Microgrid Optimal Scheduling and Risk Analysis

by
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DEDICATION

To the One Above,

For creating a world worth exploring.

To my parents Samira & Rashid,

For always offering me unconditional love and support.

Everything I’ve accomplished is because of the sacrifices you’ve made.

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ABSTRACT

Risk analysis is currently not quantified in microgrid resource scheduling optimization. This thesis proposes a conditional value at risk (cVaR) analysis on a disconnected residential microgrid with distributed energy resources (DER). We assume the infrastructure to set up an ad-hoc microgrid is already in place for a residential neighborhood with power sources such as PV, diesel, and battery generation. With this scenario in mind, we employ optimization using day-ahead scheduling to allocate various resources to match demand in scenarios where neighborhoods, especially residential, are disconnected from the overall grid such as in flooding, hurricanes, winter storms, or operational failures. These allocations are then analyzed through a cVaR algorithm to calculate the worst-case scenarios the microgrid would face with abnormally high demand. The goal is to provide an alternative framework to optimize power availability for priority customers and strengthen the overall grid against dips in power outside of normal operating considerations.

Natural disasters have been increasing in severity and length due to climate change. Additionally, the existing electric grid has been strained due to an increase in residential and commercial solar power, as well as other renewable systems and electric vehicles. This has created more reliability concerns for the overall health of the grid. It has also made it more difficult to provide consistent and reliable electricity especially when faced with large-scale disaster scenarios such as flooding, wildfires, hurricanes, or winter freezes.

The focus of this research will be taking in renewable energy sources from photovoltaic (PV) combined with diesel and Battery Energy Storage System (BESS)

while minimizing cost. This will allow for compensating on a distribution level for short-term usage in a residential microgrid configuration. Lastly, by utilizing existing infrastructure with a new energy management system, microgrids can be implemented to be for more resilient for new reliability challenges.

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NOMENCLATURE

D_{p_t} Priority customer demand defined as customers where electricity cannot be curtailed.

D_{e_t} Essential customer demand. Defined as residential customers whose electricity can be curtailed to manage load curtailment.

$D_{e_{c_t}}$ Essential customer curtailed. Defined as residential customers whose electricity is curtailed to manage load curtailment.

$D_{Net\ Load_t}$ Demand load of the system subtracted from any residential PV that is generated.

D_{Load_t} Demand total for all customers in microgrid.

P_{BESS_t} Power of the battery energy storage system.

P_{PV_t} Power value of photovoltaic residential solar panels.

P_{Di_t} Power output of diesel generator.

$P_{Di_{min}}$ Power output minimum for diesel generator.

$P_{Di_{max}}$ Power output maximum for diesel generator.

P_{Total_t} Power total available combining diesel, battery, and residential solar power.

$P^B_{D_{max}}$ The maximum discharge rate of the battery

$P^B_{D_t}$ The power rate at which battery is discharging from the system.

$P^B_{C_t}$ The power at which the battery is charging from the system.

$P^B_{C_{max}}$ The maximum charge rate of the battery.

$C_{batt,red}$ The additional price ($) of the battery cost when the battery state of charge is outside the green zone.

C_{fuel} Fuel cost ($/kW) of diesel generation.

$C_{B_{N_t}}$ Cost ($) of battery proportional to the degradation at cycle *N*.

$C_{B_{Total}}$ The capital cost ($) of the battery.

C_{D_e} Cost ($/kW) of curtailing essential customers.

U_r Binary value indicating whether the battery state of charge is outside the green zone.

U_{C_t} Binary value indicating whether a battery is charging.

U_{D_t} Binary value indicating whether a battery is discharging.

U_{di_t} Binary state determining if diesel generator is on or off.

SOC_t The energy state of the battery.

SOC_{min}^{green} Minimum state of charge at which normal battery degradation can occurs.

SOC_{max}^{green} Maximum state of charge at which normal battery degradation can occurs.

SOC_{min} Minimum possible state of charge for battery.

SOC_{max} Maximum possible state of charge for battery.

DoD_t Depth of discharge for battery. The percentage energy value which the battery has been depleted.

DoC_t Depth of charge for battery. The percentage energy level which the battery has been charged.

N Number of scenarios in which the microgrid system is processed and analyzed for one full day.

N_{bat,max_t} Rated maximum number of cycles of the battery system.

N_{bat_t} Battery cycle count.

$cVaR$ Conditional value at risk formulation used to calculate risk at high-risk low probability scenarios.

VaR Possible value at risk.

α Smallest possible cost for admissible loss.

$f(x, y)$ Unmet demand after generation is accounted.

β Confidence level.

z_i BESS power and diesel power of the specific interval.

t Time segment per analysis.

$\Delta\lambda$ Change in degradation between two-time intervals.

$\lambda_{N_{bat_t}}$ The capacity factor loss at the *N*th cycle.

ΔT The length of time segment.

γ Price normalizer value (\$/cycle).

ε Relationship between essential and priority customers.

CHAPTER 1 INTRODUCTION

1.1 Electrical Grid Reliability

There have been 500 weather events in North America impacting 50,000 customers for each event from 2005-2015 [1]. Similar increased electricity outages due to weather have been reported on other continents. These increases in the severity of natural disasters are due to the forces of climate change [2]. Also, blackouts have occurred due to operational errors resulting in millions of customers losing power [3]. Lastly, attacks against the grid have become more common from foreign actors [4]–[5]. Both trends have emphasized the need for a more distributed and decentralized electric grid which should function even if disconnected from the overall electric utility. Besides reliability issues, technological shifts have resulted in distributed generation, intermittent renewable power sources, as well as advanced customer expectations that did not exist when the grid was initially designed. Due to these considerations and the aging of grid infrastructure, today's electric grid is particularly susceptible to numerous types of damage and prolonged periods of blackouts [10].

1.2 Microgrid

A microgrid is defined by the Department of Energy as "'a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid" [6].

Microgrid technology has become increasingly more common in the past few decades due to its ability to supply areas with geographical constraints, disaster prone issues, and rural areas. It is also an effective tool for electricity distribution and reliability. Additionally, a microgrid has the capacity to disconnect from the main grid and be self-sufficient for a period of time but it can also remain connected and function alongside a larger grid system in normal operations. This is essential in a blackout or disaster scenario since a microgrid can disconnect from the other supply issues or even equipment damage that could be occurring elsewhere. This allows the microgrid to avoid cascading failures and provide reliable power in its specific area [7].

A microgrid can be a residential neighborhood, single building, or a larger subsection [7]–[8]. The advantages are numerous for each type of microgrid. A residential microgrid is chosen for the analysis covered in this research. This has also been used to design for island nations due to geographical constraints. A residential microgrid is chosen in this scenario since existing geographically connected neighborhoods can use the same microgrid configuration with high renewable penetrations and additional resources without a full grid overhaul [9].

1.3 Energy management system

The focus of this research will be on the microgrid's ability to disconnect from the larger electric grid in a time of outages and be able to reliably provide power to a specific section otherwise referred as an island state. However, this requires that a microgrid have its own energy management system (EMS) and far more refined control methods then a traditional EMS since both the energy demand and consumption is at a far more granular level [10]. These enhanced requirements are implemented in this research with two systems. Firstly, the day-ahead scheduling is used to optimize resource allocation since an emergency usually unfolds on a day-to-day basis. This system also makes sure that demand is being met. Lastly, it also allows cost approximation to allocate the correct energy supply ensuring effectiveness and ideal dispatching [11].

In addition to physical infrastructure, new forms of EMS including intermittent energy such as solar panels must be considered for resource allocation and constraints [11]. Microgrid functionality must be built into the system as more microgrids are being integrated or being developed alongside the main grid. This will have far reaching consequences in energy management systems as large changes in both the generation and consumption of energy are rapidly shifting.

The energy management system in a regular electrical system has incredible reliability and is a marvel of the modern world. Unfortunately, this reliability and interconnectedness is only guaranteed for normal conditions. The electric grid's ability to respond to issues under abnormal conditions such as storms, flooding, or other disasters may be reduced [7], [18]. Additionally, the standards of electric reliability that are expected for day-to-day operations are not the same expectations as in a disaster scenario [19].

This research is primarily focused on such circumstances where the normal standards for reliability are not available. The high standard is only possible due to a vast and durable interconnected system which relies on large-scale generation transmitted to distributed residential systems. These infrastructure advantages are guaranteed in a natural disaster where due to damage, the system can be disconnected into multiple sections. When this happens, individual residential homes or industrial systems must have previously installed redundant systems such as diesel generation or

BESS. Otherwise, their ability to receive electricity is entirely dependent on the speed at which the whole system can be reintegrated into a default state [13].

Therefore, advanced EMS software is necessary along with more resilient physical assets to harden the overall grid [1]. There are also new forms of distributed generation which change the dynamics of power transmission. All these factors require a rethinking of acceptable risk which currently is not acknowledged for existing systems. This research utilizes day-ahead scheduling with specific time segments by assigning certain cost objectives to various resources including solar power, load curtailment, BESS, and diesel generation. This allows the model to create the most effective mix of resources to supply a load while minimizing resource usage throughout the day.

This research presents one such approach to reduce unreliability by looking at day-ahead scheduling resource allocation which is then analyzed through a risk management method to determine the risk factor of load curtailment throughout the day. This framework points out how intermittent resources and load curtailment can *increase* reliability [34]–[35]. The goal is to understand that not only can load curtailment be necessary in certain situations but how to quantify this necessity to ensure that system operations and reliability is maximized in an emergency. It also creates a starting point to discuss instances where property that is currently controlled by individual use can be used in a more communal manner. This will allow a more sophisticated conversation about load curtailment instead of the current reality of demand reduction occurring haphazardly [20].

1.4 Conditional Value at Risk

Conditional value at risk is a systematic framework used to analyze the risk found in financial investments. The algorithm evolved from value at risk (VaR) which allows for general risk found in investments during normal operations. A traditional VaR would give a value of loss possible during a regular interval. In comparison, a cVaR analysis would state the risk factor in a minority of scenarios (usually 1%, 5%, or 10%) by doing an average summation of the worst returns in the past historical record [15].

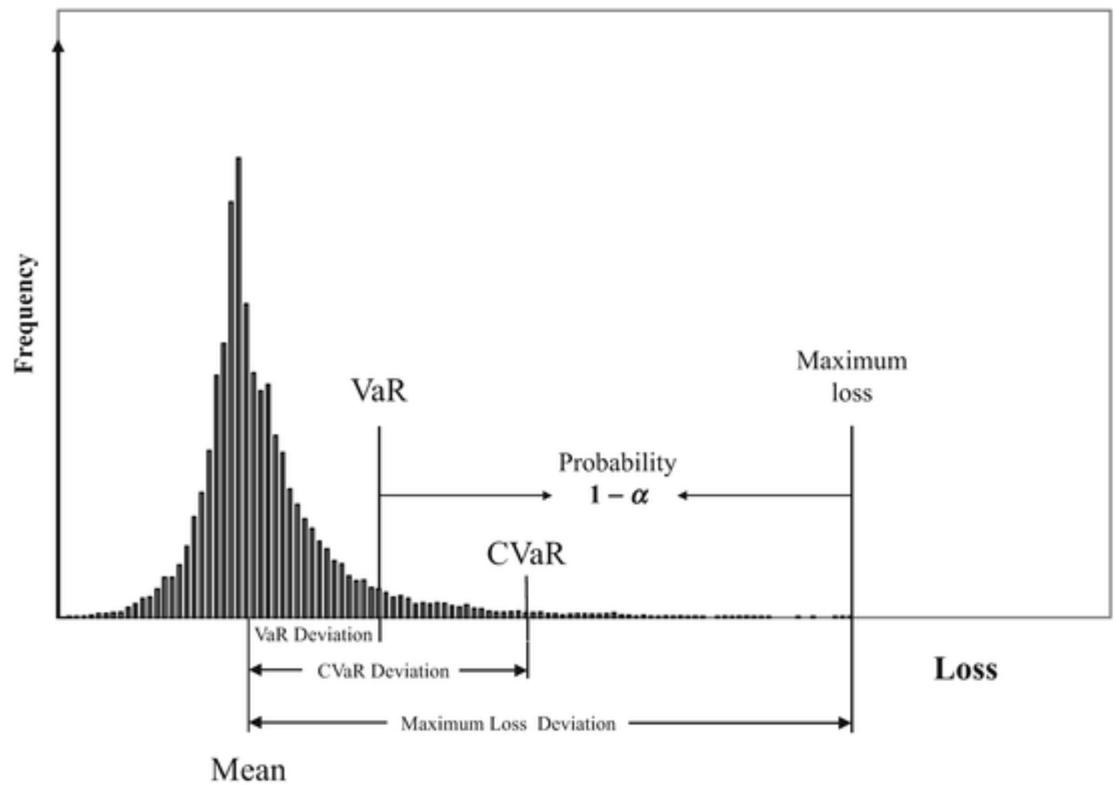

Figure 1: Traditional cVaR representation showcasing maximum loss along with traditional VaR [16].

The cVaR and VaR is represented above in graph form visualizing how cVaR is used at the end of a distribution to find maximum loss [16]. For example, a cVaR analysis would highlight if an investment is likely to lose more than half of its entire value even if the likelihood of this occurring is extremely rare. The cVaR methodology allows an evaluation of high-risk, low-probability found in investments compared to standard financial evaluations which do not consider tail-end risks [15]. In a standard distribution for cVaR analysis, tail-end or edge-case risks are defined as low probability but high-risk events.

The ability to quantify risk at edge-cases and not simple day-to-day operations has allowed cVaR analysis to transition from finance to other industries including energy management [14]. Historically, electric grids boasted extremely high reliability and have not needed edge-case risk-based analysis. However, two recent trends in the last several years have made it necessary to prepare for larger risk failures, first is the increased likelihood of blackouts and brownouts due to stronger and more frequent natural disasters as well as digital attacks on infrastructure [3]–[5]. This dangerous new reality is due to climate change and foreign state attacks and has resulted in a call for more grid hardening efforts. Although grid hardening is necessary, equally as important will be the quantification of risk to understand where and how much the grid is vulnerable. cVaR allows for probing and quantification of these vulnerabilities. This is a necessary step to increasing reliability for the overall system using probabilities of load curtailment [11].

Secondly, the proliferation of microgrids as well as distributed energy resources (DER) has resulted in larger volatilities in both demand and supply within energy management. This has created the need of cVaR techniques to better manage changing grid systems while maintaining a high state of reliability. This research allows exploration of microgrids in an island state with the inclusion of load curtailment as well as various distribution energy sources [2], [10], [32]. The mathematical formulation is explained in more detail in the problem formulation and how it is used for microgrid systems in the specific setup used in this research.

1.5 Distributed Energy Resources

Distributed Energy Resources (DER) can include both generation and storage as seen in diesel generation, BESS, and residential photovoltaic (PV). These DERs are less predictable or can store less energy than more traditional power sources. For load management, DERs have become increasingly necessary for maintaining grid stability as they provide low transmission costs and are closer to demand sources [17].

This research will consider all above mentioned DER sources in the aspect of targeted load curtailment [13]. The focus will be to increase resiliency using residential solar power, diesel generation, and BESS within a residential microgrid using day-ahead scheduling alongside advanced risk analysis modeling [12], [14].

CHAPTER 2 MICROGRID DAY-AHEAD SCHEDULING

The objective function in this research is to maximize power availability for priority customers by minimizing risk and cost of volatile power generation sources. This will be accomplished be utilizing day-ahead scheduling calculations with built in cost factors for each generation source. To do so, an overall formulation of day-ahead scheduling must be developed with cost factorization for different generation and load curtailment sources. The second portion of the chapter discusses conditional value at risk with the results of day-ahead scheduling to create a holistic risk profile of the system.

2.1 Day-Ahead Scheduling

Day-ahead scheduling provides forecasting traditionally for the next day of operation by analyzing both generation capacity and demand needs. This is done so by using a method called security constrained unit commitment (SCUC) [39]. The unit commitment position sets On and Off for generators over a set period allowing an economic best use of generators over a set period [32], [36].

TABLE 4.1 Unit Combinations and Dispatch for 550-MW Load of Example 4A

Unit 1	Unit 2	Unit 3	Max Gen	Min Gen	P_1	P_2	P_3	F_1	F_2	F_3	Total Gen Cost $F_1 + F_2 + F_3$
Off	Off	Off	0	0							Infeasible
Off	Off	On	200	50							Infeasible
Off	On	Off	400	100							Infeasible
Off	On	On	600	150	0	400	150	0	3760	1658	5418
On	Off	Off	600	150	550	0	0	5389	0	0	5389
On	Off	On	800	200	500	0	50	4911	0	586	5497
On	On	Off	1000	250	295	255	0	3030	2440	0	5471
On	On	On	1200	300	267	233	50	2787	2244	586	5617

Figure 2: An example Unit Commitment Table with Combinations for Dispatch highlighting how demand and supply can match with numerous different generator availabilities [41].

Security constraints are necessary to operate a microgrid in real world operations [11], [42]–[43]. In this system, the security constraints include battery charging and discharging constraint and diesel energy dispatch capacity with the assumption of a DC-DC model [37]. Meanwhile, spinning reserves are additional generation set aside especially for abnormal circumstances. In our formulation, the diesel generator as well as the BESS provide spinning reserves for the model.

In an integrated electric grid, there are also pricing markets for the purchase of generated electricity. For this thesis, the model is in a disconnected island state. Therefore, the pricing costs are predetermined based on the cost of fuel for diesel, existing cost function for load curtailment based on utility price rates, and battery degradation approximation for BESS [36].

This system is designed to lower the total operating cost while optimizing resources. For this research, SCUC is ideal because it allows for a mix of DERs with different constraints and advantages along with demand usage. SCUC is used to look at the existing system in that time segment as well as the viability of the whole system to allow a mix of resources that could supply an islanded microgrid in the most cost effective manner [35], [37]–[38].

2.2 Cost Formulations

The objective function is to reduce cost while providing power for customers in a residential setting as

$$\min \sum\{C_{B_{N_t}} P_{BESS_t} + C_{fuel} P_{Di_t} + C_{D_e} D_{e_{c_t}} + U_r C_{batt,red}\}. \qquad (1)$$

The objective function represented by (1) is a variation of the cost function of SCUC showing resource allocation for BESS, diesel, and load curtailment while balancing demand and PV generation. Diesel generation and load curtailment have their own cost function which is explained in the sections below. Battery systems have two components to account for when the battery swings into a higher than preferred state of charge. This can be displayed as

$$D_{Load_t} - D_{e_{c_t}} = P_{Di_t} + P_{BESS_t} + P_{PV_t}. \tag{2}$$

(2) is a basic requirement for all electric grid operations ensuring that demand meets supply. The usage of $D_{e_{c_t}}$ to minimize demand will be explained in the Load Curtailment section.

When BESS is outside of its preferred range, then an additional cost will be added. This is represented by the binary function for battery red zone, U_r, and the battery red cost function $C_{batt,red}$. The function minimizes cost by ensuring that the appropriate resource is scaled for maximum cost effectiveness. This will be essential in this research by allowing cost functions to not only account for economic prices but also more complex valuation such as load curtailment to ensure reliability for prioritized customers as well as coordinating battery systems to maximize lifecycle. Each cost function rationale for these resources is explained in the sections below including how they are used to balance both resource generation with cost approximation, resource longevity, and customer needs [38].

It is important to consider that this research is limited to short-term decision-making processes. All the necessary long-term investments made to install and purchase the initial energy sources have already been assumed to be completed. The focus for this research is on short-term considerations such as cost of fuel. Initial costs of residential PV systems and diesel generation systems are deferred since the devices are calculated in a purely operational role where installation costs have already been acknowledged.

One exception is that long term battery degradation costs are estimated in the short term by battery depth and degree of usage estimation over the period of a day and its effect over the total course of a battery's capital cost and then included as the existing cost of the system. This is taking an initial one-time investment of battery cost and estimating it as an equivalent short-term cost [30]. This allows the model to bridge the gap between research which assumes perfect battery systems in microgrids and existing research that is primarily focused on only battery models. Lastly, this research will explore the concept of taking already existing infrastructure (such as individually purchased batteries, solar panels, and diesel generators) and explore models of retrofitting them to create a residential microgrid which could be utilized in emergency scenarios [31]. Now, each resource cost can be addressed to calculate the most cost-effective method to distribute customer demand.

2.3 Microgrid Components

The main difference between a microgrid and the overall electric grid is its ability to provide power to a smaller locality including managing DERs in the microgrid. Additionally, it means microgrids have their own energy management system. Both of these features mean that a microgrid can be integrated and interact with the main grid but can also disconnect in island mode and function independently [3], [6]. These abilities allow microgrids to be incredibly helpful in load restoration and reliability as well as customer engagement in demand management since the scale of electrical systems is significantly smaller [3]–[4].

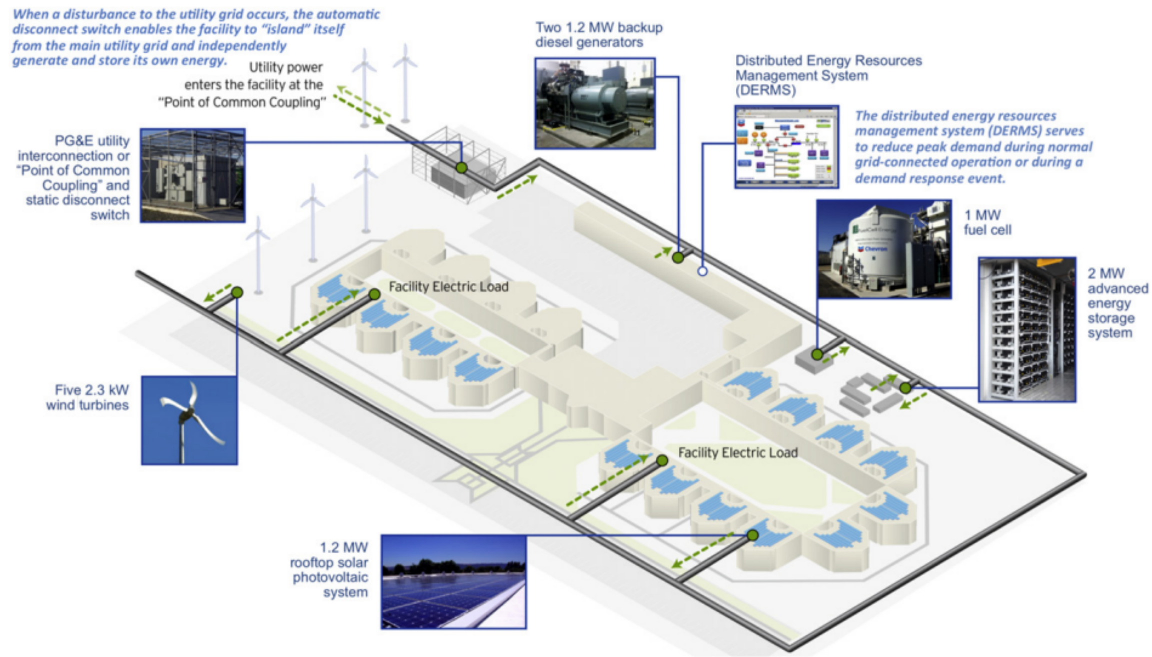

Figure 3: Microgrid example from Chevron Energy Solutions' Project showcasing BESS, diesel generation, PV, as well as other DERs [3].

The figure above showcases an ideal example of a microgrid that can utilize numerous DERs to provide for demand while also having decoupling mechanisms if it would like to remove itself from the main grid. All of this controlled by its own distributed energy management system [3].

The model used in this research includes a microgrid in an island state. The sources of generation are residential PV, BESS, and diesel generation as the three DERs. BESS is especially useful since it can absorb and discharge power. All three are DERs which can be utilized near the source of the demand. This is crucial for a microgrid to function by itself. The fourth resource is load curtailment which limits demand by prioritizing certain customers with higher requirements. The sections below address each resource in greater detail.

2.3.1 Residential Photovoltaic System

Residential PV defined in the model as the inclusion of solar panels to a residential home providing electricity as well as being able to export energy to the microgrid. Solar panels have several advantages such as the ability to provide power without any input fuel while having much smaller physical area requirements than other renewable sources. They also require less maintenance than other fuel sources. With weather forecasting, it has become easier to accurately predict the amount and time of power production [25]. Since residential solar panels are installed at or near the point of consumption, the transmission costs are dramatically reduced. Residential small scale connected PV also has the advantage of already being implemented in the central grid system as well as having their own inverter configuration for each residential unit instead of needing a centralized controlling unit as seen in solar farms [23].

The disadvantages of solar is that power production is confined from late morning to early afternoon even in ideal circumstances. Additionally, they are extremely susceptible to changing weather conditions especially rain and snow. For now, this means that BESS is necessary on a microgrid level to hedge the quickly changing nature of solar generation. There will be a focus in the model on how to best utilize excess solar energy to meet demand.

This research utilizes residential PV for input values collected from homes in Austin, Texas courtesy of Pecan Street in the model [40]. Therefore, the model can be tested with a dataset that includes the volatilities found in live systems. Since initial costs of residential PV systems are deferred and it possesses no fuel cost, PV has the advantage of not needing a cost function in the model. The main consideration of PV is accounting for the volatile nature of solar production.

2.3.2 Diesel Generation

Diesel systems are a useful fuel source around the world in grid operations as a DER alongside BESS and residential PV [3]. On a base level, they burn diesel to power a motor generating electricity. They are readily available, can provide a large amount of power, and have been well tested in the grid. Diesel will be a necessary generation source even for research focused on incorporating renewable power sources because of its long record and power capacity. It is a necessary bridge to more environmentally friendly DER system as they are already integrated into the overall system. Start-up costs are not considered in this model because of model optimization timing [32]. As a base constraint, there is a maximum discharge and charge capacity for diesel generators to meet technical limitations as

$$P_{Di_{min}} \leq P_{Di_t} \leq P_{Di_{max}}. \tag{3}$$

It is assumed that a diesel system with the necessary fuel for an entire day of operations is provided with the microgrid. The cost of the diesel is considered linear and added to ensure an appropriate mix of diesel with load curtailment, BESS, and residential PV using the energy management system [34].

2.3.3 Load *C*urtailment

Load curtailment is the practice of removing or reducing electricity for a certain time frame due to a mismatch between strong demand and limited supply. Load curtailment is traditionally discouraged in the United States and most other developed countries. However, as seen in the Texas Winter Storm Uri, load curtailment can and is unfortunately becoming more commonplace [21]. Load curtailment can occur due to a reduction or inability to generate electricity. It can also occur because demand surged due to extreme temperatures. On a day-to-day basis, the North American electric grid is reliable yet due to logistical issues caused by stronger storms, load curtailment due to limited supply of electricity is becoming more common [18].

Unfortunately, the standards for reliability are not quantitatively calculated during hurricanes or other disaster scenarios. Although there has been research on building an energy framework resilience reference, there has not been a serious discussion on the role of targeted load curtailment [18], [22]. Since the goal has always been to have no load curtailment, there has never been a conversation about how to utilize load shedding strategically to not increase larger chances of the grid failing or unnecessarily reducing load from priority customers. Some current research is attempting to score electric grid reliability post-disaster but there is no contention of disaster hardiness in a planning stage or in operations in the middle of a disaster [18]. An attempt to do so was made in the 2021 Texas Winter Storm with rolling blackouts but unfortunately was done at the time of the emergency with no planning beforehand due to weather conditions [21].

This research will explore the idea of utilizing load curtailment as a negative demand in resource allocation strategically along with BESS, PV, and diesel in an integrated energy management system. This will reduce the overall riskiness of the system as well as to ensure the adoption of microgrids in existing infrastructure. Additionally, the research will also allow an evaluation of the microgrid’s ability to exist in an island state in a post-disaster scenario instead of reliability and infrastructure planning based entirely on a grid behaving in normal operations [22].

$$D_{Net\ Load_t} = D_{p_t} + D_{e_t} - P_{PV_t} \tag{4}$$

defines the fundamental connection between how demand is configured in the system. Net Load is set to all customer demand subtracted from any PV generation. The two other equations, D_P and D_e, are two distinct groups of customer demand. This allows us to understand the total load faced by the system for generation that the model can control.

$$D_{p_t} = \varepsilon D_{e_t} \tag{5}$$

then sets the grouping of priority customers and essential customers. Priority customers are a fraction defined by ε of the essential customers. Priority customers cannot be curtailed by the model. Comparatively, the larger essential customer group can be curtailed. Of the essential customer group, only $D_{e_{c_t}}$ is defined as essential customer curtailed are removed from the system. The overall equation can be represented by

$$D_{p_t} + D_{e_t} - D_{e_{c_t}} = P_{Total_t}. \tag{6}$$

In this model, customers are only placed in the essential customer classification if they opt into the classification. C_{D_e} in (2) is defined as a multiple of the residential electric rate for essential customers who have their electricity curtailed to compensate for the inconvenience of losing power. The rationale for the priority group is to include those that are medically dependent on consistent electricity or those who have essential job requirements for their community. Classifying customers in this way has a couple of benefits. It allows the creation of a more accurate load profile of the needs of the customer base. It gives customers an opportunity to opt out if they are not in their homes at the time of the emergency and would rather be reimbursed for load curtailment since they do not require electricity.

Now, we can create a full system level equation in (6) showcasing that the two classifications of priority and essential customers subtracted from any customers curtailed must equal the total generation of the system. Therefore, the D_{e_c} is necessary in (1) to ensure that demand meets supply.

$$D_{e_t} \geq D_{e_{c_t}} \geq 0 \tag{7}$$

shows that $D_{e_{c_t}}$ must be greater than zero since customers cannot be negatively removed from the system. It can also not be greater to D_{e_t}. It is possible although rare that $D_{e_{c_t}}$ is equal to D_{e_t}.

2.3.4 Battery Energy Storage System

Battery systems are quickly becoming a necessary component to balance small scale energy production such as residential solar panels as well as larger power generation systems such as wind power plants as well as general oscillations in the central grid [11], [13]. This research takes the approach and hardware of a medium sized battery source and uses it in a smaller scale microgrid energy system to provide stabilization. This is a similar configuration to a larger battery system operation but provides even more value since there are larger fluctuations in demand and supply compared to the overall total grid power. BESS in this thesis will be incorporated into EMS day-ahead scheduling to ensure efficient allocation of power [30].

On a singular level, BESS can be used to supply power to its designated residential location for a limited period in a blackout. These batteries are usually specified for its designated residential location. On a larger setting like the Hornsdale Power Reserve, power is provided on a massive scale to hundreds of homes securing grid stability and system security [20]. BESS are also used in tandem with residential PV to extend peak solar generation hours as well as hedge power in blackouts and supply demand mismatch [28].

The model defines battery charge and discharge by two binary values defined below:

$$U_{C_t}\{1, charging\ state. 0, not\ charging\}, \tag{8}$$

$$U_{D_t}\{1, discharging\ state\ 0, not\ discharging\}, \tag{9}$$

$$\text{and } U_{C_t} + U_{D_t} \leq 1. \tag{10}$$

The *U* variables are to account for the charging and discharging state of the battery for when the system has an influx of generation or excess demand. These values are set above or equal to zero since anything else would be an impossible state for a battery system. The two binary states have then been set to be equal to or less than one. The equal state forces the battery to either be in charge or discharge system or for neither state to be activated. The power of the battery is the power discharge rate subtracted from the charge rate as shown in (11). In this research, the BESS is exporting power in most instances and absorbing power is considered a negative generator state displayed as

$$P_{BESS_t} = P_{D_t}^B - P_{C_t}^B . \tag{11}$$

As a base constraint, there is a maximum discharge and charge rate of batteries to meet technical limitations. This can be shown as

$$0 \leq P_{C_t}^B \leq U_{C_t} P_{C_{max}}^B \tag{12}$$

$$\text{and } 0 \leq P_{D_t}^B \leq U_{D_t} P_{D_{max}}^B. \tag{13}$$

2.3.5 Battery Degradation Model Approximation

Battery coordination must balance load curtailment management along with battery degradation. This is one of the core reasons why a communal battery system or multiple coordinated smaller batteries must be utilized instead of allowing separate batteries with their own cost function. This would result in battery arbitrage and will drag down the overall system. This thesis creates a formulation with one core battery system that has resulting rules in place to enhance overall system reliability. The cost function however can be used with multiple individual batteries.

The BESS degradation cost is approximated in the model to provide more accurate results for cVaR risk calculations. Battery degradation is an important aspect of fully utilized BESS assets and must be balanced by PV resource hedging throughout the day. Other approaches to battery degradation have been used for day-ahead scheduling to explore the best resource allocation of battery usage and arbitrage but does not consider battery degradation [3]. This research both considers day-ahead scheduling with unit commitment as well as battery degradation by using battery charging zones and non-linear cost functions. This will allow a short-term operation to extend the life profile of battery systems by approximating a battery capital cost in a short-term setting [28]. It will also allow more optimal charging and discharging [27].

Battery optimization rules are used to prolong life cycles of these systems. These principals include keeping state of charge (SOC) in minimum and maximum range of SOC_{max}^{green} and SOC_{min}^{green} [27]. SOC_{min}^{green} and SOC_{max}^{green} stand for state of charge green zones minimum and maximum respectively. State of charge here is defined as the energy level available at the battery at any specific time interval. The standing BESS system of this research however can go lower or higher than the defined green zone.

There are a couple of reasons to prefer SOC in this zone. One reason is to have the ability to hedge further swings in sudden generation or demand. The BESS at its minimum or maximum cannot hedge energy needs as effectively. Another reason is that research shows that battery systems in these ranges will last longer over time [27].

If SOC_t fall within the green range, it is considered to degrade normally. The model implements this constraint by adding another cost factor to any usage of the battery outside of the green zone as in (14) [32]. This results in a more accurate usage of BESS and encourages the model to maintain SOC in the green zone or face higher penalties. This is reflected in the objective function in (2). Battery usage in these intervals is considered green charging zones as seen in

$$\begin{cases} SOC_{min}^{green} \leq SOC_t \leq SOC_{max}^{green} & U_r = 0 \\ SOC_{min}^{green} > SOC_t & U_r = 1 \\ SOC_t > SOC_{max}^{green} & U_r = 1. \end{cases} \tag{14}$$

Besides zones of operation, this research considers the usage cost as a component due to the non-linear nature of degradation. The battery is said to drop by a factor after each cycle. A full cycle is defined as a battery completely discharging and then being charged to its maximum value. At its most basic premise, battery life cycle is defined as the rated maximum number of cycles ($N_{bat_{max}}$) completed before the battery is considered completely degraded. Degradation is defined as the battery being able to no longer charge to its rated energy value but instead can only charge to a fraction of its initial maximum charge [28], [30].

With the volatile nature of this model, a full cycle is unlikely to occur continuously. Therefore, the model counts the depth of discharge into fractions which can then be scaled to give an approximation of the degradation for the battery. For example, if half the battery is discharged and then charged then it will be half a cycle for the modeled equation below [27], [30]. The cost of the battery system is then connected to the maximum life cycle to calculate the overall cost of the battery as connected to cycle count. This allows us to take a specific portion of battery usage such as one day and connect it to the overall cost of the battery by

$$N_{bat_t} = \sum_{t=0}^{t} \frac{1}{2}(DoD_t + DoC_t). \tag{15}$$

After every cycle, the battery can hold slightly less charge. This depreciation is non-linear and can be approximated by modifying an infinite geometric series equation [30]. N_{bat_t} in

$$N_{bat,max_t} - N_{bat_t} = \frac{N_{bat,max_t}(1 - \lambda_{N_{bat_t}})}{\lambda_{N_{bat_t}} * \gamma} \tag{16}$$

is the number of cycles the battery is at while $\lambda_{N_{bat_t}}$ is the capacity factor loss at the *N*th cycle. The initial state of $\lambda_{N_{bat_t}}$ will be set a smaller value close to zero to correlate the infinite geometric series equation at a reasonable starting point to model a finite battery source. γ is the value equalizing value translating a theoretically infinite non-linear equation and allows $\lambda_{N_{bat_t}}$ to be approximated to a manageable value into the existing cost function. When $\lambda_{N_{bat_t}}$ equals 1, the battery is considered completely degraded. Battery degradation allows the calculation of the battery's operational cost at a specific cycle by multiplying by the capacity factor at that cycle point by the total cost of the battery ($C_{B_{Total}}$) by setting

$$C_{B_{N_t}} = \lambda_{N_{bat_t}} * C_{B_{Total}}. \tag{17}$$

The C_{B_N} indicates the total battery cost at that level of degradation and cycle count. For this research, we would like to find out the difference in degradation cost from *t* to *t-1* or the change in degradation between time intervals. This can be done by taking the difference in λ as seen in [28]

$$\Delta\lambda = \lambda_{N_{bat_t}} - \lambda_{N_{bat_{t-1}}}. \tag{18}$$

The price of the battery cost at that charge will be dependent on its cycle count multiplied by the charge used in that scenario [30].

To summarize battery storage, the system has certain set objectives and logical conditions which will determine cost approximations:

1. The BESS system has different set charging and discharging costs as the state of charge of the battery varies.
2. The state of charge for BESS is monitored and is preferred to be above a minimum limit and below a maximum limit to increase battery life cycle.
3. BESS cannot be charged and discharged at the same time.

   The next section explains how the costs defined in the model for day ahead scheduling resource allocation are used in the cVaR framework.

CHAPTER 3 CONDITIONAL VALUE AT RISK FORMULATION

This chapter explains how the costs defined in the model for day-ahead scheduling is used in the cVaR framework. The diagram below showcases the process from day-ahead scheduling to cVaR analysis. First, all the scenarios in the day-ahead scheduling must be completed. This means that for one time interval, *t*, there will be hundreds of scenarios operating with different demand constraints and PV generation. Then when all *N* scenarios have been completed, they will create a large set of data points of cost optimized resource allocation including any possible load curtailment. These load curtailment measurements can then be tested for stability and resiliency and used to create a risk profile using cVaR analysis.

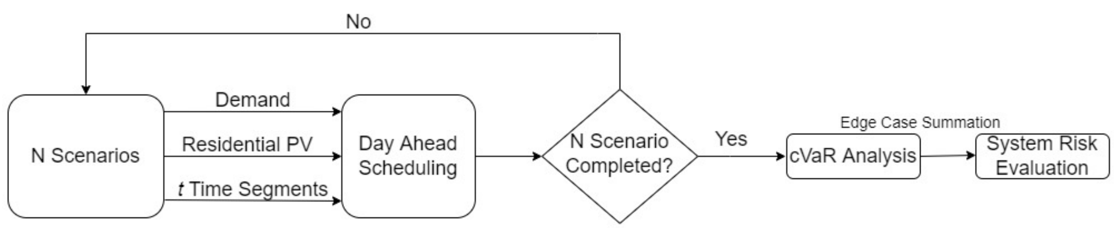

Figure 4: The analysis starts with scenario day ahead scheduling. After every scenario is completed, the full system analysis is modeled for systematic risk.

3.1 cVaR Formulation

The use of risk-constrained scenarios in financial models and utilities is to maximize profit with an internal pricing mechanism [33]. cVaR is a popular risk calculation algorithm. It is built on the work of VaR which calculates how to reduce risk within a certain confidence level (β) by minimizing loss due to the uncertainty in specific variables [33] otherwise defined as

$$VaR \ = min\{\alpha \in R: P\{f(x,y) \leq \alpha\} \geq \beta\} \quad for\ 0 \leq \beta \leq 1. \tag{19}$$

The $f(x, y)$ factor in (19) is defined as the losses calculated. The x denotes the variables available to fine tune and reduce risk where y represents the volatile uncertainty inherent in our system. By minimizing the worst-case scenario of y, the system could create an expected risk profile. This is calculated by taking the smallest possible cost (α) that is greater or equal to $f(x, y)$ and then calculated the risk factor over β. This can be used to calculate the level of risk inherent in investing in certain markets and diversification tools (such as cash or bond hedging).

Unfortunately, VaR suffers from two key issues. Mathematically, it has a lack of convexity and subadditivity making it non-ideal for intensive calculation operations. Secondly, VaR only minimizes losses within a given confidence level and does not consider losses occurring at a confidence level outside of its boundaries at 1-β. cVaR allows a better grasp for situations where a small likelihood of risk could have a huge effect [14]. cVaR as a financial constraint is seen in

$$cVaR \ = \ \mathbb{E}_y(f(x, y) | f(x, y) \geq VaR). \tag{20}$$

In this evolution of the original VaR equation, the cVaR is now taking the expected value of random variables above its VaR consideration. In other words, it is taking the loss factors inherent in the system and calculating them in situations of 1-β or above the standard confidence interval. This is a much more robust and flexible system since it allows forecasting of situations where non-likely events outside of the confidence interval occur. Additionally, a higher cVaR means the system is inherently less stable because in non-normal situations, the losses can be considerably higher.

To transition from the above equations to models with samples, (20) can be converted into

$$cVaR = min\left(\alpha + \frac{1}{N(1-\beta)} \sum_{i=1}^{N} [f(x,y) - \alpha]^{+} \right). \tag{21}$$

The first shift here is the addition of *N* moving the model from continuous to samples with *N* scenarios. The second change is that the positive component of our losses taken by known *x* and volatile *y* subtracted by α as our hedging cost. For our formulation, we can then replace [*f(x,y)*$-\alpha]^{+}$ with z_i. This can be shown as

$$z_i = [f(x,y) - \alpha]^{+}. \tag{22}$$

z_i can then be used to calculate the maximum losses seen in a market in situations outside the normal β in (1- β) [34]. The cVaR equation can now be redefined with z_i as seen in

$$cVaR = min\left(\alpha + \frac{1}{N(1-\beta)} \sum_{i=1}^{N} z_i \right). \tag{23}$$

3.2 cVaR Application in Microgrid

This section explains how cVaR will be used to maximize power reliability for priority customers. cVaR gives a weighted average of risk above the normal confidence level. This allows a calculation of the risk in high-demand scenarios that can occur in emergency situations [22]. Using this approach is more useful compared to prior work for reliability purposes. One advantage is that cVaR can now analyze load curtailment likelihood. This allows better understanding on how to maintain load for priority customers whereas in prior research, the goal was to increase economic savings [14].

$$f(x,y) = D_{Net\ Load_t} - P_{BESS_t} - P_{Di_t} \tag{24}$$

takes $f(x, y)$ from (19) and defines the combined losses as demand subtracted from diesel, PV, and BESS [14].

The last variable to form z_i in (25) is α. α is set as the smallest load curtailment while maintaining stability at the confidence level β [33]. The α value will be measured in units of kilowatts. It is the level of customer demand that can be removed from the essential customer group defined in (6) as D_{e_c}. In keeping with cVaR convention, demand load that is curtailed will be referred to as α moving forward. All this can be set as

$$z_i = [D_{Net\ Load_t} - P_{BESS_t} - P_{Di_t} - \alpha]^{+}. \tag{25}$$

P_{BESS_t} is set to be positive if discharging power as mentioned in (11). Net load power is defined as customer demand subtracted from power generated by PV as seen in (4) and constitutes the uncertain parameter of the system. The customer demand and PV values are taken from homes with built-in solar panels courtesy of Pecan Street [40]. The combination of Net Load and PV are uncertain values which BESS and diesel generation match in day-ahead scheduling. When this will not cover demand, the step of load curtailment is necessary to ensure z_i is positive in (25). *N* in (23) is the number of scenarios for various risk factors. Each scenario is a different possible variation of the demand necessary for the load as well as possible PV generation based on weather conditions. One consecutive day is defined as discrete time segments (*t*) with each interval having *N* possible scenarios. This includes both volatile generation such as PV and controllable sources such as BESS and diesel. This expectation and management of unmet load with α is essential to calculate cVaR in (23) [34].

CHAPTER 4 CASE STUDIES

This section will first introduce all the components of the test microgrid system and then the specifications for each component. The process to calculate the cVaR is then explained and then the model results are discussed.

4.1 Microgrid Configuration

The test residential microgrid is designed with currently available commercial products. It is designed with a battery system made up of twenty Tesla Powerwall batteries with a capacity of 15 [kWh] each that starts at an initial value of 10 [kWh] for each battery. B_i is the capital cost of the BESS system at $\$10{,}000$ [45]. The standard rooftop residential solar output is at 4 [kWh] during peak solar generation [44]. There are ten residential homes in need of power all with installed solar panels. ε in (5) was set to 0.5 therefore priority customers were a total of 33% of total demand. This means that a maximum of 66% of customers can be essential customers [11]–[12]**.** A simulation of all 187 possible scenarios, *N*, is run and the battery, diesel, and PV combination are recorded for each specific segment. β is defined as 5% for the confidence level in this analysis.

The input data for the scenarios including load demand and PV generation is graciously provided by Pecan Street. This is part of Pecan Street's Dataport Project [44] which includes the world's largest resource for residential energy use data, electric transportation and has been expanded to include residential water use, electric transportation, and regenerative agriculture [40]. Electricity demand as well as PV generation will have expected statistical deviation from historical data. SOC_{min}^{green} is defined as 20% and SOC_{max}^{green} as 80% in the model using values from previous research [28]. $P_{Di_{min}}$ is set as 0 and $P_{Di_{max}}$ is set as 3.75 [kWh] for the system generator. The diesel generator is assumed to have sufficient fuel to operate during the whole course of the day. $P_{D\,max}^{B}$ and $P_{C\,max}^{B}$ is defined as 5 [kW] for one Tesla Powerwall [45]. ΔT is the length of time segment which is 15 minutes in this thesis. There are 96 segments for a 24-hour period.

γ is the price normalizer ratio between dollars and battery lifecycle. This allows the theoretical battery degradation equation to match the actual capital cost of the battery. It is set as 10 which allows the cost function to approximate the overall value of the Tesla Powerwall cost. N_{bat,max_t} will be defined as 10,000 cycles for the system according to Tesla Powerwall specifications [45]. λ is the capacity factor loss with a half-life approximation of the battery cost will be set a constant value to $\frac{1}{11}$. This value was chosen to approximate the non-linear battery degradation curve to an initial starting point. When the capacity factor is at one, the battery is degraded. Degradation is defined as when the BESS can hold 80% of its initial charge [28]. The cost for diesel fuel (C_{fuel}) is 0.066 \$/kWhr, load curtailment (C_{D_e}) is \$1.2/kWhr, and battery cost outside of the green zone ($C_{batt,red}$) is \$0.66/kWhr.

The objective function and cost parameters are then modeled with day-ahead scheduling using AMPL. AMPL is language designed specifically for optimization. The day-ahead scheduling gives the resource allocation for all generation including any load curtailment. The load curtailment if any for each fifteen-minute interval is then recorded. The load curtailment is then divided by the total demand supplied and recorded in a matrix. Python is then used to take these values and calculate the conditional value at risk for the most demanding and highest load curtailment of the five percent of scenarios (nine scenarios) of the total set of 187 scenarios for all time segments.

4.2 Results

The results highlight the cVaR analysis on the microgrid system for one full day or 96 *t* segments on a total of 187 scenarios. The graph below shows in how many instances curtailment was necessary in the model. This showcases a high level of self-sufficient reliability that above would be a boon to the existing electrical grid infrastructure. The system had zero instances of load curtailment for 90% of scenarios. It had a maximum of 13 instances of load curtailment in the most challenging 5% of cases for all segments.

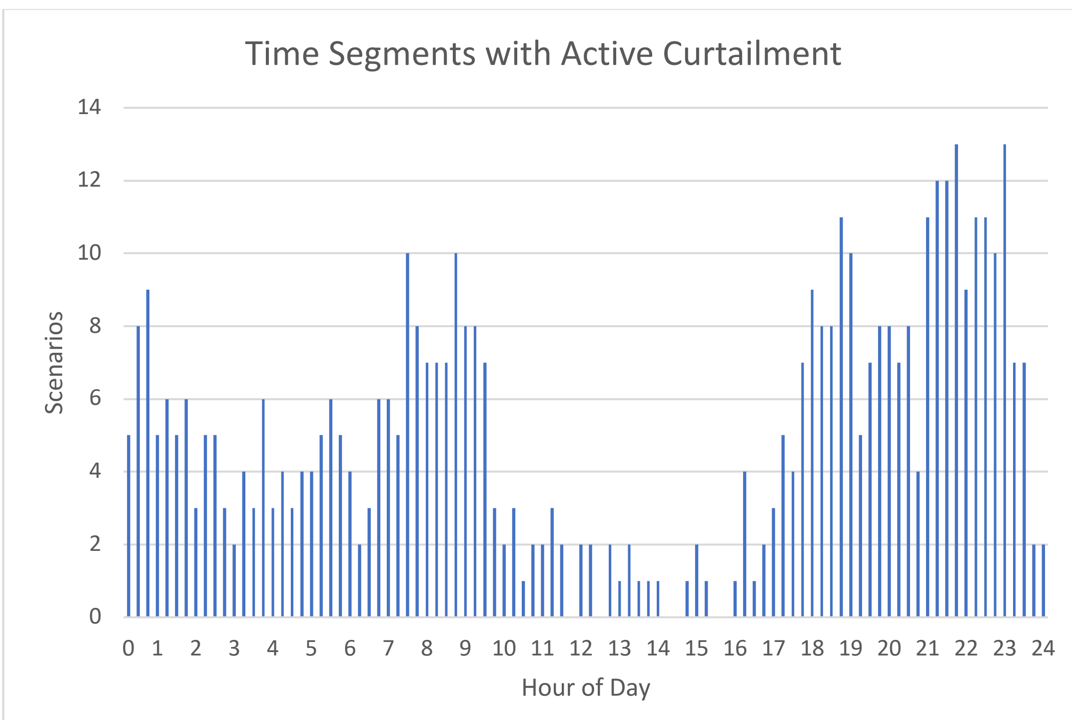

Figure 5: The above graph shows how many scenarios had active curtailment over the course of the day. Each hour represents four different segments of fifteen-minute intervals.

From a systemwide load curtailment view, now we can take a more in depth look at the 5% of challenging scenarios in terms of balancing generation and demand. The standard deviation shown below showcases the difference in values of the dataset for each segment.

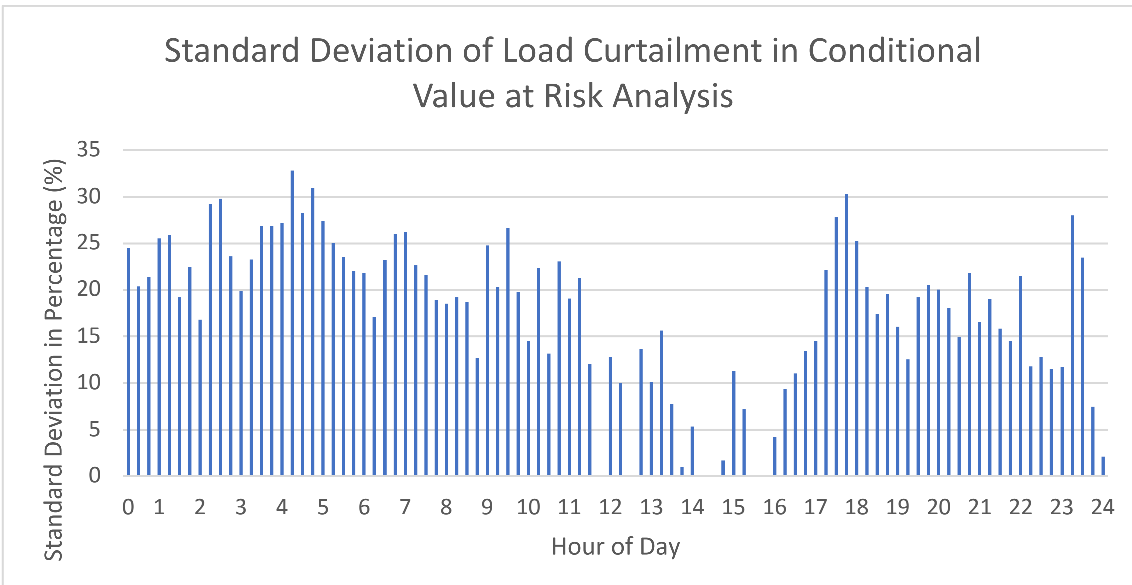

Figure 6: The Conditional Value Standard Deviation at a 5% confidence level of the model. Each hour represents four different segments of fifteen-minute intervals.

Within each segment, there is a 20-30% standard deviation indicating the model is robust. These results showcase that the model can take in very different demand constraints and respond appropriately to the need of the specific scenario. Interestingly, the standard deviation is largely consistent throughout the day, showcasing that the load curtailment deviation is not too different between sample segments. An exception to this is late mornings to end of the afternoon where due to ample residential PV, there are far less load curtailments and therefore the standard deviation is lower.

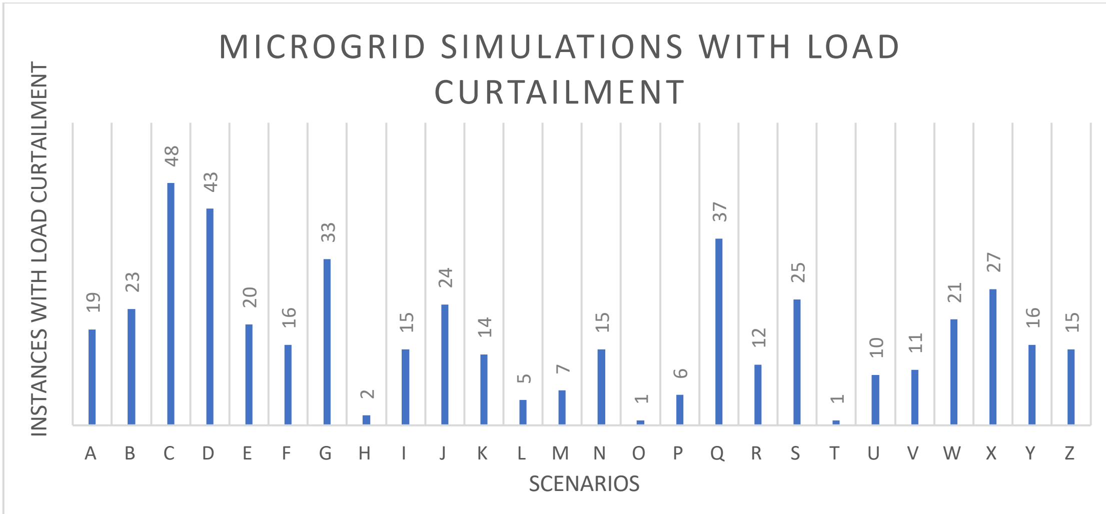

Figure 7: The above graph shows scenarios and how many instances of active curtailment during an entire day.

The chart above showcases the twenty-six scenarios or 13.9% of the entire scenario dataset that was responsible for all load curtailment. This is expected since the model was tested on a robust dataset which has microgrid scenarios with larger than expected demands. This is very likely in emergency situations due to weather conditions, and it is important to note how the microgrid would react in these scenarios.

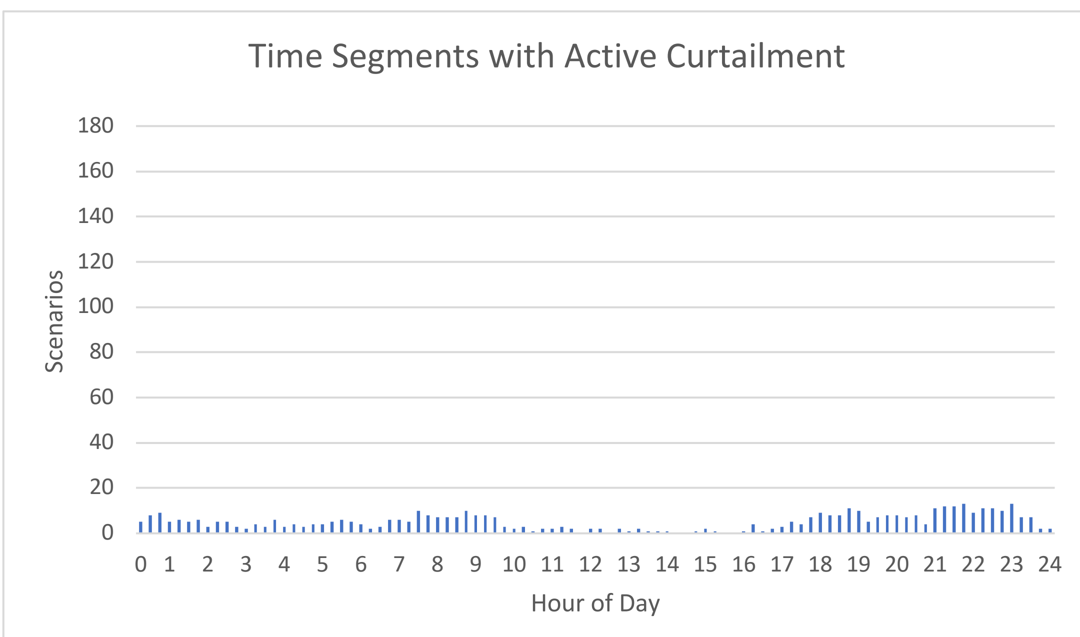

Figure 8: The Conditional Value Standard Deviation at a 5% confidence level of the model with all 187 scenarios reflected in the graph. Each hour represents four different segments of fifteen-minute intervals.

This model was able to supply demand in *most* scenarios without needing to curtail any customers. The chart above shows the actual representation of curtailment compared to all the scenarios the system processed during the course of a day.

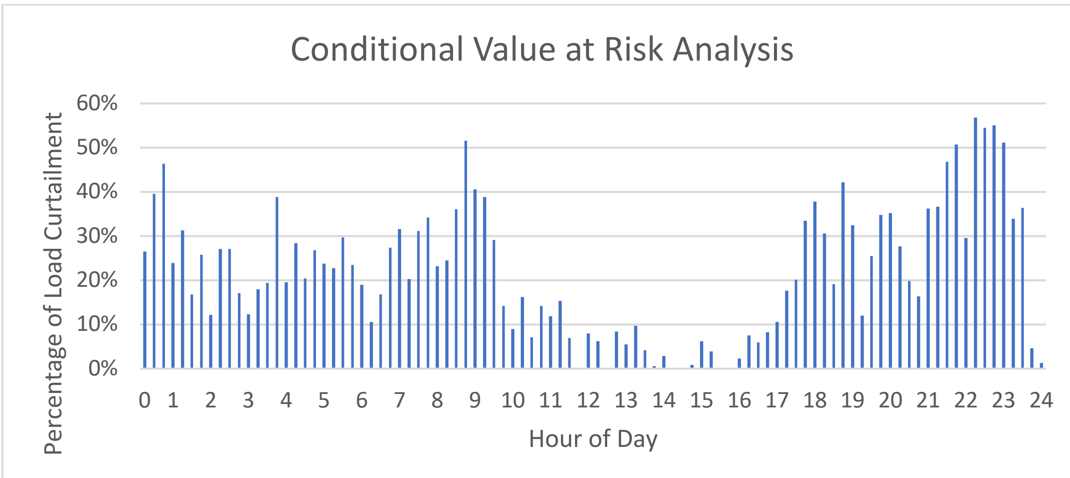

Figure 9: The Conditional Value at Risk Analysis at a 5% confidence level of the model represented by load curtailment as a percentage of total demand throughout the course of the day. Each hour represents four different segments of fifteen-minute intervals.

The behavior of the case study matched expectations in the following ways. The risk when calculating real time energy management for the hours of 10 AM to 4 PM were reduced and in some time-segments brought to zero. This means residential solar times matched demand at these times and reduced risk of load curtailment. This is one of the main benefits of residential solar. It especially helps microgrids in providing a power source for a part of the day. Coupling residential PV with a BESS system allows energy arbitrage throughout the day as well as dealing with the new problem on addressing time-intermittent power generation coming from a residential setting

Additionally, the system can withstand a lot more load added quickly into the system and adjust accordingly. This has shown in scenarios where the load increases dramatically over short periods of time, but the system is able to provide energy in most cases. It is also reflected when the evening load increases drastically partially due to the decreased ability of residential PV and due to rising demand. The system responded effectively and was able to use its mix of energy options to meet demand. Additionally, the system was able to effectively adapt in the versatility and changes in different scenarios.

Load curtailment was expected to be used in a small percentage of the case. This proved to be correct and brief and targeted load curtailments can *improve* system reliability for priority customers. This is complementary to grid hardening efforts but has the advantage of lower costs because it can be built with existing infrastructure.

Some of the more unexpected results of the case study were limitations on battery charging as well as the extent to which battery degradation approximation can change the base model for a system. The model had to increase battery storage to double what was considered necessary. There was an expectation that the ability to discharge would cause issues not the ability to charge. Initial expectation of one battery per house had to be adjusted for a standard residential house battery model because of BESS cost considerations. In the cases where there is a load curtailment, the results can be stark. Six segment intervals showcase failure rates higher than 50%.

Even if this is for a brief period, this showcases the adaptability that electricity providers must consider in the future. Additionally, this level of variability is not surprising considering the smaller scale of the grid. It is also worth considering that risk factors do decrease dramatically from time segment to time segment, but the broader trend is true of higher risk factors later in the evening and in the early morning where demand is increased and residential solar is not in effect.

CHAPTER 5 CONCLUSIONS AND FUTURE WORK

This chapter summarizes by the thesis and concludes with future topics that can be used to explore other aspects of both risk management and microgrid design and research.

5.1 Conclusion

cVaR analysis is used in a stand-alone microgrid alongside day ahead scheduling. This research showcases the adaptability of a multitude of generation sources being utilized along with load curtailment in different demand-constraint scenarios.

The objective was to conduct a risk assessment on a microgrid system to assess likelihood of load curtailment. This allows for evaluating the risk of existing system infrastructure facing controlled load curtailment in a disaster scenario. The microgrid was able to continue operations and provide for demand while also utilizing BESS efficiently both for long term asset use as well as short-term dependability.

The research results showed that a microgrid could be created from an existing residential neighborhood that is currently connected to the main grid [44]. Instead of proposing a brand new microgrid installation, existing electrical infrastructure in neighborhoods particularly those with high residential penetration can be retrofitted with additional diesel generation and battery storage services alongside its own energy management system [4], [13]. Additionally, cVaR could be applied to these existing residential neighborhoods. This will allow these areas to decouple from the existing larger grid and function successfully in the short term as microgrids. The test microgrid presented in this research can be applied to certain existing residential neighborhoods with the addition of resources such as relatively mid-sized BESS or diesel generation. These resources would be added based on the risk management analysis in emergency operations of the existing residential neighborhood.

Other considerations that became crucial in this research is day-ahead scheduling and setting both preferences and objectives in energy management to reduce cost allowing the best mix of resource allocation. Cost functions were also important because they defined what is considered valuable in the model. For most electricity providers, reliability and cost is the focus. In this research, reliability, island-state feasibility, and a value on renewable sources was paramount. Other research mentions new systems that are needed to create a grid with volatile multi-generation sources [13], [34]. The core focus of this thesis is proving the feasibility for a predominantly residential neighborhood to be able to exist in an isolated microgrid while maintaining stability and a high level of power accessibility. The configuration proposed in this research will be a post-disaster scenario such as mass flooding, hurricane, or a winter storm limiting power reliability from the central grid.

The current electric grid is not prepared for prolonged interruption in service [1]–[3]. This has resulted in millions of customers losing power with haphazard load shedding at the time of emergency [18], [21]. The microgrid proposed in this research is based on the understanding that there might not be sufficient generation in certain situations and presents different tiers of customer priority to ensure a methodical distribution of limited energy. This is a departure from the current utility system for residential customers of rolling blackouts or random residential area load curtailment. This is not an acceptance of customer load curtailment but a more thorough risk analysis implementation to understand the likelihood of curtailment. With this research, systems can add generation based on the likelihood of emergency failure instead of the standard of normal operations. This research also explains the definition of priority customers as those medically dependent on consistent electricity as well as a template for economic recompense for those customers who could have their load curtailed. Neither of these options exist in the current electrical system.

In this research, BESS was considered as a combined service to provide for the entire area. Yet, the framework also allows separate BESS systems to exist while being synchronized by a day-ahead scheduling system. Additionally, BESS capital cost approximation was utilized to benefit the entire grid. This is a more sophisticated approach to battery usage increasing the overall lifecycle of a battery system.

Existing generation sources available currently such as residential PV and diesel generation can be combined into a microgrid with its own separate EMS to safeguard and enhance the electricity reliability for consumers on a local level in the situation of an emergency.

5.2 Future Work

This thesis opens several new avenues for further research on renewable operations in microgrids, and the overall electric grid in emergency situations. Microgrid stabilization using residential PV in emergencies requires further research. Moreover, a DC microgrid setup also needs additional research to go alongside BESS and PV systems. Hardware challenges such as back feeding of electricity in situations of DERs will also need to be addressed. Other aspects that could be researched is solar inverter technology and new distribution protection schemes to be able to effectively and safely transmit and distribute electricity for residential PV systems.

Customers and utility relationships will have to be reconsidered in a disaster scenario. Consideration of reliability in storms and how increased reliability capital spending and operations should be reviewed. Certain communities and neighborhoods are poised to be ideal areas for microgrids based on their geography and DER adoption rates but whether these changes occur is dependent on community decision making, federal infrastructure spending, and individual decision making. Research could investigate the changes needed to encourage the creations of these microgrids.

Customer involvement, pricing, and communication platforms must also be developed for more sophisticated forms of pricing, electricity, and reliability expectations. On a single consumer level, providers must create platforms allowing consumers to update their load curtailment risk level. Also, consumers should be able to notify providers about future decisions in purchasing DER such as battery, residential PV, or an electrical vehicle which could be used as vehicle-to-generation (V2G) [27]. Additionally, electric providers could encourage or subsidize customers with community wide group rates for certain neighborhood PV adoption targets or specific rates to encourage DER purchases. These preferred behaviors can include certain neighborhood PV adoption targets, EV adoption, generator purchase, or even microturbine ownership. Additionally, the incentives would have to include the utility having the ability to control individual resources in certain emergency scenarios. Based on incentives, electric providers could also invest in their own distributed renewable systems such as fuel cells and micro-wind turbines depending on the cost versus risk reduction basis.

The completion of the new two-way production, storage, and usage of electricity also opens the avenue of using blockchain where consumers and providers exist on a marketplace. In this situation, electric providers could sell to consumers but also consumers could sell to producers and to other consumers. There is also the matter of how to resolve ownership access to individually owned battery systems or electric vehicles that could be used as community BESS. In this research, the battery system is considered a community investment but in future uses, individual devices could be "rented" out or certain access is given in extreme scenarios. Additionally, lifecycle costs of residential PV and diesel systems were not included since this research looked at a purely operational standpoint. Future research could calculate the cost of upgrading existing infrastructure or installing new infrastructure from a pricing perspective. An additional research topic could be looking at active and reactive power management for droop control for island microgrids [24].

The last topic that comes out of this research is managing risk factors in battery degradation cost approximation in new microgrid development. Large BESS systems are new and the effect of lifecycle degradation and their costs have had limited research. By at least taking into consideration an approximation of battery degradation costs, designers and researchers can build more durable microgrids with set limits on battery usage. For example, BESS analysis could then be prioritized with different usage schemes and limits. Battery systems could be set to different priority levels and costs, so a large-scale BESS is more likely used then an electrical vehicle's battery.

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