AMPeRRe – A Novel Program for the Analysis of Microgrid Performance, Reliability, and Resilience

Jessica Nicholson 22 September 2023

Abstract

The transition to renewable energy is critical to decarbonization and mitigation of climate change. Many industries and federal facilities aim to incorporate greater renewable energy sources in their power infrastructure, so this research paper provides a path for new and innovative power grids to accomplish this while retaining reliability and resilience. While renewable sources of energy can–and do–support several installations, uncertainty still exists about how reliably these sources of energy can support small and/or critical power systems with higher reliability standards such as Army installations, tactical microgrids, and emergency response power. Maintaining reliability and resilience are already significant challenges for power grids, and those that have a high proportion of renewable energy face particular challenges due to their variability in power production. This research project addresses the reliability challenges associated with variable renewable energy by presenting a new program called AMPeRRe that predicts the service availability, fuel consumption, resilience, and excess energy production of proposed renewable-inclusive power grids. If proposed grids are predicted to be unreliable, this program generates recommendations to achieve 100% service availability and optimize the power grid for ideal performance outcomes before monetary investment into physical construction and testing.

This research paper describes the optimization goals of proposed power grids, supporting findings, and AMPeRRe's detailed calculation process used to evaluate power grids for ideal outcomes. AMPeRRe can determine the viability of proposed grids for many applications using minimal known input parameters and data sets. This program has the potential to significantly reduce uncertainty around the reliable implementation of renewable energy in power grids. It would eliminate many costs associated with physical prototype reliability testing methods and increase the economic viability of renewable-inclusive power grids throughout their life cycle.

Table of Contents

1. Executive Summary

Energy demand continues to grow on a global scale while the detrimental effects of climate change become increasingly apparent. Due to this, implementing sustainable energy solutions is becoming increasingly critical to fulfill this energy demand while transitioning our energy infrastructure away from fossil fuels that perpetuate climate change. The long-term well-being of global communities and industry depends on our ability to make this transition while maintaining performance and reliability in addition to optimizing cost and resources. Additional renewable energy sources create additional challenges within the system, however, that must be managed. Renewable energy sources such as solar and wind power create system variability due to the uncontrolled resource inputs necessary to generate power, while fossil fuel sources have controllable generation that can be matched to load. Challenges such as these must be addressed to design effective renewable-inclusive power grids with mechanisms that manage variability and ensure continuous service.

This energy transition requires that proposed renewable-inclusive power grids be conceptualized, constructed, and evaluated for use in existing facilities. Challenges to the reliability of a renewable-inclusive power grid include small system size relative to load, disconnect from the larger electrical grid, and stringent reliability requirements. Grids with a higher proportion of renewable energy will also experience higher variability due to the solar and wind resources they rely on. Controlled power sources, however, can maintain system reliability despite renewable energy variability if they act as secondary or supporting sources during significant shortages. Implementing a high proportion of renewable energy in power grids is a necessary challenge that does not yet have a robust set of standards or evaluation methods to determine feasibility and compatibility with the needs of the facilities these grids will provide power to. This research paper provides a methodology and a program–AMPeRRe–that can guide reliable renewable implementation and optimize the full grid to ensure more cost-effective, efficient, and carbon-minimal operation.

AMPeRRe will advance understanding of renewable-inclusive power grids as valuable and sufficient replacements for fossil fuels in several sectors. Given a new level of understanding provided by this program, proposed renewable-inclusive power grids can be shown to reduce carbon footprint without compromising function or performance. This program can be applied in many specific locations, industries, and facilities that aim to decarbonize and incorporate greater proportions of renewable energy. Each of these applications can significantly benefit from the calculation process this report provides to ensure reliability, resilience, and optimize the grid configuration to achieve several ideal outcomes. The desired long-term impact of this project is to promote the reliable implementation of renewable energy in power grids rather than fossil fuels to meet increasing electric demand. Current causes of increased electrical demand include the growing use of electric vehicles, fabrication of hydrogen and other clean fuel, and increasing reliance on electrical mechanisms in our daily lives. AMPeRRe can gauge the feasibility of renewable-inclusive energy systems to support this growing electric demand given accurate projections. Results provided by AMPeRRe demonstrate renewable-inclusive power grids' capability to be reliable, resilient, clean, and cost-effective, ultimately easing the uncertainty surrounding the performance of renewable energy technologies and informing solutions that progress the implementation of renewable energy in several types of grids and microgrids.

2. Objectives and Hypothesis

As renewable energy industries continue to grow, unique challenges arise surrounding their implementation that must be overcome to ensure quality and performance are not lost in the process of decarbonization. Two primary questions have prompted research and driven the development of AMPeRRe.

- What are the outcomes associated with successful stand-alone power grids?
  - Reliability, resilience, and decarbonization-related goals
- How well can these outcomes be achieved in power grids that incorporate a high proportion of renewable energy?

This project's approach involves overarching stages to create an accurate, repeatable program that can evaluate power grids for a wide variety of applications.

- **Identify** critical power grid outcomes related to reliability, resilience, and decarbonization
- **Develop** a repeatable process / program to measurably determine how well proposed power grids will achieve these outcomes
- **Validate** that this program yields accurate numerical results using prototype testing
- **Incorporate** this program into proposed power grid projects to provide the results needed to make informed decisions

AMPeRRe is particularly applicable to federal, public, industrial, and residential power grids that have the greatest challenges maintaining reliability and resilience. These include grids that:

- Are isolated / without any utility connection
- Contain critical loads and strict reliability requirements
- Incorporate a high proportion of renewable technologies and energy storage
- Experience high variability in location-based conditions:
  - Load
  - Ambient temperature
  - Direct normal solar irradiance, generated solar power
  - Wind speed, generated wind power

Using known natural conditions, a load profile, and defined power resource parameters associated with proposed renewable-inclusive power grids, the hypothesis is that it is possible to mathematically determine the viability of these power grids before any physical testing, construction, or implementation. This possibility relies on the ability to accurately determine the generated power from renewables based on their specifications and the natural resources they draw from. A successful program will provide users the ability to create optimized renewable-inclusive power grids that prove to be more reliable, resilient, environmentally friendly, and cost-effective than current grids.

3. AMPeRRe Simulation Capabilities

3.1 Ideal Power Grid Outcomes:
AMPeRRe predicts several performance outcomes to determine the feasibility of a proposed power grid. These outcomes are critical to a successful grid, so the ability to predict these outcomes can inform better decision-making around grid design and implementation.

1. Reliability: The grid's ability to maintain service given full functionality during business-as-usual conditions.
2. Resilience: The grid's ability to maintain service during component failure or to restore power quickly in the event of an outage.
3. Cost-Effectiveness: Minimization of the grid's life-cycle cost.
4. Decarbonization: Minimization of the grid's carbon emissions to mitigate climate impact.
5. Robustness: Maximization of the grid's life and minimization of maintenance needs.

The objective of a power grid is to simultaneously maximize reliability and resilience, minimize cost, minimize fuel consumption and decarbonize. This program provides a non-costly method to evaluate each of these factors for specific sets of inputs representing proposed power grids, but tradeoffs often occur as inputs are changed. System parameter changes that benefit resilience may raise costs, while those that minimize fuel consumption may risk losing reliability. It is challenging to find a solution that meets these objectives in the most economical way.

In addition to calculating reliability, this program can be used to design a fully (100%) reliable power grid. While the quantity of rated solar power, wind power, generators, and battery capacity are consequential in cost and have interdependent impacts on the ultimate reliability of the full system, the level of battery reserve charge has a predictable impact on reliability. This is a user-input independent variable that represents the charge at which the generators begin to operate to account for a shortage of renewable power. The purpose of maintaining a reserve charge is to account for sudden load spikes and the associated onset of high-magnitude renewable power shortage. Given that enough controlled power generation exists from sources such as generators, a high enough reserve charge will ensure full reliability by providing the system time to respond rather than immediately depleting battery charge and causing a loss of service before generators can activate. Once this reserve charge is found, the user is able to change other variables to simulate additional scenarios within the constraints of being a fully reliable system.

3.2 Power Sources Available in Simulation:
AMPeRRe is capable of simulating and evaluating power grids that contain renewable energy sources, energy storage, and controlled energy production methods such as generators. Renewable energy sources supply directly to the load and any surplus power charges the battery. When the renewable power is in shortage due to low production or high load, battery storage is the first to supplement the renewable power to meet demand. If the battery storage drops below a set reserve energy level during any shortage, a controlled energy production method such as generators will supply to the load to maintain the reserve charge until the renewable power reaches a surplus again. This power supply priority mimics a grid control system that maximizes reliability, maximizes resilience, minimizes fuel consumption, and minimizes wasted energy.

Power Supply Priority:

1. Renewable Energy – Solar and Wind
2. Energy Storage – Battery
3. Liquid Fuel Combustion – Generators

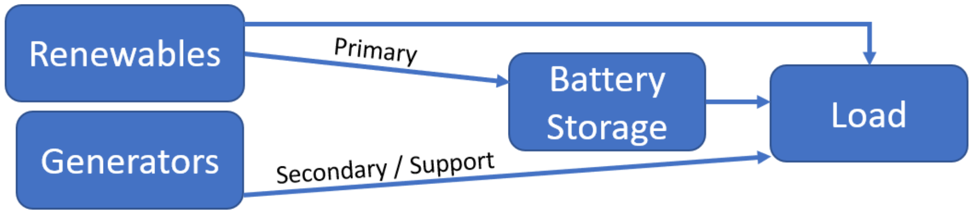

Figure 1: Simplified Power Flow from Each Source

1. **Renewable Energy – Resilience and Decarbonization**

A high proportion of clean renewable energy in a grid can promote significant decarbonization and contribute to meeting climate goals. Renewable energy integration in a power grid can be classified as "very high" if the renewable energy within the grid provides a minimum of 50% annual energy demand with the capability of providing up to 100% of the demanded instantaneous power (Kroposki 2017). Renewable energy causes greater variability in generated power, however, which leads to less predictable power generation and decreased reliability. It is important, therefore, to incorporate a balance of renewables that contributes to decarbonization objectives as much as possible without losing grid reliability.

Increased renewable energy incorporation allows a grid to supply a greater proportion of the load with renewables, decreasing the need for liquid fossil fuels. The less fuel the site needs, the less frequently it requires fuel transport. Lower fuel transport creates a more self-sufficient power grid and makes the grid more resilient to extreme conditions outside of the area. If renewables are an additional power source to a conventional fossil fuel grid, the grid may become more resilient to component failures. A greater variety of power sources decreases the chance that extreme natural conditions become fatal to the full power grid.

2. **Energy Storage – Reliability and Resilience**

The greater the battery storage capacity incorporated into the grid, the more energy the battery can capture during renewable power surplus periods. This allows renewables to contribute more energy to the grid despite their variability and prevents excess energy. Higher-capacity batteries are also more equipped to sustain power throughout renewable shortages. To maintain reliability, a reserve energy threshold is set. Fossil fuel sources will compensate for any shortage and supply to the load if the battery charge drops below this threshold to prevent the battery charge from depleting further. The reserve energy recommended to ensure reliability is dependent on the frequency and severity of power shortages. Greater shortages cause faster battery depletion and require a higher reserve energy to maintain reliability.

Using AMPeRRe, it is possible to find the battery storage capacity that captures all renewable energy regardless of how prolonged the surplus time periods are. The battery capacity that achieves this will maximize renewable energy use and can therefore minimize fossil fuel use. It is not always possible to cost-effectively achieve this, however, especially when higher proportions of renewable energy are integrated. A power grid is more likely to be resilient through component failures if it has high battery capacity and a high reserve charge. This means the battery will have more stored energy at a point of failure and therefore a longer survival time despite failure mode.

Battery charge and discharge rate are often defined relative to its capacity. The battery discharge rate must be high enough to supply power during all magnitudes of shortage. If a power shortage exceeds the discharge rate that the battery is capable of, the battery would be unable to maintain adequate service to the load and supporting controlled fossil fuel sources can supplement. A battery with a discharge rate greater than the highest anticipated power shortage can eliminate the need for fossil fuel support.

3. **Liquid Fuel – Reliability**

Realistically, many power grids still rely on controllable fossil fuels to offset renewable energy shortages and maintain reliability. AMPeRRe can therefore simulate controllable fossil fuel sources such as generators as secondary power. Several methods of generator support exist to maintain power system reliability, and AMPeRRe is capable of simulating two methods. For a simple set of included generators, generators may cyclically charge the battery at a fixed power rate when the stored energy drops below a defined threshold and then deactivate when the battery charge nears capacity. The power output of complex sets with multiple generators, on the other hand, may adhere to a control system that matches generator output to renewable power shortage when the battery charge drops below a reserve threshold.

Fuel is costly, requires transportation, and produces emissions that perpetuate climate change. While many power grids use fossil fuels as a controllable power source, it is possible to reduce the fuel consumption of a power grid. AMPeRRe prioritizes renewables in its simulated power supply using control methods that only apply generator power to maintain service in urgent scenarios. By doing this, it automatically minimizes fuel consumption for the selected energy resources. The more renewable energy sources included in the simulated power grid, the more renewable energy can contribute to the load. The higher the storage capacity in the system, the more of the produced renewable energy is captured during periods of surplus. Both changes decrease the fuel consumption required for the power grid to maintain reliability. Using AMPeRRe, users may also find the renewable energy sources and battery capacity for which the power grid can remain reliable if it eliminates all fuel use.

<u>3.3 Quantitative Results and Associated Objectives</u>:

This list describes each of the power system performance objectives supported by AMPeRRe capabilities, the guidelines defined for each consideration that this report recommends proposed systems follow, and justification of each consideration as well as background needed for subsequent sections that quantify these objectives. Proposed grids with a high proportion of variable renewable energy contribute to decarbonization, but they can also be validated as reliable and resilient to reduce the uncertainty surrounding their integration.

1. **Maximize Service Availability – Reliability**

Service availability is the percentage of time that a power grid meets demand during its period of operation. A system that provides continuous power supply to the load has a service availability of 100%. The primary objective of a power grid is to provide continuous service, so a proposed power grid's service availability must be validated as ≈100%. If high load or low power generation cause loss of power supply, AMPeRRe will calculate its service availability as a value below 100%. The service availability required from a power grid depends on the system it supports. The more critical the system, the higher the service availability standard its power grid must adhere to. Many service availability standards fall within the range of 99.99% to 99.9999%.

2. **Maximize Survival Time – Resilience**

In the event of a power grid failure, survival time is the time from the start of the failure to the loss of service. AMPeRRe's survival time output shows a user how long their grid would continue to provide service once failure occurs. Users can simulate any failure among the power sources within the power grid, as well as the start and end time of the failure. The longer the survival time determined by AMPeRRe, the more resilient the grid is to the simulated failure mode.

3. **Minimize Excess Energy – Cost-Effectiveness and Decarbonization**

If a power grid is producing more energy than it can capture, this excess energy must be managed. This is a necessity when the battery charge is nearing capacity and cannot capture additional renewable energy surplus. If the power surplus is greater than the battery charge rate, the grid must also manage excess power. Excess energy may be curtailed, sold to a connected utility, or filtered out of the grid. Curtailment occurs when a microgrid controller intentionally halts power generation from specific power sources to prevent the grid from being overloaded. Energy filtered out would be lost to the surroundings, but if the grid is connected to a utility, energy could instead be redirected back to the utility. Many additional factors inform the decision to curtail power as described by Section 5.8. These factors include limits on transmission line power flow, voltage, and the need to maintain stability. If excess energy production from a grid can be minimized, this energy can instead be used productively toward serving the load. Doing so can make the grid more cost-effective and minimize the need for fossil fuel support.

4. **Minimize Magnitude and Duration of Power Shortages – Reliability and Resilience**

The greater the variability of the system in either power generation or load, the more likely load will exceed generated power. If load exceeds generated power for a significant amount of time, there is a greater chance that stored energy reserves will fully deplete and cause a loss of service. Traditionally, engineers would over-size renewable power sources compared to the load to compensate for this variability. The greater the variability in the system, the larger the power grid must be relative to the load to maintain service availability. This is a cost-intensive solution, however. The preferable alternative is to design a grid with renewable power generation patterns that align as well as possible with the load profile. AMPeRRe provides users time-based generated power data from each source that they can compare to the load profile to select the renewable energy technologies that best fit the load. The better the grid's power generation pattern matches needs, the less frequently shortages will occur and the smaller these shortages will be. The less severe the power shortages, the more likely a system is to be both reliable and resilient.

5. **Minimize Fossil Fuel Use / Liquid Fuel Consumption – Decarbonization**

A generator's rate of fuel consumption is dependent on its power output at any given time (Section 5.5). In a generator-inclusive power grid, the rate of fuel consumption from each generator will vary depending on the power demanded from the generator. For a generator-inclusive power grid with one or multiple generators, AMPeRRe can calculate its total fuel consumption over a period of time. The more alternative energy sources included in the grid, the less power required of the generators on average and the less fuel the system will consume. The less fuel the system consumes, the closer it can get to reaching decarbonization goals. This also reduces the need for fuel transport and makes the grid more self-sufficient.

6. **Minimize Generator Duty Cycle – Cost-Effectiveness and Robustness**

AMPeRRe keeps track of the timesteps that generators are operating and provides a user with the duty cycle of the generators within the system. Similar to fuel consumption, the duty cycle of generators within a system will decrease if greater quantities of alternative energy sources are included in the grid. The more alternative energy sources included in the grid, the less frequently generators must operate to support the grid. This is reflected as lower calculated duty cycles. The lower the duty cycles of the generators, the longer their lifespan is and the lower the costs associated with maintenance and replacement.

4. Procedural Overview of Calculation Process

This section provides a high-level overview that explains how the AMPeRRe program can be used for power grid evaluation. It covers the process necessary to achieve the quantitative results described in the previous section, and it is a guide for users who can benefit from a functional understanding.

<u>4.1 Renewable Energy Incorporation</u>:

The first stage of AMPeRRe's process is to calculate the generated power from each variable renewable source and add these datasets towards the load to simulate their contribution. The program's calculation process maximizes renewable contribution to the load by prioritizing these energy sources as the first to fulfill demand. Any surplus is collected in an energy storage system, and renewable-produced energy is only curtailed when energy storage is at capacity.

1. Gather known power grid parameters and natural resource data
    a. Determine the solar, wind, battery, inverter, and generator components included in the conceptual power grid
    b. Gather load data from the facilities of interest
    c. Use the National Solar Radiation Database (NREL 2023) or a similar source to gather the annual natural resource data sets needed for the calculation process (Select the location, year, and time step length equivalent to that of the load data)
        i. Direct normal solar irradiance
        ii. Ambient temperature
        iii. Wind speed
2. Calculate generated wind power at every time step
    a. <u>Method 1</u>: Use the manufacturer power curve of each wind turbine model to create a set of generated power values that correspond to the wind speed data
    b. <u>Method 2</u>: Calculate wind power generation corresponding to each simulated wind speed, power coefficient and load time interval data point
3. Calculate generated solar power at every time step using solar irradiance data

4. Calculate a power surplus data set by taking the difference between total renewable power produced and corresponding load data
    a. Positive values represent power surplus while negative values represent a shortage
5. Using the surplus data, calculate the proportion of load supplied by renewable energy corresponding to each time step
    a. If the average proportion from this set is greater than 0.5, the power grid meets the 50% renewable energy involvement recommendation
    b. If renewable power supplies 100% of the load for any of the timesteps, the power grid meets the instantaneous power capability recommendation
6. Calculate the service availability of the renewable-only power grid; the proportion of positive surplus values
    a. Service availability calculations below 100% indicate the need for supporting energy storage and/or controlled power generation in the proposed power grid

<u>4.2 Energy Storage Inclusion and Controlled Generator Support</u>:

If the renewable sources yield a low service availability, the user can find the energy storage capacity and controlled power generation needed to support periods of shortage and reach a theoretical service availability of 100%. Existing storage and controlled generation within a proposed grid can be evaluated using this process to determine whether they create a sufficiently reliable system. This assumes a business-as-usual scenario with no considerations such as unplanned outages. These can be evaluated through power resource disconnection in the resiliency analysis (Section 5.7). If the maximum power surplus data point or the maximum shortage exceed the bounds set by the battery's maximum charge and discharge rates, the battery will limit how much energy is collected during these exceeding surplus periods and how much energy is discharged during excess shortage.

1. Create a running total of the chronological renewable power surplus data set and apply bounds so it remains between zero and the input storage capacity
2. Calculate the service availability of the renewable and storage-inclusive power grid; the proportion of time steps for which the stored energy is greater than zero
3. Implement a control system that contributes generator power to the stored energy running total when two conditions are simultaneously met:
    a. Stored energy drops below an input reserve charge
    b. The renewable energy power is in shortage
4. Choose the proportion of shortage that the generator power will offset during operation
    a. A proportion >100% of the shortage would charge the battery until it returns to a value above the reserve charge
    b. A proportion =100% of the shortage would maintain the current battery charge until the renewable power returns to a state of surplus
    c. A proportion <100% of the shortage would allow the battery to undergo slow depletion until the renewable power returns to a state of surplus
5. Calculate the service availability of the renewable, storage, and generator-inclusive power grid; the proportion of time steps for which the stored energy is greater than zero
    a. If the service availability is <100%, increase the battery reserve charge until the service availability is 100%

6. Populate the "number of generators running" data set by choosing the load factor; the proportion of rated power for which additional generators are activated
7. Calculate the rate of fuel consumption at each timestep using the known fuel consumption curves, number of generators running dataset, and generator power output dataset
8. Find the total yearly fuel consumption or average rate of fuel consumption using the rate of fuel consumption dataset
9. Calculate the number of days between fuel resupply for comparison to other scenarios
10. Calculate the excess energy at every timestep due to lack of available battery capacity
11. Calculate the excess energy at every timestep due to insufficient allowable charge rate

4.3 Resilience:

The proposed power grid will not always operate as expected and remain at business-as-usual. Extreme natural conditions, deterioration from prolonged use, power surges, and intentional attacks–among other things–have the potential to cause power resource outage(s) for a known or unknown time period. It is important to design a grid that is resilient to these possible conditions, and the design of a resilient power grid is most effective if an engineer understands how the proposed grid will respond to different failure types. AMPeRRe is capable of simulating power resource disconnections to plan for the possibility of these failures. A user can introduce disturbance signals that exclude solar, wind, generator, or battery resources from contributing to the load for a specified time period. Any combination of these failures can be simultaneously simulated. AMPeRRe then determines whether the power grid maintains service throughout the failure. If the power grid does not maintain service, AMPeRRe provides an estimated survival time for the given failure.

1. Confirm that AMPeRRe calculates 100% service availability for the business-as-usual grid
2. Choose any quantity of solar to simulate its failure or loss for a specific start and end time
3. Choose any wind turbines to simulate their failure or loss for a specific start and end time
4. Choose any quantity of battery capacity to simulate its failure or loss for a specific start and end time
5. Choose any combination of generators to simulate their failure or loss for a specific start and end time
6. Determine whether the system maintains service throughout the chosen time period
7. If AMPeRRe shows loss of service, measure the survival time from its associated failure
    a. Survival time is the elapsed time from the start of a failure to the loss of service
8. Observe resulting changes in AMPeRRe's calculated outcomes: service availability, generator duty cycle, excess energy, and fuel consumption

5. Detailed Calculation Process

This section expands the procedure and describes the full calculation process behind AMPeRRe's capabilities. It provides a thorough explanation of the variables, formulas, control factors, feedback loops, disturbance signals and other mathematical processes incorporated in AMPeRRe to achieve numerical results for proposed renewable-inclusive power grids.

5.1 Known Parameters:

To apply AMPeRRe's calculation process to a proposed power grid, users must know or define the following parameters and characteristics.

1. Solar Array Parameters:
    a. Rated power
    b. Temperature coefficient
    c. Nominal operating cell temperature
2. Wind Turbine Parameters:
    a. Manufacturer
    b. Power curve (power output vs wind speed)
    c. Blade radius
    d. Altitude / height
    e. Air density associated with altitude
3. Inverter Parameters:
    a. Size / rated power
    b. Efficiency
    c. Ramp-up rate limit
    d. Ramp-down rate limit
4. Battery Parameters:
    a. Manufacturer
    b. Battery capacity
    c. Maximum charge and discharge rate
    d. Round-trip or charge/discharge efficiency
    e. Average parasitic load (If not included in full load profile)
5. Generator Parameters:
    a. Number of generators
    b. Rated power
    c. Power acceptance rate
    d. Fuel consumption curve(s)
6. Chronological Load Data:
    a. Time step length
    b. Collective power load data from the location of interest
7. Chronological Natural Resource Data:
    a. Time step length equivalent to load data
    b. Direct normal solar irradiance
    c. Wind speed
    d. Ambient temperature

5.2 Assumptions and Generator Control System Variables:

The following assumptions are applied to the calculation process by default. Each of these can be changed, however, if the user needs to simulate alternate conditions.

1. Maximum battery charge and discharge rate (in kW) are ½ of its storage capacity (kWh)

2. The initial battery charge is set to 50% of its capacity; a half-charged battery
3. Generators will only charge the battery if renewable power is in shortage and the battery charge is below 30%, the default reserve charge threshold

AMPeRRe also has input variables that users can alter to represent different feedback and control system scenarios. These are not defined system parameters, but they change how the generators and battery storage units respond to current states.

1. Reserve battery charge – Energy threshold for which generators support shortage
2. Load factor – Proportion of rated generator power threshold for which the number of generators operating changes
3. Peak-shaving power limit – An upper bound applied to generator power output to simulate peak-shaving

<u>5.3 Renewable Power Calculations</u>:

This section describes the renewable power component of the mathematical procedure needed to evaluate each proposed renewable-inclusive power system for reliability, resilience, and fuel consumption.

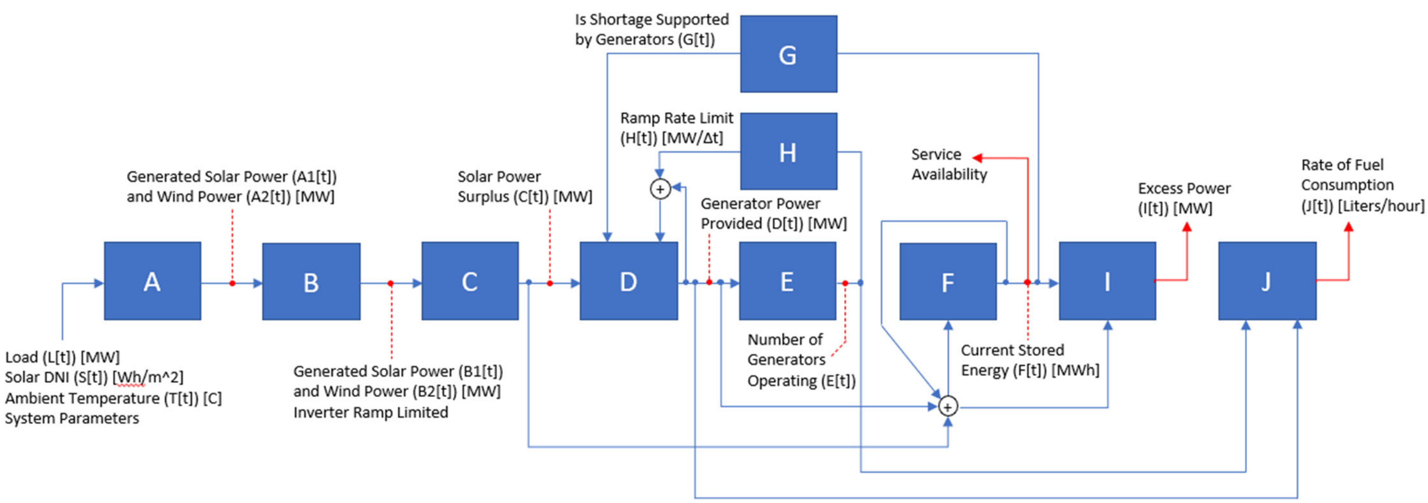

Figure 2: AMPeRRe Calculation Process Block Diagram

Equations 1, 2 and 3 represent a validated method to calculate the power produced from a solar energy source at any given moment. The background to these formulas is described in Section 7.1.

Equation 1: PV Solar Generated Power

$$A_1[t] = C * S[t] * n_{loss} * e_{inverter}$$

Equation 2: Efficiency Representing Loss due to Temperature Increase

$$n_{loss} = 1 - \lambda(T_{cell} - 25) \leq 1 \quad else \quad n_{loss} = 1$$

Equation 3: Temperature of the PV Cells

$$T_{cell} = T_{amb}[t] + (\frac{S[t]}{800} * (T_{NOCT} - 20))$$

Wind turbine models have differing power coefficients and power curves, so generated wind power must be calculated for each individual wind turbine "i" within a system. The total number of turbines in the system is represented by "m." The "m" number of generated wind power datasets are then summed together to represent the total contribution of wind power to the load at every timestep. Equation 4 is a validated formula to calculate wind power at each timestep for every turbine model included in the power grid.

Equation 4: Wind Generated Mechanical Power

$$A_2[t] = \sum_{i=1}^{i=m} 0.5 * \rho * C_{P,i} * v(t)^3 \pi r_i^2$$

Turbine models often have a specified power curve that defines their power output per wind speed. Figure 3 shows an example of this power curve. The rated power of a wind turbine "c" limits power output when the wind speed "w" exceeds its rated wind speed to adhere to mechanical limits and prevent failure.

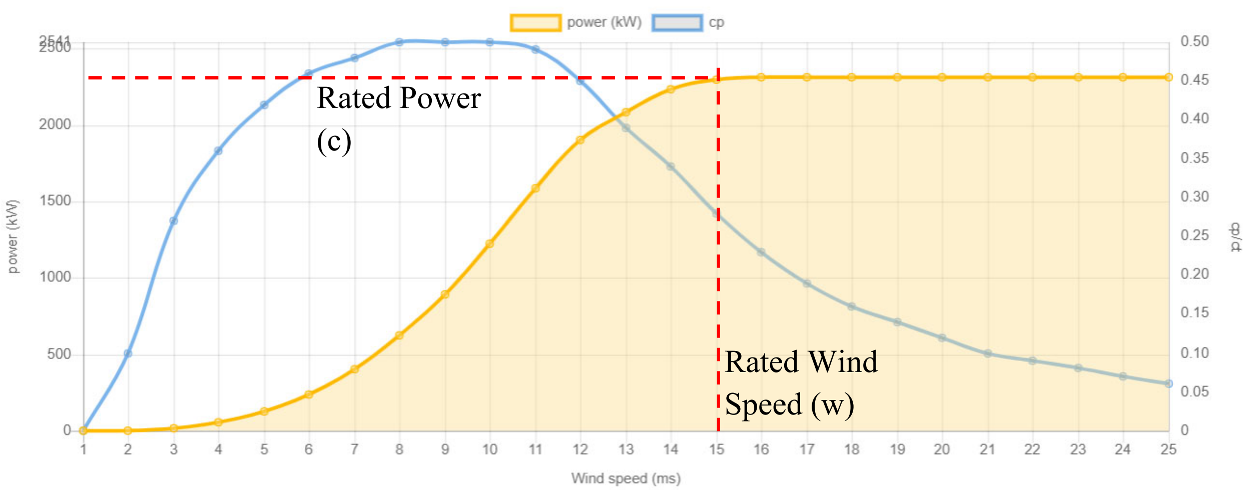

Figure 3: Enercon E-70 E4 Wind Turbine Power Curve

Equation 5: Wind Turbine Power Curve Mathematical Model

$$A_2[t] = \sum_{i=1}^{i=m} \frac{c_i}{(1 + a_i e^{-k_i w})}$$

Equation 5 is a mathematical model that can be designed to closely fit a wind turbine power curve. For each turbine, the coefficient "a" and growth rate "k" must be set to values for which the resulting formula yields the maximum correlation coefficient to the power curve it models. In Excel, the Solver tool can be used by selecting the correlation coefficient cell and setting it to "maximum." The a and k cells would be set as the "changing variable" cells. In a coding language such as C#, root-finding functions or non-linear solver functions can determine the a and k values needed to yield a maximum correlation coefficient. Figure 4 and Table 1 demonstrate how this model represented by Equation 5 closely fits two wind turbine power curves–Enercon E-70 and E-82–when the best-fit a and k coefficients are found.

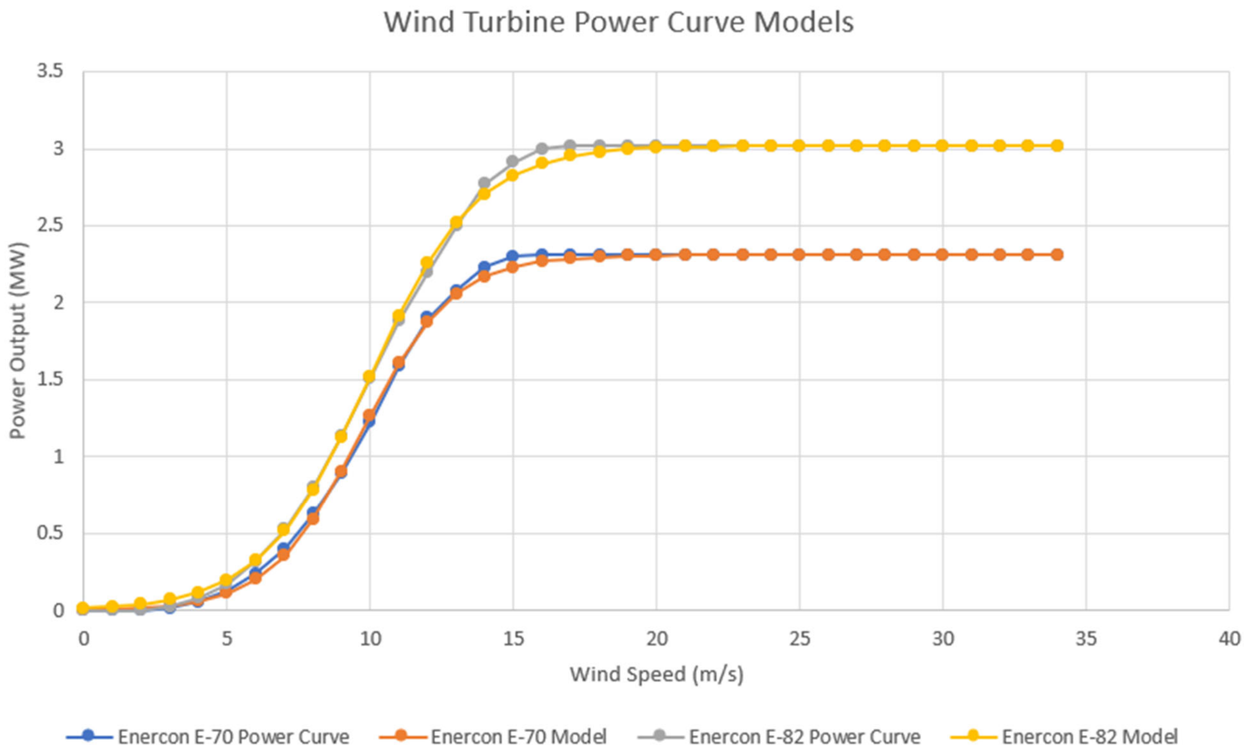

Figure 4: Examples of the Power Curve Model

Table 1: Correlation Associated with Examples of Power Curve Models

Formula Coefficients E-70		Formula Accuracy E-70	
Rated Power [c]	2.31	Correl. Coefficient	0.9997109
a	454.6984819	r^2	0.9994218
k	0.631623504		
Formula Coefficients E-82		**Formula Accuracy E-82**	
Rated Power [c]	3.02	Correl. Coefficient	0.9997004
a	203.8902398	r^2	0.9994009
k	0.533682682		

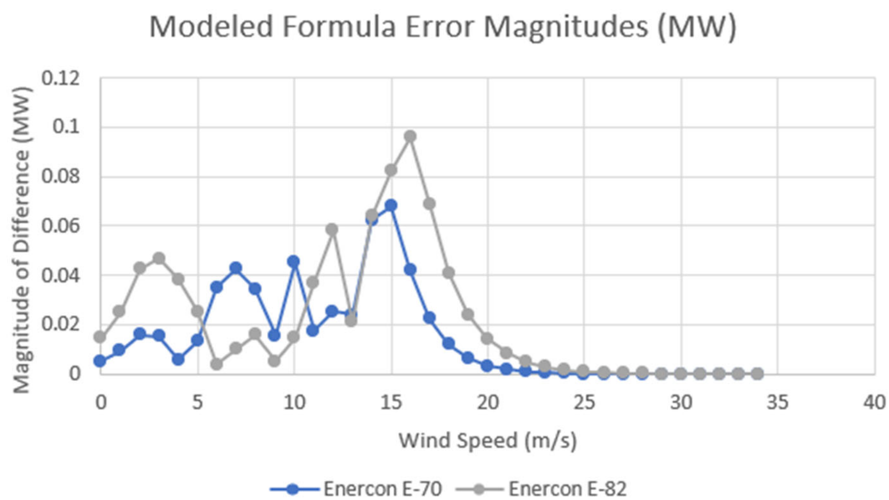

Figure 5: Error Magnitude of Power Curve Model for Each Wind Speed

The correlation coefficient of these two examples and Figure 5 demonstrate that with proper a and k coefficients, the power curve model in Equation 5 is a good match for standard power curves and will yield accurate power output results when used to calculate generated wind power from wind speed data.

Equation 6: Generated solar and/or wind power with inverter ramp rate limits

$$B[t] = A[t] \quad for \quad A[t-1] - R_{rampdown} < A[t] - A[t-1] < A[t-1] + R_{rampup}$$

Equation 7: Inverter Ramp Rate Limit on Generated Power

$$B[t] = A[t-1] + R_{rampup} \quad for \quad A[t] - A[t-1] > A[t-1] + R_{rampup}$$
$$B[t] = A[t-1] - R_{rampdown} \quad for \quad A[t] - A[t-1] < A[t-1] - R_{rampdown}$$

While the $A_1[t]$ and $A_2[t]$ functions calculate generated solar and wind power, inverter ramp rates must be taken into consideration as they place a limit on the rate of generated power increase or decrease. Equation 6 applies this limit to the calculated generated power of each timestep by maximizing the change in generated power to the ramp rate from one timestep to the next. Equation 7 shows that if the change between timesteps is calculated to be greater in magnitude than the ramp rate, a control is applied to keep the change equivalent to the ramp rate.

Equation 8: Surplus of Renewable Power (W)

$$C[t] = B[t] - L[t]$$

Equation 8 calculates the quantity of renewable power generated in excess of the load at every timestep. Positive values indicate a surplus of renewable power in the system, while negative values indicate a shortage. Equation 9 shows how a user can apply the surplus data to find the proportion of load supplied by renewable energy at any given timestep.

Equation 9: Proportion of Load Supplied by Renewable Energy

$$P_{VRE} = 1 - \frac{|C[t]|}{L[t]} \quad for \quad C[t] < 0 \quad else \quad P_{VRE} = 1$$

5.4 Generator Support and Battery Storage:

To account for periods of shortage and prevent loss of service, controlled power sources such as generators can supply power to the system.

Equation 10: Supporting Generator Power Provided to System (W)

$$D[t] = G[t] * |C[t]| \quad for \quad D[t-1] - H[t] < D[t] - D[t-1] < D[t-1] + H[t]$$
$$and \quad D[t] \leq n * P_{gen}$$

By default, generators support the full proportion of shortage when the battery charge drops below an input reserve value. The time-based variable G[t] in Equation 10 is a numerical multiplier applied to the D[t] formula to reflect generator power output that is only greater than 0 when two simultaneous conditions are met:

1. The collective power output from renewable energy sources is in a period of shortage
2. The battery charge is below a defined reserve charge

Equation 11: Default Conditions of Generator Operation

$$G[t] = 1 \quad for \quad C[t] < 0 \quad and \quad 0 < F[t] < F_{reserve} \quad else \quad G[t] = 0$$

Similar to generated renewable power, the rate of change of this time-based variable D[t] is limited by the generator power acceptance rate. Inertia is associated with the operation of both inverters and generators, so they are limited in how quickly they can adjust their power output. To simulate this limit to change in power output, Equation 12 limits the magnitude of change in D[t] to the acceptance rate H[t].

Equation 12: Generator Acceptance Rate Limit on Power Provided

$$D[t] = D[t-1] + H[t] \quad for \quad D[t] - D[t-1] > D[t-1] + H[t]$$
$$D[t] = D[t-1] - H[t] \quad for \quad D[t] - D[t-1] < D[t-1] - H[t]$$
$$D[t] = 0 \quad for \quad C[t] \geq 0 \quad or \quad F[t] \geq F_{reserve}$$

The acceptance rate is a variable rather than a constant because the number of generators operating impacts the acceptance rate H[t]. Equation 13 shows this relation between the number of generators operating E[t] and the acceptance rate H[t]. The variable R_g represents the acceptance rate limit of one generator.

Equation 13: Collective Generator Acceptance Rate

$$H[t] = E[t] * R_g$$

The number of generators operating E[t] in Equation 14 depends on the power output required by the generators D[t]. The load factor variable LF represents the maximum proportion of the total rated generator power $P_{generator}$ that the power output requirement D[t] must reach before additional generator(s) are activated to share the load so the power output of each generator can drop. The variable “n” is the number of generators in the system. If “x” must be larger than “n” to meet the D[t] condition, “x” is limited to the value of “n.”

Equation 14: Number of Generators Operating

$$E[t] = (lowest\ integer\ "x"\ for\ which\ D[t] \leq x * P_{gen} * LF) \leq n$$

Using the E[t] dataset in multi-generator systems, AMPeRRe provides a histogram displaying the proportional frequency for which a certain number of generators are operating during the measured period.

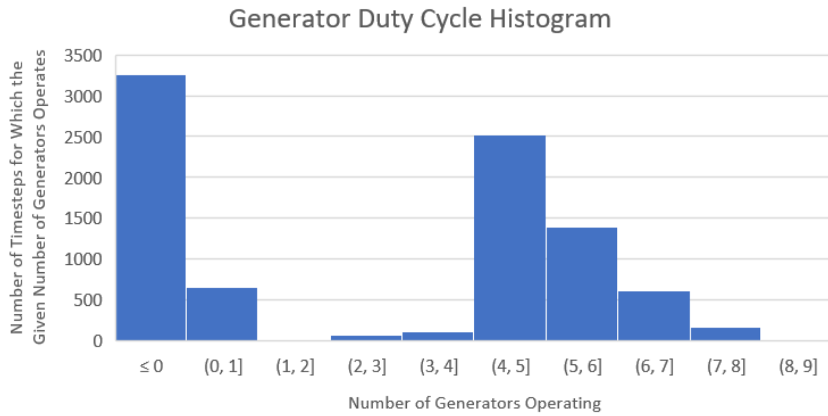

Figure 6: Example Histogram Provided by AMPeRRe for Number of Generators Operating

Figure 7 shifts this data to the time domain and shows the relationship between the generator power output D[t] and the number of generators operating E[t].

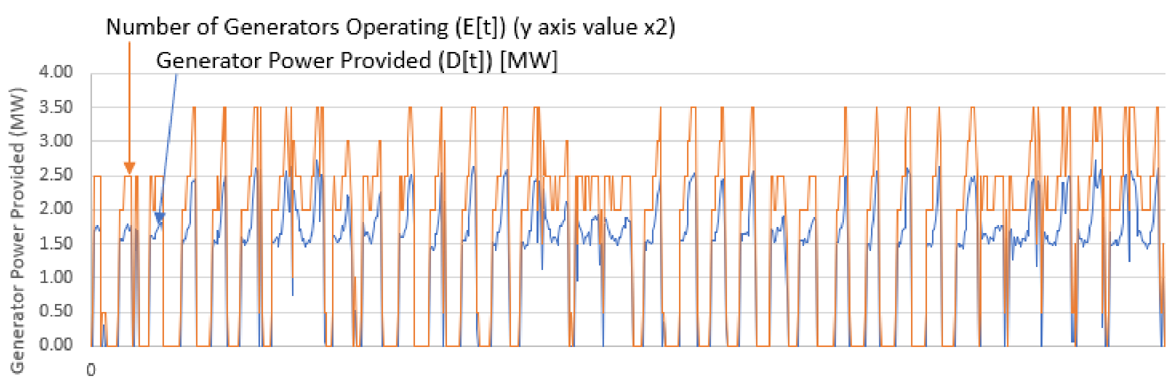

Figure 7: Generator Power Provided D[t] Impacts the Number of Generators Operating E[t]

If the system is supported by battery energy storage, the energy within the system from the renewable power surplus C[t] and generator power output D[t] contribute to the stored energy within the battery. The stored energy, or state of charge F[t], at each timestep is determined by summing these power contributions as shown in Equation 15 and adding them to the previous stored energy timestep to create a running total of energy in kilowatt-hours. Figure 8 is an example of this stored energy plotted to visualize how it changes with time.

Equation 15: Battery State of Charge (kWh)

$$F[t] = C[t] + D[t] + F[t-1] \quad for \quad 0 \leq F[t] \leq F_{cap}$$

$$F[t] = 0 \quad for \quad F[t] \leq 0 \quad and \quad F[t] = F_{cap} \quad for \quad F[t] \geq F_{cap}$$

Equation 16: Charge Rate Limit on State of Charge

$$F[t] = F[t-1] + R_{charge} \quad for \quad C[t] + D[t] > R_{charge}$$
$$else \quad F[t] = Minimum(F_{cap}, C[t] + D[t] + F[t-1])$$

Equation 17: Discharge Rate Limit on State of Charge

$$F[t] = F[t-1] - R_{discharge} \quad for \quad C[t] + D[t] < R_{discharge}$$
$$else \quad F[t] = Maximum(0, C[t] + D[t] + F[t-1])$$

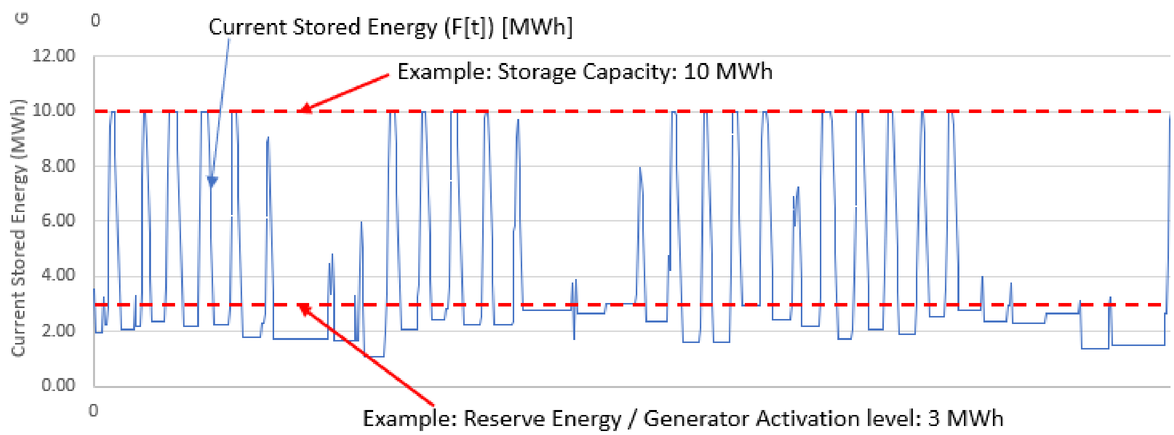

Figure 8: Battery Charge vs Time with Reserve Energy Maintained by Generators

The periods of constant battery charge in Figure 8 represent time steps of generator support. This example shows that by default, generators support the full magnitude of shortage to ensure no battery discharge. The power system must meet two simultaneous conditions to activate generator support. The renewable energy production must be in shortage ($C[t] < 0$) and the battery charge must be below the reserve threshold ($F[t] < F_{reserve}$). Generators only support the load below the battery reserve threshold because when the charge is higher, the battery can deplete to support shortage instead. Battery power is a higher priority than generator power to achieve minimal fuel consumption.

AMPeRRe inputs allow a user to change the reserve battery charge threshold and the proportion of power shortage that generators offset during periods of support. By default, this proportion is 100%, but it can be altered. The program also allows for additional tiers of shortage-proportional generator support depending on battery charge. Figure 8 and Equation 11 represent the default scenario, while Equation 18 and Figure 9 show an example of an additional battery charge tier that provides generator support for 95% of renewable power shortage.

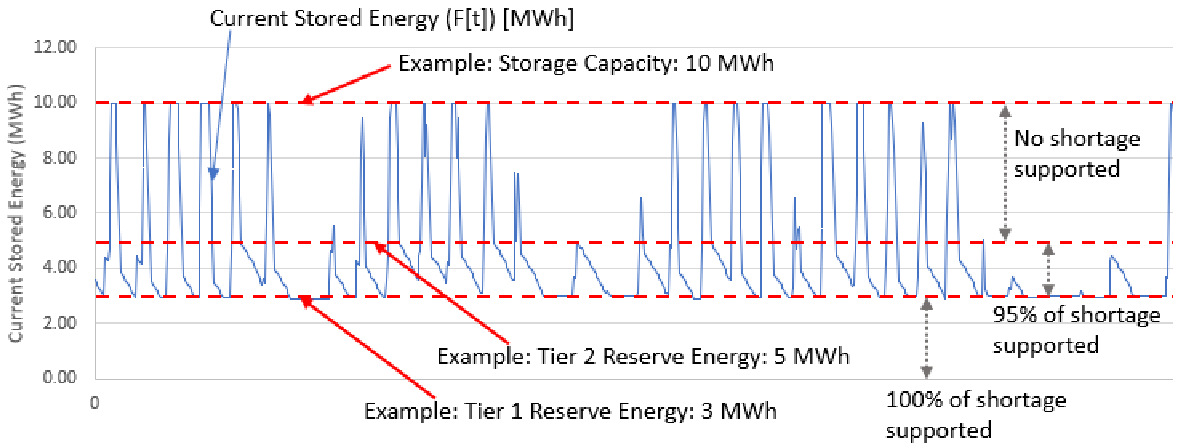

Figure 9: Battery Charge vs Time with Tiered Reserve Energy Maintained by Generators

Table 2: Inputs associated with Tiered Reserve Energy Control System

	Proportion of Shortage Supported by Generators - Tiered, Dependent on Current Battery Charge		
Minimum Charge (MWh)	0	3	5
Shortage Supported	1	0.95	0

Equation 18: Example of Tiered Generator Operation

$$G[t] = 1 \quad for \quad C[t] < 0 \quad and \quad 0 < F[t] < 3$$
$$G[t] = 0.95 \quad for \quad C[t] < 0 \quad and \quad 3 < F[t] < 5$$
$$else \quad G[t] = 0$$

Each of the values in Table 2 are represented in Equation 18 and can be altered. When the battery charge is between 3 and 5 MWh, for example, battery discharge is slower because generators offset 95% of any power shortages. This allows for a slower transition to generator support rather than the immediate ramp-up associated with the default scenario in Figure 8. As a result, the delay in generator activation does not cause significant drops below the tier 1 reserve energy.

5.5 Service Availability, Excess Power, and Fuel Consumption:

If the battery charge fully depletes during a power shortage, the power grid will lose its service to the load. The calculated battery charge dataset F[t] therefore provides the information needed to predict a power grid's service availability. Equation 19 shows that timesteps with a battery charge greater than 0 ($F_i[t] > 0$) contribute to the service availability summation while timesteps of 0 battery charge do not count towards it. This means that the service availability is calculated at 100% if the battery charge never reaches 0, and the service availability drops below this 100% for each timestep that the battery charge reaches 0.

Equation 19: Service Availability of the Power Grid (%)

$$S = 100 * \frac{\sum_{i=1}^{i=t_{total}} (1 \quad for \quad F_i[t] > 0 \quad else \quad 0)}{t_{total}}$$

If the service availability is >100% in a generator-inclusive system, two possibilities may contribute to this. The number of generators and their collective rating may be insufficient to supply to the load during the highest quantities of renewable power shortage. To address this, a user can add higher levels of alternative energy sources to reduce the magnitude of the shortages the generators must account for. If this does not significantly reduce shortage magnitudes, the user can add additional generators to raise their collective rated power. Another potential cause of insufficient service availability is a battery reserve charge that is too low. If this is the case, the user can raise the battery reserve charge until it yields 100% service availability.

During timesteps of full battery charge or power that exceeds the battery's allowable charge rate, surplus power cannot be captured and must be treated as excess power. This excess power may be curtailed, filtered out of the system, or provided to a utility if the grid is utility-connected. Equations 20 and 21 calculate excess power at each timestep, which are then summed to determine the total excess energy during the evaluated time period.

Equation 20: Excess Power due to Lack of Available Battery Capacity

$$I[t] = (C[t] + D[t] + F[t-1]) - F_{cap} \quad for \quad F[t] = F_{cap} \quad else \quad I[t] = 0$$

Equation 21: Excess Power due to Insufficient Allowable Charge Rate

$$I[t] = (C[t] + D[t]) - R_{charge} \quad for \quad C[t] + D[t] > R_{charge} \quad else \quad I[t] = 0$$

The rate of fuel consumption is dependent on the generator power output D[t] and the number of generators operating E[t]. Fuel consumption curves provided in generator model specifications define the rate of fuel consumption at different power outputs. Depending on the shape of the curve, a formula can be modeled to the curve that mathematically defines the relationship between power output and rate of fuel consumption. If the best-fit fuel consumption curve model is linear, it is represented by Equation 22a. If the model is quadratic, it is represented by equations 22b and 22c or formulas of a higher order. The variable "x" in linear and quadratic formulas is represented by the x-axis power output D[t], while the intercept is always multiplied by the number of generators running E[t]. Coefficients a, b, c, and d are associated with the best-fit curve specific to the fuel consumption curve(s) evaluated.

In a system with multiple generators of the same model, the fuel consumption curve and coefficients are the same for each generator. Equation set 23 represents the fuel consumption of this system and the number of generators running is represented by E[t]. Figure 10 shows how the intercept of the fuel consumption curve shifts and the collective rated power increases depending on how many generators within a system are operating. The number of generators operating is dependent on the power output demanded of the generator set D[t], so the red dotted-line overlay provides an example of the number of generators that would operate E[t] depending on the x-axis power output. As shown in Equation 14, the load factor LF defines E[t] thresholds as a proportion of collective operating generator rated power.

Equation Set 22: Linear and Quadratic Models

a. $y = ax + b$

b. $y = ax^2 + bx + c$

c. $y = ax^3 + bx^2 + cx + d$

Equation Set 23: Associated Fuel Consumption Curve Models

a. $J[t] = aD[t] + bE[t]$

b. $J[t] = aD[t]^2 + bD[t] + c$

c. $J[t] = aD[t]^3 + bD[t]^2 + cD[t] + d$

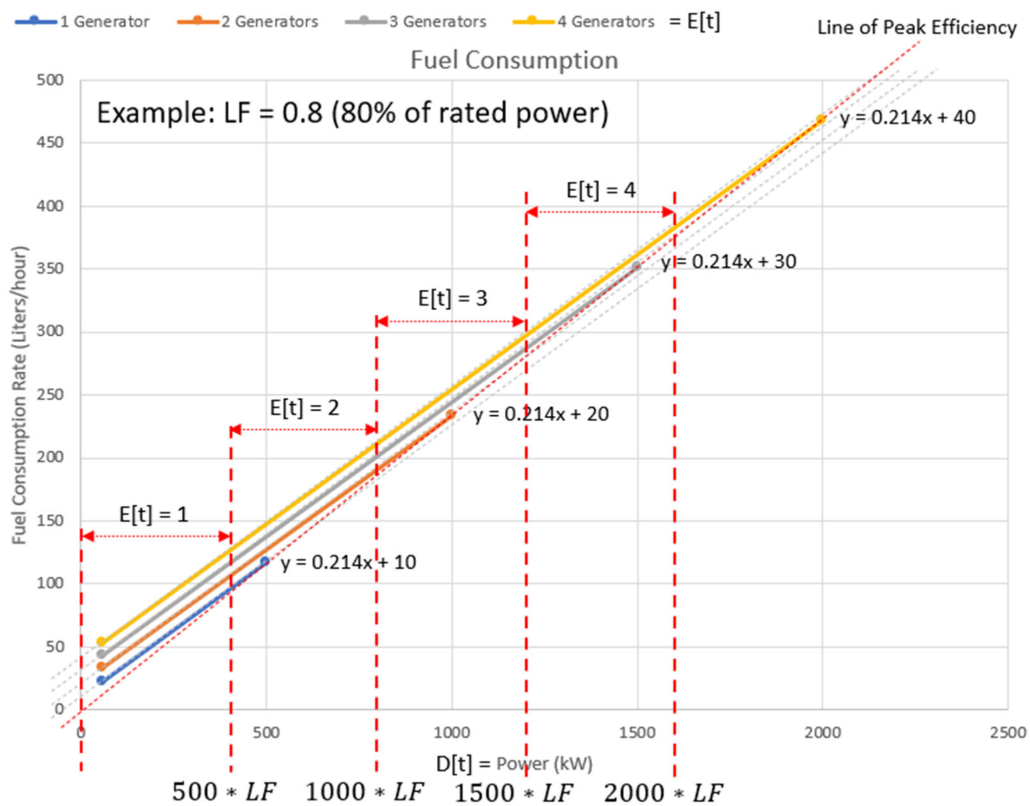

Figure 10: Example of Fuel Consumption Curve Dependence on # of Generators Operating

In a system with multiple generators and various models, Equation set 24 represents the fuel consumption curve summation of a system with multiple generator models. Each model has a different fuel consumption curve and therefore different coefficients, so the variable "n" in this case represents the number of unique generator models.

Equation Set 24: Fuel Consumption Curve Models of a Multi-Model Generator System

a. $J[t] = \sum_{i=1}^{i=n} a_i D[t] + b_i E[t]$

b. $J[t] = \sum_{i=1}^{i=n} a_i D[t]^2 + b_i D[t] + c_i$

c. $J[t] = \sum_{i=1}^{i=n} a_i D[t]^3 + b_i D[t]^2 + c_i D[t] + d_i$

Using the fuel consumption rate dataset J[t], AMPeRRe provides a histogram that shows the comparative frequency of the system's fuel consumption rate at any given time.

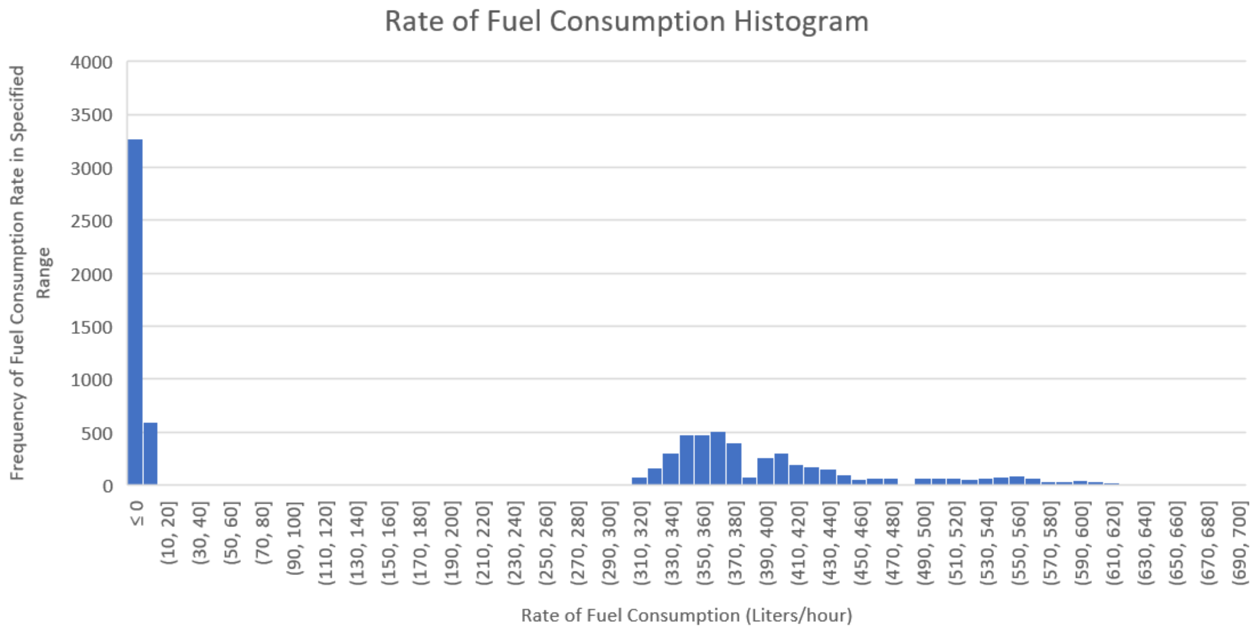

Figure 11: Rate of Fuel Consumption Histogram

Predicting a site's fuel consumption can provide insights about several aspects of its operation. Reduced fuel consumption leads to reduced costs, noise, and greenhouse gas emissions. Fuel use requires transport, so the more fuel a site uses, the more frequently it must import fuel and allocate fuel to the transport process itself. If the site knows its current fuel consumption, AMPeRRe results can derive the fuel savings associated with changes in power grid renewable sources, fossil fuels, or energy storage. If the site knows their current time needed between fuel resupply, AMPeRRe results can inform the site of the changes in time needed between resupply associated with power grid changes. Assuming an inverse relationship between the time between resupply and the fuel consumption rate, Equation 25 applies. The variable R_{fuel} is the current fuel consumption rate while R'_{fuel} is the rate found by AMPeRRe for the new scenario. d represents the current amount of time between fuel resupply.

Equation 25: Time Between Fuel Resupply given a Known Change in Fuel Consumption Rate

$$d' = \frac{R_{fuel}}{R'_{fuel}} * d$$

If a user knows the available fuel storage capacity, AMPeRRe's calculated fuel consumption rate and this fuel storage capacity can determine time needed between resupply. C_{fuel} represents the fuel storage capacity in Equation 26.

Equation 26: Time Between Fuel Resupply given a Known Fuel Storage Capacity

$$d' = \frac{C_{fuel}}{R'_{fuel}}$$

5.6 Resilience to Solar or Wind Failure:

AMPERRE predicts the service availability, fuel consumption, and energy curtailment of a system given known rated quantities of each solar, wind, generator, and battery resource. This program maintains an assumption that these resources are fully functional throughout the measured time period, but it is also capable of deviating from that assumption to simulate the disconnection or loss of a resource for a specified amount of time. For solar and generator resources, this program can simulate the loss of the full resource or a proportion of the rated power. For wind resources, it can simulate the loss of specific turbines. Assuming the total battery storage capacity is distributed between multiple batteries, it can simulate the loss of any proportion of the total capacity.

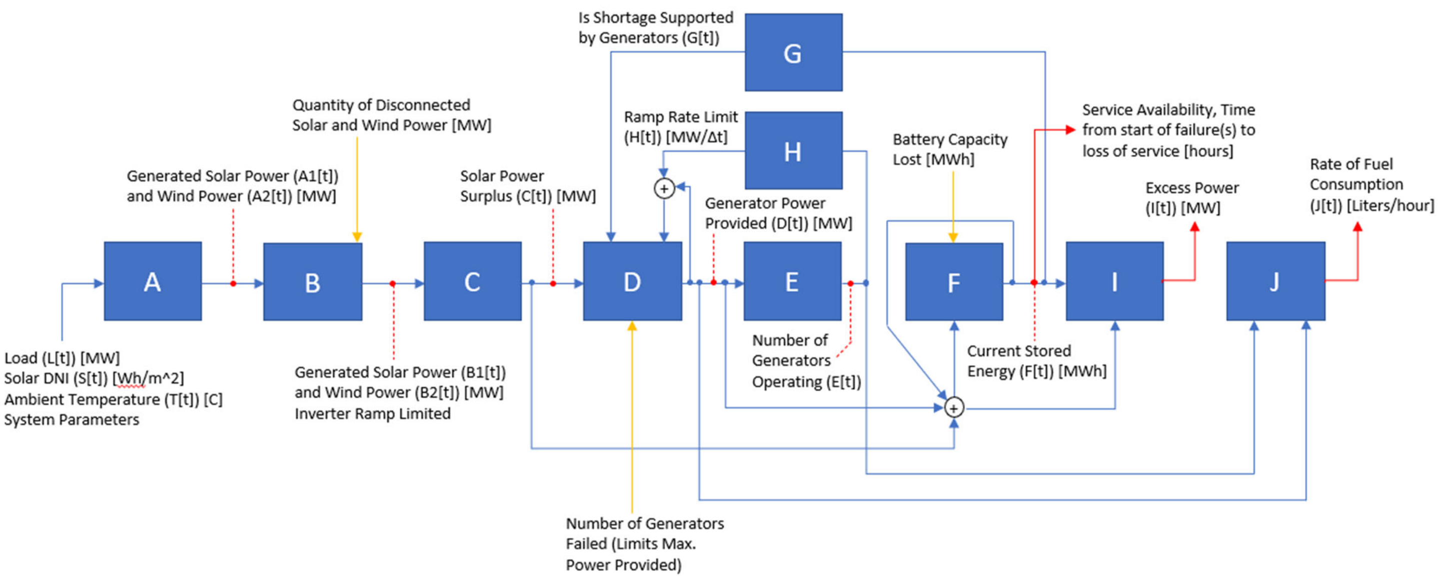

Figure 12: Block Diagram with Disturbance Signals to Simulate Failures

The rated solar power C is a constant, but Equation 27 presents a new variable C_{res} to represent the available solar power at each timestep when the evaluated time period includes a loss of solar power C_{loss} from t_1 to t_2. If this resilience condition is set, Equation 28 shows that the generated solar power is calculated using C_{res} rather than the constant capacity C.

Equation 27: Available Rated Solar Power with Loss Included

$$C_{res} = C - C_{loss} \quad for \quad t_1 < t < t_2 \quad else \quad C_{res} = C$$

Equation 28: Generated Solar Power with Non-Constant Available Solar

$$A_1[t] = C_{res} * S[t] * n_{loss} * e_{inverter}$$

The loss of installed solar power will reduce its generated power during the associated time period, so greater shortages will exist between renewable power generation and the load. Generators must therefore supply a greater proportion of power to fulfill the load, and more fuel is consumed during this period. If adequate generator power exists, the loss of solar is unlikely to have an impact on service availability. The less generator power within the system and the greater the associated solar shortage, however, the more likely the loss of solar will result in the generators reaching maximum power and being unable to supply a full shortage to prevent loss of service.

In AMPeRRe, a user can model the power curve of each wind turbine, calculate generated power at each timestep for each turbine, and sum the individual entities to calculate the collective generated wind power. Loss of wind power is simulated by omitting the disconnected turbines from the summation in Equation 5. For example, Equation 29 mathematically represents the sum of generated wind power if turbine i=3 was to disconnect from the system from timestep t_1 to t_2. Similar to solar power loss, the loss of wind power will increase the shortage between renewable power and the load. This causes the generators to contribute a greater proportion of power and consume more fuel during the time period of loss.

Equation 29: Wind Turbine Power Curve Model with a Disconnected Turbine

$$A_2[t] = \left(\sum_{i=1}^{\infty} \frac{c_i}{(1 + a_i e^{-k_i w})}\right) - \frac{c_3}{(1 + a_3 e^{-k_3 w})} \quad for \quad t_1 < t < t_2$$

$$else \quad A_2[t] = \sum_{i=1}^{\infty} \frac{c_i}{(1 + a_i e^{-k_i w})}$$

5.7 Resilience to Generator or Battery Failure:

The number of fuel-based generators supporting the system is an input constant, but AMPeRRe allows the simulated loss of some or all these generators within a specified time period. Similar to the loss of wind turbines, the loss of individual generators would cause their power contribution to be subtracted from the total rated generator power that limit the support (D[t]) the set of generators can provide. The number of generators operating E[t] is therefore limited to the available generators during the period of generator loss ($n - n_{loss}$) as shown in Equation 31.

Equation 30: Number of Generators Available with Generator Loss

$$n_{res} = n - n_{loss} \quad for \quad t_1 < t < t_2 \quad else \quad n_{res} = n$$

Equation 31: Number of Generators Operating with Generator Loss

$$E[t] = (lowest\ integer\ \mathrm{x}\ for\ which\ D[t] \leq x * P_{gen} * LF) \leq n_{res}$$

Equation 32: Supporting Generator Power Provided to System with Generator Loss (kW)

$$D[t] = G[t] * |C[t]| \quad for \quad D[t-1] - H[t] < D[t] - D[t-1] < D[t-1] + H[t]$$
$$and \quad C[t] < 0 \quad and \quad F[t] < F_{reserve} \quad and \quad D[t] \leq n_{res} * P_{gen}$$

Fuel consumption is also affected during this generator failure, as the number of generators operating and power output are both components of the rate of fuel consumption at each timestep. If the total battery storage of the system is distributed across multiple batteries, AMPERRE can simulate the loss of a proportion of the battery capacity. The control system will operate as expected during this loss, however the greater the loss and the less remaining battery capacity, the less excess renewable energy can be captured during the period of loss. This causes more curtailment, a greater need for generator power, and more fuel consumption. If the remaining battery capacity ($F_{cap} - F_{cap,loss}$) is lower than the set reserve battery capacity ($F_{reserve}$), the generators will fulfill all of the renewable shortage and maintain the battery at a constant charge. In this state, excess renewable power provides no benefit as it is not being captured within the battery. Generators therefore consume more fuel because they supply all the renewable shortage rather than battery charge.

Equation 33: Battery Capacity Available with Capacity Loss ($F_{cap,loss}$)

$$F_{cap,res} = F_{cap} - F_{cap,loss} \quad for \quad t_1 < t < t_2 \quad else \quad F_{cap,res} = F_{cap}$$

Equation 34: Battery State of Charge with Capacity Loss (Wh)

$$F[t] = C[t] + D[t] + F[t-1] \quad for \quad 0 \le F[t] \le F_{cap,res}$$

$$F[t] = 0 \quad for \quad F[t] \le 0 \quad and \quad F[t] = F_{cap,res} \quad for \quad F[t] \ge F_{cap,res}$$

Generators are the controlled source of power that support the renewables during periods of shortage, so generator failures are most likely to cause loss of service. If a system is fully reliable without any failure inputs, it may lose its fully-reliable status during a time period of failure ($t_1 < t < t_2$). Equation 35 and Figure 13 show how AMPeRRe calculates the time from the start of a failure to the loss of service. t_1 is the moment of failure, while t_{loss} is the first timestep at which the stored energy reaches zero and the system loses service.

Equation 35: Survival Time – Elapsed Time from Start of Failure to Loss of Service

$$t_{fail} = t_{loss} - t_1 \quad for \quad t_{fail} \le t_2 - t_1 \quad else \quad t_{fail} = N/A$$

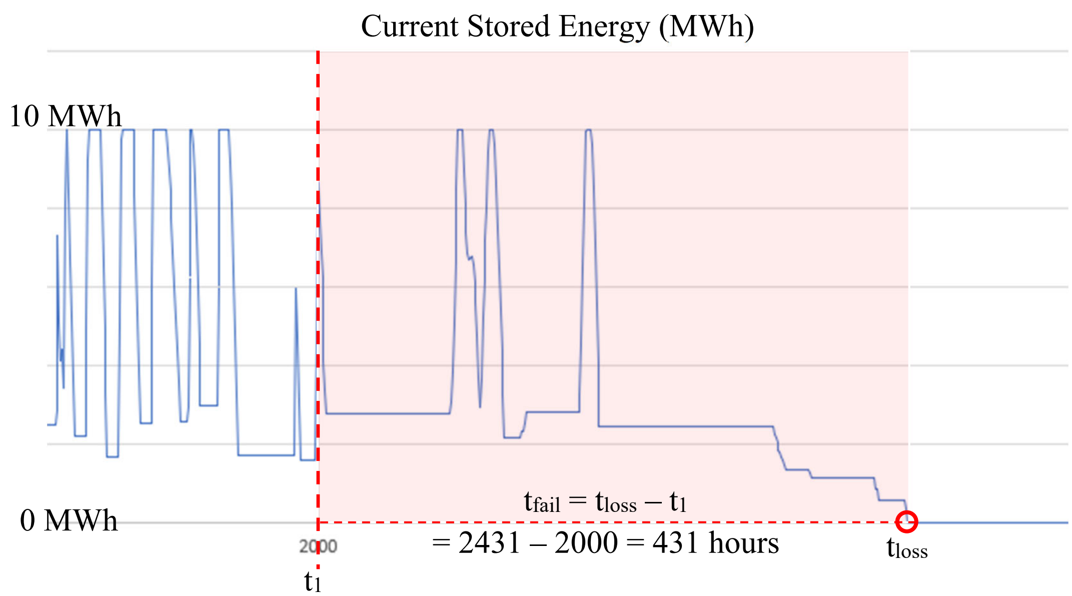

Figure 13: Example of Survival Time for a Loss of 6 of 10 Generators and 8 of 10 MW Solar

This survival time often populates a value for an input generator failure, but it also calculates time until loss of service for failures of solar, wind, and battery resources. Each of the failures can be simultaneously simulated, and the time period of each failure are variables independent of each other. While the loss of solar, wind, and battery are unlikely to cause a loss of service, each of these losses shorten the survival time associated with generator failure.

6. Supporting Findings and Methods

This section describes each of the findings that led to AMPeRRe's creation and provides detail about several of the methods needed to complete the steps in the Section 5 calculation process.

6.1 Calculating Generated Power from a PV Solar Source:

Equations 1, 2 and 3 from the detailed calculation process are a validated method to find the generated solar power at a given time (El-Bidairi 2018). Direct normal solar irradiance is a resource that varies with time at the location of interest and can be found using NREL's National Solar Radiation Database (NSRDB) (NREL 2023). NSRDB can also provide the ambient temperature data needed in this calculation process.

The efficiency representing loss due to temperature increase (n_{loss}) is defined by Equation 2. This efficiency value is fixed at 1 under ideal conditions, but once the surface temperature of the solar cell is high enough, any further increase in the surface temperature will lower the efficiency. The rate of efficiency loss due to ambient temperature increase is based on the temperature coefficient associated with the specific photovoltaic cell model. This temperature coefficient is defined for several solar PV models (Ost 2020).

6.2 Calculating Generated Power from Wind Turbines:

Wind turbine manufacturers define power curves that express the power generated by a turbine brand vs. wind speed conditions, and these charts also plot the power coefficient at different wind speeds. Figure 3 shows an example of this power curve. The rated wind speed is the point at which the wind turbine reaches its maximum power generation capability, or the rated power of the turbine.

Because this curve provides the generated power of each wind turbine within the system at each wind speed, a data set of generated wind power for each turbine can be obtained directly from the wind speed data set. The generated power data sets for each turbine can then be summed into the total generated power at each time step. Despite recorded power data at only integers of wind speed, there are two ways to use a power curve to find the corresponding generated power to each wind speed data point. One is to linearly interpolate for non-integer wind speeds, and the other is to find a mathematical close-fit curve to the power curve that can be used to calculate power directly from a wind speed value.

Figure 15 details common mathematical models that have been tested for accurate fit to the shape of a wind turbine power curve. All of these models, however, are only fit to region 2, which occurs below rated wind speed and power as shown in Figure 14. These models do not closely fit the power curve after the inflection point, particularly when the slowing growth becomes visible as power draws near the turbine rated power. The error calculated for these models as well as correlation coefficients are shown in Figure 16 and Table 3. These models have been tested on several power curves, so the correlation coefficients expressed in Table 3 are mean correlation coefficients for each model based on every power curve it has been fit-tested to.

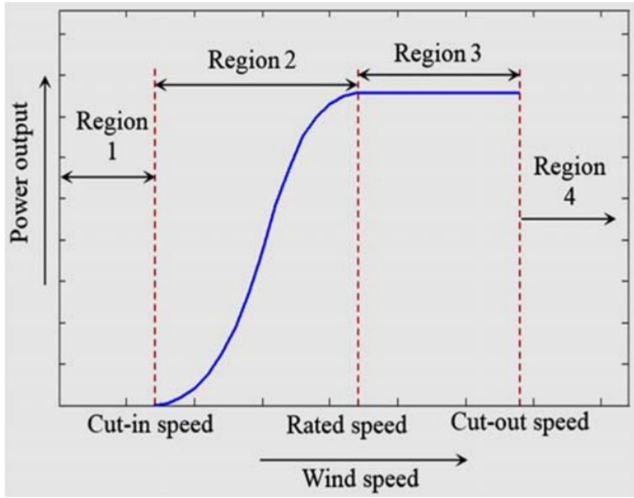

Figure 14: Wind Turbine Power Curve Regions (Teyabeen 2019)

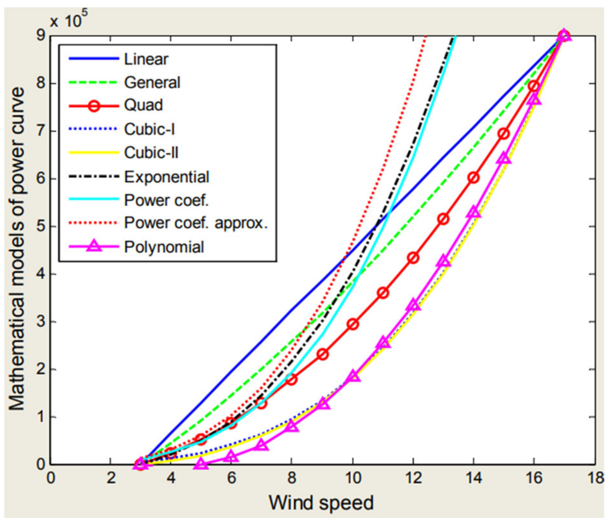

Figure 15: Existing Mathematical Models Used to Fit Power Curve Region 2 (Teyabeen 2019)

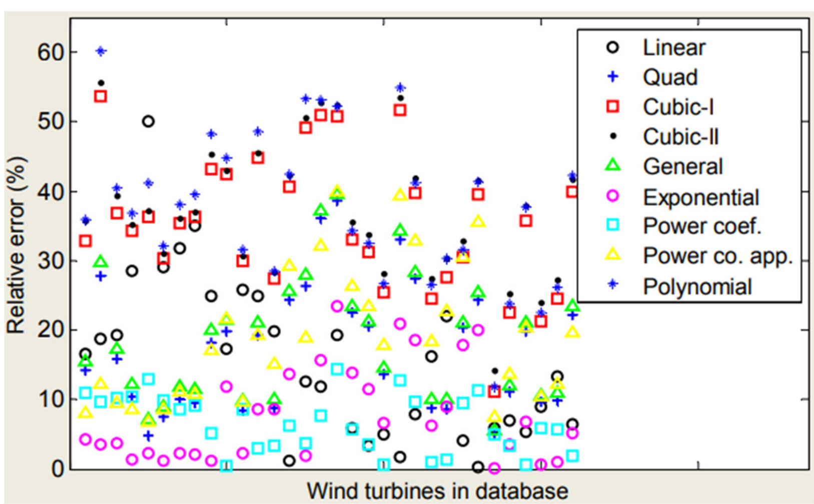

Figure 16: Error Between Each Mathematical Model and Power Curve (Teyabeen 2019)

Table 3: Average Correlation Coefficient of Each Mathematical Model (Teyabeen 2019)

Mathematical model	Mean of correlation coefficient	Mean of MAPE	Rank
Linear	0.9700	65.19	6
Quadratic	0.9718	29.76	2
Cubic-I	0.9408	42.67	3
Cubic-II	0.9408	45.99	4
General	**0.9725**	**29.61**	**1**
Exponential	0.9521	340.60	7
Power Coeff.	0.9408	405.21	8
Appr. pow. Coef.	0.9408	531.52	9
polynomial	0.9522	54.25	5

While some correlation has been found in these mathematical models, the errors are too high to justify using one of these models to fit the full power curve rather than linear interpolation of the power curve. Another mathematical formula, an exponential model represented by Equation 5 in the detailed calculation process, has been found to closely fit the shape of a power curve. This model is based on exponential limited growth shown below by Equations 36 and 37. The constant "c" is the carrying capacity, "k" is the growth rate, and "a" depends on the initial population P_0. While the limited population growth model has no connection to wind turbine power generation, its formula structure closely matches that of wind turbine power curves when wind speed is the independent variable, and the most optimal a and k coefficients are chosen to achieve the closest-fit curve. For properly-chosen coefficients, this mathematical model will achieve significantly low error when compared to the power curve it matches. An error analysis must always be applied when using Equation 5 to model a power curve.

Equation 36: Limited Population Growth vs Time – Exponential Model

$$P(t) = \frac{c}{(1 + ae^{-kt})}$$

Equation 37: "a" Coefficient Dependence on Initial Population

$$a = \frac{(c - P_0)}{P_0}$$

Wind turbines have a cut-in wind speed at which power generation begins and a cut-out wind speed due to limits on the operational stress they can endure. AMPeRRe returns a generated power value of zero for wind speeds past the cut-in to cut-out range. This ensures that the program does not overestimate the power generated by the wind turbines, particularly in proposed power grids at locations with frequent wind speeds above or below the range.

6.3 Calculating Generated Power from Wind Turbines – Alternate Formula-Based Method:

If wind turbine power curves are unavailable, an alternate method can produce a generated wind power dataset. Equation 38 is a validated model to calculate the generated power of a wind turbine (El-Bidairi 2018). Calculating generated wind power at each data point using this equation requires the known power coefficient, air density, blade radius, and wind speed data. As well as generated power, manufacturer power curves may define the power coefficient for each wind speed. Using linear interpolation or formula modeling similar to that of the previous section, this power coefficient curve can produce a set of power coefficient values that correspond to wind speed data. Substituting this data set into Equation 38 will calculate generated wind power at every wind speed data point. For a power grid with multiple wind turbine models, this formula must be applied to each model to reflect differing power coefficient curves.

Equation 38: Wind Generated Mechanical Power

$$P_{mech} = 0.5\rho C_P v(t)^3 \pi r^2$$

6.4 Generating a Load Data Set with Incomplete Metering:

If only a proportion of the evaluated installation's loads are metered, it is possible to scale up the known load data to represent a load data set that is accurate to the full location. Given the full installation's true mean load, peak load, and load factor, a numerical factor can be devised to appropriately scale both the base load and the active load components of the metered load data. Active load refers to the loads within the total profile that are variable, changing unpredictably or changing frequently according to a daily, monthly, or seasonal pattern. Base load refers to the portion of the total load that is constant and predictable. This load is attributed to electrical demands that rarely fluctuate in the power domain, and they are less likely to be metered than active loads.

Equation 39: Load Factor

$$LF = \frac{L_{avg}}{L_{max}}$$

The greater the load factor, the more of the total load can be classified as base load compared to active load. If the load factor of the full system is known, yet only a portion of the load data is available, linear-model scale values must be applied to the existing load data to simulate both additional base load and active load. The scaling factors must be applied in the correct proportions to achieve a load factor that matches the known value.

Equation 40: Linear Scaling Factor of Existing Load Profile

$$y = mx + b$$

In this scenario, the dependent variable y represents the new load data, the variable x represents the existing load data, m represents the active load scaling factor, and b represents the base load scaling factor. To apply this linear model to the existing load data, b is defined by the minimum load value and m is equal to 1 while every load data point is subtracted by b to represent the active load x. The objective of using this linear model is to change the average and maximum load of the dataset to alter the load factor calculation to match that of the full installation. This can be accomplished by altering the m and b variables. Choosing a new active load scaling factor, m, will multiply the existing mean and maximum active load by the same value. Values of m below 1 will compress the active load data and increase load factor while values above 1 will expand the data and decrease load factor. Changing the base load scaling factor, b, will shift both the mean and maximum load by the same value. Increased values of b will increase load factor while decreased values of b will decrease load factor. If the installation has a defined maximum load in addition to load factor, these methods can also be applied to ensure that the maximum load of the new load profile aligns with the maximum load defined by the installation.

6.5 Generator Power Output Considerations:

By default, AMPeRRe assumes that the operating generators share the load evenly and applies this assumption to every calculation. This mode of operation prevents complications associated with two scenarios:

A. Prolonged Operation at Full Rated Power:
    - Causes strain and reduces generator lifespan
    - Limits the capability of individual generators to respond to sudden load spikes
B. Operation at Low Power Relative to Rated Power:
    - Is an inefficient mode of operation due to mechanical friction
    - May cause wet stacking, a buildup of unburned fuel at the exhaust side of the generator that can cause a loss of performance and significantly reduce generator lifespan

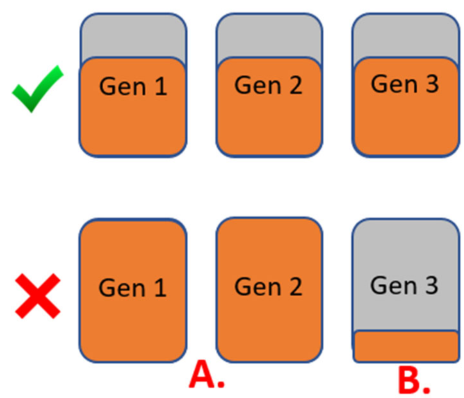

Figure 17: Ideal vs Non-Ideal Load-Sharing Between Generators

By simulating a generator control system that avoids these two extremes, AMPeRRe promotes long generator life and assumes generator operation at a proportion of their rated power that maximizes fuel efficiency.

6.6 Cyclic Generator Battery Charging Control Option:

For singular generators or a simple set containing a few generators, AMPeRRe offers an alternate control method that simplifies their operation to a fixed power output. Rather than setting generator power to match renewable energy shortage during periods of charge below a set reserve charge, the generators activate when the battery charge drops below a set activation level. The generators then operate at their collective rated power until the battery charge exceeds a set deactivation level, at which the generators then deactivate until the battery drops below the activation level again. The charge exceeds this range at times due to a one-timestep delay in generator response to crossing the activation or deactivation threshold. The activation and deactivation levels are both variables that a user can alter to ensure full system reliability and minimize excess energy production. Figure 18 shows an example of how this control system maintains battery charge between an activation level of 30% and a deactivation level of 80%.

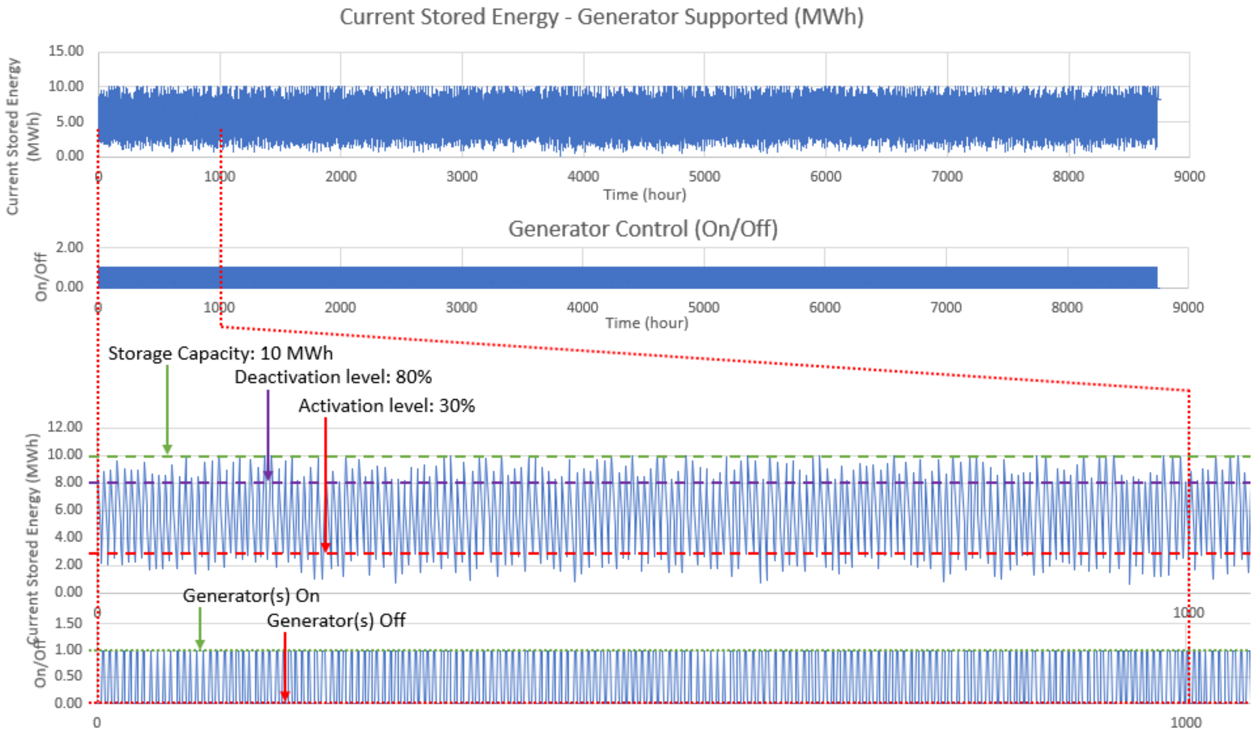

Figure 18: Example of Battery Charge vs. Time Plot with Cyclic Generator Control Applied

<u>6.7 Managing Excess Energy</u>:

AMPeRRe uses Equations 20 and 21 to calculate the excess energy of a power system during a specified time period. This excess energy can be managed through curtailment, filtered out, or sold to the utility if the power grid is utility-connected.

Curtailment is an intentional shut-off of power generation systems to control input power. If input power exceeds load enough to overwhelm storage and other input power control systems, curtailment may be necessary. Several factors influence the decision to curtail power (Bird 2014). Particularly in wind applications, one of the greatest reasons for curtailment is transmission constraints. When the development of additional renewable energy sources outpaces the development of transmission lines to transport the generated energy, curtailment is implemented to protect this transmission. System balancing may also be a challenge that requires curtailment in the scenario that input power exceeds load, storage sources, and other power routes. Voltage, interconnection, and stability issues are also prevalent causes of curtailment. Defining curtailment standards for new integrated systems based on these factors may ensure that it is implemented properly to ensure reliability.

6.8 Existing Power Grid Analysis Tools and Comparison to AMPeRRe:

Below are existing web tools and software programs that provide power grid insights to users. Many of these have common capabilities to AMPeRRe as well as several fundamental differences.

- REopt and PVWatts – energy analysis tools developed by NREL
- Energy Resilience Assessment (ERA) – energy resilience web tool
- Naval Postgraduate School (NPS) Microgrid Planner – suite of microgrid planning tools
- SMPL – CERL-based power flow analysis software
- HOMER Grid – power grid and cost analysis software

Table 6 in the Appendix represents a comprehensive comparison of the capabilities between each software program and tool. This evaluation identified gaps in existing tools that are covered by AMPeRRe's unique capabilities:

A. AMPeRRe calculates the service availability of isolated microgrids for scenarios of imperfect availability (<100%)
    - User can understand how significant a reliability gap is to make informed power grid design decisions
B. Simulates a control system with non-renewables (generators) as a supporting power source
    - Battery charge level informs the operating state of generators
    - Two control settings: Generators can maintain reserve energy or cyclically charge
    - Certain input variables define the proportion of renewable shortage that generators support
    - Minimizes fuel consumption, greenhouse gases, and excess/wasted power
C. Calculates fuel consumption using:
    - Fuel consumption curves specific to the generator models, even when multiple models are involved
    - The number of generators operating at any given time
D. Calculates the duty cycle of each generator within the system
    - Relevant to generator lifespan and maintenance
E. Incorporates inverter ramp rates and generator power acceptance rates
    - Limits rate of change of calculated renewable power and generator support
F. Models the specific power curve(s) of wind turbine(s) vs wind speed (if applicable)
    - Does not approximate based on rated power
    - Other tools use derating factor, duty cycle factor, assume duty cycle and capacity
G. Evaluates resilience for scenarios of failed or disconnected DERs
    - Survival time – Time from start of failure(s) to loss of service
    - Not limited to utility loss

Validation that these power grid analysis tools yield similar results for equal sets of inputs across parallel capabilities is critical. Table 4 provides a comprehensive set of results for a set of common inputs listed in Table 7 in the Appendix. These comparative results between AMPeRRe and other analysis tools provide critical takeaways that validate AMPeRRe's accuracy:

1. ERA and AMPeRRe predict similar service availabilities for equal grid configurations
2. REopt calculates the magnitude of electricity consumed from renewables, and this result is similar to AMPeRRe
3. REopt, PVWatts, and AMPeRRe generate similar results for the energy produced by solar during the measured time period
4. REopt's yearly fuel consumption calculation is approximately equal to AMPeRRe's
5. AMPeRRe calculates a higher level of curtailed energy over the time period, however this is due to differences in the simulated control system

Table 4: Overview of Analysis Results for a Set of Common Inputs

			Reopt	PVWatts	ERA	AMPERRE
Results and Insights	Numerical	Full system costs / life-cycle cost				
		Reliability / service availability (% time) of stand-alone VRE			34.94	30.11
		Reliability / service availability (% time) of VRE + battery storage			1. 46.51	50.46
		Reliability / service availability (% time) of VRE + storage + generator(s)			100	100
		Proportion of annual load met by full system (% magnitude)	100			
		Proportion of electricity consumed from renewables (% magnitude)	2. 38			41
		Energy produced by each power source over the evaluated time period (MWh / year)	3. 13,104	13,256		14,503
		Duty cycle of each generator / total duty cycle (%)				69.33
		Number of generator cycles / shifts per year				1704
		Generator yearly fuel consumption (Liters)	4. 2,269,161			2,249,979
		Greenhouse gas emissions (separated by greenhouse gas)				
		Fuel resilience - days between resupply of fuel - average and/or worst-case	6.12			6.17
		Energy resilience - Service availability of power system during fixed-duration blackout of one or more power sources				
		Energy resilience - Time to power restoration after blackout of one or more power sources - average and/or worst-case				
		Energy resilience - Length of time the fully-charged, stand-alone battery can supply to the load				
	Plotted	Power provided by each source vs time	From PVWatts	a		a
		Energy curtailed over the evaluated time period (MWh)	5. 6,922.80			7,430.10
		Renewable power surplus vs shortage plot of every timestep				
		Current stored energy plot / battery state of charge at every timestep				
		Project cost vs service availability of several configurations				

While Table 4 shows similarities in results that validate AMPeRRe capabilities, differences in the calculation process between these programs cause slight result variation. Among the other programs, REopt has the greatest number of parallel capabilities to AMPeRRe as well as several differences in calculation that lead to the observed variability:

1. REopt's data fidelity is fixed at hour-long timesteps
2. Imports solar power production data set from PVWatts
3. Grid-connected power systems only disconnect from the grid to simulate outages
4. Only capable of evaluating resilience in the event of grid disconnection
   - Resilience is considered to be survival time, or time from the start of a failure (in this case, grid disconnection) to loss of service (if loss of service occurs)
   - AMPeRRe can calculate survival time for failed generators, solar, wind, or battery
5. Rate of generator fuel consumption only assumes a linear relationship with power output
   - Linear models are not always the best-fit to fuel consumption curves
6. Does not calculate the survival time associated with pinpointed failure start times
   - Only yields average survival time for the full measured period and probabilities of differing survival times
7. Wind power is not included as an option for off-grid power system evaluation
8. Off-grid power balancing control system may deplete battery charge prior to renewable power surplus periods
   - Proactive feature, however incorporating it into a real power grid control system would require accurate forecasting
9. Cannot generate results for scenarios where 100% reliability is impossible

PVWatts, ERA, and NPS also have fundamental differences that explain observed variability:

10. PVWatts' solar irradiance data that factors into calculation of generated solar power is a typical-year assumption based on aggregate historical data
    - Less poised to predict solar generation in future conditions
11. ERA is an assessment limited to existing federal facilities
    - Cannot provide a custom load profile input
12. NPS Tools' wind power generation does not appear to vary with changing wind speed, assumes uniform generation
13. NPS's plotted solar power generation appears to be an assumption based on solar azimuth, no day-by-day variability
14. Neither the code nor the user interface of NPS tools are available yet, users see demonstrative results
    - Excluded this tool from results comparison
15. NPS's battery state of charge remains above 20% for a renewable-only system despite periods of power shortage

Although AMPeRRe and the other programs generate similar results across common analysis capabilities for equal energy resource inputs, AMPeRRe is capable of simulating scenarios with more optimal outcomes. These outcomes include:

1. Maintained reliability
2. Less renewable energy waste and a greater use of generated renewable power
3. Reduced need for generator operation due to greater use of renewable power
4. Less fuel consumption and more days between resupply

Table 5: Original AMPeRRe Results vs Optimized AMPeRRe Results

			AMPERRE	AMPERRE - Optimized
Results and Insights	Numerical	Full system costs / life-cycle cost		
		Reliability / service availability (% time) of stand-alone VRE	30.11	30.11
		Reliability / service availability (% time) of VRE + battery storage	50.46	50.46
		Reliability / service availability (% time) of VRE + storage + generator(s)	100	**1** 100
		Average state of battery charge (%)	8.59	4.58
		Proportion of annual load met by full system (% magnitude)		
		Proportion of electricity consumed from renewables (% magnitude)	35	35
		Energy produced by each power source over the evaluated time period (MWh / year)	14,503	14,503
		Duty cycle of each generator / total duty cycle (%)	69.33	**3** 57.26
		Number of generator cycles / shifts per year	1704	1569
		Generator yearly fuel consumption (Liters)	2,249,979	**4** 1,857,337
		Greenhouse gas emissions (separated by greenhouse gas)		
		Fuel resilience - days between resupply of fuel - average and/or worst-case	6.17	**4** 7.48
		Energy resilience - Service availability of power system during fixed-duration blackout of one or more power sources		
		Energy resilience - Time to power restoration after blackout of one or more power sources - average and/or worst-case		
		Energy resilience - Length of time the fully-charged, stand-alone battery can supply to the load		
	Plotted	Power provided by each source vs time	a	
		Energy curtailed over the evaluated time period (MWh)	7,430.10	**2** 5,702.21
		Renewable power surplus vs shortage plot of every timestep		
		Current stored energy plot / battery state of charge at every timestep		
		Project cost vs service availability of several configurations		

REopt, in particular, assumes that the battery charge must be maintained at 100% during the measured time period. The exception to this assumption occurs at the beginning of the period when the program must adhere to a user input of <100% initial charge and slowly charge to 100%. REopt also assumes slow depletion at the end of the period to make use of the collected energy. When REopt maintains this assumption, none of the battery capacity is available to capture solar power in excess of the load. This causes more significant levels of solar curtailment as shown by Figure

19. The battery also does not deplete to supply to the load during any renewable power shortage, choosing instead to allocate this load to the generators and creating more fuel consumption than necessary.

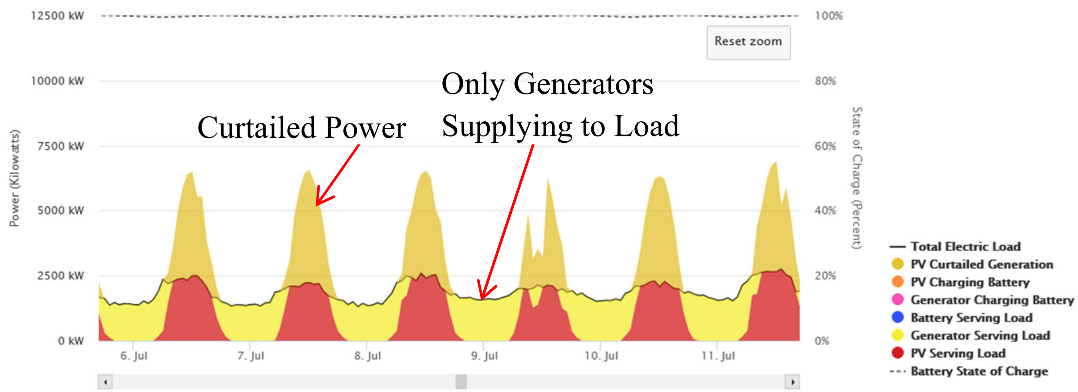

Figure 19: Sample of REopt Plotted Results

REopt's average state of charge is a fixed quantity due to their maintenance of 100% battery charge throughout most of the measured time period. To match program inputs most effectively for the sake of comparative results analysis, AMPeRRe's reserve charge was temporarily altered to achieve a REopt-equivalent average state of charge. This is shown in Figure 20. At its higher average battery charge, AMPeRRe generates the comparable results seen in Table 4. When AMPeRRe's reserve charge is returned to a lower value as shown in Figure 21, users will see more optimized results such as those reflected in Table 5.

Figure 20: Sample of AMPeRRe Plotted Battery Charge for 8.7 MWh Reserve Charge

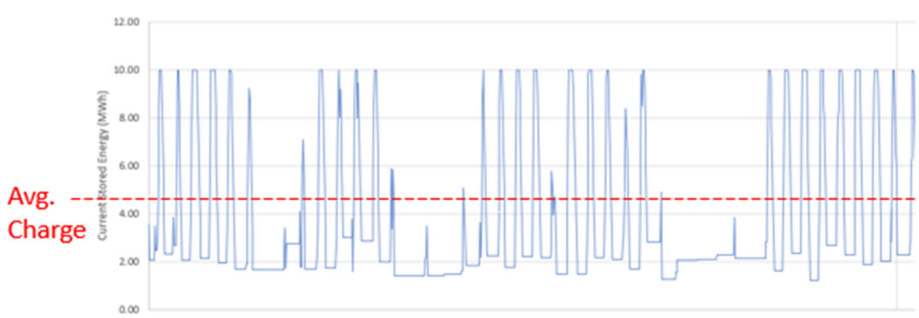

Figure 21: Sample of AMPeRRe Plotted Battery Charge for 3 MWh Reserve Charge

7. Conclusion

It is imperative that industries and organizations incorporate cleaner forms of energy in their power grids. Uncertainty and variability in renewable energy production hinder this integration, however, because the reliability and resilience risks associated with this uncertainty are not always favorable to conventional fossil fuels. Developing a greater understanding of renewable energy integration outcomes can reduce this uncertainty, leading to informed decisions that allow power grids to reach decarbonization goals without sacrificing power grid performance. AMPeRRe is a novel program that provides a greater understanding of outcomes on a case-by-case basis. This program predicts reliability, resilience, fuel consumption, generator duty cycle, and excess energy production outcomes without the need for monetary investment in physical prototype testing or construction. Rather than just ensuring adherence to baseline reliability requirements, AMPeRRe can be used to design renewable-inclusive power grids with optimal resilience, component use, and fuel consumption. Its calculation process requires a set of user-input variables that allow for the simulation of a wide variety of power grids. Given this adaptability, AMPeRRe has the potential to provide insights that positively impact many federal, public, industrial, and residential power grids.

8. Next Steps

8.1 Short-Term AMPeRRe Development:

The next stage of AMPeRRe's development will be to translate the program into a web-based platform with a quality user interface that is accessible to a wide variety of users. Some short-term continued development is needed, including the adjustment of feedback loops to represent control system response times more accurately. No aspect of the generator control system will respond more than a timestep after the battery charge level crosses the reserve energy threshold. While the current calculation process accounts for component limits such as ramp rates, battery charge rates, and wind turbine cut-out wind speed, it can predict and incorporate additional scenarios that lead to renewable power loss to plan for worst-case scenarios.

8.2 Perform Additional Accuracy Validation:

Small-scale physical prototypes of power grids will be created to evaluate within AMPeRRe and perform parallel operation to yield real-world results. This experiment will compare the real-world results to the results of AMPeRRe. An error analysis based on these results will then determine the accuracy of the current model and inform the creation of safety factors for AMPeRRe to account for any calculation error. This program will also be applied to existing USACE installation microgrids and digital twins to compare the program results to actual data from the operating grids.

8.3 Develop the Next-Generation Program:

The next generation of AMPeRRe will not only calculate the expected service availability, resilience, and fuel consumption of a proposed power grid, but will be capable of projecting future outcomes. If proper climate condition models and load-change projections are incorporated in AMPeRRe's inputs, the program will be able to determine these outcomes for a chosen number of years into the future. Climate models and predicted changes in load profiles are uncertain, however, so results will have associated probabilities and confidence intervals. This may take the form of a Monte Carlo simulation that performs multiple iterations of the calculation process with different input possibilities to plot the probability distribution of numerical outcomes.

Load, wind speed, solar irradiance, and ambient temperature data used in this evaluation will not experience the same trends long-term due to population growth, electric demand changes, the progression of climate change and other factors. For this evaluation to remain accurate in predicting long-term reliability factors, a time-based growth formula can be developed and applied to each of these data sets depending on predictive models for the change these variables will experience. Several existing projections of future global average temperature are accurate (Buis 2021) and can be used to create this growth factor for ambient temperature. Location-based projections of future load, wind speed, and solar irradiance may also be available—or possible to develop—to create associated growth formulas. With increasing capability of AI, it may be possible for AI to accurately predict these future trends of load and natural resources. Incorporating AI into this model could adjust any input datasets to simulate how the dataset will change after a given number of years input by the user. This will inform the subsequent calculations and provide the user with reliability, resilience, and fuel consumption projections accurate to the future time period that they chose.

This program will also be expanded to evaluate proposed power grids with clean and/or renewable sources other than solar panels and turbine-based wind power.

- Controllable or Semi-Controllable:
    - Hydropower
    - Geothermal energy
    - Biomass energy
    - Hydrogen fuel production
- Variable:
    - Non-turbine wind power
    - Concentrated solar power
    - Wave energy collectors

Next-generation AMPeRRe will be modular; capable of using iterations of the program itself to simulate more complex microgrids with multiple interconnected substations containing separate loads and energy resources. This modular capability would best represent microgrids that aim to incorporate complex distribution systems such as electric vehicle charging infrastructure, as this infrastructure is likely to be distributed over a wide area and needs power flow through each line modeled to account for distribution limits.

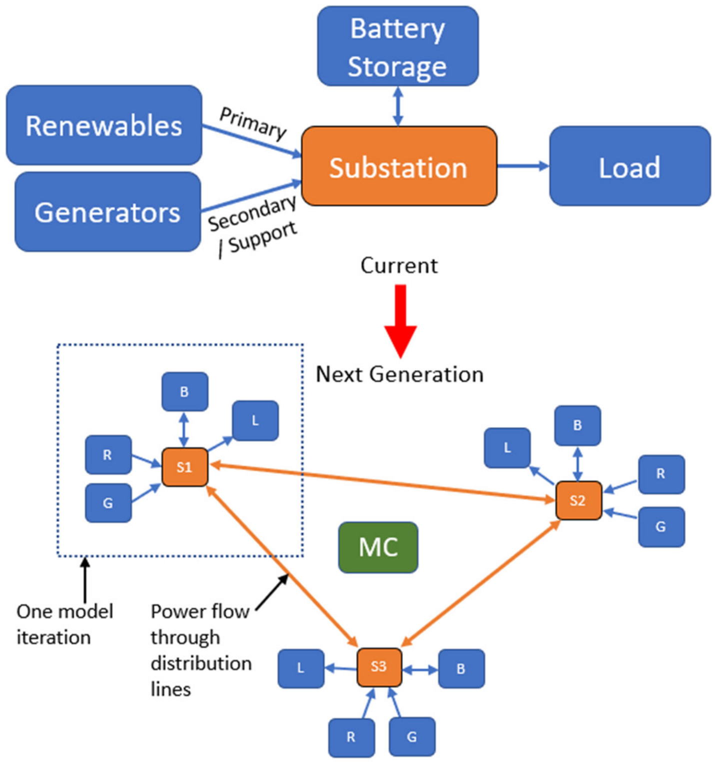

Figure 22: Example of Next-Generation Modularity in Power Grid Modeling

The current program models a simple microgrid that experiences a net renewable power surplus or shortage at any given timestep. Any shortage is managed by controlled generators when the battery charge is below a reserve threshold and any surplus is wasted. In a modular program, this surplus may be able to contribute to neighboring connected substations experiencing a power shortage rather than be wasted. Similarly, a shortage could be supplied by neighboring substations experiencing surplus power instead of activating the generators. Renewable-inclusive power grids therefore derive a benefit from interconnection with additional substations. The larger the interconnected microgrid, the greater the management of renewable power variability and the lesser the need for support from fossil-fuel sources. This translates to grid size-relative cost savings as fuel consumption decreases. Because this is a significant objective in Army and industry power projects, it is important to branch into the modeling of interconnected modular power grids.

Multiple objectives exist in the design of a microgrid (cost, reliability, resilience, minimal fuel consumption, decarbonization, etc.), and it is difficult to generate results that simultaneously meet each of these objectives without any tradeoffs. These objectives have different levels of priority depending on the project and the users that can change with varying conditions that the power system can experience. Even with the ability to predict the reliability, resilience and fuel consumption of a proposed microgrid, it is difficult to find a design that yields optimal results across all these parameters. Unlike the current program, incorporating AI-based computational capabilities such as reinforcement learning and robust optimization can derive the optimal inputs, or microgrid design, from the desired outputs. This would replace trial-and-error as a more streamlined and effective method of use for this program to achieve the desired outcomes.

9. Appendices

9.1 Abbreviations:

DNI – Direct Normal Irradiance
VRE – Variable Renewable Energy

9.2 Variables:

$A_1[t]$ = Generated solar power (kW)
$A_2[t]$ = Generated wind power (kW)
C = PV solar rated power (kW)
c = Carrying capacity
c_i = Wind turbine rated power (kW)
C_P = Power coefficient corresponding to wind speed
$C_{P,i}$ = Wind turbine rated power
F_{cap} = Battery capacity
$F_{reserve}$ = Battery reserve energy
k = Growth rate
k_i = rate of power growth with wind speed
L[t] = Chronological load data
LF = The proportion of rated generator power necessary to activate an additional generator
n = Total number of generators in the system
P_0 = Initial population
P_{gen} = Rated power of one generator
P(t) = Population
P(w) = Generated wind power (kW)
r_i = Wind turbine blade radius
R_g = Ramp rate of one generator
R_{rampup} = Maximum inverter ramp-up rate
$R_{rampdown}$ = Maximum inverter ramp-down rate
R_{charge} = Maximum battery charge rate
$R_{discharge}$ = Maximum battery discharge rate
S = Service availability
$S_{STD} = 1\ kW/m^2$ = Standard Solar Irradiance
$S(t)$ = Solar Irradiance (kWh/m^2) vs Time
t = Time
$T_a(t)$ = Ambient temperature (C) vs time
T_{NOCT} = Nominal operating cell temperature (C)
$v(t)$ = Wind speed (m/s) vs time
w = wind speed
λ = Temperature coefficient of solar panel model
ρ = Air density (kg/m^3)
$\eta_{DC/DC}$ = Inverter efficiency

9.3 Additional Figures from Power Grid Analysis Tools Comparison:

Table 6: Full Overview of Comparative Capabilities Between Existing Analysis Tools

			Reopt	PVWatts	ERA	NPS Tools	AMPERRE
Results and Insights	Applicable Power Grids	Islanded	4,8				
		Utility-connected	3,4				
		Mobile / Tactical	4,8				
		Fixed / Installation	4,8				
		Custom load input (Can account for EV charging)	8				
		Modular / multiple loads and substations					
	Numerical	Full system costs / life-cycle cost					
		Reliability / service availability (% time) of stand-alone VRE					
		Reliability / service availability (% time) of VRE + battery storage					A
		Reliability / service availability (% time) of VRE + storage + generator(s)					
		Proportion of annual load met by full system (% magnitude)	9				
		Proportion of electricity consumed from renewables (% magnitude)					
		Energy produced by each power source over the evaluated time period					
		Duty cycle of each generator					D
		Number of generator cycles per year					
		Generator fuel consumption	5,8				C
		Greenhouse gas emissions (separated by greenhouse gas)	8				
		Fuel resilience - days between resupply of fuel - average and/or worst-case					
		Energy resilience - Service availability of power system during fixed-duration blackout of one or more power sources	3,4				
		Energy resilience - Time to power restoration after blackout of one or more power sources - average and/or worst-case	3,4,6				G
		Energy resilience - Length of time the fully-charged, stand-alone battery can supply to the load					
	Plotted	Power provided by each source vs time	8			12,13	
		Energy curtailed over the evaluated time period					
		Renewable power surplus vs shortage plot of every timestep	8			12,13	
		Current stored energy plot / battery state of charge at every timestep	8			15	
		Project cost vs service availability of several configurations					
Optimization Capabilities		Size of solar, generator, and battery components for a fully-reliable system of minimum cost					
		Reliability / 100% service availability (not grid-connected)					
		Highest achievable (reliable) proportion of VRE compared to fossil fuels					
		Minimal fuel use / greenhouse gas production					
		Optimal storage capacity for full reliability and minimal energy curtailment					
		Minimum generator duty cycle and/or frequency of generator cycles					
		Minimal power transport or distribution / smallest number of components					
		Resilience - Time to power restoration after blackout					

Table 7: Common Inputs for Analysis Results Comparison

				Reopt	PVWatts	ERA	AMPERRE
System Parameters and Conditions	Location			CR, MN	CR, MN	CR, MN	CR, MN
	Time-stepped facility load data						
	Electricity rate ($)						
	Solar Sources (VRE)		Installed / rated power of each solar panel model (MW)	10	10	10	10
			Temperature coefficient				0.00485
			Nominal operating cell temperature (C)				45
			Inverter rated power (MW)	10	10		10
			Inverter efficiency	0.96	0.96		0.96
			Inverter ramp up / down rate limit				E N/A
			Module and array type	Standard, Fixed	Standard, Fixed		Standard, Fixed
			Array azimuth and tilt (degrees)	180, 20	180, 20		
			System losses (%) (shading, snow, wiring, connections, age, etc.)	14	14		14
			Location-based, time-stepped direct normal solar irradiance data				
			Location-based, time-stepped ambient temperature data				
	Diesel Generators		Generator rated power (MW)	5		5	5
			Power acceptance rate				E N/A
			Power ramp down rate				N/A
			Load factor / minimum load factor	N/A			N/A
			Fuel consumption curve(s) (Liters / kWh)	0.214x + 10			0.214x + 10
	Generators as Secondary Support - Control System Parameters	Mimimizing Shortage	Secondary generator rated power				
			Proportion of Shortage Supported by Generators, charge dependent (%)				100
			Load Factor Needed to Activate Next Generator / maximum load factor of an individual generator				0.8
			Generator peak shaving / Power output limit (MW)				B N/A
		Cyclic Battery Charging	Cutoff - Proportion of Battery Capacity (%) or nominal value (MWh)				N/A
			Activation - Proportion of Battery Capacity (%) or nominal value (MWh)				N/A
	Battery Energy Storage		Storage capacity (MWh)	10		10	10
			Maximum charge rate	5			5
			Maximum discharge rate	5			5
			Round-trip efficiency	0.94			0.94
			Charge efficiency	N/A			N/A
			Discharge efficiency	N/A			N/A
			Initial charge (%)	50			50
			Battery reserve energy / minimum state of charge (MWh)	3, 10			8.7
			Maximum state of charge (MWh)	10			10
			Parasitic load (MW)				0

9.4 Generating a Load Data Set in the Absence of Annual Load Data:

In some cases, detailed load data with data points across a significant time period is unavailable. This section describes a method to generate load data that can be used for this evaluation when detailed load data is unavailable. The parameters that must still be known, however, are peak, minimum, and mean load. Trends of monthly load per year and hourly load per day can also be used to apply weighted factors to the mean load depending on the time of day and time of year that this data point falls on. Load experiences a pattern of change throughout the day with peak hours and minimum hours that depend on operations, schedule and demand. Load over a yearly period also has peak and minimum load periods due to several conditions that change the demand depending on time of year. For each yearly period and each time of day, a multiplication factor can be created that expresses the load at its time period as a proportion of the mean load for the full annual cycle. Table 6 in the Flinders Island Analysis Section 6 shows how these multiplication factors represent trends and create a nominal load data set.

While a set of data based on larger trends provides an expected annual load profile, natural variation occurs in the actual load within a system. The known maximum and minimum load provide a view of how significantly load can spike or dip in outlier moments during the annual time period. These values can be used to model the expected variation from nominal trends, and a random number generator formula can be added to the nominal value of each data point to create slight variations in each data point representative of natural factors causing deviation from expected demand.

Equation 41: Load Profile with Added Randomized Noise

$$L = (L_{avg} * D) + (2 * (RAND() - 0.5) * (L_{peak} - L_{expected}))$$

$$L_{avg} = Monthly\ Average\ Load$$
$$D = Hourly\ Demand\ Factor$$
$$RAND() = Random\ Number\ between\ 0\ and\ 1$$
$$L_{peak} = Peak\ Load$$
$$L_{expected} = Highest\ Expected\ Load\ from\ Table\ ()$$

The deviation from expected load is most likely not uniform, however, but rather has a higher probability of being relatively small. The additional noise model shown below adds a normally distributed value to the expected load data given a standard deviation representative of the amount of variation.

Equation 42: Load Profile with Added Normally Distributed Noise

$$L = (L_{avg} * D) + NORMINV(RAND(), 0, S)$$

$$S = Standard\ Deviation$$
$$NORMINV() = Normally\ Distributed\ Value\ from\ Probability, Mean, and\ S$$

References

Al-Quraan, A., Al-Masri, H., Al-Mahmodi, M., & Radaideh, A. (2021). Power curve modelling of wind turbines- a comparison study. *IET Renewable Power Generation*, *16*(2), 362–374. https://doi.org/10.1049/rpg2.12329

Bauer, L. (n.d.). *Wind Turbines Database*. Wind turbines database. Retrieved November 22, 2022, from https://en.wind-turbine-models.com/turbines

Bird, L., Cochran, J., & Wang, X. (2014). Wind and solar energy curtailment: Experience and practices in the United States. https://doi.org/10.2172/1126842

Buis, A. (2021, January 26). *Study confirms climate models are getting future warming projections right – climate change: Vital signs of the planet*. NASA. Retrieved December 23, 2022, from https://climate.nasa.gov/news/2943/study-confirms-climate-models-are-getting-future-warming-projections-right/

Department of Defense (DoD) (2013, January 7). *UFC 3-401-01 mechanical engineering, with change 1*. WBDG. Retrieved June 7, 2022, from https://www.wbdg.org/ffc/dod/unified-facilities-criteria-ufc/ufc-3-401-01

Department of Defense (DoD) (2015, January 7). *UFC 3-440-01 facility-scale renewable energy systems*. WBDG. Retrieved June 7, 2022, from https://www.wbdg.org/ffc/dod/unified-facilities-criteria-ufc/ufc-3-440-01

El-Bidairi, K. S., Nguyen, H. D., Jayasinghe, S. D. G., Mahmoud, T. S., & Penesis, I. (2018, September 5). *A hybrid energy management and battery size optimization for standalone microgrids: A case study for Flinders Island, Australia*. Energy Conversion and Management. Retrieved October 18, 2022, from https://www.sciencedirect.com/science/article/pii/S0196890418309415#b0260

Hybrid Energy Solutions Success stories. (n.d.). Retrieved June 7, 2022, from https://www.hydro.com.au/clean-energy/hybrid-energy-solutions/success-stories

Kroposki, B. D. (2017). Integrating high levels of variable renewable energy into Electric Power Systems. https://link.springer.com/article/10.1007/s40565-017-0339-3

NREL - NSRDB, nsrdb.nrel.gov/. Accessed 25 Sept. 2023.

Ost, I. (2020, April 20). Does solar panel temperature coefficient matter? Solar.com. Retrieved December 21, 2022, from https://www.solar.com/learn/does-solar-panel-temperature-coefficient-matter/#:~:text=Most%20solar%20panels%20have%20a,decrease%20in%20efficiency%20by%200.37%25

Sohoni, V., Gupta, S. C., & Nema, R. K. (2016). A critical review on wind turbine power curve modelling techniques and their applications in wind based Energy Systems. Journal of Energy, 2016, 1–18. https://doi.org/10.1155/2016/8519785

Teyabeen, A., Akkari, F., & Jwaid, A. (2019). Mathematical modelling of wind turbine power curve. *International Journal of Simulation: Systems, Science & Technology*. https://doi.org/10.5013/ijssst.a.19.05.15