Enhancing System Reliability Utilizing Private Electric Vehicle Parking Lots Accounting for the Uncertainties of Renewables

by

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Author’s Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Integration of renewable energy sources into electric grids comes with significant challenges. The produced energy from renewable sources such as wind and solar is intermittent, non-dispatchable and uncertain. The uncertainty in the forecasted renewable energy will consequently impact the accuracy of the forecasted generation. That, in turn, will increase the difficulties for the grid operators to meet the demand-supply balance in the grids. Moreover, the shift to electric vehicles (EV) also adds complications to grid operators planning since their demand profiles are unlike anything that is currently connected to the grid.

With the advent of the smart grid, many new interesting and practical technologies will become a reality. Unfortunately, most of these elements will not be physically realized in systems for the immediate future. This thesis will maintain an overarching constraint of only using aspects of the smart grid that can be implemented, given today's infrastructure, within the next three to five years. For that reason, all loads connected to the system are considered to be uncontrollable except EVs when they are connected to a "commercial parking lot". The goal of this body of work is to investigate the benefits of the utility providing incentives, in terms of reducing the price of electricity for charging EVs through a commercial parking lot, for the sole goal of enhancing reliability through optimized scheduling of charging time periods. Moreover, since the penetration of renewable energy is only predicted to increase over time, their impact will also be investigated.

Since both EVs and renewables add uncertainty and randomness whenever connected, these elements need to be accurately and adequately modelled. There will be five electrical components that will need stochastic models built. The first two, base electric load and dispatchable/distributed generators, will be modelled based on the IEEE - Reliability Test System (IEEE-RTS), with the later using a Monte-Carlo (MC) simulation. The next two, solar and wind energy, will be extrapolated from historical weather patterns through a Markov-Chain Monte-Carlo (MCMC) simulation. Finally, the EV will be virtually generated from historical commercial parking lot data also using a MCMC.

Three scheduling algorithms were implemented in this work. The first is a base case, in which the EVs charged in a first-come first-serve basis, this situation that would arise if no information at all is shared with the parking lot owner. The results of the simulation had the value of Expected Energy Not Served (EENS) came out to be 38.05 MWh/year (the lower the better). With the second algorithm, a basic Demand Side Management (DSM) algorithm was implemented, with the result being that the EENS decreased by 8.35 %. The information shared was the demand shape of all consumers for a given day. Lastly, an algorithm that will be called Grid and Demand Side Management (GDSM) by this thesis proved to be even more successful, having the EENS reach a value of 29.85 MWh/year, a decrease of 21.55 %. The GDSM scheduling algorithm needs the grid to share not only the consumer behavior but also the expected generator behavior. Based on these results, recommendations are made to the electric utility in terms of the benefits it may reap if it expands and develops a communication infrastructure that includes information of generator availability.

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List of Abbreviation

Acronyms

BESS	Battery Energy Storage Systems
CDF	Cumulative Density Function
CV	Coefficient of Variation
DG	Distributed Generator
ENS	Energy Not Served
EENS	Expected Energy Not Served
EV	Electric Vehicle
G2V	Grid to Vehicle
LD	Load Demanded
LOL	Loss of Load
LOLE	Loss of Load Expectation
LP	Linear Programming
MC	Monte Carlo
MCMC	Markov Chain Monte Carlo
MTTF	Mean Time to Fail
MTTR	Mean Time to Repair
PDF	Probability Density Function
PV	Photovoltaic Panel
RAM	Random Access Memory
RV	Random Variable
SOC	State of Charge
TTF	Time to Fail
TTR	Time to Repair
V2G	Vehicle to Grid
WT	Wind Turbine

Chapter 1

Introduction

1.1 Preamble

The rapidly growing demand for electric power relative to the available supply, the fears of the depletion of conventional energy resources (oil and gas) and the negative environmental impact of greenhouse gas (GHG) emissions resulting from burning fossil fuels have been a strong motive to invest in cleaner alternative energy sources in the recent years. In 2012, electricity sector and transportation sector have been reported to be the largest contributors to greenhouses gas emission in USA; with about 60% of GHG emissions being attributed to them [1]. Therefore, a significant decrease in the emission from these two sectors will lead to a significant decrease in the whole emission figure.

One option to achieve the above goal is to replace the current fossil fuels sources with renewable energy sources. The deployment of these renewable sources (wind and solar) will, consequently, have a positive impact on the reduction of GHG emission in the current electric grid. Wind energy is amongst the fastest growing renewable energy sources, Figure 1-1 shows the installed capacity of wind energy worldwide for the years of 2010 to 2018. As of December 2017, the installed wind capacity in Canada is 12.25 GW, providing 6 % of the demanded electricity [2]. The Canadian Wind Energy Association believes that wind energy can satisfy 20 % of Canada's electricity demand by 2025, reaching a capacity of 55 GW [3].

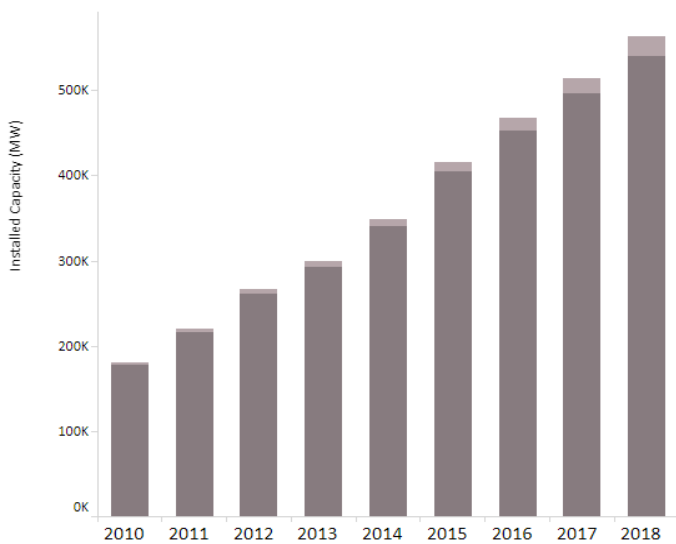


Figure 1-1: Installed Capacity of Wind Turbines [2010-2018] [2]

Photovoltaic (PV) systems, which directly convert solar energy into electricity, is another kind of renewable energy that has also been gaining traction. In 2017, solar PV capacity represented 2% of the world power output, reaching a capacity of almost 400 GW and generating 460 TWh. By 2023, solar PV is expected to grow to 580 GW as calculated by the International Energy Agency (IEA) [4]. Figure 1-2 gives the PV generation and cumulative capacity by region for the years of 2017-2023.

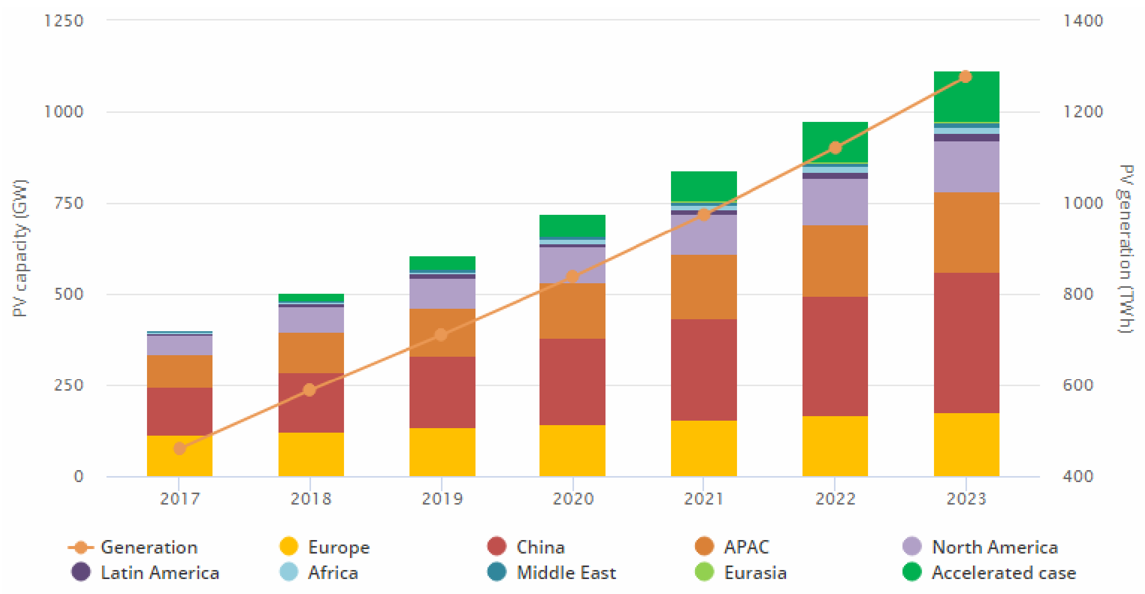


Figure 1-2: PV Generation and Cumulative Capacity by Region [2017-2023] [4]

On the other hand, at the demand side, the advent of electric vehicles (EV) looks to be very promising in decreasing the carbon footprint from transportation. In 2018, EVs emitted 38 million tonnes carbon dioxide equivalent. If these were instead gas/diesel engine cars, the wheel-to-wheel equivalent would have been 78 million tonnes of carbon dioxide [5]. Over the last few years, the sale of EVs have shown a healthy growth. Adoption of EVs was 2.1 million units in 2018, 64 % higher than for 2017. With the global EV fleet consuming the same total electricity demand of Switzerland in 2017, an estimated 58 terawatt-hours (TWh) of electricity in the year of 2018. This growth is driven by demand in China and the arrival of the popular Tesla Model-3 [6]. The global monthly sales for EVs between the years of 2016-2018 is shown in Figure 1-3 on the next page.

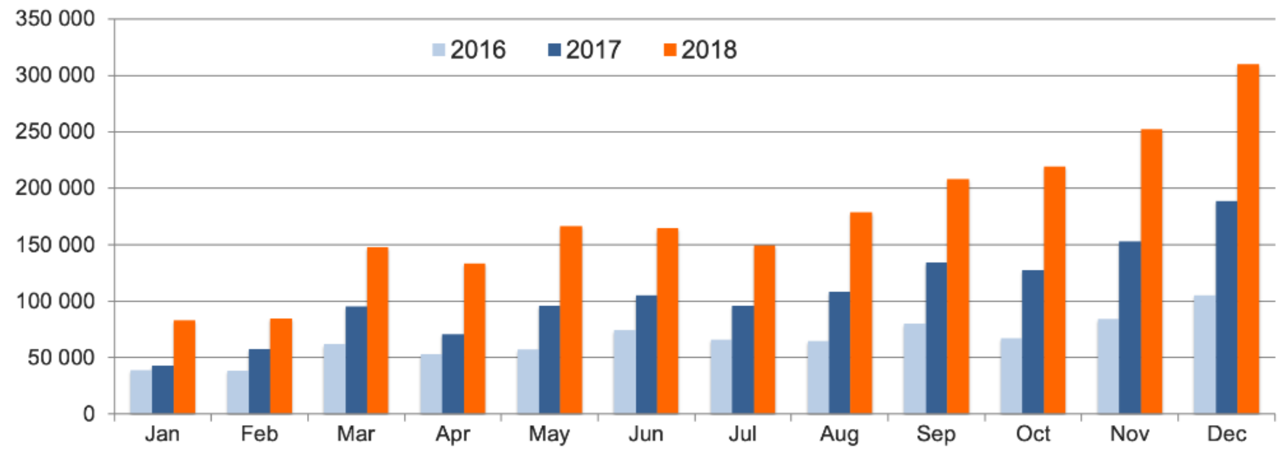


Figure 1-3: Global Monthly Sales of EV [2016-2018] [6]

The fact that electricity must be consumed the moment it is generated makes the simple issue of matching the supply of electricity with its demand a challenging problem. Because of this, it makes connecting renewable energy resources into the current conventional power grid a difficult task. The random variations in power produced by weather-based generation causes different levels of uncertainty that impact a variety of decisions. Moreover, the high penetration of EVs bring new challenges such as voltage deviations, line congestions, new load profiles and peak load elevation into the grid. This forces the current grid to limit the penetration of renewables and still use high polluting dispatchable generator to maintain reliability.

With the evolution of smart grids, many of these issues can be addressed. Since the smart grid is set to have the capability of a two-way flow of electricity and information, it will allow it to accept energy from distributed renewable energy resources and allow for the monitoring of real-time data. With this extra information, it becomes easier to match supply with demand, thereby increasing overall system reliability. With these advancements in the grid, many research institutions and individuals are investigating the potential benefits that can be had. Including the capability of shifting the power consumption of a refrigerator due to a high spike in demand recorded by smart meters into a research model may be useful, but the changes that are needed to actually realize it may need decades to fully mature. Even more complex concepts, such as bi-directional power (vehicle to grid configuration), need much more research to be implemented. The changes needed for the grid withstanding, the degradation to the EVs battery needs to be researched and compensated for. For this reason, this body of research will limit the technology used in to the models to components that can be realized realistically realized in the near future.

1.2 Motivation

As current forecasts go, the penetration of wind turbines (WTs), PV panels and EVs is set to increase in a matter that will significantly change the way that electric utilities need to operate. Of particular concern is their impact on reliability. PV panels and WTs are highly dependent on weather conditions, so they will introduce an undesired randomness to the planning of electricity generation. In addition, the EV demand profile shape is unlike any load that is currently being consumed. Therefore, it is imperative that these electrical components are considered and modelled adequately in any research endeavor that is concerned with power delivery.

With regards to scheduling the EV loads, there have been several suggestions. The most popular is demand side management (DSM), defined as "the modification of consumer demand for energy for the purpose of flattening out the demand profile shape". Since the cost of power generation and transmission is non-linear, with expenditures increasing as power demanded increases, the optimal way to minimize costs is to flatten the shape of demand. This approach works well when simulations are run in the short-term, where the maximum generational capacity of the grid is assumed to be infinite. But in the presence of non-dispatchable units such as PV and WT and increasing the time-scale to a longer-term (to a degree in which generators are allowed to fail), it can be seen that merely trying to optimize on the demand alone is insufficient. A methodology that incorporates both the demand and generation capacity needs to be developed.

Lastly, the most important overarching constraint that is to be placed on this research is to avoid using any technology that cannot be immediately realized, given today's electric grid infrastructure. With that constraint, three prominent issues spring up. The first is that the demand from consumers is considered to be unchangeable, as in the scheduling algorithm cannot shift demand for appliances such as laundry dryers and dishwashers. This is done because the infrastructure needed to allow the grid to tell a consumer to turn on/off appliances will take a long time to come to fruition. Secondly, the concept of a commercial parking lot for EVs is introduced. This means that the EVs are modeled arriving and charging in a designated parking lot that is near commercial areas. The reason for this is because it is perfectly feasible for a utility to invest in the communication infrastructure needed for scheduling algorithms to perform since there would be only a handful of these parking lots, as opposed to building this infrastructure for every home in the grid. The reliability savings of implementing these commercial parking lots will be investigated in this thesis. The last constraint that should be mentioned is that only a grid-to-vehicle configuration is allowed; the EVs cannot give back energy to the grid they can only accept it. The reasoning for this is similar to the first constraint, in that there is no power electronics circuitry on the market today that allows for bi-directional power transfer. In addition, the amount of deterioration that will inevitably happen to the consumers EV batteries has not yet been quantified.

1.3 Research Objectives

The main objective of this body of work is the investigation of the differences between two scheduling algorithms; Demand Side Management (DSM) and what this thesis calls Grid and Demand Side Management (GDSM) for the purpose of increasing reliability. In GDSM, the objective function contains both the demand profile and available generational capacity (whether it be traditional generators, photovoltaic panels or wind turbines), meaning that the grid will have to share more information with regards to its operation to the users. The proposed research is composed of the following sub-objectives:

- Build a stochastic model that can accurately and representatively model load demanded by consumers, traditional generators, PV panels, WTs and EVs.
- Vary the penetration levels of PVs, WTs and EVs and quantify their effects on reliability.
- Development of an efficient way to conduct the simulations and providing suggestions for future researchers who wish to undertake a similar methodology
- Apply different scheduling schemes to the EVs and see if it is indeed in the electric power suppliers' best interest to build an information sharing infrastructure between them and the parking lot owners with the explicit goal of enhancing overall system reliability

1.4 Thesis Outline

This thesis is comprised of six chapters. Chapter 1 is an introductory chapter presenting the preamble, motivation, research objectives and this outline. The remaining chapters are organized as follows:

Chapter 2: Background and Literature Review introduces the necessary reliability indices that will be the yard-stick in which everything is measured and compared to. After that, a review of the literature will be performed in which there will be three main topics. The first is investigating how reliability concerns have been addressed over the years, starting from the early 20th century and ending at our current time. The next is studying the various methodologies that have been used to model EVs, this is of particular concern since there is not enough empirical data regarding them. The last is reviewing how scheduling algorithms, such as DSM, was applied to solve a multitude of issues involving grid operations.

Chapter 3: Stochastic Models first introduced the concept of both Monte Carlo and Markov Chain Monte Carlo simulations. After that is explains the methodologies used to build stochastic model for the following elements: electric loads, distributed generators, photovoltaic panels, wind turbines and electric vehicles. Lastly, it delves into the stopping criteria of the simulation and discusses the benefits of utilizing the coefficient of variance instead of standard deviation.

Chapter 4: Scheduling Schemes presents the three different scheduling strategies for the electric vehicles that will be implemented and discussed within the scope of this research. The very well-known scheme of demand-side management, in which the times that the load is connected into the grid is adjusted such that it tries to flatten the shape of the demand curve, will be examined along with a base case coined “first-come first-serve”. The last case is coined as Generation and Demand Side Management, in which the demand profile tries to match both the demand and generation profile.

Chapter 5: Simulations and Results first ventures into how one can apply this research given today’s limitations in tech hardware. It gives plenty of suggestions into how the computer intensive simulation tasks can be parallelized (such that 10-15 different elements of the code can be run at once, instead of doing them serially, one at a time) and provides guidelines on to how to work with whatever computer specifications are at hand at that moment. Then it presents the results of the thesis, the outcomes of the 64 cases that are being studied. It delves deeply on the difference between each of them and quantifies the potential effects that the addition of renewable energy sources and electric vehicles might have on the grid. Furthermore, the results of the different scheduling schemes are also discussed.

Chapter 6: Conclusion is the conclusion of this thesis. It summarizes the main contributions made by this work, gives recommendations to the electrical utility based on its findings and suggests potential future research that can be built on top of this.

Chapter 2

Background and Literature Review

2.1 Preamble

The concern of this thesis is to both investigate the impact on reliability when introducing renewable energy sources and EVs, and the next is to propose a scheduling algorithm that will enhance the reliability. In the background section of this chapter, indices will be introduced that can quantify reliability in a consistent manner. Specific care has to be taken when selecting which indices to use since this is the variable in which the model will be trying to optimize for. For this thesis, the goal is to minimize outright power outage (which occurs when the demand of electricity is higher than the supply). This could happen due to a number of reasons; the demand can be higher than was expected, for example with the introduction of EVs there could be a spike in demand at an unexpected time or the supply can be too low, for example if a dispatchable generator were to go offline or if the PV panel output were to decrease due to a cloud. In addition, issues such as the transmission lines overloading or a transformer breaking can also cause an outage. In this research, the latter issues will not be considered; the model will assume that the transmission and distribution system will have no errors. The indices used to measure reliability and security of the network are the Loss of Load Expectation (LOLE) and the Expected Energy Not Served (ENS).

In the literature review section, three main areas will be studied. The first of which is investigating how reliability concerns, with respect to grid operation, have been dealt with over the years and how engineers have reacted with any new introduction to the grid. Next, the issue of how to include EVs in any research is studied. This is of particular concern since there are, as of today, still no data available publicly on a wide-scale, that gives the unique demand profile of EVs. This led to, as to the best of the authors knowledge, to there being no universally accepted methodology to stochastically model EVs. Lastly, a review of demand scheduling algorithms will be conducted. Of particular note is what assumptions were made to allow these scheduling algorithms to run and what indices were they trying to enhance.

2.2 Reliability Indices

2.2.1 Loss of Load Expectation

The Loss of Load (LOL) is an index that acts as a simple counter. It measures the amount of times in which the load demanded in an electrical system exceeded the generational capabilities. The unit that will be employed is number of hours of power outage per annum. This is given below in the formula:

$$LOL = \sum No.of\ Outages\ (in\ hours\ per\ year)$$

Since highly statistical methodologies are being utilized throughout the research, it is not guaranteed that after simulating the first year that the value of LOL calculated will be the true value of the system. If the simulation were to be repeated for a second year, it is very likely that the LOL calculated will be different. Below in Figure 2-1, it shows the values of LOL over a 5-year period.

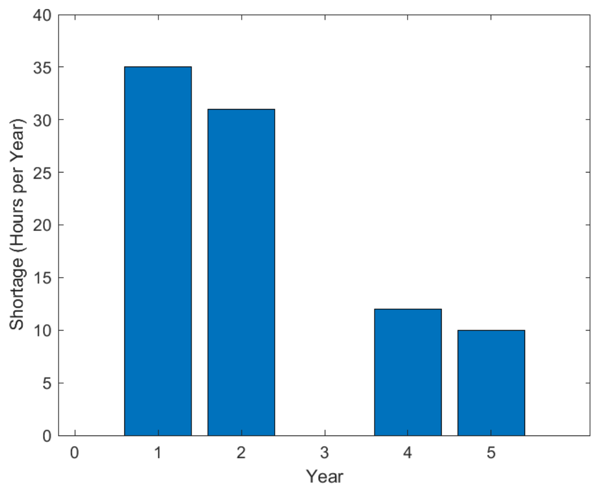


Figure 2-1: LOL Over Five Years

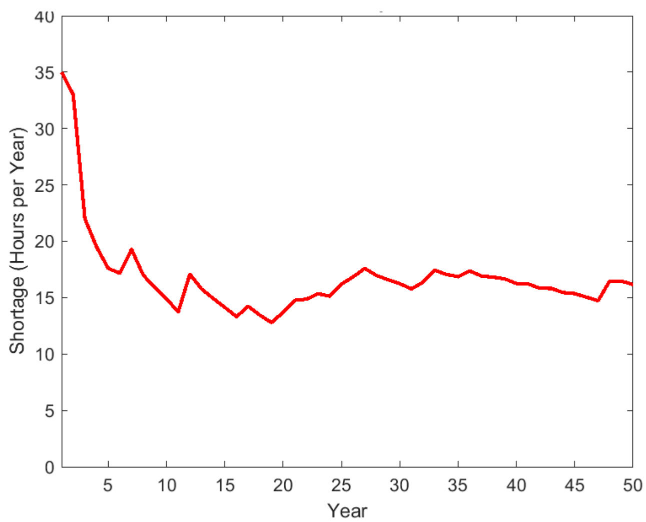


Figure 2-2: LOLE Over 50 Years

To remedy this issue, the expectation of LOL should be calculated, coined the Loss of Load Expectation (LOLE). Above in Figure 2-2, it shows the LOLE over a 50-year period. From it, it can be estimated that perhaps the true value of LOL should be around 15 hours per year. But the question arises, when should the simulation be stopped? Is one hundred years sufficient or should more be done? The issue of stopping criteria will be addressed in Section 3.10 later on.

2.2.1.1 Putting LOLE into Perspective

When designing a system, the goal is to set the LOLE to be very small. For example, in France it is predicted that there should be 30-hour disruption every ten years. Thus, the LOLE comes to be 3 hours on average per year. To put it into better perspective, a LOLE of 8 hours per year translates to a system security level of 99.90 % - i.e. 99.9% of the time all the demand can be met. Furthermore, even if a LOL does actually occur, it doesn't necessarily translate into a nation-wide blackout. But may be able to be solved by temporarily decreasing the voltage level or selectively disconnecting large industrial users. When not seen in perspective, a Loss of Load Expectation may give the wrong impression that blackouts are expected. To be able to better quantify the impact of the matters that will be researched, the base case will feature a much higher LOL than what systems are currently designed for. Reducing the LOL from 3 hours to 2 hours is not as much telling as being able to reduce the LOL from 150 hours to 100 hours, even though both are a deduction of 66.7 %.

2.2.2 Expected Energy Not Served

The Energy Not Served (ENS) index is very similar to LOL, but with one minor difference. While the LOL merely counts the amount of times a system has failed to supply its load, the ENS quantifies the amount of energy that could not be served. For example, if in a day the load demanded was higher than the supply of electricity by 1MW for 3 hours. The LOL would equal 3 hours/day while the ENS would be 3 MWh/day.

$$ENS = \frac{\sum Amount\ of\ Energy\ Not\ Served\ (MWh)}{8760\ hours}$$

Like with the LOL, the time frame that we will be looking at for ENS would be in annum. In words it would be the amount of generation (in MWh) that was needed by the load that couldn't be supplied by the generator. It is given above in the formula and its units are MWh not served/year. Figure 2-3 is an example of both the ENS and LOL metrics.

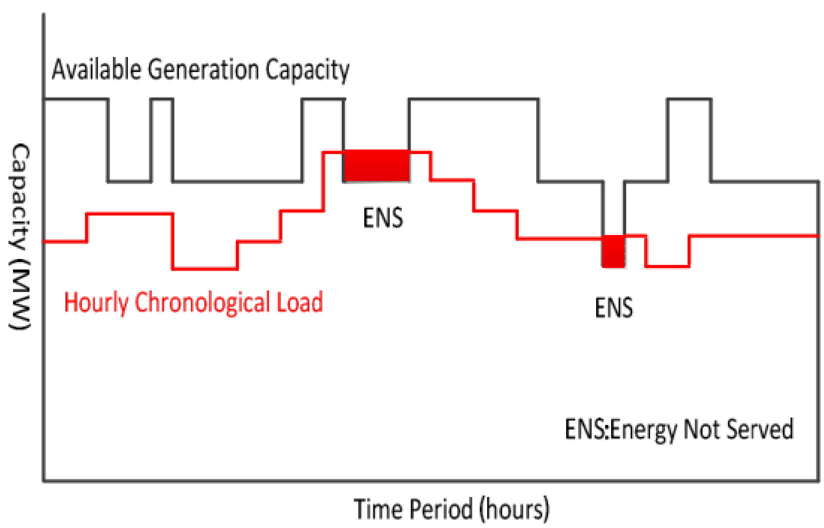


Figure 2-3: Example of Calculating the LOL and ENS

2.3 Literature Review

2.3.1 Reliability Studies

With regards to the operation of the power grid, reliability concerns have always been present. These papers, [7] - [11], ranging from 1905 to 1996 have researched various aspects of grid reliability. Ultimately, the simplest way to increase reliability in a distribution network is to increase the redundancy in the system. This is done by building more generators, transformers, power lines, etc. For example, building a system that had one extra generator in stand-by, in case of failures, would ensure there is no power outage if one generator were to fail. If there are two generators in stand-by, this would further increase reliability since the system can now handle the case if two generators were to both fail simultaneously. Ultimately, this could go endlessly on but unfortunately, trying to achieve a high reliability through creating a high redundancy alone would naturally cause the cost to increase to an unacceptable level. For this reason, there exists a delicate balance that the utility must maintain between its obligation to its consumers and to its own profit margins.

Throughout the years, whenever new innovations to the grid were added or planned to be added, their impact on the reliability of the grid is meticulously studied. The author of [7], suggested in 1905 when electrical utilities started to crop up that an "N-1" contingency should be followed for generators. In [8], they describe the procedure of planning the power system of Los Angeles in the 1950s in order to maintain reliability. They do this by taking detailed field surveys of land use and using historical data to predict likely load growth. While in 1973 and 1988, paper [9] and [10] both utilized the, then new technology of computer programming to evaluate reliability of transmission systems. And in [11], the authors investigated the impacts of Demand-Side Management (DSM) on the reliability and performing a "worth analysis" for the grid of 1996.

In today's grid, one of the major changes is the introduction of non-dispatchable renewable energy sources such as wind and solar energy. As mentioned in Section 1.1 - Preamble, their penetration levels are expected to grow over the coming years. Furthermore, states like California are setting a goal of 100 percent zero-carbon electricity by 2045 [12]. These renewable resources are of particular concern to reliability since they have a high element of randomness in their power outputs. Numerous studies have been conducted with regards to the integration of wind energy to an electrical grid. Reliability models incorporating wind energy were implemented by [13] - [17] utilizing various methods. In [13] and [14], an extensive study into the generational adequacy of a power grid that had a rapid growth of wind generation were conducted. The paper of [15] concerned themselves with attempting to provide simulation techniques to adequately determine appropriate wind power generation. The authors of [16] conducted an analytical reliability study of wind farms by modelling them as a multistate conventional unit where the probability, frequency of occurrence, and departure rate of each state was obtained using the wind regime of wind farms and wind turbine characteristics. And in [17] a sequential Monte Carlo simulation was utilized to evaluate reliability of wind turbine penetration.

Similar to wind energy, the integration of PV panels has also been studied extensively. Papers [18] - [21] specifically investigated there impacts on reliability. [18] used Markov Reward Models to estimate the reliability of PV system reliability. The authors of [19] used state enumeration to analyze real-life grid-connected PV systems for the purpose of reliability analysis. And a Monte Carlo methodology was used by [20] and [21] to adequately evaluate reliability of power grid operations. Studies examining reliability while including both PV panels and WTs have also been conducted, but not as extensively, given in these references [22] - [25].

From the load side, electric vehicles are also predicted to make a significant change. As the penetration of EVs increase, their unprecedented demand profile shape may cause reliability issues if not dealt with properly. Despite having many electrical parts, EVs can be thought of, from the perspective of the grid, to be simply as a Battery Energy Storage System (BESS). These BESSs although have two unique characteristics; the first is that they are randomly connected and disconnected to the grid and the second is that the expectation is that they will be fully charged when disconnected. Several studies have been done on EV implementation; [26] and [27] studied the impact EVs would have on the performance of a power system, in [28] economic analyses were performed and electricity market polices and opportunities were investigated by [29] and [30].

2.3.2 EV Modelling

To this effect, many studies in the literature have tried to integrate the potential impacts of EVs on the reliability of the power systems in their models assuming only the EV charging mode, which is known as grid-to-vehicle (G2V). The approaches introduced in [31] - [33] have considered that the EVs are to be charged in residential areas, for example through their personal garages. However, each has calculated the EV demand differently. The authors in [31] assumed that all EVs will be connected at 18:00 and disconnected at 6:00 the next day. The proposed models in [32] and [33] have assumed three charging periods in the day, albeit each one cut up the segments of the charging periods differently.

In [34] - [36], the authors considered only residential parking lots but in this case they also modeled the EVs as BESSs capable of bi-directional power transfer vehicle-to-grid (V2G). The authors in [34] anticipated a precondition in which users would actively let the aggregator know their expected departure time. They would be deterred from taking their car earlier/later than this through incentives such as a lifetime battery warranty. While the authors in [35] assumed two different charging time charging loads, labeled as “Valley Hours (0:00-6:00)” and “Peak Hours (16:00-21:00). The proposed EV model in [36] approximated a simple linear model for EV consumption.

More recent studies have expanded and tried to include the impact of the charging of the EV in commercial and industrial areas [37] and [38] using different models. The work introduced in [37] estimated the time of arrival and the duration of stay based on the average daily mileage of a personal vehicle. The authors in [38] utilized the daily trip data of ten vehicles for a year and then extrapolated this to build their models. There have been suggestions for standardizing the methodology of studying the effects of EVs on the grid. For example, the work in [39] suggested non-linear instead of linear models for the charging and discharging of the EVs. Displaying a significant difference on the grid impact when the batteries are modeled thusly.

A consensus seems to have been reached for papers investigating the long-term impact of EVs a consensus seems to have been reached for the number of random variables needed for accurate modelling. They use a mixture of three random variables, they are the time of arrival, the time of departure and the state of charge. The authors in both [40] and [41] stochastically based the random variables on numerous transportation reports.

2.3.3 Scheduling Algorithms

Demand response is defined by the Federal Energy Regulatory Commission [42] as "Changes in electricity use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market price or when system reliability is jeopardized." This can be achieved via direct control or indirect control. With the former, an aggregator can be made that will shift the demand of the users based on whatever optimization is needed to be done. And in the latter, pricing mechanisms are utilized to incentivize users to shift their behavior. These programs are acknowledged as useful for maintaining a uniform load level, thereby avoiding or deferring the costs of new supply resources, reducing wholesale market prices, and operating the grid reliably and efficiently. The benefits will also extend to participating customers, and they fall into two categories. First, financial benefits can be recognized throughout the bill savings and/or incentives payments received by participating customers who adjust their electricity demand in response to system critical events. Second, a proper demand response program helps in reducing the likelihood and consequences of electricity disturbances that might decrease customer comfort and satisfaction [43] - [45].

The concept of managing demand to help improve the functionality of the grid is a very attractive proposal. This could potentially enhance any type of index that we are looking for. It has been shown to help in voltage regulation [46] - [50] , in which demand is shifted away from a bus that is too overloaded at that time period. With the same working principle, it has also been used for frequency support [51] - [54] and in decreasing power loss [55] [56]. Papers [57] [58] increased reliability under the presence of wind energy, while [59] and [60] increased it under photovoltaic cells and [61] - [63] did it including the interface of electric vehicles.

In [64] - [66], they used a Home Energy Management System, in which the general behavior of consumers can be modeled as a Markov chain, whose states represent different consumer's activity level. Each activity level can influence the probability that a consumer turns ON an appliance. Each consumer has two types of appliances: controllable and noncontrollable appliances. An example of controllable appliances is a dishwasher, whose energy consumption can be deferred freely, but before a deadline dictated by the consumer's settings. In addition, a refrigerator can also be deferrable with the constraint that the temperature remains within a certain range. An uncontrolled appliance is one in which its demand cannot be deferred, like a TV.

2.3.4 Summary

Unfortunately, the infrastructure that will allow aspects such as vehicle to grid and advanced demand response will not be implemented for several years and if it were to be done today, it will most likely be on a comparatively small scale. This thesis takes upon it a constraint to assume that all loads are uncontrollable unless that they can be controlled with the current given technology and state of the smart grid. For this reason, it is assumed that only electric vehicles connected to commercial parking lots have a demand scheduling algorithm applied to them, in addition they are only considered to be connected in a grid to vehicle configuration. Moreover, this research will also vary the penetration levels of the PV panels, wind turbines and electric vehicles to see the impact on reliability for the proposed scheduling algorithms.

Thus, for this system to be employed, there are only two elements that need to be made available. The first is a system that can monitor and control the charging times of the EVs, which is something that can be easily realized today. And the second is that the utility needs to build communication mechanisms between them and the parking lot owners to coordinate the demand response. For the sake of this research, it is considered that the utility will only contact the parking lots and then and only then, will it provide them with the demand/generational profile of the grid if it predicts that there will be a loss of load during a 24-hour period. Since the potential number of commercial EV parking lots will be relatively low, probably next exceeding 3-5 per area for at least the next ten years, the communication infrastructure does not need a great investment in money. The way this research sets up the procedure, the system can potentially run via a phone call and e-mail.

Chapter 3

Stochastic Models

3.1 Preamble

To be able to investigate reliability the following components need to be adequately modelled:

1) Load Demanded (LD)
2) Distributed Generators (DG)
3) Photovoltaic Panels (PV)
4) Wind Turbines (WT)
5) Electric Vehicles (EV)

Since the LOLE and EENS needs thousands of years of simulations (ultimately over a million years were simulated for the overall research) until they reach their stopping criteria, it is imperative that this data be made available such that the research question can be answered. Ultimately, the most accurate would be to find raw empirical data for the above five units. In terms of the PV and WT, the data for the past 100 years of weather conditions could be readily found online and that extrapolated to power output for them. But unfortunately, we cannot go back further due to lack of data. And even if data was available, it would not make any sense to use it. With the advent of climate change, the weather from 200 years ago would not be at all representative of today's weather. With regards to the LD and DG data, this is even harder to find. But if it is assumed that data for 100 years is available most of it would not be useful. This is because the modern loads and DG units are very different to what it was even 30 years ago; not at all representative. Lastly, finding reliable and extensive EV data is next to impossible for more than 5 years since they are new introduced to the market.

The only solution that can be realistically realized is to try and statistically generate what are known as virtual scenarios for the above five elements. Since their statistical characteristics are very different to each other, a different and unique mathematical approach will have to be applied to each one of them to ensure a reliable and accurate representation of reality. This chapter will first describe how both a Monte Carlo and Markov Chain Monte Carlo approach can be used to tackle this issue. After that it will delve into detail on stochastically modelling each element in our system. Finally, it will conclude with talk about the stopping criteria used in the research.

3.2 Monte Carlo (MC)

When trying to model the probabilities of different outcomes in a process that cannot be easily predicted using mathematical formulas, a Monte Carlo (MC) simulation can be employed. Typically, the way to deal with a random variable in a model would be to replace it with a single average number. But if the model includes several random variables, in which their various interactions will impact the outcome of the model significantly, a single average number wouldn't suffice. It would be better instead, to attempt to simulate all the various combinations of the random variables to get a more accurate prediction of the model's performance. This is where MC simulations can be of invaluable help, the steps to apply MC are listed below with Figure 3-1 summarizing it into a flow chart:

1) Find a Probability Density Function (PDF) representing your desired random variable
2) Calculate the Cumulative Density Function (CDF)
3) Find the inverse CDF
4) Generate a uniformly distributed random variable
5) Input it into the inverse CDF to generate a virtual scenario

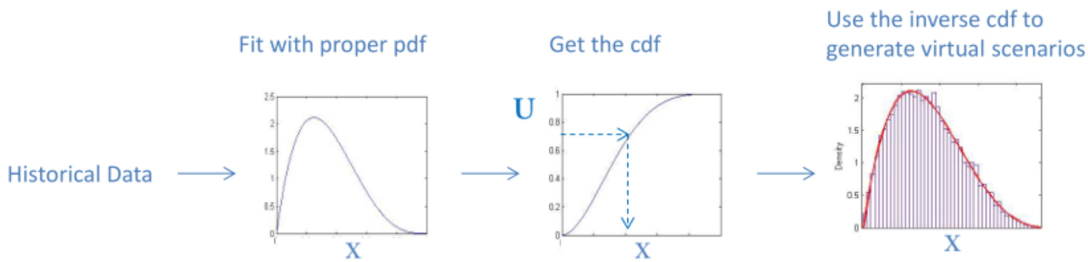


Figure 3-1: Flowchart of a Monte Carlo Simulation

3.2.1 Markov Chain Monte Carlo (MCMC)

A downside of just using MC on its own is that while the PDF of the simulated random variable would exactly represent the inputted PDF (given that the simulation is run for a long enough time), the outputs of the simulation will not be dependent on each other. For example, it is fair to assume that the solar insolation level at 11:00am depends heavily on the solar insolation level of 10:00am. Figure 3-2 on the next page showcases a MC simulation for solar insolation level over a 24-hour period. As can be seen, by only using a MC simulation, the solar insolation level at each hour is independent of the one before it.

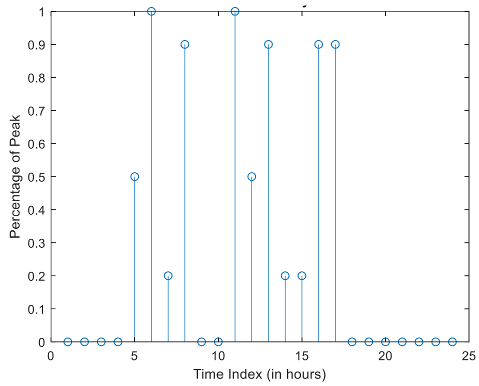


Figure 3-2: MC Simulation of Solar Insolation for One Day

To remedy this, an extension to MC called Markov Chain Monte Carlo (MCMC) is usually employed. Functionally, it is the same as MC except for the fact that they need transitional matrices representing the PDF. To find the inverse CDF of transitional matrices, the follow steps need to be taken:

1) Calculate the sum of each row
2) Divide each reach row by its own sum, thus making them into discrete PDFs
3) Compute the CDF of each row
4) Find the inverse CDF of each row

In summary, a MC simulation contains within it the information of a PDF and takes in a random variable to generate a virtual scenario. On the other hand, a MCMC contains within it the information of transitional PDF matrices and takes in both a random variable and the previous state to generate the next virtual scenario. This makes MCMC extremely powerful, enabling them to capture very difficult and intricate random process such as a cloud passing over the sun. For this research, the MCMC will only look to the immediate preceding state.

3.3 Load Demanded (LD)

To simulate the load profile per hour for the entire year, the IEEE Reliability Test System – 1996 (RTS-96) [67] will be utilized. This is a standardized set of data that is utilized by any researcher studying reliability. Ensuring that all research done in this field can be:

1) Easily reproducible
2) Reliably compared and contrasted

Given in the following pages are the Table 3.1: Weekly Peak Load in Percent of Annual Peak, Table 3.2: Daily Load in Percent of Weekly Load and Table 3.3: Hourly Peak Load in Percent of Daily Peak.

Table 3.1: Weekly Peak Load in Percent of Annual Peak

Week	Peak Load	Week	Peak Load
1	86.2	27	75.5
2	90.0	28	81.6
3	87.8	29	80.1
4	83.4	30	88.0
5	88.0	31	72.2
6	84.1	32	77.6
7	83.2	33	80.0
8	80.6	34	72.9
9	74.0	35	72.6
10	73.7	36	70.5
11	71.5	37	78.0
12	72.7	38	69.5
13	70.4	39	72.4
14	75.0	40	72.4
15	72.1	41	74.3
16	80.0	42	74.4
17	75.4	43	80.0
18	83.7	44	88.1
19	87.0	45	88.5
20	88.0	46	90.9
21	85.6	47	84.0
22	81.1	48	89.0
23	90.0	49	94.2
24	88.7	50	97.0
25	89.6	51	100.0
26	86.1	52	95.2

Table 3.2: Daily Load in Percent of Weekly Load

Day	Peak Load
Monday	93
Tuesday	100
Wednesday	98
Thursday	96
Friday	94
Saturday	77

Table 3.3: Hourly Peak Load in Percent of Daily Peak

	winter weeks		summer weeks		spring/fall weeks	
	1-8 & 44-52		18-30		9-17 & 31-43	
Hour	Wkday	Wknd	Wkday	Wknd	Wkday	Wknd
12-1am	67	78	64	74	63	75
1-2	63	72	60	70	62	73
2-3	60	68	58	66	60	69
3-4	59	66	56	65	58	66
4-5	59	64	56	64	59	65
5-6	60	65	58	62	65	65
6-7	74	66	64	62	72	68
7-8	86	70	76	66	85	74
8-9	95	80	87	81	95	83
9-10	96	88	95	86	99	89
10-11	96	90	99	91	100	92
11-noon	95	91	100	93	99	94
noon-1pm	95	90	99	93	93	91
1-2	95	88	100	92	92	90
2-3	93	87	100	91	90	90
3-4	94	87	97	91	88	86
4-5	99	91	96	92	90	85
5-6	100	100	96	94	92	88
6-7	100	99	93	95	96	92
7-8	96	97	92	95	98	100
8-9	91	94	92	100	96	97
9-10	83	92	93	93	90	95
10-11	73	87	87	88	80	90
11-12	63	81	72	80	70	85

3.3.1 Example of Generating LDs

To showcase this in action, an example of generating the first 6 hours of January 1st, 2019 is given. The characteristics of this day are that it is:

1) During week 1. From Table 3.1, the weekly peak load in percent of annual peak is **86.2 %**
2) On a Tuesday. From Table 3.2, the daily peak load in percent of weekly peak is **100 %**
3) On a weekday in Winter. From Table 3.3, the hourly peak load in percent of daily peak for the hours of 1 through 6 are **67 %, 63 %, 60 %, 59 %, 59 %** and **60 %** respectively.

Using this formula, Table 3.4 is generated.

$$Load\ Demand\ \ (Hour) = Weekly\ Peak\ Load * Daily\ Load * Hourly\ \ Peak$$

Table 3.4: Example of a Virtual Load Generated for Jan 1st, 2019

Time (Hour)	Load Demand
12-1am	57.75%
1-2	54.31%
2-3	51.72%
3-4	50.86%
4-5	50.86%
5-6	51.72%

Extending this, Figure 3-3 shows the virtual load generated for the entire year. The plot is normalized, such that the peak is one.

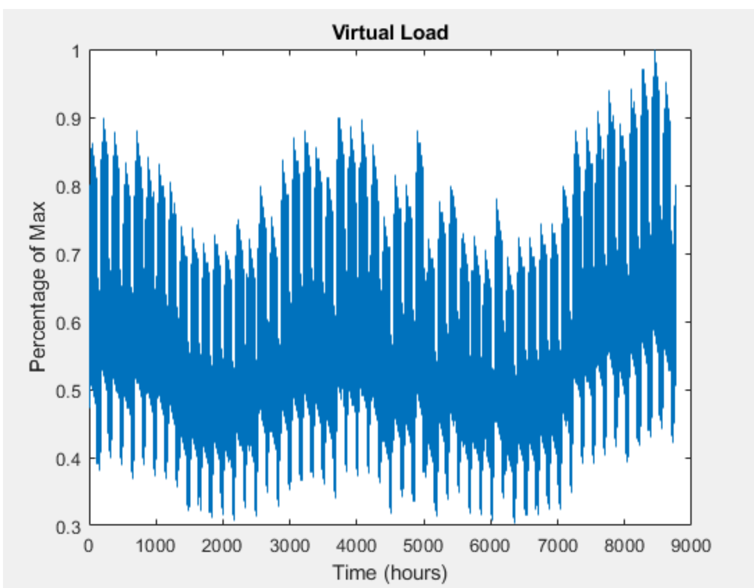


Figure 3-3: Virtual Load Generated for a Year

3.4 Dispatchable Generators (DG)

As opposed to generating load data using a static look up table in section 3.3 - Load Demanded, a statistical methodology will be utilized to generate DG data. Using the RTS-1996 again, DG unit's characteristics can be applied to a Monte Carlo (MC) simulation.

3.4.1 MC Simulations for DG

To apply MC simulations to generate virtual scenarios for dispatchable DG units, the following inverse CDFs are usually invoked:

$$TTF_i = -MTTF_i * \ln(Random\ Number)$$

$$TTR_i = -MTTR_i * \ln(Random\ Number)$$

TTF = Time to Fail

TTR = Time to Repair

MTTF = Mean Time to Fail

MTTR = Mean Time to Repair

i = the index of the generator.

3.4.2 Example of Generating DGs

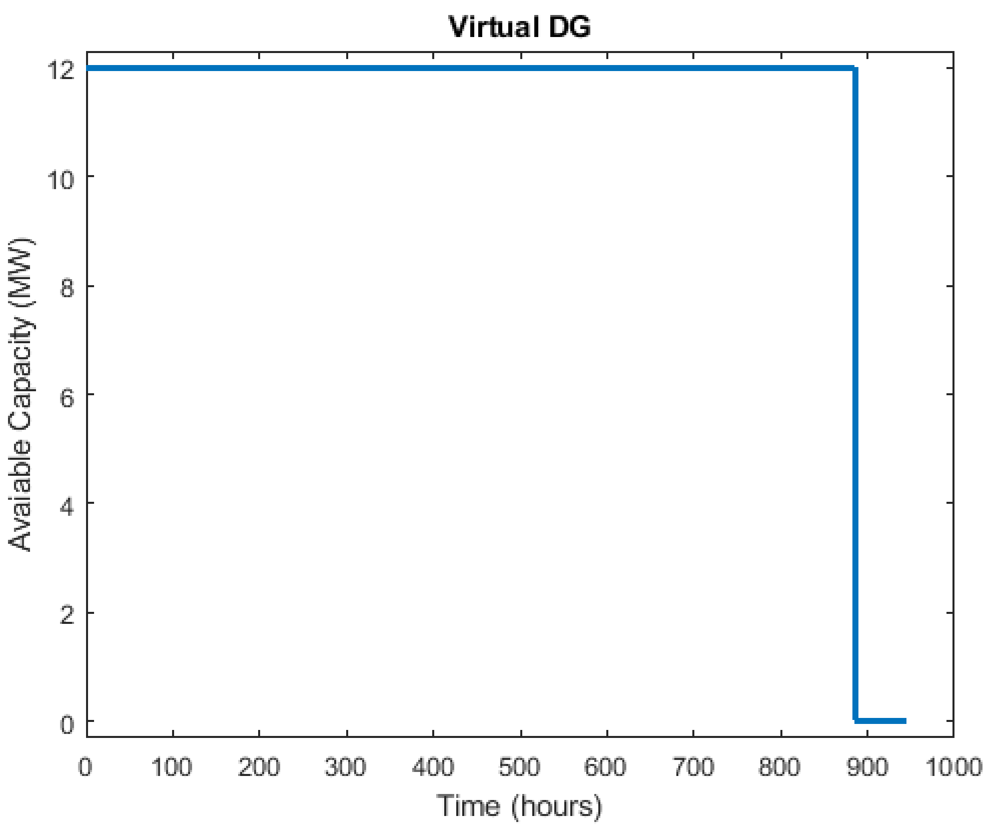


Figure 3-4: Example of 1 DG Unit

Assume the following characteristics for a DG unit:

1) Capacity is 12 MW
2) MTTF is 2940
3) MTTR is 60

The steps to generate virtual scenarios for a DG is, the output of this is shown above in Figure 3-4:

1) Input a random number in the TTF equation (for example 0.74), making the TTF be 885.24
2) Round it to the nearest hour such that the DG will be active for **885** hours before it fails
3) Input another random number in the TTR equation (for example 0.37), making the TTR be 59.65
4) Round it to the nearest hour such that the DG will be inactive for **60** hours before it is repaired and goes back online again
5) Generate an array that starts with 885 ones and then 60 zeros
6) Multiply it by 12 million (maximum available capacity)

3.4.3 Generating Multiple DG Units

In this research, 32 generators will be utilized that have the characteristics listed in Table 3.5, an example of this is given in Figure 3-5.

Table 3.5: Characteristics of DG Units

Number	Capacity	MTTF	MTTR
1	12	2940	60
2	12	2940	60
3	12	2940	60
4	12	2940	60
5	12	2940	60
6	20	450	50
7	20	450	50
8	20	450	50
9	20	450	50
10	50	1980	20
11	50	1980	20
12	50	1980	20
13	50	1980	20
14	50	1980	20
15	50	1980	20
16	76	1960	40
17	76	1960	40
18	76	1960	40
19	76	1960	40
20	100	1200	50
21	100	1200	50
22	100	1200	50
23	155	960	40
24	155	960	40
25	155	960	40
26	155	960	40
27	197	950	50
28	197	950	50
29	197	950	50
30	350	1150	100
31	400	1100	150
32	400	1100	150

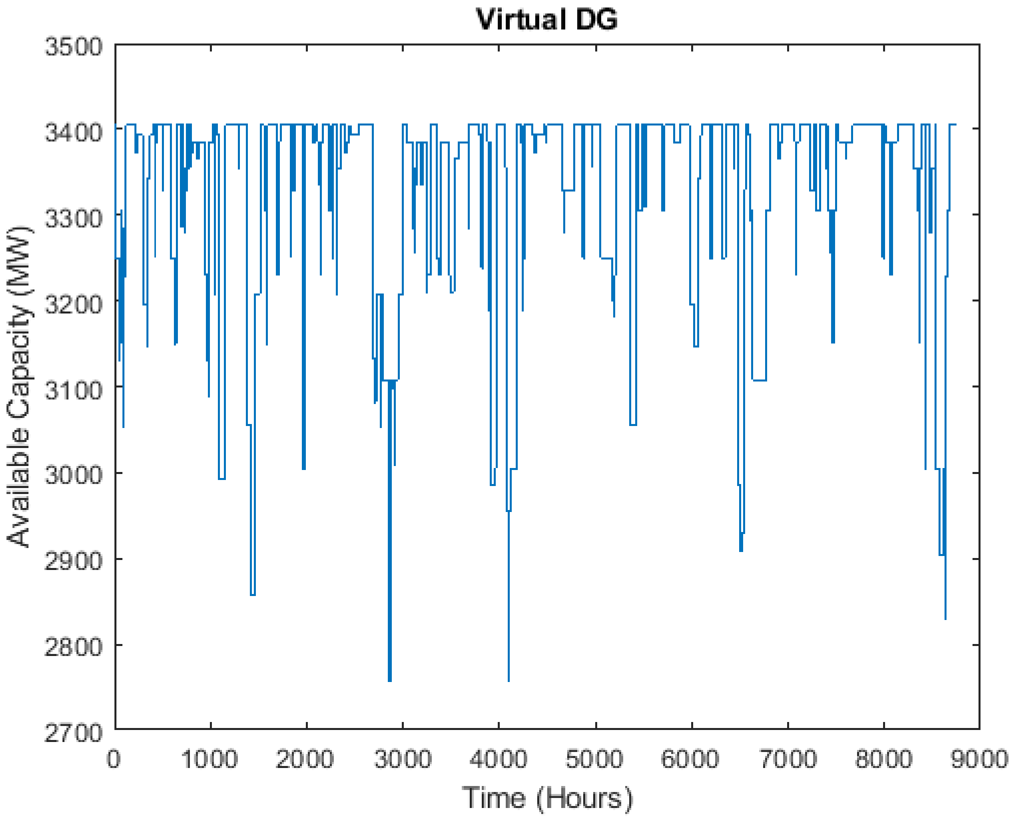


Figure 3-5: Virtual DG Generated for a Year

3.5 Photovoltaic Panels (PV)

The PV panels are like DGs, in the sense that there is not any look up tables for data. Thus, a statistical methodology has to be employed to generate virtual scenarios. Unfortunately, using the same way that was used for generating DG data cannot be used here due to three problems.

3.5.1 First Problem – PV Output Power

Electrical Data	
	SPR-E20-435-COM
Nominal Power (Pnom)[6]	435 W
Power Tolerance	+5/−3%
Avg. Panel Efficiency[7]	20.3%
Rated Voltage (Vmpp)	72.9 V
Rated Current (Impp)	5.97 A
Open-Circuit Voltage (Voc)	85.6 V
Short-Circuit Current (Isc)	6.43 A
Max. System Voltage	1500 V UL & 1000 V IEC
Maximum Series Fuse	15 A
Power Temp Coef.	−0.35% / ° C
Voltage Temp Coef.	−235.5 mV / ° C
Current Temp Coef.	2.6 mA / ° C

Figure 3-6: PV Panel Datasheet (SPR-E20-435-COM)

Looking into the literature, there is no available inverse CDF that manages to capture the properties of PV panels. To overcome this, the inverse CDF will have to be found empirically. To be able to model the output power of PV panels, two variables are needed; the temperature and the solar insolation. Assuming that all PV panels are of the model SPR-E20-435-COM given above in Figure 3-6, the power output can be found using the equations below:

$$T_{cell} = T_A + S_{IR} * \left(\frac{NOCT - 20}{0.8\ kW/m^2}\right)$$

$$I_{PV} = S_{IR} * (I_{SC} + K_i * (T_{cell} - 25))$$

$$V_{PV} = V_{OC} - K_V * (T_{cell} - 25)$$

$$FF = \frac{V_{MPP} * I_{MPP}}{V_{OC} * I_{SC}}$$

$$P_{PV} = N_{cells} * FF * V_{PV} * I_{PV}$$

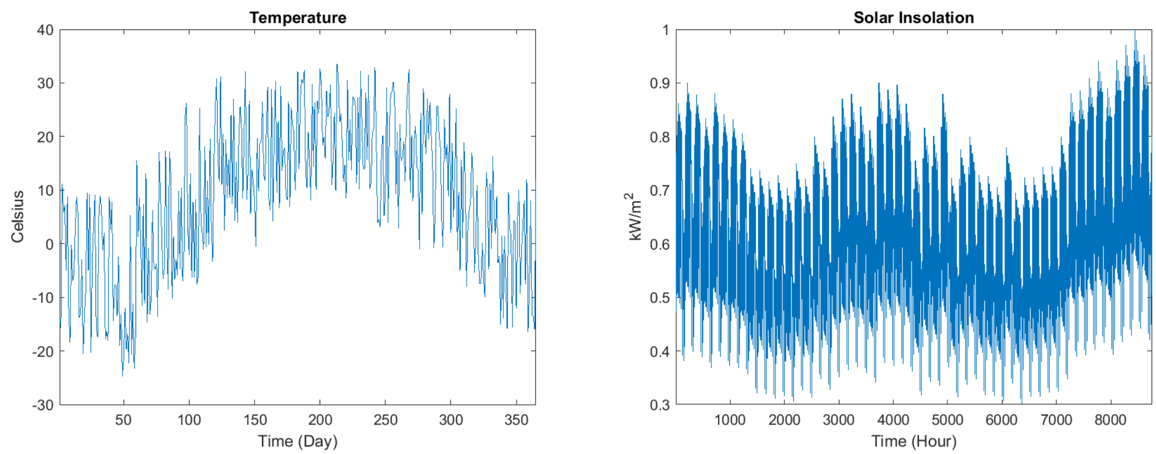


Figure 3-7: Temperature and Insolation Empirical Data for a Year

Using the temperature and solar insolation (given above in Figure 3-7), the PV maximum available output power is given below in Figure 3-8.

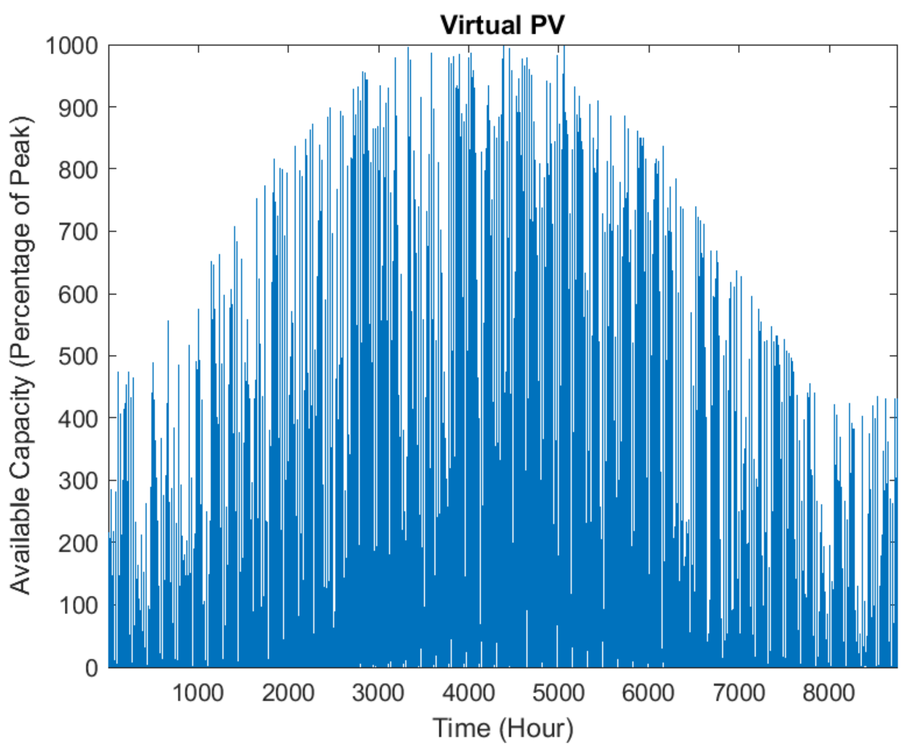


Figure 3-8: Virtual PV Output Calculated for a Year

3.5.2 Second Problem – Time Dependencies

Unfortunately, the data available for temperature and solar insolation is only for six years. Meaning that the empirical PV output data is also only available for six years. Thus, there is a need to make do with what is present and utilize a MC simulation to generate virtual scenarios from it. And this is where the second problem rises, a limiting constraint of using MC is that the data has to be independent on time. A quick cursory glance into Figure 3-8 shows the PV output power has a high correlation between the seasons and the output power. For example, during the summer months PV output is much higher than in winter. In addition, there is also a similar correlation between the hours. If we isolate for season, it can be seen that 12:00 noon would typically have a very high output power while 12:00 midnight would have a very low output power. To remove these dependencies, there will be two splits.

The first split that will be done will be to split up our data into four seasons; Winter, Spring, Summer, Fall. For consistency with the load, the RTS' definition of seasons will be followed:

1) Winter: Weeks 1-8 & 44-52
2) Spring: Weeks 9-17
3) Summer: Weeks 18-30
4) Fall: Weeks 31-43

The second split will be in terms of the 24 hours in a day. Thus, there will be 24-hour splits with 4 seasons splits, resulting in 96 different classes of input data. Each one of these classes are now time independent of each other.

3.5.3 Third Problem – Markov Chain Monte Carlo

If a MC simulation were now to be applied an output like that was shown in Figure 3-2 in Section 3.2.1 - Markov Chain Monte Carlo (MCMC) is to be expected. The problem with this should be immediately clear and it is an unfortunate downside of taking the time dependencies out of the empirical data. This is because that while a correctly applied MC simulation will reproduce any PDF that is entered into it; the outputs will be independent of each other. This is not a problem with DGs since it is fair to assume that the TTF and TTR of generator **i** is independent of the TTF and TTR of generator **i+1**. In addition, it is not far off to assume that the TTF and TTR of generator **i** is also independent of each other. However, for PV power output, the state at, for example, 3:00 pm is heavily dependent on the one that precedes at 2:00 pm. In turn, the state at 2:00 pm is also heavily dependent on that of 1:00 pm and so on and so forth. Therefore, a new technique to virtual generate scenarios that are dependent on the previous state needs to be found.

Fortunately, this can be done with Markov Chain Monte Carlo (MCMC). In functionality, it is very similar to MC except for the addition of one-step. While maintaining the 96 splits of data, instead of converting them into a simple PDFs (which simply quantifies frequency of occurrence of an event), transitional matrices are employed. This is done by first discretizing the states of PV output power (10 states were used) and then by counting the amount of times state **x** become state **y** between split **i** and split **i+1**. This will result in 95 transitional matrices, to get the 96^{th} matrix split **96** is then compared to split **1**.

Figure 3-9 below shows the output of the MCMC simulation. If it is compared it to the input data shape of Figure 3-8, is similar to it except for one thing. Which is that the transitions between the seasons are not smooth. This is to be expected since the year, which consists of 8760 hours was only discretized into four different seasons. A step of 0.1 was utilized to discretize the transitional matrices. For the purposes of this research, this is sufficient.

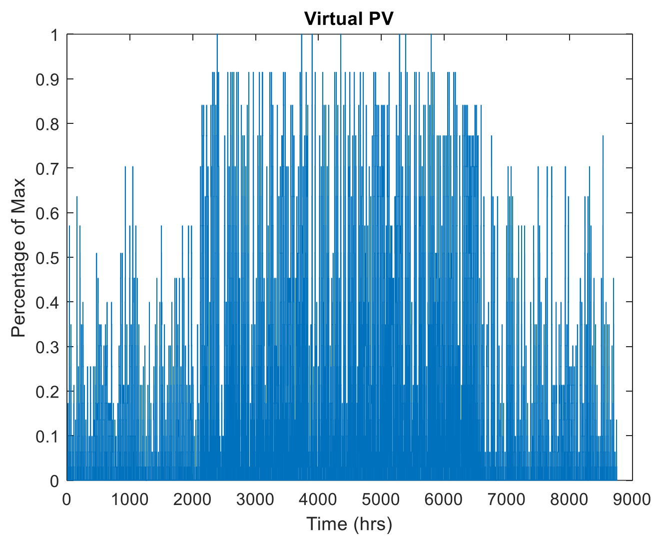


Figure 3-9: Virtual PV Generated for a Year

3.6 Wind Turbines (WT)

In virtually generating WT scenarios, a very similar methodology the one used for PVs will be applied. The only difference is that instead of converting temperature and solar insolation into PV output power, empirical data for wind speed will be converted to WT output power.

3.6.1 WT Output Power

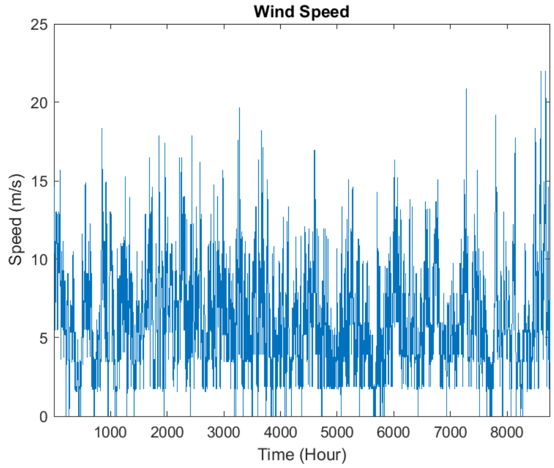


Figure 3-10: Empirical Wind Speed Data for a Year

Shown above in Figure 3-10 is empirical wind data for one year of the available ten years. To convert it into WT output power, these following rules will be followed:

1) If the input speed $\mathbf{v}$ is less than $\mathbf{v_{in}}$ then there is not enough wind to turn the wind turbines and power output is zero
2) If the input speed $\mathbf{v}$ is greater than $\mathbf{v_f}$ then the speed of the wind is too high and may be dangerous to the turbine, therefore it will be shut off and the power output is again zero.
3) If the input speed $\mathbf{v}$ is between $\mathbf{v_r}$ and $\mathbf{v_f}$ then the output of the WT is the rated power $\mathbf{P_r}$
4) If the input speed $\mathbf{v}$ is between $\mathbf{v_{in}}$ and $\mathbf{v_r}$ then the output will be a ramp function

This is summarized in the formula below and plotted in Figure 3-11 on the next page.

$$P(v) = \begin{cases} 0, & v < v_{in} \; or \; v_f \leq v \\ P_r\left(\dfrac{v - v_{in}}{v_r - v_{in}}\right), & v_{in} \leq v < v_r \\ P_r, & v_r \leq v < v_f \end{cases}$$

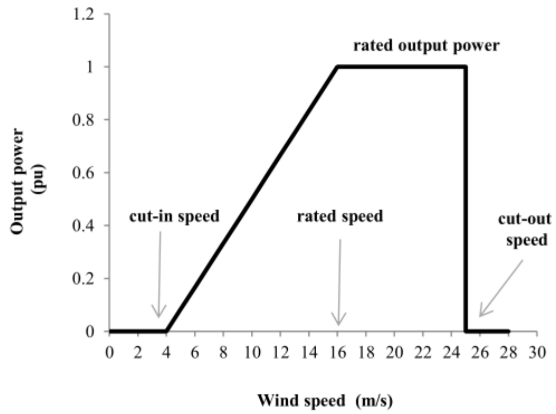


Figure 3-11: Wind Speed vs WT Output Power

Applying the formula to Figure 3-10, the output is given below in Figure 3-12. And in Figure 3-13 is the virtually generated WT output over a year period.

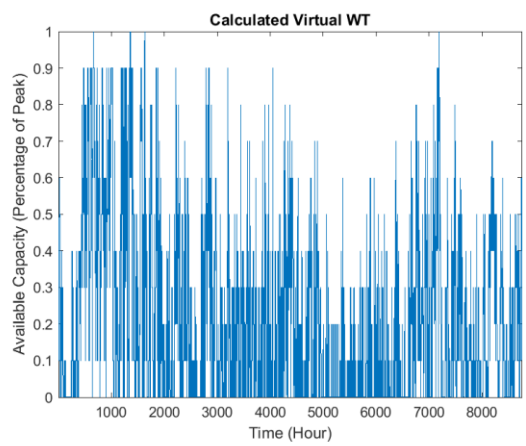


Figure 3-12: WT Output Calculated from Wind Speed for a Year

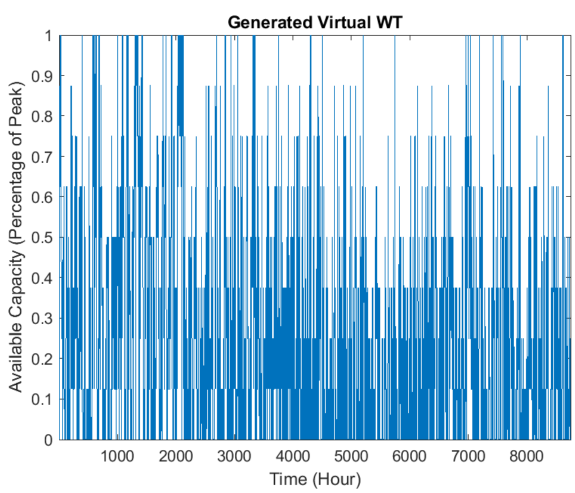


Figure 3-13: Generated Virtual WT for a Year

3.7 Electric Vehicles (EV)

There are several problems that arise when trying to find data for EVs. Like PVs and WTs, the first problem is that there is no sufficient amount of empirical data available for the scale of this research. But the problem unfortunately extends much further than that. Since the goal is to be able to control the charging and discharging of EVs, the shape of the data has to be in an un-aggregated form. With the LD, DG, PV and WT; each are only considered as just one unit. For example:

> *On day 35, hour 4 the LD is 3500 MW, the DG generates a maximum of 2500 MW, the PV generates a maximum of 100 MW and the WT generates a maximum of 300 MW. Which means that at this hour, there is indeed a LOL with ENS equal to 600 MW.*

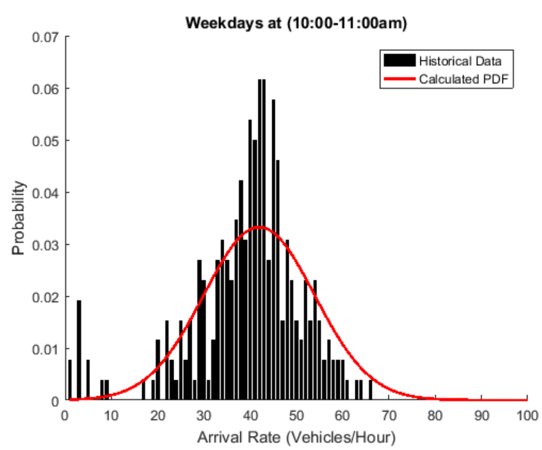
However, with EVs they cannot be thought of simply as a lumped load. Each individual car has its unique power requirements and unique times of entry/exit into the parking lot. To that regard, this research defines and uses three random variables to allow for these constraints. Two of these will be empirically based on data from the Toronto Parking Authority [68]. It contains the entry and exit times of non-EVs which will be repurposed for EVs. The major assumption made here is that the behaviors of drivers of non-EVs will be the same as the behaviors of drivers of EVs, and this is reasonable because the technology for vehicles that run on electricity has been available for a while now.

3.7.1 Random Variables

Like all the previous virtual scenarios, the time scale that will be used throughout is hours. In addition, since there is a high correlation between time. Like the PV panels and WTs, the input data will be split into 4 seasons (Winter, Spring, Summer and Fall) and 24 hours. In addition, since commercial parking lots are being modelled, there will be a time dependency between the days of the week. And thus, an additional split between weekdays and weekends will be implemented resulting in 196 splits of data.

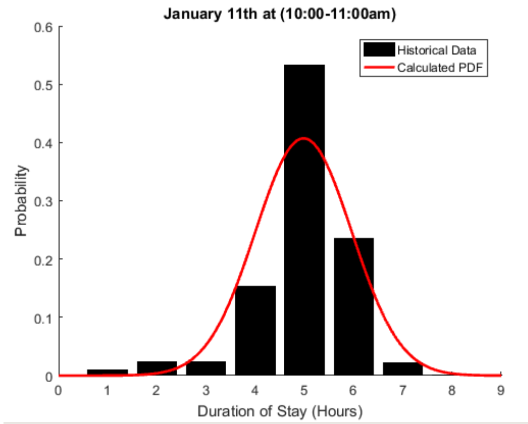
3.7.1.1 RV1 – Arrival Rate

This variable is defined as the arrival rate of cars per hour. It is empirically calculated from the Toronto Parking Authority dataset.



3.7.1.2 RV2 – Duration of Stay

This RV is also found from the Toronto Parking Authority dataset. It is built up on the previous arrival rate. If for example, 31 cars arrived at hour 3. The duration of stay is a list of 31 numbers of how long each car stayed before leaving the parking lot.



3.7.1.3 RV3 – Initial State of Charge

Unfortunately, a suitable dataset to pull data from for this RV wasn't found. Therefore, a simple Gaussian function; with mean equal to 40 %, standard deviation equal to 20 % and limited from the top to 90 % and the bottom to 10 % is utilized for generating this random variable. The PDF is given below in Figure 3-14.

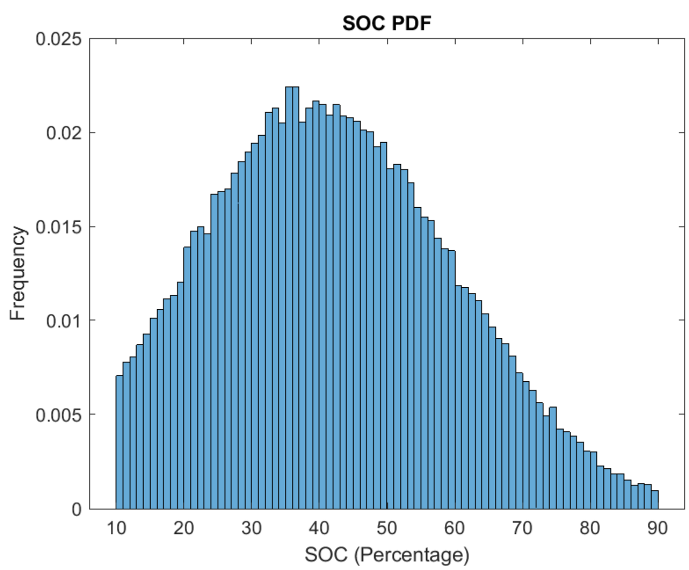


Figure 3-14: PDF for Initial State of Charge

3.7.2 Example of Generating Virtual EV Scenarios

To generate EVs for Jan 5th 2019, between 9:00am-10:00am a weekend the following steps are taking:

1) Run a MCMC simulation on the first RV of arrival rate. For example, assume the number came out to be 80.32. After rounding down, 80 cars have arrived in the parking lot at this time
2) Now run a MC simulation on the second RV of duration of stay 80 times to find how long each car stays in the lot
3) Finally, run a MC simulation on the last RV of initial SOC.

The output of this is given below in Table 3.6

Table 3.6: Example of Generating Virtual EV Scenarios

Vehicle No.	T_Arrival	Duration	T_Departure	SOC Initial
1	9:00:00 AM	6.30 Hours	3:18:00 PM	63.75%
2	9:00:00 AM	9.80 Hours	6:48:00 PM	78.33%
3	9:00:00 AM	7.20 Hours	4:12:00 PM	54.00%
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
79	9:00:00 AM	8.10 Hours	5:06:00 PM	15.23%
80	9:00:00 AM	8.70 Hours	5:42:00 PM	39.64%

3.7.3 EV and EV Charger Datasheet

According to the EV company Tesla, they are not planning on using a larger battery than 100 kWh for the foreseeable future. This will be taken to be the standard battery size of each EV in the simulation. A fourth random variable could be easily added that would contain a distribution of different size of batteries and would, technically, be more accurate of a model. But this would unnecessarily increase the needed simulation with no potential gain.

The EV charger is considered to be 100 % efficient with reference to the grid. For simulation purposes it could be made to have a more realistic efficiency, for example 90 %. And thus, when an EV comes in to charge instead of requiring, for example 50 kWh it would now draw 55.55 kWh. Since only grid-to-vehicle is considered in this research, there is no need to add this.

The maximum speed of the EV charger was decided to be 33.33 kW. Meaning that the theoretical max time a car would need to be fully charge would be 4 hours. (The last hour would be for the extra 0.01 kWh that is needed). But since, the minimum charge in our model is 10% of the battery, it would take 3 hours to fully charge an EV battery.

3.8 Combined Generation and Load Profile

As mentioned in 2.2.1.1 - Putting LOLE into Perspective, the value of LOLE needs to be made much higher than it normally should be such that any changes made to the system are much more noticeable. In addition, since the maximum total amount of energy that can be demanded by an EV at any time is limited by the speed of its charger, which is set to be 33 kWh the values of the generators and load has to allow the EV to make an impact.

Added together, the DGs have a maximum theoretical output capability of 136.2 MW (assuming all DGs are online at the same time). The LD will be set to be 92.51 % of this (coming to a maximum of 126 MW). These two values will be constants throughout the entire research.

They are added together according to this generation balance equation:

$$VS = DG + PV + WT - LD - EV$$

The values of PV will be 0 %, 5 %, 10 % and 15 %; the values of WT will also be 0%, 5 %, 10 % and 15 %; lastly the values of EV will either be 0 or 1 (with one meaning that there is one EV parking lot being simulated). In summary, there will be: 4 scenarios for PV, 4 scenarios for WT and 2 scenarios for EV. Coming to a total of 4*4*2 = 32 unique scenarios in which the LOLE and EENS will be calculated for each of them to be able to quantify the effect of both renewable energy sources and EVs to the reliability of a power grid.

Furthermore, of the 16 unique scenarios in which the EV are connected to the grid. Three different control algorithms will be applied on to them, in which each will have to have LOLE and EENS calculated. Chapter 4: Scheduling Schemes will introduce these algorithms.

In summary, there will be 16 scenarios for measuring the effect of PVs and WTs on an electric grid without EVs and 48 scenarios for measuring the effect of PVs, WTs and EVs effect on an electric grid, coming to a total of 64 scenarios generated.

3.9 Note on Parameters Used

When modeling the five elements, decisions had to be made in terms of where the data should come from and which parameters to use. With regards to the LD and DG, the matter was pretty simple. The load profile shape and the DG unit characteristics were both taken from the RTS-1996 paper. In addition, selecting the size of DG units and LD was done in a matter that would increase the LOLE and the EENS such that the differences between the scheduling algorithms would be magnified.

The PV panels and WTs were also basic; Canadian weather data was used coupled with standard power estimation equations and generic PV panel and WT datasheets. Lastly, the EVs were a little bit harder. Since the assumption was that the EV parking lots would be most profitable near industrial locations, those parking lots were chosen from the Toronto Parking Authority dataset. The parameters for the EVs and the EV battery charger was chosen to be as generic as possible also and the formulation of the state of charge was done that way due to a lack of data.

Any of these parameters can be changed to potentially have different results but it is the belief of that author that they cannot be really "tweaked" to give a better/worse performance. Since the ultimate goal is to showcase the difference between three different scheduling algorithms, it really shouldn't change the outcome a lot when comparing between a before scenario and an after scenario. For example, if datasheet "xy" was used for the PV panels and the results give us a 105 hours/year LOLE for the base case and 70 hours/year LOLE for the demand side management case, resulting in a decrease of 33.33%. Then it would be expected that if datasheet "xz" was used for the PV panels then perhaps the absolute value of numbers will change, perhaps it could be 91 hour/year for the base case and 60 hours for the demand side management case. But the difference between the two should remain almost the same at around 33.33%.

3.10 Stopping Criteria

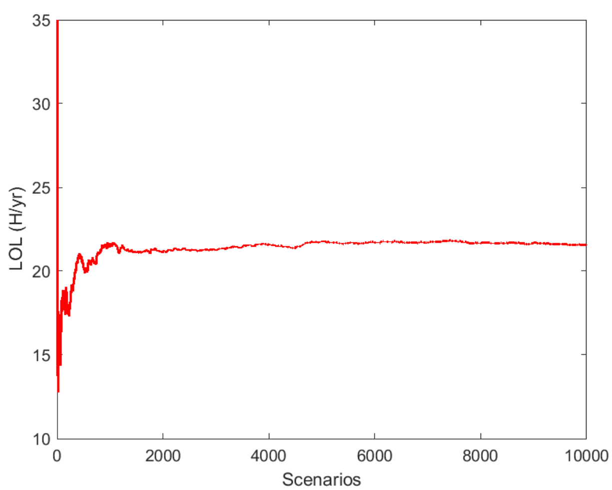


Figure 3-15: LOLE over 10,000 Years

For calculating the expected value of LOL and ENS, ultimately the best approach would be to generate virtual scenarios for an infinite amount of time to ensure that the LOLE and EENS are indeed the correct values for the system. As previously mentioned, in Figure 2-2: LOLE Over 50 Years, it can be estimated that the LOL should be around 15. But from one scenario to another the jump is too high. Figure 3-15 above shows that when taking 10,000 scenarios the LOL is actually 21.5931 hours per year and that the value starts stabilizing at around 2000 scenarios. To be able to quantify this and implement the stopping criteria in code, the standard deviation of LOLE is calculated. The formula of which is given below:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$$

To see this in effect, on the next page in Figure 3-16 is a plot of the LOL, LOLE and the standard deviation of LOLE over 10,000 years. The first thing of note is that the LOL value never stabilizes, at times it goes as high as 340 hours per year and at others it is as low as zero. More importantly than that is the LOLE in which it can be seen that past 1,000 years the value is practically constant, and this is reflected in the standard deviation. Initially, there was a high spike of about 5, but past 500 the value is essentially the same. More ever, seen over the 10,000 years, the value of standard deviation is actively decreasing each time the simulation is run. Meaning that after each scenario, the value of LOLE is closer and closer to the true value. Ultimately, running the simulation over and infinite amount of years will ensure that the expected value is the real value, but this is computationally impossible. Instead, an acceptable stopping criterion is chosen when the standard deviation is below a certain value.

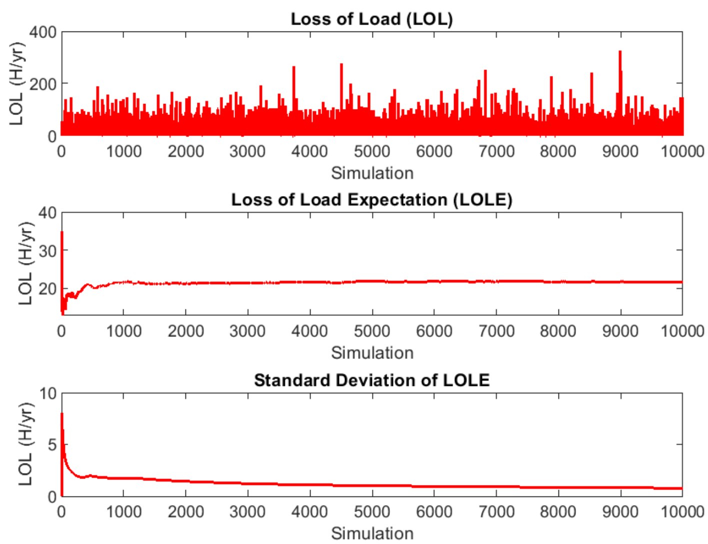


Figure 3-16: LOL, LOLE and σ(LOLE) over 10,000 Years

3.10.1 Coefficient of Variation

By definition, standard deviation is a measure of the dispersion of a set of data from its mean. The first problem that faces this research is that the standard deviation is not unitless. Therefore, the values of standard deviation cannot be compared directly between the LOLE and EENS; the unit for LOLE is hours/year while the unit for EENS MWh/yr.. Figure 3-17 shows the same plots as Figure 3-16; except for ENS, EENS and standard deviation of EENS.

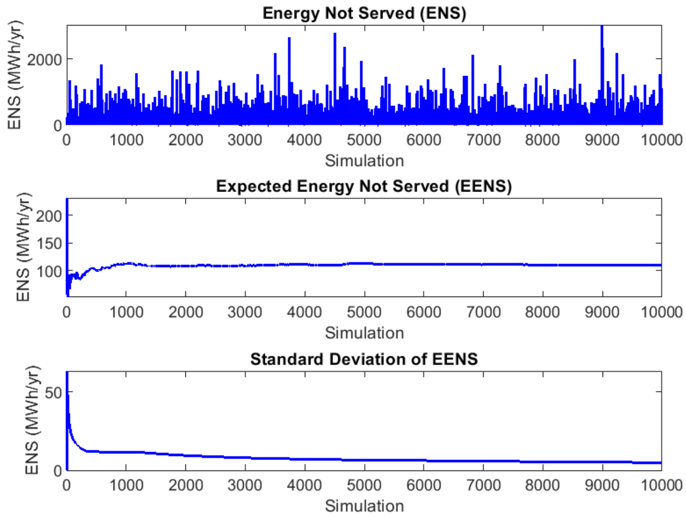


Figure 3-17: ENS, EENS and σ(EENS) of 10,000 Years

Since the value of EENS stabilizes at around 120, which is almost six times larger than the value of LOLE (of about 21), the values of standard deviation of EENS are also much larger than the values of standard deviation of LOLE. While indeed, it is expected that it should take more simulations for the EENS to stabilize as compared to the LOLE; since the latter is merely a binary counter while the former actually quantifies a value (for example, the LOL can be 3 hours/yr for 10 years in a row while the ENS can have different values each year). If the units of EENS were changed to GWh/yr instead of MWh/yr then the standard deviation would be much lower than that of the LOL. To be able to implement a stopping criterion for both the LOLE and EENS, the standard deviation needs to be converted to a unit-less value such that both can be compared against each other, and thus the coefficient of variation (CV) will be used instead, the formula of which is given below:

$$CV = \frac{\sigma}{\bar{x}}$$

As can be seen, it is simply taking the standard deviation and dividing it by the mean. This is very important since it now renders the measure of dispersion unit-less. Below in Figure 3-18 is the comparison of σ and CV for both the LOLE and EENS. From the plots, it can be seen the scale of standard deviation of EENS is almost 10 times higher than that of standard deviation of LOLE. While, when comparing the CV of both, the EENS is only twice as high. Which seems to be much more reasonable. In this research, the stopping criteria will be 5 % CV.

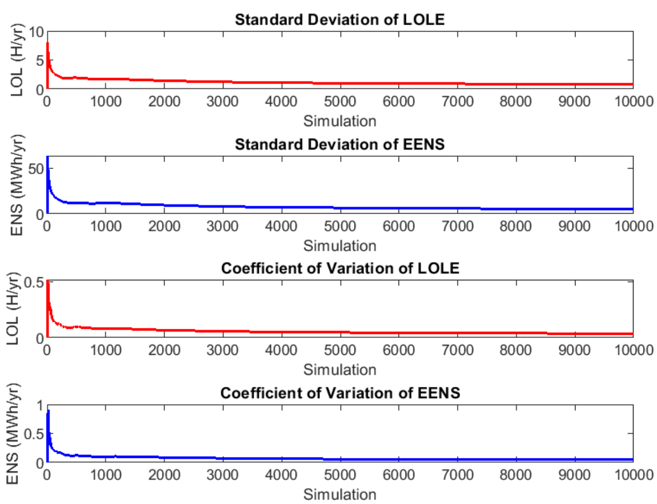


Figure 3-18: Comparison of σ and CV for LOLE and EENS

3.10.2 Step Size of 10,000 Years

For reasons due to the physical limitations of the computer, the step size of simulation is set at 10,000 years (the reasons for this will be elaborated on further in Chapter 5: Simulations and). This is how the stopping criteria is implemented:

1) If the CV goes below 5 %, then the entire 10,000 years are used for the values of LOLE and EENS and no more simulations are used
2) If the CV doesn't pass the stopping criteria, then another 10,000 years are simulated.

Chapter 4

Scheduling Schemes

4.1 Preamble

Having introduced the concept of virtual scenario generation through MC and MCMC frameworks, built the stochastic models for every element used in this research and set up a suitable stopping criterion the issue of how to schedule the EVs into loads needs to be addressed. This chapter will delve into three different types of scheduling schemes used. The first is called the uncontrolled charging, this would be the case if there was no interaction between the electric grid and the parking lot owner. The next one is a basic demand side management (DSM) algorithm, in which the goal is to flatten the demand profile of the system. Lastly, an algorithm called grid and demand side management (GDSM) is introduced, in which the scheduling of EVs considers both the demand and generational profile. The last two cases are under the assumption that the EVs are a controllable load.

4.2 Uncontrolled Charging/Base Case

As the name suggests, Uncontrolled Charging (UC) is the strategy that parking lot owners will follow with the charging of the vehicles if the power grid does not provide them any incentive to deviate from this path. The policy for charging is “First-Come, First-Serve”. As soon as a car comes into the car lot, it will receive the maximum charge it can get from the charger (in this simulation it is 33 kWh) and it is fully charged or the car leaves. It can be considered the “worst-case scenario” since this will cause the greatest disruption to the power grid. If 500 employees all come and park their EVs at 8:00 am in the industrial parking lot, a significant and ultimately unnecessary spike in demand will occur. If, for example, 400 of the EV owners are planning to leave at 5:00pm, they are indifferent to when exactly the car is charged. As long as it is fully charged when they come to leave.

Table 4.1: Example for UC

Car	Arrival	Departure	Initial SOC
1	8:00 am	2:00 pm	39 %
2	9:00 am	5:00 pm	25 %
3	8:00 am	4:00 pm	61 %
4	8:00 am	3:00 pm	73 %

For example, assume four cars arrived in the parking with the characteristics listed above in Table 4.1. Using the UC strategy, the individual demand profile for each them is given below in Figure 4-1. And in Figure 4-2 on the next page, the total demand profile is given. Since all the cars are going to be staying far longer than the amount of time they need to charge, a much flatter demand profile can be opened if a control strategy were to be applied.

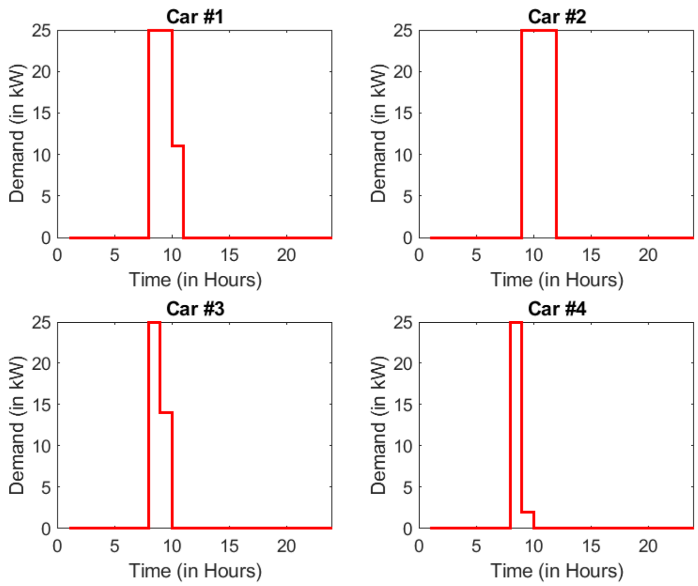


Figure 4-1: Individual Demand Profile for UC Example

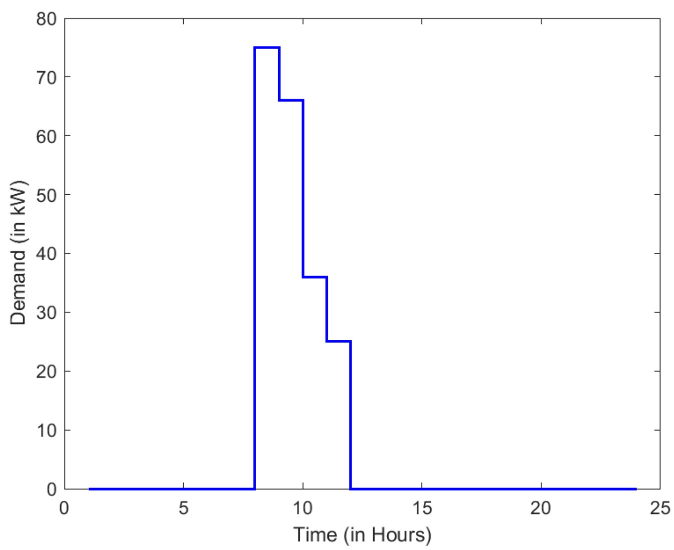


Figure 4-2: Total Demand Profile for UC Example

4.3 Controlled Charging using DSM and GDSM

The term Demand Side Management (DSM) is a catch-all for a number of techniques in which the demand profile may be managed. Figure 4-3 below lists some of the most common. Conservation/efficiency is out of the scope of this research and peak shaving is simply considered as an undesirable LOL. Throughout this research the entire focus will be on load shifting. As shown in the previous section, an undesirable outcome may occur if a simple UC charging methodology is to be applied. In essence, the goal of DSM is to flatten the demand seen by the grid as much as it is possible (given the constraints). With this in mind, it is expected the LOLE and EENS to decrease when compared to the UC case.

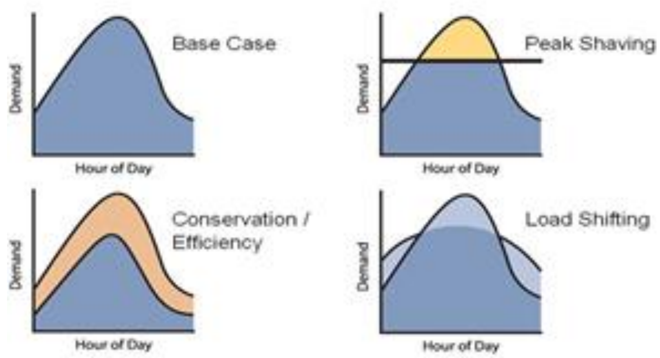


Figure 4-3: Demand Side Management

Given below in Figure 4-4 is a sample of a DSM algorithm being applied to a demand profile. In the base case (which represents the before scenario) a peak of 60 kW occurs during noon. As opposed to this is the best response case, in which a scheduling algorithm was applied. The peak has decreased by 26.67 % to 44 kW. In addition, it can also be seen that it is much flatter than the base case. This is all while both cases have the exact same total energy consumption of 742 kWh; no peak shaving or conservation was done.

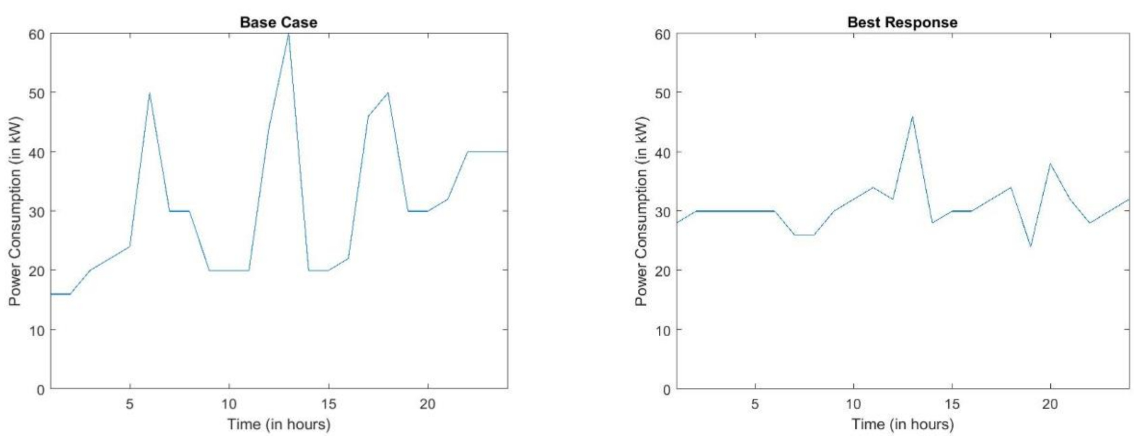


Figure 4-4: Example of DSM Before and After

The time scale of optimization is one 24-hour day. In addition, the code only optimizes for one car at a time instead of optimizing for all cars at the same time. In classical game theory, it is assumed that equilibrium is reached when none of the players have any incentive to deviate from their position. For example, if 200 cars arrived into the parking lot, the optimization algorithm will be applied to each one sequentially. This method doesn't guarantee the global optimum has been met, so it needs to be repeated until none of the 200 agents change their consumption behavior. For this application, it is too computationally intensive to find global optimum for each day since the simulation is to be run for thousands of years. In this research, only one sweep through the agents will be applied for both algorithms. This is acceptable since the marginal benefit gained by achieving global optimum is offset by the computational time, increasing it almost exponentially. Therefore, the results of this body of work will be a conservative estimate of true impacts of these scheduling schemes.

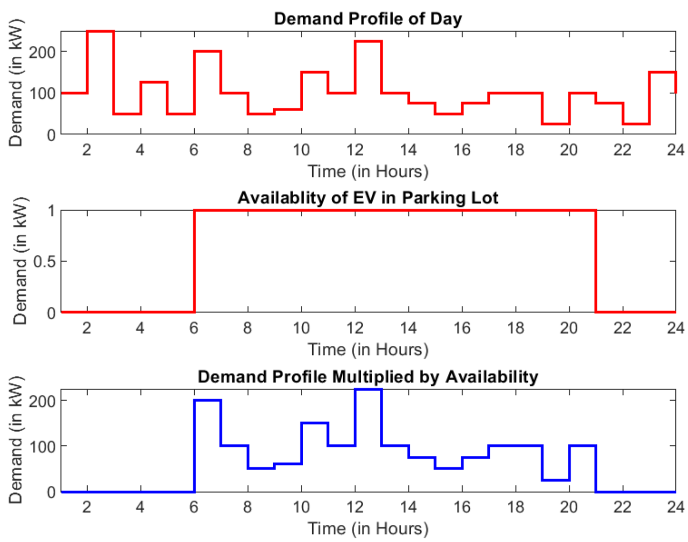


Figure 4-5: First 24 Elements of LP of DSM

Figure 4-5 above shows an example of the input to the DSM Algorithm. The first element is the current demand profile of the day given in the first graph; this is called Virtual Scenario (VS). Then it is multiplied by the availability of the EV (ava); showcasing when the car arrives and when the car leaves and this is present in the second graph. The output, which is presented in the third graph, will be multiplied by P_{charge}, the amount of power that the car consumed from the grid at any time. Since the function is trying to be minimized, the car will attempt to charge in the periods of lowest demand, thus performing demand side management. To ensure that the algorithm remains bounded, the state of charge (SOC) is capped at 100 %, while the maximum P_{charge} allowed is set to 33 kW. To ensure continuity, the next value of SOC has to equal the previous value of SOC + P_{charge}. Lastly, a constraint is set that the car has to be fully charged by the time is leaves. Therefore, the problem can be formulated as given on the next page:

$$
\begin{aligned}
\text{minimize} \quad & \sum_{t=1}^{24} Ava(t) * VS * P_{charge}(t) \\
\text{s.t.} \quad & 0.1 < \mathrm{SOC(t)} < 1 \quad \forall t \ \in \ T \\
& 0 < \mathrm{P}_{charge}(t) < 33kW \quad \forall t \ \in \ T \\
& \mathrm{SOC}(24) = 1 \\
& \mathrm{P_{charge}}(t) + SOC(t-1) = SOC(t)
\end{aligned}
$$

An example of a car entering in with an initial SOC of 39 % is given below in Figure 4-6. As can be seen the car only charges in the three periods with the lowest peak. In addition, amongst the three lowest peaks, hour 15 has the highest peak and this is when the car charges minimally. The MATLAB code used is given in Section 8.1.1.

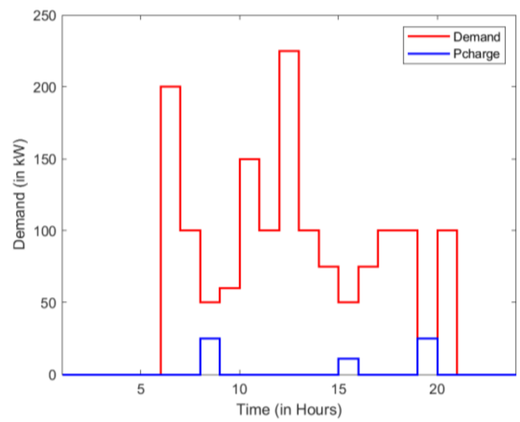


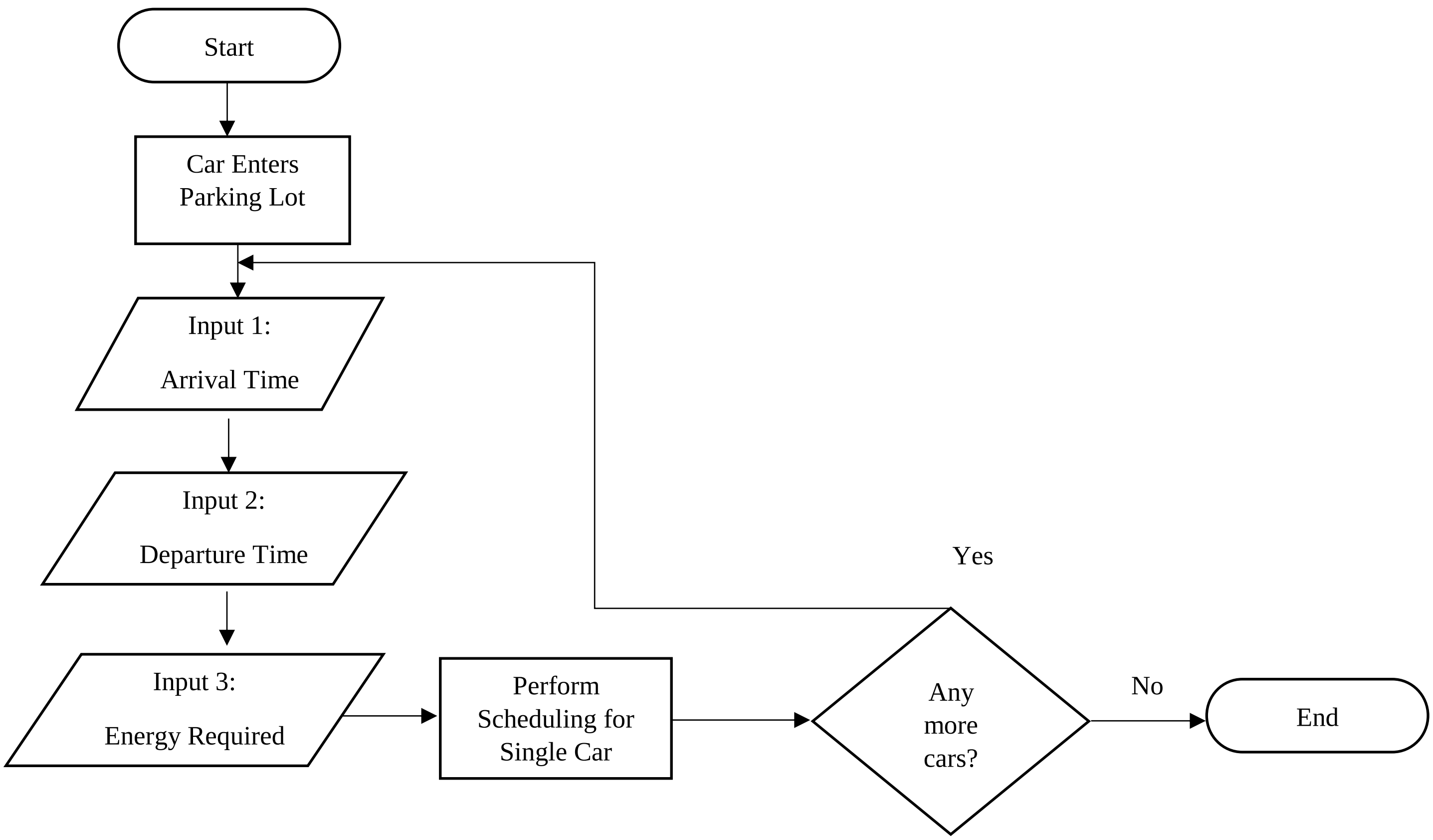
Figure 4-6: Example of DSM applied through LP

The proposed grid and demand side management (GDSM) algorithm includes both the available generation capacity and demand in the cost according to the formula given below:

$$Cost = LD + EV - DG - WT - PV$$

The difference between the two algorithms is that, in the DSM, the cost that the EV sees when choosing when to charge is based on the demand profile of the day. For example, if the demand is highest at 3:00pm, then correspondingly the cost at 3:00pm will be the highest and the scheduling algorithm will attempt to avoid charging the car at that time period if it can avoid it. While in the proposed GDSM algorithm the EVs will be charged considering both the expected available generation and demand during the day. Therefore, when optimizing the time the car needs to be charged, the algorithm will choose the time in which both demand is lowest and available generational capacity is greatest. In this case, the GDSM is better at improving reliability since it considers the random impact that is introduced to the system by the various generators connected.

4.3.1 Flow Chart for Scheduling Algorithms



4.4 Summary

In this chapter, the methodology for both the uncontrolled and controlled charging algorithms were introduced. The results of the uncontrolled case are what would be expected if the electric grid didn't provide any incentives to the parking lot owners. And since the parking lots utilized in this simulation are in commercial areas, an undesirable peak would occur in the morning at around 8:00am to 9:00am. When assuming that the EVs can indeed be controlled, the DSM algorithm attempts to manage the demand such that a spike is not seen by the grid. This is expected to improve the reliability of the grid, since the demand profile looks more uniform. But with the GDSM algorithm, an even greater improvement to reliability is expected. This is because the algorithm schedules the EVs while considering both the demand and generational capacities of the electric grid.

Chapter 5

Simulations and Results

5.1 Preamble

In chapter 3, the stochastic models were built and in chapter 4, the scheduling algorithms were introduced. This study virtually generated over 60 trillion unique scenarios and performed both power analysis and applied scheduling algorithms. The first issue that this chapter will tackle is to give recommendations to future researchers who wish to conduct a study on this scale. The second is to present the results of the thesis and discuss them.

5.2 Simulation Strategies

5.2.1 Specifications of Computer Used

In this research, four computers were utilized that had the specification listed below in Table 5.1. From the table, it can be seen that the limiting constraint for any code that is to be written is that it should not need more than 8 GB of ram to run, otherwise computers 2 and 4 would not be able to run it. In this study, the code spikes at 5.9 GB of ram, meaning that computer number 1 can run ten instances of the code, computer 2 one instance, computer 3 two instances and computer 4 one instance. For a total of fourteen simultaneous pieces of code running at any one time. If this research were to be repeated, the simulation block sizes would be reduced to have the maximum spike of needed ram be below 4 GB of ram. Theoretically allowing two instances of code to be run on computers 2 and 4, four on computer 3 and sixteen on computer 1; for a theoretical total of twenty-four parallel instances.

Table 5.1: Computers Used in Research

Computer Number	Processor Speed	RAM Speed
1	2.0 GHz	64 GB
2	2.5 GHz	08 GB
3	3.6 GHz	16 GB
4	2.2 GHz	08 GB

5.2.2 (Split 1) Virtual Scenario Generation

To be able to run the scheduling algorithms, virtually scenarios need to be first generated. To take advantage of parallelization of tasks, all of them will be generated as a batch. This is as opposed to generating them on the spot every time the code is run. There are two main benefits of doing it this way, the first is that troubleshooting the scheduling algorithm code is much easier since it is the same data being used, thus the source of any potential error can be found much quicker. The second is that if the computer crashes in the middle of any computation, the original information of the virtual scenarios remains present.

Some statistics on the hard-disk space that using MATLAB to store the various virtual scenarios are listed below:

1) LD takes the least space (0.043 MB), since only one year is stored in memory. If additional years are needed, then it is just repeated
2) The DG on the other hand, cannot simply repeat the first year and thus needs to store many years. It required on average 7.5 MB to store 10,000 years
3) The PV required 61.5 MB to store 10,000 years
4) The WT requires 42 MB to store 10,000 years
5) The EV take the longest time to simulate. It was generated in steps of 25 years and it took more time to generate it than the DG, PV and WT combined. In addition, those 25 years take 43.5 MB of space on average. Translating to 16.5 GB per 10,000 years

Loading all this data with the step of 10,000 years for LD, DG, PV and WT and the step of 25 years for the EV causes a spike of 5.9 GB of RAM. Given our current hardware, a choice of a step of 5,000 years for all LD, DG, PV and WT and a step of 20 years for the EV would be chosen to ensure that the maximum RAM needed will be below 4 GB. The files were stored in the ".mat" format, and the one million years took about 1 TB of storage. This could differ if another file format were to be used.

5.2.3 (Split 2) Control Strategy #1

After all the information has been generated and stored, 32 out of the 64 different makeups/control strategies can be simulated in parallel. The first sixteen (the ones with no EVs) can all now be done independently of any other information and so can the next sixteen (the ones with EVs using the "first-come first-serve strategy).

5.2.4 (Split 3) Control Strategy #2 and #3

The last 32 scenarios (involving DSM and GDSM) can technically also be done in split 2. But it is not at all recommended. This is because of the potential gains in speeds that can be gained due to the selection of the reliability indices. The goal of this research is to simply minimize the LOL in any given year, and if a LOL cannot be minimized then at least the ENS should be the next goal. If on average, there are 120 LOL hours in a year. Then the control strategies of DSM and GDSM only needs to be applied to those days that contain the LOL (in the worst case scenario, there is only one LOL hour per day and even then the run time of the code goes down from simulating 365 days to 120 days, a reduction by a factor of 3).

5.2.5 Summary

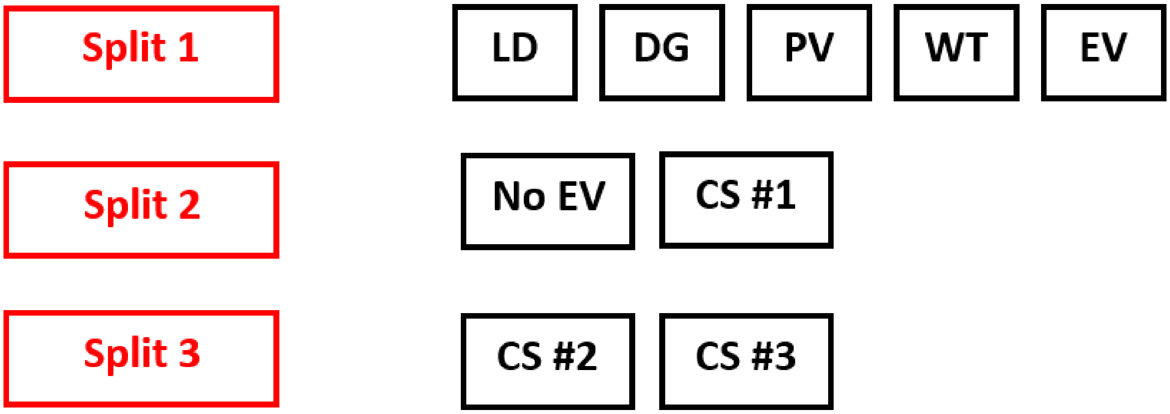


Figure 5-1: Simulation Order

The block diagram above in Figure 5-1 gives a summary of the order of simulations. In summary, all the simulations in the first split can be done at any time, independent of each other. Any simulation that will be done in the second split is also independent of each other but are dependent on the first split all being finished. Same case with the third split, anything listed there are independent on each other, but they are depended on the second split being finished).

Visualizing these splits in the tasks is essential in ensuring the simulation takes the least time as possible with the also the least probability for errors to be introduced along the ways.

5.3 Results

5.3.1 No EV

Table 5.2: LOLE with No EV

	WT 00	WT 05	WT 10	WT 15
PV 00	18.06	15.01	13.25	12.17
PV 05	13.17	11.12	9.94	9.21
PV 10	10.53	9.00	8.13	7.58
PV 15	8.98	7.74	7.04	6.58

Table 5.3: EENS with No EV

	WT 00	WT 05	WT 10	WT 15
PV 00	90.36	75.19	66.68	61.40
PV 05	64.96	54.95	49.34	45.85
PV 10	51.50	44.15	40.03	37.45
PV 15	43.88	38.00	34.68	32.59

The first thing to notice is that as more renewable energy sources are added (either the wind turbines or photovoltaic panels), the values of both the LOLE and EENS both go down. And this is to be expected, since the systems raw capacity has been increased. And this is the methodology that is utilized today to decrease these values, the increase of the generation capacity. Below in Figure 5-2 is a 3D plot of Table 5.2 and Table 5.3.

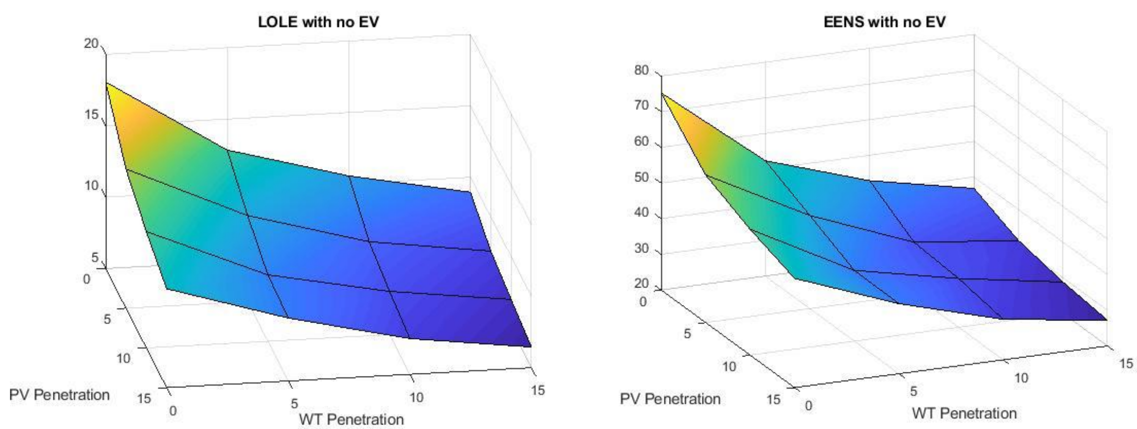


Figure 5-2: 3D Plot of LOLE and EENS for NoEV

5.3.2 Uncontrolled Charging (UC)

Table 5.4: LOLE for UC

	WT 00	WT 05	WT 10	WT 15
PV 00	21.59	18.02	15.82	14.42
PV 05	15.76	13.28	11.81	10.82
PV 10	12.53	10.69	9.57	8.83
PV 15	10.63	9.11	8.22	7.62

Table 5.5: EENS for UC

	WT 00	WT 05	WT 10	WT 15
PV 00	110.28	91.83	80.83	73.64
PV 05	79.11	66.67	59.33	54.50
PV 10	62.44	53.15	47.68	44.09
PV 15	52.83	45.48	40.98	38.05

Completely predictable results until now, by adding the EVs as an uncontrolled load the values for both the LOLE and EENS has increased. On average, the LOLE went up by 16 % while the EENS went up by 31 %. This is because a new load has been added for the exact same generational capacity. Figure 5-3 below is a 3D plot of Table 5.4 and Table 5.5. Again, they are very similar in shape to Figure 5-2 due to the fact that the load added is the same in all cases.

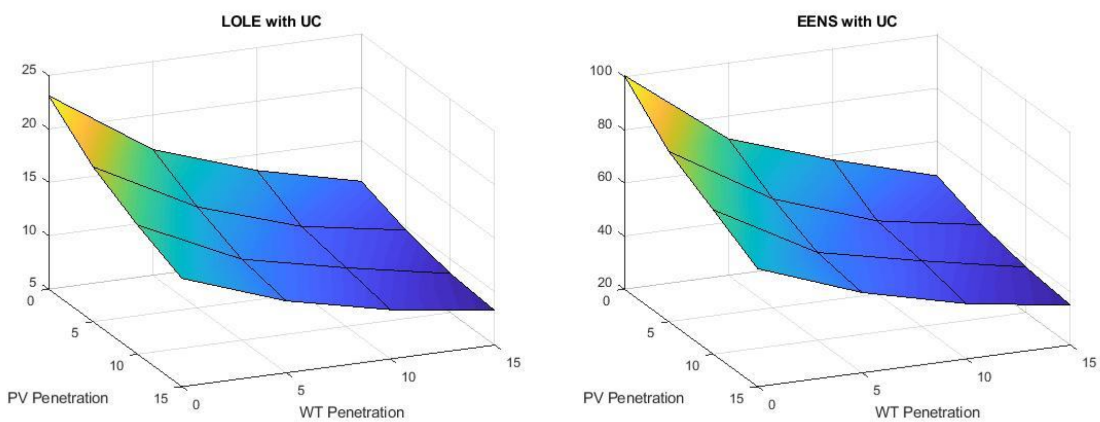


Figure 5-3: 3D Plots of LOLE and EENS for UC

5.3.3 Demand Side Management (DSM)

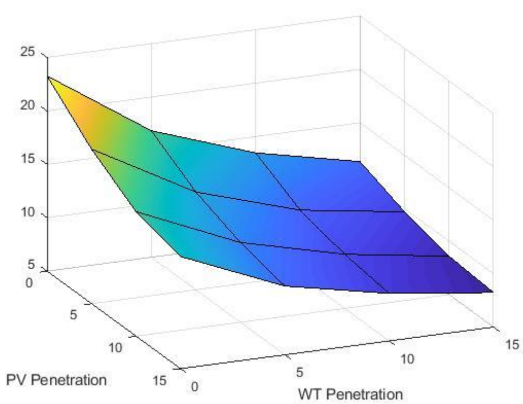
Table 5.6: LOLE for DSM

	WT 00	WT 05	WT 10	WT 15
PV 00	23.27	19.47	16.65	15.50
PV 05	16.84	14.15	12.47	11.44
PV 10	13.47	11.16	10.07	9.45
PV 15	11.36	9.70	8.59	8.24

Table 5.7: EENS for DSM

	WT 00	WT 05	WT 10	WT 15
PV 00	75.79	72.52	71.60	66.82
PV 05	71.00	59.24	52.25	48.33
PV 10	56.89	46.88	42.30	39.58
PV 15	48.70	41.24	35.88	34.87

With this control strategy, something unexpected happens. Now while the EENS goes down on average by a percentage of 12.36 % as compared to the uncontrolled load case the LOLE goes up 6.45 % on average. This could be due to a number of reasons. With the UC case, all the cars that were arriving at the exact same time were charged up immediately, thus causing a very high spike in load demanded and increasing the EENS. But with managing the demand more effectively, the DSM control scheme shifts the cars to other hours in the day. Thus, minimizing the EENS but also increasing LOLE. In the author's opinion this is an acceptable compromise, while the number of hours the system is overloaded is increased the overall energy not supplied is decreased making for a more efficient system. The plots for Table 5.6 and Table 5.7 are given below in Figure 5-4.



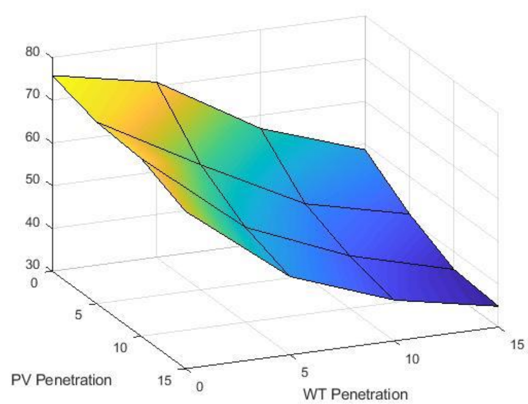


Figure 5-4: 3D Plot for LOLE and EENS with DSM

5.3.4 Grid and Demand Side Management (GDSM)

Table 5.8: LOLE for GDSM

	WT 00	WT 05	WT 10	WT 15
PV 00	18.09	14.92	13.11	11.95
PV 05	13.16	11.09	10.97	10.32
PV 10	11.49	9.00	9.07	8.30
PV 15	10.25	8.48	7.92	7.31

Table 5.9: EENS for GDSM

	WT 00	WT 05	WT 10	WT 15
PV 00	75.63	62.51	56.87	54.60
PV 05	56.79	47.43	46.40	43.20
PV 10	45.13	36.87	35.43	34.59
PV 15	42.46	34.64	33.53	29.85

When comparing the GDSM to UC, the benefits are also evident. First of all, the EENS decreases on average by 25.844 % but moreover the LOLE also decrease by on average a value of 10.38 %. This is in contrast with the DSM case in which only the EENS decreased but not the LOLE. This could be due to the very effective nature of GDSM on managing the EVs, in which it even manages to decrease the LOLE.

On comparing the GDSM to the previous DSM, it is found that both the EENS and LOLE decreased on average by 15.79 % and 15.23% respectively. Given below in is the 3D plots of Table 5.8 and Table 5.9.

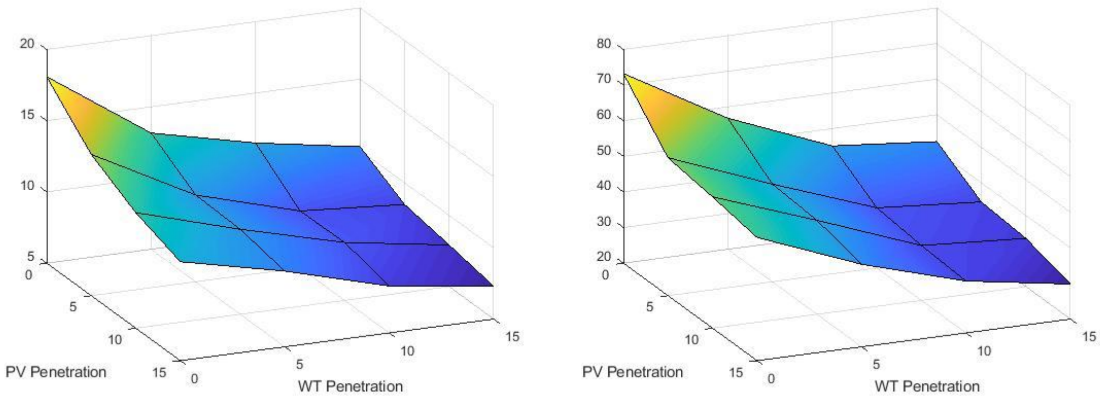


Figure 5-5: 3D Plot for LOLE and EENS with GDSM

Chapter 6

Conclusion

The introduction of PV panels and WTs have added to the instability of the grid and the fact that their penetration levels are predicted to increase will exasperate this issue. In addition, the number of EVs are also predicted to increase to a significant amount. Adding the novel demand profile of EVs with the intermittency of PVs and WTs presents itself as a unique problem. The fact that there is a comparatively low start-up cost to converting a traditional parking lot to one that is capable of charging EVs will have private investors wishing to exploit this new market. The question that this thesis attempts to answer is:

> *"Is there a benefit to a utility operator, in terms of increasing reliability, to share more information and give financial incentives to private EV parking lots if they were to participate in scheduling their demands."*

In the model built, it was found that the addition of EVs increased the EENS by 45.1% on average. To mitigate this, two scheduling algorithms were then implemented. The DSM and GDSM, was found to only increase the EENS on average by 27% and 8.02%, respectively. It is evident that forcing EVs to be charged via a scheduling algorithm is incredibly beneficial, but more importantly the results show that it is in the grids benefit to share extra information regarding the available generational capacity for GDSM.

This is further shown when comparing the changes to the reliability indices when only considering the penetration levels of renewables. With no PV panels and WTs connected, the DSM and GDSM had the EENS increase 0.66% and 0.40%, respectively. But when the penetration levels for PV panels and WTs, the DSM and GDSM increased the EENS by 28.10% and 9.75% as compared to the base case, respectively. This shows that as the penetration of renewables increase, the differences between the DSM and GDSM start to appear. Which would make sense, since as the penetration level of renewables increase, the randomness also increases.

This body of research recommends grid operators to start sharing information regarding predicted generational capacity to aid in the optimized demand scheduling. In addition, financial incentives should be provided to private EV parking lot owners to mitigate the immediate impacts of EVs on reliability, without the need for investing in increasing generational adequacy or building a modern communication infrastructure. Furthermore, this thesis finds that the as the penetration levels of renewables increase (especially PV), the benefits of sharing generational capacity information also increases.

6.1 Thesis Summary

The steps taken to achieve this is listed below:

1) The introduction and definition of the reliability indices that was made to be the objective function. These were the:
    a. LOLE (Loss of Load Expectation)
    b. EENS (Expected Energy Not Served).

   In addition, a slightly different stopping criteria was introduced for the benefits of this research

2) The building of the virtual scenario infrastructure that allowed for the simulation of over a 1,000,000 years (with the time segment being 8760 hours per year) for the:
    a. Base Load
    b. Distributed Generators (32 unique)
    c. Photovoltaic Panels (with splits for 4 seasons over 24 hours)
    d. Wind Turbines (with splits for 4 seasons over 24 hours)
    e. Electric vehicles (with an average of 273 cars per day and splits for 4 seasons, weekdays vs weekends over 24 hours).

   This resulting in the overall simulation of over 60 trillion unique scenarios throughout this thesis.

3) The setting up of the various control scenarios that would need to be applied to adequately answer the thesis question. Which were the:
    a. No EV
    b. Uncontrolled
    c. Demand Side Management
    d. Grid and Demand Side Management

   In addition, these were coupled with multiple PV and WT penetrations resulting in 64 different schemes.

4) Employing efficient simulation strategies that managed to optimize the computer resources at hand for the publication of this research. Which allowed for the parallelization of an enormous amount of computing.

6.2 Main Contributions

This thesis made the following contributions:

- The investigation of the positive effects that the different penetration levels of renewable energy resources have on system reliability. Both the photovoltaic and wind turbine penetration levels and were varied from 0 – 15 % with increments of 5 % resulting in 16 different scenarios.
- The negative impacts that EVs would potentially do if connected without any controlling schemes to the current grid
- The shortcomings associated with the traditional demand side management control algorithms. Since it only manages the EVs charging schedule based on one piece of information, the load demanded of the grid. Especially in the presence of highly random renewable energy sources this is not sufficient. And while it may work theoretically in research that is only looking towards the short-term of a couple of days of simulation it does not hold up very well when the expected value of these variables are calculated (which require thousands of years of simulation)
- The introduction of a novel control scheme, called Demand and Grid Side Management which solves the inadequacies of demand side management with the inclusion of the data of the various generators.
- Proving the benefit that a grid operator will have if they were to build the infrastructure that will allow the flow of information needed to implement Demand and Grid Side Management (25.88 % decrease in EENS).
- Giving guidelines and suggestions to future researchers that desire to undertake the same type of research such that they will be able to tweak the various hyper parameters used in this thesis to fit their own computing resources

6.3 Future Research Work

The overall objective of this research was to prove the benefit to a grid operator if they were to co-operate more with potential EV parking lot owners. But this could be expanded much further:

- Application of Demand and Grid Side Management with a different objective function. The benefits it could pose to a power system such as the decrease of power loss or an increase in voltage stability.
- The assumption made was that the parking lot owner was the only one allowed to make decision. A game theory framework could be developed that would relax that assumption
- GDSM was better than the DSM by about 15 % (for the reduction of both LOLE and EENS), but this was only applied to the case of unidirectional power flow (grid to vehicle). Would building the infrastructure for vehicle to grid, in the sole case of private EV parking lots, have a good return on investment?

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Chapter 8 Appendix

Table 8.1: DG Generators' Characteristics

Capacity	MTTF	MTTR
12	2940	60
12	2940	60
12	2940	60
12	2940	60
12	2940	60
20	450	50
20	450	50
20	450	50
20	450	50
50	1980	20
50	1980	20
50	1980	20
50	1980	20
50	1980	20
50	1980	20
76	1960	40
76	1960	40
76	1960	40
76	1960	40
100	1200	50
100	1200	50
100	1200	50
155	960	40
155	960	40
155	960	40
155	960	40
197	950	50
197	950	50
197	950	50
350	1150	100
400	1100	150

8.1.1 Example of MATLAB Code for DSM

```
%% Constants
a_Bat = 100;
a_Speed = 0.25;
a_Cha = a_Bat*a_Speed;

%% Variables
Ava = [zeros(1,5) ones(1,15) zeros(1,4)];
VS_BC  = [100 250 50 125 50 200 100 50 60 150 100 225 100 75 50 75 100 100 25 100 75 25 150 100];

SOC_initial = 0.39;

%% Setting Up
a_size = sum(Ava==0)+25;
Aeq = zeros(a_size,48);
beq = zeros(a_size,1);

Aeq(1,1) = 1/a_Bat; Aeq(1,25) = -1; beq(1,1) = -SOC_initial;

for no_hour=2:24
    Aeq(no_hour,no_hour) = 1/a_Bat;
    Aeq(no_hour,no_hour+23) = 1;
    Aeq(no_hour,no_hour+24) = -1;
end

Aeq(25,48) = 1; beq(25,1)=1;

count=25;
for no_hour=1:24
    if Ava(1,no_hour) == 0
        count=count+1;
        Aeq(count,no_hour) = 1;
    end
end

lb(1,1:24) = 0;
lb(1,25:48) = 0.1;
ub(1,1:24) = a_Cha;
ub(1,25:48) = 1;

%% Objective Function
f(1,1:24) = -Ava.*VS_BC;
f(1,25:48) = 0;
%% Linear Programming
options = optimoptions('linprog','Display','none');
z = linprog(f,[],[],Aeq,beq,lb,ub,[],options);
%% Output
Pcha = z(1:24,1);
SOC  = z(25:48,1);
```