

Determination of Storage Required to Meet Reliability Guarantees on Island-Capable Microgrids With Intermittent Sources

Joydeep Mitra, *Senior Member, IEEE*, and Mallikarjuna R. Vallem, *Member, IEEE*

Abstract—It is well known that the presence of energy storage ameliorates the reliability challenges posed by intermittent sources. However, a quantitative assessment of the exact amount of storage required to meet a reliability target or guarantee in the presence of intermittent sources is not trivial. This paper describes a practical approach to achieving this. First, an analytical approach is developed for determining the amount of storage required to meet a reliability target at a specific load point. Then the method is extended to a more complex island-capable microgrid system where initial reliability assessment and final verification of reliability guarantee are performed using sequential Monte Carlo simulation. The necessary component and system models are developed and described, and a mock military base is used to demonstrate the method. The work reported was performed under a contract from Sandia National Laboratory to determine storage need in order to provide reliability guarantee on an island-capable military microgrid, but the approach applies as well to civilian systems, both islanded and grid-connected. A method for determining an optimal storage mix is also developed.

Index Terms—Island, microgrid, reliability, reliability guarantee, storage.

I. INTRODUCTION AND MOTIVATION

IT is well known that the presence of energy storage ameliorates the reliability challenges posed by intermittent sources. It counters (to the extent of its capacity) the temporal diversity of an intermittent source, “firms” up the supply, and improves its capacity value [1]–[3]. Much of the research on countering the variability of intermittent sources with storage has focused on coordinated operation of the two resources (storage and intermittent generation) [1]–[6] and on operation of off-grid systems [7]–[10]. The latter applications can be considered as microgrid systems. Indeed, several microgrids rely on combining storage technologies with solar or wind generation, or both.

In this work, we examine the problem of sizing storage to meet reliability guarantees in island-capable microgrids. The primary motivation came from a need to supplement fuel storage on military bases with electric storage, such as batteries. This need was felt because of the rising number of casualties in transporting fuel to military bases. Although the transportation of both fuel and water to military bases involve casualties, higher numbers of casualties have been found to be associated with the transportation of fuel [11]. The work described here was intended to respond to this need, and was performed under a contract from Sandia National Laboratory (SNL). The problem was posed as that of sizing of storage required to assure specified reliability guarantees, and reliability improvements, on military bases. However, the contribution is equally useful for civilian microgrids, both islanded and grid-connected, for the following reason. Of all the benefits of microgrids, reliability is arguably one of the most compelling. It is a major consideration in cases where the cost per kW is an issue. Moreover, the ability to install distributed resources (either as storage, intermittent generation or dispatchable generation) at or near load points immediately opens up the opportunity to offer reliability-differentiated services. The approach developed in this work concomitantly addresses all these factors.

A quantitative assessment of the exact amount of storage required to meet a reliability target or guarantee in the presence of intermittent sources is not trivial. Prior work by one of the authors [12] presents an analytical method of determining the size, in terms of both power and energy capacity, to meet a reliability target at a specific load point; the present work applies and extends this method to more complex island-capable microgrid systems with intermittent resources. In such systems, with intermittent sources, storage devices, standby generators, etc., and where other factors are considered, such as maintenance of components, dependent or common mode failures, failures of generators to start, or time-dependent factors like state of charge, fairly involved methods have been found necessary [1], [13]–[16] for reliability assessment. In our work, the initial reliability assessment and final verification of reliability guarantee are performed using sequential Monte Carlo simulation, which permits modeling of such complex factors. In Sections II–IV, the method is described, the necessary component and system models are developed and described, and a mock military base, of which the schematic was developed for this purpose by SNL, is used to demonstrate the method.

Manuscript received February 29, 2012; revised April 29, 2012; accepted June 01, 2012. Date of publication August 13, 2012; date of current version October 17, 2012. The work reported in this paper was supported by Sandia National Laboratory. Paper no. TPWRS-00214-2012.

J. Mitra is with the Department of Electrical and Computer Engineering, Michigan State University, East Lansing, MI 48824-1226 USA (e-mail: mitraj@msu.edu).

M. R. Vallem is with GE Global Research, Bangalore, India (e-mail: mallikss@gmail.com).

Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/TPWRS.2012.2203831

II. DEVELOPMENT OF METHODS AND MODELS

In this section we first present the fundamental premise for sizing of storage to meet a reliability target. Then we develop appropriate reliability metrics suitable for microgrids, and describe the models and methods for determining these metrics. Finally, we show how the sizing approach is applied to this model.

A. Sizing Storage to Reliability Target

The method used here for determining the amount of storage required to meet a reliability guarantee is based on [12]. The relevant development is repeated here for the sake of completeness.

Consider a system in which the existing resources provide for supply availability A_0 . Here, *availability* implies the steady state probability that power will be served to the load [18]. Assume that of the system load there is a part P_C (where P_C is the power requirement) that is considered critical. It is intended to add sufficient storage to increase the availability of power to this critical load to A_1 . It is clear that the power capacity of the required storage unit should be at least P_C . What remains to be determined is the energy capacity.

Define the fraction α such that

$$\alpha = \frac{1 - A_1}{1 - A_0}. \quad (1)$$

This fraction α , also known as the *unavailability reduction ratio*, can be understood as follows. Suppose $A_0 = 0.9999$ and the intention is to increase the availability of power to the critical load by “an additional 9”, i.e., to $A_1 = 0.99999$; then

$$\alpha = \frac{0.00001}{0.0001} = 0.1.$$

In developing the method for determining the required energy capacity, consider the following analysis. Denote

S_F	event that the primary supply has failed;
L	event that the critical load experiences failure of power supply;
t_A	length of time for which the storage unit can support the critical load in the event of failure of the primary supply;
R	random variable representing the down time (outage duration) of the primary supply;
$f_R(r)$	probability density function of R .

Then the event L occurs when the primary supply is down for a period longer than t_A , and its probability is given by

$$\begin{aligned} P\{L\} &= P\{\{R > t_A\} \cap S_F\} \\ &= P\{R > t_A \mid S_F\} P\{S_F\} \\ &= \left(\int_{t_A}^{\infty} f_R(r) dr \right) P\{S_F\}. \end{aligned} \quad (2)$$

In (2), $P\{L\}$ is clearly $1 - A_1$ and $P\{S_F\} = 1 - A_0$. It is also clear from (1) and (2) that

$$\int_{t_A}^{\infty} f_R(r) dr = \alpha. \quad (3)$$

Equation (3) forms the basic relationship from which the required storage capacity can be determined. However, the storage device itself may have a certain probability of failure. In order to compensate for this, the storage device should have an energy capacity that enables it to provide the required power (P_C) for a period of time t_S that is given by

$$t_S = \frac{t_A}{A_S} \quad (4)$$

where t_A is given by (3) and A_S is the availability of the storage device. So the power capacity of the selected storage unit should be at least P_C , and the energy capacity should be at least $P_C t_S$.

The solution to (3) can be obtained with relative ease when the system down time R follows a known distribution. Solutions have been provided in [12] for cases where R follows exponential, Weibull and lognormal distributions, which are distributions that component down times have commonly been found to follow. However, the down times of more complex systems do not closely follow known distributions, and need to be determined by other suitable methods. Such a method is described next.

B. Reliability Metrics and Models

A microgrid is usually a distribution system or part thereof, and one of the preferred (in practice) reliability metrics in a distribution system is the customer average interruption duration index (CAIDI), which is defined as the ratio of the total duration of customer interruptions to the total number of customer interruptions [19]. It is clear that at any given load point, this directly translates to the mean down time $\bar{r}$ of the supply at that load point. In a system with intermittent sources and energy-limited sources such as backup generators (that are limited by sizes of fuel tanks and on-site fuel supply), the most convenient method of accurately determining mean down times is sequential Monte Carlo simulation (MCS) [15]–[17], [20], [21]. In fact, MCS permits modeling of several system dependencies, and provides not only the mean but the entire distribution of the down time R . Moreover, the solution to (3) can be indirectly determined from the data generated by MCS, as described in Section II-C.

Sequential MCS generates an artificial history of the system using the stochastic properties of components and random numbers. In this method, a random number is generated for every transition that can be reached from the present state, and the transition time is calculated for each such transition [17], [20]. The most imminent event, evident from the shortest of these transition times, is considered to be the next event. This procedure is repeated until the simulation converges [17], [20], i.e., the indices stabilize. The top-level algorithm used in this work is depicted in Fig. 1. This algorithm is typical of sequential Monte Carlo methods [15], [17].

We next describe the accumulation of interruption statistics, system and component models, and then the mechanism for determination of storage size.

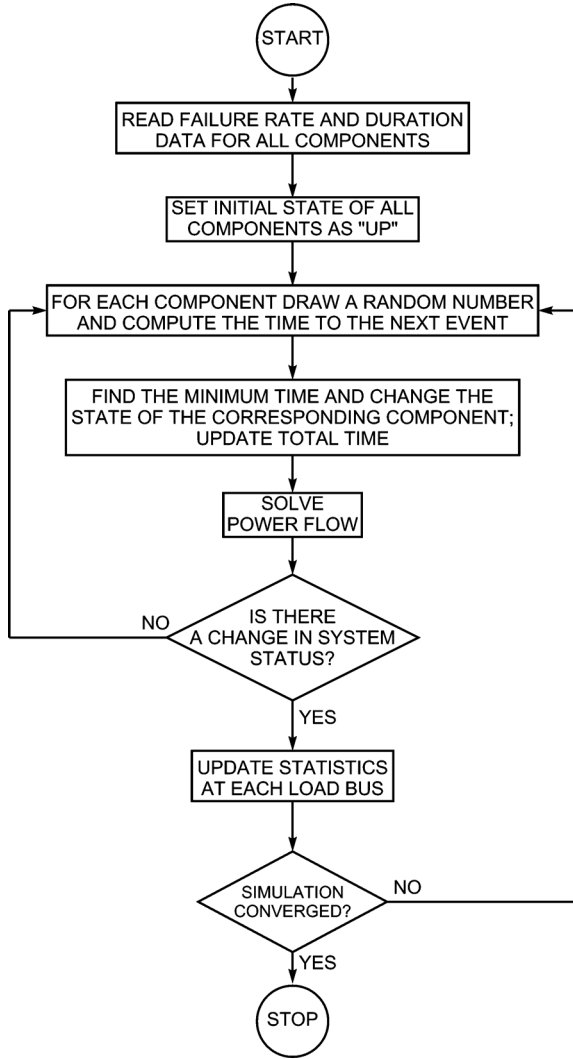


Fig. 1. Flowchart for sequential Monte Carlo simulation.

1) *Statistics From Simulation:* Interruption duration statistics [21] are collected using the sequential MCS approach described above. A hybrid sequential simulation [17] is performed: component state transitions are simulated asynchronously, by choosing the next imminent event; load and insolation states are traversed synchronously, using hourly data. This data is described later, as part of the test system data. The test system provided by SNL contained only photovoltaic (PV) panels as intermittent sources, so only insolation data was needed for this work; in the presence of other intermittent sources (such as wind), hourly resource data (such as wind speed) would be used as well.

For each hour, the system state is defined by the component states and capacities; the output of intermittent sources is determined by the corresponding component states and hourly resource data. Then a feasible dispatch is sought by solving the following optimization problem.

Minimize:

$$C_T = \left(\sum_{i=1}^{N_B} C_i \right)$$

subject to

power balance conditions;
equipment availability and capacity constraints.

C_T is the total system curtailment (i.e., power not served), C_i is the curtailed power at the i th bus, and N_B is the number of buses. The above model basically implies that for any encountered scenario (generation and feeder availability and load state) power will be routed through the network in such a manner as to minimize the system curtailment (loss of load). If the minimum C_T is zero, it implies a feasible dispatch; a positive C_T implies a loss of load, or outage state.

The power balance conditions can be modeled using an appropriate power flow model. Models in use include the transportation model, the dc flow model, and the ac flow model [22]. In this work, the transportation model [22], [23] was used, being deemed suitable due to the limited geographic extent of the military base. For other applications any of the three models deemed appropriate can be used, without affecting the validity of the method. In the transportation model, the power balance equations represent nodal power balance, and the constraints represent equipment capacities. This basically constitutes a maximal flow problem, and can be solved by any suitable method; in this work, the following linear programming (LP) formulation was used, and solved using an LP package:

$$\text{Loss of Load} = \text{Min} \left(\sum_{i=1}^{N_B} C_i \right)$$

subject to

$$\begin{aligned} \hat{A}^T F + G + C &= D \\ G &\leq G_{\max} \\ C &\leq D \\ |F| &\leq F_{\max} \end{aligned}$$

where

N_F	number of feeders;
D	N_B -dimensional vector of bus load;
$G_{\max}$	N_B -dimensional vector of generation capacity at the buses;
G	N_B -dimensional vector of dispatched generation at the buses (solution vector);
$F_{\max}$	N_F -dimensional vector of flow capacities of feeders;
F	N_F -dimensional vector of power flows in the feeders;
$\hat{A}$	$N_F \times N_B$ -dimensional element-node incidence matrix;
C	N_B -dimensional vector of bus curtailments.

The hourly curtailment data over the period simulated comprises the interruption duration statistics collected from simulation.

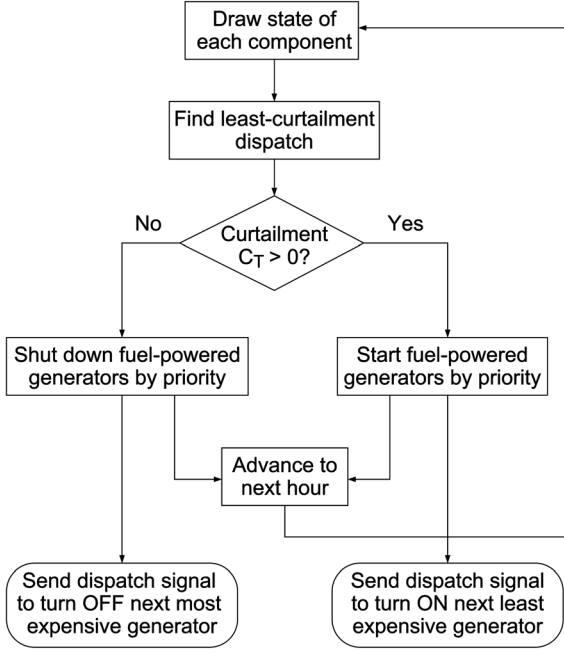


Fig. 2. Dispatch logic for fuel-powered sources.

2) *Component Models*: The use of Monte Carlo simulation permits accurate modeling of components. This work used two-state Markov models [20] for all feeders and sources; however, the approach can easily accommodate multi-state models as well as failure and repair times that follow other distributions than exponential.

The test system used was tethered to the grid at two locations, but this work assumed utility supply to be unavailable so as to simulate worst-case scenarios. For civilian systems, or for systems that normally receive grid support, utility supply is modeled as generators with given failure and repair times.

The sources within the system are dispatched with the following priority: intermittent sources are operated at their maximum output levels, determined by resource (solar or wind) availability. The remaining demand is met using fuel-powered sources (such as diesel generators), dispatching them in increasing order of generating cost. The logic for operating fuel-powered sources is shown in Fig. 2.

Fuel-powered sources and storage devices are energy limited, and an energy tracking system is used to maintain an account of the energy availability (remaining fuel or state of charge) of these components. Fuel-powered sources can provide energy as long as there is fuel in the tank; then they need to be refueled, if additional fuel is stored on-site. These sources are also subject to start-up failures and start-up delays. The logic implemented for the operation of these sources is shown in Fig. 3. This figure also shows the transitions between all three states of a fuel-powered source—up, forced outage and planned outage. The maintenance and failure rates are denoted by λ_m and λ_f , and the mean maintenance and repair times are denoted by T_m and T_f , respectively. The probability of failure of a unit to start is denoted by P_s . The values actually used in this work are provided in Section III and in Appendix. An average refueling delay of 6 h is also included in the operation logic.

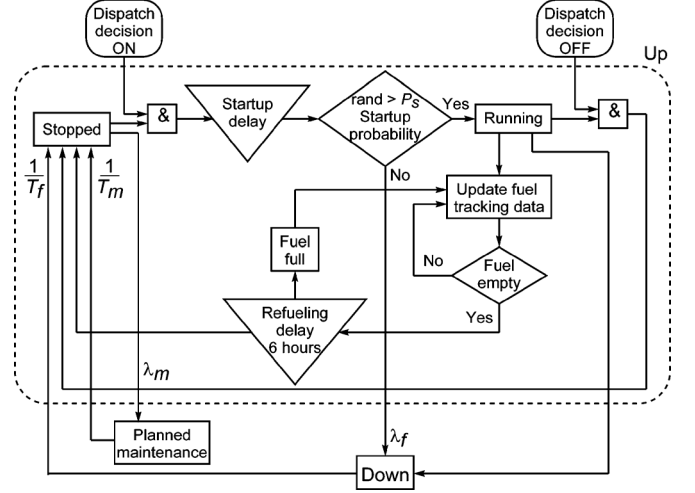


Fig. 3. Operation logic for fuel-powered sources.

C. Use of Interruption Duration Statistics for Storage Sizing

Using the models and the sequential simulation described above, an artificial history of the hourly interruption data is stored for each load bus. From this data it is possible to extract the necessary information pertaining to the down-time statistics and the length of time (t_A) for which additional storage is required at the load buses.

The estimation of interruption duration statistics is straightforward: the total outage duration at each load bus divided by the number of outages provides an estimate of the mean interruption duration $\bar{r}$ at that bus. The probability distribution functions of the interruption duration r can also be constructed from the simulation data.

The estimation of t_A from the simulation data merits discussion. As mentioned before, in view of the criticality of a military system, it is appropriate to plan for reliability targets in the absence of the grid supply. Reliability assessment of the existing system, as well as assessment of the target reliability, therefore, are made without considering the contribution of utility supply. The initial reliability is evaluated using Monte Carlo simulation, as described above. The assessment of additional storage is determined as follows.

An examination of (3) reveals that this form does not permit the direct estimation of t_A from down time statistics. However, we can use an alternative form that enables this, with acceptably small error. Consider the following postulate.

Postulate: The solution t_A of

$$\int_{t_A}^{\infty} r f_R(r) dr = \alpha \bar{r} \quad (5)$$

approximately satisfies (3).

In (5), $\bar{r}$ is the mean interruption time prior to storage augmentation, i.e., it is the expectation of the random variable R representing the down time of the primary supply. Comparing (3) and (5), we note that they are somewhat similar in form but fundamentally different; (3) is dimensionless, while (5) has the unit of time. The postulate states that the value t_A that reduces

the mean down time at a given load point from $\bar{r}$ to $\alpha\bar{r}$ also approximately reduces the unavailability at that load point from $(1 - A_0)$ to $(1 - A_1) = \alpha(1 - A_0)$. As an example, if a load point receives primary supply with availability $A_0 = 0.9999$ and mean down time $\bar{r} = 4$ h, then the amount of storage augmentation that reduces the mean down time to $\alpha\bar{r} = 0.4$ h, corresponding to $\alpha = 0.1$, will, per the above postulate, increase the availability to $A_1 \approx 0.99999$. We now prove this postulate.

Proof: We know that

$$\bar{r} = \int_0^\infty r f_R(r) dr \Rightarrow \int_0^\infty (r - \bar{r}) f_R(r) dr = 0. \quad (6)$$

If one chose a value of t_A that satisfies (3), and this value were small, then from (6) it can be stated that

$$\begin{aligned} \int_{t_A}^\infty (r - \bar{r}) f_R(r) dr &\approx 0 \\ \Rightarrow \int_{t_A}^\infty r f_R(r) dr &\approx \bar{r} \int_{t_A}^\infty f_R(r) dr \\ \Rightarrow \int_{t_A}^\infty f_R(r) dr &\approx \alpha \end{aligned} \quad (7)$$

i.e., the t_A that satisfies (5) exactly also satisfies (3), approximately. In other words, the more reliable the base system (without storage augmentation), the higher the equivalence between the two reliability targets. ■

Equation (5) can be further modified to the following form:

$$\int_0^{t_A} r f_R(r) dr = (1 - \alpha)\bar{r} \quad (8)$$

since

$$\int_0^{t_A} r f_R(r) dr = \int_0^\infty r f_R(r) dr - \int_{t_A}^\infty r f_R(r) dr = \bar{r} - \alpha\bar{r}.$$

It is straightforward to use (8) to determine t_A from the interruption duration statistics collected from sequential simulation—if the observed interruption times were sequentially stacked, then that time for which the mean of all equal and shorter interruptions is closest to $(1 - \alpha)\bar{r}$ gives the estimate of t_A . Calculating t_S in (4) is now a trivial exercise.

III. DEMONSTRATION AND VALIDATION

The methodology developed above was applied to a mock military base system, dubbed by SNL as “Base Alpha”. The schematic for Base Alpha was provided by SNL, and assumed to be in the proximity of SNL, i.e., in the service area of the Public Service Company of New Mexico (PNM). An equivalent network, shown in Fig. 4, was extracted from SNL’s schematics without loss of modeling accuracy. The system data is provided

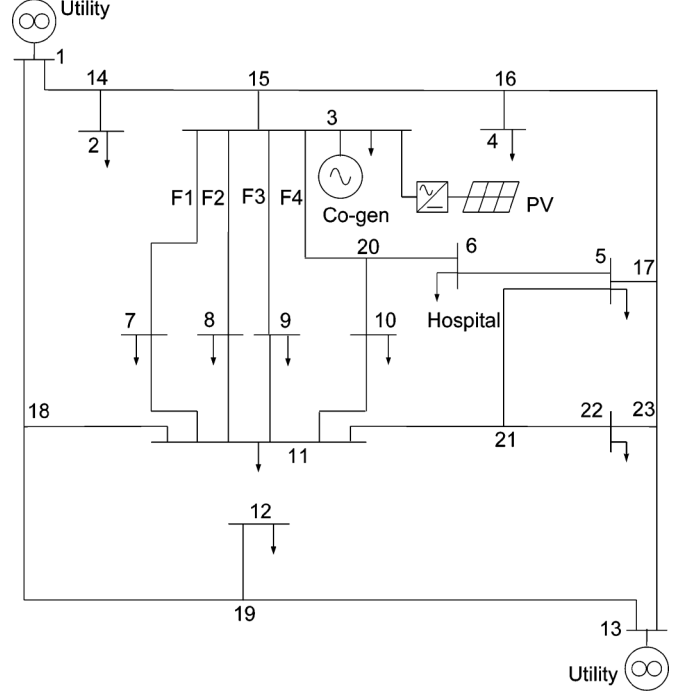


Fig. 4. Equivalent network of base alpha system.

in the Appendix. The hourly load data was developed as follows: an annual load shape was abstracted from FERC 714 filings [24] for the PNM service area, and scaled to the peak load provided for Base Alpha. Hourly insolation data for the region were obtained from public domain data available from the National Renewable Energy Laboratory (NREL) [25].

In the remainder of this section we provide more information about the data used in this study and the results obtained from applying the models and methods described in the previous section.

A. System Information

Base Alpha is a 23-bus system tethered to the utility at two locations (nodes 1 and 13). The system has 12 load buses with the bulk of the load concentrated at the center of the base. The peak load of the system is 21.45 MW and data on loads at various buses is summarized in the appendix. The system has a 1-MW photovoltaic (PV) source and a 7.2-MW gas turbine generator (GTG) at node 3. The GTG is supplied by a gas pipeline which is considered fully reliable; this means the natural gas supply to this unit is considered unlimited and reliable; the unit itself is treated as two-state Markovian. The GTG is also treated as a fully dispatchable conventional generator, unlike the other sources on the base. There are 17 diesel generators on the base; their capacity and reliability data is provided in the appendix. The system has 30 feeders; their capacity and reliability data is also provided in the Appendix.

The dispatch and operation logic for the 17 diesel units are shown in Figs. 2 and 3. Each diesel generator has a startup delay averaging 6 min. Each diesel generator also has a failure to start probability P_s of 0.15. Planned maintenance is performed once every year; this is shown in Fig. 3 as λ_m . The mean time for

TABLE I
RESULTS: CAPACITY AUGMENTATION AND RELIABILITY
IMPROVEMENT ON BASE ALPHA

Bus	LOLP without augmentation	t_A (hours)	Storage augmentation (MW)	LOLP with augmentation
2	0	0	0	0
3	0.000706	28.34	0.1885	0.0000868
4	0.000103	5.16	0.293	0.00000141
5	0.41681	16.95	4.323	0.0280723
6	0.323866	13.47	1.2	0.000998
7	0.000212	6.52	0	0
8	0.000019	14.19	0.639	0
9	0.141279	7.32	2.062	0.022622
10	0.333059	14.53	1.588	0.0236499
11	0.358185	13.38	2.466	0.0252796
12	0.121722	9.78	0.228	0.0038562
22	0.330202	14.2	1.44	0.0236543
System	0.781381	11.71	14.428	0.075569

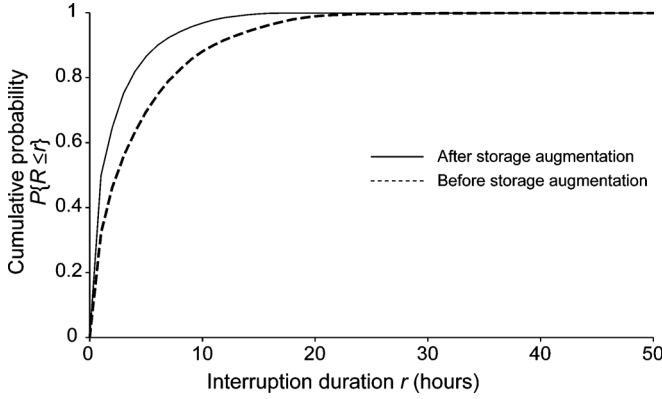


Fig. 5. Interruption duration distribution at bus 6 (hospital).

maintenance T_m is 40 h. The fuel tank capacity of each of these units is also limited. A full tank is assumed to run the unit for 10 h at the rated capacity. The mean refueling time is 6 h.

B. System Behavior and Study Results

This study applied the models and methods developed in Section II to the system described above with the objective of determining storage augmentation required to improve the reliability by “an additional 9”, i.e., to achieve an unavailability reduction ratio of $\alpha = 0.1$. Equation (8) was used to estimate t_A . Table I summarizes the results of the study. The power and energy capacity of the required storage augmentation at each load bus is apparent from these results. These results validate the approach developed in Section II.

The distributions of the interruption durations at the various buses were also constructed. Fig. 5 shows the distribution at bus 6, which is a critical bus, before and after storage augmentation. This distribution graphically illustrates the impact of the storage augmentation on interruption duration. Distributions for other buses in the system have been shown in [26].

IV. DISCUSSION AND CONCLUDING REMARKS

We have developed and presented an approach for determining the amount of storage augmentation required in an island-capable microgrid to meet specified reliability targets.

We have also demonstrated the validity of the theoretical development and the effectiveness of the method. We now discuss a variation of the case described—an optimal balance of fuel storage and battery storage if there is no reason to limit fuel transportation to and storage at a microgrid.

A. Optimization of the Storage Mix

For civilian microgrids, it is possible to achieve an optimal balance between on-site fuel storage and rechargeable (e.g., battery) storage. This is based on the following logic: in order for batteries to provide energy, they must first be charged. Hence, neglecting cycle losses, they can at serve as net-zero energy, and can be used for peak shaving and valley filling; they are not sources of energy. In order for rechargeable storage to be effective, therefore, the system must have energy generation capability that exceeds the total energy demand, or, at least, that part of the energy demand that is deemed critical. This condition was presumed in the foregoing analysis. In military microgrids, it is presumed that this condition is satisfied. In civilian microgrids, this may be imposed by satisfying the condition presented below. This is considered “optimal” because it minimizes the use of fuel, which is a consumable resource, and maximizes the use of rechargeable storage.

The power demand at bus i at hour t of the year is denoted by $D_i(t)$. The total annual energy demand E_D for the system is then given by

$$E_D = \sum_{i=1}^{N_B} \sum_{t=0}^{8760} D_i(t). \quad (9)$$

The maximum energy available from dispatchable, intermittent and fuel generators if operated at full capacity are E_{dis} , E_{int} , and E_{fuel} , respectively. Then the maximum available energy from all the sources E_{av} in the system is given by

$$E_{av} = E_{dis} + E_{int} + E_{fuel}. \quad (10)$$

The annual energy deficit in the system is

$$E_{def} = E_D - E_{av}. \quad (11)$$

A positive value of E_{def} implies that either additional generation capacity should be installed, or a certain amount of (low priority) load will have to be shed. Assume that we choose to add capacity; then the capacity that must be added is

$$P_f^{new} = \frac{E_{def}}{8760}. \quad (12)$$

In order to achieve the stipulated availability of A_1 , we have estimated that the added storage should be able to supply continuous energy for at least a period of t_S^i to bus i . The power capacity (P_C) of the storage should be equal to the maximum power demand (D_i) at that bus. The effect of this storage is to flatten the daily load curve.

The time t_S^i at bus i is estimated using (4). Then the total energy capacity required by the system is

$$E_{req}^i = D_i t_S^i. \quad (13)$$

The charging and discharging cycle of batteries is taken to be one day on an average. For this to happen there should

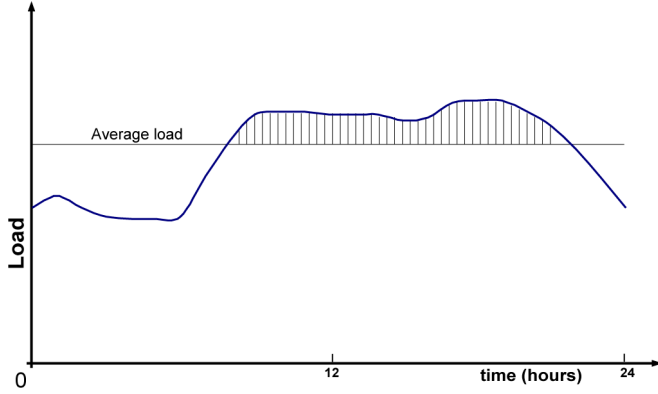


Fig. 6. Typical daily load curve.

be enough battery capacity available so as to store sufficient energy to supply the load above the daily average as shown in Fig. 6. This being a planning strategy, it is reasonable to use the average load for the day which has the largest daily load variation in the year. This battery energy capacity at bus “ i ”, E_{bat}^i , is estimated as follows:

$$E_{bat}^i = \sum_{t=1}^{24} \max(D_t - D_{avg}, 0) \quad (14)$$

where D_{avg} is the daily average power (shown by the flat line in Fig. 6).

The power capacity of the battery should equal or exceed the maximum demand at bus i . In microgrids that have large feeder capacities, transportation of energy is not a significant constraint. In such cases the total battery capacity can be lumped and deployed at critical feeders.

At each bus the capacity $E_{req}^i - E_{bat}^i$ needs to be supplied by the additional fuel storage at the generators. This analysis provides an estimate of the optimal storage mix that should be deployed at each bus in the system to achieve the stipulated reliability criterion. This estimate can be further refined by compensating for the unavailability of the new resources and the efficiency of the charge-discharge cycles of the batteries.

B. Concluding Remarks

In concluding this paper we highlight the following features of the work described above.

- 1) A method was developed to determine the amount of storage required to meet reliability targets or guarantees on island-capable microgrids with intermittent generation; the method is expected to grow increasingly useful in view of the rate at which the penetration of such microgrids is growing.
- 2) The research findings described here can potentially decrease fatalities in armed forces.
- 3) The method applies equally to military and civilian microgrids. The extension of the method to civilian microgrids is amenable to optimization of technology mix.
- 4) The method is both theoretically elegant and supported by highly conforming results.

APPENDIX SYSTEM DATA FOR BASE ALPHA

The peak bus loads and generator and feeder capacities and transition rates for the Base Alpha test system, as provided by SNL, are tabulated in Tables II–IV.

TABLE II
BASE ALPHA: BUS PEAK LOADS

Bus	Peak load (MW)	Bus	Peak load (MW)
2	0.787	8	2.166
3	0.189	9	2.071
4	0.989	10	1.588
5	4.324	11	2.466
6	1.2	12	0.228
7	4.0	22	1.441

TABLE III
BASE ALPHA: DIESEL GENERATOR CAPACITIES AND TRANSITION RATES

Bus	Capacity (MW)	Failure rate (per year)	Mean time to repair (hours)
6	1	0.434	32.7
6	1	0.434	32.7
6	1	0.434	32.7
10	0.1	0.434	32.7
10	0.2	0.434	32.7
10	0.3	0.434	32.7
12	0.5	0.434	32.7
3	1	0.434	32.7
11	0.36	0.434	32.7
11	0.25	0.434	32.7
11	0.25	0.434	32.7
7	0.2	0.434	32.7
7	0.2	0.434	32.7
7	0.3	0.434	32.7
7	0.3	0.434	32.7
7	0.55	0.434	32.7
7	0.25	0.434	32.7

TABLE IV
BASE ALPHA: FEEDER CAPACITIES AND TRANSITION RATES

From bus	To bus	Capacity (MW)	Failure rate (per year)	Mean time to repair (hours)
1	14	100	0.0059	280
14	2	11	0.0059	280
14	15	100	0.00336	16
15	16	100	0.00336	16
15	3	22	0.00197	838
16	4	11	0.0059	280
16	17	100	0.00336	16
13	19	100	0.0059	280
19	18	100	0.00336	16
19	12	11	0.0059	280
18	1	100	0.00336	16
18	11	22	0.0059	280
5	17	22	0.0059	280
6	20	11	0.0059	280
20	10	11	0.0059	280
10	11	11	0.0059	280
11	9	11	0.0059	280
11	8	11	0.0059	280
11	7	11	0.0059	280
7	3	11	0.0059	280
3	8	11	0.0059	280
3	9	11	0.0059	280
3	20	11	0.0059	280
17	23	100	0.00336	16
23	13	100	0.00336	16
23	22	22	0.00295	560
22	21	22	0.0059	280
5	21	22	0.0059	280
21	11	22	0.0059	280
6	11	11	0.0059	280

REFERENCES

- [1] J. P. Barton and D. G. Infield, "Energy storage and its use with intermittent renewable energy," *IEEE Trans. Energy Convers.*, vol. 19, no. 2, pp. 441–448, Jun. 2004.
- [2] M. Black and G. Strbac, "Value of bulk energy storage of managing wind power fluctuations," *IEEE Trans. Energy Convers.*, vol. 22, no. 1, pp. 197–215, Mar. 2007.
- [3] G. Caralis and A. Zervos, "Value of wind energy on the reliability of autonomous power systems," *IET Renew. Power Gen.*, vol. 4, no. 2, pp. 186–197, 2010.
- [4] E. D. Castronuovo and J. A. P. Lopes, "On the optimization of the daily operation of a wind-hydro power plant," *IEEE Trans. Power Syst.*, vol. 19, no. 3, pp. 1599–1606, Aug. 2004.
- [5] M. Korpaas, A. T. Holen, and R. Hildrumb, "Operation and sizing of energy storage for wind power plants in a market system," *Elect. Power Energy Syst.*, vol. 25, pp. 599–606, 2003.
- [6] B. Bagen and R. Billinton, "Incorporating well-being considerations in generating systems using energy storage," *IEEE Trans. Energy Convers.*, vol. 20, no. 1, pp. 225–230, Mar. 2005.
- [7] C. Bueno and J. A. Carta, "Technical-economic analysis of wind-powered pumped hydrostorage systems. Part I: Model development," *Solar Energy*, vol. 78, pp. 382–395, 2005.
- [8] C. Bueno and J. A. Carta, "Technical-economic analysis of wind-powered pumped hydrostorage systems. Part II: Model application to the island of El Hierro," *Solar Energy*, vol. 78, pp. 396–405, 2005.
- [9] D. A. Katsaprakakis, D. G. Christakis, A. Zervos, D. Papantonis, and S. Voutsinas, "Pumped storage systems introduction in isolated power production systems," *Renew. Energy*, vol. 33, pp. 467–490, 2008.
- [10] J. K. Kaldellis, M. Kapsali, and K. A. Kavadias, "Energy balance analysis of wind-based pumped hydro storage systems in remote island electrical networks," *Appl. Energy*, vol. 87, pp. 2427–2437, 2010.
- [11] Sustain the Mission Project: Casualty Factors for Fuel and Water Resupply Convoys, Army Environmental Policy Institute, Arlington, VA, 2009, Final Report on Contract No. W74V8H-04-D-0005, Task No. 0545.
- [12] J. Mitra, "Reliability-based sizing of backup storage," *IEEE Trans. Power Syst.*, vol. 25, no. 2, pp. 1198–1199, May 2010.
- [13] C. Singh and A. D. Patton, "Reliability evaluation of emergency and standby power systems," *IEEE Trans. Ind. Appl.*, vol. 21, no. 2, pp. 476–480, Mar./Apr. 1985.
- [14] A. Pievatolo, E. Tironi, and I. Valade, "Semi-Markov processes for power system reliability assessment with application to uninterruptible power supply," *IEEE Trans. Power Syst.*, vol. 19, no. 3, pp. 1326–1333, Aug. 2004.
- [15] C. Singh and J. Mitra, "Reliability analysis of emergency and standby power systems," *IEEE Ind. Appl. Soc. Mag.*, vol. 3, no. 5, pp. 41–47, Sep./Oct. 1997.
- [16] D. Aming, A. Rajapakse, T. Molinski, and E. Innes, "A technique for evaluating the reliability improvement due to energy storage systems," in *Proc. Canadian Conf. Electrical & Computer Engineering*, Vancouver, BC, Canada, Apr. 2007, pp. 413–416.
- [17] C. Singh and J. Mitra, "Monte Carlo simulation and intelligent search methods," in *IEEE Tutorial on Electric Delivery System Reliability Evaluation*, J. Mitra, Ed. Piscataway, NJ: IEEE, 2005, pp. 23–38.
- [18] C. E. Ebeling, *An Introduction to Reliability and Maintainability Engineering*. Long Grove, IL: Waveland Press, 1997.
- [19] IEEE Standard 1366-2003: Guide for Electric Power Distribution Reliability Indices, Piscataway, NJ, 2003, IEEE Std. 1366 working group.
- [20] C. Singh and R. Billinton, *System Reliability Modeling and Evaluation*. London, U.K.: Hutchinson Educational, 1977.
- [21] A. M. L. da Silva, W. F. Schmitt, A. M. Cassula, and C. E. Sacramento, "Analytical and Monte Carlo approaches to evaluate probability distributions of interruption duration," *IEEE Trans. Power Syst.*, vol. 20, no. 3, pp. 1341–1348, Aug. 2005.
- [22] Composite System Reliability Evaluation Methods Electric Power Research Institute, Palo Alto, CA, 1987, Final Report on Research Project 2473-10, EPRI EL-5178.
- [23] M. F. Carvalho, S. Soares, and T. Ohishi, "Optimal active power dispatch by network flow approach," *IEEE Trans. Power Syst.*, vol. 3, no. 4, pp. 1640–1647, Nov. 1988.
- [24] Federal Energy Regulatory Commission Website. [Online]. Available: <http://www.ferc.gov/>.
- [25] National Renewable Energy Laboratories Website. [Online]. Available: <http://www.nrel.gov/>.
- [26] J. Mitra, "Storage Optimization in a Microgrid," Final Report on Sandia National Laboratory Contract No. 481406, New Mexico State Univ., Las Cruces, NM, Nov. 2007.

Joydeep Mitra (S'94–M'97–SM'02) received the B.Tech. (Hons.) degree in electrical engineering from the Indian Institute of Technology, Kharagpur, and the Ph.D. degree in electrical engineering from Texas A&M University, College Station.

He is an Associate Professor of electrical engineering at Michigan State University, East Lansing. His research interests include power system reliability, distributed energy resources, and power system planning.

Mallikarjuna R. Vallem (S'03–M'09) received the B.Tech. (Hons.) degree in electrical engineering from the Indian Institute of Technology, Kharagpur, and the Ph.D. degree in electrical engineering from New Mexico State University, Las Cruces.

He is a Research Engineer with GE Global Research, Bangalore, India. His research interests are in the areas of power system reliability, distributed energy resources and system optimization.