Load-shedding probabilities with hybrid renewable power generation and energy storage

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Abstract—The integration of renewable energy resources, such as solar and wind power, into the electric grid presents challenges partly due to the intermittency in the power output. These difficulties can be alleviated by effectively utilizing energy storage. We consider, as a case study, the integration of renewable resources into the electric power generation portfolio of an island off the coast of Southern California, Santa Catalina Island, and investigate the feasibility of replacing diesel generation entirely with solar photovoltaics (PV) and wind turbines, supplemented with energy storage. We use a simple storage model alongside a combination of renewables and varying load-shedding characterizations to determine the appropriate area of PV cells, number of wind turbines, and energy storage capacity needed to stay below a certain threshold probability for load-shedding over a pre-specified period of time and long-term expected fraction of time at load-shedding.

I. INTRODUCTION

Santa Catalina Island is 26 miles off the coast of Southern California, USA. It is 21 miles long and 76 square miles in area with 54 miles of coastline. The island’s population in the 2000 census was 3,696 with 90 percent living in the two largest cities Avalon and Two Harbors [1]. Catalina is served by three 12kV distribution circuits that are separate from the grid on the mainland of California with a peak demand in 2008 of 5.7MW [2]. Currently, electricity is generated from a central diesel plant. It is desirable to reduce diesel-based generation for several reasons (both environmental and economical): to reduce the emissions from diesel power plants and to eliminate the cost of transportation of diesel fuel to the island. Furthermore, the diesel generators are most efficient when running at full capacity and are therefore inefficient for Santa Catalina Island, where the daily demand peaks for a relatively short period of time. This paper aims to assess the feasibility of replacing diesel generation with generation from intermittent renewable resources (e.g., solar, wave, and wind power generation).

Fluctuation in both the generation and demand as well as physical distance between generation sites and users make the integration of renewable sources into the electricity grid difficult [3], [4]. The potential benefits, however, can be utilized by supplementing the system with energy storage [5], [6]. Different techniques have been used in determining the correct sizing for storage needed in the presence of intermittent renewable sources as a function of storage efficiency, conventional fossil fuel generation and life cycle costs [7], [8], [9]. Reference [10] uses a probabilistic model to predict the feasibility of increased renewable penetration by investigating different types, sizes, and time scales of storage technologies. References [11] and [12] examine the integration of wind power into isolated systems, similar to Catalina Island.

In this paper, we incorporate simple storage dynamics into a load-shedding model to understand the effects of intermittency in generation and/or demand on the characteristics of the electricity network. We consider a scenario where the electricity is supplied by a combination of solar photovoltaic (PV) cells, wind turbines, and base diesel generation. With these resources, we address the following design questions: Given information about typical demand and generation profiles over certain periods of time, what are the appropriate amounts of each resource and energy storage capacity needed to ensure a certain level of reliable operation [13], e.g., that the probability of load-shedding is smaller than a pre-specified threshold and the long-term expected fraction of time spent at load-shedding is sufficiently small?

II. SET UP AND PROBLEM FORMULATION

A. Simple storage model

Consider the configuration in Figure 1. In this figure and hereafter, \( d(t) \) denotes the total amount of all loads over the time period \([t, t+1]\). Additionally, \( s(t), w(t), \) and \( f(t) \) denote the amount of energy generation by a unit area of PV cells, a wind turbine, and diesel (fossil fuel) based generators over \([t, t+1]\). The amount of energy storage at time \( t \) is denoted by \( b(t) \) and is considered to follow the first order difference equation:

\[
\dot{b}(t) = s(t) - w(t) - f(t) - d(t)
\]

The amount of energy storage at time \( t \) is denoted by \( b(t) \) and is considered to follow the first order difference equation.
equation

\[ b(t + 1) = b(t) + g(t) - d(t), \quad \text{for } t = 0, \ldots, T - 1 \]

with the initial amount \( b(0) \) of storage and the length \( T \) of the time horizon. Total generation \( g(t) \) is defined as

\[ g(t) := \gamma_s s(t) + \gamma_w w(t) + f(t), \]

where \( \gamma_s \) and \( \gamma_w \) are the numbers of unit area of PV cells and wind turbines in the system. Additionally, the following non-negativity and capacity constraints on the amount of storage are imposed

\[ 0 \leq b(t) \leq B, \quad \text{for } t = 1, \ldots, T, \]

where \( B \) denotes the storage capacity.

At time \( t + 1 \), we call the case in which the difference between demand and total generation is strictly less than the available stored energy, i.e.,

\[ b(t) < -g(t) + d(t), \tag{2} \]

as load-shedding.

**B. Problem description**

In general, the load \( d \) and renewable generation \( s \) and \( w \) feature intermittency and fluctuations [10]. For example, consider the daily \( d \), \( s \), and \( w \) profiles shown in Figure 2, which are also used in the analysis in the subsequent sections. Each of the figures show \( d \), \( s \), and \( w \) at each hour for 31 days in the month December 2009 obtained at geographical locations with characteristics similar to those of Santa Catalina Island (discussed at the end of this section). The load and solar graphs follow a profile with considerable fluctuations, while the wind profile is even less predictable.

In the face of stochasticity in both loads and generation, we are interested in quantifying the probability of having load-shedding and the effects of energy storage on this probability in configurations with different levels of intermittent renewable and diesel-based generation. Note that, in general, the likelihood of load-shedding is a function of the generation and demand profiles and, therefore, it is a function of \( \gamma_s \), \( \gamma_w \), and \( B \) (potentially along with other factors not modeled here). The total area of PV cells, number of wind turbines, and capacity of storage are design-time decisions to be made before investing in the deployment of large renewable energy generation and accompanying energy storage. In the following, we consider the question of determining appropriate values for \( \gamma_s \), \( \gamma_w \), and \( B \) that lead to an acceptable probability of load-shedding.

**C. Description of data set**

In this study, we use a data set including load \( (d) \), solar generation \( (s) \), and wind generation \( (w) \) obtained in the following way.

- **Load profile:** Only peak demand values are available for Santa Catalina Island\(^1\). Therefore, load profiles are generated from a proxy distribution circuit statistically similar to that for the island, e.g., line distances, customer count, and climate. The proxy circuit peak is scaled to match the peak data for each of the three distribution circuits on the island. Hourly averages calculated for times where more than one data point was available, while data for missing hours are interpolated.

- **Solar generation profile:** Hourly data are obtained using the Solar Advisor Model (a detailed performance model for solar technologies - available at [https://www.nrel.gov/analysis/sam/](https://www.nrel.gov/analysis/sam/)) with Long Beach, California as a geographic location and each PV cell unit measuring 35 m\(^2\).

- **Wind generation profile:** Hourly data is obtained from the National Renewable Energy Laboratory (NREL) website available at [http://wind.nrel.gov/Web.nrel/](http://wind.nrel.gov/Web.nrel/) for a station located off an island near Santa Barbara, California.

**III. PROBABILITY OF LOAD-SHEDDING**

In this section, we investigate the effects of varying amounts of renewable generation (i.e., \( \gamma_s \) and \( \gamma_w \)) and storage capacity \( B \) on the probability of load-shedding over the time horizon \( t = 1, \ldots, T \) defined as

\[ P_{LS} := \text{Prob}\{b(t) < -g(t) + d(t) \text{ for some } t \in \{0, 1, \ldots, T - 1\} \}. \]

**A. Estimating the probability of load-shedding**

In order to estimate the load-shedding probability, we quantize the allowable range \([0, B]\) of energy storage using \( n \) equally spaced points \( \beta_1 = B > \beta_2 > \cdots > \beta_{n-1} > \beta_n = 0 \) and

\[ P_{LS} := \text{Prob}\{b(t) < -g(t) + d(t) \text{ for some } t \in \{0, 1, \ldots, T - 1\} \}. \]

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assigning \( \beta_{n+1} \) as the state corresponding to load-shedding. For \( i, j = 1, \ldots, n+1 \) and time \( t = 0, \ldots, T-1 \), define

\[
M_{i,j}(t) := \text{Prob}[b(t+1) = \beta_j \mid b(t) = \beta_i]
\]
as the probability of having a storage level of \( \beta_i \) at time \( t+1 \) given that the storage level \( B \) is \( \beta_j \) at time \( t \). Using the data shown in Figure 2, we empirically estimate \( M_{i,j}(t) \) for \( t = 0, \ldots, T-1 \) as follows. Define the intervals

\[
I_1 := [\beta_1 = B, \infty),
I_i := [\beta_1, \beta_{i-1}), \quad \text{for } i = 2, \ldots, n,
I_{n+1} := (-\infty, \beta_n = 0).
\]

Then, for \( t = 0, \ldots, T-1, j = 1, \ldots, n, \) and \( i = 1, \ldots, n+1 \), an empirical estimate of \( M_{i,j}(t) \) is the fraction of points in the set of data points \( \beta_j + g(t) - d(t) \) that fall in \( I_i \), with the convention \( M_{n+1,n+1}(t) = 1 \) and \( M_{i,i+1}(t) = 0 \) for \( i = 1, \ldots, n \).

Note that \( \beta_{n+1} \) is an absorbing state of the Markov chain governed by the matrix \( M(t) \) [14].

Define

\[
M := M(T-1)M(T-2) \ldots M(0).
\]

Then, the probability

\[
\text{Prob}[b(t) < -g(t) + d(t)]
\]
for some \( t \in \{0, \ldots, T-1\} \mid b(0) = \beta_j \]
of transitioning to the load-shedding state \( \beta_{n+1} \) at some time \( t = 1, \ldots, T \) from \( b(0) = \beta_j \) is estimated by \( M_{n+1,j} \).

### B. Results

In this section, we discuss the results obtained for \( T = 24 \) hours and storage capacity \( B = 20 \) MWh using the hourly load, solar generation, and wind generation profiles in Figure 2. A quantization increment of \( \beta_{j-1} - \beta_j = 100 \) kWh for \( i = 2, \ldots, n \) over \([0, B]\) is used.

Figure 4 shows the load-shedding probabilities versus initial storage levels for different levels of solar generation with \( \gamma_2 = 1 \) (i.e., a single wind turbine), and without any base diesel generation (i.e., \( w(t) = 0 \) and \( f(t) = 0 \) for \( t = [0, T] \)). Note the transition from high \( P_{LS} \) at low levels of initial energy storage to low \( P_{LS} \) at higher levels of initial energy storage. There are at least two trends in Figure 4 that are of interest.

- As the level of solar generation increases, (i.e., \( \gamma_1 \) increases), the amount of initial storage at which the transition from high \( P_{LS} \) to low \( P_{LS} \) decreases and approaches a constant value which can be attributed to the mismatch between the generation and demand at the beginning of the day due to lack of any solar generation.
- As \( \gamma_1 \) increases, the transition from high \( P_{LS} \) to low \( P_{LS} \) sharpens. This can be attributed to the higher variability in wind generation compared to that in solar generation (see Figure 2).

Figure 5 shows the load-shedding probabilities versus initial amount of storage with a fixed level of solar generation \( \gamma_1 = 2 \times 10^3 \) for different number \( \gamma_2 \) of wind turbines. Similar to the trend with increasing \( \gamma_1 \) in Figure 4, the level of initial storage at which the transition from high \( P_{LS} \) to low \( P_{LS} \) occurs decreases with increasing \( \gamma_2 \). Unlike the trends for increasing \( \gamma_1 \), \( P_{LS} \) can be made less than one even for zero initial storage with sufficiently large \( \gamma_2 \) (e.g., \( \gamma_2 = 5 \) in Figure 5).

In the results shown in Figures 4 and 5, the base diesel generation is considered to be zero. We now include base generation and investigate the probability of load-shedding as a function of the level of penetration of renewable energy resources. Assuming that the base generation \( P_B \) is constant over time, we define the penetration ratio \( \rho \) as

\[
\rho := \frac{P_B}{P_R + P_B},
\]
where \( P_R \) is the largest value of renewable generation over a pre-specified time window of interest. For ease of presentation, we consider that solar generation is the only renewable resource, and take \( P_R \) as \( \gamma_1 \) times the largest value of solar generation in the data set shown in Figure 2 (middle). Then, \( \rho \) is a function of \( \gamma_1 \) and \( P_B \). Figure 5 shows \( P_{LS} \) versus initial
amount of storage with $\gamma_2 = 0$ for different penetration levels $\rho$.

IV. LONG-TERM DURATION OF LOAD-SHEDDING AND ENERGY NOT-SERVED

The simple load-shedding characterization discussed in Section III does not distinguish between levels of load-shedding by using a single lumped state $\beta_{n+1}$ corresponding to the condition $b(t) < -g(t) + d(t)$. In this section, we modify the load-shedding characterization to allow multiple levels of deficit $d(t) - g(t) - b(t)$. This characterization allows us to estimate the (long-term) expected time spent at a load-shedding state and expected amount of energy not-served. To this end, let $\beta_1 = B > \beta_2 > \cdots > \beta_{n-1} > \beta_n = 0$ be equally spaced points over $[0, B]$ as before and $\beta_{n+1}, \ldots, \beta_{n+m}$ be such that $\beta_n = 0 > \beta_{n+1} > \cdots > \beta_{n+m}$. Consider that the amount of energy storage evolves by following the difference equations

$$b(t + 1) = b(t) + g(t) - d(t) \text{ if } b(t) \geq 0$$
$$b(t + 1) = b(t) + g(t) \text{ if } b(t) < 0$$

with saturation at $\beta_{n+m}$ and $B$. Figure 7 depicts the transitions for three different values of “storage” at time $t$.

Note that, in (3), a negative value for $b(t)$ is used to quantify the severity of load-shedding and $\beta_{n+1}, \ldots, \beta_{n+m} < 0$ correspond to different levels of load-shedding. With potential abuse of terminology, we do not distinguish between $b(t) \geq 0$ and $b(t) < 0$ and refer to both as the amount of storage. The transitions from storage levels $\beta_j \geq 0$ and $\beta_j < 0$ are different. If the storage level $b(t) = \beta_j < 0$, then generated energy is used to reduce the severity of load-shedding.

We again empirically estimate the probability $M_{i,j}(t)$ of having $b(t+1) = \beta_i$ given that $b(t) = \beta_j$ for $t = 0, \ldots, T - 1$. To this end, define

$$I_1 := [\beta_1 = B, \infty),$$
$$I_i := [\beta_i, \beta_{i-1}), \quad i = 2, \ldots, n+m-1,$$
$$I_{n+m} := (-\infty, \beta_{n+m-1}).$$

Then, an empirical estimate of $M_{i,j}(t)$ is the fraction of points in the set of points

- $\beta_j + g(t) - d(t)$ that fall in $I_i$ for $i = 1, \ldots, n+m$ and $j = 1, \ldots, n$
- $\beta_j + g(t)$ that fall in $I_i$ for $i = 1, \ldots, n+m$ and $j = n+1, \ldots, n+m$.

Define

$$M := M(T-1)M(T-2)\cdots M(0).$$

In the case where $M$ has a unique eigenvalue at 1 with $M\pi = \pi$, $\pi_i \geq 0$ for $i = 1, \ldots, n+m$ and $\pi_1 + \cdots + \pi_{n+m} = 1$, $\pi$ is called the stationary distribution for the Markov chain induced by $M$ and the $i$-th entry $\pi_i$ of $\pi$ can be interpreted as the long-term expected fraction of time $b(t)$ spends at state $\beta_i$ (regardless of the initial conditions) at times $t = 0, T, 2T, \ldots$. 

Fig. 6. The probability of load-shedding versus initial amount of storage with $B = 20$ MWh and $\gamma_2 = 0$ for different penetration levels $\rho$. $\gamma_1 = 10^2$ (solid curves), $\gamma_1 = 10^3$ (dashed curves), $\gamma_1 = 10^4$ (solid curves with square markers).

Fig. 7. Transitions governed by (3) for three different values of storage at time $t$. 

Fig. 5. Probability of load-shedding versus amount of initial energy storage with $B = 20$ MWh, $T = 24$ hours, and fixed $\gamma_1 = 2 \cdot 10^3$ for different values of $\gamma_2$ (i.e., number of wind turbines).
The long-term expected fraction of time spent at a load-shedding state as a function of solar \( \gamma_1 \) and \( \gamma_2 \) for a storage capacities of \( B = 3 \) MWh (solid) and \( B = 10 \) MWh (dash-dot).

This final observation suggests that the amount of storage capacity will affect the tolerable level of penetration of renewable generation.

V. EFFECTS OF STORAGE EFFICIENCY

Let us re-write the evolution of the amount of storage as

\[
b(t + 1) = b(t) + e(t), \quad t = 0, \ldots, T - 1, \tag{4}
\]

where \( e(t) \) denotes the amount of energy flow into the storage over \([t, t+1]\) if \( e(t) \geq 0\) and the amount of energy flow out from the storage if \( e(t) \leq 0\). Let \( 0 < \varepsilon_2 \leq 1 \) denote the efficiency of energy in-flow and \( 0 < \varepsilon_1 \leq 1 \) the efficiency of energy out-flow. In order to investigate the effects of the efficiency of charging and discharging, let us modify (4) as

\[
b(t + 1) = b(t) + \min \left\{ \varepsilon_1 e(t), \frac{1}{\varepsilon_2} e(t) \right\}. \tag{5}
\]

Define the overall efficiency of storage as \( \varepsilon := \varepsilon_2 \varepsilon_1 \). Figure 11 shows the probability of load-shedding over 24 hours versus
amount of initial storage with $B = 20$ MWh, $\gamma_1 = 10^4$, $\gamma_2 = 1$, and $T = 24$ hours for varying values of $\varepsilon$ where $\varepsilon_i = \varepsilon_o = \sqrt{\varepsilon}$ (obtained by repeating the analysis of section III.A with the dynamics in (5)). Note that the amount of initial storage at which the transition in the probability of load-shedding from high to low values happens increases with decreasing efficiency.

Figure 12 shows the effect of variations in storage efficiency on the long-term expected fraction of time spent at a load-shedding state as a function of $\gamma_2$ for fixed $\gamma_1 = 10^4$ and $B = 3$ MWh. A similar trend is observed for increasing $\gamma_1$ with fixed $\gamma_2$. Note that, for fixed $\gamma_1$, $\gamma_2$, and $B$, a decrease in the storage efficiency leads to an increase in the expected fraction of time at load-shedding.

VI. DISCUSSION

We now discuss how the results presented in the previous section can be translated into design choices. To this end, consider the four configurations corresponding to the crosses in Figure 13 for fixed storage capacity $B = 20$ MWh. Table I shows the area of PV cells and number of wind turbines needed to guarantee specified levels of long-term expected fraction of time at load-shedding. Finally Table II provides the volume of three different storage systems that are capable of supplying $B = 20$ MWh.

![Figure 11](image1.png) Probability of load-shedding versus amount of initial storage with $B = 20$ MWh, $\gamma_1 = 10^4$, $\gamma_2 = 1$, and $T = 24$ hours for varying values of $\varepsilon$.

![Figure 12](image2.png) The effect of varying efficiency $\varepsilon$ of storage as a function of $\gamma_2$ on the long-term expected fraction of time spent at a load-shedding state for fixed values of $\gamma_1 = 10^4$ and $B = 3$ MWh.

![Figure 13](image3.png) The long-term expected fraction of time spent at a load-shedding state as a function of $\gamma_1$ and $\gamma_2$ for a fixed value of storage capacity $B = 20$ MWh.

TABLE I

<table>
<thead>
<tr>
<th>$\gamma_1$</th>
<th>$\gamma_2$</th>
<th>$B$ (MWh)</th>
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</thead>
<tbody>
<tr>
<td>$10^4$</td>
<td>$1$</td>
<td>$3$</td>
</tr>
<tr>
<td>$10^4$</td>
<td>$1$</td>
<td>$20$</td>
</tr>
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</table>

TABLE II

<table>
<thead>
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<th>Type of storage</th>
<th>Energy density $[\text{kWh/m}^3]$</th>
<th>Volume $[\text{m}^3]$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pumped-hydro</td>
<td>0.28</td>
<td>$\sim 5 \times 117 \times 117$</td>
</tr>
<tr>
<td>(100kft of altitude)</td>
<td></td>
<td>$\sim 41 \times 41 \times 41$</td>
</tr>
<tr>
<td>Compressed air</td>
<td>4.17</td>
<td>$\sim 4.1 \times 4.1 \times 4.1$</td>
</tr>
<tr>
<td>Lithium-ion battery</td>
<td>300</td>
<td>$\sim 4.1 \times 4.1 \times 4.1$</td>
</tr>
</tbody>
</table>

VII. CONCLUSIONS AND FUTURE WORK

Motivated by the challenges associated with integration of renewable energy resources in to the electric grid due to source intermittency, we considered a case study on an island off the coast of Southern California, Santa Catalina Island, and investigated the feasibility of replacing diesel generation entirely with solar photovoltaics (PV) and wind turbines, supplemented with energy storage. We used a simple storage model alongside a combination of renewables and varying load-shedding characterizations to determine the appropriate number of PV cells, wind turbines, and energy storage capacity necessary to remain below a certain threshold probability for load-shedding over a pre-specified
period of time and long-term expected fraction of time at load-shedding. Present work focuses on the validation the results using more complicated storage models and load-shedding characterizations as well as data with smaller time increments. Neglected in this paper, but a natural extension of this work is the incorporation of the effects of transmission and distribution.

ACKNOWLEDGEMENTS

This work is partially supported by Southern California Edison (SCE), the Boeing Corporation, and the National Science Foundation. The authors wish to thank Rui Huang for the generating the demand profiles using SAM.

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