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THESIS

**BUILDING RESILIENCE WITHIN DOD MICROGRIDS
BY CONSIDERING HUMAN FACTORS IN RECOVERY
PROCEDURES**

by

Marcella R. HersterDudley

March 2021

Thesis Advisor:
Co-Advisor:

Douglas L. Van Bossuyt
Daniel Eisenberg

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HUMAN FACTORS IN RECOVERY PROCEDURES**

Marcella R. HersterDudley
Lieutenant, United States Navy
BS, U.S. Naval Academy, 2011

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Approved by: Douglas L. Van Bossuyt
Advisor

Daniel Eisenberg
Co-Advisor

Ronald E. Giachetti
Chair, Department of Systems Engineering

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ABSTRACT

In support of the National Defense Strategy, the Department of Defense (DOD) has recognized energy security as an essential part of its strategic intent. In keeping with the DOD's strategic goals, the Department of the Navy announced three pillars of success to meet those goals: Resilience, Reliability, and Efficiency. To best establish energy security for DOD installations, microgrids have been embedded into the energy systems as additional energy sources and controls that support mission readiness. Previous microgrid resilience research has focused on system design and cost efficiency. Considering a different approach, this thesis will pose the question of whether established recovery procedures build resilience within DOD microgrids. Using the Human Performance Impact Recovery Analysis (HPIRA) tool developed as a part of this research, human cognition and human error are implemented into various recovery procedures to determine the most successful recovery times and the man-hours required for a successful recovery. This research demonstrates the impact of human cognition in human actions and allows microgrid stakeholders to understand how human factors impact a microgrid system's recovery.

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List of Acronyms and Abbreviations

AC	Alternating Current
ASEP	Accident Sequence Evaluation Program Human Reliability Analysis Procedure
ASME	American Society of Mechanical Engineers
BES	Budget Estimate Submission
BOE	Back of the Envelope
CAES	Compressed Air Energy storage
CPM	Critical Path Method
DC	Direct Current
DER	Distributed Energy Resources
DG	Distributed Generation
DoD	Department of Defense
DoDI	Department of Defense Instruction
DOE	U.S. Department of Energy
DoN	Department of Navy
ELMI	Expected Life Cycle Mission Impact
ESS	Energy Storage Systems
HEP	Human Error Probability
HFE	Human Failure Event
HPIRA	Human Performance Impact Recovery Analysis

HRA	Human Reliability Analysis
MCAGCC	United States Marine Corps (USMC) Air Ground Combat Center
NAVFAC	Naval Facilities Engineering Command
NAVSTA	Naval Station
NPS	Naval Postgraduate School
PDF	Probability Density Function
P(f)	Probability of Failure
POM	Program Objective Memorandum
P(s)	Probability of Success
PS	Pumped Storage
PSF	Performance Shaping Factor
PV	Photovoltaic Cell
SEP	Systems Engineering Process
SMES	Superconducting Magnetic Energy Storage
SoS	System of Systems
SPAR-H	Standardized Plant Analysis Risk-Human Reliability Analysis
TCP	Transmission Control Protocol
THERP	Technique for Human Error Rate Prediction
USMC	U.S. Marine Corps
USN	U.S. Navy

Executive Summary

Following guidance in the National Defense Strategy, the Department of Defense (DoD) has set forth initiatives to improve energy security in their energy infrastructures and systems [1]. Specifically, the DoD desires to build resilience within energy installations to ensure mission readiness [2]. Resilience research for DoD microgrids is needed since they are susceptible to their own energy disruptions while also improving resilience of DoD installations as well. To support DoD energy initiatives, the United States (U.S.) Navy (USN) established resilience as one of the three pillars of energy security with reliability and efficiency [3]. While most resilience research of microgrids have been found to focus on system design and cost, this thesis focuses on the human element involved in a microgrid recovery. Specifically, this thesis analyzes if established recovery actions improve microgrid resilience, or potentially further degrade it, when considering human factors.

This thesis provides a means of improving DoD microgrid resilience by determining manpower requirements for realistic and effective recovery events. Additionally, this thesis provides microgrid stakeholders a qualitative and quantitative source for microgrid recovery man-hour requirements. This data should be used in DoD energy and microgrid decision making efforts in regards manpower requirements and annual budgets for training, logistics, and employment.

The methodology developed in this thesis is comprised of an eleven-step process to determine the total amount of man-hours needed to recover degraded microgrid components. The eleven steps are as follows:

1. Define Microgrid Component of Interest
2. Determine Recovery Procedure for Microgrid Component of Interest
3. Perform Stakeholder Analysis
4. Create the Precedence Order of the Recovery Task List
5. Apply Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H) and Determine Human Error Probability (HEP) values for all Tasks
6. Choose the Appropriate Probability Distribution for Duration Sampling
7. Find Individual Task Duration based on chosen Probability Distribution

8. Find All Possible Task Network Paths and Durations
9. Determine Critical Path and Duration of Task Network
10. Simulate and Analyze Component Recovery Durations
11. Conduct and Analyze a Back of the Envelope (BOE) Total Duration Calculation for Multi-Component Failure Events

This methodology establishes the Human Performance Impact Recovery Analysis (HPIRA) tool that evaluates the impact of the human element on microgrid recovery procedures. The implementation of SPAR-H allows for human factors to be evaluated with eight Performance Shaping Factors (PSFs) for each recovery task in the recovery process network. The final SPAR-H provides HEP values to determine a sample duration time for each task. When all paths are determined for a given recovery task network, each respective task's sample duration is totaled to determine total recovery time of each path. A Monte Carlo simulation is applied to all recovery network paths to determine the critical recovery path and recovery time.

This thesis applies the HPIRA tool to conduct two analyses. The first analysis applies HPIRA to six different microgrid component recovery efforts to determine each recovery processes' critical path to successful completion. The critical paths are analyzed to determine the man-hours needed for each successful recovery effort and assess if whether or not human cognition plays a role in recovery efforts. In this analysis where conditions are simple and ideal, it was determined that human cognition generally impacted recovery completion efforts in a positive fashion. The second analysis evaluates two different multi-component failure events to determine the total amount of man-hours needed for each recovery event. By utilizing successful recovery times for degraded components from the first analysis, total recovery times are able to be determined for the two multi-component failure events with BOE calculations. Total man-hours required for these events are determined to see how effective a single, two-person recovery team is able to recover a severely degraded Naval Station (NAVSTA) microgrid. The total man-hours are compared to USN standards for microgrid autonomy and consideration of efforts needed to meet those standards are discussed. Given that a two-person team will not sufficiently restore a multi-component microgrid failure event, estimated recovery team numbers are determined for stakeholder interest and awareness.

List of References

- [1] Department of Defense, “Department of Defense annual energy management and resilience report (aemrr) fiscal year 2018,” Office of the Assistant Secretary of Defense for Sustainment, Washington, DC, Tech. Rep., 2019. Available: <https://www.acq.osd.mil/eie/Downloads/IE/FY%202018%20AEMR.pdf>
- [2] Department of Navy, “Installation energy resilience strategy,” Department of Navy, Washington, DC, Tech. Rep., 2020. Available: <https://www.secnav.navy.mil/eie/Documents/DON-Installation-Energy-Resilience-Strategy.pdf>
- [3] D. Capozzoli and J. Tetatzin, “Department of Navy’s energy security framework: How it relates to utility providers that support Navy and Marine Corps installations,” Nashville, TN, Tech. Rep., Apr. 2018. Available: https://www.energy.gov/sites/prod/files/2018/04/f51/fupwg_spring_2018_19-tetatzin_capozzoli.pdf

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CHAPTER 1:

Introduction

The Department of Defense (DoD) has aligned itself with the mission priorities set forth by the National Defense Strategy to “support strategic priorities expressed in theatre posture plans, operation plans, and core mission essential tasks” to include energy security [1]. To maintain and support mission readiness, DoD installations require their energy systems to be resilient, which rely on the availability and reliability of involved systems [2]. The Department of Navy (DoN) has developed an energy security framework to support DoD guidance by specifying three pillars of energy security as seen in Figure 1.1: 1) Reliability, 2) Resiliency, and 3) Efficiency. In the past, the DoD has dedicated a great amount of resources into researching and developing solutions to increase reliability and efficiency in the context of energy security. Resilience, however, has significantly less completed research work than that of reliability and efficiency. This is due to the complexity and consistency of measuring resilience, determining the proper and appropriate definition of resilience, and using a holistic perspective in the context of energy security [3]. With this in mind, the DoN and DoD are pursuing innovative avenues of research to improve resilience of energy systems within DoD installations [1].

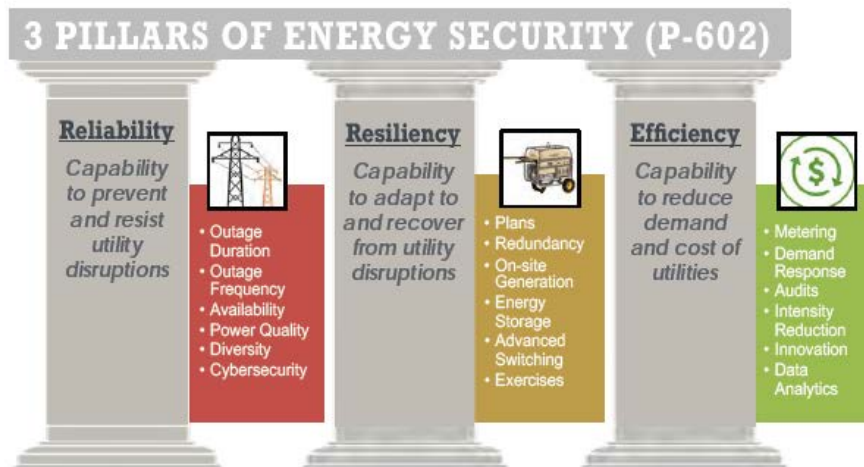


Figure 1.1. The Three Pillars of Energy Security. Source: [1].

1.1 Statement of Contribution

The primary purpose of this thesis is to improve resilience within DoD installation microgrids to support DoD directives in energy security. This thesis will apply a Human Reliability Analysis (HRA) to established recovery procedures and determine man-hours required for a successful recovery event. By understanding the human effort needed for successful microgrid recovery events, stakeholders can best plan, improve, and support DoD microgrid personnel limitations to improve microgrid resilience. The Human Performance Impact Recovery Analysis (HPIRA) tool developed within this thesis allows for the impact of human error to be assessed within recovery procedures. Results from the HPIRA tool will be assessed to determine the most successful recovery times and the man-hours required for various recovery scenarios.

1.2 Resilience within a System

In order to improve resilience of any microgrid system, an appropriate definition of resilience must be chosen along with properly identifying its contribution factors. This allows for focused analysis of potential system improvements and their impacts on improving microgrid system resilience. Woods explains that resilience is defined as an adaptation of a system's robustness, rebound, graceful extensibility, and sustained adaptability [4]. The four concepts as explained in [4] are:

- **Robustness:** How effectively a system reacts or responds to an increased set of disturbances on the system
- **Rebound:** How effectively a system can bounce back and return to its normal level or operation when impacted by disrupting event
- **Extensibility:** How effectively a system overcomes risk of sudden failure when it is pushed beyond its boundaries
- **Sustained Adaptability:** How effectively a system adapts to future surprises as conditions evolve

The concept of rebound aims to understand how certain systems return to normal operations better than others [4]. Rebound capabilities are meant to improve a system's response from significantly disrupting events that degrade normal operational conditions [4]. This concept encourages system modeling exploration of disrupted systems so that a system's rebound,

in both operation and design, can be improved and capable of taking on various disrupting events [4]. This thesis focuses on improving the rebound of a DoD microgrid system by assessing the cognitive effects of operators carrying out recovery procedures. Additionally, this thesis will present its methodology and experimentation. The findings will contribute to improving microgrid resilience within DoD installations.

1.3 Systems Engineering Application

Systems engineering is the practice of expressing needs or requirement into “operationally suitable blocks of systems” [5]. Blanchard and Fabrycky [5] explain that the Systems Engineering Process (SEP) is an iterative process that includes requirements analysis, functional analysis and allocation, design synthesis and verification, and system analysis and control. Additionally, the SEP considers a holistic approach to include concepts of design, manufacturing, test and evaluation, and support resources to best balance cost, schedule, and performance throughout the system’s life cycle [5]. By implementing systems engineering within microgrid systems, operational effectiveness and suitability can be improved [3]. A facet of operational effectiveness and suitability is reliability engineering. In [5], reliability engineering focuses on a system’s probability to operate with or without failure.

Many research efforts such as system design modifications and life cycle cost estimations have been assessed on their impacts to building resilience within microgrids, however, they do not encompass the entirety of SEP but only touch on a few considerations. This is not to say that those efforts are inadequate or incomplete, but that in fact they are an essential “piece of the puzzle” in improving microgrid system resilience. It is upon all systems engineers to take a piece of the “how to improve microgrid resilience” puzzle and iterate and synthesize their findings with one another other to improve microgrid system resilience. Microgrid recovery processes will be analyzed from the system engineering perspective to include similar and different considerations of the holistic perspective as described in [3]. This thesis will apply system engineering practices of stakeholder analysis, project management, and reliability engineering to determine if microgrid recovery processes improve microgrid resilience.

1.3.1 Microgrid System Stakeholders

The purpose of identifying system stakeholders is to ensure that all “voices” that are involved within a DoD microgrid system are considered and communicated with so that special interests, needs, and/or concerns are addressed and well known [5]. An important part of systems engineering is to determine primary and secondary stakeholders who are involved within a given task, operation, or system. By performing this analysis, end users, operators, and maintainers can be identified in performing microgrid recovery processes.

1.3.2 Microgrid System Project Management

Systems engineering project management scheduling tools such as project task networks allow for stakeholders to properly plan, organize, and coordinate project efforts. Project task networks evaluate sequential project events or activities from a “beginning” node an “end” node with corresponding duration times for each node [5]. The network tasks can be completed in parallel or series while also represents the dependencies between tasks [5]. For microgrids, project task networks can be utilized for various functions such as the system’s technical operating procedures, maintenance procedures, and recovery procedures. Assessing all tasks involved within a set of procedures allows for determining “bottle neck” points within a process in which delays or degrades the task network. Focusing on these efforts allow for potential resilience improvements within microgrid systems. Utilizing the Critical Path Method (CPM), the certain nodes and paths within a task network that dictate the progress of task completion can be identified for improvements.

Critical Path Method

The CPM is a scheduling method applied to a project task network to determine the path which represents the longest duration. In determining the critical path, the critical tasks and inter-dependencies are identified. By combining those tasks’ duration times, the shortest possible time to complete the project can be determined. This time is noteworthy for a project manager since it benchmarks times for project [5]. The critical path is also important for project managers to track in the case of issues or delays of tasks that may impact the critical path.

1.3.3 Microgrid Reliability Engineering

Reliability engineering is a facet of system design development that includes program planning, analyses and predictions, and test and evaluation [5]. Reliability engineering focuses on the Probability of Failure ($P(f)$) and/or Probability of Success ($P(s)$) tasks that determine the $P(f)$ and/or $P(s)$ of a system [5]. By researching and designing systems for reliability, one can potentially reduce the $P(f)$ and risk of a system. In result, maximum operational reliability of the system can be obtained [5].

1.4 Purpose of Microgrids

Microgrids have become a “flexible solution” for energy security concerns of modern electrical grids [6]. The U.S. Department of Energy (DOE) Microgrid Exchange Group defines microgrids as “a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid” [7]. Microgrids have provided necessary electrical power redundancy, energy cost savings, improved clean energy integration with renewable energy resources, and diverse options of electrical power supply to various rural and remote communities [6]. Hirsch, Parag, and Guerrero [6] explain how microgrids have provided improved resilience for energy systems and security by having the ability to rebound, or bounce back quickly from a problem. Resilience is a desired quality for microgrids to support DoD policy and objectives such as 10 U.S.C. § 2911(e) and 42 U.S.C. § 15852 to improve energy security [8].

1.4.1 Microgrid Description

As a System of Systems (SoS), a microgrid is a critical system within DoD energy infrastructures that is composed of various sub-systems and resources that work together to produce electrical power [5]. A simple microgrid architecture shown in Figure 1.2 provides four primary functions: 1) Generate power, 2) Distribute power, 3) Store energy, and 4) System control [8]. Figure 1.2 shows the communication and control, and the electrical network within the microgrid architecture as well as its connections to the local utility grid, various types distributed energy and resources, and various types of control units.

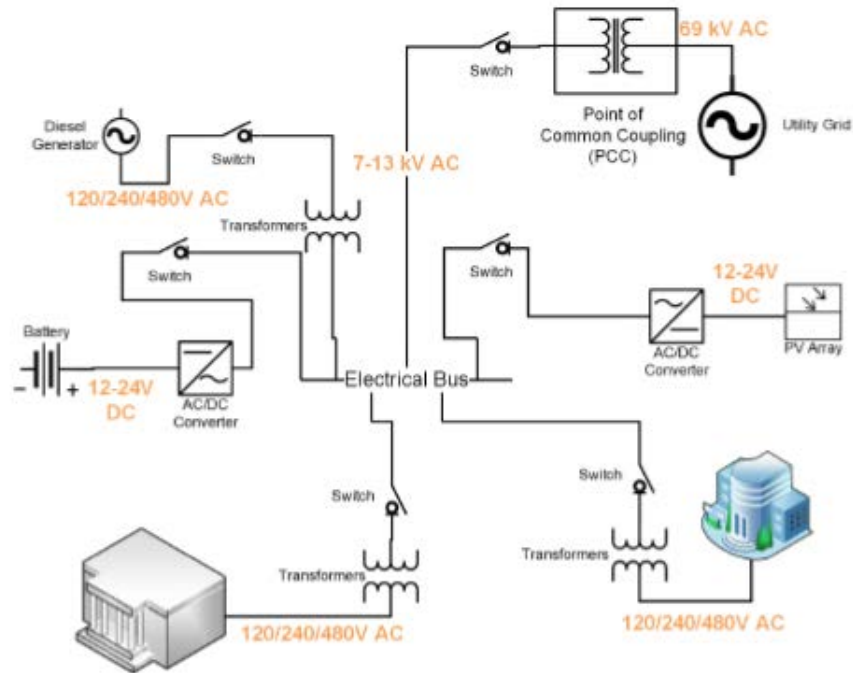


Figure 1.2. Simple Microgrid Architecture. Source: [8]

Microgrid operations rely on Distributed Energy Resources (DER) that are comprised of Distributed Generation (DG) resources and energy storage technologies [9]. Figure 1.3 describes the breakdown of DERs and the various types of DG resources and energy storage technologies that are involved in each.

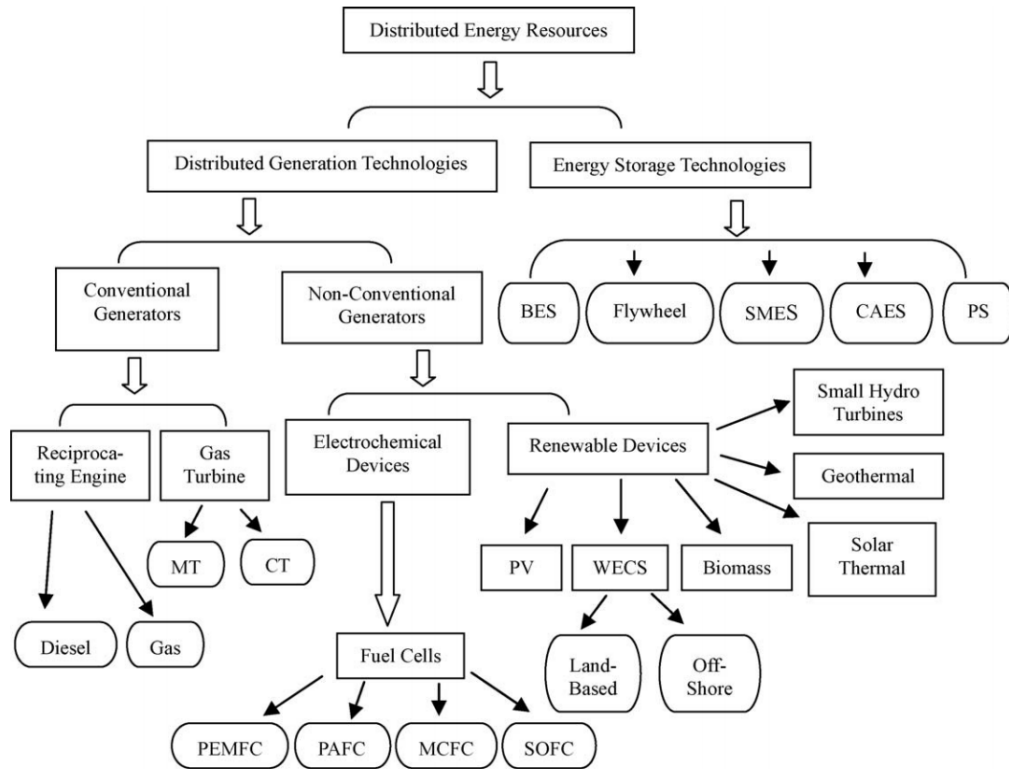


Figure 1.3. DER Resources to Include DG Resources and Energy Storage Technologies. Source: [9].

With the objective “to ensure better energy reliability, security, and efficiency” of installation power, microgrids provide two primary modes of operation: grid-connected and island mode [10]. Microgrids in grid-connected mode supports and works with the local utility grid to exchange power [11]. As the normal condition of microgrid operations, [11] describes that grid-connected mode provides energy management with the following three assets at their disposal:

1. DER controllers (DG and optional storage)
2. Load management
3. Control of the power exchange with the main grid.

Microgrids in island mode operate, control, and manage local generation of consumed energy with the ability to disconnect from the local utility grid [11]. When operating in

island mode, a microgrid must be capable of supporting its designed infrastructure of DG units, loads, and storage devices collectively [11]. Island mode operation allows for increased reliability of an installation's electric power system by integrating "different on-site sources with energy storage and load control" [11]. For critical installations that fall under entities like the DoD or healthcare systems, island mode operation provides back up system reliability so that continued power supply is maintained" [11].

Microgrids generate their own power by use of various types of DG resources. As shown in Figure 1.3, DG resources consists of conventional and non-conventional generation types. Conventional generation types such as diesel powered generators are a common means of back-up power that provides quick start up and power production. Conversely, diesel generators are inefficient, produce greenhouse gas emissions, and are costly [6], [11]. Non-conventional generation types such as photovoltaic Photovoltaic Cell (PV) generators and wind turbine generators support renewable energy initiatives that result in zero emissions and require no additional fuel costs [6]. While renewable energy sources provide many benefits, they are each dependent to their unique environments [6].

A microgrid's power distribution system is the means by which "energy [is transmitted] between generation sources, the grid, energy storage systems, and loads" [3]. Three primary distribution systems that microgrids utilize are direct current Direct Current (DC) lines, alternating current lines Alternating Current (AC), and high frequency AC lines [12]. In all three distribution systems, common elements such as distribution cabling exist. Underground power lines that are directly buried underground are one means of distributing power with all three systems. Overhead power lines and buses carry generated power between utility poles and a microgrid system as well [3]. Unlike underground cabling, overhead cabling remains exposed and vulnerable to damage or deterioration. Additionally, transformers and DC-AC converters are utilized within power distribution systems as a power conversion elements and connectors [3], [8]. Lastly, distribution systems require the use of switches to regulate the direction and load of power being transmitted between systems [13].

Microgrids are a desirable means of energy production and usage for the DoD because to their ability to store energy for emergency use, maintaining energy consistency, and allow for islanded operations among many more reasons. Microgrids are essential in supporting

certain facilities like those found in the military and medical installations [3]. The primary purpose of an Energy Storage Systems (ESS) is to balance the generated power from DG resources and its power demand [14]. Figure 1.3 shows the variation of energy storage options that can be utilized within a microgrid infrastructure to include: Battery Energy Storage, flywheels, Superconducting Magnetic Energy Storage (SMES), Compressed Air Energy storage (CAES), and Pumped Storage (PS) [9]. Microgrid systems use ESS for system stability by alleviating incidents of overvoltages and undervoltages due to power generation fluctuations from certain DG resources. These fluctuations occur because of different load demands such as various time demands such as working hours and non-working hours, as well as various environments such as cool nights and hot summer days [6], [8].

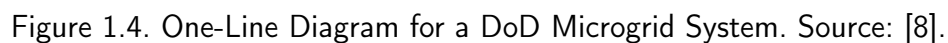
A microgrid controller monitors and controls all component functions within a microgrid architecture [10]. Microgrid controllers function with explicit commands and ensures power quality and reliability [6], [10]. As the overarching control system, microgrid controllers manage and command DG resources, stored power loads, and the power distribution system [6], [8]. The microgrid controller is capable of regulating the power flow and connection state between the entire system and any connection to an external utility power system [15]. Giachetti et. al. [3] explains how microgrids can be classified as one of three levels of authority: primary controls, secondary controls, and tertiary controls. Primary controls regulate available power with generators and storage systems by monitoring local voltage and current readings. Secondary controls coordinate microgrid generation and storage capabilities. Tertiary controls regulate the power that is distributed to and from the local utility power system [3]. Microgrid controllers are designed in either a centralized or decentralized control framework that can customize power delivery [16].

1.4.2 Microgrid System Description

This thesis leverages the system architecture and system model as used within Peterson's work [8]. The microgrid system architecture utilized in [8] represents a generic DoD installation microgrid infrastructure with following major components included:

- DG in the form of diesel generators and a PV array
- Energy Storage in the form of a chemical battery

- Figure 1.4 displays the one line diagram of Peterson’s microgrid architecture [8] that is also used in this thesis.



In an effort to build resilience within modern microgrid infrastructures, tested and proved recovery procedures can provide a quick and efficient means of restoring degraded systems back to normal operations. Similarly, the utilization of recovery actions can alleviate power

congestion that is placed on microgrids that require certain power loads to support critical equipment or facilities [6]. Van Bossuyt and O'Halloran point out that routine recovery procedures can “prevent incipient failure from causing a system-wide failure” [17].

While there are many advantages in utilizing recovery procedures for microgrid restoration, there are also many challenges that can occur. The implementation of recovery procedures are just as vital as the recovery actions being used. As discussed by Spranca, Minsk, and Baron [18], cognitive thinking factors such as omission and commission play a significant role in an operator's ability to successfully recover a system or further degrade it. Another challenge for implementing recovery procedures is the potential of emergence within the microgrid. It is important for facility managers to be cognizant of their microgrid infrastructures and the recovery procedures to be used so that when implemented, little to no further disruptions arise within the system or connected systems when being restored. Woods [4] also explains that the recovery, or rebound, of a system involves the “process of adapting to disruptions” over time since a system does not become stagnant when disrupted. With that in mind, systems must learn from past lessons to adapt to new challenges or disruptions. Additionally, it is important to remember that while the primary goal is to preserve the microgrid system when disturbed, the process of adapting to other disturbances continues to transform for both the system and the environment over time [4]. Woods provides this thought not just for rebound of a system, or even recovery procedures specifically, but also to emphasize that resilience thinking is continuous and must consider “systems, linkages, thresholds, and cycles...and [what drives them]” over time [14].

1.6 Threats to DoD Energy Security

For DoD installations, various types of energy threats and attacks have potential to degrade military readiness and effectiveness. In order to combat this, the DoD must anticipate possible threats to energy security and plan for rapid response and recovery in order to maintain mission readiness. The DoD has set its chief priority “to ensure mission readiness of the armed forces by pursuing energy security and resilience” [2]. Energy security threats for the DoD can be in the form of hostile attacks, natural disasters, and technical energy system failures. For the United States (U.S.) Marine Corps (USMC), the maximum autonomy time for installation energy systems is 14 days so minimal impact is taken on critical mission areas [19]. For U.S. Navy (USN), the maximum autonomy time is seven days [20].

Microgrids on DoD installations have become targets for various types of hostile attacks. Intentional physical attacks, such as terrorist attacks, can pose a significant threat to DoD energy security by degrading critical power infrastructures such as telecommunication sites that are essential for mission readiness [21]. Additionally, cyber-attacks can pose a significant threat to DoD energy systems by degrading a system's network and control capabilities [21]. External and internal cyber-threats, such as denial of service attacks, can disrupt normal operational services within DoD networks [21]. The DOE has found that major attacks or incidents of these kind can create significant DoD issues such as loss of personal identification information, critical performance data, or lack of support services to name a few [21].

Natural disasters and severe weather, such as hurricanes, are another type of energy security threat that can cause similar damage to the physical infrastructure of DoD installation microgrids and local utility grids. High winds and strong weather that result from hurricanes or blizzards can damage essential energy support infrastructure such as power lines and distribution centers. As the primary cause of grid disruptions, severe weather can cause regional grids to be either degraded or limited in their operations, resulting in short to long term power outages [21]. Power outages due to severe weather can pose significant operational threats to DoD installations. Restoration planning for both the installation's microgrid infrastructure and its local utility connections must be considered together since the both systems work together.

Energy infrastructures for DoD installations are also susceptible to degradation of their own energy backup sources, such as microgrids for local utility power. Most if not all energy systems on DoD installations receive primary power from local utility grids and rely on them to maintain normal energy operations. Local utility grids are dependent on the availability and reliability of their own infrastructures and sub-systems within them. Similarly, the DOE acknowledges that DoD energy systems, such as microgrids, are subject to the same security and resilience vulnerabilities in terms of reliability and availability of their systems and sub-systems [21]. The DoD must ensure that their microgrid infrastructure designs are capable of supporting the electrical loads required of them. Microgrids need to be well designed in all aspects of system suitability, to include reliability and availability, to name a few. Regardless of local utility power availability, if sufficient design parameters aren't built within a microgrid system or its components, the microgrid itself can lose its

operability to create, distribute, or store power [22].

1.7 Chapter Summary

This chapter has discussed the background and need for improving energy resilience of DoD installation microgrids. Specifically, this chapter presents the thesis question as to whether human factors impact the rebound, or recovery time, of degraded microgrids. The follow-on chapters analyze the effect of a HRA on microgrid recovery procedures and system recovery time. Chapter 2 includes a literature review of microgrid resilience work, recovery procedures, and human factors. Chapter 3 introduces the HPIRA tool developed with an 11 step methodology process. Chapter 4 applies the HPIRA tool to various microgrid recovery processes to analyze the effect of human factors on recovery time. Chapter 5 concludes this thesis with a summary of findings, recommendations, and propositions for future and follow on work.

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CHAPTER 2:

Literature Review

This chapter presents a literature review of previously conducted research work on microgrid resilience and its role within energy security. Within this chapter, each subsection will analyze different research topics, including resilience theory, recovery modeling, and human reliability models for including human factors in recovery processes. This literature review identifies and presents gaps within current research and reveals additional research questions on each topic. Each topic is evaluated for context, purpose, and added value of potential research work to improving microgrid resilience research. Synthesized together, the literature review provides a clear understanding and identification of research gaps within previously published works.

2.1 Definition of Resilience

Resilience has various definitions within literature. Depending on the purpose of the definition, one definition of resilience may differ considerably from another. For instance, the American Society of Mechanical Engineers American Society of Mechanical Engineers (ASME) considers resilience from an engineering perspective. The ASME defines resilience as “the rapid return to full function after those events that occur” [23]. Resilience in a psychology perspective is defined as “good, stable, and consistent adaption [of individual behaviors] under challenging conditions” [24]. Due to the differences of resilience definitions, it is important to choose the best fitted definition for a specific research application so that the research is properly conducted to achieve a useful outcome.

U.S. Government agencies and organizations define resilience differently from their civilian and commercial counterparts, primarily because of the nature of government work and services. For instance, DoD installations fall under the resilience definitions found in the Department of Defense Instruction (DoDI) 4170.11, 10 U.S. Code § 101(e)(6) and 10 U.S. Code § 101(e)(8). DoDI defines energy resilience as “the ability to prepare for and recover from energy disruptions that impact mission assurance on military installations” [25]. Specific to military installations, 10 U.S. Code § 101(e)(8) defines military installation resilience as “the ability to avoid, prepare for, minimize the effect of, adapt

to, and recover from anticipated and unanticipated changes” [26]. While these instructions provide strategic guidance to energy security on DoD installations, they lack the detailed focus on energy resilience. Establishing energy resilience will ensure that DoD installations are capable of preparing and recovering from local utility power interruptions to support mission assurance and installation energy security [8]. While the DoD provides overarching guidance and requirements, individual military services and federal departments establish specific instructions for their respective services or departments to follow [8]. Following DoD guidance, the USN seeks to improve energy security by means of improving resilience, reliability and efficiency with a required maximum autonomy metric of seven days [20], [27].

Over time, various definitions of resilience have developed across various domains. While there are many domains for resilience, four particular domains are considered in a research perspective: Organizational, Social, Economic, and Engineering [28]. Determining the definition of resilience in an engineering domain best suits the goal for this thesis. Unlike other domains, the engineering domain involves technical systems, human interaction, and technology [28]. Engineering resilience has been defined as a system’s “ability to anticipate and adapt from a surprise or failure” [29]. Similarly, engineering resilience is also described as knowing the normal functionality of a technical system so that if it fails, one will understand how it fails [28], [30].

While various definitions of resilience exists, Woods’ [4] categorization of four resilience concepts best defines this work’s research on microgrid resilience. Rather than defining resilience in terms of variables or as one general concept, Woods defines resilience as four concepts that each contribute to the entirety of resilience: Robustness, Rebound, Extensibility, and Sustained Adaptability [4]. By assessing resilience within these four concepts, progress and projection can be assessed within each category in order to build resilience within systems and networks [4]. For this work, focus on the concept of rebound guides the research to query “what is needed in advance of a challenge event...and how systems continue to change as they adapt, as well as how systems provoke changes through adaptation” [4]. Unlike previous definitions of resilience that focuses on reactive actions to a degraded system, Woods’ definition forces the thought of what is required of a system prior to a disruptive event, and from there, how can one best prepare for that event to minimize the disruption. For the purpose of this research, predetermined recovery procedures will be

assessed prior to a microgrid system recovery in order to evaluate the effectiveness in its contribution towards the system's "rebound."

2.2 System Recovery Procedures

Resilience, along with reliability and efficiency, are the DoN's primary objectives for energy security in order to ensure mission readiness [1]. With constant technological innovation for military weapons and base supplies and services, the DoD is becoming more reliant on installation energy support. For those reasons, it is imperative that DoD installations adapt to become as resilient, reliable, and efficient in their energy production and sustainment. While there has been research conducted on improving resilience within microgrid systems from different approaches, none specifically have focused on operator recovery procedures. For instance, Peterson's work assess the Expected Life Cycle Mission Impact (ELMI) metric in design considerations to improve of DoD microgrid resilience [8]. Hildebrand's work assesses cost estimation of DoD microgrid resilience based off of microgrid design and sustainment utilization [31]. Most resilience research has analyzed microgrid system designs and specifications as well as impacts from other factors such as life cycle costs, system redundancy, and maintenance management. Like most design efforts, improvements and modifications to microgrid systems are developed as a result of failures to improve system operability.

For most military operational systems, pre-planned responses or casualty control actions have been established in an attempt to minimize degradation and damage of a system. Additionally, those responses and actions reduce the time that the system is out of commission to improve the rebound of that system. Following Woods [4] and Hollnagel's [30] definition of resilience, proactive actions should be considered prior to disruptive events in order to improve the rebound of a system. By implementing this concept, research can focus more on increasing the number of things that can go right rather than trying to reduce the number of things that go wrong [30]. The concept of being proactive rather than reactive in improving system resilience allows for the stakeholders of the system to anticipate possible failures and develop and actions to prevent them. This thesis will simulate various sets of recovery procedures for degraded microgrids to identify factors that improve rebound or the factors that inhibit it.

The concept of being proactive rather than reactive in building resilience prepares system operators, maintainers, and managers to mitigate potential degradation issues of microgrid systems. In many cases, established recovery procedures have been created and implemented on DoD installations to improve the rebound of a microgrid system by focusing on reducing recovery time. For instance, at the United States Marine Corps (USMC) Air Ground Combat Center Twentynine Palms, attempts have been made to improve microgrid system recovery times by use of recovery procedures [32]. Similarly, the USN utilizes established Engineering Operational Casualty Control procedures for specific equipment in recovery efforts on naval vessels and shore installations. The private sector follows similar efforts to decrease recovery times based on recovery operations from experienced linemen and cablemen. References such as The Lineman's and Cableman's Field Manual [33] provide general operating and recovery guidance for microgrid system components. Even for Naval Facilities Engineering Command (NAVFAC), various sets of recovery procedures are required to properly reestablish normal conditions for a degraded system [32]. Since degradation can be a result of multiple factors, various sets of recovery procedures need to be assessed to best restore degraded microgrids. Factors such as varying weather conditions, critical load requirements, and modifications of recovery procedures need to be considered.

Many assume that implementing standardized recovery procedures will guarantee improved rebound and resilience of microgrid systems. That assumption, however, is not necessarily always true. In this thesis, the argument is raised that no, recovery actions do not ensure improved resilience of microgrid system and can potentially further degrade the system. The primary factor in testing this hypothesis will be assessing human reliability, in the form of human error, within the recovery procedures used for recovering a degraded microgrid. With a HRA applied to recovery procedures, a reliability analysis will be conducted to see at what recovery time durations do recovery procedures become more beneficial or more harmful to a recovery process.

2.3 Human Reliability Analysis

When implementing any kind of pre-planned responses such as recovery procedures to restore microgrid systems, the effectiveness of those responses depend the human reliability of the actions or tasks being taken to restore a systems. The underlying assumption is that

recovery actions improve a system's ability to recover. However, when considering the human factor, that assumption is not always the case because human beings are not perfect and make mistakes. What needs to be considered in a recovery process is if the mistakes or actions being completed are by omission or commission. When evaluating a scenario to determine if recovery procedures improve certain metrics like recovery time and speed, understanding human reliability can potentially improve those recovery metrics or further degrade them.

Human cognition is how a person gains and uses knowledge to participate in reasoning and remembering [34]. Since human cognition is primarily a psychological topic, is not always considered within engineering research. To evaluate the effectiveness of recovery procedures, an operator's human cognition must be considered in addition to the recovery tasks themselves because they both contribute to the overall success of the recovery task. From the perspective of a microgrid operator tasked with repairing a part of the system, omission and commission must be considered as contributors to human error since both can potentially limit or worsen the restoration of a system. Acts of omission "may result from ignorance" and acts of commission may "involve more malicious motives and intentions," therefore, each recovery task carries a risk of complications that can result from human error [18]. What is unknown is how much human error can be anticipated in affecting a task so much that it fails, which could result in limitations or further delay in recovering a system. For complex recovery procedures, human operators will always have some degree of omission and commission in their thought process or actions that can very well influence their performance on a task. Those influenced tasks can result in a faster or slower system recovery, or it could also cause additional failures within the system.

In every decision and action a person takes, human error can occur. One way to measure human error is to conduct a HRA. Human reliability is a challenge to assess because human factors are not predictable and are difficult to improve [35]. Events such as the 2011 Southwest Blackout is an example of one of the United States' largest power failures. The outage was a result of human error that created multiple cascading failures [36]. Various analysis methods were used to find the root cause failure but ultimately it became prudent for investigators to conduct HRAs. For a HRA, many forms of analysis methods exist. The Technique for Human Error Rate Prediction (THERP) method was initially utilized for the U.S Nuclear Regulatory Commission [37]. While the THERP method provides an

effective means of determining human reliability, it is known to require in depth training and experience for it to be correctly implemented. A similar method, the Accident Sequence Evaluation Program Human Reliability Analysis Procedure (ASEP) [37], provides results that are similar in quality and effectiveness as THERP, but in a simpler and more efficient to complete [37]. The Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H) method [37] was derived from both THERP and ASEP methods to create a simple and generalized method for determine HEP [38]. While all methods are effective in determining human reliability and error, each of the methods' applications and purposes serve different needs and consider different constraints. As shown in [35], SPAR-H is an appropriate and effective method for a power grid environment HRA because of its simplicity and consideration of multiple performance factors. For the same reasons and desired goals, the SPAR-H method will be utilized for this thesis' HRA analysis.

2.3.1 SPAR-H

As a simple and proven method, SPAR-H has become a common HRA approach in determining human reliability for various systems in different scenarios. For the SPAR-H method, each task, or Human Failure Event (HFE), is categorized as a Diagnosis and/or Action event. Each diagnosis/action HFE is then rated by the following eight performance shaping factors Performance Shaping Factor (PSF):

1. Available Time: Level of Amount of time relative to the time that is available for the HFE being assessed
2. Stress/Stressors: Level of undesirable conditions in completing the HFE being assessed
3. Complexity: Level of evaluating performance challenges an HFE being assessed, to include both the HFE and its operating environment
4. Experience/Training: Level of operator experience and/or training of the HFE being assessed
5. Procedures: Level of available operating procedures for the HFE being assessed
6. Ergonomics/Human-Machine Interference: Level of adequacy of human-machine interfaces of the HFE being assessed
7. Fitness for Duty: Level of the HFE operator's physical and mental conditions in conducting the HFE being assessed.

8. Work Processes: Level of management support and policies that are used for the HFE being assessed [39].

Each PSF is assessed individually and separately on how they impact an individual HFE. What is unique to SPAR-H over other HRA methods is that the eight PSFs can result in either positive or negative effects on performance [39]. Evaluating each PSF in this way ultimately determines the final Human Error Probability (HEP) that represents the given HFE. In Figure 2.1, HEP is represented as an output function of a single PSF input variable. The relationship shows that better performance of a PSF results in a lower HEP value, or lower $P(f)$, of an HFE. In the opposite case, having more error involved with the PSF being assessed results in a larger HEP, or greater $P(f)$, value.

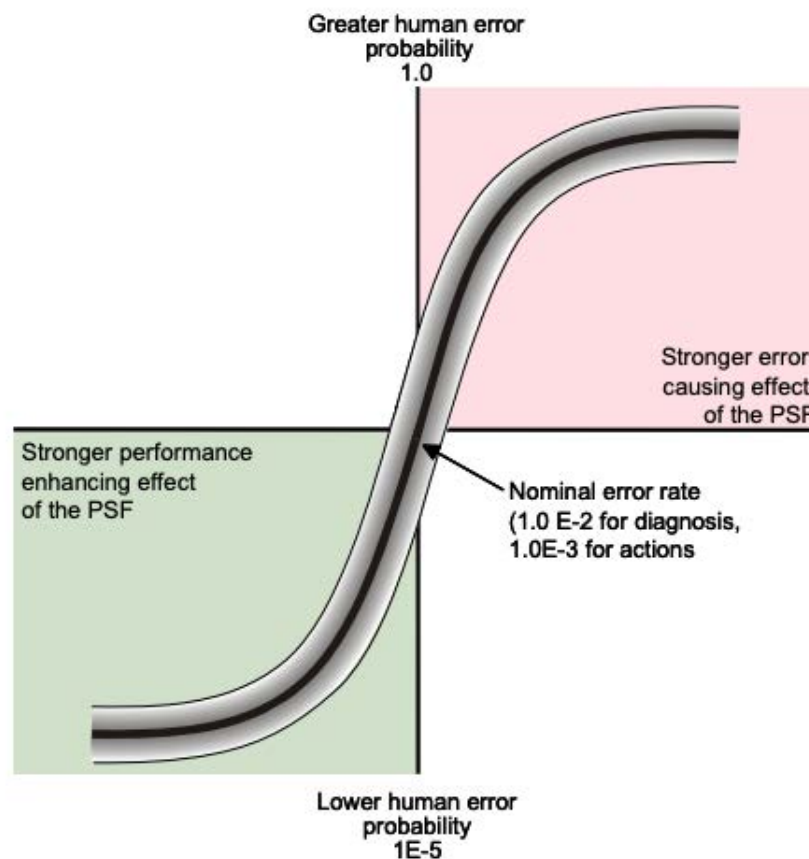


Figure 2.1. HEP as a Function of a PSF Variable. Source: [39].

In [37], SPAR-H worksheets are included to guide the PSF ratings for At-Power conditions. The worksheets walk a user through the PSF ratings to calculate each HFE's HEP, or $P(f)$. For the purpose of this thesis, At-Power conditions will be used because they provide a more conservative approach that is designed for conditions in which emergency operating procedures are utilized [37].

2.4 Chapter Summary

This chapter provided a review of literature that relates to the thesis question and the implemented research. Focus was placed on previously conducted microgrid resilience work, recovery procedures, and human factors. Chapter 3 introduces the HPIRA tool used to assess the impact of human factors on microgrid recovery times.

CHAPTER 3:

Research Method

This chapter presents the research methodology to assess the effect of human factors on microgrid recovery procedures and system resilience. The methodology developed herein involves 11 steps that lead to the development of the HPIRA tool. The logic and need for each step is detailed and explained below. This methodology will be applied in Chapter 4 to measure the effect human error has on the recovery time of microgrid infrastructure and a representative Naval Station (NAVSTA) microgrid system.

3.1 Methodology Description

This section describes the research methodology used in this thesis. The methods presented here were developed through an iterative process that evaluated the effectiveness and purpose of each step to answer the thesis question. The methodology includes existing tools and data inputs from [8] to include resource data, microgrid system architecture, and microgrid system simulation programming. The 11 step HPIRA process are as follows:

1. Define Microgrid Component of Interest
2. Determine Recovery Procedure for Microgrid Component of Interest
3. Perform Stakeholder Analysis
4. Create the Precedence Order of the Recovery Task List
5. Apply SPAR-H and Determine HEP values for all Tasks
6. Choose the Appropriate Probability Distribution for Duration Sampling
7. Find Individual Task Duration based on chosen Probability Distribution
8. Find All Possible Task Network Paths and Duration
9. Determine Critical Path and Duration of Task Network
10. Simulate and Analyze Component Recovery Duration
11. Conduct and Analyze a Back of the Envelope (BOE) Total Duration Calculation for a Multi-Component Failure Events

3.1.1 Step 1: Define Microgrid Component of Interest

In this step, the microgrid component failure scenario needs to be chosen and defined. Each scenario needs to include the following:

1. Description of scenario background
2. Definition of the microgrid architecture
3. Statement of assumptions

Describe the scenario background to include environmental conditions that can affect microgrid operations. For instance, note extreme weather conditions and/or extreme load demands. Define the microgrid architecture so that all possible components can be assessed as a cause of failure to be analyzed. Additionally, determine the microgrid system's operating mode so it can be established as the recovery benchmark. State all assumptions within the scenario environment, microgrid system operation, and microgrid system design. Include the complexity of the microgrid system as well as the available support services. By clarifying these scenario details, simulation results can be analyzed for true and meaningful conclusions for stakeholder interests. Finally, for DoD installation microgrids, ensure that all details remain within Distribution A classification.

Example: Microgrid Component of Interest

Assume a single microgrid component degrades a microgrid in island mode. Choose a microgrid component to be assessed as the degraded component of interest.

3.1.2 Step 2: Determine the Recovery Task List for the Microgrid Component of Interest

When Step #1 is complete, determine the system recovery procedure tasks list based on the root cause of failure within the microgrid infrastructure. Utilizing procedure guidance such as "The Lineman's and Cableman's Field Manual" [33] and/or referring to subject matter experts such as facility utility managers and facility engineers, create a task list in order of sequential completion. Additionally, note the minimum, median, and maximum duration time estimations for each task completion. Next, note which tasks are predecessors of other tasks.

Example: Recovery Task List

The recovery procedure set, or task list, that will be evaluated is found in Table 3.1. All tasks will be named sequentially from Task “A” to Task “F.”

Table 3.1. Example Recovery Procedure Task List and Durations (hr)

Recovery Task	Min	Max	Mean	Follow On Task
Task A	0.50	1.00	1.50	B,D,E
Task B	2.50	3.00	3.50	C
Task C	0.50	1.00	1.50	F
Task D	3.00	5.00	7.00	F
Task E	3.50	4.00	4.50	F

3.1.3 Step 3: Perform a Stakeholder Analysis

To determine the recovery team members, or those who will be participating in the task list recovery procedures, create a stakeholder analysis matrix. List all individuals or services that participate in operating, supervising, and supporting DoD microgrid systems. Additionally, include the stakeholders’ specific interests and estimated impact level.

Example: Stakeholder Analysis

Consider a recovery team manager that needs to restore the microgrid system with three team members. The members will complete the five tasks presented in Table 3.1 to successfully restore the system. The assumptions for the scenario are: 1) Team members are fully trained and capable of completing tasks, 2) Team members are fully supported and equipped to complete tasks, and 3) Environmental conditions are ideal for efficient task completion.

A stakeholder analysis of the given scenario is shown in Table 3.2. Refer to this stakeholder analysis to identify recovery team members and additional stakeholders.

Table 3.2. Example System Stakeholder Analysis

Stakeholders	Interest	Est. Impact
Manager	Supervisor of operating team	High
Senior Team Member	Lead team member in operation	High
Team Member	Team member in operation	High
Supply Team	Provides resource support	Medium

3.1.4 Step 4: Create the Precedence Order of the Recovery Task List

Referring to the recovery task list as generated in Step #2 and with consideration of the recovery team, walk through the generated task list and determine which tasks show dependency of completion on others. Document this dependency as a precedence list showing how the completion of one node initiates another. Specify this precedence with “From” and “To” nodes until the last node. The starting node will be the initial task and the final node will be the recovered task.

Example: Precedence List

Follow each recovery member and task completion dependency to determine the precedence order of each node task. Table 3.3 summarizes the precedence order.

Table 3.3. Example System Precedence List

From	To	Avg. Duration (hr)
A	B	1.00
B	C	4.00
A	D	1.00
A	E	1.00
C	F	1.00
D	F	3.00
E	F	4.00

3.1.5 Step 5: Apply SPAR-H and Determine HEP Values for all Tasks

The next step is to evaluate the effect of human cognition on the successful completion of each recovery task, or HFE. Human cognition can be attributed to two thought processes: Omission and Commission. For the purpose of this work, actions/tasks/events will be of omission because it will be assumed that any error that takes place is not intentional. To determine the human error by omission, apply the five-step SPAR-H analysis to each task. The result of the SPAR-H analysis for each task is the HEP value for each task. The HEP value represents the $P(f)$ of that task given the impact of human error. Refer to [37] for the SPAR-H worksheets and follow guidance as described. For the purpose of this work, the At-Power worksheets will be utilized for a more conservative analysis. The five-step process of the SPAR-H worksheets is as follows:

1. Categorize the task being assessed as “Diagnosis” and/or “Action”
2. Rate each PSF for the task being assessed
3. Calculate the PSF-Modified HEP for the task being assessed if applicable
4. Account for dependence of the task being assessed
5. For all completed tasks, calculate the the final HEP based on dependence between tasks

Apply the first four steps of SPAR-H analysis to each task within the network task list.

Once all tasks analyses are complete, follow step #5 and calculate the total network HEP as instructed in the SPAR-H worksheets.

Example: HEP Calculation for Task A

Conduct a SPAR-H analysis on Task A. Follow the SPAR-H analysis guide in [37] for At-Power conditions. First, Task A will be categorized and evaluated as a Diagnosis task and an Action task to determine its HEP. Eight PSFs will then be rated for both the Diagnosis HEP and Action HEP calculations with respect to Task A. Tables 3.4, 3.5, and 3.6 show the chosen ratings and associated multipliers for each rated PSF and task dependency.

Table 3.4. Example Diagnosis PSF Ratings for Task A

PSF	Level	Multiplier
Available Time	Nominal	1
Stressors	Nominal	1
Complexity	Nominal	1
Experience	High	0.5
Procedures	Nominal	1
Ergonomics/HMI	Nominal	1
Fitness for Duty	Nominal	1
Work Processes	Good	0.5

Table 3.5. Example Action PSF Ratings for Task A

PSF	Level	Multiplier
Available Time	Nominal	1
Stressors	High	2
Complexity	Nominal	1
Experience	High	0.5
Procedures	Nominal	1
Ergonomics/HMI	Nominal	1
Fitness for Duty	Nominal	1
Work Processes	Good	0.5

Table 3.6. Example Task Dependency Rating for Task A

Dependency on Previous Task	Final P(f)
Zero	$P(f) = \text{HEP}$

Follow the calculation in the SPAR-H worksheets to include Diagnosis HEP, Action HEP, and dependency categorization to determine the final HEP value for Task A. All final HEP values for all five tasks are summarized in Table 3.7.

Table 3.7. Example HEP Values for all Tasks

Task	Final HEP
Task A	0.02
Task B	0.51
Task C	0.07
Task D	0.06
Task E	0.53

3.1.6 Step 6: Choose the Appropriate Probability Distribution for Duration Sampling

Review all possible types of probability distributions and choose the most appropriate distribution for the work being assessed. For the purpose of this work, a continuous variable (duration) will be monitored as well as its minimum/mean/maximum parameter values. The probability distribution will determine stochastic duration times to be utilized in individual task duration calculations. In [40], the following recommendations and descriptions of failure analysis probability distributions are:

- Weibull Distribution
- Normal Distribution
- Lognormal Distribution
- Exponential Distribution

Example: Probability Distribution

Each tasks' duration time will initially be based on mean duration values. Additionally, the duration time will be depend on the SPAR-H analysis to determine if the task has a higher $P(f)$ or $P(s)$ of completion. For evaluating a randomly generated or stochastic duration values, an exponential probability distribution would best suit the $P(f)$ analysis [40].

3.1.7 Step 7: Find the Individual Stochastic Task Durations based on chosen Probability Distribution

First, generate a random number based on the probability distribution chosen in Step #6 for the task being completed. Use the mean duration time from Table 3.1 as the mean parameter.

Next, generate two probability distributions representing $P(f)$ and $P(s)$ of each task being completed. Use Table 3.1's minimum and maximum duration values as the mean parameter values for the $P(f)$ and $P(s)$ distributions. The $P(f)$ distribution will use the mean low, or minimum duration value, as the mean input parameter. The $P(s)$ distribution will use the mean high, or maximum duration value, as the mean input parameter.

Compare the task's generated random number against its HEP value found in Step #5. When the generated random number is greater than the HEP value, apply the $P(f)$ distribution to find the task's sample duration. When the generated random number is less than the HEP value, apply the $P(s)$ distribution.

Apply this process to each task in Table 3.1 to generate new sample duration values for each task.

Example: Task A Duration Sample

Based on an exponential probability distribution and values from Table 3.7, calculate each task's sample duration. Table 3.8 summarizes a sample duration value set for each task or node.

Table 3.8. Example: Probabilistic Sample Duration for each Task

Recovery Task	Sample Duration (hr)
Task A	0.33
Task B	1.30
Task C	0.18
Task D	0.97
Task E	4.35

3.1.8 Step 8: Find All Possible Task Network Paths and Duration

Create a network diagram that represents the task network in the precedence order as determined in Step #4. To do this, refer to each task as a named node in sequential order. Graphically demonstrate the precedence order with the named nodes and directional arrows. Next, map out all possible network paths from beginning task to the end task. Record all possible tasks that can be completed.

Example: Network Diagram with All Possible Paths

Referring to Step #4, create a network diagram using the network tasks. Starting with Task “A,” three possible recovery paths can be taken to the final node, Task “F.” Figure 3.1 shows the task network where three possible network paths exist: 1) ABCDF, 2) ADF, 3) AEF.

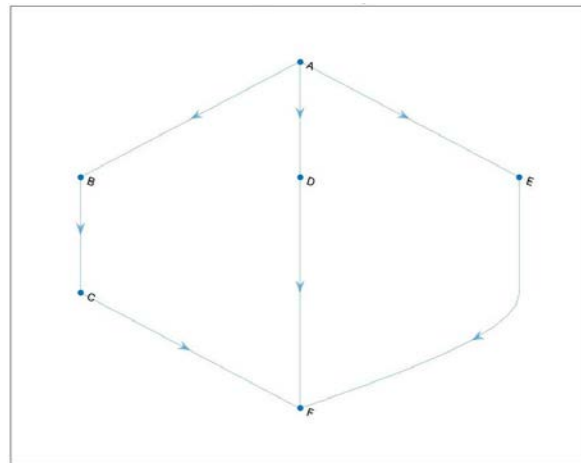


Figure 3.1. Recovery Procedure Task Network Diagram

For each possible path, calculate the total duration sum of all nodes within the path to determine the path duration. Remember to use the stochastic sample duration values from Step #7. To do this, refer to Table 3.8 and sum the duration values for the corresponding nodes within the path name. For example, for path "ABCF," the duration calculation is

$$Duration_{ABCF} = Weight_{AtoB} + Weight_{BtoC} + Weight_{CtoF}.$$

Table 3.9 shows all possible paths and their duration within the network. Note that the duration values for each path are a summation of stochastic results for each task or node.

Table 3.9. Task Network Paths and Duration

Paths	Duration (hr)
ABCF	1.81
ADF	1.29
AEF	4.68

3.1.9 Step 9: Determine Critical Path and Duration of Task Network

Apply the CPM to identify the longest duration path from Step #7. The path with the longest duration represents the critical path, that when completed, assures that all other tasks have been completed as well. The critical path also identifies which tasks need to be completed and monitored for successful recovery completion.

Example: Critical Path and Total Duration

Refer back to Table 3.9 and identify the path with the longest duration. The recovery network's critical path is AEF with a duration of 4.68 hours.

3.1.10 Step 10: Simulate and Analyze Component Recovery Results

Apply Steps #1-9 to determine the critical path and duration of a given microgrid recovery task network. Apply a Monte Carlo Simulation of no less than 10,000 iterations so that stronger and more meaningful results can be analyzed. By applying multiple iterations to this simulation, duration samples can be randomly chosen to best predict the success of each task, path, and ultimately, critical path of a network being assessed. Create the following plots for further analysis and conclusions in Step #11.

Plot #1: PDF for the Modeled Recovery Scenario

Create a histogram plot that shows the occurrence frequency of all 10,000 scenarios against the continuous variable, recovery time, to produce a Probability Density Function (PDF). Determine the bin that represents the highest frequency grouping and its associated recovery time range. Figure 3.2 shows the desired PDF with the red highlight representing the most common recovery time.

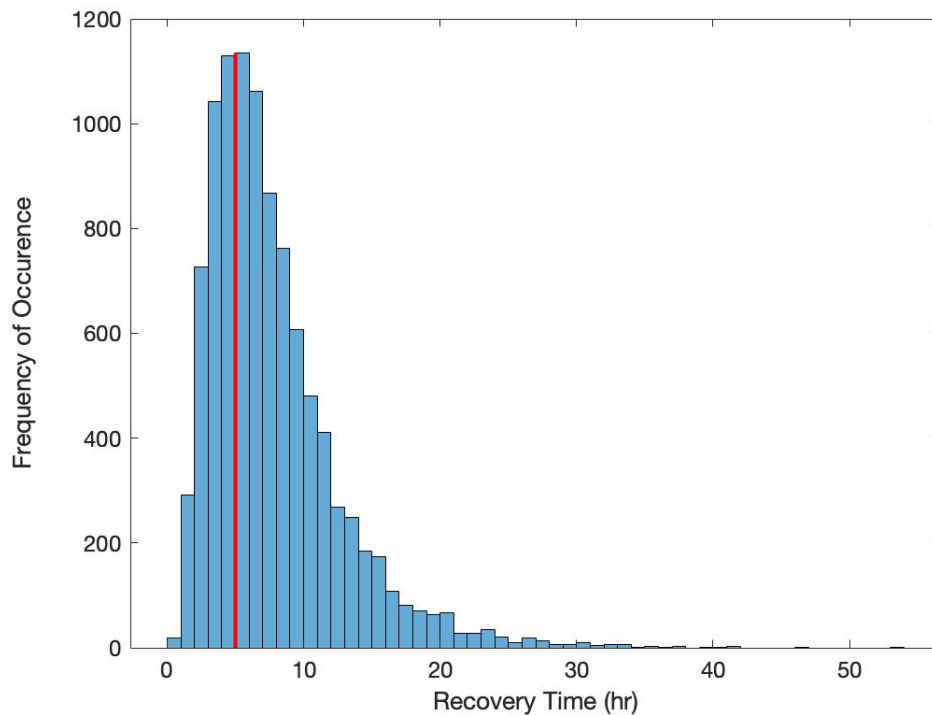


Figure 3.2. PDF for Modeled Recovery Scenario

Plot #2: All Possible Recovery Paths and Durations for 10,000 Iterations

Create a line plot that presents the relationship of each path and its duration over all iterations. Set the input variable as each possible recovery path. Set the output variable to be each path's duration. Connect all data points in a line to represent each of the 10,000 iterations. Determine the most common, longest duration, path of all scenarios. Do this by rounding each scenario's longest recovery time up to the nearest integer. Then find the most common recovery time and the path that associates with it to determine the critical path. Figure 3.3

displays all possible recovery paths and their durations over each of the 10,000 iterations. This plot allows for the observation of shorter and longer recovery time points or ranges that correlate to specific recovery paths. Paths that are of longer durations, or are shown as greater recovery time points, will likely be critical paths for the recovery task network.

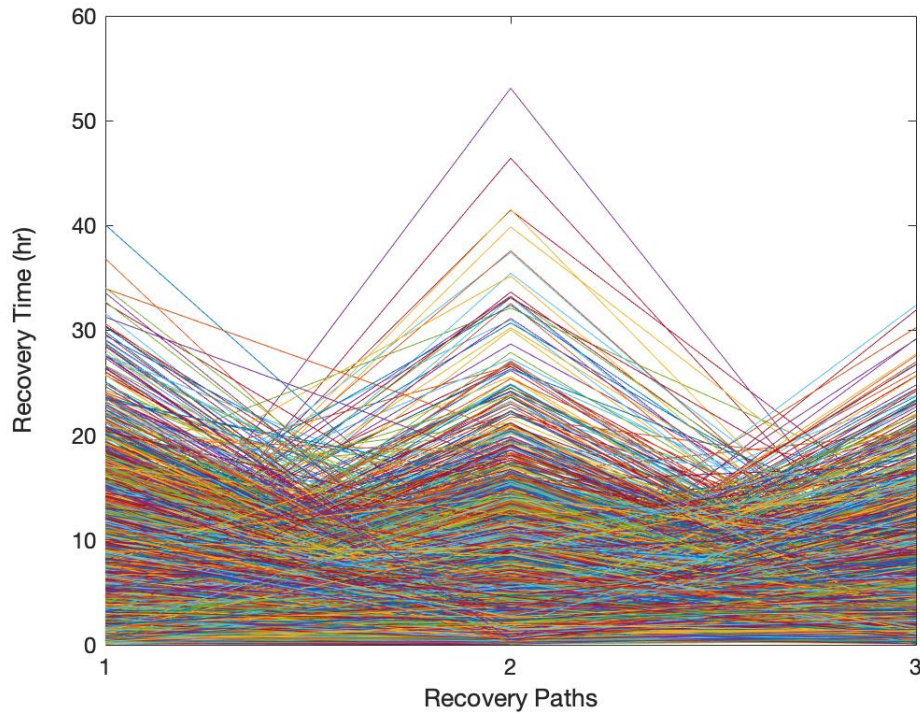


Figure 3.3. Duration Required to Recover a Component for 10,000 Modeled Scenarios

Plot #3: PDF for Component Recovery's Critical Path

Based off of the critical path determined in Plot #2, find the path duration for that path amongst all 10,000 scenarios. Create a histogram plot that shows the occurrence frequency of all 10,000 scenarios against the determined critical path recovery time to produce a PDF. Determine the bin that represents the highest frequency grouping and its associated recovery time range. Figure 3.2 shows the desired PDF with the red highlight representing the most common recovery time.

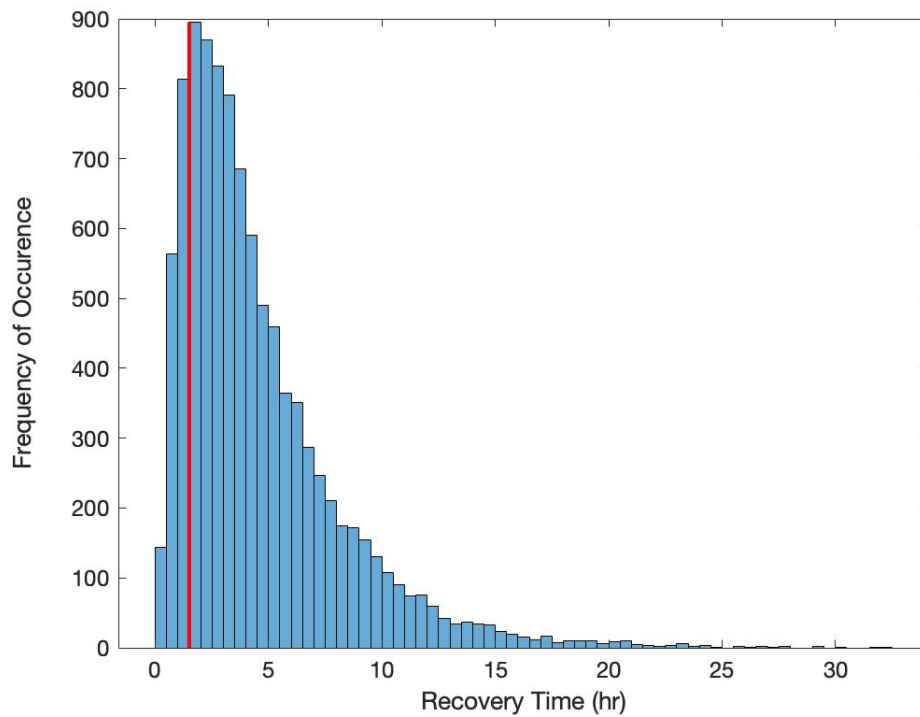


Figure 3.4. PDF for Component Recovery Critical Path

Assess Plot #1 and Plot #3 with Figure 3.5 to understand the distribution relationship between paths and durations. Figure 3.5 is a PDF of a component's reliability over time with the red highlight representing the most common recovery time. As recovery time increases, the $P(f)$ increases while the $P(s)$ decreases. Consider possible factors or reasons that may attribute Plot #1 and Plot #3's relationships to include SPAR-H PSFs.

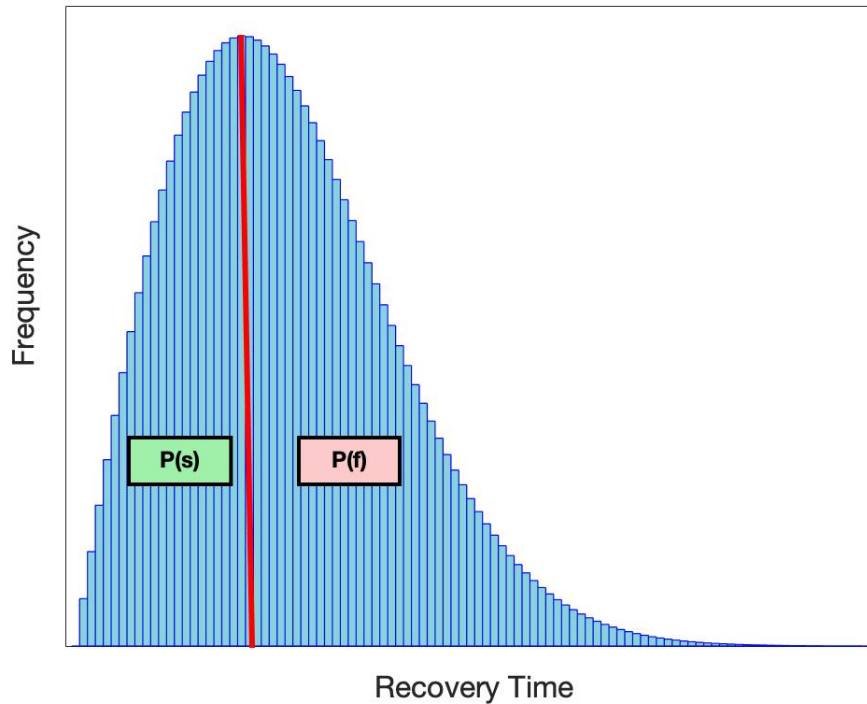


Figure 3.5. PDF of Component Reliability over Recovery Time

3.1.11 Step 11: Conduct and Analyze a BOE Total Duration Calculation for a Multi-Component Failure Event

Select microgrid component(s) to be assessed within a total microgrid restoration event. Develop a BOE calculation for the total microgrid system recovery duration. The calculation should summate individual component duration times for how ever many components are chosen to be degraded or failed. The individual duration times should correlate to the component's iterated duration values from Step #10. Analyze total system recovery time and what factors led to it.

This methodology establishes the HPIRA tool that determines recovery times for the most successful critical recovery paths within a recovery process task network. The HPIRA tool will be applied to six microgrid component recovery efforts in Chapter 4. Resulting recovery times will be considered man-hours needed for a successful microgrid recovery effort.

3.2 Chapter Summary

This chapter described the 11-step methodology process to determine if human factors impact the rebound, or recovery time, of a degraded microgrid. Within the methodology process, the HPIRA tool was developed to assess the recovery of various microgrid component failures or degradations. The output metric of the HPIRA tool is the total recovery time or man-hours required to recover a microgrid system. Chapter 4 will apply the HPIRA tool to six different microgrid component recovery processes.

CHAPTER 4: Research Results

The purpose of this chapter is to present the results of the HPIRA tool for various microgrid recovery scenarios. In this chapter, the research methodology as described in Chapter 3 will be applied to answer the original thesis question. The HPIRA tool will produce comparable recovery time statistics of different microgrid components to show how human factors affects a microgrid recovery process. Additionally, it will present the $P(s)$ versus $P(f)$ for a microgrid system recovery. The research question will be analysed in two perspectives: 1) The influence of human factors on individual microgrid component recovery processes and 2) The influence of human factors on a multi-scale microgrid component recovery process. The results will be analyzed to provide meaningful conclusions and recommendations for microgrid system recovery. This research utilizes firsthand, user data inputs from experienced microgrid recovery personnel.

4.1 Individual Microgrid Component Recovery

The methodology developed in Chapter 3 simulate individual component recovery processes to restore a microgrid to normal operations. Exponential distributions are selected to model $P(f)$ and $P(s)$ of all tasks within all generated network paths since they measure a continuous, random variable with high and low parameter values. Six individual microgrid component recoveries will be evaluated with the HPIRA tool: Downed Pole, Generator, Substation, Multicell Battery, PV, and Rechargeable Battery. The data for each component recovery model is based off of firsthand knowledge from [32] to determine an appropriate recovery task list and task order precedence. All tasks are representative recovery actions that are found in [33].

We assume the following about the recovery scenario and team for each component recovery model and analysis. The component analyzed is part of a NAVSTA microgrid. It is the only component to fail. The indecent of failure is unintentional and specific to a single microgrid component. The recovery team is a fully qualified and rested 2-person team consisting of a High Voltage Supervisor and a Lead Electrician. Environmental conditions will be ideal and all tools and supplies are available and in supply.

4.1.1 Downed Pole Recovery

For the downed pole recovery process, 18 recovery tasks, as shown in Table A.1, will be simulated as a recovery task network. The recovery task list includes all tasks and durations in Table 4.1. The recovery procedure task list identifies all tasks sequentially from Task “A” to Task “S.” Appendix A provides the generated precedence list of all tasks in Table A.2.

Table 4.1. Downed Pole Recovery Procedure Task List and Durations (hr)

Task	Min	Max	Mean	Follow On Task
A	0.15	0.25	0.20	B
B	0.17	0.25	0.21	C, D
C	0.22	0.30	0.26	E
D	0.17	0.25	0.21	E
E	0.17	0.33	0.25	F
F	0.33	0.50	0.42	G, H
G	0.17	0.33	0.25	J
H	0.17	0.25	0.21	I
I	0.25	0.33	0.29	J
J	0.50	1.00	0.75	K, L
K	0.25	0.33	0.29	L
L	2.50	3.50	3.00	M, N
M	1.50	2.50	2.00	N
N	3.00	4.00	3.50	O
O	3.50	4.50	4.00	Q, P
P	0.17	0.25	0.21	R
Q	0.17	0.25	0.21	R
R	0.25	0.33	0.29	S
S	0.00	0.00	0.00	
Total	13.62	19.47	16.54	

From the task list and task precedence order, 32 possible recovery paths can be taken from

the beginning node to the end, or “recovered,” node. Based on the 10,000 iterated scenarios through the HPIRA tool, 10,000 path recovery sample times are produced for each of the 32 paths. Appendix A displays Table A.3 which shows all 32 possible paths and the first five, of the 10,000, recovery sample times within the network. Figure 4.1 shows the downed pole recovery task network with all tasks represented as alphabetical nodes and all potential recovery paths from start to completion.

By implementing CPM process to the downed pole recovery network, the path that significantly impacts a recovery’s progression can be identified. Within the task network, individual task completions occur in a single direction as either parallel or in series. Not one single path represents all tasks to be completed for a full downed pole recovery. Instead, each path represents specific tasks that, when taken in order, are subject to the successful completion and length of completion time of each prior task. The path with the longest duration, or recovery time, is the critical path. The critical path represents the combination of the most complicated tasks and longest task recovery times that are involved within a microgrid system’s recovery process. The critical path is important to identify because if any delay or obstruction occurs to the tasks within the path, the longest recovery duration will only be extended and will delay the successful restoration of the microgrid and the services it supports.

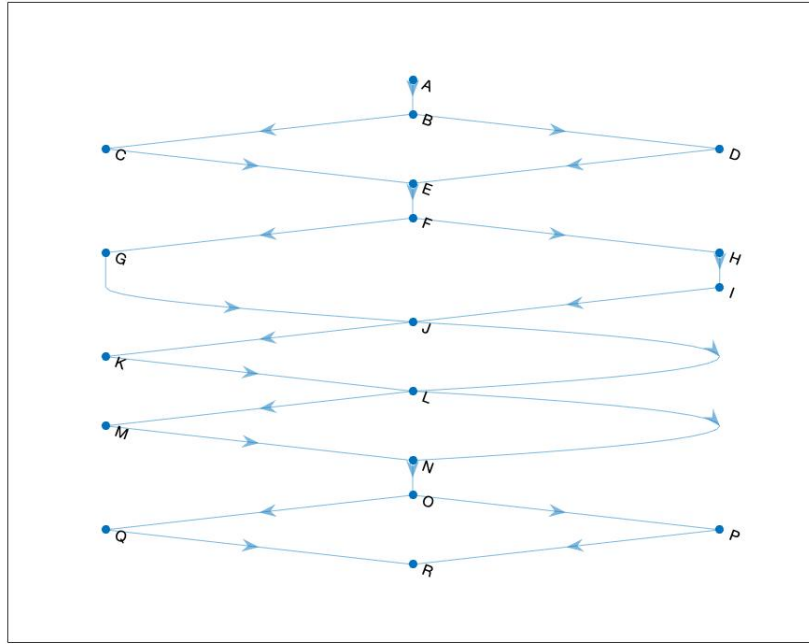


Figure 4.1. Downed Pole Recovery Network Diagram

Figure 4.2 displays a PDF for the modeled downed pole recovery simulation. The plot summarizes the longest recovery times of each of the 10,000 scenarios by how often they occurred. Plotting the occurrence frequency against the continuous variable, recovery time, produces a PDF where the $P(s)$ and $P(f)$ of the downed pole recovery can be assessed with respect to recovery time. In Figure 4.2, the red highlighted bin represents the most occurred grouping of the longest path recovery times.

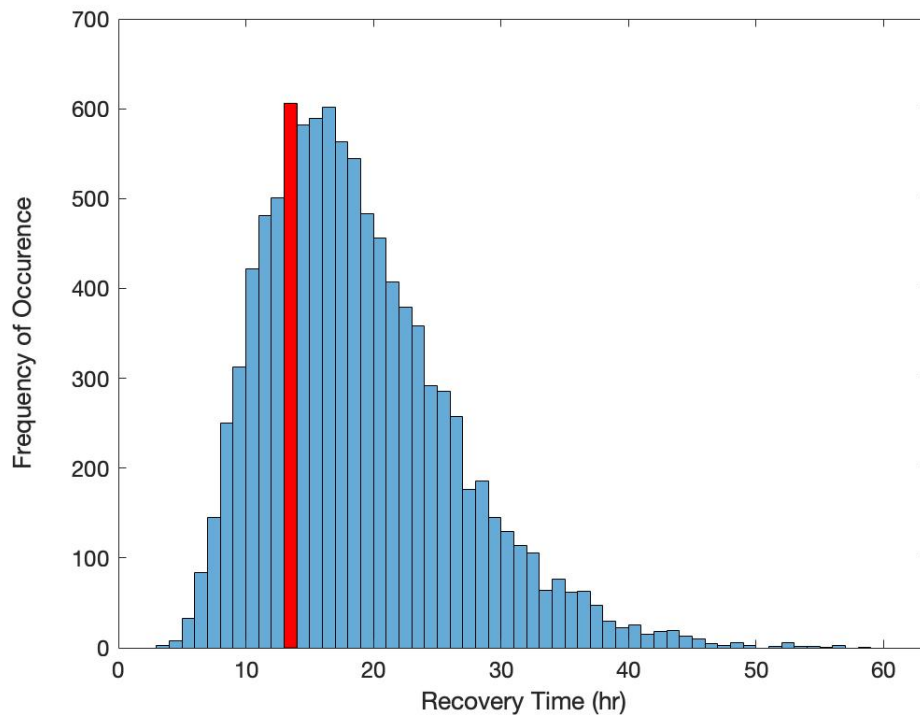


Figure 4.2. PDF for the Modeled Downed Pole Recovery Process. The Most Frequent Scenario Frequency Grouping is 606 of 10,000 Scenarios. The Mode Recovery Time Range is 13.0 to 14.0 Hours with a 0.06 Probability of Occurrence.

The greatest frequency occurrence bin represents the highest $P(s)$ for a downed pole recovery. Therefore, the most successful restoration paths will take approximately between 13.0 to 14.0 hours to complete. Restoration path recovery times range from a minimum recovery time of 3.70 hours and to a maximum recovery time of 63.56 hours. Referring back to Figure 3.5, the $P(s)$ and $P(f)$ of recovery processes can be estimated in respect to the system's recovery time. For a downed pole recovery, paths with recovery times that range between 3.70 hours to 13.0 hours have a higher likelihood of success than failure. Paths with recovery times closer to 13.0 hours have the highest $P(s)$ of recovery while paths that fall near the minimum recovery time have a lower $P(s)$. In opposite, paths that range from 14.0 hours to 63.56 hours have a higher likelihood of failure than success. Similar to the success ranges, path recovery times that fall near 14.0 hours have a less likely chance to fail,

but as the maximum recovery time of 63.56 hours is approached, the likelihood of failure increases.

After conducting the modeled recovery of 10,000 downed pole recovery scenarios, all of the 10,000 longest recovery times were found to fall between 3.70 and 63.56 hours. Table 4.2 compares statistical values between the predicted and modeled recovery scenarios. The predicted modeled scenario is based off of the initial task list that does not consider human error or task precedence. Since the modeled recovery scenario utilized is based off of SPAR-H analysis and is of stochastic nature, the values are expected to vary considerably from predicted values.

Table 4.2. Recovery Time Statistics for Downed Pole Recovery

Recovery Scenario	Min	Max	Mean	SD	Var
Predicted	13.62	19.48	16.54	4.14	17.11
Model	3.70	63.56	18.91	7.54	56.90

The modeled downed pole recovery simulation produces the longest recovery time for 32 possible recovery paths for 10,000 scenarios. Figure 4.3 shows these outputs with common trends. In Figure 4.3, high and low recovery time ranges occur over certain recovery paths. Paths #1 to #8 and paths #17 to #24 produce the highest recovery time ranges that represent potential critical recovery paths.

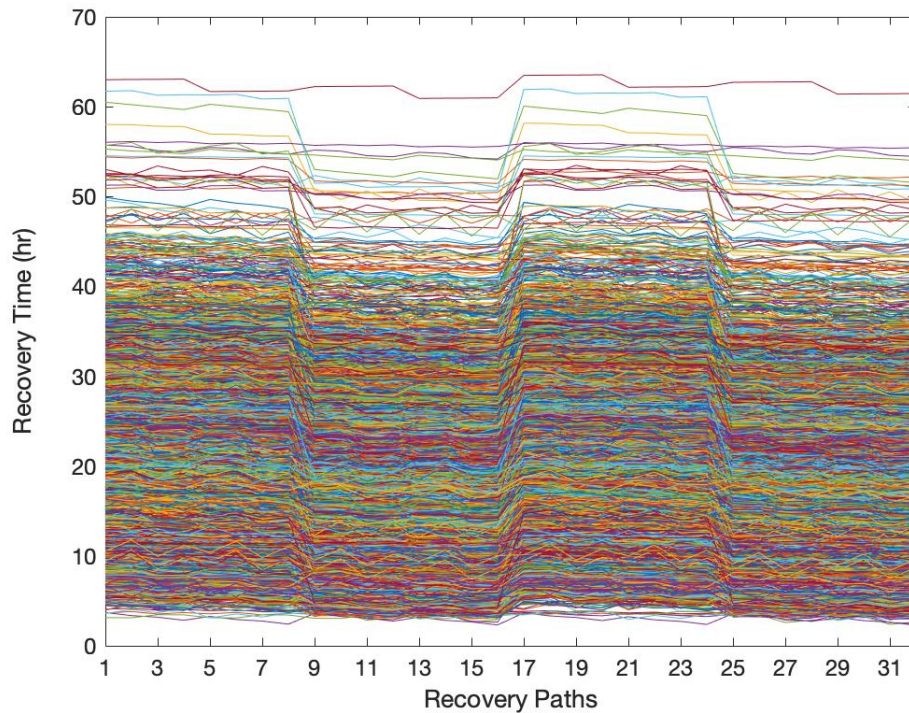


Figure 4.3. Duration Required to Recover a Downed Pole for 10,000 Modeled Scenarios

For the purpose of this work, paths with high peaks or ranges are most important since they likely represent critical paths. Paths #1 to #8 and paths #17 to #24 include certain tasks that lead to longer recovery times. This can be due to task complexity and long task recovery times. When these tasks are combined, factors such as complexity and task completion times drive the elongation of total recovery time. Critical paths drive the successful completion of the recovery network or process. When assessing all 10,000 downed pole scenarios, Path #18 was determined to be the most common critical path. Figure 4.4 identifies the Downed Pole Recovery Network critical path, Path #18, and the path's associated recovery time. The nodes specified within that path are of significance since they have the greatest potential to slow down the recovery process. The recovery process is dependent on the critical path since the recovery completion is only as fast as the longest timed path within the recovery network. The longest recovery time durations are estimated to the nearest hour in order to determine mode value, or most frequent recovery time, that existed. The modeled recovery

time mode was determined to be 16 hours. Based off of the mode value, Path #18 is the critical path for the downed pole recovery model. It is important to note that the critical path is not necessarily the critical path for all of the pole recovery scenarios; however, it does dominate over the other potential paths.

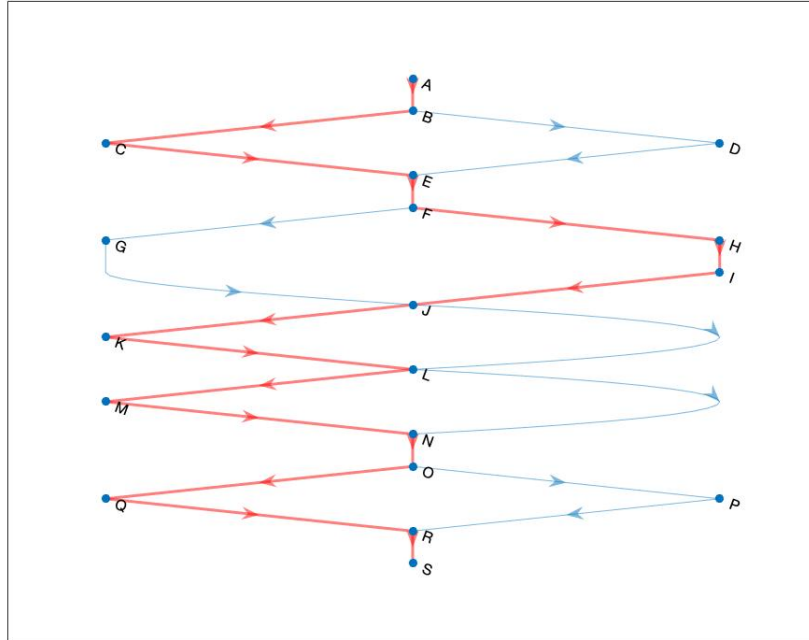


Figure 4.4. Downed Pole Recovery Network Diagram Showing the Critical Recovery Path #18 with an Estimated Recovery Time of 16 Hours.

With the critical path identified, the recovery time for that path was compared amongst all 10,000 recovery scenarios. Figure 4.5 is a PDF summarizing the relationship between all 10,000 recovery times and how often they occurred. This plot allows for assessment of whether Path #18 has a higher likelihood of success or failure in respect to recovery time. Figure 4.5 identifies the most occurred grouping of the 10,000 critical path recovery times with the red highlighted bin.

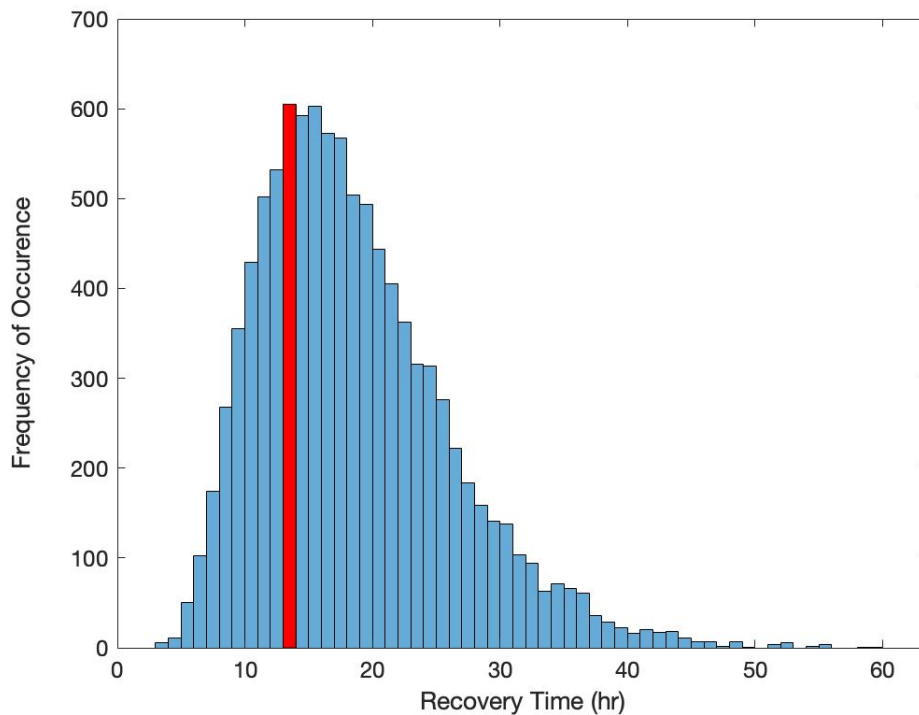


Figure 4.5. PDF for the Modeled Downed Pole Recovery Path #18. The Most Frequent Scenario Frequency Grouping is 605 of 10,000 Scenarios. The Mode Recovery Time Range is 13.0 to 14.0 Hours with a 0.06 Probability of Occurrence.

For the downed pole critical recovery path, Path #18, recovery times that fall under 13.0 hours have a have a higher likelihood of success than failure. Paths with recovery times closer to 13.0 hours have the highest $P(s)$ of recovery while shorter paths have a lower $P(s)$. In opposite, paths that range from 14.0 hours or longer have a higher likelihood of failure than success. Similar to the success ranges, path recovery times that fall near 14.0 hours have a less likely chance to fail, but as the path's recovery time increases so does its likelihood of failure.

4.1.2 Generator Recovery

For the generator recovery process, 16 recovery tasks, as shown in Table B.1, will be simulated in the recovery task network. The task list includes all tasks and durations in

Table 4.3. The recovery procedure task list identifies all tasks sequentially from Task “A” to Task “Q.” Appendix B provides the generated precedence list of the task list in Table B.2.

Table 4.3. Generator Recovery Procedure Task List and Durations (hr)

Task	Min	Max	Mean	Follow On Task
A	0.15	0.25	0.20	B
B	0.17	0.25	0.21	C
C	0.08	0.12	0.10	D,E
D	0.08	0.12	0.10	F
E	0.42	0.67	0.54	F
F	0.25	0.50	0.38	G
G	0.42	0.67	0.54	H,I
H	0.17	0.33	0.25	J
I	0.17	0.33	0.25	J
J	0.17	0.25	0.21	K
K	0.25	0.33	0.29	L
L	6.00	12.00	9.00	M,N
M	0.25	0.50	0.38	P
N	0.17	0.25	0.21	O
O	0.33	0.50	0.42	Q
P	0.33	0.50	0.42	Q
Q	0.00	0.00	0.00	
Total	9.40	17.57	13.48	

From the task list and task precedence order, eight possible recovery paths can be taken from the beginning node to the end, or “recovered,” node. Based on the 10,000 iterated scenarios through the HPIRA tool, 10,000 path recovery sample times are produced for each of the eight paths. Appendix B displays Table B.3 which shows all eight possible paths and the first five, of the 10,000, recovery sample times within the network. Figure 4.6 shows the generator recovery task network with all tasks represented as alphabetical nodes and all

potential recovery paths from start to completion. Like the downed pole task network, the generator recovery network's critical path is determined with the same CPM process.

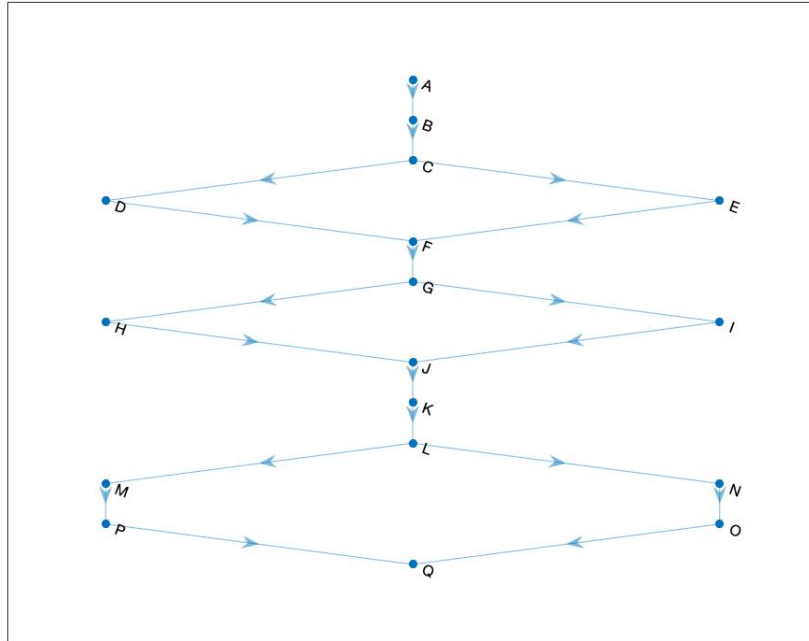


Figure 4.6. Generator Recovery Network Diagram

Figure 4.7 displays a PDF for the modeled generator recovery simulation. The plot summarizes the longest recovery times of each of the 10,000 scenarios by how often they occurred. Plotting the occurrence frequency against the continuous variable, recovery time, produces a PDF where the $P(s)$ and $P(f)$ of the generator recovery can be assessed with respect to recovery time. In Figure 4.7, the red highlighted bin represents the most occurred grouping of the 10,000 critical path recovery times.

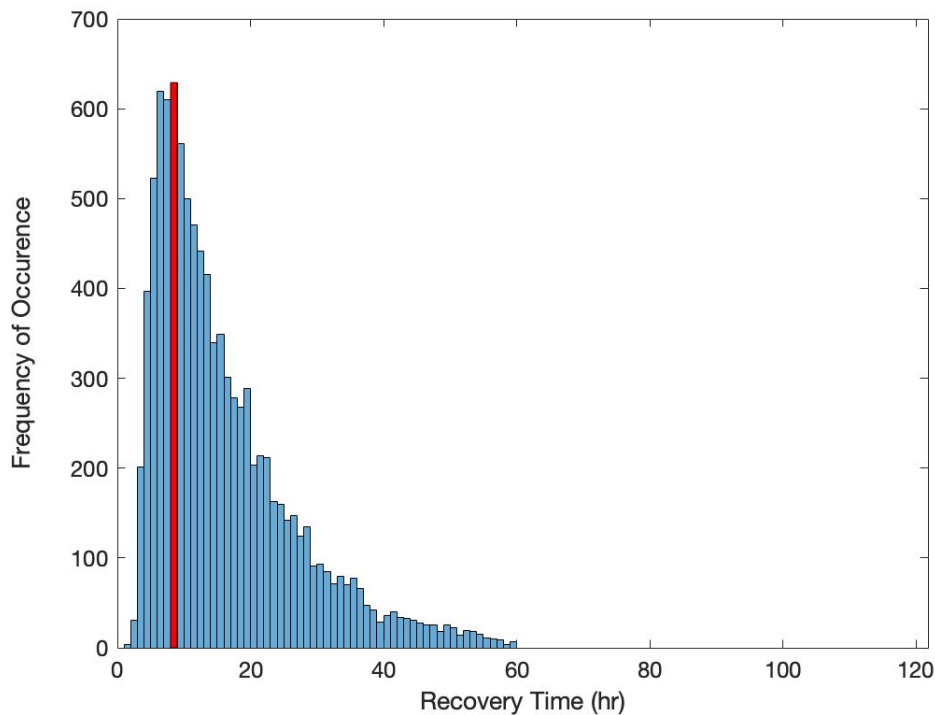


Figure 4.7. PDF for the Modeled Generator Recovery Process. The Most Frequent Scenario Frequency Grouping is 629 of 10,000 Scenarios. The Mode Recovery Time Range is 8.0 to 9.0 Hours with a 0.06 Probability of Occurrence.

The greatest frequency occurrence bin represents the highest $P(s)$ for a generator recovery. Therefore, the most successful critical restoration paths will take approximately between 8.0 to 9.0 hours to complete. The critical restoration path recovery times range from a minimum recovery time of 1.79 hours and at a maximum recovery time of 121.8 hours. Referring back to Figure 3.5, the $P(s)$ and $P(f)$ of recovery processes can be estimated in respect to the system's recovery time. For a generator recovery, paths with recovery times that range between 1.79 hours to 8.0 hours have a higher likelihood of success than failure. Paths with recovery times closer to 8.0 hours have the highest $P(s)$ of recovery while paths that fall near the minimum recovery time have a lower $P(s)$. In opposite, paths that range from 9.0 hours to 121.8 hours have a higher likelihood of failure than success. Similar to the success ranges, path recovery times that fall near 9.0 hours have a less likely chance

to fail, but as the maximum recovery time of 121.8 hours is approached, the likelihood of failure increases.

After conducting the modeled recovery of 10,000 generator recovery scenarios, all of the 10,000 longest recovery times were found to fall between 1.79 and 121.8 hours. Table 4.4 compares statistical values between the predicted and modeled recovery scenarios. Like the downed pole recovery scenarios, modeled recovery values are based off of SPAR-H analysis and are of stochastic nature, resulting in values that are expected to vary considerably from predicted values.

Table 4.4. Recovery Time Statistics for Generator Recovery

Recovery Scenario	Min	Max	Mean	SD	Var
Predicted	9.40	17.57	13.48	5.77	33.35
Model	1.79	121.8	16.55	11.92	142.1

The modeled recovery scenario produced eight possible network paths with 10,000 recovery times for each path. Figure 4.8 shows these outputs with common trends. In Figure 4.8 there are no significant high or low peaks or ranges of recovery times for certain recovery paths. With no paths showing significantly higher recovery times than others, all recovery paths have the potential to be considered critical recovery paths.

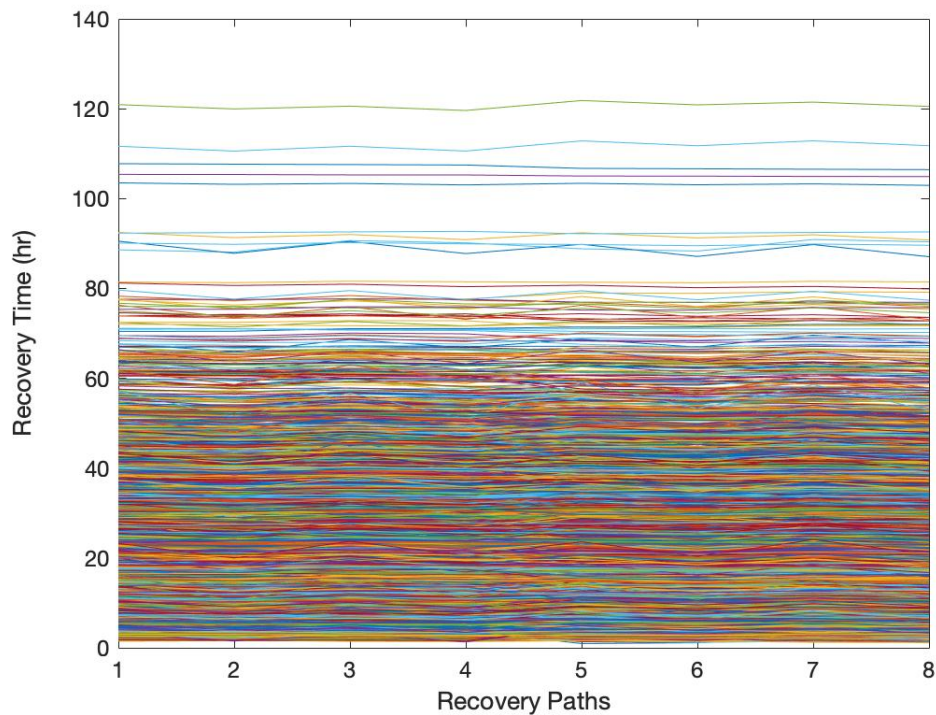


Figure 4.8. Duration Required to Recover a Generator for 10,000 Modeled Scenarios

Critical paths drive the successful completion of the recovery network or process. When assessing all 10,000 generator recovery scenarios, Path #7 was determined to be the most common critical path. Figure 4.9 identifies the Generator Recovery Network critical path, Path #7, and the path's associated recovery time. Based off of the most common, longest recovery time, Path #7 is the critical path for the generator recovery model. It is important to note that the critical path is not necessarily the critical path for all of the generator recovery scenarios; however, it does dominate over the other potential paths.

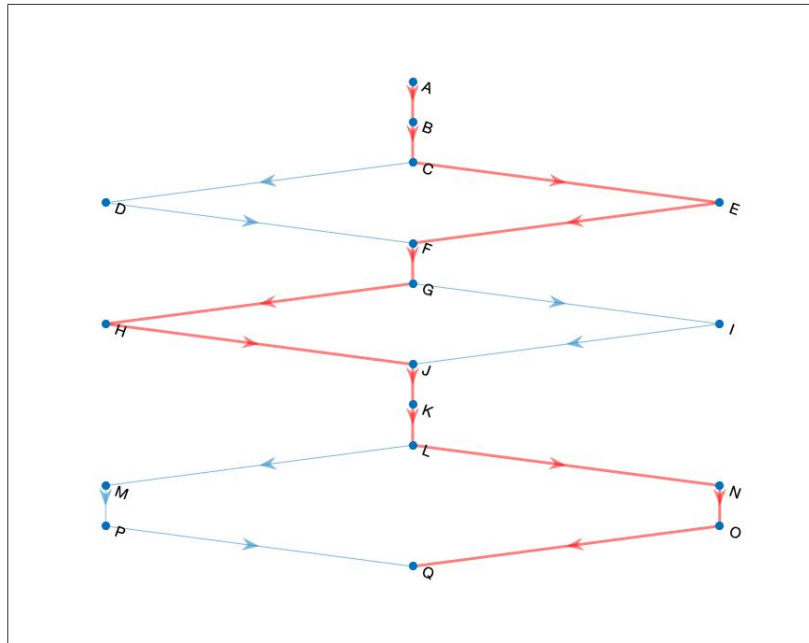


Figure 4.9. Generator Recovery Network Diagram Showing the Critical Recovery Path #7 with an Estimated Recovery Time of 7 Hours.

With the critical path identified, the recovery time for that path was compared amongst all 10,000 recovery scenarios. Figure 4.10 is a PDF summarizing the relationship between all 10,000 recovery times and how often they occurred. This plot allows for assessment of whether Path #7 has a higher likelihood of success or failure in respect to recovery time. Figure 4.10 identifies the most occurred grouping of the 10,000 critical path recovery times with the red highlighted bin.

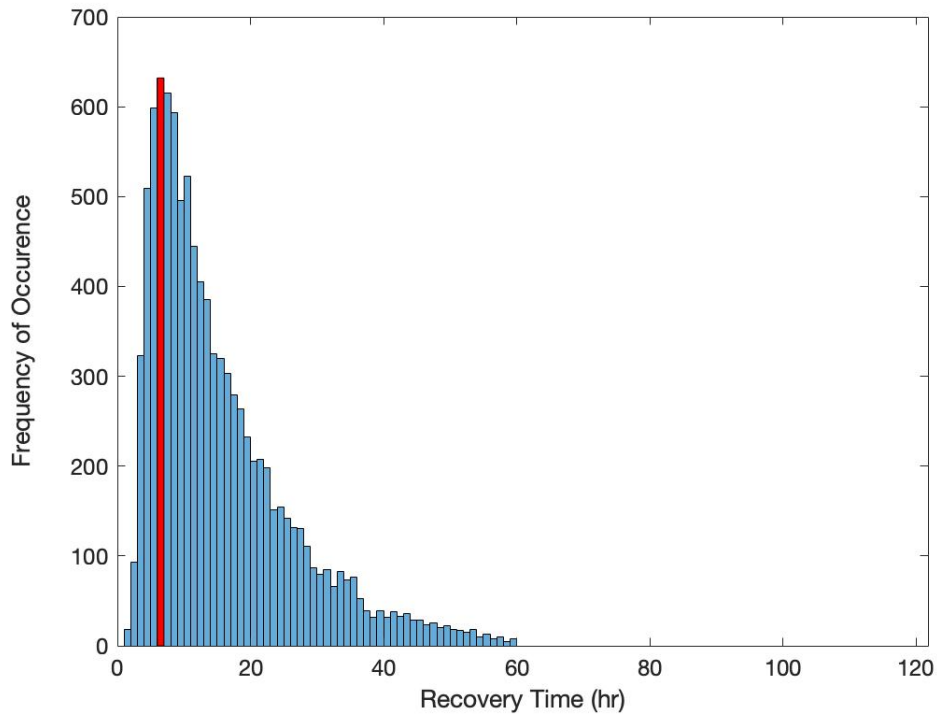


Figure 4.10. PDF for the Modeled Generator Recovery Path #7. The Most Frequent Scenario Frequency Grouping is 632 of 10,000 Scenarios. The Mode Recovery Time Range is 6.0 to 7.0 Hours with a 0.06 Probability of Occurrence.

For the generator critical recovery path, Path #7, recovery times that fall under 6.0 hours have a have a higher likelihood of success than failure. Paths with recovery times closer to 6.0 hours have the highest $P(s)$ of recovery while shorter paths have a lower $P(s)$. In opposite, paths that range from 7.0 hours or longer have a higher likelihood of failure than success. Similar to the success ranges, path recovery times that fall near 7.0 hours have a less likely chance to fail, but as the path's recovery time increases so does its likelihood of failure.

4.1.3 Substation Recovery

For the substation recovery process, 18 recovery tasks, as shown in Table C.1, will be simulated in the recovery task network. The task list includes all tasks and durations in

Table 4.5. The recovery procedure task list identifies all tasks sequentially from Task “A” to Task “S.” Appendix C provides the generated precedence list of the task list in Table C.2.

Table 4.5. Substation Recovery Procedure Task List and Durations (hr)

Task	Min	Max	Mean	Follow On Task
A	0.15	0.25	0.20	B
B	0.17	0.25	0.21	C
C	0.17	0.25	0.21	D,F
D	0.25	0.33	0.29	E
E	0.25	0.33	0.29	G
F	0.33	0.50	0.42	G
G	0.17	0.33	0.25	H,I
H	0.17	0.33	0.25	J
I	0.17	0.25	0.21	J
J	0.25	0.33	0.29	K,N
K	0.42	0.58	0.50	L
L	2.00	3.00	2.50	M
M	0.25	0.50	0.38	O
N	8.00	11.00	9.50	O
O	1.50	2.50	2.00	P
P	0.25	0.50	0.38	Q
Q	0.17	0.25	0.21	R
R	0.33	0.50	0.42	S
S	0.00	0.00	0.00	
Total	14.98	22.00	18.49	

From the task list and task precedence order, eight possible recovery paths can be taken from the beginning node to the end, or “recovered,” node. Based on the 10,000 iterated scenarios through the HPIRA tool, 10,000 path recovery sample times are produced for each of the eight paths. Appendix C displays Table C.3 which shows all eight possible paths

and the first five, of the 10,000, recovery sample times within the network. Figure 4.11 shows the substation recovery task network with all tasks represented as alphabetical nodes and all potential recovery paths from start to completion. Like the the previous recovery task networks, the substation recovery network's critical path is determined with the same CPM process.

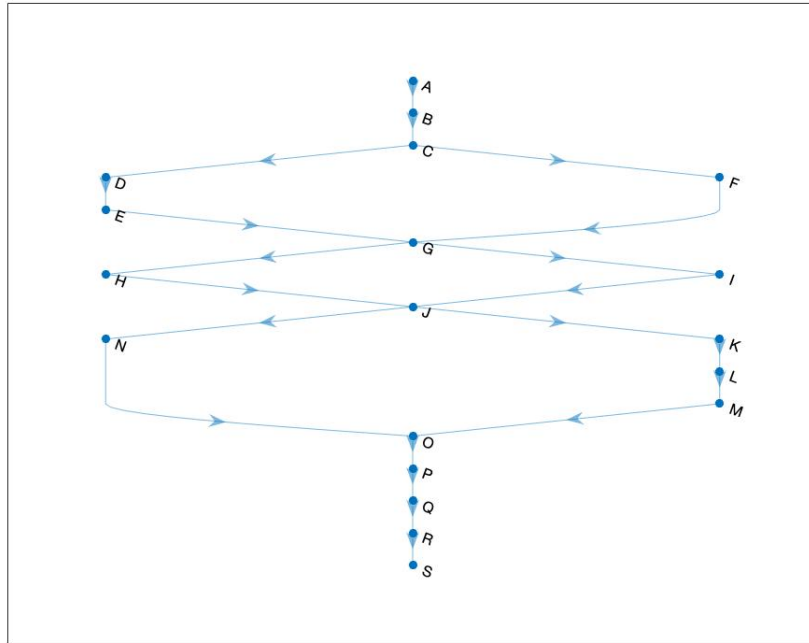


Figure 4.11. Substation Recovery Network Diagram

Figure 4.12 displays a PDF for the modeled substation recovery simulation. The plot summarizes the longest recovery times of each of the 10,000 scenarios by how often they occurred. Plotting the occurrence frequency against the continuous variable, recovery time, produces a PDF where the $P(s)$ and $P(f)$ of the substation recovery can be assessed with respect to recovery time. In Figure 4.12, the red highlighted bin represents the most occurred grouping of the 10,000 critical path recovery times.

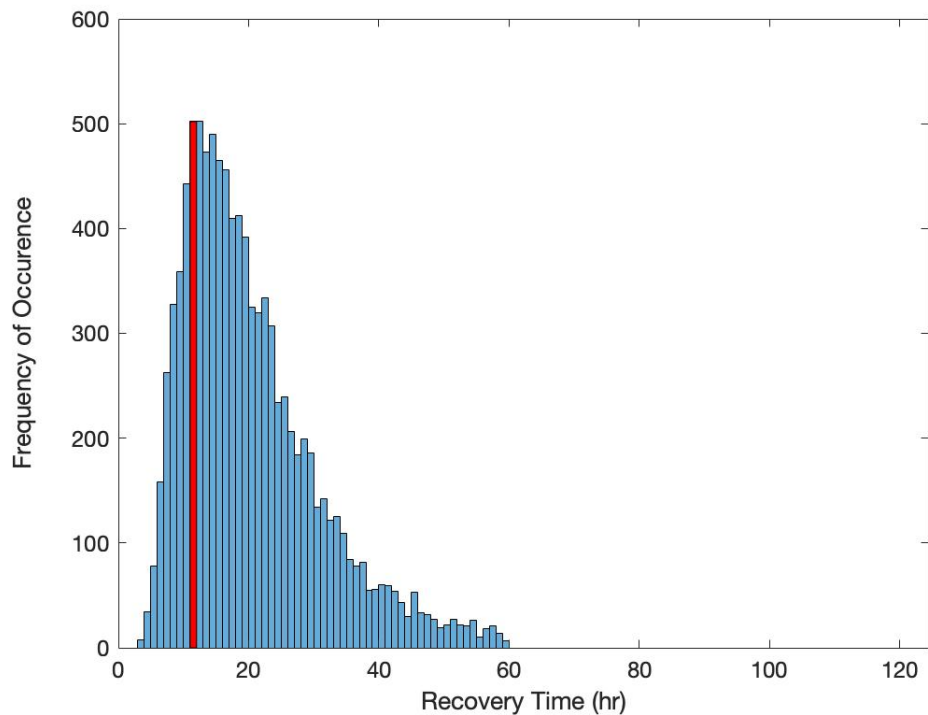


Figure 4.12. PDF for the Modeled Substation Recovery Process. The Most Frequent Scenario Frequency Grouping is 502 of 10,000 Scenarios. The Mode Recovery Time Range is 11.0 to 12.0 Hours with a 0.05 Probability of Occurrence.

The greatest frequency occurrence bin represents the greatest $P(s)$ for a substation recovery. Therefore, the most successful critical restoration paths will take approximately between between 11.0 to 12.0 hours to complete. The critical restoration path recovery times range from a minimum recovery time of 3.49 hours and a maximum recovery time of 124.5 hours. Referring back to Figure 3.5, the $P(s)$ and $P(f)$ of recovery processes can be estimated in respect to the system's recovery time. For a substation recovery, paths with recovery times that range between 3.49 hours to 11.0 hours have a higher likelihood of success than failure. Paths with recovery times closer to 11.0 hours have the highest $P(s)$ of recovery while paths that fall near the minimum recovery time have a lower $P(s)$. In opposite, paths that range from 12.0 hours to 124.5 hours have a higher likelihood of failure than success. Similar to the success ranges, path recovery times that fall near 12.0 hours have a less likely chance

to fail, but as the maximum recovery time of 124.5 hours is approached, the likelihood of failure increases.

After conducting the modeled recovery of 10,000 substation recovery scenarios, all of the 10,000 longest recovery times were found to fall between 3.49 and 124.5 hours. Table 4.6 compares statistical values between the predicted and modeled recovery scenarios. Like the previous recovery scenarios, modeled recovery values are based off of SPAR-H analysis and are of stochastic nature, resulting in values that are expected to vary considerably from predicted values.

Table 4.6. Recovery Time Statistics for Substation Recovery

Recovery Scenario	Min	Max	Mean	SD	Var
Predicted	14.98	22.00	18.49	4.96	24.62
Model	3.49	124.5	28.85	11.64	135.4

The modeled recovery scenario produced eight possible network paths with 10,000 recovery times for each path. Figure 4.13 shows these outputs with common trends. In Figure 4.13 high and low recovery time ranges occur amongst certain recovery paths. Paths #1 to #4 produce high recovery time ranges that represent potential critical recovery paths.

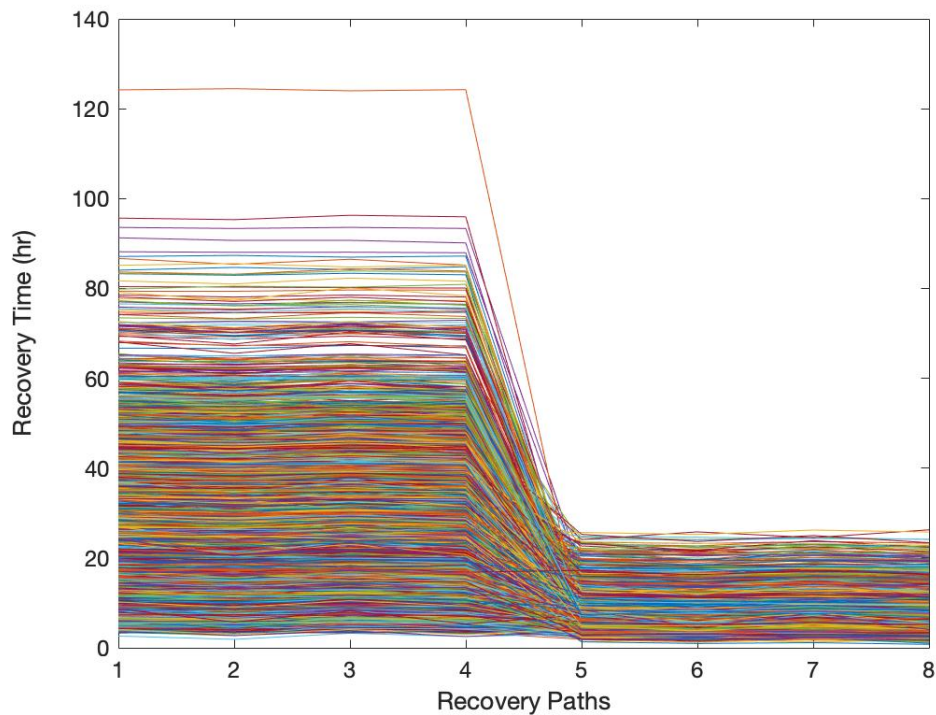


Figure 4.13. Duration Required to Recover a Substation for 10,000 Modeled Scenarios

Critical paths drive the successful completion of the recovery network or process. When assessing all 10,000 substation recovery scenarios, Path #3 was determined to be the most common critical path. Figure 4.14 identifies the Substation Recovery Network critical path, Path #3, and the path's associated recovery time. Based off of the most common, longest recovery time, Path #3 is the critical path for the substation recovery model. It is important to note that the critical path is not necessarily the critical path for all of the generator recovery scenarios; however, it does dominate over the other potential paths.

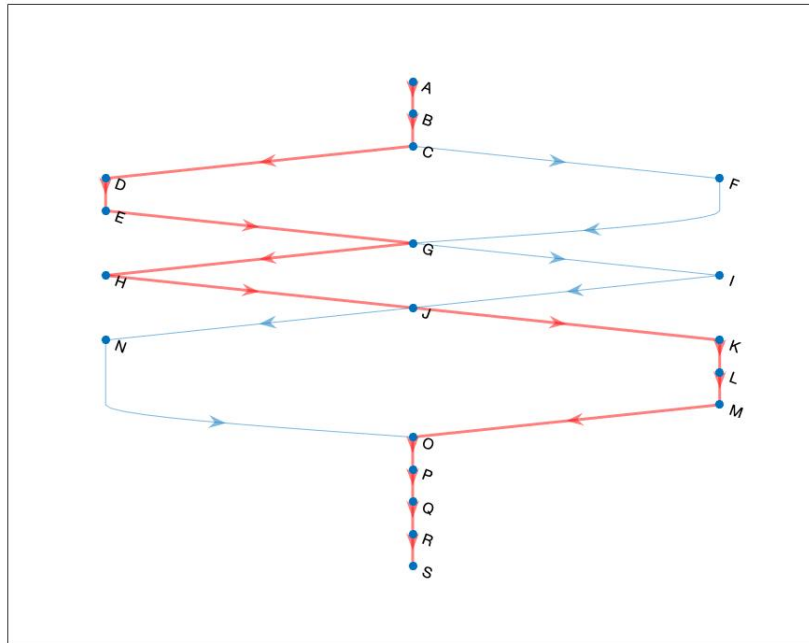


Figure 4.14. Substation Recovery Network Diagram Showing the Critical Recovery Path #3 with an Estimated Recovery Time of 12 Hours.

With the critical path identified, the recovery time for that path was compared amongst all 10,000 recovery scenarios. Figure 4.15 is a PDF summarizing the relationship between all 10,000 recovery times and how often they occurred. This plot allows for assessment of whether Path #3 has a higher likelihood of success or failure in respect to recovery time. Figure 4.15 identifies the most occurred grouping of the 10,000 critical path recovery times with the red highlighted bin.

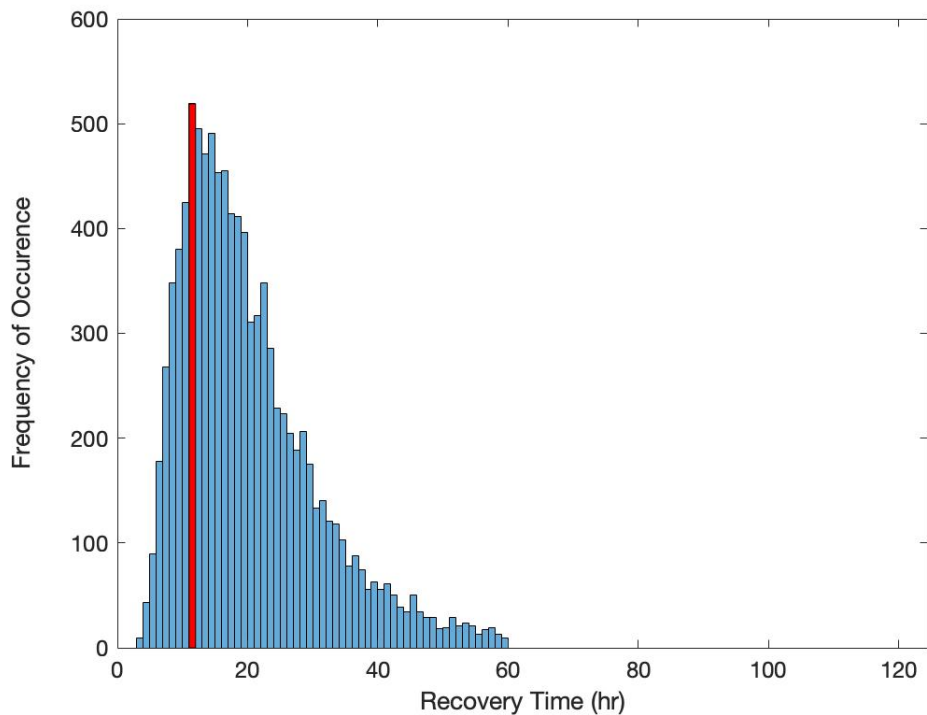


Figure 4.15. PDF for Substation Recovery Path #3. The Most Frequent Scenario Frequency Grouping is 519 of 10,000 Scenarios. The Mode Recovery Time Range is 11.0 to 12.0 Hours with a 0.05 Probability of Occurrence.

For the substation critical recovery path, Path #3, recovery times that fall under 11.0 hours have a higher likelihood of success than failure. Paths with recovery times closer to 11.0 hours have the highest $P(s)$ of recovery while paths that fall near the minimum recovery time have a lower $P(s)$. In opposite, paths that range from 12.0 hours or longer have a higher likelihood of failure than success. Similar to the success ranges, path recovery times that fall near 12.0 hours have a less likely chance to fail, but as recovery time increases so does the likelihood of failure.

4.1.4 PV Recovery

For the PV recovery process, 13 recovery tasks, as shown in Table D.1, will be simulated in the recovery task network. The task list includes all tasks and durations are presented in

Table 4.7. The recovery procedure task list identifies all tasks sequentially from Task “A” to Task “N.” Appendix D provides the generated precedence list of the task list in Table D.2.

Table 4.7. PV Recovery Procedure Task List and Durations (hr)

Task	Min	Max	Mean	Follow On Task
A	0.15	0.25	0.20	B
B	0.17	0.25	0.21	C
C	0.17	0.33	0.25	D,E
D	1.50	3.50	2.50	G
E	0.17	0.33	0.25	F
F	0.17	0.33	0.25	G
G	0.08	0.17	0.13	H,I
H	0.42	0.58	0.50	J
I	0.25	0.33	0.29	K
J	0.50	0.67	0.58	K
K	0.25	0.50	0.38	L
L	0.17	0.25	0.21	M
M	0.33	0.50	0.42	N
N	0.00	0.00	0.00	
Total	4.32	8.00	6.16	

From the task list and task precedence order, four possible recovery paths can be taken from the beginning node to the end, or “recovered,” node. Based on the 10,000 iterated scenarios through the HPIRA tool, 10,000 path recovery sample times are produced for each of the four paths. Appendix D displays Table D.3 which shows all four possible paths and the first five, of the 10,000, recovery sample times within the network. Figure 4.16 shows the PV recovery task network with all tasks represented as alphabetical nodes and all potential recovery paths from start to completion. Like the previous recovery task networks, the PV recovery network’s critical path is determined with the same CPM process.

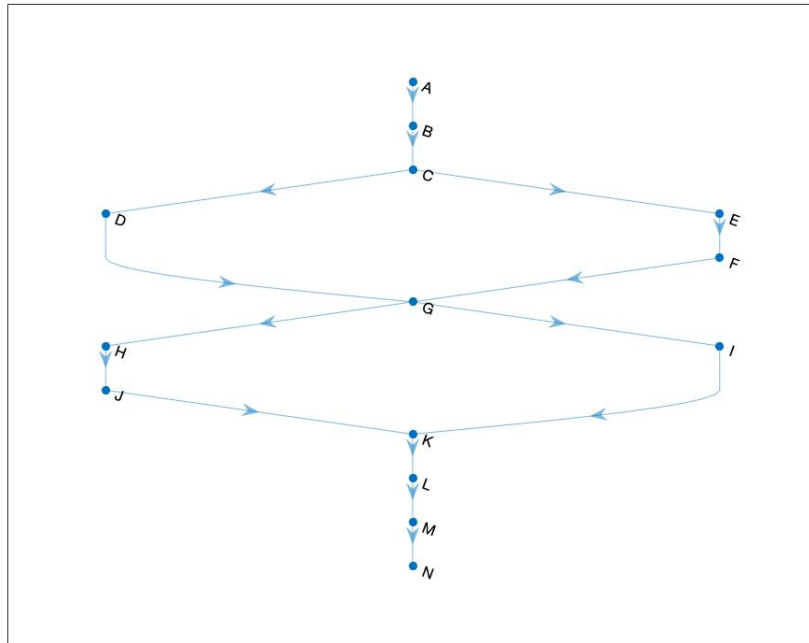


Figure 4.16. PV Recovery Network Diagram

Figure 4.17 displays a PDF for the modeled PV recovery simulation. The plot summarizes the longest recovery times of each of the 10,000 scenarios by how often they occurred. Plotting the occurrence frequency against the continuous variable, recovery time, produces a PDF where the $P(s)$ and $P(f)$ of the PV recovery can be assessed with respect to recovery time. In Figure 4.17, the red highlighted bin represents the most occurred grouping of the 10,000 critical path recovery times.

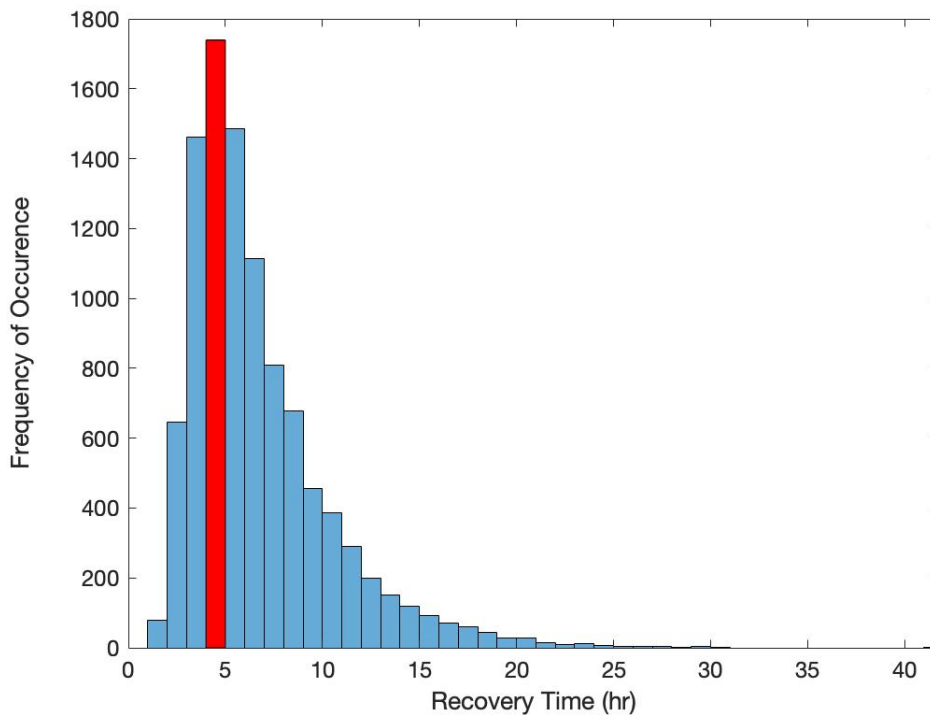


Figure 4.17. PDF for the Modeled PV Recovery Process. The Most Frequent Scenario Frequency Grouping is 1,739 of 10,000 Scenarios. The Mode Recovery Time Range is 4.0 to 5.0 Hours with a 0.17 Probability of Occurrence.

The greatest frequency occurrence bin represents the greatest $P(s)$ for a PV recovery. Therefore, the most successful critical restoration paths will take between between four to 5.0 hours to complete. The critical restoration path recovery times range from a minimum recovery time of 1.06 hours and a maximum recovery time of 41.77 hours. Referring back to Figure 3.5, the $P(s)$ and $P(f)$ of recovery processes can be estimated in respect to the system's recovery time. For a PV recovery, paths with recovery times that range between 1.06 hours to four hours have a higher likelihood of success than failure. Paths with recovery times closer to four hours have the highest $P(s)$ of recovery while paths that fall near the minimum recovery time have a lower $P(s)$. In opposite, paths that range from 5.0 hours to 41.77 hours have a higher likelihood of failure than success. Similar to the success ranges, path recovery times that fall near 5.0 hours have a less likely chance to fail, but as the maximum recovery time of 41.77 hours is approached, the likelihood of failure increases.

After conducting the modeled recovery of 10,000 PV scenarios, all 10,000 generated critical path recovery times fell between 1.06 and 41.77 hours. Table 4.8 compares statistical values between the predicted and modeled recovery scenarios. Like the previous recovery scenarios, modeled recovery values are based off of SPAR-H analysis and are of stochastic nature, resulting in values that are expected to vary considerably from predicted values.

Table 4.8. Recovery Time Statistics for PV Recovery

Recovery Scenario	Min	Max	Mean	SD	Var
Predicted	4.32	8.00	6.16	2.60	6.78
Model	1.06	41.77	6.70	3.67	13.49

The modeled recovery scenario produced four possible network paths with 10,000 recovery times for each path. Figure 4.18 shows these outputs with common trends. In Figure 4.18 high and low recovery time instances occur amongst certain recovery paths. Paths #2 and #4 tend to produce the highest recovery time ranges that represent potential critical recovery paths.

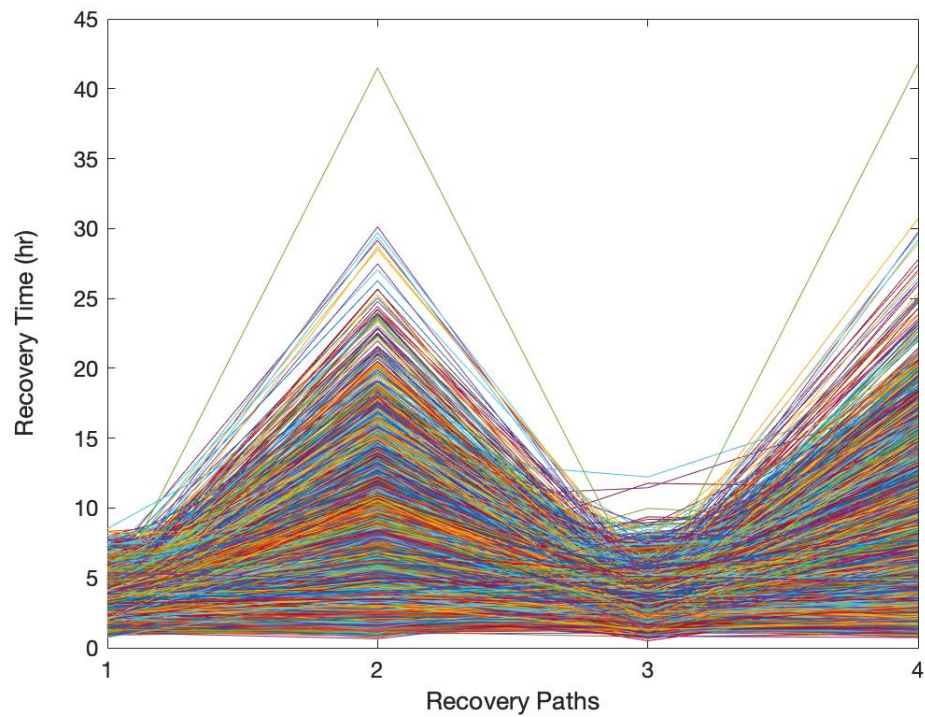


Figure 4.18. Duration Required to Recover a PV for 10,000 Modeled Scenarios

Critical paths drive the successful completion of the recovery network or process. When assessing all 10,000 PV scenarios, Path #4 was determined to be the most common critical path. Figure 4.19 identifies the PV Recovery Network critical path, Path #4, and the path's associated recovery time. Based off of the most common, longest recovery time, Path #4 is the critical path for the PV recovery model. It is important to note that the most common critical path is not necessarily the critical path for all of the pole recovery scenarios; however, it does dominate over the other potential paths.

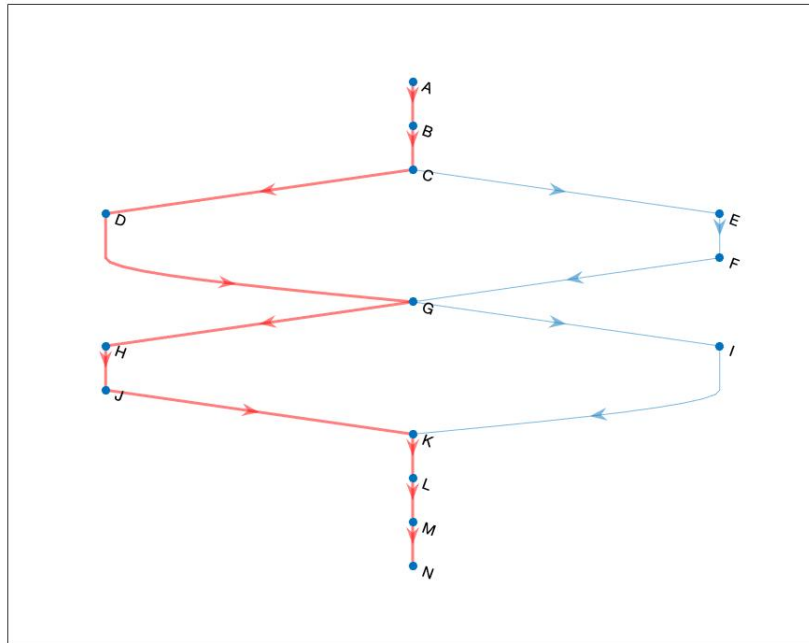


Figure 4.19. PV Recovery Network Diagram Showing the Critical Recovery Path #4 with an Estimated Recovery Time of 3 Hours.

With the critical path identified, the recovery time for that path was compared amongst all 10,000 recovery scenarios. Figure 4.20 is a PDF summarizing the relationship between all 10,000 recovery times and how often they occurred. This plot allows for assessment of whether Path #4 has a higher likelihood of success or failure in respect to recovery time. Figure 4.20 identifies the most occurred grouping of the 10,000 critical path recovery times with the red highlighted bin.

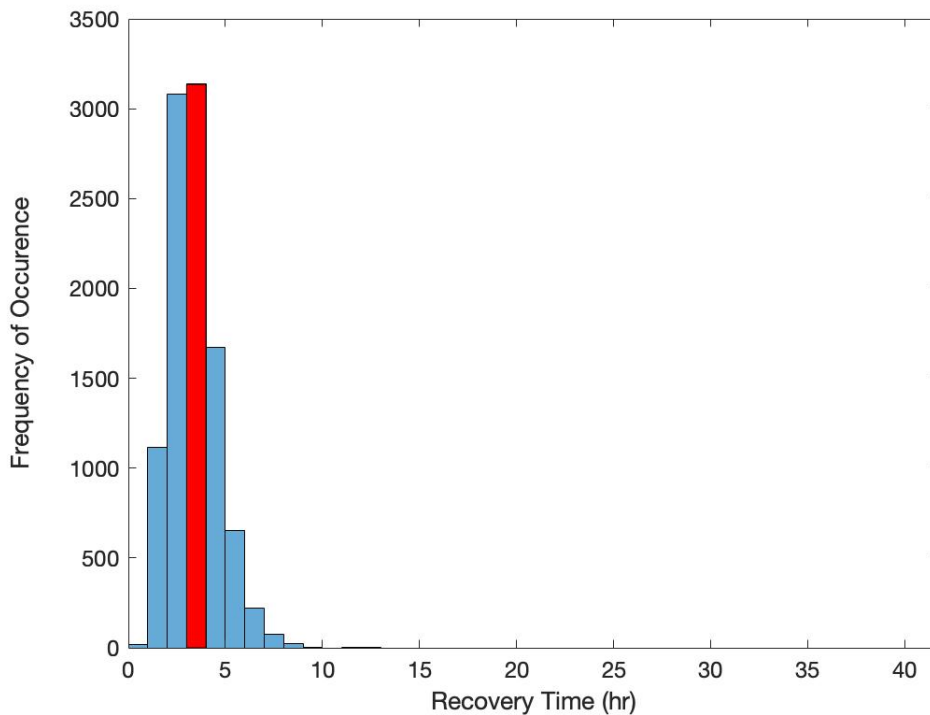


Figure 4.20. PDF PV Recovery Path #4. The Most Frequent Scenario Frequency Grouping is 3,136 of 10,000 Scenarios. The Mode Recovery Time Range is 3.0 to 4.0 Hours with a 0.31 Probability of Occurrence.

For the PV critical recovery path, Path #4, recovery times that fall under 3.0 hours have a have a higher likelihood of success than failure. Paths with recovery times closer to 3.0 hours have the highest P(s) of recovery while paths that fall near the minimum recovery time have a lower P(s). In opposite, paths that range from 4.0 hours or longer have a higher likelihood of failure than success. Similar to the success ranges, path recovery times that fall near 4.0 hours have a less likely chance to fail, but as recovery time increases so does the likelihood of failure.

4.1.5 Rechargeable Battery Recovery

For the rechargeable battery recovery process, 13 recovery tasks, as shown in Table E.1, will be simulated in the recovery task network. The task list includes all tasks and durations are presented in Table 4.9. The recovery procedure task list identifies all tasks sequentially

from Task “A” to Task “N.” Appendix E provides the generated precedence list of the task list in Table E.2.

Table 4.9. Rechargeable Battery Recovery Procedure Task List and Durations (hr)

Task	Min	Max	Mean	Follow On Task
A	0.15	0.25	0.20	B,C
B	0.17	0.25	0.21	D
C	0.25	0.33	0.29	D
D	0.17	0.33	0.25	E,F
E	0.17	0.33	0.25	G
F	0.25	0.33	0.29	G
G	0.17	0.25	0.21	H
H	0.33	0.50	0.42	I
I	0.50	0.75	0.63	J
J	3.00	4.00	3.50	K,L
K	0.25	0.33	0.29	M
L	0.33	0.50	0.42	M
M	0.08	0.17	0.13	N
N	0.00	0.00	0.00	
Total	5.82	8.33	7.08	

From the task list and task precedence order, eight possible recovery paths can be taken from the beginning node to the end, or “recovered,” node. Based on the 10,000 iterated scenarios through the HPIRA tool, 10,000 path recovery sample times are produced for each of the eight paths. Appendix E displays Table E.3 which shows all eight possible paths and the first five, of the 10,000, recovery sample times within the network. Figure 4.21 shows the rechargeable battery recovery task network with all tasks represented as alphabetical nodes and all potential recovery paths from start to completion. Like the the previous recovery task networks, the rechargeable battery recovery network’s critical path is determined with

the same CPM process.

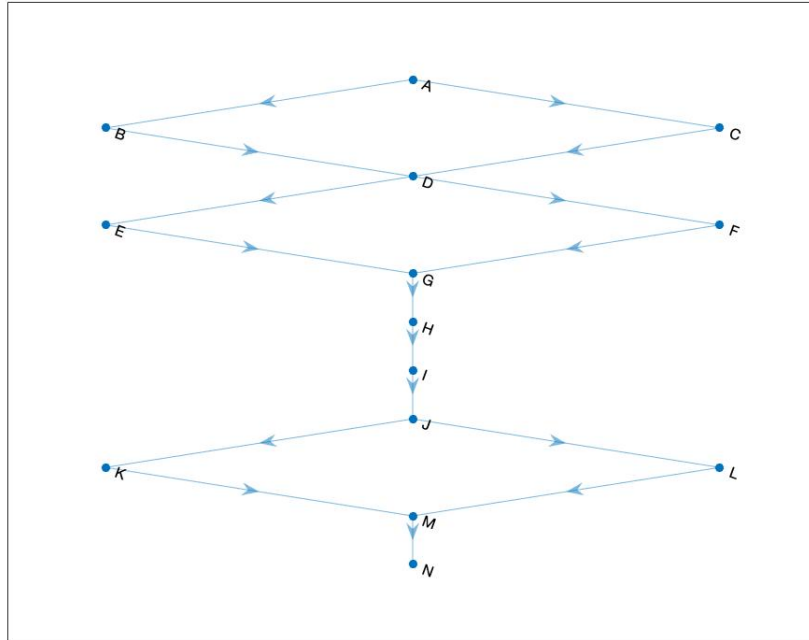


Figure 4.21. Rechargeable Battery Recovery Network Diagram

Figure 4.22 displays a PDF for the modeled rechargeable battery recovery simulation. The plot summarizes the relationship between all 10,000 critical path recovery times and how often they occurred. Plotting the occurrence frequency against the continuous variable, recovery time, produces a PDF where the $P(s)$ and $P(f)$ of the downed pole recovery can be assessed with respect to recovery time. In Figure 4.22, the red highlighted bin represents the most occurred grouping of the 10,000 critical path recovery times.

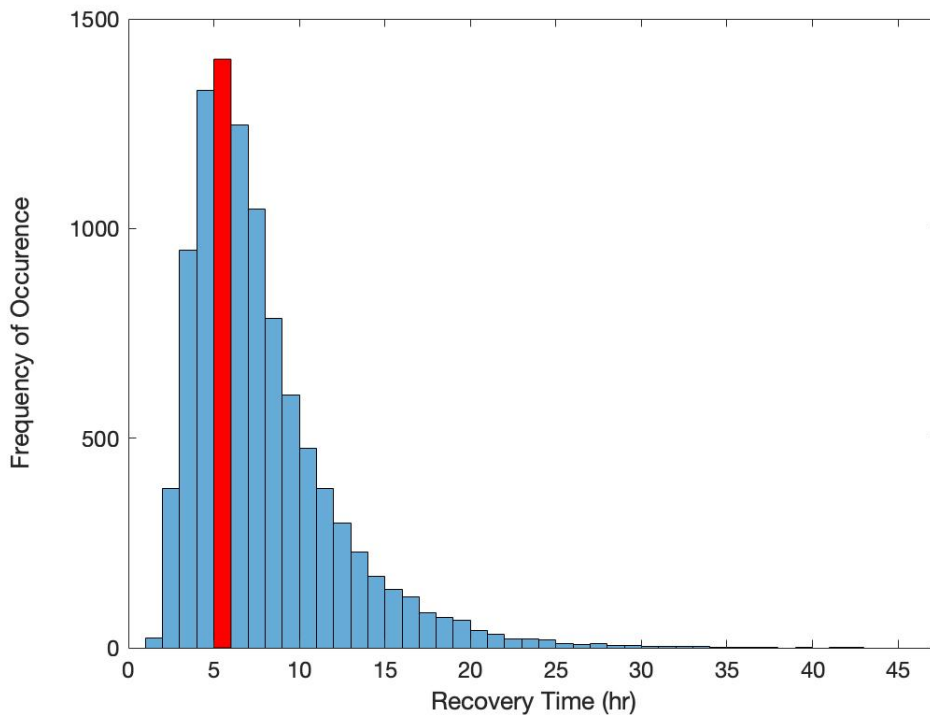


Figure 4.22. PDF for the Modeled Rechargeable Battery Recovery Process. The Most Frequent Scenario Frequency Grouping is 1,404 of 10,000 Scenarios. The Mode Recovery Time Range is 5.0 to 6.0 Hours with a 0.14 Probability of Occurrence.

The greatest frequency occurrence bin represents the greatest $P(s)$ for a rechargeable battery recovery. Therefore, the most successful critical restoration paths will take approximately between 5.0 to 6.0 hours to complete. The critical restoration path recovery times range from a minimum recovery time of 1.38 hours and a maximum recovery time of 47.40 hours. Referring back to Figure 3.5, the $P(s)$ and $P(f)$ of recovery processes can be estimated in respect to the system's recovery time. For a rechargeable battery recovery, paths with recovery times that range between 1.38 hours to 5.0 hours have a higher likelihood of success than failure. Paths with recovery times closer to 5.0 hours have the highest $P(s)$ of recovery while paths that fall near the minimum recovery time have a lower $P(s)$. In opposite, paths that range from 6.0 hours to 47.40 hours have a higher likelihood of failure than success. Similar to the success ranges, path recovery times that fall near 6.0 hours have

a less likely chance to fail, but as the maximum recovery time of 47.40 hours is approached, the likelihood of failure increases.

After conducting the modeled recovery of 10,000 rechargeable battery scenarios, all 10,000 longest recovery times fell between 1.38 and 47.40 hours. Table 4.10 compares statistical values between the predicted and modeled recovery scenarios. Like the downed pole recovery scenarios, modeled recovery values are based off of SPAR-H analysis and are of stochastic nature, resulting in values that are expected to vary considerably from predicted values.

Table 4.10. Recovery Time Statistics for Rechargeable Battery Recovery

Recovery Scenario	Min	Max	Mean	SD	Var
Predicted	5.82	8.33	7.08	1.78	3.17
Model	1.38	47.40	7.82	4.35	18.93

The modeled recovery scenario produced eight possible network paths with 10,000 recovery times for each path. Figure 4.23 shows these outputs with common trends. In Figure 4.8 there are no significant high or low peaks or ranges of recovery times for certain recovery paths. With no paths showing significantly higher recovery times than others, all recovery paths have the potential to be considered critical recovery paths.

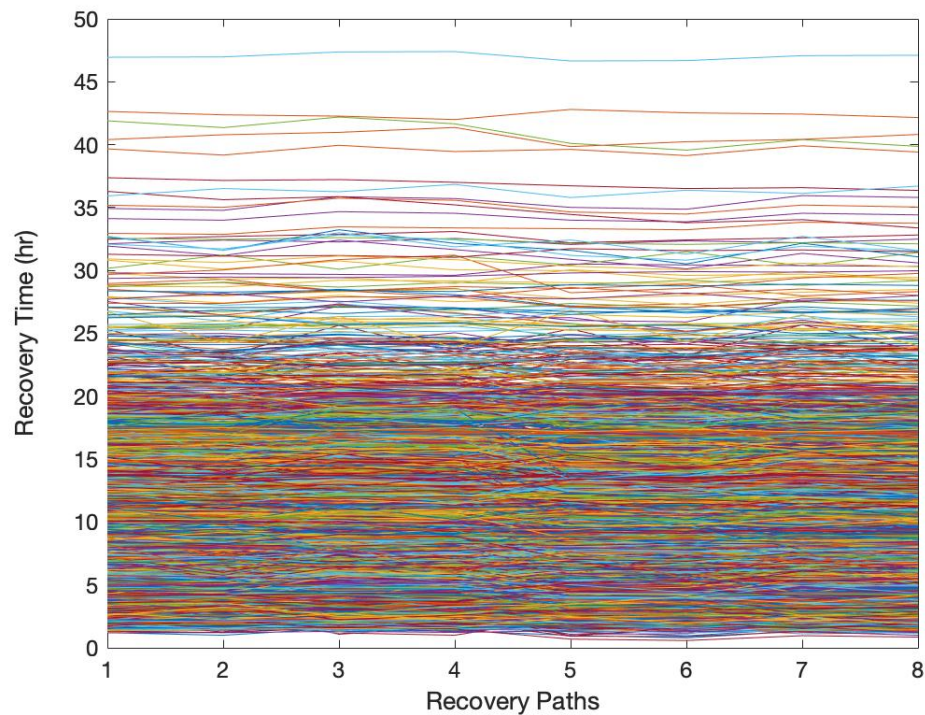


Figure 4.23. Duration Required to Recover a Rechargeable Battery for 10,000 Modeled Scenarios

Critical paths drive the successful completion of the recovery network or process. When assessing all 10,000 rechargeable battery recovery scenarios, Path #1 was determined to be the most common critical path. Figure 4.24 identifies the Rechargeable Battery Recovery Network critical path, Path #1, and the path's associated recovery time. Based off of the most common, longest recovery time, Path #1 is the critical path for the rechargeable battery recovery model. It is important to note that the critical path is not necessarily the critical path for all of the generator recovery scenarios; however, it does dominate over the other potential paths.

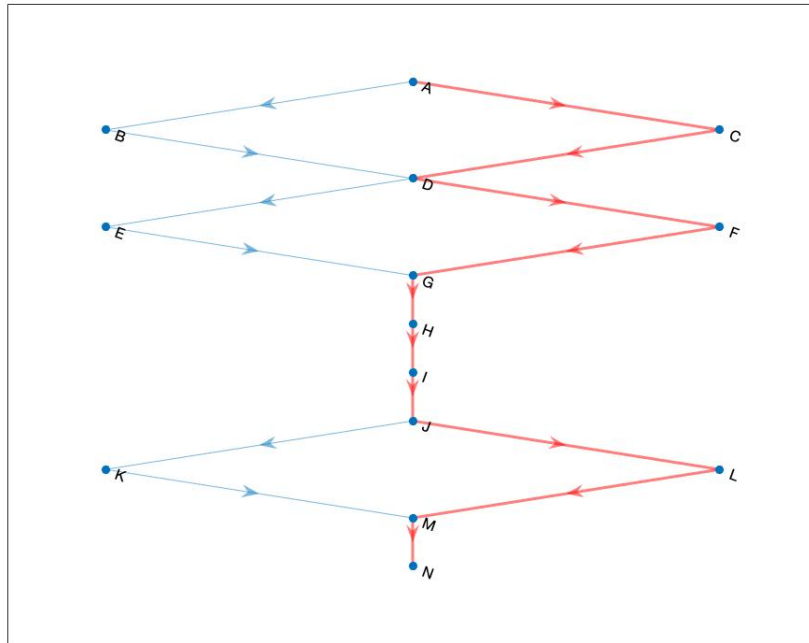


Figure 4.24. Rechargeable Battery Recovery Network Diagram Showing the Critical Recovery Path #1 with an Estimated Recovery Time of 5 Hours.

With the critical path identified, the recovery time for that path was compared amongst all 10,000 recovery scenarios. Figure 4.25 is a PDF summarizing the relationship between all 10,000 recovery times and how often they occurred. This plot allows for assessment of whether Path #1 has a higher likelihood of success or failure in respect to recovery time. Figure 4.25 identifies the most occurred grouping of the 10,000 critical path recovery times with the red highlighted bin.

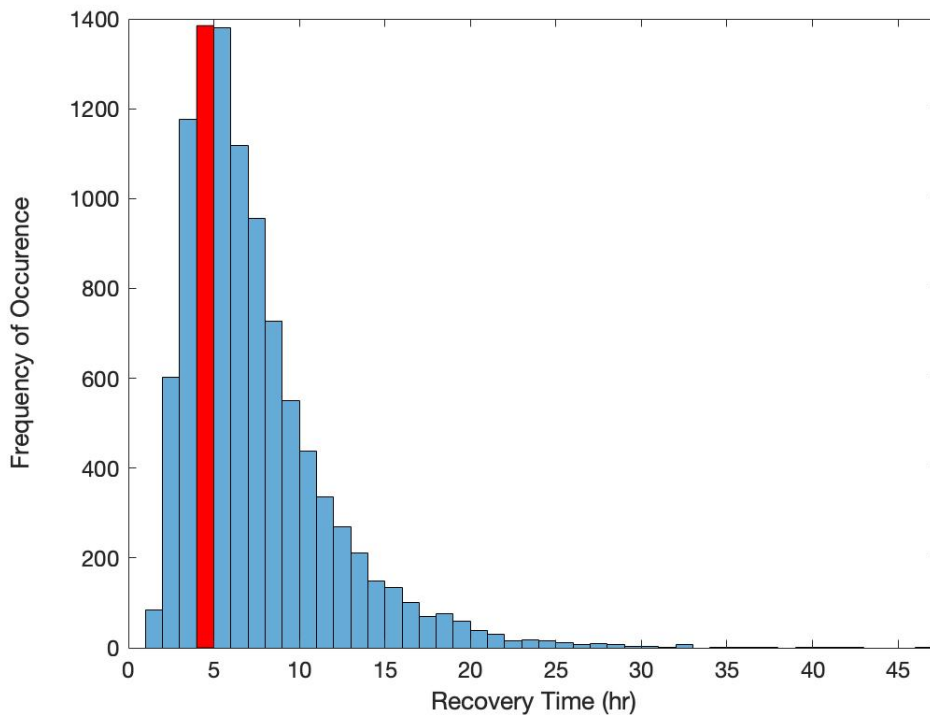


Figure 4.25. PDF of Rechargeable Battery Recovery Path #1. The Most Frequent Scenario Frequency Grouping is 1,385 of 10,000 Scenarios. The Mode Recovery Time Range is 4.0 to 5.0 Hours with a 0.14 Probability of Occurrence.

For the rechargeable battery critical recovery path, Path #1, recovery times that fall under 4.0 hours have a higher likelihood of success than failure. Paths with recovery times closer to 4.0 hours have the highest $P(s)$ of recovery while paths that fall near the minimum recovery time have a lower $P(s)$. In opposite, paths that range from 5.0 hours or longer have a higher likelihood of failure than success. Similar to the success ranges, path recovery times that fall near 5.0 hours have a less likely chance to fail, but as recovery time increases so does the likelihood of failure.

4.1.6 Mutlicell Battery Recovery

For this recovery process, 12 recovery tasks, as shown in Table F.1, will be simulated in the recovery task network. The task list includes all tasks and durations are presented in Table

4.11. The recovery procedure task list identifies all tasks sequentially from Task “A” to Task “M.” Appendix F provides the generated precedence list of the task list in Table F.2.

Table 4.11. Multicell Battery Recovery Procedure Task List and Durations (hr)

Task	Min	Max	Mean	Follow On Task
A	0.15	0.25	0.20	B
B	0.17	0.25	0.21	C
C	0.17	0.33	0.25	D,E
D	0.17	0.33	0.25	F
E	0.08	0.25	0.17	F
F	0.17	0.25	0.21	G
G	0.25	0.33	0.29	H,I
H	0.08	0.17	0.13	J
I	0.08	0.17	0.13	J
J	24.00	48.00	36.00	K
K	0.08	0.25	0.17	L
L	0.17	0.25	0.21	M
M	0.00	0.00	0.00	
Total	25.57	50.83	38.20	

From the task list and task precedence order, four possible recovery paths can be taken from the beginning node to the end, or “recovered,” node. Based on the 10,000 iterated scenarios through the HPIRA tool, 10,000 path recovery sample times are produced for each of the four paths. Appendix F displays Table F.3 which shows all four possible paths and the first five, of the 10,000, recovery sample times within the network. Figure 4.26 shows the multicell battery recovery task network with all tasks represented as alphabetical nodes and all potential recovery paths from start to completion. Like the the previous recovery task networks, the multicell battery recovery network’s critical path is determined with the same CPM process.

Figure 4.26 shows the task network for the recovery procedure task list.

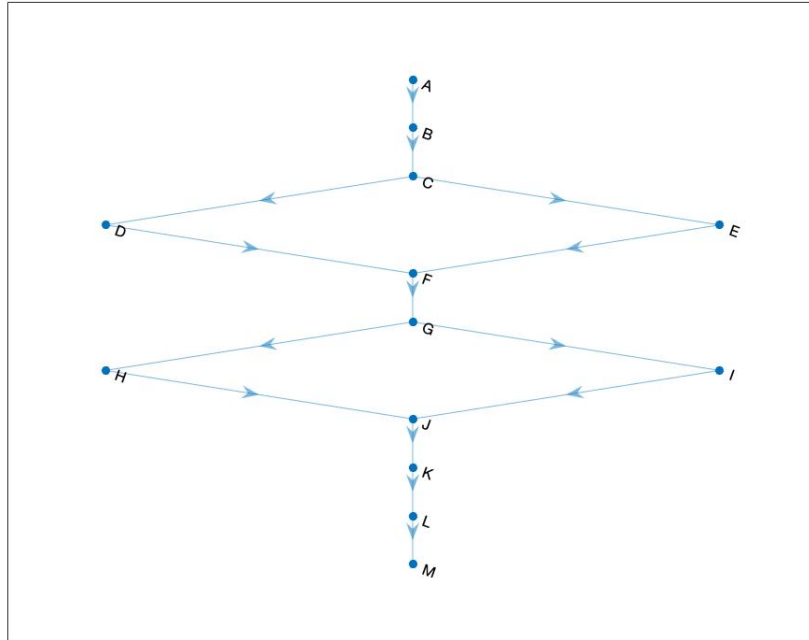


Figure 4.26. Multicell Battery Recovery Network Diagram

Figure 4.27 displays a PDF for the modeled multicell battery recovery simulation. The plot summarizes the relationship between all 10,000 critical path recovery times and how often they occurred. Plotting the occurrence frequency against the continuous variable, recovery time, produces a PDF where the $P(s)$ and $P(f)$ of the downed pole recovery can be assessed with respect to recovery time.

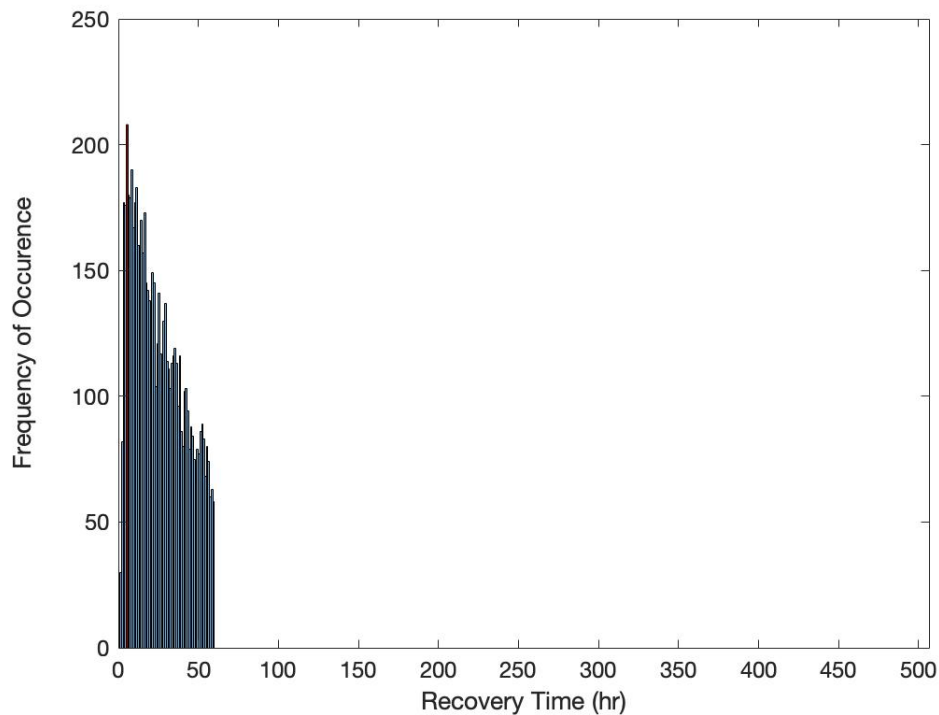


Figure 4.27. PDF for the Modeled Multicell Battery Recovery Process. The Most Frequent Scenario Frequency Grouping is 208 of 10,000 Scenarios. The Mode Recovery Time Range is 5.0 to 6.0 Hours with a 0.02 Probability of Occurrence.

The greatest frequency occurrence bin represents the greatest $P(s)$ for a multicell battery recovery. Therefore, the most successful critical restoration paths will take approximately between 5.0 to 6.0 hours to complete. The critical restoration path recovery times range from a minimum recovery time of 1.10 hours and a maximum recovery time of 506.5 hours. Referring back to Figure 3.5, the $P(s)$ and $P(f)$ of recovery processes can be estimated in respect to the system's recovery time. For a multicell battery recovery, paths with recovery times that range between 1.10 hours to 5.0 hours have a higher likelihood of success than failure. Paths with recovery times closer to 5.0 hours have the highest $P(s)$ of recovery while paths that fall near the minimum recovery time have a lower $P(s)$. In opposite, paths that range from 6.0 hours to 506.5 hours have a higher likelihood of failure than success. Similar to the success ranges, path recovery times that fall near 6.0 hours have a less likely chance

to fail, but as the maximum recovery time of 506.5 hours is approached, the likelihood of failure increases.

After conducting the modeled recovery of 10,000 multicell battery scenarios, all 10,000 generated critical path recovery times fell between 1.10 and 506.5 hours. Table 4.12 compares statistical values between the predicted and modeled recovery scenarios. Like the previous recovery scenarios, modeled recovery values are based off of SPAR-H analysis and are of stochastic nature, resulting in values that are expected to vary considerably from predicted values.

Table 4.12. Recovery Time Statistics for Multicell Battery Recovery

Recovery Scenario	Min	Max	Mean	SD	Var
Predicted	25.57	50.83	38.20	17.87	319.2
Model	1.10	506.5	50.78	47.63	2270

The modeled recovery scenario produced four possible network paths with 10,000 recovery times for each path. Figure 4.28 shows these outputs with common trends. In Figure 4.28 there are no significant high or low peaks or ranges of recovery times for certain recovery paths. With no paths showing significantly higher recovery times than others, all recovery paths have the potential to be considered critical recovery paths.

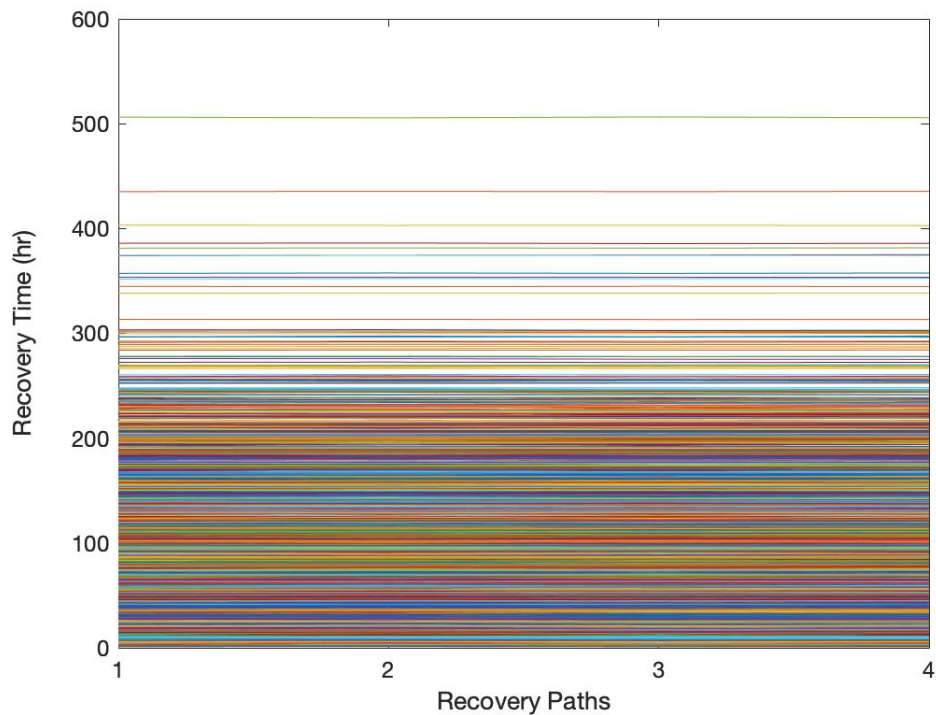


Figure 4.28. Duration Required to Recover a Multicell Battery for 10,000 Modeled Scenarios

Critical paths drive the successful completion of the recovery network or process. When assessing all 10,000 multicell battery recovery scenarios, Path #3 was determined to be the most common critical path. Figure 4.29 identifies the Multicell Battery Recovery Network critical path, Path #3, and the path's associated recovery time. Based off of the most common, longest recovery time, Path #3 is the critical path for the multicell battery recovery model. It is important to note that the critical path is not necessarily the critical path for all of the generator recovery scenarios; however, it does dominate over the other potential paths.

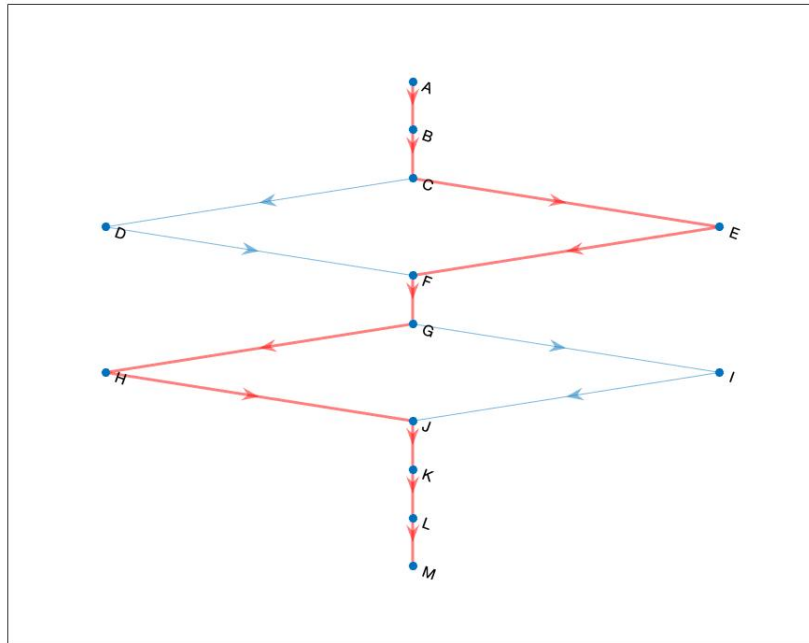


Figure 4.29. Multicell Battery Recovery Network Diagram Showing the Critical Recovery Path #3 with an Estimated Recovery Time of 7 Hours.

With the critical path identified, the recovery time for that path was compared amongst all 10,000 recovery scenarios. Figure 4.30 is a PDF summarizing the relationship between all 10,000 recovery times and how often they occurred. This plot allows for assessment of whether Path #3 has a higher likelihood of success or failure in respect to recovery time.

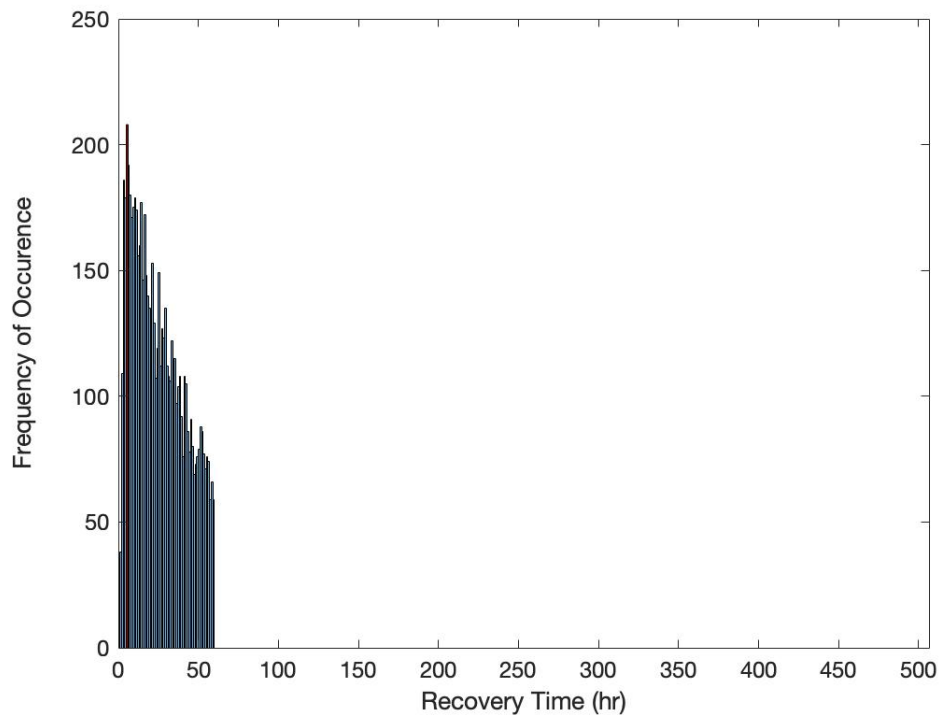


Figure 4.30. PDF of Multicell Battery Recovery Path #3. The Most Frequent Scenario Frequency Grouping is 208 of 10,000 Scenarios. The Mode Recovery Time Range is 5.0 to 6.0 Hours with a 0.02 Probability of Occurrence.

For the multicell battery critical recovery path, Path #3, recovery times that fall under 5.0 hours have a higher likelihood of success than failure. Paths with recovery times closer to 5.0 hours have the highest $P(s)$ of recovery while paths that fall near the minimum recovery time have a lower $P(s)$. In opposite, paths that range from 6.0 hours or longer have a higher likelihood of failure than success. Similar to the success ranges, path recovery times that fall near 6.0 hours have a less likely chance to fail, but as recovery time increases so does the likelihood of failure.

4.2 Multi-Scale Microgrid Component Recovery

This section will build off of individual component data results from the previous section. In addition to observing SPAR-H and stochastic simulations for individual components, obser-

uations will be made for combined component failure events. This section will provide two multi-component failure event assessments that will evaluate how human error influences the successful restoration of the entire microgrid architecture. A BOE assessment will be completed for each failure event to determine the total microgrid recovery duration time as well as provide data to assess whether human factors influenced that duration time.

Like the previous section, this section assesses a notional NAVSTA's ability to rebound a degraded microgrid system with a hypothetically combined component failure event. The NAVSTA microgrid has a simple architecture that performs at normal operations under ideal conditions. The incident of failure is unintentional and isolated to a single microgrid component. The NAVSTA microgrid has a simple architecture that performs at normal operations under ideal conditions. The recovery plan for the two multi-component failure events will include the same fully qualified two-person team consisting of a High Voltage Supervisor and a Lead Electrician. The two-person team will be recovering every component that fails with no breaks, rest periods, or days off. Environmental conditions will be ideal and all tools and supplies are available and in supply.

Table 4.13 summarizes the installed and fully operating component capability for the NAVSTA simple microgrid architecture.

Table 4.13. Total Number of NAVSTA Microgrid Components

Microgrid Component	# of Components
Power Pole	2000
Diesel Generator Sets	80
Substation	13
PV	54
Rechargeable Battery	78
Multicell Battery	5

4.2.1 Multi-Component Failure Event #1

For this multi-component failure event, Table 4.14 summarizes the total number of components that have been damaged or degraded. All components listed need to be fully repaired in order to restore the NAVSTA microgrid back to normal operations.

Table 4.14. Number of Degraded Microgrid Components Applied for Failure Event #1 BOE Analysis

Microgrid Component	# Degraded Components
Power Pole	50
Diesel Generator Sets	10
Substation	3
PV	25
Rechargeable Battery	18
Multicell Battery	2

The simulated BOE analysis conducted on the multi-component failure event considers each component's modeled scenario's critical path recovery times. The same simulated BOE analysis was conducted with maximum and minimum predicted duration values provided from [32]. Total duration times represent man-hours needed to recover all components in the given failure event. In all three BOE analyses, resulting total durations exceeded USMC's and USN's maximum autonomy times for energy security. By not meeting standardized autonomy metrics, the NAVSTA of interest is unable to support mission critical areas and is vulnerable in its ability to maintain energy security. All BOE final recovery durations results are found in Table 4.15.

Table 4.15. Failure Event #1 BOE Total Recovery Man-Hours Results for a Two-Person Recovery Team

Recovery Scenario	Man-Hours (hrs)	Man-Hours (days)
Modeled	1,588	66
Predicted Max	1,667	70
Predicted Min	1,084	46

4.2.2 Multi-Component Failure Event #2

For this multi-component failure event, Table 4.16 summarizes the total number of components that have been damaged or degraded. All components listed need to be fully repaired in order to restore the NAVSTA microgrid back to normal operations.

Table 4.16. Number of Degraded Microgrid Components Applied for Failure Event #2 BOE Analysis

Microgrid Component	# Degraded Components
Power Pole	500
Diesel Generator Sets	25
Substation	8
PV	50
Rechargeable Battery	54
Multicell Battery	4

Like failure event #1, The simulated BOE analysis conducted on the multi-component failure event considers each component's modeled scenario's critical path recovery times. The same simulated BOE analysis was conducted with maximum and minimum predicted

duration values provided from [32]. Total duration times represent man-hours needed to recover all components in the given failure event. In all three BOE analyses, resulting total durations exceeded USMC's and USN's maximum autonomy times for energy security. By not meeting standardized autonomy metrics, the NAVSTA of interest is unable to support mission critical areas and is vulnerable in its ability to maintain energy security. All BOE final recovery durations results are found in Table 4.17.

Table 4.17. Failure Event #2 BOE Total Recovery Man-Hours Results for a Two-Person Recovery Team

Recovery Scenario	Man-Hours (hrs)	Man-Hours (days)
Modeled	10,900	454
Predicted Max	11,350	473
Predicted Min	7,761	324

4.3 Chapter Summary

This chapter applied the HPIRA tool that was developed in Chapter 3 to six different microgrid component recovery processes and two multi-scale microgrid recovery events. Successful recovery time durations are considered equal to the man-hours required for a successful recovery of a degraded microgrid system. Additionally this chapter determined recovery time bounds for each recovery process where microgrid restoration efforts were likely to succeed and to fail. Chapter 5 summarizes Chapter 4's findings, presents recommendations HPIRA applications, and potential follow on work.

CHAPTER 5:

Conclusion

Energy security for DoD installations has never been a more important topic of study. The DoD recognizes that modern energy infrastructures and systems have limitations in regards to ensuring reliability, resilience, and efficiency [1]. Current safeguards designed within energy systems alone do not place the DoD in secure conditions to maintain mission readiness. It is incumbent upon all DoD installations to investigate new and diverse avenues to support DoD initiatives in improving energy security. The USN firmly supports these initiatives and strives to build on the three pillars of energy security within its own energy infrastructures and systems. The goal of this thesis is to investigate and develop a method to improve resilience within DoD microgrids. While most microgrid resilience research focuses on system design, this thesis places focus on the operators of the microgrid system. Specifically for microgrid recovery scenarios, this thesis draws attention to recovery personnel's cognitive states during their restoration efforts in recovery degraded microgrid systems. This chapter shares closing thoughts about how human factors affect recovery procedures. By considering these factors, DoD leadership can better prepare and manage its workforce and resources to improve and strengthen energy security measures. This chapter provides a summary of findings, presents recommendations, and suggests future work for building DoD microgrid resilience with respect to microgrid recovery procedures.

5.1 Summary of Findings

In an effort to improve DoD microgrid resilience, this thesis investigates the influence of human cognition in microgrid recovery procedures. While it is assumed that recovery procedures improve the rebound of a degraded microgrid system, it does not guarantee it. In fact, there is always a chance that recovery procedures can be further degraded if the procedures are not properly performed. Within this thesis, six different microgrid component recovery procedures are assessed as predicted recovery scenarios and as modeled recovery scenarios with SPAR-H applications. Both scenarios' recovery time results are shown in Table 5.1. For all components assessed, their respective critical path's most successful recovery time ranges fell under their average predicted recovery time values.

This indicates that when considering human factors within recovery procedures, it does not negatively impact the successful completion of component recoveries. While this data reflects promising results, the scenarios are based on ideal situations where the recovery team members are fully qualified, rested, and bear no other daily responsibilities or stressors. Additionally, environmental conditions are ideal and introduce no further challenges or complications in the recovery process.

Table 5.1. Most Successful Modeled Recovery Time Range and Average Predicted Recovery Times for all Assessed Microgrid Components

Component	Modeled (hr)	Average Predicted (hr)
Pole	13.0 - 14.0	16.54
Generator	6.0 - 7.0	13.48
Substation	11.0 - 12.0	18.49
PV	3.0 - 4.0	6.16
Rechargeable Battery	4.0 - 5.0	7.08
Multicell Battery	5.0 - 6.0	38.20

Any paths that are completed in shorter durations than the most successful modeled recovery durations have strong chances of successful system recovery. It is important to note that even while the shortest duration time proves the success of a microgrid component and system restoration, it may not necessarily occur, because rushing to complete tasks does not guarantee successful recovery and could potentially cause inadvertent errors or mistakes. That is why a higher likelihood of success will typically occur near the most successful recovery time range. Also, each recovery path is dependent on the combination of task complexity and longevity. The successful completion of the recovery path and/or process is only as good as the persons completing it. There are pros and cons to evaluating a single two-person restoration team in modeled recovery scenarios. By utilizing the same recovery team members, familiarity and knowledge of component specifications allow for more efficient reparations. However, the more damaged a component is, the more time consuming the recovery tasks are. Familiarity and knowledge of a subject can only take

a human so far if they are not mentally or physically fit. Fatigue and stress contribute to prolonged completion of tasks and can very well result in further damage of a component. Regardless of which component is being recovered, recovery duration times that take longer than the most successful recovery time ranges will have an increased probability of failure that can increase the risk of further system degradation or personnel injury. This will most likely cause recovery personnel with experience greater fatigue as time goes on, which can potentially increase the complexity of completing the recovery path.

This project compared modeled multi-component recovery events with human factors. When comparing modeled versus predicted man-hour outputs for recovering two different events, it was determined that human factors did not significantly differ from predicted man-hour estimations. These results are not rigorous enough to be used as proven data for the given events in Tables 4.15 and 4.17. While these two events used SPAR-H implemented stochastic values, the data resulting from various failed component combinations is not truly realistic. Each event assumes continuous repair operations with a single two-person repair team. In these assessments, huge factors such as working hours, non-working hours, weekends, rest time, and repair location travel time are not considered. Given these limitations, the total man-hours determined in both assessments still failed USN and USMC standards for installation energy autonomy. Therefore, if the important factors as mentioned are considered, it is expected that the recovery duration will be even longer if the recovery effort is left to a single two-person recovery team.

To improve the total recovery time, or better manage man-hours, a considerable amount of additional, fully qualified recovery teams need to be utilized to meet USN and USMC standards. It is essential that not only are the recovery teams fully qualified, but also that they have the same adequate experience to perform all skill sets so that they can be interchanged between teams if needed. By adding recovery teams to these events, recovery efforts can potentially be sped up. For both failure events, Table 5.2 compares the single two-person recovery team and associated man-hour totals as well as estimated recovery team numbers that are needed to meet USN autonomy standards. Event required team totals are a conservative estimates considering predicted maximum man-hour totals. Those teams will work continuously with rotating 12-hour shifts.

Table 5.2. Number of Recovery Teams and Personnel for Modeled Events and Required Autonomy Standards

Event Response	Recovery Man-Hours (days)	# Teams	# Personnel
Event #1	70	1	2
	7	5	10
Event #2	473	1	2
	7	34	68

In conclusion, established recovery procedures generally do improve the rebound of a degraded microgrid when considering the influence of human cognition. This conclusion is not consistent through every recovery procedure since human cognition is affected by various factors as pointed out in the SPAR-H analysis. What is consistent in the analysis is that as an event's recovery time extends, the more likely a microgrid system recovery process will fail. Additionally, as observed in Section 4.2, the more complicated a recovery event is, the more man-hours will be needed to successfully recover all microgrid components. In order to meet USN autonomy standards, DoD installations must consider increasing their energy facility workforce with enough qualified and experienced personnel to adequately respond to wide-scale microgrid failure events.

5.2 Recommendations

Determining recovery man-hours for various unexpected microgrid disturbances, with human factors consideration, allows for stakeholders to assess safety risks. Safety within the DoD is a major factor for all personnel, equipment, and installation operations. When stakeholders identify man-hours that are expected for a specific recovery effort, adequate planning to support that effort should be taken. Within this planning effort, stakeholders can identify the amount of recovery personnel needed so that teams are not overly worked. Fatigued recovery team members are subject to unintentional mistakes that can cause injury or harm to themselves or others and/or cause further equipment damage. Additionally, the potentially extraordinary volume of effort required in recovery scenarios can cause additional stress on

recovery team personnel, resulting in similar outcomes of fatigued personnel. Recognizing the amount of man-hours needed in recovery efforts will also highlight any weaknesses of an installation's manpower and training. It is imperative that DoD leadership is aware of man-hour needs of potential microgrid recovery efforts so that recovery personnel are kept safe. Ensuring safety of the DoD's most important asset, its people, will build and support resilience in the DoD's energy security initiative.

Results from this thesis can be used as strong data sources for DoD installation stakeholders for personnel manning and budget discussions. Simulating various component failures and multi-component failure events allows for stakeholders to determine adequate man-hours needed to ensure that DoD installations support energy security initiatives. By determining man-hour requirements for installation demands, deficiencies in manning, training, and system supply can also be identified. It is recommended that DoD installation commanding officers and facility managers communicate their data findings early and often to their reporting chain of commands and respective program offices to ensure that their needs are included in their annual Program Objective Memorandums (POMs) and Budget Estimate Submissions (BESs). This consistent data-based communication will highlight energy security vulnerabilities to DoD leadership so that yearly budgets can account for costs to hire more qualified personnel, to provide adequate training resources, and to provide purchasing budgets for spare parts and equipment. This effort will build and support the DoD's energy security initiative with improved resilience.

While recovery procedures provide a consistent and available approach strategy for microgrid recoveries, they must also be used with optimistic caution. Like any type of instruction or reference, procedures and guidance need to stay updated and relevant with system developments and specifications. This is a challenge with constantly changing technologies that replace broken or outdated equipment or components. If recovery guidance or references are not kept up to date, application of the procedures will not reflect the proper actions needed to restore a degraded component or system. Additionally, the recovery personnel applying those procedures need to be knowledgeable of the new procedures by receiving enough training to effectively perform them. If these forethoughts are not considered, the recovery process can be dragged out for long durations or even cause further damage to a system. Similar to performing recovery tasks, the recovery process is only as good as the constant maintaining of the procedures themselves, the adequate training of those new

procedures, and the proper planning and coordination of newly installed system and component integration efforts. Without these considerations, DoD installation microgrids are vulnerable in having their once proven recovery procedures fail and backfire, causing cascading challenges and issues. It is recommended that DoD installation commanding officers and facility managers maintain microgrid recovery procedures at least quarterly to identify issues early so that energy security risks can be mitigated early.

5.3 Future Work

This thesis leverages a simple microgrid architecture from [8] to develop the HPIRA tool for various component recovery process simulations. The HPIRA tool generates recovery duration times for successful recovery processes, however, the recovery durations best represent the man-hours needed to recover downed components. In order to better and more accurately determine man-hours needed for failure events, further investigation should be taken into different human cognitive states. This thesis provides the foundation of analysing the effect of human cognition on successfully completed recovery tasks and processes, however, the SPAR-H PSF ratings are based off of ideal conditions. More rigorous cognitive scenarios can provide a more realistic and conservative recovery assessment for DoD microgrids. Additionally, research should consider how PSFs change as failure events are prolonged or emerge into cascading failure events. This research applies the initial state of PSF ratings for all failure scenarios, but in reality, factors such as stress and fitness for duty become more relevant as they change over time.

While this thesis focuses on unintentional microgrid failure scenarios, research should be done on microgrid failures that result from commission, or intentional malicious attacks. Consideration and focus on high value assets on DoD installations should be assessed so that in the case of events like targeted terrorist attacks, DoD installations have system protections and responses in place. This research may lead towards classified distributions, but it will allow stakeholders to have greater knowledge and awareness of microgrid recovery efforts on critical microgrid supported infrastructures. Additionally, this research can lead towards assessing cyber attack recovery processes that influence electric systems such as microgrids. This effort will most likely require coordination and assistance from information technology and software development personnel to best capture electronic recovery procedures.

The HPIRA tool's framework provides a valid data source for personnel manning, support, and training that can be used for other types of analysis. With generated recovery time durations, or man-hour requirements, HPIRA data can be used within cost analysis research. Man-hours for various microgrid recovery scenarios that do not include normal operations and maintenance actions, can influence budget factors that cover personnel overtime and training as well as salary costs for government and contracted personnel. Additionally, HPIRA data can be used for system suitability research in considering reliability, availability, and maintainability of microgrid systems and components. These considerations can and should be included in life cycle cost estimations for DoD microgrid systems.

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APPENDIX A: Downed Pole Data

Table A.1 summarizes the Downed Pole Recovery Task Descriptions.

Table A.1. Downed Pole Recovery Task Descriptions

Node	Recovery Task
A	2-man crew identified & depart
B	Crew investigates scene
C	Crew Member A walks the line
D	Crew Member B voltage checks
E	Crew reports fault(s)/repair actions
F	Connect temporary Gen to Connection Pt w/Tie In
G	Secure Physical Area of Incident
H	Electrically isolate @ Breakers w/tag outs
I	Safety Checks
J	Stabilize Damaged Pole with Utility Truck Pinchers
K	Pull & Replace Damaged Fuses
L	Repair 3 Line Pole with Cross Arms
M	Clean Oil Spill from Transformer Damage
N	Transport New Transformer to Site w/Crane
O	Secure & Restore Connections to new transformer
P	Re-energize power lines @ breakers
Q	Verify power outputs at substation controllers, no faults
R	Disconnect temporary Generator
S	Recovery

Table A.2 summarizes the precedence order for the Downed Pole Task List.

Table A.2. Downed Pole Recovery Precedence List

From	To	Avg. Duration (hr)
A	B	0.20
B	C	0.21
B	D	0.21
C	E	0.26
D	E	0.21
E	F	0.25
F	G	0.42
F	H	0.42
H	I	0.21
I	J	0.29
G	J	0.25
J	K	0.75
J	L	0.75
K	L	0.29
L	M	3.00
L	N	3.00
M	N	2.00
N	O	3.50
O	Q	4.00
O	P	4.00
P	R	0.21
Q	R	0.21
R	S	0.29

Table A.3 shows all possible paths and their duration within the network. Note that the duration values for each path are a summation of stochastic results for each task or node.

Table A.3. Downed Pole Recovery Network Paths and Duration for 5 Iterations

Paths	1	2	3	4	5
ABDEFHIJKLMNOPRS	25.645	15.641	28.673	19.222	6.6002
ABCEFHIJKLMNOPRS	25.667	15.401	28.51	19.267	6.762
ABDEFGJKLMNOPRS	24.437	14.42	28.823	19.866	7.8396
ABCEFGJKLMNOPRS	24.46	14.18	28.66	19.911	8.0014
ABDEFHIJLMNOPRS	25.322	14.843	28.399	18.728	6.0917
ABCEFHIJLMNOPRS	25.345	14.603	28.236	18.772	6.2535
ABDEFGJLMNOPRS	24.115	13.621	28.549	19.371	7.3311
ABCEFGJLMNOPRS	24.137	13.382	28.386	19.416	7.4929
ABDEFHIJKLNOPRS	23.09	14.997	25.109	12.03	5.8433
ABCEFHIJKLNOPRS	23.112	14.757	24.946	12.075	6.005
ABDEFGJKLNOPRS	21.882	13.775	25.259	12.673	7.0826
ABCEFGJKLNOPRS	21.905	13.536	25.096	12.718	7.2444
ABDEFHIJLNOPRS	22.767	14.199	24.835	11.535	5.3347
ABCEFHIJLNOPRS	22.79	13.959	24.672	11.58	5.4965
ABDEFGJLNOPRS	21.56	12.977	24.985	12.179	6.5741
ABCEFGJLNOPRS	21.582	12.737	24.822	12.223	6.7359
ABDEFHIJKLMNOQRS	25.623	15.682	28.214	19.171	6.7659
ABCEFHIJKLMNOQRS	25.646	15.442	28.052	19.216	6.9277
ABDEFGJKLMNOQRS	24.416	14.46	28.364	19.815	8.0053
ABCEFGJKLMNOQRS	24.438	14.221	28.202	19.86	8.1671
ABDEFHIJLMNOQRS	25.301	14.884	27.94	18.676	6.2574
ABCEFHIJLMNOQRS	24.093	13.662	28.09	19.32	7.4968
ABDEFGJLMNOQRS	25.301	14.884	27.94	18.676	6.2574
ABCEFGJLMNOQRS	24.116	13.422	27.928	19.365	7.6585
ABDEFHIJKLNOQRS	23.068	15.038	24.651	11.978	6.0089
ABCEFHIJKLNOQRS	23.091	14.798	24.488	12.023	6.1707
ABDEFGJKLNOQRS	21.861	13.816	24.801	12.622	7.2483
ABCEFGJKLNOQRS	21.883	13.576	24.638	12.667	7.4101
ABDEFHIJLNOQRS	22.746	14.24	24.377	11.483	5.5004
ABCEFHIJLNOQRS	22.768	14.00	24.214	11.528	5.6622
ABDEFGJLNOQRS	21.538	13.018	24.527	12.127	6.7398
ABCEFGJLNOQRS	21.561	12.778	24.364	12.172	6.9016

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APPENDIX B: Generator Loss Data

Table B.1 summarizes the Generator Recovery Task Descriptions.

Table B.1. Generator Recovery Task Descriptions

Node	Recovery Task
A	2-man crew identified & depart
B	Crew investigates scene
C	Crew investigates status of generator (running or not)
D	GEN Running: Check ATS status & protection breaker status
E	Check status of main breakers (not tripped) & connection points (on buildings)
F	If #5 SAT, investigate circuits - fault found: short circuit
G	Measure amperage draw: Circuit Overload (>20amp)?
H	Crew reports fault(s)/repair actions
I	Secure Physical Area of Incident
J	Electrically isolate @ Breakers w/tag outs
K	Safety Checks
L	Split Circuit (split load & modify plugs)
M	Secure and restore connections
N	Reenergize @breakers
O	Measure load (verify load below rating capacity)
P	Verify power outputs at substation controllers, no faults
Q	Recovery

Table B.2 summarizes the precedence order for the Generator Loss Task List.

Table B.2. Generator Recovery Precedence List

From	To	Avg. Duration (hr)
A	B	0.20
B	C	0.21
C	D	0.10
C	E	0.10
D	F	0.10
E	F	0.54
F	G	0.38
G	H	0.54
G	I	0.54
H	J	0.25
I	J	0.25
J	K	0.21
K	L	0.29
L	M	9.00
L	N	9.00
N	O	0.38
M	P	0.21
P	Q	0.42
O	Q	0.42

Table B.3 shows all possible paths and their duration within the network. Note that the duration values for each path are a summation of stochastic results for each task or node.

Table B.3. Generator Recovery Network Paths and Duration for 5 Iterations

Paths	1	2	3	4	5
ABCEFGIJKLMPQ	8.4379	20.515	28.085	15.479	24.156
ABCDGFIJKLMPQ	6.4322	20.189	28.025	14.39	23.941
ABCEFGHJKLMPQ	8.7386	20.686	27.647	15.68	24.562
ABCDFGHJKLMPQ	6.7329	20.36	27.587	14.591	24.347
ABCEFGIJKLNOQ	8.2951	21.51	27.814	13.646	23.476
ABCDGFIJKLNOQ	6.2894	21.192	27.754	12.556	23.261
ABCEFGHJKLNOQ	8.5958	21.689	27.376	13.847	23.881
ABCDFGHJKLNOQ	6.5901	21.363	27.316	12.758	23.666

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APPENDIX C: Substation Loss Data

Table C.1 summarizes the Substation Recovery Task Descriptions.

Table C.1. Substation Recovery Task Descriptions

Node	Recovery Task
A	2-man crew identified & depart
B	Investigate Substation Status w/remote SCATA-find open breakers
C	Crew investigates scene
D	Investigate 1247 transformer circuit panel for Open Feeder Breaker
E	Investigate 1247 transformer circuit panel for Open Main Feeder Breaker
F	Investigate 345 transformer circuit panel - outside fault out in the field (due to insulator split on pole)
G	Crew reports fault(s)/repair actions
H	Secure Physical Area of Incident
I	Electrically isolate @ Breakers w/tag outs
J	Safety Checks
K	Deploy and use bucket truck to investigate insulator crack
L	Replace insulation materials and verify connections all secure
M	Inspect transformer for wet/dry sump blown fuses, or windings
N	Remove and replace blown wet sump fuse
O	Perform Frequency & MEGGER Tests (static voltage on windings) on each transformer phase to ensure no other damage
P	Secure and restore connections
Q	Re-energize @breakers
R	Verify power outputs at substation controllers, no faults
S	Recovery

Table C.2 summarizes the precedence order for the Substation Loss Task List.

Table C.2. Substation Recovery Precedence List

From	To	Avg. Duration (hr)
A	B	0.20
B	C	0.21
C	D	0.21
C	F	0.21
D	E	0.29
F	G	0.42
E	G	0.29
G	H	0.25
G	I	0.25
H	J	0.25
I	J	0.21
J	N	0.29
J	K	0.29
K	L	0.50
L	M	2.50
M	O	0.38
N	O	9.50
O	P	2.00
P	Q	0.38
Q	R	0.21
R	S	0.42

Table C.3 shows all possible paths and their duration within the network. Note that the duration values for each path are a summation of stochastic results for each task or node.

Table C.3. Substation Recovery Network Paths and Duration for 5 Iterations

Paths	1	2	3	4	5
ABCDEGHIJKLMOPQRS	12.61	25.038	19.718	93.579	18.592
ABCFGHIJKLMOPQRS	10.084	24.107	19.398	93.339	18.267
ABCDEGHJKLMOPQRS	12.996	25.211	19.557	93.589	18.441
ABCFGHJKLMOPQRS	10.47	24.28	19.237	93.349	18.116
ABCDEGIJNOPQRS	9.7187	9.0098	4.6135	16.645	6.5564
ABCFGIJNOPQRS	7.1927	8.0786	4.2935	16.405	6.2314
ABCDEGHJNOPQRS	10.105	9.1826	4.4525	16.654	6.4054
ABCFGHJNOPQRS	7.5791	8.2514	4.1325	16.414	6.0805

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APPENDIX D: PV Loss Data

Table D.1 summarizes the PV Recovery Task Descriptions.

Table D.1. PV Recovery Task Descriptions

Node	Recovery Task
A	2-man crew identified & depart
B	Crew investigates scene
C	Crew examines single inverter for a simple reset
D	Perform voltage checks to identify degraded PV panel
E	Crew reports fault(s)/repair actions
F	Secure Physical Area of Incident
G	Open identified PV panel - Identify fault - ground
H	Electrically isolate @ Breakers & Combiner Box w/tag out
I	Safety Checks
J	Modify Wiring: Disconnect wiring, bypass failed panel to next panel, Reconnect Wiring
K	Secure and restore connections
L	Re-energize @breakers
M	Verify voltage/amperage with voltage checks
N	Recovery

Table D.2 summarizes the precedence order for the PV Loss Task List.

Table D.2. PV Recovery Precedence List

From	To	Avg. Duration (hr)
A	B	0.20
B	C	0.21
C	D	0.25
C	E	0.25
E	F	0.25
D	G	2.50
F	G	0.25
G	H	0.13
G	I	0.13
I	K	0.29
H	J	0.50
J	K	0.58
K	L	0.38
L	M	0.21
M	N	0.42

Table D.3. PV Recovery Network Paths and Duration for 5 Iterations

Paths	1	2	3	4	5
ABCEFGIKLMN	4.6936	3.535	3.2827	3.1377	2.5475
ABCDGIKLMN	4.0722	10.038	10.27	1.7316	3.1813
ABCEFGHJKLMN	6.3943	3.8543	3.9293	3.2103	3.1925
ABCDGHJKLMN	5.7729	10.358	10.917	1.8042	3.8263

APPENDIX E:

Rechargeable Battery Loss Data

Table E.1 summarizes the Rechargeable Battery Recovery Task Descriptions.

Table E.1. Rechargeable Battery Recovery Task Descriptions

Node	Recovery Task
A	2-man crew identified & depart
B	Crew investigates scene
C	Crew examines alarm panels to indicate equipment with failed batteries
D	Crew reports fault(s)/repair actions
E	Secure Physical Area of Incident
F	Safety Checks
G	Open breakers to lighten load on COGEN
H	Electrically isolate battery
I	Remove module & clean connectors & replace module
J	Charge battery module
K	Secure and restore connections
L	Re-energize @breakers & restart substation battery
M	Verify equipment indications are SAT @substation
N	Recovery

Table E.2 summarizes the precedence order for the Rechargeable Battery Task List.

Table E.2. Rechargeable Battery Precedence List

From	To	Avg. Duration (hr)
A	B	0.20
A	C	0.20
B	D	0.21
C	D	0.29
D	E	0.25
D	F	0.25
E	G	0.25
F	G	0.29
G	H	0.21
H	I	0.42
I	J	0.63
J	K	3.50
J	L	3.50
K	M	0.29
L	M	0.42
M	N	0.13

Table E.3 shows all possible paths and their duration within the network. Note that the duration values for each path are a summation of stochastic results for each task or node.

Table E.3. Rechargeable Battery Recovery Network Paths and Duration for 5 Iterations

Paths	1	2	3	4	5
ACDFGHIJLMN	3.9254	10.604	13.848	3.2448	7.7349
ABDFGHIJLMN	4.5573	10.652	14.064	3.2567	7.5405
ACDEGHIJLMN	3.6225	10.403	13.208	2.7794	6.8727
ABDEGHIJLMN	4.2544	10.451	13.424	2.7912	6.6783
ACDFGHIJKMN	3.7262	10.085	13.525	3.2843	7.1654
ABDFGHIJKMN	4.3581	10.133	13.741	3.2962	6.971
ACDEGHIJKMN	3.4233	9.884	12.885	2.8189	6.3032
ABDEGHIJKMN	4.0552	9.9316	13.101	2.8308	6.1088

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APPENDIX F:

MultiCell Battery Loss Data

Table F.1 summarizes the Multicell Battery Recovery Task Descriptions.

Table F.1. Multicell Battery Recovery Task Descriptions

Node	Recovery Task
A	2-man crew identified & depart
B	Crew investigates scene
C	Crew reports fault(s)/repair actions
D	Secure Physical Area of Incident
E	Electrically isolate battery rack
F	Disconnect leads & remove battery rack
G	Replace with new battery rack, connect leads
H	Safety checks
I	Restart storage system
J	Charge battery rack
K	Reenergize @breakers & restart battery rack
L	Verify power output by each rack controller: voltage and amperage readings check at each disconnect and breaker
M	Recovery

Table F.2 summarizes the precedence order for the Multicell Battery Loss Task List.

Table F.2. Multicell Battery Recovery Precedence List

From	To	Avg. Duration (hr)
A	B	0.20
B	C	0.21
C	D	0.25
C	E	0.25
D	F	0.25
E	F	0.17
F	G	0.21
G	H	0.29
G	I	0.29
H	J	0.13
I	J	0.13
J	K	36.00
K	L	0.17
L	M	0.21

Table F.3 shows all possible paths and their duration within the network. Note that the duration values for each path are a summation of stochastic results for each task or node.

Table F.3. Multicell Battery Recovery Network Paths and Duration for 5 Iterations

Paths	1	2	3	4	5
ABCEFGIJKLM	55.141	24.593	24.327	102.89	8.6922
ABCEFGIJKLM	54.868	25.212	24.502	102.85	9.219
ABCEFGHJKLM	55.14	24.632	24.422	102.64	8.5736
ABCEFGHJKLM	54.866	25.251	24.597	102.6	9.1005

APPENDIX G:

PIRA Matlab Model & Supporting Functions

Matlab Code for the HPIRA Test Model for an Example Failed Component

```
1
2 % Manual Update for Lines: 37,38,55,80
3
4 %% Import SPAR-H PSF Data
5 [~,sheet_name]=xlsinfo('SPAR-H PSF Inputs_Example.xlsx');
6 for k=1:numel(sheet_name);
7     [~,~,data{k}]= xlsread('SPAR-H PSF Inputs_Example.xlsx',
8         sheet_name{k});
9
10 a = 1;
11 % Diagnosis/Action PSF Data Inputs
12 for k = 1:2:numel(sheet_name);
13     Diagnosis{a} = data{k}(2:numel(sheet_name),5);
14     PSF_Diagnosis{a} = cellfun(@rmmissing, Diagnosis{a},
15         'UniformOutput', false);
16     PSF_Diagnosis{a} = PSF_Diagnosis{a}(~cellfun('
17         isempty',PSF_Diagnosis{a}));
18 % Calc the Diagnosis_HEP (Part B & C & D)
19 Negative_Multiples_Diagnosis{a} = cell2mat(
20     PSF_Diagnosis{a}) >= 1;
21 Diagnosis_HEP{a} = 1E-2*prod(cell2mat(PSF_Diagnosis{
22     a}));
23 if sum(Negative_Multiples_Diagnosis{a}) >= 3; %
24     greater than or just 3 of 8 PSFs are Negative
25     PSFs (>1 value)
```

```

20         Diagnosis_HEP{a} = (Diagnosis_HEP{a})/(1E-2*(
            prod(cell2mat(PSF_Diagnosis{a}))-1)+1);
21     end
22     Action{a} = data{k+1}(2:numel(sheet_name),5);      %
        Even #d Sheets: Action PSF Tabs
23     PSF_Action{a} = cellfun(@rmmissing, Action{a}, '
        UniformOutput', false);
24     PSF_Action{a} = PSF_Action{a}(~cellfun('isempty',
        PSF_Action{a}));
25     % Calc the Action_HEP (Part B & C & D)
26     Negative_Multiples_Action{a} = cell2mat(PSF_Action{a
        }) >= 1;
27     Action_HEP{a} = 1E-3*prod(cell2mat(PSF_Action{a}));
28     if sum(Negative_Multiples_Action{a}) >= 3;      %
        greater than or just 3 of 8 PSFs are Negative
        PSFs (>1 value)
29         Action_HEP{a} = (Action_HEP{a})/(1E-3*(prod(
            cell2mat(PSF_Action{a}))-1)+1);
30     end
31     P_WOD{a} = Diagnosis_HEP{a} + Action_HEP{a};
32     a = a + 1;
33 end
34 %% Import RA Set Node (Task) Precedence
35 opts = spreadsheetImportOptions("NumVariables", 3);
36 opts.Sheet = "RA_Set_Example";                      %
        Update
37 opts.DataRange = "I4:K10";                          %
        Update
38 opts.VariableNames = ["VarName5", "VarName6", "VarName7"];
39 opts.VariableTypes = ["char", "char", "char"];
40 opts = setvaropts(opts, ["VarName5", "VarName6", "VarName7
        "], "WhitespaceRule", "preserve");
41 opts = setvaropts(opts, ["VarName5", "VarName6", "VarName7

```

```

    "], "EmptyFieldRule", "auto");
42 RecoveryActionSets = table2array(readtable("Microgrid
    Recovery Paths Test/Input Data/Recovery Action Sets.xlsx",
    opts, "UseExcel", false));
43
44 opts = spreadsheetImportOptions("NumVariables", 4);
45 opts.Sheet = "RA_Set_Example"; %
    Update (Sheet Name)
46 opts.DataRange = "C3:F7";
    % Update (Task List
    Range)
47 opts.VariableNames = ["InsertAsGeneral", "VarName2", "
    InsertAsGeneral1", "VarName4"];
48 opts.VariableTypes = ["char", "char", "char", "char"];
49 opts = setvaropts(opts, ["InsertAsGeneral", "VarName2", "
    InsertAsGeneral1", "VarName4"], "WhitespaceRule", "
    preserve");
50 opts = setvaropts(opts, ["InsertAsGeneral", "VarName2", "
    InsertAsGeneral1", "VarName4"], "EmptyFieldRule", "auto")
    ;
51 Task_Duration_Times = str2double(table2array(readtable("
    Input Data/Recovery Action Sets.xlsx", opts, "UseExcel",
    false)));
52
53 %% RA Critical Path & Duration
54
55 % Convert Matrix to column vectors & Adjacency Matrix &
    Diagraph & Network Diagram
56 s = RecoveryActionSets(:,1);
57 t = RecoveryActionSets(:,2);
58 RA = digraph(s, t);
59 figure(1)
60 Network_Diagram = plot(RA); % Network Diagram

```

```

61 title("Recovery Network Diagram");
62 Task_Network = RA.Edges;           % Task Network Activity &
    Edge Listings
63 iterations = 10000;               % Change based off
    preference
64
65 % Find Human Error Probable (HEP), or Probability of Error,
    for individual tasks
66 [HEP] = findHEP(PSF_Diagnosis , PSF_Action);
67
68 % Find all Paths within the Recovery Set
69 [Critical_Paths] = findCriticalPaths(HEP);
70 storage_paths = Critical_Paths;
71 Critical_Paths = str2double(Critical_Paths);
72
73 % Pre-Allocate Memory for Paths & Durations
74 Durations = zeros(length(Critical_Paths),iterations);
75 Durations(:,1) = (Critical_Paths);
76
77 % Determine Path Durations for each #iterations
78 for w = 1:iterations
79     [Sample_Duration] = findSampleDuration(Critical_Paths ,
        HEP);
80     Sample_Duration = transpose(Sample_Duration);
81     Durations(:,w) = transpose(Sample_Duration);
82 end
83
84 % Table of All Paths & Durations
85 Paths_Durations = table(storage_paths , Durations);
86 Paths_Durations.Properties.VariableNames = {'Recovery Path'
    'Duration (hr)'};
87 Paths_Durations = splitvars(Paths_Durations , 'Duration (hr)')
    ;

```

```

88 csvwrite('Example.csv', Durations)           % Update based on
    Iterations
89
90 % Determine Max Duration of each Iteration -> Critical Path
    of each Duration
91 [Max_Duration, Max_Index] = max(Durations);
92 [I_row, I_col] = ind2sub(size(Paths_Durations), Max_Index);
93
94 % Example: Looking at just the 1st iteration
95 p = 1;
96 CP = transpose(cell2mat(storage_paths(I_row(p))));
97 CP_Duration = Max_Duration(p);
98 fprintf('Critical Path & Duration for 1st iteration: %s %g
    hrs', CP, CP_Duration)
99
100 %% Clear temporary variables
101 % clear opts

```

Matlab Code for HPIRA Test Supporting Functions

Function: findCriticalPaths

```

1
2 %% Find Critical Paths
3
4 function [Critical_Paths] = findCriticalPaths(HEP)
5
6 opts = spreadsheetImportOptions("NumVariables", 3);
7 opts.Sheet = "RA_Set_Example";
8 opts.DataRange = "I4:K10";
9 opts.VariableNames = ["VarName5", "VarName6", "VarName7"];

```

```

10 opts.VariableTypes = ["char", "char", "char"];
11 opts = setvaropts(opts, ["VarName5", "VarName6", "VarName7",
    "], "WhitespaceRule", "preserve");
12 opts = setvaropts(opts, ["VarName5", "VarName6", "VarName7",
    "], "EmptyFieldRule", "auto");
13 RecoveryActionSets = table2array(readtable("Microgrid
    Recovery Paths Test/Input Data/Recovery Action Sets.xlsx",
    opts, "UseExcel", false));
14
15 opts = spreadsheetImportOptions("NumVariables", 4);
16 opts.Sheet = "RA_Set_Example";
    % Update (Sheet Name)
17 opts.DataRange = "C3:F7";
    % Update (Task List
    Range)
18 opts.VariableNames = ["InsertAsGeneral", "VarName2", "
    InsertAsGeneral1", "VarName4"];
19 opts.VariableTypes = ["char", "char", "char", "char"];
20 opts = setvaropts(opts, ["InsertAsGeneral", "VarName2", "
    InsertAsGeneral1", "VarName4"], "WhitespaceRule", "
    preserve");
21 opts = setvaropts(opts, ["InsertAsGeneral", "VarName2", "
    InsertAsGeneral1", "VarName4"], "EmptyFieldRule", "auto")
    ;
22 Task_Duration_Times = str2double(table2array(readtable("
    Microgrid Recovery Paths Test/Input Data/Recovery Action
    Sets.xlsx", opts, "UseExcel", false)));
23
24 s = RecoveryActionSets(:,1);
25 t = RecoveryActionSets(:,2);
26 RA = digraph(s, t);
27
28 [RA_paths, RA] = getpaths(RA);    % Generates All Possible

```

```

    Paths
29 a = 1;
30 for k = 1:numel(RA_paths)
31     [Weights] = findWeights(Task_Duration_Times , HEP);
32     for y = 1:length(Task_Duration_Times)
33         RA.Nodes.Weight{y} = Weights{y};
34     end
35     path{:,k} = cell2mat(RA.Nodes.Name(RA_paths{k}));
        % All Paths w/Node Precedence as Integers in
        columns
36     Critical_Paths = transpose(path);
        % Specify Nodes Precedence as
        Characters (in sequential order , not in order of
        Edge List) in rows
37 end
38 end

```

Function: findHEP

```

1
2 %% Find HEP
3
4 function [HEP] = findHEP(PSF_Diagnosis , PSF_Action)
5
6 % Import SPAR-H PSF Data
7 [~,sheet_name]=xlsinfo('SPAR-H PSF Inputs_Example.xlsx');
        % Update
8 for k=1:numel(sheet_name);
9     [~,~,data{k}]= xlsread('SPAR-H PSF Inputs_Example.xlsx',
        sheet_name{k}); % Update
10 end
11
12 a = 1;
13 % Diagnosis/Action PSF Data Inputs

```

```

14 for k = 1:2:numel(sheet_name);
15     Diagnosis{a} = data{k}(2:numel(sheet_name),5);
16     PSF_Diagnosis{a} = cellfun(@rmmissing, Diagnosis{a},
        'UniformOutput', false);
17     PSF_Diagnosis{a} = PSF_Diagnosis{a}(~cellfun('
        isempty',PSF_Diagnosis{a}));
18 % Calc the Diagnosis_HEP (Part B & C & D)
19     Negative_Multiples_Diagnosis{a} = cell2mat(
        PSF_Diagnosis{a}) >= 1;
20     Diagnosis_HEP{a} = 1E-2*prod(cell2mat(PSF_Diagnosis{
        a}));
21     if sum(Negative_Multiples_Diagnosis{a}) >= 3; %
        greater than or just 3 of 8 PSFs are Negative
        PSFs (>1 value)
22         Diagnosis_HEP{a} = (Diagnosis_HEP{a})/(1E-2*(
        prod(cell2mat(PSF_Diagnosis{a}))-1)+1);
23     end
24     Action{a} = data{k+1}(2:numel(sheet_name),5); %
        Even #d Sheets: Action PSF Tabs
25     PSF_Action{a} = cellfun(@rmmissing, Action{a}, '
        UniformOutput', false);
26     PSF_Action{a} = PSF_Action{a}(~cellfun('isempty',
        PSF_Action{a}));
27 % Calc the Action_HEP (Part B & C & D)
28     Negative_Multiples_Action{a} = cell2mat(PSF_Action{a
        }) >= 1;
29     Action_HEP{a} = 1E-3*prod(cell2mat(PSF_Action{a}));
30     if sum(Negative_Multiples_Action{a}) >= 3; %
        greater than or just 3 of 8 PSFs are Negative
        PSFs (>1 value)
31         Action_HEP{a} = (Action_HEP{a})/(1E-3*(prod(
        cell2mat(PSF_Action{a}))-1)+1);
32     end

```

```

33     P_WOD{a} = Diagnosis_HEP{a} + Action_HEP{a};
34     a = a + 1;
35 end
36
37 %% Calc P_WD (with dependence)
38
39 a = 1;
40 for k = 2:2:numel(sheet_name);
41     Dependency{a} = data{k}(4,10);
42     x = Dependency{a};
43     if strcmpi(x, 'Complete')
44         P_WD{a} = 1;
45     elseif strcmpi(x, 'High')
46         P_WD{a} = (1+ P_WOD{a})/2;
47     elseif strcmpi(x, 'Moderate')
48         P_WD{a} = (1 + (6*P_WOD{a}))/7;
49     elseif strcmpi(x, 'Low')
50         P_WD{a} = (1 + (19*P_WOD{a}))/20;
51     else strcmpi(x, 'Zero');
52         P_WD{a} = P_WOD{a};
53     end
54     HEP{a} = P_WD{a};
55     a = a + 1;
56 end
57
58 end

```

Function: findSampleDuration

```

1
2 %% Find 1 Sample Duration for All Paths
3
4 function [Sample_Duration] = findSampleDuration(
    Critical_Paths ,HEP)

```

```

5
6  opts = spreadsheetImportOptions("NumVariables", 3);
7  opts.Sheet = "RA_Set_Example";                                     %
    Update (Sheet Name)
8  opts.DataRange = "I4:K10";
                                                                    % Update (Precedence
    List Range)
9  opts.VariableNames = ["VarName5", "VarName6", "VarName7"];
10 opts.VariableTypes = ["char", "char", "char"];
11 opts = setvaropts(opts, ["VarName5", "VarName6", "VarName7
    "], "WhitespaceRule", "preserve");
12 opts = setvaropts(opts, ["VarName5", "VarName6", "VarName7
    "], "EmptyFieldRule", "auto");
13 RecoveryActionSets = table2array(readtable("Microgrid
    Recovery Paths Test/Input Data/Recovery Action Sets.xlsx
    ", opts, "UseExcel", false));
14
15 s = RecoveryActionSets(:,1);
16 t = RecoveryActionSets(:,2);
17 RA = digraph(s, t);
18
19 opts = spreadsheetImportOptions("NumVariables", 4);
20 opts.Sheet = "RA_Set_Example";                                     %
    Update (Sheet Name)
21 opts.DataRange = "C3:F7";
                                                                    % Update (Task List
    Range)
22 opts.VariableNames = ["InsertAsGeneral", "VarName2", "
    InsertAsGeneral1", "VarName4"];
23 opts.VariableTypes = ["char", "char", "char", "char"];
24 opts = setvaropts(opts, ["InsertAsGeneral", "VarName2", "
    InsertAsGeneral1", "VarName4"], "WhitespaceRule", "
    preserve");

```

```

25 opts = setvaropts(opts, ["InsertAsGeneral", "VarName2", "
    InsertAsGeneral1", "VarName4"], "EmptyFieldRule", "auto")
    ;
26 Task_Duration_Times = str2double(table2array(readtable("
    Input Data/Recovery Action Sets.xlsx", opts, "UseExcel",
    false)));
27
28 [RA_paths, RA] = getpaths(RA);
29 [Weights] = findWeights(Task_Duration_Times, HEP);
30     for k = 1:numel(RA_paths)
31         for y = 1:length(Task_Duration_Times)
32             RA.Nodes.Weight{y} = Weights{y};
33         end
34         path_duration(k) = sum(cell2mat(RA.Nodes.Weight(
            RA_paths{k})));
35         Sample_Duration(k) = path_duration(k);
36     end
37 end

```

Function: findWeights

```

1
2 %% Find Node Weight (Duration Times)
3
4 function [Weights] = findWeights(Task_Duration_Times, HEP)
5 %% Set up the Import Options and import the data
6
7 % Sample time from P(fail/success) of Exponential
    Distriubtion
8 mu_low = Task_Duration_Times(:,2);
9 mu_high = Task_Duration_Times(:,3);
10 mu = Task_Duration_Times(:,4);
11
12 a = 1;

```

```

13 % Random number from Exponential Distribution
14 for i = 1:length(Task_Duration_Times)
15     r{i} = random('Exponential',mu);
16     if r{i} > HEP{a};
17         Weights{a} = exprnd(mu_low(i));
18     else
19         Weights{a} = exprnd(mu_high(i));
20     end
21     a = a + 1;
22 end
23 end

```

Function: getpaths

```

1
2 %% Find All Paths
3
4 % Path Code from MatlabCentral
5 % (https://www.mathworks.com/matlabcentral/answers/417396-
   calculating-all-paths-from-a-given-node-in-a-digraph#
   answer_335365)
6
7 function [paths,topo_g] = getpaths(g)
8     %return all paths from a DAG.
9     %the function will error in toposort if the graph is not
   a DAG
10    paths = {}; %path computed so far
11    [nid topo_g] = toposort(g, 'Order', 'stable'); % sets
   the algorithm to stable [see link]. Shows Nodes as
   Integers.
12    endnodes = []; %current end node of each path for
   easier tracking
13    % for i = toposort(topo_g) %iterate over all nodes
14    for i = nid;

```

```

15         if indegree(topo_g, i) == 0      %node is a root,
            simply add it for now
16             paths = [paths; i]; %ok<AGROW>
17             endnodes = [endnodes; i]; %ok<AGROW>
18         end
19         %find successors of current node and replace all
            paths that end with the current node with
            cartesian product of paths and successors
20         toreplace = endnodes == i;      %all paths that need
            to be edited
21         s = successors(topo_g, i);
22         if ~isempty(s)
23             [p, tails] = ndgrid(paths(toreplace), s); %
                cartesian product
24             paths = [cellfun(@(p, t) [p, t], p(:), num2cell(
                tails(:)), 'UniformOutput', false); %append
                paths and successors
25                 paths(~toreplace)];
26             endnodes = [tails(:); endnodes(~toreplace)];
27         end
28     end
29 end

```

Matlab Code for HPIRA Test Plots and Statistics

```

1 % CVS Import of each Component Recovery Duration Times
2 [example] = table2array(readtable('Example.csv'));
3 % [pole] = table2array(readtable('Downed Pole.csv'));
4 % [generator] = table2array(readtable('Generator Loss.csv'))
    ;
5 % [substation] = table2array(readtable('Substation Loss.csv
    '));
6 % [pv] = table2array(readtable('PV Loss.csv'));

```

```

7 % [rb] = table2array(readtable('RechargeableBattery Loss.csv
   '));
8 % [mcb] = table2array(readtable('MulticellBattery Loss.csv')
   );
9
10 data = example;
11
12 % Statistics
13 [Critical_Path_Duration , Critical_Path] = max(data);
14 [Max_Recovery_Time , Path_Index_Max] = max(
   Critical_Path_Duration);
15 [Min_Recovery_Time , Path_Index_Min] = min(
   Critical_Path_Duration);
16
17 Mean_Recovery_Time = mean(Critical_Path_Duration);
18 SD = std(Critical_Path_Duration);
19 Variance = var(Critical_Path_Duration);
20
21 x = Critical_Path_Duration;
22
23 % Plots
24 % Line
25 plot(data)
26 hold on
27 plot(Critical_Path(Path_Index_Max))
28 % plot(Critical_Path(Path_Index_Min),Min_Recovery_Time,'g*')
29 xlabel({'Recovery Paths',' '})
30 ylabel({'Recovery Time (hr)',' '})
31 set(gca,'FontSize',12,'XTick',[1:numel(data)])
32 figure
33
34 % Histogram 1
35 edges = [0:1:60];

```

```

36 h1 = histogram(x,edges);
37 [N1,edges1,bin1] = histcounts(x); % Number of Bins
38 [maximum_ocurrences1, ocurrence_bin1] = max(h1.Values);
39 xlabel({'Recovery Time (hr)', ' '})
40 ylabel({'Frequency of Occurence', ' '})
41 set(gca,'FontSize', 12)
42 xlim([0,Max_Recovery_Time]);
43 i = max(ocurrence_bin1);
44 r1 = h1.BinEdges(i:i+1);
45 r1 = [r1 fliplr(r1)];
46 y1 = [0 0 repmat(h1.Values(i), 1, 2)];
47 h1_patch = patch(r1, y1, 'red');
48 hold off
49 figure
50
51 % Histogram 2
52 most_common_duration = mode(round(Critical_Path_Duration));
53 most_common_path = Critical_Path(most_common_duration);
54 d = data(most_common_path,:);
55 edges = [0:1:60];
56 h2 = histogram(d,edges);
57 [N2,edges2,bin2] = histcounts(d); % Number of Bins
58 [maximum_ocurrences2, ocurrence_bin2] = max(h2.Values);
59 xlabel({'Recovery Time (hr)', ' '})
60 ylabel({'Frequency of Occurence', ' '})
61 set(gca,'FontSize', 12)
62 xlim([0,Max_Recovery_Time]);
63 c = ocurrence_bin2;
64 r2 = h2.BinEdges(c:c+1);
65 r2 = [r2 fliplr(r2)];
66 y2 = [0 0 repmat(h2.Values(c), 1, 2)];
67 h2_patch = patch(r2, y2, 'red');
68 hold off

```

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APPENDIX H: BOE Matlab Models

Matlab Code for Modeled Multi-Scale Microgrid Failure Event BOE Calculation

```
1
2 % CVS Import of each Component Recovery Duration Times
3 [pole] = table2array(readtable('Downed Pole.csv'));
4 [generator] = table2array(readtable('Generator Loss.csv'));
5 [substation] = table2array(readtable('Substation Loss.csv'))
   ;
6 [pv] = table2array(readtable('PV Loss.csv'));
7 [rb] = table2array(readtable('RechargeableBattery Loss.csv')
   );
8 [mcb] = table2array(readtable('MulticellBattery Loss.csv'));
9
10 % Desired Inputs – Manual Inputs of Failed Systems
11 Pole = 500;
12 Generator = 25;
13 Substation = 8;
14 PV = 50;
15 RB = 6*Substation;
16 MCB = 4;
17
18 % Total Recovery Time
19 format bank
20
21 for k = 1:Pole
22     Pole_Duration(k) = sum(max(pole(:,k)));
23     total_pole = sum(reshape(Pole_Duration,[],1));
24 end
```

```

25
26 for k = 1:Generator
27     Generator_Duration(k) = sum(max(generator(:,k)));
28     total_generator = sum(reshape(Generator_Duration,[],1));
29 end
30
31 for k = 1:Substation
32     Substation_Duration(k) = sum(max(substation(:,k)));
33     total_substation = sum(reshape(Substation_Duration,[],1)
34                               );
35 end
36
37 for k = 1:PV
38     PV_Duration(k) = sum(max(pv(:,k)));
39     total_pv = sum(reshape(PV_Duration,[],1));
40 end
41
42 for k = 1:RB
43     RB_Duration(k) = sum(max(rb(:,k)));
44     total_rb = sum(reshape(RB_Duration,[],1));
45 end
46
47 for k = 1:MCB
48     MCB_Duration(k) = sum(max(mcb(:,k)));
49     total_mcb = sum(reshape(MCB_Duration,[],1));
50 end
51 % Total Recovery Time (hrs)
52 Total_Recovery_Time_hours = sum(total_pole + total_generator
53                                   + total_substation + total_pv + total_rb + total_mcb)
54
55 Total_Recovery_Time_days = Total_Recovery_Time_hours/24
56
57 clear

```

Matlab Code for Predicted Multi-Scale Microgrid Failure Event BOE Calculation

```
1
2 % Recovery Predicted Max/Min Values Import of each Component
   Recovery Duration Times
3 [~,sheet_name]=xlsinfo('Recovery Action Sets.xlsx');
4 for k=1:numel(sheet_name);
5     [~,~,predicted{k}]= xlsread('Recovery Action Sets.xlsx',
        sheet_name{k}); % Update
6 end
7
8 % Desired Inputs – Manual Inputs of Failed Systems
9 Pole = 500;
10 Generator = 25;
11 Substation = 8;
12 PV = 50;
13 RB = 6*Substation;
14 MCB = 4;
15
16 % Total Recovery Time
17 format bank
18
19 % Pole Predicted Values
20 Pole_Min = cell2mat(predicted{2}(26,4));
21 Pole_Max = cell2mat(predicted{2}(26,5));
22 Total_Pole_Min = times(Pole,Pole_Min);
23 Total_Pole_Max = times(Pole,Pole_Max);
24
25 % Generator Predicted Values
26 Generator_Min = cell2mat(predicted{3}(26,4));
27 Generator_Max = cell2mat(predicted{3}(26,5));
28 Total_Generator_Min = times(Generator,Generator_Min);
29 Total_Generator_Max = times(Generator,Generator_Max);
```

```

30
31 % Substation Predicted Values
32 Substation_Min = cell2mat(predicted{4}(26,4));
33 Substation_Max = cell2mat(predicted{4}(26,5));
34 Total_Substation_Min = times(Substation,Substation_Min);
35 Total_Substation_Max = times(Substation,Substation_Max);
36
37 % PV Predicted Values
38 PV_Min = cell2mat(predicted{5}(26,4));
39 PV_Max = cell2mat(predicted{5}(26,5));
40 Total_PV_Min = times(PV,PV_Min);
41 Total_PV_Max = times(PV,PV_Max);
42
43 % MCB Predicted Values
44 MCB_Min = cell2mat(predicted{6}(26,4));
45 MCB_Max = cell2mat(predicted{6}(26,5));
46 Total_MCB_Min = times(MCB,MCB_Min);
47 Total_MCB_Max = times(MCB,MCB_Max);
48
49 % RB Predicted Values
50 RB_Min = cell2mat(predicted{7}(26,4));
51 RB_Max = cell2mat(predicted{7}(26,5));
52 Total_RB_Min = times(RB,RB_Min);
53 Total_RB_Max = times(RB,RB_Max);
54
55 % Total Predicted Recovery Time (hrs)
56 Total_Recovery_Min_hours = sum(Total_Pole_Min +
    Total_Generator_Min + Total_Substation_Min + Total_PV_Min
    + Total_MCB_Min + Total_RB_Min)
57 Total_Recovery_Min_days = Total_Recovery_Min_hours/24
58 Total_Recovery_Max_hours = sum(Total_Pole_Max +
    Total_Generator_Max + Total_Substation_Max + Total_PV_Max
    + Total_MCB_Max + Total_RB_Max)

```

```
59 Total_Recovery_Max_days = Total_Recovery_Max_hours/24
60
61 clear
```

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List of References

- [1] Department of Navy, “Installation energy resilience strategy,” Department of Navy, Washington, DC, Tech. Rep., 2020. Available: <https://www.secnav.navy.mil/eie/Documents/DON-Installation-Energy-Resilience-Strategy.pdf>
- [2] Department of Defense, “Department of Defense annual energy management and resilience report (aemrr) fiscal year 2018,” Office of the Assistant Secretary of Defense for Sustainment, Washington, DC, Tech. Rep., 2019. Available: <https://www.acq.osd.mil/eie/Downloads/IE/FY%202018%20AEMR.pdf>
- [3] R. Giachetti, D. V. Bossuyt, G. W. Parker, and C. J. Peterson, “Systems engineering issues in microgrids for military installations,” presented at 30th Annual INCOSE International Symposium, Cape Town, South Africa, 2020.
- [4] D. D. Woods, “Four concepts for resilience and the implications for the future of resilience engineering,” *Reliability Engineering and System Safety*, vol. 141, pp. 5–9, 2015.
- [5] B. S. Blanchard and W. J. Fabrycky, *Systems Engineering and Analysis*, 4th ed. Englewood Cliffs, NJ: Prentice Hall, 2011.
- [6] A. Hirsch, Y. Parag, and J. Guerrero, “Microgrids: A review of technologies, key drivers, and outstanding issues,” *Renewable and Sustainable Energy Reviews*, vol. 90, pp. 402–411, 2018.
- [7] D. T. Ton and M. A. Smith, “The U.S. Department of Energy’s microgrid initiative,” *The Electricity Journal*, vol. 25, no. 8, pp. 84–94, 2012.
- [8] J. Peterson, Christopher, “Systems architecture design and validation methods for microgrid systems,” Master’s thesis, 2019. Available: <https://calhoun.nps.edu/handle/10945/63493>
- [9] M. F. Akorede, H. Hizam, and E. Pouresmaeil, “Distributed energy resources and benefits to the environment,” *Renewable and Sustainable Energy Reviews*, vol. 14, no. 2, pp. 724–734, 2010.
- [10] S. Borlase, M. Ganji, M. Shahidehpour, W. Tian, P. Burgess, R. Hourdouillie, and A. Zheng, “Microgrids,” in *Smart Grids: Advanced Technologies and Solutions*, 2nd ed. CRC Press, 2017, pp. 591–604.

- [11] M. Glinkowski, A. Guglielmo, A. Oudalov, G. Rackliffe, B. Rose, E. Scholtz, L. Verma, and F. Yang, "Microgrids," in *Smart Grids: Clouds, Communications, Open Source, and Automation*, 1st ed. CRC Press, 2014, pp. 213–249.
- [12] L. Mariam, M. Basu, and M. F. Conlon, "Microgrid: Architecture, policy and future trends," *Renewable and Sustainable Energy Reviews*, vol. 64, pp. 477–489, 2016.
- [13] R. Lasseter, A. Akhil, C. Marnay, J. Stephens, J. Dagle, R. Guttromsom, A. S. Meliopoulos, R. Yinger, and J. Eto, "Integration of distributed energy resources. the certs microgrid concept," Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States), Tech. Rep., 2002.
- [14] B. Walker, *Resilience Thinking Sustaining Ecosystems and People in a Changing World*. Washington, DC, USA: Island Press.
- [15] W. I. Bower, D. T. Ton, R. Guttromson, S. F. Glover, J. E. Stamp, D. Bhatnagar, and J. Reilly, "The advanced microgrid. integration and interoperability," Tech. Rep. 10.2172/1204100, 2 2014.
- [16] C. Colson and M. Nehrir, "A review of challenges to real-time power management of microgrids," in *2009 IEEE Power & Energy Society General Meeting*. IEEE, 2009, pp. 1–8.
- [17] D. L. Van Bossuyt and B. M. O'halloran, "A method to choose between automation and human operators for recovery actions during a cyber attack," *Procedia Computer Science*, vol. 153, pp. 352–360, 2019.
- [18] M. Spranca, E. Minsk, and J. Baron, "Omission and commission in judgment and choice," *Journal of Experimental Social Psychology*, vol. 27, pp. 76–105, 1991.
- [19] Installation Next, "Installation next Hawaii-resilience symposium report," Installation NExt, Ohau, HA, Tech. Rep., 2017. Available: <https://www.mccom.marines.mil/Portals/57/G7%20Docs/Installation%20neXt%20Hawaii%20Symposium%20Report.pdf?ver=2019-03-05-110455-507>
- [20] Department of Defense, "Ufc 3-540-01 engine-driven generator systems for prime and standby power applications, with change 2," Department of Defense, Washington, DC, Tech. Rep., 2014. Available: https://www.wbdg.org/FFC/DOD/UFC/ufc_3_540_01_2014_c2.pdf
- [21] I. International, "Electric grid security and resilience," 2016. Available: <https://www.energy.gov/sites/prod/files/2017/01/f34/Electric%20Grid%20Security%20and%20Resilience--Establishing%20a%20Baseline%20for%20Adversarial%20Threats.pdf>

- [22] R. E. Brown, *Electric Power Distribution Reliability*, 2nd ed. (Power Engineering (Willis)). CRC Press, 2017.
- [23] “All-hazards risk and resilience: Prioritizing critical infrastructures using the ram-cap plus approach.(american society of mechanical engineers bookshelf)(brief article)(book review),” *Mechanical Engineering-CIME*, vol. 131, no. 3, p. 50, 2009.
- [24] A. Masten, *Resilience in Individual Development: Successful Adaptation Despite Risk and Adversity: Challenges and Prospects*. Lawrence Erlbaum, 1994, pp. 3–25.
- [25] Department of Defense, “Installation energy management,” Department of Defense, Washington, DC, Tech. Rep., 2009. Available: <https://www.esd.whs.mil/Portals/54/Documents/DD/issuances/dodi/417011p.pdf>
- [26] Department of Defense, “Title 10,” Department of Defense, Washington, DC, Tech. Rep., 1956. Available: <https://uscode.house.gov/view.xhtml?jsessionid=788B5DDFB7E25AA34CB761B6FBEEF4CA?req=granuleid%3AUSC-prelim-title10&saved=%7CZ3JhbnVsZWlkOlVTQyIwcmVsaW0tdGl0bGUxMC1zZWNOaW9uNTAy%7C%7C%7C0%7Cfalse%7Cprelim&edition=prelim>
- [27] D. Capozzoli and J. Tetatzin, “Department of Navy’s energy security framework: How it relates to utility providers that support Navy and Marine Corps installations,” Nashville, TN, Tech. Rep., Apr. 2018. Available: https://www.energy.gov/sites/prod/files/2018/04/f51/fupwg_spring_2018_19-tetatzin_capozzoli.pdf
- [28] S. Hosseini, K. Barker, and J. Ramirez-Marquez, “A review of definitions and measures of system resilience,” *Reliability Engineering and System Safety*, vol. 145, pp. 47–61, 2016.
- [29] *Resilience Engineering: Concepts and Precepts*, 1st ed. CRC Press, 2006.
- [30] E. Hollnagel *et al.*, “Prologue: The scope of resilience engineering,” *Resilience engineering in practice: A guidebook*, pp. xxix–xxxix, 2011.
- [31] P. Hildebrand, Joshua, “Estimating the life cycle cost of microgrid resilience,” Master’s thesis, Naval Postgraduate School, 2020. Available: https://cle.nps.edu/access/content/group/8ea42785-66da-4656-9d7d-4da6dbd04f4d/Student%20Research%20Files/Josh%20Hildebrand%20Cost%20of%20Resilience%20Model/20Dec_Hildebrand_Joshua%20Final.pdf
- [32] G. Morrisett, private communication, Oct. 2020.

- [33] T. Shoemaker and J. Mack, “The lineman’s and cableman’s field manual,” 2009. Available: http://www.linemantrainer.com/uploads/1/9/7/8/1978252/lineman_and_cablemans_field_manual_2nd_edition.pdf
- [34] R. K. Guenther and R. K. Guenther, *Human cognition*. Prentice Hall Upper Saddle River, NJ, 1998.
- [35] J. M. Abreu, N. Hardy, F. C. Pereira, and M. Zeifman, “Modeling human reliability in the power grid environment: An application of the spar-h methodology,” in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, no. 1. Los Angeles, CA: SAGE Publications, 2015, vol. 59, pp. 662–666.
- [36] M. Lee, *Feds blame 6 groups for 2011 blackout*, The San Diego Union-Tribune, San Diego, CA, USA, Feb. 2014. [Online]. Available: <https://www.sandiegouniontribune.com/sdut-violations-southwest-power-outage-2014feb04-story.html>
- [37] D. Gertman, H. Blackman, J. Marble, J. Byers, and C. Smith, *The SPAR-H Human Reliability Analysis Method*, Idaho National Laboratory, Idaho Falls, ID, USA, Aug. 2005. [Online]. Available: <https://www.nrc.gov/reading-rm/doc-collections/nuregs/contract/cr6883/cr6883.pdf>
- [38] R. L. Boring and H. S. Blackman, “The origins of the spar-h method’s performance shaping factor multipliers,” in *2007 IEEE 8th Human Factors and Power Plants and HPRCT 13th Annual Meeting*, 2007, pp. 177–184.
- [39] W. J. Galyean, A. M. Whaley, D. L. Kelly, and R. L. Boring, “Spar-h step-by-step guidance,” Tech. Rep. 10.2172/1027888, 6 2012. Available: <https://www.osti.gov/biblio/1027888>
- [40] GE Digital Solutions, “Reliability distribution: Administration” accessed jan. 29, 2021.” Available: <https://www.ge.com/digital/documentation/meridium/Help/V43060/IOGE1ZjMyODEtOTlhNi00OWY3LTk1NmMtNjQ5OTQ1NDZhNGQ5.html>

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