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An Adaptive Optimal Monthly Peak Building Demand Limiting Strategy Considering Load Uncertainty

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Abstract: Peak demand limiting is an efficient means to reduce the electricity cost during a billing cycle in cases where peak demand charge is applied. Most previous studies focus on the daily peak demand limiting without considering load uncertainty, which is a big challenge in making proper and reliable decisions in applications. This paper presents an adaptive optimal peak building demand limiting strategy in a month considering load uncertainty. The core element and major innovation of the strategy is the optimal threshold resetting scheme, which involves two major functions as follows. The uncertain economic benefits (i.e., gains and losses) of a demand limiting control are quantified on the basis of probabilistic load forecasts. The optimal monthly limiting threshold is identified using the expectation metric based on the quantified economic benefits. The strategy optimizes and updates the monthly limiting threshold by adapting it to the ever-changing weather forecast and actual peak power use. Case studies are conducted and the results show that this strategy can effectively reduce the monthly peak demand cost under load uncertainty in different seasons. In addition, sensitivity analysis on the cost benefits of the developed strategy using different means of demand limiting and under different electricity demand charges is conducted.

Keywords: building demand management, peak demand limiting, optimal threshold resetting, uncertain load forecast, uncertainty quantification.

Nomenclature

ToU	Time-of-use
PCM	Phase change material
TES	Thermal energy storage
BTM	Building thermal mass
PAD load	Peak abnormal differential load
$PD_{set,j}$	A particular limiting threshold among a set of potential thresholds (kVA)
$PD_{set,opt}$	The optimal monthly limiting threshold for demand limiting control in the remaining days of a month (kVA)
CS_j	Cost saving of implementing demand limiting using $PD_{set,j}$ in the remaining days of a month (HKD)
G_j	Gain of implementing demand limiting using $PD_{set,j}$ in the success scenario in the remaining days of a month (HKD)
L_j	Loss of implementing demand limiting using $PD_{set,j}$ in the failure scenario in the remaining days of a month (HKD)
P_{non}	Monthly nonactivation probability of implementing demand limiting using $PD_{set,j}$ in the remaining days of a month
P_{suc}	Monthly success probability of implementing demand limiting using $PD_{set,j}$ in the remaining days of a month
P_{fail}	Monthly failure probability of implementing demand limiting using $PD_{set,j}$ in the remaining days of a month
$PD_{set,lower}$	Lower boundary of the potential threshold
$PD_{set,upper}$	Upper boundary of the potential threshold
J	Total number of potential thresholds
$D_i(t)$	A particular value of the hourly probabilistic load forecast for time t (kVA)
$D_{PAD}(t)$	Hourly probabilistic peak abnormal differential load forecast for time t (kVA)
$D_{norm}(t)$	hourly probabilistic normal load forecast for time (hour) t (kVA)
$D_{norm,i}$	A particular value of the hourly probabilistic normal load forecast (kVA)
$D_{PAD,j}$	A particular value of the hourly peak abnormal differential load forecast (kVA)
$P_{PAD,oc}(t)$	Occurrence probability of the hourly PAD load for time (hour) t
N	Number of the future remaining days of a month, including the current day

P_{non}^{d}	Daily nonactivation probability of implementing demand limiting using $PD_{set,j}$ on the dth day
PD^{d}	Daily probabilistic peak demand forecast on the dth day (kVA)
d	Future day of the month
K	Duration of the weather forecast
P_{suc}^{d}	Daily success probability of implementing demand limiting using $PD_{set,j}$ on the future dth day
x_i	A particular value of the monthly peak demand in the success scenario (kVA)
ΔE^{d}	Possible maximum daily demand limiting effort under x_i and $PD_{set,j}$ in the success scenario (kWh)
Cap	Demand limiting Capacity using an active thermal storage (kWh)
a	Unit price of the electricity demand (HKD/kVA)
b	Unit price of the demand limiting effort (HKD/kWh)
λ	Coefficient between the demand limiting effort using the ideal thermal storage and the electrical energy consumption reduction during the limiting period
$P_{suc+non}^{d}$	Probability of both success and nonactivation scenarios of implementing demand limiting using $PD_{set,j}$ on the dth day

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 resilience in commercial or non-residential buildings can change their power usage, under special incentives, due to the cooling or heating load limiting/shifting potentials [3]. The change of power usage in a building might be activated autonomously to reduce peak demands in response to the electricity tariffs such as the Time-of-Use (ToU) pricing or the critical peak pricing (CPP). Reducing building peak demand is beneficial to relieve the stress on capacities of power generation at the supply side and facilities of power distribution and therefore reduce the operating cost and net emission of the power grid or the supply side [4]. Moreover, peak demand reduction could contribute to the significant reduction of the electricity cost in a billing cycle for the demand side if the peak demand is a 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]. Hence, increasing attention has been attracted to developing effective building demand limiting strategies to reduce the monthly peak demand and the monthly electricity bill.

To reduce the monthly peak demand, different demand limiting control strategies have been developed for commercial or non-residential buildings. 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 in commercial buildings is consumed by the HVAC systems [6]. These existing studies can be classified into three categories: demand limiting with building thermal mass only, demand limiting with active storage facilities only, and demand limiting with both building thermal mass and active storages. For demand limiting using building thermal mass only, P. Xu et al. [7] employed an indoor room temperature resetting strategy in a site study to reduce the daily peak demand in a medium-weight building. This strategy involves maintaining zone temperatures at the lower comfort limit during off-peak time and resetting zone temperatures to the upper thermal comfort limit during on-peak time. To make the building zone temperature set-point more applicable, K. H. Lee et al. [8] used three different methods to estimate the set-point trajectories which affect the discharged cooling in building thermal mass for reducing the daily peak thermal load. With regard to demand limiting using active storage facilities only, G. P. Henze et al. [9] developed a predictive optimal controller for ice storage system to determine the optimal storage charging and discharging rates based on the predictive load and weather information. Results showed that significant daily electricity cost savings could be achieved under the real-time electricity tariff. A similar conclusion on the daily cost saving was drawn in the study of D. D. Massie et al. [10] in developing a neural-network based optimal controller for ice storage systems. K. H. Drees et al. [11] also proposed a rule-based control strategy, which integrates the storage-priority and chiller-priority strategies. The strategy could be easily implemented as it only requires measurements of the building cooling load, building electrical usage and the state-of-charge of the ice storage. In terms of the combined use of the building thermal mass and the active storage facilities, G. P. Henze [12] conducted site investigation on the operation cost savings and energy consumption in the combined usage of building thermal mass and active thermal storage under the ToU electricity tariff. G. Zhou et al. [13] also conducted parametric analysis to investigate the effects of building mass, utility rate, thermal comfort, central plant capabilities and economizer on the cost saving performance of demand limiting control using the building thermal mass and active thermal storage. However, most of these control strategies are used for demand limiting over a short period, e.g., one day rather than an entire billing cycle (e.g., a month). They are applicable for daily demand limiting only, while some consider the limiting efforts on a daily basis and others ignore the corresponding limiting effort (energy rise). Therefore, these studies might not achieve the maximum cost saving due to the fact that the effective peak demand used for electricity charge calculation is usually the peak over a billing period (e.g., a month) rather than the peak on a day, and some of the limiting efforts would be wasted if the limiting controls are conducted on a daily basis.

Besides the demand limiting control strategies, load prediction is another critical issue in developing a predictive optimal control strategy for demand limiting. Most previous studies utilize deterministic load prediction models. In practice, load uncertainty is inevitable due to uncertain weather conditions, special events, etc., and it significantly affects the economic performance of implementing demand limiting [14]. The 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 in a month, the load uncertainty needs to be considered sufficiently and properly. However, no existing study has considered the uncertainty of building loads in peak demand limiting in the billing cycle of a month.

This study, therefore, aims to develop an adaptive optimal monthly peak demand limiting strategy considering load uncertainty for a building or buildings associated with a charging account. Compared with existing demand limiting strategies, the main novelty and contributions of the adaptive optimal monthly peak demand limiting strategy developed in this study are listed as follows.

- A new peak building demand limiting strategy is developed for demand limiting control considering load uncertainty over the effective demand limiting duration or billing cycle, which is capable of conducting adaptive peak demand limiting to achieve the near-maximum electricity cost saving practically in a billing cycle;
- A novel optimal threshold resetting scheme is developed to identify and update the optimal demand limiting threshold under load uncertainty in short/medium period, i.e., one day to a month;
- Uncertain economic benefits and probability of success of implementing demand limiting due to load uncertainty are quantified in a billing cycle.

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 case studies in different seasons. Real-time case studies are conducted to validate the developed demand limiting strategy. This paper presents the monthly demand limiting threshold optimization, the probabilistic load forecasting model, the quantification of economic benefit and probability of success of a demand limiting control as well as the results of the real-time case studies.

2. Adaptive optimal 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 and challenging issues 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 cycle. Therefore, this study focuses on how to identify an optimal demand limiting threshold for an individual building considering load uncertainty in a month using an adaptive mechanism.

2.1. Why adaptive optimal limiting threshold is needed and the typical scenarios

As we all know, an uncertain gambling outcome (i.e., win, loss or draw) has to be faced when making a gambling decision. Similarly, an uncertain cost saving of demand limiting has to be encountered when selecting a threshold for the demand limiting control in a billing cycle, largely due to load uncertainty. Hence, it is necessary to obtain an optimal or practically effective and doable limiting threshold to achieve the maximum or near-maximum cost saving under load uncertainty. Moreover, as the major factors (such as weather forecasts and the actual peak power use up to the moment of decision-making) affect the optimal achievable threshold change from time to time, the optimal or proper limiting threshold needs to be adaptive to achieve the maximum or near-maximum monthly cost saving.

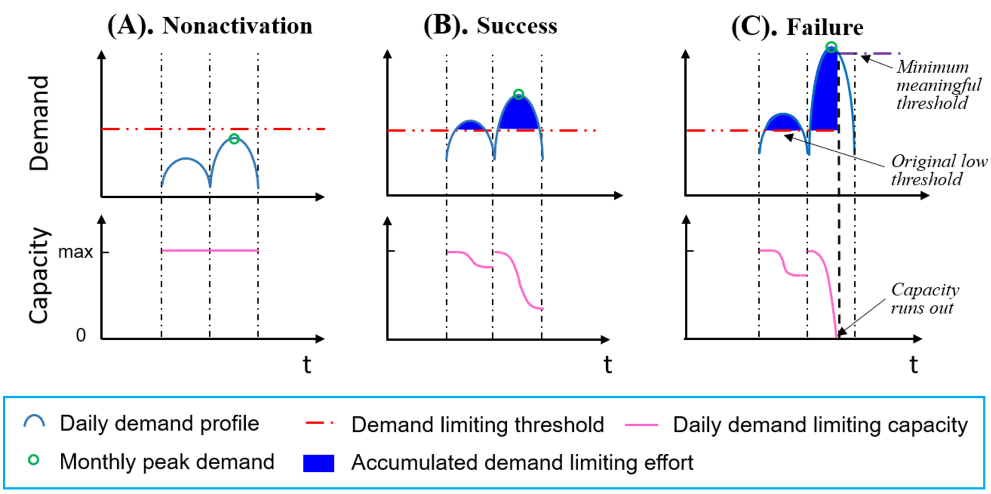

Fig. 1. Demand, available limiting capacity and accumulated limiting effort *vs.* limiting threshold in three typical scenarios when implementing monthly peak demand limiting

In this study, three typical scenarios are categorized and considered, i.e., nonactivation, success and failure, which are similar and corresponding to draw, win or loss in gambling respectively, as shown in Fig. 1. Detailed descriptions of these scenarios are given as follows.

The “*nonactivation scenario*” represents the case where a relatively high threshold is used and the peak demand limiting control is not activated in the billing cycle. In this case, the monthly peak demand remains below the limiting threshold, as shown in Fig. 1(A). It achieves no peak demand reduction and requires no demand limiting effort, which is comparable to the “*draw scenario*” in gambling.

The “s*uccess scenario*” represents the case where a moderate threshold is used and the peak demand limiting control is activated and successful. In this case, the limiting capacity is sufficient for demand limiting control in the billing cycle. The monthly peak demand is higher than the limiting threshold and the corresponding accumulated limiting effort does not exceed the limiting capacity, as shown in Fig. 1(B). It achieves peak demand reduction successfully as expected, which is comparable to the “*win scenario*” in gambling.

The “*failure scenario*” represents that case where a relatively low threshold is used and the peak demand limiting control is activated but fails. In this case, the limiting capacity is not sufficient for the need of demand limiting control in some days in the billing cycle. In these days, the monthly peak demand is much higher than the limiting threshold and the corresponding accumulated demand limiting effort exceeds the limiting capacity as shown in Fig. 1(C). It wastes all or most of the previous demand limiting efforts, which is comparable to the “*loss scenario*” in gambling. Moreover, at the moment of failure, the original low threshold is not meaningful anymore and the minimum meaningful threshold is forced to the actual peak power use up to this moment.

2.2. Outline of monthly peak demand limiting strategy and optimal threshold resetting scheme

The basic approach of the developed monthly peak demand limiting strategy for an individual building is shown in Fig. 2. It includes the building load model, the optimal threshold resetting scheme and the demand limiting control. 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 probabilistic demand profiles as well as power pricing and power use (i.e., electricity charge tariff, measured power use). The optimal monthly limiting threshold is used for demand limiting via controlling operation of building energy systems (i.e., HVAC systems and thermal storages). The monthly peak demand limiting strategy works in an adaptive manner in the billing cycle of a month and starts again in a new billing cycle.

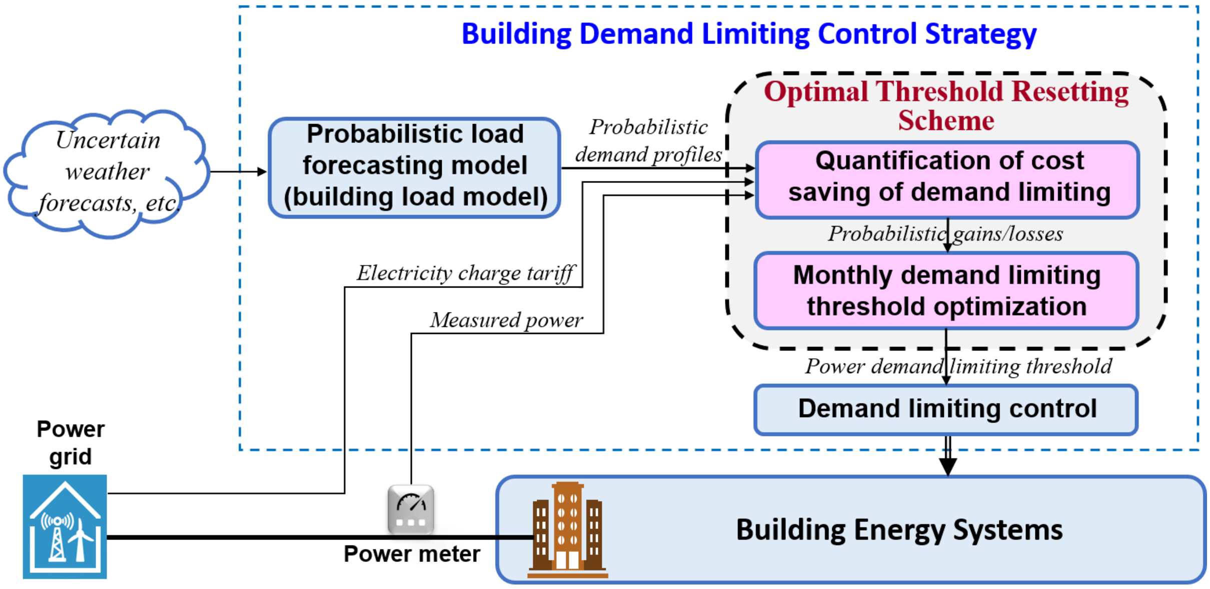

Fig. 2. Basic approach of the developed monthly peak building demand limiting strategy

In this study, an optimal threshold resetting scheme is developed to determine and continuously update the optimal limiting threshold under load uncertainty. The optimal threshold resetting scheme includes the quantification of economic benefit (cost saving) and the probability of success of a demand limiting control, and the monthly demand limiting threshold optimization. The monthly demand limiting threshold optimization and the probabilistic load forecasting model are introduced in the following subsections. The detailed quantification methods of economic benefit and the probability of success are presented in section 3. 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 monthly peak building demand limiting strategy in the case studies.

In this paper, 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 (e.g., thermal comfort). The 'resetting scheme' is a control scheme which updates the limiting threshold for the building automation system to control the building power demand.

2.3. Optimization of monthly demand limiting threshold

Load uncertainty results in uncertain cost savings when implementing demand limiting using a particular threshold in a month. To measure the uncertain monthly cost savings, the expectation metric is used, which is the most common criterion in the stochastic programming and a commonly-used criterion appealing to many decision-makers [15]. With the expectation metric, the optimal monthly limiting threshold is identified, which has the maximum expected value of the monthly cost saving among all potential thresholds, as given by Eq. (1). In addition, the expected value of monthly cost saving of implementing demand limiting using a particular threshold is estimated on the basis of the expected gain and loss in the success and failure scenarios respectively, as given by Eq. (2).

$$PD_{set,opt} = \max{}^{-1}{}_{\forall\ j\in[1,\mathrm{J}]}(\mathbb{E}[CS_j]) \tag{1}$$

$$\mathbb{E}[CS_j] = \mathbb{E}[G_j] \times P_{suc}(PD_{\mathrm{set},j}) - \mathbb{E}[L_j] \times P_{fail}(PD_{set,j}), PD_{set,low} \leqq PD_{\mathrm{set},j} \leqq PD_{set,up} \tag{2}$$

where, $PD_{set,opt}$ represents the optimal monthly limiting threshold for demand limiting control in the remaining days of a month, which should be no less than the actual peak power use up to the moment of decision-making. max^{-1} is the inverse function for computing the maximum value among a set of data. $\mathbb{E}$ is the expected value of a variable. $PD_{set,j}$ is a particular threshold among a set of potential thresholds. $PD_{set,low}$ and $PD_{set,up}$ are the lower and upper boundaries of the potential threshold respectively. In this study, these two boundaries are selected simply as the mean values of the forecasted probabilistic demand profiles at the 50% and 97.5% quantiles, respectively. CS_j represents the cost saving of implementing demand limiting using $PD_{set,j}$ in the remaining days of a month. G_j represents the gain of implementing demand limiting using $PD_{set,j}$ in the success scenario in the remaining days of a month. L_j represents the loss of implementing demand limiting using $PD_{set,j}$ in the failure scenario in the remaining days of a month. P_{suc} is the probability of success of implementing demand limiting using $PD_{set,j}$ in the remaining days of a month. P_{fail} is the probability of failure of implementing demand limiting using $PD_{set,j}$ in the remaining days of a month. J is the total number of potential thresholds. The expected gain ($\mathbb{E}[G_j]$) and expected loss ($\mathbb{E}[L_j]$) can be obtained as the weighted averages of the gains and losses (weighted using their corresponding probabilities) of all possible monthly peak demands when a particular threshold is used.

2.4. Probabilistic load forecasting model

To determine the optimal monthly limiting threshold, the probabilistic building load forecasts of are essentially needed. In this study, a probabilistic building load forecasting model is adopted to forecast the probabilistic demand profiles [16]. This model considers the weather forecasting uncertainty and uncertain peak load, which are the major factors for 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 ($D_{PAD}(t)$). They are regarded independent with each other, due to the fact that the normal load is mainly affected by outdoor weather conditions while the peak abnormal differential (PAD) load is usually the result of extreme and random events [16].

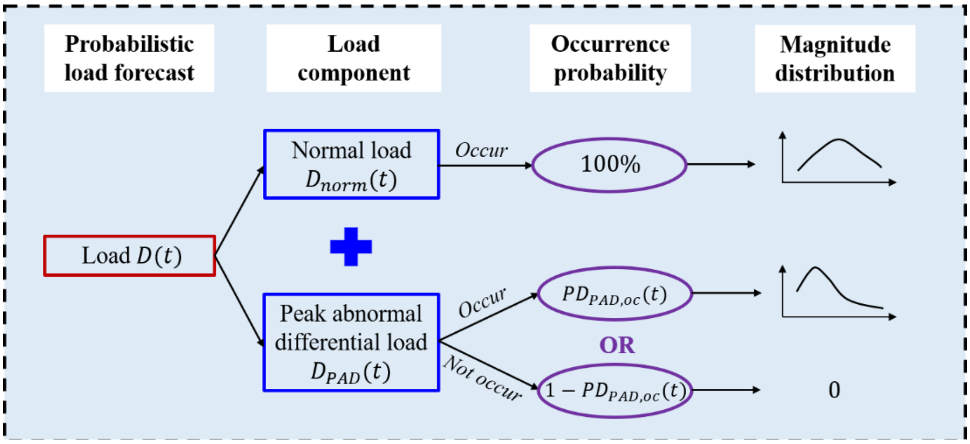

Fig. 3. Load combination schematic for the hourly probabilistic load forecast

Fig. 3 shows how to combine these two load forecasts into the hourly load forecast. It can be seen that, at each hour, the normal load occurs with a particular magnitude, while the PAD load might occur with a particular magnitude or not occur. Based on the conditional probability theory, the probability of the hourly load with a particular value ($D_i(t)$) is obtained, as given by Eq. (3). The probability of the normal load with a particular value ($D_{norm,i}(t)$) is defined as the cumulative probability of that load ($D_{norm,i}(t)$) to occur within a range of 1.0 kVA (i.e., ±0.5 kVA), as given by Eq. (4). Similarly, the probability of the PAD load with a particular value ($D_{PAD,j}(t)$) is defined as the cumulative probability of that load ($D_{PAD,j}(t)$) to occur within a range of 1.0 kVA (i.e., ±0.5 kVA), as given by Eq. (5).

$$P(D_i(t)) = \begin{cases} P(D_{norm,i}(t)) \times P(D_{PAD,j}(t)) \times P_{PAD,oc}(t), & D_i(t) = D_{norm,i}(t) + D_{PAD,j}(t) \\ P(D_{norm,i}(t)) \times (1 - P_{PAD,oc}(t)), & D_i(t) = D_{norm,i}(t) \end{cases} \quad (3)$$

$$P(D_{norm,i}(t)) = P(D_{norm,i}(t) - 0.5 \leq D_{norm}(t) \leq D_{norm,i}(t) + 0.5) \quad (4)$$

$$P(D_{PAD,j}(t)) = P(D_{PAD,j}(t) - 0.5 \leq D_{PAD}(t) \leq D_{PAD,j}(t) + 0.5) \quad (5)$$

where, $D_i(t)$ is a particular value of the hourly probabilistic load forecast for time (hour) t. $D_{norm,i}(t)$ 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. Quantification of economic benefit and probability of success of a demand limiting control

Based on the forecasted probabilistic demand profiles, the economic benefit and the probability of success of implementing a demand limiting control using a particular threshold in a month can be quantified. Moreover, the probabilities of nonactivation and failure of implementing a demand limiting control should also be quantified. This is because these two possible scenarios affect the expected monthly cost saving together with the success scenario. Specifically, the expected economic benefit and the probability of each scenario are quantified.

3.1. Nonactivation scenario

Monthly nonactivation probability

In the nonactivation scenario, all daily peak demands remain below the limiting threshold in the remaining days of a month. Therefore, the monthly nonactivation probability is regarded as the product of the daily nonactivation probability of all the remaining days, as given by Eq. (6). Here, the daily nonactivation probability represents the probability that the daily peak demand remains below the limiting threshold, as shown in Fig. 4 and given by Eq. (7). Fig. 4(A) illustrates the forecasted daily probabilistic demand profiles at different quantiles. Fig. 4(B) illustrates the probability density of the daily peak demand and the daily nonactivation probability.

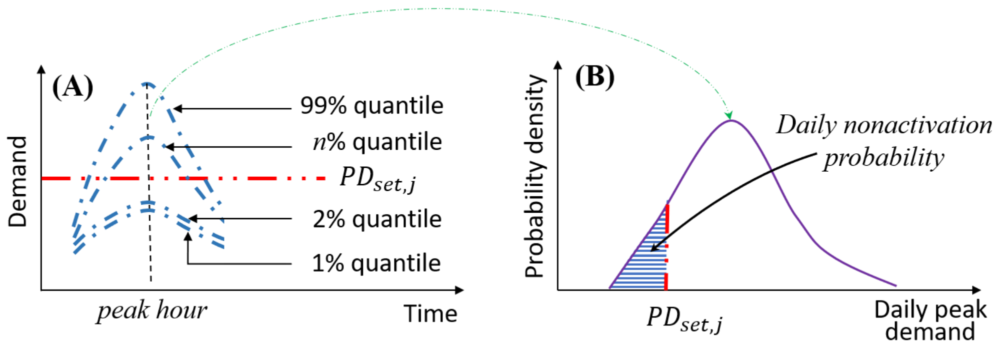

Fig. 4. Mechanism for determining the daily nonactivation probability: (A) Forecasted daily building demand profiles; (B) Probability density of the daily peak demand and daily nonactivation probability.

$$P_{non}(PD_{set,j}) = \prod_{d=1}^{N} P_{non}^{d}\left(PD_{set,j}\right) \quad (6)$$

$$P_{non}^{d}\left(PD_{set,j}\right) = P\left(PD^{d} \le PD_{set,j}\right), \quad d = 1, \dots, N \tag{7}$$

where, P_{non} is the monthly nonactivation probability of implementing demand limiting using $PD_{set,j}$ in the remaining days of a month. N is the number of the remaining days of a month, including the current day. P is the probability of an event. P_{non}^{d} is the daily nonactivation probability of implementing demand limiting using $PD_{set,j}$ on the dth day. PD^{d} is the daily probabilistic peak demand forecast on the dth day, which is regarded as the probabilistic demand/load forecast at the peak hour on the dth day. Here, the peak hour is simply taken as the hour that has the maximum expected value of the hourly probabilistic demand forecasts on one day. The superscript d represents a future day of a month. d=1 represents the current day. d=N represents the last future day of the month.

As the probabilistic demand profiles account for K days ahead due to the limitation of the K-day weather forecast duration, the identified optimal limiting threshold based on the probabilistic demand profiles is effective in the future K days (K=9 in this study for current applications in Hong Kong). Therefore, the number (N) of remaining days might be larger than the number of days for weather forecast, K. In this case, the monthly nonactivation probability in the remaining N days is assumed to equal the nonactivation probability in the future K days. The identified optimal limiting threshold based on K days ahead load forecast is preferable for demand limiting control in a month and better than the traditional threshold based on one day ahead load forecast.

3.2. Success scenario

Monthly success probability

In the success scenario, all daily demand limiting efforts needed are not over the limiting capacity. Here, a critical quantile of daily demand profile is defined as the specific quantile, at which the daily demand limiting effort needed is equal to the limiting capacity for demand limiting control using a particular limiting threshold, $PD_{set,j}$. The peak demand of this critical quantile of daily demand profile is then the upper limit of the limiting threshold for success scenario. The corresponding value of this critical quantile is therefore chosen as the daily probability of both success and nonactivation scenarios ($P_{suc+non}^{d}(PD_{set,j})$) under a limiting threshold $PD_{set,j}$. The monthly success probability can be therefore calculated on the basis of this combined probability and the daily nonactivation probability, as given by Eq.(8). Where, P_{suc} is the monthly success probability of implementing demand limiting using $PD_{set,j}$ in the remaining days of a month.

$$P_{suc}\left(PD_{set,j}\right) = \prod_{d=1}^{N} P_{suc+non}^{d}\left(PD_{set,j}\right) - \prod_{d=1}^{N} P_{non}^{d}\left(PD_{set,j}\right) \quad (8)$$

<u>*Quantification of monthly gain*</u>

In a particular success case, the monthly gain of a limiting control is determined by the difference between reduction of peak demand cost and the extra total cost of accumulated limiting efforts in a month, as given by Eq (9). The net reduction of electrical energy consumption of an entire demand limiting event is assumed as 0, considering the fact that there is usually a rebound after the demand limiting or enregy loss using TES, which offsets the reduction of energy consumption. A peak demand (x_i) is regarded as the demand of the same quantile at the peak hour in the remaining days. The corresponding accumulated limiting efforts are regarded as the sum of all the possible maximum daily limiting efforts needed. The probability of this particular monthly gain ($G_j(x_i)$) is considered having the same probability of x_i in the success scenario at that peak hour.

$$G_j(x_i) = a \times \left(x_i - PD_{set,j}\right) - b \times \sum_{d=1}^{N} \Delta E^{d}(x_i, PD_{set,j}) \quad (9)$$

where, a is the unit price of the electricity demand. b is the unit price of the demand limiting effort using the active thermal storage. x_i is a particular value of the monthly peak demand in the success scenario. ΔE^d is the possible maximum daily demand limiting effort under x_i and $PD_{set,j}$ in the success scenario, which is assumed proportional (with the coefficient λ) to the corresponding daily electrical energy consumption reduction during the demand limiting period. In this study, the loss of storage is ignored, and then λ is assumed as 2.5 since the overall COP of the air-conditioning system assumed to be 2.5 [17]. The daily electrical energy consumption can be calculated on the basis of the demand profile at a particular quantile.

When the number (N) of remaining days is larger than the number of days for weather forecast, K, the peak demand reduction in the remaining N days is assumed to equal that in the future K days. Moreover, the accumulated limiting efforts needed in the remaining *N* days are assumed to equal *N*/K times of those in the future K days.

3.3. Quantification in the failure scenario

Monthly failure probability

In the failure scenario, the monthly failure probability is complementary to the sum of the monthly nonactivation and success probabilities, as given by Eq. (10). Where, P_{fail} is the monthly failure probability of implementing demand limiting using $P_{set,j}$ in the remaining days of a month.

$$P_{fail}(PD_{set,j}) = 1 - P_{suc}(PD_{set,j}) - P_{non}(PD_{set,j}) \quad (10)$$

Quantification of monthly loss

In a failure case, a proactive control might simply force the limiting threshold to the minimum meaningful threshold after the limiting capacity runs out, as shown in Fig. 5(A). However, such proactive adjustment of the limiting threshold might not be the choice for the most effective limiting control and result in less reduction of monthly peak demand when the possible maximum daily limiting effort in the remaining days is not considered. Therefore, a perfect adjustment of the limiting threshold is assumed and adopted to guarantee the future possible maximum daily limiting effort equal to the limiting capacity, as shown in Fig. 5(B).

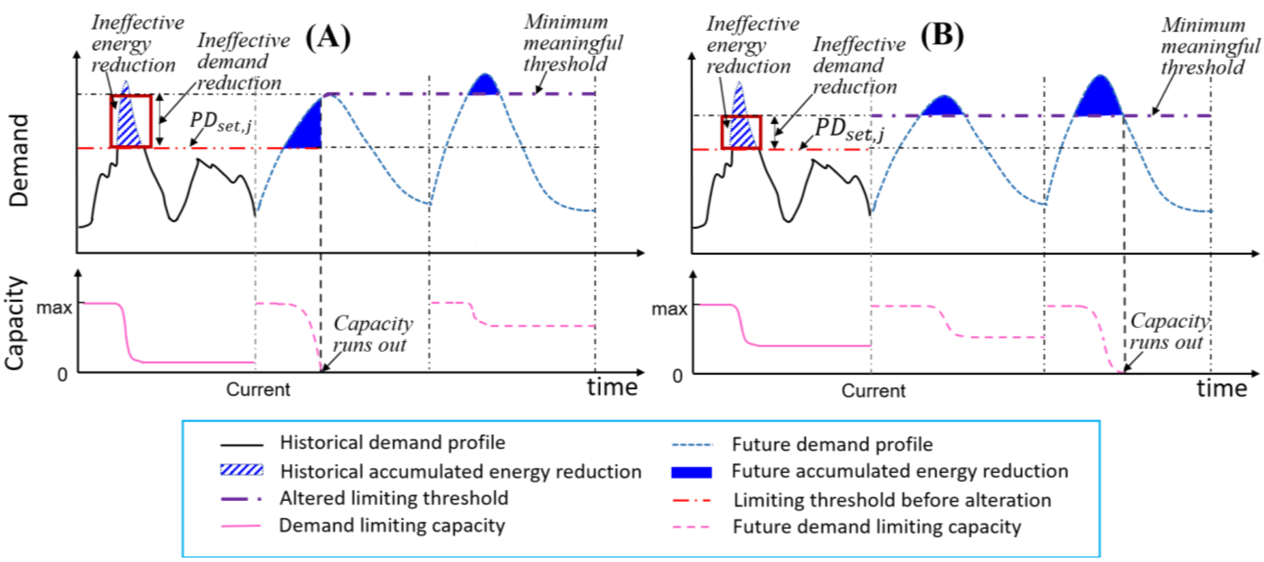

Fig. 5. Demand, available limiting capacity and accumulated limiting effort *vs.* limiting threshold in a failure case: (A) An imperfect proactive adjustment of limiting threshold; (B) A

perfect proactive adjustment of limiting threshold.

The monthly loss is equivalent to the total cost of the accumulated previous limiting efforts below the new adjusted threshold, i.e., the ineffective energy reduction multiplied by the factor λ, as shown in Fig. 5. A building model [18] is used to estimate the original hourly power use without implementing demand limiting control, based on the actual hourly power use in the condition with the implementation of the demand limiting control.

4. Case studies and test results

4.1. Description of test cases

An educational building named 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 equipped with different research facilities, laboratories, classrooms, lecture theaters and staff offices. Its gross floor area and the building surface area are 26,264 m^2 and 36,800 m^2, respectively. In Hong Kong, the peak demand of commercial/nonresidential buildings usually occurs during the on-peak time (i.e., from 9:00 AM to 21:00 PM, excluding Sundays and public holidays). Peak demand limiting is a critical issue and could contribute significantly to the monthly electricity cost saving. The datasets of the building demand and weather variables only during the on-peak time are used for case studies. Two typical months in winter and summer (i.e., December and June) 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) are recorded daily. In addition, sensitivity analysis of the cost benefits of the developed strategy using different means of demand limiting and different electricity demand tariffs is conducted, as reported in the last subsection.

4.2. Identification of parameters in quantification formulae

To quantify the optimal threshold resetting scheme, some parameters in quantification formulae are identified. The unit price of the electricity demand (i.e., *a* in Eq. (9)) is set as 120 HKD/kVA and the unit price of the electricity consumption is 0.6 HKD/kWh, according to a real tariff (Large Power Tariff) from the Hong Kong CLP power company. The unit price of the demand limiting effort using the ideal thermal storage (i.e., *b* in Eq. (9)) is calculated as 0.24 HKD/kWh, when assuming that the overall COP of the air-conditioning system is 2.5 earlier [17]. A simplified cold active storage model [19] is used to quantify the demand limiting capacity for the Phase 7 building and a rather small active storage with the limiting capacity (*Cap*) of 4763 kWh is adopted.

4.3. Winter case study and test results

In the winter case study, the datasets during the office hours in Dec/2017 are used for the validation test. The 9-day weather forecast data reported/updated daily by the HKO in December are recorded each day. They are used to forecast/update the 9-day probabilistic demand profiles each day, which are then used to identify/update the optimal monthly limiting threshold. In the following subsections, the first workday in December is selected to illustrate the identification procedure of the optimal monthly limiting threshold. Afterward, the procedure is conducted repeatedly to obtain/update the monthly limiting threshold in an adaptive manner for demand limiting control in the following days of the month.

4.3.1. Optimal monthly limiting threshold identification on the first workday of December

On the first workday of December (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 probabilistic demand profiles are shown in the figure, such as 20%, 40%, 60% and 99%. In addition, the range of the tested thresholds was identified as [1149 kVA, 1287 kVA].

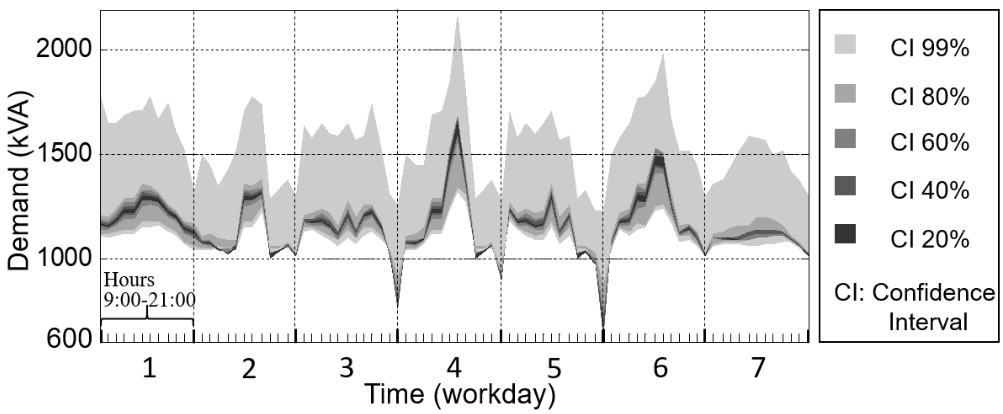

Fig. 6. Probabilistic demand profiles during office hours between 01/Dec and 09/Dec/2017

forecasted in the early morning of 01/Dec

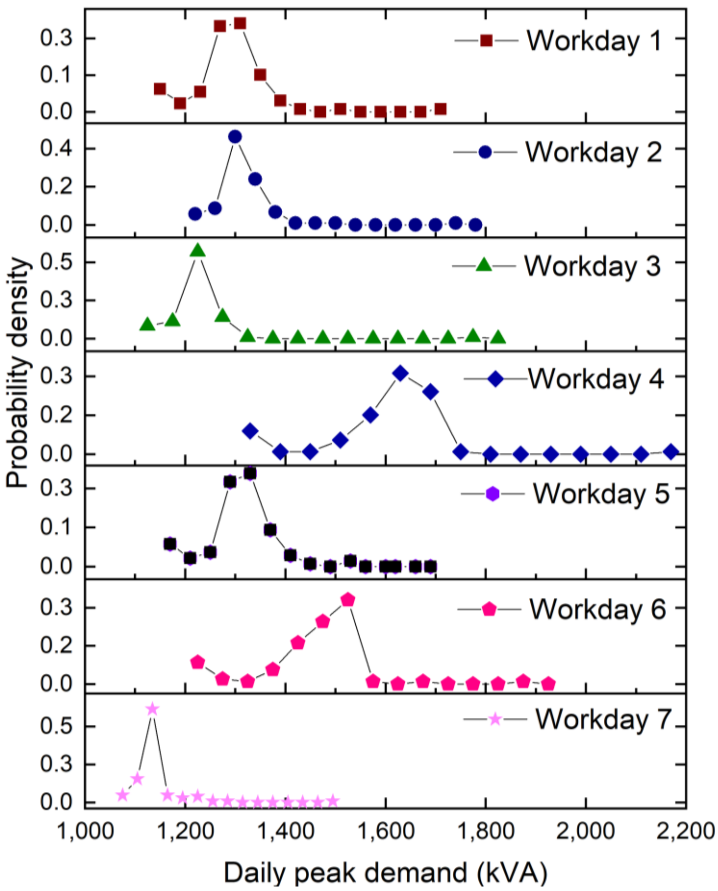

Fig. 7. Probability density of the daily peak demand in workdays between 01/Dec and 09/Dec/2017 forecasted in the early morning of 01/Dec

Based on the forecasted probabilistic demand profiles, the probability density distributions (PDFs) of the daily peak demand in workdays between 01/Dec and 09/Dec were obtained, as shown in Fig. 7. With these PDFs of the daily peak demand, the probability of each scenario (nonactivation, success and failure) was quantified when a particular threshold was used on one day. Based on these quantified daily probabilities, the monthly probability of each scenario using that threshold was estimated, as shown in Fig. 8. It can be seen that all the monthly success probabilities accounted for over 85%, all the monthly failure probabilities were less than 16%, and all the monthly nonactivation probabilities were 0%.

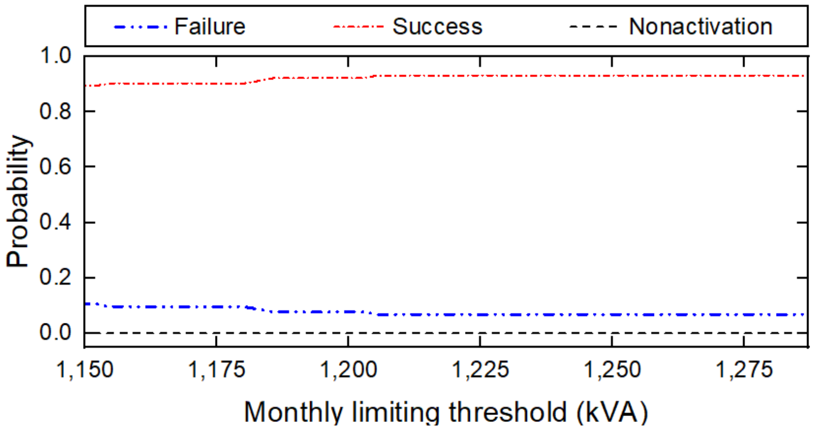

Fig. 8. Quantified monthly probabilities of three scenarios when implementing demand liming using different thresholds on the first workday of Dec/2017

Based on the quantified monthly probabilities at different thresholds, the expected monthly cost savings and the expected monthly gains were quantified, as shown in Fig. 9. It can be seen that they changed in the same trend along with the increase of the limiting threshold. After the quantification of the expected monthly cost savings among different thresholds, the optimal monthly limiting threshold was identified of 1,287 kVA, and the corresponding cost saving was 14,592 HKD.

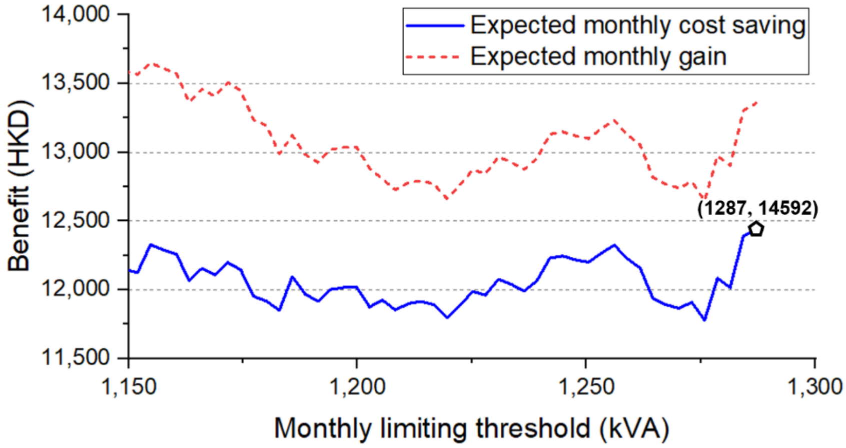

Fig. 9. Expected monthly cost savings and expected monthly gains when implementing demand limiting using different thresholds on the first workday of Dec/2017

4.3.2. Validation of the developed strategy for monthly peak demand limiting in December

Similarly, on each of the following workdays, the identification procedure using the optimal threshold resetting scheme is conducted repeatedly to obtain and update the optimal limiting threshold. In addition, the ideal demand limiting control is conducted on the basis of the identified adaptive optimal limiting threshold. The difference lies in that the actual peak power use was considered in updating the optimal limiting threshold. Fig. 10 shows the validation results of demand limiting using the adaptive optimal monthly peak demand limiting strategy in Dec/2017.

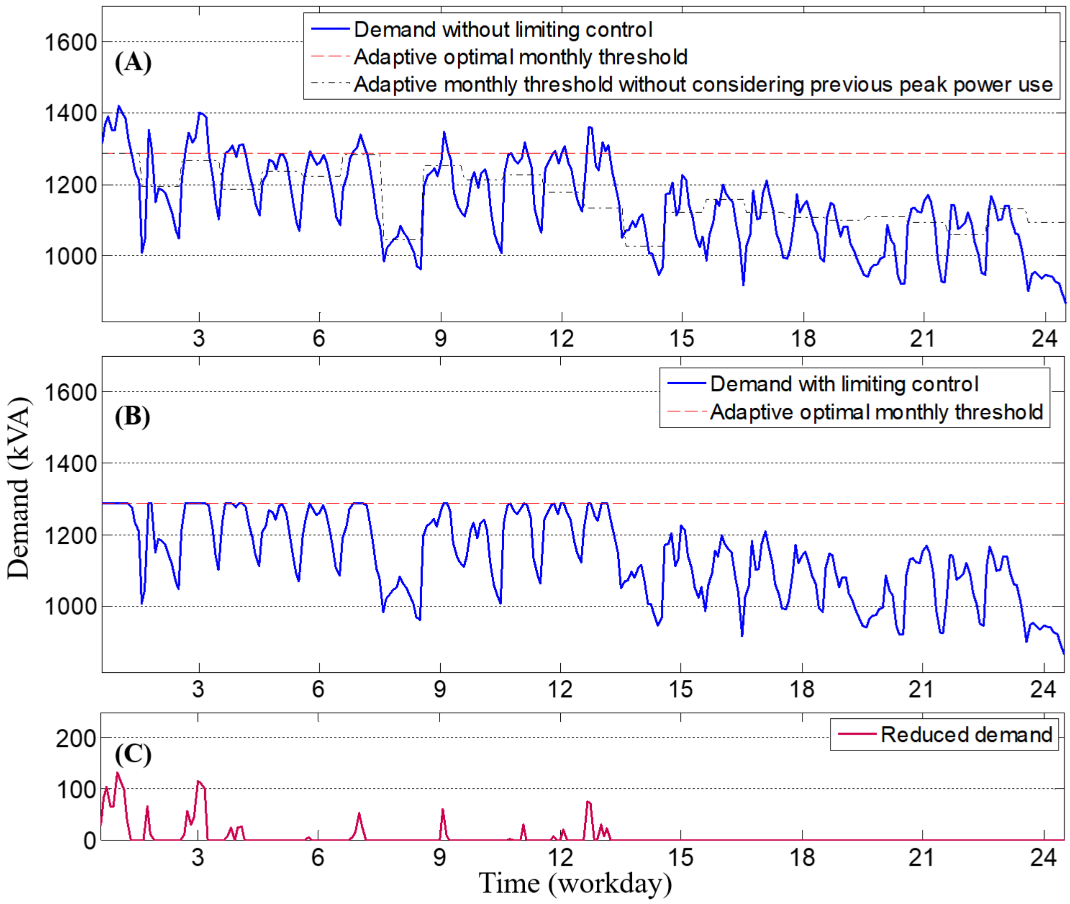

Fig. 10. Building demand profiles in Dec/2017 under different situations: (A) no demand limiting; (B) demand limiting using the developed strategy; (C) Actual demand reduction using the developed strategy.

Fig. 10(A) shows the power demand profile of the Phase 7 building, without implementing demand limiting, measured in Dec/2017. It can be seen that the monthly peak demand occurred on the first workday. The actual demands in the second half of the month were smaller. Two adaptive thresholds are included. One is the adaptive optimal monthly limiting threshold, and the other is the adaptive monthly limiting threshold without considering the actual peak of previous power use. The second threshold fluctuated due to the changes of the updated load forecast and could be even lower than the actual peak of previous power use. In contrast, the adaptive optimal monthly limiting threshold remained stable in the whole month. This is because the peak power use occurred on the first workday and the adaptive optimal limiting threshold was not allowed to be less than the actual peak power use.

Fig. 10(B) shows the power demand profile when implementing demand limiting using the developed adaptive optimal monthly peak demand limiting strategy. Fig. 10(C) shows the demand reduction when implementing the developed strategy for monthly peak demand limiting. During the demand limiting periods, the active thermal storage was discharged to restrict peak demands over the adaptive optimal monthly limiting threshold. After implementing demand limiting using the developed strategy in Dec/2017, the achieved monthly peak demand reduction was 132 kVA, 9.3% of the actual monthly peak demand (1,419 kVA). That contributed to the actual monthly net cost saving of 14,769 HKD (3.07% of the actual electricity charge of that month).

4.4. Summer case study and test results

In the summer case study, the datasets during the office hours in Jun/2018 are used for the validation test. Similar to the winter case, the 9-day weather forecast data reported/updated daily by the HKO in June are recorded each day. They are used to forecast/update probabilistic demand profiles to further identify/update the optimal monthly limiting threshold. In the following subsections, the first workday in June is selected to illustrate the identification procedure of the optimal monthly limiting threshold. This procedure is conducted repeatedly to obtain/update the monthly limiting threshold in an adaptive manner for demand limiting control in the following days of the month.

4.4.1. Optimal monthly limiting threshold identification on the first workday of June

On the first workday of 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. 11. Different confidence intervals of the probabilistic demand profiles are shown in the figure, such as 20%, 40%, 60% and 99%. In addition, the range of the tested thresholds was identified as [1822 kVA, 1973 kVA].

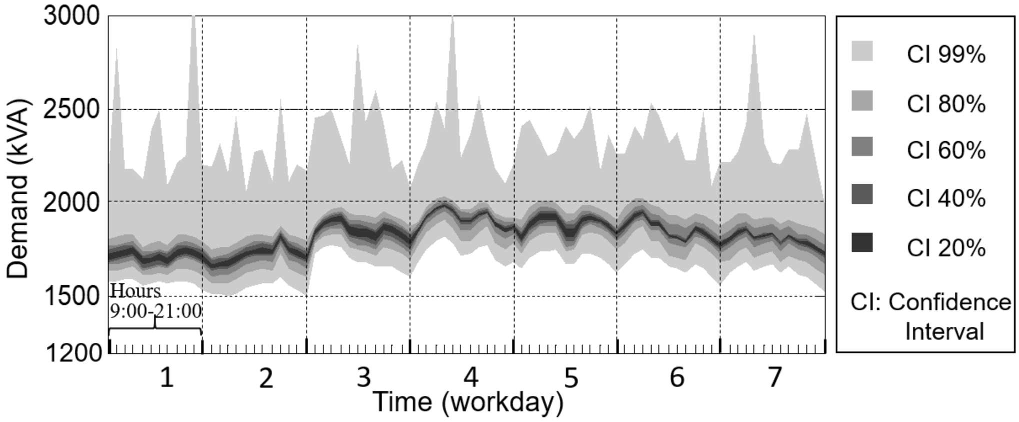

Fig. 11. Probabilistic demand profiles during office hours between 01/Jun and 09/Jun/2018 forecasted in the early morning of 01/Jun

Based on the forecasted probabilistic demand profiles, the monthly probabilities of each scenario using particular thresholds were estimated in the same way as that in the winter case, as shown in Fig. 12. It can be seen that all the monthly success probabilities accounted for over 80%, the monthly failure probabilities varied between 7% and 19%, and the monthly nonactivation probabilities varied between 0% and 12%.

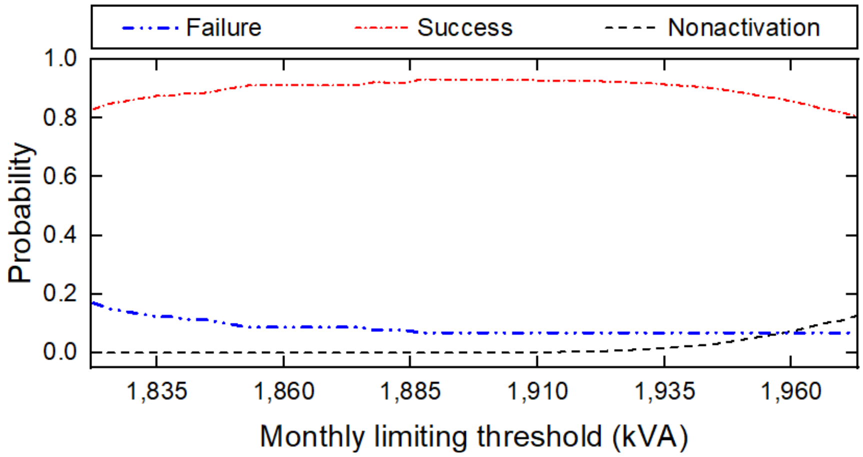

Fig. 12. Quantified probabilities of three scenarios when implementing demand limiting using different thresholds on the first workday of Jun/2018

Based on the quantified monthly probabilities at different thresholds, the expected monthly cost savings and the expected monthly gains were quantified, as shown in Fig. 13. It can be seen that the optimal monthly limiting threshold was identified of 1,887 kVA, and the corresponding cost saving was 3,673 HKD.

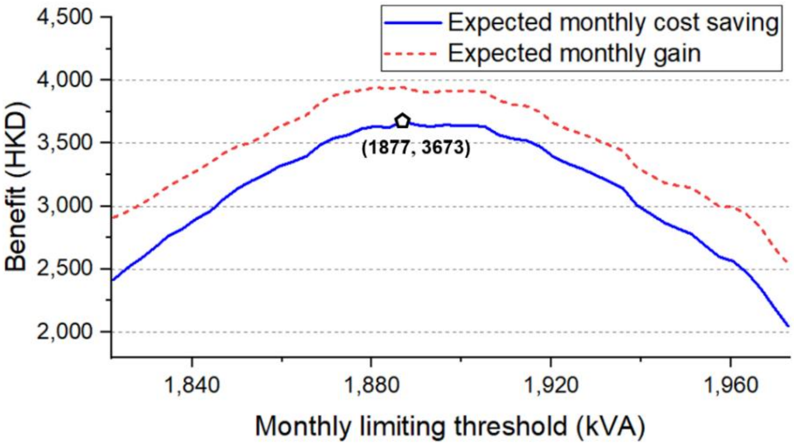

Fig. 13. Expected monthly cost savings and expected monthly gains when implementing demand limiting using different thresholds on the first workday of Jun/2018

4.4.2. Validation of the developed strategy for monthly peak demand limiting in June

Similarly, on each of the following workdays, the identification procedure using the optimal threshold resetting scheme is conducted repeatedly to obtain/update the optimal limiting threshold. In addition, the ideal demand limiting control is conducted on the basis of the identified adaptive optimal limiting threshold. Fig. 14 shows the validation test results of demand limiting using the adaptive optimal monthly peak demand limiting strategy in Jun/2018.

Fig. 14(A) shows the power demand profile of the Phase 7 building, without implementing demand limiting, measured in Jun/2018. It can be seen that the monthly peak demand occurred on the sixteenth workday. Two adaptive thresholds are also included. One is the adaptive optimal monthly limiting threshold, and the other is the adaptive monthly limiting threshold without considering the actual peak of previous power use. On the first three workdays, both thresholds were updated in the same trend since they were determined on the predicted power demand profile only as the actual peak of previous power use was below the thresholds.

Fig. 14(B) shows the power demand profile when implementing demand limiting using the developed adaptive optimal monthly peak demand limiting strategy. Fig. 14(C) shows the demand reduction when implementing the developed strategy for monthly peak demand limiting. During the demand limiting periods, the active thermal storage was discharged to restrict peak demands over the adaptive optimal monthly limiting threshold. After implementing demand limiting using the developed strategy in Jun/2018, the achieved monthly peak demand reduction was 278 kVA, 13.0% of the actual monthly peak demand (2,135 kVA). That contributed to the actual monthly net cost saving of 20,686 HKD (1.99% of the actual electricity charge of that month).

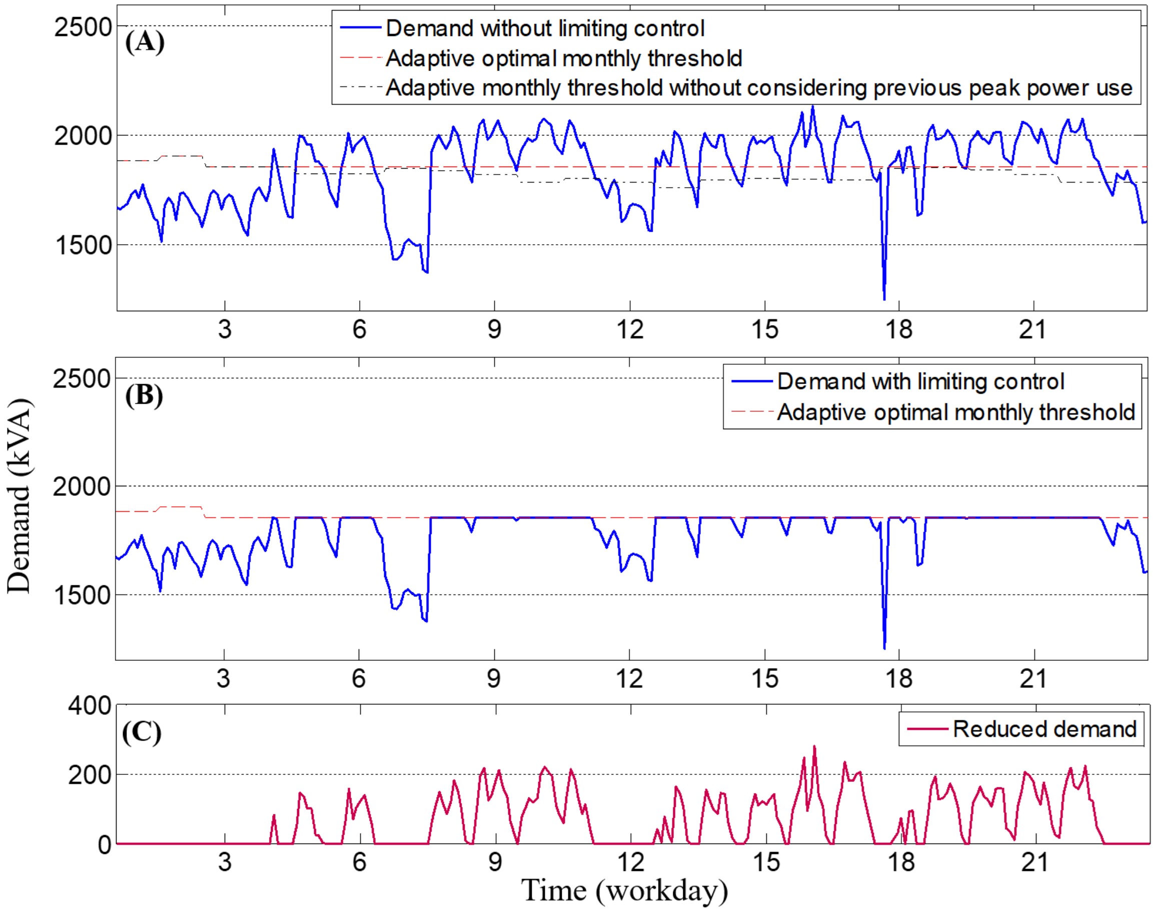

Fig. 14. Building demand profiles in Jun/2018 under different situations: (A) no demand limiting; (B) demand limiting using the developed strategy; (C) Actual demand reduction using the developed strategy.

4.5. Sensitivity analysis results

To further study the performance of demand limiting using the developed strategy, sensitivity analysis is conducted on the effects of means of demand limiting and electricity charge tariff on the monthly economic benefit. The means of demand limiting could be any of the existing building storage systems, e.g., phase change material, ice storage, etc. Their demand limiting capacity and the unit price of limiting effort are abstracted to quantify the economic benefit of demand limiting. As for the electricity charge tariff, there are different options in different regions and countries. In this section, the summer month (i.e., Jun/2018) is chosen to conduct sensitivity analysis and the parameters used in validation case studies are used as the baseline case. Tables 1-3 show the results of sensitivity analysis using the three parameters on the cost-benefit metrics of demand limiting (i.e., monthly cost saving, monthly accumulated limiting effort, peak demand reduction and percentage of peak demand reduction).

Table 1. Effects of the unit price of limiting effort on the cost-benefit metrics of demand limiting using the developed strategy

Unit price of limiting effort (HKD/kWh)	Monthly cost saving (HKD)	Monthly accumulated limiting effort (kWh)	Peak reduction (kVA)	Percentage of peak reduction
0.24 (baseline)	20,686	45,107	278	13.0%
0.32	18,894	43,830	274	12.8%
0.4	14,718	39,149	253	11.9%
0.48	12,929	36,351	253	11.9%
0.56	11,750	25,396	216	10.1%
0.64	11,274	20,669	204	9.6%

Table 1 shows how the unit price of limiting effort affects the cost-benefit metrics of demand limiting when the developed strategy is used. It can be seen that both the monthly cost saving and the monthly accumulated limiting effort decrease with the increase of the unit price of limiting effort. In addition, the less the unit price of limiting effort is, the more the monthly peak demand reduction will be.

Table 2. Effects of the unit price of electricity demand on the cost-benefit metrics of demand limiting using the developed strategy

Unit price of electricity demand (HKD/kVA)	Monthly cost saving (HKD)	Monthly accumulated limiting effort (kWh)	Peak reduction (kVA)	Percentage of peak reduction
120 (baseline)	20,686	45,107	278	13.0%
110	17,909	45,107	278	13.0%
100	15,203	41,322	268	12.5%
90	12,574	40,089	264	12.4%

80	9,814	37,278	253	11.9%
70	7,541	36,355	253	11.9%

Table 2 shows how the unit price of electricity demand affects the cost-benefit metrics of demand limiting when the developed strategy is used. It can be seen that the monthly cost saving decreases with the decrease of the unit price of electricity demand. In addition, the less the unit price of electricity demand is, the less the monthly accumulated limiting effort and the monthly peak demand reduction and will be.

Table 3. Effects of the limiting capacity on the cost-benefit metrics of demand limiting using the developed strategy

Limiting capacity (kWh)	Monthly cost saving (HKD)	Monthly accumulated limiting effort (kWh)	Peak reduction (kVA)	Percentage of peak reduction
4,763 (baseline)	20,686	45,107	278	13.0%
4,250	17,113	32,308	218	10.2%
3,750	13,079	15,860	146	6.8%
3,250	13,404	14,698	146	6.8%
2,750	11,237	10,437	118	5.5%
2,250	*6,243*	*6,845*	*68*	*3.2%*

Table 3 shows how the limiting capacity affects the cost-benefit metrics of demand limiting when the developed strategy is used. It can be seen that the monthly cost saving decreases with the decrease of the unit price of electricity demand in most cases. In addition, the less the limiting capacity is, the less the monthly accumulated limiting effort and the monthly peak demand reduction and will be. When a storage of very small limiting capacity is used for demand limiting, the limiting capacity could run out and the limiting threshold might be forced to the actual peak power use. In this situation, little monthly cost saving and peak demand reduction could be achieved, as the last case shown in Table 3 (the marked italic row).

5. Conclusions

This paper presents an adaptive optimal monthly peak demand limiting strategy for demand limiting under load uncertainty in the billing cycle of a month. An optimal threshold resetting scheme is developed to identify the optimal monthly limiting threshold in an adaptive manner. The uncertain economic effects and the probability of success of a demand limiting control in the billing cycle are quantified. Based on the case studies and test results, the following conclusions can be made:

- This strategy can successfully reduce the monthly peak demand and achieve a considerable monthly net cost saving under load uncertainty.
- This scheme can optimize the monthly limiting threshold based on the quantified probabilistic economic benefits (considering both gains and losses) of demand limiting and update the limiting threshold, following the ever-changing weather forecast and actual peak power use.
- In a typical winter month, demand limiting using the developed strategy achieved a considerable monthly peak demand reduction under load uncertainty, i.e., 9.3% of the actual monthly peak demand (1,419 kVA). That contributed to the monthly net cost saving of 14,769 HKD, 3.07% of the actual electricity charge of that month.
- In a typical summer month, demand limiting using the developed strategy also achieved a considerable monthly peak demand reduction under load uncertainty, i.e., 13.0% of the actual monthly peak demand (2,135 kVA). That contributed to the monthly net cost saving of 20,686 HKD, 1.99% of the actual electricity charge of that month.
- Results of sensitivity analysis show that the monthly cost saving decreases with the increase of the unit price of limiting effort or the decrease of the unit price of electricity demand. With the decrease of limiting capacity, the monthly cost saving decreases in most cases. It is worthwhile to identify the optimal storage capacity of a building based on the actual load characteristics and the potential cost benefits.

Acknowledgment

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