DISSERTATION

FRAMEWORK FOR OPTIMIZING SURVIVABILITY IN COMPLEX SYSTEMS

Submitted by

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ABSTRACT

FRAMEWORK FOR OPTIMIZING SURVIVABILITY IN COMPLEX SYSTEMS

Increasing high probability low frequency events such as extreme weather incidents in combination with aging infrastructure in the United States puts the nation's critical infrastructure such as hydroelectric dams' survivability at risk. Maximizing resiliency in complex systems can be viewed as a multi-objective optimization that includes system performance, survivability, economic and social factors. Systems requiring high survivability: a hydroelectric dam, typically require one or more redundant (standby) subsystems, which increases system cost. To optimize the tradeoffs between system survivability and cost, this research introduces an approach for obtaining the Pareto-optimal set of design candidates ("resilience frontier"). The method combines Monte Carlo (MC) sampling to estimate total survivability and a genetic algorithm (GA), referred to as the MCGA, to obtain the resilience frontier. The MCGA is applied to a hydroelectric dam to maximize overall system survivability. The MCGA is demonstrated through several numerical case studies. The results of the case studies indicate that the MCGA approach shows promise as a tool for evaluating survivability versus cost tradeoffs and also as a potential design tool for choosing system configuration and components to maximize overall system resiliency.

ACKNOWLEDGMENTS

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CHAPTER 1: INTRODUCTION

The power grid could be considered the most important infrastructure since electricity is used every day by billions of people across the world from residential to businesses. The United States uses various types of dams for flood risk management, navigation, recreation, power generation, water supply, ecosystems/fish/wildlife, and waste management. Each dam has a unique design based of the intended function of the dam.

As large power generators and flood water management systems, hydroelectric dams are a critical part of the nation's infrastructure. During physical (e.g., weather) or cyber-attacks, it is even more necessary for dams to perform their intended function. The aging power infrastructure in the U.S. and increased fragility of the grid during extreme weather events both increase the probability that dams will lose primary (grid) power. Furthermore, loss of dam functionality can result in a cascading (two-way) effect that can lower overall grid resiliency. Hydroelectric dams must be able to operate during high impact low frequency events. The consequences of a hydroelectric dam not being able to perform its intended function ranges from economic burden to life loss.

In systems where survivability is critical, the network commonly includes backup ("standby") subsystems, added for intentional design redundancy. Standby subsystems are not always active; rather, they become active only when another portion(s) of the system fails. Standby subsystems are used because they provide higher system survivability compared to systems with no standby. Moreover, they also provide higher system survivability compared to always-active parallel redundancy; this higher relative survivability is a result of avoiding wear time when idle. As a practical matter however, computing total system reliability in systems that include standby redundancy is often difficult, which presents a challenge when implementing a multi-objective design optimization strategy.

Unanimity for standardization of quantification of resilience or resilience metrics in the power engineering community has not been established. Different events demand different systems response strategies. Performance based metrics which are the focus of this research can be divided into technical and social metrics. Technical metrics are computed from factors such as system performance to design requirements and system survivability, while social metrics are computed from inputs such as economic, health and safety, and geographic factors. The development of resilience metrics are multi-domain and separated by the event timeline, typically before, during, and after the event which requires the multi-dimensional analysis to understand the preparedness, robustness, and recovery potential of the system. Based on the components of resilience that have been previously mentioned the design optimization requires a multi-objective approach, focusing on resilience metrics such as survivability and economic costs. Design costs are directly related to system resilience. The Pareto-optimal set of system design choices presented in this research that maximize survivability and minimize costs is referred to as the resilience frontier.

The existing literature focuses on resiliency of a specific system such as the power grid or community grid and the metrics used; there is no extant literature focusing on power system resiliency of critical infrastructure such as hydroelectric dams. The survivability of complex systems such as critical infrastructure is typically difficult to calculate. Previous research has explored exploring tradeoffs between system survivability and cost by using percolation theory approach with generating functions to obtain nonlinear relations between system survivability and cost in smart grid applications. However, while the overall objective was the same, this research employs a method that combines stochastic sampling with an evolutionary search algorithm. While proposals for various resiliency metrics have been made in the literature, little research has been done specifically addressing hydroelectric dam resiliency, or the approach for quantifying and optimizing design trade-offs for maximizing resilience developed in this research.

The primary objective of this research was to develop a model and computational framework for optimizing the design trade-offs in complex systems. The secondary objective was to quantify the "cost for incremental resiliency" of inverter-based resources, such as microgrids, battery energy storage and solar PV. This analysis focuses primarily on survivability (technical) and costs (economic) contributions to dam resiliency, consisting of the following steps:

1) Review existing literature on resiliency metrics for electrical power systems, particularly applied (or relevant) to hydroelectric dams.
2) Describe and categorize dams in terms of functional relations among subsystems.
3) Define parameterized survivability and cost models for a representative dam.
4) State and solve a formal multi-objective optimization problem for determining Pareto-optimal designs of dam survivability versus cost, with the objective of maximizing dam resiliency.

This dissertation is organized as follows. In Chapter 2 a background on resiliency concepts, high impact low frequency events, hydropower, and hydroelectric dams is provided. Chapter 3 provides mathematical background on survivability modeling and network reduction. Chapter 4 outlines how Monte Carlo Sampling is used for estimating total system survivability. Chapter 5 introduces the Monte Carlo Genetic Algorithm Approach (MCGA). Chapter 6 presents multiple case studies and their parameters using the Monte Carlo Genetic Algorithm Approach.

Chapter 7 presents a resiliency analysis done on a lock and dam. The dissertation concludes with a summary conclusion in Chapter 8.

CHAPTER 2: BACKGROUND

2.1 Electric Power System & Other Critical Infrastructure

In order to understand the importance of an electric power system, an understanding of critical infrastructure and the electric power system's interdependences are required. The following section describes the general characteristics and interdependencies the electric power system has on critical infrastructure.

The Critical Infrastructure Assurance Office (CIAO) defined infrastructure as the framework of interdependent networks and systems comprising identifiable industries, institutions (including people and procedures), and distribution capabilities that provide a reliable flow of products and services essential to the defense and economic security of the United States, the smooth functioning of governments at all levels, and society as a whole. [1] The aging power infrastructure in the U.S. is electrically and physically volatile. During extreme weather events such as floods, windstorms, ice storms, snowstorms, hurricanes, and heat waves the utility grid is less reliable. In recent years, these weather-related invents are increasing. [2]Major events affecting power system resilience are resilience against natural disasters and pandemic events, human-made cyber and physical attack events, events stemming from system design, aging, and human error. [3] Extreme weather events (flooding, drought, strong winds, ice, snowstorms, extreme heat or cold, wildfires, earthquakes, etc.) are the most common disruptions that test power systems' resilience. These events can cause severe power system infrastructure damage, large blackouts, and major destructions of power grids. [4] [3] The grid is being stressed by increasing electricity demand as well as increasing weather events. [5]

The power system could be considered the most crucial infrastructure. [6] There are many dependencies between the electric power system and other critical infrastructure such as water, oil, gas, natural gas, transportation, and telecommunications. Electric power supplies power for pumping lift stations and control systems to the oil and water infrastructure. Electric power supplies power for storage and control systems for the natural gas infrastructure. Electric power supplies power for switching and signaling to the telecommunications infrastructure. Telecommunications supplies SCADA and communication to all critical infrastructure. Transportation receives fuel to transport and then transports fuel to electric power to be used for generators. Water supplies water for production, cooling, and emission reduction to oil, electric power, natural gas, and telecommunications. [3] [6] Figure 1 visualizes the electric power interdependencies.

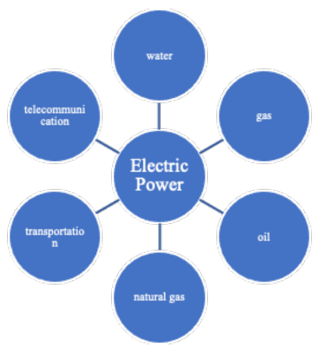

Figure 1-Electric Power Interdependencies (inspired from [SR01])

2.2 High Impact Low Probability Events/Low Frequency

In order to assess the hydroelectric dam resiliency, an understanding of a high impact low frequency event is needed. The following section defines a high impact low frequency event and the different hazards needed for the event to occur.

As defined by Pacific Northwest National Laboratory, a high impact low frequency (HILF) event risk is the realization of a specific hazard that has the potential to produce a high impact on grid operability. [7] Examples of natural hazards that could produce a HILF are meteorological (e.g., hurricane, tornado), geological (e.g., volcanic), hydrological (e.g., flooding), and space weather (e.g., geomagnetic storm). An example of a biological hazard that could produce a HILF event is a pandemic. Examples of human hazards that could cause a HILF are operational error human, physical attack, cyber-attack, coordinated cyber-physical attack, and electromagnetic pulse. The most common consequence of a HILF event is a loss of a single grid that then is followed by cascading events such as reduced performance ability. [7]

In 1965 the Northeast Blackout effected 30 million people, leaving them without power for up to 13 hours. The major cause of this blackout was human error. In 1997 a lightning strike strikes a substation by the Hudson River causing New York to lose power and riots and looting occurred. In 1982 high winds caused the West Coast Blackout which estimated that 2 million homes and business lost power. In 2012 Hurricane Sandy impacted 24 states in the U.S. where people lost power for up to two weeks with an estimated 35 billion dollars in damage. [8]

The U.S. experienced 28 weather/climate events in 2023 that caused 492 fatalities which is the most disaster related fatalities since 1980. There were 1 winter storm/cold wave event, 1 wildfire event, 1 drought and heat wave event, 4 flooding events, 2 tornado outbreaks, 2 tropical cyclones, and 17 severe weather/hail events. [9] From 2000 to 2021 83% of the major outages in the U.S. were from weather events. From 2010 to 2021 there was a 78% increase in major power outages from weather related events compared to 2000-2010. The outages were caused by winter weather (22%), tropical cyclones (15%), and other severe weather (58%). [10] Extreme events such as the ones mentioned above have caused large blackouts and damaged power infrastructure resulting in economic loss.

2.3 Resiliency

In order to develop and assess the hydroelectric dam resiliency, an understanding of electric power resiliency, resiliency metrics, and resilience characteristics are desired. The following section defines resiliency, different resiliency metrics and characteristics.

Resiliency has multiple definitions throughout different industries. For example, the US Department of Defense (DoD) has defined resilience as the “ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions.” [11] The US Department of Energy (DOE) refers to the term “resilience” is defined in Presidential Policy Direction 21 (PPD-21) as “the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. Resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents.” [12] The UK Cabinet Office has defined infrastructure resilience as ‘The ability of assets, networks and systems to anticipate, absorb, adapt to and/or rapidly recover from a disruptive event.’ [13] The National Infrastructure Advisory Council (NIAC) of the United States has identified energy as critical infrastructures and key resource (CIKR) sector. The Council has defined infrastructure resilience as ‘The ability to reduce the magnitude and/or duration of disruptive events.’ [14] According to the United Nations Office for Disaster Risk Reduction (UNDRR), resilience is defined as ‘The ability of a system, community or society exposed to hazards to resist, absorb, accommodate, adapt to, transform and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions.’ [15] Idaho National Laboratory (INL) defines resilience of an electric energy distribution system (EEDS) as a characteristic of the people, assets, and processes that make up the EEDS and its ability to identify, prepare for, and adapt to disruptive events (in the form of changing conditions) and recover rapidly from any disturbance to an acceptable state of operation. [16] As defined by [17] the power distribution system (PDS), resiliency is the 'ability of the network to resist discontinuity of power supply to critical loads during stressful operating conditions, and recover from any damages during unfavorable events'. Even though there is not an agreement on what resilience should be defined as, there are overlapping fundamental concepts.

2.3.1 Resilience Triangle

The resilience triangle represents a measure of both loss of functionality of a system after the disaster and the amount of time it takes for the system to return to normal performance levels. [18] The resilience triangle is a single-phase resilience assessment that is threat specific. It lacks corrective actions during progress of an event and lacks post disturbance of a degraded state. For example, if there is a flood event the resilience triangle would not be able to capture the evolution of the event. [19]

2.3.2 Resilience Trapezoid

The resilience trapezoid shown in typically evaluates resilience in five stages: original state, the event, the degraded state, the restoration state, and the final functional state. [20] [21] The resilience trapezoid is a multiphase resilience assessment that is applicable to any threat and considers corrective actions and post disturbance degraded state and duration. [19]

2.3.3 Resiliency Characteristics

The NIAC office has given three key characteristics of resilience:

- Robustness: the ability to maintain critical operations and functions in the face of crisis
- Resourcefulness: the ability to skillfully prepare for, respond to and manage a crisis or disruption as it unfolds.
- Rapid recovery: the ability to return to and/or reconstitute normal operations as quickly and efficiently as possible after a disruption. [14]

The UK Cabinet Office has given four characteristics of resiliency:

- Resistance: focused on providing protection. The objective is to prevent damage or disruption by providing the strength or protection to resist the hazard or its primary impact.
- Reliability: concerned with ensuring that the infrastructure components are inherently designed to operate under a range of conditions and hence mitigate damage or loss from an event.
- Redundancy: concerned with the design and capacity of the network or system.
- Response and recovery: aims to enable a fast and effective response to and recovery from disruptive event. [13]

The Multidisciplinary center for earthquake engineering research has given four characteristics of resiliency:

- Robustness: strength, or the ability of elements, systems, and other units of analysis to withstand a given level of stress or demand without suffering degradation or loss of function.

- Redundancy: the extent to which elements, systems, or other units of analysis exist that are substitutable, i.e., capable of satisfying functional requirements in the event of disruption, degradation, or loss of functionality.
- Resourcefulness: the capacity to identify problems, establish priorities, and mobilize resources when conditions exist that threaten to disrupt some element, system, or other unit of analysis.
- Rapidity: the capacity to meet priorities and achieve goals in a timely manner to contain losses and avoid future disruption. [22]

IDL has given five core functions of resilience.

- Identify: assess and develop an understanding of the system resilience relative to potential disturbances to EEDS and associated people, assets, data, and capabilities.
- Prepare: evaluates the results from the event analysis and develops solutions to the system/processes as needed to best mitigate the highest risks.
- Detect: the system detects disturbances and begins mitigating their impact.
- Adapt: Apply mitigations. The adapt stage is where all the plans for resiliency are sanctioned.
- Recover: the system is brought back up to full levels of performance and incorporates lessons learned. [16]

Figure 2 shows resilience in three stages of an event: before, during, and after. During each stage of the event different characteristics and resilience metrics can be analyzed. Before the event, the threat to the system can be identified, the system preparedness can be evaluated, the resiliency metrics can be defined, if there are prevention schemes, they can be applied, and finally the resiliency metric can be computed. During the event, the system's evaluate robustness, redundancy and degradation of systems can be evaluated, resilience metrics can be defined, the systems robustness can be improved, and resilience metrics can be computed. After the event, the system recovery capital can be evaluated, the resilience metrics can be defined, the recovery capacity can be improved, and the resilience metrics can be computed. [17]

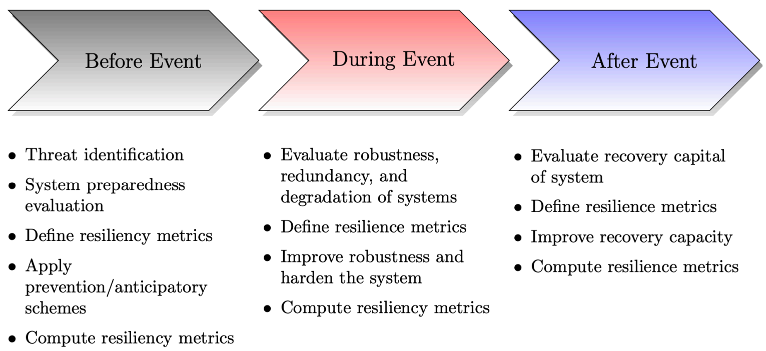

Figure 2. Resiliency (inspired from [KS20])

2.3.4 Resiliency Metrics

Quantifying resilience is not a straightforward process. It is a challenging task because resilience is a multidimensional, dynamic model with several inherent complexities. Being able to quantify resilience is necessary to evaluate the effectiveness of resilience frameworks and methods. [23] There are no standard power system resilience metrics. According [24] [17] [25] metrics are separated into two main categories: performance-based metrics and attribute-based metrics. Performance-based metrics typically use resilience attributes in their calculation but are described based on function. Performance-based metrics can be complex and have significant data requirements. [25] Attribute based metrics identify power system attributes that affect the resilience of the system such as robustness, resourcefulness, adaptivity, recoverability, and situational awareness. [17] Attribute-based metrics are relatively simple in terms of the mathematics needed for calculations. [25] Performance based metrics are generally quantitative while attribute-based (qualitative) metrics are what makes the system more/less resilient. [24] There have been proposed approaches for creating power system resilience metrics. Below is a summary of them from [4] [23] [26] [4] [27] [28] [24]

- Resilience metrics should be identified in the context high impact low probability (HILP) events and their consequences.
- Resilience metrics should be based off the performance of the system rather than attribute-based metrics.
- Resilience metrics should quantify the consequences of a disruption to the power system.
- Resilience metrics should be reflective of the characteristic uncertainties that constrain response and preparation.
- Resilience metrics should provide global and component-specific resilience indicators.
- Resilience metrics must consider recovery time.
- Resilience metrics should be easy to understand and implement.
- Resilience metrics should be verifiable.
- Resilience metrics should be reflective of the likelihood of an event.
- Resilience metrics should be replicable.

2.3.5 Quantitative Resiliency

Quantitative resilience evaluation methods are based on the quantification of system performances. Common methods include simulation based, analytical, and statistical analysis of historic outage data. Simulation based method includes cost of resilience method, ratio between targeted and real performance, and component connectivity based on complex system method. Analytical method includes the probability that network performs its intended function. Statistical analysis of historic outage data method includes analyzing time to restoration and rapidity of restoration. [29] [3]

2.3.6 Qualitative Resiliency

Qualitative resilience evaluation methods include analyzing different aspects and capabilities. The aspects include power systems, energy infrastructure, information system, and business structure. Capabilities include preparedness, mitigation, response, and recovery. Capabilities can include emergency plan, or personnel training. Evaluation methods can include matrix scoring, system combining different aspects of resilience, analytical hierarchy process, checklist, and questionnaires. These frameworks can typically provide a thorough picture of the system. [29] [3]

2.3.7 Performance/Consequence Based Resiliency Metrics

According to [24] resilience metrics are separated into two categories: performance based, and nonperformance based. Performance based metrics rely on the system's performance while nonperformance-based metrics do not. Performance-based metrics are broken into two categories: performance and consequences. Under performance five metrics are analyzed and summarized in Table 1.

Table 1-Performance Metric

Performance Category	Resilience Metric
Power	Power metrics include the load being supplied or not, and generation capacity.
Duration	Duration metric includes recovery time and load curtailment time.
Frequency	Frequency metric includes number of customer outages only looking at system equipment/customers.
Probability	Probability metric shows the probability of aspects of disasters effects on power system.
Curve	Curve metrics are the area under real performance.

Consequence metrics include how the failure of the power system will affect society. Economic, social, geographic and safety and health metrics are summarized in Table 2.

Table 2-Consequence Metrics

Consequence Category	Resilience Metric
Economic	Economic metrics show cost and economic impacts of power systems on the society
Social	Social metrics show social effect of disaster.
Geogrpahic	Geogrpahic show the distribution of the disaster.
Health & Safety	Safety and health metrics show the effect of human life and health.

DOE's Grid Modernization Laboratory Consortium (GMLC) has developed two main categories of metrics: performance-based metrics and multi-criteria decision analysis metrics (MCDA). MCDA metrics can assess the system's baseline resilience relative to other systems. The metrics include categories of system properties beneficial to resilience. These performance-based metrics interpret quantitative data that describe infrastructure performance during events.

This data can be collected from historical events, subject matter estimates, and computational models. The performance-based metrics are summarized in Table 3. [3]

Table 3-DOE Performance Metrics

Impact	Consequence Category	Resilience Metric
Direct	Electric Service	Cumulative customer-hours of outages
		Cumulatuve customer energy demand not served
		Average number of customers experiencing an outage during a specified time
	Critical Electric Service	Cumulative critical customer hours of outages
		Critical customer energy demand not served
		Average number of critical loads that expirence an outae
	Restoration	Time to recovery
		Cost of recovery
	Monetary	Loss of utility revenue
		Cost of grid damage
		Cost of recovery
		Avoided outage cost
Indirect	Community Function	Critical services without power (hospitals, fire station, police station, etc.)
	Monetary	Loss of assets and perishables
		Business interruption costs
		Impact on the gross municipal product or gross regional product
	Other Ciritical Assets	Key production facilities without power
		Key military facilties without power

The IEEE PES Distribution Resilience Working Group under the Transmission and Distribution Committee has designed two draft metrics: storm resilience metric and non-storm resilience metric. The storm metric focuses on speed of system recovery. The non-storm metric focuses on robustness and the ability to withstand events. [3] Resilience metrics are a tool to measure the resilience level of power systems. While multiple power system resilience metrics, methods, and improvement strategies have been proposed in the literature, there are no standardized definitions or metrics to measure hydroelectric dam power system resilience.

Resiliency consists of both technical (design) and economic (cost) factors. These are the two objectives that will be the focus of this research, highlighted in Figure 3. Their trade-off suggests a novel view: a multi-objective (Pareto-optimal) set of “best” design choices for a given resiliency objective.

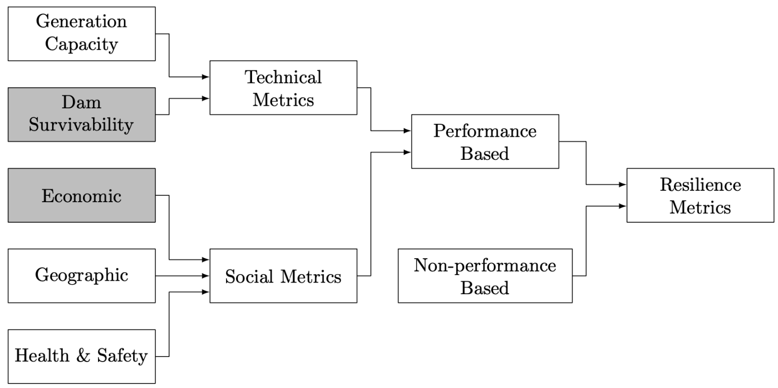

Figure 3. Research Focused Resilience Metrics

2.4 Resilience Enhancement Methods

In order to improve the hydroelectric dam resiliency, an understanding of resilience enhancement methods is desired. The following section details different types of resilience enhancement methods and examples of methods from literature.

There are multiple resilience enhancement strategies throughout literature and can be broken up into three main categories. First proactive strategies utilize the available assets to prepare for the extreme event. This can include maintenance planning, mobile storage allocation, defensive islanding, hardening and microgrid formation. Second, corrective strategies which aim to control power system components during an event to improve the system performance. Common corrective strategies include network reconfiguration and leveraging DERs. Third, restorative strategies try to retain the power to partial loads fast and efficiently. [30] Examples of restorative strategies include generator, mobile power sources, and microgrid based restoration. [31] In [32] proactive scheduling was used agist extreme floods. For example, during flood events outdoor substations and ground cables are at a high risk of outage since they are exposed to the water. The vulnerable components are tripped out then a power flow was run while employing network reconfiguration, energy storage commitment and demand-side resources.

[32] Authors from [33] used microgrids to enhance power system resilience during weather events. Load shedding was used to increase system resilience. [33] In [19] the power system resilience was increased during an extreme weather event by using defensive islanding.

2.5 Previous Survivability Modeling Methods

To model survivability of the hydroelectric dam, an understanding of survivability modeling is required. A literature review of previous methods was completed. The following section details survivability modeling methods from literature.

Previous researchers have investigated the analysis of survivability in systems using a variety of methods which can be qualitative or quantitative. Quantitative examples include graph theory analysis, probabilistic statistics analysis, model checking analysis, and others. [34] The authors in [35] [36] [37] used incorporating probabilistic models of component or agent behavior to analyze survivability. Survivability methods also include model-based systems engineering methods that include continuous-time Markov Chains [38] or stochastic agent behavior. [39] Researchers in [40] used subjective probability modeling using nonlinear Boolean programming to evaluate survivability. [41] simulated the evaluation of survivability using weighted hypergraphs. The authors in [42] used support vector machines to analyze the survivability of a complex system. State of the art Monte Carlo search tree methods include game theory, decision theory, and Markov decision Process. [43]

Research in [44] used MC analysis to evaluate survivability in damaged ships by using the MC to take in consideration the random quantities related to the damage and loading conditions during the event. In [45] calculated distribution system reliability using MC to obtain enhanced samples. The authors in [45] state a disadvantage of MC is long execution time, and an advantage is not based on a specific system configuration, or dependent on extensive mathematics. In [46] the MC was used to evaluate the reliability of power distribution systems on both the microgrid and primary grid level.

In addition, fault-tree analysis (FTA) and Monte Carlo (MC) for evaluating system survivability have been widely demonstrated throughout literature. [47] combined MC and FTA to approximate failure rate values of the microgrid as the design is beginning. [48] used a combination of FTA and MC to calculate the probability of the importance index of each component in the system. [49] used MC and FTA to consider the impact of redundancy on electric power supply systems. The papers described in [35]– [50] focused on survivability evaluation, instead of iterative design optimization, which is the objective of the research described in this dissertation.

In [50], researchers combined MC simulation with a genetic algorithm (GA) to improve the performance of a search algorithm. [51] compared MC to GA to obtain a better optimization result on wind turbines which resulted in MC having better optimization.

Prior literature that is closest to the research in this dissertation are given in [52], [53]. In [52], historical measurements from World War II and Korean War were used with a uniform random number generator for simulating probability of the aircraft being damaged, failure events and a simplified conditional diagram to determine minimum lifecycle cost for an unmanned vehicle. However, in [52], used exhaustive (non-iterative) grid-search applied to component reliability models rather than complex systems that include standby subsystems.

In [53] researchers described a percolation theory approach with generating functions to obtain nonlinear relations between system survivability and cost in smart grid applications. The authors concluded that it is important to find a tradeoff between expenditure and performance while building smart grid infrastructures. They also concluded that the system robustness against random failure can be improved by controlling cost which in their research was adding more control links for each target power station. While the overall objective in [53] was the same as in this dissertation; exploring tradeoffs between system survivability and cost, this dissertation employs a method that combines stochastic sampling with an evolutionary search algorithm.

2.6 Basics of Hydropower

In order to model the hydroelectric dam resiliency, an understanding of hydropower is needed. The following section details different types of hydropower and their functions.

There are three different types of hydropower facilities, not all facilities use dams. Impoundment facility uses a dam to store water in a reservoir then the water that is released from that reservoir flows through a turbine which spins the turbine that acts like a generator to be able to produce electricity. Impoundments are the most common type of hydropower facility. A run of river facility channels water through the canal of a river to use the natural flow of the riverbed elevation to produce energy. It can also use a penstock which is a closed channel to channel the flow of water to turbines. The last type of facility is a pumped storage facility. The pumped storage facility can store electric power then pump water from lower elevation reservoir to a high elevation reservoir for storage. Then when electricity is needed the water will be released back to the low reservoir to turn a turbine, therefore generating electricity. There are different sizes of hydropower plants. The DOE defines a large hydropower plant has a capacity of more than 30 megawatts while a small hydropower plant has a capacity of 100 kilowatts to 10 megawatts. [54] Hydropower is a clean and a renewable source of energy since the hydropower is fueled by water. Hydropower is also a domestic source of energy and can create opportunities such as fishing, swimming, and boating by creating reservoirs. [55] Hydroelectric dams produce 8-12% of this nations power. [56] Figure 4 visualizes hydropower in the U.S.

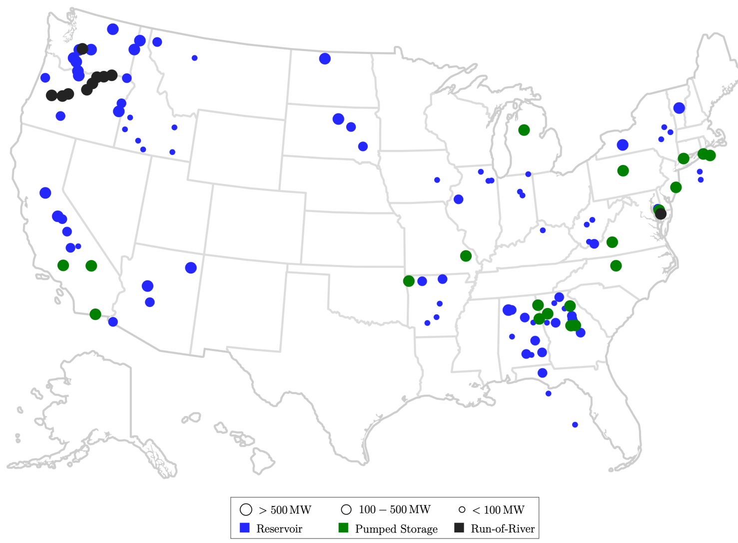

Figure 4-Hydropower in the U.S.

2.7 Basics of Dams

To assess and model hydroelectric dams, knowledge of their systems, functions, and consequences are required. The following section details different types of dams and their functions.

As defined by the National Inventory of Dams (NID), a dam is “a structure that is built across a river or body of water to hold, divert, or regulate water”. [57] Dams can be used for: flood risk management, navigation, recreation, power generation, water supply, space for fish and wildlife, and waste management. The NID has defined over 90,000 dams on America's waterways, 75% of those dams are “High Hazard Potential Dams with an EAP,” meaning if the dam has failure or mis-operation it will cause loss of human life and property damage. [57] [58]

The domestic waterways are used to transport 630 million tons of consumer goods each year with an annual value of $73 billion. The waterways represent a good piece of the U.S. economy by carrying close to 17% of cargo. Over 50% of the locks and dams operated by USACE are over 50 years old. [59] USACE defines risk as the combination of the probability and consequences of failure. Failure occurs when a structure no longer performs as intended. [59]

The consequences of dams failing vary by type, size, location, and population. For example, to estimate the consequences of a power generation dam, the amount of power not being generated, and the value of that power must be estimated. To estimate the consequences of a navigation dam failing, the increased cost of shipping due to rerouting and use of alternative shipping modes must be estimated. [60] To estimate the consequences of a flood risk management dam, the population, property damage, and loss of life must be estimated. To prevent the dam from causing the consequences mentioned above, it is important that the dam can always perform its function, including during a high impact low frequency (HILF) event.

The following are examples of consequence metrics that could be used for a dam. First, the metrics can be divided into the two main categories of performance based and non-performance based. Performance-based metrics may be further categorized into technical and social. Under the performance-technical metrics, the outage frequency and generation capacity of the dam will be defined. A duration metric can then be defined for load recovery. A frequency metric can be defined for utility outages and extreme weather events including duration of the outages. Social metrics include, economic, geographic, and health and safety metrics.

In (1), total economic cost is calculated by adding recreational loss to the public, fish and wildlife loss, loss of power generation from the dam, loss of water supply to the public, and loss of navigation on the river. Total economic loss, T_{EL}, may be computed as:

$$T_{EL} = L_R + L_{FW} + L_{PG} + L_{WS} + L_N \tag{1}$$

where L_R is loss from recreational use fees, L_{FW} is loss of fish and wildlife, L_{PG} is loss from power generation, L_{WS} is loss of municipal and industrial water supply to the community, and L_N is navigation loss.

A geographic consequence can be defined as the area of which a dam failure impacts, flooding and property damage. In (2), total geographic loss is calculated by adding property damage, emergency response cost, and dam repair cost of the affected area. Total geographic loss, T_G, may be computed as:

$$T_G = C_{PD} + C_{DR} + C_{ERC} \tag{2}$$

where C_{PD} is property damage cost, C_{DR} is dam repairs cost, and C_{ER} is emergency response cost.

In (3), outage frequency is calculated by multiply the outage duration by the probability of the outage Total outage frequency, T_{OF}, may be computed as:

$$T_{OF} = L_{DO} L_{OP} \tag{3}$$

where L_{DO} is duration of outage and L_{OP} is outage probability.

In (4), the generation capacity is calculated as the full load capability of the system added with the generation capacity of the reserve system (generator or microgrid). Total generation capacity of a dam, T_{GCD}, may be computed as:

$$T_{GCD} = G_{FL} + G_{RS} \tag{4}$$

where G_{FL} is full load (kW) and G_{RS} is reserve capacity. A health and safety metric an include loss-of-life and injuries resulting from a dam failure.

In (5), the flood severity will be multiplied by the amount of time the people had to leave the area (warning time) multiplied by the population of the affected area multiplied by the (x) value for loss of life. Total health and safety loss T_{HS}, may be computed as:

$$T_{HS} = L_{FS} L_{WT} L_{PAA} L_{MPF} \tag{5}$$

where L_{FS} is flood severity, L_{WT} is warning time, L_{PAA} is population of affected area, and L_{MPF} is an assigned value (x) per life lost.

For nonperformance-based metrics, aspects affecting dam failures within three stages may be evaluated. These metrics may include age and condition of equipment, and number of spare parts on hand.

2.7.1 Dam Gates

The most common gates on spillway crests and navigation locks are roller gates (Figure 5) that are lifted directly upward and Tainter gates that are radial in form and rotate about trunnion pins that are anchored to adjacent piers. [59] To lift the gates a crane or hoist is used. Both gate systems consist of the gate, a supporting structure, a lifting device in the form of a crane or a motor, cables, gears, and an electrical power supply. [59] The purpose of a spillway on a dam is to convey water from the reservoir to the tail water for all discharges up to design flood level. [61] The gates control the flow of water that raises and lowers to permit the flow of water. [59]

Figure 5. Roller Gates

2.7.2 Dam Block Diagrams

Each dam will be designed differently based on the purpose of the dam. For this research the following block diagrams and dam layout will be used. Dam power distribution systems typically receive power from the local utility grid. The dam distribution system load typically includes a motor control center, switchboard, or distribution panel from which supplies power to the controls for dam gate motors. There is also a backup generator in case of loss of power, typically with a manual or automatic transfer switch to switch from one source of power to another. Each dam has different loads: some of the smaller flood risk management (FRM) dams only have two gates while larger navigation dams have ten or more gates. In Figure 6**,** a high-level overview of an example FRM is depicted. There is utility power that feeds a service breaker and intake structure. The service breaker feeds the spillway breaker which feeds the spillway. The service breaker also feeds the intake structure and then the intake structure feeds the spillway.

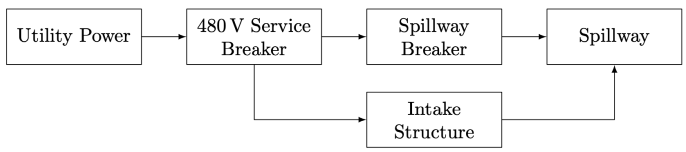

Figure 6. FRM Overview.

In Figure 7, the dam's intake structure is depicted. The intake structure gets utility power from the service breaker and has a generator inside for secondary power. Both sources feed the MCC. The MCC feeds hydraulic pumps that operate gates and supplies generator power to the spillway.

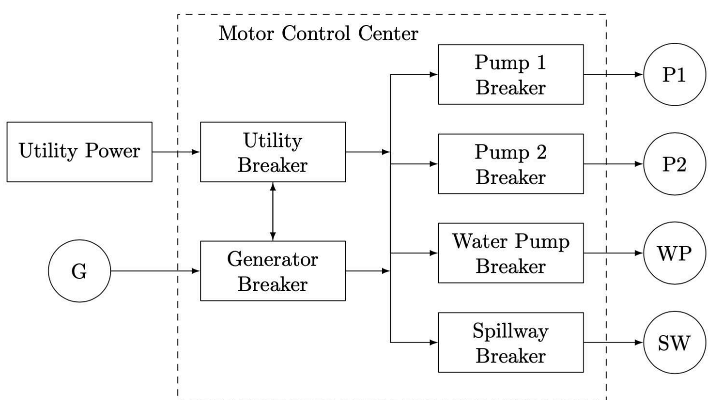

Figure 7. FRM Detailed

In Figure 8**,** the dam's spillway is shown. The utility power from the spillway breaker feeds the spillway breaker stand. The spillway can also get generator power from the intake structure (see Figure 7**)**. The spillway breaker stand feeds the motor controllers and each motor controller feeds a motor. [62]

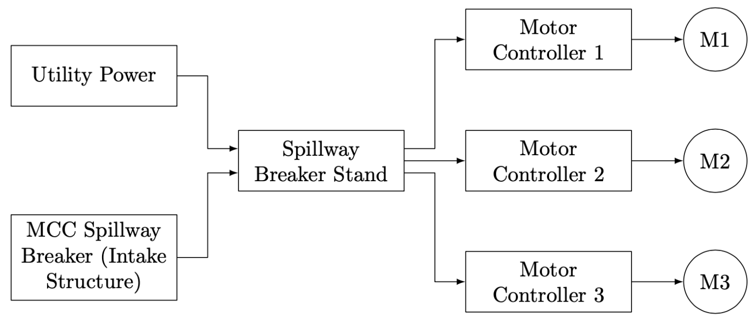

Figure 8. FRM Spillway.

2.7.3 Example Cases of Dam Failures: 1

The following is an example of a different designed dam failure. The main purpose of this example dam is flood risk management.

- Utility powers a disconnect, the disconnect then powers a manual transfer switch, the manual transfer switch powers a motor control center the motor control center then powers the motors. The motors operate the dam gates which allow us to open or close the gate as needed. The motor control center also powers the crane. The crane is used to set an emergency bulkhead if needed. There is also a backup generator, if the utility goes out then someone switches the manual transfer switch from utility to generator and the generator supplies power to the dam.

- If there is now power to the motors in a high-water event and the gates are not able to operate, then the dam will overtop and flood what is downstream of the dam which could result in life loss.
- If there is no power to the crane, then there is no way to set the emergency bulkhead if it is needed which leads to the dam losing pool.

2.7.4 Example Cases of Dam Failures: 2

The following is an example of a different designed dam failure. The main purpose of this example dam is flood risk management with six gates powered hydraulically.

- Utility powers a disconnect, the disconnect then powers the motor control center the motor control center then powers the motors. The motors operate the dam gates which allow us to open or close the gate as needed. There is also a backup generator, if the utility goes out then someone switches the kirk key interlock from utility to generator and the generator supplies power to the dam. Only three out of the 6 gate motors can be run at the same time. The motor control center also supplies power to the HPU system and sump pumps.
- If there is now power to the motors in a high-water event and the gates are not able to operate, then the dam will overtop and flood what is downstream of the dam which could result in life loss.
- If there is no power to the sump pumps in a high-water event and the water gets inside the intake, then the electric equipment could become submersed in water.
- If there is no power to the HPU then the pumps cannot provide pressurized oil to the hydraulics actuation system.

2.7.5 Example Cases of Dam Failure: 3

The following is an example of a different designed dam failure. The main purpose of this example dam is flood risk management with a manual transfer switch.

- Utility powers a disconnect, the disconnect then powers a manual transfer switch, the manual transfer switch powers a motor control center the motor control center then powers the motors. The motors operate the dam gates which allow us to open or close the gate as needed. There is also a backup generator, if the utility goes out then someone switches the manual transfer switch from utility to generator and the generator supplies power to the dam.
- If there is no power to the motors in a high-water event and the gates are not able to operate, then the dam will overtop and flood what is downstream of the dam which could result in life loss.
- If there is no power to the sump pumps in a high-water event and the water gets inside the intake, then the electric equipment could become submersed in water.
- If there is no power to the HPU then the pumps cannot provide pressurized oil to the hydraulics actuation system.

CHAPTER 3: SURVIVABILITY MODELING

In order to model a hydroelectric dam, an understanding of survivability modeling including different electrical and mechanical system connections are required. The following section details provides background on survivability modeling and network reduction for several common system configurations and failure distributions.

3.1 Survivability

Based off of multiple definitions the researchers in [63] defined survivability as the ability of a system to minimize the impact of a finite disturbance on value delivery, achieved through either the satisfaction of a minimally acceptable level of value delivery during and after a finite disturbance or the reduction of the likelihood or magnitude of a disturbance.

In practice a system can be represented as a network where the subsystems are connected in series, parallel or standby connections. The overall system can be simplified into a simplified version of the system by network reduction or synthesis rules with identical overall system survivability. The overall system can be simplified into a simplified version of the system by network reduction or synthesis rules with identical overall system survivability. [64] A conceptual illustration of this process is depicted in Figure 9. In Figure 9, each block in the network represents a component or subsystem. The network is synthesized into progressively simpler networks moving counterclockwise (depicted by arrows). Typically, the reliability network is not identical to the physical system. The physical system must be translated into the reliability system before network reduction can begin. [65]

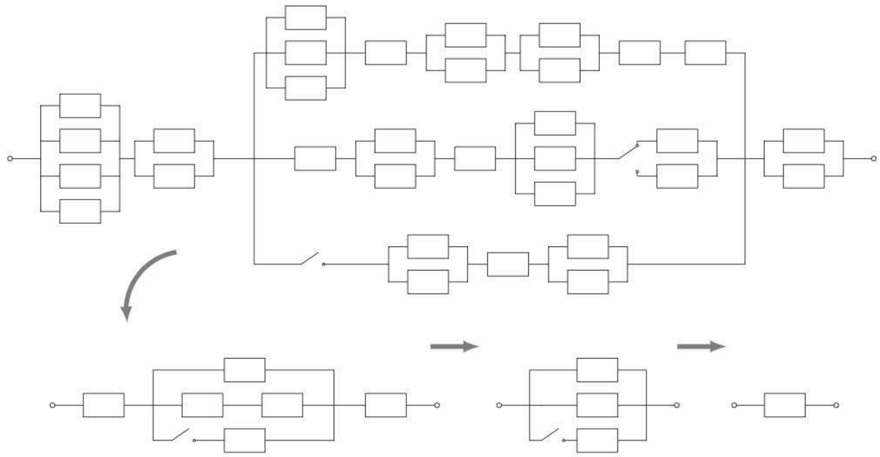

Figure 9. Network Reduction

Notation: herein, a random variable is denoted by capital letter X; a specific instance of the random variable is symbolized by lower-case letter $x \in X$. A probability density function (pdf) for random variable X with parameter set α is denoted $f_X(x;\alpha)$; a cumulative density function (cdf) for random variable X with parameter set α is denoted $F_X(x;\alpha)$.

Subsystem failure time is probabilistic and generally influenced by factors such as operating conditions, number of operating hours, environmental factors, etc. Let X be a random subsystem failure time, $f_X(x;\alpha)$ the pdf of failure times with subsystem parameters α, and $F_X(x;\alpha)$ the corresponding cdf.

Definition: survivability, $S(x;\alpha)$, is the probability that a system does not fail before time x, computed as:

$$S(x;\alpha) = 1 - F_X(x;\alpha) = \int_x^\infty f_x(\tau;\alpha)d\tau. \tag{6}$$

Practical systems can be modeled by using only Weibull, Exponential and Binomial distributions. The subsystems considered in this research consist of mechanical and electrical components, with failure time distributions (purposely) limited to Weibull, Exponential and

Binomial distributions. Where the subsystem failure time is probabilistic and generally influenced by factors such as operating conditions, number of operating hours, environmental factors, preventative maintenance and more.

3.2 Weibull-distributed Failure Times

To model different pure mechanical and some electro-mechanical failures an understanding of the Weibull distribution is desired. The following section details Weibull distributed failure times.

Pure mechanical and some electro-mechanical failures are modeled herein as 2-parameter Weibull probability density functions of the form:

$$f_X(x;\gamma;k) = \frac{k}{\gamma}\left(\frac{x}{\gamma}\right)^{k-1} e^{-(x/\gamma)^k}, \tag{7}$$

where k > 0 and γ > 0 are associated with wear and mean time before failure (MTBF), respectively, X is the time to failure and x ≥ 0 is the actual failure time.

The cumulative probability distribution function for the distribution above is:

$$F_X(x;\gamma;k) = 1 - e^{-(x/\gamma)^k}. \tag{8}$$

Each component therefore has a survivability of the form:

$$S(x;\gamma,k) = 1 - F_X(x;\gamma;k) = e^{-(x/\gamma)^k}. \tag{9}$$

3.3 Exponentially distributed Failure Times

To model different pure electrical failures an understanding of the exponential distribution is desired. The following section details exponential distributed failure times.

Some pure electrical failure times are modeled herein as Exponential density functions of the form:

$$f_X(x;\lambda) = \lambda e^{-\lambda x}, \tag{10}$$

where λ is associated with the MTBF, respectively, X is the time to failure and $x \geq 0$ is the actual failure time.

The cumulative probability distribution function for the distribution above is:

$$F_X(x;\lambda) = 1 - \lambda e^{-\lambda x}, \tag{11}$$

Each component therefore has a survivability of the form:

$$S(x;\lambda) = 1 - F_x(x;\lambda) = e^{-\lambda x}. \tag{12}$$

3.4 Binomial Failures

To model different other component failures an understanding of the binomial distribution is desired. The following section details binomial distributed failure times.

In addition, some component failures (e.g., switches) are modeled as Binomial trials, where p is the probability of success (no failure) and $q = 1 - p$ is the probability of failure. For example, p, is perfect switching is that the switch does not fail during operation and does not fail from switching from the normal operating position to the standby position. Imperfect switching, q, has a probability of failing when the switch is switching to the standby subsystem.

3.5 Connections

In order to model a hydroelectric dam, an understanding of survivability modeling including different electrical and mechanical system connections are required. The following section details different types of system connections.

3.5.1 Series Connections

Suppose that a set of N subsystems are connected in a series configuration, as depicted in Figure 10. In Figure 10, parameters for subsystem $n \in \{1,2,...,N\}$ are contained in set αn. If a set of N subsystems comprising a system are connected in a series configuration (if any subsystem fails, the collective system fails), the total survivability of the system is:

$$S(x;\alpha) = S_1(x;\alpha_1)S_2(x;\alpha_2)\ldots S_N(x;\alpha_N) = \prod_{n=1}^{N} S_n(x;\alpha_n) \tag{13}$$

where α collects all parameters sets $\alpha_n, \forall n \in N$.

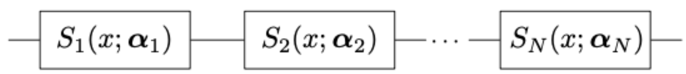

Figure 10. Series Connection

3.5.2 Active Parallel Connections

If a set of N subsystems are connected in a parallel configuration, where all subsystems are always activated (e.g., processing energy, material, information), this is referred to as an active parallel configuration. An active parallel configuration is depicted in Figure 11. In the active parallel configuration, if all subsystems fail, the collective system comprising the subsystems fails. Total survivability of the active parallel subsystem is:

$$S(x;\alpha) = 1 - (1 - S_1(x;\alpha_1))\,(1 - S_2(x;\alpha_2))\ldots\big(1 - S_N(x;\alpha_N)\big) = 1 - \prod_{n=1}^{N}(1 - S_n(x;\alpha_n)) \tag{14}$$

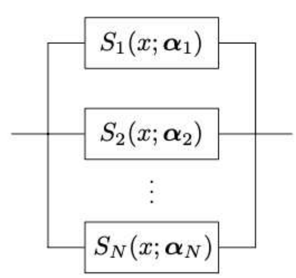

Figure 11. Parallel Connection

3.5.3 Standby Connections

In contrast to an active parallel configuration, in a system with standby subsystems, only one subsystem is active at a given time. Referring to Figure 12, after the first subsystem fails, the second subsystem becomes activated through a switch. After the second subsystems fails, the third is activated, etc. System failure occurs only after all subsystems have sequentially failed. The total survivability of the system is dependent on the individual subsystem failure times.

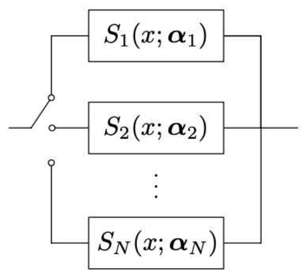

Figure 12. Standby Connection

Let $Z = X_1 + X_2 + \cdots X_N$ be a random variable denoting the time until all N standby subsystems have failed. If the failure times of each subsystem are independent, the probability density $f_Z(z)$ is computed as an N−fold convolution:

$$f_Z(z) = f_{X_1}(x_1) * f_{X_2}(x_2) * \cdots f_{X_N}(x_N) \tag{15}$$

where $*$ denotes the convolution operator defined as follows. If W is the sum of two random variables Y,U:

$$\{f_X(x) * f_Y(y)\}(w) := \int_{-\infty}^{\infty} f_x(w) f_Y(w-x)dx. \tag{16}$$

To be able to perform design optimizations on a system the overall system failure distribution is needed. However, for complex systems such as hydroelectric dam standby subsystems are used, which requires the computation of the convolution integral which is difficult to compute. Therefore, an alternative method of estimating the composite failure distribution of systems with standby subsystems is desirable and is addressed in the Chapter 4.

CHAPTER 4: MONTE CARLO SAMPLING

In order to model a hydroelectric dam, an understanding of Monte Carlo Sampling is desired. The following section details Monte Carlo Sampling and shows examples of how the Monte Carlo sampling can be used to sample a hydroelectrical dam.

4.1 Monte Carlo Sampling

Monte Carlo simulation is often used for systems that are complex. The complex dependences make calculation of the system resiliency difficult to calculate. Repeated sampling is used to generate numerical results and the random numbers that are used, regenerate at each step. By repeating the sample more times, the results should model real world problems. [66]

For systems with standby subsystems, estimation of the system survivability function may be obtained using MC sampling by implementing the following steps:

1) Specify the pdfs of failure times for each subsystem. (Exponential, Weibull, binomial)

2) Specify the logic of the subsystem interactions, e.g., when standby subsystems should be switched on or off. (series, activate parallel or standby connections)

3) Use inverse sampling to draw pseudo-random samples of failure times from the pdfs.

4) Implement the logic of the subsystem interactions on the samples to numerically determine the composite pdf of the system and compute overall survivability.

4.2 Inverse Sampling Procedure

Let U (0, 1) denote a uniform distribution over the range (0, 1), and u ~ U (0, 1) a sample from the distribution. A pseudo-random sample from the distribution is selected using the following procedure:

1. Draw a sample $u \sim U(0,1)$.

2. Set x to the value:

$$F_X^{-1}(u) := \inf\{x | F_X(x) \geq u\},$$

where $\inf\{\cdot\}$ is the infinum function (used in case a closed-form inverse doesn't exist).

A complex system can normally be grouped with redundancy into multipart primary and redundant branch(es). Computing overall system survivability with redundancy is difficult. Next, two examples show how Monte Carlo can be used to obtain a failure time more easily compared to solving analytically.

4.3 First Example

Consider the system comprising two subsystems illustrated in Figure 13. If subsystem 1 (primary) fails, subsystem 2 (standby) is immediately activated via a switch. Suppose both subsystem failure times are exponentially distributed with failure rates λ_1 and λ_2, respectively. Let X be the time until the primary subsystem fails and Y the time until the standby subsystem fails. Since the failure times are exponentially distributed, $f_X(x) = \lambda_1 e^{-\lambda_1 x},\ x \geq 0$, and $f_Y(y) = \lambda_2 e^{-\lambda_2 y}, y \geq 0$. Let the time until both failures be denoted $Z = Y + X$.

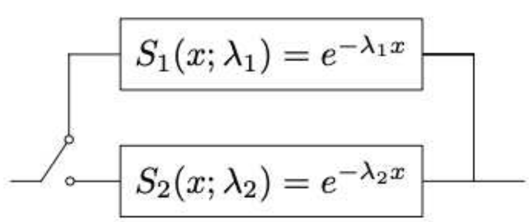

Figure 13. One Primary w/ Standby

Let X be the time until failure of the first component failure and Y the time until the second component failure. Since the failure times are exponentially distributed:

$$f_X(x) = \lambda_1 e^{-\lambda_1 x}, x \geq 0 \tag{17}$$

$$f_Y(y) = \lambda_2 e^{-\lambda_2 y}, y \geq 0 \tag{18}$$

We are interested in the time until both failures, designated by random variable Z=X+Y.

The probability density $f_Z(z)$ is computed from (11) as:

$$f_Z(z) = \int_{-\infty}^{\infty} f_X(x) f_Y(z-x)dx$$

$$= \lambda_1 \lambda_2 e^{-\lambda_{2z}} \int_0^z e^{-(\lambda_1 - \lambda_2)x} dx, \tag{19}$$

where the upper limit of integration on the final integral is because $z - x \geq 0 \ \rightarrow x \leq z \rightarrow \ 0 \leq x \leq z$.

$$f_Z(z) = \begin{cases} \frac{\lambda_1 \lambda_2}{\lambda_{2-} \lambda_1} \left(e^{-\lambda_{1z}} - e^{-\lambda_{2z}}\right) & \lambda_1 \neq \lambda_2 \\ \lambda^2 z e^{-\lambda_z} & \lambda := \lambda_1 = \lambda_2 \end{cases} \tag{20}$$

Note: only in the second case will total survivability be $\lambda^{-\lambda x} + \lambda z e^{-\lambda z}$.

The probability the system survives until t_{min} is the probability it does not fail before that time:

$$P(Z > t_{min}) = 1 - P(Z < t_{min})$$

$$= 1 \int_{-\infty}^{t_{min}} f_z(z)dz$$

$$= 1 - k \int_0^{t_{min}} \left(e^{-\lambda_{1z}} - e^{-\lambda_{2z}}\right)dz, \tag{21}$$

where $k = {}^{\lambda_1 \lambda_2}/_{(\lambda_1 - \lambda_2)}$

After some work, we arrive at:

$$P(Z \geq t_{min}) = 1 - \int_{-\infty}^{t_{min}} f_z(z)dx = 1 - \left[\frac{k}{\lambda_1}\left(1 - e^{-\lambda_1 t_{min}}\right) - \frac{k}{\lambda_2}\left(1 - e^{-\lambda_2 t_{min}}\right)\right] \tag{22}$$

The time to failure of the second component is independent of the failure time of the first component. The cdfs for the exponential distribution are well-known and expressed as:

$$F_X(x) = 1 - e^{-\lambda_1 x} \tag{23}$$

$$F_{Y|X}(x, y) = F_Y(y) = 1 - e^{-\lambda_2 y} \tag{24}$$

We can use inverse sampling (or a built-in function) to obtain many samples of x and y and then add them to obtain samples of z.

4.4 Algorithm 1

As a numerical example, consider the system shown in Figure 13 with parameters $\lambda_1 = 1$ failure per 500 days = 0.002 per day, $\lambda_2 = 1$ failure per 1000 days = 0.001per day, $t_{min} = 2000$ days, and $N_{samps} = 10^5$. The algorithm to estimate the probability in (22) is shown in Algorithm 1. The first steps of the Algorithm 1, steps 1-4 set the parameters of the code. Then z is put into an array and samples of X and Y are taken. Then the samples are added together to get the system failure times. The find function is used to return the array of samples that met the minimum failure time (2000 days) and finally the probability is calculated by taking the samples from I divided by the total number of samples.

Algorithm 1 Calculation of Probability of Failure using MC

```
1:  λ1 ← 0.002
2:  λ2 ← 0.001
3:  t_min ← 2000
4:  N_samps ← 10^5
5:  z ← [0] * N_samps
6:  for n = 1 to N_samps do
7:      X ← exprnd(λ1)
8:      Y ← exprnd(λ2)
9:      z[n] ← X + Y
10: end for
11: I = find(z(:) >= t_min)
12: P ← length(I)/N_samps
```

Figure 14. Algorithm 1

Algorithm 1 was applied to MATLAB and the results are shown in Figure 15. In Figure 15, the system failure pdf is shown as the gray histogram; the theoretical pdf in (20) is shown as the solid line. Using the samples, the estimated probability P (Z ≥ 2000) = 0.2533, a 0.37% error with respect to the theoretical value of 0.2500 computed from (22). This indicates that MC sampling is a sufficient method to calculate survivability of complex systems.

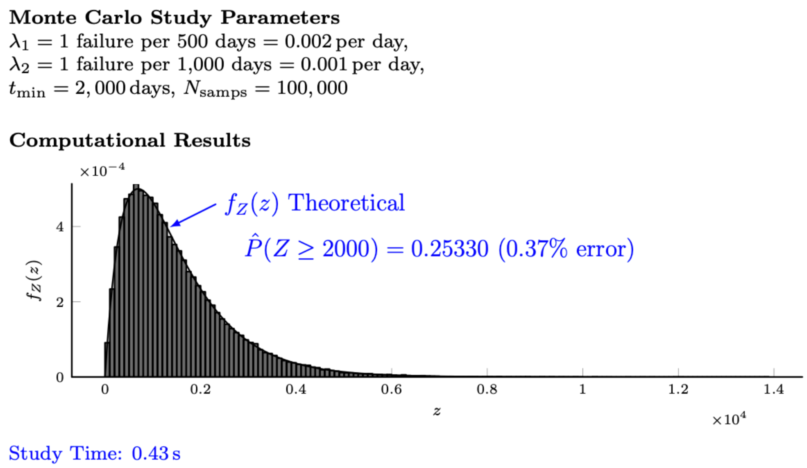

Figure 15. Sampled distribution of system failure times (gray histogram) vs. theoretical (solid line).

4.5 Second Example

For a system with one backup (N = 2), and two backups (N = 3), and λ = 0.002 hr. (for all components) and drawing 10,000 samples. The exact survivability with one and two backups are, $S_1 = e^{-\lambda x} + \lambda x e^{-\lambda x}$and $S_2 = e^{-\lambda x} + \lambda x e^{-\lambda x} + (\lambda x)^2 e^{-\lambda z}/2$, respectively. Estimated (sampled) survivabilities $\widehat{S_1}$, $\hat{S}_2$, were computed from the sampled pdfs using Algorithm 1, with integration replaced by discrete summation. The sampled versus theoretical survivability functions are shown in Figure 16, indicating a good match. Computation time in MATLAB: 0.39 and 0.52 s.

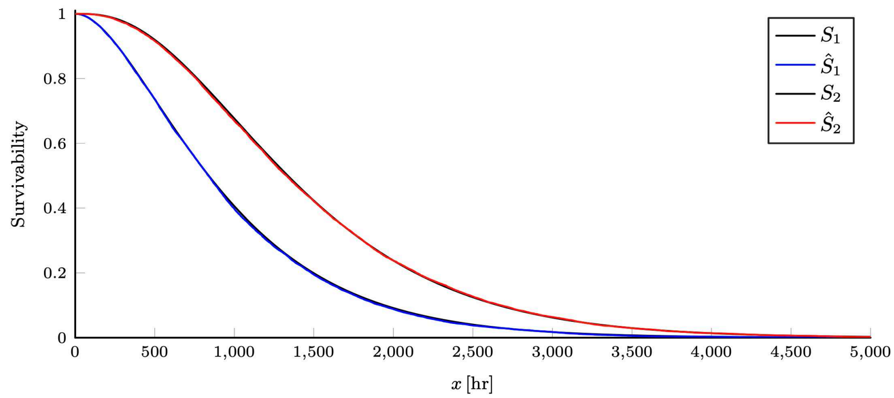

Figure 16. System survivability functions using MC sampling for a system with one and two standby subsystems.

As shown in the previous two examples Monte Carlo Sampling can be used to estimate system survivability functions, based on failure parameters of subsystems and the logic of their interactions including the those with standby subsystems. This prevents the need to calculate an N-fold convolution.

CHAPTER 5: MONTE CARLO GENETIC ALOGRITHIM

In order to find the resilience frontier for a hydroelectric dam, design optimization requires a multi-objective approach, focusing survivability and economic costs. The following section details the Monte Carlo Genetic Algorithm and multi-objective optimization problem.

Increased system survivability can be achieved using a variety of approaches such as increasing individual component or subsystem MTBFs, including standby subsystems, etc. However, because these design changes generally result in higher implementation costs, there is a tradeoff between system survivability and cost. This section proposes a method for exploring the set of Pareto-optimal tradeoffs between survivability and cost, i.e., the resilience frontier.

It was demonstrated in the previous section that MC sampling can be used to estimate total system survivability functions in complex systems, including those with standby subsystems, if failure parameters of individual subsystems and their network interactions are specified. We propose a method for combining the MC sampling technique with a GA to determine the resilience frontier of a complex system, herein referred to as the Monte Carlo Genetic Algorithm (MCGA).

5.1 MCGA Flowchart

A flow-diagram for the MCGA is depicted in Figure 17. The steps in the MCGA are as follows. First, an initial population of design candidates is specified, the algorithm iteration number k is initialized to zero, and the initial MC sample size, Ns, is set to Nmin. Next, the iteration number is checked to see it is greater than kmin; if so, the MC sample size is set to Nmax > Nmin. The purpose of this step is to provide better overall computational efficiency by "kick-starting" the GA. In particular, the sample size is initially set to Nmin, which provides less fidelity in sampled failure distributions, but requires less computational time. Using this smaller sample size, the GA converges within a general region in the solution space. After the iteration threshold, kmin, is met, the sample size is increased to obtain higher fidelity in the estimated failure distributions and a refined convergence on Pareto-optimal solutions. After the survivability estimation step, the subsequent steps in Figure 17 employ the basic genetic algorithm (see [67]) until the stop criteria are met.

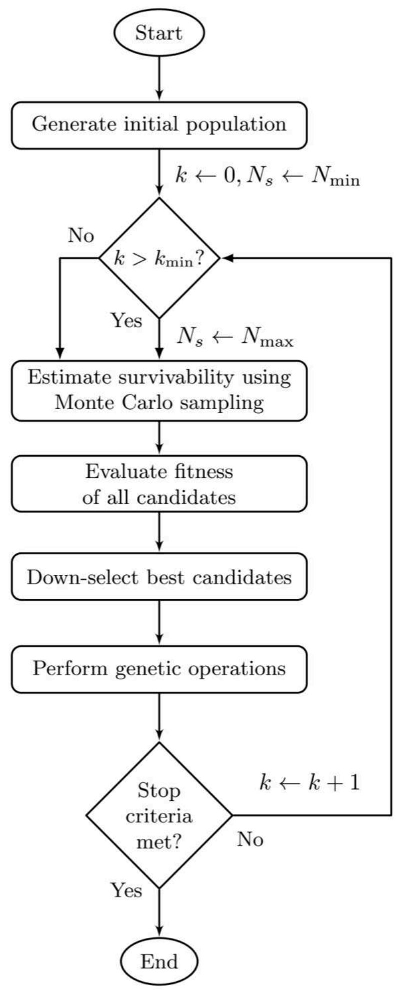

Figure 17. MCGA Flowchart

5.2 Multi-Objective Optimization Problem

The purpose of the multi-objective optimization is to determine the set of Pareto- optimal design choices for maximizing survivability while minimizing design cost. Let the vector of design parameters be collected into a vector defined as:

$$\theta \coloneqq \{\theta_n\} = \left[\lambda_1 \cdots \lambda_{Ne} | \, \gamma_1 \cdots \gamma_{Nw} \mid p_1 \cdots P_{Nu}\right]^T \tag{25}$$

where the scalars N_e, N_w, N_u, are the number of components with Weibull, Exponential, and Binomial failures, respectively. From (25) $|\theta| = N,$ where $N = N_e + N_w + N_u$.

The objective functions to maximize are:

$$f_1(\theta) = \hat{S}_{tot}\,(x;\theta) \tag{26}$$

$$f_2(\theta) = \frac{1}{\sum_{n=1}^{N} c(g(\theta);\theta) + \epsilon} \tag{27}$$

where $\hat{S}_{tot}\,(x;\theta)$is the estimated total system survivability, $N = N_e + N_w + N_u$, ϵ is a small positive scalar (to avoid a divide-by-zero error), and g(·) is a function relating the reliability parameters to MTBF.

The overall vector of functions to maximize is:

$$f(\theta) = [f_1(\theta) \quad f_2(\theta)]^T \tag{28}$$

Next, supplementary functions are defined to enforce constraints on the design. Let the "less-than" function be defined as:

$$ltn(x; x_{max}, \Delta x) = \begin{cases} -1, & x < x_{max} \\ \dfrac{1}{1 + (x - x_{max})/|\Delta x|}, & x \geq x_{max} \end{cases} \tag{29}$$

where x_{max} is the maximum desired value of x and Δx determines the "sharpness" of the function around x_{max}.

Similarly, the "greater-than" function is defined as:

$$gtn(x; x_{min}, \Delta x) = \begin{cases} \dfrac{1}{1 + (x - x_{min})/|\Delta x|}, & x < x_{min} \\ 1, & x \geq x_{min} \end{cases} \tag{30}$$

where x_{min} is the minimum desired value of x. Plots of (29)- (30) with x_{min} = 0, Δx = 0.05 are shown in Figure 18.

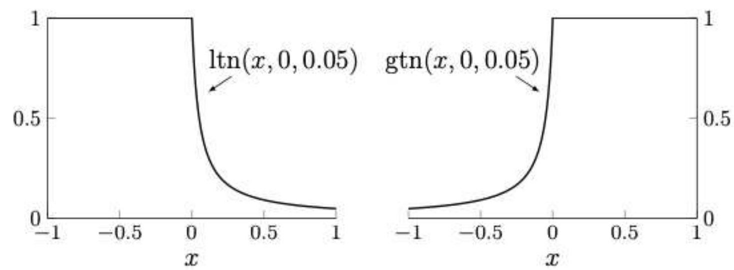

Figure 18. Example plots of less than (left) and greater than (right) with xmin =0, Δx=0.05

Next, let $f_1(x; \theta, \,)$ be the fitness function for total survivability of the system at time x, with design parameters θ, and minimum constraint on survivability at time x :

$$f_1(x; \theta, x_{min}, \Delta x) = gtn(x; x_{min}, \Delta x)\hat{S}_{tot}\,(x; \theta), \tag{31}$$

where $\hat{S}_{tot}$ is the estimated total system survivability, computed using the MC sampling method.

Generally, the cost of a subsystem increases as the MTBF increases. For example, [68] suggest a linear relation between MTBF and cost. Herein, we express the cost versus MTBF, $\overline{x}$, as:

$$c(\overline{x}; \beta) = \beta_2 \overline{x}^2 + \beta_1 \overline{x} + \beta_0 \tag{32}$$

where the scalars $\beta_i \geq 0$ are cost coefficients, that can be obtained from vendor data or estimated. The cost parameters for all components that are in the system are in the matrix:

$$\beta = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \vdots & \vdots & \vdots \\ \beta_{N_1} & \beta_{N_2} & \beta_{N_3} \end{bmatrix}$$

Let $g(\theta_n)$ be a function to relate the parameters in θ to $\bar{x}$. For example, if $1 \leq n \leq N_e, g(\theta_n) = 1/\lambda_n$. The fitness function for the total system cost with the maximum constraint on cost is:

$$f_2(x; \theta, \beta, x_{max}, \Delta x) = ltn(x; x_{max}, \Delta x) * \sum_{n=1}^{N} B_{n1} g(\theta_n)^2 + B_{n2} g(\theta_n) + \beta_{n3} \tag{33}$$

Lastly, the fitness vector function that is used to evaluate the Pareto solution is:

$$f(x; \beta, \theta, x_{max}, x_{min}, \Delta x) = \begin{bmatrix} f_1(x; \theta, x_{min}, \Delta x) \\ f_2(x; \theta, x_{max}, \Delta x) \end{bmatrix} \tag{34}$$

where the Pareto-optimal candidates are defined as those where no change in the parameters θ can lead to an improvement in survivability at time x without increasing cost.

5.3 Case Studies

This section demonstrates the MCGA through case studies. All the studies were conducted in MATLAB® using the Genetic Optimization System Engineering Toolbox. [67] The genetic algorithm settings were:

- design candidate population size $N_p = 200$,
- number of design iterations $N_i = 1000$,
- minimum number of MC samples $N_{min} = 500$,
- maximum number of MC samples $N_{max} = 2000$ and
- iteration threshold for kick-start $k_{min} = .25, N_p N_i = 50000$.

System survivability in all studies was evaluated at x = 500hrs, and was constrained to be a minimum of 0.5 at time x. A cost constraint was imposed to limit the total design cost to less than \$750k. Cost coefficients for all components were selected as: $\beta_{i1} = 1.0, \beta_{i2} = 0.5$, and $\beta_{i3} = 0.05$.

5.3.1 *Case Study I: Resiliency Enhancement with an Added Identical Standby Subsystem*

In this study, resilience frontiers were examined in a system with zero or one standby subsystems. The purpose of this study was to assess whether a system could be designed with greater resilience by adding a standby subsystem, despite the additional cost of the standby subsystem. In this study it was assumed that all subsystems were identical, with survivability functions $S_i(x; \lambda_i) = e^{-\lambda_i x}$, $\lambda_i = \lambda$, i for $\in \{1,2\}$. In this case study, λ was a free variable over the range $\lambda \in (10^{-5}, 10^{-1})$. The Pareto-optimal cost versus survivability tradeoff is shown in Figure 19. The gray set of circles on the left correspond to no standby subsystem; the set of black circles on the right are for one standby subsystem.

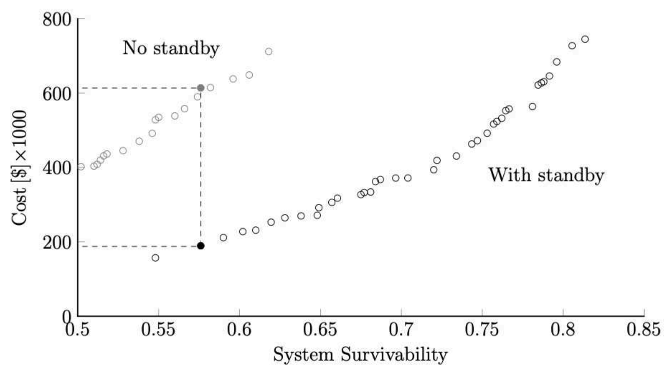

Figure 19. Pareto-optimal fronts for no standby (gray) and one standby (black).

The vertical dashed line in Figure 19 highlights two designs— one with standby and one without—that have approximately the same survivability. However, as indicated by the horizontal dashed lines, the system that includes standby has a lower design cost at this survivability. This equivalent survivability at reduced cost (i.e., higher resiliency) compared to the system with no standby is a result of the design flexibility inherent in choosing λ in both subsystems. Also shown in Figure 19 is that the system with standby can achieve higher survivabilities over no standby, but at the expense of higher design cost (as expected) for survivability over approximately 0.63.

5.3.2 *Case Study II: Resilience Frontier with Two Standby Subsystems and Similar Failure Distributions*

In this study, the resilience frontier was computed in a system with two standby subsystems, where the failure distributions were all exponential form, but different failure parameters. The survivability functions were defined as: primary subsystem: $S_1(x;\lambda_1) = e^{-\lambda_1 x}$, , secondary subsystem (first standby): $S_2(x;\lambda_2) = e^{-\lambda_2 x}$ and tertiary subsystem (second standby): $S_3(x;\lambda_3) = e^{-\lambda_3 x}$. In this case study, λ was a free variable over the range $\lambda \in (10^{-5}, 10^{-1}), i \epsilon \{1,2,3\}$. The Pareto-optimal cost versus survivability is shown in Figure 20. Comparison of Figure 19 and Figure 20 indicates that an additional standby subsystem results in higher system survivability than with a single standby subsystem, at the expense of higher system design cost.

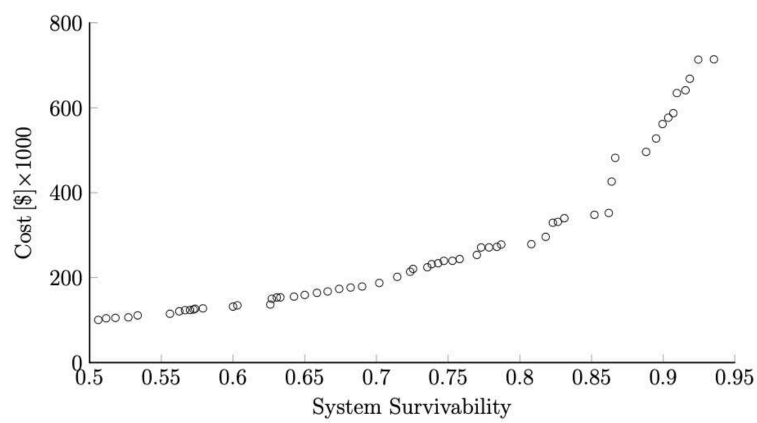

Figure 20. Pareto-optimal fronts for system with two standby subsystems and similar failure distributions.

5.3.3 *Case Study III: Resilience Frontier with Two Standby Subsystems and Mixed Failure Distributions*

In the final study, the resilience frontier was computed in a system with two standby subsystems, where the failure distributions included a mixture of Weibull and exponential forms with different failure parameters. The survivability functions were primary subsystem: $S_1(x;\gamma_1,k_1) = e^{-\left(\frac{x}{\gamma_1}\right)^{k_1}}$, secondary subsystem (first standby): $S_2(x;\gamma_2,k_2) = e^{-\left(\frac{x}{\gamma_2}\right)^{k_2}}$, tertiary subsystem (second standby): $S_3(x;\lambda) = e^{-\lambda x}$. In this study, λ, k, γ_i were free variables over the range $\gamma_i \in (10^1, 10^5),\ k_i \in (1,5),\ \ i \in \{1,2\}, and\ \ \lambda_i \in (10^{-5}, 10^{-1})$. The Pareto-optimal cost versus survivability is shown in Figure 21, again showing the clear tradeoff between system survivability and system design cost.

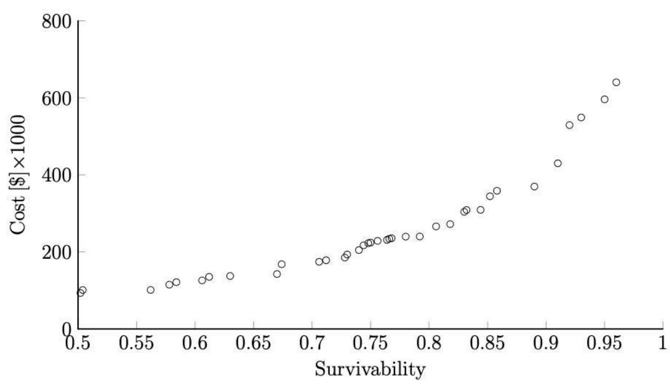

Figure 21. Pareto-optimal fronts for system with two standby subsystems and mixed failure distributions

CHAPTER 6: DAM CASE STUDIES

In order to model a hydroelectric dam, an understanding of the consequences of the dam system failures required. The following section detail's the dam's network diagram, different fault tree analysis for the example hydroelectric dam, costs for each subsystem, and MTBF for each subsystem.

6.1 Network Diagram

The physical hydroelectric dam system is then put into a network model to analyze the reliability of the system. Network reduction was completed on this model in order to simplify the survivability calculations. The hydroelectric dam can be represented as a network where the subsystems are connected in series, parallel, and standby connections. The utility system is in standby with controls, fuel, synchronous generator, shaft, and pulley. These subsystems are in active parallel with control, battery, battery inverter, PV inverter, and a PV array. All of the previously mentioned subsystems are in series with switch and sensor, circuit breakers and cabling, cabling, the main switch, and lower switches. the overall Network diagram of the hydroelectric dam is shown in Figure 22.

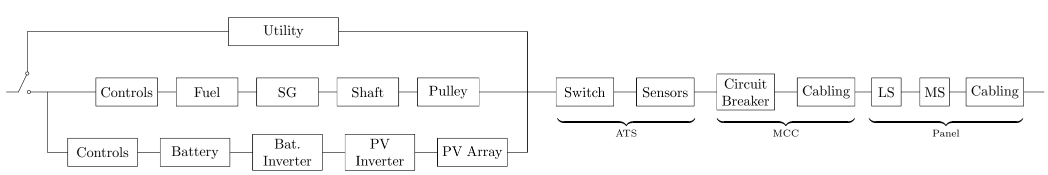

Figure 22-Overall Network Diagram of Hydroelectric Dam

The hydroelectric dam's survivability can be simplified into a simpler version with the same overall system survivability by completing network reduction. The subsystems will be combined into a total of three subsystems: backup generator, IBR, and plant controls.

The backup generator system includes controls, fuel, synchronous generator, shaft, and pulley. The inverter-based resources include control, battery, battery inverter, PV inverter, and a PV array. These systems are in series with the plant controls. The plant controls include an automatic transfer system, motor control center, and panel. The automatic transfer switch includes switch and sensor. The motor control center includes circuit breakers and cabling. The panel includes cabling, the main switch, and lower switches.

The overall hydroelectric dam system was simplified into a simplified version of the system by network reduction with identical overall system survivability shown in Figure 23. The simplified network diagram shows the utility power in standby connection with the microgrid subsystem which includes: the backup generator subsystem and inverter-based resources subsystem which are connected in an active parallel connection. The utility and microgrid subsystems are in series with the "plant" (hydroelectric dam) controls shown in Figure 23.

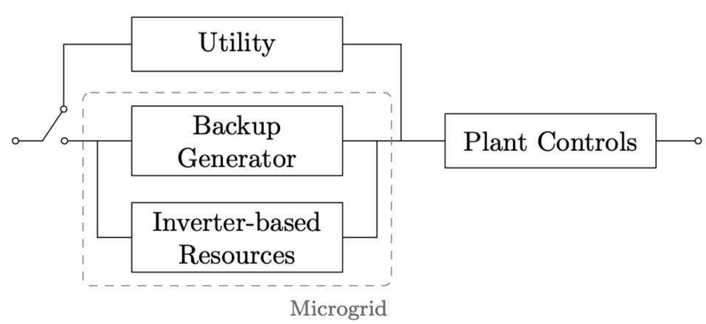

Figure 23-Simplified Network Diagram of Hydroelectric Dam

The subsystems failure time is probabilistic, it is usually influenced by operating conditions, operating hours, environmental conditions, preventative maintenance, etc. The total dam survivability is dependent on the individual subsystem failure times. The general dam survivability calculated from the network graph (without specific failure distributions) in Figure 23 is:

$$S_{dam}(x;\alpha) = \prod_{n=1}^{N} S_n(x;\alpha_n) * (\int_{-\infty}^{\infty} f_X(x) f_Y(w-x)dx) * 1 - \prod_{n=1}^{N}(1 - S_n(x;\alpha_n)) \tag{35}$$

6.2 Fault Tree Analysis

In order to model a hydroelectric dam, an understanding of the consequences of the dam system failures required. The following section detail's different fault tree analysis for our example hydroelectric dam. The hydroelectric dam is comprised of subsystems connected in a series, active parallel, and standby configuration.

A high-level fault tree analysis was done on a flood risk management dam. Each dam will have a different fault tree analysis based on the design of the dam. The following fault trees were used for the case studies presented in this research.

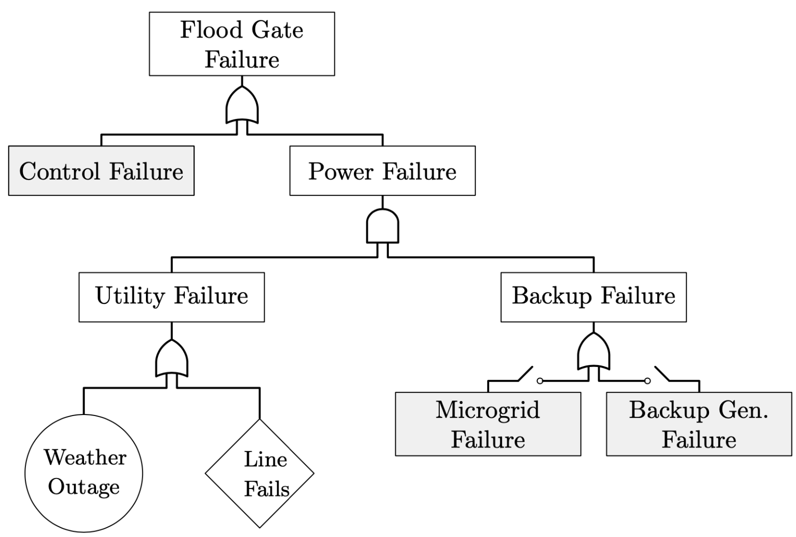

Figure 24. FTA Top Level Failure

Figure 24 is the overall fault tree for a flood gate failure. For the flood gates to fail meaning they are not operating normally which can cause loss of pool or flooding the following must be true: the control system must fail OR the power system must fail. To have a power system failure; the utility system must fail AND the backup power must fail. For the utility power to fail there must be a weather outage or transmission line failure. For the backup power to fail the inverter-based resources must fail or the generator must fail. Note that the backup generator and inverter-based resources are in a standby connection meaning that both systems must fail to have a backup power failure.

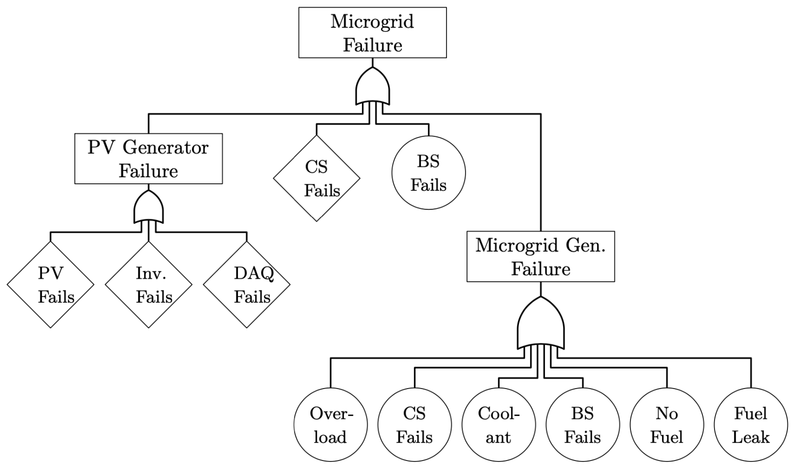

Figure 25. Microgrid FTA

Figure 25 shows the fault tree analysis of the inverter-based resources. To have a microgrid failure the PV generator, control system, OR battery system must fail. The PV generator would fail if the solar panel fails OR the inverter fails or the DAQ system fails.

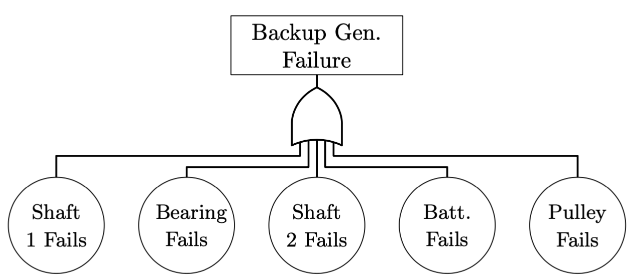

Figure 26. Generator FTA

Figure 26 show the fault tree analysis of a backup generator. To have a backup generator failure, a shaft, pully, battery, OR synchronous generator must fail.

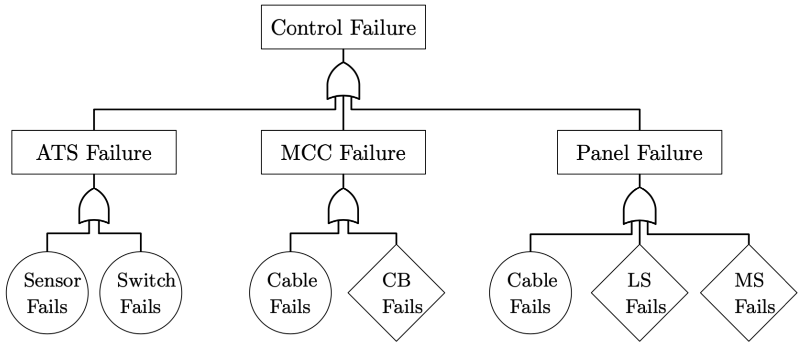

Figure 27. Control FTA

Figure 27 is the fault tree analysis for the control failure. To have a control failure the automatic transfer switch (ATS) OR motor control center (MCC) OR a panel must fail. To have an ATS failure; a switch OR a sensor must fail. To have a MCC failure; a cable OR circuit breaker (CB) must fail. To have a panel failure; a cable OR switch or main switch (MS) must fail.

6.3 Costs & MTBF Parameters

In order to model a hydroelectric dam accurately, costs of subsystems and mean time before failure (MTBF) for the subsystems is needed. The following section details the costs and MTBF for the subsystems. The subsystems were purposely limited to three types of distribution: Weibull, Exponential, and Uniform. Many costs and MTBF were found to be used as reference throughout this research. Table 4 shows the uniform distribution.

Table 4-Uniform Distributed Parameters

Description	Symbol	Probability	Ref.
During HILP Event	X_{24}	8% less	[69]
Transmission Line	X_{25}	$2.3E^{-6}$	[70], [71]

Some pure electrical failure times are modeled as Exponential density function shown in Table 5.

Table 5-Exponentially Distributed Parameters

Description	Symbol	λ (years)	MTBF (hours)	Ref.
Control Panel	X_{18}	$1.8E^{-5}$	$4.8E^{8}$	[72]
Grid Pot	X_{19}	$1.8E^{-2}$	$4.9E^{5}$	[73]
Charge Controller	X_{20}	$2.0E^{-2}$	$4.4E^{5}$	[73]
Metering	X_{21}	$7.8E^{-2}$	$1.1E^{5}$	[74]

Pure mechanical and some electro-mechanical failures are modeled herein as 2-parameter Weibull distribution shown in Table 6. Table 7 depicts the MTBF from multiple sources for the Weibull components. The MTBF and Beta shape factor was obtained from manufacturer data, industry standards, and literature.

Table 6-Weibull Distribution Parameters

Part	Symbol	γ (years)	MTBF (hours)	Ref.	β Shape Factor	Ref.
Shaft	X_1	$7.6E^{-5}$	$1.2E^{7}$	[75]	1.2	[76]
Pully-Shaft	X_2	$7.6E^{-5}$	$1.2E^{7}$	[75]	1.2	[76]
Gen Battery	X_3	$4.0E^{-5}$	$4.4E^{5}$	[73]	1.5	[77]
Bearing	X_4	$7.6E^{-5}$	$1.2E^{7}$	[75]	1.3	[76]
Fan Belt	X_5	$1.1E^{-4}$	$1.2E^{7}$	[75]	1.2	[76]
PV Panel	X_6	$2.0E^{-2}$	$4.3E^{5}$	[70]	1.2	[78]
DC/AC Inverter	X_7	$1.2E^{-1}$	$7.0E^{4}$	[73]	1.4	[78]
Battery System	X_8	$4.0E^{-5}$	$4.4E^{5}$	[73]	1.5	[77]
AC Switch	X_9	$1.1E^{-4}$	$7.9E^{7}$	[73]	0.35	[78]
DC Switch	X_{10}	$1.8E^{-3}$	$4.7E^{6}$	[73]	1.0	[76]
Bypass Diode	X_{12}	$2.2E^{-2}$	$3.9E^{5}$	[73]	1.0	[79]
ACCB	X_{13}	$1.8E^{-2}$	$4.9E^{5}$	[73]	3.2	[80]
Diff CB	X_{14}	$1.8E^{-2}$	$4.9E^{5}$	[73]	3.2	[80]
MCC	X_{15}	$1.87E^{-7}$	$4.7E^{10}$	[81]	3.6	[80]
ATS	X_{16}	$3.3E^{-7}$	$2.7E^{10}$	[75]	3.6	[80]

Connector	X_{17}	$6.5E^{-4}$	$1.3E^{7}$	[73]	1.0	[76]

Table 7-MTBF of Subsystem Components

Part	Brand 1	MTBF 1 (hours)	B2	MTBF 2 (hours)	B3	MTBF 3 (hours)
ATS	[82]	$8.0E^{4}$	[83]	$4.5E^{3}$	[84]	$2.0E^{5}$
PLC	[85]	$2.5E^{5}$	[86]	$1.5E^{4}$	[87]	$8.8E^{5}$
CB	[84]	$2.5E^{5}$	[88]	$1.5E^{4}$	[89]	$1.7E^{4}$
PV Panel	[90]	$4.0E^{4}$	[91]	$3.0E^{3}$	[92]	$8.7E^{6}$
Inverter	[93]	$2.6E^{5}$	[94]	$1.5E^{4}$	[95]	$1.5E^{1}$
Battery	[96]	$2.0E^{7}$		$3.0E^{3}$†		$1.5E^{4}$†
Metering	[74]	$9.7E^{3}$		$3.0E^{3}$†		$1.5E^{4}$†
DC Switch	[97]	$1.4E^{5}$	[92]	$1.0E^{6}$		$2.5E^{5}$†
AC Switch	[97]	$1.4E^{5}$	[92]	$1.0E^{6}$		$2.5E^{5}$†
Bypass Diode	[98]	$5.0E^{1}$	[99]	$7.0E^{2}$		$3.0E^{3}$†
Diff CB	[97]	$2.5E^{5}$		$3.0E^{3}$†		$1.7E^{4}$ †
Generator	[100]	$6.0E^{1}$	[101]	$5.0E^{3}$	[97]	$5.0E^{3}$
Motor	[74]	$7.0E^{4}$	[97]	$1.0E^{4}$		$5.0E^{3}$†
Cable	[102]	$3.0E^{5}$	[103]	$3.0E^{4}$		$5.0E^{3}$†
Control Panel	[72]	$2.0E^{2}$		$3.0E^{3}$†		$1.5E^{4}$†
MCC		$5.3E^{5}$†		$3.0E^{3}$†		$1.5E^{4}$†

The costs of the different electrical equipment were obtained from manufacture data, research or estimated. Cost from up to 3 sources for each piece of equipment were obtained to ensure nonbiased data. Table 8 depicts the cost of the different subsystem components.

Table 8-Costs of Subsystem Components

Part	Brand 1	Cost 1 ($)	B2	Cost 2 ($)	B3	Cost 3 ($)
ATS	[82]	$2E^{3}$	[83]	$5E^{3}$	[84]	$7E^{3}$
PLC	[85]	$3E^{4}$	[86]	$2.6E^{3}$	[87]	$4E^{5}$
CB	[84]	$3E^{3}$	[88]	$8E^{4}$		$2E^{3}$†

PV Panel	[104]	$2.7E^3$	[104]	$2.3E^3$	[104]	$2E^3$
Inverter	[93]	$2E^2$	[94]	$6E^2$	[95]	$1.8E^2$
Battery	[96]	$3.5E^2$		$3E^3$†		$2.2E^2$†
DC Switch	[97]	$8E^3$	[92]	$7E^3$		$5.1E^2$†
AC Switch	[97]	$8E^3$	[92]	$7E^3$		$5.1E^2$†
Bypass Diode	[98]	13.00	[99]	$2E^2$		$1.5E^2$†
Generator	[100]	$1.3E^3$	[101]	$1.7E^3$	[97]	$9.7E^2$
Cable	[102]	$8E^3$	[103]	$7E^3$		$5E^3$†
Control Panel	[72]	$3E^3$		$2.6E^2$†		$1.9E^2$†
MCC		$3E^4$†		$2.6E^3$		$1.9E^3$†

† If the data could not be found, a nominal value was used.

6.4 Case Studies

This section demonstrates the MCGA through case studies applied to a hydroelectric dam. All the studies were conducted in MATLAB® using the Genetic Optimization System Engineering Toolbox. [67] The case studies that are presented in this research are high level, meaning the utility, battery, fuel, and solar variability are ignored. The analysis was completed assuming that there is utility power, there is fuel for the generator, the battery is fully charged (IBS subsystem) and there is solar (IBS subsystem). The reason that these variables were excluded is that for this is that for the purpose of the research i.e. finding design tradeoffs to maximize system survivability, that these specific variables are not needed. The genetic algorithm settings were:

- design candidate population size $N_p = 200$,
- number of design iterations $N_i = 1000$,
- minimum number of MC samples $N_{min} = 500$,
- maximum number of MC samples $N_{max} = 2000$ and

- iteration threshold for kick-start $k_{min} = .25, N_p N_i = 50000.$

System survivability in all studies was evaluated at x = 500hrs, and was constrained to be a minimum of 0.91 at time x. The survivability constraint that is used in this research came from research in the nuclear industry. [105] [106] A cost constraint was imposed to limit the total design cost to less than $100k. The cost only includes purchase cost of the equipment. Labor, preventative maintenance, and other costs were excluded from this research. The MTBF that can be used as a reference for the subsystems in the hydroelectric dam case studies are shown in Table 9. Costs that were used in the matrix β for the hydroelectric dam case studies are shown in Table 10.

Table 9. Case Study MTBF

Part	Symbol	γ (years)	λ (years)	MTBF (hours)	Ref.	β Shape Factor	β Ref.
Control Panel	X_1		$1.8E^{-5}$	$2.0E^{2}$	[72]		
Fuel	X_2						
SG	X_3	$1.2E^{-3}$		$7.2E^{2}$	[81]	3.9	[76]
Shaft	X_4	$7.6E^{-5}$		$1.2E^{7}$	[75]	1.2	[76]
Pully-Shaft	X_5	$7.6E^{-5}$		$1.2E^{7}$	[75]	1.2	[76]
Control s	X_6		$2.0E^{-2}$	$4.4E^{5}$	[73]		
Battery	X_7	$4.0E^{-5}$		$4.4E^{5}$	[96]	1.5	[77]
Battery Inverter	X_8	$1.2E^{-1}$		$7.0E^{4}$	[73]	1.4	[33]
DC/AC Inverter	X_9	$1.2E^{-1}$		$7.0E^{4}$	[73]	1.4	[33]
PV Panel	X_{10}	$2.0E^{-2}$		$4.3E^{5}$	[70]	1.2	[33]
AC Switch	X_{11}	$1.1E^{-4}$		$7.9E^{7}$	[73]	.35	[78]
Sensor	X_{12}		$4.0E^{-2}$	$2.1E^{5}$	[107]		
ACCB	X_{13}	$1.8E^{-2}$		$4.9E^{5}$	[73]	3.2	[80]
Cable	X_{14}		$4.2E^{-2}$	$3.0E^{5}$	[102]		
LS	X_{15}	$3.3E^{-7}$		$2.7E^{10}$	[81]	3.6	[80]
MS	X_{16}	$3.3E^{-7}$		$2.7E^{10}$	[81]	3.6	[80]
Cable	X_{17}		$4.2E^{-2}$	$3.0E^{5}$	[102]		

Table 10. Hydroelectric Dam Subsystem Costs

Part	Symbol	Cost 1	Ref.	Cost 2	Ref.	Cost 3	Ref.
Control Panel	X_1	$3.0E^3$	[108]	$2.6E^3$†		$1.9E^3$†	
Fuel	X_2	$4.4E^2$	[109]	$3.2E^2$	[110]	$1.9E^2$†	
SG	X_3	$9.4E^3$	[111]	$4.6E^3$	[112]	$1.6E^3$	[113]
Shaft	X_4	$3.7E^3$	[114]	$2.1E^3$	[115]	$2.0E^3$	[116]
Pully-Shaft	X_5	$1.2E^3$	[117]	$9.7E^2$	[118]	$2.7E^3$†	
Control s	X_6	$3.4E^3$	[119]	$2.4E^3$	[120]	$2.3E^3$	[121]
Battery	X_7	$3.5E^2$	[96]	$3.0E^3$†		$2.2E^2$†	
Battery Inverter	X_8	$2.0E^2$	[93]	$6.0E^2$	[94]	$1.8E^2$	[95]
DC/AC Inverter	X_9	$2.0E^2$	[93]	$6.0E^2$	[94]	$1.8E^2$	[95]
PV Panel	X_{10}	$2.7E^3$	[104]	$2.3E^3$	[104]	$2.0E^3$	[104]
AC Switch	X_{11}	$8.0E^3$	[97]	$7.0E^3$	[92]	$5.1E^2$†	
Sensor	X_{12}	$8.0E^3$	[107]	$3.0E^3$	[122]	$1.3E^3$	[123]
ACCB	X_{13}	$3.0E^3$	[84]	$8.0E^4$	[88]	$2.0E^3$†	
Cable	X_{14}	$8.0E^3$	[102]	$7.0E^3$	[103]	$5.0E^3$†	
LS	X_{15}	$7.8E^3$	[124]	$6.8E^3$†		$5.1E^3$†	
MS	X_{16}	$7.8E^3$	[124]	$6.8E^3$†		$5.1E^3$†	
Cable	X_{17}	$8.0E^3$	[102]	$7.0E^3$	[103]	$5.0E^3$†	

† If the data could not be found, a nominal value was used.

6.4.1 Plant Control System

In this study, resilience frontiers were examined in a hydroelectric dam with zero standby subsystems. The purpose of this study was to optimize the parameters. In this study the subsystems were the plant control subsystems: ATS, MCC, and a panel connected in series as exponential functions with different failure parameters. The survivability functions were defined as ATS: $S_1(x;\lambda_1) = e^{-\lambda_1 x}$, MCC: $S_2(x;\lambda_2) = e^{-\lambda_2 x}$, and panel system: $S_3(x;\lambda_3) = e^{-\lambda_3 x}$. In this case study, λ was a free variable over the range $\lambda \in (10^{-5}, 10^{-2})$.

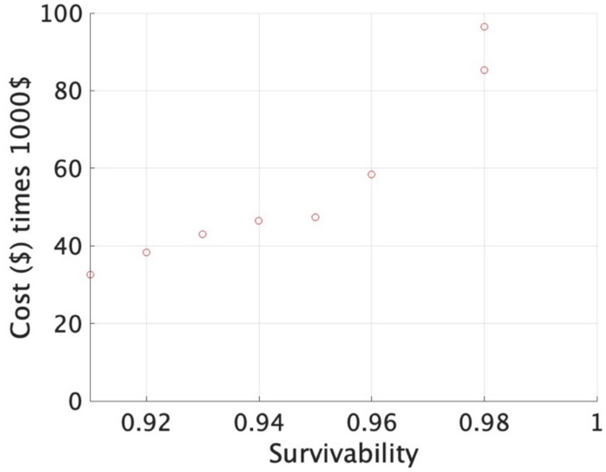

Figure 28-Hydroelectric Dam: Plant Control System

6.4.2 Plant Control System with Generator Standby

In this study, resilience frontiers were examined in a hydroelectric dam with one standby subsystem. The purpose of this study was to assess whether a dam could be designed with greater resilience by adding a standby generator subsystem, despite the additional cost of the generator. In this study the subsystems were the plant control subsystem as exponential in series with a standby parallel generator subsystem in Weibull. The survivability functions were defined as plant controls: ATS: $S_1(x;\lambda_1) = e^{-\lambda_1 x}$, MCC: $S_2(x;\lambda_2) = e^{-\lambda_2 x}$, and panel system: $S_3(x;\lambda_3) = e^{-\lambda_3 x}$. (standby) generator system: $S_4(x;\gamma_1,k_1) = e^{-\left(\frac{x}{\gamma_1}\right)^{k_1}}$. In this study, λ_i, γ_i were free variables over the range $\gamma_i\ \in (10^1, 10^5),\ k_i \in (1{,}5),\ \ i\ \in \{1,2,3,4\}, and\ \ \lambda_i\ \in (10^{-5}, 10^{-1}).$ Figure 29 indicates there is high dam survivability with a standby system, at the expense of higher system design cost. To have maximized system survivability (99%) the design cost would be around $58k.

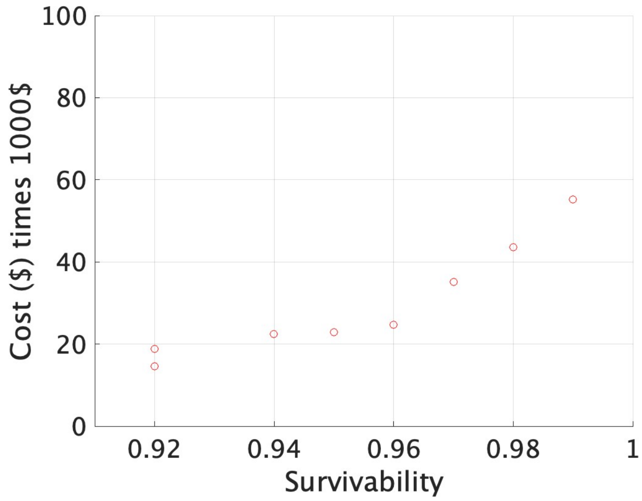

Figure 29- Hydroelectric Dam: Plant Control System & Generator

6.4.3 Plant Control System with Microgrid: Generator and IBR

In this study, resilience frontiers were examined in a dam with two standby subsystems. The purpose of this study was to assess whether a system could be designed with greater resilience by adding a second standby subsystem, despite the added cost. The microgrid standby system which includes the generator and the inverter bases resources, subsystems were all in series with the control system as an exponential function. The survivability functions were defined as ATS: $S_1(x;\lambda_1) = e^{-\lambda_1 x}$, MCC: $S_2(x;\lambda_2) = e^{-\lambda_2 x}$, and panel system: $S_3(x;\lambda_3) = e^{-\lambda_3 x}$. (standby) generator system: $S_4(x;\gamma_1,k_1) = e^{-\left(\frac{x}{\gamma_1}\right)^{k_1}}$, inverter based resources: $S_5(x;\gamma_2,k_2) = e^{-\left(\frac{x}{\gamma_2}\right)^{k_2}}$. In this study, λ_i, γ_i were free variables over the range $\gamma_i \in (10^1, 10^5)$, $k_i \in (1,5),\ \ i \in \{1,2,3,4,5\}, and\ \ \lambda_i \in (10^{-5}, 10^{-1})$. Comparison of Figure 29 and Figure 30 indicates that by adding the microgrid standby system which includes the generator and the inverter bases resources, the hydroelectric dam survivability is maximized (100%), at the expense of a higher design cost ($95k).

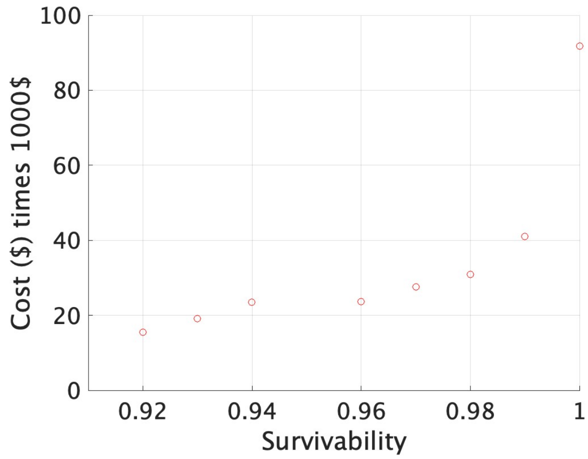

Figure 30- Hydroelectric Dam: Plant Control System & Microgrid

CHAPTER 7: EXAMPLE RESILIENCY ANAYLSIS

To emphasis the importance of a resiliency analysis, one was completed on a real-world dam. Winfield Lock and Dam was chosen for the case study because it is a high hazard dam, includes hydropower, has had multiple studies completed on it, and personal experience at this dam.

Winfield Locks and Dam is located on the Kawana River in Winfield West Virginia. The dam includes six roller crest gates and one Tainter gate. The lock includes four miter gates. Winfield also includes five recreation areas at lock site, visitors center, overlook, observation areas, several nature/wildlife habit ponds and over 1 1/2 miles of fishing access. The hydropower plant includes forebay area, intake structure, a powerhouse, a tailrace, a substation, and a transmission line. [125] Winfield is a high hazard potential classification meaning that failure or mis-operation will probably cause loss of human life. [126] The hydropower is a run of river type. [127] There are three turbines that can generate 14.76MW. [128]

The total economic will be $215,453,324.30. The total economic cost can be calculated from recreation use fees, loss of fish and wildlife, power generation, loss of municipal and industrial water supply to the community, and navigation loss. The loss from recreational use fees for WIN can be estimated by getting the federal use prices: $5 per car per day, $2 per adult walk in, 20$ per bus. [129] Then estimating the number of people to visit the dam by taking the population from Winfield and data that shows about 10% of the population will visit the dam at least once a year. 237 Estimated people per year. [130] [131], estimated (50 cars = 250$ = 200 people, 37 walk ins = 74$). The total recreation loss will be $324. Loss of fish and wildlife is estimated to be $123,000.00. $23,000 being wetland restoration [132] and estimated $50,000 restoration fee each pond. [133] [134] [135] The costs associated with wetland restoration and creation projects vary substantially across different parts of the country and different parcels of land. [132] The loss of power generation will be $200,027,000.28. It can be calculated by taking the total kW the hydropower produces (14760kW) multiply by the cost of kW per hour (8.47c/kWh [136]) and the number of hours the plant is operating (16 hours). Winfield does not supply water to the community therefore the loss of municipal and industrial water supply to the community is $0. Coal, and petroleum are the largest commodity groups transported through Winfield lock. Next largest would-be aggregate commodities which include limestone, sands, pebbles, and gravel. Other groups that transport through the lock include the Ores and minerals commodity group and chemicals. The transportation rate can be obtained by referencing competitive rates charged shippers. [137] The total navigation loss is $15,220,000.00. [137]

The total geographic loss is $9,786,133.00. Property damage cost such as John Amos Power Plant, primary care, residential, and roads is estimated to be $2,000,000.00. [138] using historical data from a similar dam failure in 2019. Emergency response cost is estimated to be $6,376,133. [139] involved fire fighters' men and volunteers, total sum of service hours, share of clean-up, material losses of local fire brigades, total costs of emergency services and total private and public losses per municipality. The dam repairs cost is estimated to be $1,410,00 based on height, age, and fair condition. [140]

Total outage frequency may be computed as: duration plus probability of outage. For duration of outage assume 7 days. For outage probability assume if extreme weather event and dam fails 100% probable.

Total generation capacity of a dam is calculated by the reserve capacity and the full load capacity of the hydropower plant. The reserve capacity of this dam would be the on-site generator which is estimated to be 70kW and the full load capacity of the hydropower plant which is what the turbines can produce with water upstream which is dependent on how fast the dam is losing pool.

Total health and safety loss is estimated to be $252,000,000. We will use historic data to assume actual life loss from Shadyside OH in 1990, 24 lives were lost. [141] A value of $10,500,000 per life came from the EPA. [142]

In conclusion, the loss from a failure would be detrimental to the economy, community, and wildlife with the assumptions that were made. Each dam failure will have different consequences depending on the event, location, dam design and duration. Resiliency of critical power infrastructure is crucial to the safety and economy of the surrounding community.

CHAPTER 8: CONCLUSION

Increases in severe weather events and an aging dam infrastructure in the U.S. poses future risks to overall grid resiliency. There is no standardized definition of resiliency or resilience metrics in the power community. Systems that require high survivability generally require standby subsystems, at an increased cost. Furthermore, the addition of standby subsystems makes the computation of closed-form parameterized expressions for total survivability difficult, which also precludes the use of gradient based optimization methods. To solve this problem, this research introduced a method that combines Monte Carlo (MC) sampling with a non-gradient based search method (a GA), referred to as the MCGA, to examine the resilience frontier in complex systems. The MCGA was demonstrated through several numerical case studies, indicating that the MCGA approach can be used as an evaluation tool for quantifying survivability versus cost tradeoffs and also as a potential design tool for maximizing resiliency in complex systems, based on choices in system configuration and component selection.

The MCGA can be used as a framework to analyze survivability of complex systems. The framework presented here is general and can be used for any complex system. The MCGA was then applied to a complex system: a hydroelectric dam, to increase the survivability of the dam. FTA and network reduction were used to complete the survivability analysis. Historical data such as MTBF and subsystem costs were collected and used in the studies. The MCGA displays as the number of standby systems added, the higher the hydroelectric dam’s survivability, however the design cost increases. The hydroelectric dam’s survivability is maximized when having a microgrid added to the system with an IBR system in an active parallel configuration with a generator. The key contributions of this research are:

- This dissertation introduced an approach for obtaining the Pareto-optimal set of design candidates (“resilience frontier”). The method combined Monte Carlo (MC) sampling to estimate total survivability and a genetic algorithm (GA), to obtain the resilience frontier.
- Reduction of computational time by selectively lowering the MC sample count at the beginning of an analysis is included in the MCGA algorithm.
- The MCGA approach can be used as an evaluation tool for quantifying survivability versus cost tradeoffs.
- The MCGA approach has potential as a design tool for maximizing resiliency in complex systems, based on choices in system configuration and component selection.

Some limitations of this research are limited system evaluations were performed, for example the fuel, solar, and battery variables excluded from the study and nominal values were used for some unavailable cost parameters. It was problematic to find the exact size and specification of electrical equipment and costs for each component; for example, three 30kW, 3 phase, 480V generators. The unavailable cost data was calculated based off the difference between available subsystem costs. For example, the PV data was able to be entirely found so the percentage difference between the costs were applied to subsystem component’s data that could not be found. The utility, fuel, solar, and battery variables were not needed for the purpose of this research i.e. maximizing design tradeoffs between system survivability vs. cost. This research was completed on a time scale of thousands of hours (MTBF) to include these variables the time scale would need to be analyzed in minutes.

Suggested future work includes analyzing the survivability of the hydroelectric dam at the beginning of the event which would be on the time scale of minutes. Approximate Dynamic Programming (ADP) could be used to solving the larger time scale. In addition, synthesizing the two methods (thousands of hours and minutes) could be completed.

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APPENDIX A: MATLAB CODES

A.1 No Backup Constrained Fit

```
%------------------------------------------------------------------------%
% Description: this function calculates fitness of design candidates for a
% system comprising a primary subsystem with no standby systems.
%
% Inputs:
%   - x      : vector of design choices
%   - params : structure of parameters including:
%     t      % time to evaluate survivability [hrs]
%     Nsamps % number of Monte Carlo samples
%     beta   % matrix of cost coeffients
%
% Outputs:
%   - f = [ f_1 f_2 ]', where f_1 is a fitness for survivability and f_2
%         is a fitness for cost
%
% Written by:
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%
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% Contact: bates60@colostate.edu
% Revision Date: 19 Nov 2023

function [f] = noBackupConstrained_fit(x,params)

global iterationCount;

% extract genes
lambda = x(1);

t       = params.t;          % time to evaluate survivability [hr]
beta    = params.beta    ;   % matrix of cost coeffients
costMax = params.costMax ;   % maximum cost constraint [$]
sMin    = params.sMin    ;   % minimum survivability at t
delta   = params.delta   ;   % penalty severities
Nmin    = params.Nmin    ;   % minimum number of MC samples
Nmax    = params.Nmax    ;   % max number of MC samples
kmin    = params.kmin    ;   % if iterations <= kmin, use Nmin MC samples
                             % if iterations > kmin, use Nmax MC samples

% set number of MC samples
Nsamps = Nmin*(iterationCount<=kmin) + Nmax*(iterationCount>kmin);

%------------------------------------------------------------
%          Use MC Sampling to Estimate Survivability
%------------------------------------------------------------
```

```
% define cdf of Exponential Distribution
F = inline ( '1-exp(-lambda*x)', 'x','lambda' );

% define domain (time elements)
x = linspace(0,10*(1/lambda),1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s1 = F(x,lambda);

% pre-allocate memory
X = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u1 = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) = u
    indices = find(F_s1(:)<=u1);
    index_1 = indices(end);

    % save the failure time
    X(n) = x(index_1);

end

% compute samples for total system failure times
Z = X ;

% compute total system survivability
indices = find(Z(:)>=t);
s       = length(indices)/length(Z);

%-----------------------------------------------------------
%           Compute Cost
%-----------------------------------------------------------

% compute subsystem costs
g1 = 1/lambda; % in exponential g_n = 1/lambda_n

c1 = beta(1,:)*[g1^2 g1 1]';
cost = c1;

%-----------------------------------------------------------
%           Compute Penalties
%-----------------------------------------------------------

p1 = gtn( s, sMin, delta(1));
p2 = ltn( cost, costMax, delta(2));

% compute fitness vector
f(1,1) = p1*s;           % to maximize
f(2,1) = p2/(cost+eps);  % to minimize ( = max of the inverse)
```

```
%------------------------------------------------------------------------%
% Description: this script calculates the Pareto-optimal front of cost vs
% survivability for a system comprising a primary and no backup
% subsystems; the primary subsystem is exponentially distributed. The
% multi-objective optimization is constrained in terms of maximum cost and
% minimum survivability.
%
% Inputs:
%   - none (stand-alone script)
% Outputs:
%   - note (plots to screen)
%
% Written by:
% James Cale, Ph.D.
% Colorado State University
% Contact: jcale@colostate.edu
%
% Megan Younes
% Colorado State University
% Contact: bates60@colostate.edu
% Revision Date: 19 Nov 2023


Npop  = 200;    % design candidate population size
Niter = 1000;   % design iterations to perform

% Initialize the parameters
GAP = gapdefault(2,0,Npop,Niter);


% Plotting parameters
GAP.op_list = [];               % objectives list for objective plots
GAP.pp_sign = [ 1, 1];          % sign of fitness for each objective
                                % (1=positive,-1=negative)

% Gene setup
% variable        x1
% gene            1
GAP.gd_min  = [  1e-5 ];
GAP.gd_max  = [  1e-1 ];
GAP.gd_type = [   2  ];
GAP.gd_cid  = [   1  ];

params.t       = 500;           % time to evaluate survivability [hrs]
params.beta    = [ 1 .5 .05;    % cost coeffients
                   1 .5 .05];
params.costMax = .75e6;          % maximum cost constraint [$]
params.sMin    = 0.5;           % minimum survivability at t
params.delta   = [1e-3 1e2];    % severity of penalties [cost, surv.]
params.Nmin    = 500;           % minimum number of MC samples
params.Nmax    = 2000;          % max number of MC samples
params.kmin    = round(0.25*Npop*Niter); % if iterations <= kmin, use Nmin MC
samples
                                % if iterations > kmin, use Nmax MC samples
```

```
global iterationCount;
iterationCount = 0;

%tic
% Perform optimization
[P,GAS,best]= gaoptimize(@noBackupConstrained_fit,GAP,params);
%toc

% plot non-dominated (Pareto-optimal) designs, showing survivability
% vs cost [$k]
close all
myParetoPlotRed(P,GAP)

xlabel('Survivability')
ylabel('Cost\,[\$]$\times 1000$')
title('')
set(gca,'Fontsize', 20,'Fontname','Latin Modern Math');
set(gcf,'color','white');
box off
ylim([ 0   params.costMax/1000])
xlim([params.sMin 1])

% save results
P_case1b = P
GAP_case1b = GAP
save P_case1b
save GAP_case1b
```

A.2 Two Backups Mixed Constrained Fit

```
%-----------------------------------------------------------------------%
% Description: this function calculates fitness of design candidates for a
% system comprising a primary and two standby (secondary and tertiary)
% subsystems. The primary and secondary subsystems are Weibull distributed
% with different failure parameters. The tertiary subsystem is
% exponentially distributed. All components have the same
% cost coefficients. The multi-objective optimization is constrained in
% terms of maximum cost and minimum survivability.
%
% Inputs:
%   - x      : vector of design choices
%   - params : structure of parameters including:
%     t      % time to evaluate survivability [hrs]
%     Nsamps % number of Monte Carlo samples
%     beta   % matrix of cost coeffients
%
% Outputs:
%   - f = [ f_1 f_2 ]', where f_1 is a fitness for survivability and f_2
%         is a fitness for cost
%
% Written by:
% James Cale, Ph.D.
```

```
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%
% Megan Younes
% Colorado State University
% Contact: bates60@colostate.edu
% Revision Date: 19 Nov 2023

function [f] = twoBackupsMixedConstrained_fit(x,params)

global iterationCount;

% extract genes
gamma1  = x(1);  % Weibull scale parameter for primary subsystem
k1      = x(2);  % Weibull shape parameter for primary subsystem
gamma2  = x(3);  % Weibull scale parameter for secondary (first standby)
k2      = x(4);  % Weibull shape parameter for secondary (first standby)
lambda  = x(5);  % failure rate for tertiary (second standby) subsystem

t       = params.t;          % time to evaluate survivability [hr]
beta    = params.beta    ;   % matrix of cost coeffients
costMax = params.costMax ;   % maximum cost constraint [$]
sMin    = params.sMin    ;   % minimum survivability at t
delta   = params.delta   ;   % penalty severities
Nmin    = params.Nmin    ;   % minimum number of MC samples
Nmax    = params.Nmax    ;   % max number of MC samples
kmin    = params.kmin    ;   % if iterations <= kmin, use Nmin MC samples
                             % if iterations > kmin, use Nmax MC samples


%--------------------------------------------------------------------------
%          Use MC Sampling to Estimate Survivability
%--------------------------------------------------------------------------

% set number of MC samples
Nsamps = Nmin*(iterationCount<=kmin) + Nmax*(iterationCount>kmin);

% define cdf of Weibull Distribution
Fw = inline ( '1-exp(-x/gamma).^k', 'x','gamma', 'k' );

% define cdf of Exponential Distribution
F  = inline ( '1-exp(-lambda*x)', 'x','lambda' );

%--------------------------------------------------------------------------
%                  Sample Primary Subsystem
%--------------------------------------------------------------------------

meanWeibull1 = gamma1*gamma(1+1/k1);

% define domain (time elements)
x = linspace(0,10*meanWeibull1,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s1 = Fw(x,gamma1, k1);
```

```
% pre-allocate memory
X = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) = u
    indices = find(F_s1(:)<=u);
    index_1 = indices(end);

    % save the failure time
    X(n) = x(index_1);

end

%--------------------------------------------------------------------------
%            Sample Secondary (First Backup) Subsystem
%--------------------------------------------------------------------------

meanWeibull2 = gamma2*gamma(1+1/k2);

% define domain (time elements)
y = linspace(0,10*meanWeibull2,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s2 = Fw(y,gamma2, k2);

% pre-allocate memory
Y = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) = u
    indices = find(F_s2(:)<=u);
    index_1 = indices(end);

    % save the failure time
    Y(n) = y(index_1);

end

%--------------------------------------------------------------------------
%            Sample Tertiary (Second Backup) Subsystem
%--------------------------------------------------------------------------

meanExponential = 1/lambda;

% define domain (time elements)
```

```
z = linspace(0,10*meanExponential,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s3 = F(z,lambda);

% pre-allocate memory
Z = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) = u
    indices = find(F_s3(:)<=u);
    index_1 = indices(end);

    % save the failure time
    Z(n) = z(index_1);

end


% compute samples for total system failure times
W = X + Y + Z;

% compute total system survivability
indices = find(W(:)>=t);
s       = length(indices)/length(W);

iterationCount = iterationCount + 1;

%------------------------------------------------------------
%           Compute Cost
%------------------------------------------------------------

% compute subsystem costs
g1 = meanWeibull1;      % in Weibull g_n = \gamma_n\Gamma(1+1/k_n)
g2 = meanWeibull2;      % in Weibull g_n = \gamma_n\Gamma(1+1/k_n)
g3 = meanExponential;   % in exponential g_n = 1/lambda_n

c1 = beta(1,:)*[g1^2 g1 1]';
c2 = beta(2,:)*[g2^2 g2 1]';
c3 = beta(3,:)*[g3^2 g3 1]';
cost = c1+c2+c3;

%------------------------------------------------------------
%           Compute Penalties
%------------------------------------------------------------

p1 = gtn( s, sMin, delta(1));
p2 = ltn( cost, costMax, delta(2));

% compute fitness vector
```

```
f(1,1) = p1*s;           % to maximize
f(2,1) = p2/(cost+eps);  % to minimize ( = max of the inverse)

%------------------------------------------------------------------------%
% Description: this script calculates the Pareto-optimal front of cost vs
% survivability for a system comprising a primary and two standby
% (secondary and tertiary) subsystems. The primary and secondary subsystems
% are Weibull distributed with different failure parameters. The tertiary
% subsystem is exponentially distributed. All components have the same
% cost coefficients. The multi-objective optimization is constrained in
% terms of maximum cost and minimum survivability.
%
% Inputs:
%   - none (stand-alone script)
% Outputs:
%   - note (plots to screen)
%
% Written by:
% James Cale, Ph.D.
% Colorado State University
% Contact: jcale@colostate.edu
%
% Megan Younes
% Colorado State University
% Contact: bates60@colostate.edu
% Revision Date: 19 Nov 2023

Npop  = 200;    % design candidate population size
Niter = 1000;   % design iterations to perform

% Initialize the parameters
GAP = gapdefault(2,0,Npop,Niter);

% Plotting parameters
GAP.op_list = [];              % objectives list for objective plots
GAP.pp_sign = [ 1, 1];         % sign of fitness for each objective
                               % (1=positive,-1=negative)

% Gene setup
% variable      gamma1  k1    gamma2    k2    lambda
% gene            1     2       3        4       5
GAP.gd_min  = [  1e1   1e0     1e1      1e0    1e-5];
GAP.gd_max  = [  1e5   5e0     1e5      5e0    1e-1];
GAP.gd_type = [   2     2       2         2      2];
GAP.gd_cid  = [   1     1       1         1      1];

params.t       = 500;          % time to evaluate survivability [hrs]
params.beta    = [ 1 .5 .05;    % cost coefficients
                   1 .5 .05;
                   1 .5 .05];
params.costMax = .75e6;         % maximum cost constraint [$]
params.sMin    = 0.5;           % minimum survivability at t
params.delta   = [1e-3 1e2];    % severity of penalties [cost, surv.]
params.Nmin    = 100;           % minimum number of MC samples
params.Nmax    = 500;          % max number of MC samples
```

```
params.kmin    = round(0.25*Npop*Niter); % if iterations <= kmin, use Nmin MC
samples
                                % if iterations > kmin, use Nmax MC samples

global iterationCount;
iterationCount = 0;

%tic
% Perform optimization
[P,GAS,best]= gaoptimize(@twoBackupsMixedConstrained_fit,GAP,params);
%toc

% plot non-dominated (Pareto-optimal) designs, showing survivability
% vs cost [$k]
close all
myParetoPlotRed(P,GAP)

xlabel('Survivability')
ylabel('Cost\,[\$]$\times 1000$')
title('')
set(gca,'Fontsize', 20,'Fontname','Latin Modern Math');
set(gcf,'color','white');
box off
ylim([ 0   params.costMax/1000])
xlim([params.sMin 1])

% % save results
% P_case3 = P
% GAP_case3 = GAP
% save P_case3
% save GAP_case3
```

A.3 Two Backups Same Constrained Fit

```
%-------------------------------------------------------------------------%
% Description: this function calculates fitness of design candidates for a
% system comprising an always-on and two standby subsystems; all subsystems
% are exponentially distributed, with different failure rates.
%
% Inputs:
%   - x      : vector of design choices
%   - params : structure of parameters including:
%     t      % time to evaluate survivability [hrs]
%     Nsamps % number of Monte Carlo samples
%     beta   % matrix of cost coeffients
%
% Outputs:
%   - f = [ f_1 f_2 ]', where f_1 is a fitness for survivability and f_2
%         is a fitness for cost
%
% Written by:
% James Cale, Ph.D.
% Colorado State University
% Contact: jcale@colostate.edu
```

```
% Megan Younes
% Colorado State University
% Contact: bates60@colostate.edu
%
% Revision Date: 19 Nov 2023

function [f] = twoBackupsSameConstrained_fit(x,params)

global iterationCount;

% extract genes
lambda1 = x(1); % failure rate for primary subsystem
lambda2 = x(2); % failure rate for secondary (first standby) subsystem
lambda3 = x(3); % failure rate for secondary (second standby) subsystem

t       = params.t;          % time to evaluate survivability [hr]
beta    = params.beta    ;   % matrix of cost coeffients
costMax = params.costMax ;   % maximum cost constraint [$]
sMin    = params.sMin    ;   % minimum survivability at t
delta   = params.delta   ;   % penalty severities
Nmin    = params.Nmin    ;   % minimum number of MC samples
Nmax    = params.Nmax    ;   % max number of MC samples
kmin    = params.kmin    ;   % if iterations <= kmin, use Nmin MC samples
                             % if iterations > kmin, use Nmax MC samples
%-----------------------------------------------------------
%          Use MC Sampling to Estimate Survivability
%-----------------------------------------------------------

% set number of MC samples
Nsamps = Nmin*(iterationCount<=kmin) + Nmax*(iterationCount>kmin);

% define cdf of Exponential Distribution
F = inline ( '1-exp(-lambda*x)', 'x','lambda' );

% define domain (time elements)
x = linspace(0,10*(1/lambda1),1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s1 = F(x,lambda1);

% pre-allocate memory
X = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) = u
    indices = find(F_s1(:)<=u);
    index_1 = indices(end);

    % save the failure time
    X(n) = x(index_1);
```

```
end

% define domain (time elements)
y = linspace(0,10*(1/lambda2),1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s2 = F(y,lambda2);

% pre-allocate memory
Y = zeros(1,Nsamps);  % failure times for standby subsystem one

% obtain samples for standby subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value in which F^{-1}(x) = u
    indices = find(F_s2(:)<=u);
    index_1 = indices(end);

    % save the failure time
    Y(n) = y(index_1);

end

% define domain (time elements)
z = linspace(0,10*(1/lambda3),1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s3 = F(z,lambda3);

% pre-allocate memory
Z = zeros(1,Nsamps);  % failure times for standby subsystem two

% obtain samples for standby subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value in which F^{-1}(x) = u
    indices = find(F_s3(:)<=u);
    index_1 = indices(end);

    % save the failure time
    Z(n) = z(index_1);

end

% compute samples for total system failure times
W = X + Y + Z;

% compute total system survivability
```

```
indices = find(W(:)>=t);
s       = length(indices)/length(W);

iterationCount = iterationCount + 1;

%------------------------------------------------------------
%           Compute Cost
%------------------------------------------------------------

% compute subsystem costs
g1 = 1/lambda1; % in exponential g_n = 1/lambda_n
g2 = 1/lambda2; % in exponential g_n = 1/lambda_n
g3 = 1/lambda3; % in exponential g_n = 1/lambda_n

c1 = beta(1,:)*[g1^2 g1 1]';
c2 = beta(2,:)*[g2^2 g2 1]';
c3 = beta(3,:)*[g3^2 g3 1]';
cost = c1+c2+c3;

%------------------------------------------------------------
%           Compute Penalties
%------------------------------------------------------------

p1 = gtn( s, sMin, delta(1));
p2 = ltn( cost, costMax, delta(2));

% compute fitness vector
f(1,1) = p1*s;           % to maximize
f(2,1) = p2/(cost+eps);  % to minimize ( = max of the inverse)


%--------------------------------------------------------------------------%
% Description: this script calculates the Pareto-optimal front of cost vs
% survivability for a system comprising an always-on and two standby
% subsystems; all subsystems are exponentially distributed with different
% failure rates and same cost coeffients. The multi-objective optimization
% is constrained in terms of maximum cost and minimum survivability.
%
% Inputs:
%   - none (stand-alone script)
% Outputs:
%   - note (plots to screen)
%
% Written by:
% James Cale, Ph.D.
% Colorado State University
% Contact: jcale@colostate.edu
%
% Megan Younes
% Colorado State University
% Contact: bates60@colostate.edu
% Revision Date: 19 Nov 2023

Npop  = 200;    % design candidate population size
Niter = 1000;   % design iterations to perform
```

```
% Initialize the parameters
GAP = gapdefault(2,0,Npop,Niter);

% Plotting parameters
GAP.op_list = [];                % objectives list for objective plots
GAP.pp_sign = [ 1, 1];           % sign of fitness for each objective
                                 % (1=positive,-1=negative)

% Gene setup
% variable      lambda1 lambda2  lambda3
% gene            1       2        3
GAP.gd_min  = [  1e-5   1e-5    1e-5];
GAP.gd_max  = [  1e-1   1e-1    1e-1];
GAP.gd_type = [   2     2       2   ];
GAP.gd_cid  = [   1     1       1   ];

params.t       = 500;            % time to evaluate survivability [hrs]
params.beta    = [ 1 .5 .05;     % cost coefficients
                   1 .5 .05;
                   1 .5 .05];
params.costMax = .75e6;          % maximum cost constraint [$]
params.sMin    = 0.5;            % minimum survivability at t
params.delta   = [1e-3 1e2];     % severity of penalties [cost, surv.]
params.Nmin    = 500;            % minimum number of MC samples
params.Nmax    = 2000;           % max number of MC samples
params.kmin    = round(0.25*Npop*Niter); % if iterations <= kmin, use Nmin MC
samples
                                 % if iterations > kmin, use Nmax MC samples

global iterationCount;
iterationCount = 0;

%tic
% Perform optimization
[P,GAS,best]= gaoptimize(@twoBackupsSameConstrained_fit,GAP,params);
%toc

% plot non-dominated (Pareto-optimal) designs, showing survivability
% vs cost [$k]
close all
myParetoPlotRed(P,GAP)

xlabel('Survivability')
ylabel('Cost\,[\$]$\times 1000$')
title('')
set(gca,'Fontsize', 20,'Fontname','Latin Modern Math');
set(gcf,'color','white');
box off
ylim([ 0   params.costMax/1000])
xlim([params.sMin 1])

% % save results
% P_case2 = P
% GAP_case2 = GAP
```

```
% save P_case2
% save GAP_case2
%
```

A.4 Plant Control System Constrained Fit

```
%------------------------------------------------------------------------%
% Description: this function calculates fitness of design candidates for a
% system comprising the plant controls which includes an ATS in series with a
% MCC in series with a panel and no backup subsystems
%
% Inputs:
%   - x      : vector of design choices
%   - params : structure of parameters including:
%     t      % time to evaluate survivability [hrs]
%     Nsamps % number of Monte Carlo samples
%     beta   % matrix of cost coeffients
%
% Outputs:
%   - f = [ f_1 f_2 ]', where f_1 is a fitness for survivability and f_2
%         is a fitness for cost
%
% Written by:
% James Cale, Ph.D.
% Colorado State University
% Contact: jcale@colostate.edu
%
% Megan Younes
% Colorado State University
% Contact: bates60@colostate.edu
% Revision Date: 15 March 2024

function [f] = UtilityMixedConstrained_fit(x,params)

global iterationCount;


% extract genes
lambda   = x(1);  % failure rate for ATS subsystem
lambda2  = x(2);  % failure rate for MCC subsystem
lambda3  = x(3);  % failure rate for Panel subsystem


t       = params.t;          % time to evaluate survivability [hr]
beta    = params.beta    ;   % matrix of cost coeffients
costMax = params.costMax ;   % maximum cost constraint [$]
sMin    = params.sMin    ;   % minimum survivability at t
delta   = params.delta   ;   % penalty severities
Nmin    = params.Nmin    ;   % minimum number of MC samples
Nmax    = params.Nmax    ;   % max number of MC samples
kmin    = params.kmin    ;   % if iterations <= kmin, use Nmin MC samples
                             % if iterations > kmin, use Nmax MC samples
```

```
%-------------------------------------------------------------------------------
%          Use MC Sampling to Estimate Survivability
%-------------------------------------------------------------------------------

% set number of MC samples
Nsamps = Nmin*(iterationCount<=kmin) + Nmax*(iterationCount>kmin);

% define cdf of Weibull Distribution
Fw = inline ( '1-exp(-x/gamma).^k', 'x','gamma', 'k' );

% define cdf of Exponential Distribution
F  = inline ( '1-exp(-lambda*x)', 'x','lambda' );


%-------------------------------------------------------------------------------
%                  Sample Primary Control Subsystem in Series with
%                  subsystems
%-------------------------------------------------------------------------------
meanExponential1 = 1/(lambda);

% define domain (time elements)
a = linspace(0,10*meanExponential1,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s1 = F(a,lambda);


% pre-allocate memory
A = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) = u
    indices = find(F_s1(:)<=u);
    index_1 = indices(end);

 % save the failure time
    A(n) = a(index_1);
end
%-------------------------------------------------------------------------------
%                  Sample Primary MCC Subsystem in Series with
%                  subsystems
%-------------------------------------------------------------------------------
meanExponential2 = 1/(lambda2);

% define domain (time elements)
m = linspace(0,10*meanExponential2,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
```

```
F_s2 = F(m,lambda2);

% pre-allocate memory
M = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) =

    indices = find(F_s2(:)<=u);
    index_2 = indices(end);

 % save the failure time
    M(n) = m(index_2);
end
%----------------------------------------------------------------------
%                  Sample Primary Panel Subsystem in Series with
%                  subsystems
%----------------------------------------------------------------------
meanExponential3 = 1/(lambda3);

% define domain (time elements)
p = linspace(0,10*meanExponential3,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf

F_s3 = F(p,lambda3);

% pre-allocate memory
P = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) =

    indices = find(F_s3(:)<=u);
    index_3 = indices(end);

 % save the failure time
    P(n) = p(index_3);
end

% compute samples for total system failure times
W = A.*M.*P;

% compute total system survivability
indices = find(W(:)>=t);
```

```
s       = length(indices)/length(W);

iterationCount = iterationCount + 1;

%-----------------------------------------------------------
%           Compute Cost
%-----------------------------------------------------------

% compute subsystem costs

g1 = meanExponential1;          % in exponential g_n = 1/lambda_n
g2 = meanExponential2;          % in exponential g_n = 1/lambda_n
g3 = meanExponential3;          % in exponential g_n = 1/lambda_n

c1 = beta(1,:)*[g1^2 g1 1]';        %ATS system cost
c2 = beta(2,:)*[g2^2 g2 1]';        %MCC system cost
c3 = beta(3,:)*[g3^2 g3 1]';        %panel system cost
cost = c1+c2+c3;

%-----------------------------------------------------------
%           Compute Penalties
%-----------------------------------------------------------

p1 = gtn( s, sMin, delta(1));
p2 = ltn( cost, costMax, delta(2));

% compute fitness vector
f(1,1) = p1*s;           % to maximize
f(2,1) = p2/(cost+eps);  % to minimize ( = max of the inverse)

%-----------------------------------------------------------------------%
% Description: this script calculates the Pareto-optimal front of cost vs
% survivability for a system comprising of the plant controls which inlcudes
an ATS in series with a
% MCC in series with a panel and no backup subsystems; the systems are are
exponentially distributed.
% The multi-objective optimization is constrained in terms of maximum cost
and minimum survivability.
%
% Inputs:
%   - none (stand-alone script)
% Outputs:
%   - note (plots to screen)
%
% Written by:
% James Cale, Ph.D.
% Colorado State University
% Contact: jcale@colostate.edu
%
% Megan Younes
% Colorado State University
% Contact: bates60@colostate.edu
% Revision Date: 15 March 2024

Npop  = 200;    % design candidate population size
```

```
Niter = 1000;   % design iterations to perform

% Initialize the parameters
GAP = gapdefault(2,0,Npop,Niter);

% Plotting parameters
GAP.op_list = [];               % objectives list for objective plots
GAP.pp_sign = [ 1, 1];          % sign of fitness for each objective
                                % (1=positive,-1=negative)

% Gene setup
% variable      lambda  lambda2 lambda3
% gene            1        2       3
GAP.gd_min  = [  1e-5   1e-5    1e-5];
GAP.gd_max  = [  1e-1   1e-1    1e-1];
GAP.gd_type = [   2     2       2];
GAP.gd_cid  = [   1     1       1];


params.t       = 500;                   % time to evaluate survivability
[hrs]
params.beta    = [  20  8     4.5;      %cost of ATS system
                    53  15    3;        %cost of MCC system
                    3   2.6   1.9];     %cost of Panel system


params.costMax = .1e6;         % maximum cost constraint [$]
params.sMin    = 0.91;           % minimum survivability at t
params.delta   = [1e-3 1e2];    % severity of penalties [cost, surv.]
params.Nmin    = 100;           % minimum number of MC samples
params.Nmax    = 500;           % max number of MC samples
params.kmin    = round(0.25*Npop*Niter); % if iterations <= kmin, use Nmin MC
samples
                                % if iterations > kmin, use Nmax MC samples

global iterationCount;
iterationCount = 0;

%tic
% Perform optimization
[P,GAS,best]= gaoptimize(@UtilityMixedConstrained_fit,GAP,params);
%toc

% plot non-dominated (Pareto-optimal) designs, showing survivability
% vs cost [$k]
close all
myParetoPlotRed(P,GAP)

xlabel('Survivability')
ylabel('Cost ($) times 1000$')
title('')
set(gca,'Fontsize', 20,'Fontname','Latin Modern Math');
set(gcf,'color','white');
box off
ylim([ 0   params.costMax/1000])
```

```
xlim([params.sMin 1])

% % save results
P_utilityonly = P
GAP_utilityonly = GAP
save P_utilityonly
save GAP_utilityonly
```

A.5 Plant Control System with Generator Constrained Fit

```
%------------------------------------------------------------------------%
% Description: this function calculates fitness of design candidates for a
% system comprising of plant controls which inlcudes an ATS in series with a
% MCC in series with a panel and one standby (generator secondary) subsystem
% in series with the plant control subsystem.
%
% Inputs:
%   - x      : vector of design choices
%   - params : structure of parameters including:
%     t      % time to evaluate survivability [hrs]
%     Nsamps % number of Monte Carlo samples
%     beta   % matrix of cost coeffients
%
% Outputs:
%   - f = [ f_1 f_2 ]', where f_1 is a fitness for survivability and f_2
%         is a fitness for cost
%
% Written by:
% James Cale, Ph.D.
% Colorado State University
% Contact: jcale@colostate.edu
%
% Megan Younes
% Colorado State University
% Contact: bates60@colostate.edu
% Revision Date: 15 March 2024

function [f] = GenMixedConstrained_fit(x,params)

global iterationCount;

% extract genes

% extract genes
lambda   = x(1);  % failure rate for ATS subsystem
lambda2  = x(2);  % failure rate for MCC subsystem
lambda3  = x(3);  % failure rate for Panel subsystem

gamma1  = x(4);  % Weibull scale parameter for gen subsystem
k1      = x(5);  % Weibull shape parameter for gen subsystem


t       = params.t;          % time to evaluate survivability [hr]
beta    = params.beta    ;   % matrix of cost coeffients
```

```
costMax = params.costMax ;   % maximum cost constraint [$]
sMin    = params.sMin    ;   % minimum survivability at t
delta   = params.delta   ;   % penalty severities
Nmin    = params.Nmin    ;   % minimum number of MC samples
Nmax    = params.Nmax    ;   % max number of MC samples
kmin    = params.kmin    ;   % if iterations <= kmin, use Nmin MC samples
                             % if iterations > kmin, use Nmax MC samples

%--------------------------------------------------------------------------
%          Use MC Sampling to Estimate Survivability
%--------------------------------------------------------------------------

% set number of MC samples
Nsamps = Nmin*(iterationCount<=kmin) + Nmax*(iterationCount>kmin);

% define cdf of Weibull Distribution
Fw = inline ( '1-exp(-x/gamma).^k', 'x','gamma', 'k' );

% define cdf of Exponential Distribution
F  = inline ( '1-exp(-lambda*x)', 'x','lambda' );
%--------------------------------------------------------------------------
%                  Sample ATS Subsystem in Series with
%                  subsystems
%--------------------------------------------------------------------------
meanExponential1 = 1/(lambda);

% define domain (time elements)
a = linspace(0,10*meanExponential1,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s1 = F(a,lambda);


% pre-allocate memory
A = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) = u
    indices = find(F_s1(:)<=u);
    index_1 = indices(end);

 % save the failure time
    A(n) = a(index_1);
end
%--------------------------------------------------------------------------
%                  Sample Primary MCC Subsystem in Series with
%                  subsystems
%--------------------------------------------------------------------------
meanExponential2 = 1/(lambda2);
```

```
% define domain (time elements)
m = linspace(0,10*meanExponential2,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s2 = F(m,lambda2);

% pre-allocate memory
M = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) =

    indices = find(F_s2(:)<=u);
    index_2 = indices(end);

 % save the failure time
    M(n) = m(index_2);
end
%-------------------------------------------------------------------------
%                  Sample Primary Panel Subsystem in Series with
%                  subsystems
%-------------------------------------------------------------------------
meanExponential3 = 1/(lambda3);

% define domain (time elements)
p = linspace(0,10*meanExponential3,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf

F_s3 = F(p,lambda3);

% pre-allocate memory
P = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) =

    indices = find(F_s3(:)<=u);
    index_3 = indices(end);

 % save the failure time
    P(n) = p(index_3);
end

%-------------------------------------------------------------------------
```

```
%             Sample Secondary (First Backup) Generator Subsystem
%------------------------------------------------------------------------

meanWeibull4 = gamma1*gamma(1+1/k1);

% define domain (time elements)
y = linspace(0,10*meanWeibull4,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s4 = Fw(y,gamma1, k1);

% pre-allocate memory
Y = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) = u
    indices1 = find(F_s4(:)<=u);
    index_1 = indices1(end);

    % save the failure time
    Y(n) = y(index_1);

end

% compute samples for total system failure times
C = (A.*M.*P);      %plant controls

W = C.*Y;           %overall system

% compute total system survivability
indices = find(W(:)>=t);
s       = length(indices)/length(W);

iterationCount = iterationCount + 1;

%----------------------------------------------------------
%           Compute Cost
%----------------------------------------------------------

% compute subsystem costs

g1 = meanExponential1;          % in exponential g_n = 1/lambda_n
g2 = meanExponential2;          % in exponential g_n = 1/lambda_n
g3 = meanExponential3;          % in exponential g_n = 1/lambda_n
g4 = meanWeibull4;              % in Weibull g_n = \gamma_n\Gamma(1+1/k_n)

c1 = beta(1,:)*[g1^2 g1 1]';        %ATS system cost
c2 = beta(2,:)*[g2^2 g2 1]';        %MCC system cost
c3 = beta(3,:)*[g3^2 g3 1]';        %panel system cost
c4 = beta(4,:)*[g4^2 g4 1]';        %generator system cost
```

```
cost = c1+c2+c3+c4;

%-----------------------------------------------------------
%            Compute Penalties
%-----------------------------------------------------------

p1 = gtn( s, sMin, delta(1));
p2 = ltn( cost, costMax, delta(2));

% compute fitness vector
f(1,1) = p1*s;           % to maximize
f(2,1) = p2/(cost+eps);  % to minimize ( = max of the inverse)


%-------------------------------------------------------------------------%
% Description: this script calculates the Pareto-optimal front of cost vs
% survivability for a system comprising a plant controls which inlcudes an
ATS in series with a
% MCC in series with a panel and one standby (generator secondary) subsystem
% in series with the control subsystem. The subsystems are exponetial and
Weibull
% distributed with different failure parameters. The components have the
different cost coefficients.
% The multi-objective optimization is constrained in terms of maximum cost
and minimum survivability.
%
% Inputs:
%   - none (stand-alone script)
% Outputs:
%   - note (plots to screen)
%
% Written by:
% James Cale, Ph.D.
% Colorado State University
% Contact: jcale@colostate.edu
%
% Megan Younes
% Colorado State University
% Contact: bates60@colostate.edu
% Revision Date: 15 March 2024

Npop  = 200;    % design candidate population size
Niter = 1000;   % design iterations to perform

% Initialize the parameters
GAP = gapdefault(2,0,Npop,Niter);

% Plotting parameters
GAP.op_list = [];               % objectives list for objective plots
GAP.pp_sign = [ 1, 1];          % sign of fitness for each objective
                                % (1=positive,-1=negative)

% Gene setup
```

```
% variable      lamda  lambda2  lambda3 gamma1   k1
% gene            1     2       3        4
GAP.gd_min  = [  1e-5  1e-5     1e-5    1e1      1e0];
GAP.gd_max  = [  1e-1   1e-1    1e-1    1e5      5e0];
GAP.gd_type = [   2     2       2       2         2];
GAP.gd_cid  = [   1     1       1       1         1];


params.t       = 500;                    %time to evaluate survivability
[hrs]
params.beta    = [  20   8     4.5;       %cost of ATS system
                    53   15    3;         %cost of MCC system
                    3    2.6   1.9;       %cost of Panel system
                    17    13   9.7]       %cost of generator

params.costMax = .1e6;                      % maximum cost constraint [$]
params.sMin    = 0.91;                        % minimum survivability at t
params.delta   = [1e-3 1e2];                % severity of penalties [cost,
surv.]
params.Nmin    = 100;                       % minimum number of MC samples
params.Nmax    = 500;                       % max number of MC samples
params.kmin    = round(0.25*Npop*Niter);    % if iterations <= kmin, use
Nmin MC samples
                                            % if iterations > kmin, use Nmax
MC samples

global iterationCount;
iterationCount = 0;

%tic
% Perform optimization
[P,GAS,best]= gaoptimize(@GenMixedConstrained_fit,GAP,params);
%toc

% plot non-dominated (Pareto-optimal) designs, showing survivability
% vs cost [$k]
close all
myParetoPlotRed(P,GAP)

xlabel('Survivability')
ylabel('Cost ($) times 1000$')
title('')
set(gca,'Fontsize', 20,'Fontname','Latin Modern Math');
set(gcf,'color','white');
box off
ylim([ 0   params.costMax/1000])
xlim([params.sMin 1])

%save results
P_gen = P
GAP_gen = GAP
save P_gen
save GAP_gen
```

A.6 Plant Control System with Microgrid: Generator and IBR Constrained Fit

```
%---------------------------------------------------------------------------%
% % Description: this function calculates fitness of design candidates for a
% system comprising plant controls which inlcudes an ATS in series with a
% MCC in series with a panel. The plant controls are connected in series with
the microgrid.
% The microgrid susytem includes the (generator secondary) subsystem and the
IBR subsytem which
% are connected in active parallel.
%
%
% Inputs:
%   - x      : vector of design choices
%   - params : structure of parameters including:
%     t      % time to evaluate survivability [hrs]
%     Nsamps % number of Monte Carlo samples
%     beta   % matrix of cost coeffients
%
% Outputs:
%   - f = [ f_1 f_2 ]', where f_1 is a fitness for survivability and f_2
%         is a fitness for cost
%
% Written by:
% James Cale, Ph.D.
% Colorado State University
% Contact: jcale@colostate.edu
%
% Megan Younes
% Colorado State University
% Contact: bates60@colostate.edu
% Revision Date: 15 March 2024

function [f] = DamMixedConstrained_fit(x,params)

global iterationCount;

% extract genes

lambda   = x(1);  % failure rate for ATS subsystem
lambda2  = x(2);  % failure rate for MCC subsystem
lambda3  = x(3);  % failure rate for Panel subsystem


gamma1  = x(4);  % Weibull scale parameter for generator (first standby)
k1      = x(5);  % Weibull shape parameter for generator (first standby)

gamma2  = x(6);  % Weibull scale parameter for IBR (secondary standby)
k2      = x(7);  % Weibull shape parameter for IBR (secondary standby)

gamma3  = x(8);  % Weibull scale parameter for IBR (secondary standby)
k3      = x(9);  % Weibull shape parameter for IBR (secondary standby)
gamma4  = x(10);  % Weibull scale parameter for IBR (secondary standby)
k4      = x(11);  % Weibull shape parameter for IBR (secondary standby)
gamma5  = x(12);  % Weibull scale parameter for IBR (secondary standby)
k5      = x(13);  % Weibull shape parameter for IBR (secondary standby)
gamma6  = x(14);  % Weibull scale parameter for IBR (secondary standby)
```

```
k6      = x(15);  % Weibull shape parameter for IBR (secondary standby)


t       = params.t;           % time to evaluate survivability [hr]
beta    = params.beta    ;   % matrix of cost coeffients
costMax = params.costMax ;   % maximum cost constraint [$]
sMin    = params.sMin    ;   % minimum survivability at t
delta   = params.delta   ;   % penalty severities
Nmin    = params.Nmin    ;   % minimum number of MC samples
Nmax    = params.Nmax    ;   % max number of MC samples
kmin    = params.kmin    ;   % if iterations <= kmin, use Nmin MC samples
                             % if iterations > kmin, use Nmax MC samples

%--------------------------------------------------------------------------
%          Use MC Sampling to Estimate Survivability
%--------------------------------------------------------------------------

% set number of MC samples
Nsamps = Nmin*(iterationCount<=kmin) + Nmax*(iterationCount>kmin);

% define cdf of Weibull Distribution
Fw = inline ( '1-exp(-x/gamma).^k', 'x','gamma', 'k' );

% define cdf of Exponential Distribution
F  = inline ( '1-exp(-lambda*x)', 'x','lambda' );

%--------------------------------------------------------------------------
%                  Sample ATS Subsystem in Series with
%                  subsystems
%--------------------------------------------------------------------------
meanExponential1 = 1/(lambda);

% define domain (time elements)
a = linspace(0,10*meanExponential1,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s1 = F(a,lambda);


% pre-allocate memory
A = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) = u
    indices = find(F_s1(:)<=u);
    index_1 = indices(end);

 % save the failure time
    A(n) = a(index_1);
end
```

```
%-----------------------------------------------------------------------
%                  Sample Primary MCC Subsystem in Series with
%                  subsystems
%-----------------------------------------------------------------------
meanExponential2 = 1/(lambda2);

% define domain (time elements)
m = linspace(0,10*meanExponential2,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s2 = F(m,lambda2);

% pre-allocate memory
M = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) =

    indices = find(F_s2(:)<=u);
    index_2 = indices(end);

 % save the failure time
    M(n) = m(index_2);
end
%-----------------------------------------------------------------------
%                  Sample Primary Panel Subsystem in Series with
%                  subsystems
%-----------------------------------------------------------------------
meanExponential3 = 1/(lambda3);

% define domain (time elements)
p = linspace(0,10*meanExponential3,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf

F_s3 = F(p,lambda3);

% pre-allocate memory
P = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) =

    indices = find(F_s3(:)<=u);
    index_3 = indices(end);
```

```
 % save the failure time
    P(n) = p(index_3);
end

%------------------------------------------------------------------------
%            Sample Secondary (First Backup) Generator Subsystem
%------------------------------------------------------------------------

meanWeibull4 = gamma1*gamma(1+(1/k1));

% define domain (time elements)
y = linspace(0,10*meanWeibull4,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s4 = Fw(y,gamma1, k1);

% pre-allocate memory
Y = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

    % draw a random sample from F
    u = rand;

    % perform inverse sampling to find the value at which F^{-1}(x) = u
    indices1 = find(F_s4(:)<=u);
    index_1 = indices1(end);

    % save the failure time
    Y(n) = y(index_1);

end


%------------------------------------------------------------------------
%            Sample Secondary (Second Backup) IBR Subsystem
%------------------------------------------------------------------------

%------------------------------------------------------------------------
%            PV Pannels
%------------------------------------------------------------------------
meanWeibull5 = gamma2*gamma(1+1/k2);

% define domain (time elements)
p = linspace(0,10*meanWeibull5,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s5 = Fw(p,gamma2, k2);

% pre-allocate memory
P = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
```

```
for n = 1:Nsamps

     %draw a random sample from F
     u = rand;

     %perform inverse sampling to find the value at which F^{-1}(x) = u
     indices1 = find(F_s5(:)<=u);
     index_1 = indices1(end);

  % save the failure time
   P(n) = p(index_1);

end

%---------------------------------------------------------------------------
%            Energy Storage
%---------------------------------------------------------------------------
meanWeibull6 = gamma3*gamma(1+1/k3);

% define domain (time elements)
e = linspace(0,10*meanWeibull6,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf
F_s6 = Fw(e,gamma3, k3);

% pre-allocate memory
E = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

     %draw a random sample from F
     u = rand;

     %perform inverse sampling to find the value at which F^{-1}(x) = u
     indices1 = find(F_s6(:)<=u);
     index_1 = indices1(end);

  % save the failure time
   E(n) = e(index_1);

end
%---------------------------------------------------------------------------
%            Sample controls IBR Subsystem
%---------------------------------------------------------------------------
meanWeibull7 = gamma4*gamma(1+1/k4);


% define domain (time elements)
ic = linspace(0,10*meanWeibull7,1000); % ensure samples go out to 10*mean


% obtain samples for the pdf and cdf
F_s7 = Fw(ic,gamma5, k5);
```

```
% pre-allocate memory
IC = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

     %draw a random sample from F
     u = rand;

     %perform inverse sampling to find the value at which F^{-1}(x) = u

     indices3 = find(F_s7(:)<=u);
     index_3 = indices3(end);

  % save the failure time
   IC(n) = ic(index_3);

end
%---------------------------------------------------------------------------
%            Sample battery inverter IBR Subsystem
%---------------------------------------------------------------------------
meanWeibull8 = gamma5*gamma(1+1/k5);

% define domain (time elements)
bv = linspace(0,10*meanWeibull8,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf

F_s8 = Fw(bv,gamma5, k5);

% pre-allocate memory
BV = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

     %draw a random sample from F
     u = rand;

     %perform inverse sampling to find the value at which F^{-1}(x) = u

     indices4 = find(F_s8(:)<=u);
     index_4 = indices4(end);

  % save the failure time
   BV(n) = bv(index_4);

end
%---------------------------------------------------------------------------
%            PV Inverter IBR Subsystem
%---------------------------------------------------------------------------

meanWeibull9 = gamma6*gamma(1+1/k6);
```

```
% define domain (time elements)
pv = linspace(0,10*meanWeibull9,1000); % ensure samples go out to 10*mean

% obtain samples for the pdf and cdf

F_s9 = Fw(pv,gamma6, k6);

% pre-allocate memory
PV = zeros(1,Nsamps);  % failure times for primary subsystem

% obtain samples for primary subsystem failure times
for n = 1:Nsamps

     %draw a random sample from F
     u = rand;

     %perform inverse sampling to find the value at which F^{-1}(x) = u

     indices5 = find(F_s9(:)<=u);
     index_5 = indices5(end);

  % save the failure time
   PV(n) = pv(index_5);

end


% compute samples for total system failure times
I = (P.*E.*IC.*BV.*PV);   %IBR
C = (A.*M.*P);            %plant controls
W = C.*(Y+I);             %overall system

% compute total system survivability
indices = find(W(:)>=t);
s       = length(indices)/length(W);

iterationCount = iterationCount + 1;

%-----------------------------------------------------------
%           Compute Cost
%-----------------------------------------------------------

% compute subsystem costs

g1 = meanExponential1;          % in exponential g_n = 1/lambda_n
g2 = meanExponential2;          % in exponential g_n = 1/lambda_n
g3 = meanExponential3;          % in exponential g_n = 1/lambda_n

g4 = meanWeibull4;              % in Weibull g_n = \gamma_n\Gamma(1+1/k_n)

g5 = meanWeibull5;              % in Weibull g_n = \gamma_n\Gamma(1+1/k_n)
g6 = meanWeibull6;              % in Weibull g_n = \gamma_n\Gamma(1+1/k_n)
g7 = meanWeibull7;              % in Weibull g_n = \gamma_n\Gamma(1+1/k_n)
g8 = meanWeibull8;              % in Weibull g_n = \gamma_n\Gamma(1+1/k_n)
g9 = meanWeibull9;              % in Weibull g_n = \gamma_n\Gamma(1+1/k_n)
```

```
c1 = beta(1,:)*[g1^2 g1 1]';        %ATS system cost
c2 = beta(2,:)*[g2^2 g2 1]';        %MCC system cost
c3 = beta(3,:)*[g3^2 g3 1]';        %panel system cost
c4 = beta(4,:)*[g4^2 g4 1]';        %generator system cost

%starting cost of IBR system%

c5 = beta(5,:)*[g5^2 g5 1]';    %cost of PV panels
c6 = beta(6,:)*[g6^2 g6 1]';    %cost of battery
c7 = beta(7,:)*[g7^2 g7 1]';    %cost of IBR control
c8 = beta(8,:)*[g8^2 g8 1]';    %cost of IBR battery inverter
c9 = beta(9,:)*[g9^2 g9 1]';    %cost of IBR PV inverter

cost = c1+c2+c3+c4+c5+c6+c7+c8+c9;

%-----------------------------------------------------------
%           Compute Penalties
%-----------------------------------------------------------

p1 = gtn( s, sMin, delta(1));
p2 = ltn( cost, costMax, delta(2));

% compute fitness vector
f(1,1) = p1*s;           % to maximize
f(2,1) = p2/(cost+eps);  % to minimize ( = max of the inverse)




%-------------------------------------------------------------------------%
% Description: this script calculates the Pareto-optimal front of cost vs
% survivability for a system comprising a primary in standby with two standby
% (secondary and tertiary) in active parallel subsystems all in series with a
control subsystem.
% The primary and control subsystems are exponetially distributed with
different failure parameters. The standby
% subsystems are Weibull distributed with different failure parameters. The
components have different
% cost coefficients. The multi-objective optimization is constrained in
% terms of maximum cost and minimum survivability.
%
% Inputs:
%   - none (stand-alone script)
% Outputs:
%   - note (plots to screen)
%
% Written by:
% James Cale, Ph.D.
% Colorado State University
% Contact: jcale@colostate.edu
%
% Megan Younes
% Colorado State University
% Contact: bates60@colostate.edu
% Revision Date: 15 March 2024
```

```
Npop  = 200;    % design candidate population size
Niter = 1000;   % design iterations to perform

% Initialize the parameters
GAP = gapdefault(2,0,Npop,Niter);

% Plotting parameters
GAP.op_list = [];               % objectives list for objective plots
GAP.pp_sign = [ 1, 1];          % sign of fitness for each objective
                                % (1=positive,-1=negative)

% Gene setup
% variable      lamda  lambda2  lambda3 gamma1   k1      g2        k2    g3
k3      g4      k4      g5      k5      g6      k6
% gene            1      2        3        4      5          6       7
GAP.gd_min  = [  1e-5  1e-5     1e-5    1e1     1e0     1e1      1e0   1e1
1e0    1e1      1e0    1e1      1e0    1e1      1e0];
GAP.gd_max  = [  1e-1  1e-1     1e-1    1e5     5e0     1e5      5e0    1e5
5e0    1e5      5e0    1e5      5e0    1e5      5e0];
GAP.gd_type = [   2     2       2        2        2     2          2     2
2     2         2     2         2     2          2];
GAP.gd_cid  = [   1     1       1        1        1     1          1     1
1     1         1     1         1     1          1];


params.t       = 500;           % time to evaluate survivability [hrs]


params.beta    = [ 20   8     4.5;       %cost of ATS system
                   53   15     3;        %cost of MCC system
                   3    2.6    1.9;      %cost of Panel system
                   17    13    9.7;      %cost of generator
                   2.7   2.3   2.0;      %cost of PV panels
                   3.5   3.0   2.2;      %cost of energy storage (battery)
                   3.0   2.6   1.9;      %cost of IBR controls
                   6.0   2.0   1.8;      %cost of IBR battery inverter
                   6.0   2.0   1.8]      %cost of IBR solar inverter

params.costMax = .1e6;         % maximum cost constraint [$]
params.sMin    = 0.91;           % minimum survivability at t
params.delta   = [1e-3 1e2];    % severity of penalties [cost, surv.]
params.Nmin    = 100;           % minimum number of MC samples
params.Nmax    = 500;           % max number of MC samples
params.kmin    = round(0.25*Npop*Niter); % if iterations <= kmin, use Nmin MC
samples
                                % if iterations > kmin, use Nmax MC samples

global iterationCount;
iterationCount = 0;

%tic
% Perform optimization
[P,GAS,best]= gaoptimize(@DamMixedConstrained_fit,GAP,params);
%toc
```

```
% plot non-dominated (Pareto-optimal) designs, showing survivability
% vs cost [$k]
close all
myParetoPlotRed(P,GAP)

xlabel('Survivability')
ylabel('Cost ($) times 1000$')
title('')
set(gca,'Fontsize', 20,'Fontname','Latin Modern Math');
set(gcf,'color','white');
box off
ylim([ 1   params.costMax/1000])
xlim([params.sMin 1])

% % save results
P_dam = P
GAP_dam = GAP
save P_dam
save GAP_dam
```