NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

SYSTEMS ENGINEERING CAPSTONE REPORT

EFFECTS OF INTERNET OF THINGS (IOT) INTEGRATION ON ENERGY EFFICIENCY, PERFORMANCE, AND RELIABILITY AT NAVAL INSTALLATION MICROGRIDS

by

Scott A. Butler, Jared L. McCallum, Andrew L. Nolen,
Brock O. Oakes, and Michael J. Schartung

September 2023

Advisor: Douglas L. Van Bossuyt
Co-Advisor: Ronald E. Giachetti

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REPORT DOCUMENTATION PAGE	Form Approved OMB No. 0704-0188

Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington, DC, 20503.

1. AGENCY USE ONLY *(Leave blank)*	2. REPORT DATE September 2023	3. REPORT TYPE AND DATES COVERED Systems Engineering Capstone Report

4. TITLE AND SUBTITLE EFFECTS OF INTERNET OF THINGS (IOT) INTEGRATION ON ENERGY EFFICIENCY, PERFORMANCE, AND RELIABILITY AT NAVAL INSTALLATION MICROGRIDS	5. FUNDING NUMBERS
6. AUTHOR(S) Scott A. Butler, Jared L. McCallum, Andrew L. Nolen, Brock O. Oakes, and Michael J. Schartung	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A	10. SPONSORING / MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.

12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release. Distribution is unlimited.	12b. DISTRIBUTION CODE A

13. ABSTRACT (maximum 200 words)

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14. SUBJECT TERMS energy, reliability, IoT, internet of things, devices, sensor, monitor, microgrid, discrete-event model	15. NUMBER OF PAGES 117
	16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	UU

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18

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Scott A. Butler, Jared L. McCallum, Andrew L. Nolen,

Brock O. Oakes, and Michael J. Schartung

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN SYSTEMS ENGINEERING MANAGEMENT

from the

NAVAL POSTGRADUATE SCHOOL
September 2023

Lead Editor: Jared L. McCallum

Reviewed by:
Douglas L. Van Bossuyt
Advisor

Ronald E. Giachetti
Co-Advisor

Accepted by:
Oleg A. Yakimenko
Chair, Department of Systems Engineering

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ABSTRACT

This study employs model-based simulations to compare a smart microgrid, integrating internet of things (IoT) capabilities, with a baseline conventional microgrid seen in naval installation power systems. The research assesses IoT technologies' potential to boost energy efficiency, performance, and reliability in microgrids. The models encompass renewable and diesel generators, along with battery storage systems. Differing in power generation switching logic and demand anticipation, simulations span a year of islanded microgrid operations under varying power sources and environmental conditions. Results offer insights into power generation, supply to critical loads, and more, for baseline and IoT smart microgrid configurations. Findings reveal that the IoT-enabled microgrid outperforms the baseline microgrid in overall demand satisfaction. Notably, after a 10-year Monte Carlo simulation a 102.1-hour increase to average annual availability for the IoT smart microgrid over the baseline microgrid occurred. Moreover, energy efficiency gains of 2.35% translate to extended diesel generator operational hours. Each microgrid model contains simplifications and assumptions, potentially limiting its representation of real-world complexities. By incorporating IoT-based sensing and control systems, the overall energy management and reliability of microgrid systems can be enhanced thus enabling a more readily available power supply for critical operations.

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LIST OF ACRONYMS AND ABBREVIATIONS

°C	degrees Celsius
°F	degrees Fahrenheit
AMI	advanced metering infrastructure
BAT	battery
CAIDI	customer average interruption duration index
CoAP	constrained application protocol
COIIoT	CoAP and OSGP integration for IoT
DOD	Department of Defense
DON	Department of the Navy
ESF	energy security framework
FDD	fault detection and diagnostics
FEMA	Federal Emergency Management Agency
gal/hr	gallons per hour
GPU	graphics processing unit
H	hospital
HMI	human machine interface
I/O	input and output
IAW	in accordance with
IDG	start up generating power
IEEE	Institute of Electrical and Electronic Engineers
IoT	Internet of Things
IPR	instantaneous power requirement
kB	kilobytes
kW	kilowatt
kWh	kilowatt-hour
li-ion	lithium-ion
LMO	lithium manganese oxide
m/s	meters per second

m^2	square meters
MDMS	meter data management system
MGCQ	microgrid clustering algorithm
MHz	megahertz
MQTT	message queue telemetry transport
MTBF	mean time between failure
MTTR	mean time to repair
MW	megawatt
NAVFAC	Naval Facilities Engineering Systems Command
NMC	nickel manganese cobalt oxide
NPS	Naval Postgraduate School
Op	operation area
OSGP	open smart grid protocol
pIPR	predicted instantaneous power requirement
PV	photovoltaic
Res	residential area
RTU	remote terminal unit
SCADA	supervisory control and data acquisition
SAIDI	system average interruption duration index
SAIFI	system average interruption frequency index
SBC	single board computer
STC	standard test condition
TIP	total instantaneous power
W/m^2	watts per meter squared
WSN	wireless sensor networks
WT	wind turbine

EXECUTIVE SUMMARY

Availability and access to reliable energy is a persistent need for Department of Defense (DOD) installations to accomplish their missions. In February 2020, the Department of the Navy (DON) released its Installation Energy Resilience Strategy setting out three driving goals of Resiliency, Reliability, and Efficiency (Department of the Navy 2020). Reliability is ultimately determined by the duration of outages where power is not being delivered to users. The DON utilizes multiple metrics such as the System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI) to annually characterize the energy reliability of its facilities (Department of the Navy 2021).

Microgrids are a primary method in which DOD facilities improve energy security and reliability for critical assets and infrastructure. In the event of a power outage from the main energy grid, a microgrid can "function as a grid resource for faster system response and recovery" (Department of Energy n.d.). Microgrids have begun to increasingly utilize renewable energy sources to reduce dependency on fuel supplies for onsite diesel and gas generators. However, renewable energy introduces a new dependency on weather conditions to provide sufficient power.

Internet of Things (IoT) technology includes devices capable of performing actions and communicating information to a central hub (Wang, Xu, and Khanna 2011; Viel, Augusto Silva et al. 2020). Often referred to as smart devices, IoT technology can serve many purposes and can be broadly categorized into sensors, processors, actuators, and communication devices (Maharjan and Khakurel 2023). Advanced metering infrastructure (AMI) and supervisory control and data acquisition (SCADA) are two prominent examples of IoT technology implemented in some microgrids' operations (Department of the Navy 2023).

This research begins investigation towards the energy reliability impact of integrating IoT technologies into the operations of DOD installation microgrids. In doing so, the authors developed a methodology which can be categorized in three areas:

- IoT Capabilities
- Microgrid and User Requirements
- Modeling Analysis

For Area 1, an initial compilation of IoT technologies was generated with defined capabilities in the context of smart microgrids. The authors then categorized specific functionalities and applications within microgrids as seen in Figure 1.

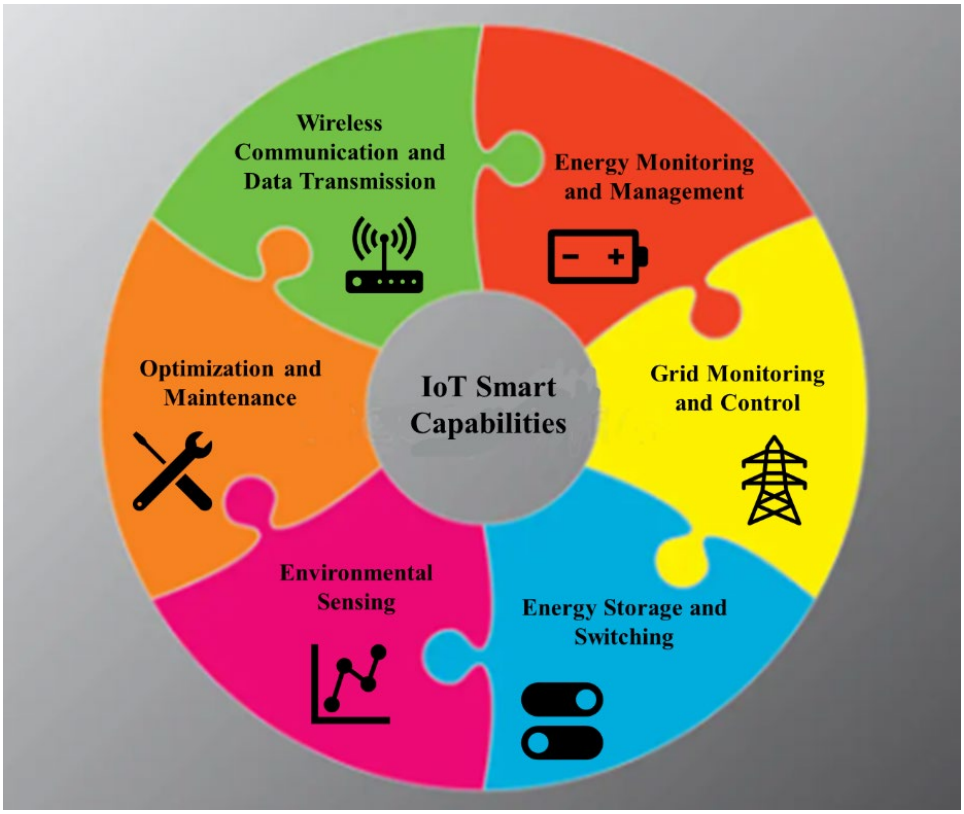

Figure 1. IoT Smart Capabilities

After researching the IoT smart capabilities and categories in Area 1, the authors decomposed perceived stakeholder requirements for energy security and reliability to determine where integration of IoT technologies may provide a solution. An initial operational context was developed to illustrate relationships between components of the

IoT-integrated smart grid along with external interactions such as disconnection from the main energy grid and introduction of energy disruption events. Specific components and functions of IoT-integrated smart grid were then refined into further detail to distinguish the unique differences between the smart IoT microgrid and a conventional, manually operated microgrid. The analysis of Area 2 culminated in Figure 2 which highlights the IoT components layered on top of the definition for a conventional microgrid. Wireless transmitters are strategically positioned at each power source, enabling the transmission of smart meter data via Advanced Metering Infrastructure (AMI) technology. The integration of AMI with the SCADA system enables rapid and seamless switching of power sources within the smart microgrid. This automated switching capability facilitates independent power direction to the three designated demand loads.

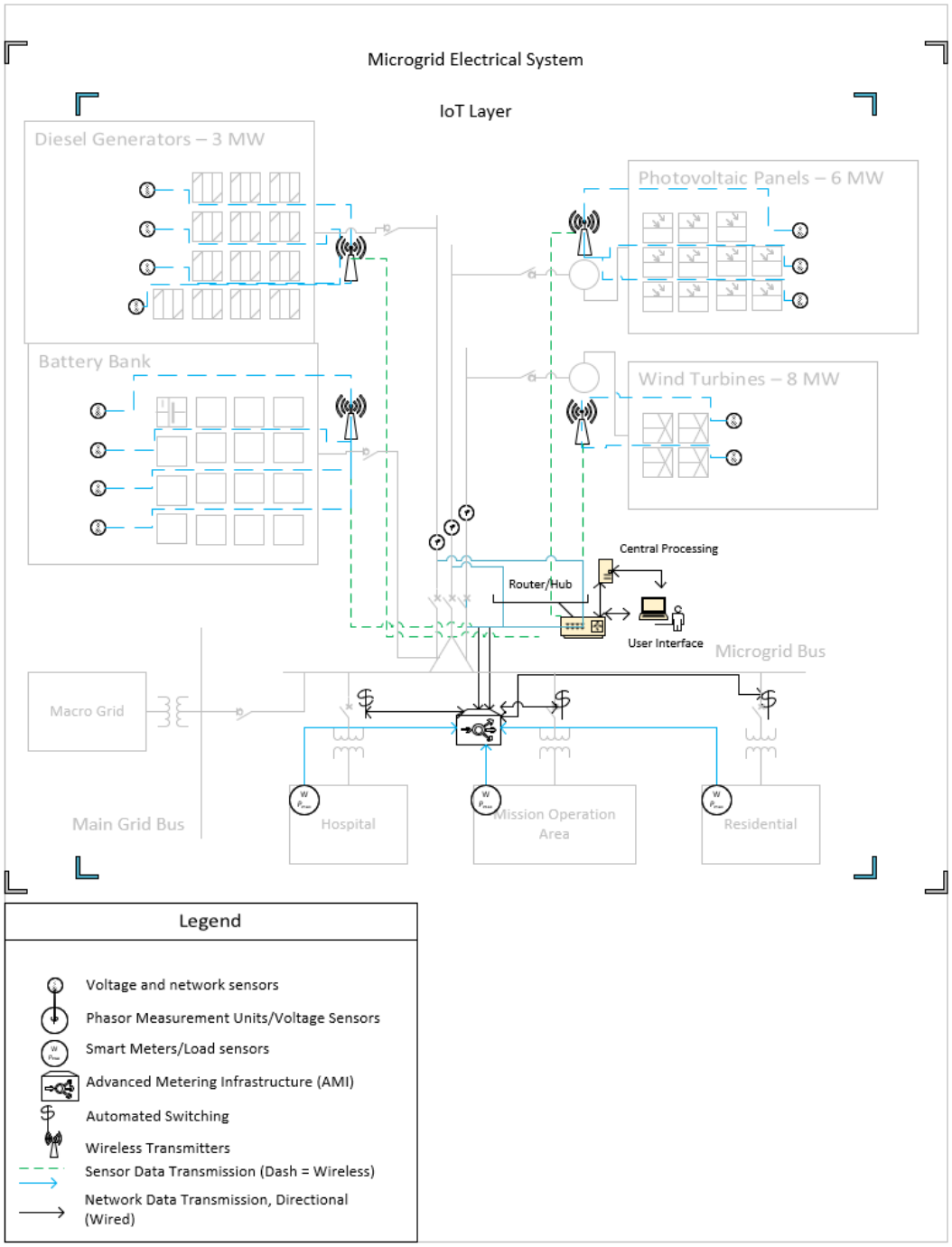

Figure 2. Microgrid IoT Layer

For Area 3, a discrete-event model was developed utilizing the ExtendSim Pro modeling and simulation software version 10.0.9. The model defines a baseline microgrid and implements several IoT capabilities identified previously in Area 1. Simulations occur

for the duration of a year of islanded microgrid operation with varied operational conditions. These varied conditions require switching operations to occur alternating power sources between renewable energy devices, diesel and gas generators, or battery energy storage systems. Utilizing Monte Carlo simulations, the model outputs several iterations of metrics detailing the power generated and provided to critical loads for both the baseline and smart microgrid configurations.

While the models yield valuable insights, it is crucial to recognize inherent assumptions and their potential impact on the model's reliability. The simplifications in our model and the use of hourly simulation intervals could limit its ability to fully represent the intricacies of real-world microgrids. Additionally, the absence of explicit power transmission considerations in our assumptions may introduce uncertainties when applying our findings to practical scenarios. The research team strongly recommends that future users of the model replace inputs with their specific conditions to provide a more accurate analysis for their operating environment.

The simulations conducted determined that IoT devices increased the response of the microgrid to changes in supply and demand. The simulations found an increase in average availability of 102.1-hours in favor of the IoT smart microgrid across a 10-year Monte Carlo simulation in which both models are subjected to the same variations at the same time intervals. Although a small percentage difference over a year, it represents a statistically significant ($p < 0.032$) increase in energy availability for critical systems which may otherwise not receive required power. These results were based on a simulated DOD installation microgrid developed to analyze the impact of IoT technology on microgrid energy reliability. Future improvements to the model could include losses and failures from transmission lines and modeling of the communication network needed for IoT. The team also recommends that stakeholders consider other aspects outside of this research such as system life cycle costs to make a fully informed decision as to whether integration of IoT technology would be beneficial to a microgrid.

References

Department of the Navy. 2021. "P-602 3 Pillars of Energy Security (Reliability, Resilience, & Efficiency)."

———. 2023. "Unified Facilities Criteria (UFC): Engine-Driven Generator Systems for Prime and Standby Power Applications." NAVAL FACILITIES ENGINEERING COMMAND.

Department of the Navy, (DON). 2020. "Installation Energy Resilience Strategy."

Wang, Wenye, Yi Xu, and Mohit Khanna. 2011. "A Survey on the Communication Architectures in Smart Grid." Computer Networks 55 (15): 3604–29. https://doi.org/10.1016/j.comnet.2011.07.010.

Viel, Felipe, Luis Augusto Silva, Valderi Reis Quietinho Leithardt, Juan Francisco De Paz Santana, Raimundo Celeste Ghizoni Teive, and Cesar Albenes Zeferino. 2020. "An Efficient Interface for the Integration of IoT Devices with Smart Grids." MDPI 20 (10): 1–18. https://doi.org/10.3390/s20102849

Maharjan, Asim, and Saju Khakurel. 2023. "Introduction to IoT." In IoT, Machine Learning and Blockchain Technologies for Renewable Energy and Modern Hybrid Power Systems, 1st ed., 1–28. Gistrup, Denmark ; River Publishers.

Department of Energy. n.d. "Grid Systems." Energy.Gov. Accessed May 10, 2023b. https://www.energy.gov/oe/grid-systems.

I. INTRODUCTION

A. PURPOSE

The purpose of this capstone project is to investigate and assess the impact of integrating Internet of Things (IoT) capabilities in smart microgrids compared to conventional microgrids at Naval installations. While energy resilience remains a critical focus, we explore energy efficiency, performance and reliability of microgrids both using IoT capabilities and without IoT through a modeling and simulation process. By incorporating IoT-based sensing and control systems, it is possible that the overall energy management and reliability of microgrid systems may be enhanced thus enabling a more readily available power supply for mission-critical operations. Through an in-depth analysis of IoT-integrated microgrids, we seek to identify key performance indicators and trade-offs to ensure improved energy performance.

B. BACKGROUND

The availability and access to reliable energy will continue to be a persistent need for Department of Defense (DOD) installations to accomplish their mission. In February 2020, the Department of the Navy (DON) released its Installation Energy Resilience Strategy setting out three driving goals: Resiliency, Reliability, and Efficiency. This document was refined from the DON Energy Security Framework (ESF) from 2017 which directed installations to develop means and methods to "enhance mission assurance through assured energy, defining benchmarks for: resiliency, reliability, and efficiency necessary for installations to enable assured missions" (Department of the Navy 2020, 7). A common method for energy assurance at DOD installations is to have microgrids which are capable of meeting requirements when connection to the main power grid is interrupted. This research investigates the potential benefits and risks of introducing smart technologies, generally referred to as Internet of Things (IoT), into microgrid operations for the overall purpose of improving energy security at DOD installations.

The primary stakeholder for this research is DOD land-based installations as they move toward compliance with Executive Order 14057, which sets goals for carbon

pollution free energy generation, net zero building, and increases in climate resilience, among other requirements (The White House 2021). Other groups of stakeholders include the installation facilities personnel responsible for managing microgrids as well as those who depend on the power provided to perform mission critical functions. For example, risk managers and emergency responders would benefit from an awareness of an installation's critical systems, which retain prioritized service during limited power generation scenarios.

Microgrids have emerged as a promising solution to address energy challenges by providing localized and reliable electrical supply. These small-scale power grids can operate independently or in parallel with the main grid, offering a more resilient energy infrastructure. However, microgrids also face disruptions such as power fluctuations, cyber threats, and environmental disturbances.

To bolster the performance efficiency of microgrid systems, the integration of IoT-based sensing and control systems has gained traction. IoT devices, such as advanced metering infrastructure (AMI), smart switches, and supervisory control and data acquisition (SCADA), enable real-time monitoring, data analysis, and automated responses to energy demands. By leveraging IoT capabilities, microgrids can optimize energy distribution, enhance grid stability, and adapt to dynamic power requirements.

This capstone project builds on prior research and scholarly work, which has explored various aspects of microgrids and IoT applications for energy management (Giachetti et al. 2021). Studies have highlighted the potential of IoT to enable situational awareness in microgrid operations and improve decision-making processes. By conducting a comprehensive analysis of smart IoT microgrids and comparing them to conventional, or baseline, microgrids, this project aims to contribute valuable insights to the field of microgrid optimization. The outcomes of this study will facilitate informed decision-making, enhance energy efficiency, and bolster the overall performance of microgrid systems on Naval installations. As the USN continues to prioritize energy reliability and efficiency, this capstone project will provide inputs for leveraging IoT technologies to meet the evolving energy challenges of the future.

C. CONTRIBUTION

This capstone study presents a novel exploration of the impact of IoT integration on energy efficiency, performance, and reliability within microgrids, specifically focused on Naval installations. By employing a comprehensive simulation model and analyzing key measures of performance and effectiveness, this research sheds new light on how IoT technologies can enhance energy reliability and efficiency and address critical energy requirements in complex and mission-critical environments. The study's integration of advanced metering infrastructure, IoT sensors, and control systems into the microgrid model provides unique insights into the potential benefits and challenges of deploying IoT-based smart technologies, contributing valuable knowledge to the existing literature on microgrid energy management and optimization.

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II. LITERATURE REVIEW

A. NAVFAC MICROGRID ISSUANCES AND DIRECTION

The Naval Facilities Engineering Systems Command (NAVFAC) published its P-602 document in January 2021 with the purpose to "provide guidelines for evaluating and measuring energy and water security articulated to best practices for utility system management" (Department of the Navy 2021, 9). The document refers to the "3 Pillars of Energy Security" which correspond directly to the three driving goals of the DON Installation Energy Resilience Strategy. NAVFAC defines these three pillars as:

- Reliability—capability to resist utility failures
- Resilience—capability to withstand and recover from utility failures
- Efficiency—capability to reduce demand and cost of utilities (Department of the Navy 2021, 10)

Each DOD installation has its own unique priorities between energy reliability, resilience, and efficiency. Improvements to any area, however, generally provide an overall benefit to energy security so long as the other aspects are not degraded. The DON's intent is to "achieve 100% mission continuity for Defense and Task Critical Assets and Infrastructure by establishing the capability to operate off grid for 14 days or a longer duration" (Department of the Navy 2020). The military's energy production and delivery methods, further referred to as the energy grid, will always be susceptible to being targeted by adversaries. Due to various risks such as adversary actions, natural disasters, and regular failures from routine operation, an entirely 100% reliable energy service would be unlikely to achieve for any installation's energy grid. However, maximizing reliability to the greatest extent practicable helps to ensure critical loads are more often available when they are needed. For DOD installations, critical loads consist of several users that consume the energy grid's power to perform necessary functions such as power air conditioning, lighting, or life support systems at a hospital.

As one of the three main pillars for energy security, energy reliability serves an important role in accomplishing any facility's mission. The Navy's P-602 document considers energy reliability to be "the percentage of time energy delivery systems (utilities) can serve mission functions at acceptable levels" (Department of the Navy 2021, 12). Reliability is ultimately determined by the duration of outages where power is not being generated and/or delivered to the users. The Navy considers system monitoring, controls, regular maintenance, and cybersecurity protections to all be important metrics for assessing energy reliability (Department of the Navy 2021).

There are multiple metrics available for characterizing energy reliability. The DON utilizes Institute of Electrical and Electronic Engineers (IEEE) standards to quantify reliability with the System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), and overall availability (Department of the Navy 2021).

2.1)

$$SAIDI = \frac{\sum Outage\ Duration}{\sum Customers}$$

SAIDI measures the total annual downtime of power outages in total minutes experienced by all customers divided by affected customers. For example, if two customers had power outages totaling 20 minutes for a year and three customers had outages totaling 10 minutes for a year the sample SAIDI calculation would look like:

2.1.1)

$$SAIDI_s = \frac{\sum(20+20+10+10+10)}{\sum(1+1+1+1+1)} = \frac{70}{5} = 14\ minutes/year$$

In the example above the grid would have a SAIDI score, or system average outage duration, of 14 minutes per year.

SAIFI measures the frequency at which these outages occur. The two metrics are also combined to form the Customer Average Interruption Duration Index (CAIDI) by taking the SAIDI metric and dividing by the SAIFI.

2.2)

$$SAIFI = \frac{\sum Outages}{\sum Customers}$$

2.3) $$Availability = 1 - \left(\frac{SAIDI}{\text{min}/\,per\,year}\right)$$

SAIDI is also used to calculate the overall facility's energy availability by dividing the number of minutes, typically 525,600 for a year, and subtracting that amount from one (Department of the Navy 2021)

2.4) $$CAIDI = \frac{SAIDI}{SAIFI}$$

The CAIDI serves as a reliability index to indicate the anticipated amount of downtime to occur for the year. This provides the percentage of uptime commonly expected for reliability and availability assessments. Each of these metrics present different aspects for evaluating a facility's energy reliability. Any method to reduce outage durations or frequency would improve a facility's energy reliability and thus its energy security as well. This is where the Navy and DOD can and are employing redundant systems in the form of microgrids to minimize outage downtime durations.

B. MICROGRIDS

One method for achieving energy security for the Navy is developing and designing microgrids for critical assets and infrastructure. These microgrids are both installation and asset specific to meet the unique requirements found at each location (Roosa 2021). According to the Department of Energy, "Microgrids can disconnect from the traditional grid to operate autonomously and locally. Microgrids can strengthen grid resilience and help mitigate grid disturbances with their ability to operate while the main grid is down and function as a grid resource for faster system response and recovery" (Department of Energy n.d.). Microgrids can run independently of the grid to operate islanded or with other microgrids in a network to form a system of microgrid systems (Department of Energy n.d.; Wattjes and Slootweg 2013). Trade-offs in energy generation, transmission, storage, and reliability must be balanced for each microgrid. For example, in space-constrained microgrids a generator and fuel setup may be more applicable by balancing the higher energy density of fuel over batteries or utilizing batteries for efficient delivery of power on demand (Auld et al. 2022; Schlachter 2012).

Microgrids were first utilized by colleges and universities as they had several buildings in close proximity with well-defined load requirements, making it simpler to supply energy from their own microgrid (Cohn 2019). Local microgrids have become a popular method to increase local resilience and reduce dependency on external grids while meeting critical energy requirements (Ton and Smith 2012).

The switch to renewable energy within microgrids marks a shift in strategy from when onsite diesel and gas generators were considered sufficient to provide critical needs with little consideration for long-term fuel supplies (Giachetti et al. 2021). However, the integration of renewable sources does not come without risk to reliability. For example, weather dependent generators, such as wind turbines (WT) and photovoltaic (PV) solar panels, may not always produce sufficient power for the demand when environmental conditions are not supportive. The reality of inclement weather situations likely means microgrids will often require multiple sources of power generation to maintain critical functions under various environmental circumstances (Kain, Van Bossuyt, and Pollman 2021).

Improvements to either resilience, reliability, or efficiency may also involve trade-offs with one another. For example, underground power lines are often more reliable in extreme weather but become less resilient due to higher costs and time to repair when they are damaged (Keogh and Cody 2013). Having multiple generators, each operating at half capacity to meet the total requirement, ensures sufficient power resilience is available in the event that a generator fails. The redundancy of multiple generators thus improves resilience at the cost of efficiency (Department of the Navy 2023). The design and implementation of any microgrid system will need to consider these potential trade-offs for the intended operating environment.

An increase in redundancy improves reliability and resilience but also increases costs for facilities. The lack of standardization across various microgrids creates interoperability and scalability issues, resulting in failure to create more reliable and resilient systems. This is where Internet of Things (IoT) devices and smart grids may become a potential solution by bridging these gaps with smart control systems. The

improvements from IoT technology may help optimize performance of the microgrid and reduce component downtimes (Siano 2014).

C. INTERNET OF THINGS IN MICROGRIDS

Internet of Things (IoT) devices are, at their core, devices that perform an action, either passively or actively but also communicate information about their measurements, actions, or activities to a central hub (Wang, Xu, and Khanna 2011; Viel, Silva et al. 2020). As such, IoT is not restricted to solely internet communication but can also be intranet-based or closed loop communicating devices that inform a process controller. IoT devices can be broadly categorized into sensors, processors, actuators, and communication devices (Maharjan and Khakurel 2023). IoT devices are a powerful tool that can be used to improve efficiency, save money, and improve safety. As technology continues to grow, we can expect to see even more innovative uses for IoT devices.

Sensors are a key component of IoT devices. They provide data that can be transformed into usable information for rapid decision making and fault analysis. Some examples of IoT sensors are included in Table 1.

Table 1. Smart Sensors. Source: Sehrawat and Gill (2019).

IoT Applications	Type of Sensors
Smart City	Velocity, Light, Accelerometer, Position, Temperature, Proximity, Humidity, Pressure, Infrared
Smart Environment	Light Temperature, Humidity, Chemical, Gyroscope, Bio Sensors, Chemicals, Accelerometer, Optical
Smart Water	Temperature, Humidity, Occupancy, Water Quality
Smart Building	Light, Accelerometer, Chemical, Gyroscope, Magneto
Smart Health	Light, Gyroscope, Biosensors, Chemicals, Magneto, Accelerometer, Pressure
Smart Home	Light, Gyroscope, Biosensors, Chemicals, Magneto, Accelerometer, Temperature, Proximity, Position, Infrared
Smart Transport	Gyroscope, Pressure, Chemicals, Magneto, Accelerometer, temperature, Motion, Infrared
Smart Security	Light, Gyroscope, Chemical, Magneto, Accelerometer, Temperature, Infrared
Smart Agriculture	Temperature, Humidity, Water Quality, Chemical, Proximity, Position
Smart Retail	Light, Gyroscope, Chemical, Magneto, Accelerometer, Pressure, Position

Smart sensor devices like those mentioned in Table 1 can be used in wireless sensor networks (WSNs) to provide two-way communication between power generation sites and base stations (Hussein and Erol-Kantarci 2017). This communication between sensors allows for the collection and analysis of data from a variety of sources, which would enable power managers to make better informed decisions about operating an energy grid. For example, IoT sensors can be used to monitor the temperature and humidity of a building. This data can then be used to control the heating and cooling system, which can save energy and money. IoT sensors can also be used to monitor the condition of machinery. This data can be used for predictive maintenance to identify potential problems before they cause a failure, which can prevent costly downtime (Kadechkar et al. 2020).

Additional categorization of IoT devices can be done based on capabilities; in these sub-categories a device can be low, middle, or high-end based on its processing complexity. These categorizations are inherent in the design constraints of the devices. While all IoT devices share the ability to receive information, they also perform processing of that data and generate an output (Ojo et al. 2018). Higher complexity does not always mean a device generates improvements in the desired focus area. An example of a wireless network utilizing IoT is the series of Wireless Sensor Networks (WSN) which have rapidly developed due to interest in wireless technology and integrated devices. WSNs are made up of small devices known as nodes (Wagh, Bhende, and Thakare 2022). Each node can contain sensors and a small amount of computing power to monitor the environment around them before communicating back to the main hub. The downside to a wireless system is the amount of effort it will require to maintain it will increase due to the need to replace batteries over the system's life cycle. Conversely, using a wired network can provide a continuous power supply that does not require battery replacement. Wired networks favor the design of simple sensors and complex processors. These are found in energy grid systems often combined with multimodal devices such as advanced metering infrastructure (AMI) and SCADA systems (Department of the Navy 2023).

AMI is one specific type of IoT technology which holds several potential benefits for smart microgrid applications. The differences in the baseline microgrid and smart IoT microgrid are discussed in later sections. "AMI refers to the deployment of interconnected smart meters that enable bidirectional flow of communication in order to ensure timely monitoring of meter data, reporting of outages, and service connect or disconnect updates" (Smend, Mnatsakanyan, and Sgouridis 2021, 1–2). AMI is a collection of meters and can be broken up into three main components: smart meters to collect power consumption data, communications networks to transmit the power consumption data to the grid manager, and meter data management system (MDMS) to store and process the data (Zhou, Qingyang Hu, and Qian 2012). AMI's can be used to facilitate dynamic controlling of local loads and increase efficiency through load balancing (Wasserman 2023).

With the information provided by AMI smart meters, additional IoT devices would help to make decisions for operating a microgrid. A SCADA system fits in well for this

purpose by allowing for smart, automatic switching of power generators and routing to different load demands (ScienceDirect Topics n.d.). The SCADA system is made up of several component IoT devices. The Remote Terminal Unit (RTU) is considered to be "the eyes, ears, and hands of a SCADA system" (ScienceDirect Topics n.d.). Another SCADA component is the communications system which involves the transfer of data between the different nodes across the microgrid network. The main node in this SCADA microgrid network would be the master station component which is defined as "a collection of computers, peripherals, and appropriate input and output (I/O) systems that enable the operators to monitor the state of the power system (or a process) and control it" (ScienceDirect Topics n.d.). Lastly, a SCADA system must also include a human machine interface (HMI) which refers to "the interface required for the interaction between the master station and the operators or users of the SCADA system" (ScienceDirect Topics n.d.).

A sensor's extent of data gathering along with the subsequent processing requirements predicates the communication backbone requirement. Interfaces and protocols between sensors, processors, and actuators will influence the complexity of requirements for the smart grid network. A variety of protocols and interfaces have been utilized or proposed to include Message Queue Telemetry Transport (MQTT), Constrained Application Protocol (CoAP), Microgrid clustering algorithm (MGCQ), and Open Smart Grid Protocol (OSGP) (Marzal et al. 2019). Viel et al. (2020, 2), proposes a model to unify these variations for integration across home, industry, and smart grid in a protocol named COIIoT, which is a combination of "CoAP and OSGP Integration for Internet of Things." This model eschews security concerns as a topic for future research.

The integration of multiple IoT devices into a microgrid network can also introduce unique vulnerabilities and risks. For example, choosing between a wireless, wired, or hybrid connection will impact the effectiveness of data exchange and may allow entrances for malicious cyber criminals. Integration of devices to one or more central processing hubs is a key consideration for adopters of IoT devices. As different sensors or actuators are added to the IoT network, care must be taken to not introduce new vulnerabilities to the IoT network without a trade-off analysis of gained functions or capabilities. A passive

sensor system that feeds data wirelessly over open radio frequency channels to a processor may still be able to provide adversaries critical information thus creating a vulnerability. If the processing unit is connected to controllers, even circuitously, the risk of effective tampering, introduction of malicious code, or induced failures rises beyond the gain of added capability of remote decision making from that processor (Keogh and Cody 2013).

Power is another consideration for IoT devices which presents an additional requirement for a microgrid's power generation. An argument can be made for batteries or a hard-wired connection depending on the microgrid's mission and location. The implementation of IoT devices, their quantity, and different processing requirements will affect the power drawn on a microgrid. IoT devices connected to sensors do not require a significant amount of power on their own, from a few milliwatts (mW) to a few watts (W), but if an installation uses hundreds of sensors, then the power demand will increase accordingly (Wagh, Bhende, and Thakare 2022).

D. THREATS AND RISK OF IOT TECHNOLOGY

Disaster scenarios are increasing in likelihood meaning energy reliability will continue to be an important aspect for microgrids. Having measures to better withstand and recover from disasters will help to improve the overall energy security for DOD installations. Historically, most disasters are environmental; however, the president can declare a state of emergency for several reasons, including adversarial (Federal Emergency Management Agency 2023). Many of these disasters have caused widespread outages in various electrical grids.

The National Academies of Sciences, Engineering, and Medicine describes eleven reasons the electrical grid can experience outages (Committee on Enhancing the Resilience of the Nation's Electric Power Transmission and Distribution System et al. 2017). They can be broken into three main categories: adversarial, nominal, and natural. Adversarial threats include disturbances in the electrical grid caused by intentional human interaction with the grid. Adversarial interaction can be a physical attack (such as a missile strike or car bomb), an electromagnetic pulse caused by a nuclear explosion in the Earth's atmosphere over the target, or a cyber-attack. Nominal threats include disturbances in the

electrical grid caused by unintentional human interaction, or lack of interaction, with the grid. A couple examples of nominal threats are operational errors and maintenance issues. Natural threats include disturbances in the electrical grid caused by uncontrollable, non-human activities. There are several types of natural threats such as earthquakes, tsunamis, regional weather, ice storms, floods, space weather (non-nuclear electromagnetic threats), hurricanes and tropical cyclones, volcanic activity, wildfires, and droughts (Committee on Enhancing the Resilience of the Nation's Electric Power Transmission and Distribution System et al. 2017).

All three categories of threats are present, at least in some respect, at every electric grid around the world no matter the size. However, with the use of IoT devices, the impact of the threats may be reduced, increasing the reliability of the grid in which they are implemented. This study does not directly address or model disaster scenarios for the purposes of further analysis but does incorporate mean time between failure (MTBF) as a means to draw disaster comparisons as discussed in the subsequent sections.

E. MICROGRID MODELING AND SIMULATION TOOLS

Several past research efforts have investigated microgrid performance and its role with respect to energy resilience. Past studies have looked into the sizing and redundancy determinations for distributed energy resources such as diesel generators, photovoltaic panel arrays, wind turbines, and battery energy storage systems. By focusing on energy resilience, these studies generally are concerned with the microgrid's responsive performance to a high-impact, low-probability event such as a natural disaster or adversarial attack.

Giachetti establishes resilience and cost models to evaluate multiple microgrid architecture alternatives in response to a major disruptive event (Giachetti et al. 2021). Siritoglou utilized MATLAB-based software to specifically size photovoltaic arrays and battery storage for achieving desired microgrid resilience levels (Siritoglou, Oriti, and Van Bossuyt 2021). Anglani et al. built upon this MATLAB-based software to incorporate diesel generators into the microgrid architecture and also allowed for temperature conditions to become an input affecting microgrid performance (Anglani et al. 2022).

Peterson developed MATLAB scripts which accounted for failures to occur both at power generation components as well as the transmission lines to multiple loads. Peterson's study also introduced a new resilience metric known as the "expected electrical disruption mission impact" which results from the "Mission Dependency Index" characterizing mission criticality of different power loads (Peterson et al. 2021). Although Peterson's model incorporates transmission between multiple energy resources and loads, the model does not consider any switching actions and assumes power to be automatically routed to the most critical demands (Peterson et al. 2021). Anuat et al. built upon Peterson's MATLAB scripts to include consideration for the fuel supply chain necessary for backup diesel generators (Anuat 2021)

Reich and Oriti created a new software framework to capture the design space of microgrid architectures by using a "simulation-based nested binary search methodology" (Reich and Oriti 2021). This framework allows for multiple feasible solutions to be considered by the software user rather than providing only a single output. The software framework's simulation includes conditional statements to switch between states such as the charging or discharging of batteries, but the framework does not appear to include time delays in order for the state switching to occur (Reich and Oriti 2021).

Many of these past studies and their respective models do not consider routine operations of switching and routing power from multiple sources to multiple demands. Previous models often assume that available power generation will instantly route to appropriate loads. Doing so allows these studies to focus analysis on the various components of a microgrid rather than the interactions amongst the components.

The team chose to utilize a discrete-event modeling tool to begin investigation towards the integration of IoT technology in routine microgrid operation. By incorporating conditional logic and delay functions, this new model can begin to account for the operations needed to manage multiple power sources and loads within a microgrid. For example, the new approach focuses on the smart switching and utilization of diesel generators and batteries when renewable energy generation is not sufficient, or when components fail from regular operation. The incorporation of this new modeling approach is what allows for an investigative analysis of smart IoT technologies' contributions

towards microgrid energy reliability and efficiency. The team aims to ultimately contribute to others' work with modeling microgrid performance by first establishing an approach to incorporate modeling IoT devices within a microgrid.

III. METHODOLOGY

This methodology encompasses data driven analysis, IoT impact evaluation, use of discrete event modeling, and alignment with user requirements. The overall purpose is to determine whether the addition of IoT technologies to a microgrid will impact the ability to consistently provide reliable power. To assess the benefits and consequences of introducing smart technologies, or IoT, into microgrid operations for improving energy security, the authors have provided a review of IoT capabilities and a simulation analysis which is broken up in three areas:

1. STEP 1: IoT Capabilities
2. STEP 2: Microgrid and User Requirements
3. STEP 3: Modeling Analysis

A. STEP 1: IOT CAPABILITIES

In Chapter 2, an initial literature review of IoT technologies was conducted, laying the groundwork for a comprehensive analysis in the subsequent sections. The main objective is to provide a thorough overview of how these technologies can be effectively applied to microgrid operations and their potential to transform conventional microgrids into IoT-integrated or "smart" grids. This comprehensive analysis forms the basis for discussions on the benefits and implications of IoT integration in microgrid systems, as well as informs the design of the proposed model. In this step of the methodology, we delve into the exploration and categorization of various IoT technologies that hold relevance to the design and implementation of smart IoT microgrids. By thoroughly investigating and evaluating these technologies, we aim to ascertain their potential impact on enhancing microgrid efficiency, resilience, and overall performance.

B. STEP 2: MICROGRID AND USER REQUIREMENTS

This research area centers on investigating user requirements, derived from stakeholder needs and performance criteria, to translate into functional diagrams, representative diagrams, and a simulation model utilizing system engineering principles.

The objective is to demonstrate the progression from user needs to the design of the IoT integrated "smart" microgrid in the model. Functional diagrams illustrate the composition of functions within the microgrid models and highlight the variations between the baseline microgrid and a smart IoT microgrid. By employing system engineering principles, this research area ensures a systematic and comprehensive approach to capturing and representing user requirements, setting the foundation for the subsequent modeling analysis.

Requirements provide the foundation for defining a clear understanding of what the stakeholders' needs are and the specific performance criteria and goals for the microgrid system. The simulation model is developed to represent the microgrid system and the needs of the users. The requirement assessments in Table 2 serves as the foundation for the analysis conducted when determining performance, behaviors, and effectiveness.

Table 2. Microgrid User Requirements

Requirements	**Definitions**
Continuous Power Supply	Supply reliable and uninterrupted power to critical systems and equipment (Kroposki et al. 2010)
Rapid Recovery	Recover and restore power quickly in the event of disturbances or outages, minimizing downtimes (Tang and Chen 2022)
Remote Control and Monitoring	Monitor performance, identify issues, and ensure effective and efficient operation (Takriti et al. 2020).
Cybersecurity	Protect against cyber threats to ensure integrity of microgrid and availability of systems (Llaria et al. 2021)
Flexibility and Scalability	Design to accommodate changes and upgrades.
Energy Efficiency	Optimize energy usage to reduce costs (Department of the Navy 2020).

Requirements	Definitions
Integration of Renewable Energy Sources	Reduce dependency on fossil fuels using established renewable energy technology. (Giachetti et al. 2021)
Predictive Maintenance	Leverage data and analytics to detect potential faults or failures, enabling faster and fewer repairs (Amini, Nazari, and Hosseinian 2023)
Training and Support	Equip user friendly interfaces for proper operation (Chakrabortty and Bose 2019)
Compliance with Regulatory Standards	Adhere to all relevant standards, guidelines, protocols etc. (National Electrical Manufacturers Association (NEMA) 2016).

These requirements serve as the basis for understanding the desired functionalities, performance criteria, and goals for the microgrid system as it will relate to IoT capabilities. This is done to establish a clear connection between the desired system performance and the evaluation conducted in the analysis phase. The identified user requirements will be translated into specific metrics that serve as evaluation criteria for the analysis. Other analysis of the requirements will assess the performance of the microgrid system.

The Measure of Effectiveness (MOE) of primary interest is availability represented, in part, by SAIDI. SAIDI counts the minutes of outage for each customer and divides it by the number of customers. For our model, each demand center is considered a customer, for a total of three customers. This metric quantifies the total annual time that energy meets demand as a percentage value from 0% – 100%. A high availability signifies a reliable and robust microgrid that ensures continuous power supply during mission-critical operations.

We also gathered the SAIFI and CAIDI metrics to provide more context to our microgrid's availability. We modified the base metrics from equations B.1 – B.4 to fit the model outputs as follows:

3.1) $$mSAIDI = \sum Outage\ Duration$$

The SAIDI metric requires outage duration, but our model counts time in hours met. To convert to outage duration, the total hours in the year (8760) are subtracted by the count of demand hours met (IPR_m) into minutes out. This is done for both the IoT enabled microgrid and the baseline microgrid (IPR_{mI}, or IPR_{mC}).

3.2) $$Outage\ Duration = 8760 - \sum IPR_{m(I,C)} * 60$$

3.3) $$mSAIFI = \sum Outages$$

At each (X) hour (ranging from 0 to 8,759), Outage creates a count of state changes when IPR_m changes from meeting (1) to not meeting (0) the total demand.

3.4) $$Outage = at\ hour(X),\ IPR_m = 0\ AND\ at\ hour\ (X-1), IPR_m = 1$$

These formulas are modified to remove the customers divisor since algebraically all customers are affected at each hour for *IPR* model outputs and thus cancel out. Availability and CAIDI metrics use the modified formulas found in equations B.1 and B.3. These scores will be calculated against the two baseline scenarios of baseline microgrid and smart IoT microgridl

Measures of Performance (MOP) are highlighted in Table 3 that are output from the model. Additional MOP's recorded by hour include (variables with "p" are exclusive to the baseline microgrid):

Table 3. Model Metrics and Descriptions.

#	Metric	Description
1	Time	Hour register
2	Instantaneous Power Requirement (per hour)	IPR – Total Demand
3	Crit Load 1	The minimum load to meet critical requirements (60%) of IPR by demand center
4	Crit Load 2	30% of IPR – Additive to Crit Load 1
5	Crit Load 3	10% of IPR – Additive to Crit Load 1 & 2
6	Instantaneous PV Power	PVp x PVr – Value in kWh of PV panels at Time X
7	Instantaneous WT Power	WTp x WTr – Value in kWh of WT at Time X
8	Instantaneous DG Power	IDG – Value in kWh of DG at Time X
9	PVsInUse	Count of working PVs
10	WTsInUse	Count of working WTs
11	DGsInUse	Count of working DGs in IoT model
12	Total Instantaneous Power (TIP)	Sum of **6** & **7**
13	BAT Charge (kWh)	Positive value when TIP > IPR
14	BAT Discharge (kWh)	Negative value when TIP < IPR
15	BATDelta	Value of **13** or **14** at Time X
16	BAT Stored Power (kWh)	kWh of available battery power starting at 5000
17	TIP+BATR	Sum of **12** and **15**
18	TIP + BAT+ DG	Sum of **17** and **11**
19	pBAT Charge (kWh)	Positive value when TIP > pIPR
20	pBAT Discharge (kWh)	Negative value when TIP < pIPR
21	pBAT Delta	Value of **19** or **20** at Time X
22	pBAT Stored Power (kWh)	kWh of available battery power starting at 5000
23	TIP+ pBATR	Sum of **12** and **21**
24	TIP + pBATR + pDG	Sum of **23** and **25**
25	pDG Power (kWh)	pIDG – value in kWh of pDG at Time X
26	pDGsInUse	Count of working DG's in baseline model
27	BAT Fail IoT	Count of battery failures under IoT model
28	pBAT Fail	Count of battery failure under baseline model
29	DG Fail	Count of DG's that failed at Time X
30	pDG Fail	Count of pDG's that failed at Time X
31	DG Fuel Level	Register of fuel consumption for IoT DG's starting at 100,000 gallons
32	pDG Fuel Level	Register of fuel consumption for pDG's starting at 100,000 gallons

Comparisons are made on the frequency at which the models and various scenarios reach *IPR* and Critical Load 1 with all generation methods available (metrics 18 and 24 for the IoT grid and baseline grid, respectively), probabilities to meet *IPR* and Critical Load 1 by hour, generator use relative to available fuel, total hours meeting *IPR*, and whether any scenario meets or exceeds the 14-day renewable-only standard. Scenarios were measured against the mean and standard deviations of the 10-year baseline data to determine deviations of significance from the mean with a $p < 0.05$.

The total power generated, measured in megawatts, provides valuable insights into the microgrid's overall energy generation capacity. This is a sum of all hourly generation for the microgrid. This information is then further analyzed to understand how well the microgrid aligns with the critical load requirement. The battery discharge rate, measured in kilowatts per hour, sheds light on the efficiency of the microgrid's energy storage and management. A lower discharge rate suggests improved balance and optimization of power supply and demand.

Furthermore, we evaluate the ratio of power generated versus critical load requirement, which indicates the surplus or deficit of generated power compared to the essential load demand. A higher ratio suggests a microgrid with excess power capacity. We assess the utilization rate of diesel generators, which provides insights into their role in power generation. A lower utilization rate indicates a decreased reliance on diesel generators and potentially signifies the adoption of renewable energy sources and improved energy efficiency. The data collected through these MOEs and MOPs is vital for understanding the microgrid models' effectiveness in meeting energy demands and withstanding disruptions. By analyzing these metrics, we gain valuable insights that will aid in decision-making, optimization, and further enhancement of the microgrid systems.

C. STEP 3: MODEL DEVELOPMENT

A discrete event simulation software, ExtendSim, is employed to model both a baseline microgrid and an IoT integrated "smart" microgrid. By comparing the performance of these two systems, the analysis focuses on evaluating the performance, behaviors, and effectiveness of the smart microgrid. The analysis will provide insights into

the effects on the MOE's of introducing IoT technologies into microgrid operations, allowing for informed decision-making and identification of areas for improvement.

1. Model Procedures

The scenarios developed are intended to provide extreme case comparisons to assess and validate the impact of IoT on microgrid systems. The scenarios are designed to represent different variations of generating conditions compared to varied demand profiles and critical load values. The simulation model incorporates solar radiance, wind speed, diesel fuel consumption, MTBF and mean time to repair (MTTR) as key independent variables to evaluate the reliability and performance of the microgrid system. The incorporation of MTBF into the model enables failure events based on statistical distributions simulate and determine their effects on the microgrid's operation. The following scenarios were chosen to observe the performances of a baseline and smart IoT microgrid under different power generation situations. The scenarios the team investigated are:

Nominal One-Year Power Supply Scenario: This scenario represents the microgrid system under 100% islanded operating conditions without any specific disruption or anomaly. This represents the microgrid system operating in a completely isolated manner, without any reliance on external power sources or connection to the larger grid. This deliberate choice emphasizes one extreme end of the spectrum, where the microgrid is functioning independently and self-sufficiently throughout the year. Historical weather patterns for one calendar year at an oceanside location around 40 degrees north latitude approximately at Naples, Italy are used for renewable power generation calculations (National Renewable Energy Laboratory 2023a). This sets the parameters for the solar irradiance, averaging 5.41 kWh per m^2 per day, and average wind speeds, 2.6 m/s, by which the renewable energy generation portion of the model operates. Thirteen diesel generators operating at 500 kW/h and using 36 gallons of fuel per hour on a normal distribution with a standard deviation of 1 gal. A fuel reserve starting at 100,000 gallons is used to provide approximately 9 days of full generator operation. A 5 MW battery bank also starts the model fully charged.

No refueling or macrogrid reconnection are employed in the model. This provides an extreme case to analyze the effects of employing renewables in meeting The White House requirements as well as providing data on whether IoT systems as modeled improve that capability or the capability to meet the MOE's.

Change of Mean Wind Speed Scenarios: Two wind speed variations, 7.8 mph (3.5 m/s) and 15.7 mph (7 m/s) mean wind speed set on a normal distribution were selected to compare increases to renewable power generation versus the 5.8 mph (2.6 m/s) average from the historical data from the nominal model. All wind speed calculations were performed in metric units and converted to imperial units after the fact. The 7.8 mph (3.5 m/s) average is used to demonstrate what effects a minor average wind speed increase, in line with a light breeze from the Beaufort scale (US Department of Commerce 2023), can have on the models. Across the U.S. at 262.4 ft (80 m) this is the lower end of expected wind speeds (National Renewable Energy Laboratory 2023b). A 15.7 mph (7 m/s) average is used to demonstrate what a moderate breeze on the Beaufort scale (US Department of Commerce 2023), which is still reasonable for a large area of middle states or off-shore (National Renewable Energy Laboratory 2023b), increase would do to the model MOE's.

Lower Generator Output: This scenario variation reduces the power output of the generator bank to 250 kWh and reduces the fuel consumption proportionally to 18 gal/hr. This increases the number of generators potentially needed to meet the demand but may develop higher efficiency through less overages. As the model doesn't simulate load following through the diesel generators and instead signals a number of generators operating at a select generation value this was a means to adjust for efficiency and possibly resilience to ensure we had sufficient generators in the microgrid model.

Higher Battery Storage: This scenario increases the storage capacity of the battery bank to 10 MW. This is expected to allow for increased capture of renewable energy overgeneration, in turn, reducing generator output.

a. Modeling and Simulation

The simulation model was derived from the operational context diagram (Figure 1), defined in block definition diagrams (Figure 2), and refined into representative model

diagrams (Figure 3 and Figure 4) before it was translated and developed using ExtendSim, a discrete event simulation software. The ExtendSim software is used for the model build, execution, and analysis based on randomized variables data needed for the modeled microgrid performance. The software provides the capability to generate thousands of variations to allow for Monte Carlo type analysis to assess the behavior of the microgrid system under different conditions.

b. The Model

The simulation model uses two, time sequenced, tracks to evaluate a combination of IoT technologies against a baseline microgrid's performance. Both models are measured against their ability to provide power to the demand loads and a lower critical load. The components of the model include the three power generation resources (PV, WT, and DG), energy storage, control systems, and load demand which comes from three notional, mission critical areas, hospitals, port operations, and housing facilities.

The baseline model serves as the reference point and represents the basic configuration of the microgrid, without the integration of IoT technologies. This version of the model uses a predictive demand table to signal diesel generators and batter discharge levels. In contrast, the IoT microgrid model reflects the implementation of a smart microgrid, where IoT technologies like AMI, SCADA systems, and sensors are incorporated to enhance its reaction speed to changes. The inclusion of the various IoT systems allows for real-time monitoring and generation signaling which is reflected in the model.

2. The Simulation

Monte Carlo simulation technique involving multiple iterations of the nominal scenario models was run for a total of 87,600 hours, simulating 520 weeks, or 10 years of real-world operations. This was done to create a large enough sample to reliably establish a population mean and standard deviation for any MOE, MOP, or calculation of interest. The simulations use random seeds to generate random samples within the defined parameters of the probability distributions. This reduces the chances that we generate repetitive data elements which may result in increasing errors for the analysis.

Each of the scenarios analyzed in comparison is run for only one year. With a robust sample size to determine our population metrics the scenario samples can be analyzed against them more quickly to determine if further exploration is warranted.

IV. ANALYSIS

A. ANALYSIS SUMMARY

In this section of the paper the previously described methodology steps are expanded upon and explored in depth. The IoT capabilities are further described and explored through their application to microgrids, which technologies are then applied to the model, and differences between our IoT capable model versus the baseline microgrid model. From there the microgrid user requirements are expanded through demonstrations of how our model evolved through representative diagrams and descriptions. Finally, a modeling analysis provides descriptive information on the model, results obtained from the model simulation, followed by a synthesis of the results.

B. STEP 1: IOT CAPABILITIES

In the IoT Capabilities step we examine a compilation of IoT technologies and their capabilities in the context of microgrids. The objective is to provide a comprehensive overview of how these technologies can be applied to microgrid operations and their potential impact on transforming conventional microgrids into IoT-integrated or "smart" grids. This analysis serves as a foundation for discussing the benefits and implications of integrating IoT technologies in microgrid systems and contributes to the design of the proposed model.

We explore and categorize various IoT technologies that are relevant to the design and implementation of smart IoT microgrids. To provide a comprehensive analysis, we categorize the IoT technologies based on their specific functionalities and applications within microgrids. In Figure 1, the categories include energy monitoring and management, environmental sensing, energy storage and switching, grid monitoring and control, optimization, and maintenance, as well as wireless communication and data transmission. Within each category, we explore the descriptions, applications, and interactions of the IoT technologies, highlighting their unique traits and contributions to microgrid systems. By understanding the different categories and their associated technologies, we identify the most suitable IoT technologies to be incorporated into the design of smart IoT microgrids.

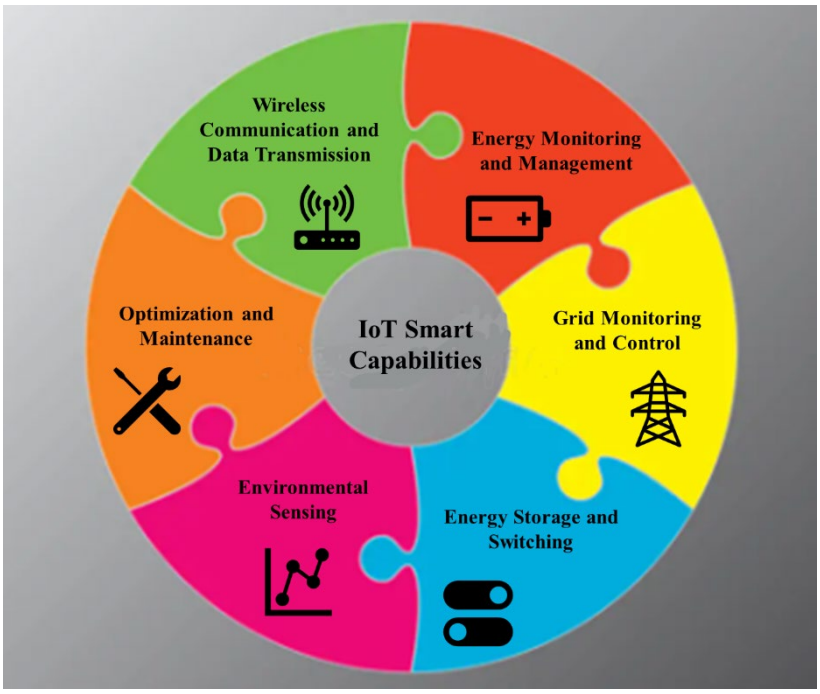

Figure 1. IoT Smart Capabilities

Energy Monitoring and Management: This category includes smart meters and AMI systems, as well as SCADA systems. Smart meters, equipped with communication capabilities, provide detailed information on energy usage patterns and enable two-way communication (Kathiresh, Mahaboob Subahani, and Kanagachidambaresan 2021). They enable real-time monitoring of energy consumption at individual buildings or loads within the microgrid, supporting demand response and load management strategies for optimized energy distribution. AMI systems, which incorporate smart meters and communication infrastructure, facilitate automated, real-time meter reading, data collection, and monitoring of energy consumption across naval installations (National Energy Technology Laboratory 2008). This enables accurate load profiling, demand-side management, and more efficient energy operations. SCADA systems provide centralized control and monitoring capabilities for microgrid operations, allowing for efficient coordination of energy generation, storage, and distribution.

Environmental Sensing: Another category of IoT technologies is environmental sensing. This category includes weather sensors and solar irradiance sensors. Weather

sensors measure various parameters such as temperature, humidity, wind speed, and solar radiation (National Energy Technology Laboratory 2008). These sensors provide real-time weather data, which is crucial for optimizing microgrid operation and predicting renewable energy generation. Weather forecasting based on this data can improve energy planning and resource allocation. Solar irradiance sensors, integrated into solar panels, measure solar irradiance levels and optimize the positioning and operation of solar power generation in microgrids (Sehrawat and Gill 2019). By ensuring maximum solar power generation and efficient utilization of renewable energy resources, these sensors contribute to the overall performance and sustainability of the microgrid system.

Energy Storage and Switching: IoT technologies related to energy storage and switching play a vital role in microgrid design. Intelligent energy storage systems combine advanced energy storage solutions with smart technologies, such as sophisticated software and algorithms (Artale et al. 2019). These systems monitor, store, and distribute electrical energy based on demand and grid connections, optimizing energy management within the microgrid (Ali et al. 2023). Smart/automatic switching refers to the capabilities of microgrids to autonomously switch between different operating modes based on predefined conditions or real-time monitoring. By using intelligent algorithms and control systems, microgrids can transition seamlessly between grid-connected and islanded modes. This technology enhances the reliability and performance of microgrids, allowing them to respond to changes in the grid connection and ensuring continuous power supply in critical situations.

Grid Monitoring and Control: IoT technologies for grid monitoring and control are essential for microgrid operations. Synchrophasor sensors are devices that measure electrical waveforms and provide real-time information on voltage, current, and frequency for grid monitoring and control (Mukherjee et al. 2015). They enhance the microgrid's ability to respond to changes in power quality, detect faults, and support islanding operations. Grid frequency sensors monitor and maintain grid stability by detecting frequency variations and enabling appropriate load shedding or power management within the microgrid (Sharma and Mishra 2020). Grid connection sensors enable the monitoring and control of grid connection status, supporting seamless transitions between grid-

connected and islanded modes for microgrid operation (Artale et al. 2019). Power quality sensors measure and analyze various parameters of power quality, such as voltage stability, frequency accuracy, harmonics, and transients. These sensors ensure a high-quality and stable power supply within the microgrid system, detecting and mitigating power disruptions and irregularities that may impact performance and stability. Voltage sensors provide real-time monitoring and control of voltage levels in microgrid systems, ensuring optimal performance stability and protection against voltage irregularities (Farhangi and Joos 2019).

Optimization and Maintenance: IoT technologies that focus on optimization and maintenance are crucial for maximizing microgrid efficiency and reliability. Microgrid optimization algorithms employ advanced algorithms to optimize microgrid operation based on factors such as load demand, energy storage levels, and renewable energy availability (Artale et al. 2019). These algorithms enable microgrids to maximize self-consumption of renewable energy, minimize peak demand, and optimize energy dispatch. Fault detection and diagnostics (FDD) systems, which utilize artificial intelligence based analysis of sensor data, can detect faults, anomalies, and potential failures in microgrid components (Aqamohammadi et al. 2023). By enabling proactive maintenance, reducing downtime, and optimizing component performance, FDD systems ensure reliable operation of the microgrid.

Wireless Communication and Data Transmission: Many IoT technologies within microgrid design rely on wireless communication and data transmission. Wireless sensor networks, consisting of interconnected wireless sensors deployed across the microgrid, provide real-time monitoring and control of various parameters such as temperature, voltage, humidity, and other environmental conditions (National Energy Technology Laboratory 2008). They enhance situational awareness, support condition-based maintenance, and enable effective management and control of microgrid operations (National Energy Technology Laboratory 2008).

1. Applications to Microgrids

Table 4 provides a comprehensive overview of various IoT technologies that are more commonly used and have significant impacts on microgrid operations. It lists different types of technologies and their functionalities, highlighting their significance in optimizing energy reliability and efficiencies within microgrids and enhancing resilience and performance.

The IoT technologies mentioned are broken out into three categories of devices: low-end, middle-end, and high-end. The reason for categorizing IoT devices is to distinguish their capabilities and resource constraints. This classification helps in understanding the varying levels of performance and functionality offered by different IoT devices. It also provides insights into the suitability of these devices for specific applications, ranging from simple sensing tasks to complex computing requirements with machine learning capabilities. They can be summarized as follows (Ojo et al. 2018):

- **Low-end IoT devices:** These devices have limited resources, such as random access and flash memories. They are commonly used in basic sensing and actuating applications where resource constraints are acceptable.

- **Middle-end IoT devices**: These devices offer improved capabilities compared to low-end devices. They have higher memory clock speeds, typically in the hundreds of megahertz (MHz), and larger memory capacities, measured in kilobytes (KB).

- **High-end IoT devices:** High-end IoT devices are typically single board computers (SBCs) with abundant resources. They have enough processing power and memory to host traditional operating systems like Linux or Windows and may also include a built-in graphics processing unit (GPU). These devices can handle more complex tasks and are suitable for applications that involve machine learning algorithms.

Table 4. Extended List of IoT Technologies

IoT Technology	Capability Level	Description	Application to Microgrids
Smart Meters	Medium	Advanced energy meter that provide detailed information on energy usage patterns and enable two-way communication	Enable real-time monitoring of energy consumption at individual buildings or loads within the microgrid. Support demand response and load management strategies for optimized energy distribution (Kathiresh, Mahaboob Subahani, and Kanagachidambaresan 2021).
Advanced Metering Infrastructure (AMI)	High	Smart meters equipped with communication capabilities to monitory energy consumption and facilitate bidirectional communication between consumers and the grid.	AMI systems with smart meters and communication infrastructure to enable automated, real-time meter reading, data collection, and monitoring of energy consumption across military installations. This facilitates accurate load profiling, and demand-side management based on granular energy usage data. AMI also enables remote configuration and control of meters, allowing for more efficient operations and improved energy management (Kathiresh, Mahaboob Subahani, and Kanagachidambaresan 2021).
Supervisory Control and Data Acquisition (SCADA) Systems	High	SCADA systems that allow remote monitoring and control of microgrid components	Provide centralized control and monitoring capabilities for microgrid operations. Enable efficient coordination of energy generation, storage, and distribution (Artale et al. 2019; Farhangi and Joos 2019)
Other Than SCADA	High	Human-Machine Interface (HMI), mobile applications, or web-based dashboards	Provides operators with remote access and real-time data visualization, control options, and status monitoring to facilitate grid management (Artale et al. 2019).
Weather sensors	Medium	Sensors that measure the various weather parameters such as temperature, humidity, wind speed, and solar radiation.	Provide real-time weather data for optimizing microgrid operation and predicting renewable energy generation. Facilitate weather forecasting for improved energy planning (Sehrawat and Gill 2019).

IoT Technology	Capability Level	Description	Application to Microgrids
Solar Irradiance Sensors	Medium	Sensors integrated into solar panels to measure solar irradiance levels, optimizing the performance and output of solar power generation.	Measures solar irradiance levels to optimize the positioning and operation of solar panels in microgrids, ensuring maximum solar power generation and efficient utilization of renewable energy resources (Sehrawat and Gill 2019).
Intelligent Energy Storage Systems	High	Advanced energy storage solution integrated with smart technologies to optimize energy management	Combines energy storage devices with sophisticated software and algorithms to intelligently monitor, store, and distributed electrical energy based on demand and grid connections
Smart / Automatic Switching	High	Smart or automatic switching refers to the capabilities of microgrids to autonomously switch between different operating modes based on predefined conditions or real-time monitoring. It involves the use of intelligent algorithms and control systems to manage the transition between grid-connected and islanded modes.	Smart switching enhances the reliability and performance of microgrids by enabling seamless and timely transitions between grid and islanded modes. It allows microgrids to respond to changes in the grid connection, such as power outages or voltage/frequency deviations, by disconnecting from or reconnecting to the main grid and operating in islanded mode using distributed energy resources. This technology improves grid stability, reduces downtime, and ensures continuous power supply in critical situations.

IoT Technology	Capability Level	Description	Application to Microgrids
Synchrophasor Sensor	Medium	Devices that measure electrical waveforms and provide real-time information on voltage, current, and frequency for grid monitoring and control.	Utilized in microgrids to monitor grid stability, detect anomalies, and enable real-time situational awareness. Synchrophasor sensors enhance the microgrid's ability to respond to changes in power quality, detect faults, and support islanding operations (Mukherjee et al. 2015).
Battery Management System (BMS)	High	Advanced control and monitoring system for batteries, integrating sensors, algorithms, and communications.	Monitors and optimizes the charging and discharging process, ensures cell balancing, tracks battery health, and protects against overcharging, over-discharging, and thermal issues. (Carpinelli, De Falco, and Mottola 2020; Varilone 2021; Miao et al. 2014).
Intelligent State-of-Charge (SoC) Management	High	Accurate estimation of battery state-of-charge (SoC) using advanced algorithms and data analytics	Improves the SoC estimation accuracy, maximizing energy storage system utilization and extending battery lifespan. Enables optimal charging and discharging decisions based on load profiles and grid controls (Miao et al. 2014).
Grid Frequency Sensor	Medium	Measures and monitors the frequency of the electrical grid.	Helps maintain grid stability by detecting frequency variations and enabling appropriate load shedding or power management within the microgrid (Sharma and Mishra 2020).
Grid Connection Sensors	Low	Includes sensors for detecting grid presence, synchronization, and islanding events.	Enables the monitoring and control grid connection status, supporting seamless transitions between grid-connected and islanded modes for microgrid operation (Artale et al. 2019).

IoT Technology	Capability Level	Description	Application to Microgrids
Power Quality Sensor	Medium	Measures and analyzes various parameters of power quality, including voltage stability, frequency accuracy, harmonics, and transients.	Helps ensure a high-quality and stable power supply within the microgrid systems, detecting and mitigating power disruptions, harmonics, and other irregularities that may impact performance and stability (Farhangi and Joos 2019).
Voltage Sensor	Low	Measures and monitors the electrical voltage level within circuits or specific components providing real-time data on voltage fluctuations.	Enables real-time monitoring and control of voltage levels in microgrid systems, ensuring optimal performance stability, and protection against voltage irregularities (Farhangi and Joos 2019).
Microgrid Optimization Algorithms	High	Advanced algorithms that optimize microgrid operation, considering factors such as load demand, energy storage levels, and renewable energy availability.	Optimizes microgrid operation by considering various factors such as demand forecasting, energy storage management, and renewable energy integration to maximize self-consumption of renewable energy, minimize peak demand, and optimize energy dispatch (Artale et al. 2019; Takriti et al. 2020).

IoT Technology	Capability Level	Description	Application to Microgrids
Fault Detection and Diagnostics (FDD) Systems	High	Artificial intelligence based systems that analyze data from sensors to detect faults, anomalies, and potential failures in microgrid components, improving maintenance and reducing downtime	Detects faults, anomalies and potential failures in microgrid components (e.g., inverters, batteries, generators) to enable proactive maintenance, reduce downtime, optimize component performance, and ensure reliable operation of the microgrid (Aqamohammadi et al. 2023).
Wireless Sensor Networks	Medium	Networks of wireless sensors deployed across the microgrid to select real time data in various parameters such as temperature, voltage and humidity.	Enables real-time monitoring and control of various microgrid parameters such as temperature, voltage, humidity and other environmental conditions, enhances situational awareness, supports condition-based maintenance, and enables effective management and control of microgrid operations (Hojabri et al. 2019).

NOTES:

	Modeled in our smart IoT model
	Not Modeled in our smart IoT model

2. IoT Technologies for the Model

As categorized by Table 4, the team carefully chose the recommended IoT technologies due to their unique capabilities that offer a transformative potential for conventional microgrids, effectively turning them into smart microgrids. These technologies provide a foundational framework that enables the integration of intelligent and automated features into the microgrid infrastructure. By incorporating these technologies, the microgrid gains advanced monitoring, control, and optimization capabilities, potentially resulting in improved operational efficiency, reliability, and

sustainability. The technologies selected for incorporation of the model are as follows (also depicted in Figure 6):

- **Smart Meters and AMI Systems**: These technologies provide detailed energy consumption data and bidirectional communication, enabling real-time monitoring, demand response, and optimized energy distribution in the microgrid.

- **SCADA Systems**: By offering centralized control and monitoring capabilities, SCADA systems facilitate efficient coordination of microgrid components, ensuring seamless energy generation, storage, and distribution.

- **Smart/Automatic Switching**: Smart/automatic switching enables microgrids to autonomously transition between grid-connected and islanded modes, enhancing resilience and ensuring continuous power supply during grid disturbances.

- **Voltage Sensors**: Real-time monitoring and control of voltage levels within the microgrid optimize performance stability, protect against irregularities, and safeguard critical equipment.

- **Wireless Sensor Networks**: Deploying interconnected wireless sensors enables real-time monitoring, situational awareness, condition-based maintenance, and effective management of microgrid operations.

- **Microgrid Optimization Algorithms**: These intelligent algorithms optimize energy dispatch, minimize peak demand, and maximize renewable energy self-consumption, improving efficiency and reducing environmental impact in microgrid systems.

3. Baseline Microgrid Versus Smart IoT Microgrid

The information provided in Table 5 examines the distinctions between a baseline microgrid and a smart IoT microgrid, emphasizing the transformative impact of integrating

IoT technologies. The chosen IoT technologies for our model are aimed at incorporating these advanced features, effectively converting a conventional microgrid into a smart IoT microgrid. Through our analysis, we evaluate the potential benefits and outcomes of implementing these technologies in the microgrid system. The model will explore the enhanced capabilities of real-time monitoring, optimization, automation, and overall improved performance that can be achieved with the integration of IoT technologies.

Table 5. Baseline Microgrid versus Smart IoT Microgrid

Baseline Microgrid		**Smart IoT Microgrid**	
Feature	**Description**	**Feature**	**Description**
Solar Panels	Standard solar panels without integrated IoT capabilities	Sensor-integrated Solar Panels	Solar panels with integrated sensors for real-time monitoring and positioning control
Manual Switching	Load management is done manually by operators	Automatic Switching	Load management is automated using IoT sensors and controls
Manual Maintenance Scheduling	Ad hoc maintenance scheduling without proactive planning and prediction	Predictive Maintenance	Data-driven maintenance scheduling and prediction for optimal system performance
Few Sensors	Reliance on limited number of sensors deployed within microgrid offering only limited visibility.	Sensor Networks	Sensors deployed throughout the system to gather real-time data on grid parameters. Enables advanced monitoring and other detailed insides into microgrid's performance
Limited Data Analytics	Limited data collection and analysis capabilities – only historical data	Advanced Data Analytics	Real-time data collection, analysis, and optimization to gain insights into microgrid performance, energy usage patterns, and system efficiency.
Traditional Demand Forecasting	Limited accuracy and predictability in forecasting power demand	Advanced Demand Forecasting	Utilization of machine learning and predictive modeling to forecast power demand with higher accuracy, aiding in load planning

Baseline Microgrid		**Smart IoT Microgrid**	
Feature	**Description**	**Feature**	**Description**
Limited Energy Storage	Absence or limited capacity for energy storage systems	Advanced Energy Storage	Integration of advanced energy storage technologies, such as battery systems, for efficient load balancing, peak shaving, and backup power.
Manual Checks	Manual methods of checking and testing grid components and systems	Remote Checks/Test	Operators remotely monitor, diagnose, and test grid components and system without the need for physical presence.
Traditional Fuel Management	Manual tracking and management of fuel inventory and consumption	Smart Fuel Management	Integration of fuel monitoring sensors and IoT-based fuel management systems for real-time tracking, optimization, and efficient fuel consumption
Manual Emergency Response	Manual coordination and response to emergency situations	Automated Emergency Response	Integration of real-time sensors, alarm systems, and automated emergency response protocols for rapid detection and mitigation of emergencies.

The analysis of IoT technologies highlights their transformative potential in the context of microgrids. In the next section, the focus will be on analyzing microgrid and user requirements as a crucial step before designing and implementing the model. This analysis will involve identifying the specific needs, goals, and constraints of the microgrid system and its users. Analysis will also provide valuable insights for designing an effective

and efficient smart IoT microgrid solution that meets the specific requirements and delivers the desired outcomes.

C. STEP 2: MICROGRID AND USER REQUIREMENTS

In the microgrid and user requirements step, we delve into the user requirements analysis, bridging stakeholder needs and the model design. This process transforms user needs into representative diagrams while adhering to system engineering principles. Through this methodical approach, we establish the basis for a systematic transition from IoT technology exploration, to requirements, and then to the design of the baseline model and smart IoT model.

The team first generated an operational context diagram shown in Figure 2 to convey the envisioned environment of a microgrid enabled with IoT technology based upon interpretation of stakeholder requirements. The diagram portrays the multiple layers of components involved with a facility attempting to meet its power requirements. The macrogrid serves as the primary source of energy under normal circumstances. The microgrid layer provides alternative power sources either to complement the macrogrid power or serve as a backup in the event of an outage. The integration of multiple IoT devices allows for the monitoring and switching of microgrid components. The utilization of IoT sensors also facilitates the detection of potential threats such as extreme weather conditions or an adversarial actor.

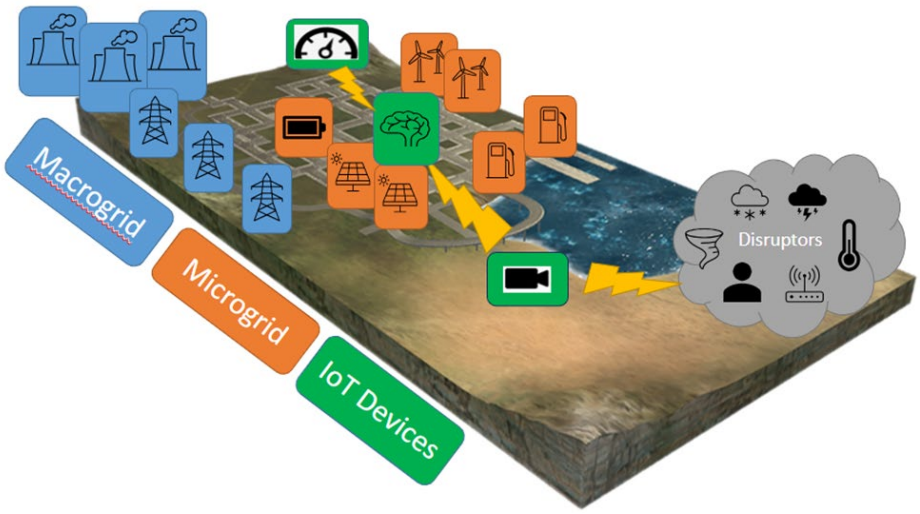

Figure 2. Operation Context Diagram

Following the derivation of stakeholder requirements and the operational environment, the team conducted a functional decomposition to identify different aspects of a notional microgrid system. Figure 2 shows the functional components within the conventional microgrid definition and their corresponding relationships.

Originally our microgrid was envisioned as a modular portion of a networked installation microgrid. This blended an operational area and hospital with previously existing microgrid enabled diesel generator(s) with a larger capacity renewable energy microgrid. The left side of the block definition diagram forms the microgrid generators, consisting of the PV panels, WT, and diesel generators. These are connected to the transmission systems (middle) which carry the power to the storage (bottom-middle) and demand centers (right). From the Transmission System and Mission Operational Microgrid, initial IoT systems were added in the form of a smart controller and smart meter.

Connections with black lines represent a containment relationship such as how an installation microgrid contains microgrid generators which consist of PV panels, diesel generators, and/or wind turbines. Yellow line connectors show the linkage between power sources, transmission systems, and concluding at the load demand functions. Finally, the blue line connections show the data connections available from the integration of smart, IoT technology.

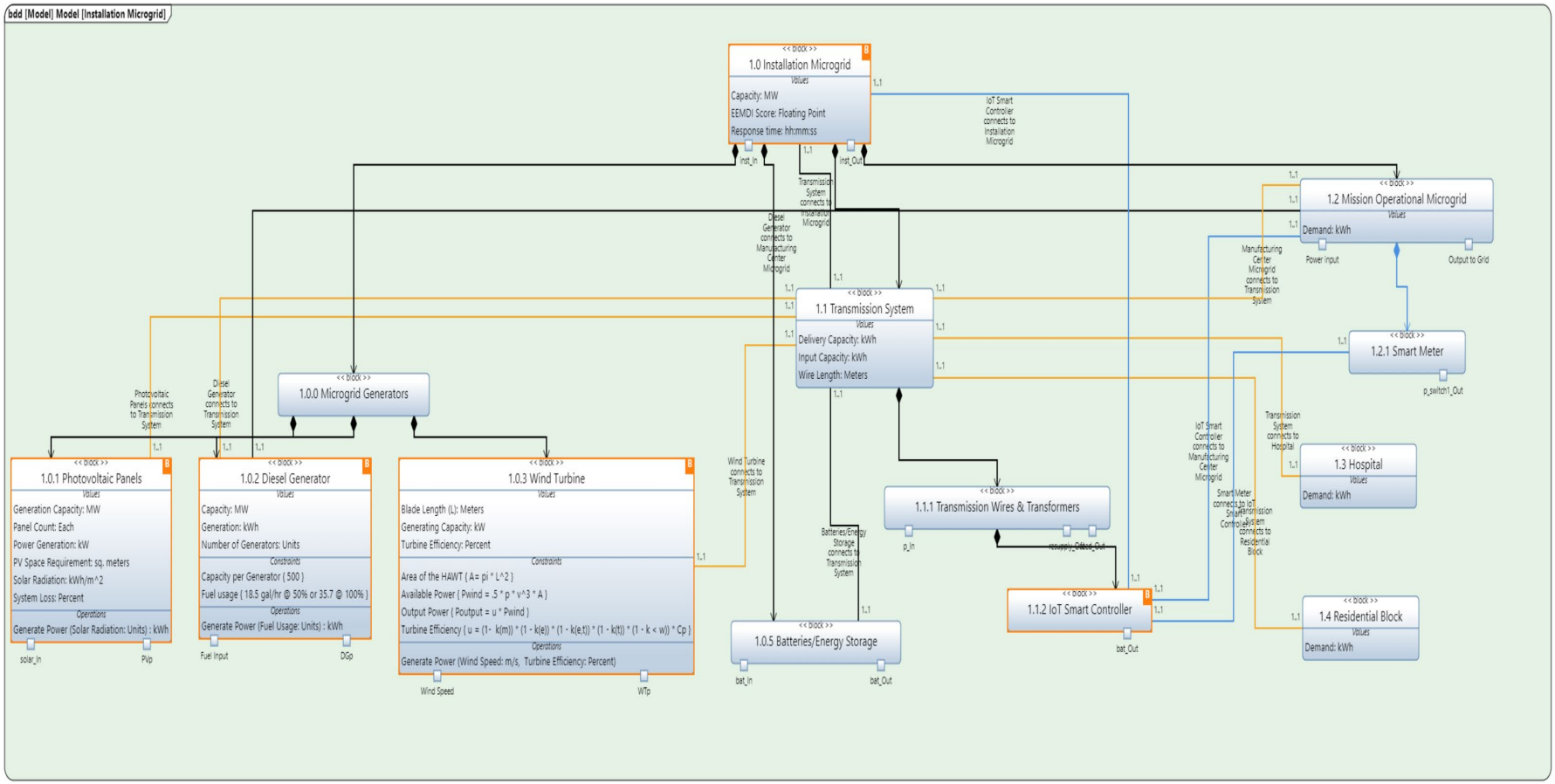

Figure 3. Smart IoT Microgrid Functional Decomposition

After identifying the different functional components of the model, the team began to identify specific quantities and power generation for the various distributed energy resources. Figure 4 defines these quantities and provides an alternative view to show the functional components and their electrical power linkages within the microgrid. This is the high-level view of the baseline microgrid modeled in ExtendSim reformatted for this report.

The microgrid consists of 330 PV panels, 4 wind turbines, 13 diesel generators, and 1 battery bank to provide power to the installation. Each item, including the 330 PV panels, is a unique entity in the model with a potential for failure. These microgrid power sources each connect through the switching station to reach the microgrid bus and supply power to the three loads: a hospital, a mission operation area, and a residential area. In this case, the switching of power sources would be done manually by human operators. This microgrid configuration represents the baseline model prior to any IoT smart technology incorporation.

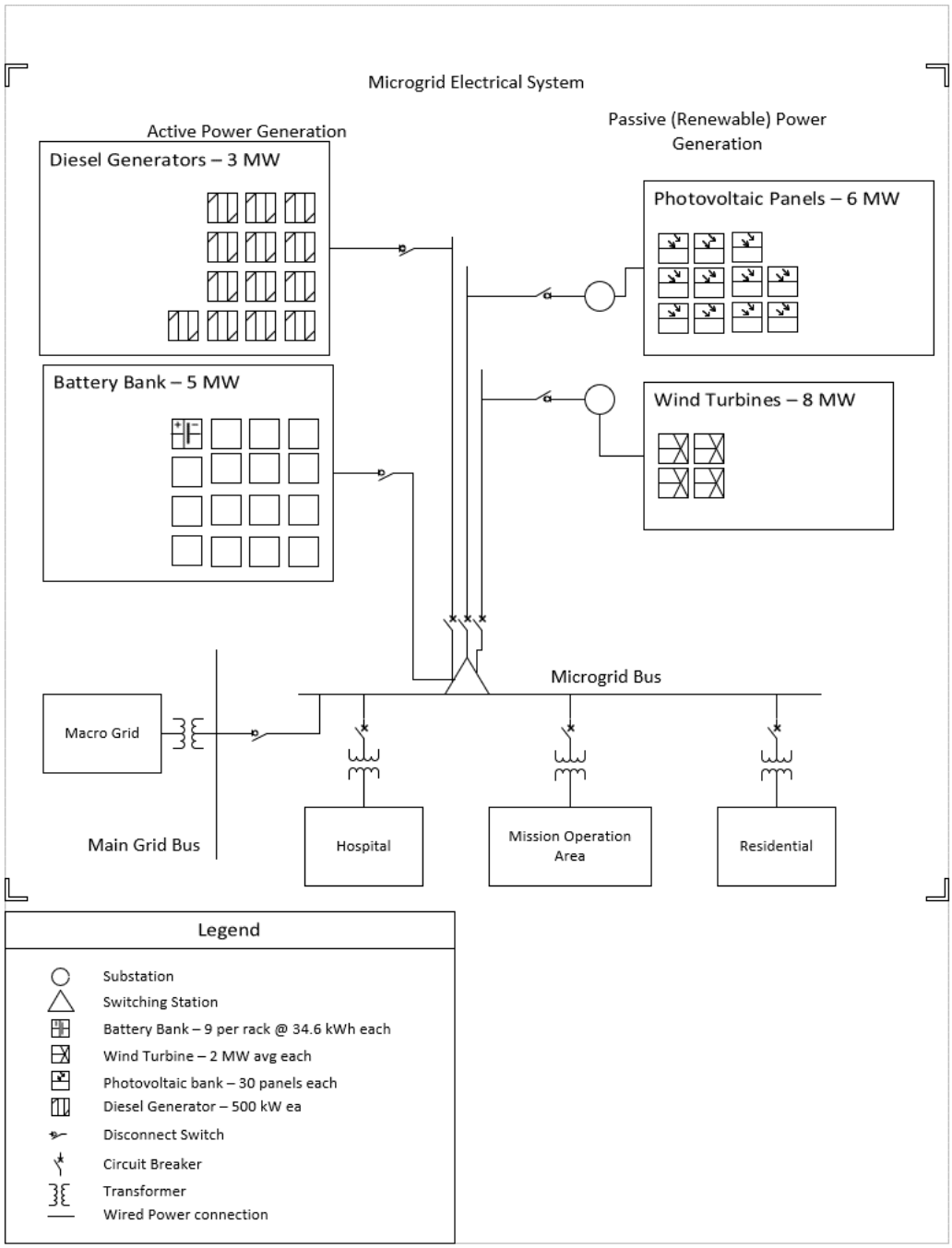

Figure 4. Baseline Microgrid Electrical System

To compare against the baseline model, an IoT layer is next added to incorporate a more efficient smart switching capability as shown in Figure 5. Wireless transmitters are located at each type of power source in order to provide smart meter data via AMI technology. The AMI in conjunction with the SCADA system allows for the smart

microgrid to quickly switch the various power sources on and off. The automatic switching also allows for power to be independently directed to each of the same three demand loads.

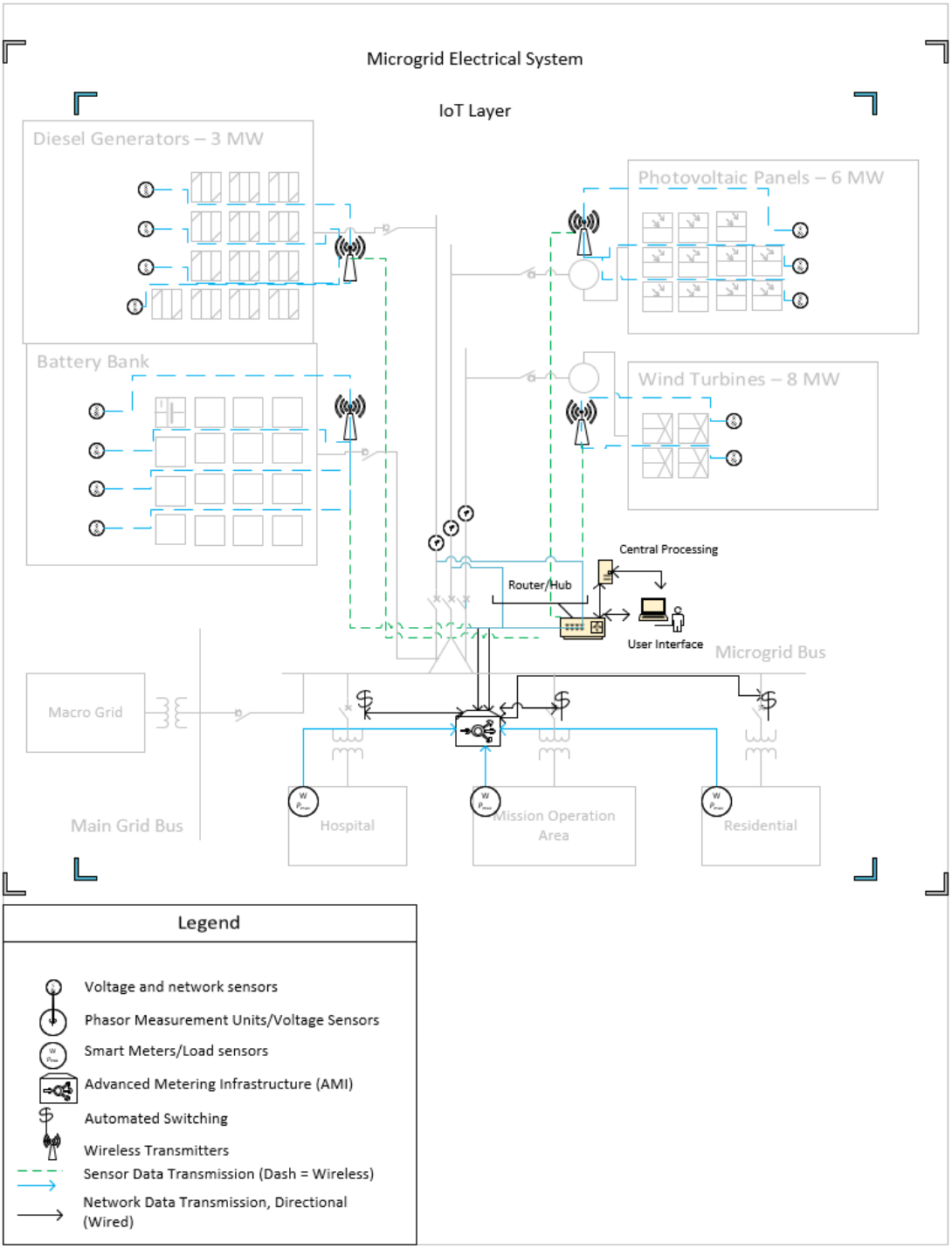

Figure 5. Microgrid IoT Layer

The two microgrid configurations represented in the previous figures are translated to the model to test reliability over the full course of a year. Through simulation of different failures, and the responsiveness of switching between the power sources and demands, the analysis will look to answer the question as to whether the addition of an IoT layer in the microgrid substantially improves the overall ability of the microgrid to consistently provide reliable power. A comparison of the SAIDI, SAIFI, and availability metrics will drive discussion and conclusions as to whether the benefits of IoT smart technologies are significant enough to incorporate along with its added risks and costs.

D. STEP 3: MODELING ANALYSIS

The modeling analysis step provides a comprehensive exploration of the microgrids' performance using the methodology previously laid out. Initially, an explanation of the model's components, inputs, and limitations are provided. It then delves into a detailed examination of the distinctions between the baseline model and the smart IoT model. Subsequently, the focal point shifts towards the pivotal aspect of the analysis: the tangible outcomes extracted from the model. Through a meticulous examination of these observations, the impact of IoT integration on the microgrid's dynamics is observed.

1. Model Description

Applying principles from model-based systems engineering and simulation modeling and analysis (Law 2015), we developed a discrete-event model using ExtendSim Pro modeling and simulation software version 10.0.9. The model requirements were derived from prior research and notional design parameters, aligning with objectives outlined in Executive Order on Catalyzing Clean Energy Industries and Jobs Through Federal Sustainability 08 December 2021. Our model grid is designed to comply with the 2030 requirements of, "100 percent carbon pollution-free electricity on a net annual basis by 2030, including 50 percent 24/7 carbon pollution-free electricity…"(The White House 2021) to simulate a small military installation microgrid with a daily average power requirement of 65,600 kilowatt-hours (kWh) (Giachetti et al. 2021) split between a hospital, an operational area, and a residential zone. The model uses the renewable systems as passive generators operating continuously. The battery serves to store excess generation

and discharge as part of the responsive power system when demand exceeds passive supply. Diesel generators serve as the last resort for meeting the load demand with responsive power.

Critical loads are defined as 60% of the total demand within the notional model. The goal of the model is to determine the likelihood at which the design meets the critical load requirements on an hourly basis (Mohammadi et al. 2014; DeVilbiss and Lee 2020) across a year of islanded operations. Transmission modes, interchanges and transformers can become a source of grid interruption and failure, however that is not modeled or analyzed in this paper.

The model uses a single seed, randomized between yearly runs, for the random distribution tables. Both the baseline and IoT model are compared against the same demand rate at the same time as they run concurrently through un-batching of a single signal which is then looped hourly through each modeled generation unit. This provides a direct comparison between models during each hour.

The model system consists of 330 PV panels with a 360-watt output. The panels are expected to provide most of the load and charge the battery to full during the day while sitting idle at night. Each panel is individually modeled for failure or output with a 24-hr re-validation loop. A failure rate probability of 0.2% per hour is utilized across all panels in operation for each hour. A MTTR of 4 hours under an exponential distribution is used before the panels are brought back to operation.

The model utilizes four wind turbines each with a 52-meter blade sweep (Department of Energy 2023) and a real efficiency coefficient of 28.8%. The failure rate probability for each turbine used is 10.7% per hour with an MTTR of 4 hours using an exponential distribution (Dao, Kazemtabrizi, and Crabtree 2019). Each turbine is modeled individually for failure rate tracking.

To increase grid reliability in response to stress events, 3.5 MW of diesel generators are modeled with a 500 kilowatt (kW) capacity running at either 50% load (250-kW) or 100% load for a total of 13 generators, each individually modeled. The generators have a MTBF of 636 hours per year which reduces to an hourly probability of 7.26% (Marqusee,

Ericson, and Jenket 2020). This allows for increased microgrid reliability but lowers compliance to the executive order when employed. The model can be run with fuel consumption as an aspect of diesel generator usage. This using a normal distribution the mean of fuel consumption is 18 gallons per hour at 250 kW or 36 gallons per hour at 500 kW ("Diesel Generator Fuel Consumption Chart" 2023).

The model uses a single battery bank modeled off a series of Samsung 136S Lithium Manganese Oxide / Nickel Manganese Cobalt Oxide mix (LMO / NMC). These batteries have a capacity of 67 ampere-hours with an energy rating of 34.6 kWh at a maximum discharge rate 184 kW. The model also assumes that the batteries will be kept at nominal operating temperatures (64°F to 82°F or 18°C to 28°C). Optimal sizing of the storage capacity varies across several factors which are not explored in this model (Mozafari and Mohammadi 2014). A failure rate probability of 1% per hour is used based on assumed system failures that would prevent discharge to the grid. The MTTR for the battery bank also uses an assumed 48-hour replacement mean. Within the model, the battery capacity can be run to zero. However, for optimal longevity li-ion battery cycles should be kept above 15% (Miao et al. 2014)

The verification data feed uses historical weather patterns for one calendar year at an oceanside location around 40 degrees north latitude approximately at Naples, Italy (National Renewable Energy Laboratory 2023a). This sets the parameters for the solar irradiance and wind speeds by which the renewable energy generation portion of the model is verified. Parameters are modified hourly across the year for a total of 8760 inputs.

a. Model Logic

The model generates two tracks of data, one for an IoT enabled microgrid and another for a baseline grid, based off of predictive demand. The two tracks of data are created from the same initialization, thus the differences between the two microgrids can not be attributed to different randomized seed inputs from the simulation. The smart IoT microgrid is first defined by instantaneous feedback of power demand and generation capacity allowing for more real-time leveling of responsive power. The cumulative demand of the three loads, Hospital – *H*, Operation Area – *Op*, and Residential Area – *Res* are

determined randomly by a random normal distribution seen in Table 5 which are summed to create an instantaneous power requirement (IPR) at hour (*h*).

4.1) $$H + Op + Res = IPR_h$$

The instantaneous power requirement is first compared against renewable power generation or total instantaneous power (TIP). TIP_h is the sum of PV and wind turbine assets at a specific hour (*h*). A base rate per hour (PVR_h or WTR_h) is multiplied against each panel or turbine which goes through an MTBF pass/fail check (*PVp* or *WTp*), where *PVp* or *WTp* is 0 when unit *p* fails a reliability check, and 1 otherwise, before being sum totaled to get total instantaneous power (*TIP*).

4.2) $$TIP_h = (\sum_{p=0}^{330} PV_p \times PVR_h) + (\sum_{p=0}^{4} WT_p \times WTR_h)$$

TIP is used across the model in both data tracks for all passive generation calculations. For the smart IoT microgrid, *TIP* is then used to determine if the stored battery power (BAT_p) needs to be discharged (BAT_{dc}) otherwise the battery will charge (BAT_c). The stored battery power (BAT_p) is considered a recharging reservoir that varies from 0 to 4750.

4.3) $$\text{If: } IPR_h \geq TIP_h \text{ and } BAT_p > 0$$
$$\text{Then: } BAT_{dc} = (IPR - TIP) \times 0.95$$

When demand is greater or equal than renewable energy and the battery power available is greater than zero then the battery discharge rate is 95% of the difference between demand and renewables. The 95% represents a 5% loss for power received to power stored.

4.4) $$\text{If: } IPR_h \geq TIP_h \text{ and } BAT_p = 0$$
$$\text{Then: } BAT_{dc} = 0$$

When demand is greater or equal than renewable energy and the battery power available is zero then the battery discharge rate is also zero.

4.5) $$\text{If: } IPR_h \leq TIP_h \text{ and } BAT_p \leq 5000$$
$$\text{Then: } BAT_c = (TIP - IPR) \times 0.95$$

When demand is less or equal than renewable energy and the battery power available is less than or equal to 5000 kWh then the battery charge rate is 95% of the difference of renewable power less the demand.

When *TIP* and BAT_{dc} are not sufficient to meet the *IPR* then the diesel generators' (*DG*) are signaled to start generating. Instantaneous diesel generations at each hour (*h*) (IDG_h) are based on equation 4.6. The total diesel generators that pass the MTBF check (DG_p) are multiplied by the diesel generation rate at a given hour (DGR_h)

4.6) $$IDG_h = DG_p \times DGR_h$$

Each *DG* is demand gated, which allows the demand signal to be sent when:

4.7) $$(TIP_h + BAT_{dc}) \geq IPR_h \text{ and } IDG_h \geq IPR_h$$

From there each *DG* has a MTBF failure check before it generates an output signal (DG_p). That signal is again checked to determine:

4.8) $$\text{If: } TIP_h + BAT_{dc} + IDG_h \geq IPR_h$$

When true, this releases DG_p to populate *IDG*. This approach is employed to minimize the occurrence of excess power generation from diesel generators within the model. This is used to mimic the effects of the data exchange from cumulative sensors and AMI's to a SCADA system allowing for rapid demand reporting, feedback, and scaling through automated switching.

The baseline system in contrast, uses a mean demand by hour table to define the predicted demand at a given hour ($pIPR_h$) in Table 5. This results in a battery discharge and generator capacity activating on expected demand before responding to actual. The battery logic alters equation 1.3 where predicted demand $pIPR_h$ must be greater than renewable energy generated and the baseline model battery storage level (pBATp) is greater than zero:

4.9) $$\text{If: } pIPR > TIP_h \text{ and } pBAT_p > 0$$

$$\text{Then: } pBAT_{dc} = (pIPR - TIP_h) * 0.95$$

This results in releasing power from the battery in anticipation of the load, which would be expected to meet the load but may also exceed more often than needed.

Similarly, the generator logic modifies 1.6 and 1.8 to read, respectively:

4.10) $$TIP_h + pBATdc > pIPR \text{ and } pIDG_h > pIPR_h$$

4.11) $$TIP_h + pBAT_{dc} + pIDG_h \geq IPR_h$$

This final equation gate logic allows the microgrid to respond to demand that exceeds the predicted load but critically does not stop it from over-generating based on predicted demand.

Table 6 shows the model load inputs for the simulation. The predictive load is from prior research which distributed the loads into hourly means (Giachetti et al. 2021).

Table 6. Model Load Determination Tables – Repeating Every 24-hours

Time	Predictive Load Demand (kWh)	Hospital Mean (kWh)	Hospital Std Dev	Ops Mean (kWh)	Ops Std Dev	Residential Mean (kWh)	Residential Std Dev
0	2000	895	110	1000	740	25	5
1	2400	895	110	1000	740	25	5
2	2600	895	110	1000	740	25	5
3	2800	895	110	1000	740	25	5
4	3000	895	110	1200	740	25	5
5	3400	895	110	1400	740	25	5
6	3800	895	110	1600	740	28	5
7	4000	895	110	2000	740	32	5
8	4000	1340	180	2200	740	36	5
9	4000	1340	180	2400	740	38	5
10	3600	1340	180	2600	740	38	5
11	3000	1340	180	2600	740	38	5
12	2800	1340	180	2600	740	38	5
13	2800	1340	180	2400	740	38	5
14	2800	1340	180	2200	740	38	5
15	2600	1340	180	2000	740	38	5
16	2000	1340	180	2000	740	38	5
17	2000	1340	180	2000	740	38	5
18	2000	1340	180	2000	740	45	5
19	2000	1340	180	1800	740	42	5

Time	Predictive Load Demand (kWh)	Hospital Mean (kWh)	Hospital Std Dev	Ops Mean (kWh)	Ops Std Dev	Residential Mean (kWh)	Residential Std Dev
20	2000	895	110	1000	740	42	5
21	2000	895	110	1000	740	38	5
22	2000	895	110	1000	740	32	5
23	2000	895	110	1000	740	25	5

The individual loads were adapted from several sources and are generally representative for the center across their distribution ("U.S. Energy Information Administration – EIA – Independent Statistics and Analysis" n.d.; Naval Medical Center Camp Lejeune (NMCCL) 2020; Morgenstern et al. 2016). The data used for model verification averaged 5.41 solar radiation (kwh/ m2 / month) across the year as seen in Figure 6. Figure 7 shows the monthly average wind speed modeled at m/sec (National Renewable Energy Laboratory 2023a).

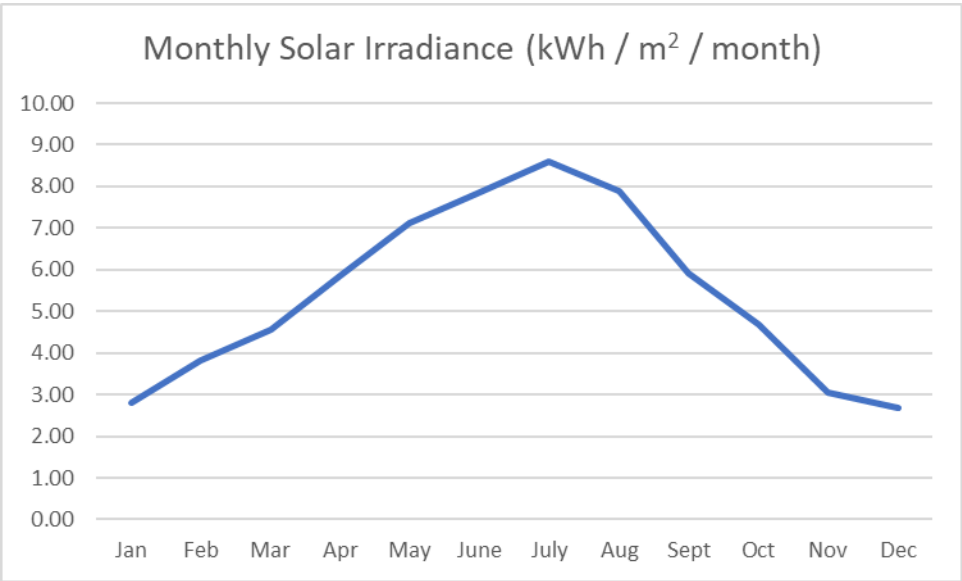

Figure 6. Solar Radiance by Month

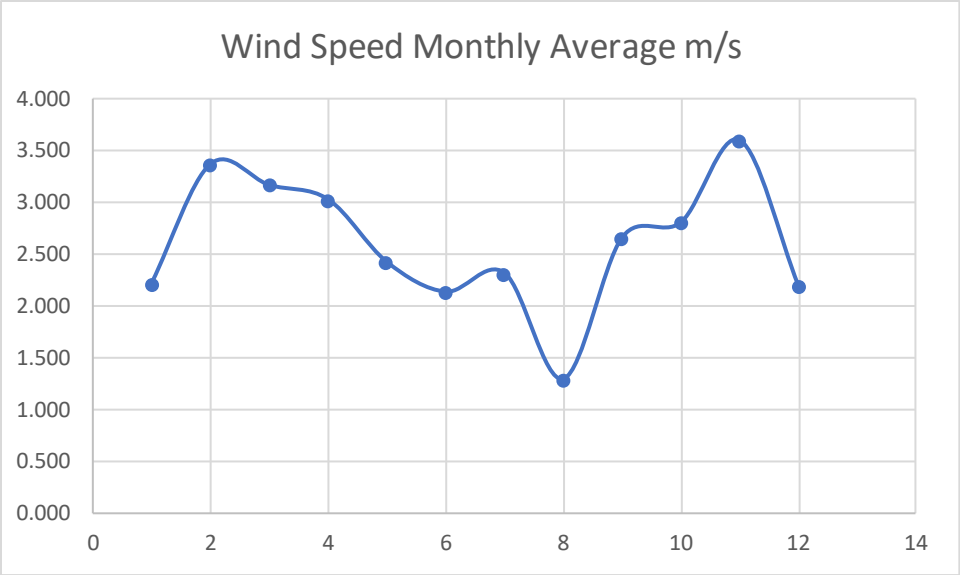

Figure 7. Wind Speed Average Per Month

b. Limitations of the Model

It is essential to acknowledge the presence of certain limitations in our analysis, which are crucial to address for a comprehensive understanding of the model's applicability and implications. These limitations highlight potential areas where further refinements and enhancements can contribute to more accurate and insightful results in the field of microgrid systems engineering.

- Simplified Notional Model: The microgrid model used in our analysis, while carefully constructed, may not fully represent the complexity and variations present in real-world microgrid implementations. Real-world microgrids often encompass diverse configurations, power generation sources, and operational constraints, which were somewhat simplified in our model to facilitate analysis.

- Temporal Resolution: The hourly simulation intervals used in our model may limit the capture of time-sensitive events that occur within shorter time frames. Certain transient phenomena, such as generators ramping up or down, may appear instantaneous in our model when, in reality, they

may take minutes or even longer. This could impact the accuracy of the model's predictions in scenarios that require higher temporal resolution.

- Lack of Power Transmission Considerations: Our model does not explicitly account for power transmission considerations, such as line-loss and substation availability. This omission overlooks aspects that impact overall energy efficiency in real-world microgrids. The lack of power transmission calculations assumes all power generated reaches its intended loads without further loss, which may not accurately reflect practical constraints in actual microgrid deployments.

c. Microgrid IoT Capabilities Modeled

The following section and Table 7 delve into a detailed comparison between the baseline microgrid model and the smart IoT microgrid model within the ExtendSim framework. For a deeper understanding of the inner workings and mechanisms of the model, additional explanations can be found in Appendix A of the ExtendSim model. This comprehensive exploration will shed light on the transformative potential of IoT technologies in microgrid operations.

Table 7. Baseline and Smart IoT Microgrid Model Differences.

IoT Compatible Technology	Baseline Model	Smart IoT Model
Smart Meters and AMI Systems	Not Modeled. In the notional baseline microgrid, metering is communicated one way and necessitates human response if any action is required.	Smart meters and AMI systems is modeled through the use of decision blocks comparing load requirements versus available power. Decision blocks output either a 1 or 0 depending on if the condition is true or not, respectively. PV Panel Logic, WT Logic, and DG Logic each have a series of gates allow/prevent each source of power to flow through the model after each gate requirement is satisfied. Each gate is opened based on the condition that its critical load is met. This forces critical load 1 to be met prior to critical loads 2 and 3. Additionally, the number of available power sources is re-evaluated every 24 hours to account for the potential for hardware failure.
SCADA Systems	The less-automated version, reflective of a notional baseline	Implicit in Smart Meters/AMI Systems/Smart Switching.

IoT Compatible Technology	Baseline Model	Smart IoT Model
	microgrid, uses decision blocks that link to activity blocks to super impose a delay representing human interaction. Activity blocks are added to each DG location for a duration of approximately 1 minute to simulate operator initiation of the generator using a remote SCADA system.	
Smart/Automatic Switching	Not modeled. Switching occurs due to information from SCADA systems and human response to data. Activity blocks are added to each DG location for a duration of approximately 1 minute to simulate operator initiation of the generator using a remote SCADA system.	Smart/automatic switching is modeled using decision blocks and conditional equations that compare load requirements to available power. Decision blocks output 1 or 0 depending on whether the condition is true or not. The model continuously compares renewable power available to required power. If renewable power is higher, it charges the battery until full or the condition changes. If required power is higher, it draws from the battery until empty or the condition changes. If required power surpasses both instant renewable power and battery charge, the model activates DG power to meet load needs.
Voltage Sensors	Not modeled. Information flows one way and requires human intervention if changes are necessary.	Implicit in Smart Meters/AMI Systems/Smart Switching. Representative of sensors deployed throughout the system to gather real-time data on grid parameters.
Wireless Sensor Networks	Real-time data exchange is absent. Failure condition is captured within the MTBF of each individual power source.	Implicit in assumption of communication network Sensors communicate wirelessly, forming a network that continuously exchanges information about voltage levels, power generation, and distribution. This data is then used to make informed decisions for optimizing power distribution, enhancing efficiency, and ensuring a reliable power supply. Failure condition is captured within the MTBF of each individual power source.
Microgrid Optimization Algorithms	This section of the model uses predictive loads based on historical analysis and therefore does not allow for optimization.	Modeled through use of decision blocks and conditional equations to redirect power in the event of power available greater than power required.

Bottom line, the smart IoT model is optimized to simulate the impact of the chosen IoT technologies and the impacts or relevance they may have over the baseline microgrid. Simply, these are:

- Human Interaction: The baseline model relies on manual decision-making with activity blocks imposing delays to reflect human operators' response times. The smart IoT model utilizes decision blocks for real-time processing, simulating the instantaneous response and smart switching of a smart IoT microgrid.

- Instantaneous Power: The baseline model uses fixed predictions, lacking the capability to adjust power generation in real-time. Conversely, the smart IoT model adjusts power generation dynamically based on real-time data and conditions.

- Power Utilization: The baseline model has fixed priority settings and requires manual adjustments, while the smart IoT model employs conditional equations for real-time, dynamic assessment and decision-making, allowing instant switches between power sources.

- Voltage Sensors and Wireless Sensor Networks: The baseline model does not incorporate these features, leading to a lack of real-time monitoring and data exchange. In contrast, the smart IoT model implicitly assumes the presence of voltage sensors and wireless sensor networks, enabling real-time monitoring and data exchange between microgrid components.

2. Model Simulation Results

This section provides a detailed analysis of the model data results, focusing on the metrics specified in the Measure of Effectiveness (MOE) and Measure of Performance (MOP) sections.

a. Observation 1: Primary Model Availability

Using the SAIDI, SAIFI, Availability, and CAIDI standards our model shows in Table 8 that the IoT enabled baseline model is significantly ($p = 0.032$) more capable of meeting the overall demand requirements than the baseline grid. When comparing the alternative scenarios mentioned in the methodology, in the models where the wind speed

averaged 3.5 m/s, the results are significantly worse ($p < 0.0022$) against both the IoT and baseline models, except for the 3.5WS_500DG where there was no difference. For that scenario, while the overall CAIDI metric is better, the lower SAIFI, availability, and SAIDI metrics indicate a less reliable microgrid. The 7 m/s wind speed variations are all significantly more effective ($p < 0.001$) at meeting demand when compared to either baseline scenario or the other scenarios. This is quickly evidenced by the availability metric, which is almost double the other scenarios.

Table 8. MOE's measured against full demand requirement (IPR) for each scenario

Model Scenario	SAIDI (min/year)	SAIFI (outages/year)	Availability	CAIDI (min/year)
IoT Microgrid	289,134	402	44.99%	719
Baseline Microgrid	295,260	470	43.82%	628
3.5WS_500DG IoT	299,160	553	43.08%	541
3.5WS_500DG Baseline	296,160	640	43.65%	463
3.5WS_250DG IoT	290,400	650	44.75%	447
3.5WS_250DG Baseline	296,700	692	43.55%	429
7WS_500DG IoT	90,300	896	82.82%	101
7WS_500DG Baseline	98,220	956	81.31%	103
7WS_250DG IoT	91,140	1007	82.66%	91
7WS_250DG Baseline	99,120	986	81.14%	101
2xBat_500DG IoT	260,280	453	50.48%	575
2xBat_500DG Baseline	239,160	498	54.50%	480

b. Observation 2: Optimal Energy Output

Across scenarios, variations in the 250-kWh diesel generator output enhance availability. Of note, across all scenarios the 250-kWh diesel generator output variations result in slightly higher availability by meeting the demand loads more frequently without excess over-generation resulting in better fuel efficiency and a longer operational window that they can support. In the 7 m/s_250DG scenario the original 100,000 gallons of fuel is never fully depleted under the IoT enabled grid.

Table 9 shows the cumulative power generation of the smart IoT microgrid reached 543,141 MW. Notably, most of the power generation occurred during the summer months from June to August, with an average monthly power generation of 5,070,217 kW. This increase in power generation during the summer months can be attributed to the higher output of PV systems, taking advantage of the abundant sunlight. The contribution was particularly significant, with average power output per months totals of 3,316,980 kW, 3,697,702 kW, and 3,352,141 kW during June, July, and August, respectively, as seen in

Figure 8 and Figure 9. These findings align with previous research indicating the seasonal variations in renewable energy generation.

Table 9. Total Power Generation Data

	Smart IoT Microgrid	Baseline Microgrid
Total Power Gen (10 yr)	543,141MWh	699,489MWh
%Total Power Excess	-	29%
Avg DGs in Use	6.20	9.39
Bat Discharge	1317.42	1336.560

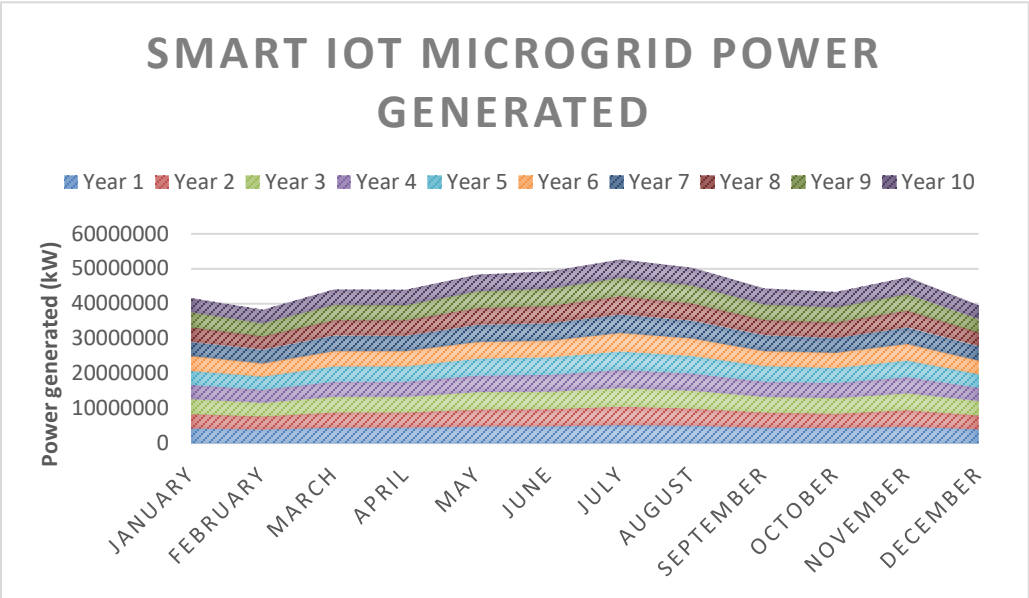

Figure 8. Smart IoT Model Power Generated Sand Chart

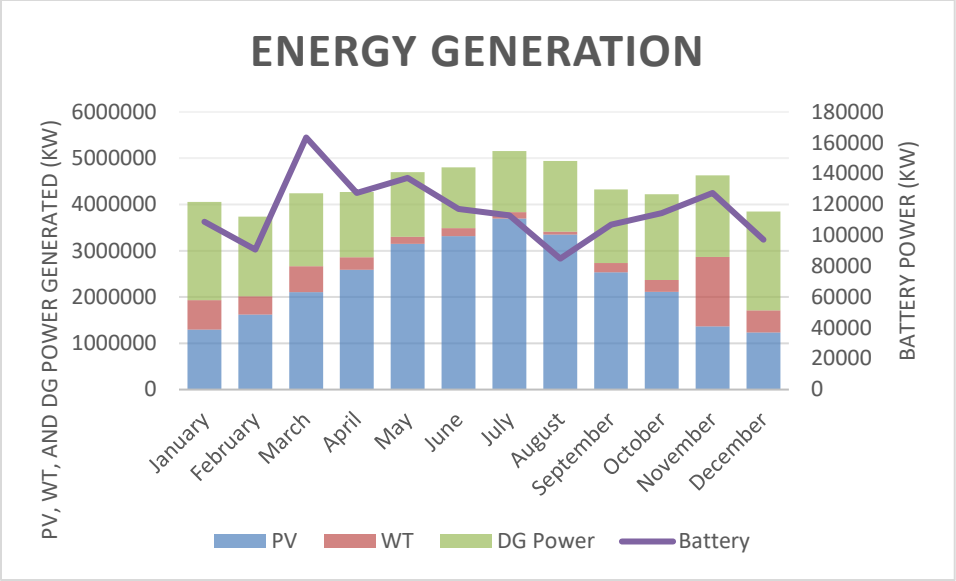

Figure 9. Smart IoT Model Energy Generation Bar Chart

The baseline microgrid showcases a 29% excess power generation attributed to greater diesel generator reliance. The baseline microgrid exhibited a cumulative power generation of 699,489 MW, representing a 29% growth in excess power generation compared to the critical load requirement. This surplus generation can be attributed to the utilization of an average of 9 diesel generators, as opposed to the smart IoT microgrid's average of 6 diesel generators. The reduced reliance on diesel generators in the smart IoT microgrid signifies the effective integration of renewable energy sources and the optimization of power generation.

While the observed difference might not carry statistical significance, it is worth noting the smart IoT microgrid demonstrated a slightly lower battery discharge rate of 1,317 kW per hour compared to the baseline microgrid's rate of 1,336 kW per hour. This juxtaposition hints at the potential of the smart IoT microgrid to enhance storage utilization efficiency, leading to enhanced battery performance and longevity.

Figure 10 illustrating 52 weeks of power generation from the model, with wind turbine, photovoltaic, and diesel generator power overlaid with the critical load requirement, provides valuable insights into the performance of the smart IoT microgrid. It demonstrates the variability of renewable energy sources such as wind and solar power

throughout the year, showing peak generation during certain periods, particularly in the summer months. By comparing the power generated by renewable sources to the critical load requirement, it becomes evident how the system adjusts and utilizes diesel generators to meet any shortfall in power supply. This analysis highlights the effectiveness of the smart IoT microgrid in optimizing the utilization of renewable energy sources while ensuring reliable power supply to meet critical load demands.

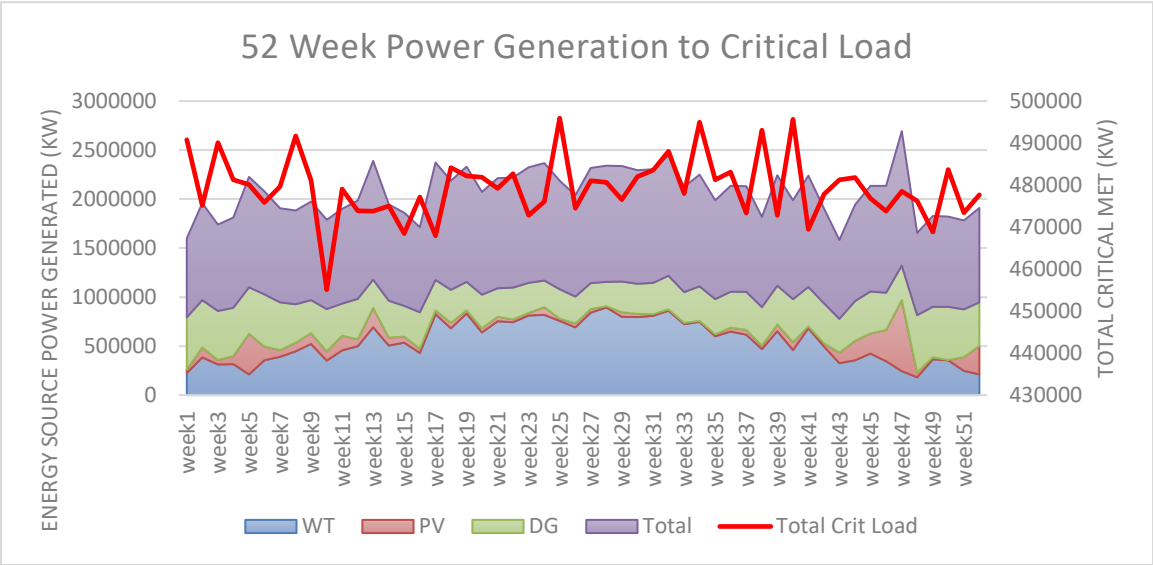

Figure 10. Smart IoT Model 52 Week Power Averages

c. *Observation 3: Dynamic Power Source Adaptation*

The smart IoT microgrid's adept adaptation to increased critical loads during high renewable energy generation is evident. In terms of the utilization of diesel generators, the smart IoT microgrid showed a better compensation for the increased critical loads during periods of higher power generation from renewable energy sources. During the summer months, the diesel generators contributed only an average of 1,427,000 kW of power per month, while renewable energy sources accounted for the majority of the power generation. Conversely, during the winter months, the diesel generators played a more significant role, providing over 50% of the power. This observation, highlighted in Figure 11, shows the

dynamic nature of the smart IoT microgrid in adapting power generation sources based on renewable energy availability and critical load demands.

The analysis of charts depicting the power generation levels in kW over each month, adjusted to the critical load, reveals the smart IoT model's ability to meet critical demands while optimizing the use of diesel generators. As the renewable power generation increases, the reliance on diesel generators diminishes, allowing for instantaneous power utilization from PV panels or wind turbines.

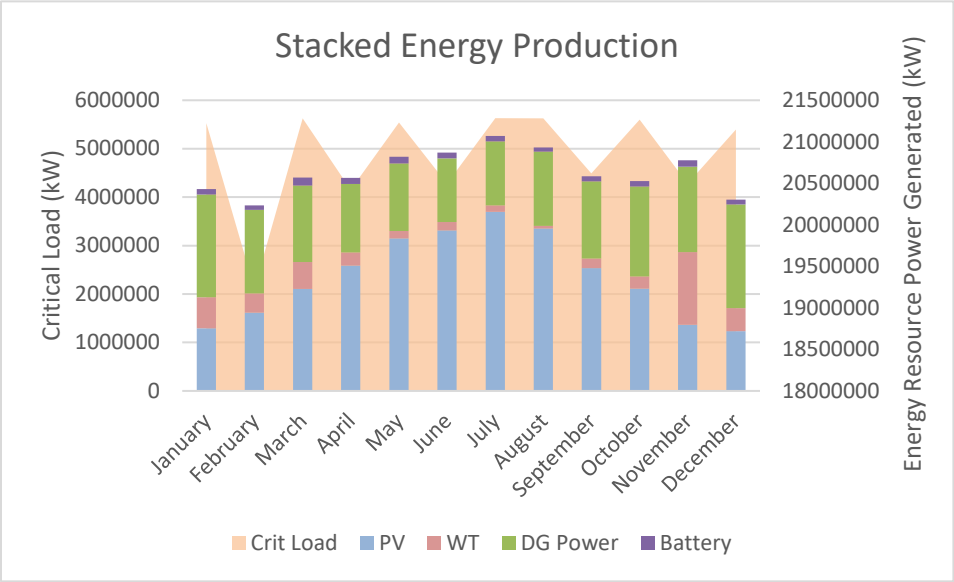

Figure 11. Smart IoT Model Critical Load Performance

d. Observation 4: Critical Loads Met

During the process of data aggregation, it was observed that certain critical load values occasionally surpassed expected ranges, including instances where the critical load exceeded the total demand. However, these occurrences were identified as outliers in the model output data. Upon analysis, it was determined that the cumulative critical load values accounted for 59.96% of the full demand over the course of the 10-year period, confirming the alignment of the model with its intended purpose.

The table presents the average timing throughout a 24-hour period, considering a 10-year test duration, indicating the anticipated instances when both the baseline model and the smart IoT model are projected to meet the power requirements. This is expressed as the probability of meeting (p-met). The left side of the table represents the achievement of fulfilling full demand (IPR), while the right side represents the attainment of meeting the critical load. Across the span of a 10-year test, the smart IoT model is anticipated to offer power to critical loads and IPR more frequently compared to the baseline model (Table 10, Figure 12, and 13). Notably, the baseline model is projected to supply the load demand more frequently only during a three-hour interval starting at hour 18.

Table 10. Probability to meet IPR and Critical Load

Model	Baseline	IoT
Hour	*% to Meet*	*% to Meet*
0	5.21%	7.40%
1	6.58%	7.95%
2	5.21%	7.67%
3	4.38%	6.85%
4	5.21%	8.22%
5	4.66%	6.85%
6	10.14%	15.34%
7	40.27%	46.85%
8	67.95%	72.33%
9	87.40%	90.68%
10	90.14%	95.07%
11	94.79%	99.73%
12	96.44%	99.73%
13	96.16%	99.45%
14	96.71%	99.73%
15	95.34%	96.99%
16	92.88%	93.42%
17	83.84%	84.66%
18	68.77%	66.58%
19	49.59%	46.03%
20	20.00%	17.26%

Model	Baseline	IoT
Hour	*% to Meet*	*% to Meet*
0	7.95%	12.05%
1	8.77%	12.05%
2	8.49%	12.33%
3	7.95%	12.05%
4	8.49%	13.42%
5	7.95%	12.05%
6	13.42%	20.55%
7	43.56%	52.05%
8	71.23%	77.26%
9	88.77%	92.33%
10	90.68%	96.16%
11	95.62%	99.73%
12	96.99%	99.73%
13	96.71%	99.73%
14	97.26%	99.73%
15	96.16%	97.81%
16	93.70%	94.25%
17	85.75%	86.85%
18	71.78%	71.78%
19	52.88%	51.23%
20	23.56%	21.37%

Model	Baseline	IoT
Hour	*% to Meet*	*% to Meet*
21	9.59%	14.25%
22	10.14%	12.33%
23	6.85%	9.32%

Model	Baseline	IoT
Hour	*% to Meet*	*% to Meet*
21	12.60%	18.63%
22	13.15%	16.99%
23	9.86%	13.97%

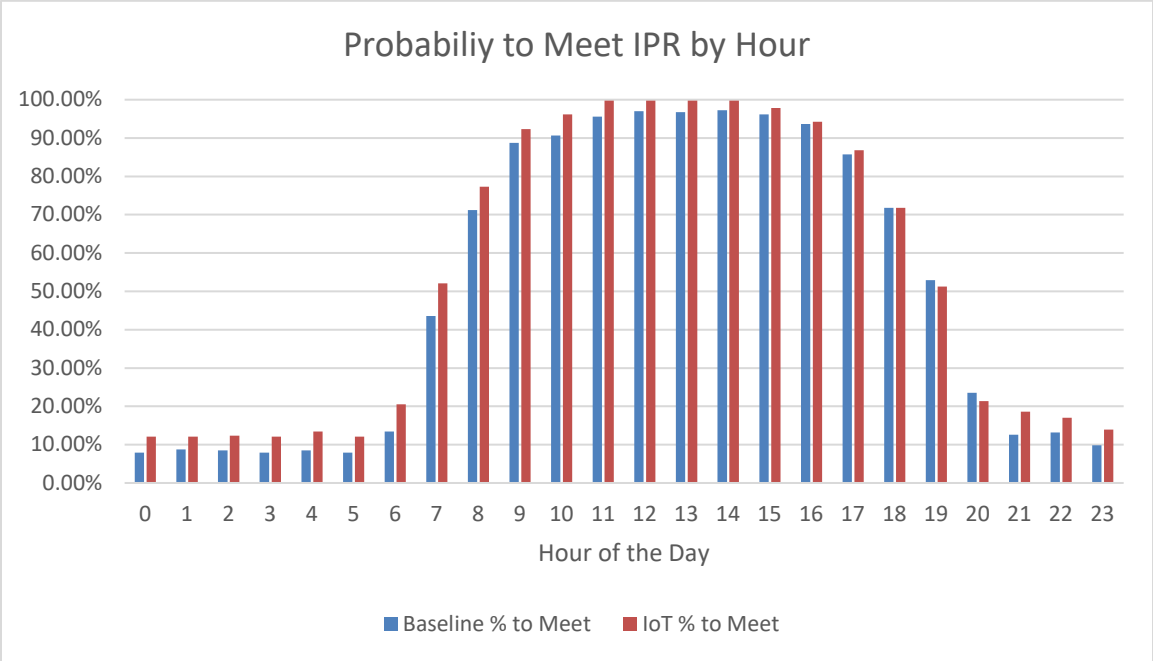

Figure 12. Probability to Meet IPR by Hour.

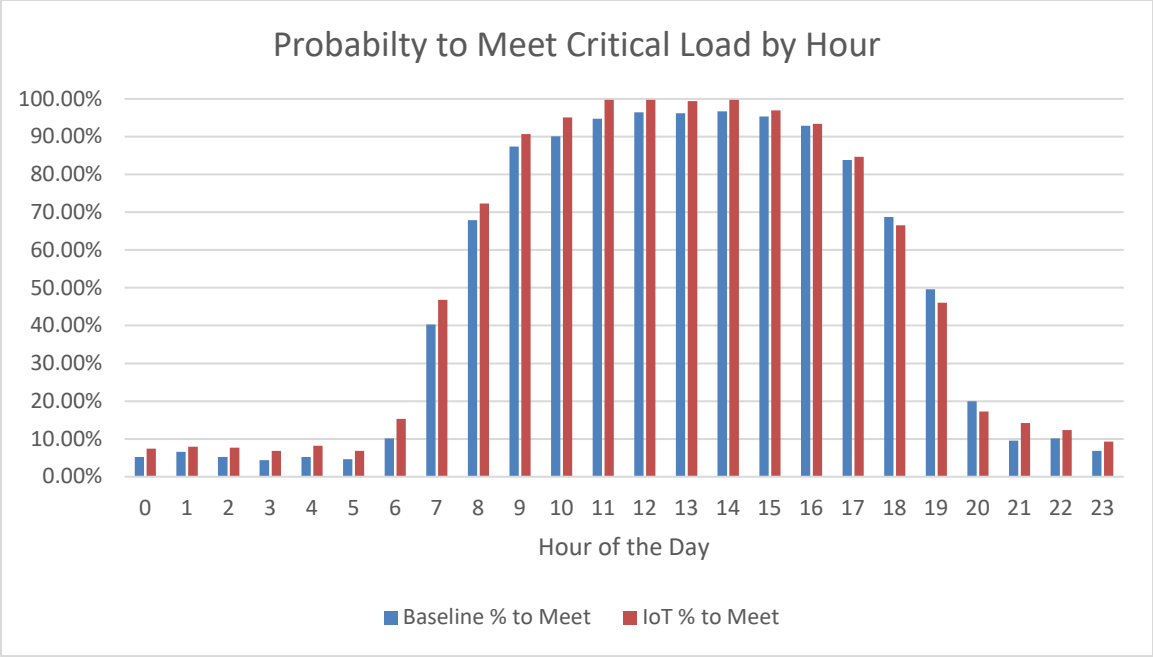

Figure 13. Probability to Meet Critical Load by Hour.

e. Observation 5: Fuel Efficiency and Operational Hours

The operational efficiency of the smart IoT model is evident through reduced generator operational hours and optimized fuel consumption. One contributing factor is the smart IoT model's effective fuel conservation strategy. By catering to actual demand rather than predicted requirements, the smart IoT model maintains an average generator operational duration of 459.6 hours across the 13 generators, with a standard deviation of 18.39 hours. In the base simulation, the smart IoT model's operational hours spanned from 433 to 487 before fuel depletion. Table 11 highlights this data. In contrast, the baseline model's average operational hours were 296.5, with a standard deviation of 8.87 hours, ranging from 287 to 311 hours before running out of fuel.

Across the 10-year model the IoT portion signals for a total of 321,772 hours of generator time while the baseline model signals for 790,569 hours across the same time series. When normalized for fuel consumption, the smart IoT model averages 2,847 generator hours with a standard deviation of 13.26 hours and a range of 2,823 to 2,867 hours of operations. The baseline model averages 2,781 hours with a standard deviation of 3.56 hours and a range of 2,778 to 2,789 hours. In total the smart IoT model reached 28,471

operational hours with generators while the baseline model reached 27,817; a 2.35% difference in favor of the smart IoT model. Across the fueled hours of operation, the baseline model averages nearly 50% more generators per hour at 9.39 vs. 6.20 in the smart IoT model.

Table 11. MOE's against critical load by demand center.

Scenario	Demand Center	SAIDI (min/year)	SAIFI (each)	Availability	CAIDI (min/year)
IoT Microgrid	Hospital	240,012	395	54.34%	607
	Ops Center	269,028	388	48.82%	692
	Residential	269,424	388	48.74%	694
3.5WS_500DG	Hospital	190,380	1,114	63.78%	171
	Ops Center	257,520	737	51.00%	349
	Residential	259,080	728	50.71%	356
3.5WS_250DG	Hospital	175,200	1,033	66.67%	170
	Ops Center	241,140	723	54.12%	334
	Residential	242,940	722	53.78%	336
7WS_500DG	Hospital	19,140	104	96.36%	184
	Ops Center	41,760	453	92.05%	92
	Residential	42,660	464	91.88%	92
7WS_250DG	Hospital	6,840	378	98.70%	18
	Ops Center	35,040	381	93.33%	92
	Residential	35,880	379	93.17%	95
2xBAT_500 DG	Hospital	205,320	378	60.94%	543
	Ops Center	231,300	381	55.99%	607
	Residential	232,020	379	55.86%	612

When focusing on individual demand centers within the IoT-enabled model, our prioritization emphasizes higher availability for the Hospital, followed by the Ops Center and then the Residential area. The values in the Residential lines for each scenario are equivalent to the overall MOE's when measured against the critical load by scenario.

Only the 7.5WS_500DG scenario, baseline model, met or exceeded the 14-day (336 hour) goal of islanded operations when supplying critical load by reaching 383 hrs of uninterrupted service. No IoT enabled models reached that goal. The closest was the smart IoT model from the 7.5WS_500DG scenario at 306 hrs. Additionally, none of the scenarios met this goal when providing IPR.

3. Analysis Summary

In summary, this analysis provides a comprehensive examination of the model data results, focusing on the key metrics outlined in the MOE and MOP section, as well as making additional observations on the behaviors of the baseline and smart IoT microgrids.

Observation 1 highlights the primary model availability and MOE. The IoT-enabled baseline model outperforms the baseline grid in meeting overall demand requirements, with significant differences observed in various scenarios. In optimized energy output, variations in 250-kWh diesel generator output improve availability without excessive over-generation, resulting in better fuel efficiency and extended operational windows. On dynamic power source adaptation, the smart IoT microgrid adapts power sources effectively based on renewable energy availability, ensuring efficient power generation. On the topic of critical loads met, our model closely aligns with intended purposes, with cumulative critical load values matching expected demand. For fuel efficiency, the smart IoT model excels in reducing generator hours and optimizing fuel consumption compared to the baseline model, achieving significant operational hour differences.

In addition, demand center prioritization is evident, favoring higher availability for the Hospital and Ops Center. While only the 7.5WS_500DG baseline model met or exceeded the 14-day islanded operations goal, no IoT-enabled models achieved this for critical loads.

These results offer valuable insights for decision-making and system enhancement. The conclusions drawn from these observations will be discussed in the upcoming section.

V. CONCLUSION

In this study, we conducted a comprehensive analysis of the impact of IoT integration on the efficiency, effectiveness, and performance of microgrid systems. Our investigation focused on comparing a smart IoT microgrid with a baseline microgrid. The investigation sought to identify the potential benefits and risks associated with adopting IoT technologies for enhancing energy security and mission assurance.

A. FINDINGS

From the IoT capabilities analysis, various technologies were examined to understand their application in smart microgrids. Categorized into functionalities such as energy monitoring, environmental sensing, storage, grid control, optimization, maintenance, and wireless communication, these technologies hold transformative potential for conventional microgrids. By integrating these technologies, microgrids gain advanced monitoring, control, and optimization capabilities, potentially improving microgrid efficiency, reliability, and performance.

The models and simulations generated showed the smart IoT microgrid increases the availability across a 10-year period compared to a baseline microgrid. Two models were created: one represented a smart IoT microgrid and the other represented a baseline microgrid without any IoT devices. Both models consist of the same photovoltaic panels and wind turbines while the diesel generators and battery bank operated under different logic to provide power generation based on actual demand or predicted demand. Both microgrids also included the same loads with 60% of the total load defined as critical. The model prioritizes meeting the 60% critical load prior to addressing the remaining load. The addition of IoT devices to the smart IoT microgrid, e.g., smart meters, AMI, SCADA, smart switching, voltage sensors, optimization algorithms, and wireless sensor networks were all simulated through the acquisition of real-time demand and response algorithms.

Four scenarios were tested for each microgrid: nominal, higher wind speed, lower generator output, and higher battery storage. All four were used in the analysis to represent variations in generation and to validate the impact of IoT on a microgrid.

The analysis confirmed IoT devices increase the response of the microgrid to changes in supply and demand. The 10-year simulations found the smart IoT microgrid performed significantly better meeting total demand requirements, controlling backup generators, and limiting fuel consumption. Only one scenario reached a 14-day islanded operation without interruption. However, the baseline IoT scenarios average maximum was 13.75 days providing uninterrupted critical load.

B. RECOMMENDATIONS

Based on the findings, it is recommended the model be presented to stakeholders to better inform future DOD microgrid decisions. Based on the findings, implementing IoT devices into DOD installations should be considered. The adoption of IoT in microgrids offers several advantages, such as real-time monitoring, automated decision-making, and improved situational awareness. These capabilities enable microgrid operators to optimize power distribution, respond rapidly to changing energy demands, and minimize downtime during disruptions. The integration of IoT devices can lead to a more flexible, adaptive, and responsive microgrid infrastructure, better suited to meet mission-critical energy requirements. The increased energy availability along with decreased energy generated through fossil fuels establishes a path forward to meet the DON's intent to achieve mission continuity, as well as meet Executive Order 14057.

However, it is essential to acknowledge and address the potential shortfalls and risks associated with IoT integration. Cybersecurity becomes a paramount concern as IoT devices increase the attack surface and potential vulnerabilities. Ensuring robust security measures, implementing encryption protocols, and regular security audits are crucial to safeguarding the microgrid from cyber threats. Moreover, a comprehensive risk assessment, as discussed in future work, should be conducted to identify and mitigate potential hazards and vulnerabilities that IoT devices might introduce to the microgrid system.

Additionally, the adoption of IoT technologies requires careful planning, initial investment, and ongoing maintenance. Proper training and capacity building for personnel

responsible for operating and managing the IoT-enabled microgrid are essential to harness the full potential of these technologies effectively.

Further research and experimentation are warranted to explore the long-term effects of IoT integration in microgrid systems. Given the current model represents a fictional microgrid, system engineers should modify the parameters of the model to represent the microgrid at their installation for a better analysis. The model was built as modular as possible to facilitate modifications. Engineers should update the amount of power generated, the sources of power generation, the impact of IoT devices on their facility, the load requirements, and the MTBF and MTTR for all chosen systems.

To ensure the successful implementation of IoT-based microgrid systems, a comprehensive risk assessment is essential. Future work should focus on conducting in-depth risk assessments, including identifying potential vulnerabilities, threats, and points of failure. This assessment should encompass various scenarios, including cyberattacks, environmental disruptions, and equipment failures, to develop effective mitigation strategies. Future work may explore developing advanced cybersecurity solutions specifically tailored to microgrid operations. This should include the implementation of intrusion detection systems, secure communication protocols, and regular security audits to protect against potential cyber threats.

Subsequent projects can expand on the current model by incorporating a broader range of IoT devices. Table 3 illustrates a selection of 18 IoT technologies currently available to consumers, with the existing model integrating seven of these technologies. The inclusion of more IoT devices in the model has the potential to generate additional data and insights for microgrid operators. This augmentation may further enhance the overall availability and reliability of power supply, empowering operators with richer information to make informed decisions and optimize microgrid performance. By embracing emerging IoT technologies, future projects can unlock even greater potential to bolster energy efficiency, effectiveness, and resilience within microgrid operations.

The cost to implement IoT devices to create a smart microgrid should be analyzed to provide stakeholders with a cost-benefit analysis. On top of the cost for each IoT device,

the inclusion of IoT devices into a microgrid requires infrastructure to accurately and safely transmit information. Alternative infrastructure plans should be researched and compared to inform the stakeholder of the best option for the funding available.

The NPS microgrid team developed open-source tools to help plan the early stages of microgrid incorporation (Reich and Oriti 2021). Data generated through the smart IoT microgrid model can be included in the NPS open-source tools to help users make an informed decision about incorporating IoT devices into their microgrid.

SUPPLEMENTAL

An “ExtendSim Model with Baseline Data” is included as a supplemental data reference, which can be requested from the NPS Library. The model was built in ExtendSim version 17 and is a discrete event model designed to the parameters described in this paper and shown in the Appendix.

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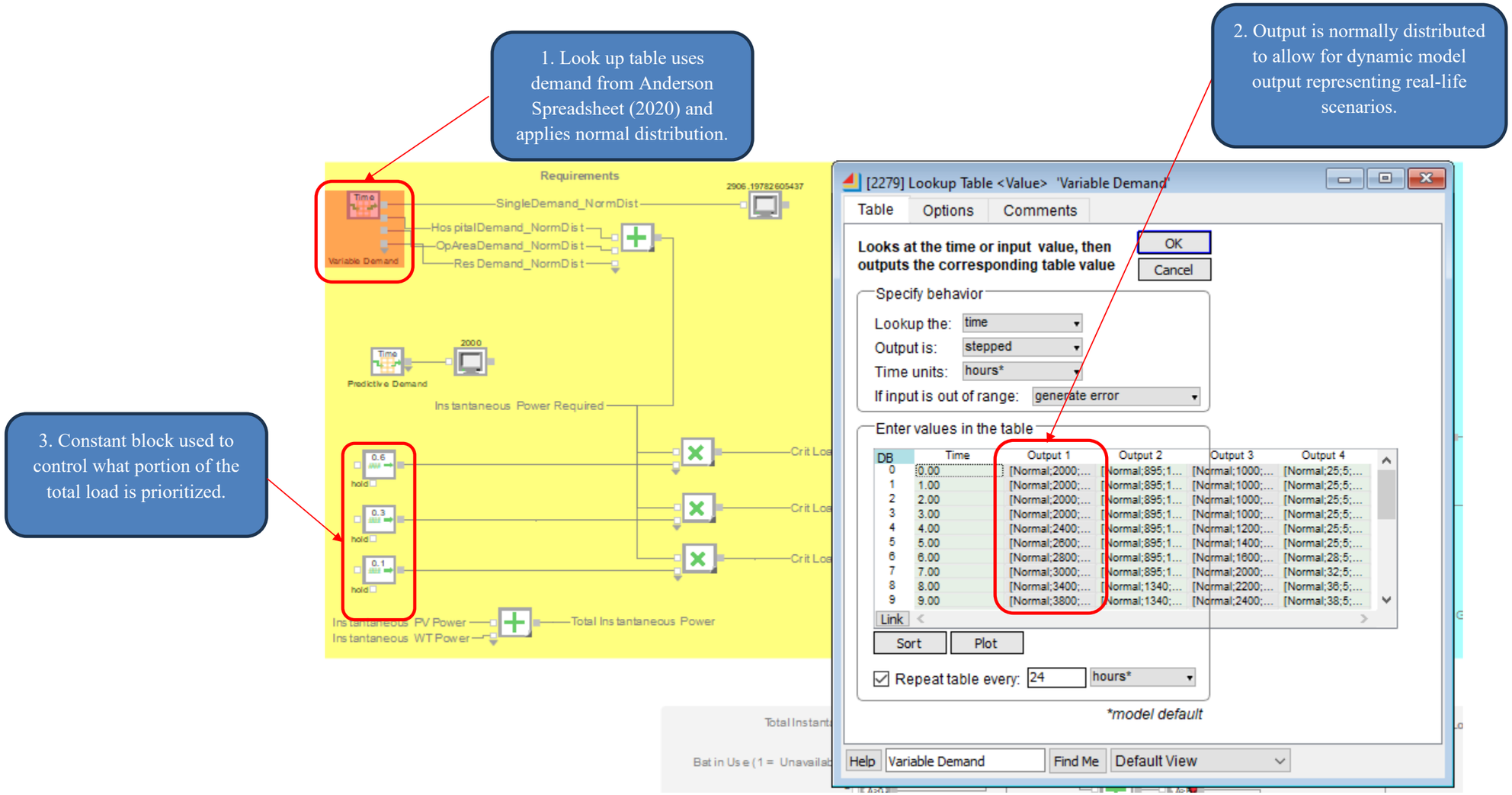
APPENDIX. EXTENDSIM MODEL DEMONSTRATION

How the model determines load requirements:

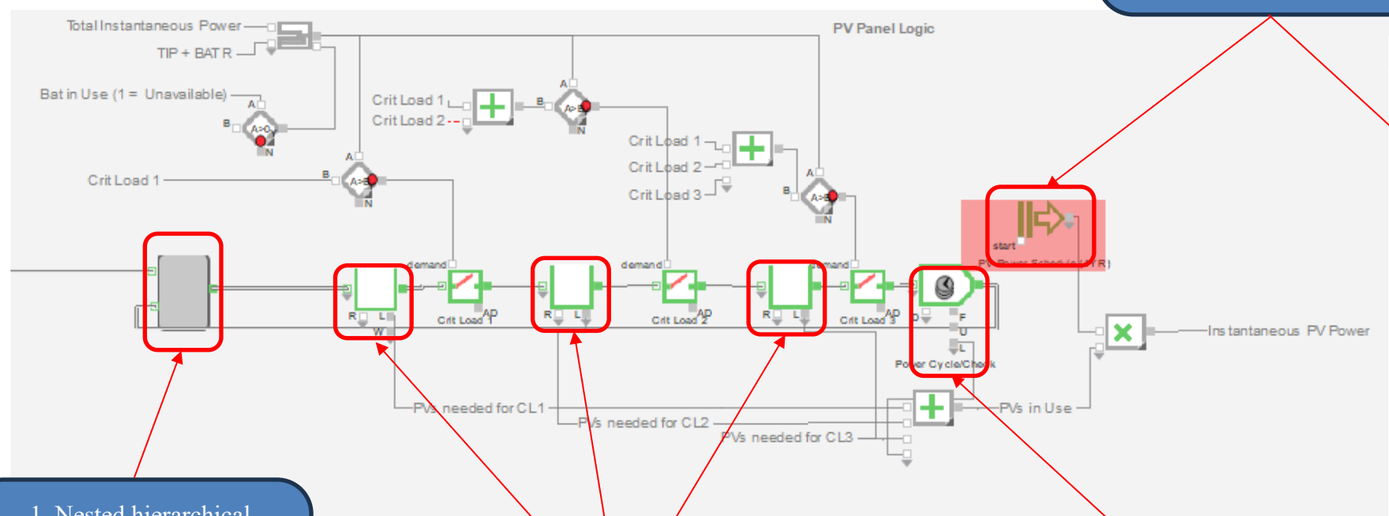
1. The ExtendSim model references a lookup table that is linked to an ExtendSim Database.
2. Normal distribution is applied to lookup table values.
3. Distributed values from lookup table are proportionately multiplied by numbers between 0 and 1 to facilitate critical load requirements.

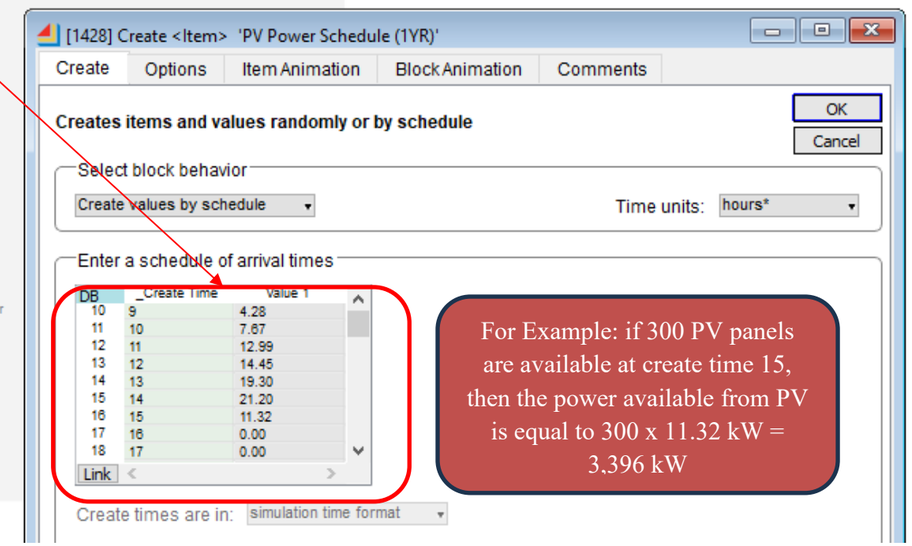


How renewable power is determined:

1. Individual PV panels or wind turbines go through a phase of availability determination by evaluating individual MTBF probabilities.
2. Once the number of available sources of power is determined, queues are populated in series until the required number of power sources to satisfy the gate requirement is met.
3. Available power is determined by multiplying the number of available power sources by the value schedule established by the create block.
4. The final activity block in the event series cycles all sources of power for periodic failure checks.

3. The create block is tied to a schedule of values that generates a value at a specific hour based on type of power supply.





1. Nested hierarchical blocks embedded to evaluate probability of failure to determine available sources of power.

2. Queue length provides the number of sources of power supply that are multiplied by the values referenced by the create block resulting in a total amount of power based on available sources of power at a specific time.

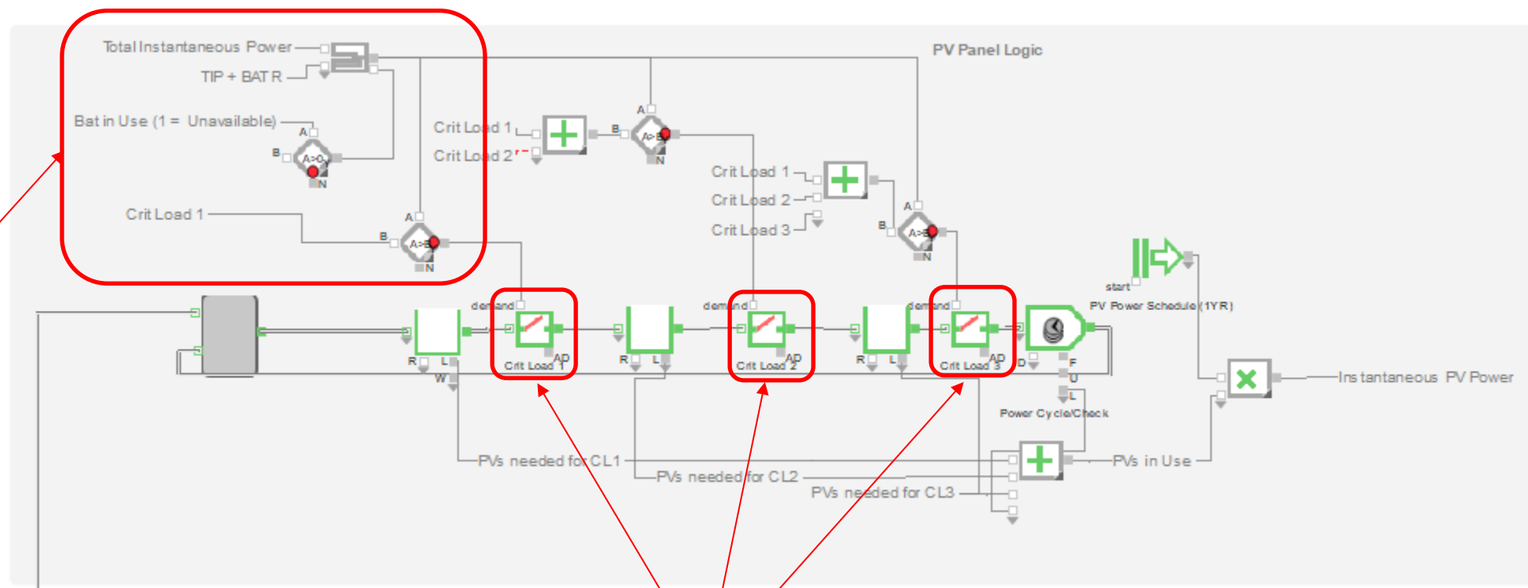
4. Activity block allows cycling of power sources through failure check once daily.

For Example: if 300 PV panels are available at create time 15, then the power available from PV is equal to 300 x 11.32 kW = 3,396 kW

How are loads prioritized:

1. All gates are initially blocked forcing the queues in series to populate prior to the gate condition being met.
2. As queues are filled by available sources of power, those sources of power are multiplied by the value schedule at the corresponding hour with the product being available power (detailed previously).
3. Gate conditions are met by comparing available power to the power required to open specific gates. As an example, the first gate in queue is linked to Crit Load 1 and will not open unless the power available is greater that the load requirement for Crit Load 1.
4. As the queues and gates are in series, crit load 1 must be met prior to crit load 2 being met, and so on.

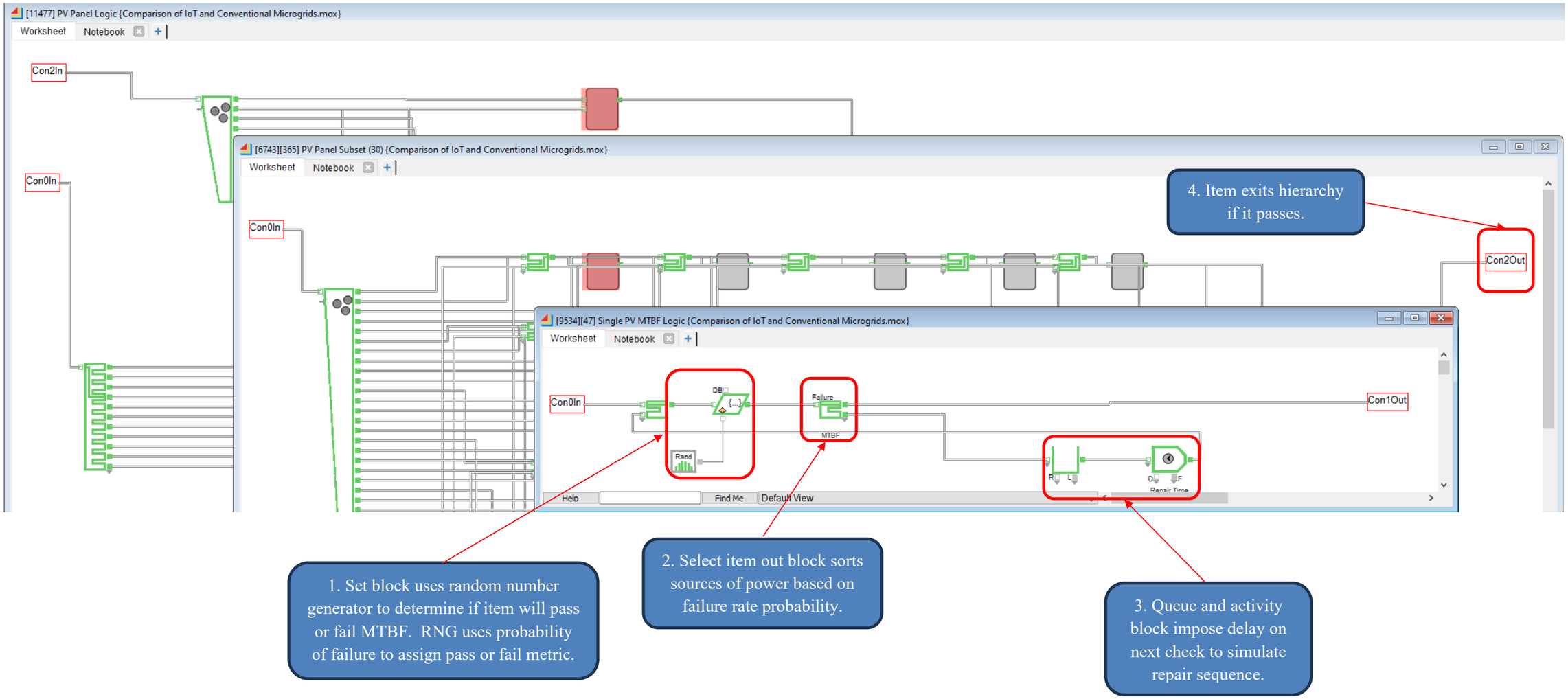
3. Decision block determines if battery is available to switch power source between renewable power (TIP) and renewable power plus battery remaining. That value is then compared to load requirements for each gate via another decision block.



1. Gates prevent power from being supplied to secondary and tertiary load requirements based on decision block comparing available power to required power.

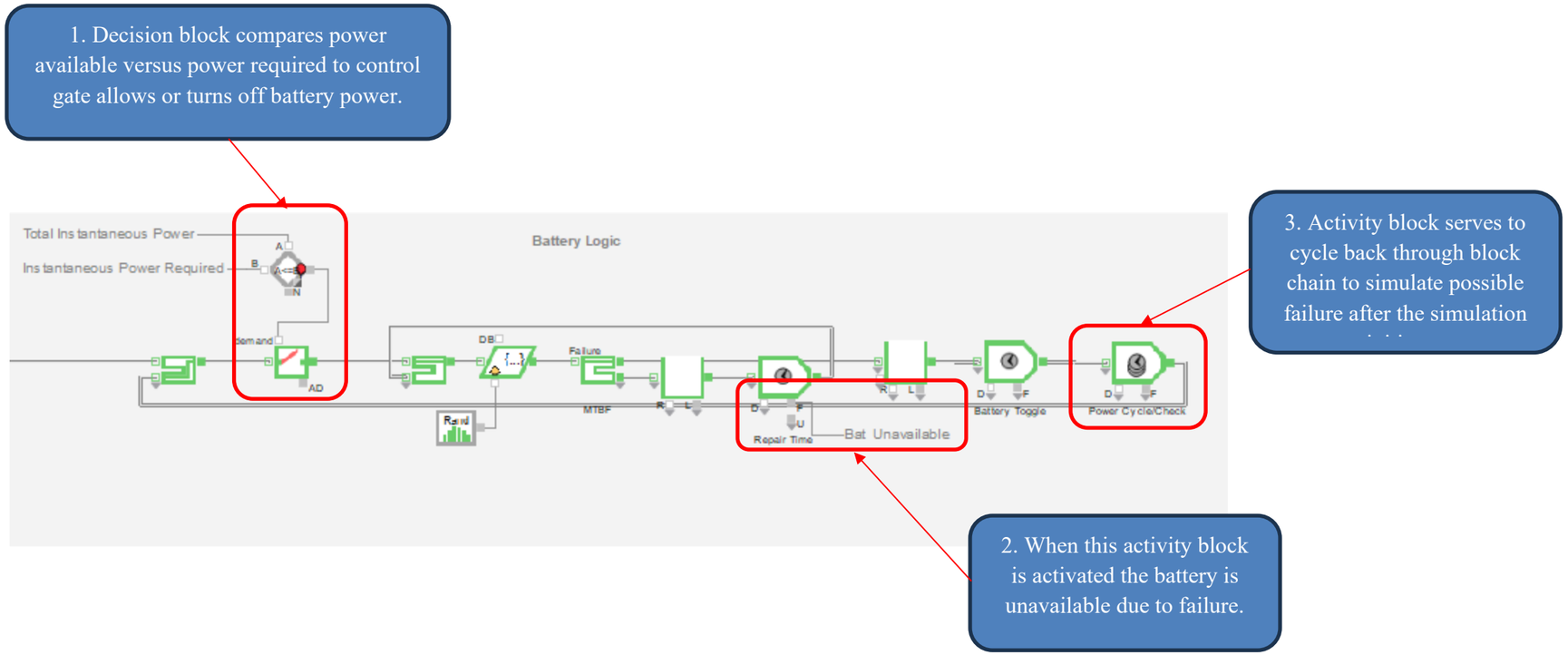
How power source failure is evaluated:

1. Each source or power is randomly ascribed a pass or fail attribute based on the MTBF of the individual system.
2. If a system fails, it is diverted to a separate queue and activity block to simulate a repair cycle.
3. If a system fails, it is not counted in the available sources of power until it passes.
4. Once the source of power passes, it exits the hierarchy.



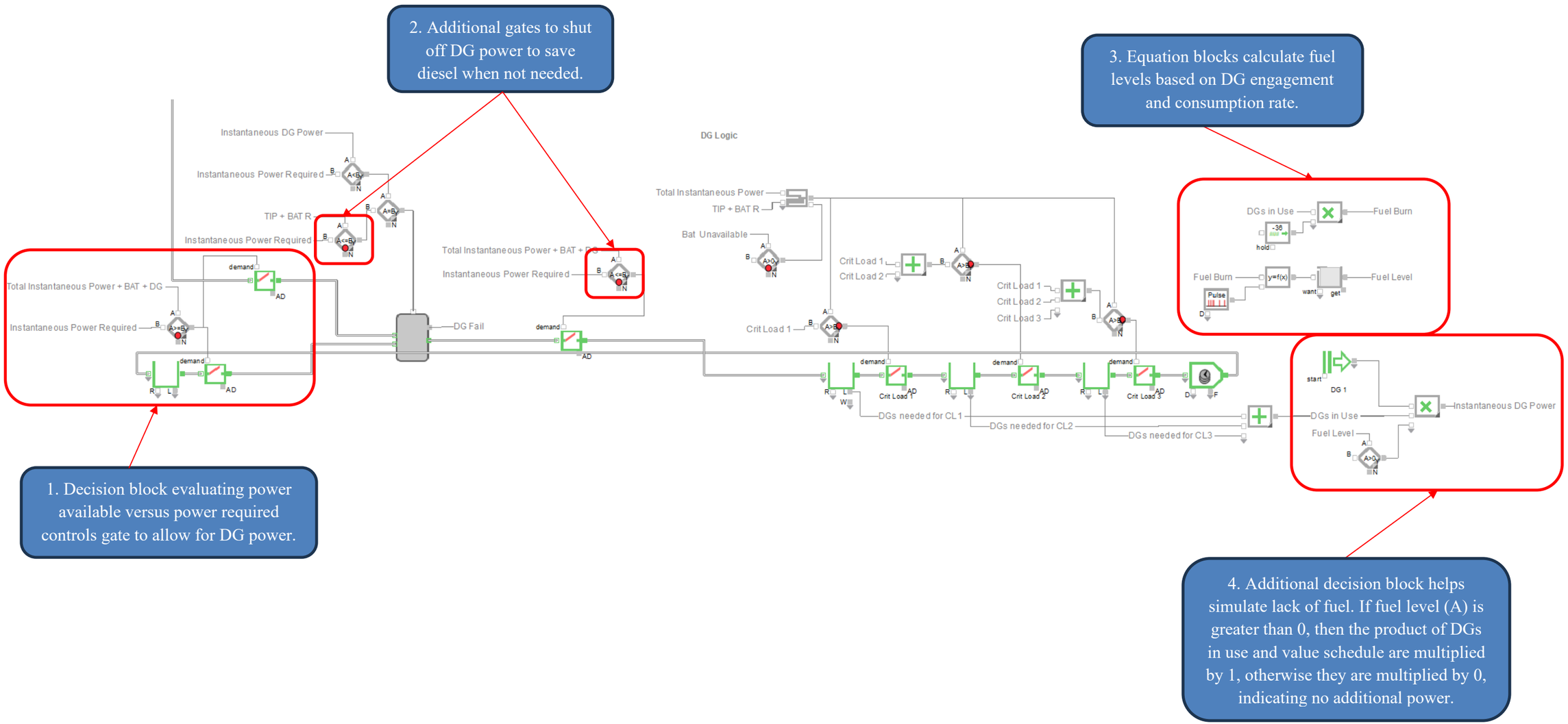
How the battery is engaged:

1. Like critical load prioritization, the battery is only engaged once the gate logic is met, that being less renewable power than power required.
2. Once the need for the battery is established, the battery goes through a failure check and if the battery is in a failed condition, a message is sent to inform the model that the battery is unavailable.
3. After a set amount of time, the system is cycled again to determine if the battery is needed or has failed since its initial engagement.



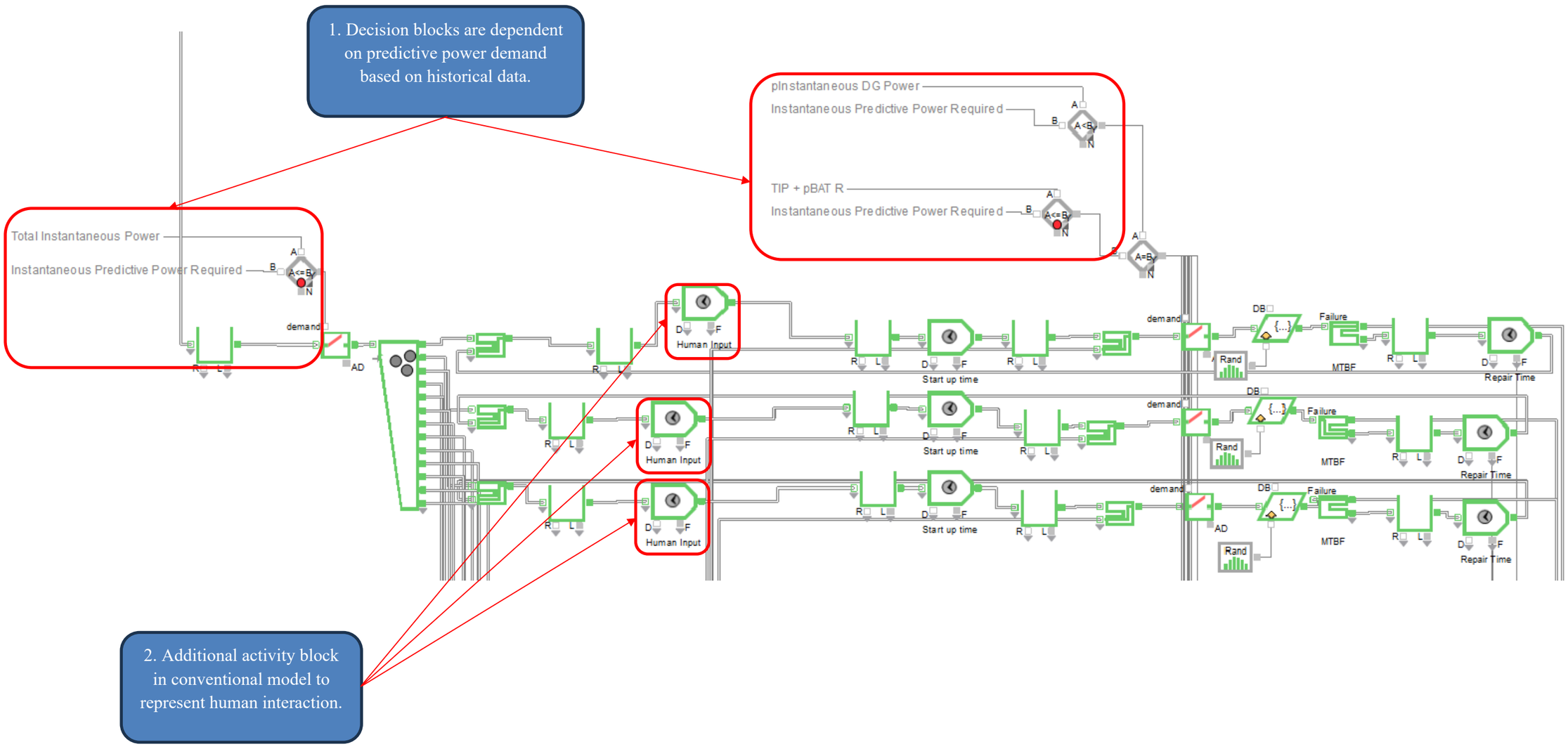
How diesel gensets are engaged:

1. DG power is gated pending the power requirement being greater than the sum of the available renewable power and available battery power.
2. Multiple gates are employed at multiple phases in the event the power requirement is met during the DG ramp up period.
3. Fuel levels are monitored to respond to a shortage of fuel.
4. Available fuel determines if any auxiliary power is supplied to microgrid.



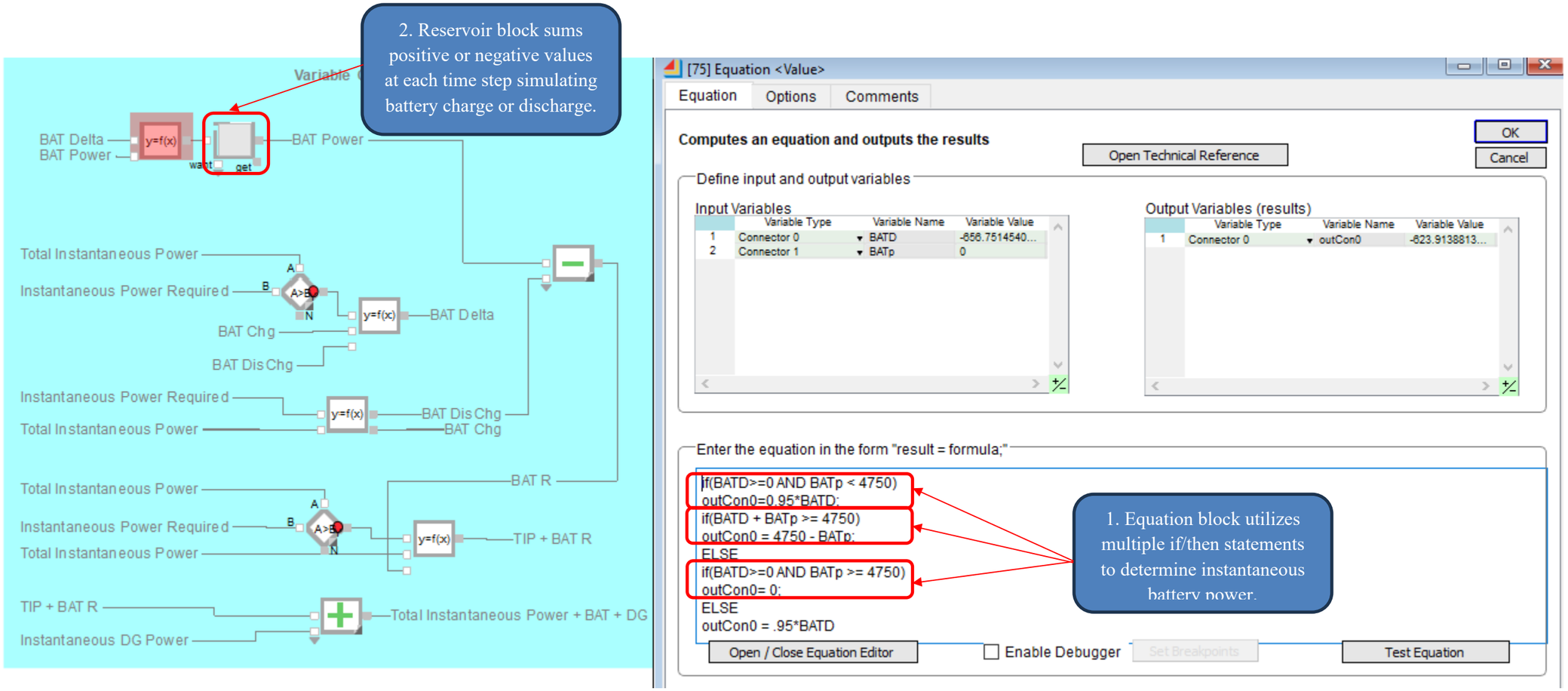
Conventional Model:

1. IoT Model is reactive to load requirement variance while the conventional model response is based on predicted load requirements.
2. Additional activity block added to diesel genset simulation section to simulate human interaction depending on need for diesel generator.
3. The conventional model follows the same logic patterns otherwise.



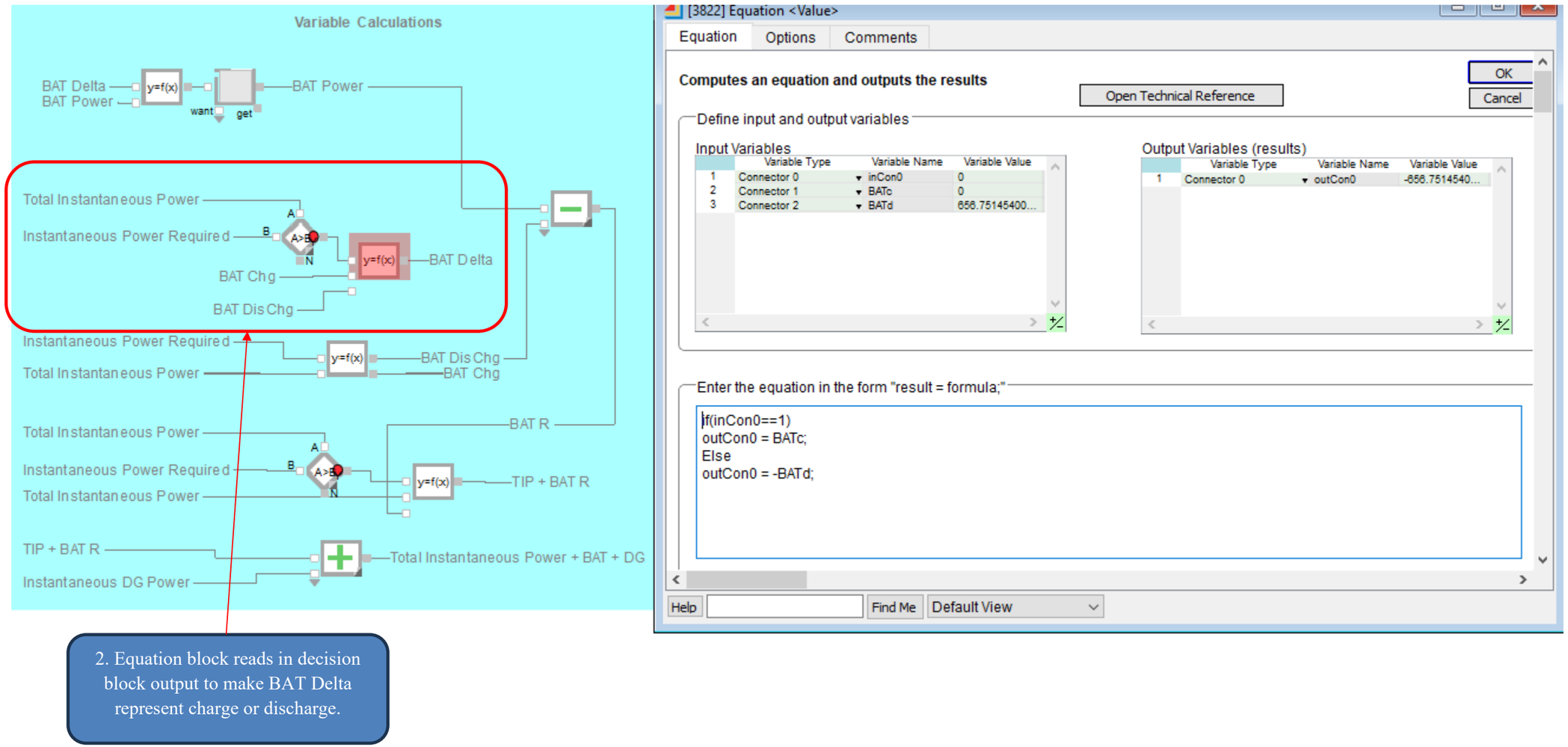
How the battery functions assuming it is needed and available:

1. BAT Power is calculated based on previous BAT Power plus/minus BAT Delta
2. Since BAT Power represents the storage of power, the addition or subtraction of power occurs every time-step the model simulates (hourly).



How the battery functions assuming it is needed and available:

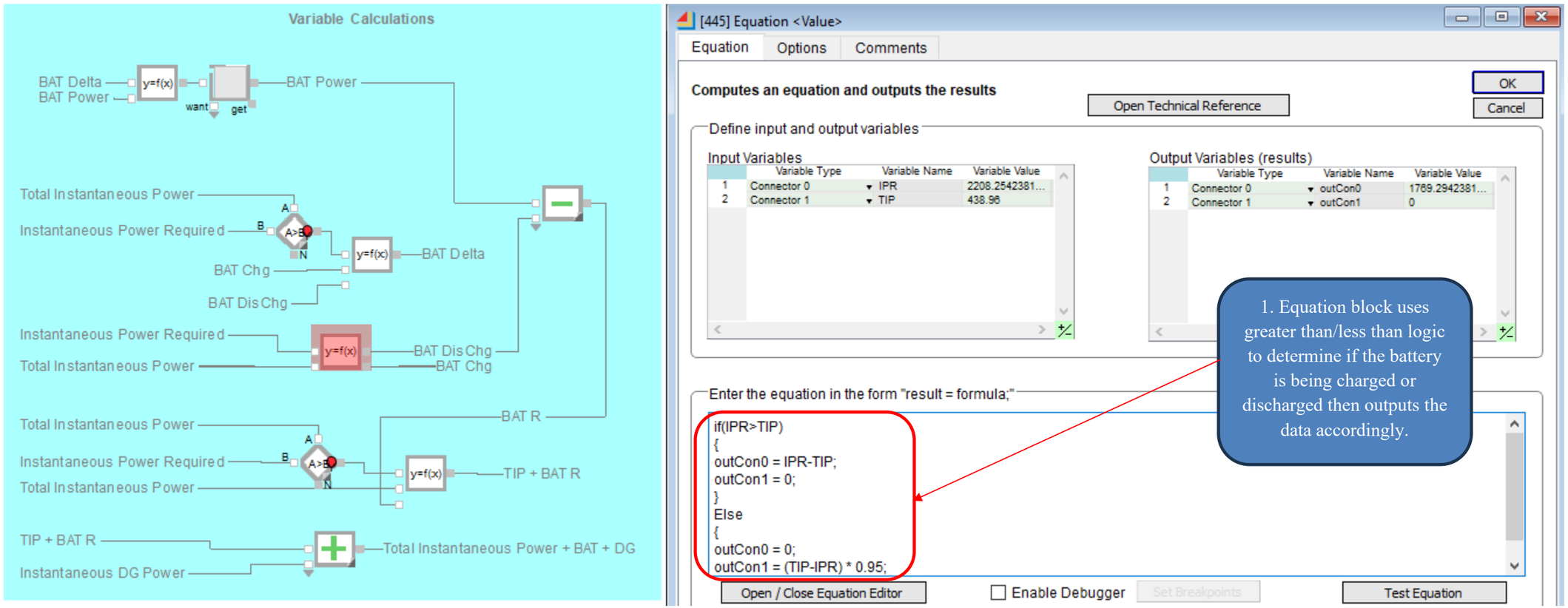
1. BAT Delta is either representing battery charge or battery discharge.
2. Charge or discharge is dependent on decision block comparing total instantaneous power to instantaneous power required.



2. Equation block reads in decision block output to make BAT Delta represent charge or discharge.

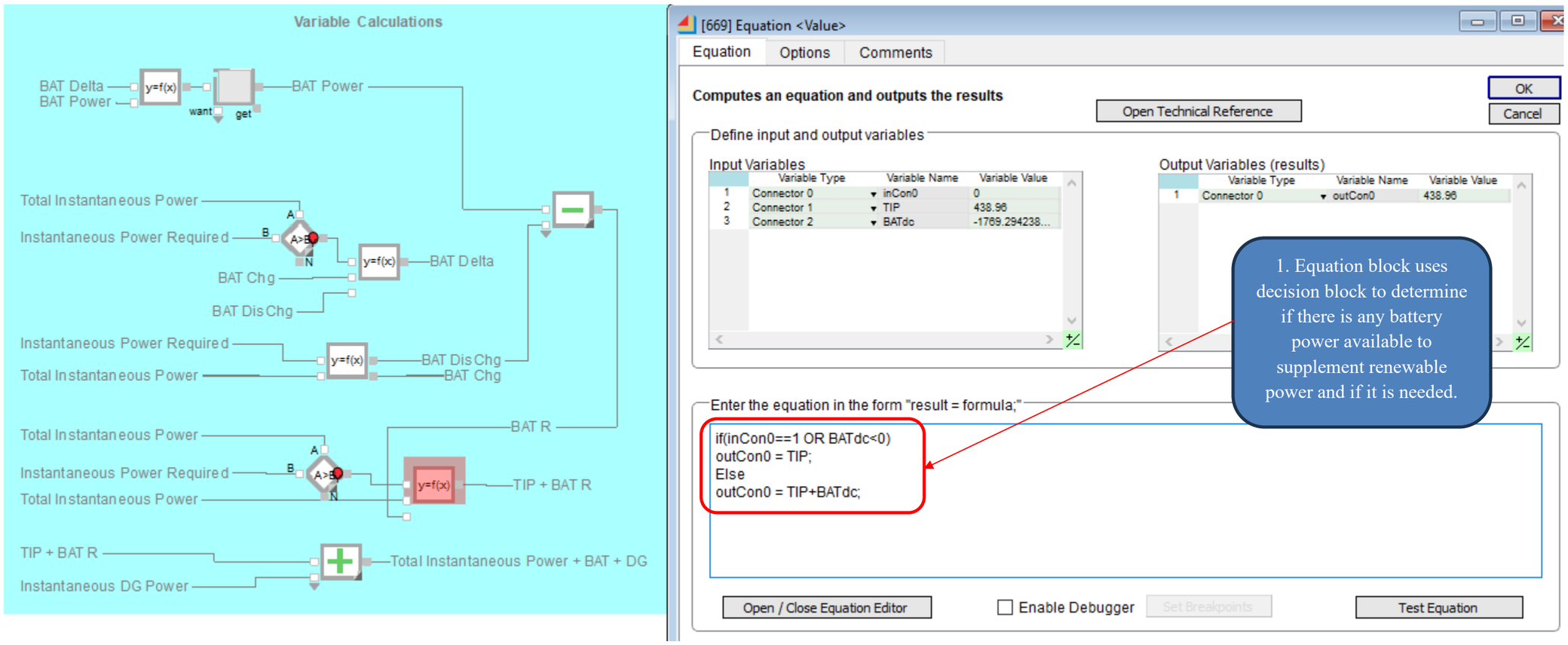
How the battery functions assuming it is needed and available:

1. Battery charge or discharge is calculated by comparing the available renewable power to the total load requirement.



How the battery functions assuming it is needed and available:

1. Battery power remaining is added to the renewable power resulting in TIP+ BAT R, which is a primary comparison metric for critical load allocation and determination if diesel generators are needed.



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LIST OF REFERENCES

Ali, Amad, Hafiz Abdul Muqeet, Tahir Khan, Asif Hussain, Muhammad Waseem, and Kamran Ali Khan Niazi. 2023. "IoT-Enabled Campus Prosumer Microgrid Energy Management, Architecture, Storage Technologies, and Simulation Tools: A Comprehensive Study." *MDPI* 16 (4): 1–19. https://doi.org/10.3390/en16041863.

Amini, Mohammad, Mohammad Hassan Nazari, and Seyed Hossein Hosseinian. 2023. "Predictive Energy Management Strategy for Battery Energy Storage Considering Battery Degradation Cost." *IET Renewable Power Generation* 17 (5): 1119–38. https://doi.org/10.1049/rpg2.12669.

Anglani, Norma, Giovanna Oriti, Ruth Fish, and Douglas L. Van Bossuyt. 2022. "Design and Optimization Strategy to Size Resilient Stand-Alone Hybrid Microgrids in Various Climatic Conditions." *IEEE Open Journal of Industry Applications* 3: 1–9. https://doi.org/10.1109/OJIA.2022.3201161.

Anuat, Edward A. 2021. "Energy Resilience Impact of Supply Chain Network Disruption to Military Microgrids." Thesis, Monterey, CA: Naval Postgraduate School.

Aqamohammadi, Amir Reza, Taher Niknam, Sattar Shojaeiyan, Pierluigi Siano, and Moslem Dehghani. 2023. "Deep Neural Network with Hilbert–Huang Transform for Smart Fault Detection in Microgrid." *MDPI* 12 (3): 1–16. https://doi.org/10.3390/electronics12030499.

Artale, Giovanni, Antonio Cataliotti, Valentina Cosentino, Dario Di Cara, Salvatore Guaiana, Nicola Panzavecchia, and Giovanni Tine. 2019. "Real-Time Power Flow Monitoring and Control System for Microgrids Integration in Islanded Scenarios." *IEEE Transactions on Industry Applications* 55 (6): 7186–97. https://doi.org/10.1109/TIA.2019.2932967.

Auld, Sean G., Daniel V. Camp, Paul Kylander, Nathan Vey, and Jerald J. Willis. 2022. "Battery Usage in the Future Fleet." Systems engineering capstone report, Monterey, CA; Naval Postgraduate School. https://calhoun.nps.edu/handle/10945/71135.

Carpinelli, Guido, Pasquale De Falco, and Fabio Mottola, eds. 2020. *Distributed Energy Storage Devices in Smart Grids*. St. Alban-Anlage 66 4052 Basel, Switzerland: MDPI. https://doi.org/10.3390/books978-3-03928-435-1.

Chakrabortty, Aranya, and Anjan Bose. 2019. "Smart Grid Simulations and Control." In *Power Electronics in Renewable Energy Systems and Smart Grid*, 585–624. John Wiley & Sons, Ltd. https://doi.org/10.1002/9781119515661.ch11.

Cohn, Lisa. 2019. "History of Microgrids in the US: From Pearl Street to Plug-and-Play." Microgrid Knowledge. July 22, 2019. https://www.microgridknowledge.com/about-microgrids/article/11429549/history-of-microgrids-in-the-us-from-pearl-street-to-plug-and-play.

Committee on Enhancing the Resilience of the Nation's Electric Power Transmission and Distribution System, Board on Energy and Environmental Systems, Division on Engineering and Physical Sciences, and National Academies of Sciences, Engineering, and Medicine. 2017. *Enhancing the Resilience of the Nation's Electricity System*. Washington, D.C.: National Academies Press. https://doi.org/10.17226/24836.

Dao, Cuong, Behzad Kazemtabrizi, and Christopher Crabtree. 2019. "Wind Turbine Reliability Data Review and Impacts on Levelised Cost of Energy." *Wind Energy* 22 (12): 1848–71. https://doi.org/10.1002/we.2404.

Department of Energy. 2023. "How a Wind Turbine Works – Text Version." Energy.Gov. 2023. https://www.energy.gov/eere/wind/how-wind-turbine-works-text-version.

———. n.d. "Grid Resilience and Innovation Partnerships (GRIP) Program." Energy.Gov. Accessed May 11, 2023a. https://www.energy.gov/gdo/grid-resilience-and-innovation-partnerships-grip-program.

———. n.d. "Grid Systems." Energy.Gov. Accessed May 10, 2023b. https://www.energy.gov/oe/grid-systems.

Department of the Navy. 2021. "P-602 3 Pillars of Energy Security (Reliability, Resilience, & Efficiency)."

———. 2023. "Unified Facilities Criteria (UFC): Engine-Driven Generator Systems for Prime and Standby Power Applications." NAVAL FACILITIES ENGINEERING COMMAND.

Department of the Navy, (DON). 2020. "Installation Energy Resilience Strategy."

DeVilbiss, Jonathan, and April Lee. 2020. "EIA's Hourly Electric Grid Monitor Provides Timely Data about Electricity Usage Patterns." April 6, 2020. https://www.eia.gov/todayinenergy/detail.php?id=43295.

"Diesel Generator Fuel Consumption Chart." 2023. *Hardy Diesel* (blog). 2023. https://hardydiesel.com/resources/diesel-generator-fuel-consumption-chart/.

Farhangi, Hassan, and Geza Joos. 2019. *Microgrid Planning and Design: A Concise Guide*. First Edition. Newark: Wiley. https://doi.org/10.1002/9781119453550.

Federal Emergency Management Agency. 2023. "How a Disaster Gets Declared." FEMA.Gov. April 25, 2023. https://www.fema.gov/disaster/how-declared.

Giachetti, Ronald E., Douglas L. Van Bossuyt, William W. Anderson, and Giovanna Oriti. 2021. "Resilience and Cost Trade Space for Microgrids on Islands." *IEEE Systems Journal* 16 (3): 3939–49. https://doi.org/10.1109/JSYST.2021.3103831.

Hojabri, Mojgan, Ulrich Dersch, Antonios Papaemmanouil, and Peter Bosshart. 2019. "A Comprehensive Survey on Phasor Measurement Unit Applications in Distribution Systems." *Energies* 12 (23): 4552. https://doi.org/10.3390/en12234552.

Hussein, Mouftah, and Melike Erol-Kantarci, eds. 2017. *Smart Grid: Networking, Data Management, and Business Models*. Boca Raton: CRC Press. https://doi.org/10.1201/b19664.

"Industrial Control – an Overview | ScienceDirect Topics." n.d. Accessed May 16, 2023. https://www.sciencedirect.com/topics/engineering/industrial-control.

Kadechkar, Akash, Jordi-Roger Riba, Manuel Moreno-Eguilaz, and Joan Perez. 2020. "SmartConnector: A Self-Powered IoT Solution to Ease Predictive Maintenance in Substations." *IEEE Sensors Journal* 20 (19): 11632–41. https://doi.org/10.1109/JSEN.2020.2998157.

Kain, Alissa, Douglas L. Van Bossuyt, and Anthony Pollman. 2021. "Investigation of Nanogrids for Improved Navy Installation Energy Resilience." *Applied Sciences* 11 (9): 4298-. https://doi.org/10.3390/app11094298.

Kathiresh, M., A. Mahaboob Subahani, and G.R. Kanagachidambaresan, eds. 2021. *Integration of Renewable Energy Sources with Smart Grid*. 1st ed. 100 Cummings Center, Suite 541J Beverly, MA 01915-6106: Scrivener Publishing. https://doi.org/10.1002/9781119751908.fmatter.

Keogh, Miles, and Christina Cody. 2013. "Resilience in Regulated Utilities." The National Association of Regulatory Utility Commissioners.

Kroposki, Benjamin, Christopher Pink, Richard DeBlasio, Holly Thomas, Marcelo Simões, and Pankaj K. Sen. 2010. "Benefits of Power Electronic Interfaces for Distributed Energy Systems." *IEEE Transactions on Energy Conversion* 25 (3): 901–8. https://doi.org/10.1109/TEC.2010.2053975.

Law, Averill. 2015. "Building Valid, Credible, and Appropriately Detailed Simulation Models." In *Simulation Modeling and Analysis*, 5th ed. McGraw-Hill Education.

Llaria, Alvaro, Jessye Dos Santos, Guillaume Terrasson, Zina Boussaada, Christophe Merlo, and Octavian Curea. 2021. "Intelligent Buildings in Smart Grids: A Survey on Security and Privacy Issues Related to Energy Management." *Energies* 14 (9): 2733. https://doi.org/10.3390/en14092733.

Maharjan, Asim, and Saju Khakurel. 2023. "Introduction to IoT." In *IoT, Machine Learning and Blockchain Technologies for Renewable Energy and Modern Hybrid Power Systems*, 1st ed., 1–28. Gistrup, Denmark ; River Publishers.

Marqusee, Jeffrey, Sean Ericson, and Donald Jenket. 2020. "Emergency Diesel Generator Reliability and Installation Energy Security."

Marzal, Silvia, Raul González-Medina, Robert Salas-Puente, Gabriel Garcerá, and Emilio Figueres. 2019. "An Embedded Internet of Energy Communication Platform for the Future Smart Microgrids Management." *IEEE Internet of Things Journal* 6 (4): 7241–52. https://doi.org/10.1109/JIOT.2019.2915389.

Miao, Zhixin, Ling Xu, Vahid R. Disfani, and Lingling Fan. 2014. "An SOC-Based Battery Management System for Microgrids." *IEEE Transactions on Smart Grid* 5 (2): 966–73. https://doi.org/10.1109/TSG.2013.2279638.

Mohammadi, Sirus, Babak Mozafari, Soodabe Solymani, and Taher Niknam. 2014. "Stochastic Scenario-based Model and Investigating Size of Energy Storages for PEM-fuel Cell Unit Commitment of Micro-grid Considering Profitable Strategies." *IET Generation, Transmission & Distribution* 8 (7): 1228–43. https://doi.org/10.1049/iet-gtd.2013.0026.

Morgenstern, Paula, Maria Li, Rokia Raslan, Paul Ruyssevelt, and Andrew Wright. 2016. "Benchmarking Acute Hospitals: Composite Electricity Targets Based on Departmental Consumption Intensities?" *Energy and Buildings* 118 (April): 277–90. https://doi.org/10.1016/j.enbuild.2016.02.052.

Mozafari, Babak, and Sirus Mohammadi. 2014. "Optimal Sizing of Energy Storage System for Microgrids." *Sadhana* 39 (4): 819–41.

Mukherjee, Anupam, Ranganath Vallakati, Valentin Lachenaud, and Prakash Ranganathan. 2015. "Using Phasor Data for Visualization and Data Mining in Smart-Grid Applications." In *2015 IEEE First International Conference on DC Microgrids (ICDCM)*, 13–18. Atlanta, GA, USA: IEEE. https://doi.org/10.1109/ICDCM.2015.7152002.

National Electrical Manufacturers Association (NEMA). 2016. "NEMA SG 4–2016 Smart Grid Interoperability Process Reference Manual."

National Energy Technology Laboratory. 2008. "ADVANCED METERING INFRASTRUCTURE." chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://netl.doe.gov/sites/default/files/Smartgrid/AMI-White-paper-final-021108--2--APPROVED_2008_02_12.pdf.

National Renewable Energy Laboratory. 2023a. "PVWatts Calculator." 2023. https://pvwatts.nrel.gov/pvwatts.php.

———. 2023b. “WINDExchange: U.S. Average Annual Wind Speed at 80 Meters.” 2023. https://windexchange.energy.gov/maps-data/319.

Naval Medical Center Camp Lejeune (NMCCL). 2020. “Military Health Systems (MHS) Section 703 Workgroup Use Case Decision Package.”

Ojo, Mike O., Stefano Giordano, Gregorio Procissi, and Ilias N. Seitanidis. 2018. “A Review of Low-End, Middle-End, and High-End Iot Devices.” *IEEE Access* 6 (December): 70528–54. https://doi.org/10.1109/ACCESS.2018.2879615.

Peterson, Christopher, Douglas I. Van Bossuyt, Ronald E. Giachetti, and Giovanna Oriti. 2021. “Analyzing Mission Impact of Military Installations Microgridfor Resilience.” *Systems* 9 (69). https://doi.org/10.3390/systems9030069.

Reich, Daniel, and Giovanna Oriti. 2021. “Rightsizing the Design of a Hybrid Microgrid.” *Energies (Basel)* 14 (14): 4273-. https://doi.org/10.3390/en14144273.

Roosa, Stephen A., ed. 2021. *Fundamentals of Microgrids: Development and Implementation*. First edition. Boca Raton: CRC Press, Taylor & Francis Group.

Schlachter, Fred. 2012. “The Back Page: Has the Battery Bubble Burst?” APSNews. September 2012. http://www.aps.org/publications/apsnews/201208/backpage.cfm.

Sehrawat, Deepti, and Nasib Singh Gill. 2019. “Smart Sensors: Analysis of Different Types of IoT Sensors.” In *2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)*, 523–28. Tirunelveli, India: IEEE. https://doi.org/10.1109/ICOEI.2019.8862778.

Sharma, Dushyant, and Sukumar Mishra. 2020. “Disturbance-Observer-Based Frequency Regulation Scheme for Low-Inertia Microgrid Systems.” *IEEE Systems Journal* 14 (1): 782–92. https://doi.org/10.1109/JSYST.2019.2901749.

Siano, Pierluigi. 2014. “Demand Response and Smart Grids—A Survey.” *Renewable and Sustainable Energy Reviews* 30 (February): 461–78. https://doi.org/10.1016/j.rser.2013.10.022.

Siritoglou, Petros, Giovanna Oriti, and Douglas L. Van Bossuyt. 2021. “Distributed Energy-Resource Design Method to Improve Energy Security in Critical Facilities.” *Energies (Basel)* 14 (10): 2773-. https://doi.org/10.3390/en14102773.

Smend, Joshua, Ashot Mnatsakanyan, and Sgouris Sgouridis. 2021. “A Smart Grid Solution Integrating DistributedGeneration and Internet of Things Sensors ForDemand Side Management and Fault Identification:Case Study.” *IEEE 12th International Symposium on Power Electronics for Distributed Generation Systems (PEDG)*, May. https://doi.org/10.1109.

Takriti, Mazen, Zina Boussaada, Ines Sansa, Octavian Curea, and Najiba Mrabet Bellaaj. 2020. "Wireless Sensors Networks Applications For Micro-Grids Management: State of Art." In *2020 6th IEEE International Energy Conference (ENERGYCon)*, 1058–61. Gammarth, Tunis, Tunisia: IEEE. https://doi.org/10.1109/ENERGYCon48941.2020.9236519.

Tang, Sijia, and Chen Chen. 2022. "Multi-Time Step Distribution System Recovery Method Based on Fault Information Acquisition After Natural Disasters." In *2022 IEEE 5th International Electrical and Energy Conference (CIEEC)*, 3716–21. https://doi.org/10.1109/CIEEC54735.2022.9846560.

The White House. 2021. "Executive Order on Catalyzing Clean Energy Industries and Jobs Through Federal Sustainability." The White House. December 8, 2021. https://www.whitehouse.gov/briefing-room/presidential-actions/2021/12/08/executive-order-on-catalyzing-clean-energy-industries-and-jobs-through-federal-sustainability/.

Ton, Dan, and Merrill Smith. 2012. "The U.S. Department of Energy's Microgrid Initiative." *The Electricity Journal* 25: 84–94. https://doi.org/10.1016/j.tej.2012.09.013.

U.S. Department of Commerce, NOAA. 2023. "Beaufort Wind Scale." NOAA's National Weather Service. 2023. https://www.weather.gov/mfl/beaufort.

"U.S. Energy Information Administration – EIA – Independent Statistics and Analysis." n.d. Accessed August 10, 2023. https://www.eia.gov/consumption/residential/data/2015/.

Varilone, Pietro, ed. 2021. *Microgrid Energy Management*. St. Alban-Anlage 66 4052 Basel, Switzerland: MDPI. https://doi.org/10.3390/books978-3-0365-0389-9.

Viel, Felipe, Luis Augusto Silva, Valderi Reis Quietinho Leithardt, Juan Francisco De Paz Santana, Raimundo Celeste Ghizoni Teive, and Cesar Albenes Zeferino. 2020. "An Efficient Interface for the Integration of IoT Devices with Smart Grids." *MDPI* 20 (10): 1–18. https://doi.org/10.3390/s20102849.

Viel, Felipe, Luis Augusto Silva, Valderi Reis Quietinho Leithardt, Juan Francisco De Paz Santana, Raimundo Celeste Ghizoni Teive, and Cesar Albenes Zeferino. 2020. "An Efficient Interface for the Integration of IoT Devices with Smart Grids." *Sensors* 20 (2849). https://doi.org/doi:10.3390/s20102849.

Wagh, Sanjeev J., Manisha Sunil Bhende, and Anuradha D. Thakare. 2022. *Energy Optimization Protocol Design for Sensor Networks in IoT Domains*. Boca Raton: CRC Press. https://doi.org/10.1201/9781003310549.

Wang, Wenye, Yi Xu, and Mohit Khanna. 2011. "A Survey on the Communication Architectures in Smart Grid." *Computer Networks* 55 (15): 3604–29. https://doi.org/10.1016/j.comnet.2011.07.010.

Wasserman, Kevin. 2023. "AMI Load Shedding: Ensuring Power Supply to Critical Customers." Presented at the conEdison, February 7. https://content-cdn.sessionboard.com/content/Doq2PIwTuCzZyViwSyQg_Distributech%20Load%20Shed%20Presentation.pdf.

Wattjes, F. D., and J. G. Slootweg. 2013. "Design Considerations for Smart Microgrids." In *2013 48th International Universities' Power Engineering Conference (UPEC)*, 1–6. New York: IEEE. https://doi.org/10.1109/UPEC.2013.6714879.

Zhou, Jiazhen, Rose Qingyang Hu, and Yi Qian. 2012. "Scalable Distributed Communication Architectures to Support Advanced Metering Infrastructure in Smart Grid." *IEEE Transactions on Parallel and Distributed Systems* 23 (9): 1632–42. https://doi.org/10.1109/TPDS.2012.53.

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