Peak reduction for commercial buildings using energy storage

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Abstract. Battery-based energy storage has emerged as a cost-effective solution for peak reduction due to the decrement of battery’s price. In this study, a battery-based energy storage system is developed and implemented to achieve an optimal peak reduction for commercial customers with the limited energy capacity of the energy storage. The energy storage system is formed by three bi-directional power converter rated at 5 kVA and a battery bank with capacity of 64 kWh. Three control algorithms, namely fixed-threshold, adaptive-threshold, and fuzzy-based control algorithms have been developed and implemented into the energy storage system in a campus building. The control algorithms are evaluated and compared under different load conditions. The overall experimental results show that the fuzzy-based controller is the most effective algorithm among the three controllers in peak reduction. The fuzzy-based control algorithm is capable of incorporating a priori qualitative knowledge and expertise about the load characteristic of the buildings as well as the useable energy without over-discharging the batteries.

1. Introduction

The growth of electrical energy demand has urged the utility companies to build more power plants when the peak demands approach the system’s load carrying capacity. However, power plants are massive industrial complexes that can affect the environment by its construction as well as its operation. Hence, alternatives are sought to overcome the high peak demands growth.

Demand response is a tariff or program established to motivate customers to change their electric use pattern such a way to reduce the peak demands and reduce the need for expensive peaking plants [1-3]. Various price-based demand response such as time-of-use (TOU), real-time pricing (RTP), and critical-peak pricing (CPP) have been introduced by the utility companies to induce lower electricity use during peak demand hours. Besides, incentive-based demand response programs offer incentives to the customers who shift their peak period activities to off-peak periods [4-6]. However, there are still many technical and legal issues to be tackled for the implementation of demand response programs such as huge investment on advanced metering infrastructure and vague legislation [2,3].

Battery-based energy storage has emerged as a promising technology in reducing peak demands for both the utility and end users. Many large-scale battery-based storage systems have been installed for the purposes of peak reduction worldwide as illustrated in table 1.

A small-scale battery-based storage system is a good choice for the end users to shave their peak demands. High portability, short setup time, simple installation and commission, low capital cost investment, minimal space occupation and low maintenance and operating cost are the superiority of the battery-based storage system as compared to other storage technologies [10-12]. An assessment has been carried out to investigate the economic benefits of the ESS in providing peak reduction for
both the utility and end users [13]. A simple method has been proposed by [14] for peak-load reduction using battery ESS. The study compares the aggregated load profile with its average value during a specific period and operates the energy storage devices based on the proposed weighting factors. The average load reduction is 0.35 - 1%. A dynamic programming method was proposed by [15] to optimize the operation of the ESS and 8% of peak reduction has been achieved. In [16], the peak reductions of 27 – 45 % has been achieved using a demand tracking management model. Lu et al have proposed an optimal sizing and control of battery-based storage system for peak reduction at the utility scale [17]. The study has diminished the difference between the peak load and the valley load via the optimal control of the energy storage system (ESS) and the peak reduction is 4.5 - 6.6%.

Although there are many studies carried out for peak reduction using battery-based storage systems, most of the research work are simulation-based [17-26]. However, there is a dearth of public research in real-time peak reduction for commercial buildings. The real-time peak reduction is more challenging than that of the simulation because the actual peak demands can be quite different from the forecasted load profiles. When the actual peak demands are unexpectedly high, the ESS may fail to reduce the peak due to the limited capacity of the power converters. Also, the actual peak can happen much earlier or later than the forecasted one. The ESS may fail to cut down the peak if it supplies the power at the wrong time. Another possibility is that the actual peak can happen for an extended period of time. The ESS may not have enough energy to sustain the supply of power. Considering the possible variation in the actual load profiles, any control strategies used for the ESS has to be evaluated empirically through experiments. Since the cost of the batteries is still high at present, the capacity of the ESS has to be limited or reduced in order to justify the financial viability of the system.

This paper presents three control algorithms, namely the fixed-threshold, adaptive-threshold, and fuzzy-based control algorithms for the ESS to shave the peak demands under various load conditions. The fixed-threshold controller instructs the ESS to supply power whenever the actual load demand exceeds a specified threshold. The adaptive-threshold controller adjusts the threshold when the peak demands are unexpectedly high or happen over an extended period. However, these two controllers do not take into account the available energy from batteries. This may result in insufficient energy for peak reduction. The fuzzy-based controller is capable of estimating the useable energy from the batteries and incorporating it into the fuzzy inference rules to determine the appropriate output power to be delivered to the load in order to prevent insufficient energy supply from the batteries during peak reduction. The performance of the three controllers was evaluated at two different buildings at Universiti Tunku Abdul Rahman (UTAR), Malaysia, to evaluate the effectiveness of the control

### Table 1. Worldwide large-scale battery-based storage systems for peak reduction.

| Project                             | Operational dates | Location            | Battery type       | System size |
|-------------------------------------|-------------------|---------------------|--------------------|-------------|
| Crescent Electric Membership System | 1987 to 2002      | Carolina, USA       | Flooded cell, lead acid | 0.5         |
| Cooperative BESS System             | 2002              | USA                 | Vanadium redox flow | 0.5         |
| Sumitomo Densetu Office Battery     | 2000 to present   | Japan               | Sodium-sulphur     | 3.0         |
| New York Bus Terminal Energy Storage Systems | 2008 to present | New York, USA       | Zinc-bromine       | 1.2         |
| ZBB Energy Corporation Battery      | 2005 to present   | California, USA     | Li-ion             | 1.0         |
| Zurich Battery Energy Storage System | 2012 to present   | Dietikon, Switzerland |               | 0.5         |

a Data collected from [7]
b Data collected from [8]
c Data collected from [9]
algorithms in reducing peak demands under various load profiles.

2. Configuration of the ESS

![Experimental ESS setup](image1)

![Electrical diagram of the ESS](image2)

**Figure 1.** (a) Experimental ESS setup; (b) Electrical diagram of the ESS.

An experimental three-phase ESS is set up for peak reduction at two different buildings at two different time frames. The ESS consists of three single-phase bi-directional power converters rated at 5 kVA and 48 pieces of 12 V valve-regulated lead-acid (VRLA) batteries. Each bi-directional power converter is connected to 4 strings of batteries and each string of batteries is formed by 4 series-connected batteries to provide a 48 V DC supply to the converter. The total energy capacity of the
whole ESS is 64 kWh. A data acquisition system is developed using the C-series voltage and current measuring modules manufactured by National Instruments (NI). LabVIEW graphical programming software is used to develop the control system for the ESS. Figure 1(a) shows the experimental ESS setup and figure 1(b) shows the electrical diagram of the ESS connected to the 415 V, 50 Hz, 3-phase utility grid.

3. Formulation of control strategies for peak reduction

Usually, the commercial and industrial customers require a significant amount of power over a short time interval of about 2 to 4 hours during peak periods. The high peak demand during these short time intervals results into high maximum demand charges to the customers. In this study, the ESS is controlled to deliver power during peak periods and restore energy during off-peak periods. The ESS is installed in two different buildings, namely building A and building B to evaluate the effectiveness of the control algorithms in reduction peak demands under various load profiles. The load profiles of these two buildings are forecasted based on the historical load profiles. The predicted daily load profile provides information on the amount of energy required to shave the peak demands. The depth-of-discharge (DOD) of the batteries is limited to 50% based on the recommendation from the battery manufacturer. The grid power ($P_{grid}$) as measured by the utility power meter is equal to the sum of load demand ($P_{load}$) and the power of the energy storage ($P_{ES}$) as follows:

$$P_{grid} = P_{load} - P_{ES}$$

The sign of $P_{ES}$ is positive when it delivers power and it is negative when it absorbs power.

3.1. Fixed-threshold control algorithm

Fixed-threshold control algorithm is the most basic control strategy developed to control the ESS for peak reduction. Figure 2 shows an example of a daily load profile of the building. The daily load profile can be assorted into three sections to reflect 3 different possible operations of the ESS, namely the charging, discharging and idle modes.

![Figure 2. Daily load profile and the desired response of the ESS.](image)

The lower power threshold ($P_{LTh}$) and an upper power threshold ($P_{UTh}$) are set such that the ESS operates when the load demand falls within a certain range of the thresholds. During the period from 0:00 to $t_1$ and $t_4$ to 24:00, $P_{load}$ is lower than $P_{LTh}$. The ESS charges the batteries if it is not fully...
charged or stays in the idle mode if the batteries are fully charged. During the period from \( t_1 \) to \( t_2 \) and from \( t_3 \) to \( t_4 \), the ESS stays idle because \( P_{load} \) is in between \( P_{UTh} \) and \( P_{UTh} \). During the period from \( t_2 \) to \( t_3 \), the ESS delivers power to the load because \( P_{load} \) is greater than \( P_{UTh} \). The energy required to reduce the peak demands for each day can be determined by calculating the area under the graph between the load demand and \( P_{UTh} \) as illustrated in figure 2.

During the discharging mode, the load demand is greater than \( P_{UTh} \). The ESS begins to supply power to the load if the state-of-charge (SOC) is greater than 50%. If the SOC is below 50%, the discharging of the batteries is forbidden to prevent the over-discharging of the batteries and prolong the service life of the batteries. If the difference between \( P_{load} \) and \( P_{UTh} \) is less than the rated power of the ESS \( P_{E\text{max}} \), then the ESS will inject power with the magnitude being the same as \( P_{load} \) minus \( P_{UTh} \) as shown in the following equation:

\[
P_{ES} = P_{load} - P_{UTh}
\]

If the difference between \( P_{load} \) and \( P_{UTh} \) is greater than the rating \( P_{E\text{max}} \), then the ESS injects its nominal power to the load as follows:

\[
P_{ES} = P_{E\text{max}}
\]

If the SOC is equal to or less than 50%, then the power converter will stop injecting power to the load.

During the charging mode, the ESS starts to charge the batteries when the actual load demand is lower than \( P_{UTh} \) in order to restore the batteries’ energy for the next day of peak reduction. If the SOC of the batteries is less than 90%, then the batteries will be charged at a moderate rate of 6 kW. If the SOC is greater than or equal to 90%, then the battery is charged at a low rate of \( 3*[[0.7 \ln(t) - 2] \text{ kW}}.\) These charging rate expressions are chosen from the battery converter handbook with a view to prevent the overcharging of the batteries and to prolong the service life of the batteries.

During the idle mode, the ESS should output zero power as follows:

\[
P_{ES} = 0
\]

### 3.2. Adaptive-threshold control algorithm

Adaptive-threshold controller is an improved version of the fixed-threshold controller because the output power of the ESS can be reduced to preserve the energy of the batteries when the actual peak demands occur for an extended period of time. The operation of the charging and idle modes of the adaptive-threshold controller is the same as that of the fixed-threshold control algorithm except for the operation of the discharging mode. During the discharging mode, if the difference between \( P_{load} \) and \( P_{UTh} \) is greater than \( P_{E\text{max}} \) within a specific duration of time \( (N) \) in minutes, then the high load demand is considered as temporary. The ESS will inject its nominal power of \( P_{E\text{max}} \). When the difference between \( P_{load} \) and \( P_{UTh} \) is greater than \( P_{E\text{max}} \) for more than \( N \) minutes, the high load demands is no longer temporary. Hence, the new upper threshold \( (P_{UTh}) \) will be moved to a new value based on the following equation:

\[
P_{UTh'} = P_{load} - P_{E\text{max}}
\]

The adaptive feature enables the ESS to deliver power to the load over the longest possible period.

### 3.3. Fuzzy-based control algorithm

The fuzzy-based control algorithm takes into account the useable energy \( (E_U) \) during the time of operation \( (t_{op}) \) to determine the amount of power to be delivered to the grid during the peak reduction. The \( t_{op} \) is defined as the time where the energy storage begins to supply its power. When the \( E_U \) has declined at the certain time, the power injection from the ESS is also decreased to ensure that the \( E_U \) can be sustained until the end of the peak reduction process. The input variables for the fuzzy-based controller are the SOC of the batteries and the \( t_{op} \) while the output variable is the power injection of the
ESS, $P_{ES}$. Table 2 shows the definition of the fuzzy sets of the SOC, $t_{op}$, and $P_{ES}$ in linguistic terms. There are five membership functions for both the SOC and the $P_{ES}$ while there are seven membership functions for the $t_{op}$.

**Table 2. Definition of the fuzzy sets of the SOC, $t_{op}$ and $P_{ES}$ in linguistic variables.**

| SOC       | Time of Operation ($t_{op}$)       | $P_{ES}$       |
|-----------|-----------------------------------|----------------|
| VL – Very Low | EE – Extremely Early              | VL – Very Low  |
| L – Low    | VE – Very Early                   | L – Low        |
| M – Middle | E – Early                         | M – Middle     |
| H – High   | M – Middle                        | H – High       |
| VH – Very High | L – Late                       | VH – Very High |
|           | VL – Very Late                    |                |
|           | EL – Extremely Late               |                |

The rules in the fuzzy inference system are derived from the desired responses of the ESS based on the predicted load demands. Table 3 shows the values of the fuzzificated SOC, $t_{op}$, and the corresponding $P_{ES}$ of the fuzzy controller.

**Table 3. The fuzzificated SOC, $t_{op}$ and the corresponding $P_{ES}$ of the fuzzy controller.**

| $t_{op}$ | VL | L  | M  | H  | VH |
|----------|----|----|----|----|----|
| EE       | VL | VL | VL | VL | VL |
| VE       | VL | VL | VL | VL | VL |
| E        | VL | L  | L  | M  | M  |
| M        | VL | L  | M  | M  | H  |
| L        | L  | M  | H  | VH | VH |
| VL       | M  | H  | VH | VH | VH |
| EL       | M  | H  | VH | VH | VH |

4. Experimental results

4.1. Performance evaluation of the fixed-threshold control algorithm

Case study 1 evaluates the performance of the fixed-threshold control algorithm conducted at building A for the scenario where the load demand is higher than the predicted value and the actual peak occurs for a much longer duration than the predicted duration. The actual peak demands are unexpectedly higher than the predicted value where its maximum demand is 97.21 kW while the predicted maximum demand is 95 kW. Initially, $P_{UTh}$ and the $P_{LTh}$ are set at 80 kW and 30 kW, respectively according to the predicted value. Figure 3 shows the results of the peak reduction using the fixed-threshold control algorithm for the case study 1. It can be seen that when the load has exceeded 80 kW at 10:00, the ESS begins to deliver power to the load based on the difference between the $P_{load}$ and $P_{UTh}$. The SOC of the batteries has declined to 50% at 13:00, triggering the ESS to stop delivering power to the load. As a result, the ESS fails to shave the peak after 13:00. In this case study, the ESS has failed to cut down the peak demand due to the limited rating of the power converters. It is also found that the actual peak occurs for a much longer duration than the prediction. Hence, the ESS does not have enough energy to sustain the delivery of its power over such a long duration.

Case study 2 evaluates the performance of the fixed-threshold control algorithm conducted at building B. The $P_{UTh}$ is set at 70 kW according to the predicted value while the $P_{LTh}$ is set at 50 kW. Figure 4 shows the results of the peak reduction. It can be seen that when the load has exceeded 70 kW at 7:45, the ESS begins to deliver power to the load based on the difference between the $P_{load}$ and
$P_{UTh}$. The peak demand has been reduced from 78.4 kW to 70.9 kW. It is found that the peak reduction in this case study is 7.5 kW.

**Figure 3.** The peak reduction using the fixed-threshold control algorithm for case study 1.

**Figure 4.** The peak reduction using the fixed-threshold control algorithm for the case study 2.

### 4.2. Performance evaluation of the adaptive-threshold control algorithm

Case study 3 evaluates the performance of the adaptive-threshold control algorithm conducted at building A. This case study illustrates the scenario where the actual peak is unexpectedly higher than the predicted value. Figure 5 shows the results of the peak reduction using the adaptive-threshold control algorithm for the case study 3. It is found that the maximum demand is 90.2 kW while the predicted maximum demand is 86 kW. Initially, the $P_{UTh}$ is set at 71 kW according to the predicted value while the $P_{LTh}$ is set at 30 kW. It can be seen that when the load demand has exceeded 71 kW at 12:00, the ESS begins to deliver power to the load. At 13:30, $P_{load}$ has increased to 89.2 kW and prolonged for more than 10 minutes. The corrective mechanism in the adaptive-threshold algorithm
adjusts the $P_{UTh}$ to 74.5 kW at 13:45. At 14:00, $P_{load}$ has increased to 90.2 kW and prolonged for more than 10 minutes and the $P_{UTh}$ is adjusted to 77.3 kW at 14:15. The ESS begins to restore its energy at 17:00. The peak demand has been reduced from 90.2 kW to 78.5 kW. In this case, the peak shaved is 11.7 kW.

Figure 5. The peak reduction using the adaptive-threshold control algorithm for the case study 3.

Case study 4 evaluates the performance of the adaptive-threshold control algorithm conducted at building B. The $P_{UTh}$ is set at 68 kW according to the predicted value while the $P_{LTh}$ is set at 50 kW. Figure 6 shows the results of the peak reduction. The peak demand is 82.78 kW while the predicted $P_{UTh}$ is 83 kW. It can be seen that the ESS starts to deliver power to the load at 7:15 when the $P_{load}$ is greater than the $P_{UTh}$. At 12:15, the SOC of the ESS has dropped to 50%. Consequently, the ESS stops to deliver power to the load. As a result, the ESS failed to reduce the peak demand when the load has increased to 82.78 kW at 12:30. This case study shows that when the actual peak occurs for a much
longer duration than the predicted one, the ESS fails to deliver power to the load because it does not have enough energy to sustain the delivery of its power over such a long duration.

4.3. Performance evaluation of the fuzzy-based control algorithm
Case study 5 evaluates the performance of the fuzzy-based control algorithm conducted at building A. In this case, the $P_{UTh}$ and $P_{LTh}$ are set at 80 kW and 30 kW, respectively. The estimated peak demand is 95 kW. At 10:30, $P_{load}$ is greater than $P_{UTh}$ and the ESS begins to deliver power to the grid such that $P_{grid}$ is not higher than $P_{UTh}$. It can be seen that at 13:45, $P_{load}$ has reached 100.5 kW and it is higher than the estimated peak demand. The fuzzy-based controller delivers up to 12.1 kW instead of its full capacity of 15 kW to preserve energy so that the remaining energy is sufficient to shave the peak for the rest of time. Figure 7 shows the experimental results for the case study 5. The peak demand has been reduced from 100.5 kW to 88.4 kW. The peak demand reduction for this case is 12.1 kW.

Figure 7. The peak reduction using the fuzzy-based control algorithm for the case study 5.

Figure 8. The peak reduction using the fuzzy-based control algorithm for the case study 6.
Case study 6 evaluates the performance of the fuzzy-based control algorithm conducted at building B. \( P_{UTB} \) and \( P_{LTB} \) are set at 70 kW and 50 kW, respectively. The peak demand occurs earlier than the predicted time of occurrence at 6:45. It can be seen that at 9:30 when \( P_{load} \) is 80 kW, the ESS restricts the power injection to only 5.9 kW in order to preserve energy for the rest of the time. Figure 8 shows the experimental results for the case study 6. The peak demand has been reduced from 82.2 kW to 74 kW. The peak demand shaved for this case is 8.2 kW.

5. Conclusion

The fixed-threshold and adaptive-threshold control algorithms may fail to shave the peak demand when the high peak demand is higher than that of the predicted value and when the actual peak demand occurs for a much longer duration than the predicted duration. By estimating the useable energy from the batteries and incorporating it into the fuzzy inference rules, the fuzzy-based control algorithm can determine the appropriate output power to be delivered to the load in order to prevent insufficient energy supply from the batteries. The fuzzy-based control algorithm is capable of incorporating a priori qualitative knowledge and expertise about the load characteristic of the buildings as well as the useable energy of the energy storage in peak reduction. The experimental results show that the fuzzy-based control algorithm has achieved the highest performance in peak reduction as compared to that of the fixed-threshold and adaptive-threshold control algorithms.

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