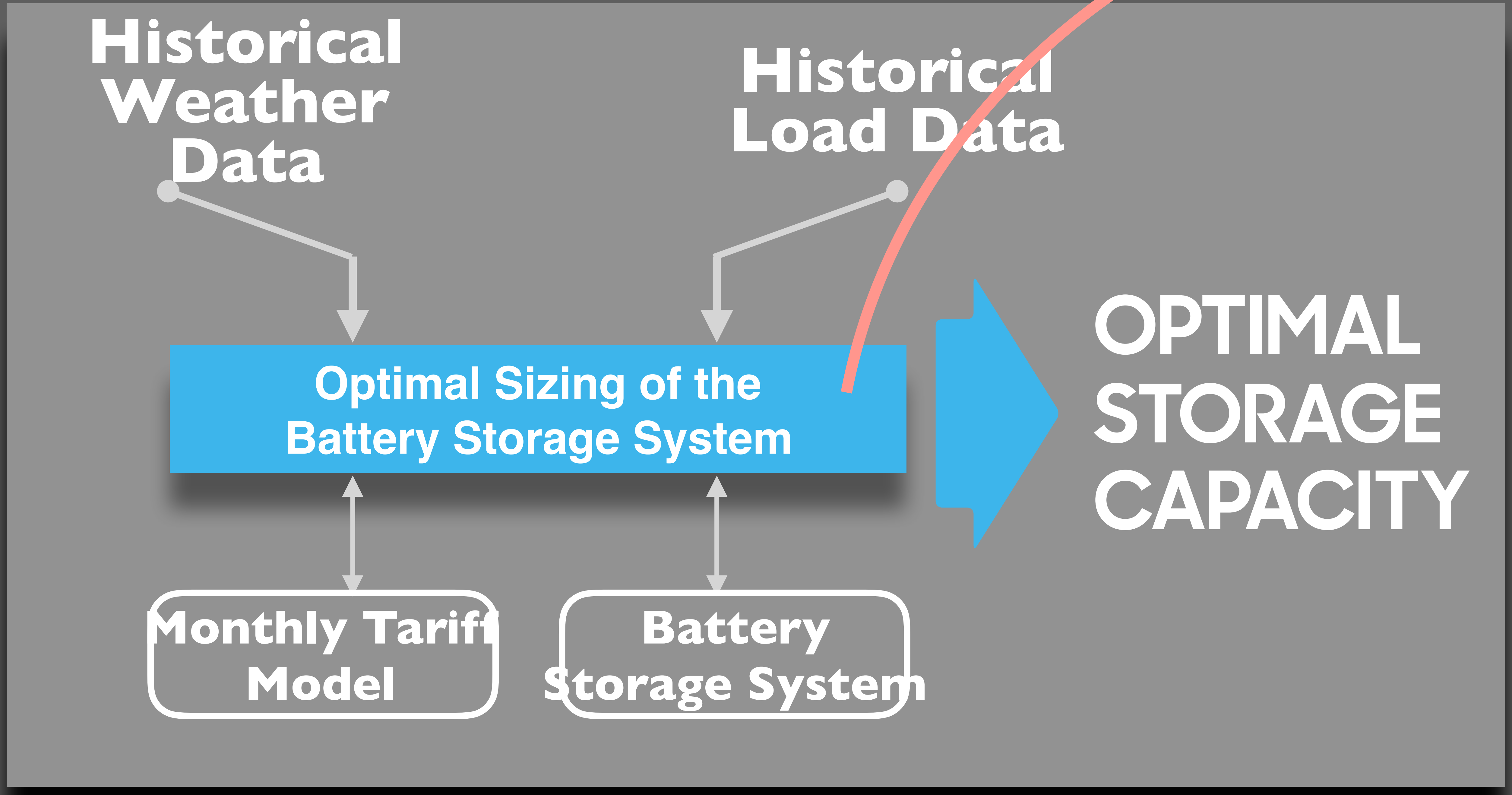
Financing Cost

MODEL PREDICTIVE CONTROL - DSM

$Min : E_{elec} + E_{lcc}$

$st .$

Battery Operational Constraints



DSM Optimization | Mixed-integer NL Programing

Methodology

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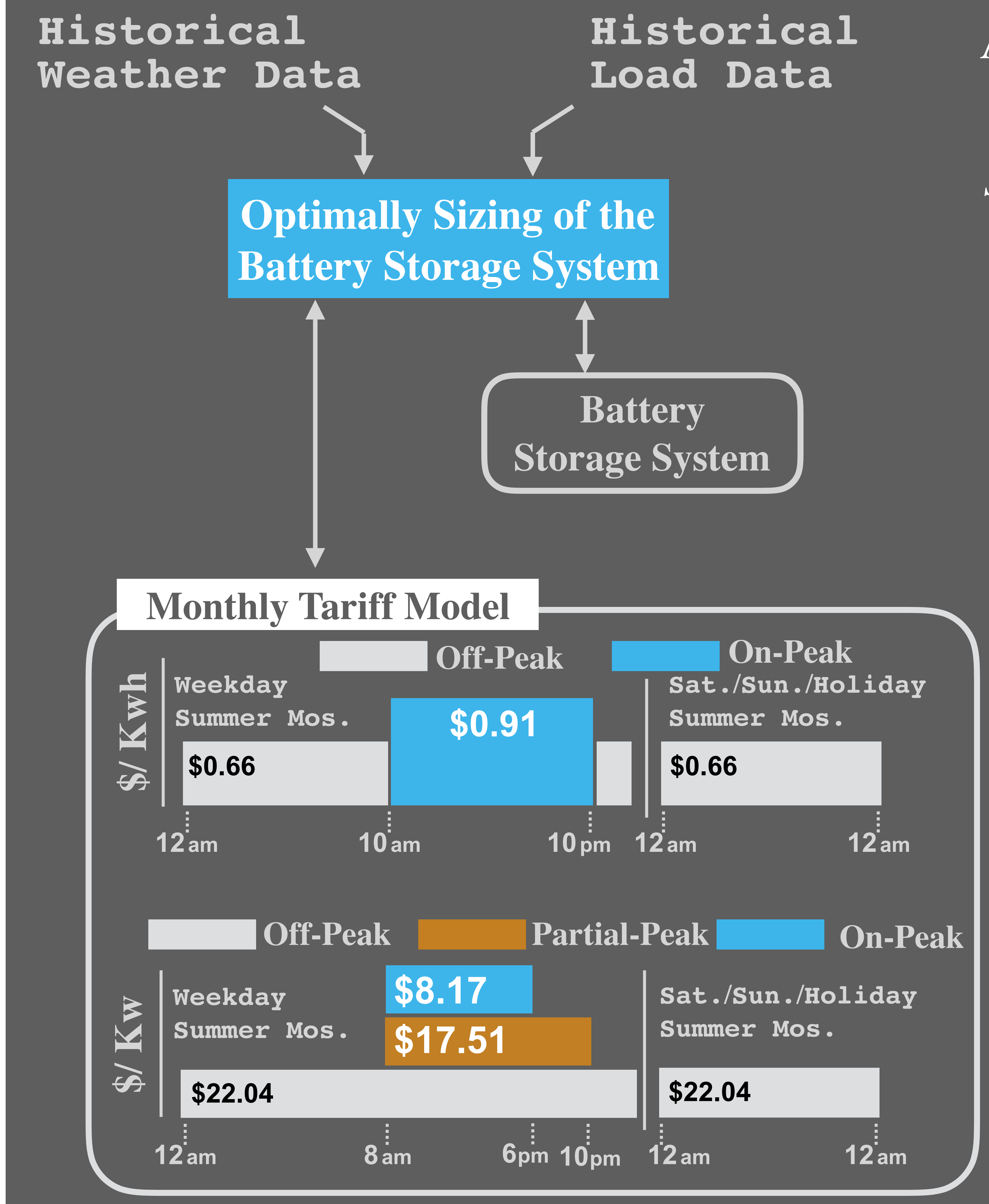

$$\Lambda^* = argmax\left(\sum_{n=1}^{12}\left[\mathbb{P}(G_n^{w/o}) - \mathbb{R}(\Lambda) - \mathbb{P}(G_n^w(\Gamma_n^*,\Lambda))\right]\right)$$

subject to : *Battery storage system constraints*

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

$$\Lambda \in \mathbb{Z}_{>0}, \Lambda \le \Lambda^{max}$$

$$\mathbb{P}(.) = P^{EC}(.) + P^{DC}(.)$$

Λ^*	Optimal Storage Capacity
$\mathbb{P}$	ToU Tarif Model
$G^{w/o}$	Grid load w/o Battery
G^w	Grid load w Battery
Γ^*	Optimal Demand Limit
$\mathbb{R}$	Monthly Equipment Cost

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Methodology

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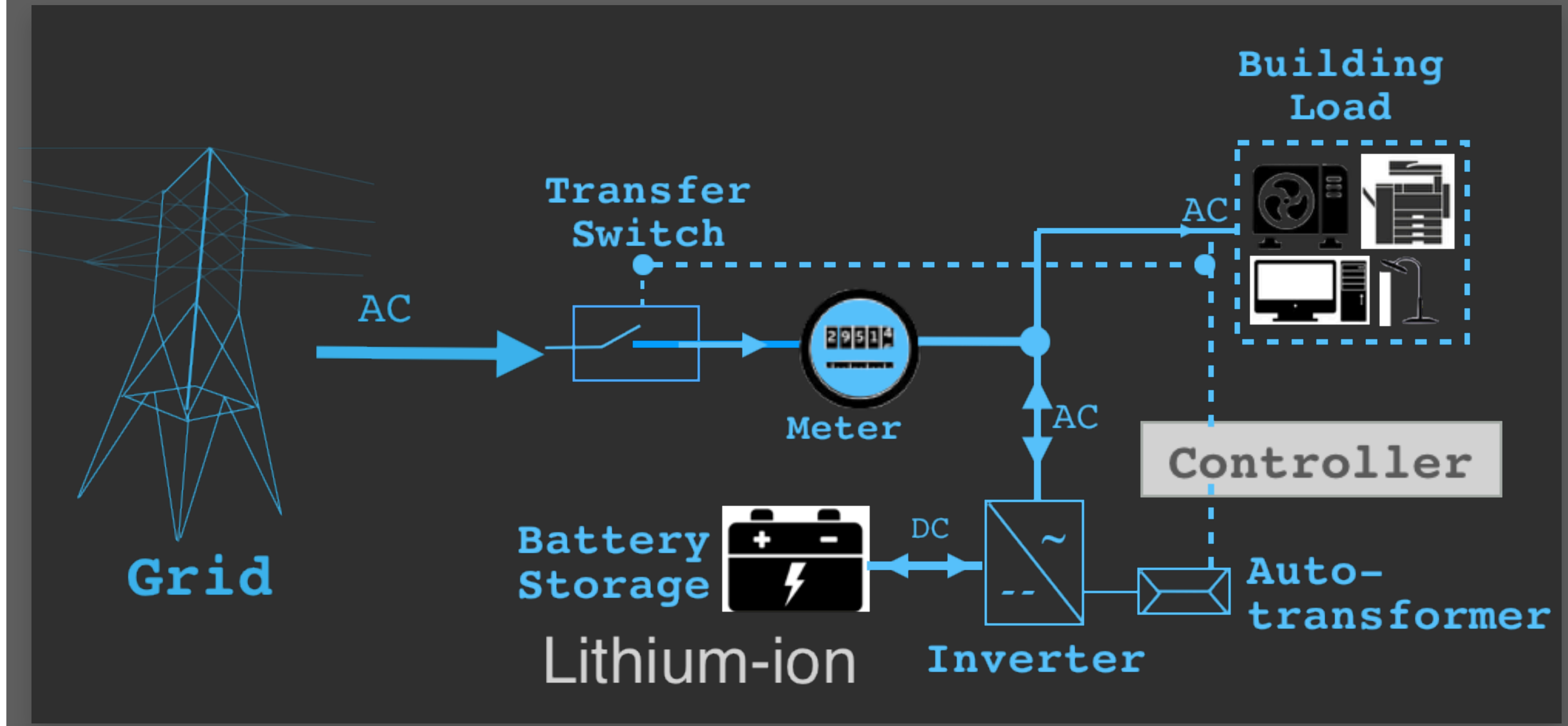
Battery Dispatch Strategy



Properties

Round Trip Efficiency	η_R	80%
Inverter Efficiency	η_C	95%
Depth of Discharge		0.90
Cycle Life		4000
Max. Battery life span		15Y
Cost of Battery		$200/kWh
Max. Rate of Charge	R_C	1C

Charging mode; $E(t) < \Gamma(t)$ → $SoC(t) = SoC(t-1) + min\left(|E(t) - \Gamma(t)|, R_C\right) \times \Delta t \times \eta_C / \Lambda$

Discharging mode; $E(t) > \Gamma(t)$ → $SoC(t) = SoC(t-1) - min\left(\frac{|E(t) - \Gamma(t)|}{\eta_D}, R_D\right) \times \Delta t \times \eta_D / \Lambda$

Neutral mode; $E(t) = \Gamma(t)$ or $E(t) = 0$ → $SoC(t) = SoC(t-1)$

State of Charge

Λ	Storage Capacity
E	Building Load
Γ	Demand Limit

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Methodology

Passive DSM Optimization

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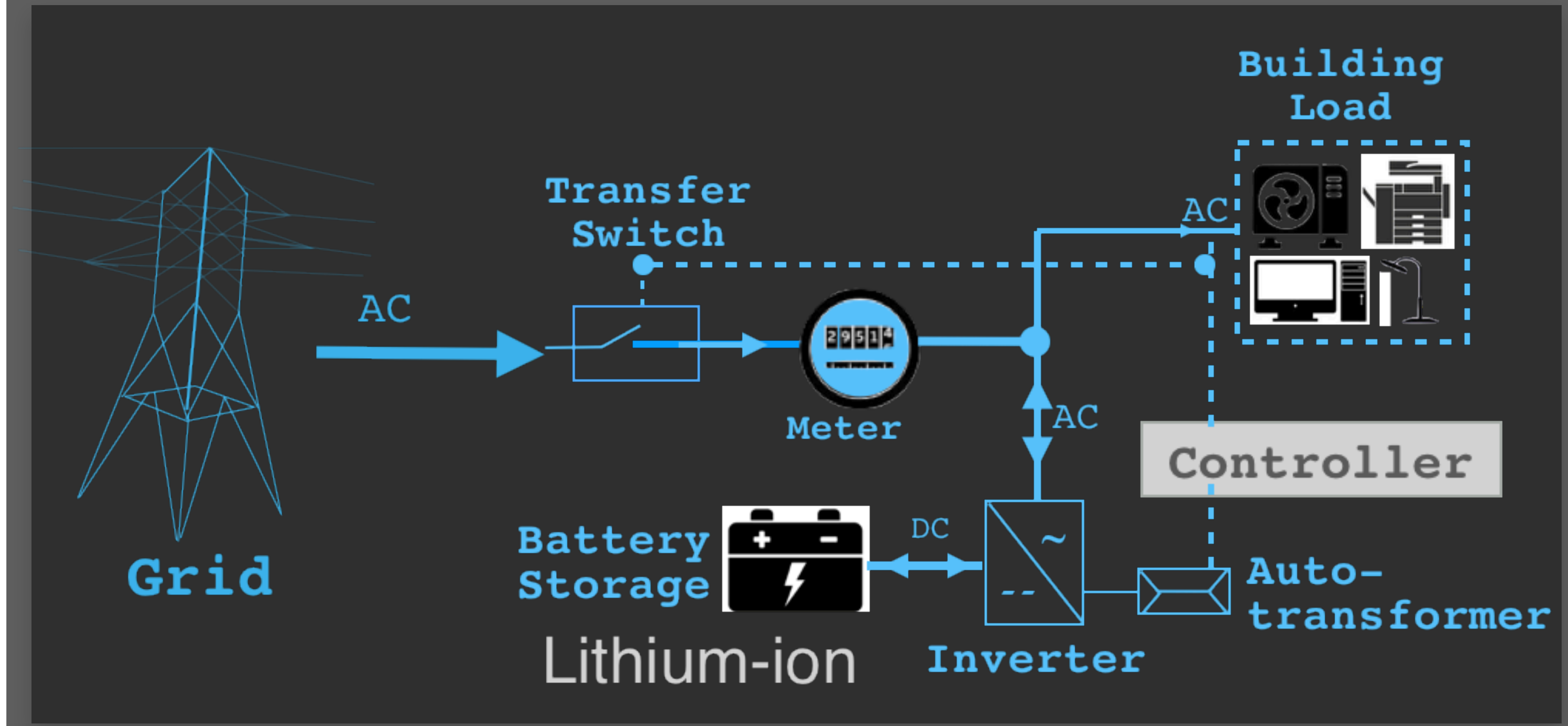
Real-time DSM Opt.

- Hierarchical opt. Formulation

Battery Degradation



- Battery degradation is a complex non-linear process that is dependent on many factors:
  - Calendar aging
  - Number of charge/discharge cycles
  - Depth of discharge
- We approximate the non-linear degradation process by a two-segment piecewise linear function of charge throughput.

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Methodology

Passive DSM Optimization

- Capacity Optimization
- Dispatch Strategy
- Degradation

Real-time DSM Opt.

- Hierarchical opt. Formulation

Real-time DSM Optimization

- This step performs concurrent one-day-ahead optimization of the setpoint temperature profile and dispatch strategy of the battery.
- The objective of this step is to minimize the electricity cost subject to the human comfort and storage constraints.

Methodology

Passive DSM Optimization

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Real-time DSM Opt.

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Real-time DSM Optimization

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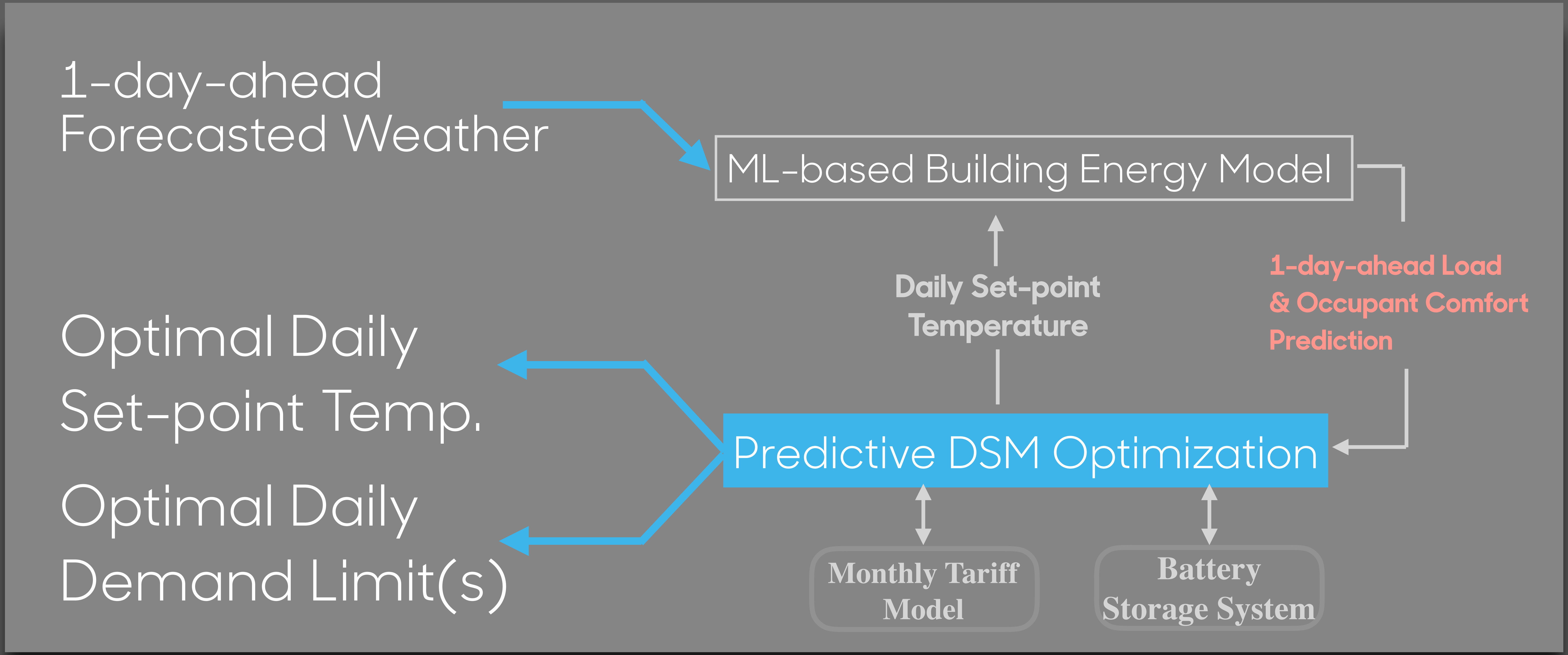

Methodology

Passive DSM Optimization

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- Dispatch Strategy
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Real-time DSM Opt.

- Hierarchical opt. Formulation

Real-time DSM Optimization

$$Min: \ \mathbb{H}(X_{temp})$$
$$st. \ X_t^{lb} \le X_{temp} \le X_t^{ub}$$
Thermal Comfort const.

Upper-level Optimization

X_{temp} $\quad$ $\mathbb{H}(X_{temp})$

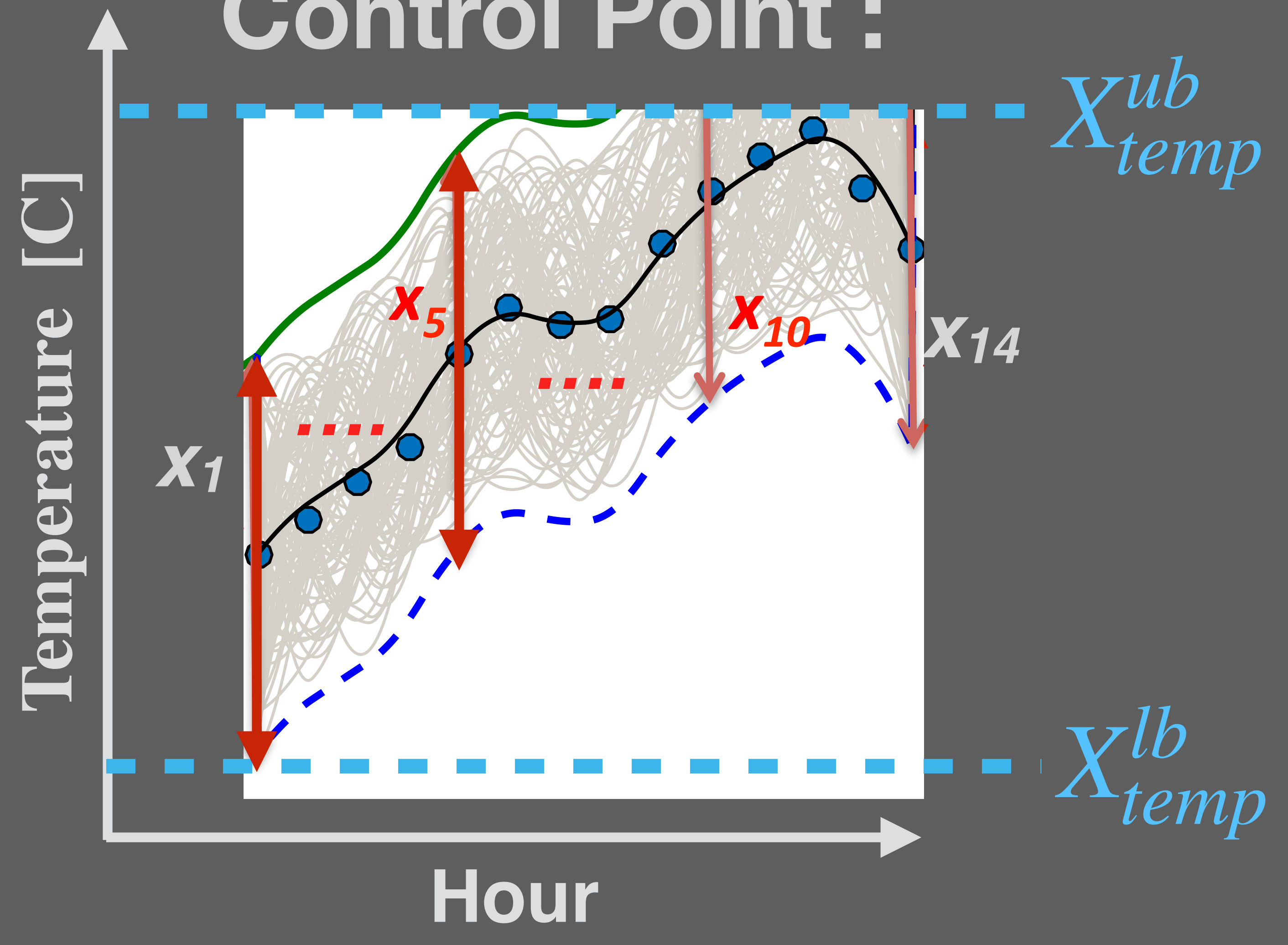
$$\mathbb{H}(X_{temp}) = \min_{\Gamma_m} \left[\mathbb{P}\left(G_k(X_{TEMP}, \Gamma_m, \Lambda^*) \right) \right]$$
$st.$ Battery Storage Constraints

Lower-level Optimization

Minimize

Energy Cost
Demand Cost
Loss of Comfort

Hourly temp. Control Point :



ToU Tarif Model :

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

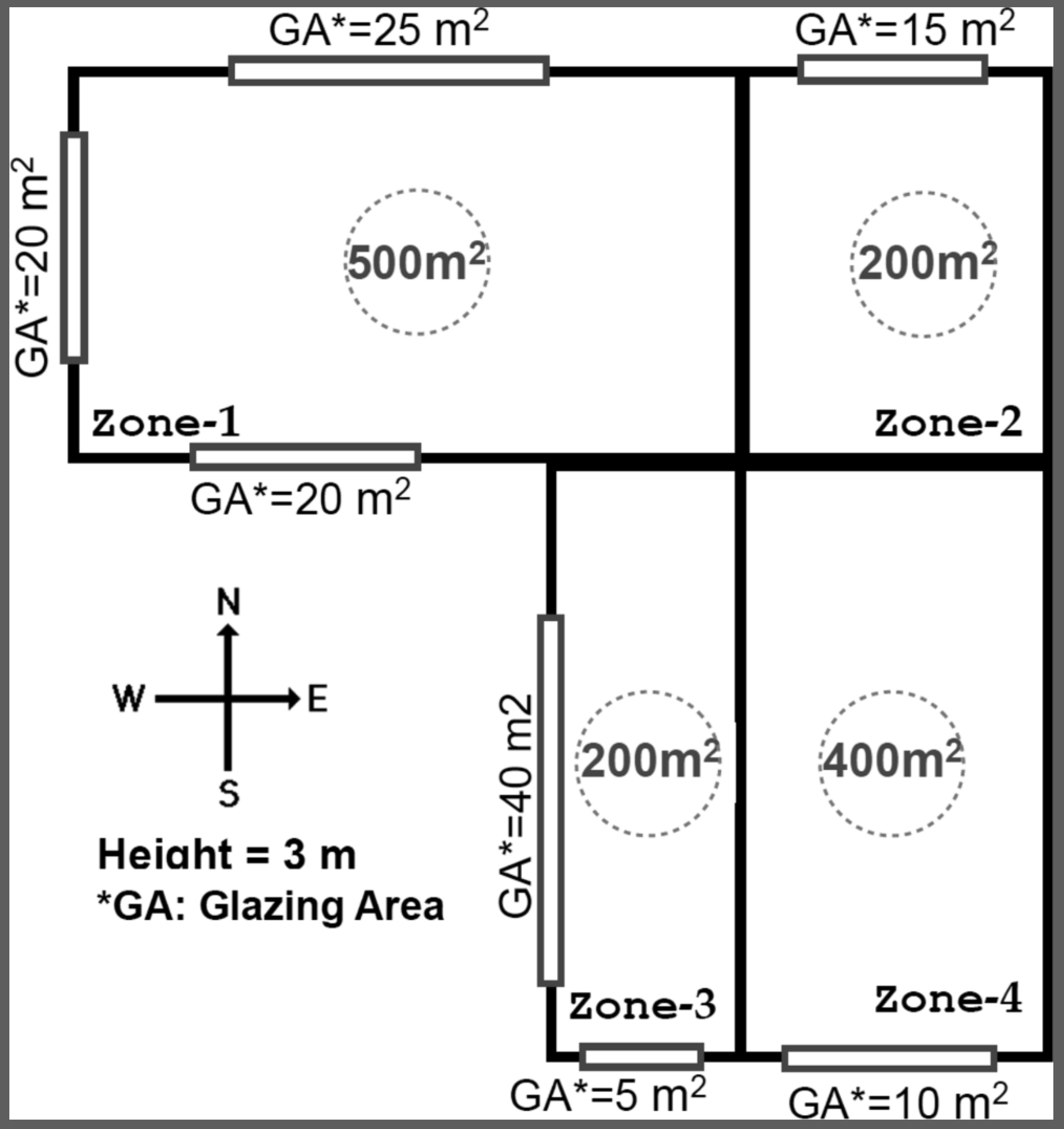
$$P^{EC} = \sum_{k=1}^{N} r_{e,k} G_k \Delta t$$

Energy Charge

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

Demand Charge

Testbed

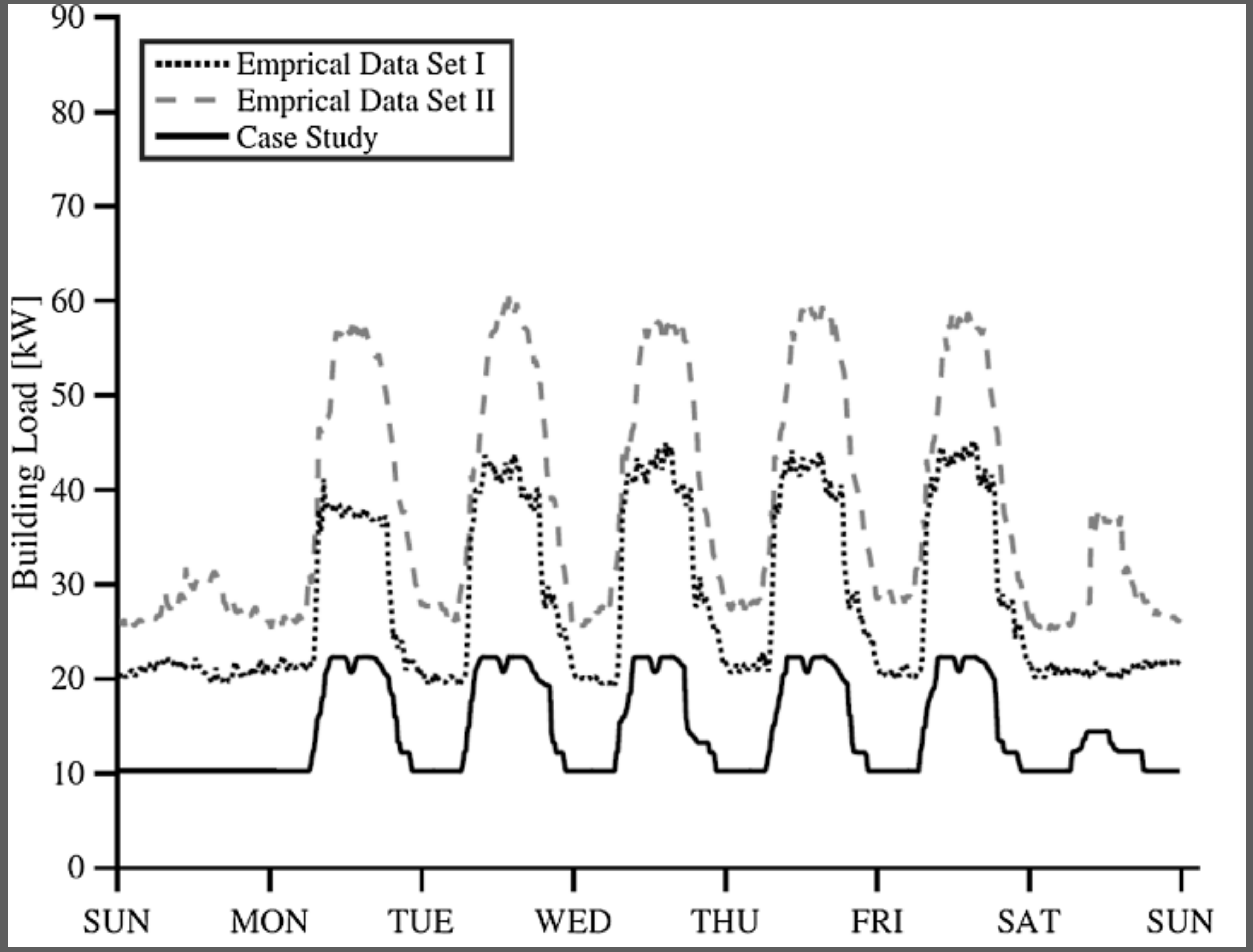


Plug loads for the case study building electric load (all for 4 zones). N denotes the number of people in the office and ⌊...⌋ denotes the floor function.

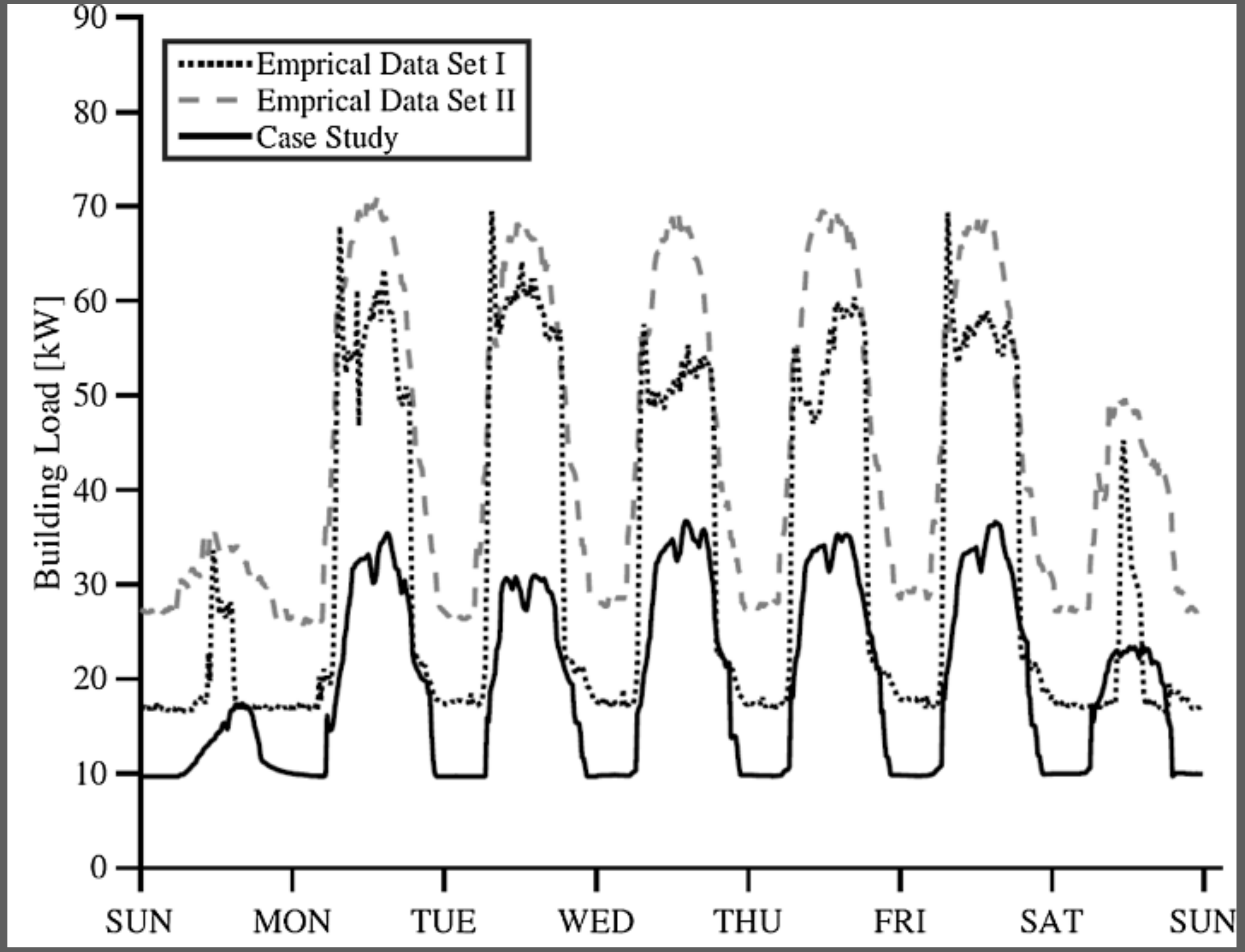
Equipment	Quantity	Peak power [W/unit]	Fraction of time used (occupied)	Fraction of time used (not occupied)
Computer (server)	2	65	0.75	0.75 × 40%
Computer (desktop)	$\lfloor N/2 \rfloor$	65	0.75	0.75 × 40%
Computer (laptop)	$\lfloor N/2 \rfloor$	19	0.75	0.75 × 40%
Monitor (desktop)	$\lfloor N/2 \rfloor$	35	0.75	0.75 × 40%
Monitor (server)	2	35	0.75	0.75 × 40%
Photo copier	1	1100	0.75	0.75 × 40%
Fax	2	35	0.75	0.75 × 40%
Refrigerator	2	52	0.90	0.90
Water cooler	2	350	0.75	0.75 × 40%
Coffee maker	2	1050	0.50	0.50 × 40%
Misc. loads (e.g., network routers)	N	4	0.75	0.75 × 40%

Testbed

Comparison of load profiles simulated for the case study office building versus observed data.



Load in Typical Winter Week



Load in Typical Summer Week

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Testbed

Breakdown of electricity consumption in various US building types, by end-use.

Electricity end use [all figures in %, for 2012]	Office building	Commercial	Commercial in North East US	Case study building
Lighting	39	17	18	39
Equipment	15	14	15	16
Ventilation	9	16	18	14
Cooling	14	15	11	10
Refrigeration & cooking	5	18	17	3
Fans	1	0.5	0.5	1
Other	17	19.5	20.5	17

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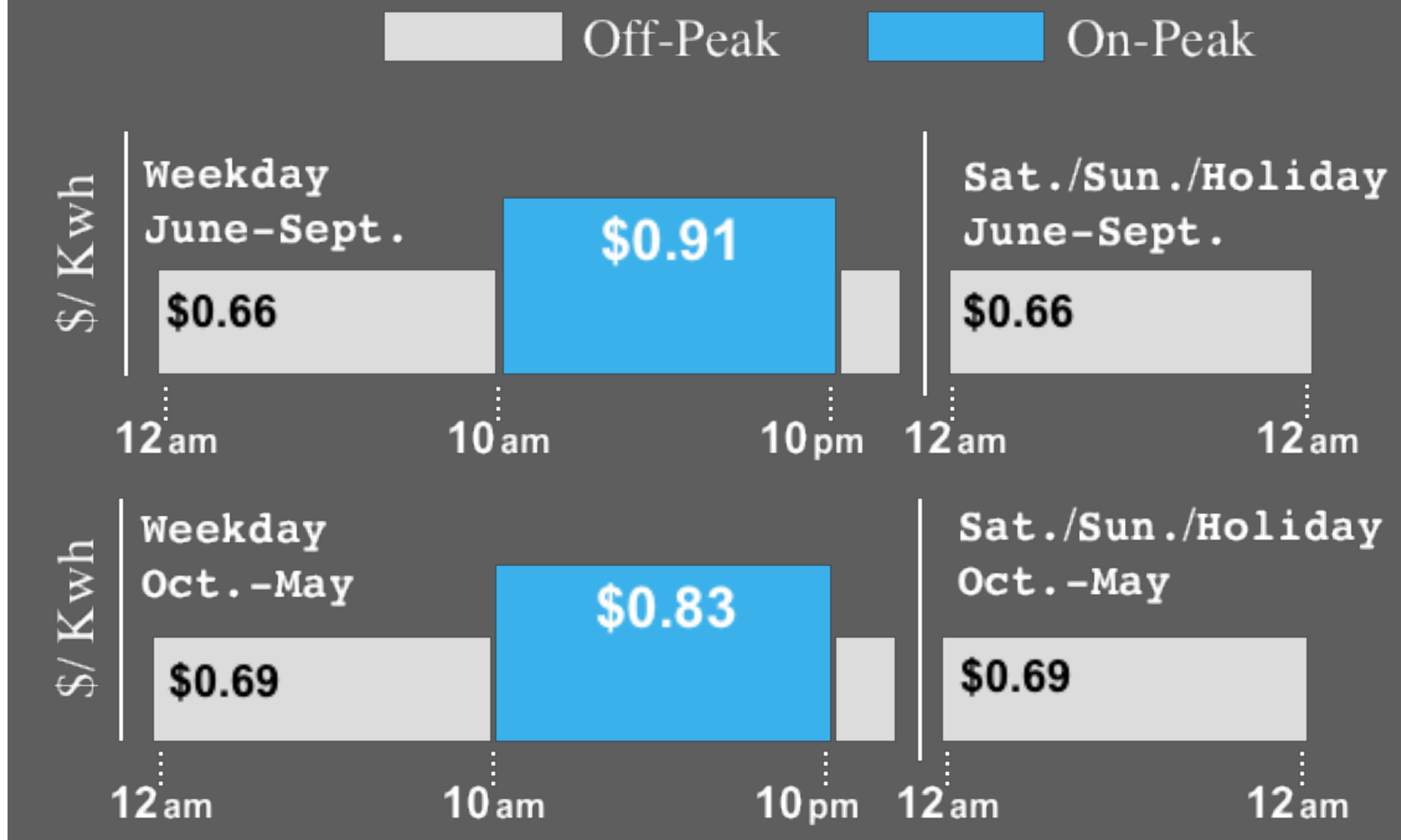
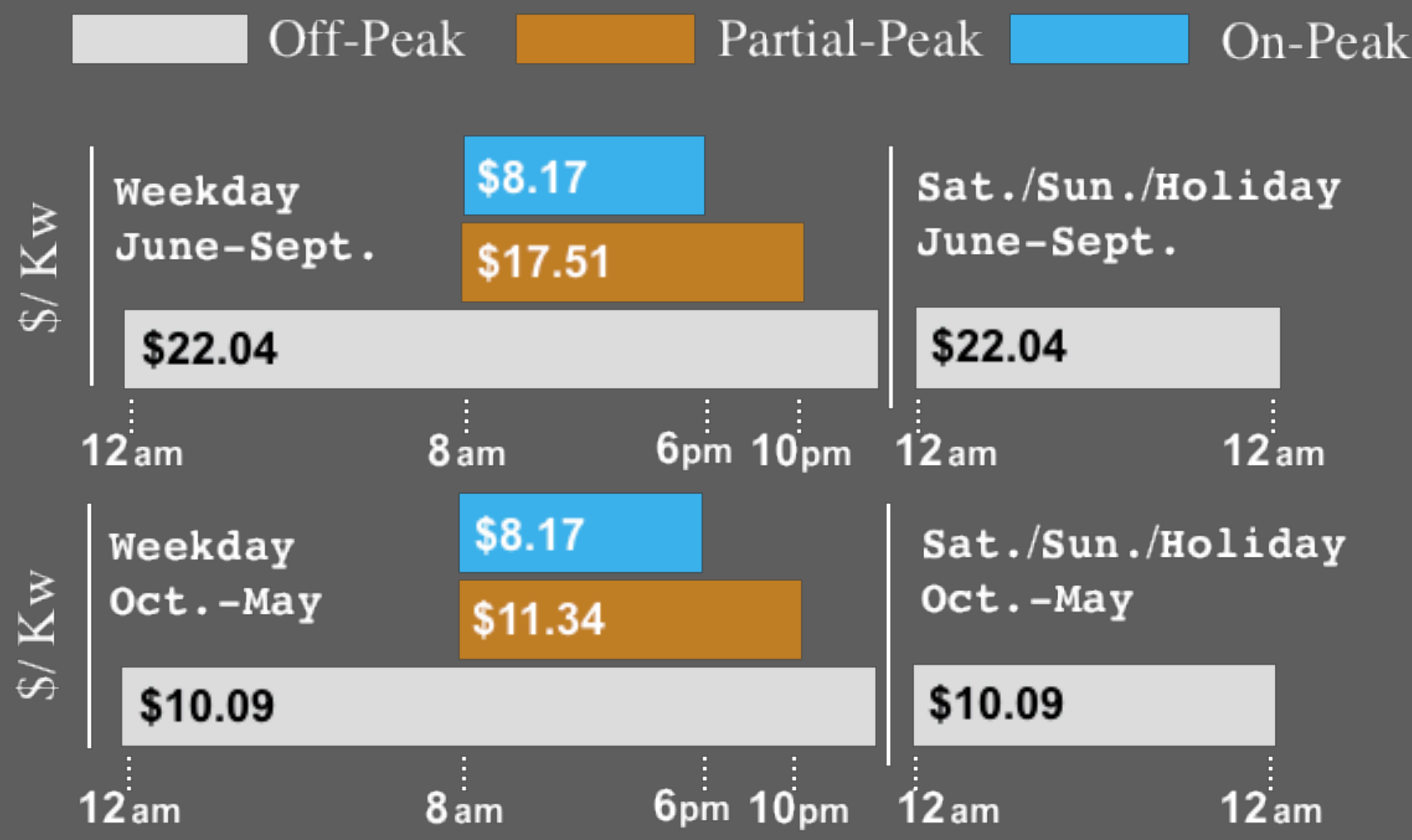
Results & Discussion

Determining the optimal battery size (passive DSM optimization)





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$$subject\ to:\ \ Battery\ storage\ system\ constraints$$

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

$$\mathbb{P}(\,.\,) = P^{EC}(\,.\,) + P^{DC}(\,.\,)$$

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Results & Discussion

- Optimal demand limits for each month as determined via the passive DSM algorithm.
- Demand further vary with time of day to optimize vis- à-vis the three time windows in the tariff:

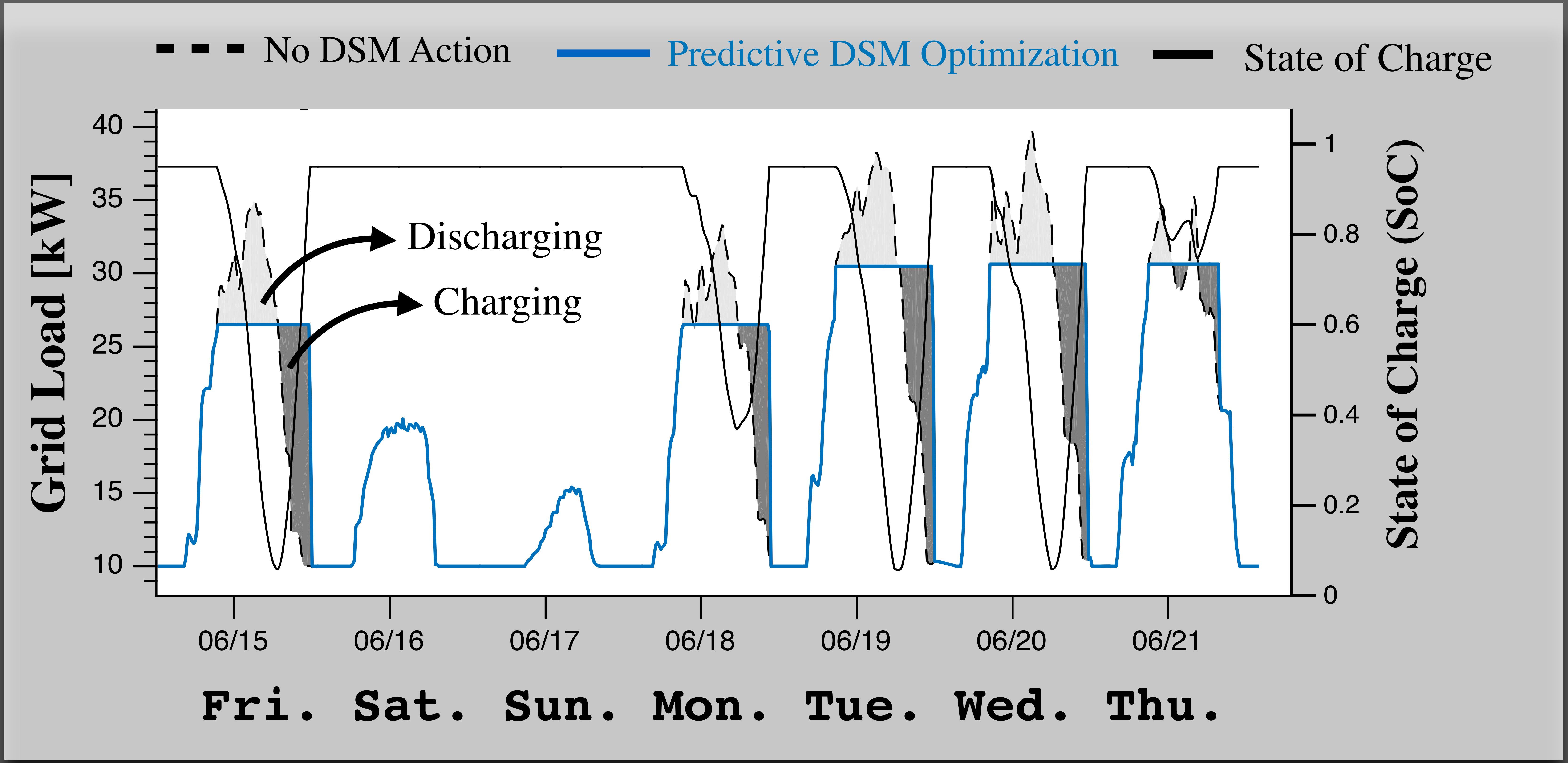
    Off peak hours (OPh),

    Peak hours (Ph), and

    Partial peak hours (PPh).

Month	Γ^{OPh} [kW]	Γ^{Ph} [kW]	Γ^{PPh} [kW]
January (n = 1)	18.46	19.16	n/a
February (n = 2)	18.49	18.88	n/a
March (n = 3)	16.62	18.70	n/a
April (n = 4)	16.36	18.56	n/a
May (n = 5)	24.85	28.31	n/a
June (n = 6)	28.26	32.54	11.95
July (n = 7)	30.39	33.55	20.58
August (n = 8)	23.26	31.73	22.98
September (n = 9)	18.24	29.11	19.23
October (n = 10)	18.24	18.60	n/a
November (n = 11)	18.44	18.95	n/a
December (n = 12)	18.59	19.05	n/a

Results & Discussion



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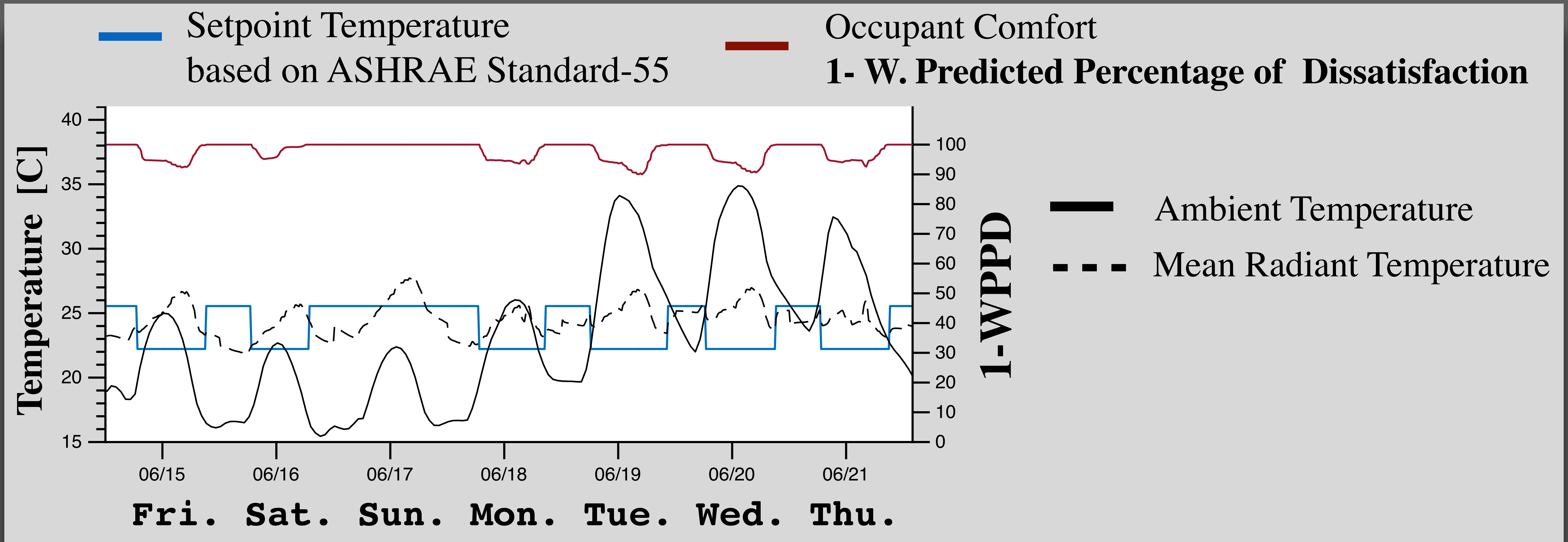
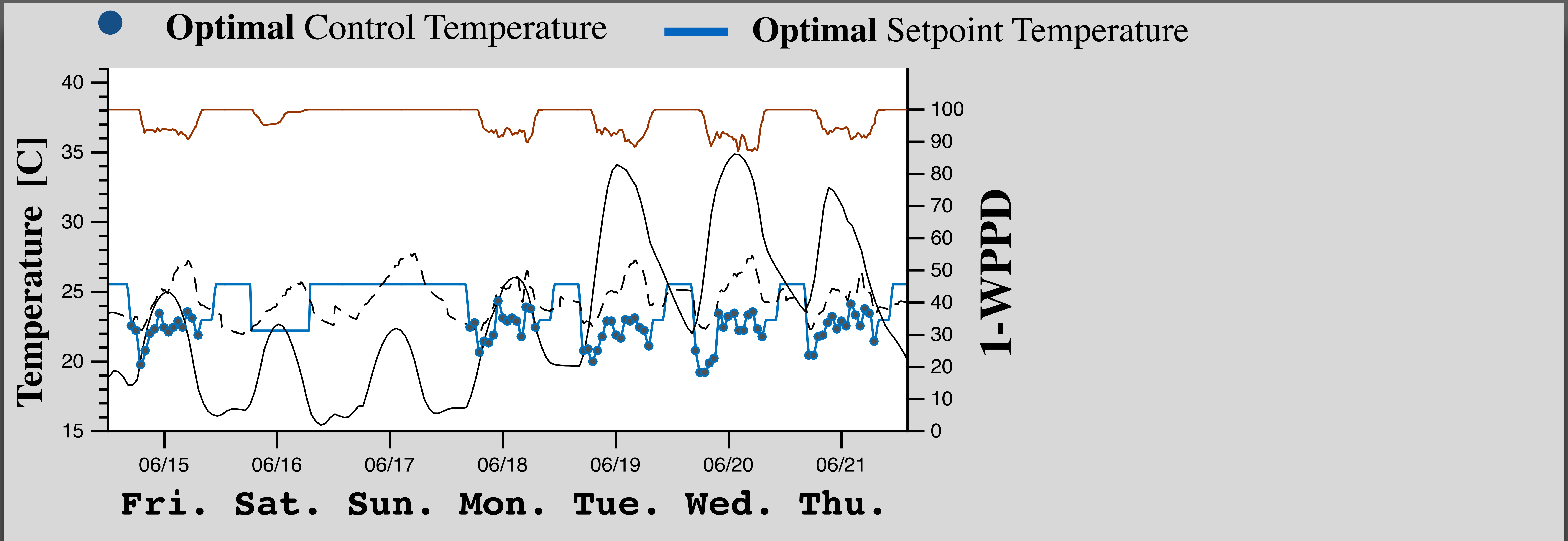
Results & Discussion





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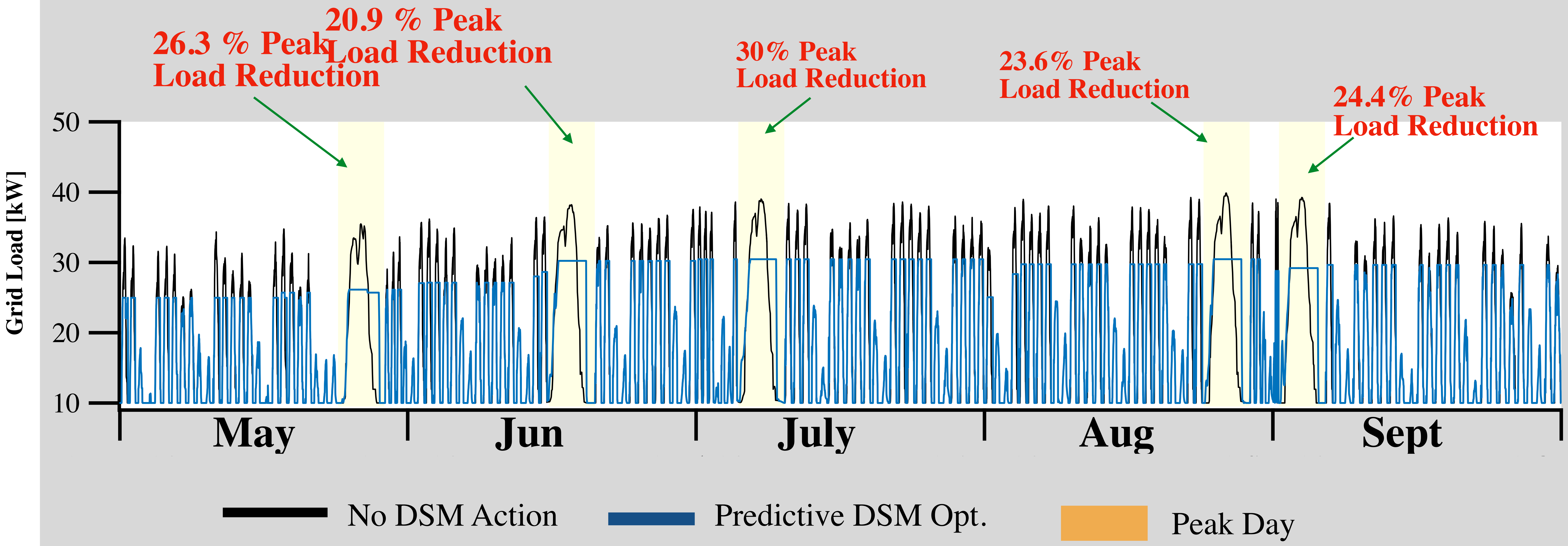
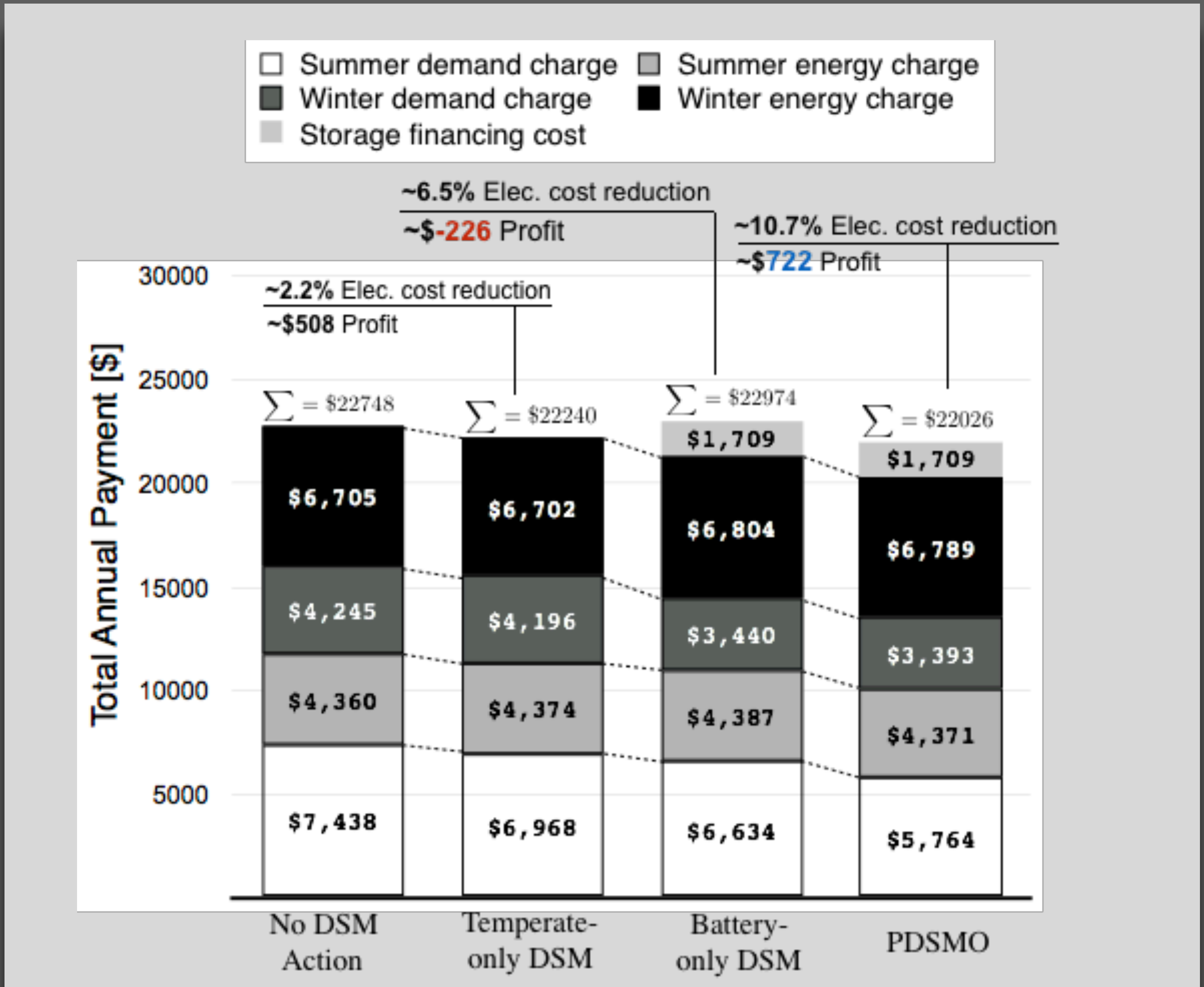
Results & Discussion

- Grid peak load reduction in summer months via PDSMO



Results & Discussion

- Breakdown of total annual costs



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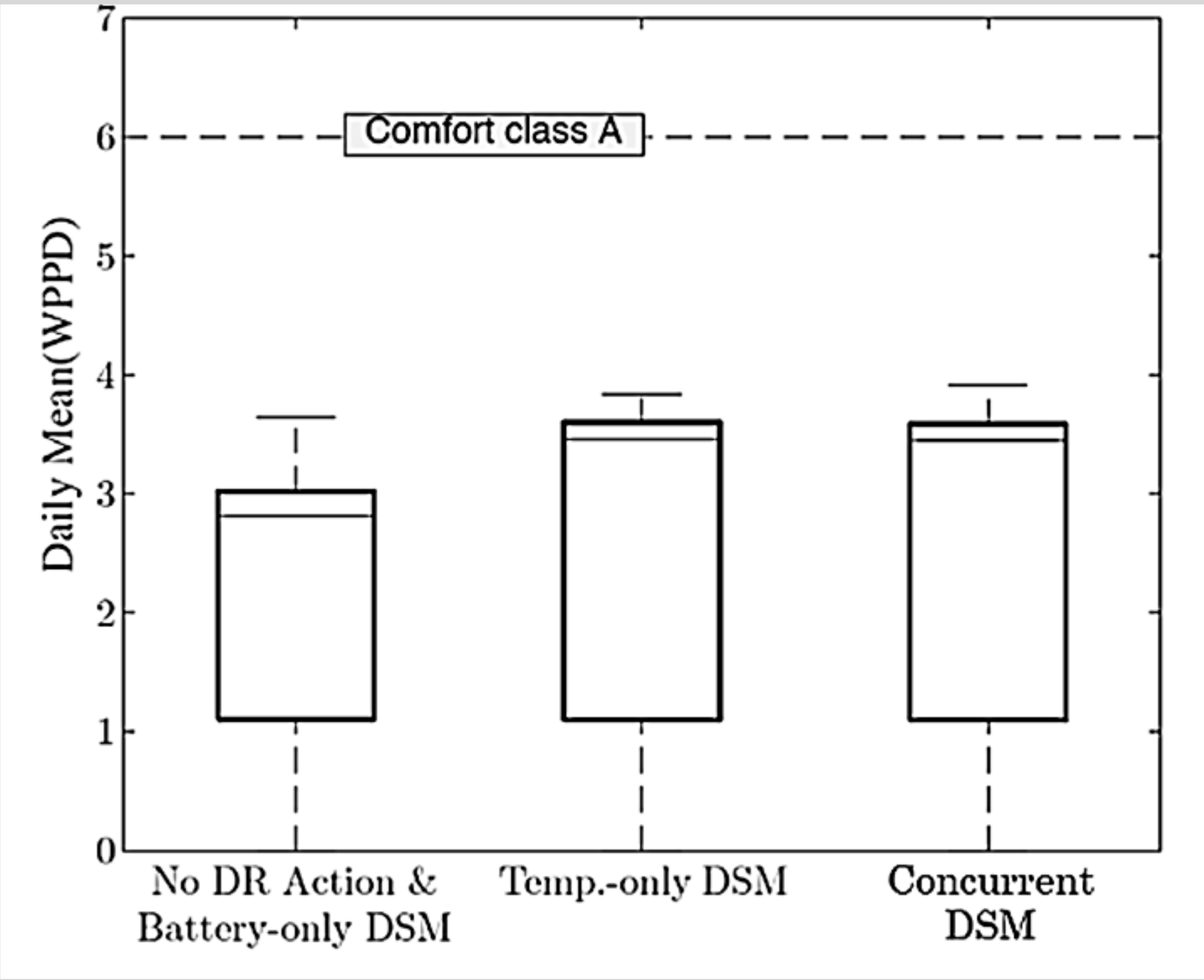
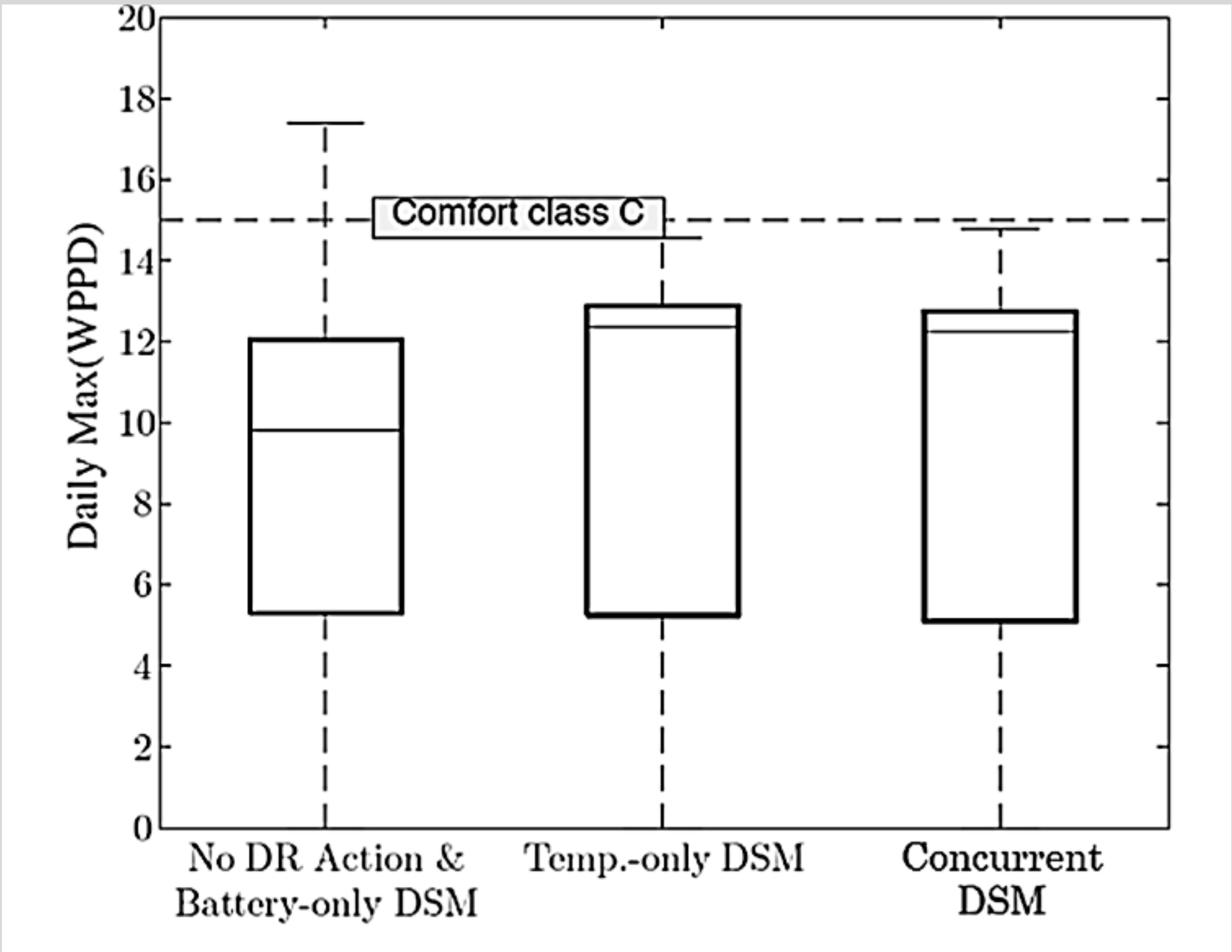
Results & Discussion

- Human thermal comfort in different DSM approaches





Concluding Remarks

- A novel DSM framework that concurrently optimizes the electric and thermal storage in office buildings where a Time-of-Use (ToU) and/or demand-based rate structure is developed.
- The initial implementation indicates that PDSM reduces the maximum monthly grid peak load by up to 26%
- The annual electricity cost (demand and energy charges) is also reduced significantly by 10.7%, enough to more than offset the equipment cost.

Thank You!

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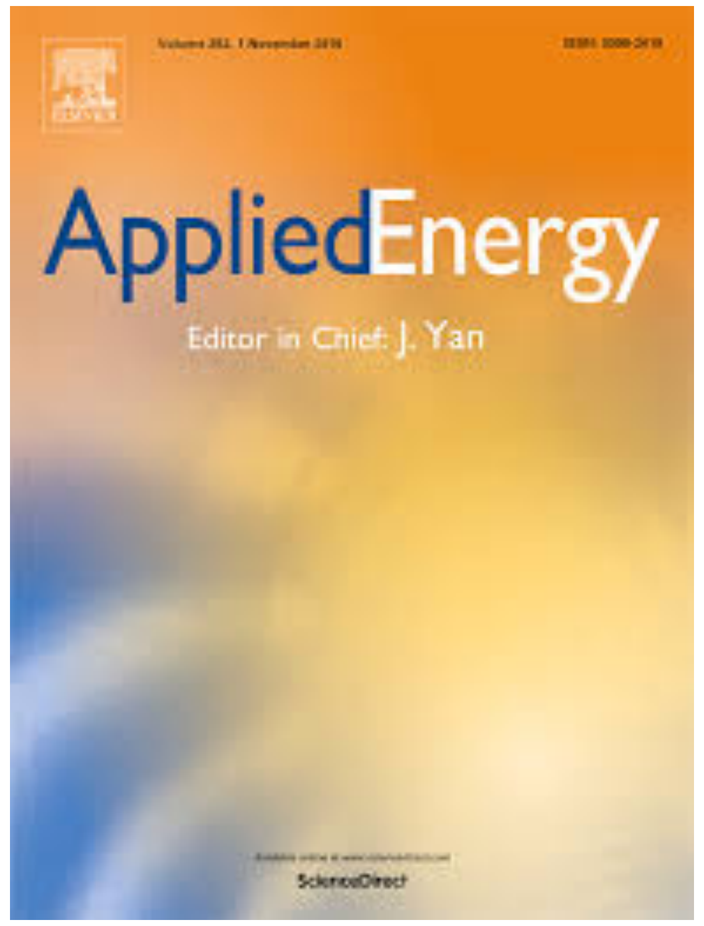
Head, Core Research, Prescriptive Data
Research Scientist, Data Science Institute, Columbia University



Published on
Sept. 2019

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