An operation optimization and decision framework for a building cluster with distributed energy systems

Xi Wang Li^{a,b,*} Jin Wen^b Ali Malkawi^a

^a Center for Green Building and Cities, Graduate School of Design, Harvard University, Cambridge, MA, 02138, USA

^b Department of Civil, Architectural and Environmental Engineering, Drexel University, Philadelphia, PA 19104, USA

Abstract

Driven by the development of smart buildings and smart grids, numerous of research has focused on developing optimal operation strategies for smart buildings with the aims of reducing energy consumption and cost, as well as improving the grid reliability. Unfortunately, most of the studies from smart building perspective only target on a single building with elaborated energy forecasting models. Few of them addresses the effects of multiple buildings on power grid operation. On the other hand, a few studies from smart grid area focus on multiple buildings and their influence on power grid, they usually, however, use simplified linear energy forecasting models, which are hard to guarantee the findings reflecting the cases in real fields. As a result, this research proposes to bridge this research gap, through developing and validating high fidelity energy forecasting models for a building cluster with multiple buildings and distributed energy systems, as well as creating a collaborative operation framework to determining the optimal operation strategies of this building cluster. The operation framework utilizes multi-objective optimizations to determine the operation strategies: building temperature setpoints, energy storage charging and discharging schedules, etc., using particle swarm optimization. Pareto curves for energy cost saving and thermal comfort maintaining are also derived with different thermal comfort requirements. The results from this study show that the developed building cluster collaborative operation framework is able to reduce the energy cost by 12.1% to 58.3% under different electricity pricing plans and thermal comfort requirements.

Keywords

Smart building, Smart grid, Multi-objective optimization, Particle swarm optimization, Demand response

Highlights

- Developed and validated energy forecasting models for a building cluster with distributed energy systems
- Proposed an operation optimization and decision framework for the building cluster

* Corresponding author. Tel.: +1 267 563 0576; Email addresses: xiwang_li@gsd.harvard.edu (X. Li)

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- 1 • Optimized the operation strategies through particle swarm algorithm based multi-objective
- 2 optimizations
- 3 • Derived the Pareto frontiers to balance the energy cost saving and thermal comfort

Nomenclature

U_τ : excitation signal

a_τ : excitation function magnitude scale parameter

ω_τ : periodic frequency parameter

T : sampling time

φ_τ : phase lag parameter

MP_E : Markov parameters for energy forecasting

MP_P : Markov parameters for PMV forecasting

P_{PV} : power generation from PV panel

P_m : power generation from a PV module

M_s, M_p : number of PV module strings in series and in parallel

T_{db} : ambient dry-bulb temperature

G : absorbed solar irradiance on the PV panel

$G_{bt}, G_{dt},$ and G_r : direct, diffuse and reflected hourly solar irradiance on the PV panel

$F_B, F_D,$ and F_R : angular loss factors for direct, diffuse and reflected irradiance

C_{bat}, C_{ice} : capacity of battery and ice tank thermal storage system

$SOC_{bat,k}, SOC_{tes,k}$: state of charge of battery and ice tank thermal storage system

$I_{bat,k}, P_{bat,k}$: battery charging/discharging current and power

$V_{bat,k}$: battery terminal voltage

N_{bs}, N_{bp} : number of battery units in series and parallel

η_t : battery charging efficiency

u_k : ice tank charging/discharging rate

c_f : specific heat of the chilled water

$P_{HVAC,t}^k, P_{other,t}^k$: energy consumption of HVAC system and non-cooling systems

$P_{p,t}^k, P_{s,t}^k$: purchasing and selling electricity energy

$T_{stp,t}^k, Q_{ice,t}^k, I_{bat,t}^k$: temperature setpoint, ice tank and battery charging/discharging rate

w_i : weighting factor for thermal comfort

$RMSE$: root mean square error

$NRMSE$: normalized root mean square error

R^2 : coefficient of determination

1. Introduction

Buildings consume about 41.1% of primary energy and 74% of the electricity in the U.S. [1]. Moreover, it is estimated by the National Energy Technology Laboratory that more than 1/4 of the 713 GW of U.S. electricity demand in 2010 could be dispatchable if only buildings could respond to that dispatch through advanced building energy control and operation strategies and smart grid infrastructure [2]. Fortunately, the development of smart grids and smart buildings, this dispatch can be realized through energy sharing, information exchanging and operation optimization. To these challenges and opportunities, optimal control of building operation and interaction with power grid is critical to improve the energy efficiency and the reliability of power grids.

Numerous of research has started to study the operation of the buildings as well as distributed energy generation and storage systems for the purpose of saving energy consumption, cost as well as improving reliability. Most of these studies come from the two different perspectives: smart building area and smart grid area, with different emphases. Most of the literature in smart building prospective uses energy forecasting models with more physical meanings for building as well as distributed energy generation and storage system operation optimization [3]. For example, Lu et al. [4] developed a serial of energy forecasting models for a building with a PV panel system, a combined cooling and power system, and a thermal storage system. Upon these energy forecasting models, a mixed-integer nonlinear programming based optimal scheduling framework is developed to reduce the energy cost. Pascual et al. [5] studied the energy management strategy for a residential micro-grid with renewable energy generation. Ikeda and Ooka [6] proposed a metaheuristic optimization method for optimal scheduling of a battery, a thermal energy storage (TES), and heat sources in a building. Jones and Powell [7] modeled and presented the electrical load shifting capability of distributed TES with solar power generation. Arteconi et al. [8] investigated the application of TES and PV panels in an industrial building for cooling load management. Besides using multiple energy systems, there are even more studies developing efficient operation strategies for using single energy systems within buildings, such as: TES [9, 10], PV panels [11, 12], and batteries [13, 14]. Braun [15] developed a near-optimal control strategy for TES with dynamic real-time electricity rates. The results indicated that the annual cost under this control method is close to optimum. Henze et al. [16] further developed model-based predictive optimal control of active and passive building thermal storage and successfully achieved 18% and 7% of cost savings compared to the reference case. Liu and Henze [17] also proposed and demonstrated a model-free reinforcement learning control for TES to save energy cost. Steen et al. [18] improved a TES model and implemented it in a mixed integer linear programming distributed energy resources management system. Using this management system, this research studied six buildings and evaluated the difference in technology adoption between different TES models. Ruddell et al. [19] estimated the cooling electricity demand during summer time in Phoenix and

1 studied the application of using distributed TES for peak demand shifting. Moreover, there also are
2 extensive literature improving the building energy efficiency by optimizing the operation HVAC systems
3 [20-23] without using any distributed energy systems. Chen et al. [24] developed a model predictive
4 controller for a residential building with considering the time-varying energy price and building thermal
5 comfort. Summarizing these studies, even though most of these studies have reduced the energy
6 consumption or cost, they only focus on the operation of single buildings. The energy sharing and
7 resource allocation have not studied in most of these studies. On the other hand, this energy sharing and
8 resource allocating problem is very popular in demand side management from the power grid perspective.

9 Ahadi et al. [25] developed a novel approach for optimal combination and operation of wind and PV
10 energy generation, as well as energy storage. Malysz et al. [26] presented a mixed-integer linear
11 programming based online optimal energy/power control method for the operation of energy storage in
12 grid-connected electricity micro-grids. Shi et al. [27] proposed a distributed energy management strategy
13 for managing a micro-grid with distributed energy generation and storage systems. Nguyen et al. [28]
14 investigated an optimal day-ahead price based power scheduling system for a community scale micro-grid.
15 The proposed scheduling system is able to balance the energy saving and occupant thermal comfort.
16 Wang et al. developed a series operation optimization models for building HVAC system operation and
17 building to grid interaction [29, 30]. Hu et al. [31, 32] developed a decentralized operation determination
18 model for an integrated building cluster with distributed energy systems. They also published a following
19 study to investigate the building cluster self-organizing for heterogeneity settings [33]. Similar to these
20 building cluster studies, another recent publication proposed a multi-party energy management for smart
21 building cluster with PV energy generation for demand response [34]. A non-cooperative game theory
22 and a multi-objective optimization are developed and achieved 4.6% energy cost saving. Most these
23 studies from smart grid perspective mainly target on the power grid operation and resource allocating, but
24 most of them use simplified and unvalidated linear energy forecasting models for buildings, energy
25 generation, and storage systems. It is hard to guarantee the performance achieved from these simplified
26 models to be realized in real fields.

27 In order to bridge the gap between research in smart building and smart grid areas, this paper
28 proposes to develop and validate high fidelity energy forecasting models for buildings, PV panel energy
29 generation systems, battery and ice tank TES. Based on these validated energy forecasting models, an
30 operation collaborative optimization framework is then developed to determine the operation and resource
31 allocating among all these systems with considering the dynamic energy prices and building thermal
32 comfort. As a result, besides the energy saving potentials in typical load aggregation approaches [35], this
33 building cluster collaborative optimization framework is also able to fully utilize the potentials in
34 resources sharing and allocating. In the following sections, section 2 and 3 introduce the development and

validation of energy forecasting models, section 4 discusses the methods for system operation optimization, and section 5 presents the optimal operation results.

2. Building Cluster Model Development

As introduced before, the objective of this paper is to study the operation and resource allocating within multiple buildings and distributed energy systems, while maintaining the building thermal comfort, using high fidelity energy forecasting models. For this purpose, either detailed physics based energy forecasting models or simplified linear models is not suitable in this study, due to the calculation burden and model performance.

In order to develop a building energy forecasting model which has higher extendibility to perform better in demand response (temperature setpoint shifting) scenarios, a proactive system identification approach is used in this study for building energy forecasting. At the same time, simplified physics based models are used for distributed energy systems. After all these models are developed, they are validated against an existing pre-validated emulator in EnergyPlus and TRNSYS. This study also proposes a novel thermal comfort forecasting model using the system identification approaches similar to that for building energy forecasting. Other than the building energy and thermal comfort forecasting models, this study also proposes to develop simplified physics based grey box models for distributed energy systems.

2.1 Building energy and thermal comfort forecasting model

Figure 1 illustrates the overall forecasting procedure for building energy and thermal comfort forecasting model development.

Figure 1 Building energy and thermal comfort forecasting

The excitation signals are temperature setpoints generated from a multi-sine function with considering the information entropy:

$$U_{\tau+1} = U_{\tau} + \sqrt{2a_{\tau}} \sin(\omega_{\tau} t T + \varphi_{\tau}) \quad \text{Eq. 1}$$

Where U is the excitation signal (such as temperature setpoint); $\sqrt{2a_{\tau}}$ is a magnitude scale parameter from 0 to 1; t is the current time step, τ ; T is the sampling time; and φ is the phase lag parameter from 0 to 2π ,

which does not affect the signal spectrum; ω is periodic frequency parameter from 0 to 2π . All these parameters, including $\sqrt{2\alpha}$, T , φ , and ω , will be updated at each time step, τ . The details about the excitation signal generation, adaptation and evaluation can be found in [36]. The forecasting models employ expert knowledge and correlation studies for feature selection, as summarized in Table 1.

Table 1 Feature selection for energy and PMV forecasting

Variable	Variable Name
T_{out}	Outdoor air temperature (C)
RH_{out}	Outdoor air relative humidity ratio (-)
$T_{zone, stp, i}$	Zone i temperature setpoint (C)
$R_{in, i}$	Lighting/Equipment schedule in zone i (-)
Q_{dir}	Direct solar radiation (W/m ²)
Q_{dif}	Diffuse solar radiation (W/m ²)
V_{oa}	Ventilation rate (m ³ /s)

The system identification approach uses a frequency response function to capture the dynamic correlation between the system inputs and outputs. In the real on-line application, the forecasting models will be trained off-line first and the used online in the forecasting period. After the forecasting models are trained, they are saved as Markov parameters which will be used for energy and thermal comfort forecasting:

$$\begin{bmatrix} E_k \\ PMV_k \end{bmatrix} = \sum_{i=1}^M \begin{bmatrix} MP_{E,To,k}^i & MP_{E,RH,k}^i & MP_{E,TS,k}^i & MP_{E,R,k}^i & MP_{E,Qr,k}^i & MP_{E,Qf,k}^i & MP_{E,V,k}^i \\ MP_{P,To,k}^i & MP_{P,RH,k}^i & MP_{P,RH,k}^i & MP_{P,RH,k}^i & MP_{P,RH,k}^i & MP_{P,RH,k}^i & MP_{P,RH,k}^i \end{bmatrix} \begin{bmatrix} T_{out,k} \\ RH_{out,k} \\ T_{set,k} \\ R_{i,k} \\ Q_{dir,k} \\ Q_{dif,k} \\ V_{oa,k} \end{bmatrix} + e_k \quad \text{Eq. 2}$$

Where MP_E and MP_P are the Markov parameters for energy and PMV forecasting, M is the system order, and e_k is the process error. Each system input, X_k , has two serials Markov parameters $MP_{E,X,k}^i$ and $MP_{P,X,k}^i$ to capture the dynamic relationship with energy consumption and PMV.

In this study, three buildings: DOE reference small office building (post-1980), DOE reference medium office building (post-1980) and a real small size commercial building are used [37, 38]. Table 2 summarizes the key features of these three buildings used in this paper. Details about the building energy forecasting model development and Markov parameters calculation can be found in [36, 38, 39]. The same forecasting procedure is used to predict the indoor thermal comfort. Appendix A provides the occupant related parameters for PMV estimation. Section 5.1 presents the forecasting and validation results.

Table 2 Building construction and HVAC features

Feature	Small reference	Medium Reference	Real small
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Floors	1	3	1
Total floor area (m ²)	511	4982	855.5
Window to wall ratio	0.21	0.33	0.54
Glazing U-factor (W/(m ² ·K))	3.35	3.35	2.73
Glazing SHGC	0.36	0.36	0.85
Occupant Density (m ² /person)	18.6	18.6	12.4
Lighting Power Density (W/m ²)	19.5	16.89	6.88
Equipment Power Density (W/m ²)	10.8	10.8	8.1
HVAC	Packaged CAV	Packaged MZ VAV	AHU + VAV

2.2 PV panel model

Adapted from [40], the power generated from PV panel, P_{PV} is modeled as:

$$P_{PV} = P_m M_s M_p = \{-(aG + b)(T_{db} + cG) + dG\} M_s M_p \quad \text{Eq. 3}$$

where P_m is the power generation of one PV module. M_s and M_p are the number of module strings in series and parallel, respectively. A forecasting models is then used to predict the power generation from one PV module from absorbed solar irradiance on the PV panel surface, G (W/m²), and ambient dry-bulb temperature, T_{db} . a , b , c , and d are coefficients that needed to be determined during the model training period. The absorbed solar irradiance, G , on the PV panel can be estimated as from solar irradiance on the PV panel and the loss factors for solar irradiance:

$$G = G_{bt}(1 - F_B) + G_{dt}(1 - F_D) + G_r(1 - F_R) \quad \text{Eq. 4}$$

where G_{bt} , G_{dt} , and G_r (W/m²) are direct, diffuse and reflected solar irradiance on the PV panel. F_B , F_D , and F_R are angular loss factors for direct, diffuse and reflected irradiance, respectively. Appendix A introduces the calculation procedure for these three angular loose factors. The model training process will determine all the coefficients in Eq. 3: a , b , c , d , and e .

In this study, the location is selected at Philadelphia, PA. The area of each PV module is 0.63 m², M_s and M_p are 12 and 9 for small reference building and real small building. They are 25 and 20 for the medium reference building.

2.3 Battery model

The general battery sate of charge, $SOC_{bat,k}$, estimation function is [40]:

$$SOC_{bat,k+1} = \begin{cases} SOC_{bat,k} + \frac{I_{bat,k}\Delta t}{C_{bat}}, & \text{charging} \\ SOC_{bat,k} - \frac{I_{bat,k}\Delta t}{C_{bat}}, & \text{discharging} \end{cases} \quad \text{Eq. 5}$$

where, $I_{bat,k}$ (Ah) is the charging/discharging current at time k , Δt is the time step, and C_{bat} (Ah · hour) is the capacity of the battery. $I_{bat,k}\Delta t$ is the total electricity charged/discharged at each time step. The charging and discharging currents are decision variables in the optimization, but their constraints are:

$$I_{bat,k} \leq \begin{cases} (SOC_{max} - SOC_{bat,k})C_{bat}/(\eta_t \Delta t), & \text{charging} \\ (SOC_{bat,k} - SOC_{min})C_{bat}/\Delta t, & \text{discharging} \end{cases} \quad \text{Eq. 6}$$

This constraint is the maximum charging/discharging current which is derived from charging from zero of charge to full of charge, or discharge from full of charge to zero of charge during one time step.

Based on the currents, the battery charging/discharging power, $P_{bat,k}$, can be estimated as:

$$P_{bat,k} = V_{bat,k} I_{bat,k} N_{bs} N_{bp} \quad \text{Eq. 7}$$

where, $V_{bat,k}$ is the terminal voltage. $V_{bat,k} I_{bat,k}$ estimates the stored/released power in one battery module. N_{bs} and N_{bp} are the number of battery units in series and parallel. The calculation of terminal voltage is provided in Appendix A.

The capacity of the battery is selected as 100 Ah. N_{bs} and N_{bp} are 15 and 10 in small reference building and real small building. They are 30 and 20 in the medium reference building.

2.4 Thermal storage model

This study adapts the ice tank TES model structure from [41]. Similar to the battery model, the overall governing equations are as follows:

$$SOC_{tes,k+1} = \begin{cases} SOC_{tes,k} + \frac{u_k \Delta t}{C_{ice}}, & \text{charging} \\ SOC_{tes,k} - \frac{u_k \Delta t}{C_{ice}}, & \text{discharging} \end{cases} \quad \text{Eq. 8}$$

where, $SOC_{tes,k}$ is the ice tank state of charge at time k , u_k (W) is the charging/discharging rate at time k , Δt is the time step, and C_{ice} (J) is the capacity of the ice tank storage. The charging/discharging rate, u_k , can be calculated from the heat transfer between the chilled water and stored ice:

$$u_k = \begin{cases} \varepsilon_{c,k} m_c c_f (T_s - T_{chws}), & \text{charging} \\ \varepsilon_{d,k} m_c c_f (T_{chws} - T_s), & \text{discharging} \end{cases} \quad \text{Eq. 9}$$

where $\varepsilon_{c,k}$ and $\varepsilon_{d,k}$ are the heat transfer effectiveness for charging and discharging at time k . m_c (kg/s) is the chilled water (water/glycol mixture) flow rate. c_f (J/kgK) is the specific heat of the chilled water, which is 0.96. T_s (K) is storage temperature, which is 0°C, T_{chws} (K) is chilled water temperature, which is -5°C and 7°C at charging and discharging stage in this study. The ice tank electricity is then estimated from its charging rate u_k , and chiller COP: $P_{ice,k} = u_k / COP$. For the simplification of this building cluster model, the nominal chiller COP is used. Appendix A also provides the calculation of $\varepsilon_{c,t}$ and $\varepsilon_{d,t}$. The capacity of the TES is 0.6 GJ in this study.

3. Forecasting Model Training and Validation

The building energy forecasting model training and validation are based on the DOE reference EnergyPlus models for small and medium office buildings, as well as a real small size commercial building. The details about the building energy forecasting model development and validation are published in [36, 38]. The overall approach for the energy device forecasting model training is to firstly develop the physics based models using Eq. 3 to Eq. 9, and then identify the parameters based on the mature simulation models from a validated emulator in TRNSYS [42]. Figure 2 illustrates the overall procedure of the energy forecasting model developing and parameter identification. Firstly, the emulator and the forecasting models will share the same operation strategies, boundary conditions and system inputs. The parameter identification techniques will then determine the parameters to allow the forecasting models behave similarly to the emulator models. Section 5 discusses the model forecasting results and performance.

Figure 2 Energy forecasting model training process

4. Method for Multi-objective Optimization

4.1 Optimization framework

Figure 3 illustrates the operation and resource sharing within the building cluster, which consists of three buildings, PV panel energy generation systems, battery and ice tank energy storage systems. Within this cluster, each building has its own PV panel and battery system, but ice tank TES is shared among all the buildings in this cluster.

Figure 3 Building cluster operation: resource share

The energy balance for each building can be expressed as:

$$P_{PV,t}^k + P_{bat,t}^k + P_{p,t}^k = P_{HVAC,t}^k + P_{other,t}^k + P_{s,t}^k \quad \text{Eq. 10}$$

$$Q_{CL,t}^k + Q_{TES,t}^k = Q_{HVAC,t}^k \quad \text{Eq. 11}$$

where, $P_{PV,t}^k$, and $P_{bat,t}^k$ are energy provided to building k , from PV panel and battery at time t . $P_{p,t}^k$ and $P_{s,t}^k$ are purchasing and selling electricity energy of building k at time t . $P_{HVAC,t}^k$ and $P_{other,t}^k$ are the energy consumption of HVAC system and other systems, such as lighting and equipment. $Q_{CL,t}^k$, $Q_{TES,t}^k$, and $Q_{HVAC,t}^k$ are the chilled water provided by the base chiller and ice tank TES, as well as the chilled water consumed by the HVAC system of building k at time t . Considering the characteristics of each forecasting models as well as the optimization algorithm, the time step is selected as 15 minutes.

The objective of this multi-objective optimization framework is to reduce the energy cost and maintain the indoor thermal comfort, PMV (Eq. 12):

$$\begin{aligned} & \text{Min } J(T_{stp,t}^k, Q_{ice,t}^k, I_{bat,t}^k) \\ & = \sum_{k=1}^N \sum_{t=1}^H (r_{p,t} P_{p,t}^k - r_{s,t} P_{s,t}^k) + \sum_{t=1}^H r_{p,t} P_{ice,t} + P_d \max(P_{p,t}) + \sum_{k=1}^N \sum_{t=1}^L w_i |PMV_t^k| \end{aligned} \quad \text{Eq. 12}$$

where $T_{stp,t}^k$, $Q_{ice,t}^k$, and $I_{bat,t}^k$ are decision variables, which are temperature setpoints, ice tank chilled water supply, battery charging/discharging current of each building, k , at time step, t . $r_{b,t}$ and $r_{s,t}$ are electricity purchasing and selling price at time step, t , $P_{ice,t}$ is the ice tank electricity consumption, which can be calculated using the methods presented in section 2.4, P_d is the demand charge rate, $\max(P_{p,t})$ is the peak demand for demand charge calculation. $P_d \max(P_{p,t})$ estimates the peak demand charge during the study period. w_i is the weighting factor for thermal comfort and PMV_t^k is the thermal comfort PMV index for building k at time step t . H and L are the total studying and the occupancy hours, respectively. As a

result, $\sum_{k=1}^N \sum_{t=1}^H (r_{p,t} P_{p,t}^k - r_{s,t} P_{s,t}^k)$ is the total net electricity cost of all the buildings in this cluster. $\sum_{t=1}^H r_{p,t} P_{ice,t}$ is the total electricity cost of the shared thermal storage system. $P_d \max(P_{p,t})$ calculates the total demand cost of this cluster. $\sum_{k=1}^N \sum_{t=1}^L w_i |PMV_t^k|$ is the thermal comfort penalty, which only considers the PMV during occupied periods. As PMV is usually ranged between -3 and +3, the absolute value is used in the objective function. Comparing with the typical electricity costs, the objective of thermal comfort is relatively small. Therefore the summation of the absolute value of PMV at each time step is used in Eq. 12. As there are 40 time steps during the occupied hours, the total summation of the PMV penalty is then competitive with the electricity cost objective. All of the variables on the right hand side of Eq. 12 are either provided as known conditions or calculated from the simulation models (Figure 4).

Figure 4 Building cluster operation optimization

4.2 Optimization conditions

The study applies the proposed optimization framework for a cluster with three buildings located in Philadelphia, PA. The model training period is August 1st to 7th, the model validation period is August 24th to 28th, and the optimization study is for August 29th. The real time electricity price (plan A) and time-of-use price (plan B) are obtained from PJM and a local utility company¹. Figure 5 (a) plots these two pricing rates during the study period. The demand charging is 8.4 \$/kW during the peak hours from 12 pm to 6 pm. This study assumes the selling price to be the same as purchasing price. Figure 5 (b) shows the ambient temperature and the solar radiation during the studying period, which are collected from typical meteorological year (TMY) file of Philadelphia.

¹ Real time price: <http://www.pjm.com/markets-and-operations/energy.aspx>

Time-of-use price: <https://www.directenergy.com/pa/electricity-plans/best-hourly-rate/msid/5501>

Figure 5 Operation optimization condition, (a): electricity price, (b): weather condition

4.3 Optimization method

As the optimization problem formulated in section 4.1, it is difficult to calculate the gradients of the objective function or converted it to a convex problem. As a result, a heuristic searching based optimization algorithm, particle swarm optimization (PSO), is selected in this study. The two most important variables: velocity, v_p^{i+1} , and position, x_p^{i+1} in the general PSO formulation are updated using the following equations:

$$v_p^{i+1} = w_p v_p^i + c_1 r_{1,p}^{i+1} \times (P_p^i - x_p^i) + c_2 r_{2,p}^{i+1} \times (P_g^i - x_p^i) \quad \text{Eq. 13}$$

$$x_p^{i+1} = x_p^i + v_p^{i+1} \quad \text{Eq. 14}$$

5. where V_p^i is the velocity of the p^{th} particle at time step i , x_p^i is the position of the p^{th} particle at time step i , P_p^i is the best position found so far by the p^{th} particle, P_g^i is the best position found so far by the swarm, $r_{1,p}^i$ and $r_{2,p}^i$ are two independent random numbers uniformly distributed between 0 and 1. c_1 and c_2 are the cognitive acceleration and social acceleration factors, which are 2.5 and 0.5, respectively. w_p is inertia weight, which is 0.72 in this study. The number of particles is 100, and the maximum number of generations is 1000. The parameter selection is based on the testing results in [43]. Results

5.1 Building forecasting results

As introduced before, the building energy forecasting models used in this study are adapted from the previous studies. The details about the HVAC energy forecasting model development and validation can be found in [36, 38]. The non-HVAC energy consumption is modeled as scheduled values, since they are assumed unchangeable in this study. Figure 6 (a) and (c) are energy forecasting validation results, (b) and (d) are the results for average PMV forecasting from August 24th to August 28th for the small and medium size reference building. Figure 6 (e) and (f) are the results for the real building energy and average PMV forecasting on August 28th, 2015. As discussed previously, the real field PMV is hard to measure. So the real field PMV forecasting has not been validated in this study.

Figure 6 Building energy and thermal comfort forecasting results

Generally speaking, these plots show that the energy forecasting models are able to get very good forecasting accuracy. In order to evaluate the forecasting accuracy, this study uses three indexes, namely, Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE) and Coefficient of Determination (R^2). They are formulated as Eq. 15 to Eq. 17:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_i - \hat{x}_i)^2}{n}} \quad \text{Eq. 15}$$

$$NRMSE = \sqrt{\frac{\sum_{i=1}^n (x_i - \hat{x}_i)^2}{n}} / (x_{max} - x_{min}) \quad \text{Eq. 16}$$

$$R^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})(\hat{x}_i - \bar{\hat{x}})}{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (\hat{x}_i - \bar{\hat{x}})} \quad \text{Eq. 17}$$

Table 3 summarizes accuracy evaluation indexes for all the building related forecasting. The energy forecasting accuracy (R^2) is above 0.9 for the small and medium building, comparing with EnergyPlus simulation results. The energy forecasting accuracy (R^2) for the real building is 0.85. Considering the measurement uncertainty, this accuracy is acceptable. The forecasting error (NRMSE) for all the forecasting is below (or at) 10%. Figure 6 (b) and (d) are the PMV forecasting validation results for the DOE small and medium reference buildings. As summarized in Table 3, the PMV forecasting accuracy (R^2) is 0.9 and 0.88 for the small building and medium building, respectively.

Table 3 Building energy and PMV forecasting accuracy

	Forecasting	RMSE	NRMSE	R^2
Small building	Energy	0.4 kWh	9%	0.94
	PMV	0.16	7.2%	0.90
Medium building	Energy	6.7 kWh	10%	0.91
	PMV	0.1	8%	0.88
Real building	Energy	0.65 kWh	8.4%	0.85
	PMV	-	-	-

As it was very difficult to measure the PMV in real field, so the PMV forecasting model for the real commercial building is not developed using the save method. It is modeled using AHSRAE standard 55 [44]. It is also very difficult to measure the temperature of wall and floor, so the radiative temperature is assumed to be the same as room air temperature.

5.2 Energy device forecasting results

To coordinate with the building forecasting models, training period for all the energy device model development is from August 1st to 7th, and the model forecasting period is from August 24th to August 28th. Appendix B summarizes the parameters identification results for the PV panel model, battery model, and ice tank TES model. Figure 7 illustrates the forecasting results for all these three systems. The PV and battery results shown in this figure are for these two devices for the small reference building. They results showed in Figure 7 (b) and (c) are the value of charging power subtracting discharging power. Therefore, the value above zero is charging power and the value below zero is discharging power.

Figure 7 Energy device forecasting results, (a): PV panel forecasting results, (b): battery forecasting results, (c): ice tank forecasting results

Table 4 tabulates the forecasting accuracy evaluation indexes for all these three models. The accuracy (R^2) is above 0.9 and the error (NRMSE) is below 6% for all the forecasting.

Table 4 Energy device model forecasting accuracy

	RMSE, kW	NRMSE	R^2
PV panel	0.59	5.1%	0.98
Battery	1.14	5.5%	0.93
Ice tank	0.84	4.2%	0.96

Even though certain forecasting errors exist in the forecasting models, the overall dynamics and general trends are captured in those forecasting models. As proven in previous studied in how to select forecasting models for building model predictive control [45, 46], all the models developed in this study are suitable for model based control, and the optimization results from these models are able to reflect the real situations.

5.3 Optimization results

In this study, the multi-objective optimization framework applies different weighting factors for thermal comfort to investigate the balance between energy cost saving and thermal comfort maintaining. Eight scenarios with weighting factor as 0, 0.1, 0.2, 0.5, 1, 2, 5 and 10 are tested in this study. As introduced in section 4.2, all these eight scenarios are studied under both electricity price plan A and plan B. In order show the effectiveness of optimal control, a baseline rule based operation is also tested and compared with the optimized control calculated in previous sections. The rule based operation schemes is as follows:

1. Temperature setpoint: 24.0 °C from 8 am to 6 pm, and 26.7 °C for other time;
2. Battery charging/discharging: charging at maximum from 12 am to 6 am until full, and discharging at maximum from 12 pm to 6 pm until depleting;
3. Ice tank: changing at maximum from 12 am to 6 am until full, and discharging at maximum from 12 pm to 6 pm until deplete; 20% chilled water to small reference building, 20% chilled water to the real small building, and 60% to the medium reference building.

The first scenario investigates the optimal operation with thermal comfort weighting factor as 0. Since no thermal comfort is considered in this operation scheme, the only objective is to minimize the energy cost. Figure 8 (a) makes clear the optimized temperature setpoints, energy consumption for all of these three buildings as well as the total energy purchased from power grid under this scenario. As expected, the temperature setpoints are close to the upper limit during the peak hours and the control scheme decreases the temperature at early morning to pre-cool the building when electricity price is lower. The total energy purchased results from this figure show that the optimized control strategy: building temperature setpoints, battery, and TES charging/discharging schedules reduced the energy purchasing in

the peak hours significantly. Under this optimized scheme, the averaged PMV is 1.58, which is relatively high as the temperature setpoints are at the upper limits, and the total cluster energy cost is \$91.9, among which \$41.3 is the total building (together with PV and battery) energy cost, \$11.6 is the TES energy cost, and \$52.0 is the demand cost. But this cluster earned \$13.0 from selling electricity to the power grid. Figure 8 (b) shows the optimization results of the scenario with weighting factor as 1. As considered the thermal comfort in the objective function, the temperature setpoints are between 24 °C and 26 °C during the occupied period and they are also decreased at the early morning from 4 am to 7 am. The averaged PMV is 0.64, which is more comfortable than the case with weighting factor as 0. In this case, the total cost is \$118.2, among which \$58.5 is the energy cost of these three buildings, \$17.1 is the TES energy cost, and \$42.6 is the demand charge.

Figure 8 Building temperature optimal control results under plan A (a: $w=0$, b: $w=1$).

Following these two scenarios, all the cases are studied with different weighting factors defined previously. Figure 9 plots the Pareto curves for the optimization results of the building cluster and buildings alone. As shown in this figure, the building cluster energy cost is much lower than that of buildings alone in all the studied cases, which means the distributed energy systems have significant impacts on energy cost saving. With higher weighting factors for thermal comfort, the energy costs are higher and PMV indexes are more close to 0. As introduced in Figure 5 (a), electricity plan A is more expensive than plan B, so energy costs under plan A are higher than that under plan B. However, they are more close to each other at the scenarios with highest weighting factors. This is because under these scenarios the demand charge dominates the total costs, and demand charge rates are identical under electricity pricing plan A and B.

Figure 9 Multi-objective optimization Pareto curves for the building cluster operation

Figure 9 also plots the operation results under the baseline rule based operation scheme. Comparing with the optimized operation cases, the energy cost savings are summarized in Table 5. Considering the thermal comfort (shown in Figure 9), the energy cost savings under optimized operation with $w = 10$ are emphasized. This optimized operation scheme with weighting factor as 10 is able to reduce the energy cost by 31.9% and 12.1% for the total building cluster under electricity plan A and B, respectively. It also can reduce the cost by 19.1% and 10.1% for the buildings only scenarios. Without considering the thermal comfort but only consider the temperature setpoint limits, the optimized operation scheme is able to save over 50% under plan A and over 30% under plan B. The savings under other optimized schemes are between these two and are all tabulated in Table 5. The energy cost savings in plan A are higher than those in plan B, which is because that the peak to off-peak electricity price ratio in plan A is higher than that in plan B, and, therefore, the energy stored (actively or passively) in the off-peak period can be reduced.

more energy cost during the peak period. Table 5 Operation operation energy cost savings: compared with baseline operation

Weight	Plan A				Plan B			
	Building cluster		Building		Building cluster		Building	
	Cost (\$)	Saving	Cost (\$)	Saving	Cost (\$)	Saving	Cost (\$)	Saving
0	91.9	58.3%	431.9	65.4%	64.4	39.2%	357.8	46.3%
0.1	96.5	56.2%	470.8	61.2%	72.2	33.7%	381.3	42.8%
0.2	104.9	52.4%	476.6	55.3%	83.2	32.9%	407.3	38.9%
0.5	114.2	48.2%	491.4	53.7%	86.3	30.8%	445.2	33.2%
1	118.0	46.5%	501.8	51.0%	91.2	29.4%	455.5	31.6%
2	133.0	39.7%	547.5	42.9%	106.4	22.9%	483.6	27.4%
5	142.0	35.6%	576.0	37.6%	116.3	18.9%	546.1	18.0%
10	150.0	31.9%	624.3	19.1%	150.7	12.1%	599.0	10.1%
Rule	220.4	-	710.4	-	186.3	-	666.3	-

6. Conclusion and Discussion

This paper develops and validates forecasting models for a building cluster, including three buildings, three PV-battery systems and a shared thermal storage system. A multi-objective optimization based building cluster operation framework is also developed and demonstrated. The Pareto frontiers are derived for the balance the energy saving and thermal comfort maintaining. Results show that the energy forecasting models are able to achieve over (or around) 90% accuracy (R^2) when comparing with the validated detailed physics based models in EnergyPlus and TRNSYS. Comparing with a baseline rule based operation scheme, the multi-objective optimized operation strategies are able to achieve energy cost saving by 31.9% to 58.3% with different weighting factors for thermal comfort under electricity price plan A, and 12.1% to 39.2% under electricity price plan B for the building cluster. Only considering the three buildings without the distributed energy systems, the optimized operation strategies reduce energy costs by 19.1% to 65.4% and by 10.1% to 46.3% under electricity price plan A and B. The results from this study also show that the distributed energy systems and operation optimization are able to reduce the peak demand significantly. The derived Pareto frontiers can be used for determining operation decision under different pricing structures as well as improving the resilience of buildings and power grids, which also provide guidelines for building operators to choose suitable optimal control schemes according to their requirements. The collaborative building cluster operation framework can be easily used in different locations with different systems.

Considering the forecasting errors in the forecasting models, the real energy costs and savings may slightly different to the predicted values. This slight difference is hard to quantify, as the model based optimization approach is hard to implement on the original emulator or the real buildings. However,

proved from previous studies, the overall trend of the performance and cost saving are reasonable and reflect the real situation.

Moving forward, more different buildings and distributed energy systems at different locations with different electricity pricing plans will be included and studied in this building cluster operation framework. Real field studies are also useful to demonstrate the performance of this model based optimization framework. Another exploring direction is to utilize this building cluster operation framework to assist the electricity pricing mechanism determining and selection for the utility companies.

Acknowledgement

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Appendix A

1. PMV estimation

In the PMV estimation of these three buildings the occupant metabolic level is 1.2, work level is 0, clothing factor is 0.5. For the PMV estimation in the two DOE reference buildings, all these coefficients are considered in the EnergyPlus model. Therefore, the model training process is able to capture them and reflect them in the forecasting period. However, they are all used explicitly in the PMV estimation in the real small building. Besides these three buildings, the air velocity is assumed as 0.1 m/s. The details about the PMV calculation can be found in ASHRAE 55 [44].

2. PV panel modeling

F_B , F_D , and F_R are angular loss factors for direct, diffuse and reflected irradiance respectively. They are calculated as follows [47]:

$$F_B = \frac{\exp\left(-\frac{\cos\theta}{a_r}\right) - \exp\left(-\frac{1}{a_r}\right)}{1 - \exp\left(-\frac{1}{a_r}\right)} \quad \text{Eq. A1}$$

$$F_D = \exp\left[-\frac{1}{a_r}\left[c_1\left(\sin\beta + \frac{\pi - \frac{\beta\pi}{180} - \sin\beta}{1 + \cos\beta}\right) + c_2\left(\sin\beta + \frac{\pi - \frac{\beta\pi}{180} - \sin\beta}{1 + \cos\beta}\right)^2\right]\right] \quad \text{Eq. A2}$$

$$F_R = \exp\left[-\frac{1}{a_r}\left[c_1\left(\sin\beta + \frac{\frac{\beta\pi}{180} - \sin\beta}{1 - \cos\beta}\right) + c_2\left(\sin\beta + \frac{\frac{\beta\pi}{180} - \sin\beta}{1 - \cos\beta}\right)^2\right]\right] \quad \text{Eq. A3}$$

Where θ is the angle of solar incidence; β is the slope angle of inclined surface. The solar angle, θ , can be calculated from the solar time angle, surface azimuth angle, latitude of the local location, and the solar declination. c_1 , c_2 , and a_r are also determined in the model training period.

3. Battery modeling

The battery charging/discharging power, $P_{bat,k}$, can be estimated as:

$$P_{bat,k} = V_{bat,k} I_{bat,k} N_{bs} N_{bp} \quad \text{Eq.A4}$$

where, $V_{bat,k}$ is the terminal voltage, $I_{bat,k}$ is the charging/discharging current. $V_{bat,k} I_{bat,k}$ estimates the charging/discharging power of each battery cell. N_{bs} and N_{bp} are the number of battery units in series and parallel. $V_{bat,k}$ can be calculated from the full rest voltage and internal voltage decreasing:

$$V_{bat,k} = VF + a \log(SOC_{bat,k}) - I_{bat,t} R_{bat,t} \quad \text{Eq.A5}$$

where, VF is the full charge rest voltage, which is 13.2 V and 12.6 V at charging and discharging mode. $R_{bat,t} = r_1 + r_2 SOC_{bat,k} + \frac{1}{r_3 - r_4 SOC_{bat,k}}$ is the internal resistance. $a \log(SOC_{bat,k})$ represents the voltage changes due to state of charge change. All the parameters: a and r_s are determined at the model training stage.

4. Ice tank modeling

$u_{c,k}$ and $u_{d,k}$ can be calculated as:

$$u_{c,k} = \varepsilon_{c,k} m_{chw} c_f (T_s - T_{chws}) \quad \text{Eq.A6}$$

$$u_{d,k} = \varepsilon_{d,k} m_{chw} c_f (T_{chws} - T_s) \quad \text{Eq.A7}$$

where $\varepsilon_{c,k}$ and $\varepsilon_{d,k}$ are the heat transfer effectiveness for charging and discharging at time k , respectively.

They can be estimated as a empirical function of relative state of charge $SOC_{r,k}$:

$$\varepsilon_{c,t} = a_0 + a_1 SOC_{r,t} + a_2 SOC_{r,t}^2 + a_3 SOC_{r,t}^3 + a_4 SOC_{r,t}^4 + a_5 SOC_{r,t}^5 \quad \text{Eq.A8}$$

$$\varepsilon_{d,t} = b_0 + b_1 SOC_{r,t} + b_2 SOC_{r,t}^2 + b_3 SOC_{r,t}^3 + b_4 SOC_{r,t}^4 + b_5 SOC_{r,t}^5 + b_6 SOC_{r,t}^6 + b_7 SOC_{r,t}^7 \quad \text{Eq.A9}$$

All the coefficients a_s and b_s will be determined in the model training process. The details about relative state of charge estimation are obtained from [48].

Appendix B

Table B1 Energy device model parameter identification results

PV		Battery		Ice tank			
Variable	Value	Variable	Value	Variable	Value	Variable	Value

a	0.0002	a	6.13 (4.93 [*])	a ₀	1.11	b ₁	2.29
b	-0.0027	r ₁	0.07 (0.005)	a ₁	0.48	b ₂	-1.33
c	0.0715	t ₂	-0.94(1.72)	a ₂	0.19	b ₃	-1.25
d	0.7749	r ₃	10 (-5.15)	a ₃	0.73	b ₄	0.23
c ₁	0.4244	r ₄	-5 (6.98)	a ₄	1.31	b ₅	0.49
c ₂	5			a ₅	0.66	b ₆	0.0032
a _r	35.9			b ₀	0.33	b ₇	-0.077

* Parameters at discharge stage are in parenthesis

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Figure

Figure 1 Building energy and thermal comfort forecasting

Figure 2 Energy forecasting model training process

Figure 3 Building cluster operation: resource share

Figure 4 Building cluster operation optimization

Figure 5 Operation optimization condition, (a): electricity price, (b): weather condition

Figure 6 Building energy and thermal comfort forecasting results

Figure 7 Energy device forecasting results, (a): PV panel forecasting results

Figure 8 Building temperature optimal control results under plan A (a: $w=0$, b: $w=1$).

Figure 9 Multi-objective optimization pareto curves for the building cluster operation

Table 1 Feature selection for energy and PMV forecasting

Variable	Variable Name
T _{out}	Outdoor air temperature (C)
RH _{out}	Outdoor air relative humidity ratio (-)
T _{zone, stp, i}	Zone i temperature setpoint (C)
R _{in,i}	Lighting/Equipment schedule in zone i (-)
Q _{dir}	Direct solar radiation (W/m ²)
Q _{dif}	Diffuse solar radiation (W/m ²)
V _{oa}	Ventilation rate (m ³ /s)

Table 2 Building construction and HVAC features

Feature	Small reference	Medium Reference	Real small
Floors	1	3	1
Total floor area (m ²)	511	4982	855.5
Window to wall ratio	0.21	0.33	0.54
Glazing U-factor (W/(m ² ·K))	3.35	3.35	2.73
Glazing SHGC	0.36	0.36	0.85
Occupant Density (m ² /person)	18.6	18.6	12.4
Lighting Power Density (W/m ²)	19.5	16.89	6.88
Equipment Power Density (W/m ²)	10.8	10.8	8.1
HVAC	Packaged CAV	Packaged MZ VAV	AHU + VAV

Table 3 Building energy and PMV forecasting accuracy

	Forecasting	RMSE	NRMSE	R ²
Small building	Energy	0.4 kWh	9%	0.94
	PMV	0.16	7.2%	0.90
Medium building	Energy	6.7 kWh	10%	0.91
	PMV	0.1	8%	0.88
Real building	Energy	0.65 kWh	8.4%	0.85
	PMV	-	-	-

Table 4 Energy device model forecasting accuracy

	RMSE, kW	NRMSE	R ²
PV panel	0.59	5.1%	0.98
Battery	1.14	5.5%	0.93
Ice tank	0.84	4.2%	0.96

Table 5 Operation operation energy cost savings: compared with baseline operation

Weight	Plan A				Plan B			
	Building cluster		Building		Building cluster		Building	
	Cost (\$)	Saving	Cost (\$)	Saving	Cost (\$)	Saving	Cost (\$)	Saving
0	91.9	58.3%	431.9	65.4%	64.4	39.2%	357.8	46.3%
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1	118.0	46.5%	501.8	51.0%	91.2	29.4%	455.5	31.6%
2	133.0	39.7%	547.5	42.9%	106.4	22.9%	483.6	27.4%
5	142.0	35.6%	576.0	37.6%	116.3	18.9%	546.1	18.0%
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PV		Battery		Ice tank			
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b	-0.0027	r ₁	0.07 (0.005)	a ₁	0.48	b ₂	-1.33
c	0.0715	t ₂	-0.94(1.72)	a ₂	0.19	b ₃	-1.25
d	0.7749	r ₃	10 (-5.15)	a ₃	0.73	b ₄	0.23
c ₁	0.4244	r ₄	-5 (6.98)	a ₄	1.31	b ₅	0.49
c ₂	5			a ₅	0.66	b ₆	0.0032
a _r	35.9			b ₀	0.33	b ₇	-0.077

* Parameters at discharge stage are in parenthesis