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Calculating the Capacity Value and Resource Adequacy of Energy Storage on High Solar Grids

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SUMMARY

With the increasing integration of renewable generation, adoption of battery energy storage systems is starting to increase across many power grids as well. This paper investigates the resource-adequacy impact of incorporating energy storage (ES) into power systems with high concentrations of renewable energy, and the ability of ES resources to replace the need for conventional generation. In the context of this paper, the schedule of ES is optimized so that the system's risk of having a loss of load event is minimized, and the ES potential to improve the system's resource adequacy can be fully exploited. A two-layer optimization model is proposed to optimize the ES schedule. GE's Multi-Area Reliability Simulation Software (GE MARS) was used to conduct a resource-adequacy study on the Hawaii (Island of Oahu) system through sequential Monte Carlo simulation to determine the impact of integrating the ES. The attained results are as follows: 1) the resource adequacy impacts of ES are different from those of a conventional generating unit. 2) the energy rating (MWh) of ES is critical to its resource-adequacy contribution. 3) ES, when optimized to minimize the system production cost, can also help improve resource adequacy, though not to the extent as when ES is optimized to reduce system risk. 4) a "saturation" effect (capacity value decreases with more ES installed) occurs, and the capability of moving energy among different days (optimize the ES operation within multiple days) will be important, especially when the energy rating (MWh) of ES is larger. 5) increasing the amount of solar generation helps mitigate the "saturation" effect, since solar can provide more charging power for ES, and hence further improve the ES capacity value. Solar plus ES can be a good combination to improve resource adequacy.

KEYWORDS

Energy Storage, reliability, solar, Monte Carlo, LOLE, capacity value.

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I. Introduction

As renewable generation is increasingly integrated, battery energy storage systems have seen increased adoption across many power grids, due to their potential capability to smooth out fluctuations of power from renewables, and consequently reducing the total production cost [1-5]. While ES remains a small portion of the grid at present, the pace of adoption has accelerated, largely due to industry innovation and the declining costs associated with ES. ES is differentiated from conventional generators. For the sake of both system security and for enhancing the integration of renewables, further investigation of the resource-adequacy impact of ES is becoming necessary. A better understanding of ES effective load-carrying capability (ELCC) [6] is needed to determine to what extent ES, coupled with renewable energy, can displace the need for conventional generation to satisfy resource-adequacy needs.

Several studies have focused on evaluating the impact of ES on the power system: refs [7-14] evaluate the resource-adequacy impact of ES when coordinated with the solar or wind generation; refs [15-22] assess ES impact when ES is scheduled based on the system's condition. Among those studies, most [8-15, 17,18] operate the ES in such a way that ES is charged when there is some excess power and discharged when needed. In this way, the operation of ES may not be fully optimized, since such way of operation does not look ahead to check the potential future need for battery energy. On the other hand, some studies [7, 16, 22] operate the ES to make the best use of the combined system (ES and renewable), the distribution system, and the total system, respectively, to maximize profit; this may not fully explore the value of ES as a *capacity* resource in improving resource adequacy. Meanwhile, except for [7], the other studies were conducted on a smaller scale, based on some relatively small test systems. Moreover, National Renewable Energy Lab (NREL) recently studied the potential of ES to provide peaking capacity [23] without considering the possible unavailability of ES devices or other random outages on the grid. It is pointed out in [21] that there is no sufficient work on this field, though increasingly important.

Motivated by the research listed above, the primary focus in this paper is on examining the resource-adequacy impact and firm-capacity contribution of ES (in contrast to energy arbitrage or grid service use cases), when ES is operated to minimize the system risk, and when ES availability is considered. The contribution of our work primarily concerns: 1) an examination of optimizing ES to minimize the system risk of loss of load and the related value of ES in supporting resource adequacy; 2) a proposed two-layer optimization model to schedule the ES operation; 3) comprehensive analysis on an actual power system with ambitious renewable energy and ES goals, to provide more insights of integrating ES into the power system.

This paper is organized as follows: Section II contains some basic information on the resource-adequacy study; Section III outlines our process for evaluating the resource-adequacy impact of ES through Monte Carlo simulation, with ES scheduled to minimize the system risk; Section IV evaluates the resource-adequacy impact of adding ES to a high-renewable future Hawaii power system; and finally, Section V presents some takeaways and future work.

II. Background

Resource-adequacy analysis measures the grid's ability to serve the load, accounting for the context of uncertainties such as load, generator outages, and fuel scarcity (including natural gas availability as well as wind, solar and hydro resource variability). Some commonly used indices are: loss of load probability (LOLP), that is, the probability that the loss of load event may occur; loss of load expectation (LOLE), which shows the expected number of days or hours that the system experiences a loss of load event in a year; and loss of energy expectation (LOEE), used to estimate the expected loss of energy within a year. General industry practice targets a daily LOLE not to exceed one day in 10 years (or, a daily LOLE of 0.1 days/year).

Estimating resource adequacy may be performed in two ways: an analytical method, and by Monte Carlo simulation. The analytical method requires formulating a capacity outage probability table (COPT) [24] to record the probability of different capacity outages, and calculates the indices based on the information in the COPT. Some weaknesses of this method are: 1) as systems become more complex, and more information is considered (e.g., the outage rate of a tie line), it becomes increasingly difficult to generate a COPT table; 2) this same difficulty in generating a COPT table pertains to systems with renewable capacity; 3) it is difficult to generate information on the duration and frequency of events just based on the COPT which is necessary to assess the impacts of an energy limited resource like ES. In contrast, statistical results using Monte Carlo simulations come from repeated, random sampling until certain convergence criteria are met. With this method it is possible to simulate large systems with more factors, including renewables. It is for this reason that we employed Monte Carlo simulations in our study.

When a generator is added to the grid, its resource-adequacy impact can be assessed not only by the improvement on the resource adequacy but also by the capacity value (CV) of the unit. The CV of the unit is defined in this paper as the fraction of the generator's installed capacity that can be statistically counted on at all times for resource adequacy given uncertainty in the unit's availability. This is shown in equation (1), although there are multiple definitions of CV [25].

$$\text{Capacity Value} = P_{ELCC} \,/\, P_{MAX} \tag{1}$$

where P_{MAX} is the installed capacity of the unit; P_{ELCC} is the amount by which the system's load can be constantly increased when the generator is added to the system, while still maintaining resource adequacy (e.g., LOLE) [6]. Calculating P_{ELCC} is an iterative process [26]: 1) calculate the original LOLE of the system prior to the addition of the new unit; 2) add the unit and calculate the new LOLE; 3) keep adding constant load until the updated LOLE becomes the same as the original LOLE. The methodology used to determine the P_{ELCC} of ES is outlined further in the following section.

III. Methodology

A. Estimating the System's Resource Adequacy

Simulating the resource adequacy of a power grid was done using GE's Multi-Area Reliability Simulation Software (GE MARS), a sequential Monte Carlo simulation which calculates the time-correlated measures such as frequency (outages/year) and duration (hours/outage), compared with non-sequential Monte Carlo simulation and analytic methods. This program allows for modeling various types of generation (such as thermal units, energy-limited hydro, storage and demand-response, renewables, etc.); contracts and transfer limits among different areas; and emergency operating procedures (EOPs) during the operation, etc. GE MARS delivers a detailed representation of the grid sufficient to assess the resource adequacy of the generation system accurately, and enables the electric utility planner to quickly and effectively access resource adequacy. The output of this step includes the base system's LOLE and an hourly profile of capacity margin (surplus capacity), used in subsequent steps of this methodology.

B. Optimizing the ES Scheduling

Leveraging the results of the base system's resource-adequacy estimation, we schedule the ES to minimize the system risk of having a loss of load event. To achieve that, ES discharges when the system is at high risk (lacking surplus generation capacity), as is illustrated in Fig. 1. The concept of "margin" in Fig. 1 is defined as the total available generation capacity minus the load in an area, and can reflect the system risk of loss of load (higher margin means lower risk, and lower margin shows higher risk).

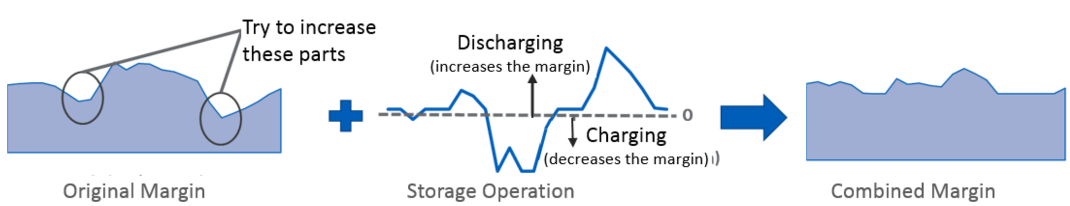

Fig. 1 Illustration on ES Scheduling

We propose a two-layer optimization model to optimize the daily ES scheduling. The first layer, presented in equations (2) – (7), is intended to maximize the possible minimum margin, and thus leads to a minimized system risk:

Objective $$\max \min_{t\in[1,T]} m_t \tag{2}$$

such that $$m_t = M_t + p_t^+ - p_t^- \quad t \in [1,T] \tag{3}$$

$$Q_{t-1} - Q_t = \left(\frac{1}{\eta^+} p_t^+ - \eta^- p_t^-\right)\Delta T \quad t \in [1,T] \tag{4}$$

$$0 \le Q_t \le Q_{MAX} \quad t \in [1,T] \tag{5}$$

$$0 \le p_t^+ \le p_{MAX}^+ \quad 0 \le p_t^- \le p_{MAX}^- \quad t \in [1,T] \tag{6}$$

$$Q_{t|t=T} \ge Q_{REQ} \tag{7}$$

where M_t is the original hourly margin (without ES considered) at time t; η^+ and η^- are the ES discharging and charging efficiency, respectively; Q_{MAX} is the maximum energy capacity of the ES; P^+_{MAX} and P^-_{MAX} are the maximum discharging/charging power capacity of the ES, respectively, Q_{REQ} is the required ES energy by the end of a certain time period; Q_0 is the initial energy in the ES; T is the duration of time that ES operation is optimized over; Q_t denotes the ES energy at time t; p^+_t and p^-_t are the discharging and charging power of the ES at time t, respectively; m_t is the combined margin state at time t when ES is considered.

Equation (2) is the objective function used to maximize the minimum margin (min-margin) with ES integrated; equation (3) presents the relationship between the original system margin and the final combined margin; equation (4) describes the relationship between ES charging/discharging power and its remaining energy, considering charging/discharging efficiencies; equation (5) sets the limitation on the energy in the ES to be between 0 and its energy rating (MWh); equation (6) regulates the charging/discharging power of the ES to be within the capacity rating (MW); equation (7) guarantees the remaining energy of the ES is higher than a certain level by the end of an optimization cycle. Constraints (2) to (6) should be met at all hours from 1 to T, while (7) is only set for the final hour T.

After solving the optimization model above, one can obtain from the objective function (2) a possible maximum min-margin when ES is integrated. However, the operation of the ES suggested by the above model may not be acceptable: 1) the model above has multiple solutions, and in some of the solutions, the ES may not be scheduled to charge during those peak margins, while the optimal min-margin may still be maintained; 2) the results may show simultaneous ES charging and discharging. Consequently, we propose a second layer of optimization, as shown below, to further schedule the ES based on the maximum min-margin obtained from the first layer, denoted as M_{MIN}.

Obj. $$\min \sum_{t\in[1,T]} \frac{1}{M_t}(p_t^+ + p_t^-) \tag{8}$$

Such that $$m_t \ge M_{MIN} \quad t \in [1,T] \tag{9}$$

Equations (3) – (7)

The objective function in (8) is to ensure that the ES will charge during those peak margins. Equation (9) guarantees that the combined margin will be greater than the value obtained in the first layer at any time. Other than the constraints modeled in (9), this model inherits the same constraints from the model in the first layer. The efficiency (p^+_t and p^-_t) together with the objective function (8) eliminates the simultaneous ES charging and discharging.

C. Calculating ES Capacity Value

The full process of evaluating the resource-adequacy impact and the CV of the ES is as follows: Steps 1 to 4 calculate the resource adequacy indices of the system with ES added, while Steps 5 to 6 calculate the CV of the ES.

Step 1: Run GE MARS to estimate the daily LOLE (days/year) of the original system (without the ES), output all the margins in those thousands of replications, and average them to obtain the original margins (denoted as M_t in the optimization model).

Step 2: Run the two-layer optimization model with the obtained original margins in **Step 1** to optimally schedule the operation of ES;

Step 3: Break the ES into small blocks, simulate their availability through Monte Carlo simulation assuming certain forced outage rate for each block, and re-calculate the total output of ES based on their simulated availability;

Step 4: Model the ES in GE MARS using the output from **Step 3** and run GE MARS to calculate the new LOLE (days/year). If CV shall be calculated, go to **Step 5**, otherwise, stop;

Step 5: Add new constant load to the system with ES integrated and run GE MARS to calculate the new LOLE (days/year);

Step 6: Compare the LOLE in **Step 5** with that in **Step 1**: if they are the same or close enough to be regarded as the same, stop the whole process; otherwise, go to **Step 5**.

IV. Case Study

A. System Description

Using the methodology discussed in the previous section, a case study was conducted based on the utility's proposed Power Supply Improvement Plan ("PSIP E3 Plan"), a potential capacity expansion plan for Hawaii (Island of Oahu). In this case the 2030 study year was selected to simulate a grid with significant penetration of solar PV and ES resources. The basic system configuration is shown below in Fig. 2. Two types of demand response (DR), capacity DR and spinning DR, are considered during the resource-adequacy study; and are used when the system needs more generation, even though all the generating capacity (including storage) is used up. In our study, the system should have enough generating capacity to not only serve the load, but to maintain a certain reserve margin, which is assumed to be 180MW. Otherwise, the system is assumed to have a loss of load event.

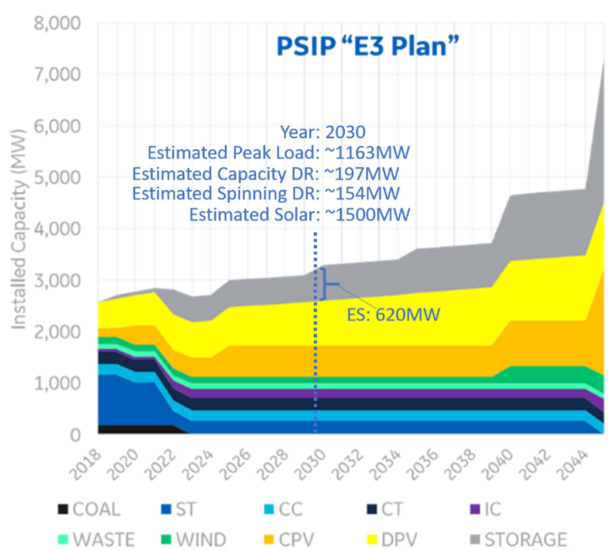

Fig. 2 Illustration on PSIP E3 Plan

B. ES Operation Optimization

Fig. 3 demonstrates how ES is scheduled to maximize the potential minimum margin, in which the ES is assumed to have (620×4hr) MWh energy rating and is optimized within one day. The solid lines are the margins before and after the ES is integrated, while the dotted line is the ES operation (negative: discharging; positive: charging). One can observe that the minimum margin is increased with optimal scheduling of the ES.

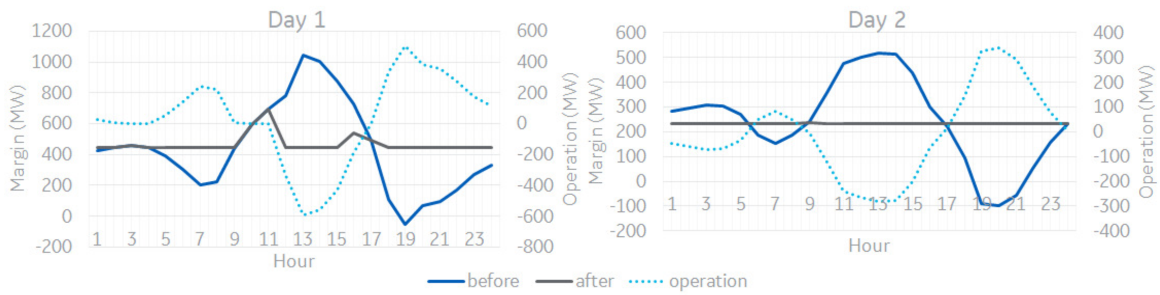

Fig. 3 Illustration on the ES Operation Optimization

C. Resource-adequacy Impact of ES

To study the resource-adequacy impact of ES, the system LOLE is assessed under different scenarios, as illustrated in Fig. 4, based on these assumptions: 1) the ES is optimized within one day; 2) by the end of each day, at least 10% of the energy should remain, in case of emergency. Four scenarios are studied: *Scenario1* assumes no ES in the system; *Scenario2* models the ES as sixty-two 10MW traditional capacity units with an assumed outage rate, but without energy limits; *Scenario3* optimizes the ES to minimize the system risk, and tests various energy ratings (620MW with 2hr, 2.5hr, 4hr 8hr, 12hr & 20hr); and *Scenario4* operates the ES (620MW×4h) to minimize the system production cost (as opposed to resource-adequacy objective), and is conducted through production cost simulations.

It is observed that: 1) the resource-adequacy impact of ES is different from that of conventional units; 2) when scheduled to minimize the system cost, ES can also improve resource adequacy, although not to the extent that it does when optimized to raise the min-margin; 3) ES tends to reduce the system LOLE more with higher energy ratings (MWh), but with decreasing marginal benefit.

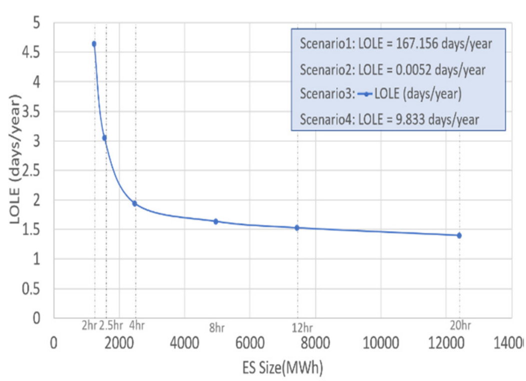

Fig. 4 System LOLE under Different Scenarios

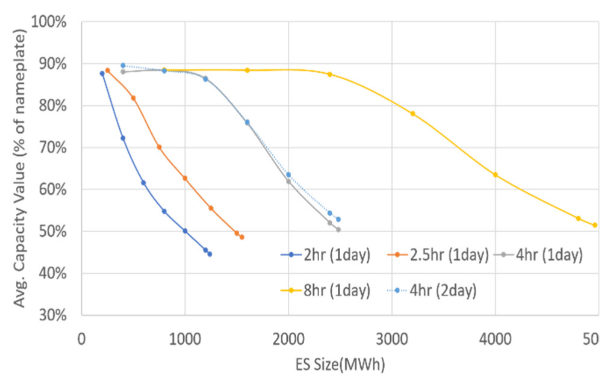

Fig 5. CV of ES

Fig. 5 illustrates the CV of ES, as scheduled to minimize the system risk for different energy ratings (1day - ES optimized within one-day horizon; 2day - ES optimized with two-day horizon and one-day rolling ahead; the ES capacity rating (MW) is selected to be in 100MW intervals; 2hr means the ES can discharge at its maximum power capacity for 2 hours when fully charged, and so on.). The CV of the ES in *Scenario4* is around 38%, which is lower than the 4hr ES in *Scenario3*. It can be concluded from Fig. 5 that: 1) while P_{ELCC} defined in equation (1) increases, CV decreases when ES capacity rating increases, which indicates a clear "saturation" effect; 2) the longer the ES can discharge at its maximum capacity rating (MW) when fully charged, the larger CV it has, and the later the “saturation” effect may occur.

Two factors mainly contribute to this “saturation” effect:

1) the energy-limited nature of ES: as shown in Fig. 6, each subsequent increase in the minimum margin by 100MW requires much more ES energy. The decreased capacity improvement starts to occur once the energy requirement cannot be met, which explains why ES with larger energy ratings (MWh) starts to saturate later;

2) the shape of the margin: since ES must first charge then discharge, the optimal margin would become a flat line, and cannot improve once ES becomes large enough, as shown in Fig. 6, and also in Fig. 4 (Day 2). The second factor implies that the extent to which ES can help resource adequacy can be affected by the solar generation in the system, which may greatly change the margin shape and provide more charging energy for ES, as illustrated in Fig. 6.

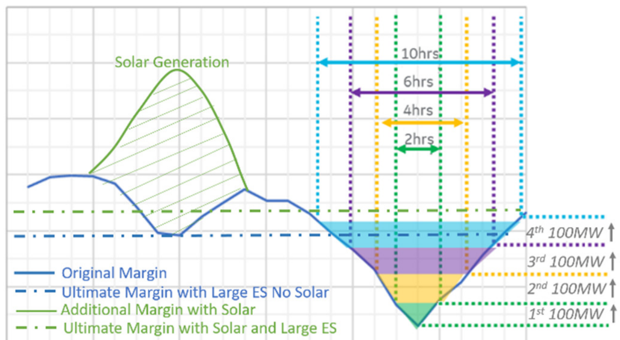

Fig. 6 Reasons for “Saturation” Effect

Solar generation’s impact on the resource-adequacy contribution of ES is further validated in our study, in the observable system LOLE with various solar and ES combinations, as shown in Fig. 7. This study investigates how much solar and ES would be needed to bring the system LOLE down below the target (HECO’s reliability criteria of 0.22 days per year), which can be achieved by adding 115MW internal combustion engine capacity.

The results in Fig. 7 show that: 1) the marginal resource-adequacy benefit from adding more ES is decreasing (close to 0 when the ES becomes large) when solar installation is fixed; 2) the system LOLE is improved with the same ES installation but more solar installed; 3) the capability of shifting energy among different days becomes more important with larger solar and battery installations, since energy charged on sunny days can be reserved to help on cloudy days when there is not enough charging energy for ES. In the base case with 4hr ES and no extra solar, the LOLE is around 1.9 days/year and 1.5 days/year with 1-day and 2-day optimization. The CVs also correspond under those two scenarios, as observed in Fig. 6. However, Fig. 7 shows substantial improvement in LOLE with a 2-day optimization, when more solar and ES are assumed to be installed); 4) with the same amount of solar, ES with larger energy capacity gets lower LOLE.

The result of Fig. 7 also implies that solar plus ES resources are interdependent: large ES without solar may lack shifting energy and hence has limited ability to improve resource adequacy; without ES, solar generation may not be able to help during peak load hours after the sun-set. However, the ability for solar and ES to replace conventional generation capacity from a resource-adequacy perspective is limited due to the “saturation” effect of energy limited resources. As solar and ES penetration increases multi-day ES shifting and solar forecasting becomes critical to maintain resource adequacy.

V. Conclusion and Future Work

This paper investigates the resource-adequacy impact of ES on the power grid, with ES scheduled to minimize the system risk. From this study, it can be concluded that: 1) the resource-adequacy impact of ES is different from conventional generation; 2) the energy rating (MWh) of ES is critical to its resource-adequacy contribution; 3) when ES optimized to minimize the system production cost, it also contributes to the resource adequacy, though not to the same extent as when it is scheduled to minimize system risk; 4) the "saturation" effect may occur when the ES pentration increases and the capability of moving energy among different days (optimize the ES operation within multiple days) will become more important; 5) adding more solar can help further improve the resource-adequacy contribution of ES, and solar plus ES is an effective combination to improve the resource adequacy.

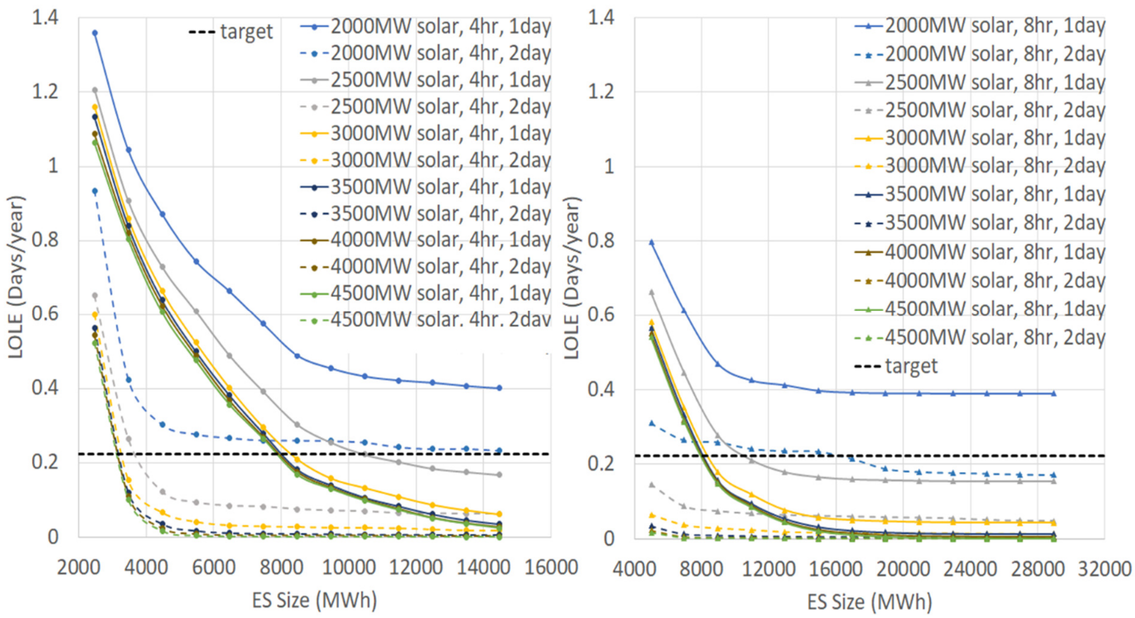

Fig. 7 LOLE (Days/year) under Various Solar & ES Scenarios

Potential future work can lie in optimizing the ES schedule within more than two days, so that energy usage can be better scheduled. In addition, the work in this paper assumes perfect renewable forecast. The impact of the forecast error on the resource-adequacy contribution of ES can also be further explored in future work, to better understand the uncertainty in renewable resources and potential errors in storage scheduling.

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