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Evaluation of methods for determining demand-limiting setpoint trajectories in buildings using short-term measurements

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Abstract

This paper presents the evaluation of three different methods for determining zone temperature setpoint variations that limit peak electrical demand in buildings. The methods were developed in a companion paper [Lee K-H, Braun JE. Development of methods for determining demand-limiting setpoint trajectories in commercial buildings using short-term measurements. Building and Environment 2007, in press.] and are evaluated in the current paper through simulation for a small, medium, and large commercial building. Inverse models were employed for the simulation where the parameters were estimated with nonlinear regression techniques using hourly data. Two of the demand-limiting methods are based on the use of simple building models that capture dynamics of the building cooling loads in response to setpoint variations over a short time scale. The third method is data driven and only relies on load data to directly determine setpoint variations that minimize peak cooling demand. All three demand-limiting methods work well in terms of peak demand reduction for individual buildings. However, the data-driven method has slightly better performance than the other methods, is easier to implement, and is directly applicable for peak load reduction of aggregated buildings.

Keywords: Building thermal mass; Demand-limiting control; Commercial buildings; Simplified methods

1. Introduction

It is possible to achieve significant reductions in peak cooling loads for buildings by making use of the structural thermal mass through adjustments in zone temperature setpoints within the limits of comfort. The thermostat settings are lowered prior to the demand-limiting period and then adjusted upwards in an optimal way to minimize peak demand. A companion paper by Lee and Braun [1] develops three simplified demand-limiting methods, termed the SA (semi-analytical), ESA (exponential setpoint equation-based SA), and WA (weighted-averaging) methods that determine zone temperature setpoint trajectories during the on-peak period that attempt to minimize peak demand. The SA and ESA methods employ simple inverse building models trained with short-term data and use analytical solutions from the models for the setpoint trajectories. The WA method exploits a locally linear relation between zone temperature and cooling loads. The setpoint trajectory that minimizes the peak cooling load is estimated through a weighted averaging of two control setpoint trajectories which should produce load variations that intersect at some point during the on-peak period. The simple methods do not require measurements of solar radiation and only require 1 or 2 days of hourly data for outdoor temperatures and cooling loads.

The primary purpose of the current paper is to evaluate the performance of the simplified demand-limiting methods. A simulation study was performed for a small, medium, and large commercial building. Inverse models were employed for the simulation where the parameters were estimated with nonlinear regression techniques using hourly data.

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Nomenclature

A	area
BKN	broken/mostly cloudy sky condition
C	thermal capacitance
c_g	thermal contact factor
c_{pa}	specific heat of air
CC	conventional control
DL	demand-limiting control strategy
d	effective building thickness
d_{win}	window thickness
FEW	clear or with a few clouds sky condition
g_m	magnitude factor in approximate equation for radiative heat gain
g_s	shift factor in approximate equation for radiative heat gain
g_t	time lag factor in approximate equation for radiative heat gain
h	convective heat transfer coefficient
ht	height
k_{dl}	final time stage during the on-peak period
k	thermal conductivity or time stage
LR	linear-rise setpoint control strategy
min	minimum
N	number
NS	night-setup control strategy
OVC	overcast sky condition
PC	precooling control strategy
PLR	peak load ratio defined as ratio of peak load under demand-limiting control to peak load under conventional control
$\dot{Q}$	heat transfer rate
R	thermal resistance
R_a	thermal resistance between zone air and outdoor air
R_d	thermal resistance between shallow mass and deep mass
R_g	thermal resistance between ground and effective entire building mass
R_i	thermal resistance between zone air and effective entire building mass
R_o	thermal resistance between outdoor air and effective entire building mass
R_s	thermal resistance between zone air and shallow mass
r_c	ratio of effective shallow mass capacitance to building capacitance
$r_{A,\mathrm{win,side}}$	ratio of window area to building side surface area
SCT	scattered/partly cloudy sky condition
SU	step-up setpoint control strategy
T	temperature
$\dot{V}$	volume flow rate
$\dot{V}_{\mathrm{in,volume}}$	air exchange rate by infiltration (l/h)

Subscripts

a	ambient or air
b	building
cc	conventional control (night-setup)
dl	demand-limiting control
dm	deep mass in simple building indoor mass model
eff	effective
floor	floor
g	ground
g,c	convective gain
k	time stage
m	effective building mass
max	maximum
ns	night-setup control
o	outside
person	per person
r	roof and ceiling
sm	shallow mass in simple building indoor mass model
side	side wall of buildings
story	story of building
vent	ventilation
win	window
z	building zone air

Greek letters

τ	effective time constant in simple exponential setpoint equation
ρ	density

2. Description of buildings

2.1. ERS building

The Iowa Energy Center Engineering Resource Station (ERS) building is typical of small commercial buildings that employ packaged air conditioning equipment. It is a single-story building having a slab floor and is located in Ankeny, Iowa. The ERS building is a demonstration and test facility built to compare different energy-efficient measures, to record energy consumption, and to disseminate information concerning energy-efficient design and operation of buildings. A schematic diagram of the floor plan for the ERS is shown in Fig. 1. Each test room has 26 m^2 (275 ft^2) of floor area with a ceiling height of 2.59 m (8.5 ft). The height of plenum zones above the test zones is 1.68 m (5.5 ft). The test room zones within a pair are identical and labeled 'A' and 'B'. Power densities for lighting and electric equipment are 23.7 and 36.6 W/m^2 (2.2

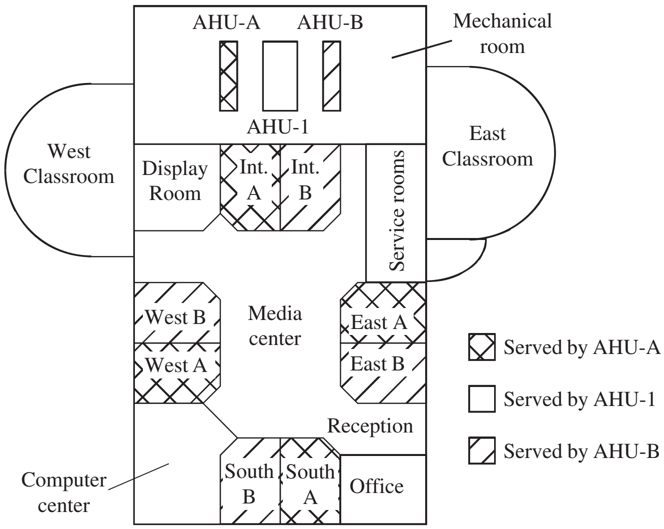

Fig. 1. Schematic diagram of floor plan for the ERS.

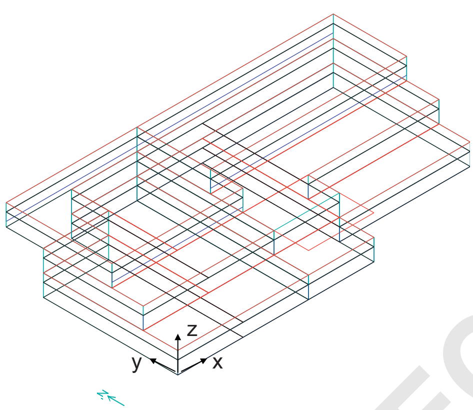

Fig. 2. Three-dimensional isometric diagram of Santa Rosa Federal building [4].

and 3.4 W/ft^2). Detailed descriptions of the building were presented by Lee and Braun [2,3].

2.2. *Santa Rosa Federal building*

The Santa Rosa Federal building is a medium-sized governmental office building located in Santa Rosa, CA [4]. The floor area is about 7400 m^2 (80,000 ft^2) and about half of the space is for offices and half for courtrooms. The office area is located to the west of the space for courtrooms. The west wing for the office spaces is only considered in this study. It has three stories with moderate structural mass, having 15 cm (6 in.) concrete floors and 10 cm (4 in.) exterior concrete walls. The office area has a medium furniture density and standard commercial carpet on the floor. Window-to-wall area ratio is 0.67 and the windows are floor-to-ceiling glazing on the north and south façades. Glazing fractions are negligible on the east and west faces of the building. The windows have single-pane tinted glazing. The internal lighting and electric equipment gains for the Santa Rosa building model are approximately 2.15 and 3.23 W/m^2 (0.2 and 0.3 W/ft^2), respectively. The total number of occupants in the office areas is approximately 100. Fig. 2 presents a three-dimensional isometric diagram of the building.

2.3. *Ameritech building*

This large commercial building is the former headquarter for Ameritech and is located near Chicago at Hoffman Estates, IL [5]. Fig. 3 represents a layout of the building. The building has four stories and the floor area is around 130,000 m^2 (1.4 million ft^2). The building has two identical wings on either side of a reception area that is conditioned with a separate system. The building was constructed mostly of heavy weight concrete. The window area is approximately 45% of the areas of the north, south, east, and west side walls. The occupied period is from 7 a.m. to 5 p.m., Monday through Friday.

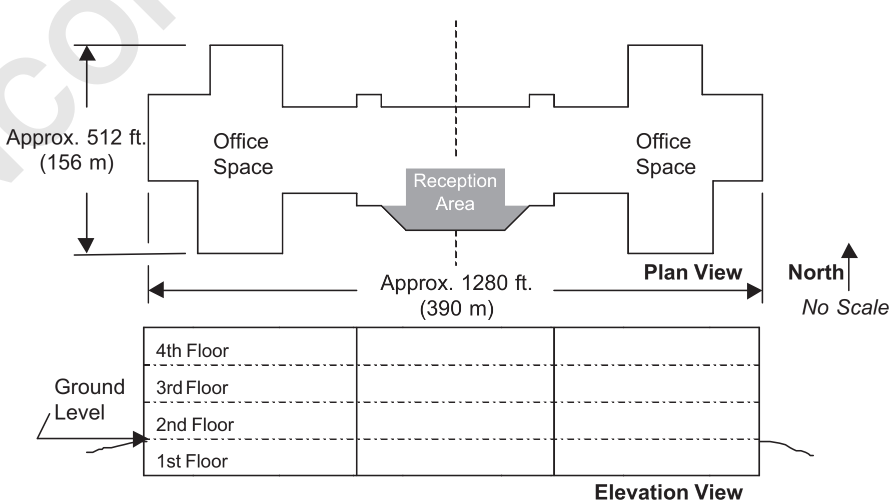

Fig. 3. Ameritech facility layout [5].

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3. Description of building models

Measurements on an hourly time scale were available for all three buildings considered in this study under both conventional control and strategies involving precooling and afternoon setpoint adjustments. For both the ERS and Ameritech buildings, sufficient data were available to train an inverse model that allows predictions of building cooling loads based on ambient conditions, internal gains, and zone temperature setpoints. More limited data were available for the Santa Rosa building that did not include solar radiation. Therefore, a calibrated forward model was employed to generate hourly data that was then used to train an inverse model. The method presented by Chaturvedi and Braun [5] was used as the basis of determining the inverse building models.

Lee and Braun [2,3] present inverse model development and evaluation for the ERS building. The collection of test zones (West, East, South, and Interior) for the ERS was modeled as a single zone. The model was trained with 35 days of data that included night-setup, load-shifting, and demand-limiting control strategies operated over a range of weather conditions. The integrated RMS (root-mean-squared) error of the building model for training was 7.27% for zone sensible cooling load prediction. Fig. 4 shows an example comparison of predicted and actual cooling loads for a single day. Similar results were obtained for other days and the other buildings.

Lee [6] presents development and evaluation of the inverse model for the Santa Rosa building. First of all, data from Xu et al. [4] were used to calibrate an EnergyPlus [7] model of this building that included six zones (two zones per floor). Tuning of the forward model was conducted by comparing simulated chiller power to measured power and primarily adjusting window shading. Fine-tuning was performed by changing the internal mass surface area and ventilation flow rate within reasonable bounds. Since solar radiation was not available for the building, TMY data for this region of California over the same time period were used instead. This is reasonable because the climate is dry and clear most of the time. A sample comparison between measured and predicted chiller power is shown in Fig. 5. The simulated chiller power has a similar magnitude and variation as the actual chiller power. The results from the building model simulation are in relatively good agreement with the measured data.

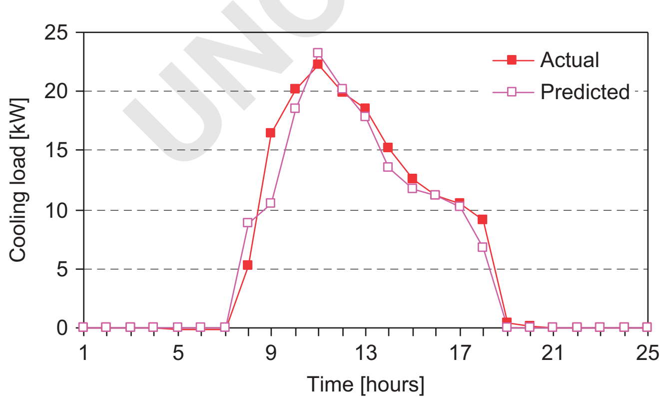

Fig. 4. Testing of trained inverse model for ERS building.

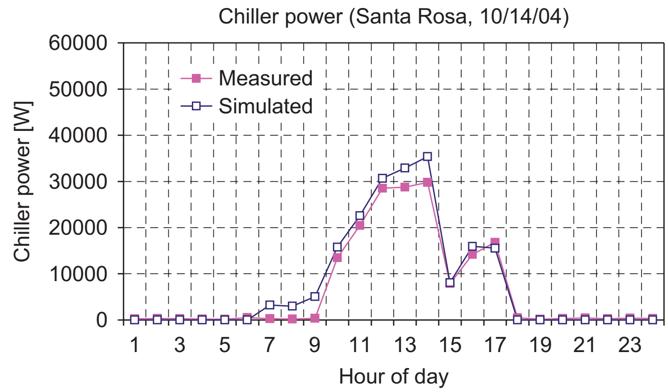

Fig. 5. Comparison of simulated and actual chiller power on 10/13 in 2004 for Santa Rosa building.

The next step was to use data generated by the forward model for cooling load to develop an inverse model for the Santa Rosa building. One month of sensible cooling load data was used for training and a separate month for testing of the model. The data included conventional, load-shifting, and demand-limiting control strategies. Integrated root mean square error for training of the inverse model was 2.66%, whereas the error for sensible cooling load prediction was 4.11%. The accuracy of the trained model for predicting results from the forward model is somewhat better than the results for application to real data because the model inputs are known.

An inverse building model of the Ameritech building for large commercial buildings was developed and validated by Chaturvedi and Braun [5]. The model was trained using 14 days of data that included both night-setup and load-shifting control strategies. A separate set of data was used for testing the model performance. The resulting model had an root mean square error of 8.6% for training and 9.8% error for the test set based on sensible cooling load predictions.

For simulation of building aggregates, it was assumed that the three different building types were arranged within an aggregation pool. The numbers of the Ameritech, ERS, and Santa Rosa buildings were determined so that the total peak loads for each building type were similar. In this study, the building aggregate was comprised of 400 ERS buildings, 60 Santa Rosa buildings, and 1 Ameritech building. California climate zone 2 weather data were used for simulation of aggregated buildings. Fig. 6 shows cooling loads for the aggregated buildings. Each building type has a very different cooling load profile that leads to an aggregate load profile that is much flatter.

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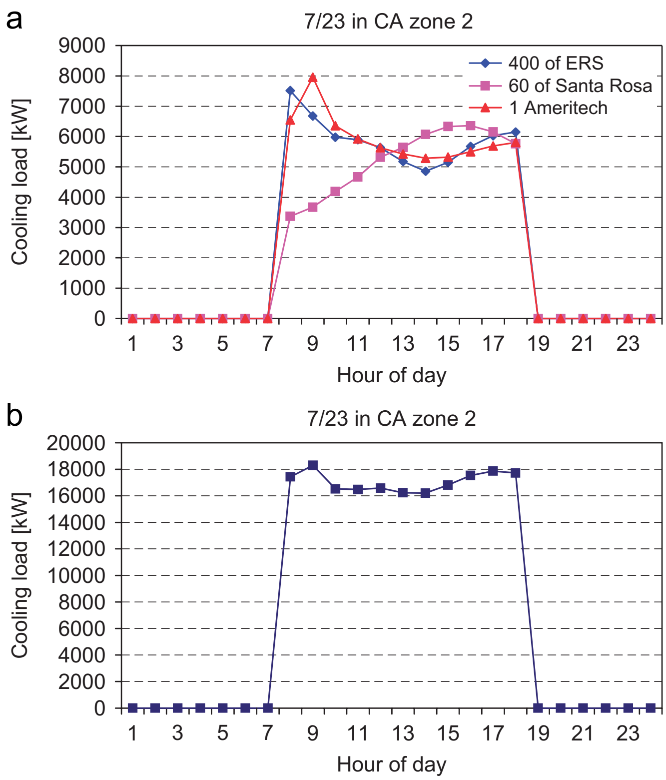

Fig. 6. Aggregation of three building types: (a) cooling loads for each building group and (b) aggregated cooling load.

4. Simulation method

4.1. Environmental weather data

Weather data used in simulations were typical meteorological data for Des Moines, Iowa (TMY2 format), California climate zone 2 (EPW format), and Chicago, Illinois (TMY2 format) for the ERS, Santa Rosa Federal, and Ameritech buildings, respectively. The time step and time interval for setpoint changes were 1 h. The simulations were performed for the period from April to September. Day light savings time was assumed during the whole simulation period.

4.2. Simulated control strategies

For demand-limiting control, precooling was assumed from 8 a.m. to 12 p.m. at 21.1 °C (70 °F) and then the setpoints were varied from 21.1 to 25.6 °C (70–78 °F) during a demand-limiting period from 12 to 6 p.m. Setpoint trajectories for the demand-limiting period were determined using the SA, ESA, and WA methods with generated data from the inverse building models.

The base case is night-setup (NS) control, where setpoint temperatures from 8 a.m. to 6 p.m. were fixed at 23.3 °C (74 °F) and then reset to 32.2 °C (90 °F) during other times. For comparison, the demand reduction compared to the base case associated with trajectories determined with the three methods were compared with 'optimal', 'linear-rise (LR)', and 'step-up (SU)' strategies. With the 'linear-rise' strategy, the setpoint was increased linearly from 21.1 to 25.6 °C (70–78 °F) during the demand-limiting period. The 'step-up' demand-limiting strategy involved resetting the setpoint at 25.6 °C (78 °F) at the beginning of the demand-limiting period until the end of the period. The 'optimal' demand-limiting strategy refers to the inverse model-based demand-limiting strategy presented by Lee and Braun [3]. It was assumed that building modeling and weather prediction were perfect in the simulation for the optimal control. The optimal demand-limiting strategy provides demand-limiting setpoint trajectories that yield the minimum peak cooling demand during the demand-limiting period. The optimal demand-limiting setpoint trajectories were determined each day during the simulated period from June to September.

4.3. Simulation scenario

In the simulations, demand-limiting control was applied on every day from June to September. However, to evaluate performance under conditions where demand-limiting might actually be employed, the highest 5 days were selected from each month based on daily afternoon peak cooling loads for night-setup control. Peak load reduction performance for the demand-limiting control is evaluated based on these 5 peak days from each month.

4.4. Peak load reduction performance index

Performance of peak demand reduction is evaluated in terms of the peak load ratio (PLR) defined as:

$$\mathrm{PLR} = \frac{\max\{\dot{Q}_{\mathrm{dl},k}\}}{\max\{\dot{Q}_{\mathrm{cc},k}\}} \quad \text{for} \quad k = 1, \ldots, k_{\mathrm{dl}}, \tag{1}$$

where $\dot{Q}_{\mathrm{cc},k}$ is cooling load at time k in conventional control, $\dot{Q}_{\mathrm{dl},k}$ is cooling load at time k in demand-limiting control, and k_{dl} is final time stage during the demand-limiting period.

Peak load ratios for each of the three simplified demand-limiting methods were averaged for the 5 highest peak days each month and compared with those from the 'linear-rise', 'step-up', and 'optimal' control strategies.

Table 1
Characterization of different weather conditions used for training days

Maximum outdoor temperature		Average sky cover (%)	
Hot	Over 29.4 °C (over 85 °F)	Clear (FEW)	0–10
Warm	23.9–29.4 °C (75–85°F)	Scattered/partly cloudy (SCT)	10–50
Cool	18.3–23.9 °C (65–75 °F)	Broken/mostly cloudy (BKN)	50–90
Cold	Below 18.3 °C (below 65 °F)	Overcast (OVC)	90–100

Table 2
Criteria for selection of training days

	Des Moines, IA	California zone 2	Chicago, IL
Maximum outdoor temperature during on-peak times	26.7 °C (80 °F)	29.4 °C (85 °F)	26.7 °C (80 °F)
Allowable maximum of average sky cover for on-peak times (%)	35	35	35

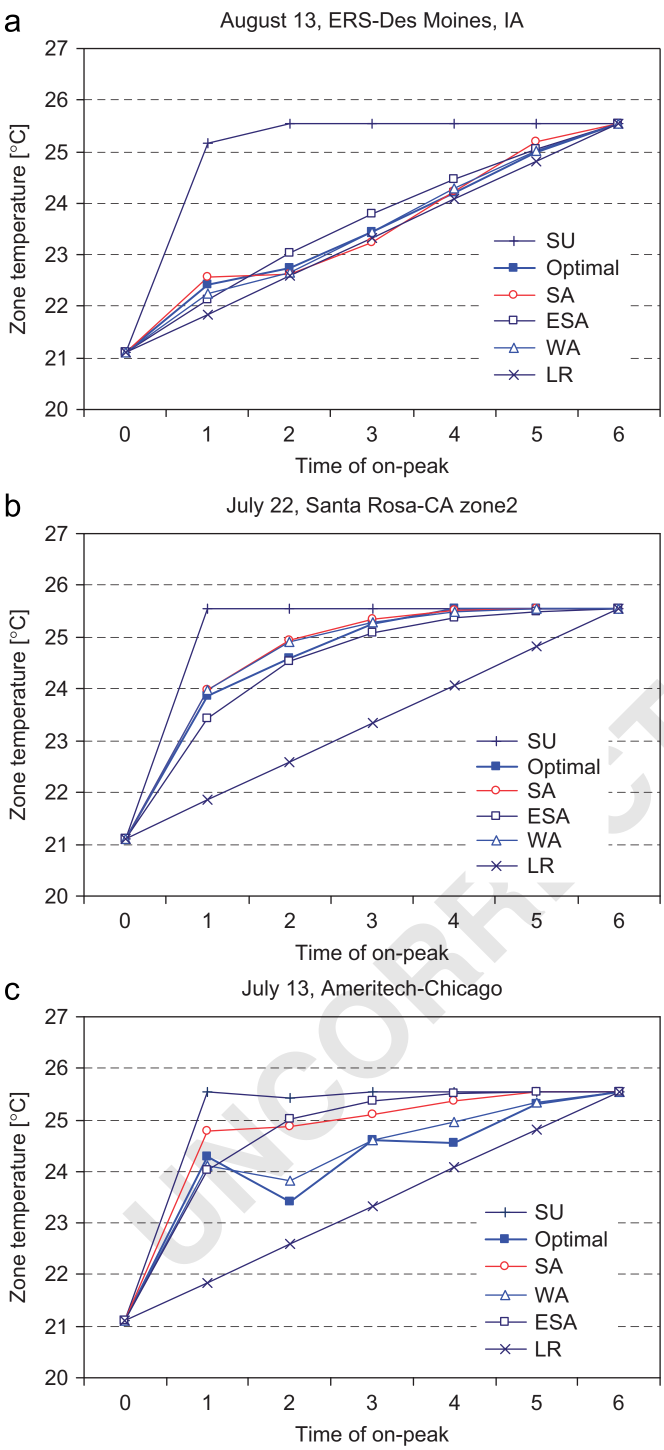

Fig. 7. Comparison of demand-limiting setpoint trajectories for basic SA, ESA, and WA methods with LR, SU, and optimal control: (a) ERS building, (b) Santa Rosa, and (c) Ameritech building.

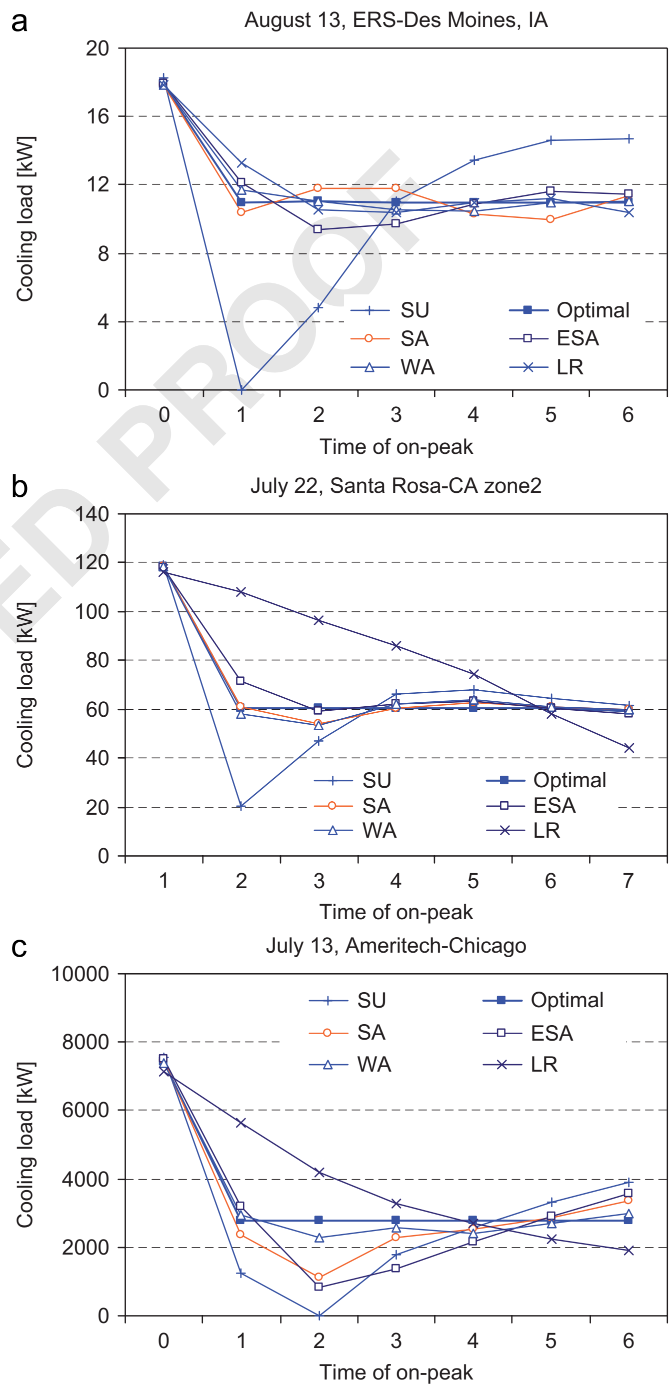

Fig. 8. Comparison of peak cooling loads for different demand-limiting methods: (a) ERS, (b) Santa Rosa, and (c) Ameritech building.

4.5. Building parameters

Training days for the three demand-limiting methods were selected based on the weather criteria described in the next section. For the SA method, training data with night-setup control were utilized. For the ESA method, training days under night-setup ('control 1') and simple step-up or other simple exponential setpoint trajectories from Eq. (13) in the companion paper [1] were employed. Tables A.1–A.3 show the bounds on basic building properties and parameters used to determine estimates and bounds for parameters within the three inverse building models associated with the optimal, SA, and ESA methods. For the ERS, since no ventilation was provided directly within the test zones and there were no occupants, upper and lower bounds for the number of people in the building were taken as very small numbers. Upper and lower bounds and estimated values for the parameters used in the SA and ESA methods are presented in Tables B.1–B.6.

4.6. Weather criterion for training days

4.6.1. Impact of different weather types for training days

Unless otherwise stated, the training data used for the simplified methods was chosen based on the outdoor temperature and sky cover criteria that are given in the first row of Table 2. However, the impact of the weather used for training was also considered by utilizing the different weather criteria defined in Table 1 for 'hot', 'warm', 'cool', or 'cold' days with 'clear (FEW)', 'partly cloudy (SCT)', 'mostly cloudy (BKN)', or 'overcast (OVC)' skys. There are a total of 16 combinations of outdoor temperatures and sky conditions from this table that were considered in the training studies. In all cases, the first days within May

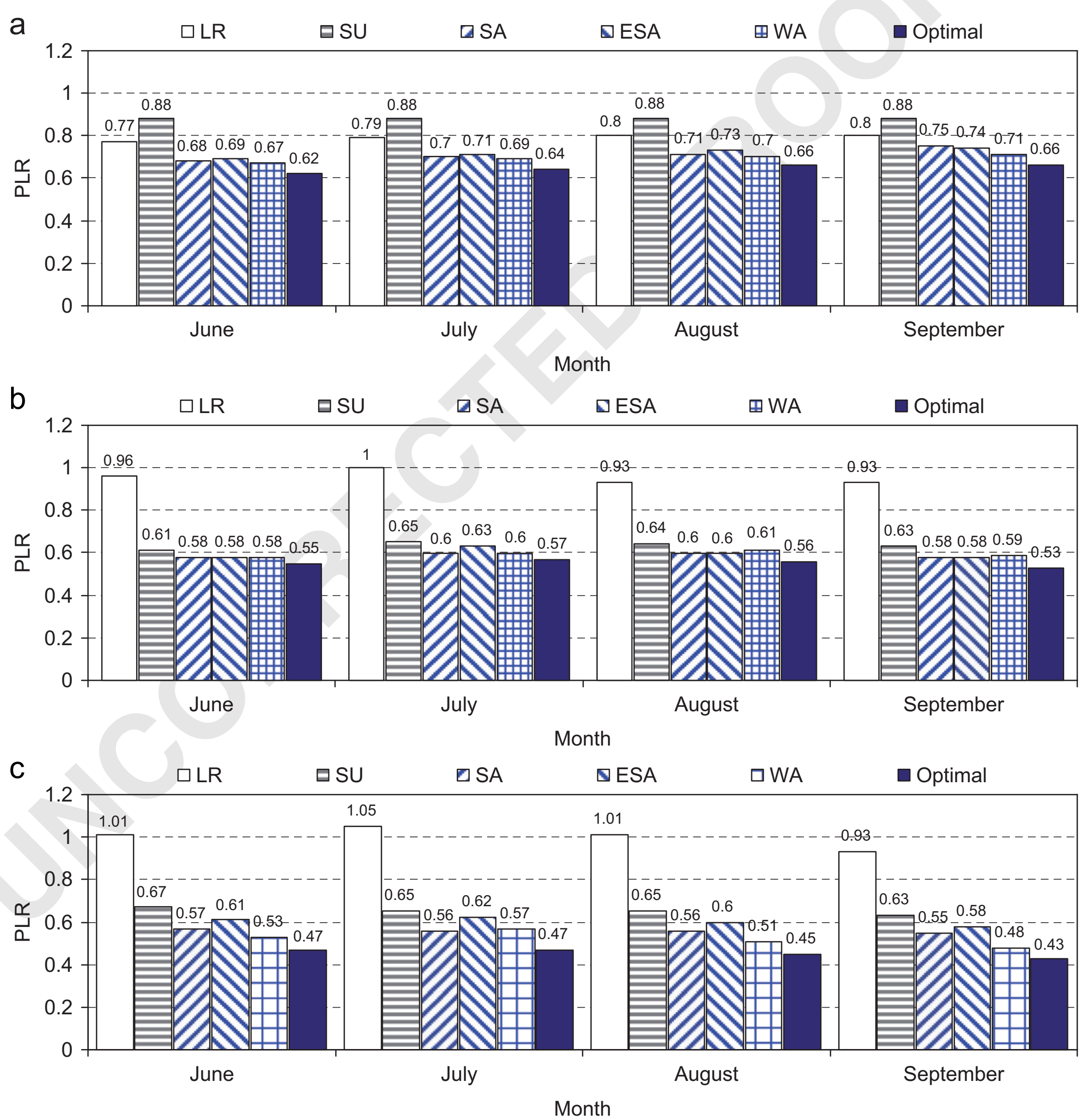

Fig. 9. Comparison of peak load ratio (PLR) of simplified demand-limiting methods (SA, ESA, and WA) with LR, SU, and optimal control for (a) ERS, (b) Santa Rosa, and (c) Ameritech buildings.

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satisfying the criteria were used for training. For the SA method, all 16 combinations were considered as individual training days and the overall performance of the method was evaluated for each case by determining the average PLR for the 5 highest peak days in each month. In some cases, there were not sufficient days in May that satisfied the criteria and these cases were excluded in the simulation.

For the ESA method, it is necessary to have at least 2 training days with similar outdoor temperatures and sky conditions. To evaluate the impact of weather conditions on training for the ESA method, four different cases were considered: (i) 2 days having 'warm' and 'scattered/partly cloudy (SCT)' conditions, (ii) 2 days with 'warm' and 'broken/mostly cloudy (BKN)' conditions, (iii) 2 days with 'cool' and 'scattered/partly cloudy (SCT)' conditions, and (iv) 2 days with 'cool' and 'broken/mostly cloudy (BKN)' conditions. The combination of 'hot' and 'clear' sky were not considered because there were no days that satisfied the condition in the weather data for the ERS and the Ameritech buildings. For each case, performance of the ESA method was evaluated in terms of average PLR for 20 peak days that come with the 5 highest peak days within each month.

The WA method requires 2 different days having similar weather conditions, i.e., similar outdoor temperatures and sky conditions. In this method, cooling loads during the demand-limiting period are normalized with an initial cooling load so as to compensate for different weather conditions. The impact of different weather types training was evaluated using the same four cases described for the ESA method.

4.6.2. Impact of training duration

Unless stated otherwise, the minimum number of required training days were utilized for each method (one for the SA method and two for the ESA and WA methods). However, more than the minimum number of required training days can be used to determine setpoint trajectories using the SA and ESA methods as long as the days have similar weather conditions during the demand-limiting period in terms of maximum outdoor temperature and average sky cover (%). In order to consider the impact of training duration on-peak load reduction, different numbers of training days were considered having hot and clear conditions for the month of May. The criteria for hot and clear conditions for the three locations are presented in Table 2.

5. Simulation results

5.1. Comparison of basic demand-limiting methods

Fig. 7 shows sample comparisons of zone setpoint trajectories for the three demand-limiting methods applied to the three different buildings. For comparison, trajectories with the simple linear-rise (LR), simple step-up (SU), and optimal control are also presented. In all three cases, the optimal trajectory is between the linear and step-up strategies. However, for the ERS building it is close to the linear-rise strategy, whereas for the Santa Rosa, it is closer to the step-up strategy. The optimal trajectory for the Ameritech is highly nonlinear and only the WA method came close to replicating this variation. The SA and ESA methods produce smoother trajectories with continuously varying time derivatives (i.e., trajectories that do not have discontinuities in derivatives of zone temperature setpoint with respect to time).

Fig. 8 shows load variations for the same days and strategies used for the results of Fig. 7. The shape of the cooling load profile is sensitive to the variation in setpoints. The optimal control provides 'flat' load profiles. Of the

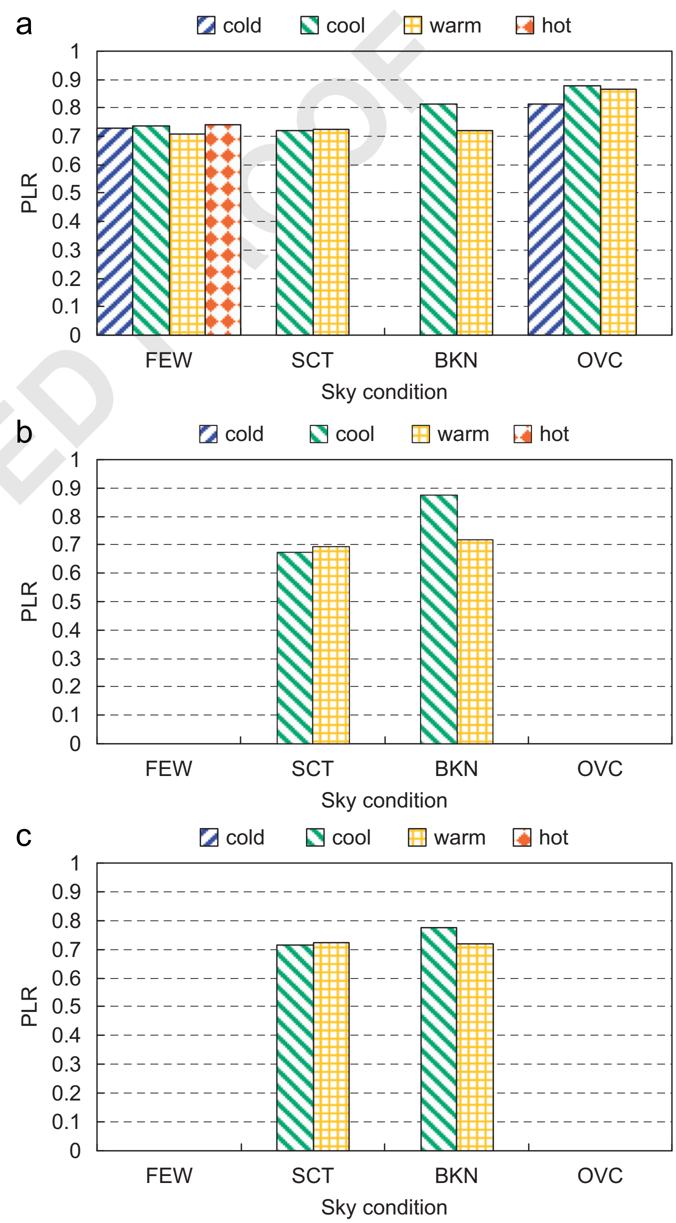

Fig. 10. Comparison of peak load ratio (PLR) for different weather types used for training with the ERS building: (a) SA, (b) ESA, and (c) WA methods.

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three simplified methods, the WA method produces load profiles that are closest to the optimal profile. In contrast, the linear and step change strategies do not produce very flat load profiles.

Fig. 9 shows average peak load reduction for the 5 days with the highest peak cooling loads for the months of June, July, August, and September. Even though the SA method gave the best performance compared to optimal control in August and September for the Santa Rosa building, the WA method provided the best performance in most cases. The WA method resulted in peak load reduction of between about 30% and 50% and achieved more than 90% of the peak load reduction associated with optimal control for all the three buildings. The ESA method, which is based on a simple exponential setpoint trajectory, resulted in the worst performance compared to the SA and WA methods for the Ameritech building. The common characteristic of the SA and WA method is that the setpoint trajectories have a more flexible form than the exponential profile of the ESA method. The simple step-up (SU) strategy shows better performance than the simple linear-rise (LR) strategy except for the ERS building. The peak reduction performance of the LR strategy is much lower than for the other strategies in most cases and even worse than NS control in some cases.

5.2. Impact of training data

Fig. 10 shows the effects of type of day(s) used for training on-peak load reduction potential of the three control strategies for the ERS building. The ERS building was chosen as an example because it had the largest variation in both sky conditions and ambient temperature and the largest impact of choice of training data on

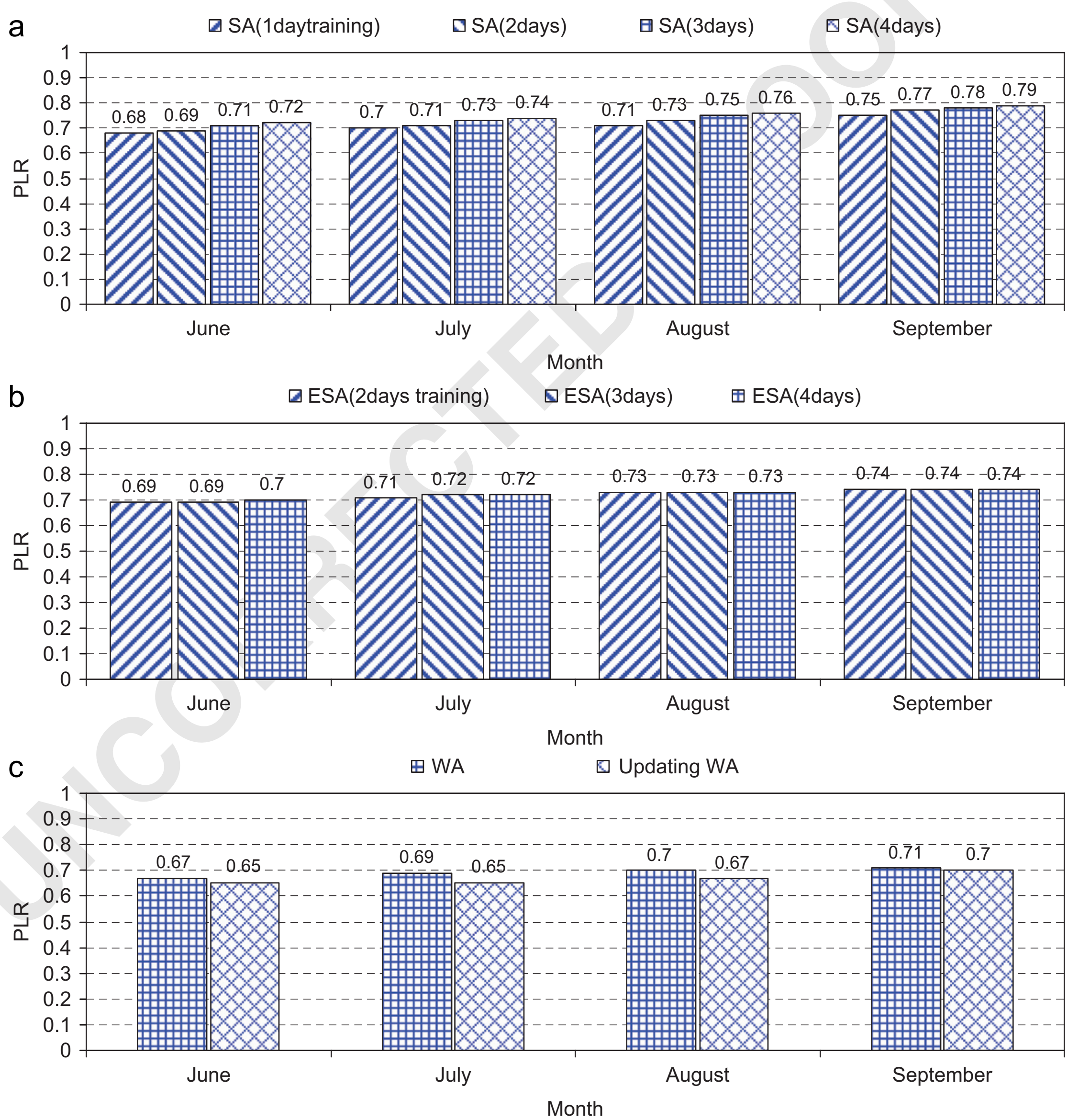

Fig. 11. Comparison of peak load reduction (PLR) for different strategies and durations of training data for the ERS building: (a) SA, (b) ESA, and (c) WA methods.

performance. The results are presented in terms average PLR for the 5 peak days from each summer month (total of 20 peak days). For all of the control methods, the minimum amount of training data was employed (1 day for the SA and 2 days for the ESA and WA methods).

In general, the performance of the methods was not affected significantly by outdoor temperature conditions for training but was influenced by sky conditions. For the ERS building, the use of training data for 'cool' or 'cold' ambient temperatures and broken (BKN) or overcast (OVC) sky conditions resulted in lower peak load reduction performance. The performance of the basic WA method is more sensitive to sky conditions than the other methods. It is recommended that training days be selected so as to not have sky conditions with cloud cover greater than 50%. When sky cloud cover is higher than 50%, the time variation of solar radiation can be quite different for 2 training days having the same average daily cloud cover. This training strategy was found to work well for all three buildings and strategies.

Fig. 11 shows the effects of duration of training data on the peak load reduction potential of the three different control strategies for the ERS building. The weather data for training were selected using the criteria in Table 2 from the beginning of May. In general, the training duration does not improve the peak load reduction for the SA and ESA methods. In fact, the SA method performance degraded with additional training data for the ERS building. Setpoint trajectories determined with the SA and ESA methods did not change significantly with increased training duration. In general, 1 day of data is sufficient for training with the SA method, whereas the ESA method requires 2 days of training data.

Fig. 11 shows that daily updating of trajectories determined with the WA method did provide some slight improvement in peak load reduction. For the WA method, simple linear-rise and step-up controls are used to generate initial loads for WA that bound the optimal solution. The basic WA method involves WA of these loads and then local setpoint adjustment. The updating WA method alternates WA and 180° load phase cancellation steps as described in the companion paper [1]. A maximum allowable adjustment temperature of 0.22 °C (0.4 °F) was used for the local setpoint adjustment trajectory in the WA method. A parametric study of the adjustment temperature showed that a range from 0.11 to 0.44 °C (0.2–0.8 °F) gives reasonable performance, but values higher than 0.56 °C (1.0 °F) degraded performance significantly.

5.3. Application of WA method to building aggregates

Peak load reduction of the basic and updating WA methods was simulated for building aggregates comprised of 400 ERS buildings, 60 Santa Rosa buildings, and 1 Ameritech building. It was assumed that all the buildings are located in California climate zone 2.

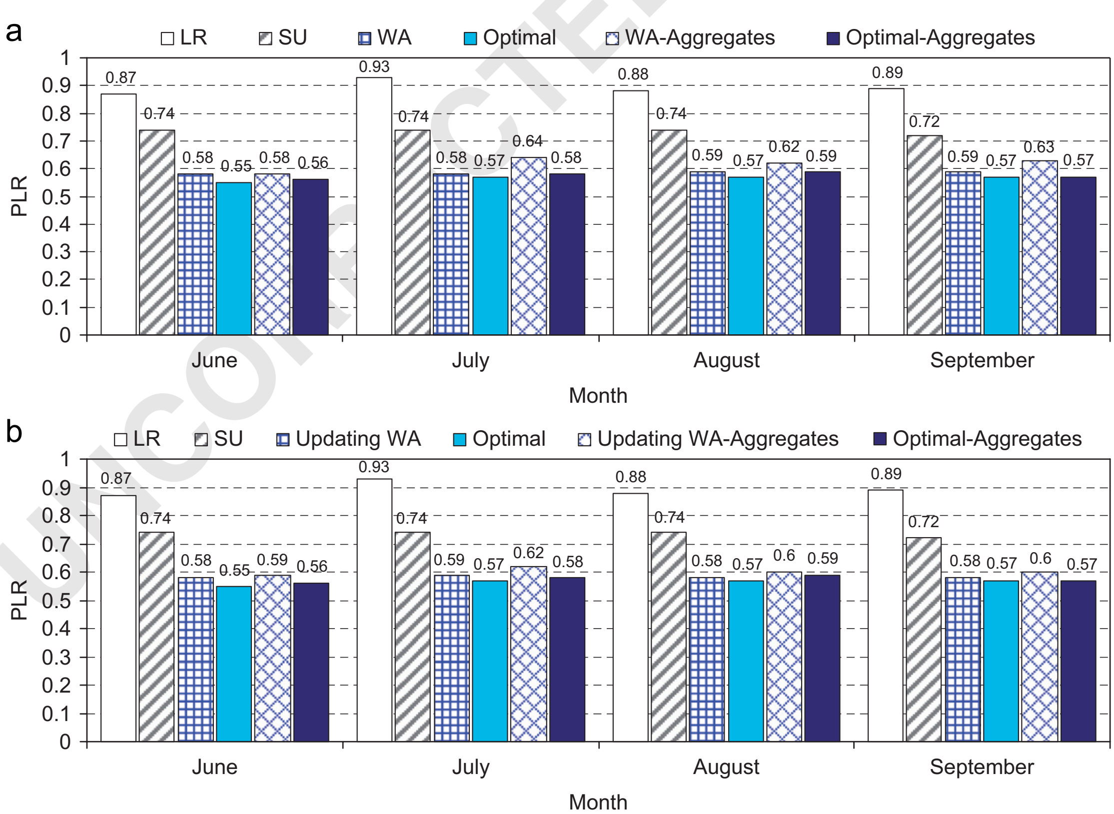

Fig. 12. Comparison of peak load ratio (PLR) of WA method for building aggregates with LR, SU, and WA for individual buildings, optimal control for individual buildings, and optimal control for building aggregates: (a) basic WA and (b) updating WA.

Fig. 12 compares average of PLR for the 5 highest peak days for each month from June to September when different controls were applied to the building aggregates. The terms 'WA' and 'Optimal' denote results determined with methods applied to individual buildings resulting in different setpoint trajectories for each type of building. 'WA-Aggregates' and 'Optimal-Aggregates' denote results determined with methods applied to aggregated building loads resulting in a single demand-limiting setpoint trajectory for all building types. It is observed that peak load reduction was slightly better when the optimal control was applied to individual buildings than the control determined for aggregated buildings with a single optimal setpoint trajectory. Similar results were obtained for the basic and updating WA methods. When a single optimal setpoint trajectory is determined for the building aggregates, then the peak cooling load of each individual building is not minimized but rather the peak aggregated cooling load is minimized. The dimensionality of the optimization problem is reduced by going from individual building optimization with multiple setpoint trajectories to aggregate building optimization with a single setpoint trajectory. In general, this loss of degrees of freedom should lead to lower peak load reduction. However, the decrease in peak load reduction due to an aggregated solution was relatively small for the case studies considered here. In general, WA methods applied for individual buildings produced similar performance as for optimal control applied to building aggregates. The basic WA method for building aggregates achieved 86% or higher of the peak load reduction for the basic WA method applied to individual buildings. The updating WA method for building aggregates provided slightly better performance than the basic WA method applied to building aggregates.

Fig. 13 shows setpoint trajectories and associated cooling loads for the highest peak day with the different control methods. The optimal setpoint trajectory in the figure is the single optimal trajectory for the building aggregates. The two trajectories for the WA methods show good agreement with the optimal setpoint trajectory resulting in a nearly flat shape for cooling loads during the demand-limiting period.

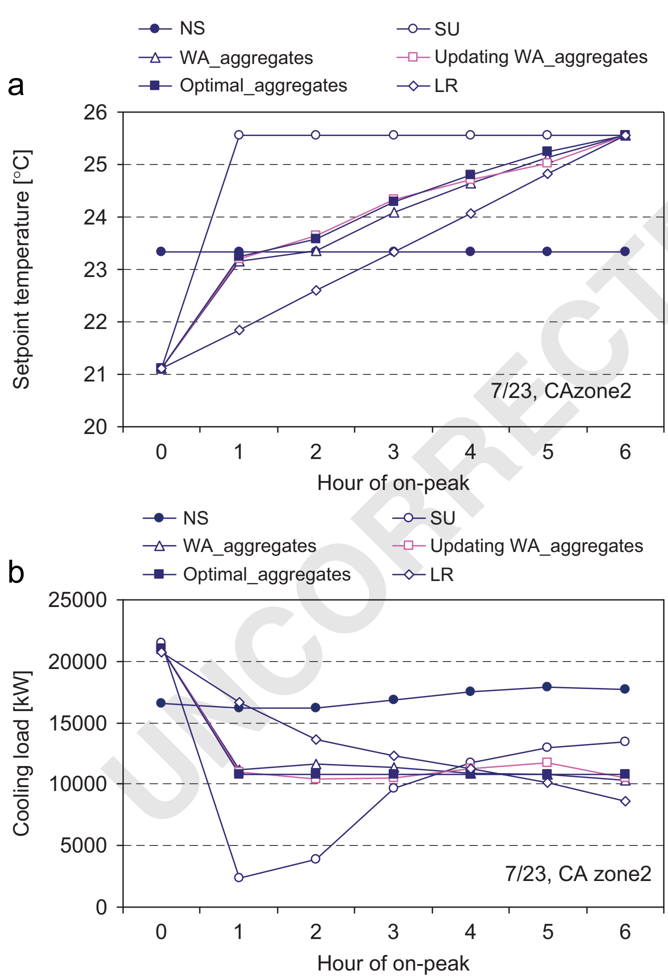

Fig. 13. Comparison of setpoint trajectories and associated cooling loads of WA methods for building aggregates with NS, LR, SU, and optimal control for building aggregates: (a) setpoint trajectories and (b) cooling loads.

6. Conclusions

The SA, ESA, and WA methods developed in a companion paper [1] were tested through simulation for buildings representative of small (ERS), medium (Santa Rosa), and large (Ameritech) commercial sites. From the results of this study, the WA method is recommended because it is the easiest to implement, has the best performance, and is directly applicable to building aggregates. For the ERS, Santa Rosa, and Ameritech buildings, the percent reduction in peak cooling load for the WA method compared to conventional control was estimated to be 33%, 42%, and 51%, respectively, when considering the average of 5 peak days from each of the summer months. These peak load reductions correspond to about 22–32 W/m^2 (2–3 W/ft^2) of peak cooling load reduction.

If it is difficult to obtain 2 days of preliminary data that bound the optimal solution as required for the WA method, then it is recommended that the SA method be employed. This method only requires data for conventional control. Once a trajectory has been determined using the SA method, then it could be updated using the procedure of setpoint adjustment in the basic WA method or updated on a daily basis with the updating WA method.

For study of demand-limiting control of aggregated building loads, more diverse building types could be considered to demonstrate the benefit of demand-limiting for aggregated buildings. In this study, only three different buildings were aggregated by adjusting the number of each building to have a similar magnitude of peak cooling load for each group. Aggregation of buildings with different load profiles but having similar size buildings should be considered for further case studies.

Appendix A

Upper and lower bounds for building parameters for ERS, Santa Rosa and Ameritech are shown in Tables A.1–A.3.

Table A.1
Upper and lower bounds of building parameters for ERS

Building parameters	Minimum	Maximum	Fixed
A_{floor}, m^2 (ft^2)	–	–	179.8 (1935.7)
N_{story}	–	–	1
ht_{story}, m (ft)	–	–	2.591 (8.5)
$r_{A,win,side}$ (dimensionless)	–	–	0.562
$r_{A,win,roof}$ (dimensionless)	–	–	0
d_{win}, m (ft)	–	–	0.03048 (0.1)
k_{win}, W/m K (Btu/h ft °F)	–	–	1.400 (0.8089)
ρ_a, kg/m^3 (lbm/ft^3)	–	–	1.191 (0.07433)
c_{pa}, J/kg K (Btu/lbm °F)	–	–	1007 (0.2404)
ρ_s or ρ_b, kg/m^3 (lbm/ft^3)	–	–	240.3 (15)
c_b, J/kg K (Btu/lbm-°F)	–	–	837.4 (0.2)
r_c (dimensionless)	0.01	0.15	–
d, m (ft)	0.03048 (0.1)	0.1524 (0.5)	–
c_g, W m^2/K (Btu ft^2/h °F)	0.09802 (2.0)	0.245 (5.0)	–
h_i, W/m^2 K (Btu/h ft^2 °F)	2.271 (0.4)	0.8 (4.543)	–
h_o, W/m^2 K (Btu/h ft^2 °F)	11.36 (2.0)	22.71 (4.0)	–
k_b, W/m^2 K (Btu/h ft °F)	0.05678 (0.01)	2.271 (0.4)	–
$V_{vent,person}$, m^3/h person (cfm/person)	22.09 (13)	30.58 (18)	–
$N_{person,floor}$, people/1000 m^2 (people/1000 ft^2)	0.0 (0.0)	3.531 (0.1)	–
$V_{in,volume}$ (l/h)	0.0	0.001	–

Table A.2
Upper and lower bounds of building parameters for Santa Rosa building

Building parameters	Minimum	Maximum	Fixed
A_{floor}, m^2 (ft^2)	–	–	179.8 (1935.7): first floor; 1330 (14311): second floor; 980.8 (10557): third floor
N_{story}	–	–	3
ht_{story}, m (ft)	–	–	3.962 (13.0)
$r_{A,win,side}$ (dimensionless)	–	–	0.4
$r_{A,win,roof}$ (dimensionless)	–	–	0
d_{win}, m (ft)	–	–	0.006096 (0.02)
k_{win}, W/m K (Btu/h ft °F)	–	–	0.900 (0.52)
ρ_a, kg/m^3 (lbm/ft^3)	–	–	1.191 (0.07433)
c_{pa}, J/kg K (Btu/lbm °F)	–	–	1007 (0.2404)
ρ_s or ρ_b, kg/m^3 (lbm/ft^3)	–	–	961.1 (60)
c_b, J/kg K (Btu/lbm °F)	–	–	837.4 (0.2)
r_c (dimensionless)	0.01	0.15	–
d, m (ft)	0.03048 (0.1)	0.1524 (0.5)	–
c_g, W m^2/K (Btu ft^2/h °F)	0.09802 (2.0)	0.245 (5.0)	–
h_i, W/m^2 K (Btu/h ft^2 °F)	2.271 (0.4)	4.543 (0.8)	–
h_o, W/m^2 K (Btu/h ft^2 °F)	11.36 (2.0)	22.71 (4.0)	–
k_b, W/m^2 K (Btu/h ft °F)	0.5678 (0.1)	4.543 (0.8)	–
$V_{vent,\ person}$, m^3/h person (cfm/person)	25.49 (15)	42.48 (25)	–
$N_{person,floor}$, people/1000 m^2 (people/1000 ft^2)	35.31 (1)	176.6 (5)	–
$V_{in,volume}$ (l/h)	0.0	0.001	–

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Table A.3
Upper and lower bounds of building parameters for Ameritech building

Building parameters	Minimum	Maximum	Fixed
A_{floor}, m^2 (ft^2)	–	–	477752 (514000)
N_{story}	–	–	4
ht_{story}, m (ft)	–	–	3.353 (11)
$r_{A,\mathrm{win,side}}$ (dimensionless)	–	–	0.45
$r_{A,\mathrm{win,roof}}$ (dimensionless)	–	–	0
d_{win}, m (ft)	–	–	0.006096 (0.02)
k_{win}, W/m K (Btu/h ft °F)	–	–	0.900 (0.52)
ρ_{a}, kg/m^3 (lbm/ft^3)	–	–	1.191 (0.07433)
c_{pa}, J/kg K (Btu/lbm °F)	–	–	1007 (0.2404)
ρ_{s} or ρ_{b}, kg/m^3 (lbm/ft^3)	–	–	1121 (70)
c_{b}, J/kg K (Btu/lbm °F)	–	–	837.4 (0.2)
r_{c} (dimensionless)	0.01	0.15	–
d, m (ft)	0.03048 (0.1)	0.1524 (0.5)	–
c_{g}, W m^2/K (Btu ft^2/h °F)	0.09802 (2.0)	0.245 (5.0)	–
h_{i}, W/m^2 K (Btu/h ft^2 °F)	2.271 (0.4)	0.8 (0.8)	–
h_{o}, W/m^2 K (Btu/h ft^2 °F)	11.36 (2.0)	22.71 (4.0)	–
k_{b}, W/m^2 K (Btu/h ft °F)	0.5678 (0.1)	4.543 (0.8)	–
$V_{\mathrm{vent,person}}$, m^3/h person (cfm/person)	25.49 (15)	42.48 (25)	–
$N_{\mathrm{person,floor}}$, people/1000 m^2 (people/1000 ft^2)	0.0 (0.0)	3.531 (0.1)	–
$V_{\mathrm{in,volume}}$ (l/h)	0.0	0.001	–

Appendix B

Bounds and estimated results for parameters in the SA and ESA methods for ERS, Santa Rosa and Ameritech are shown in Tables B.1–B.6.

Table B.1
Bounds for initial guesses, estimated results for parameters, and predicted peak demand for SA method applied to ERS building

Parameters	Lower bound	Upper bound	Estimated
C_{s}, J/K (Btu/°F)	5.870E+04 (3.091E+01)	5.694E+06 (2.998E+03)	2.876E+06 (1514.462)
R_{d}, K h/J (°F h/Btu)	1.492E−10 (2.834E−07)	2.703E−07 (5.135E−04)	1.801E−07 (3.42E−04)
R_{s}, K h/J (°F h/Btu)	4.711E−08 (9.061E−05)	1.918E−07 (3.643E−04)	9.583E−08 (1.82E−04)
R_{a}, K h/J (°F h/Btu)	1.472E−04 (2.795E−01)	1.877E−03 (3.564E+00)	4.355E−04 (0.826964)
g_m	5.000E−01	3.000E+00	1.541667
g_t (h)	1.000E−03	1.000E+00	8.42E−02
g_{s}, W (Btu h)	−3.663E+04 (−1.250E+05)	1.220E+04 (4.165E+04)	−1.609E+04 (−54884.8)
$T_{\mathrm{dm,cc}}$,°C (°F)	23.9 (75.0)	32.2 (90.0)	28.80 (83.75)
$\dot{Q}_{\mathrm{g,c}}$, W (Btu h)	4.883E+03 (1.666E+04)	7.324E+03 (2.499E+04)	5.027E+03 (17151.51)

Table B.2
Bounds for initial guesses, estimated results for parameters, and predicted peak demand for ESA method applied to ERS building

Parameters	Lower bound	Upper bound	Estimated
C_m, J/K (Btu/°F)	3.428E+6 (1.805E+03)	4.632E+07 (2.439E+04)	3.344E+07 (17605.9)
R_{o}, K h/J (°F h/Btu)	1.045E−07 (1.985E−04)	3.658E−06 (6.947E−03)	3.254E−06 (6.18E−03)
R_{i}, K h/J (°F h/Btu)	4.771E−08 (9.061E−05)	1.918E−06 (3.643E−04)	5.029E−08 (9.55E−05)
R_{a}, K h/J (°F h/Btu)	1.472E−04 (2.795E−01)	1.877E−03 (3.564E+00)	3.043E−04 (0.577928)
R_{o}, K h/J (°F h/Btu)	5.439E−07 (1.033E−03)	1.360E−06 (2.583E−03)	5.424E−07 (1.03E−03)
τ_{eff} (h)	–	–	7.01E+00
min $Q_{z,\mathrm{dl,max}}$, W (Btu/h)	–	–	9.581E−03 (32690.4)

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Table B.3
Bounds for initial guesses, estimated results for parameters, and predicted peak demand for SA method applied to Santa Rosa building

Parameters	Lower bound	Upper bound	Estimated
C_s, J/K (Btu/°F)	2.456E+06 (1.293E+03)	2.266E+08 (1.193E+05)	1.893E+08 (99668.9)
R_d, K h/J (°F h/Btu)	7.477E−12 (1.420E−08)	4.510E−09 (8.564E−06)	3.760E−09 (7.14E−06)
R_s, K h/J (°F h/Btu)	4.794E−09 (9.105E−06)	1.834E−08 (3.483E−05)	1.606E−08 (3.05E−05)
R_a, K h/J (°F h/Btu)	7.967E−08 (1.513E−04)	4.105E−07 (7.795E−04)	1.348E−07 (2.56E−04)
g_m	5.000E−01	3.000E+00	1.5025
g_t (h)	1.000E−03	1.000E+00	8.42E−02
g_s, W (Btu/h)	−4.472E+04 (−1.526E+05)	1.490E+04 (5.087E+04)	−1.956E+04 (−66724.9)
$T_{dm,cc}$, °C (°F)	23.9 (75.0)	32.2 (90.0)	28.80 (76.25)
$Q_{g,c}$, W (Btu/h)	5.349E+03 (1.825E+4)	1.070E+04 (3.651E+04)	1.155E+04 (39428.34)

Table B.4
Bounds for initial guesses, estimated results for parameters, and predicted peak demand for ESA method applied to Santa Rosa building

Parameters	Lower bound	Upper bound	Estimated
C_m, J/K (Btu/°F)	1.434E+08 (7.552E+04)	1.844E+09 (9.711E+05)	3.169E+08 (166850.5)
R_o, K h/J (°F h/Btu)	8.720E−09 (1.656E−05)	3.052E−07 (5.796E−04)	3.312E−08 (6.29E−05)
R_i, K h/J (°F h/Btu)	4.794E−09 (9.105E−06)	1.834E−08 (3.483E−05)	1.732E−08 (3.29E−05)
R_a, K h/J (°F h/Btu)	7.967E−08 (1.513E−04)	4.105E−07 (7.795E−04)	1.427E−07 (2.71E−04)
R_g, K h/J (°F h/Btu)	5.734E−08 (1.089E−04)	1.433E−07 (2.722E−04)	5.740E−08 (1.09E−04)
τ_{eff} (h)	–	–	1.07E+00
min $Q_{z,dl,max}$, W (Btu/h)	–	–	3.373E+04 (115106.3)

Table B.5
Bounds for initial guesses, estimated results for parameters, and predicted peak demand for SA method applied to Ameritech building

Parameters	Lower bound	Upper bound	Estimated
C_s, J/K (Btu/°F)	6.846E+07 (3.605E+04)	6.856E+09 (3.610E+06)	1.200E+09 (631784.6)
R_d, K h/J (°F h/Btu)	2.883E−13 (5.476E−10)	1.887E−10 (3.584E−07)	1.574E−10 (2.99E−07)
R_s, K h/J (°F h/Btu)	1.849E−10 (3.511E−07)	7.677E−10 (1.458E−06)	2.822E−10 (5.36E−07)
R_a, K h/J (°F h/Btu)	1.013E−07 (1.925E−04)	1.481E−06 (2.813E−03)	1.253E−06 (2.38E−03)
g_m	5.000E−01	3.000E+00	2.791667
g_t (h)	1.000E−03	1.000E+00	8.42E−02
g_s, W (Btu/h)	−1.444E+07 (−4.928E+07)	4.815E+06 (1.643E+07)	−6.448E+06 (−2.2E+07)
$T_{dm,cc}$, °C (°F)	23.9 (75.0)	32.2 (90.0)	28.80 (76.25)
$Q_{g,c}$, W (Btu/h)	1.444E+07 (4.928E+06)	2.407E+06 (8.213E+06)	1.524E+07 (52017621.3)

Table B.6
Bounds for initial guesses, estimated results for parameters, and predicted peak demand for ESA method applied to Ameritech building

Parameters	Lower bound	Upper bound	Estimated
C_m, J/K (Btu/°F)	3.998E+09 (2.105E+06)	5.580E+10 (2.938E+07)	5.286E+10 (27834372)
R_o, K h/J (°F h/Btu)	4.784E−10 (9.086E−07)	1.674E−08 (3.180E−05)	1.527E−08 (2.90E−05)
R_i, K h/J (°F h/Btu)	1.849E−10 (3.511E−07)	7.677E−10 (1.458E−06)	1.848E−10 (3.51E−07)
R_a, K h/J (°F h/Btu)	1.013E−07 (1.925E−04)	1.481E−06 (2.813E−03)	2.269E−07 (4.31E−04)
R_o, K h/J (°F h/Btu)	2.049E−09 (3.891E−06)	5.122E−09 (9.728E−06)	4.844E−09 (9.20E−06)
τ_{eff} (h)	–	–	9.50E−01
min $Q_{z,dl,max}$, W (Btu/h)	–	–	2.094E+06 (7144342.2)

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