OPTIMISATION AND RESOURCE PLANNING USING ENERGY STORAGE DEVICES

A Project Report

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JITENDRA KUMAR PRADHAN (EE17M006)

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THESIS CERTIFICATE

This is to certify that the thesis titled **OPTIMISATION AND RESOURCE PLANNING USING ENERGY STORAGE DEVICES**, submitted by **Jitendra Kumar Pradhan**,to the INDIAN INSTITUTE OF TECHNOLOGY, MADRAS, for the award of the degree of **Master Of Technology**, is a bona fide record of the research work done by him under our supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree ordiploma.

Prof.K.Shanti Swarup
Research Guide
Professor
Dept. of Electrical Engineering
IIT-Madras, 600 036

Place: Chennai

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ABSTRACT

KEYWORDS: Grid-to-Vehicle (G2V), Intelligent charging, Plug-In Electric Vehicle (PEV), Priority Charging, Priority Premium, Vehicle-to-Grid (V2G)

Energy storage is the key to allow for integration of clean energy in power girds. We study two forms of energy storage devices in this thesis.

In the first part we propose an intelligent charging scheduling problem for an Electric Vehicle (EV) aggregator considering vehicle-to-grid (V2G) and grid-to-vehicle (G2V) capabilities with an objective to minimize the total charging cost. Since electricity price at the charging node may be subject to uncertainties, Information Gap Decision Theory (IGDT) is proposed in this paper to handle uncertainties in the price. The original intelligent charging scheduling problem is non-linear. We proposes a modified Mixed Integer Linear Programming (MILP) based reformulation and solves with CPLEX using GAMS as an aggregator.

In the second part we propose a stochastic resource investment planning model for Microgrids. The paper considers that the microgrid in study has a local load, renewable generation, energy storage unit and a link to the main grid. The microgrids cannot influence the market prices and is modeled as a price taker. The operational objectives of the microgrid is to schedule its assests in order to serve the load in such a way so as to minimize the cost of operation. The operational aspect of microgrids is modeled as a Linear program (LP). We then continue to use this LP operational model and find an optimal investment strategy for microgrid in a new stochastic LP model where the objective is to minimize the sum of investment and expected operational cost. The assets considered for investment include energy storage units. The proposed stochastic LP model is tested on a Microgrid test system and simulated on GAMS.

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ABBREVIATIONS

V2G	Vehicle To Grid
G2V	Grid To Vehicle
BE	Battery Energy
PEV	Plug-In Electric Vehicle
EV	Electric Vehicle
SoC	State Of Charge
GAMS	General Algebraic Modeling System
NLP	Non-Linear Programming
MILP	Mixed Integer Linear Programming
LP	Linear Programming

NOTATION

Chapter - Electric Vehicle Aggregator

$\mathbf{U}_{V\_Gij}$	Energy transferred from j^{th} vehicle to grid in i^{th} time slot,kWh
$\mathbf{U}_{G\_Vij}$	Energy transferred from grid to j^{th} vehicle in i^{th} time slot,kWh
T	Number of Time Slots in a day
N	No of cars available for charging in Parking
η_j	Efficiency of jth PEV battery and converter(same for charging and discharging)
π_j	Price of one unit electricity in ith time slot,Rs/kWh
$\mathbf{P}_{ij}$	1 if in ith time slot jth EV is present in parking for charging , 0 otherwise
$\mathbf{BatConst}_j$	Battery constant for jth EV's Battery
$\mathbf{P}_{max}$	Maximum power rating of each charging station,kW
μ_{ij}	System's Priority of jth EV at starting of timeslot i
$\mathbf{d}_{ij}$	Duration for which jth EV will remain in parking station at the start of timeslot i,Hr
maxload	Maximum load which can be connected to grid from parking station,kWh
$\mathbf{W}_j$	Weight given by user for charging his/her vehicle at high priority
M	A very large number say 10000 for NLP to MILP conversion using Big-M method
$\mathbf{b}_{ij}$	Binary variable which decides whether V-G or G-V operation takes place
$\mathbf{BE}_{ij}$	Energy contained in the jth EV's Battery at end of timeslot i,kWh
$\mathbf{BE}_{ijopt}$	Optimal battery energy should be stored in battery
$\mathbf{BE}_{ijmax}$	Maximum battery energy which can be stored in a battery
$\mathbf{BE}_{ijmin}$	Minimum battery energy which can be stored in a battery
$\mathbf{cr}_j$	Charging rate of jth vehicle in terms of fraction it can charge w.r.t new battery
p_s	Probability of event s
D	Difference between Cost of charging with priority and without priority among PEVs

Chapter - Microgrid

t	Time intervals
z	Stochastic Scenarios
T	Set of Time intervals
Z	Set ofStochastic Scenarios
$\mathbf{g}_t$	Generation purchased from main grid in time interval t
$\mathbf{d}_t$	Power discharge from energy storage unit in time interval t
$\mathbf{c}_t$	Power charging into energy storage unit in time interval t
$\mathbf{s}_t$	State-of-charge in energy storage unit in time interval t
D	The maximum charge and discharge rate of the installed energy storage unit (kW)
$\overline{S}$	Upper limit of installed state-of-charge in energy storage asset (kWh)
$\mathbf{I}_p$	Marginal rate of expanding the charge/discharge rate of energy storage asset (Rs/kW)
$\mathbf{I}_e$	Marginal rate of expanding the storage capacity of energy storage asset (Rs/kWh)
$\lvert \cdot \rvert$	Cardinality of the set
$\mathcal{I}(\cdot)$	Conditional set index operator
$\mathbf{R}_t$	Local wind power generation in time interval t (kW)
$\mathbf{L}_t$	Local microgrid load in time interval t (kW)
$\underline{S}$	Lower limit of state-of-charge in energy storage asset (kWh)
$\mathcal{S}$	Minimum required state-of-charge level at the end of operational dispatch (kWh)
S_0	State-of-charge level at the beginning of operational dispatch (kWh)
$\mathbf{F}_t$	Locational marginal price for buying electrcity from main grid at time interval t
η_c, η_d	Charging and discharging efficiencies of energy storage asset

CHAPTER 1

INTRODUCTION

Energy Storage is meant by the method of changing the electrical energy that is derived from an electrical power grid network into a stored configuration that can be reverted back into required electrical energy when required. The first works on this can be seen of the storage devices of the 20th century, where electrical stations were shut down, with lead-acid storage devices that supplied to the residual loads on the direct current networks.The unpredictable nature of load profiles of renewable energy and constant pressure of the green house gases has led to change in the production and distribution of electrical energy. Thus,the evolution of energy storage devices has the potential to reduce these pressures in today's energy scenario. The Energy Storage will be an integral part of ever changing demand scenario, thus the mere increase in the supply of renewable energy by allowing renewable energy to be delivered during peak times when it is most required and deliver stored energy when the renewable energy is not efficient will lead to restoration of the demand-supply chain.

The upward swing in production and supply of increasing amount of renewable energy into transmission and distribution grids and the rapid increase in the rooftop solar photo-voltaic installations in households gives a picture of how the energy storage devices are helping in un-tapping of a new market in renewable energy and enabling new opportunity.This trend is expected to overflow into the electricity transmission and distribution arena in the form of Grid-Scale Battery Storage; in the pursuit of greater flexibility, control and utilization of electrical power. The introduction and application of cost effective grid-scale battery storage will be a game-changer for the distribution and control of electrical energy[1].

In general there are two main categories of The energy storage devices can be broadly classified into 2 categories. The electrical energy storage devices such as batteries, Superconducting Magnetic Energy Storage (SMES) and capacitors can be counted in the first category,where as the non-electrical energy storage devices that convert other energy forms such as thermal and kinetic energy into electrical energy such as flywheels, pumped air and pumped hydro storage systems can be counted in the second category[2].

Utilities still face a lot of technical glitches,despite numerous development work in the field of renewable energy generation,with the key being intermittent supply of energy. The introduction of energy storage devices and their usage will provide more value to renewable energy and power system operators.

Key concept requirements are as follows:
a) To check and prove that efficacy of all storage devices in meeting grid standards in terms of reliability,safety and quality.
b) To prove that grid support can me met when required with increased focus on energy storage devices.
c) To have sense of profitability in theCommercial sense to deploy energy storage devices, drivers, applications and challenges
d) Framing of the regulatory body to give the rights of owner, operator and maintainer along with various storage devices and tariff structures.

A brief brief classification of energy storage systems is as follows:
1.**Electrical Energy Storage** : (i) Use of Electrostatic nature (Capacitors, Supercapacitors); (ii) Use of Magnetic/Current energy (SMES).
2.**Mechanical Energy Storage** : (i) Use of Kinetic energy (Flywheels); (ii) Use of Potential energy (PHES).
3.**Electrochemical Energy Storage**: (i) Use of Electrochemical energy (conventional batteries such as Lead-acid, Nickel Metal hydride, Lithium ion and flow-cell batteries like Vanadium Redox and Zinc Bromine); (ii) Use of Chemical energy (Fuel cells, Molten-Carbonate fuel cells (MCFCs) and Metal-Air batteries).
4.**Thermal Energy Storage** : (i) Use of Low temperature energy (Aquiferous cold storage, Cryogenic storage); (ii) High temperature storage (Sensible heat systems like Hot water Accumulators, Graphite, Hot Rocks and Latent heat systems like Phase change materials).

The figure 1.1gives the basic classification in a nut shell indicating various groups and their categories.

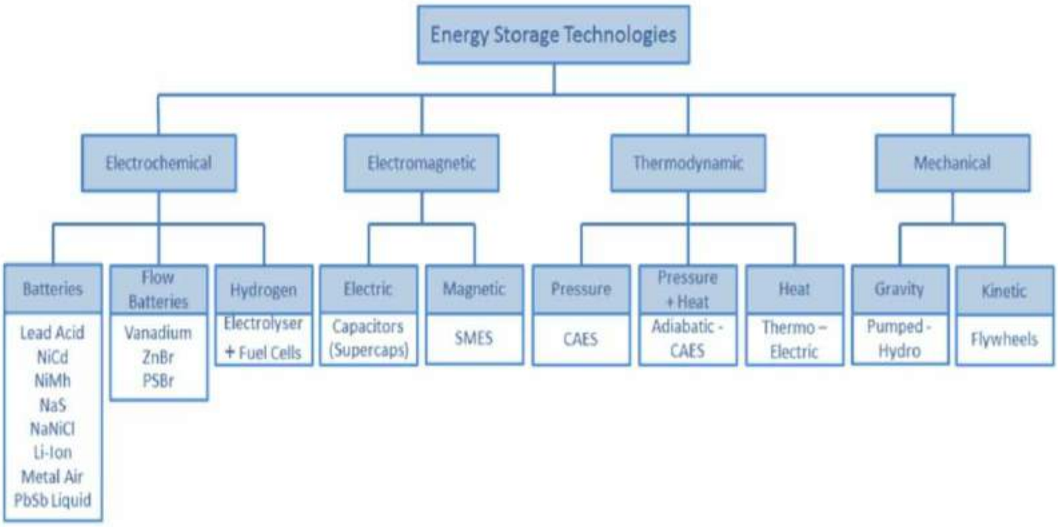

Figure 1.1: Different Methods of Energy Storage

Storage Technology	Energy Efficiency (%)	Power Density (W/kg)	Energy Density (Wh/kg)	Energy Installation Cost (€/kWh)	Life Time (cycles)	Deployment Time	Applications
PHES	80-82	-	0.5 - 1.5	5 to 20	40 years	about 3 min	Voltage control, Load Levelling, Peak shaving, Standing Reserve
CAES	60-70	-	30-60	40 to 80	30 years	3 to 10 min	Voltage control, Load Levelling, Peak shaving, Standing Reserve
Flywheel	85-87	1500-5000	5-50	3000 to 10000	10^6	about 10 milliseconds	Primary Frequency control, Voltage control, Peak shaving, UPS
Lead Acid	75-90	<1000	30-40	100 to 250	10^3-10^4	3 to 5 milliseconds	Residential Storage Systems, Uninterruptable Power Supply, Load Levelling, Peak shaving
Lithium-ion	87-94	800-2000	80-170	300 to 800	10^3-10^4	3 to 5 milliseconds	Residential Storage Systems, Voltage control, Load Levelling, Peak shaving
Vanadium redox	65-75	80-150	25-35	300 to 500	10^3-10^4	Seconds	Frequency control, Island Grid
Supercapacitors	90-94	1000 - 10000	<50	10,000 to 20,000	10^6	< 10milliseconds	Primary Frequency control, Voltage control, Peak shaving, UPS
SMES	95	-	30-100	350	10^6	1 to 10 milliseconds	Primary Frequency control, Voltage control, Peak shaving, UPS

Figure 1.2: Application of Energy Storage Technologies

1.1 Energy Storage System Comparison

A comparison between the various Energy Storage devices and technologies is shown in the table where the grouping has been categorised in terms of Energy Efficiency,Power Density,Energy Density,Energy Installation Cost,Life Time (cycles),Deployment Time and Applications is enumerated in the table above as per fig 1.2.

1.2 Range of requirement of storage devices

Over the last two decades,with an increase in the variety of drive types, along with the increasing volume of their application in various spheres, the problem arises of choosing a particular type of storage device [3].

Broadly the whole range of requirements for storage devices can be divided into two groups:

a) On the basis of using the storage device in a particular way.

b) on the basis of its energy characteristics.

Here,The requirements of the second group refer to the storage of any types and actually determine the expediency of using a particular drive in each specific case. First of all, these are indicators such as efficiency of storage and efficiency of discharge.

When choosing a drive, these indicators are crucial since, because they affect the magnitude of the overall effect of the application of the drive. The use of the drive becomes ineffective if during the process of charging and storage some significant part of the energy is lost due to the drive's non-perfection (selfdischarge, friction), i.e. there is a connection with the time of energy storage.

1.3 Electrochemical Energy Storage and their Energy Density

Electrochemical batteries consists of mainly three constituentâĂŹs positive electrode (cathode), negative electrode (anode), and electrolyte (solid/liquid). In batteries the electrodes are immersed in electrolyte in which ions exchange during charging converting the electrical energy into chemical, and during discharging this chemical energy is converted back into electrical with the help of moving ions.

Different types of electrochemical storage system are listed below:

1. Lead-Acid battery
2. Lithium-ion battery
3. Vanadium-Redox flow
4. Hydrogen Fuel cell

The voltage rating of these storage devices should not exceed more than 2V, hence number of modules are connected in series and parallel combinations to increase the rating. Batteries have been using from earlier days, Lead-acid battery is invented in 1859, Nickel âĂŞcadmium in 1950s, SodiumSulphur is accepted in mid 1990s, Lithium-ion is commonly used nowadays because of its high energy density, long life cycle values and high power density which is applicable for large storage. Fig. 1.3 shows increase in energy densities of various batteries. According to the variance in the characteristics and battery working, they are used for different applications. Batteries having very high response rate, and some particular batteries respond within 20 milliseconds for load change.

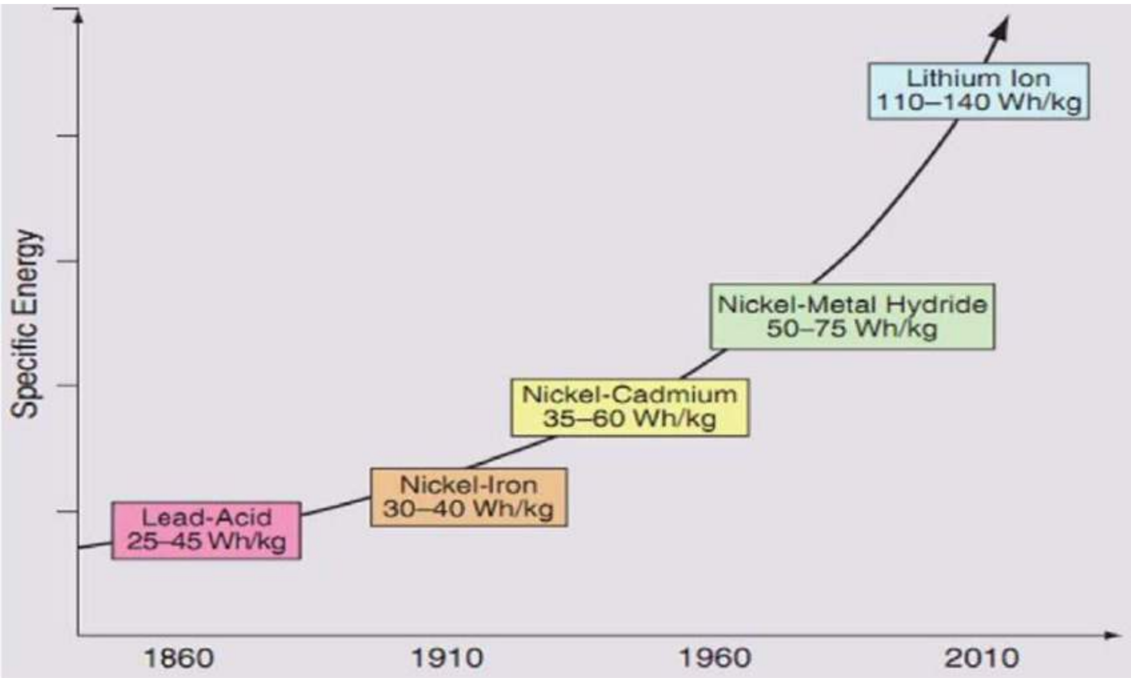

Figure 1.3: Increase in the Energy Density of Batteries

CHAPTER 2

Motivation and Literature survey

In recent years,the Energy storage devices has an increasingly important role to play in the electrical grid . This is because of the applications requiring quite a large amount of power or voltage for a short period of time. Energy storage devices have the capability of being used as independent power sources. To match the electricity supply to the load demand ,the ability to store energy at off peak times then re-apply that energy to the system when required without the need for further generation is highly desirable and is being made possible through the energy storage devices. Recent state-of-the art surveys [4, 5] have observed that commercially viable integration of energy storage assets in the grid has been popular in form of:

1. Electric Vehicles
2. Microgrids Storage Assets

Recently due to the reduction in costs associated with energy storage devices, these distributed energy storage sources are being introduced in the grid.

2.0.1 Electric Vehicles

The increasing content of carbon dioxide in atmosphere have alarmed to reduce the production and use of fossil fuels in order to check climate changes [6]. From the statistics of the United States Environmental protection Agency(EPA), the transportation sector alone contributes around 28% of the total U.S. greenhouse gas emissions by economic sectors in 2016 [7]. With these trends of increasing uses of fossil fuels, many countries across the globe have put forward their own national-level policies and plans [8] to cater for carbon emissions. Now with advancement in technology and as an alternative to the age-old fossil fuel based transport system, the electrification of the transport system is a major breakthrough to control the carbon emission. The PEVs, in particular, has gained ground over last few years and the Indian government has an ambitious target for achieving a fleet of seven million EVs [9] by year 2020. Thus, the above figures give an appropriate view of the vast spreading of the new technology and its implementation on a large scale.

The demand for Plug-in Electric Vehicles (PEVs) have increased drastically [10], [11] as they can reduce CO2 emissions and because of their higher fuel economy. Hence PHEVs have the potential to shift energy requirement from fossil fuels to electricity in personal transportation [12]. The atmospheric pollution can hence be reduced, alleviating climatic threats caused by oil extraction and combustion. In addition to that PHEVs/PEVs have the potential of exchanging power with the grid for reducing peak power demand and to provide ancillary services [13]. PHEVs can be a distributed source of energy for scheduled charging in networked Microgrids [14]. The PEV charging will be uncoordinated and this random charging will lead to increased load demand during peak times. This may lead to failure of the grid, if suitable smart charging techniques are not kept in place. Due to the LV distribution system, the PEVs can potentially overload the distribution transformers and distribution lines during charging. However, as a stationary PEV can act like a battery and with smart charging techniques, can be used to store and provide electricity during peak demand hours, large-scale use of PEVs can supplement grid power by the V2G operation. While smart charging techniques can help in curbing peak loads due to PEV charging. The widespread popularity of EVs with the advent of Tesla and Honda EVs, has given rise to a new player in the retail electricity markets called as Aggregator. An aggregator is a player that provides cheap charging services to the EVs in the region and tries to make profit due to the price volatility. Such aggregators can also help in reducing the peak demand and employ the intelligent charging scheduling techniques to achieve their profits while satisfying their EV consumers.

With the advancement of time, recently the charging strategies, both G2V and V2G is being used as per the requisite need of the user.However,different charging strategies suggested in various literature's shows reduction in impacts of PEVs on the given power system[15], [16].Even various charging strategies have been formulated that uses either of the two G2V or V2G mode [17],[18] that studies the impact of PEVs and their penetration levels in determining power losses and voltage security of the distribution system under study. The biggest drawback of the above methodologies is that they use either of the two methods as discussed. Later different models of charging strategies using both V2G and G2V modes in a single window operation to optimize the load scheduling over the given frame of time and resources.

Computational Intelligence Techniques in Electric Vehicles

Plug in Electric Vehicles are an integral part of the future smart grid [19]. Electric vehicles (EV) are gaining popularity due to their low emission and low noise aspects [20]. The widespread penetration of EV will bring in extra burden on the electric grid. A level 2 standard EV load [21], will be almost twenty times the load of a typical North American home [22]. The impact of EVs will be even higher when there is an aggregator involved and proper charging strategies should be developed for a smart grid with high penetration of EVs. A lot of computational intelligence techniques have been implemented to realized the proper charging and planning of charging stations in smart grid. Deciding the charging station location is an important planning problem in smart grid planning. GA was employed by authors in [23] to minimize the active and indirect losses to find the optimal location and sizing of EV charging station. In practical situations the site locations is effected by social, economic and environmental factors. A multi-criteria decision making (MCDM) is generally employed for such problems. Such a MCDM was solved with NSGA-II based techniques in [24] for optimal sizing and siting of charging stations. The authors in [24] only considered two technical factors: active losses and total voltage deviation to study the siting and sizing of charging stations. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a compensatory aggregation MCDM techniques which has been employed with fuzzy techniques in [25]. [25] employed fuzzy system to consider some factors that cannot be incorporated in the MCDM technique and to reflect the ambiguity and vagueness, a fuzzy TOPSIS method was employed to select the optimal charging station site from all the alternatives. Five different criterion were studied which included aspects based on environment, economy, society, electric power system and transportation system. In a completely different school of thoughts [26] employed GA to minimize the number of trips lost by EV drivers, thus increasing the electric miles traveled by vehicles by optimally siting the public charging stations. The paper concluded that level 1 charging stations, with their small budget could cover the entire road network optimally to reduce the number of trips being lost on pubic charging stations. [27] proposed a cost benefit analysis using a modified DE algorithm for proper sizing and siting of the EV charging stations to reduce the distribution system reinforcement cost. The Life cycle cost was considered for the cost-benefit analysis, and it was seen that for a distribution system: public battery swapping stations were better than charging stations. Focusing only on the design aspect of EVs, [28] proposed a neural network based energy management system for hybrid EVs. The work shows a 28.7% efficiency improvement in terms of km/kWh with proposed neural networks and no regenerative energy source. In the operational aspect of EV charging stations, the charging strategy is an important aspect. The authors in [29] proposed two smart charging strategies with objectives to minimize the total daily cost and peak-to-average ratio. Both the proposed charging strategies were implemented using GA.

2.0.2 Distribution System Networks

With the introduction of technologies like EVs, DSM, Distributed energy resources, etc, the distribution system network is bound to be under stress and proper reinforcements and planning is needed. A multi-stage distribution system planning problem was addressed in [30] with the objective to minimize the total investment and operation cost. Considering the operational aspect of the Distribution network [31], implemented PSO to minimize the active losses by optimal sizing and siting the Distributed generators in the network. [32] is one of the very few studies that include reliability index maximization as an objective, in the multi-objective optimization framework of distribution system with fixed load. Some of the works in multi-objective optimization consider the fitness function as a linear combination of various objectives [30]. [32] is one of the works that does an accurate simultaneous multi-objective optimization in the distribution system to obtain a non-dominant solution set. Studies [30], [32] cannot handle the uncertainty in future loads. Some studies have used fuzzy variables to represent an uncertain load level [33]. To overcome these limitations, [34] in 2004 proposed a possibilistic model based on fuzzy theory to solve a multi-objective distribution system planning problem to determine optimal location and size of future feeders. Power demand was modeled as a fuzzy variable to account for uncertainty and the problem was solved by Tabu search method. Continuing the representation of uncertain load with fuzzy numbers, in 2011 [35] proposed a fuzzy tool to evaluate the effect of DG operation and investment by DG owners on active losses and load delivery. The fuzzy trapezoidal number represents the uncertain parameters like load, DG installation, and operation. [36] used Monte-Carlo simulation model to analyze the effect of uncertain parameters in solving a multi-objective DG planning problem in 2011. The various uncertainties included wind source risk, market price change, and load uncertainty. A Weibull PDF was used to model the wind turbine generation, and a normal distribution PDF was used to model the uncertainty in load and the uncertainty in market price. The same authors in [37] proposed a hybrid possibilistic-probabilistic method for evaluating the effect of uncertainties on the active power losses. The wind turbine generation was modeled as a Weibull PDF, while a membership function modeled DG generation pattern and load. The aforementioned work was extended in 2012, and [38] proposed a hybrid possibilistic-probabilistic method for evaluating the effect of uncertainties due to investment model of DG owners and operation of renewable energy sources. This paper considered the investment pattern of generation owners into account for the assessment of distribution network. The installed capacity of each DG unit was modeled as a fuzzy number. The authors in [39] proposed a fuzzy based multi-agent system for distributed energy management in smart grids. This paper proposed an adaptive fuzzy system designed to impart a decision making capability in agents when there is uncertainty involved with renewable sources and load. The model was tested on Hybrid renewable energy system (HRES) which had two solar panels, one energy storage unit, one diesel generator, DC/AC loads and one wind turbine. [40] proposed bio-inspired algorithms: GA, PSO, Artificial immune system (AIS) algorithm and VAccine-AIS algorithm for optimizing the operation of a distribution network by simultaneous dispatching and network reconfiguration. The results showed that simultaneous reconfiguration and dispatching of resources could lead to lower operating cost of distribution system.

2.0.3 Microgrids

Modern power systems are moving towards decentralized generation and has led to widespread developments of Smart Grids. US Department of Energy [41], defines smart grid as a consumer friendly, hack proof, self-healing, attack resistant grid with energy storage and renewable energy source integration options. Literature surveys [4, 5] show that microgrids are an integral part for realizing the futuristic Smart Grids. Various microgrids studies have considered presence of local load, local generation, energy storage and renewable energy sources [42, 43].

Microgrid (MG) can be ascertained as a single controlled unit in a power system scenario that can be operated as a single aggregated load. The unit can be described to be made up of generators, energy storage, load controller and power electronic interfaces like inverters. The Microgrid has two critical components a static switch and micro source, which consists of generator, storage and an inverter [44].Automatic tripping of the interconnected generators of a power system are laid down as per the IEEE 1547 standard. However a MG islands itself whenever an IEEE 1547 power quality event occur. After the tripping event is removed the MG reconnects itself to the power system. Fig. 2.1 shows the layout of a typical microgrid.

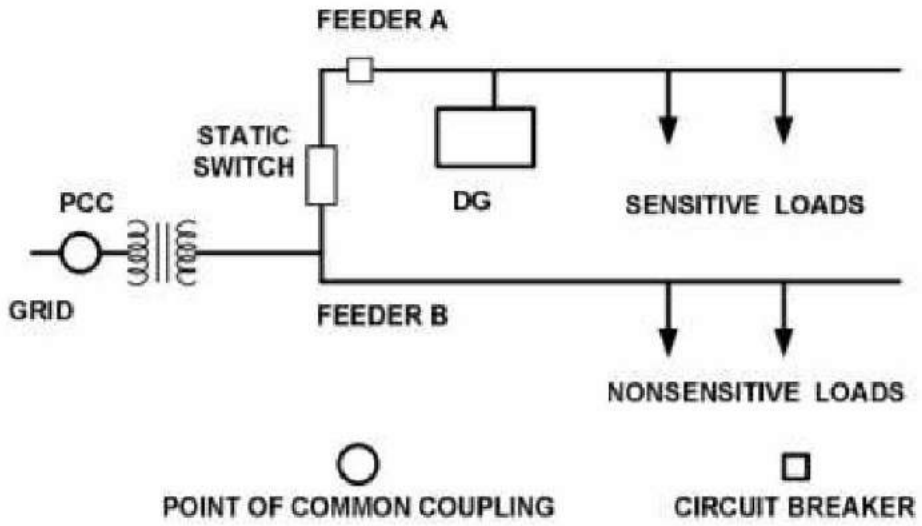

Figure 2.1: Layout of typical Microgrid

As mentioned before, lucrative from a technical point-of-view due to fast ramp-up and ramp-down rates; the energy storage investments have suffered due to their high costs until now. However, the investors who procure and utilize the energy storage devices: both in form of Electric Vehicles and local storage assets in Microgrids, have to manage the operation with arbitrage to cut down on operation cost associated and make more economic sense in the investment.

2.0.4 Literature Survey

This shall be the focus of our thesis, where we discuss smart arbitrage tools for Electric vehicle aggregator and arbitrage influenced storage sizing in Microgrids. We look at two important questions:

1. Risk Constrained operation of an PHEV aggregator to maximize its profits
2. Arbitrage influenced investment decisions for Microgrid owners

Uncertainty handling for Electric Vehicle aggregatorusing IGDT

PEVs do suffer from a lot of uncertainties, in terms of energy consumption rates and emission rates, as these are specific to vehicle technologies, uncertainties in cost, different driving patterns, and charging behaviour.The price uncertainties are catered in [45][46].Monte Carlo technique for handling various uncertainties[47] is used for getting the optimal solution. However, to implement the Monte Carlo technique for handling the price uncertainties will require prerequisite Probability Distribution Function (PDF), which is commonly estimated from the historical data of the uncertain prices that evolves with the dynamic market. It is always not feasible to obtain the historical data at all the distribution nodes where the aggregator installs the charging facility. Monte Carlo simulation is therefore not a feasible technique for such aggregators. Survey paper [5] suggests Information-Gap Decision Theory(IGDT) as a possible uncertainty handling technique for uncertain parameters with unknown PDFs.

Stochastic resource investment for Microgrids

One of the major challenges in widespread developments of microgrids has been its high investment costs [43]. This is evident from [43] which mentions that there is a plethora of studies on microgrid operations, but little works has focused on extending it to a resource planning problem. [43] presents a bender's decomposition approach to microgird investment planning problem. Rahbar et. al in [42, 48, 49, 50] provide a very complete and robust operational model for microgrids operartion in presence of renewable energy sources and energy storage assets.

Literature is filled with wide variety of optimization techniques that have been proposed to solve the microgrid optimization and planning problems. Authors in [4, 5] review and observe that majority of optimization problems for microgrids can be widely classified into two categories:

1. Classical Optimization techniques [43, 51, 52, 42, 48, 49, 50]
2. Meta heuristic techniques [53, 54, 55, 56, 57, 58, 59, 60]

Meta-heursitc methods are more suitable for non-convex and NP hard problems [61]. Authors in [62] point out the suitability of classical solution techniques over meta-heursistc techniques for planning problems that can be convexified. Due to this, we put our efforts to linearize the non-linear operational problem for microgrids and solve the resource investment problem with a classical optimization solver

2.1 Thesis Structure

The rest of the thesis is developed in the following order:

Chapter 3: Uncertanty handling for EV aggregator

Chapter 4: Stochastic Microgrid Investment planning

Chapter 5: Solution Methodology

Chapter 6: Conclusion and Future scope.

CHAPTER 3

UNCERTANITY HANDLING FOR ELECTRIC VEHICLE AGGREGATOR USING IGDT

The commonly known Electric Vehicles,Plug-in hybrid electric vehicles (PHEVs) have the potential to curb the emission as compared to the fossil fuel and comes at a more cheaper price,thus resulting in reduction of the cost of transportation [63]. The other unique advantage in favour of the PHEVs is their capability to integrate the onboard energy storage units with the power grid which can improve the efficiency and increase the reliability of the power grid. The demand for Plug-in Electric Vehicles (PEVs) have increased drastically [10], [11] as they can reduce CO2 emissions and because of their higher fuel economy. Hence PHEVs have the potential to shift energy requirement from fossil fuels to electricity in personal transportation [12].

3.1 Problem Definition

Here,we are trying to find the solution to a three-fold problem:

- a) Intelligent charging scheduling technique aimed at minimizing the total charging cost for electric vehicle aggregator with both V2G and G2V power flows.
- b) Using IGDT for the handling the price uncertainties in the charging scheduling problem.
- c) Reformulation of a non-linear problem into Mixed Integer Linear Problem for optimal solution

This chapter is organized with the following sections: Intelligent Charging Schedule,IGDT,Disjunctive Inequalities,Problem Formulation,Test System, Simulation Result and finally the Conclusion is covered in the end section.

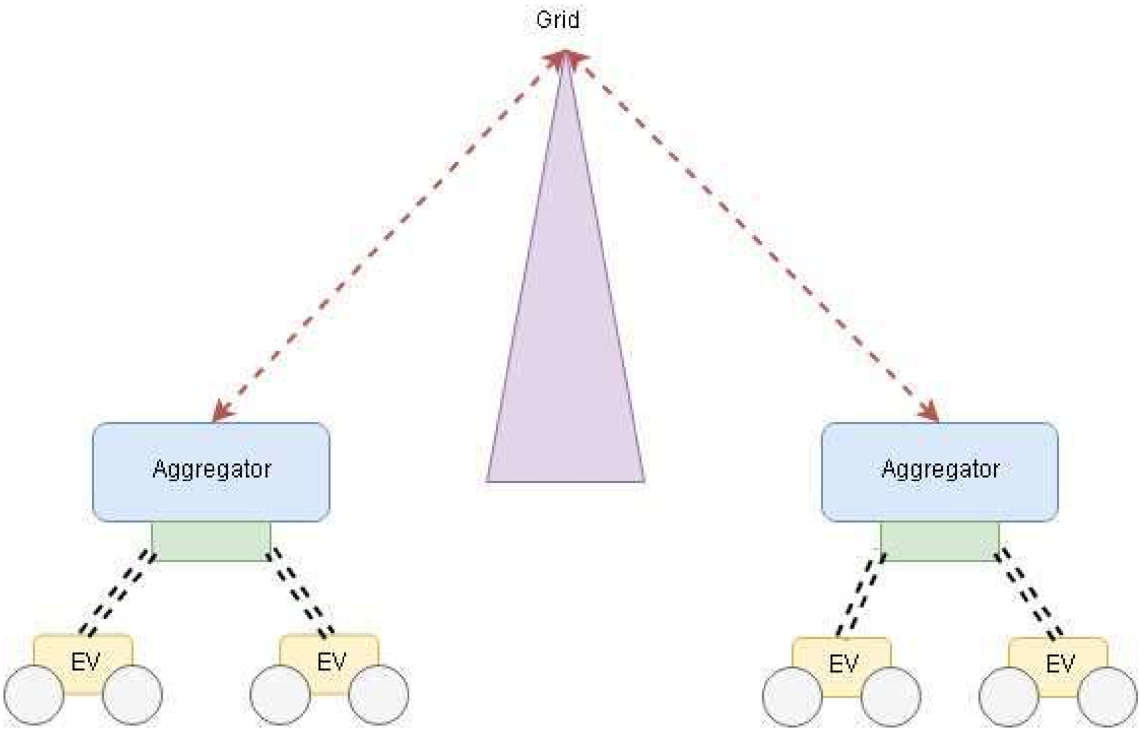

Figure 3.1: Schematic of charging process

3.2 Intelligent Charging Schedule (ICS)

The dynamic pricing in the electricity grids will encourage the aggregator to charge (G2V) the available PEVs at low tariff slots and discharge (V2G) the available PEVs at high tariff slots. It is well studied that this type of intelligent charging can lead to lower cost of charging by optimal scheduling the PEV charging [64].

As shown in Figure 3.1, assume that there are two identical PEVs which are to be charged in a parking station. The time of arrival, the time for which they remain parked in the charging station and the battery energy on arrival is considered different for both. Considering Time-of-Use (ToU) pricing to analyze the impacts of unscheduled PEV charging on the aggregator is analyzed.

Two PEVs are named as PEV1 & PEV2. Two scenarios are considered:

1. First Scenario: PEV charges without scheduling (no V2G).
2. Second Scenario: PEV charges with the V2G and G2V operation

3.2.1 First Scenario

Suppose the PEV1 arrives at T1 with 60% of battery energy remaining and stays in the parking slot till T2 & PEV2 arrives at T1 with 40% of battery energy remaining and stays till T2. Charging rate is 10% of Battery energy /Time slot. The prices of electricity are [T1: 100, T2:10]. In scenario 1, the vehicles start charging immediately after arrival. Hence by the end of T2, PEV1 is at 80% charge and PEV2 is at 60% charge.

Table 3.1: Battery energy change of PEV1

Time Slot	Operation	Battery status	cost
T1	G2V	60% to 70%	100
T2	G2V	70% to 80%	10

Table 3.2: Battery energy change of PEV2

Time Slot	Operation	Battery status	cost
T1	G2V	40% to 50%	100
T2	G2V	50% to 60%	10

Cost for charging PEV1=110 & for PEV2=110, so Total cost =220.

3.2.2 Second Scenario

In this scenario all conditions are same as the first scenario except the V2G operation takes place when the 50% battery energy status is achieved. So at the end of time slot T2, PEV1 & PEV2 both are charged to 60%.

Table 3.3: Battery energy change of PEV1

Time Slot	Operation	Battery status	cost
T1	V2G	60% to 50%	-100
T2	G2V	50% to 60%	10

Table 3.4: Battery energy change of PEV2

Time Slot	Operation	Battery status	cost
T1	G2V	40% to 50%	100
T2	G2V	50% to 60%	10

Cost for charging PEV1=-90 & for PEV2=110, so Total cost =20.

As compared to the first scenario it can be observed that there is a significant reduction in charging cost without compromising the optimal charge level of PEVs and PEV1 makes a profit on its schedule.

3.3 Information Gap Decision Theory (IGDT)

The information gap decision theory (IGDT) can be effectively used for considering uncertainties, especially if sufficient statistics is not obtained from the uncertainties input parameters [65]. IGDT is effective and it is robust even in the presence of prediction errors. IGDT can be successfully applied to various applications such as:

1. Power purchases in distribution networks
2. scheduling of GenCos considering Risk-constrains
3. Calculating Optimal bidding strategy for generating station

An IGDT based model [66] is effectively used for incorporating variability in wind power generation, load pattern changes and in heating loads. IGDT framework can be mathematically formulated as follows:

$$min_x f(x, \psi) \tag{3.1}$$

$$H_i(x, \psi) \leq 0, i \in \Gamma \tag{3.2}$$

Where,

Γ= represents all constraints.

ψ = Set of all uncertain parameters.

For present paper formulation for energy management based on IGDT is done as below

$$max_x \hat{l} \tag{3.3}$$

$$H_i(x, \psi) \le 0, i \in \Gamma \quad (3.4)$$

$$\hat{l} = max_l(f(x, \psi)) - \Lambda_c \le 0 \quad (3.5)$$

$$\psi \in U(\bar{\psi}, l) = \{\psi : |\frac{\psi - \bar{\psi}}{\bar{\psi}}|\} \le l \quad (3.6)$$

Where,
Λ_c = Objective function's critical value for a given value of X
$\bar{\psi}$ = Forecasted value of ψ.
l = Unknown radius of uncertainty

IGDT re-optimizes a problem in such a way that the objective function can suffer a deterioration but does not touch or cross the limit Λ_c while optimizer tries to maximize the extend to which the uncertainty can occur given by l . In some of the literature it can be reformulated as maximization over l when $\hat{l}$ is under a limiting constraint [65]. This paper follows the reformulated version of IGDT as described in [65] section C (Robustness of IGDT).

3.4 Disjunctive Inequalities

This section gives a brief idea on the linearization technique used to linearize the bilinieear terms in the optimization formulation. Disjunctive inequalities are used to represent a feasible region when the region is separated into islands. In such cases it is possible to write the feasible region in sets of equality and inequalities joined with an OR symbol (logical OR). A Disjunctive inequality representation of $x.y = 0$ when y is a binary variable would be $\{x = 0, y = 0\} \vee \{y = 1, x \in R^+\}$. This disjunctive inequality has an equivalent representation: $0 \le x \le M.(1 - y) \wedge 0 \le x \le M.(y)$ where M is a big positive constant. This is popularly known as big-M reformulation. It is possible to reformulate a variety of disjunctive inequalities by introducing a new or using an existing binary variable.

3.5 Problem Formulation

This section discusses a general intelligent charging problem formulation from EV aggregator's perspective.

$$min. \sum_{i=1}^{T}\sum_{j=1}^{N}(\frac{U_{G\_Vij}}{\eta_j} - \eta_j.U_{V\_Gij}).P_{ij}.\pi(i) \tag{3.7}$$

subject to:

$$\frac{U_{G\_Vij}}{\eta_j} - \eta_j.U_{V\_Gij} \leq P_{max}.\frac{24}{T}.cr_j \;\forall i,j \tag{3.8}$$

$$\sum_{j=1}^{N}(\frac{U_{G\_Vij}}{\eta_j} - \eta_j.U_{V\_Gij}) \leq maxload \;\forall i \tag{3.9}$$

$$BE_{i,j} = BE_{i-1,j} + U_{G\_Vij} - U_{V\_Gij} \;\forall i,j \tag{3.10}$$

$$BE_{jopt} \leq BE_{i,j} \leq BE_{jmax} \;\forall i,j \tag{3.11}$$

$$U_{G\_Vij} \times U_{V\_Gij} = 0 \;\forall i,j \tag{3.12}$$

$$U_{G\_Vij}, U_{V\_Gij}, BE_{i,j} \geq 0 \;\forall i,j \tag{3.13}$$

where j is the index for PEVs, i is the index for time intervals, T represents total time intervals, N is the aggregation of all PEVs, $(\frac{U_{G\_Vij}}{\eta_j} - \eta_j.U_{V\_Gij})$ is the sum of energy bought from grid during the given interval of time i for jth PEV. U_{G_Vij} is the energy transferred from grid to jth PEV in ith time slot. $\eta_j.U_{V\_Gij}$ is the energy transferred from jth PEV in ith time interval, η_j is the battery efficiency for car j, π_i is the electricity cost at time interval i, P_{ij} represents the element of a presence matrix and is 1 when the EV is present at the charging station, BE_{ij} is the energy stored in battery for jth EV at ith time interval, P_{max} is the maximum power rating for each charging station, BE_{jmax} is the maximum capacity of energy stored in the battery for PEV j, BE_{jopt} is the minimum energy level that should be maintained in battery of $j\ ^{th}$ PEV at all times, cr_j is a constant factor representing charging rate as fraction of power it can charge, of the peak power rating of charging station and $maxload$ is the maximum load which can be connected to grid from parking station. (2) and (3) are charging rate constraints on PEV and charging station respectively, (4) links battery energy levels with temporal energy flows, (5) gives the upper and lower limit for battery energy levels, and (6) is to ensure that charging and discharging does not happen simultaneously for any PEV at the same time interval. The objective (1) minimizes the aggregate cost of charging and discharging energy for the study duration.

The formulation explained above is non-linear due to (6). The non-linear problem can be linearized using binary variables using disjunctive inequalities as explained below: (6) can be replaced by:

$$0 \leq U_{G\_Vij} \leq M.(1-b_{ij}).P_{ij} \tag{3.14}$$

$$0 \leq U_{V\_Gij} \leq M.(b_{ij}).P_{ij} \tag{3.15}$$

where, M is a big positive constant, b_{ij} is a binary variable.

The above MILP formulation does not consider any uncertainty in the nodal price for the aggregator. To accommodate the uncertainty in price, Information Gap Decision Theory is proposed here. The aggregator optimization problem is reformulated to account for the price uncertainty in an interval as follows:

$$max.\ \alpha \tag{3.16}$$

subject to:

$$obj = \sum_{i=1}^{T}\sum_{j=1}^{N}(\frac{U_{G\_Vij}}{\eta_j} - \eta_j.U_{V\_Gij}).P_{ij}.(\pi(i) \pm \alpha) \tag{3.17}$$

$$TP_{i,j} = (\frac{U_{G\_Vij}}{\eta_j} - \eta_j.U_{V\_Gij})\forall i,j \tag{3.18}$$

$$obj \leq obj_b + (\beta.obj_b) \tag{3.19}$$

$$\frac{U_{G\_Vij}}{\eta_j} - \eta_j.U_{V\_Gij} \leq P_{max}.\frac{24}{T}.cr_j\ \forall i,j \tag{3.20}$$

$$\sum_{j=1}^{N}(\frac{U_{G\_Vij}}{\eta_j} - \eta_j.U_{V\_Gij}) \leq maxload\ \forall i \tag{3.21}$$

$$BE_{i,j} = BE_{i-1,j} + U_{G\_Vij} - U_{V\_Gij}\ \forall i,j \tag{3.22}$$

$$BE_{jopt} \leq BE_{i,j} \leq BE_{jmax}\ \forall i,j \tag{3.23}$$

$$0 \leq U_{G\_Vij} \leq M.(1-b_{ij}).P_{ij}\ \forall i,j \tag{3.24}$$

$$0 \leq U_{V\_Gij} \leq M.(b_{ij}).P_{ij} \ \forall i, j \tag{3.25}$$

$$U_{G\_Vij}, U_{V\_Gij}, BE_{i,j} \geq 0 \ \forall i, j \tag{3.26}$$

where, α is the degree of uncertainty in price parameter, obj_b is the optimized cost obtained from the base optimization problem discussed in (1) without any uncertainty (on average forecasted prices), and β is the budget of uncertainty or the maximum percentage allowed deviation from the obj_b. We see that equation (11) again makes the problem nonlinear. We can linearize (11) as follows:

$$\alpha = \sum_{s \in S} \alpha_s.K \tag{3.27}$$

$$obj = \sum_{i=1}^{T} \sum_{j=1}^{N} (TP_{i,j}).P_{ij}.(\pi(i)) \pm (\sum_{s \in S} K.z_{i,j,s}.P_{ij}) \tag{3.28}$$

$$-M.\alpha_s \leq zz_{i,j,s} \leq M.\alpha_s \tag{3.29}$$

$$TP_{i,j} - M.(1 - \alpha_s) \leq zz_{i,j,s} \leq TP_{i,j} + M.(1 - \alpha_s) \tag{3.30}$$

where α_s is the binary variable used to discretize the variable α into S segments with index s. $\pm$ sign is used to denote that the uncertainty in price will be added when the aggregator is drawing overall power from the grid in the base case and vice versa to get the worst case scenario. K is the step size of discretization of variable α.

3.6 System Data

In this paper an aggregator with 5 EVs is considered. The presence of different EVs due to their driving pattern is known and shown in Presence matrix here:

The average forecasted electricity prices at the aggregator node is given as follows:

The upper and lower limits of battery energy levels is set to 13.5 Kw and 6 Kw respectively.

Table 3.5: Presence Matrix

Time slots	N1	N2	N3	N4	N5
1	1	1	1	1	1
2	1	1	1	1	1
3	0	1	1	1	0
4	0	0	1	1	0
5	0	0	0	0	0
6	0	0	0	0	0
7	0	0	0	0	0
8	1	0	1	0	1

Table 3.6: Electricity Prices in Dynamic Day-Ahead Market

Time Slot	Price (Euros/kWh)
1	0.03667
2	0.03746
3	0.05695
4	0.05736
5	0.04758
6	0.04834
7	0.05494
8	0.03908

3.7 Results and Observations

Table 3.7: Aggregator profit (Yearly)

Test	Profit per year (Euros)
IGDT	50.74
Base Case	93.805

The figures show the V2G and G2V charging schedules for each EV in the aggregator parking station throughout the day. The spider diagrams (figure 5,6) show the battery energy levels of each EV throughout the day.

Table 3.7 shows the profit that the aggregator would make in a year (estimated with a projection) in case of IGDT based uncertainty handling vs the absolute forecast based intelligent charging. It can be seen that the IGDT based uncertainty handling causes the profit to be considerably lower but this case has accounted for the uncertainties in the prices throughout the day. This shows that with the IGDT based charging scheduling the profit per year would be atleast $50.74euros$ or more with for certain interval of uncertainty which is represented by α in the formulation. There is a cost associated with the price fluctuations and a price associated for the value of true prices in future.

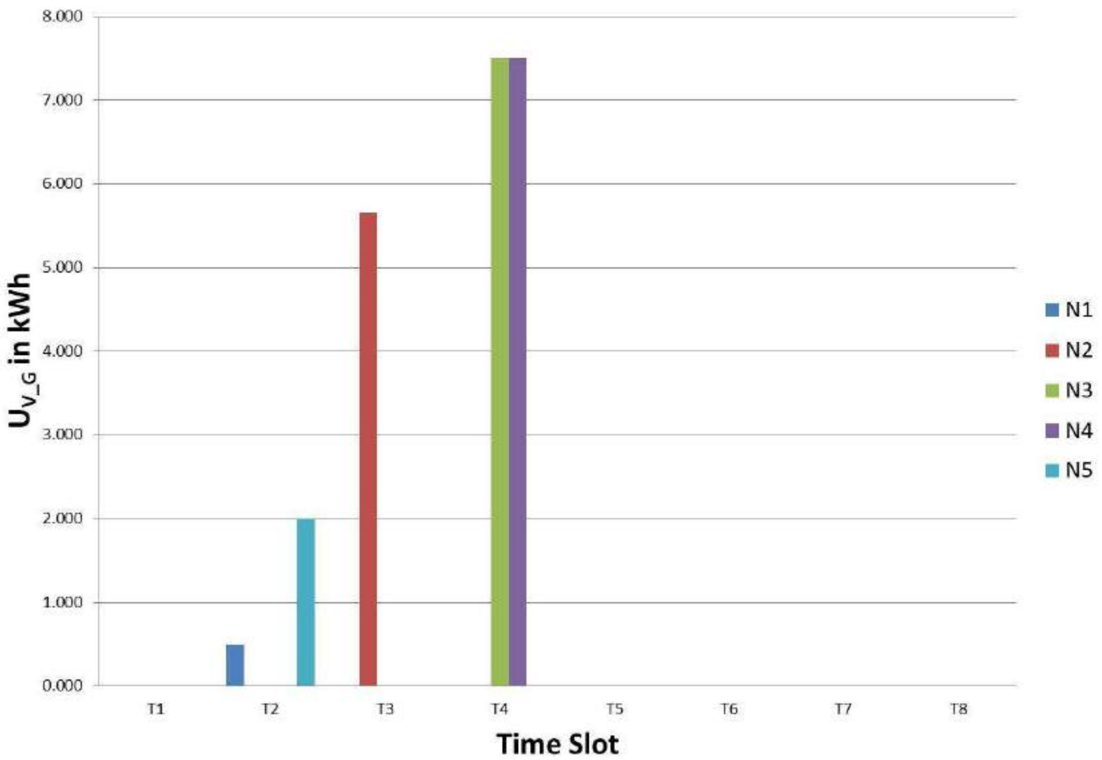

Figure 3.2: V2G Schedules for all PHEVs- Base Case

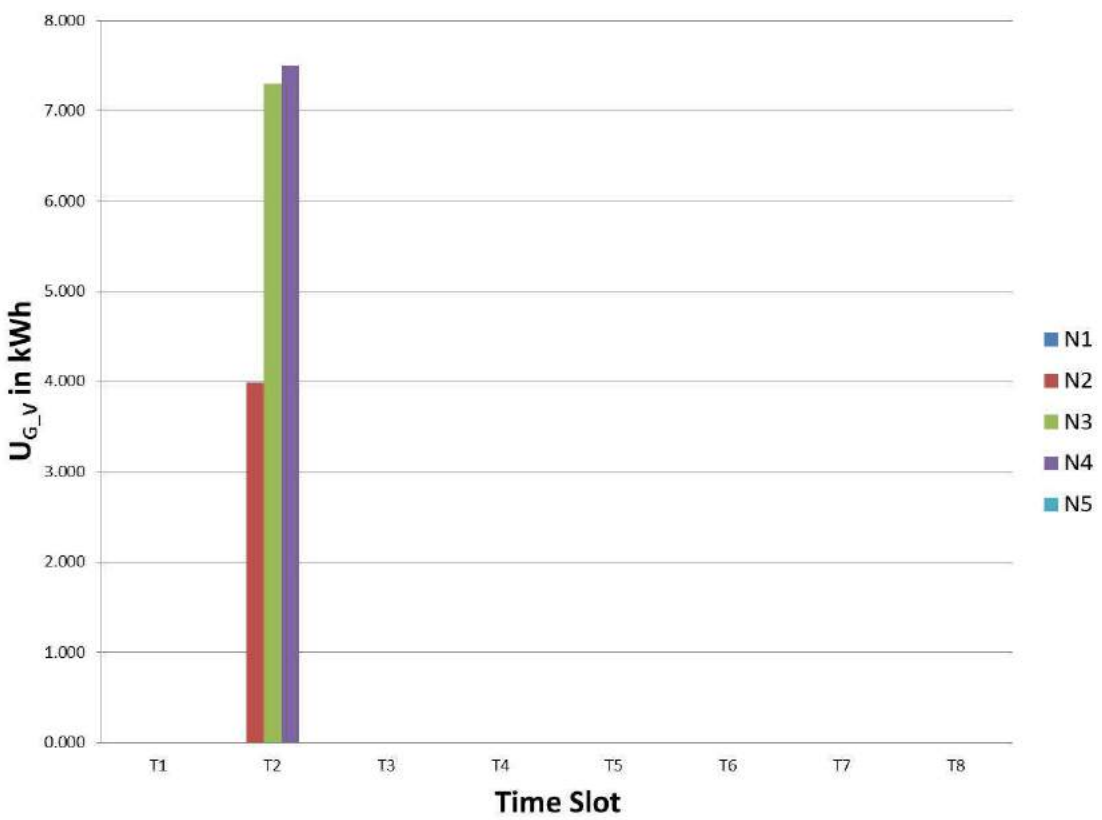

Figure 3.3: G2V Schedules for all PHEVs- Base Case

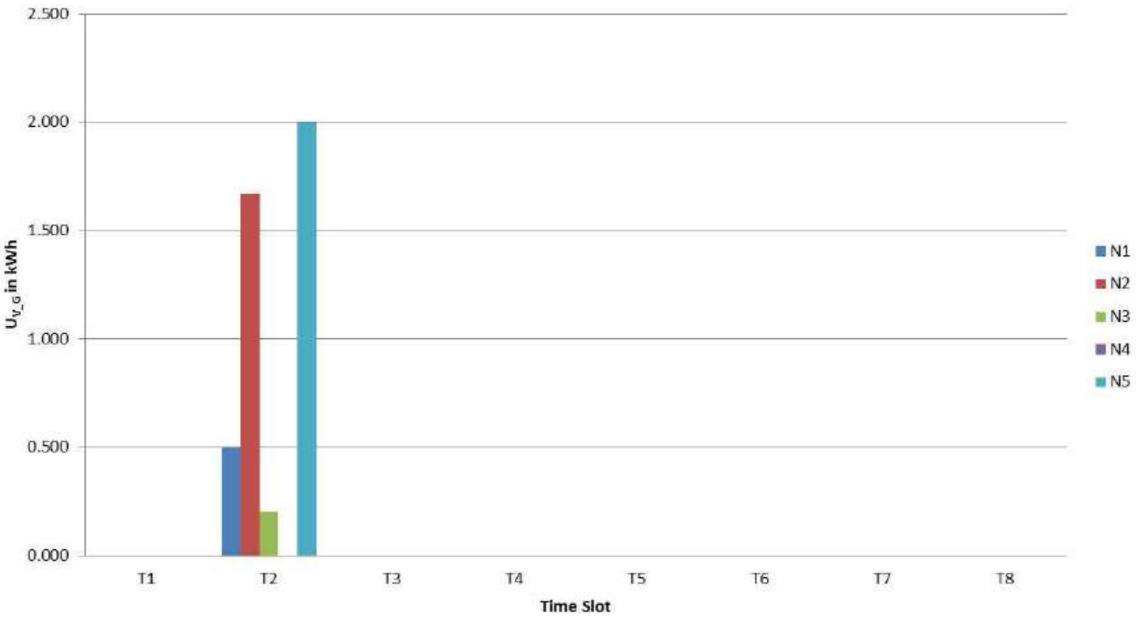

Figure 3.4: V2G Schedules for all PHEVs- IGDT

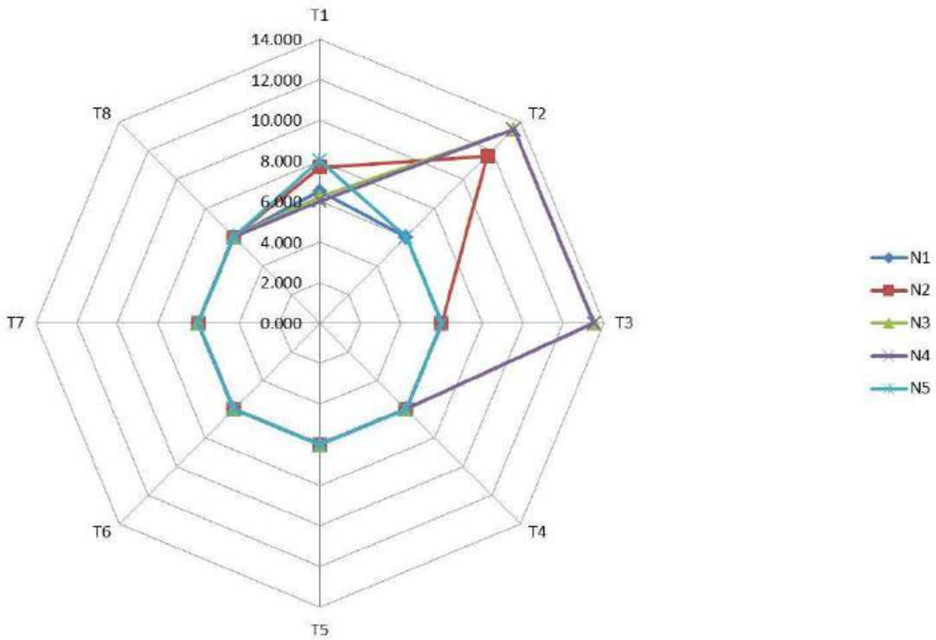

Figure 3.5: Battery Energy Levels- Base Case

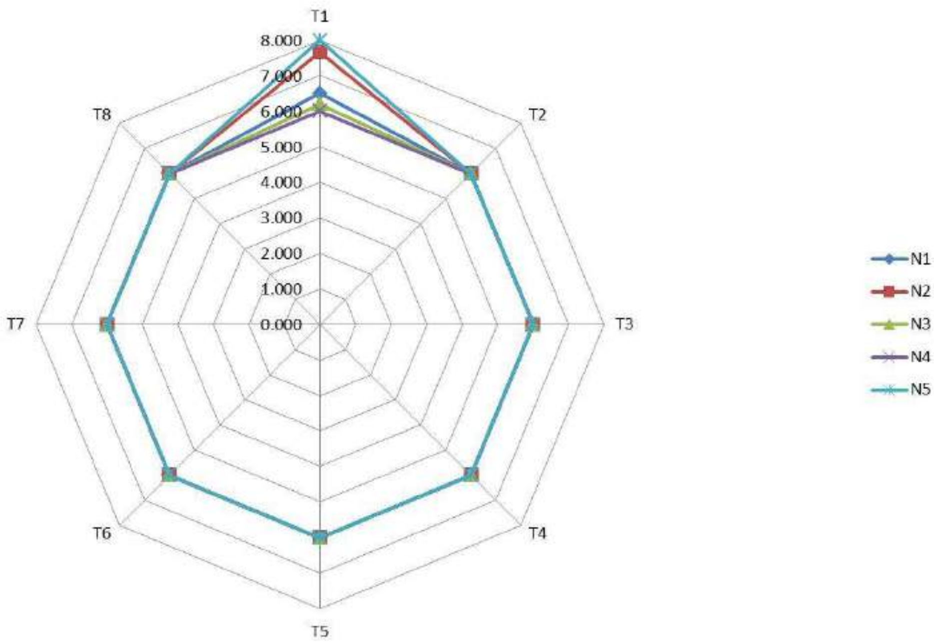

Figure 3.6: Battery Energy Levels- IGDT

The cost associated with price fluctuations is the difference between the IGDT objective value and Base case objective value with average prices. The cost associated with true prices in future is the difference between the objective values of the function when true future prices are known and the objective value of the IGDT schedule with true prices. In case the price fluctuations vary in a small interval, these differences would be very low. In such scenarios an average forecast is enough to solve the problem. In cases when the price fluctuations can vary in a large interval, it becomes necessary to handle this uncertainty with IGDT.

CHAPTER 4

STOCHASTIC RESOURCE INVESTMENT FOR MICROGRID

In the scenario of today,the implementation of microgrid systems have many advantages both from the user and from the electric utility point of view.If we see from the user view, microgrid is connected to the grid, it can improve network quality, reduce emissions and can reduce the cost to be incurred by the user. whereas,the utility sees it as an opportunity where implementation of distributed generation systems with the ability microgrid can reduce the power flow on transmission and distribution lines, so as to reduce losses and reduce costs for additional power. Moreover microgrid can also reduce the load on the network by eliminating the impasse in meeting electricity needs and help repair network in case of errors[67].

4.1 Problem Definition

The main contributions of this chapter can be enumerated as follow:

- a) Recast the non-linear non-convex operational problem into a Linear program
- b) Generalize the linear program for all possible parametric inputs
- c) Extend the operational problem into a resource investment problem
- d) Show the superiority of stochastic modelling over average forecast modelling.

The rest of the sections are covered as:Microgrid Architecture,Problem Formulation,Test system, Results and Discussions and finally Conclusion with future scope covered at the end in a separate section.

4.2 Microgird Architecture

The microgrid architecture is shown in the Fig 4.1. There exists solar and wind units as a local source of generation. The local load in microgrid has to be met always. The

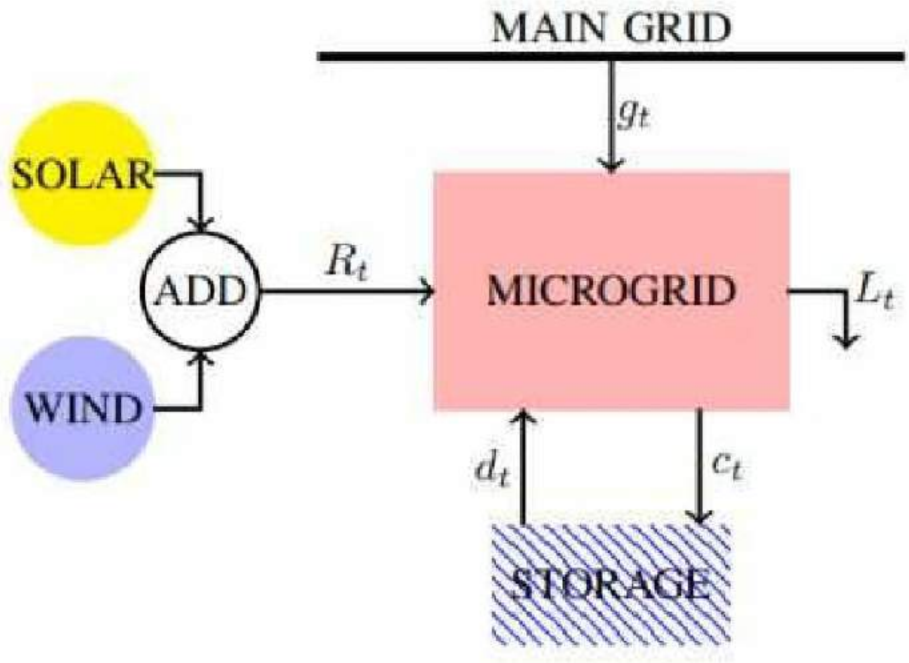

Figure 4.1: Microgrids Architecture

microgrid can decide to purchase power from the Main grid in order to satisfy load balance at all time intervals. However, in out microgrid architecture we do not allow the microgrids to sell power to the main grid. This assumption in in line with Rahbar et al [42]. We also see that there is an option for the microgrid owner to invest in a storage asset. This storage asset can be utilized to play an arbitrage at operational level to minimize the total cost of operation.

The microgrid owner in this paper shall solve an optimization problem for optimal sizing of energy storgae assets in order to minimize the total sum of investment and expected operation costs.

4.3 Problem Formulation

In this section we first formulate the operational model for microgrids and then extend it to a resource investment planning model.

4.3.1 Operational Level Dispatch Problem

In this subsection we shall discuss and concretely formulate the operational model of the microgrid.

$$\underset{g_t,d_t,c_t,s_t}{Minimize} \sum_{t \in T} F_t g_t \tag{4.1a}$$

$$Subject\ to:$$

$$s_t = s_{t-1}\mathcal{I}(t > 1) + S_0\mathcal{I}(t = 1) + \eta_c c_t - \frac{d_t}{\eta_d},\ \forall t \in T \tag{4.1b}$$

$$\underline{S} \leq s_t \leq \overline{S},\ \forall t \in T \tag{4.1c}$$

$$s_{t=|T|} \geq \mathcal{S} \tag{4.1d}$$

$$g_t + R_t + d_t = c_t + L_t,\ \forall t \in T \tag{4.1e}$$

$$d_t c_t = 0,\ \forall t \in T \tag{4.1f}$$

$$0 \leq d_t \leq D,\ \forall t \in T \tag{4.1g}$$

$$0 \leq c_t \leq D,\ \forall t \in T \tag{4.1h}$$

$$0 \leq g_t \leq G,\ \forall t \in T \tag{4.1i}$$

We note that the above set of equations (4.1) representing the operations level dispatch problem is non-linear and non-convex due to (4.1f). However, we can drop this non-linear equation without affecting the final solution. This is proved in Lemma 1. The optimal solution to (4.1) does not change by dropping the constraint (4.1f)

4.3.2 Proof of Lemma 1

To begin let us assume that the optimization problem ((4.1)\(4.1f)) represent a new optimization problem with described by set of equations (4.1a)-(4.1e) and (4.1g)-(4.1i). We have to show that ((4.1)\(4.1f)) and (4.1) have the same solution. Let the search space of ((4.1)\(4.1f)) and (4.1) be represented by $\Omega_{((4.1)\setminus(4.1f))}$ and $\Omega_{(4.1)}$ respectively. It is easy to see that $\Omega_{((4.1)\setminus(4.1f))} \supseteq \Omega_{(4.1)}$. This is due to the fact that imposing extra constraints shall restrict the search space. Therefore, an optimal solution to (4.1), $(4.1)^* \in \Omega_{(4.1)}$, shall imply $(4.1)^* \in \Omega_{((4.1)\setminus(4.1f))}$. Let us assume that the optimal solution for $\Omega_{((4.1)\setminus(4.1f))}$, $((4.1) \setminus (4.1f))^* \neq (4.1)^*$. This discussion shall imply that, $objective\{((4.1) \setminus (4.1f))^*\} < objective\{(4.1)^*\}$ and $((4.1) \setminus (4.1f))^* \notin \Omega_{(4.1)}$ occurs at a point that violates (4.1f). This shall imply that at $((4.1) \setminus (4.1f))^*\{\ \exists\, t \in T \ni c_{t,((4.1)\setminus(4.1f))^*} > 0 \wedge d_{t,((4.1)\setminus(4.1f))^*} > 0\} \implies \{\ \exists\, t \in T \ni s_{t,((4.1)\setminus(4.1f))^*} < s_{t,(4.1)^*}\}$. This argument is due to the fact that $0 \leq \eta_c, eta_d < 1$ and (4.1b). This argument shows that the SoC level of $(4.1)^*$ has been translated to a lower value than SoC level of $((4.1) \setminus (4.1f))^*$, i.e $\exists t \in T, \ni\ s_{t_i,((4.1)\setminus(4.1f))^*} < s_{t_i,(4.1)^*} \forall t_i \in T\ t_i > t$. To enhance the last argument we assume that if there exists a $t_i \in T$ where the SoC levels in both problems were to come back to equal levels, then due to (4.1b), $((4.1) \setminus (4.1f))^*$ would have to charge more than $((4.1)*$. This means at some $\exists t_i > t\ \ni c_{t_i,((4.1)\setminus(4.1f))^*} > c_{t_i,((4.1)*}$. Due to load balance (4.1e), this would imply $\exists t_i > t\ \ \ni g_{t_i,((4.1)\setminus(4.1f))^*} > g_{t_i,((4.1)*}$, which shall increase the cost of $objective\{((4.1) \setminus (4.1f))^*\}$ and would not be an optimal strategy.

The above argument ensures that $\exists t \in T, \ni\ s_{t_i,((4.1)\setminus(4.1f))^*} < s_{t_i,(4.1)^*} \forall t_i \in T\ t_i > t$. Lower limit of s_t and g_t is imposed in both optimization problems due to (4.1c) and (4.1i). To maintain the load balance (4.1e) the energy storage unit shall discharge or import from main grid $(d_t > 0 \vee g_t > 0) \forall t \in T\ \ni\ R_t < L_t$. We have noted that $\exists\, t \in T \ni s_{t,((4.1)\setminus(4.1f))^*} < s_{t,(4.1)^*}$. If for some $t_1 \in T \ni t_1 > t$ in the bounded sequence of elements in T, $R_{t_1} < L_{t_1}$; this shall invoke $(d_{t_1} > 0 \vee g_{t_1} > 0)$ for both the problems. It can be observed that $\exists \underline{S} > 0\ \ni\ d_{t_1,((4.1)\setminus(4.1f))^*>0}$ shall be infeasible due to lower bounds on SoC levels (4.1c) and charge balance (4.1b). This shall imply that at such t_1, solutions $((4.1) \setminus (4.1f))^*$ and $((4.1)^*$ shall have different strategies: $d_{t_1,(4.1)*} > 0 \wedge g_{t_1,(4.1)*} = 0$, while $d_{t_1,((4.1)\setminus(4.1f))^*} = 0 \wedge g_{t_1,((4.1)\setminus(4.1f))^*} > 0$. This shall lead to $objective\{((4.1) \setminus (4.1f))^*\} > objective\{(4.1)^*\}$ from (4.1a), which contradicts our assumption. Hence our assumption $objective\{((4.1) \setminus (4.1f))^*\} < objective\{(4.1)^*\}$ can never be true and it implies $objective\{((4.1) \setminus (4.1f))^*\} \geq objective\{(4.1)^*\}$. Since $\Omega_{((4.1)\setminus(4.1f))} \supseteq \Omega_{(4.1)}$, this ensures that equality holds $objective\{((4.1) \setminus (4.1f))^*\} = objective\{(4.1)^*\}$. Hence, the optimal solution to (4.1) does not change by dropping the constraint (4.1f)

Due to Lemma 1, we can rewrite a new operational dispatch problem as:

$$\underset{g_t,d_t,c_t,s_t}{Minimize} \sum_{t \in T} F_t g_t \tag{4.2a}$$

$$Subject\ to:$$

$$s_t = s_{t-1}\mathcal{I}(t > 1) + S_0\mathcal{I}(t = 1) + \eta_c c_t - \frac{d_t}{\eta_d},\ \forall t \in T \tag{4.2b}$$

$$\underline{S} \leq s_t \leq \overline{S},\ \forall t \in T \tag{4.2c}$$

$$s_{t=|T|} \geq \mathcal{S} \tag{4.2d}$$

$$g_t + R_t + d_t = c_t + L_t,\ \forall t \in T \tag{4.2e}$$

$$0 \leq d_t \leq D,\ \forall t \in T \tag{4.2f}$$

$$0 \leq c_t \leq D,\ \forall t \in T \tag{4.2g}$$

$$0 \leq g_t \leq G,\ \forall t \in T \tag{4.2h}$$

We note that problem (4.2) can be further relaxed to an easier LP by relaxing equality (4.2e) shall not alter the solution and make the problem feasible for wider range of R_t, L_t. Relaxing (4.2e) from (4.2) shall make the problem general for all ranges of R_t, L_t.

4.3.3 Proof of Lemma 2

Let us create a scenario where (4.2) shall be infeasible and we will need to relax (4.2e). Let $\exists t \ni L_t = 0, R_t > D$. We note that at such a t, load balance (4.2e) cannot be satisfied in any way and problem is infeasible. This enforces us to relax (4.2e) to an inequality for a general case of load and renewable energy generation. Thus relaxing (4.2e) to an inequality shall make the problem general for all ranges of R_t, L_t.

Lemma 2 also makes the problem well defined by allowing the uncertain data $R_t, L_t \in \mathcal{L}_1$ as mentioned in [68]. The general dispatch can be written as:

$$\underset{g_t,d_t,c_t,s_t}{Minimize} \sum_{t \in T} F_t g_t \tag{4.3a}$$

$$Subject\ to:$$

$$s_t = s_{t-1}\mathcal{I}(t > 1) + S_0\mathcal{I}(t = 1) + \eta_c c_t - \frac{d_t}{\eta_d},\ \forall t \in T \tag{4.3b}$$

$$\underline{S} \leq s_t \leq \overline{S},\ \forall t \in T \tag{4.3c}$$

$$s_{t=|T|} \geq \mathcal{S} \tag{4.3d}$$

$$g_t + R_t + d_t \geq c_t + L_t,\ \forall t \in T \tag{4.3e}$$

$$0 \leq d_t \leq D,\ \forall t \in T \tag{4.3f}$$

$$0 \leq c_t \leq D,\ \forall t \in T \tag{4.3g}$$

$$0 \leq g_t \leq G,\ \forall t \in T \tag{4.3h}$$

(4.3) and (4.2) are equivalent.

4.3.4 Proof of Lemma 3

Let us assume that (4.3) and (4.2) are not equivalent. The only difference between the two problems is inequality (4.3e) and (4.2e). Let us assume that at optimality of problem (4.3), strict inequality of (4.3e) is maintained at some time instant t. In such a case the microgrid shall have to discard some of the renewable generation available. Where as at the same time instant t, equality of (4.2e) ensures that the available energy is stored in energy storage assets. This shows that at this time instant t, SoC level of microgrid under (4.3e) is higher than the microgrid under (4.2e) strategy. From arguments in Appendix 4.3.3, we can see that the strict inequality has made (4.3) suboptimal. Therefore, our assumption is wrong and through proof by contradiction: (4.3) and (4.2) are equivalent.

4.3.5 Resource Investment Problem

In this subsection we shall extend the operational dispatch problem to a resource investment problem where the investment in energy storage assets can be decided. The resource investment planning problem has an abuse of notation to allow for various scenarios of operational level problem.

$$\underset{g_{t,z},d_{t,z},c_{t,z},s_{t,z},D,\overline{S}}{Minimize}\{I_pD + \overline{S}I_e + \sum_{t\in T,z\in Z}\rho_z F_{t,z}g_{t,z}\} \tag{4.4a}$$

$$Subject\ to:$$

$$s_{t,z} = s_{t-1,z}\mathcal{I}(t>1) + S_0\mathcal{I}(t=1) + \eta_c c_{t,z} - \frac{d_{t,z}}{\eta_d},$$

$$\forall t \in T, z \in Z \tag{4.4b}$$

$$\underline{S} \leq s_{t,z} \leq \overline{S},\ \forall t \in T, z \in Z \tag{4.4c}$$

$$s_{t=|T|,z} \geq \mathcal{S},\ \forall z \in Z \tag{4.4d}$$

$$g_{t,z} + R_{t,z} + d_{t,z} \geq c_{t,z} + L_{t,z},\ \forall t \in T, z \in Z \tag{4.4e}$$

$$0 \leq d_{t,z} \leq D,\ \forall t \in T, z \in Z \tag{4.4f}$$

$$0 \leq c_{t,z} \leq D,\ \forall t \in T, z \in Z \tag{4.4g}$$

$$0 \leq g_{t,z} \leq G,\ \forall t \in T, z \in Z \tag{4.4h}$$

4.4 Test System

We consider a Microgrid with following installed assets:

1. Local Load (500 kWh)
2. Local Renewable unit (600 kWh)

The local renewable energy unit may be composed of various renewable energy sources like solar and wind. In our simulations we considered 400 kWh or installed solar and 200 kWh of installed wind unit. The uncertainty in wind and solar sources are modelled as a Weibull and beta distribution respectively [5]. The uncertainty in load is modelled as a normal distribution [5]. The market price uncertainty was modelled based on historical prices obtained at IEX website. Based on the various sequential scenarios of net renewable energy output, load and market prices the upper and lower bounds of the forecasts are shown in Fig 4.4, Fig 4.3 and Fig 4.2 respectively.

The various scenarios generated were reduced to dominant scenarios based on scenario reduction technique described in [69]. The investment options available for test microgrids was assumed to be an energy storage unit. The investment cost of energy storage asset is calculated based on:

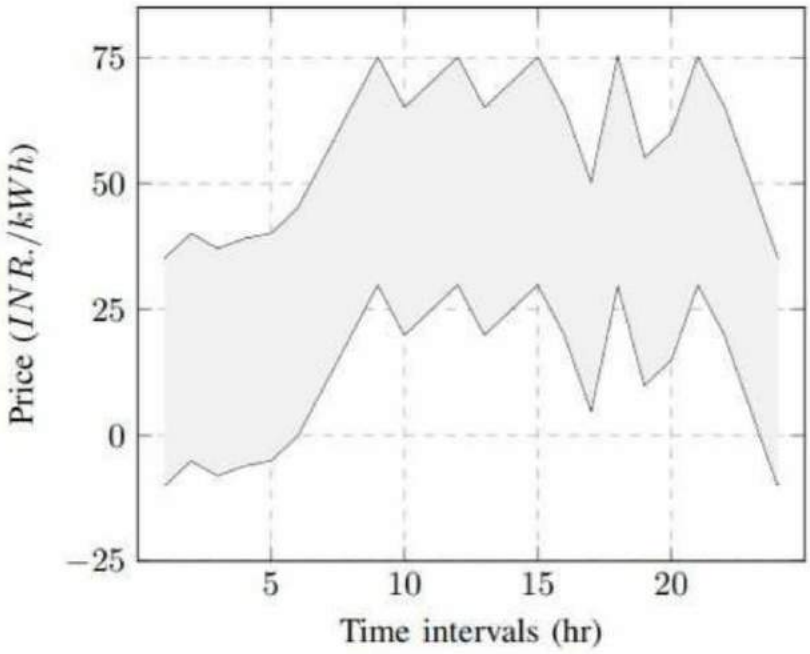

Figure 4.2: Price Forecast Bounds

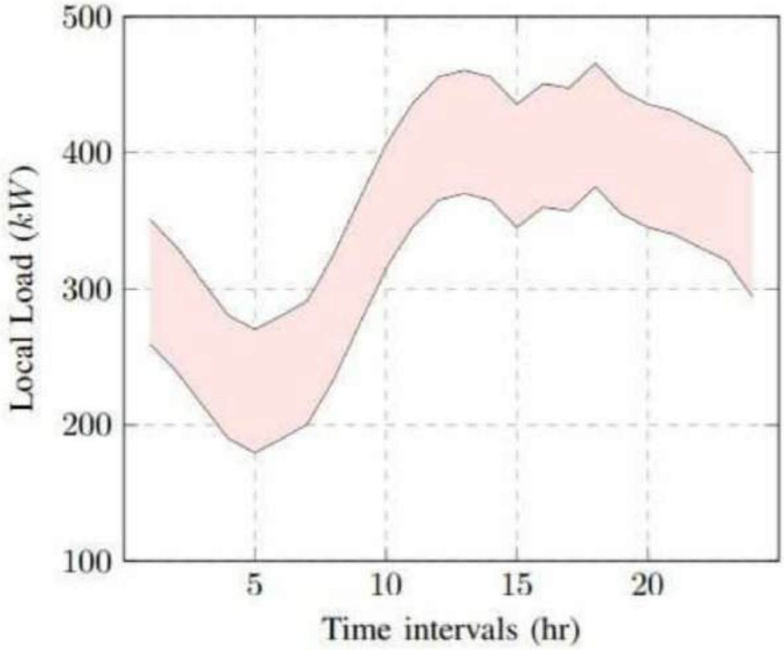

Figure 4.3: Load Forecast Bounds

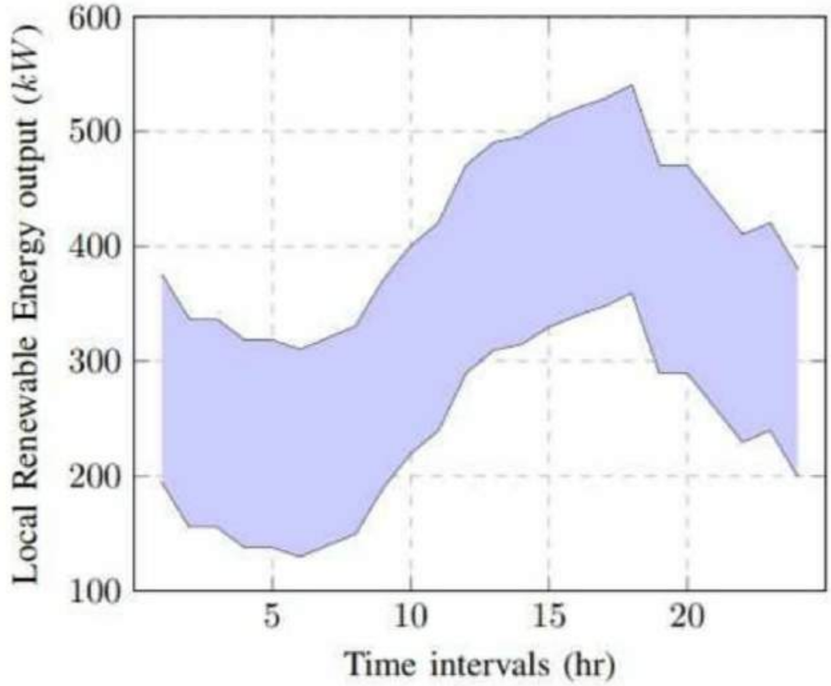

Figure 4.4: Net Renewable energy Forecast Bounds

1. Power rating cost : $10\$/kW$
2. Energy rating cost : $100\$/kWh$

No budget constraints were assumed in our simulations. The proposed model was simulated in GAMS on a computer with i7-7700K processor at 4.2GHz speed and 16 GB of RAM.

4.5 Results and Discussion

We run ths imulation in two test cases:

1. Stochastic Investment (SI)
2. Investment on average forecasts (IAF)

SI is proposed in (4.4), where as IAF refers to a model with single scenario in (4.4) representing the average forecasts. The optimal energy storage asset specifications for installation, opration cost, and investment cost solutions for SI and IAF are given in Table 4.1. We see that SI allows for investment in energy storage asset of higher power

Table 4.1: Optimal Energy storage Investments

Solution	IAF	SI
Power Rating (kW)	6.961	8.91
Energy Rating (kWh)	9.9	9.9
Expected Operation Cost (\$)	20063.9	19519.3
Investment Cost (\$)	1059.6%	1079.1
Total Cost (\$)	21123.5	20598.4

rating. This increases the Investment cost of SI over IAF, but a higher power rating energy asset allows the microgrid to save on expected operation cost. This results in total cost for SI being lower than that of IAF. The state of charge of the energy storage asset in case of SI for 5 most probable scenarios are shown in Fig 4.5. The shaded region in Fig 4.5 shows the most expected state of charge for energy storage at various time intervals over the operational period. The usage of higher power rating is evident from big jumps in state of charge shown in Fig 4.5. We realize that this allows microgrid to play arbitrage over the price fluctuations and save on operational cost.

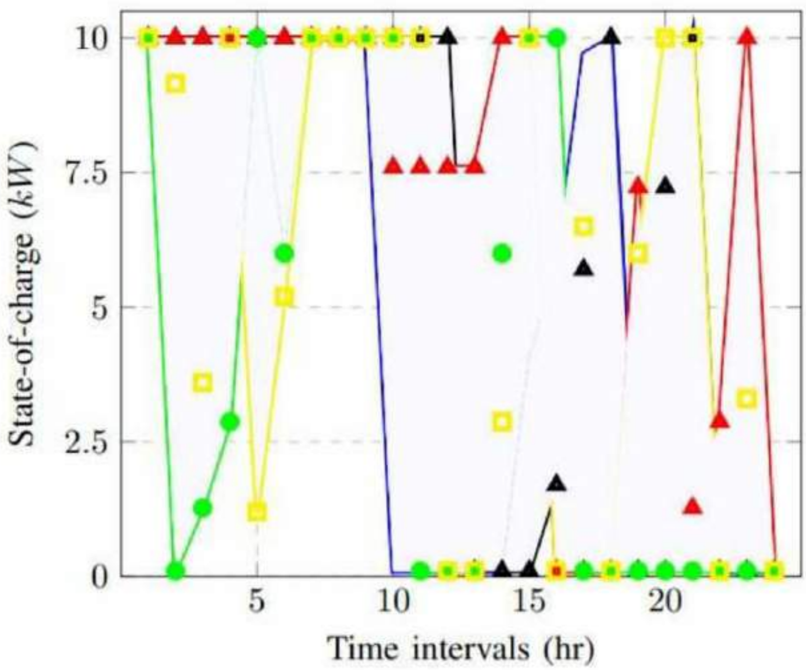

Figure 4.5: State-of-charge (kWh) in energy storage assets

Our simulations show that SI is a better model for resource investment planning for microgrid as compared to IAF. Fig 4.6 compares the power purchased from the grid under one SI scenario operation and IAF operation. It can be seen evidently that SI operation purchased much lower power from the grid as compared to IAF operation. This is the reason for low expected operation cost of SI over IAF in Table 4.1.

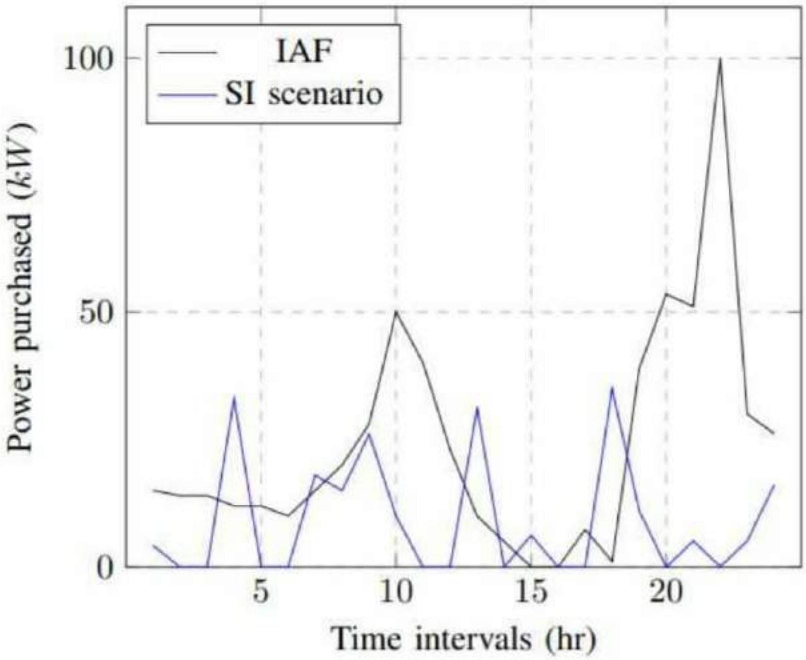

Figure 4.6: Power purchased from main grid

CHAPTER 5

SOLUTION METHODOLOGY

Till now ,we have discussed the need for optimisation and the method to optimise the objective function to get the desired result taking all the constraints into picture.

The first part of the thesis discusses about intelligent charging scheduling problem for an Electric Vehicle (EV) aggregator considering vehicle-to-grid (V2G) and grid-to-vehicle (G2V) capabilities with an objective to minimize the total charging cost.Here,the aggregator is an entity through which we are trying to reduce the cost as an objective function. With the uncertanities dwindling with the price of electricity price at the charging nod,the Information Gap Decision Theory (IGDT) is used to handle uncertainties in the price. The original intelligent charging scheduling problem is non-linear. We proposes a modified Mixed Integer Linear Programming (MILP) based reformulation and solves with CPLEX using GAMS as an aggregators studying the impact of priority and intelligent charging of PEV.An example also simplifies the need of the literature survey as discussed in chapter 2.

The second part of the thesis also deals with another optimisation problem.Here, A stochastic resource investment planning model for Microgrid was used to get the objective function achieved. This part considers that the microgrid in study has a local load, renewable generation, energy storage unit and a link to the main grid. Here,the microgrid is modeled as a price taker as it cannot influence the market prices.The operational objectives is to minimize the cost of operations by scheduling the assests of the microgrid.he operational aspect of microgrids is modeled as a Linear program (LP). We then continue to use this LP operational model and find an optimal investment strategy for microgrid in a new stochastic LP model where the objective is to minimize the sum of investment and expected operational cost. The assets considered for investment include energy storage units. The proposed stochastic LP model is tested on a Microgrid test system and simulated on GAMS.

Now using all the information and assumptions described in above chapters, we will try to solve the optimization problem and determine the premium to be levied upon users.The methodology used, to come up with a solution for our problem of intelligent charging scheduling and for each PEV is discussed in detail in this section.A brief description of tool and technique used for solving the problem is also discussed.

As described in Chapter 3 and 4, the problem is formulated as an optimization problem for different scenarios to minimize the objective function including the cost of charging the PEV under the constraints which ensures that overloading of distribution system, overcharging/undercharging of batteries and feasible operation takes place.To solve the problem, we will use GAMS modeling system and cplex solver.As presence matrices are stochastic, so Monte Carlo Sampling-Based Method for Stochastic Optimization is used to estimate the cost of charging.A brief description on GAMS,cplex solver & Monte Carlo simulation follows :

GAMS

GAMS(**G**eneral **A**lgebraic **M**odeling **S**ystem) is a high-level modeling system for mathematical programming and optimization.Different type of optimization problems like linear, nonlinear, and mixed-integer can be modelled and solved effectively in GAMS. The system is tailored for complex, large-scale modeling applications and allows the user to build large maintainable models that can be adapted to new situations. The system is available for use on various computer platforms. Models are portable from one platform to another [70]. Advantages of using GAMS are as follows [71]:

1. Access to a large set of existing solution algorithms.So the user is not constrained to use a particular solver, and many different solvers can be tried without changing the formulation.
2. Another important feature of GAMS is independence between model formulation and the model data which means that GAMS allows to formulate the model without direct reference to a specific data set and therefore enables to use the same model code with different data sets or different aggregations of the same data set.So, the model may increase dramatically in size with a new data set, but the formulation remains the same.
3. The model representation in GAMS closely follows the way a model is written using mathematical symbols.It helps in better understanding of model and allows to change the code simply and safely ,without creating lots of errors.
4. GAMS is flexible with respect to both computer type and user interface ,so it can be used on different platforms easily.

5. It can be used together with many other programs like built-in GDX-utility (GDX stands for GAMS Data Exchange) for interfacing with Microsoft Excel.There are many utilities developed and contributed by other GAMS modelers which can provide interface with other software.

Because of the numerous benefits and ease of writing formulation for solving problem in GAMS, it is becoming quite popular among scientific community .In our literature survey,[72] has used GAMS to optimize the priority scores they got from fuzzy expert system.

CPLEX Solver

CPLEX was the first linear optimizer commercially distributed by IBM,which was written in C language. It gave operations researchers unprecedented flexibility, reliability and performance to create novel optimization algorithms, models, and applications [73]. The Simplex algorithm, invented by George Dantzig in 1947 became the basis for the entire field of mathematical optimization and provided the first practical method to solve a linear programming problem. CPLEX evolved over time to embrace and become a leader in the children categories of linear programming, such as integer programming, mixed-integer programming and quadratic programming, too. Now it is one of the most used solver for solving MILP problems also.For solving MILP, CPLEX uses Branch & Cut Method [74], which is based on Branch & Bound Method, a well known algorithm to solve MILP problem, by solving a sequence of linear relaxations to provide bounds. Mathematically, if general MILP formulation is given by :

$$Z(X) = min.\ cx + fy : x, y \in X \tag{5.1}$$

where

$$X = (x, y) \in \Re^n_+ + 0, 1^n : Ax + By \geq b \tag{5.2}$$

Then, the relaxation can be given as

$$Z(P_X) = min.\ cx + fy : x, y \in X \tag{5.3}$$

where

$$X = (x, y) \in \Re^p_+ + \mathbf{[0,1]}^p : Ax + By \geq b \tag{5.4}$$

The linear relaxation in Eq.5.4 provides a lower bound on the optimal objective value as

$$Z(P_X) \leq Z(X) \tag{5.5}$$

Monte Carlo Simulation

Monte Carlo simulation is used to build models of possible results by substituting a range of values for any parameter or variable that has inherent uncertainty. It then calculates results over and over, each time using a different set of random values from some probability distribution which the variable follows or is assumed to follow. Then it produces distributions of possible outcome values.In this way, Monte Carlo simulation provides a much more comprehensive view of what may happen.

Monte Carlo simulation provides a number of advantages over deterministic, or single-point estimate analysis [75]:

1. Results show not only what could happen, but how likely each outcome is.
2. Because of the data a Monte Carlo simulation generates, itâĂŹs easy to create graphs of different outcomes and their chances of occurrence.
3. With just a few cases, deterministic analysis makes it difficult to see which variables impact the outcome the most. In Monte Carlo simulation, itâĂŹs easy to see which inputs had the biggest effect on bottom-line results.
4. In deterministic models, it's very difficult to model different combinations of values for different inputs to see the effects of truly different scenarios. Using Monte Carlo simulation, analysts can see exactly which inputs had which values together when certain outcomes occurred.
5. In Monte Carlo simulation, it's possible to model interdependent relationships between input variables. It's important for accuracy to represent how, in reality, when some factors goes up, others go up or down accordingly.

The solution is found for each of the three scenarios defined in section **??** using GAMS, for the objective function which includes priority and excludes priority. Monte Carlo simulations are performed over uncertain presence matrices. Each presence matrix is assigned some probability based on the fact that each PEV's Arrival & Departure follows a Normal distribution [76]. The difference is found between the estimates of "Cost of charging with priority" & "Cost of charging without priority", and the estimated difference is levied upon the PEV owners in proportion to their priority weight demanded.

The methodology of solving the problem and different tools used for solving the problem are discussed in this chapter.

CHAPTER 6

CONCLUSION & FUTURE SCOPE

6.1 Conclusion

In Chapter 3, a novel method for Intelligent charging scheduling and and price uncertainty handling with IGDT proposed. The reformulation is imposed to convert Non-Linear Programming (NLP) problem to Mixed-Integer Linear Programming (MILP) problem. It is seen that, assuming price uncertainties the IGDT gives a pessimistic charging and discharging schedule. The intelligent charging scheduling allows the aggregator to make profits while assuring a minimum profits in case of any price fluctuations in an uncertain interval. IGDT based uncertainty handling can easily complement Monte Carlo based method in handling uncertainties of other uncertain parameters whose probability distribution is known.

Chapter 4, proposes a stochastic resource investment planning model for Microgrids. The paper considers that the microgrid in study has a local load, renewable generation, energy storage unit and a link to the main grid. The microgrids cannot influence the market prices and is modeled as a price taker. The operational objectives of the microgrid is to schedule its assests in order to serve the load in such a way so as to minimize the cost of operation. The operational aspect of microgrids is modeled as a Linear program (LP). The chapter then continues to use this LP operational model and find an optimal investment strategy for microgrid in a new stochastic LP model where the objective is to minimize the sum of investment and expected operational cost.

6.2 Future Scope

This work can be further expanded to include the cases where the number of EV become variable or follows a distribution.Also, there are numerous techniques which don't require distribution of random variable for estimation.Those methods can be applied in conjunction with proposed strategy.This will help to utilize the solution for commercial parking station and commercial charging stations as well.

Effect of charging -discharging cycle on the health of Batteries can be taken into account, as in real world, health and life estimation of battery are also important to ascertain profitability of EVs and estimate the lost opportunity cost.

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