STUDY OF POWER RECOVERABILITY THROUGH OPTIMAL

DESIGN OF ENERGY STORAGE SYSTEMS

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ABSTRACT OF THE THESIS

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While electrical power has nowadays become an indispensable part of modern life, natural disasters are one of the most severe causes of power outages. Power outages could be catastrophic when they hit critical infrastructures (CIs), such as hospitals, airports and data centers resulting in cascade failures among vital services that have life-dependent functionalities. For example, we have recently seen Hurricane Irma's devastation which completely destroyed critical power infrastructure and caused one of the largest power outages in U.S. history leaving expansive regions without power for weeks. Although energy storage is widely deployed in CIs as a source of backup power during times of adverse events, e.g., taking over when blackouts occur, there have been little work done in allocating them in the systems considering resiliency scenarios. This study aims to come up with a new and unique approach to design CI systems with inherent power resiliency in order to reduce vulnerabilities, limit the consequences of failures, and reduce time to recovery for vital services. The proposed method includes:

1. Techniques for optimizing design strategies of different energy storages for post-event infrastructure recovery.
2. Increase infrastructure resilience in terms of fast recoverability for extreme events with respect to time and cost.
3. Considering uncertainty in the electrical demand load of any infrastructures after a blackout.
4. Considering uncertainty in length of power outage for capacity estimation of energy storage systems needed at the infrastructures site.

We saw that all the factors mentioned above make considerable differences as we compare the results. This method can be used to find the energy storage systems capacities needed and the optimal configuration for a specific infrastructure during power outage. Meanwhile, a time dependent model is also represented that might be critical for some facilities.

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1. Introduction

We are living in the era that everything depends on electricity, making reliable and sufficient power as the foundation for our modern society to operate effectively. The global electricity demand is increasing almost twice as fast as overall energy consumption [1]. World dependency on electricity is growing in such a way that even a short period of power outage can cause many losses in term of costs and data.

1.1 Power Outage

Over the past years, there have been many large blackouts for various reasons such as accidents, supply shortages, equipment failures and degradation. However, natural disasters have caused the biggest power outages in the world history (Figure 1). Extreme events like hurricane or flooding not only damage the power grid, but also cause damage to the power system by making disturbances. Mostly large blackouts happen as the result of these disturbance on the power system frequency and voltage instability causing cascading failures [2].

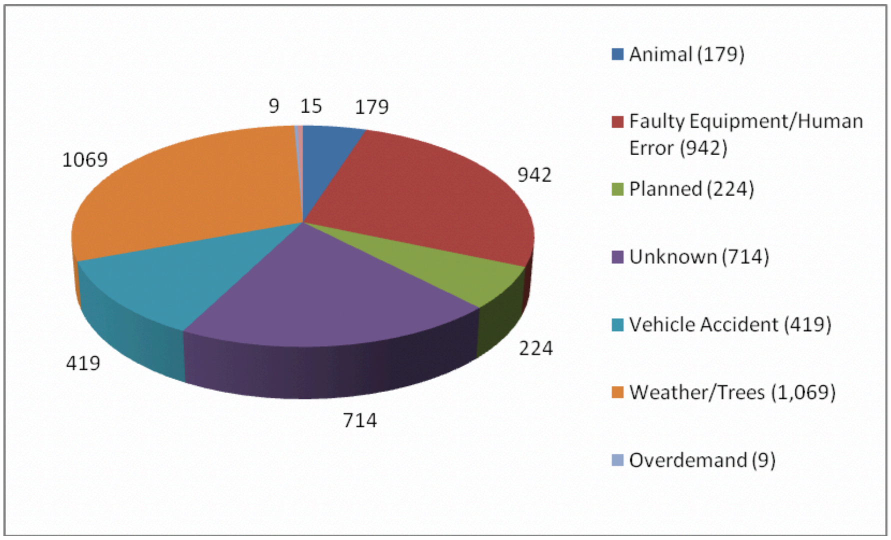

Figure 1 - Power outage causes in 2015 [3]

Researchers at Lawrence Berkeley National Lab (LBNL) have conducted a study on 13 years of U.S. electricity power interruption claim that "increasingly severe weather events are linked to a 5 to 10 percent increase in the total number of minutes customers are without power each year" [3]. The authors of this study claim that as the climate continues to change and the number of extreme events is rising each year, U.S. electric power system must adapt by increasing reliability of electrical grids and dynamic inspection of distributed resources (DR's) [4], [5].

Recent blackouts in several power systems in the U.S and their impacts are as following: Southwest blackout (2011) that affected 5 separate power grids and left nearly seven million people without power[6] , Derecho blackout (2012) caused damage to 4.2 million people across 11 states , hurricane Sandy (2012) impacted 24 American states [7] and recently hurricane Irma which the damages are still to be recovered.

Power outage for different regions within U.S. between 2008 to 2015 is shown in Figure 2. We can see an increasing trend through the past years for almost every region.

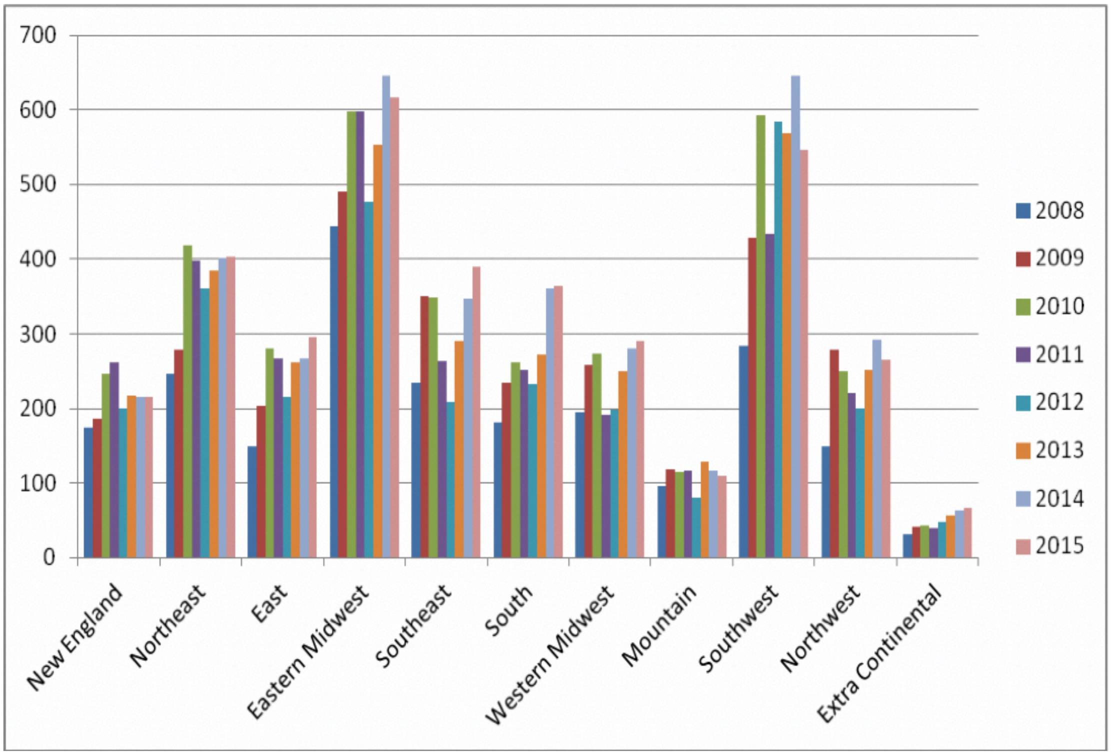

Figure 2 - Reported power outages by region [3]

The top 10 states experiencing weather outages between 2008 and 2014 are as follows: [8]

1. California, 525 outages

2. New York, 399 outages

3. Texas, 335 outages

4. Michigan, 328 outages

5. Pennsylvania, 294 outages

6. Ohio, 265 outages

7. Illinois, 251 outages

8. Washington, 226 outages

9. North Carolina, 225 outages (tie)

9. New Jersey, 225 outages (tie)

As previously mentioned component failures and degradation [9], human error and many other reasons can cause a power outage but since the number of power outages due to natural disasters are increasing, the cost of power outages is on the rise as well. Studies published by the Ponemon Institute suggest that other than the resiliency aspect of power systems we must consider the cost associated with power outages. Comparative studies in 2010, 2013 and 2016 are listed below [10]:

- The average total cost per minute of an unplanned outage increased from $5,617 in 2010 to $7,908 in 2013 to a current price tag of $8,851
- The average cost of a data center outage rose from $505,502 in 2010 to $690,204 in 2013 to $740,357 in the latest study, representing a 38 percent increase in the cost of downtime
- Maximum downtime costs are rising faster than average, increasing 81 percent since 2010 to a current high of $2,409,991

The impacts of power outages are exacerbated by disruptions to critical infrastructure systems. In [11], we can see that power outages caused by extreme events affect health sector in many aspects such as the difficulties of accessing healthcare and maintaining frontline services. The huge impact of power loss on these critical sectors bring up the need for safe reliant power operation and planning for power outages.

1.2 Critical Infrastructure

The definition of Critical Infrastructure (CI) has been the center of attention for years as it has been evolving constantly. An unclear and ambiguous meaning of CI can mislead to inadequate use of limited resources by simply protecting the wrong facilities or too many of them [12]. The most recent definition of CI is for after September 11, 2001 terror attack as a result of which USA PATRIOT Act of 2001 was passed defining “Critical Infrastructure” as:

"Systems and assets, whether physical or virtual, so vital to the United States that the incapacity or destruction of such systems and assets would have a debilitating impact on security, national economic security, national public health or safety, or any combination of those matters."

The National Infrastructure Protection Plan (NIPP) established the following 16 critical infrastructure sectors [13]:

- Chemical
- Commercial Facilities
- Communications
- Critical Manufacturing
- Dams
- Defense Industrial Base
- Emergency Services
- Energy
- Financial Services
- Food and Agriculture
- Government Facilities
- Healthcare and Public Health
- Information Technology
- Nuclear Reactors, Materials, and Waste
- Transportation Systems
- Water and Wastewater Systems

In large scale complex systems, a major vulnerability would be the interdependency of infrastructures which makes the control procedures hard and increase the potential cascading failures impacts [14], [15].

In [16] O'Rourke states how the dependency of pipeline pumping stations on electricity power caused interruption in the supply of oil and petroleum products after Hurricane Katrina. As a result of loss of electrical power at three major pipeline stations about 1.4 million barrels per day of the crude oil supply were lost, accounting for 90 percent of the production in the Gulf of Mexico. The three major pipelines were not fully restored until more than 17 days after Katrina made landfall. He claims similar experience occurred for water-supply pumping stations after the 1994 Northridge earthquake. In this regard, we are considering individual infrastructures independent of each other in our research and dependent infrastructures will not be studied.

Each of these sectors have critical services that are dependent of power supply and would be disrupted by power outages of a few hours to several weeks. In [17] the author conducted a summary for the services of each sector and their dependence of power energy some of which are most important are in the following table:

Table 1- Examples of Critical Social Services That Depend on the Availability of Electric Power [17]

Service Category	Specific Service	Typical Existing Backup
Emergency Services	911 and related dispatch centers	Most have comprehensive backup power systems. Fuel supply and reliability could be an issue in long outages.
	Police headquarters and station houses	Varies. Some stations do not have backup. AC power is often required for recharging hand-held radios.
	Fire protection services	Same as above.
	Emergency medical services	Same as above.
	Hazardous materials response teams	Same as above.
Medical services	Ambulance and other medical transport services	Limited.
	Life-critical in-hospital care (such as emergency rooms, life support systems, operating rooms)	Full back up in most major facilities, but some failed during the blackout of August 14, 2003. Some systems have inadequate testing procedures. Fuel supply and reliability could be an issue in long outages.

	Less-critical in-hospital services (refrigeration, heating and cooling, sanitation, etc.)	Availability of backup varies. Many smaller facilities lack backups.
	Clinics and pharmacies	Many have no backup.
	Nursing homes	Same as above.
Communications and cyber services	Radio broadcast media	Major stations have backup systems with several days of fuel on hand.
	Television broadcast media	Many stations have backup power systems with several days of fuel.
	Cable television and broadband services	Minimal backup.
	Conventional telephone	Conventional phone systems have backup power systems.
	Wireless (cellular) telephone and data systems	Modest backup. Battery backup typically provides only 2-8 hours of service.
	Wired data service	Many backbone systems have backup. Most local systems do not.
	Computer services (on and off premise)	backups with several days of fuel on hand and priority fuel contracts. On-site typically limited to several minutes.

Water and sewer	Water supply	Limited backup. Most systems require pumping in treatment plants. Many systems also require pumping for delivery.
	Sewer systems	Very limited backup. Many systems require pumps for collection. Most require power for treatment.
Financial	Cash machines	Typically no backup.
	Credit card systems	Little or no backup at most retail outlets.
	Banks	Little or no backup at smaller banks except for security systems.

However, some of these services are essential for the functionality of the infrastructure and require power for restoration sooner than the others. The level of importance and vulnerability of each of these CIs and their services is different for each city and region depending on the geographic location, backup policies and many other factors.

Consequently, here our primary focus is on reducing the vulnerability of these vital services which have priority compared to the others in times of blackouts through sustaining and rapidly restoration of them.

1.3 Resiliency of Critical infrastructures

After catastrophic infrastructures performance and failures of Hurricane Katrina in 2003, resilience of the CIs was drawn to attention, however, we can say after September 11, a significant emphasis was put for promoting CI resiliency planning studies and coordination.

A general definition of CI Resilience can be as the level of preparedness to a disaster, response to it and recovery process time.

The NATIONAL INFRASTRUCTURE ADVISORY COUNCIL (NIAC) defines it as:

"Infrastructure resilience is the ability to reduce the magnitude and/or duration of disruptive events. The effectiveness of a resilient infrastructure or enterprise depends upon its ability to anticipate, absorb, adapt to, and/or rapidly recover from a potentially disruptive event." [13]

Bruneau et al. [18] , started working on CI resilience in 2003, defining resilience systems with four fundamental qualities:

- Robustness: the inherent strength or resistance in a system to withstand external demands without degradation or loss of functionality.
- Redundancy: system properties that allow for alternate options, choices, and substitutions under stress.
- Resourcefulness: the capacity to mobilize needed resources and services in emergencies.
- Rapidity: the speed with which disruption can be overcome and safety, services, and financial stability restored.

NIAC characterizes critical infrastructure resilience similarly with few differences by three key features: [13]

- Robustness: the ability to maintain critical operations and functions in the face of crisis. This can be reflected in physical building and infrastructure design (office buildings, power generation and distribution structures, bridges, dams, levees), or in system redundancy and substitution (transportation, power grid, communications networks).
- Resourcefulness: the ability to skillfully prepare for, respond to and manage a crisis or disruption as it unfolds. This includes identifying courses of action, business continuity planning, training, supply chain management, prioritizing actions to control and mitigate damage, and effectively communicating decisions.
- Rapid recovery: the ability to return to and/or reconstitute normal operations as quickly and efficiently as possible after a disruption. Components include carefully drafted contingency plans, competent emergency operations, and the means to get the right people and resources to the right place.

Here in this study we define resiliency of CIs considering recoverability of the system as: Recoverability is the ability of the system to recover in the least possible time at low cost from disruptive events. Further explanations will be given in the next section.

1.4 Energy Storage Systems

The broadest definition of energy storage includes any system for absorbing energy in some form at one time and releasing at a later time [19] . There has been an increasing interest toward Energy Storage Systems (ESS) studies in the past decades due to many applications they provide in electrical power. Many studies have been focused on using ESSs combined with renewable energy generators and microgrids in order to improve power balancing, shifting demand in peak hours, more flexibility to variable renewable energy resources power generation, minimizing demand load and cost associated with it and most importantly back-up power [20], [21]. In this regard, different energy storage technologies have been launched to meet the technical feasibility of such applications. Energy storages are now able to store very large quantities of energy for weeks or months.

Energy storages have many attributes that are characterized by their technology and affect their employment in power systems to meet reliable electrical needs. Most Important attributes include:

- Power rating storage /discharge rates (MW)
- Energy storage capacity (MWh)
- Capital costs
- Efficiency
- Ramp rate
- Utilization rates
- Maintenance costs
- Emissions
- Response time
- Discharge duration
- Minimum generation levels
- Black start capability (the ability of a generator to begin operation without station service which is important for recovering from power outages.)

Each of the energy storages have a set of these attributes which specify the services they are best suited for.

1.4.1 Classification of Electrical Energy Storages Systems (EES)

Nowadays Distributed Energy Resources (DERs) and renewable energy along with storage systems and batteries have become employed widely in order to increase resiliency of systems especially during power outage [22]. Based on the aforementioned information we can conclude that energy storages and batteries are the most common and reliable source for back-up plans in times of blackouts. Here we will go through different types of energy storages, their characteristics and applications.

Most common way for classifying EES systems is based on the form of energy used in their technology shown in Figure 3.

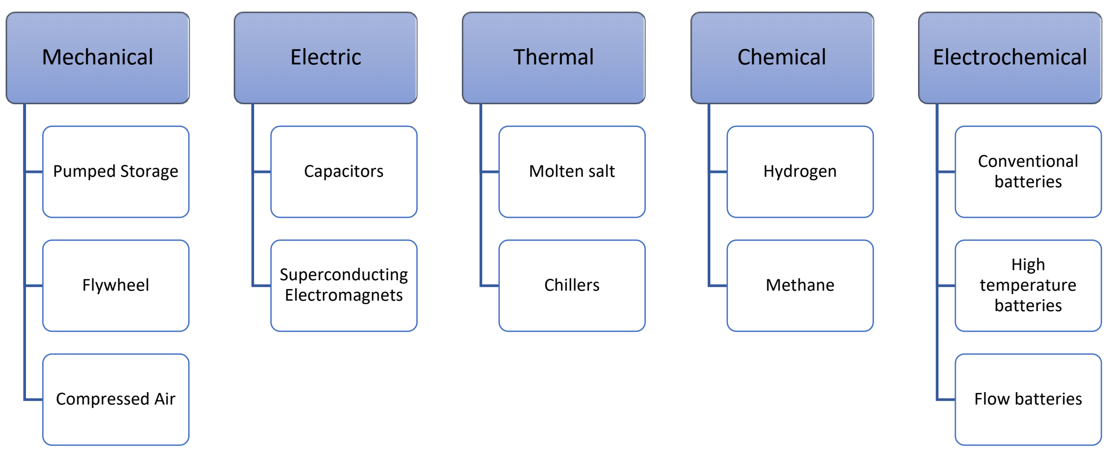

Figure 3 - Classification of electrical energy storage systems according to energy form [23]

Another common approach which is more useful in our study is classification based on discharge duration as their applications are largely determined by the length of discharge. On this basis EES technologies can be categorized into 3 groups as following:

Table 2 - Electrical energy storage classification based on discharge length [18]

Common Name	Discharge Time	Example Applications	Discharge Time Required
Power Quality	Short	Transient Stability, Frequency Regulation	Seconds to Minutes
Bridging Power	Medium	Contingency Reserves, Ramping	Minutes to hour
Energy Management	Long	Load Leveling, Firm Capacity, T&D Deferral	Hours

Power quality applications require rapid response (within less than a second) with short discharge time (seconds to minutes). Their energy-to-power ratio is less than 1. Technologies in this group conclude:

- double-layer capacitors (DLC)
- superconducting magnetic energy storage (SMES)
- flywheels (FES)

Bridging power applications generally requires rapid response (seconds to minutes) with medium discharge time (minutes to hours) with an energy-to-power ratio of between 1 and 10. This application is generally associated with several battery technologies as:

- lead-acid (LA)
- Lithium ion (Li-ion)

- sodium sulphur (NaS) batteries
- flywheels (FES)

Energy management applications include longer timescales and generally require continuous long discharge time (hours to days): For these EES systems the energy-to-power ratio is considerably greater than 10.

- Compressed air energy storage (CAES)
- Pumped hydro storage (PHS)
- high-temperature battery (sodium-sulfur battery, sodium-nickel chloride (ZEBRA) battery)
- liquid electrolyte “flow” battery (batteries – vanadium redox, zinc-bromine)
- thermal energy storages (molten salt, chillers)

Figure 4 demonstrates all energy storage technologies as the rated power (W) is plotted against the energy content (Wh) and the nominal discharge time at rated power can also be seen, covering a range from seconds to months.

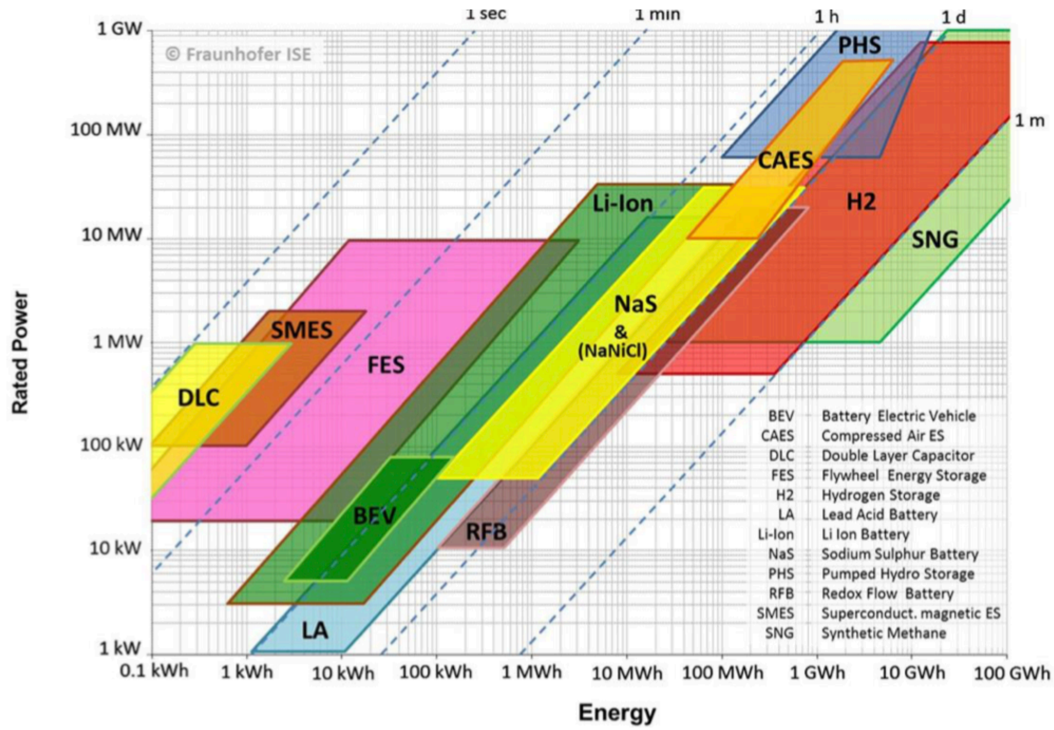

Figure 4 - Comparison of rated power, energy content and discharge time of different EES technologies [19]

1.4.2 EES Sizing and Cost Comparison

In our study, we will compare different energy storage systems to find the optimal cost-effective design for specific critical infrastructures. We aim to find the best design of storage systems in our facilities by optimizing different characteristic of storage systems in terms of resiliency. Other studies have been done using the same approach in energy industry because of uncertainty of parameters that depend on the environment [24].

Unlike other energy systems, there are different energy-cost metrics defined as means of comparing the costs for electrical energy storage systems.

Energy Storage sizes are reported in terms of storage power capacity (kW) and energy capacity (kWh). Depending on the storage application, some energy storages are designed to deliver high power capacity, whereas others are optimized for longer discharges through more energy capacity (Figure 5). The amount of energy that a battery can store is determined by its energy capacity (kWh), whereas the rate at which it charges, or discharges is determined by its power rating (kW) [25].

Lithium battery for instance is widely used in Electrical Vehicles because of their unique characteristics such as high energy density and power rating [26]–[28]. On the other hand, Pumped Hydro and Compressed air storage systems are more used when you have large space in your facility and looking for long term discharging.

Consecutively, another important attribute of energy storage technology is defined as storage costs estimated based on capacity (kWh) or power (kW). Energy storages costs measured in $/kW are generally favorable economics for high-power systems which are mostly used to provide electricity for short period of time such as frequency regulation whereas storage costs in $/kWh are suitable for high-energy systems delivering electricity for longer periods like hours to weeks.

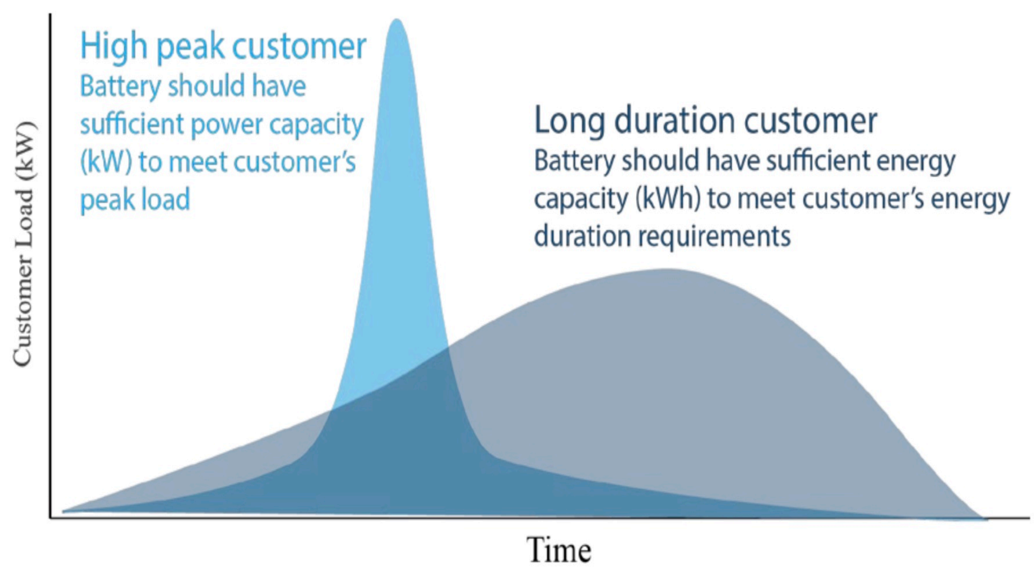

Figure 5 - load profiles of "high peak" and "long duration discharge" customers [25]

The table below represents both defined cost for storage systems along with some other characteristics such as maturity.

Table 3 - Summary characteristics of various energy storage technologies [25]

Technology	Maturity	Cost ($/kW)	Cost ($/kWh)	Efficiency	Response Time
Pumped Hydro	Mature	1,500 - 2,700	138 - 338	80 - 82%	Seconds to Minutes
Compressed Air (Underground)	Demo to Mature	960 - 1,250	60 - 150	60 - 70%	Seconds to Minutes
Compressed Air (Aboveground)	Demo to Deploy	1,950 - 2,150	390 - 430	60 - 70%	Seconds to Minutes
Flywheels	Deploy to Mature	1,950 - 2,200	7,800 - 8,800	85 - 87%	Instantaneous
Lead Acid Batteries	Demo to Mature	950 - 5,800	350 - 3,800	75 - 90%	Milliseconds
Lithium-ion Batteries	Demo to Mature	1,085 - 4,100	900 - 6,200	87 - 94%	Milliseconds
Flow Batteries (Vanadium Redox)	Develop to Demo	3,000 - 3,700	620 - 830	65 - 75%	Milliseconds
Flow Batteries (Zinc Bromide)	Demo to Deploy	1,450 - 2,420	290 - 1,350	60 - 65%	Milliseconds

Sodium Sulfur	Demo to Deploy	3,100 - 4,000	445 - 555	75%	Milliseconds
Power To Gas	Demo	1,370 - 2,740	NA	30 - 45%	10 Minutes
Capacitors	Develop to Demo	-	-	90 - 94%	Milliseconds
SMES	Develop to Demo	-	-	95%	Instantaneous

Generally, we can conclude that higher capital cost resources with low operating costs tend to be more useful for continuous power supply.

A database provided by DOE in 2013, reported 202 with a mix of storage technologies storage system deployments in the US with a cumulative operational capability of 24.6 GW [29]. The extent and range of energy storage systems deployments and the contribution of each technology to the overall operational capability is shown in Figure 6.

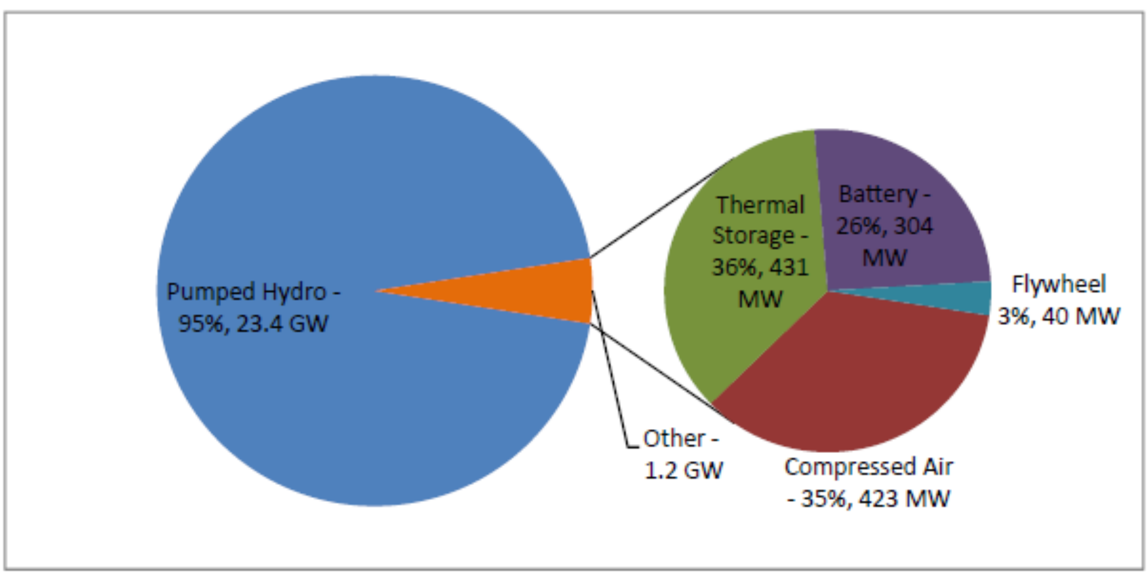

Figure 6 - Electrical storage systems deployed in US. [30]

Following table gives a summary of most of the characteristics of energy storage systems and batteries [22], [30].

Table 4 - Summary of EES systems[30]

Technology	Primary Application	Current knowledge	Challenges
CAES	• Energy management • Backup and seasonal reserves • Renewable integration	• Better ramp rates than gas turbine plants • Established technology in operation since the 1970's	• Geographically limited • Lower efficiency due to roundtrip conversion • Slower response time than flywheels or batteries • Environmental impact
Pumped Hydro	• Energy management • Backup and seasonal reserves • Regulation service also available through	• Developed and mature technology • Very high ramp rate • Currently most cost-effective form of storage	• Geographically limited • Plant site • Environmental impacts • High overall project cost

	variable speed pumps		
Fly wheels	• Load leveling • Frequency regulation • Peak shaving and off-peak storage • Transient stability	• Modular technology • Long cycle life • High peak power without overheating concerns • Rapid response • High round trip energy efficiency	• Rotor tensile strength limitations • Limited energy storage time due to high frictional losses
Advanced Lead-Acid	• Load leveling and regulation • Grid stabilization	• Mature battery technology • Low cost • High recycled content • Good battery life	• Limited depth of discharge • Low energy density • Large footprint • Electrode corrosion limits useful life
NaS	• Power quality • Congestion relief • Renewable source integration	• High energy density • Long discharge cycles	• Operating Temperature required between 250° and 300° C

		• Fast response • Long life • Good scaling potential	• Liquid containment issues (corrosion and brittle glass seals)
Li-ion	• Power quality • Frequency regulation	• High energy densities • Good cycle life • High charge/discharge efficiency	• High production cost - scalability • Extremely sensitive to over temperature, overcharge and internal pressure buildup • Intolerance to deep discharges
Flow Batteries	• Ramping • Peak Shaving • Time Shifting • Frequency regulation • Power quality	• Ability to perform high number of discharge cycles • Lower charge/discharge efficiencies • Very long life	• Developing technology, not mature for commercial scale development • Complicated design • Lower energy density

1.5 Problem Statement

As mentioned previously, hurricanes among other natural disasters are one of the main reasons for power outages as we saw recently Hurricane Irma's caused one of the largest power outages in U.S. history resulting large-scale devastations. Here in this study we aim to improve resiliency by the means of electrical energy storages to reduce the probability of infrastructures' failure during power outages, as well as the consequences from such failures and the time to recovery. As we went through different energy storages we saw each of them have different set of characteristics that make them favorable for various applications. We aim to use these attributes corresponding to each electrical energy storage and come up with different design scenarios finding the optimal case which will restore electrical power to the most important services within each critical infrastructure and at the same time it is cost efficient. Therefore, this study explores the resilience of critical infrastructures considering the impact on time to recovery in all possible cases.

The proposed framework makes it possible to assess CIs' fragilities with tools to quantify resilience and improve them considering uncertainties under different scenarios.

Therefore, the next steps would be defining resiliency of critical infrastructures and finding cost-effective configuration of electrical storage systems as back-up power systems in order to improve resiliency considering uncertainties.

This study will focus on the interplay between resiliency and recoverability to develop a general framework for quantitative assessment of CIs resiliency. Due to complexity of infrastructure systems, in our approach these systems are considered independent of each other and isolated in times of natural disaster which means there is no connection between main grid and the CIs.

1.6 Objectives

This study aims at

1) Proposing a methodology to analyze dynamics of infrastructures;
2) Considering priorities for different services within each critical infrastructure;
3) Developing time-dependent resilience quantification in infrastructures with recovery metrics;
4) Developing design parameters for electrical energy storages considering their set of attributes;
5) Comparing each recovery process for different design scenarios;
6) Finding the optimal cost-effective design cases considering uncertainties in each step;
7) Providing insights to decision makers for improving critical infrastructure resilience.

2. literature Review on Previous Studies

2.1 Quantifying Resilience

The concept of disaster resilience was first formally introduced by Bruneau et al. [18] in 2003 and evolved in years as there was a debate between the many academic researchers. He introduced a new technique for measuring performance of the system for post-disaster recovery process. As shown in Figure 7, this technique considers the quality of infrastructure versus time providing a quality curve or response curve. The quality of the infrastructure can change from 1(operating) to 0 (inoperable) and Response Curve measures infrastructure systems' initial response to a disaster and the restoration process over time. It is providing a tracking system behavior after a disruptive event.

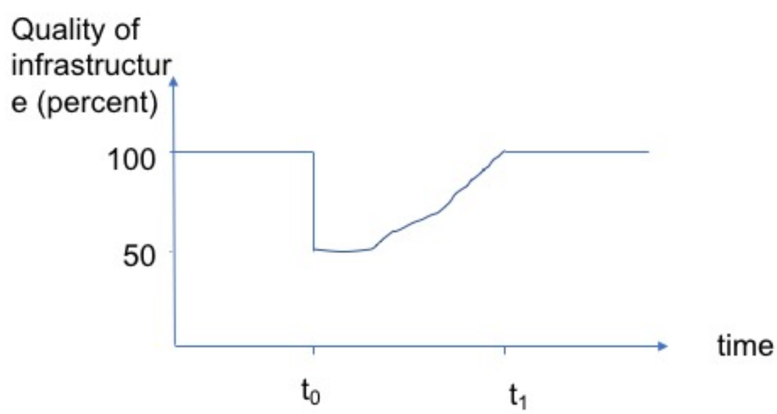

Figure 7 - Measure of resilience definition. [16]

This approach builds on performance and changes in the number of components in a system functioning in order to quantify disaster resilience and the extent to which a system has recovered. Mathematically defining resiliency as:

$$R = \int_{t_0}^{t_1} [100 - Q(t)]dt \tag{1}$$

Their work was mainly focused on the amount of loss and the remaining time to recovery in order to measure the area above the quality curve of a system, named resilience triangle, as it recovers from the impact a disaster.

Later on, they extended their work on disaster resilience and defined disaster resilience graphically as the shaded area underneath the functionality function of a system, defined as Q(t) [31].

Q(t) is a piecewise continuous function as the one shown in Figure 8(a), where the functionality function Q(t) is measured as a dimensionless (percentage) function of time. Resilience definition is given by the following equation:

$$R = \int_{t_{OE}}^{t_{OE}+T_{LC}} Q(t)/T_{LC}dt \tag{2}$$

where

$$\begin{aligned} Q(t) = {} & [1 - L(I, T_{RE})][H(t - t_{0E}) - H(t - (t_{0E} + T_{RE}))] \\ & \times f_{Rec}(t, t_{0E}, T_{RE}) \end{aligned} \tag{3}$$

where L (I, T_{RE}) is the loss function; f_{Rec} (t, t_{0E}, T_{RE}) is the recovery function; H is the Heaviside step function, TLC is the control time of the system, T_{RE} is the recovery time from event E and t_{0E} is the time of occurrence of event E.

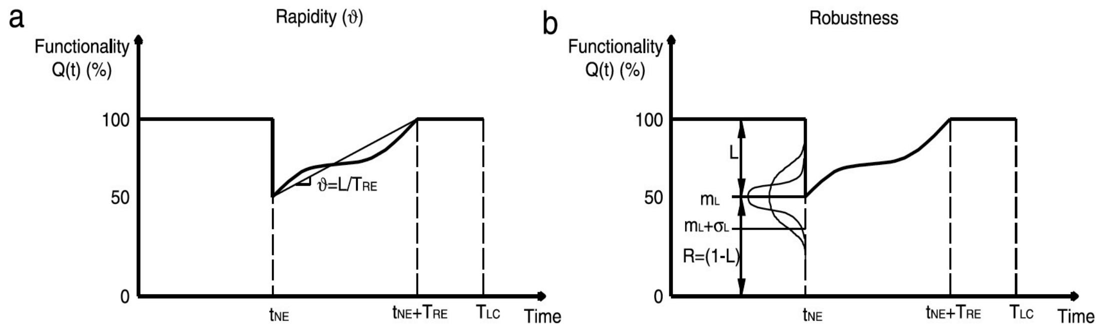

Figure 8 - Dimensions of resilience: Rapidity (a) and Robustness (b). [31]

As mentioned previously Bruneau et al. [18] with MCEER (Multidisciplinary Center of Earthquake Engineering to Extreme Event) have identified four dimensions of disaster resilience along which resiliency can be improved. here we will go through these aspects and their quantification in terms of the disaster resilience graph.

- Rapidity: "capacity to meet priorities and achieve goals in a timely manner in order to contain losses and avoid future disruption''[18]

Mathematically it represents the slope of the functionality curve during the recovery time and it can be expressed by the following equation [31]:

for $t_{0E} \leq t \leq t_{0E} + T_{RE}$:

$$Rapidity = \frac{\mathrm{d}Q(t)}{\mathrm{d}t}; \tag{4}$$

where Q(t) is the functionality of the system and d/dt is the differential operator.

An average estimation of rapidity is defined by the total losses over the total recovery time to full functionality of system, as follows:

$$Rapidity = \frac{L}{T_{\mathrm{RE}}} \tag{5}$$

where L is the loss, or drop of functionality, right after the extreme event.

- Robustness: ‘‘the ability of elements, systems or other units of analysis to withstand a given level of stress, or demand without suffering degradation or loss of function’’ [18].

Which is the residual functionality right after the extreme event (Fig. 8(b)) and can be represented by the following relation: [31]

$$Robustness = 1 - \tilde{L}(m_L, \sigma_L); (\%) \tag{6}$$

where $L\tilde{}$ is a random variable expressed as function of the mean m_L and the standard deviation σ_L.

It is quite difficult to quantify Redundancy and Resourcefulness, but we can say that the Rapidity and Robustness of an entire system is improved through them as they affect the shape and the slope of the recovery curve and the recovery time T_{RE}.

Furthermore, they came up with an equation for loss function L (I, T_{RE}) which is expressed as a function of earthquake intensity I. However, in our study we will have a more general view and consider any power outage caused by natural disaster, not only earthquakes.

O’Rourke et al. [32] defines Quality Function Q(t) as:

$$Q(t) = Q_\infty - (Q_\infty - Q_0)e^{-bt} \tag{7}$$

where Q_∞ is capacity of the fully functioning structural system, Q_0 is post-event capacity; b parameter derived empirically from restoration data following the event. And Q(t)=1 is considered system fully functioning and Q(t)=0 is when the system is inoperable.

In this modeling, the ratio of (Q_∞ - Q_0) to Q_∞ is a measure of system robustness and the parameter “b” as a measure of the rapidity of the recovery process. The integration of the area under the quality curve for any time interval between t_1 and t_2 is Resilience with the equation:

$$R = \frac{\int_{t_1}^{t_2} Q(t)dt}{(t_2 - t_1)} \tag{8}$$

2.2 Simplified Recovery Function Models

Since the recovery time and the recovery curve are essential for evaluating resilience, there have been studies to estimate it accurately. Modeling recovery of a critical infrastructure is a complex subject as information that describe the recovery process is very limited.

Some simplified types of recovery functions are defined depending on the system and the community preparedness. Three possible recovery functions defined are linear [31], exponential and trigonometric [33] shown in Figure 9.

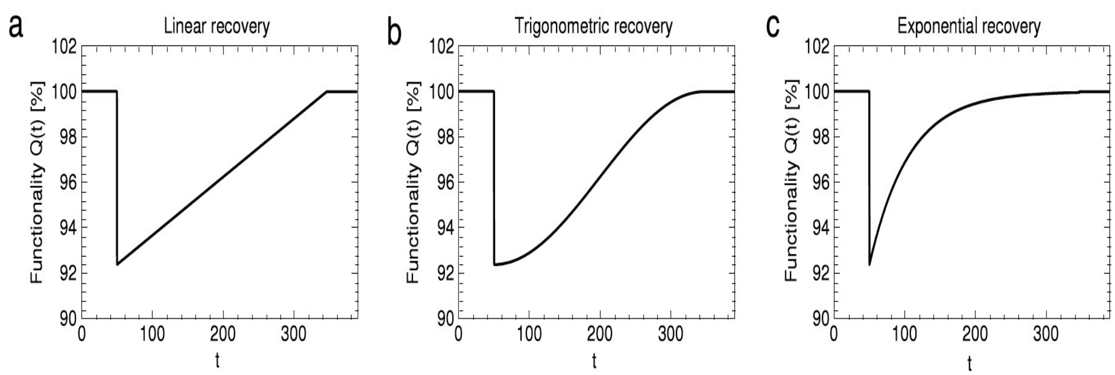

Figure 9 - Recovery curves (a) average prepared community, (b) not well-prepared community, (c) well prepared community. [31]

authors in [34] have considered resiliency associated with the response curve, naming it measure of performance (MOP), and defined rapidity the same as before, as the slope of the curve. However, they considered a different definition for robustness as the Absorptive capability of the system which is refers to the strength of the system to resist disruption and the ability to reduce the impacts events and minimize consequences.

In order to quantify robustness (R) they considered the system absorptive capability which is the minimum MOP value as follows:

$$R = \min\{\, MOP(t) \,\}(\text{ for } td \leq t \leq t\, ns) \tag{9}$$

where here t_d is the time of disruptive event; t_{ns} represents the time when the system reaches the new steady phase.

They also give a simplified quantified definition for recoverability (RA) as follows:

$$RA = \left| \frac{MOP(t_{ns}) - MOP(t_r)}{MOP(t_o) - MOP(t_r)} \right| \tag{10}$$

where t_r is the time the system performance reaches the lowest level and t_o represents the time when the system is in original steady phase. They applied their model on Swiss electric power supply system (EPSS) as an exemplary system for resilience assessment.

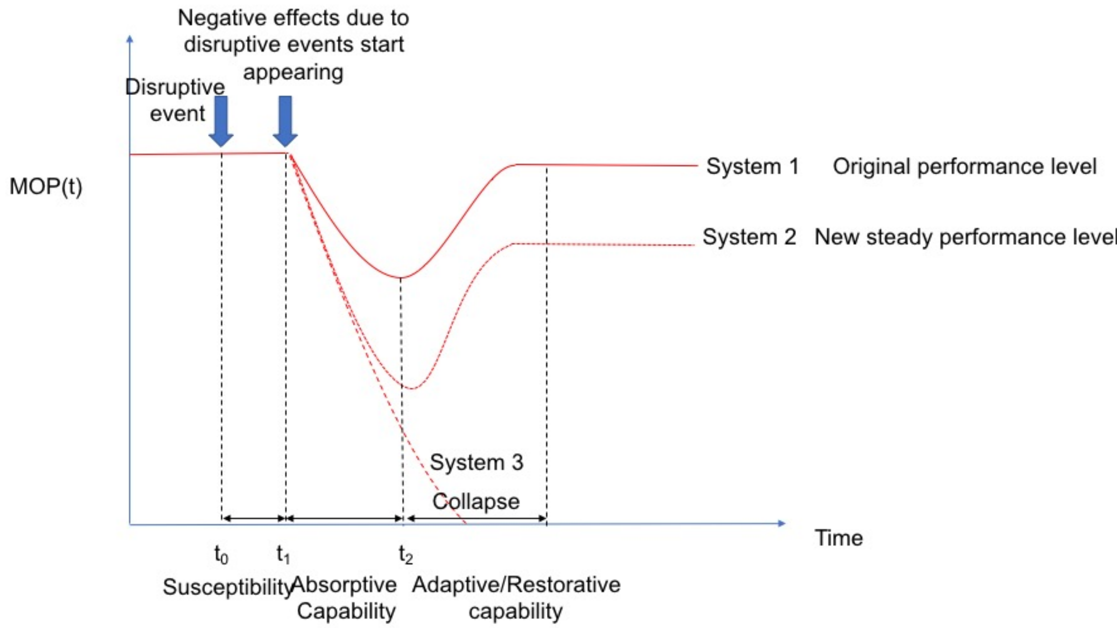

Figure 10 - System resilience transitions and phases [34].

3. Deterministic Model

3.1 Model Assumptions

The preliminary model is a linear deterministic problem, which is used as a basic scenario in this study. In this modeling, we try to improve the disaster resilience by tracking recoverability of the system and the number of services functioning in a critical infrastructure. Each of the services functioning fully is equivalent to some levels of the system recovery. Here we assume some recovery level as the goal and try to meet the electrical demand associated with it.

A deterministic resource-constraint model for assessing the electrical restoration process of any critical infrastructure is considered. we evaluate different energy storage systems and determine the optimal configuration of Energy Storage Systems for specific infrastructure and the capacities needed for each one based on the storage systems' attributes and the infrastructure's needs. The set of properties specify the services they are best suited for.

The preliminary model assumptions are as follows:

- As previously mentioned, each energy storage system has a response time as the time it takes for the energy storage to supply electricity for demand. Here we have considered this response time as t_r in our model due to its importance in times of disaster
- Since many infrastructures such as hospital or airport have services which are more critical, like emergency services for hospitals, in this study we assume priority for CI's different services by putting more weight for more important services in order to restore energy to those important services sooner and longer. In this way, each CI have K_1 to K_n services

which k_1 is the most important service (associated with weight w_1) and K_n is the least critical one (associated with weight w_n). However, some sectors like residential communities may not have electrical restoration priority, which still this methodology can be used with randomizing priority of each service.

- As mentioned previously, electrical power system is critical infrastructure itself so in order to improve the resiliency of infrastructures during extreme events we must consider them independent of each other. In this regard, here we consider that the connection between CI's and main grid is disrupted completely during the recovery process and electrical restoration is only provided by energy storages installed on-site.
- In the modeling, we consider a limit of time for the recovery process as that would be the maximum time allowance (t^*) for power restoration using energy storages as if after that time the connection to main grid will be back. In this stage for the primary model we considered this time t^* to be deterministic but in the next chapter we will extend the model considering uncertainties regarding time which the connection between facility and main grid is back.

3.2 Variables and Parameters

t^*: maximum number of days for recovery

L_j: demand load of service j (kWh)

l_{ij}: energy discharged from storage i to service j (kWh)

x_i: total capacity needed for storage i (kWh)

$S_{min}\,i$: minimum capacity of storage i (kWh)

$S_{max}\,i$: maximum capacity of storage i (kWh)

w_j: weight associated to service j

c_i: storage i installation cost ($/kWh)

Ys_i: storage i efficiency

Re: recovery level (%)

D: demand load energy (kWh)

V_i: storage i energy density (L)

V^*: maximum space (volume) available (Wh/L)

Z_i : binary variable for determining the state of the ESS

CS_i: the starting-up cost for storage i

tr_i: response time for storage i

D_{up}: ramp-up rate limit

D_{down}: ramp-down rate limit

3.3 Mathematical Model

The mathematical modeling consists of two optimization problems which the main one is for minimizing cost and the other is for maximizing priority restoration. In the first problem, the objective function is to minimize the installation cost of ESS's (maintenance costs are negligible since they're pretty low compared to the installation costs) while finding the total energy capacity needed for each one. The primary constraints are for recovery level required and ESS's energy density associated with maximum space available.

$$minimze \sum_{i=1}^{k} x_i . c_i \quad (11)$$

subject to:

$$\sum_{i=1}^{k} YS_i . x_i \geq Re. \sum_{t=1}^{t*} D(t) \quad (12)$$

$$\sum_{i=1}^{k} x_i . \frac{1}{v_i} \leq V^* \quad (13)$$

$$0 \leq x_i \leq Re. \sum_{t=1}^{t*} D(t) \quad for\ all\ i = 1\ to\ k \quad (14)$$

$$S_{min_i} \leq x_i \leq S_{max\ i} \qquad for\ all\ i = 1\ to\ k \qquad (15)$$

In equation (12) we are looking to meet the energy requirement based on the fact that each storage has a storing efficiency (Ys) and the summation of the energy requirement of the whole t* days of disruption should be satisfied at least at the Reliability level (Re). Here we are assuming that we know the electrical demand (D) of our infrastructure.

As mentioned before energy density is the amount of energy that can be stored per unit volume. The above formulation is based on the fact that energy density is of great importance when deciding which storage system to use for a specific infrastructure. For instance, consider Pumped Hydroelectric Storage has a low energy density requiring space versus Lithium-ion battery which has a very high energy density and can be used in places with limited space (13). Equations (14) and (15) are to consider limitations of ESSs capacities.

Now that we have the capacity and total amount of energy for each of the ESS's, In the second problem, we will maximize restoration to the most critical demand loads based on their priority which is the weight assigned to them.

$$maximize \sum_{i=1}^{k} w_i . L_{ij} \quad (16)$$

subject to:

$$0 \leq \sum_{j=1}^{n} L_{ij} \leq x_i \;\; for\ all\ i = 1\ to\ k \quad (17)$$

$$0 \leq \sum_{i=1}^{k} L_{ij} \leq L_j \;\; for\ all\ j = 1\ to\ n \quad (18)$$

the constraints would be in a way that the total amount of energy discharged from a storage would not exceed its capacity and on the other hand, the total amount of energy discharge to service j would not exceed its demand.

3.4 Time Dependency Modeling

The second step here would be to find the optimal scheduling of the ESSs which is a time-dependent optimization problem. The mathematical formulation will be the same except the fact that everything is time-dependent, meaning that the decision variables, xi(t), are discharge energy of i_{th} storage at hour t. Here, we try to find the optimal discharge of energy storages to meet the energy demand of our critical infrastructure in each time interval of 1 hour.

Consequently, constraints and variables related to time management will be added. Variables to determine staring up and shutting down ESSs and constraints for response time, ramp rate, minimum up time, … are among the important ones. We go through each one of them in what follows.

$$minimze \sum_{i=1}^{k}\sum_{t=1}^{t*} x_i(t).c_i + \sum_{i=1}^{t*} Z_i\,(t)\,.\,CS_i \quad (19)$$

subject to:

$$\sum_{i=1}^{k} YS_i.x_i(t) \geq Re.D(t) \quad (20) \qquad for\ t = 1\ to\ t*$$

$$\sum_{i=1}^{k}\sum_{t=1}^{t*} x_i(t).\frac{1}{v_i} \leq v^* \quad (21)$$

$$x_i(t) = \ 0 \qquad for\ t = 1\ to\ t_r\ and\ for\ all\ i = 1\ to\ k \qquad (22)$$

$$y_i(range\,) \geq \ y_i(t) - \ y_i(\,t-1) \qquad for\ range = t\ \text{to}\ \min\{t^*, t + minup(i) - 1\}\ (23)$$

$$Ch_{min}\,(i).y_i\,(t) \leq \ x_i(t) \leq \ Re.D(t).y_i(t) \qquad for\ all\ i = 1\ to\ k \quad (24)$$

$$x_i(t-1) - \ x_i(t) \leq D_{down}(i) \qquad for\ all\ i = 1\ to\ k \quad (25)$$

$$x_i(t) - x_i(t-1) \leq D_{up}(i) \qquad for\ all\ i = 1\ to\ k \qquad (26)$$

The main difference here would be that the decision variables are for each time step so that we have i times ti* decision variables. An on-off binary variable (*yi*) has been defined in order to find start-ups and shut-downs.

In the objective function a second part is added since there is usually a starting-up cost associated with ESSs. Z is a binary indicator (defined by yi) which is 1 when system has started up at time t and 0 otherwise. And CS(i) is the starting-up cost for storage i.

In the energy requirement constraint (20) the main difference is that instead of summing the energy requirement of the whole t^* days, we try to meet the requirement for each time step. Since this section is the deterministic modeling we are assuming we know the load demand of our critical infrastructure in each time interval.

Maximum volume limit constraint (21) is also the same except the fact that now we have to sum up the total energy of each time step to find the space taken by each storage. Equation (22) is to consider response time of the storage systems.

Most storage systems have a minimum up-time, meaning once they have been turned on they should operate for a certain amount of time before shutting down. Equation (23) is to formulate the required up-time of storages. The right-hand side of the equation will be 1 only when the storage has been started and the left-hand side is to make sure the storage system will work for the required amount of time.

Constraint (24) is to make sure if a storage system is on it should discharge not less than the minimum discharge rate and not more than the demand load at time t.

Equations (25,26) are to consider ramp rate limitations of ESSs.

3.5 Results: Case study

MATLAB has been used for simulating this model with historical data of a hospital. Also, MATLAB package Yalmip has been used for optimization. The results for recovery process are plotted below. In the tested results t* of 3 days which is equal to 72 hours was considered.

We considered four most used and common energy storage systems in our case study so that each of which vary in the characteristics that are important in decision making of our model.

For instance, Pumped Hydro Storage (PHS) has a very low installation cost but also very low energy density as it requires huge amount of land and water. On the other hand, Lithium-ion batteries have high installation cost and high energy density so that we can say these two are ends of a spectrum. Flow batteries (VRB) and Compressed Air Energy Storage (CAES) stand in between with moderate energy densities and installation costs.

Other than these two critical characteristics, other features like storage efficiency, rated capacity and … are also very different as well. For instance, despite the fact that CAES has a low installation cost but higher energy density compared to PHS, it has a lower energy density which makes it quite difficult to choose between them. This is main reason each infrastructure would best work during disasters with different EESs configurations.

The data used for simulating the model is the hourly load profile data for a hospital based on the U.S. Department of Energy (DOE) commercial reference buildings. The U.S. Department of Energy has commercial reference buildings which is available online and can be used for energy modeling studies. There are 16 building types that represent approximately 70% of the commercial buildings in the U.S. and hospital is one of the reference buildings. Moreover, 16 climate zones have been used to create the reference buildings presented by DOE which represent all U.S. climate zones. The data presented is for a hospital with floor area 241,351 ft^2 and 5 number of floors located in New Jersey [26, 27].

The plot for illustrating the variation in electrical demand of the hospital we are studying with respect to time, known as the load curve, is shown in figure 11. The daily load shape for one year of this hospital (24 hours each day) consists of 365 curves shows a pattern which can be explained by peak hours from hour 10^{th} to 18^{th} and a general variation in the curves possibly affected by seasonality. Usually the demand is comparatively higher during summers than winters. In fact, electrical load curve dependents on large number of factors i.e. weather condition, geographical diversity, sunrise and sunset times and seasonal diversity.

Despite the fact that variation in load curves are pretty high, in our study we considered all the data we have for the whole year to find a distribution for the demand load and did not consider seasonality since we should be prepared for a blackout during any time.

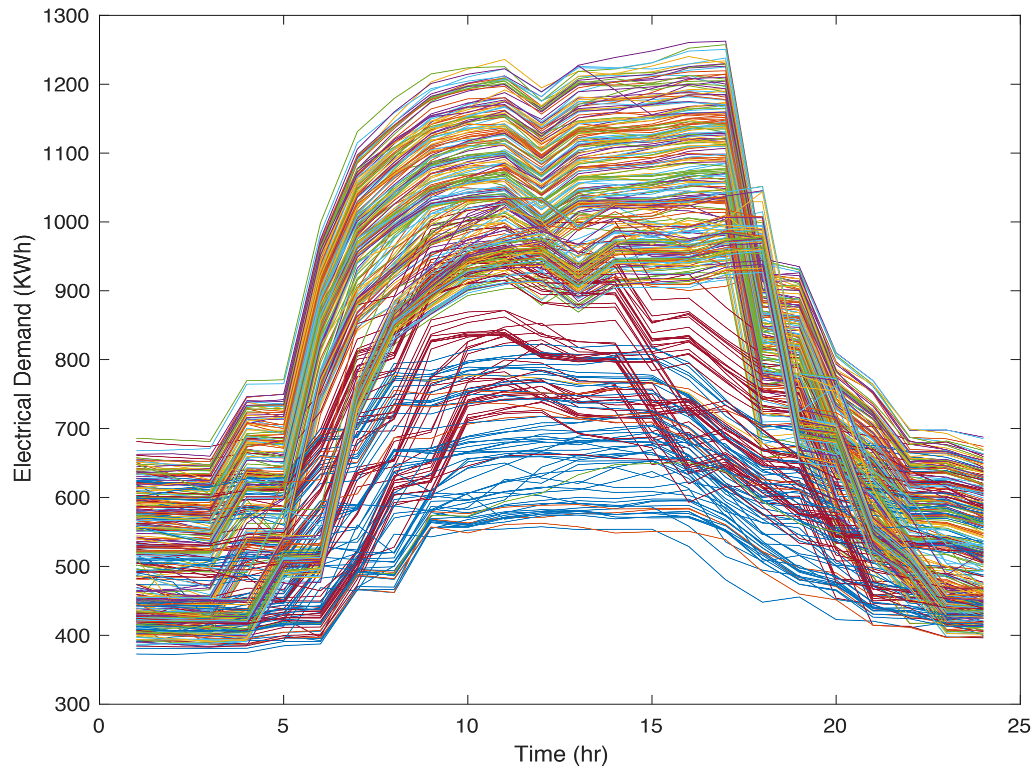

Figure 11 - Demand load for one year

We assumed 70 percent recovery of the system is required throughout the whole time after the disaster (until the main grid is back). In this way, 70 percent of the infrastructure which is mainly the critical loads within the system should be up during the disruption time. The figure below shows a sample of the estimated load curve and the 70% required demand to be met. As you can see it is a daily load curve from hour 1 to 24.

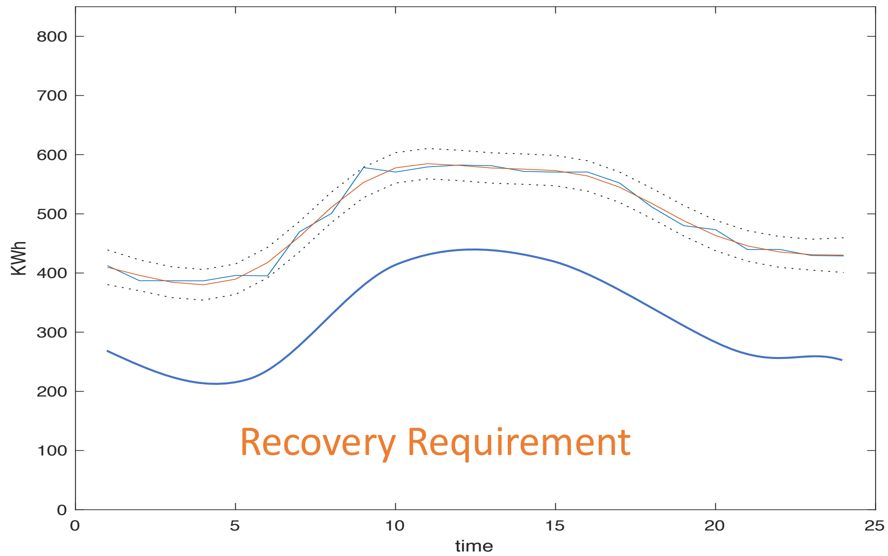

Figure 12 - required reliability level of demand

Considering all above information, the optimal configuration and sizing of ESSs would vary a lot based on size of the infrastructure, available space, budget limitation and so on. Here we show the results for this particular infrastructure by insisting on some constraints while relaxing others to show different configurations and their effect on the whole system. We plot the histogram of the demand load to see its behavior and how it can be similar to a known distribution, similar to most real-life data structures, we see that it does not look like a particular distribution (figure). In this regard, we will use the kernel density estimator.

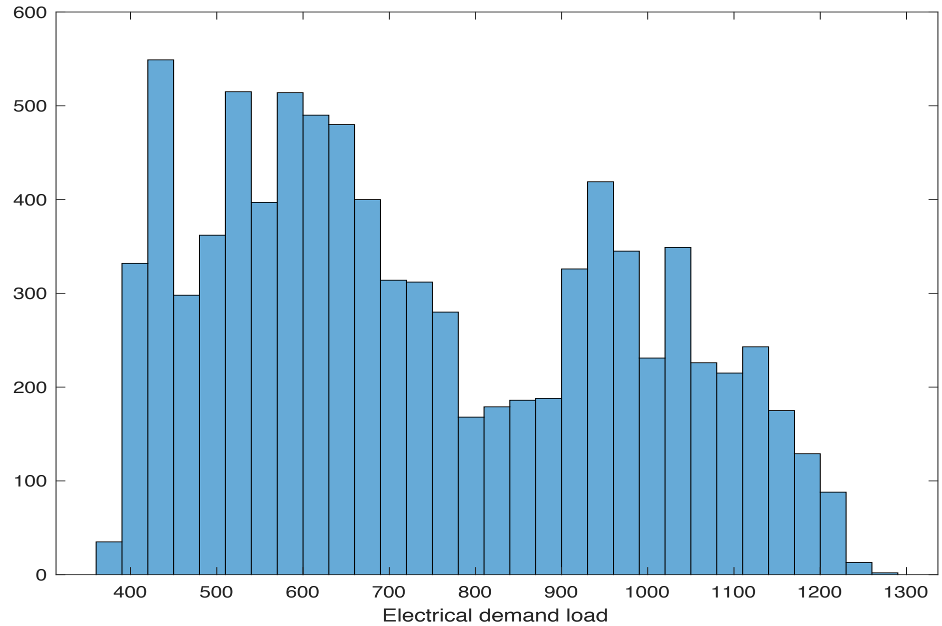

Figure 13 - Demand load histogram

In this section, first we will go through the results for the deterministic case and then stochastic case. We will discuss the optimum capacity modeling of the ESS's for the hospital and then the scheduling of the ESS's based on the determined capacities.

The energy densities, efficacies of each storage system and also installation costs play an important role in required capacity estimation. Going over the literature we assumed the following quantities for these storages [37].

Table 5 - ESS's properties used

Storage type	Storage efficiency	Energy density(Kwh/L)	Cost ($/Kwh)
Pumped Hydro	0.87	1/1000	50
Lithium battery	0.85	300/1000	1000
Vanadium redox battery	0.8	30/1000	500
Compressed Air	0.75	4.5/1000	250

In figure below the results for different scenarios are shown; a comparative figure in which the available space changes from 200 m^3 (which is the minimum space for a feasible solution here) and goes up by 100 m^3 each step until 40,000 m^3. s assumed for each storage type by going through literature is as following:

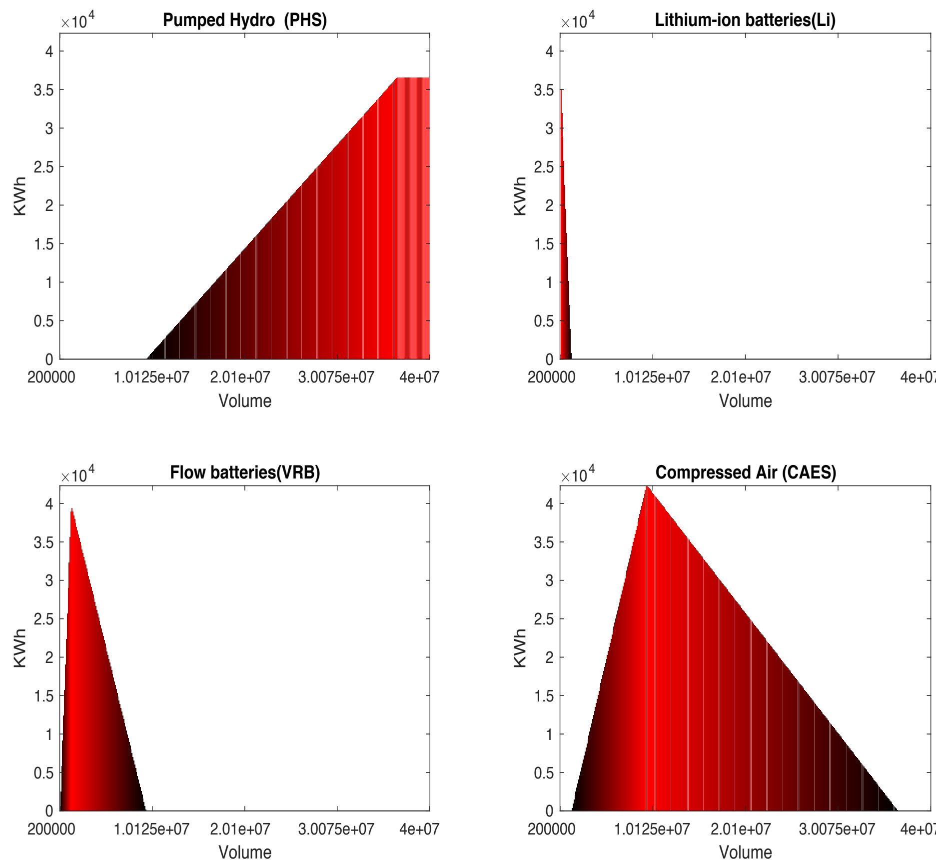

Figure 14 - ESSs optimal capacities for different volume availability

This figure illustrates that when we have little space, Lithium-ion batteries are the best choice but as the space increases combinations of Lithium-ion batteries and Flow batteries is more reasonable since installation cost of Flow batteries is lower and this is a cost minimization. And this trend goes on until using Flow batteries does not make sense and Compressed Air Energy Storage replaces it completely. As the point where, available volume reaches 10,000 m^3, using Compressed Air decreases and Pumped Hydro Storage is more convenient instead. Finally, when we have large enough space, Pumped Hydro will be used alone.

It would be useful to see the cost change as the available volume changes. Figure below shows the gradual decrease in cost as the space increase. The sudden changes in the slope are for specific volume units that the storage design changes; meaning that one storage is dropped from the optimal ones and another one becomes feasible and optimum based on the available volume.

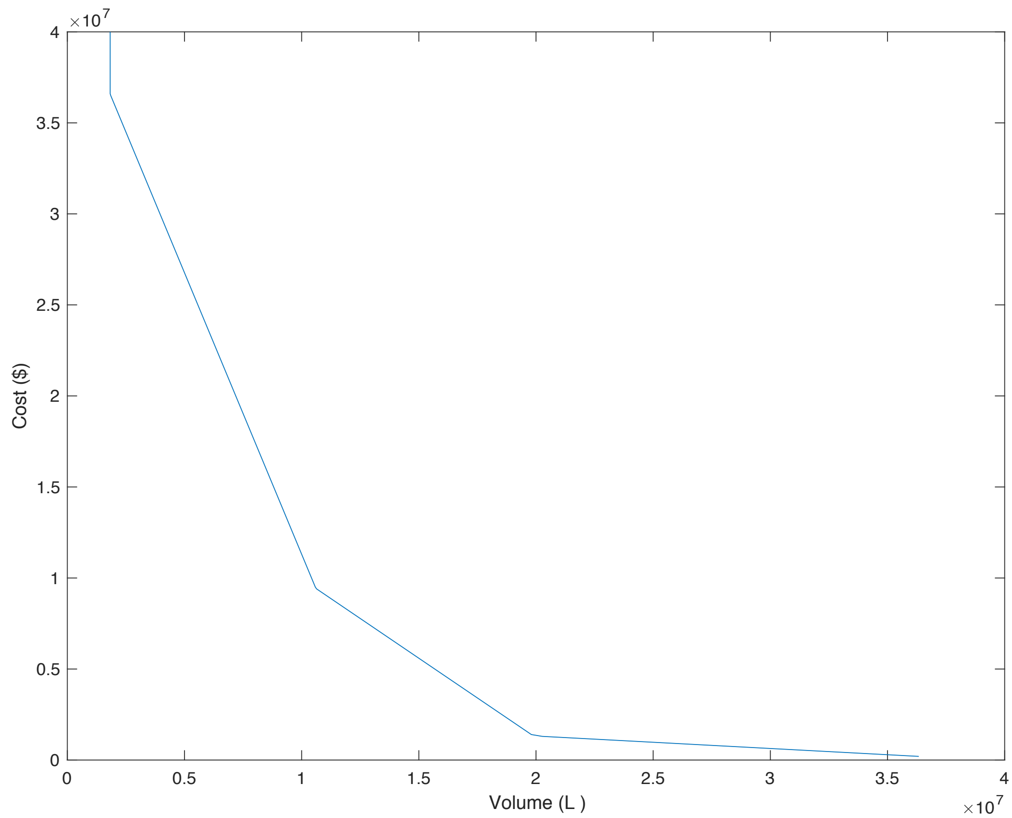

Figure 15 - cost versus volume availability

As mentioned before, available volume at the infrastructure is among one of the factors that affect the optimal configuration of ESSs. Another important parameter is the reliability level we want for our system. Now if we consider a fix value for volume, we can observe the design (or capacity) change with respect to different reliability level. For instance, consider available space at the hospital under study is 10,000,000 (L) (V^{*}= 10,000 m^3). The figure below shows different designs of the four ESSs while reliability level changes from 70% to 100%. Meaning how will the optimal design for our infrastructure change if we want to satisfy 70% recovery of the total demand versus 80%, 90% and up until 100% recovery for demand satisfaction.

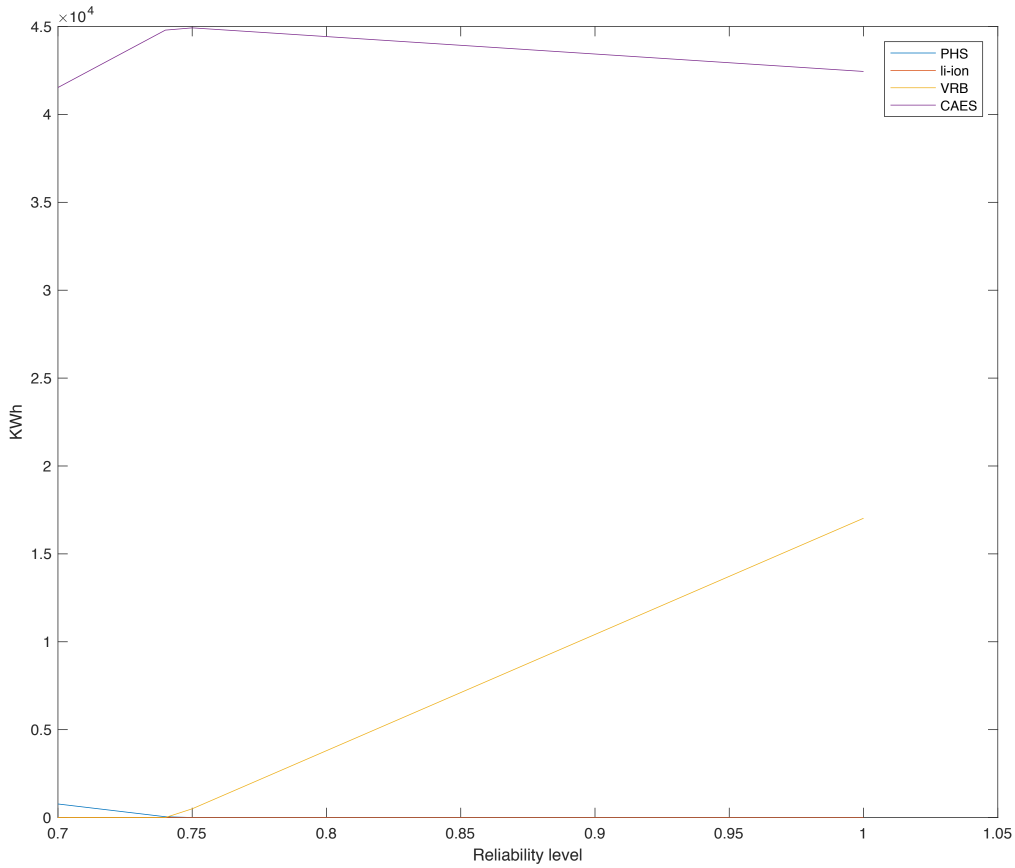

Figure 16 - ESSs capacities for different reliability levels

As the reliability level for demand requirement goes up the cost (objective function in our problem) will also go up. The figure below shows once you change reliability level from 70% to 100%, the cost associated with it will be twice as much as the 70% reliable system.

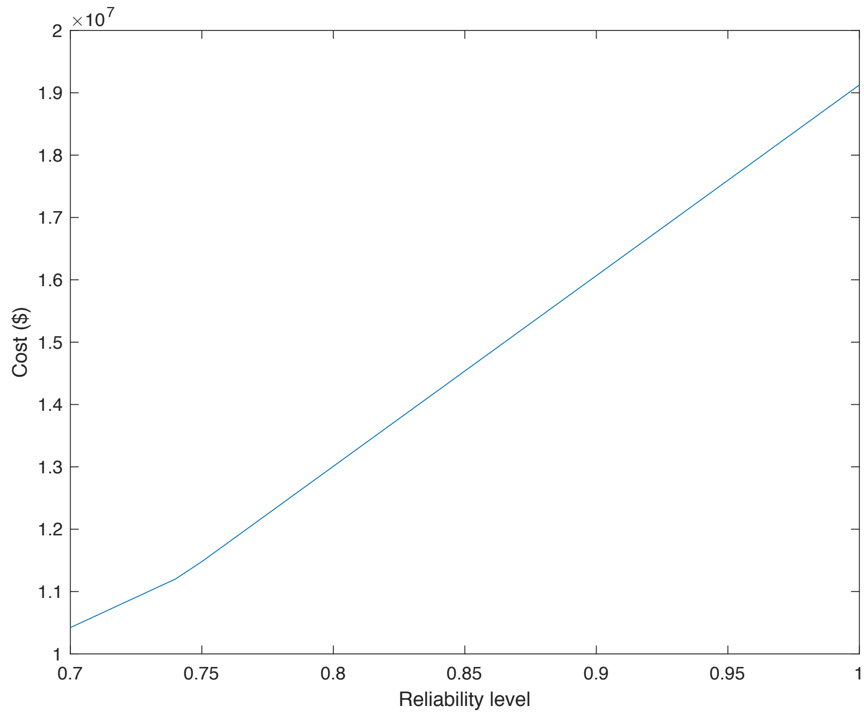

Figure 17 - cost versus reliability level

now if we want to look at the optimal scheduling of the ESS, sometimes the capacities and configuration is different than just finding the capacities. It is because of all the different constraints such as maximum discharge rate, minimum discharge rate or minimum up time. Consider the case above where we have maximum space V^{*}= 10,000 m^3, the optimal discharge of ESS is in the figure below.

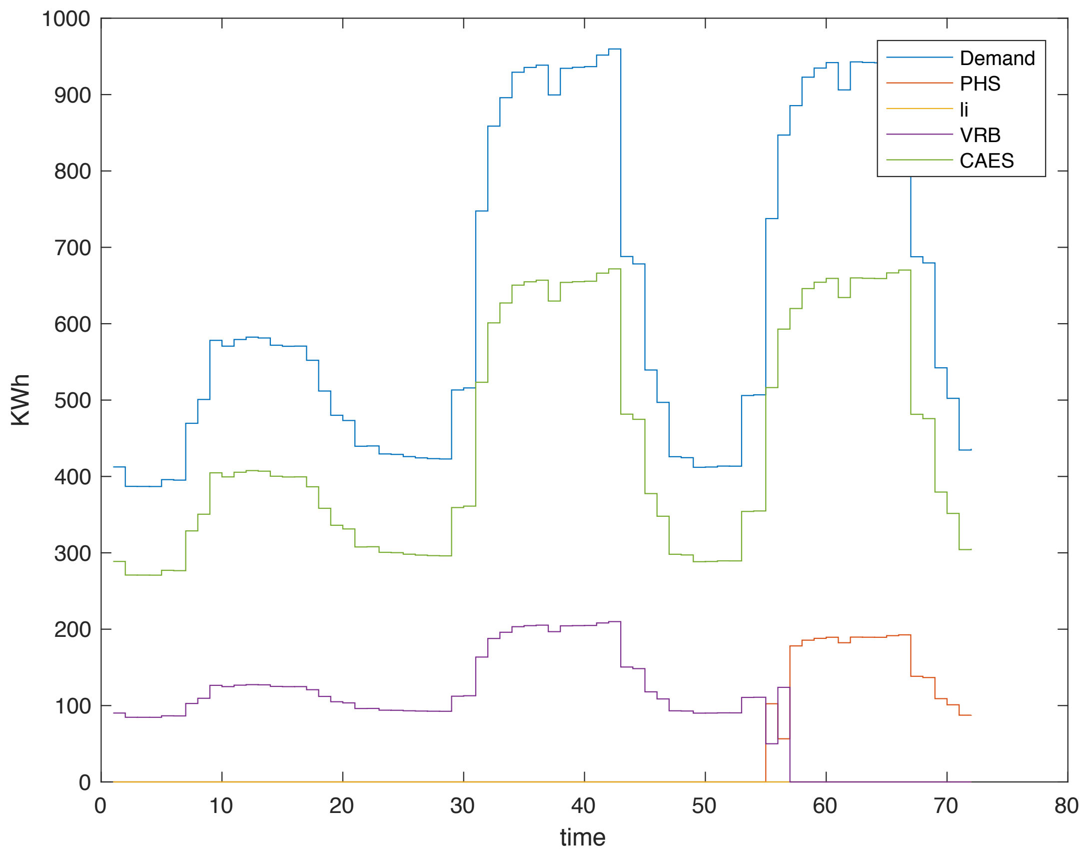

Figure 18 - ESSs optimal discharge in deterministic case

the optimal discharge of ESSs matters since important factors such as response time or black start is considered in the time dependent model and they are parameters that should be under attention during power outage. In figure below, we considered the same case above but with a response time of 5 hours for Compressed Air Storage. The difference can be noted. For the first 5 hours Pumped Hydro is used instead of Compressed Air.

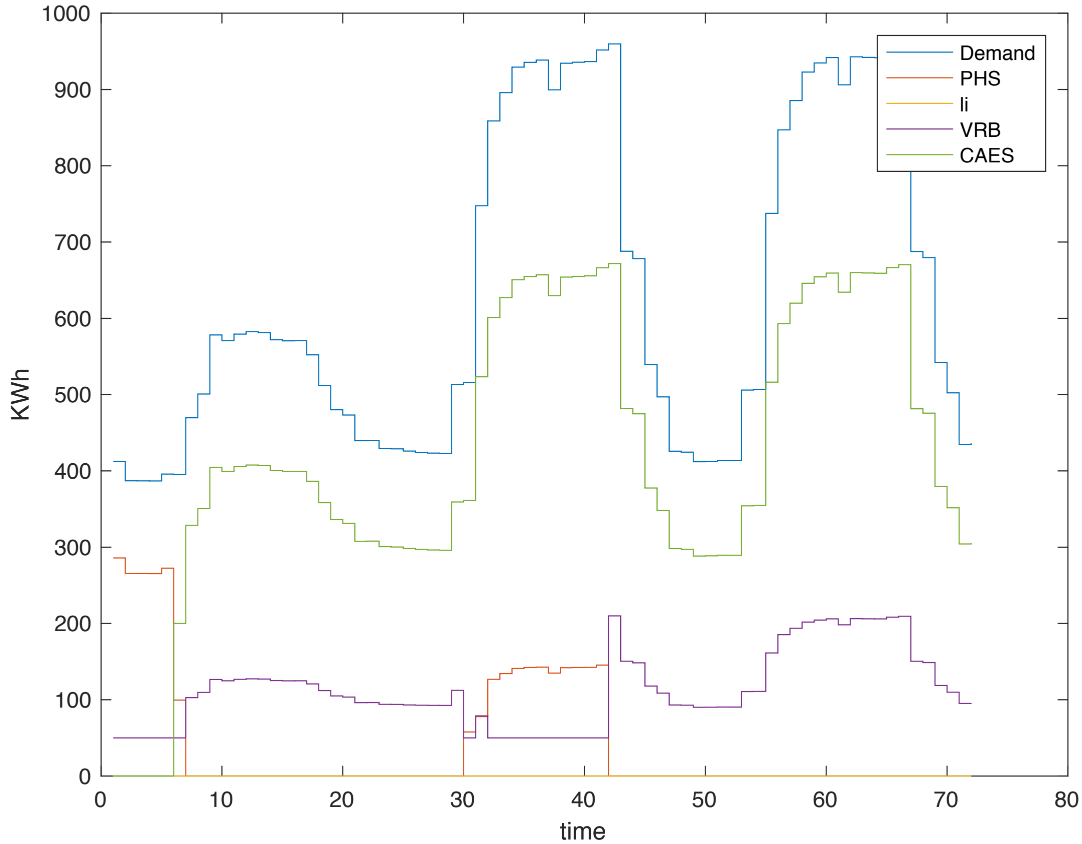

Figure 19 - ESSs optimal discharge with response time

4. Stochastic Model

In an event of natural disasters, due to the uncertainty of the event, actions should be taken before and after it. In this section, we will consider uncertainties associated with different aspects of this problem.

Chance constraint is a known way for mathematical modelling in stochastic programs with uncertainties. Generally, this methodology is adopted in decision making based on incomplete information about random effects of different parameters in the problem. Many methods exists for considering uncertainty in your optimization model [38],but the main idea here for us is chance-constrained programming which is used to assume certain reliability levels for random constraints. Therefore, it can be used to model systems reliability.

This methodology has many applications in which planning or designing reliability-constrained systems that need to be modeled as an optimization problem with probabilistic constraints which is a very common situation in optimization models in engineering applications.

Likewise, in designing and scheduling energy storage systems, we need to consider the uncertainty in electrical demand.

Chance-constrained optimization was first introduced by Charnes and Cooper (1959) [39], [40]. In literature, there are two types of chance constraints; individual and joint. Here we will only talk about individual chance constraint.

Chance constrained optimization models are commonly constraints with right hand side uncertainty which are required to be satisfied with a presumed probability threshold called confidence level. In other words, chance constraints (CCs) allows us to define a confidence level or reliability level of satisfying constraints in an optimization model. In this way, the solution to the problem satisfies the constraints with at least a given level of probability for all possible scenarios. Simple format would be:

$P\{g(x) \geq \xi\} \geq 1 - \alpha$ (27)

where g(x) is the decision variable function, ξ is the random variable, $1 - \alpha$ is the confidence level (here for us reliability level), and α is the risk level.

The Complexities of CCs such as convexity of the optimization problem have been investigated by Prekopa [41]–[44]. In particular, it has been shown that if the random variable is log-concave (in our case normal / Gaussian) and g(x) function is concave (in our case linear), then the chance constraint can be reformulated algebraically. It is beyond the scope of our research study to provide a full literature review of the theory and solution methods for CCs and their application [45]–[47].

Furthermore, we can say that in stochastic programming the probability distribution of the random parameters is usually unknown, but we can estimate it from historical data.

Here we use a data-driven approach to solve the chance constraint optimization with right-hand side uncertainty. The approach consists of using kernel density estimate to approximate unknown probability distribution of the electrical demand. This technique consists in approximating the probability density function (PDF) of a random variable with unknown distribution from a given sample. Kernel Density Estimation is a nonparametric statistical method that do not require to specify functional forms for random variables. Other approaches such as Gene Expression Programming (GEP) or Genetic Programming (GP) approach has also been used by researchers for non-parametric prediction in energy reserve and consumption [48], [49] .

We will use the historical data for the random variable in the optimization model (uncertain demand) to find the cumulative distribution function and the quantile function and then solve the chance constrained problem with the Monte Carlo method. Monte Carlo algorithm consists of sampling variables and parameters of a problem in order to get numerical results. The general reformulating would as follow:

$Min \sum_{j=1}^{n} c_j . x_j$ (28)

subject to:

considering $\tilde{b}i \sim Fi$

$P\{ \sum_{j=1}^{n} a_{ij} x_j \geq \tilde{b}_j \} \geq \alpha_j \quad for\ i = 1 \ldots m$ (29) $\rightarrow \sum_{j=1}^{n} a_{ij} x_j \geq Fi^{-1}(\alpha_j)$ (30)

4.1 Model Assumptions

1. Since in power outages, the time connection to the main grid (maximum time allowance t^*) is back is uncertain so we consider it as a random variable with a certain distribution in the following work.
2. Total amount of demand load is usually stochastic especially in case of a disaster it can vary from normal times pretty much. In this section, we find an estimation for the demand load shape.

4.2 Variables and Parameters

t^*: maximum number of days for recovery

L_j: demand load of service j (kWh)

l_{ij}: energy discharged from storage i to service j (kWh)

xi: total capacity needed for storage i (kWh)

S_{min_i}: minimum capacity of storage i (kWh)

$S_{max\ i}$: maximum capacity of storage i (kWh)

w_j: weight associated to service j

c_i: storage i installation cost ($/kWh)

Ys_i: storage i efficiency

Re: recovery level (%)

D: demand load energy (kWh)

V_i: storage i energy density (L)

V^*: maximum space (volume) available (Wh/L)

η : risk level

Z_i: binary variable to determine the status of the i_{th} ESS

CS_i: the starting-up cost for storage i.

tr_i: response time of storage i

D_{up}: ramp-up rate limit

D_{down}: ramp-down rate limit

4.3 Mathematical modeling

As mentioned, in order to model the uncertainty of the demand associated with our problem, we consider demand (*D*) as random variable and fit historical data we have for it to find the estimated distribution.

Here we consider disruption time ($t*$) to follow normal distribution with known mean and standard deviation but for actual determination of this matter, further data and investigation is needed. Since we couldn't find enough accurate data about maximum time until electrical power is back from main grid to different infrastructures after the blackout, we just simply assumed a certain mean and standard deviation for it.

$$Minimze \sum_{i=1}^{k} x_i . c_i \ \ (31)$$

subject to:

$$Pr\{\sum_{i=1}^{k} YS_i . x_i - \ Re. \sum_{t=1}^{t*} D(t) \geq 0 \} \geq 1 - \eta \ \ (32)$$

$$\sum_{i=1}^{k} x_i . \frac{1}{v_i} \leq V^* \ (33)$$

$$0 \leq \ x_i \leq \ Re. \sum_{t=1}^{t*} x_{de}(t) \ \ (34) \qquad for\ all\ i = 1\ to\ k$$

$$S_{min_i} \leq x_i \leq S_{max\ i} \qquad (35) \quad for\ all\ i = 1\ to\ k$$

Here same as the previous section we try to meet the demand for the summation of all 1-hour intervals during the disruption time but this time we are considering the demand to be met as confidence level to be unknown.

4.4 Time Dependency Modeling

As we have determined the capacity needed for each storage type considering demand as random variable in the previous step, now we can schedule for optimal discharge ESS's accordingly. This is a time-dependent optimization problem again like the time dependency modeling in chapter 2 but with respect to the uncertainty in electrical demand and maximum time allowance that the infrastructure is disconnected from the main grid.

Consequently, constraints and variables related to time management will be added. Variables to determine staring up and shutting down ESSs and constraints for response time, ramp rate, minimum up time are added too.

As mentioned, in order to model the uncertainty of the demand associated with our problem, we consider demand (*D*) as random variable to fit historical data we have for it and find the estimated distribution and normal distribution for *t** as the maximum time of the disruption.

$$minimze \sum_{i=1}^{k}\sum_{t=1}^{t*} x_i(t).\ C_i + \sum_{i=1}^{t*} Z_i\,(t)\,.\,CS_i \quad (36)$$

subject to:

$$Pr\{\sum_{i=1}^{k} YS_i.\,x_i(t) - \ Re.\,D(t) \geq 0\,\} \geq 1-\eta\ . \quad (37) \qquad for\ t = 1\ to\ t*$$

$$\sum_{i=1}^{k}\sum_{t=1}^{t*} x_i(t).\frac{1}{v_i} \leq v * (38)$$

$$x_i(t) = \ 0 \qquad for\ t = 1\ to\ t_r \quad (39)$$

$$y_i(range\,) \geq \ y_i(t) - \ y_i(\,t-1) \quad for\ range = t \text{ to} \min\{t *, t + minup(i) - 1\}\,(40)$$

$$Ch_{min\ i}.\,y_i\,(t) \leq \ x_i(t) \leq \ Re.\,D(t).\,y_i(t) \quad for\ all\ i = 1\ to\ k \quad (41)$$

$$x_i(t-1) - \ x_i(t) \leq D_{down_i} \qquad for\ all\ i = 1\ to\ k \quad (42)$$

$$x_i(t) - x_i(t-1) \leq D_{up_i} \quad for\ all\ i = 1\ to\ k \qquad (43)$$

The main difference here would be that the decision variables are for each time step so that we have i times ti* decision variables. An on-off binary variable (yi) has been defined in order to find start-ups and shut-downs.

In the objective function a second part is added since there is usually a starting-up cost associated with ESSs. Z is a binary indicator (defined by yi) which is 1 when system has started up at time t and 0 otherwise. And CS(i) is the starting-up cost for storage i.

In the energy requirement constraint (37) the main difference is that instead of summing the energy requirement of the whole t* days, we try to meet the requirement for each time step. Since this section is the deterministic modeling we are assuming we know the load demand of our critical infrastructure in each time interval. Equation (37) should be true in each time step, meaning that we try to meet the electrical demand in each time interval of 1 hour with respect to the uncertainty in demand and disruption time

Maximum volume limit constraint (38) is also the same except the fact that now we have to sum up the total energy of each time step to find the space taken by each storage. Equation (39) is to consider response time of the storage systems.

Most storage systems have a minimum up-time, meaning once they have been turned on they should operate for a certain amount of time before shutting down. Equation (40) is to formulate the required up-time of storages. The right-hand side of the equation will be 1 only when the storage has been started and the left-hand side is to make sure the storage system will work for the required amount of time.

Constraint (41) is to make sure if a storage system is on it should discharge not less than the minimum discharge rate and not more than the demand load at time t.

Equations (42,43) are to consider ramp rate limitations of ESSs.

4.5 Results

In figure below the results for different scenarios (with same characteristics as the one mentioned in deterministic case) are shown; a comparative figure in which the available space changes from 200 m^3 and goes up by 100 m^3 each step until 40,000 m^3.

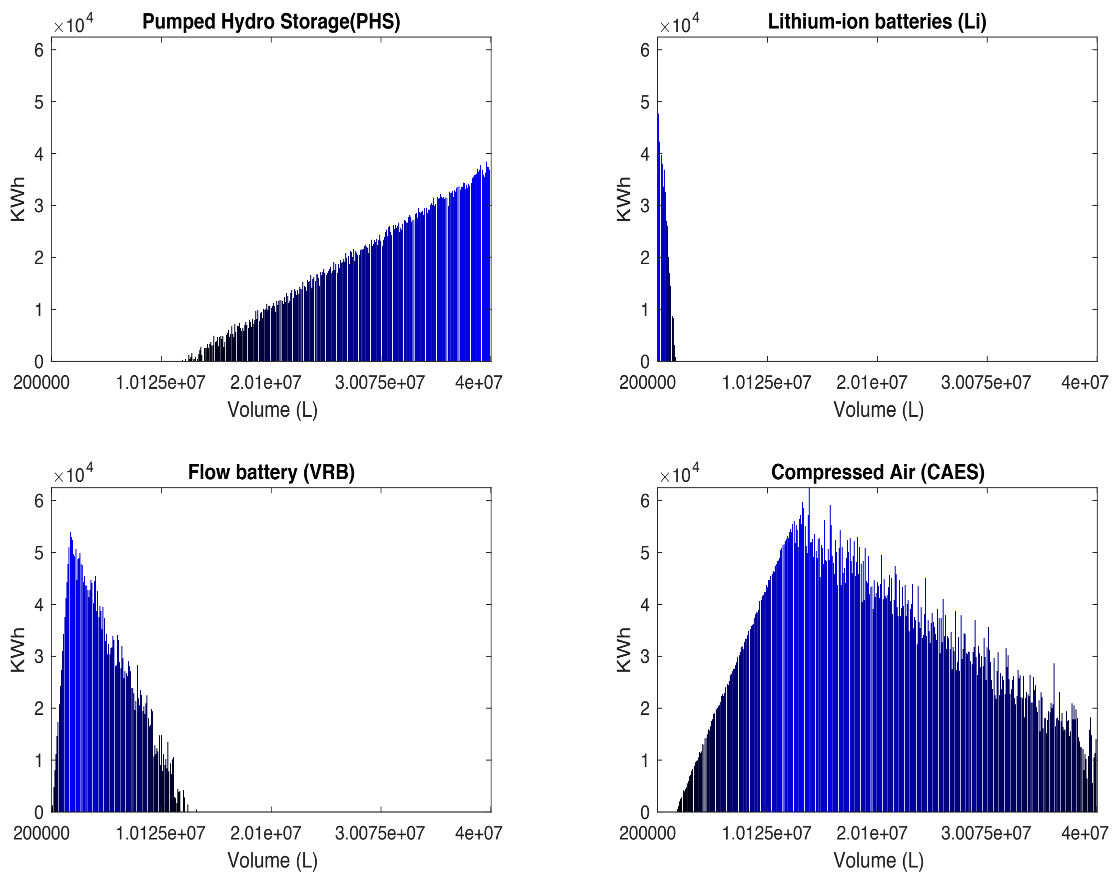

Figure 20 - ESS capacities for different volume in uncertain case

As the figure above shows, the stochastic model has a lot of variation. The same thing goes for the cost (figure 21). this variation can be explained by the uncertainty in considered variables of the model.

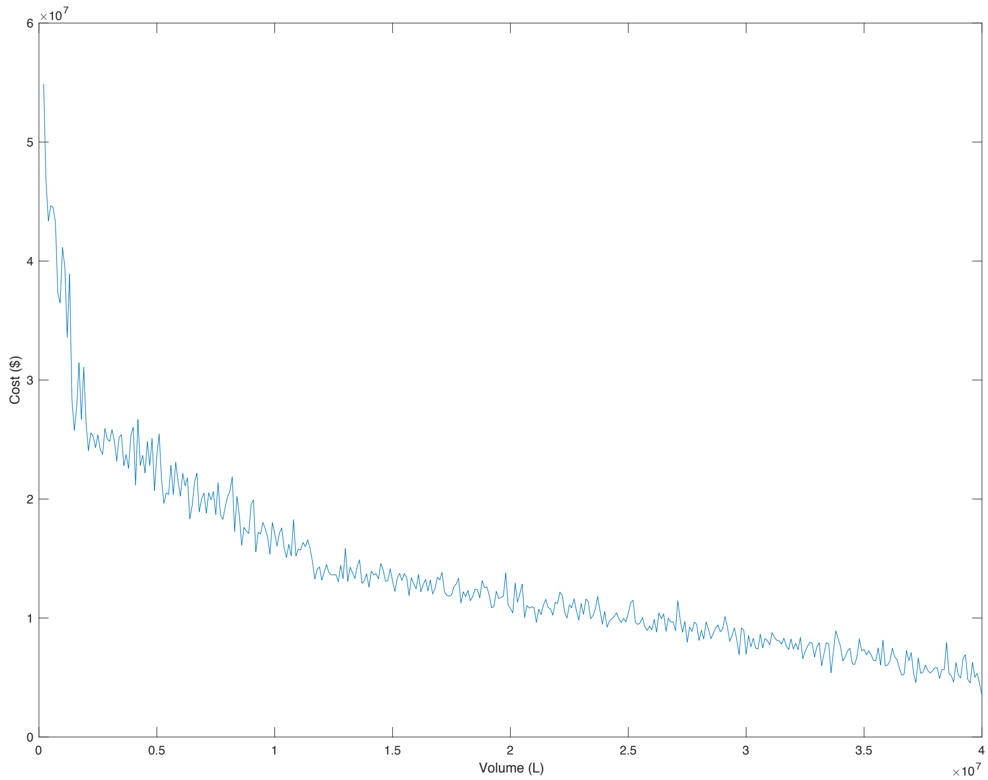

Figure 21 - cost versus volume in uncertain case

The optimal discharge scheduling of ESSs can also be evaluated in the uncertain case, but because of the variations in the demand it does not reveal any important information. To be more specific, in the stochastic case the demand is considered a random variable from a certain distribution and each time we run the simulation new random variables will be generated randomly. In this regard, the timely schedule of discharge varies each time and does not contain new information. If we consider the same scenario we had in deterministic case with the maximum space $V^*= 10{,}000\ m^3$ but this time we set a very low limit of 2 kwh for ramp rate (equations 42 and 43) to avoid these variations on discharge scheduling. The optimal discharge of ESS is in the figure below.

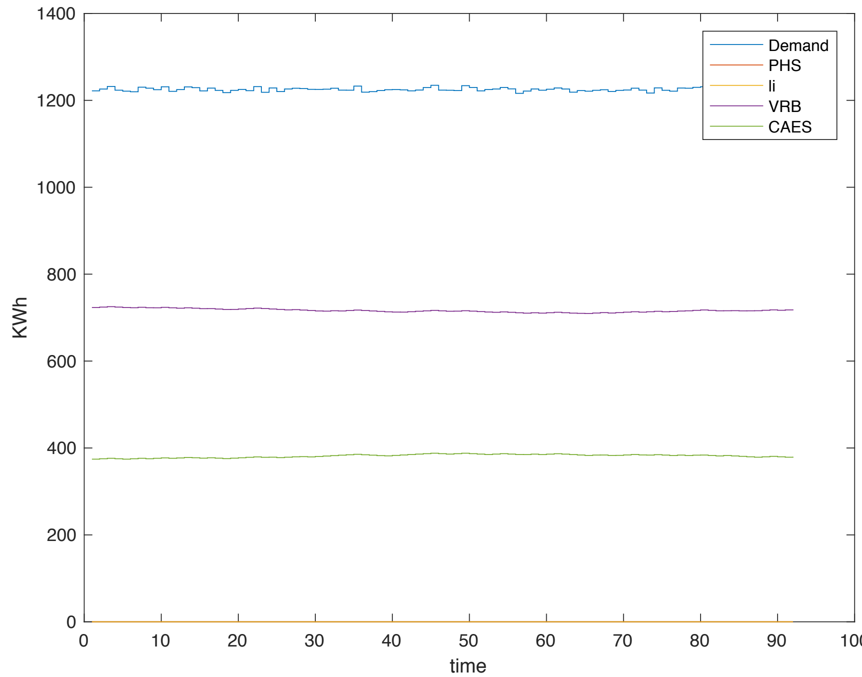

Figure 22 - ESSs optimal discharge in uncertain case

4.6 Comparison

In this section, the comparison between stochastic case versus deterministic case will be presented to show the importance of the uncertainties associated in the problem. In the uncertainty modeling we considered our confidence level to be 0.99 meaning that the demand will definitely be much more than the deterministic case.

now we can compare the two models of stochastic and deterministic and see the uncertainty affecting decision making. Figure below shows this comparison. The blue plots are for the stochastic case and the red ones are for deterministic case.

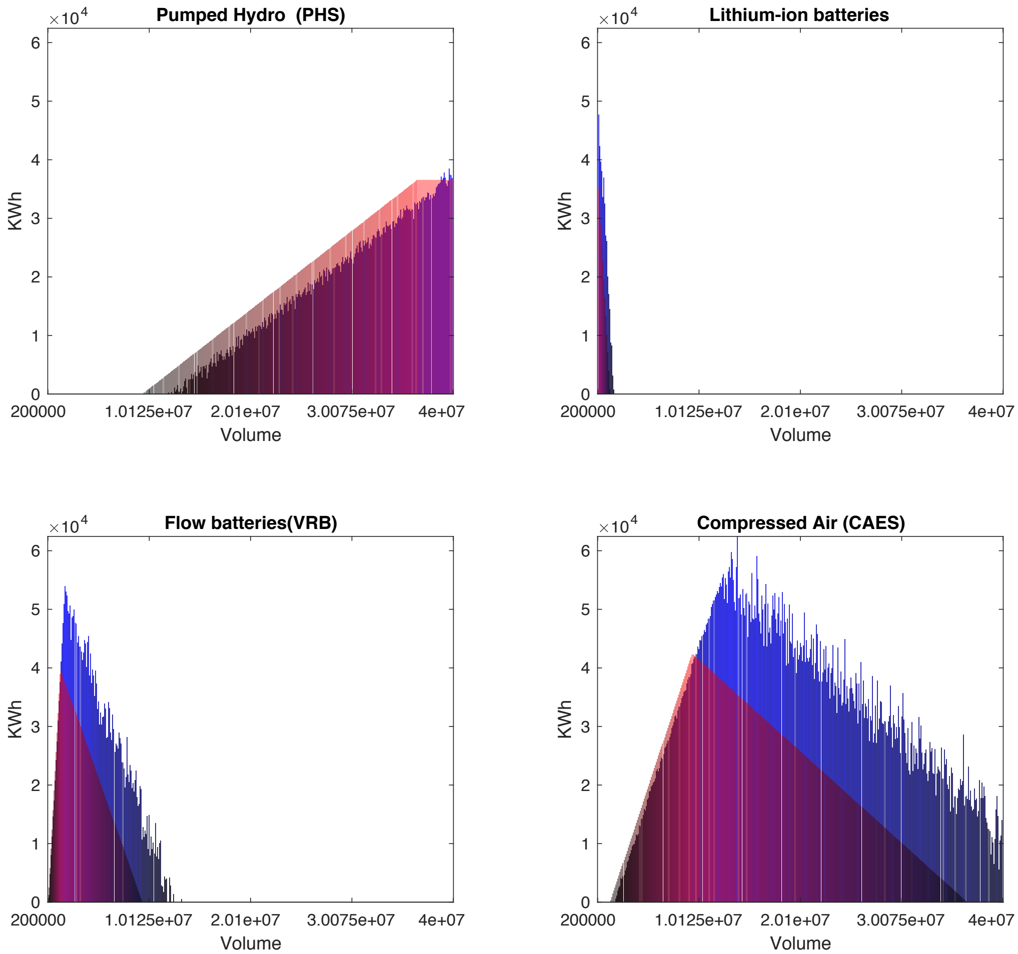

Figure 23 - comparison of ESSs capacities in deterministic and uncertain cases

5. Conclusions

Although the number of natural disasters such as hurricanes are increasing each year because of the global warming and environmental causes, however the reliability of infrastructures can be improved by certain actions and plans ahead. In this study, we came up with a methodology for enhancing the resiliency of infrastructures during power outage by implementing energy storage systems and evaluating different design scenarios considering reliability. We defined reliability of the infrastructure in terms of meeting the critical demand load necessary for the facility to function at a required level with is also defined by the vital services that the infrastructure has.

In modeling this problem, first we learned about critical infrastructures (CI) and how their resiliency is defined in different studies. Going through the 16 most critical infrastructures, we evaluated different aspects of them and different causes that effect their reliability in order to consider them in our modeling. Certainly, for a data center factor "time" is the most important matter affecting the functionality and consequently the reliability of the facility. On the other hand, other facilities like hospital may depend on "time" in milliseconds as a data center do.

Knowing the aspects of critical infrastructure, we evaluated different properties of energy storage systems to find the important and real-life characteristics that should be in our model. Properties such as energy densities, installation costs, response times, etc. are among the important ones that affect decision making for each infrastructure.

After understanding both the critical infrastructure and energy storages, we came up with a methodology that includes the important features of both ESSs and infrastructure in the model and come up with solutions based on those features. The solutions consist the optimal set of energy storage systems and the capacities need for the specific infrastructure that would satisfy the electrical demand during blackouts. The modeling part is divided in two parts; in the first part, we considered everything including the demand to be deterministic which might be the case in some situations. However, in most real-life situations many parameters affecting the problem have uncertainties associated with them. In our case, when it comes to natural disasters and power outages the probabilities of having unexpected and varying behavior in factors of the problem increases. In this regard, in the second part of modeling we considered uncertainties of demand load during power outages and also the duration of the outage.

After assessing the capacities need and the optimal configuration, we presented a time dependent model that considers other properties that might be important to some facilities. In this model, we have the optimal discharge scheduling of different energy storage systems based on the requirements of the critical infrastructure and their load demand.

At last, to present the model we considered a hospital as our case study and used the online available data for it. We evaluated this hospital in deterministic and stochastic case using our model and showed different results based on the infrastructure's requirements and properties. We considered four main infrastructure that are widely used and have significate differences from each other in some properties.

References

[1] IEA; OECD, "World Energy Energy," 2012.
[2] B. Oral and F. Dönmez, "The impacts of natural disasters on power systems: Anatomy of the marmara earthquake blackout," *Acta Polytech. Hungarica*, vol. 7, no. 2, pp. 107–118, 2010.
[3] LBNL, "Assessing changes in the reliability of the U.S. electric power system," p. August, 2015.
[4] N. Yousefi and D. W. Coit, "DYNAMIC INSPECTION PLANNING FOR SYSTEMS WITH INDIVIDUALLY REPAIRABLE COMPONENTS."
[5] N. Yousefi and D. W. Coit, "RELIABILITY ANALYSIS OF SYSTEMS SUBJECT TO MUTUALLY DEPENDENT COMPETING FAILURE PROCESSES WITH CHANGING DEGRADATION RATE."
[6] M. B. Johnson, "i. Table of Contents," *MEAUS Diss.*, pp. vi–viii, 2000.
[7] M. Diakakis, G. Deligiannakis, K. Katsetsiadou, and E. Lekkas, "Hurricane Sandy mortality in the Caribbean and continental North America," *Disaster Prev. Manag.*, vol. 24, no. 1, pp. 132–148, 2015.
[8] Eaton, "Blackout Tracker: United States Annual Report 2015," *Eat. Power Qual. Report, Power Outage Annu. Rep.*, vol. 2, p. 73, 2015.
[9] N. Yousefi, D. W. Coit, S. Song, and Q. Feng, "Optimization of on-condition thresholds for a system of degrading components with competing dependent failure processes," *Reliab. Eng. Syst. Saf.*, no. January 2018, p. 106547, 2019.
[10] Ponemon Institute LLC, "2016 Cost of Data Center Outages," *Ponemon Inst. LLC*, no. January, p. 21, 2016.
[11] C. Klinger, O. Landeg, and V. Murray, "Power Outages, Extreme Events and Health: A Systematic Review of the Literature from 2011-2012," *PLoS Curr.*, no. JAN, 2014.
[12] J. Moteff and P. Parfomak, "Critical Infrastructure and Key Assets: Definition and Identification," *Time*, p. 19, 2004.
[13] NIAC, "Crticial Infrastructure Resilience Final Report and Recommendations," 2009.
[14] J. Zhou, N. Huang, D. W. Coit, and F. A. Felder, "Combined effects of load dynamics and dependence clusters on cascading failures in network systems," *Reliab. Eng. Syst. Saf.*, vol. 170, no. February 2017, pp. 116–126, 2018.
[15] J. Zhou, N. Huang, X. Sun, L. Xing, and S. Zhang, "Strategia realokacji zasobów sieciowych oparta o udoskonalony model przepustowości-obciążenia," *Eksploat. i Niezawodn.*, vol. 17, no. 4, pp. 487–495, 2015.
[16] "Infrastructure Interdependencies and Resilience," *Chile Earthq. 2010*, pp. 365–386, 2013.
[17] S. Citation, *Terrorism and the electric power delivery system*. 2012.
[18] M. Bruneau *et al.*, "A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities," *Earthq. Spectra*, vol. 19, no. 4, pp. 733–752, 2003.
[19] ECOFYS, "Energy Storage Opportunities and Challenges, a Wst Coast Perspective White Paper," p. 61, 2014.
[20] S. D. Nazemi, K. Mahani, A. Ghofrani, B. E. Kose, and M. A. Jafari, "Techno-

economic analysis and optimization of a microgrid considering demand-side management," 2019.

[21] A. Ghofrani, S. D. Nazemi, and M. A. Jafari, "HVAC load synchronization in smart building communities," *Sustain. Cities Soc.*, vol. 51, no. September 2018, p. 101741, 2019.

[22] S. Tsianikas, J. Zhou, N. Yousefi, and D. W. Coit, "Battery selection for optimal grid-outage resilient photovoltaic and battery systems," *arXiv Prepr. arXiv1901.11389*, pp. 10–15, 2019.

[23] P. Denholm, E. Ela, B. Kirby, and M. Milligan, "The role of energy storage with renewable electricity generation," *Energy Storage Issues Appl.*, no. January, pp. 1–58, 2011.

[24] S. D. Nazemi and M. Boroushaki, "Design, analysis and optimization of a solar dish/stirling system," *Int. J. Renew. Energy Dev.*, vol. 5, no. 1, pp. 33–42, 2016.

[25] K. Ardani, E. O'Shaughnessy, R. Fu, C. Mcclurg, J. Huneycutt, and R. Margolis, "Installed Cost Benchmarks and Deployment Barriers for Residential Solar Photovoltaics with Energy Storage: Q1 2016," *NREL Tech. Rep.*, no. February 2017, 2017.

[26] P. Sharifi, A. Banerjee, and M. J. Feizollahi, "Leveraging Owners' Flexibility in Smart Charge/Discharge Scheduling of Electric Vehicles to Support Renewable Energy Integration," pp. 1–18, 2019.

[27] M. Dahmardeh and Z. Xi, "State-of-charge uncertainty of lithium-ion battery packs considering the cell-to-cell variability," *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part B Mech. Eng.*, vol. 5, no. 2, pp. 1–9, 2019.

[28] Z. Xi, M. Dahmardeh, B. Xia, Y. Fu, and C. Mi, "Learning of Battery Model Bias for Effective State of Charge Estimation of Lithium-ion Batteries," *IEEE Trans. Veh. Technol.*, no. July, pp. 1–1, 2019.

[29] P. Policies and D. Visualization, "DOE Global Energy Storage Database The DOE Global Energy Storage Database provides free , up-to-date information on grid-connected energy storage projects and relevant state."

[30] U.S. Department of Energy, "Grid Energy Storage Report," no. December, p. 67, 2013.

[31] G. P. Cimellaro, A. M. Reinhorn, and M. Bruneau, "Framework for analytical quantification of disaster resilience," *Eng. Struct.*, vol. 32, no. 11, pp. 3639–3649, 2010.

[32] T. D. O. Rourke, S. Jeon, R. T. Eguchi, and C. K. Huyck, "Advanced GIS for Loss Estimation and Rapid Post-Earthquake Assessment of Building Damage," *Earthquake*, pp. 157–164, 1999.

[33] S. E. Chang and M. Shinozuka, "Measuring improvements in the disaster resilience of communities," *Earthq. Spectra*, vol. 20, no. 3, pp. 739–755, 2004.

[34] C. Nan and G. Sansavini, "A quantitative method for assessing resilience of interdependent infrastructures," *Reliab. Eng. Syst. Saf.*, vol. 157, pp. 35–53, 2017.

[35] United States Department of Energy, "Commercial Reference Buildings," *Http://Energy.Gov/Eere/Buildings/Commercial-Reference-Buildings*, p. accessed May 5, 2015, 2015.

[36] Office of Energy Efficiency & Renewable Energy (EERE), "Building Characteristics for Residential Hourly Load Data," *OpenEI.org*, p. 49246, 2015.

[37] X. Luo, J. Wang, M. Dooner, and J. Clarke, "Overview of current development in electrical energy storage technologies and the application potential in power system operation," *Appl. Energy*, vol. 137, pp. 511–536, 2015.

[38] M. Salari, N. Yousefi, and M. M. Asgary, "Cost Performance Estimation in Construction Projects Using Fuzzy Time Series," *Int. J. Inf. Technol. Proj. Manag.*, vol. 6, no. 1, pp. 66–75, 2015.

[39] M. Science, "Chance-Constrained Programming Author (s): A . Charnes and W . W . Cooper Reviewed work (s): Published by : INFORMS Stable URL : http://www.jstor.org/stable/2627476 .," vol. 6, no. 1, pp. 73–79, 2012.

[40] "Deterministic Equivalents for Optimizing and Satisficing under Chance Constraints Author (s): A . Charnes and W . W . Cooper Published by : INFORMS Stable URL : http://www.jstor.org/stable/168141 JSTOR is a not-for-profit service that helps scholars , r," vol. 11, no. 1, pp. 18–39, 2016.

[41] A. Prekopa, "R utcor R esearch R eport Programming Under Probabilistic Constraint and Maximizing a Probability Under Constraints Programming Under Probabilistic Constraint and Maximizing a Probability Under Constraints," 1993.

[42] A. Prékopa In Budapest, "Logarithmic concave measures with application to stochastic programming," *Acta Sci. Math.*, vol. 32, pp. 301–316, 1971.

[43] A. Prekopa and T. Szantai, "Flood Control Reservoir System Design Using Stochastic Programming.," *Math Progr. Study*, vol. 9, no. 9, pp. 138–151, 1978.

[44] A. Prékopa, S. Ganczer, I. Deák, and K. Patyi, "The STABIL stochastic programming model and its experimental application to the electrical energy sector of the Hungarian economy," *Stoch. Program.*, pp. 1–18, 1980.

[45] N. N. Dec, B. L. Miller, and H. M. Wagnert, "Chance Constrained Programming with Joint Constraints Author (s): Bruce L . Miller and Harvey M . Wagner All use subject to JSTOR Terms and Conditions CHANCE CONSTRAINED PROGRAMMING WITH JOINT CONSTRAINTS," vol. 13, no. 6, pp. 930–945, 2013.

[46] R. Henrion, "Metric regularity and quantitative stability in stochastic programs with probabilistic constraints," *Math. Program. Ser. B*, vol. 84, no. 1, pp. 55–88, 1999.

[47] W. Römisch and R. Schultz, "Distribution sensitivity for certain classes of chance-constrained models with application to power dispatch," *J. Optim. Theory Appl.*, vol. 71, no. 3, pp. 569–588, 1991.

[48] S. Hajirezaie, A. Hemmati-Sarapardeh, A. H. Mohammadi, M. Pournik, and A. Kamari, "A smooth model for the estimation of gas/vapor viscosity of hydrocarbon fluids," *J. Nat. Gas Sci. Eng.*, vol. 26, pp. 1452–1459, 2015.

[49] S. Hajirezaie, A. Pajouhandeh, A. Hemmati-Sarapardeh, M. Pournik, and B. Dabir, "Development of a robust model for prediction of under-saturated reservoir oil viscosity," *J. Mol. Liq.*, vol. 229, pp. 89–97, 2017.