# Distributed Energy Resource (DER) Reliability for Backup Electric Power Systems


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*1 National Renewable Energy Laboratory*
*2 Army Corps of Engineers, Power Reliability Enhancement Program*



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# List of Acronyms

| | |
|---|---|
| BESS | battery energy storage system |
| CHP | combined heat and power |
| DER | distributed energy resource |
| EDG | emergency diesel generator |
| ESTCP | Environmental Security Technology Certification Program |
| FTS | failure to start |
| MTBF | Mean Time Between Failure |
| MTBM | Mean Time Between Maintenance |
| MTTF | Mean Time to Failure |
| MTTM | Mean Time to Maintenance |
| MTTR | Mean Time to Repair |
| NREL | National Renewable Energy Laboratory |
| ORNL | Oak Ridge National Laboratory |
| PREP | Power Reliability Enhancement Program |
| PV | photovoltaic |
| RBD | reliability block diagram |

# Executive Summary

Hospitals, emergency services, military bases, ports, airports, industries, commercial facilities, and others rely on backup power systems to provide electricity for their critical loads during grid outages. The purpose of this report it to provide accurate reliability information on commonly deployed distributed energy resources (DERs) to improve quantitative estimates for the reliability of these backup power systems during a grid outage. A backup power system consists of DERs, an electric distribution system with its associated switches and other devices, and mechanisms to control and manage the flow of electricity.

Too often, facilities and campuses fail to properly quantify the reliability of their backup power systems. DERs are assumed to be 100% reliable, with the only concern being the availability of fuel. Such assumptions can lead to gross errors in the backup system's reliability estimates, particularly for long-duration outages. This report provides a set of estimates for reliability of emergency diesel generators (EDGs), natural gas prime generators and combined heat and power (CHP) prime movers, solar photovoltaics (PV), wind turbines, and Li-ion battery energy storage systems (BESS). The estimates are derived from empirical data when available and supplemented by modeling results when needed. These reliability estimates are for the DER's ability to provide power during a grid outage, ranging from an hour to 2 weeks.

The estimates below are recommended as default values for the Mean Time to Failure (MTTF) during a grid outage and the operational availability ($A_o$) to estimate the likelihood a DER will be available at the start of a grid outage. $A_o$ is defined as the probability a DER will be in a state at any given time in the year in which it can operate if called upon. Sensitivity of the system-level reliability can be investigated by using a range of reliability values discussed in this report.

**Table ES- 1. Summary Recommended Default Values for DER Electric Power Reliability Metrics**

| DER | Type and Fuel | Size Restriction | MTTF (hours) | $A_o$ |
|---|---|---|---|---|
| Emergency Generator | Packaged Diesel | <4,000 kW | 1,100 | 99.5% |
| CHP Prime Movers and Prime Generator | Reciprocating Natural Gas Engine | < 800 kW | 920 | 96% |
| | | >800 kW | 2,300 | 98% |
| | Natural Gas Turbine | < 5,000 kW | 1,040 | 98% |
| | | >5,000 kW | 3,250 | 97% |
| Solar PVs | Silicon | >25 kW | 13,500 to 300,000[1] | 98% |
| Wind Turbine | Land Based | Not Applicable | 7,540 | 97% |
| BESS | Stationary Li-ion | Not Applicable | >10,000 | 97% |

The survival probability for common energy generation assets using the recommended default values assuming no fuel limitations are shown below for a 1-hour to a 2-week outage. In assessing survival probability for actual sites, fuel availability should be considered. Using the

[1] For systems with a single central inverter, the shorter MTTF is appropriate. For systems with more than one central inverter, the larger number is appropriate.

recommended values for $A_o$ and MTTF, we can calculate the survival probability for each DER component for varying outage durations. Survival probability is determined using $A_o$ to estimate the probability that the equipment will be "up" at the beginning of the outage, and MTTF to estimate the likelihood that the component will not experience a failure over the outage period.

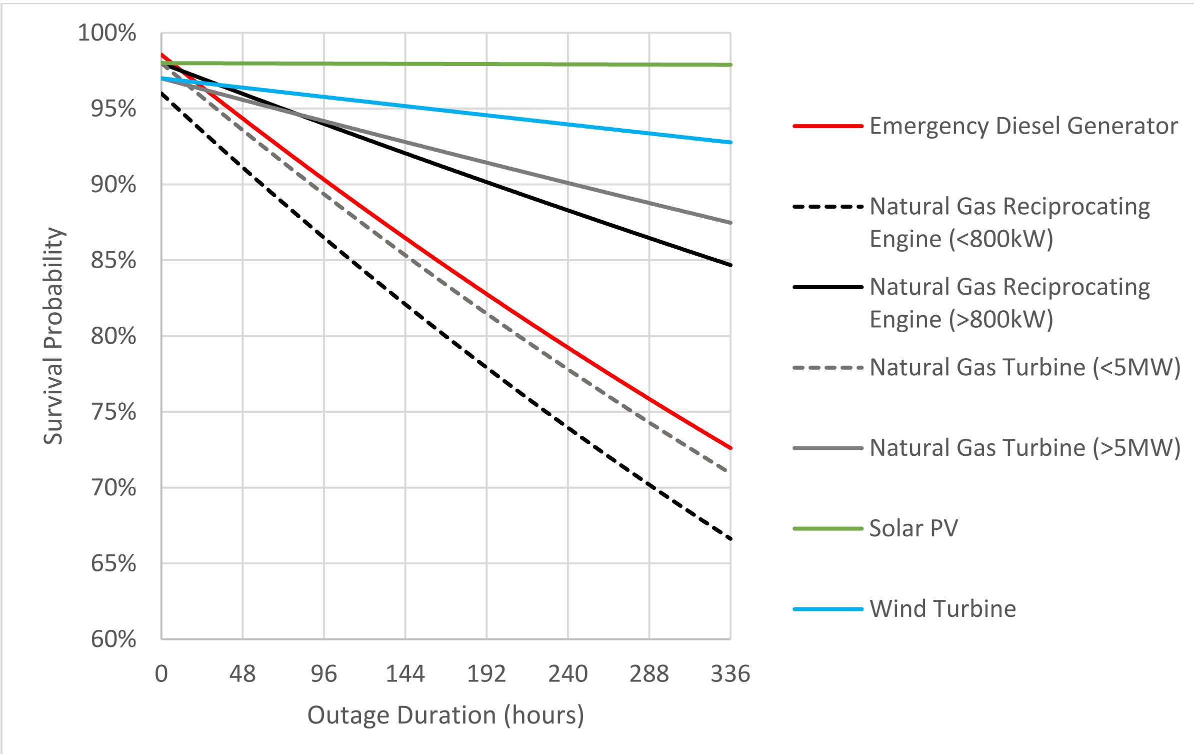


**Figure ES- 1. Survival probability of common DERs**

The results for wind and solar energy represent the potential for generating power. The actual available power will be constrained by available solar and wind resources at a site hour by hour. These results assume the DERs are well maintained. Poor maintenance can dramatically decrease the reliability of all these systems.

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# 1 Introduction

## 1.1 Background

Available and reliable electric power is essential to modern society. We depend on it for health, safety, economic vitality, and national security. Hospitals, emergency services, military bases, ports, airports, industries, commercial facilities, and others rely on backup power systems to provide electricity for their critical loads during grid outages. The risks of blackouts and loss of electric power are not new concepts. Outages of just a few hours are common, but longer duration outages are becoming more frequent (1). In the United States, outages longer than an hour are most often driven by severe storms (thunderstorms, blizzards, hurricanes, and other high-wind events), fires, and increased load demand and strain due to extreme temperature events. These outage threats are increasing due to climate change and unlikely to return to historical norms in the future. In addition to natural hazards, the commercial grid is vulnerable to manmade threats, both physical and cyber. Energy infrastructure has become a major target of cyberattacks (2). More frequent and sophisticated attacks are likely from both nation-states and cyber criminals. Each of these threats will likely increase in frequency in the future, and utilities are already seeing a statistically significant increase in major event days (1).

## 1.2 Report's Purpose

The purpose of this report it to provide accurate reliability information on commonly deployed distributed energy resources (DERs) to improve quantitative estimates for the reliability of electric energy backup power systems. A backup power system consists of DERs, an electric distribution system with its associated switches and other devices, and mechanisms to control and manage the flow of electricity. This report addresses the commonly used commercial DERs that provide backup electric power in case of a grid outage. The report provides information on the expected reliability of emergency generators, prime power and combined heat and power (CHP) prime movers, battery energy storage systems (BESS), solar photovoltaics (PV), and wind turbines.

Too often, the design of backup power for critical loads fails to properly quantify the reliability of their backup power systems. DERs are assumed to be 100% reliable, with the only concern being the availability of fuel, or simple reliability metrics such as N+1 are used without regard to the individual reliability of the DER components of the system. Such assumptions can lead to gross errors in the backup system's reliability estimates, particularly for long-duration outages (3). Similarly, most software tools used to assess, design, or optimize backup power configurations do not account for DER reliability at all (4) (5) (6) (7), or provide no recommendations for how to model the individual DER reliability (8) or use inappropriate values (9).

This report provides a set of estimates for the reliability of common commercial DERs used for backup electric power. The estimates are derived from empirical data when available and supplemented by modeling results when needed. These reliability estimates are for the DER's ability to provide power during a grid outage ranging from an hour to 2 weeks.

In the next section, we review reliability assessments and metrics, how to use them, and sources of our data. In Section 3, we summarize the recommended reliability metrics values for the different DERs. We conclude with a discussion on the importance of these estimates. The appendices provide details on the reliability metrics for each individual DER.

# 2 Reliability Assessments

## 2.1 Reliability Metrics and Terminology

Appropriate metrics are crucial for quantifying DER reliability and evaluating backup power system performance. Current industry practice utilizes a variety of system assessment methods, each with their own requirements for input data. The following section provides an overview of the metrics used to evaluate component and system performance, how these metrics should be defined for backup power capability, how those metrics can be used in system assessments, and what the results of those assessments can tell us.

### *2.1.1 Reliability and Availability*

Two common metrics for assessing the performance of backup power systems are reliability and availability.

Reliability is defined as the ability of a component or system to perform the required functions under stated conditions for a stated period (10) (11). For any DER, reliability is typically high during the early hours of a grid outage when backup power is initially required, but declines as the length of the outage increases and the probability of a DER failing to provide power grows. Reliability is useful for assessing the risk of experiencing a failure over a specified time interval but does not account for the expected downtime associated with that failure.

There are two metrics for measuring failures. One is based on the number of failures during a DER's lifetime, and one is based on the number of failures during a DER's run time. The reliability literature is not consistent on its terminology. In this report, we call these the Mean Time Between Failures (MTBF) and the Mean Time to Failure (MTTF):

$$MTBF = \frac{lifetime}{number\ of\ failures}$$

And:

$$MTTF = \frac{total\ runtime}{number\ of\ failures\ while\ running}$$

As we discuss in Section 2.1.3, MTTF is the preferred metric for assessing the contributions of generator-based backup power systems for outage scenarios. MTTF considers failures to be a function of runtime, whereas published MTBF values (12) are based on the annual probability of failure, independent of runtime. As a result, MTBF may provide an overly optimistic estimate of reliability for outage scenarios, and lead to under-designed backup power systems. For systems that are always on, including energy storage, solar PV, and wind systems, these two metrics are the same.

In analyzing DERs in backup power systems, we assume that they have passed acceptance testing, were properly engineered and manufactured, and are not near the end of their lifetime. In terms of the reliability literature's "Bathtub Model" (Figure 1), the DER is in its useful life period and is assumed to have a constant failure rate.

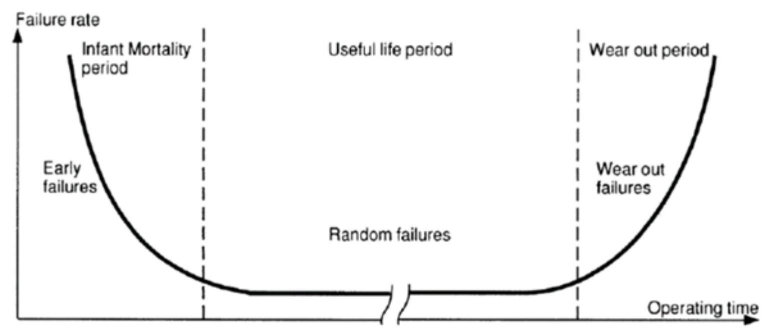


**Figure 1. A reliability bathtub model showing a low constant failure rate during the useful life period**

When a constant failure rate is assumed, reliability R($t$) decays exponentially and is given by:

$$R(t) = e^{-\lambda t}$$

Where λ is failure rate of the component, and t is the length of the time period being considered**.** For several DERs we will discuss, failures may not lead to complete power loss but will result in reduced power. In general, reliability is defined for a minimum required performance.

Availability is defined as the ability of an item to perform its required function when called upon at the start of an outage (11). Essentially, availability is a measure of the percentage of "potential uptime" as opposed to the actual "uptime" for a DER over a year. There are 8760 hours in a year, so availability is defined as:

$$Annual\ Availability = \frac{8760 - hours\ offline\ per\ year\ due\ to\ repairs\ and\ maintenace}{8760}$$

For assessing the availability of DERs for backup power, "potential uptime" is not the same as run time. For EDG, the operation is limited to times when the grid goes down and for testing periods. Other DERs are often not in operation due to economic or market constraints. They often do not run for a significant fraction of a year because it is not economically efficient to run them. Their availability to provide backup power at the start of an outage is not limited due to grid-tied economic constraints.

There are two principal measures of availability used in the literature: inherent availability ($A_i$) and operational availability ($A_o$) (13).

**Inherent availability:** When only reliability and corrective maintenance or repair (i.e., design) effects are considered, we are dealing with inherent availability. This level of availability is solely a function of the inherent design characteristics of the system.

**Operational availability:** Availability is determined not only by reliability and repair, but also by other factors related to preventative or corrective maintenance and logistics. When these effects of preventative or corrective maintenance and logistics are included, we are dealing with operational availability. Operational availability is a "real-world" measure of availability and accounts for delays, such as those incurred when spares or maintenance personnel are not immediately on-hand to support maintenance.

We will use operational availability to quantify the probability a DER will be available at the start of a grid outage and assume that during a grid outage no routine maintenance activities will take place.

Operational availability can be directly measured or calculated by:

$$\mathrm{Ao} = 1 - \frac{MTTR}{MTBF} - \frac{MTTM}{MTBM}$$

Where MTTR is the Mean Time to Repair, MTTM is the Mean Time to Maintain, and MTBM is the Mean Time Between Maintenance events. Unlike reliability, MTBF must be used as opposed to MTTF for calculating availability. MTBF considers the average time interval between failures independent of runtime, and provides a more accurate "snapshot" of whether or not a component will be up when called upon. MTTR and MTTM must include the logistical time to bring parts and personnel to the DER. Availability can be low, due to frequent failures or maintenance events and/or due to long repair or maintenance times.

Finally, for DERs that are run very infrequently or intermittently, such as emergency generators, it is important to understand the failure to start (FTS):

$$FTS = \frac{number\ of\ failures\ to\ start}{number\ of\ attempted\ starts}$$

FTS can represent a significant number of observed annual failures and must be separated out from run time failures to obtain accurate failure rates.

Table 1 provides a summary of reliability, availability, and maintainability metrics used in this report.

**Table 1. Reliability Terminology Summary**

| Term | Definition |
|---|---|
| $A_o$ | Operational availability considers down time for scheduled and unscheduled maintenance and repairs, including logistics time. |
| FTS | FTS is the number of failures to start divided by the number of attempted starts. |
| MTBF | MTBF is the average time calculated between failure occurrences. |
| MTBM | MTBM is the average time between maintenance events. |
| MTTF | MTTF is the average time for a failure as a function of run time and is the inverse of failure rate λ. |
| MTTM | MTTM is the average time to accomplish maintenance, including logistics time. |
| MTTR | MTTR is the average time to accomplish repairs due to failures on an item, including logistics time. |
| Reliability R(t) | The ability of a component or system to perform required functions under stated conditions for a stated period of run time. |
| λ | Failure rate, usually expressed in number of failures per hour of run time; it is the inverse of MTTF. |

The probability of an individual DER being operational during an outage, the survival probability (S) (3) (14), is the product of its operational availability, one minus its FTS, and its reliability as a function of outage duration (t).

$$S(t) = Ao\ x\ (1 - FTS)\ x\ e^{-\lambda t}$$

### 2.1.2 Repairability

Most causes of a DER failure can be repaired without replacement of the entire system. The time to repair includes the time to diagnose the fault's existence and its cause, the logistical time associated with obtaining any needed parts and staff with appropriate expertise, and time to repair or replace the failed component.

It is important to recognize that almost all data on repair times is obtained under "blue sky" conditions. That is, the repairs have taken place due to failures when the grid is operating or after a short-duration grid failure. These estimates are appropriate to use when calculating the DER's operational availability but may be overly optimistic when considering the repairability during a multiday grid outage. Under blue sky conditions, MTTR are often measured in days. During a "black sky" event, such as a multiday grid outage, it is unlikely that parts and staff with appropriate expertise will be available in the same amount of time. It is recommended that in modeling an extended grid outage, depending on availability of parts and labor, a failed DER may be assumed to remain offline until grid electricity is restored.[2]

### 2.1.3 Prime and Emergency Generators

Care must be used in calculating and using metrics described in Section 2.1.2 when evaluating prime as well as emergency generators.[3] MTTF must be used for both types of generators when

[2] Black-start testing indicates that some emergency support contracts have terms that limit the scenarios and time frames in which personnel will respond to failures (61). If support agreements, personnel, spare parts, and system documentation have been verified, then some failures may be considered repairable on a case-by-case basis.

[3] Emergency generators are also referred to as standby generators. From a reliability perspective, they are the same.

considering backup power systems. Prime generators only run between 30% to 80% of the time in almost all locations because of economic conditions. Standby or emergency generators are run even less, usually less than 100 hours per year. Measuring run time failures (MTTF) as opposed to annual frequency of failures (MTBF) isolates the generator's reliability from its frequency of use. The frequency of failures ($\lambda$) and reliability should be calculated based on run time as opposed to a duration of operations.

The other issue to recognize is that standby or emergency generators sit in a cold state most of the time, so FTS must be considered. Isolating FTS events from the pool of failures during run times is important. Standby equipment should be modeled as a combination of its FTS probability and its likelihood of failure while running. This is particularly important for analyzing the system's response to outage events, and for predicting the survivability of a system during an extended outage.

### 2.1.4 Reliability Data Estimates

The optimal approach to estimating reliability metrics is based on empirical data for DERs in operational situations. Accurate, current, and applicable reliability data are essential to assessing system design and performance. Several datasets exist, which are discussed in more detail in the appendices. The data that make up these databases are obtained from maintenance records, periodic system testing, and real-world outage events. For datasets such as the Army's Power Reliability Enhancement Program (PREP) database (15), data are pooled from a variety of sources, and the published results represent average values for families of equipment across a wide range of operating conditions.

Establishing failure statistics from maintenance records requires a great deal of information and a high level of recordkeeping fidelity throughout the life of the equipment. Consequently, many maintenance records are inadequate for determining accurate failure statistics. Computerized maintenance management systems allow for centralized access to equipment data, but the records entered must contain the detailed nameplate, maintenance, and failure information required to calculate the necessary metrics. Table 2 provides a sample checklist demonstrating the information that must be included.

**Table 2. Required Information for Maintenance and Repair Records**

| |
|---|
| **Nameplate Information** |
| Equipment make/model |
| Equipment type |
| Equipment size/rating |
| Serial number or unique identifier |
| Manufacture/install date |
| **Maintenance Information** |
| Start/end date and time for maintenance actions |
| Equipment run time at start and end of maintenance actions |
| Description of work performed |
| Status of equipment during work (i.e., was the equipment down or offline?) |
| Downtime associated with maintenance |
| **Failure Information** |
| Nature of failure (operational or test-generated) |
| Date/time failure occurred |
| Equipment run hours at time of failure |
| Equipment downtime associated with failure |
| Information on logistics delays (i.e., was the equipment down while awaiting replacement parts?) |

In the absence of quality empirical data, one should not assume a DER has perfect reliability. Estimates can be made with caution in the absence of sufficient data by using modeling approaches. DER failure rates can be calculated based on the failure rates of the DER's components and the DER system design. Availability can then be estimated based on industry standards for maintenance and repair times. These modeling approaches should be used only if data are not available. In the appendices, we cite data sources available for each type of DER.

## 2.2 System Assessment Methods

Component reliability data are useful for providing the failure behavior of individual DERs, but are unable to capture the overall behavior of an integrated backup power system. To accurately model a complex system, the model must include the individual failure behavior of its constituents, as well as the interactions between the components. Two common methods of assessing system reliability are through use of reliability block diagrams (RBDs) and Markovian analysis.

RBDs are an intuitive way to view a system and identify single points of failure and redundant paths of power. In an RBD, each component in the system is represented by a block with an assigned failure distribution. Connections are created between the blocks to model the reliability dependencies of the system. It is important to note that the connections in an RBD will not necessarily reflect physical connections in the real-world system.

A Markovian analysis uses the failure behavior of individual components to determine the probability that the overall system will transition from one state of operation to another. A Markov diagram consists of blocks that each represent a state of operation for the system, and connections between the blocks to model the probability that the state will transition from one state to another. Markovian analysis is a memoryless process that traces the system from an initial state to steady-state operation.

### 2.2.1 Input Data Requirements

Reliability assessments require different input data depending on both the method (RBD or Markovian) and the desired output metric (e.g., reliability and operational availability). As the desired level of detail for the simulation results increases, so does the level of detail required for the input data.

RBD models require reliability or availability parameters for every component in the system. Input data for individual components are usually expressed as constant values, but a more complex distribution may sometimes be required, such as when analyzing the effects of specific failure modes that are known to be strongly age dependent.

Markov diagrams require the transition rates between system states. This data can be more difficult to obtain than the reliability statistics that are input to an RBD. For example, to model a simple system with two identical redundant generators and a load with an RBD, you would need the failure, repair, and maintenance distributions for the generator. To model the system with a Markov diagram with three states (both generators operational, one generator operational, no generators operational), you would need the transition rates between each of the states.

### 2.2.2 Analytical vs. Monte Carlo Solutions

Once the real-world system has been translated into either an RBD or Markov diagram, it is possible to calculate Reliability, Availability, Maintainability metrics for the overall system. In both cases, the model can be solved either analytically or through Monte Carlo simulation.

For simple systems, it is relatively easy to reduce the model to a mathematical formula that represents the overall behavior of the system. However, as the size and complexity grow, it has historically been difficult to reduce the model analytically, but new techniques have demonstrated efficient methodology for conducting assessments (16) (14). Analytical solutions typically assume constant Reliability, Availability, Maintainability parameters for all components, so failure rate does not change.

Where more complex failure behavior must be considered, a Monte Carlo simulation may be necessary. A Monte Carlo simulation involves generating random failure times depending on the failure distribution of individual components. System reliability and availability metrics can then be determined through empirical calculation. As a result, Monte Carlo simulations can incorporate more complex failure distributions with respect to equipment age, improving the fidelity of the simulation to the real-world system. Due to the increased complexity of the model, computing power and time can become a limiting factor with sufficiently large or complex systems.

### 2.2.3 Incorporating FTS Data

Incorporating FTS data into reliability assessments can be challenging. Commercial software options can offer a way to include FTS probabilities for simple systems by incorporating active and standby paths into standard RBDs. FTS data can be included in the RBD in the probability that the system successfully switches from the active to the standby path. An FTS event for a generator results in a failed switch between paths.

Markovian diagrams can incorporate FTS events through an additional system state. System failure transitions would lead to a system state with instantaneous transition probabilities of a successful generator start or FTS. The transition that corresponds to a successful start would lead to a system UP state, and the transition that corresponds with an FTS would lead to a system DOWN state.

# 3 DER Reliability Data Summary

This report focuses on DERs commonly used for backup power for facilities or campuses that are grid-tied. Emergency diesel generators (EDGs) are by far the most deployed, as they can be adapted to various applications and utilize a consistent fuel source. As currently deployed, EDGs are an integral part of most backup power systems, but tend to have lower MTTF values than other DERs, and may be more likely to experience equipment failure during an outage. Centralized CHP systems fueled by natural gas are also common. Prime power natural gas engines and turbines are also used, particularly in markets where they provide economic benefits. Today there is a growing use of intermittent renewable energy, mostly solar PV but in isolated cases wind turbines as well. Wherever intermittent renewable energy DERs are deployed for backup power, they are integrated with a Li-ion BESS. There are other potential DERs, such as prime diesel generators, fuel cells, micro turbines, and flow batteries, that we do not include because they are rarely used, the technology is immature, and/or insufficient data exists to determine their reliabilities.

Table 3 summarizes recommended default values for these DERs commonly used in backup power systems. These values represent best estimates for the performance expected for well-maintained DERs in operation in the United States. Where large empirical datasets are available, the mean performance for DERs that are well maintained in accordance with industry and/or government standards is reported, and when limited data are available, engineering judgment and modeling results have been used. In each appendix, details on the data used and ranges of values expected are provided.

In the absence of better or model-specific information, these default values should be used. They are estimates, and the actual reliability of existing or new DERs may differ. Using these as a baseline value is recommended, and, if necessary, we recommend looking at the sensitivity of the system-level reliability though sensitivity analysis using a range of reliability values in accordance with the descriptions below. The values are appropriate for the sizes of the DERs listed in the table.

**Table 3. Summary Recommended Default Values for DER Reliability Metrics**

| DER | Type and Fuel | Size Restriction | MTTF (hours) | $A_o$ |
|---|---|---|---|---|
| Emergency Generator | Packaged Diesel | <4,000 kW | 1,100 | 99.5% |
| CHP Prime Movers and Prime Generator | Reciprocating Natural Gas Engine | < 800 kW | 920 | 96% |
| | | >800 kW | 2,300 | 98% |
| | Natural Gas Turbine | < 5,000 kW | 1,040 | 98% |
| | | >5,000 kW | 3,250 | 97% |
| Solar PV | Silicon | >25 kW | 13,500 to 300,000[4] | 98% |
| Wind Turbine | Land Based | Not Applicable | 7,540 | 97% |
| BESS | Stationary Li-ion | Not Applicable | >10,000 | 97% |

The descriptions below and the data in the appendices provide additional information.

*EDG:* Well-maintained EDGs are expected to have an MTTF of approximately 1,100 hours, but it may range between 800 hours and 2,400 hours. Well-maintained EDGs are expected to have an FTS between 0.9% and 1.0%. Poorly maintained EDGs can have MTTFs of as short as 50 hours and FTS as large as 2%. Operational availability is expected to be greater than 99% and can be as high as 99.9%. These reliability and availability estimates assume no constraint on fuel availability. In a long-duration outage, resupply of diesel fuel can be an important vulnerability but is outside the scope of this report.

*CHP Prime Movers and Prime Generators:* Natural gas-driven CHP prime movers and prime generators may have either a reciprocating engine or a turbine. For larger-size systems, MTTFs range for reciprocating engine from approximately 1,840 hours to 2,900 hours and turbines from 2,990 hours to 3,660 hours. Smaller prime generators have MTTFs approximately one-third of these values closer to what is seen in emergency generators.

*Wind Turbine:* Land-based wind is not commonly used as part of a backup power system, but where wind turbines exist, their use to support critical loads has been demonstrated (17). Wind turbines are variable or intermittent DERs. The reliability and availability of a wind turbine system refers to the capability of the system to produce power as expected if the wind resource is available and not the variability of intermittency resulting from changes in wind speed. The reliability metrics are reported for land-based turbines. The MTTR repair wind turbines is on the order of 100 hours, and operational availability ranges from 94% to 98.5%.

*Solar PV*: PV systems used to support critical loads are predominately commercial (25 kW to 1,000 kW) and utility- (>1,000 kW) scale. Smaller residential scales systems are rarely deployed or considered for support for critical loads. PV systems are variable or intermittent DERs. Power is generated only when solar irradiation is available. The reliability and availability of a PV system refers to the capability of the system to produce power as expected if the solar resource is

[4] For systems with a single central inverter, the shorter MTTF is appropriate. For systems with more than one central inverter, the larger number is appropriate.

available. Inverter failures account for most PV failures. Based on component reliability data, modeling indicates that MTTF of a PV system is quite long. PV availability is driven by the time it takes to repair the system, which is measured in days to months and typically leads to operational availabilities in the range of 95% to 99%.

*BESS:* Stationary Li-ion BESS are being deployed more often as part of a backup power system. The rapid drop in price and increase in volume of deployment signals a technology that is maturing rapidly. The reliability of a BESS is influenced not only by the reliabilities of its subcomponents, but also by the system topology and management strategies. Availability and MTTF of stationary BESS are currently not routinely reported, and the industry does not have significant enough operating experience to quantify an estimate. These numbers should be viewed as rough guidance on what should be expected.

# 4 Conclusion

In designing or assessing a backup power system, the probability it can provide the required power for the required duration is the critical performance metric. A backup power system consists of DERs, an electric distribution system with its associated switches and other devices, and mechanisms to control and manage the flow of electricity. The reliability of the distribution system and its associated equipment is a site-specific issue and may be critical. But often the primary driver of reliability is the reliability of the DERs that produce the power required to meet the critical loads. Too often, assessments of backup power systems are made assuming perfect reliability of generation assets and only factor in potential fuel availability issues.

In this report, we have provided recommended default values for the availability and reliability (expressed as the MTTF) of commercially used DERs. The appendices provide details on their derivation and ranges that should be considered. Next, we compare the survival probability of the five common energy generation assets using the recommended default values, assuming no fuel limitations. In assessing survival probability for actual sites, fuel availability should be considered.

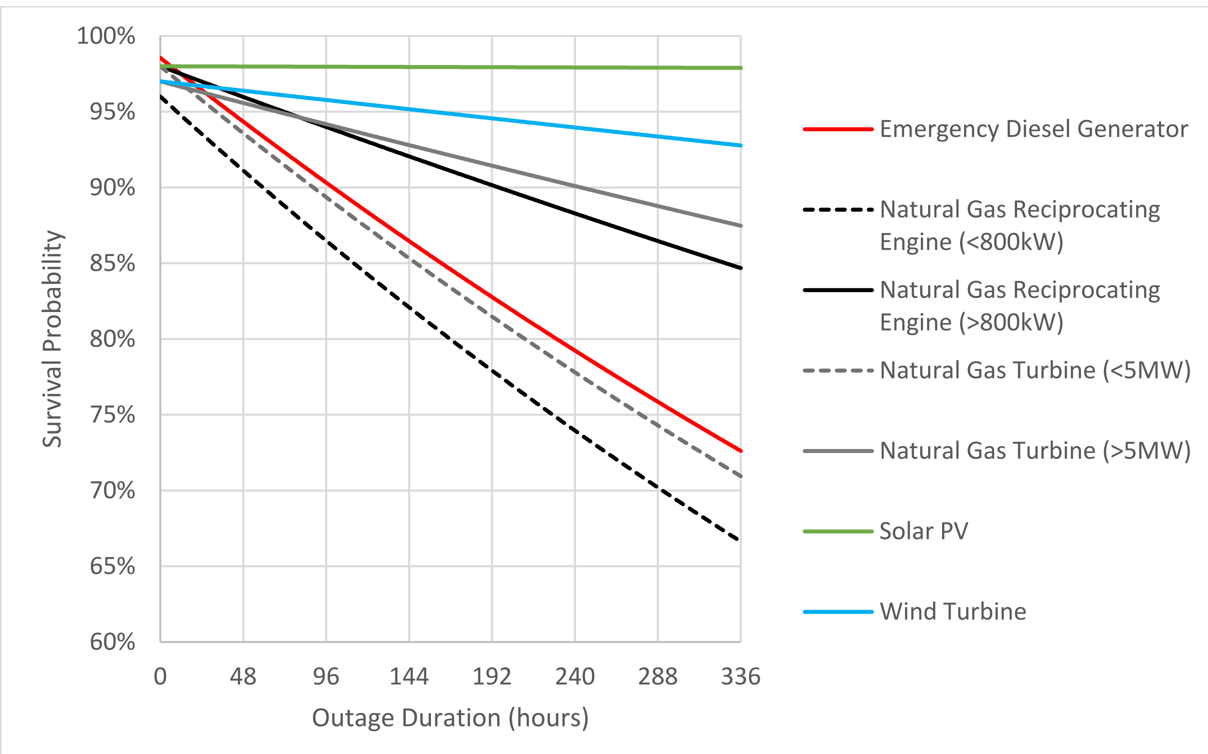


**Figure 2. Survival probability of common DERs**

These results assume the DERs are well maintained. Poor maintenance can dramatically decrease the reliability of all these systems. The least reliable DER for long-duration outages are small natural gas generators (reciprocating engines and turbines) and EDGs, which are also subject to fuel limitations. This is followed by larger prime generators running on natural gas. Renewable energy, such as solar and wind, is highly reliable for long-duration outages but is not dispatchable, so must be coupled with energy storage. The actual solar and wind power will be constrained by available solar and wind resources at a site hour by hour. These results are for individual DERs. To support critical loads, facilities and campuses need to assess the system-level reliability. The results for the system's performance will depend on both the type and number of DERs used, as well as how they are connected or networked.

# Appendices

## A. EDGs

Emergency or standby diesel generators are the most-used DERs for providing backup power for critical loads. The Department of Homeland Security's Enhanced Critical Infrastructure Program (18) reports that 85% of backup power for critical infrastructure is provided by emergency or standby diesel generators. EDGs are complex machines that include an engine, alternator, fuel system, voltage regulator, cooling system, exhaust system, lubrication system, starter and battery system, and often an automatic transfer switch. Attempts have been made to calculate reliability from first principles (19), but the complexity of EDGs and the resulting large number of failure mechanisms make such attempts of limited value.

Empirical field data are required to estimate reliability metrics. Because environmental regulations in the 1990s led to significant design changes in diesel engines, older data may no longer be representative of emergency generators fielded today (20). In addition, datasets that do not distinguish between FTS and failure to run will not provide accurate estimates. Only the five datasets listed in Table A- 1 provide relevant data and are large enough to derive statistically meaningful results.

**Table A- 1. Datasets on EDG Reliability**

| Source (Ref) | EDG Years of Observation | Level of Maintenance |
|---|---|---|
| PREP (12) | 2,298 | • Mixed |
| Hong Kong (21) | 790 | • Poor |
| Nuclear Regulatory Commission (22) | 1,790 | • Well maintained |
| Fehr (23) | 1,281 | • Well maintained |
| PowerSecure (24) | 5,327 | • Well maintained |

The data collected by PREP, which forms the basis for all reported IEEE reliability results, was collected from over 200 sites in the United States and Canada. The sites include military facilities, hospitals, and universities. PREP collects data by surveys from facilities and follows up with site visits when possible. The PREP data for packaged EDGs are divided into two classes: <250 kW and 250 kW–1,500 kW. In Table A- 1, we have combined that data. Data on large (750 kW to 7,000 kW) unpackaged EDGs are also reported but not included here.

The PREP data (25) do not include information on the number of attempted starts or run time of the generators. Thus, estimates for FTS and MTTF cannot be constructed. PREP data include the number of failures as a function of the observation time or MTBF. The PREP data also include detailed data on the time required for maintenance activities and the time to repair in cases of failures including logistics, which can be used to estimate availability.

A study conducted in Hong Kong (21) reported data on 147 EDGs monitored for an average of five years. The data were collected via a generator reliability survey followed up by site visits when feasible. The generators ranged in size from 80 kW to 1,500 kW. The generators were reported to have poor maintenance practices and provide a benchmark for generators that are poorly maintained.

The Nuclear Regulatory Commission requires that the performance data on EDGs that support nuclear power plants be reported routinely. The demands and run hours are reported on a quarterly or semi-annual basis, and existing regulations established the requirements for testing of these on-site power sources. Therefore, an extensive database on these generators exists (26). Recent analysis of this database (22) has calculated the EDGs' reliability metrics. These generators range in size from 50 kW to 499,999 kW, but most are between 250 kW and 5 MW, and failure frequency across generator sizes is statistically consistent with the full dataset averages. Many of the generators are likely to be unpackaged, as most manufactures do not offer packaged emergency generators larger than a few MWs. In addition, most nuclear EDGs are started with compressed air, whereas packaged EDGs are typically started with battery-powered electric starters. Thus, the probability of FTS may not be representative of EDGs commonly used for backup power. Because this dataset represents all EDGs used at U.S. nuclear power plants, it provides insight into an industry that requires high reliability, and the generators are assumed to be well maintained.

The third dataset we consider was collected in support of a Ph.D. thesis (23) supported by the U.S. Navy and previously used to estimate EDG reliability metrics (27) (25). The scope of the study was limited to modern, high-efficiency, low-emission generator sets from multiple manufacturers. Maintenance logs that followed current government regulations were collected and entered into a structured database. The sample population included EDGs between 10 kW and 2,000 kW. The database contains information on run times, as well as attempted starts and failures. Detailed information on the maintenance practices were recorded but do not include data on downtime due to maintenance time or repair time due to failures. The data shows no statistically significant differences based on size of generators nor manufacturer.

The final dataset was collected on EDGs operated by PowerSecure (24), a subsidiary of Southern Company. They operate many microgrids with a large fleet of standby diesel generators that are used while grid-tied for load management and islanded during grid outages. These commercial EDGs range in size from 125 kW to 2,800 kW. A reliability program was instituted in 2012. The data was collected from January 1, 2016, through February 28, 2019.

The MTTF and their 90% confidence intervals[5] are shown in Figure A- 1 for the four datasets that contain MTTF data for EDGs.

[5] Confidence intervals reported here and in other sections of this report were calculated based on classical frequentist statistics and represent the confidence intervals due to the finite duration of the run times observed. They do not account for sampling errors due to the selection of generators observed.

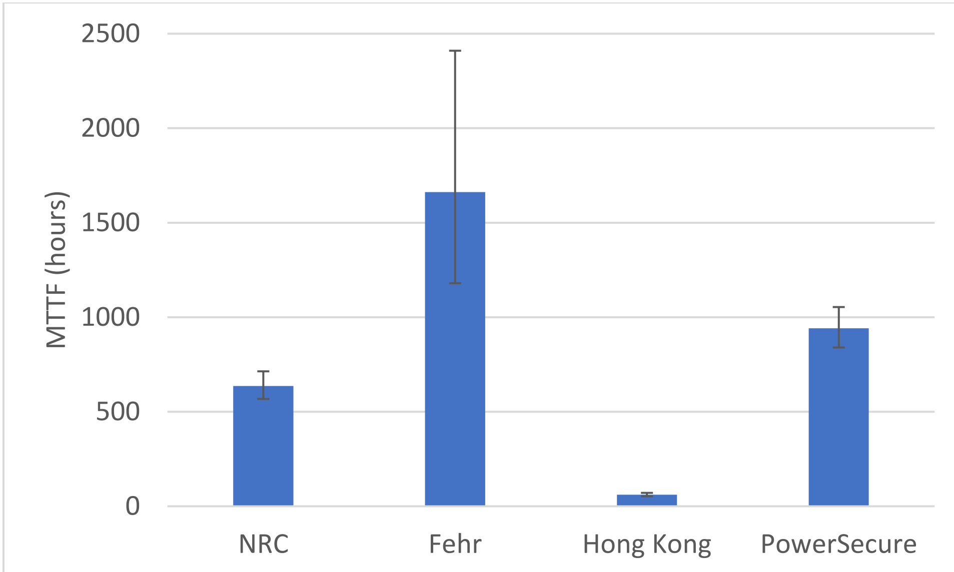


**Figure A- 1. MTTF for EDGs**

The Hong Kong data has an MTTF of only 61 hours and is statistically different than the other three datasets. It illustrates how sensitive MTTF is to level of maintenance. As stated previously, these were not well maintained, a practice all too common. The Nuclear Regulatory Commission data has an MTTF of 636 hours. It does not include run time failures of less than an hour and is for large generators not commonly used by facilities and campuses. The results found by analyzing the Fehr (23) and PowerSecure (24) data are for well-maintained EDGs, and of similar size and model commonly used. The PowerSecure results are found by aggregating their data for all generator sizes and for generators runs used for both load management and standby power so as not to bias our estimates due to run times. Their MTTFs are 1,662 and 942 hours respectively. Their 90% confidence intervals almost overlap. Combining these two datasets yields an average MTTF of approximately 1,100 hours, which we recommend be used in reliability assessments of systems that use EDGs.

Figure A- 2 provides estimates based on the relevant datasets for FTS and their 90% confidence intervals.

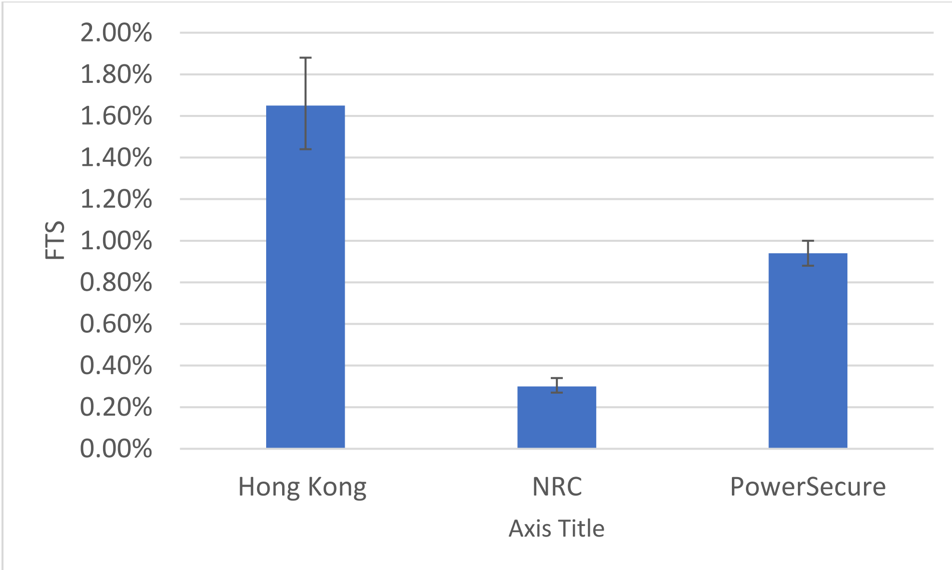


**Figure A- 2. FTS for EDGs**

The Hong Kong data has an FTS of 1.65% and is statistically different from the other three datasets. It again illustrates how sensitive reliability is to level of maintenance. The NRC data has an FTS of only 0.3%, but given the qualitative differences between the starters on nuclear power plants, EDGs, and commercial packaged EDGs, these results should not be used in modeling typical systems. The PowerSecure result of an FTS of 0.94% should be used for modeling well-maintained EDGs. The data from the Fehr dataset reported 44 FTS, but the number of attempted starts was not consistently reported, and therefore an estimate for FTS is not listed.

The expected reliability of well-maintained EDGs, including its FTS, is shown in Figure A- 3 and compared to one poorly maintained EDG.

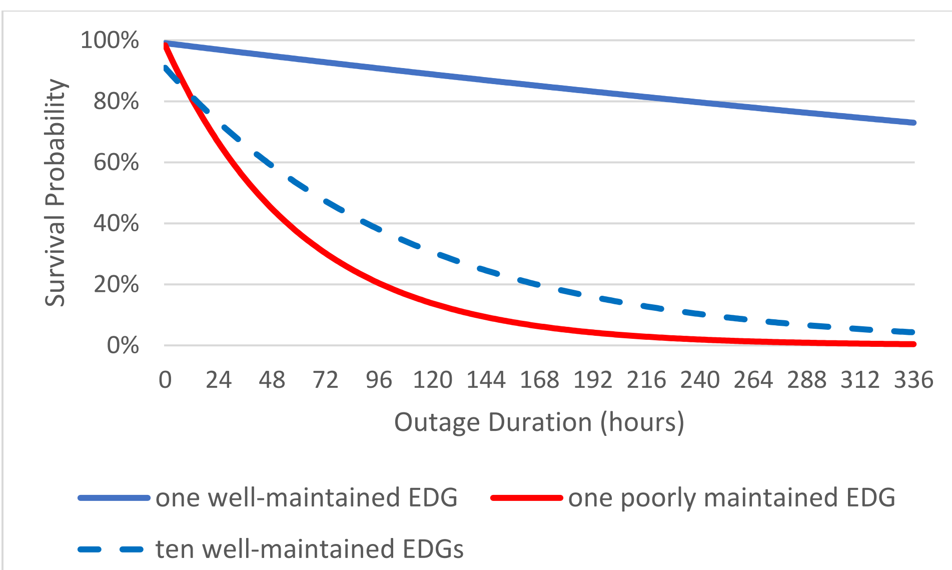


**Figure A- 3. The EDG survival probability as a function of outage duration**

Even a single well-maintained EDG has only a 73% survival probability over 2 weeks. A poorly maintained EDG is more likely to fail than survive after only 2 days. For a set of 10 critical buildings, each with their own generator, even well-maintained EDGs are likely to fail to meet the loads in all 10 buildings in less than 3 days (3) (28). These survival probabilities assume no fuel availability constraint. In a long-duration outage, the resupply of diesel fuel can be an important vulnerability, but this is outside the scope of this report.

To calculate operational availability ($A_o$) requires estimates for MTTR, MTTM, MTBF, and MTBM. Only PREP data (27) provide MTTR, MTTM, and MTBF. Table A- 2 provides a summary of the PREP data for EDGs with sizes commonly found in backup power applications.

**Table A- 2. MTTR, MTTM, and MTBF for EDGs**

| Data Source | MTTR (hours) | MTTM (hours) | MTBF |
|---|---|---|---|
| PREP | 37.3 | 1.70 | 31,497 |

Given the small values found for MTTM, operational availability is relatively insensitive to maintenance frequency (MTBM). Availability can be calculated based on an assumed frequency of maintenance events. Table A- 3 provides the expected availability, assuming either a biweekly or bimonthly maintenance schedule.

**Table A- 3. Operational Availability of EDGs**

| Maintenance Frequency | Operational Availability |
|---|---|
| Biweekly | 99.4% |
| Bimonthly | 99.8% |

This high availability is driven by the emergency generator infrequent usage, and, thus, the potential for failures is limited, as is the short time required for maintenance. Even if an emergency generator is used more while grid-tied for demand response or peak shaving, availability is expected to still be quite high.

## B. Natural Gas Prime Generators and CHP Prime Movers

Natural gas prime generators and CHP system are used for base load support while grid tied, where it is economically justified. The use of natural gas-fueled prime generators and CHPs are frequently being integrated into backup power systems today. The prime movers in a CHP are the same equipment that can be used as a stand-alone baseload generator. The energy flow in a typical CHP plant is illustrated below.

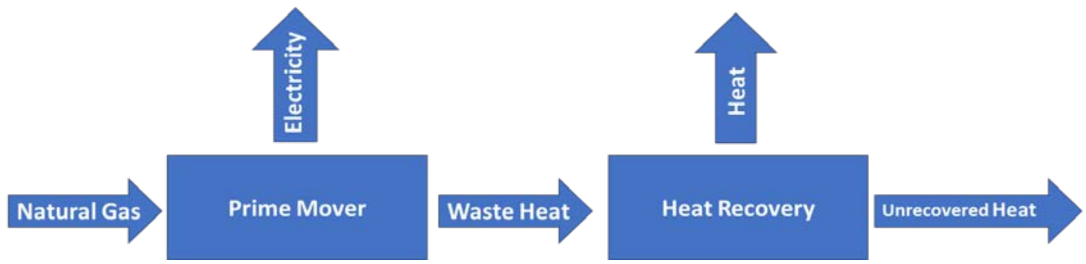


**Figure B- 1. Energy diagram of typical natural gas CHP system**

In this report, we consider only the reliability of the CHP's prime movers, which provide electricity and do not treat failures associated with the heat recovery system. Prime movers or prime generators are either a reciprocating engine or a turbine.

We will use empirical data to estimate the reliability and availability of natural gas prime generators and CHP prime movers. Reliability data depends not only on the type of prime mover (reciprocating engine vs. turbines), but on its size as well. CHP systems can and do group multiple prime movers into a single system. When this is the case, the reliability of the full system must consider the probability that one of the prime movers may fail. In our discussion below, we provide values for a single prime mover in a CHP system. In the case of multiple prime movers, the prime generator reliabilities can be used to construct an estimate for the specific system.

To our knowledge, there is only one recent dataset on the reliability and availability of natural gas-driven prime movers in CHP systems. Oak Ridge National Laboratory (ORNL) sponsored a collection effort (32) from 2000 to 2002 to create a database populated with information on multiple types of CHP units using the approach described in Section 2.1.4. Datasets on stand-alone natural gas prime power generators are limited but can be combined with this CHP datasets by removing those failure or maintenance activities associated with the heat recovery portion of the CHP system. Below, we summarize the characteristics of the datasets reviewed.

Datasets on stand-alone natural gas prime power generators are limited but can be combined with this CHP datasets by removing those failure or maintenance activities associated with the heat recovery portion of the CHP system. Below, we summarize the characteristics of the datasets reviewed.

**Table B- 1. Datasets on Natural Gas Prime Generators**

| Data Source | Type | Sizes | Unit Years of Observation |
|---|---|---|---|
| ORNL | Reciprocating Engine | 100 kW–800 kW | 25.3 |
| ORNL | Reciprocating Engine | 800 kW–3 MW | 36.2 |
| PREP | Reciprocating Engine | >250 kW | 51.7 |
| ORNL | Turbine | 500 kW–5 MW | 91.1 |
| ORNL | Turbine | 5 MW–20 MW | 90.3 |
| PREP | Turbine | 750 kW–7 MW[6] | 185.9 |
| Smith | Turbine | 600 kW–1,800 kW | 38.1 |

Although these are modest-sized datasets, they are large enough to draw conclusions. This dataset includes both observational and run time hours, which are critical for calculating the reliability parameters defined in Section 2.1. As discussed in the body of the report, DERs may not run a significant fraction of the time for economic reasons, even if they could do so. For these cases, the reciprocating engine CHPs ran only 40.6% of the time, while the larger turbine systems ran 82.2% of the time. Unfortunately, the PREP data does not contain information on runtimes and thus it cannot be used to estimate MTTF values.

The ORNL results for reciprocating prime engines are shown in Table B- 2.

**Table B- 2. Natural Gas Reciprocating Engines Prime Generator Reliability**

| Size | MTBF (hours) | MTTF (hours) | MTTR (hours) | MTTM (hours) | MTBM (hours) | $A_o$ |
|---|---|---|---|---|---|---|
| 100 kW–800 kW | 1,773 | 917 | 20.0 | 96.0 | 3,887.3 | 96% |
| 800 kW–3 MW | 5,666 | 2,300 | 32.5 | 7.1 | 630.8 | 98% |

The 90% confidence intervals for the MTTF are on the order of +/- 100 hours for the smaller reciprocating engines and +/- 600 hours for the larger reciprocating engines. The PREP data report an MTBF of 2,116 hours, consistent with the ORNL data. The ORNL data report that these reciprocating engines run only 40% to 50% of the time, for economic reasons. Because PREP data does not contain run times, MTTF cannot be calculated but it is likely similar. For larger reciprocating prime generators, an MTTF of 2,300 hours should be assumed, but for cases where small reciprocating engines are used, a smaller MTTF similar to EDGs is more appropriate. The survival probability for large and a small natural gas reciprocating engine over a 2-week grid outage is shown below.

[6] These are packaged units.

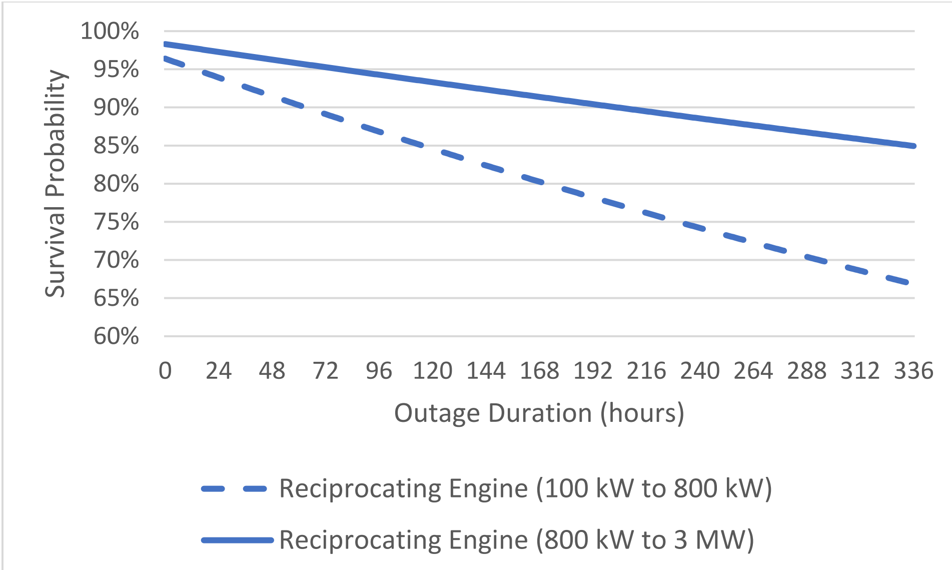


**Figure B- 2. Prime reciprocating engine generator survival probability as a function of outage duration**

For either size prime generator, it is important to recognize that these DERs may fail during an extended grid outage.

The ORNL and Smith results for natural gas turbine prime engines are shown in Table B- 3.

**Table B- 3. Reliability Metrics for Natural Gas Turbines.**

| Data Source | Size | MTBF (hours) | MTTF (hours) | MTTR (hours) | MTTM (hours) | MTBM (hours) | $A_o$ |
|---|---|---|---|---|---|---|---|
| Smith | 600 kW–1,800 kW | 1,919 | 1,173 | 7.2 | 21.2 | 1,582.4 | 99% |
| ORNL | 500 kW–5 MW | 1,790 | 1,037 | 14 | 39 | 3,913 | 98% |
| ORNL | 5 MW–20 MW | 3,955 | 3,253 | 33 | 93 | 3,935 | 97% |

The 90% confidence intervals for the MTTF are on the order of +/- 100 hours for the turbines and +/- 400 hours for the larger turbines. The PREP data reports a MTBF of 5,507 hours for packaged turbines ranging from 750 kW to 7 MW is larger than the ORNL data. The ORNL and Smith data report that these reciprocating engines run from 58% to 83% of the time for economic reasons. Because PREP data does not contain run times, MTTF cannot be calculated. For large turbine generators, a MTTF of approximately 3,260 hours should be assumed, but for cases where smaller turbines are used, a smaller MTTF of approximately 1,800 to 1,900 hours is recommended. The survival probability for a turbine ranging from 500 kW to 5 MW and a smaller turbine of 500 kW to 5 MW over a 2-week grid outage is shown below.

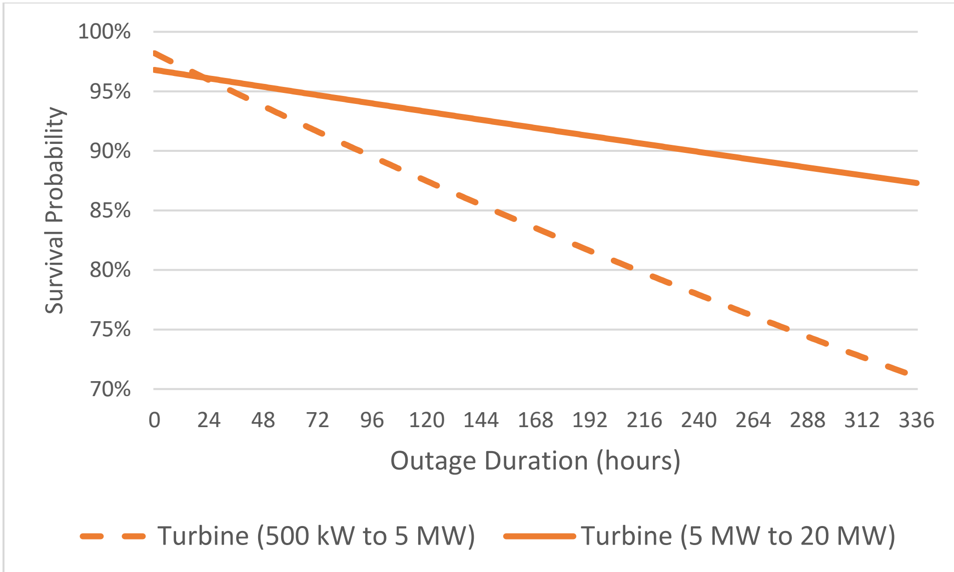


**Figure B- 3. Prime turbine generator survival probability as a function of outage duration**

It is important to recognize that turbine DERs may fail during an extended grid outage.

## C. Solar PV Systems

Solar PV systems are widely deployed but only recently have been considered for use as DERs to provide backup power when the grid is down (14). PV systems are typically characterized by their size as being residential (<25 kW), commercial (25 kW to 1,000 kW), and utility (>1,000 kW) scale. Due to both design and maintenance procedures, the scale of the system can impact reliability. In this report, we restrict our review to commercial and utility-scale systems. Use of solar PV systems for backup power is expected to predominately use large commercial systems of hundreds of kWs to modest-sized utility systems of one to tens of MWs. Smaller residential-scale systems are rarely deployed or considered for backup power support for critical load applications.

PV systems are variable or intermittent DERs. Unlike most DERs used in backup power situations, their power output changes throughout the day and year and depends on location. Power is generated only when solar irradiation is available. The diurnal cycle and solar angle based on location during the year leads to a predictable variation in output, but weather (i.e., clouds) causes large variation on the time scale of minutes to hours that can be characterized statistically but is stochastic. The reliability and availability of a PV system refers to the capability of the system to produce power as expected if the solar resource is available and not the variability of intermittency resulting from changes in the solar irradiance.

PV systems are complex power systems in which most component failures do not lead to complete power loss (33). PV systems include PV modules aggregated into a string (typically 8 to 30) that generate DC power, a set of inverters to transform the power to AC, a transformer, and the integration of multiple strings, fuses, and breakers. Inverter failures account for the vast majority of component failures (34) (35) (36). Data from recently fielded utility-scale systems shows that inverters account for 94% of reported hardware faults (37). All utility-scale and most commercial-scale systems have multiple inverters. Centralized inverters are commonly used. PV systems can also use smaller distributed inverters called string inverters.

In estimating PV system reliability, it is critical to differentiate a fault that causes a reduction in power capacity versus a fault or set of faults that results in the total loss of power production capacity. Given the dominant role of inverter failures, we focus on the more common centralized inverter design. Systems with string inverters typically have an order of magnitude more and use inverters that are expected to be more reliable (38). To understand the likelihood of faults that cause total loss of power versus partial loss and to quantify the magnitude of partial power losses requires us to look at the subsystem faults and their resulting impacts. Below is a diagram of common PV configurations based on a set of central inverters.

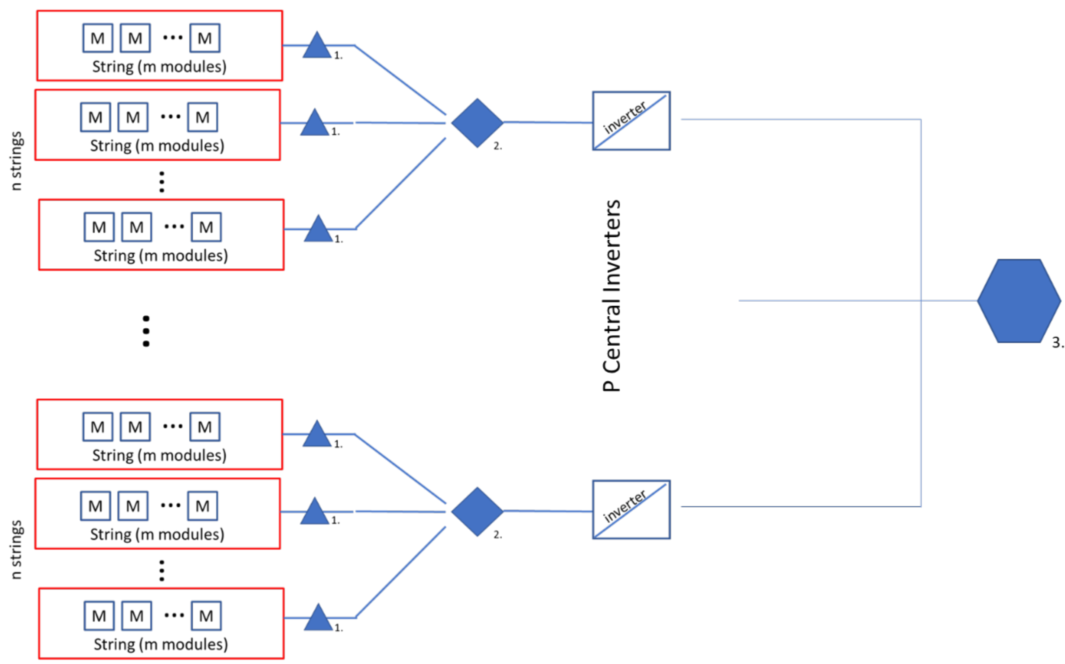


**Figure C- 1. A simplified diagram of a PV system with central inverters**

This system has $m$ PV modules in $n$ strings linked to $p$ inverters. Where Component 1 is string connectors and protectors (fuses), Component 2 is the DC combiner box containing a DC disconnect, and Component 3 is a transformer.

Given the design illustrated above, a simple fault tree can be created for this system. Combining components that are in series, we find (Figure C- 2) a three-tier tree.

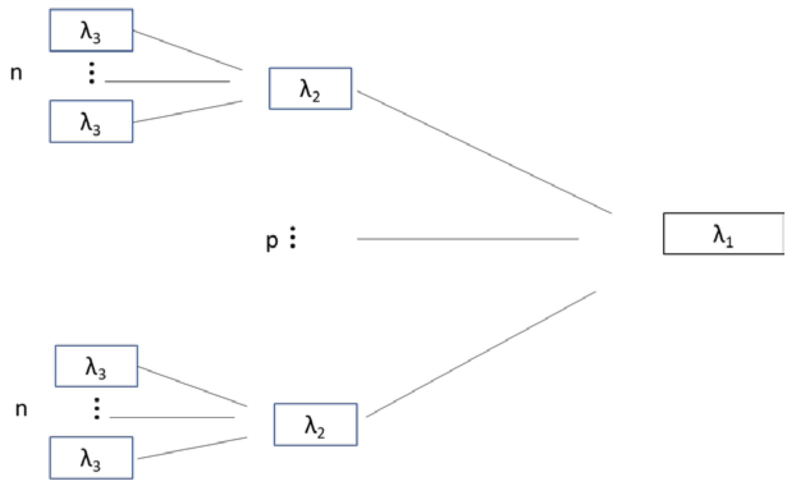


**Figure C- 2. Central inverter PV system fault tree**

Where $\lambda_i$ represents the failure rate for that block and $\lambda_1 = \lambda_{transformer}$, $\lambda_2 = \lambda_{DC\ combiner} + \lambda_{central\ inverter}$, and $\lambda_3 = m \times \lambda_{module} + \lambda_{string\ connector} + \lambda_{string\ protector}$..

Failure rates based on data collected from fielded systems (38) are listed in Table C- 1.

**Table C- 1. PV System Component Failure Rates**

| **Component** | **λ Failure Rate ($10^{-6}$ per hour)** | **MTBF (hours)** |
|---|---|---|
| PV modules | 0.035 | $28.6 \times 10^6$ |
| String connector | 0.0056 | $179 \times 10^6$ |
| String protector | 0.063 | $15.9 \times 10^6$ |
| DC combiner box[7] | 3.14 | 318,000 |
| Central inverter[8] | 74.0 | 13,500 |

The high reliability of PV modules is well established and has been confirmed in multiple studies (35). Estimates for central inverter failure rates range 11 to 138 x $10^{-6}$ per hour (35) and are consistent with this estimate. The transformer represents in most cases the only single point failure for the system. A summary of the recent estimates is shown in Table C- 2.

[7] The DC combiner box is assumed to have a DC switch, terminal screws, fuses, and DC cables in series (see Reference 32).
[8] The inverter reliabilities include the DC and AC circuit breakers associated with the inverters.

**Table C- 2. Transformer Failure Rate Data**

| **Data Source**[9] | **Ref** (39) | **Ref** (34) | **Ref** (38) |
|---|---|---|---|
| λ Failure Rate ($10^{-6}$ per hour) | 0.30 | 0.24 | 2.01 |
| MTBF (hours) | 3.3 x $10^6$ | 4.2 x $10^6$ | 0.50 x $10^6$ |
| Number of units | 8982 | 574 | Not reported |
| Unit years of observation | 144,205 | 2,870 | Not reported |

Given the consistency between the failure rate from a very large reliability dataset and the data from a large set of fielded PV systems, we assumed that an average value of 0.30 x $10^{-6}$ failure per hour is representative of transformers deployed in PV systems of interest.

Given these subsystem failure rate estimates, we can analyze the likelihood of a total loss of power and the expected magnitude of partial losses over a grid outage of 1 hour to 2 weeks. A total loss of power occurs if and only if all PV modules fail, or all inverters fail, or the transformer fails. The probability that all PV modules would fail is essentially zero, and the details on the number of modules per string ($m$) is irrelevant. The only design issue of concern is the number of central inverters. In Figure C- 3, the probability of a total loss of power due to component failures is shown for a PV system with one, two, or four centralized inverters.

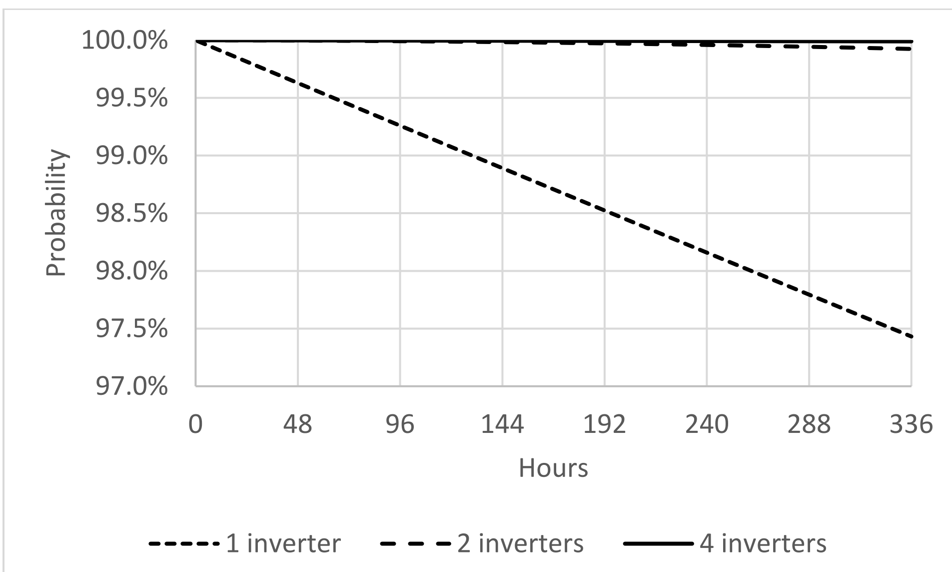


**Figure C- 3. Probability a PV system has the capability to produce power**

A PV system with two or more inverters has a very high likelihood (>99.9%) of being able to produce power if operational at the start of a grid outage for 2 weeks. Thus, PV systems with two or more inverters have an effective MTBF >300,000 hours due to the high reliability of

[9] Reference 33 reports on a wide set of transformers, Reference 28 is analysis of transformers for utility-scale systems in that dataset, and Reference 32 is from a dataset of Juni utility-scale PV systems.

transformers and the need to lose all the inverters. If it has only one inverter, the system has effectively an MTBF of approximately 13,000 hours.

Even if a PV system can produce power, component faults can lead to a reduced level of power. Any failure in the fault tree shown in Figure C- 2 will lead to a reduction in capacity. We define the cumulative probability of a component in tier "i" to be working at time t as:

$$R_i(t) = Exp(-\lambda_i t)$$

And the cumulative probability that it fails as:

$$F_i(t) = 1- R_i(t)$$

For a system of N components in parallel, the cumulative probability that k components are working is (14):

$$P_i(k,N) = (N!/[k!(N-k)!])\ R_i^k F_i^{N-k}$$

The fraction of power that flows through a given tier "i" if k component out of N operating is k/N. Thus, for the central inverter system, the expected fraction of capacity relative to capacity at the start of the outage, C(t) is simply:

$$C(t) = R_1(t) \text{ x } R_2(t) \text{ x } R_3(t)$$

The fractional power capacity is therefore independent of the number of inverters, but it does depend on the length of the string. Figure C- 4 shows the mean fractional power capacity as a function of outage duration for a central inverter system, assuming a string of 24 modules and the same component failure rates as listed previously.

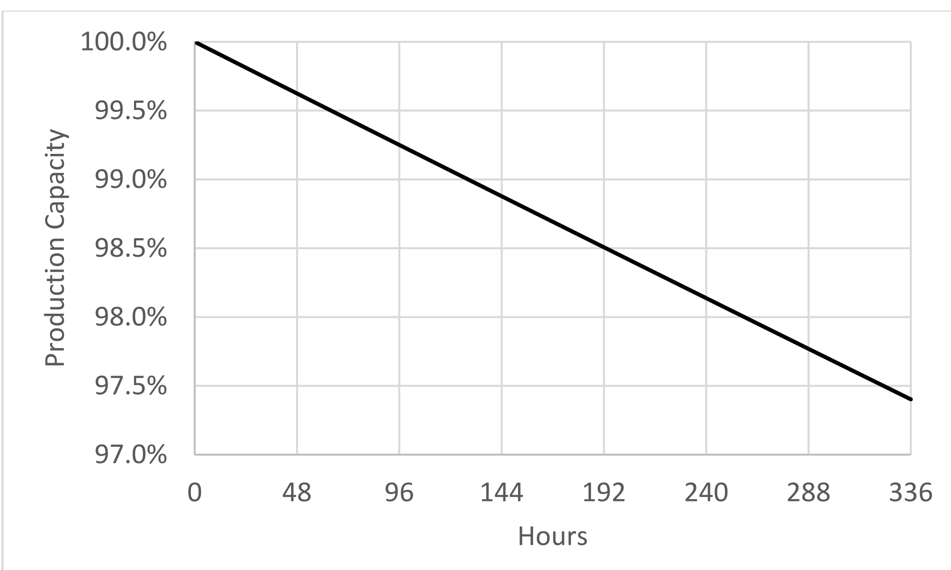


**Figure C- 4. The average reduction generation capacity due to component failures**

A change of less than 3% over a 2-week outage is minor compared to the uncertainty in the solar power production due to weather variability (i.e., cloud cover). Thus, in estimating the reliability of a PV system, one can in most cases safely assume that if it is operational at the start of the outage, it will be operational with a very similar capacity for the next 2 weeks.

Although component failures are rare, it can take days to months to repair a PV system (34), and MTTR is highly variable (Figure C- 5).

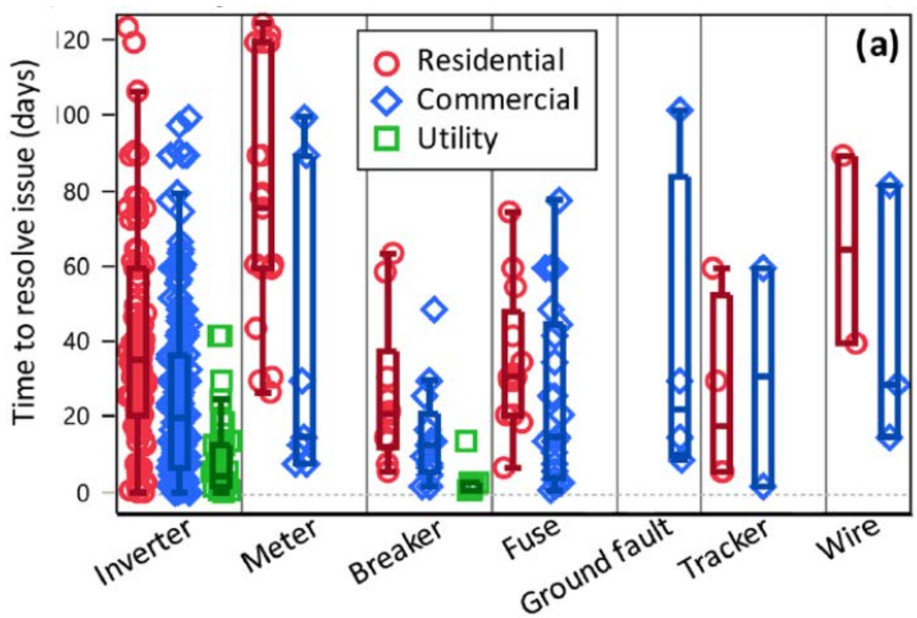


**Figure C- 5. Time to repair faults as a function of comment failure and system size (34)**

Availability should not be assumed to be 100%. Because solar PV is intermittent, care must be taken when defining availability. Availability is the actual measured hours of production divided by the expected or modeled hours of production. A related but distinct set of metrics is the performance ratio or index. This is a measure of the actual energy production compared to modeled energy production, and takes into account times the system is operational but not at its full capacity. Most data collections have been motivated by a need to quantify the economic performance of a PV system and thus include external causes such as curtailment or grid outages, when PV systems not installed as part of a microgrid automatically shut off, along with internal fault-driven issues. We are concerned with the PV system's availability to support an islanded operation, so the estimates shown below should be viewed as conservative bounds.

Two relevant studies of PV availability in the United States have been reviewed: one focused on federal systems and one focused on privately owned systems (Table C- 3).

**Table C- 3. Characteristics of Recent PV System Studies**

| Data Source | Ownership | PV Size Range | Number of Systems | Years of Data |
|---|---|---|---|---|
| Ref (40) | Federal | 1 kW to 4,043 kW | 74 | 9 |
| Ref (34) | Private | 25 kW to 1,000 kW | 7,260 | 5 |
| Ref (34) | Private | >1,000 kW | 574 | 5 |

Their results are shown in Table C- 4.

**Table C- 4 Average And Mean Availability.**

| Data Source | Average Availability | Median Availability |
|---|---|---|
| Ref (40) | 95.1% | 98.0% |
| Ref (34): 25 kW to 1,000 kW | 92.5% | 98.8% |
| Ref (34); >1,000 kW | 97.6% | 98.6% |

The differences between the reported average and median reflect a small number of systems that take an extremely long time to repair. Thus, the median better reflects the anticipated performance of most systems. Based on these data, an availability of at least 98% should be assumed unless other information is available.

## D. Wind Turbines

Wind turbines are rapidly being deployed in the United States and across the globe. The United States has over 120 GW of wind power already deployed, with over 60 GW expected to be deployed over the next few years (41). Wind is relatively uncommon in backup power systems, but where it exists, its use to support critical loads has been demonstrated (42). Historically, wind turbines were constrained to being land-based, but in recent years, an increasing number have been deployed offshore or are being considered for offshore deployment. Offshore deployed turbines have added complexity, in particular in terms of their maintenance. Offshore wind turbines are not expected to be used as a source of backup power. We therefore restrict our discussion to the reliability and availability of onshore assets.

Wind turbines are variable or intermittent DERs. Unlike most DERs used in backup power situations, their power output changes throughout the day and year and depends on the weather. The reliability and availability of a wind turbine system refers to the capability of the system to produce power as expected if the wind resource is available and not the variability of intermittency resulting from changes in wind speed.

Wind turbines are large and complex power systems in which failures can be due to one of roughly a dozen subsystems. Significant failure rates are observed in the rotor, air or mechanical brakes, gear box, yaw and pitch control systems, generator, power converter, electrical systems, and other sub-assemblies (43).

There have been multiple large-scale studies on wind turbine reliability and availability to help improve maintenance processes and predict wind turbine economic performance. Two significant reviews have recently been published on existing empirical studies (44) (45). Below we list those studies with data on reliability or availability for on shore wind turbines we have used. We eliminated studies specifically on Chinese wind turbines, because they are unlikely to be used in the United States for security reasons, very small studies of dozen or so turbines, and studies that did not provide data on the number of turbines and years they were observed.

**Table D- 1 Reliability Land-Based Wind Studies**

| Study Name | Number of Turbines | Approximate Turbine-Years | Ref. |
|---|---|---|---|
| CIRCE | 4,300 | 13,000 | (44) |
| CREW | 900 | 1,800 | (44) |
| DNV KEMA/NREL | 1,895 | 9,475 | (46) |
| Elforsk/Vindstat | 786 | 3,100 | (44) |
| EPRI | 290 | 580 | (44) |
| LWK | 643 | 6,000 | (44) |
| NEDO | 924 | 924 | (44) |
| VTT | 96 | 356 | (44) |
| Windstats -GE | 2,500 | 30,000 | (44) |
| Windstats -DK | 153 | 20,000 | (44) |
| WinDPool | 456 | 2,086 | (44) |
| WMEP | 1,593 | 15,357 | (44) |

These studies collectively recorded performance for almost 15,000 wind turbines, representing over 100,000 years of turbine operation. Below are a set of figures that show the derived values for MTBF (Figure D- 1), operational availability (Figure D- 2), and MTTR (Figure D- 3).

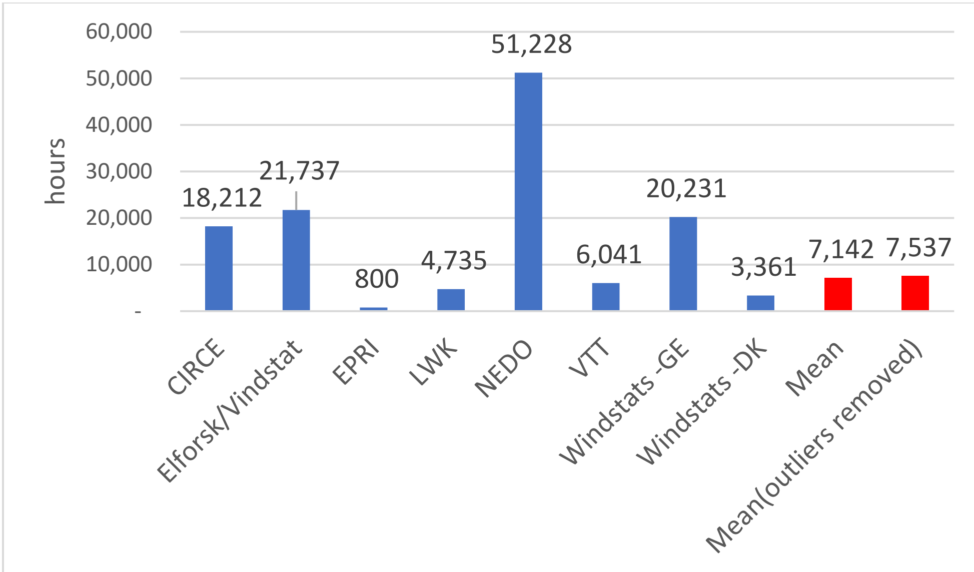


**Figure D- 1. Wind turbine MTBF based on eight empirical datasets**

The mean values shown weigh each individual dataset result by the number of turbine hours. The EPRI data collected in the late 1980s yields a very low value for the MTBF, and the NEDO data yields a very high, beyond the 0%, confidence interval. Both datasets are modest in size and thus do not impact the mean value weighted by each dataset's number of turbine years. The mean values without the EPRI and NEDO results is shown as the "Mean (outliers removed)" and is the recommended default value for wind turbines.

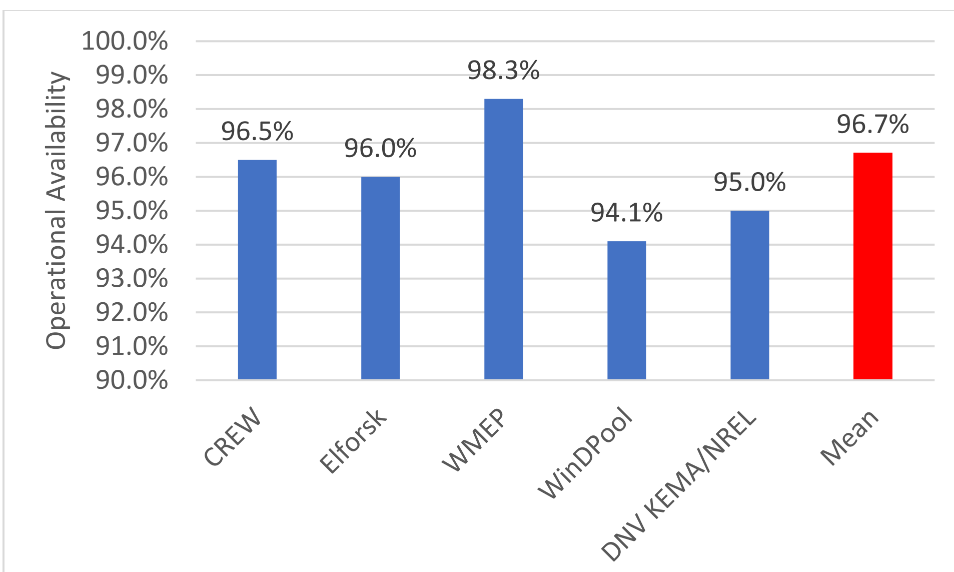


**Figure D- 2. Wind turbine operational availability based on five datasets**

The operational availability from each dataset is weighted by the number of turbine hours to calculate the mean value. The operational availability values are consistent across the datasets, which were collected in different countries and for different manufacturers.

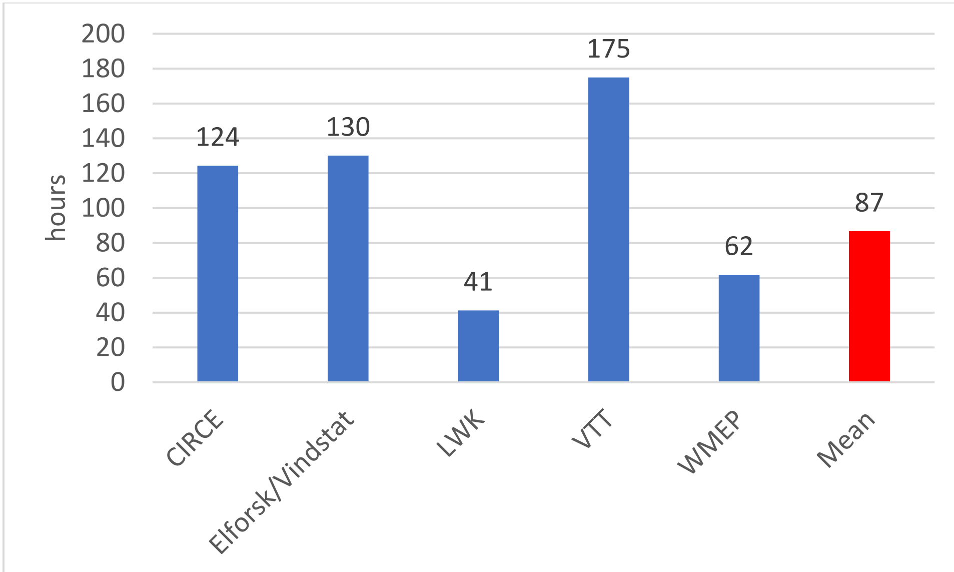


**Figure D- 3. Wind turbine's MTTR failures from five datasets**

The MTTR failure from each dataset is weighted by the number of turbine hours to calculate the mean value.

## E. BESS

Stationary BESS are being deployed more often as part of a backup power system. BESS are frequently being integrated with solar and wind renewable energy to support the power grid and provide backup power. Most of these applications are met using Li-ion batteries.

Li-ion battery fires and explosions have occurred worldwide due to thermal runaway. However, the probability of Li-ion battery accidents is extremely rare, occurring anywhere from 1 in 1 million to 10 million batteries (47). These are almost exclusively associated with mobile uses and not stationary BESS and can be traced to design or manufacturing issues (47). For these reasons, these rare events are not considered in our estimates of BESS reliability for backup power.

A BESS consists of multiple battery modules connected in series and parallel combined with battery management system (battery pack), a power control system, and thermal management system. The DC output of the battery is connected the power control system. The power control system consists of a bidirectional converter that changes DC to AC in the discharge mode and converts AC to DC in the charge mode. The thermal management system will include HVACs and fire suppression systems. Large stationary BESS often have redundant HVAC systems for improved reliability, and thus the thermal management system's reliability does not set the system-level reliability. The reliability of a BESS is influenced not only by the reliabilities of its subcomponents, but also by the system topology (particularly for the battery pack) and management strategies.

Availability of stationary BESS performance is currently not routinely reported, and industry does not have significant enough operating experience to quantitively estimate stationary Li-ion BESS availability (47). Based on current claims, we recommend that values of 95%–99% be used, depending on system configuration. One field study (48) of a 1-MW/250-kWhr BESS tracked for 3 years found an availability of 95%, which is consistent with industry guarantees (49). A review from 2015 (50) cites an availability of 97%. A recent modeling analysis (51) estimated an availability for Li-ion BESS ranging from 97% to 99%.

MTTF data are also quite limited, and modeling results are sensitive to assumptions on the system's topology. A supplier of BESS (49) has quoted an MTTF of 58,400 hours, while modeling efforts for the BESS system's MTTF range approximately from a low of 3,400 (52) hours to 28,000 (53) hours and values in between (51). Given these large uncertainties and the extensive development in Li-ion stationary BESS, we believe that values between 10,000 and 20,000 hours should be assumed, or manufacturers estimates should be used if available.

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