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A Proactive-adaptive Monthly Peak Demand Limiting Strategy for Buildings with Small-scale Thermal Storages Considering Load Uncertainty

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Abstract

Peak demand limiting is an efficient means to reduce the monthly electricity cost in a billing period (typically a month) in cases where peak demand charge is applied. This paper presents an online proactive-adaptive peak demand limiting strategy for buildings with very small-scale thermal energy storages considering load uncertainty in a billing cycle. The proposed strategy involves three major functions as follows. Firstly, the probabilistic demand profiles are forecasted using a building load model. Secondly, the adaptive optimal monthly limiting threshold is identified using an optimal threshold resetting scheme based on the forecasted probabilistic demand profiles. Thirdly, a proactive-adaptive demand limiting control scheme is developed to online update the limiting threshold and conduct online limiting control before using up the storage capacity. Real-time tests are conducted, and the results show that this strategy can effectively reduce the monthly peak demand cost for buildings with small-scale thermal storages under load uncertainty.

Keywords: building demand management, peak demand limiting, optimal threshold resetting, load uncertainty, proactive-adaptive control

Nomenclature

ToU	Time-of-use
PCM	Phase change material
TES	Thermal energy storage
BTM	Building thermal mass
P	Probability of an event
D_{EXP}	Expected hourly load forecast (kVA)
D	Hourly probabilistic demand forecast (kVA)
D_i	A particular value of the hourly probabilistic load forecast (kVA)
D_{act}	Actual hourly power use (kVA)
H	Last hour of the demand limiting period
t	Hourly time step
ε	Moving average prediction error
h_c	Current hour
m_c	Current step
$PD_{set}^{m_c}$	Online limiting threshold at the current step (kVA)
PD_{Red}	Estimated peak demand reduction for the future remaining time of the day (kVA)
$E_{BTS}^{m_c}$	Remaining storage capacity at the current step (kWh)
$D_{act}^{k_c}$	Online measured electricity demand at the current step (kVA)
$Q_{dis}^{m_c}$	Discharge rate of the active thermal storage at the current time step (kWh)
λ	Coefficient between the discharged thermal energy and the reduced cooling energy consumption during the demand limiting period
$PD_{set,opt}$	Optimal monthly limiting threshold in the remaining days of a month (kVA)
f	A function
a	Unit price of the electricity demand (HKD/kVA)
b	Unit price of the demand limiting effort using an active thermal storage (HKD/kWh)
Cap	Demand limiting capacity of an active thermal storage (kWh)

$P_{PAD,oc}$ Occurrence probability of the hourly peak abnormal differential load

D_{norm} Hourly probabilistic normal load forecast (kVA)

D_{PAD} Hourly probabilistic peak abnormal differential load forecast (kVA)

$D_{norm,i}$ A particular value of the hourly probabilistic normal load forecast (kVA)

$D_{PAD,j}$ A particular value of the hourly probabilistic peak abnormal differential load forecast (kVA)

1. Introduction

Buildings, as the largest electricity consumer at the demand side, account for 32% of global final energy consumption [1] and even over 90% of total electricity consumption in high-density urban areas like Hong Kong [2]. The high flexibility and elasticity of commercial buildings can change power use profile under special incentives [3]. The change of power use in a building might be activated autonomously in response to Time-of-Use (ToU), dynamic electricity pricing, or high demand charge. Reducing building peak demand is beneficial to relieve the stress on capacities of power generation at the supply side and the power distribution facilities[4]. Moreover, peak demand reduction could contribute to the significant reduction of the electricity cost over a billing period for the demand side if the peak demand is a major charge factor. John E. Seem reported that the monthly peak demand cost of a commercial building contributed a considerable part to the monthly electricity bill, sometimes even exceeding 50% in the US [5], and it is typically above 30% in Hong Kong according to the field survey of the authors. Therefore, increasing attention has been attracted to developing an effective building demand limiting strategy to reduce the monthly peak demand and the monthly electricity cost.

To reduce the monthly peak demand, different demand limiting control strategies have been developed for commercial buildings [6-17]. Existing studies mainly focus on the demand shifting/limiting control of the HVAC (Heating, Ventilation and Air Conditioning) systems, as a major part of the energy consumption in commercial buildings is used by the HVAC systems [6]. Moreover, thermal storages can be integrated or used together with the HVAC systems to further reduce fluctuations of daily demand profiles and achieve more peak demand reduction. Four different types of thermal storages have been widely used in the existing demand limiting control strategies concerning the HVAC systems, including phase change material (PCM) [7, 8], thermal energy storage (TES) [9-12], building thermal mass (BTM) [13-15] and the combination of TES and BTM [16, 17]. However, most of these studies only focus on demand limiting control in a short period, e.g., one day rather than an entire billing period. These studies might not achieve the maximum cost saving due to the partial/complete offset between the monthly peak demand cost reduction and the total cost of the associated limiting efforts over the billing period of a month.

Besides the demand limiting control strategies, load prediction is another critical issue in the development and application of demand limiting control strategies. In practice, load uncertainty is inevitable, and it significantly influences the economic performance of implementing demand limiting [18]. Load uncertainty significantly affects the identification of the proper/optimal demand limiting threshold and the actual achievement of monthly peak demand cost reduction. To achieve an effective demand limiting and maximize the actual cost saving over a month, the load uncertainty needs to be considered sufficiently and properly. However, few existing studies consider the load uncertainty for peak demand limiting over a month. One recent study considers the load uncertainty for monthly peak building demand limiting control in individual buildings, and results show that demand limiting using the developed strategy can successfully achieve considerable peak demand reductions in different seasons [19]. Sensitivity analysis results in this study also illustrate that adopting a rather small storage capacity could result in a high risk of failure in demand limiting. But this study has not explored the reset of monthly peak demand limiting threshold by using latest estimates of the potential risks in the future proactively. It also has not considered the actual approach to realize peak demand limiting, particularly by adopting small-scale active storages in buildings, which is an operationally convenient and cost-effective means.

In actual building demand limiting, small-scale storages are usually preferred due to the low initial investment cost and space cost. However, in practical real-time demand limiting control applications, small-scale storages could lead to the shortage of backup energy supply for peak demand limiting when the actual peak demands are much larger than the predicted peak demands. In the situation of very limited storage capacity, proactive-adaptive control is needed for peak demand limiting before using up the storage capacity, which can reset the limiting threshold online and proactively according to the remaining storage capacity. The literature on the building demand limiting with small storage capacity is quite limited. Recently, an active control strategy using the limited battery energy storage capacity is applied to reduce the monthly peak demand based on the deterministic short-term load forecast, in which the real-time limiting threshold is adjusted [20]. However, no existing study has considered the peak building demand limiting under the situation of demand limiting duration of a billing period (e.g., a month), load uncertainty and small-scale thermal storages simultaneously.

This research, therefore, aims to develop a proactive-adaptive monthly peak demand limiting strategy for buildings with a small-scale thermal storage considering load uncertainty. Compared with the existing demand limiting strategies for individual buildings, the main novelty and contributions of this study are listed as follows. A new proactive-adaptive monthly peak demand limiting strategy is proposed for online demand limiting control considering both small-scale thermal storage capacities and load uncertainty over a month (billing period). Moreover, a proactive-adaptive demand limiting control scheme is proposed to reset the limiting threshold online and proactively before using up the storage capacity.

In this study, a probabilistic load forecasting model is adopted to forecast the probabilistic building demand profiles. An educational building in Hong Kong is chosen for the case studies in different seasons. Real-time dynamic power load data of the building are used to validate the proposed proactive-adaptive monthly peak demand limiting strategy, while integrated with a small-scale active thermal storage. This paper presents the proactive-adaptive demand limiting control scheme, the optimal threshold resetting scheme, the probabilistic load forecasting model as well as the results of real-time tests.

2. Proactive-adaptive monthly peak demand limiting strategy

There have been many studies on the control strategies using the HVAC systems with/without thermal storages, and one of the important challenges is the identification of the optimal or practically effective and doable demand limiting threshold considering various constraints and uncertainties in a particular period, e.g., a billing period. A recent study develops an optimal threshold resetting scheme to identify the adaptive optimal limiting threshold under load uncertainty over a month [19]. But this study has not explored the proactive-adaptive demand limiting control, particularly when only a small-scale storage is available. Therefore, this study focuses on online proactive-active monthly peak demand limiting control for buildings with small-scale active thermal storages considering load uncertainty.

2.1 Outline of proactive-adaptive monthly peak demand limiting strategy

The basic approach of the proposed proactive-adaptive monthly peak demand limiting strategy for individual buildings is shown in Fig. 1. It includes a building load model, the optimal threshold resetting scheme and the proactive-adaptive demand limiting control scheme. The building load model is used to forecast the probabilistic demand profiles considering uncertain weather forecasts, etc. The optimal threshold resetting scheme is used to identify the optimal limiting threshold based on the forecasted probabilistic demand profiles as well as power pricing and power use. The proactive-adaptive demand limiting control scheme is conducted by controlling the active thermal storage operation based on the identified optimal limiting threshold, which is proactively reset online before using up the storage capacity. The proactive-adaptive monthly peak demand limiting strategy works in an adaptive manner in the billing period of a month and starts again in a new billing period. Specifically, on each day (e.g., before office hour, 9:00 AM), the probabilistic demand profiles are forecasted and used to identify the optimal limiting threshold for proactive-adaptive demand limiting control until the end of a month.

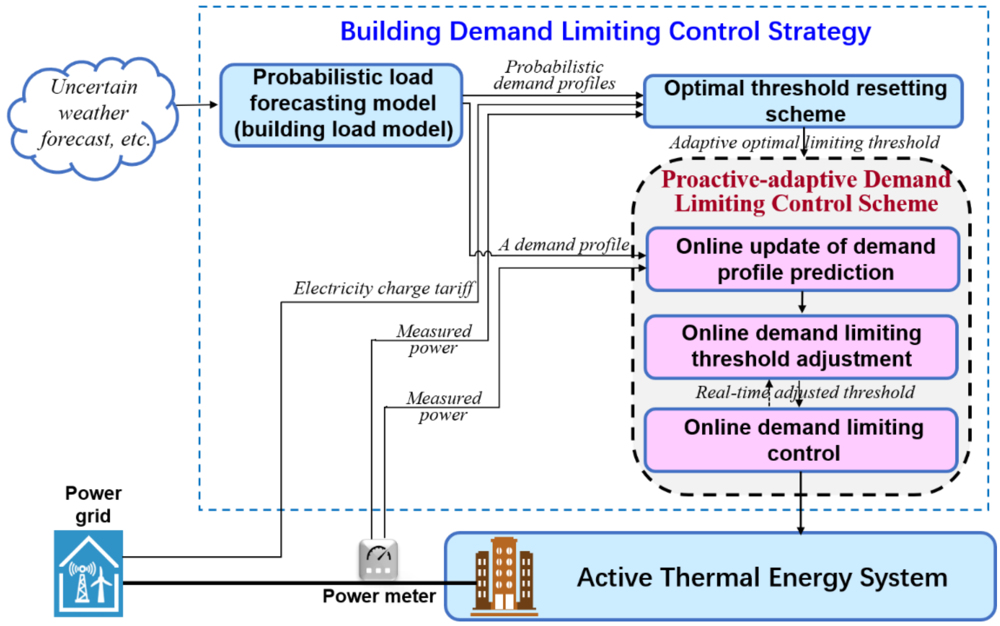

Fig. 1. Basic approach of the proposed proactive-adaptive monthly peak demand limiting strategy

In this study, a proactive-adaptive demand limiting control scheme developed to online reset the limiting threshold for online demand limiting control. This scheme includes the online update of the demand profile prediction, the online demand limiting threshold reset and the online demand limiting control. The demand limiting control scheme, the optimal threshold resetting scheme and the probabilistic load forecasting model are introduced in the following subsections. As there are many studies and methods on the use of HVAC systems and/or thermal storages for reducing building peak demands, the system and actual control are not the focus of this study. Instead, an ideal active thermal storage with ideal control is used in the validation tests of the proposed demand limiting strategy in the case studies. The energy dissipation when using the ideal active thermal storage is also neglected mainly due to the fact that the economic effect of the thermal energy losses is quite smaller compared to that of peak demand reduction.

In this paper, the term 'proactive-adaptive control' represents a control approach which continuously adapts the setpoint/threshold of an energy system control to the best alternative based on the ever-changing situation at the current moment and latest estimates of the potential risks in the future. The term 'monthly limiting threshold' represents the threshold determined for peak demand limiting control, which is updated from time to time. The term 'demand limiting effort' represents the cost paid to achieve a certain demand reduction, which might be the auxiliary energy (e.g., thermal storage) and weighted cost due to the sacrifice of service quality.

2.2. Proactive-adaptive demand limiting control scheme

The proactive-adaptive demand limiting control scheme includes three major functions: the update of demand profile prediction, the online demand limiting threshold reset and the online demand limiting control, as shown in Fig. 2. On each day (e.g., during office hours, 9:00 AM-21:00 PM), this developed scheme is conducted on the basis of the identified optimal threshold as follows. The online update of demand profile prediction updates the daily demand profile prediction at the 1-hour interval, based on the moving average prediction error (ε). The online demand limiting threshold rest updates the limiting threshold at the 1-minute interval, based on the remaining storage capacity ($E_{TS}^{m_c}$) and the updated daily demand profile prediction. The online demand limiting control is activated to discharge the active thermal storage (with the rate ($Q_{dis}^{m_c}$) when the online measured demand ($D_{act}^{m_c}$) is over the current limiting threshold ($PD_{set}^{m_c}$).

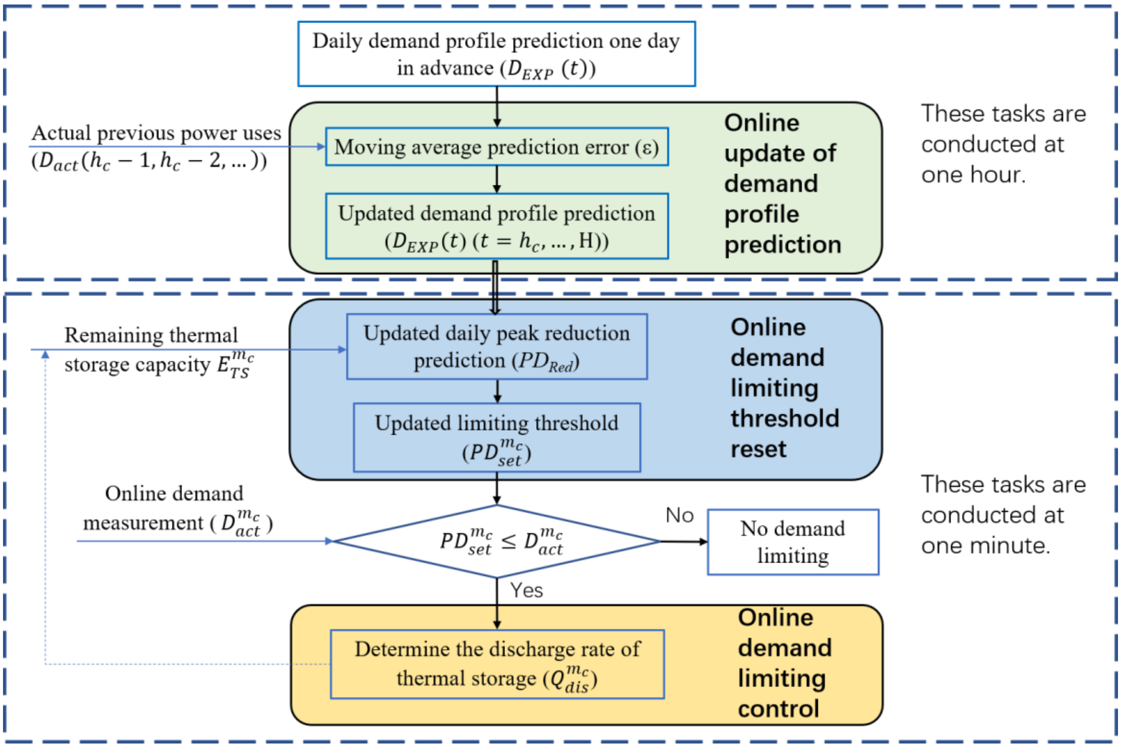

Fig. 2. Flowchart of the proactive-adaptive demand limiting control scheme

Online update of daily demand profile prediction

The probabilistic load forecasts can be obtained using a building load forecasting model [21], which is introduced in the later section. In this study, the expected hourly load/demand forecasts in a whole day are regarded to constitute the predicted deterministic daily demand profile. This is mainly because the expectation metric is a risk-neutral criterion for decision-making and is commonly-used in the decision-making area [22]. The expected hourly load forecasts in the remaining day are updated on the basis of the moving average prediction error, as given by Eq. (1). The moving average prediction error is calculated as the average difference between the actual power uses and the expected hourly demand forecasts in the previous three hours, as given by Eq. (2). This moving average difference method can reduce the short-term fluctuation response of the forecast errors.

$$D_{EXP}(t) = \sum D_i(t) * P\big(D_i(t)\big) + \varepsilon, (t = h_c, \dots, \mathrm{H}) \quad (1)$$

$$\varepsilon = \left(\sum_{t=h_c-3}^{h_c-1} D_{act}(t) - \sum_{t=h_c-3}^{h_c-1} D_{EXP}(t)\right)/3 \quad (2)$$

where, $D_{EXP}(t)$ represents the expected hourly load forecast for time (hour) t. $D_i(t)$ represents a particular value of the hourly probabilistic load forecast for time t. P is the probability of an event. ε represents the moving average prediction error for updating the daily demand profile. h_c represents the current hour. H represents the last hour of the demand limiting period. $D_{act}(t)$ is the actual hourly power use for time t.

Online demand limiting threshold reset

Based on the updated daily demand profile prediction, the demand limiting threshold is updated (or reset) online on the basis of the possible daily peak demand reduction, as given by Eq. (3). The possible daily peak demand reduction for the remaining time of a day can be estimated according to the updated daily demand profile prediction and the remaining storage capacity at the current step (i.e., minute).

$$PD_{set}^{m_c} = \max_{t\in[h_c,\mathrm{H}]}(D_{EXP}(t)) - PD_{Red} \quad (3)$$

where, $PD_{set}^{m_c}$ is the online limiting threshold at the current step, m_c, which should be no less than the peak power use up to the current step. The superscript m_c represents the current step. PD_{Red} is the estimated peak demand reduction when the remaining storage capacity equals the daily limiting effort for the remaining time of a day. $E_{TS}^{m_c}$ is the remaining storage capacity at the current step, m_c.

Online demand limiting control

Based on the current threshold updated at the 1-minute interval, the online demand limiting action is activated when the online measured demand ($D_{act}^{m_c}$) is over the online threshold ($PD_{set}^{m_c}$). In such a case, a certain amount of the thermal energy is discharged in the rate of $Q_{dis}^{m_c}$ to reduce the cooling load of the air-conditioning system (e.g., the chiller plant and the primary air unit). This discharged thermal energy is assumed proportional (assuming a constant overall COP of the air-conditioning system, λ) to the corresponding reduction in the power use of the air-conditioning system during the demand limiting period. In this study, the loss of stored energy is ignored, and the overall COP is assumed as 2.5 [23].

2.3. Optimal threshold resetting scheme

To implement peak demand limiting over a month under load uncertainty, an optimal limiting threshold is essentially needed, which should take the load uncertainty into account. In this study, an optimal threshold resetting scheme is adopted to identify and update the optimal monthly limiting threshold under load uncertainty. Interestingly, this scheme quantifies probabilities of the typical three scenarios when implementing a demand limiting control, i.e., success, failure and nonactivation, which are similar and corresponding to draw, win or loss in gambling respectively. Additionally, the identified adaptive optimal threshold using this scheme can update itself to the ever-changing weather forecast and actual peak power use up to the moment of decision making.

This scheme includes two major functions [19]. Firstly, the uncertain economic benefits (i.e., gains and losses) and probabilities of the typical scenarios of implementing demand limiting are quantified on the basis of probabilistic load forecasts. Secondly, the optimal monthly limiting threshold is identified using the expectation metric based on the quantified economic benefits and probabilities. The major steps of applying the optimal threshold resetting scheme are concluded as follows:

- Forecast probabilistic building load profiles in the remaining days of a month;
- Quantify the uncertain economic benefits and the probabilities of success, failure and nonactivation of implementing demand limiting;
- Identify the optimal monthly limiting threshold using the expectation metric based on the quantified economic benefits of implementing demand limiting.

The identified optimal limiting threshold using this scheme includes several main factors, i.e., the electricity charge tariff, the means of demand limiting (i.e., cost and capacity of the used storage) and the probabilistic load forecast, as given by Eq. (5).

$$PD_{set,opt} = f\big(a, b, Cap, D(t)\big) \tag{5}$$

where, $PD_{set,opt}$ is the optimal monthly limiting threshold for demand limiting in the remaining days of a month. f is a function. a is the unit price of the electricity demand. b is the unit price of demand limiting effort using an active thermal storage. Cap is the demand limiting capacity of an active thermal storage. $D(t)$ is the hourly probabilistic load forecast for time t.

2.4. Probabilistic load forecasting model

To apply the aforementioned optimal threshold resetting scheme, the probabilistic forecast of uncertain building load is needed. In this study, a probabilistic load forecasting model [21] for individual buildings is adopted. This model considers the weather forecasting uncertainty and uncertain peak load, which are the major factors for building electrical load uncertainties in individual buildings. Two basis load forecasts can be obtained using this model: the hourly probabilistic normal load forecast ($D_{norm}(t)$) and the hourly probabilistic peak abnormal differential load forecast ($D_{PAD}(t)$). The combination procedure of these two basis load forecasts for the hourly probabilistic load forecast ($D(t)$) is presented in [19]. The probability that the hourly probabilistic load forecast takes a particular value is estimated, as given by Eq. (6).

$$P(D_i(t)) = \begin{cases} P(D_{norm,i}(t)) \times P(D_{PAD,j}(t)) \times P_{PAD,oc}(t), & D_i(t) = D_{norm,i}(t) + D_{PAD,j}(t) \\ P(D_{norm,i}(t)) \times (1 - P_{PAD,oc}(t)), & D_i(t) = D_{norm,i}(t) \end{cases} \tag{6}$$

where, $D_{norm,i}(t)$ is a particular value of the hourly probabilistic normal load forecast for time t. $D_{PAD,j}(t)$ is a particular value of the hourly peak abnormal differential load forecast for time t. $P_{PAD,oc}(t)$ is the occurrence probability of the hourly PAD load for time t. $D_{norm}(t)$ is the hourly probabilistic normal load forecast for time t. $D_{PAD}(t)$ is the hourly peak abnormal differential load forecast for time t.

3. Case study and test results

3.1. Description of the test cases

An educational building, i.e., Phase 7, in the campus of The Hong Kong Polytechnic University (in Hong Kong within the sub-tropic climate zone), is selected in the study. It is used for various functions and research facilities including laboratories, classrooms, lecture theaters and staff offices. The gross floor area is 26,264 m^2. In Hong Kong, the peak demand of commercial buildings usually occurs during the on-peak time/office hours (i.e., from 9:00 AM to 21:00 PM, excluding Sundays and public holidays), which results in a critical issue for peak demand liming and contributes to the high monthly electricity cost. This strategy considers the peak demand of the on-peak hour only. For simplicity, datasets of the building demand and weather variables during the on-peak time are used for case studies. The daily electrical demand profile of the Phase 7 building shows daily variation and abnormal peak loads on different typical workdays, as shown in Fig. 3. Two typical months in winter and summer (i.e., December and June) respectively are selected for real-time case studies, and in each month the 9-day weather forecast data reported daily by the Hong Kong Observatory (HKO) were recorded daily.

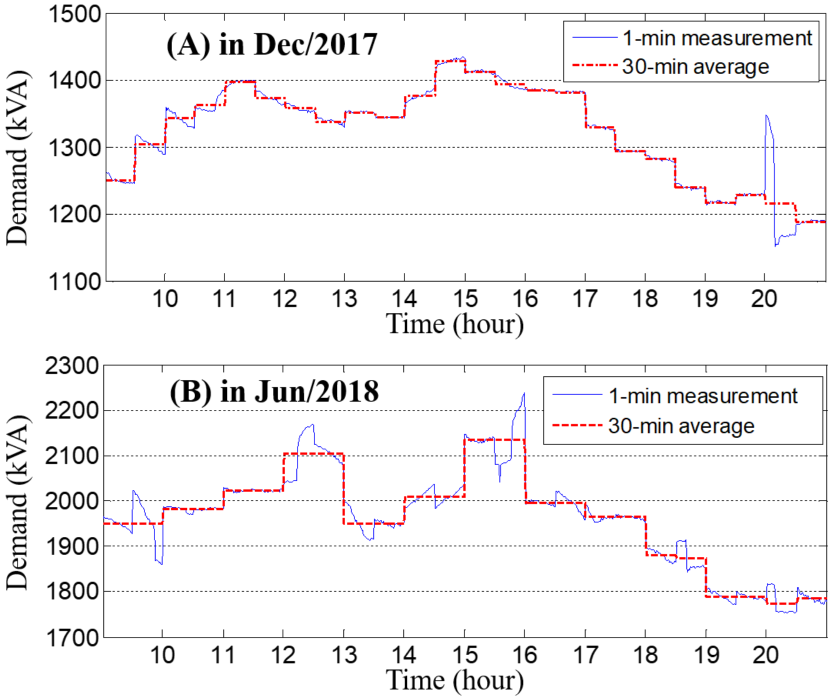

Fig. 3. 1-min and 30-min average electrical demand profiles of the Phase 7 building during office hours on typical workdays

3.2. Identification of parameters for optimal threshold resetting scheme

The sensitivity analysis of the main parameters (i.e., *a, b, Cap* in Eq. (6)) of the optimal threshold resetting scheme on the monthly demand limiting benefit has been conducted in [19]. Based on the results of sensitivity analysis, a particular set of these three parameters are selected for case studies, i.e., *a*=70 HKD/kVA, *b*=0.32 HKD/kWh, *Cap*=2250 kWh. This selection attempts to explore online optimal limiting threshold resetting when only a small-scale active storage is available, which has a high risk of failure in peak demand limiting.

With these identified parameters, the uncertain economic benefits and probabilities of success/failure/nonactivation of implementing a demand limiting control (using a particular threshold) can be quantified based on the forecasted probabilistic demand profiles, which is a major work in [19]. According to [19], if a limiting threshold was set relatively low/high, the uncertain load could result in a high failure/nonactivation risk of demand limiting control (i.e., risk of wasting the previous limiting efforts or achieving no peak demand reduction). Hence, a moderate metric for decision-making on uncertainty (i.e., the expectation metric) is selected to determine the optimal limiting threshold based on the quantified uncertain loads, which is not the main focus of this study.

3.3. Winter case study and test results

In the winter case study, the datasets during the office hours in Dec/2017 were used for the validation test. The 9-day weather forecast data reported/updated daily by the HKO in December were recorded each day. They were used to forecast/update the 9-day probabilistic demand profiles each day, which were then used to identify/update the optimal monthly limiting threshold. In the real-time demand limiting control, the proposed proactive-adaptive monthly peak demand limiting strategy is validated and compared with the baseline demand limiting strategy (i.e., the adaptive optimal monthly peak demand limiting strategy without proactive-adaptive control presented in [19]).

Validation of the developed strategy for online demand limiting in winter

Validation tests of demand limiting using both the baseline demand limiting strategy and the developed proactive-adaptive monthly peak demand limiting strategy were conducted, as shown in Fig. 4.

Fig. 4(A) shows the real-time demand profile of the building, without implementing demand limiting, measured in Dec/2017. It can be seen that the effective monthly peak billing demand (i.e., maximum 30-min average demand) occurred as 1419 kVA on the 1st workday, and some real-time higher strikes of very short time occurred on the 3rd and 9th workdays. Note, in Hong Kong, the peak demand charge is based on the maximum 30-min average demand (kVA) over a month.

Fig. 4(B) shows the power demand profile when implementing demand limiting using the baseline demand limiting strategy. During the demand limiting periods, the active thermal storage was discharged to restrict peak demands over the adaptive optimal monthly limiting threshold. It can be seen that the adaptive monthly threshold was updated twice at the end of the 2nd and 11th workdays. As the storage capacity is sufficient for demand limiting control in the winter month, no failure of demand limiting occurred.

Fig. 4(C) shows the power demand profile when implementing demand limiting using the developed proactive-adaptive monthly peak demand limiting strategy. It can be seen that the adaptive monthly threshold appeared the same as that in Fig. 4(B). This is because the storage capacity is sufficient for demand limiting control and the online threshold reset action is not activated in the whole month.

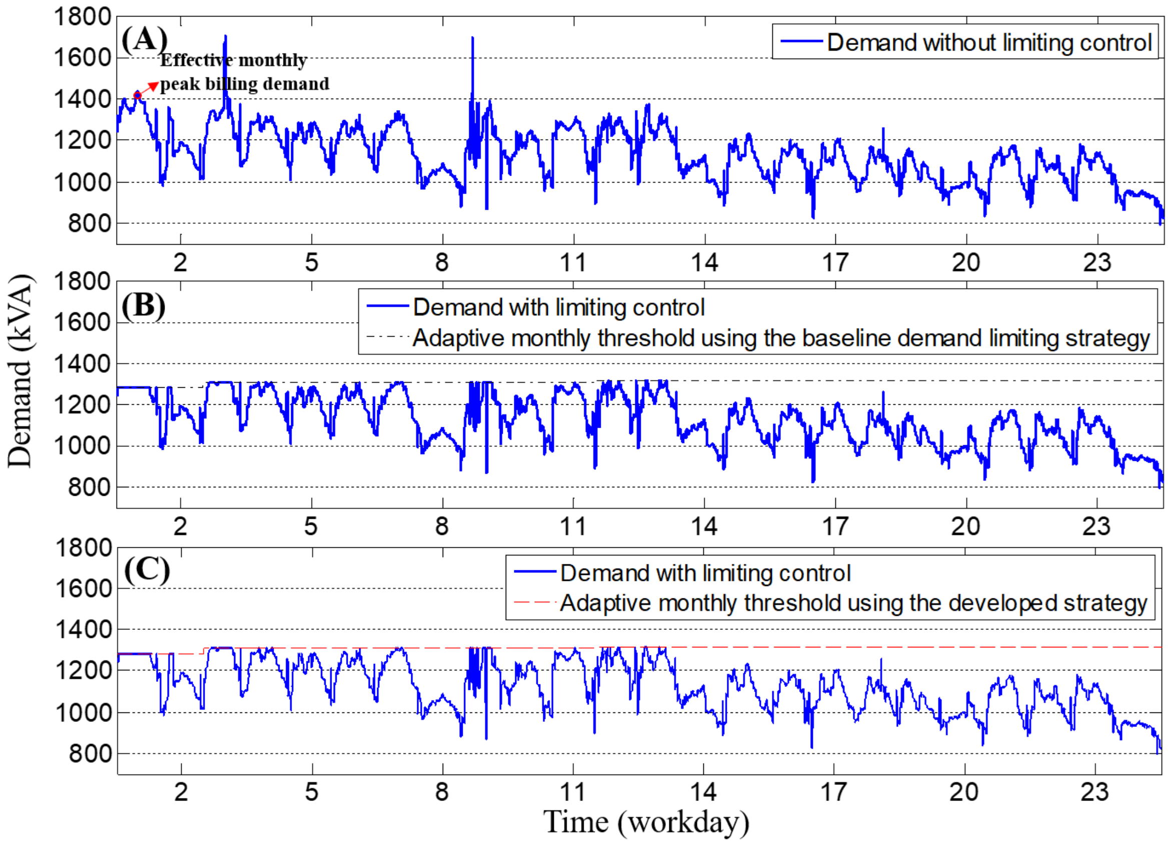

Fig. 4. Real-time building demand profiles in Dec/2017 under different situations

(A) no demand limiting; (B) demand limiting using the baseline demand limiting strategy; (C) demand limiting using the developed strategy

<u>*Comparison between cost-benefit metrics of two demand limiting strategies in winter*</u>

Table 1. Cost-benefit metrics of demand limiting using two different strategies in Dec/2017

Demand limiting strategy	Peak demand (kVA)	Peak reduction (kVA)	Percentage of peak reduction	Accumulated monthly limiting effort (kWh)	Monthly net cost saving (HKD)
No demand limiting	1419	0	0	0	0
Baseline strategy	1316	103	7.3%	3147	6203
Developed strategy	1316	103	7.3%	3147	6203

After implementing demand limiting using the above two strategies in Dec/2017, some cost-benefit metrics of the monthly peak demand limiting are listed in Table 1. It can be seen that demand limiting using both strategies can achieve the same considerable monthly peak demand reduction. The achieved monthly peak reduction was 103 kVA, 7.3% of the actual monthly peak demand (1419 kVA). That contributes to the monthly net cost saving of 6203 HKD. The equivalent peak demand limiting performance between the two strategies is due to the fact that the storage capacity adopted is also sufficient for demand limiting control using the baseline strategy in the winter month and the online threshold reset is not activated and the proposed strategy did not demonstrate its advantage.

3.4. Summer case study and test results

In the summer case study, the datasets during the office hours in Jun/2018 were used for the validation test. The 9-day weather forecast data reported/updated daily by the HKO in June were recorded each day. They were used to forecast/update the 9-day probabilistic demand profiles each day, which were then used to identify/update the optimal monthly limiting threshold. In the real-time demand limiting control, the developed proactive-adaptive monthly peak demand limiting strategy is validated and compared with the baseline demand limiting strategy as well. In addition, one specific workday is selected to illustrate how the proactive-adaptive demand limiting control scheme works before using up the storage capacity.

Validation of the developed strategy for online demand limiting in summer

Validation tests of demand limiting using both the baseline demand limiting strategy and the developed proactive-adaptive monthly peak demand limiting strategy were conducted, as shown in Fig. 5.

Fig. 5(A) shows the real-time demand profile of the building, without implementing demand limiting, measured in Jun/2018. It can be seen that the effective monthly peak billing demand occurred as 2135 kVA on the 16th workday, and some real-time higher strikes of very short time occurred on the 10th, 13th and 16th workdays.

Fig. 5(B) shows the power demand profile when implementing demand limiting using the baseline demand limiting strategy. On the first three workdays, the adaptive monthly threshold using the baseline demand limiting strategy was updated and determined according to the predicted power demand profile only, as the peak of previous power use was below the thresholds. From the 4th to 8th workday, the threshold was updated not only according to the updated power demand profile but also no less than the actual peak of previous power uses. On the 9th workday, the threshold rose suddenly and straightly at about 17:00 PM due to running out of the limiting capacity. After the 9th workday, the threshold remained flat due to the sufficient storage capacity for demand limiting control under the new limiting threshold.

Fig. 5(C) shows the power demand profile when implementing demand limiting using the developed proactive-adaptive monthly peak demand limiting strategy. It can be seen that the adaptive monthly threshold before the 9th workday appeared the same as that in Fig. 5(B). On the 9th workday, the threshold rose gradually and slightly before using up the limiting capacity. After the 9th workday, the threshold remained flat due to the sufficient storage capacity for demand limiting control.

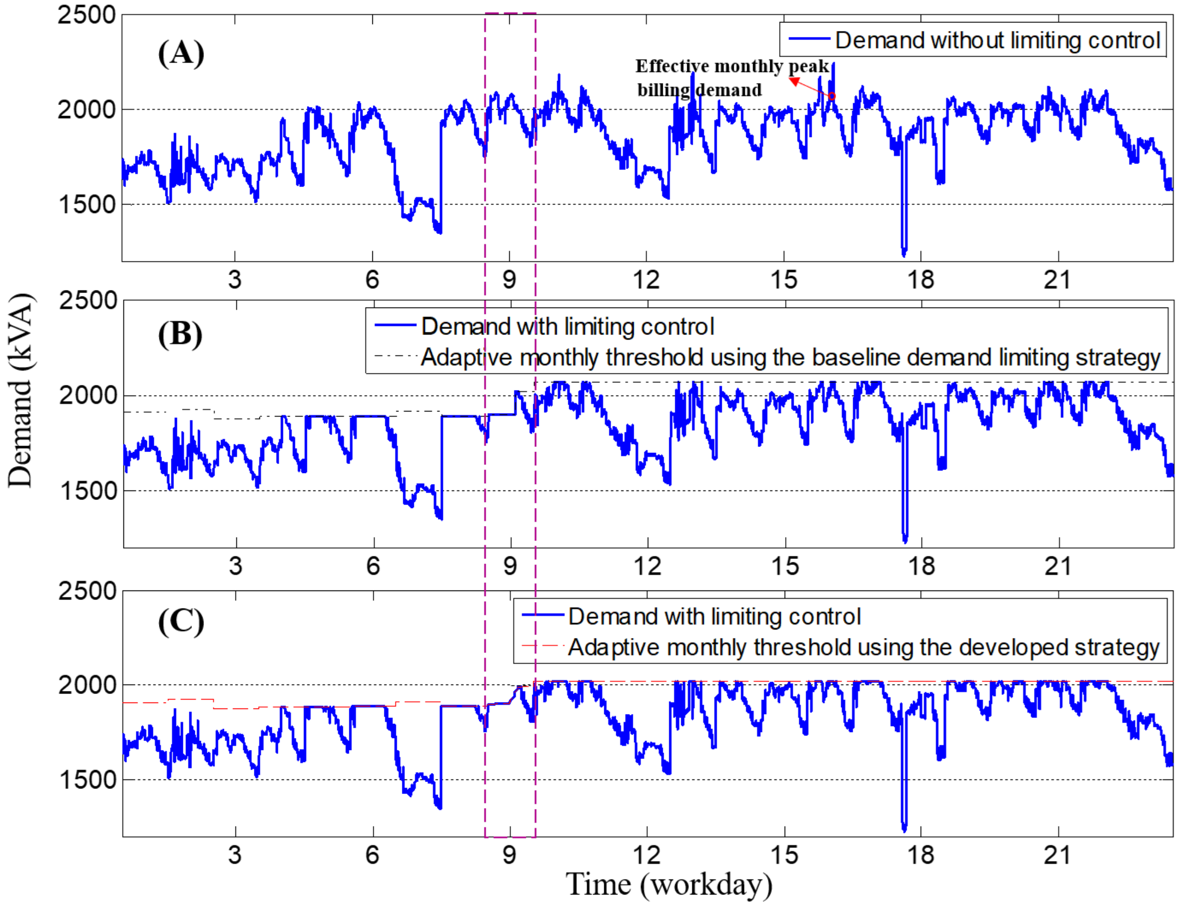

Fig. 5. Real-time building demand profiles in Jun/2018 under different situations

(A) no demand limiting; (B) demand limiting using the baseline demand limiting strategy; (C) demand limiting using the developed strategy

Comparison between cost-benefit metrics of two demand limiting strategies in summer

After implementing the above two demand limiting strategies in Jun/2018, some cost-benefit metrics of the monthly peak demand limiting are listed in Table 2. It can be seen that demand limiting using both strategies can achieve considerable monthly peak reductions. In the validation test using the baseline demand limiting strategy, the monthly peak reduction achieved was 146 kVA (6.8%). Moreover, considering the offset of the overall limiting effort cost using the thermal storage, the monthly net cost saving achieved was 4550 HKD. In the validation test using the developed strategy, the monthly peak reduction achieved was 184 kVA (8.6%). Similarly, when the offset of the overall limiting effort cost using the thermal storage is considered, the monthly net cost saving achieved was 7236 HKD. Comparing these two strategies, it can be seen that the proposed strategy achieved better performance, with 26% more peak demand reduction than that from the baseline demand limiting strategy.

Table 2. Cost-benefit metrics of demand limiting using two different strategies in Jun/2018

Demand limiting strategy	Peak demand (kVA)	Peak reduction (kVA)	Percentage of peak reduction	Monthly accumulated limiting effort (kWh)	Monthly net cost saving (HKD)
No demand limiting	2135	0	0	0	0
Baseline strategy	1989	146	6.8%	11235	4550
Developed strategy	1951	184	8.6%	17719	7236

Validation of the developed strategy for online demand limiting on a summer workday

11/Jun/2018 (i.e., the 9th workday in June) is selected to illustrate the mechanism of the developed proactive-adaptive demand limiting control scheme before using up the limiting capacity. On 11/June (before office hour, e.g., 9:00 AM), the probabilistic demand profiles during office hours in the following 9 days were forecasted in advance, as shown in Fig. 6. Different confidence intervals of the forecasted probabilistic demand profiles are shown in the figure, such as 20%, 40%, 60% and 99%.

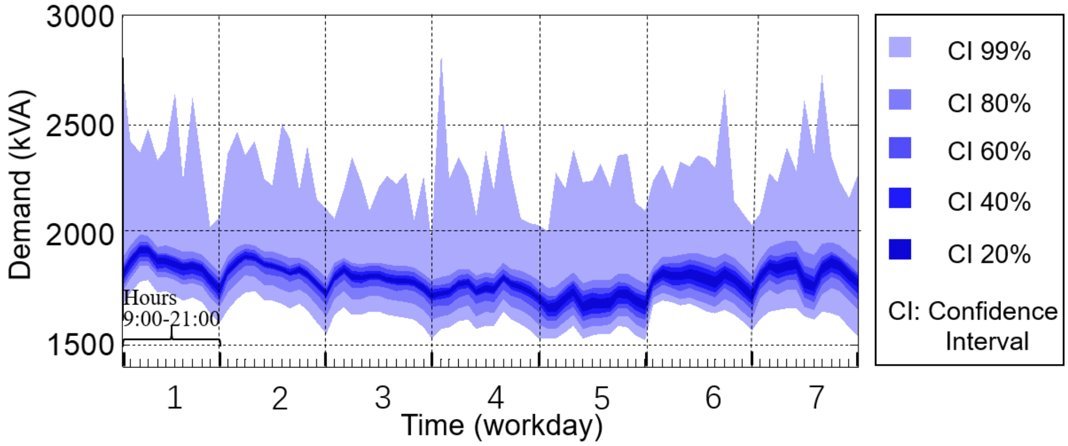

Fig. 6. Probabilistic demand profiles during office hours between 11/June and 19/June forecasted in the early morning of 11/June

Based on the forecasted demand profiles and the actual peak power use, the optimal limiting threshold was updated on the 9th workday. Then specific validation tests of demand limiting using both the developed strategy and the baseline demand limiting strategy were conducted based on this threshold, as shown in Fig. 7.

Fig. 7(A) shows the real-time demand profile of the building, without implementing demand limiting, measured on 11/June. It can be seen that peak demands occurred in the periods of 11:00-12:00 AM and 15:00-16:00 PM in this day.

Fig. 7(B) shows the power demand profile when implementing demand limiting using the baseline demand limiting strategy. It can be seen that most of the peak demands from 9:10 AM to 17:00 PM were reduced by discharging the active thermal storage when actual demands exceeded the adaptive monthly threshold. However, the storage capacity ran out at 17:00 PM and the threshold was immediately forced to the actual peak power use at this moment.

Fig. 7(C) shows the power demand profile when implementing demand limiting using the developed proactive-adaptive monthly peak demand limiting strategy. It can be seen that, before 16:00 PM, demand limiting control was conducted in the same way as that using the baseline demand limiting strategy. After 16:00 PM, the limiting threshold was gradually and slightly updated before using up the storage capacity at 18:00 PM.

After demand limiting using the baseline demand limiting strategy on 11/June, the daily peak reduction achieved was 86 kVA (4.1% of the daily peak demand). After demand limiting using the developed strategy on 11/June, the daily peak reduction achieved was 124 kVA (6.0% of the daily peak demand). In terms of the daily accumulated limiting effort for demand limiting on this day, the entire storage capacity (i.e., 2250 kWh) was used in both strategies. It can be seen that the developed strategy is capable of achieving more peak demand reduction than the baseline demand limiting strategy in the cases when the storage capacity is insufficient.

In this study, the entire confidence interval (from 1% to 99%) of the probabilistic demand profiles is used to identify the optimal limiting threshold for proactive-adaptive demand limiting control. Almost all levels of the risks corresponding to the entire confidence interval are considered in this study. If a smaller confidence interval was selected for limiting threshold optimization, some risks of extreme uncertain peak loads would be ignored. In such a case, a lower optimal limiting threshold could be resulted in and the failure risk of demand limiting control would increase (i.e., the risk of using up the storage capacity).

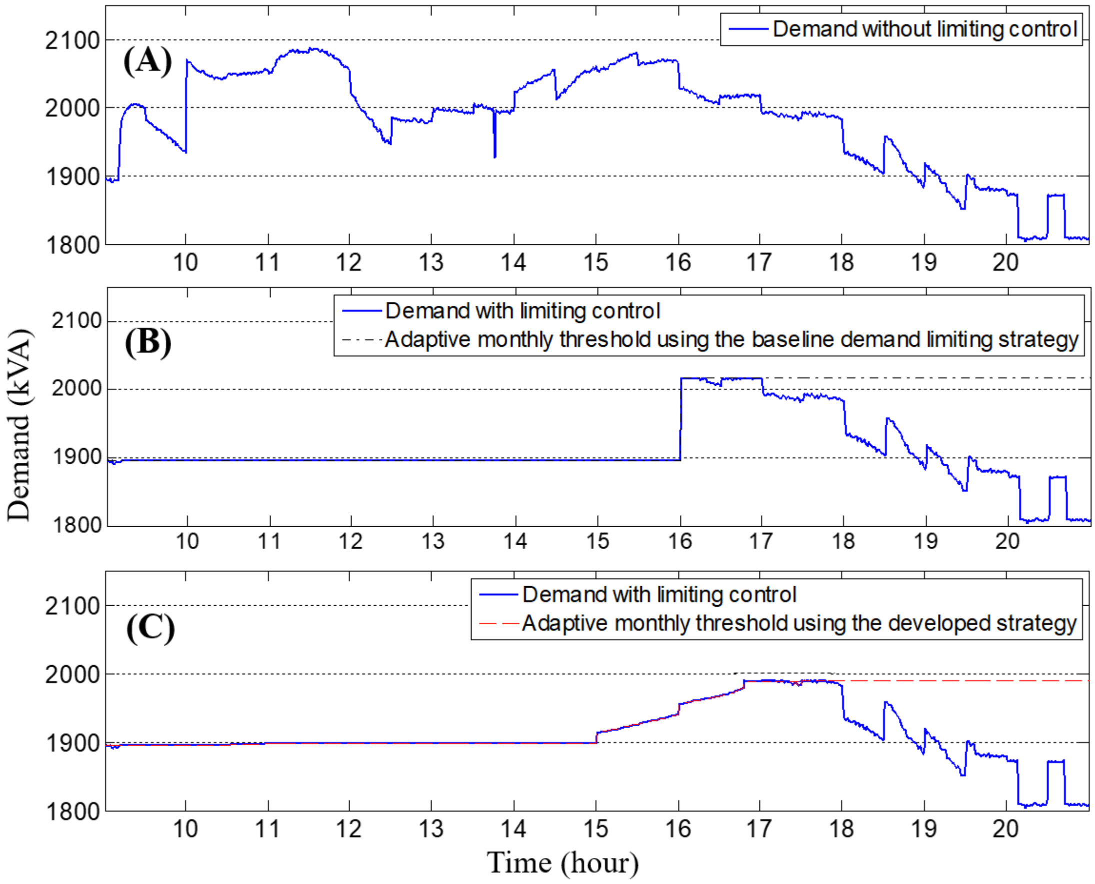

Fig. 7. Real-time building demand profiles on 11/June under different situations

(A) no demand limiting; (B) demand limiting using the baseline demand limiting strategy; (C) demand limiting using the developed strategy

4. Conclusions

This paper presents a proactive-adaptive monthly peak building demand limiting strategy for buildings with small-scale thermal storages considering load uncertainty. An online proactive-adaptive demand limiting control scheme is developed for online threshold reset and online demand limiting control. Based on the case studies and test results, the following conclusions can be made:

- The proposed strategy can effectively reduce the monthly peak demand and achieve a significant monthly peak reduction for buildings with very small active thermal storages under load uncertainty.
- The developed scheme is capable of online resetting the limiting threshold before using up the storage capacity when only a small-scale thermal storage is available.
- In a typical winter month, demand limiting using both the developed strategy and baseline demand limiting strategy can achieve a significant monthly peak demand reduction, i.e., 7.3% of the actual monthly peak demand (1419 kVA).
- In a typical summer month, demand limiting using the proposed strategy also can achieve a significant monthly peak demand reduction, i.e., 8.6% of the actual monthly peak demand (2135 kVA). Compared with the baseline demand limiting strategy, the proposed strategy shows better performance (i.e., 26% more peak demand reduction).

The proposed strategy still has some limitations, which need to be addressed in future studies. The used real-time weather forecast duration affects the effectiveness of the proposed strategy. Additionally, the proposed strategy only uses the common expectation metric in the threshold resetting scheme. The proposed strategy can be further improved when the weather forecast of longer duration is available. Moreover, different decision-making criteria might be considered in the threshold resetting scheme to fit the risk attitudes of different decision-makers.

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