Electric vehicles in Smart Grids: Performance considerations

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by

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USE OF THESIS

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Abstract

Distributed power system is the basic architecture of current power systems and demands close cooperation among the generation, transmission and distribution systems. Excessive greenhouse gas emissions over the last decade have driven a move to a more sustainable energy system. This has involved integrating renewable energy sources like wind and solar power into the distributed generation system. Renewable sources offer more opportunities for end users to participate in the power delivery system and to make this distribution system even more efficient, the novel "Smart Grid" concept has emerged. A Smart Grid: offers a two-way communication between the source and the load; integrates renewable sources into the generation system; and provides reliability and sustainability in the entire power system from generation through to ultimate power consumption. Unreliability in continuous production poses challenges for deploying renewable sources in a real-time power delivery system. Different storage options could address this unreliability issue, but they consume electrical energy and create significant costs and carbon emissions. An alternative is using electric vehicles and plug-in electric vehicles, with two-way power transfer capability (Grid-to-Vehicle and Vehicle-to-Grid), as temporary distributed energy storage devices. A perfect fit can be charging the vehicle batteries from the renewable sources and discharging the batteries when the grid needs them the most. This will substantially reduce carbon emissions from both the energy and the transportation sector while enhancing the reliability of using renewables. However, participation of these vehicles into the grid discharge program is understandably limited by the concerns of vehicle owners over the battery lifetime and revenue outcomes. A major challenge is to find ways to make vehicle integration more effective and economic for both the vehicle owners and the utility grid. This research addresses problems such as how to increase the average lifetime of vehicles while discharging to the grid; how to make this two-way power transfer economically viable; how to increase the vehicle participation rate; and how to make the whole system more reliable and sustainable. Different methods and techniques are investigated to successfully integrate the electric vehicles into the power system. This research also investigates the economic benefits of using the vehicle batteries in their second life as energy storage units thus reducing storage energy costs for the grid operators, and creating revenue for the vehicle owners.

The declaration page
is not included in this version of the thesis

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Nomenclature

ψ_i	Emission penalty factor for thermal genearting unit i
$\boldsymbol{EC}_i$	Emissions cost for thermal genearting unit i
$\boldsymbol{FC}_i$	Fuel cost for thermal genearting unit i
$\boldsymbol{P}_i$	Power generated from thermal genearting unit i
Ψ_{dep}	Departure state of charge of a vehicle
Ψ_{max}	Maximum state of charge of a vehicle
Ψ_{min}	Minimum state of charge of a vehicle
Ψ_{pre}	Present state of charge of a vehicle
ζ	Efficiency of the battery system
$\boldsymbol{D}$	Total demand
$\boldsymbol{gbest}$	PSO parameter: Particle's global best position.
$\boldsymbol{H}$	Number of hours in a day
$\boldsymbol{Ite}$	PSO parameter: Current iteration number.
$\boldsymbol{Losses}$	Total losses in the line
$\boldsymbol{MaxIte}$	PSO parameter: Maximum iteration number.
$\boldsymbol{N}$	Number of thermal generating units
$\boldsymbol{N}_{V2G-Dsch}$	Number of GVs discharging and participating in the bi-directional power transfer after cost-benefit analysis.
$\boldsymbol{N}_{V2G}$	Number of vehicles discharging to the grid

$\boldsymbol{N}_{V2G}^{max}$ Maximum number of GV registered for charging/discgarging.

$\boldsymbol{pbest}$ PSO parameter: Particle's present best position.

$\boldsymbol{P}_i^{max}$ Maximum power generated from thermal genearting unit i

$\boldsymbol{P}_i^{min}$ Minimum power generated from thermal genearting unit i

$\boldsymbol{P}_{pv}$ Power from solar photovoltaic panels

$\boldsymbol{P}_{vj}$ Power from vehicle j

$\boldsymbol{P}_{wind}$ Power from wind farm

$\boldsymbol{Range}$ PSO parameter: Range of values for velocity vector.

$\boldsymbol{R}$ Total reserve

$\boldsymbol{w}_c$ Weight factor for fuel cost

$\boldsymbol{w}_e$ Weight factor for emissions cost

Abbreviations

GV	Gridable Vehicles
RES	Renewable Energy Sources
SG	Smart Grid
PEV	Plug-in Electric Vehicles
PHEV	Plug-in Hybrid Electric Vehicles
GHG	Green House Gas
G2V	Grid-to-Vehicle
V2G	Vehicle-to-Grid
APM	Availability Planning Model
BLIM	Battery Lifetime Improvement Model
PSO	Particle Swarm Optimization
SOC	State-of-Charge
DOD	Depth-of-Discharge
SLB	Second Life Battery
CS	Conventional Storage
EALT	Effective Average Lifetime
AMI	Advanced Metering Infrastructure
ISO	Independent System Operator
EOL	End-of-Life
NPV	Net Present Value
TOU	Time-of-Use

Chapter 1

Introduction

An electrical power system delivers electrical power to the consumer loads to meet their everyday electricity needs. A power system is operated by an independent system operator (ISO), who manages the business transactions amongst the stakeholders to ensure continuous supply of power to the ultimate users. In concert with the rapid social and technological changes, electricity consumer needs and demand types have also changed over the course of time. Electric power systems have thus been faced with new requirements. Environment-friendly, reliable, and economic power supply has been the main focus of the consumers to date. However, the existing electricity grid is not fully capable of meeting all these consumer requirements. A new grid system, called a 'Smart Grid' has been proposed to accommodate these new requirements.

A Smart Grid (SG) is an intelligent electricity grid, which employs advanced automatic control and communication techniques and some forms of information technology to generate, transmit and distribute electric power in a secure, economic and sustainable way according to both the consumer and the utility needs. The future goals of the SG are: integrating various types of generating sources, including renewable energy sources and storage options; enabling end users' interactions in demand response; optimizing resources and operating efficiency; ensuring good power quality and self-healing capability; building resiliency against physical and cyber attacks; and providing rooms for new products and services [1]. Enhanced reliability and sustainability have been the main focus around the SG concept in recent years. Technology and resources are being deployed to transform the current electricity grid to a SG. To this end, a major introduction is the use of renewable energy sources (RESs), such as wind and solar power as a compulsory generating source along with the conventional thermal generators. Least emissions margin and negligible running costs have made them even more attractive to the entrepreneurs and consumers. Unfortunately, RESs have their own problems of genera-

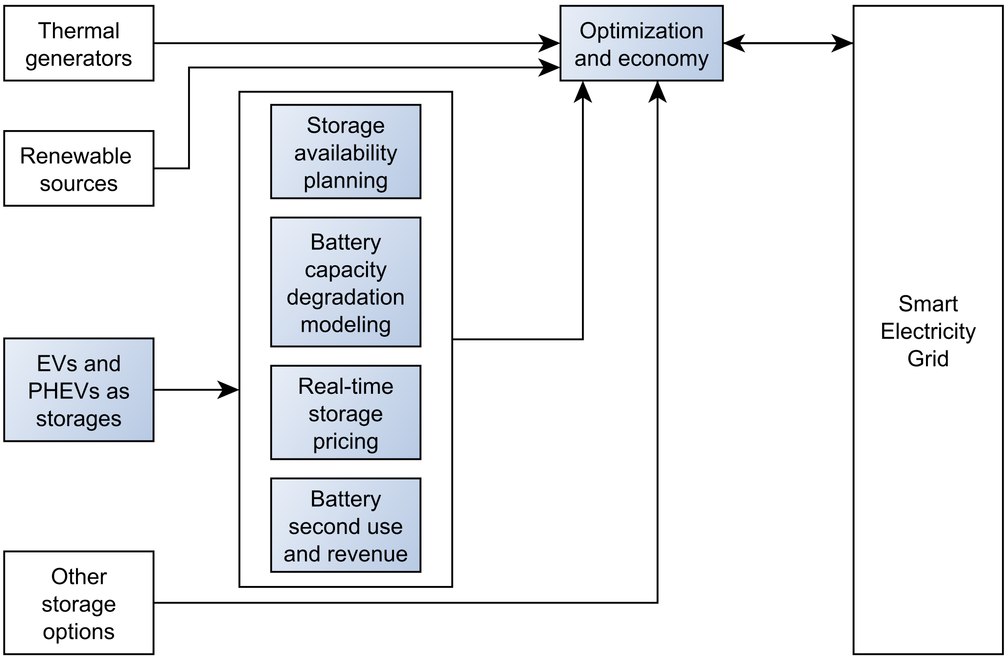

Figure 1.1: Issues related to a SG and the sections where contributions have been made (shaded blocks).

tion intermittency that has made them unreliable in the real-time scenario. Variations in wind speed and solar insolation rate are the sources of unreliability in wind and solar power generation, respectively. If this intermittency is not carefully managed, an ultimate consequence of blackouts is not unlikely. Researchers have been working on efficient power generation considering real-time uncertainties of RESs. One straightforward solution to this problem is to use sufficient energy storage, which are rather costly. Optimal sizing of energy storage has thus become a topic of further interest. Another solution to this intermittency problem is to use the Electric Vehicles (EVs) and the Plug-in Hybrid Electric Vehicles (PHEVs), with the capacity to charge/discharge from/to the utility grid , recently defined as 'Gridable Vehicles' by some researchers [2], as distributed storage devices.

Gridable Vehicles (GVs) have already been accepted as storage devices by engineers as they considerably reduce running costs and emissions. Reduction of green house gas (GHG) emissions from vehicles has been reported in a technical report [3] from the National Renewable Energy Laboratory (NREL). A study by the Electric Power Research Institute (EPRI), California, establishes the justification of using PHEVs from the cost perspectives [4]. As the GVs can be charged from and discharged to the grid, they are suitable to be used along with the intermittent RESs to balance the grid in real-time. Therefore, maximum utilization of RESs directly depends on the success of using GVs as distributed storage devices in the SG. As the fleet of vehicle charging or discharging from or to the grid can be selected according to the real-time need of the grid, independent system operators can balance for any range of variations within the limit of the fleet size. Grid-to-vehicle (G2V) power transaction has also been considered as a useful operation by research community to maintain source and load balance in the practical networks, with charging the vehicles as well as storing energy during the off-peak hours being the most significant G2V operations [5][6]. With no or insignificant direct carbon emission and flexibility to use them both as loads or sources have made the GVs suitable for this particular purpose. However, using GVs as storage greatly depends on the adoption rate of GVs in this process. GV owners are reluctant to participate in the grid discharge program fearing about the vehicle lifetime and revenue losses. The concern is real as each battery comes up with a specific number of depletion cycles and lifecycle, and discharging at grid's request affect the battery lifecycle. The success of using GVs to balance the SG, therefore, depends on the economics and efficiency of the battery use. Another potential concern is the drivers' behaviour from the mobility perspectives that also determines the effectiveness of using GVs in the real-time load balancing. The following aspects have been identified as the research challenges regarding the use of GVs as small portable energy storage such as how to improve reliability of the SG with GVs; how to make the total energy system more sustainable; how to nullify the vehicle owners' concerns over their cars' lifetime and economy; and how to make balances among charging/discharging time and cost with the real-time power demand and effective resource scheduling process. A pictorial representation of the issues related to a SG and the sections where contributions have been made in particular in this research (shaded blocks and text in bold fonts) is given in Figure 1.1.

1.1 Research motivation

The main motivation of this research was providing necessary and sufficient facilities and provisions for integrating Electric and Plug-in hybrid electric vehicles in the SG environment, to ensure a greener and sustainable power system. The alarming rate of depleting mineral energy reserves has already been identified as a major concern at economic, environmental, industrial and community levels [7]. A substantial portion of the global emission comes from the power and energy industry which comprises around 40% followed by the transportation industry that is responsible for around 24% [8]. The adverse effects of excessive GHG emissions are now well established and have serious consequences on human health and society. Almost all countries in the world acknowledge this problem and consider sustainable energy systems as a potential solution to this problem. Increasing concern over sustainable energy production and environmental adversities of fossil fuel usage has led to the paradigm of producing clean and sustainable power in substantial quantities from the RESs. RESs such as wind and solar power have proven themselves as potential sustainable energy sources. Almost zero emissions and insignificant running costs have made them even more attractive to the entrepreneurs and consumers.

However, generation from RESs, such as wind and solar sources, is subject to variations due to the variations in wind speed and solar insolation, respectively. Given that installing a new RES involves capital investments and is time dependent, these variations in RESs generation need to be balanced with proper alternative sources. Energy storage devices such as chemical batteries are a reliable option for this purpose. However, cost of such energy and the space required brings about the extra overhead for using such storage. Electric vehicles and Plug-in hybrid electric vehicles, with capability to charge from and discharge to the utility grid called the Gridable Vehicles, can replace these chemical batteries thus reducing the cost and space requirements for the operators.

While GVs are suitable to be used as storage devices, GV owners' willingness to participate in the two-way energy transfer process is a major issue to be addressed. GV battery lifetime, cost-effectiveness of two-way energy transfer process, and real-time and real life viability of such integration is also equally important. GV owners should be convinced that discharging their vehicle batteries for the grid's purpose is beneficial to them as well. This is directly related to the success of GV integration in the SG. Finding ways of integrating the GVs in the SG environment thus requires further investigation that motivated this research work.

1.2 Aims of this thesis

The principal aim of this thesis is to propose different models and techniques towards integrating GVs into the SG environment ensuring both economy and reliability of the power system. More specifically, the thesis introduces new ideas to enable the GVs to participate in the bi-directional power transfer process that will ultimately benefit both utility and consumers in a SG environment. This main aim is achieved by pursuing the following objectives:

1. Identifying the impact of integrating GVs into the SG environment along with other energy sources including the RESs. Analysing if GVs can be used to balance for the variations in power generation from RESs is the main focus in this stage. The result of this analysis is the basis for deciding further with the use of GVs as distributed energy storage devices.

2. Studying ways of using GVs as distributed energy sources and identifying the most ef-

fective way of using them to maximize benefits. Allocation of GVs for charging from and discharging to the grid according to the real-time variation of load demands so as to discharge them at the peak hours and charge them at the off-peak hours.

3. Modeling selection criteria for the GVs to decide on discharging to the grid on the basis of GV and its battery parameters to ensure that GVs do not lose for discharging on grid's purpose from the financial point of view. Cost of energy discharged from GVs is also modeled and then revenue-sensitive participation of GVs into the grid discharge program is implemented to encourage GV owners to register themselves with the operators for bi-directional energy transfer.

4. Identifying potential applications of GV batteries both in their automotive and post-automotive life towards recovering a portion of the capital cost for GV purchase, and modeling such cost recovery from second life use by using different battery, economic and environmental parameters.

5. Implementing the energy cost modeling for automotive and post-automotive batteries in using GVs as backup energy storage in real applications.

1.3 Thesis contributions

The contributions of this thesis come from analysing the existing barriers in integrating the Electric and Plug-in Hybrid Electric vehicles into the SG environment and then developing new methods and ways to alleviate those barriers. The novelty of this work is found in:

- Analysing the real time mobility behaviour of the GVs to determine how many of the registered GVs are available at the parking stations to be able to discharge to the utility grid. From this analysis, a distribution of the GVs availability is proposed to better reflect the real time mobility as well as meeting the grid demands for GVs' energy. This availability distribution is expected to follow the real time load variations in the utility grid under a particular operator. Modeling the availability distribution would prevent the chances of un-noticed blackouts to consumer loads and improve system reliability.

- Developing a selection model to select vehicles from the real time available vehicles, on the basis of specific criterion, to discharge to the grid so that those discharging to the grid do not incur loss in terms of battery lifetime. Because battery lifetime is a major concern from the GV owners' perspectives, this selection model has been developed to exclude the GVs with lower remaining battery lifetime from discharging, and allowing the GVs to discharge only if a predetermined average battery lifetime of the GV fleet is maintained. This selection model is expected to improve the overall battery lifetime of a fleet of GVs under a particular operator to ensure deliberate participation of the GV owners in the grid discharge program.

- Modeling cost of vehicle energy in terms of the capital cost and capacity degradation cost of a GV battery. This model assists the GV owners to decide on discharging to the grid by comparing their GV energy cost with the real time energy selling price. Owners are given freedom to set their own revenue margin and decide on discharging. The operators also have the same freedom to buy or not to buy the GV energy based on their consumer demand, available energy sources, and revenue margin. This cost modeling and decision taking algorithm help both the GV owners and the operators to trade energy on both party's interests, yet maintaining economic load dispatch to the consumers.

- Modeling cost recovery from the second use of GV batteries, retired from their automotive life, towards shedding a portion of the initial battery purchase cost that hinders the widespread adoption of GVs as energy storage devices. A number of potential applications of the second life batteries have also been identified to ensure revenue outcome from selling the retired batteries at a certain cost. Second life use of the retired batteries help defer the disposal overheads and environmental issues, which are equally important to ensure a sustainable SG system. Contributions of second life use of retired GV batteries in ensuring further economic load dispatch is also demonstrated with example system parameters.

- Developing a cost model for both GV energy and second life battery energy to provide the operators with useful information as to how far the GVs and their second life batteries can be used as real time distributed energy sources. The capital cost and the capacity degradation cost of both GV batteries and second life batteries are taken into considerations in modeling their energy costs. This cost modeling also help the GV owners to have a transparent picture of their revenue outcomes from adopting a GV and participating in the grid discharge program.

- Demonstrating an example of using both GVs and second life batteries as storage devices for providing backup energy during short-notice maintenance periods. In this demonstration an algorithm has been proposed to decide when to use the GV and second life battery energy, and in what amount, to ensure that energy sources are intelligently used to avoid potential blackouts and improve system reliability. To illustrate the benefits of using GVs and second life batteries during the maintenance period, the same load is met from the conventional battery storage and cost comparison is done to enumerate the financial benefits. Also, the benefits of using the second life batteries only have been identified to justify the capital cost of purchasing the second life batteries.

1.4 Publications from this thesis

1. U. K. Debnath, I. Ahmad, D. Habibi, and A. Y. Saber, "Improving Battery Lifetime of Gridable Vehicles and System Reliability in the Smart Grid," IEEE Systems Journal, vol. PP, no. 99, January 2014 (IEEE Early Access Article).

2. U. K. Debnath, I. Ahmad, D. Habibi, and A. Y. Saber, "Energy Storage Model with Gridable Vehicles for Economic Load Dispatch in the Smart Grid," International Journal of Electrical Power and Energy Systems (Elsevier), vol. 64, pp. 1017-1024, January 2015 (Currently published online).

3. U. K. Debnath, I. Ahmad, D. Habibi, "Quantifying Economic Benefits of Second Life Batteries of Gridable Vehicles in the Smart Grid," International Journal of Electrical Power and Energy Systems (Elsevier), vol. 63, pp. 577-587, December 2014 (Currently published online).

4. U. K. Debnath, I. Ahmad, D. Habibi, "Gridable Vehicles and Second Life Batteries for Generation Side Asset Management in the Smart Grid," International Journal of Electrical Power and Energy Systems (Elsevier), (Under review).

1.5 Thesis outline

This thesis is organised in seven chapter as follows:

- **Chapter 1** introduces the main research content of this thesis, including research motivation, aim of the thesis and the contributions in the relevant field from this thesis. This chapter also expands on the vision for this research and expected outcome in terms of providing the utility grid with extra energy storage devices like GVs to improve the system reliability, and ensure economic load dispatching.

- **Chapter 2** provides a detailed review of the relevant literature and describes the current state of knowledge in the field of vehicle-to-grid integration in the SG environment. This chapter then identifies the research needs in the relevant area and provides the background for undertaking this research on integrating the Electric- and Plug-in Hybrid Electric vehicles along with thermal and renewable sources in the SG system.

- **Chapter 3** proposes an Availability Planning Model (APM) and a Battery Lifetime Improvement Model (BLIM) to facilitate the adoption rate of GVs by the owners and their participation rate in the grid discharge program. The APM provides a novel way of distributing the incoming GVs for discharging to the grid in a way supportive to the real time load variation in a daily schedule. The BLIM provides another novel way of selecting GVs to discharge from the real time available GVs on the basis of the remaining lifetime of the individual GVs and that of the whole GV fleet. While GVs are selected for discharging to the grid, the BLIM ensures that the fleet of GVs under the operator in question still have a predetermined average battery lifetime to be used thereafter.The APM improves the reliability of the SG system whereas the BLIM improves the useful lifetime of GV batteries by excluding the lower remaining life GVs from discharging pool. This chapter also implements an optimization method (Particle Swarm Optimization) using our proposed APM and BLIM to minimize the fuel and emissions cost while dispatching electric power to the consumers. The financial justification of using our proposed models is also provided in this chapter.

- **Chapter 4** proposes a system model, for economic and efficient use of GVs as energy storage devices, which will bring about enough confidence in the GV owners to allow their vehicles for discharging to the grid. This chapter models the actual costing of a GV for discharging in terms of its battery opportunity cost and the capacity degradation cost. This cost modeling is used to select the GVs that are discharging at the real time. An improved optimization model is developed, including the cost incurred for vehicle energy in the model, for fuel and emissions cost minimization and reliable power supply to the ultimate consumers.

- **Chapter 5** proposes a new area of research around the gridable vehicles. Second use of gridable vehicles has been introduced in this chapter in an attempt to recover a portion of the initial battery purchase cost and to earn some revenue from their second use. The ultimate goal of the second life use of GV batteries is to bring down the GV adoption cost to a range acceptable by the general consumers. This chapter models the capacity degradation of batteries both in automotive and second life, and quantifies the range of cost recovery from second use of GV batteries in other applications. In the end, impact of this cost recovery is quantified by taking the second life use and associated revenue into account while implementing an optimal economic load dispatch system.

- **Chapter 6** demonstrates an example of using both GV batteries and second life batteries as backup storage units during short-notice and emergency shut downs of thermal generating units. Energy costs from both GV batteries and second life batteries are modeled first, after which a storage selection model is proposed to be able to economically distribute the available storage units over 24 hours period in a day. An optimization model is developed to economically dispatch the consumer load during the maintenance shut down period with the help of GV and second life storage unit backups. Cost reduction in providing such backup energy is calculated in comparison with providing the same from conventional energy storage. Justification for the capital cost for second life battery purchase and its recovery time are also discussed in this chapter.

- Finally, **Chapter 7** summarises the overall contribution of this thesis and draws a general conclusion of this research work. This chapter also details the limitations of this research and recommends further research directions as future extensions to this work.

Chapter 2

Background and Literature Review

This chapter introduces the concept of power systems operations from both technological and financial point of views. Distributed power systems operations have been explored from the sustainability perspective. Study of the current technology trends and ongoing research revealed that along with the cost reduction of power generations, emissions reduction from the power industry has become a prime necessity for ensuring a sustainable power infrastructure. Current literature has been critically revised and the points demanding further research were identified. Factors affecting that integration have been studied and the need for cheaper and viable storage devices has been found as inevitable. Considering the environmental aspects and financial viability, Electric Vehicles (EVs) have been chosen as a potential energy storage option to assist the utility grid to balance for the real-time variations in generated power and load demands. Current developments on integrating EVs into the Smart Electricity Grid have been thoroughly studied and issues hindering the mass participation of EVs into the storage energy systems have been identified. This thesis ultimately came up with novel solutions to a few of the identified problems to enhance the potentiality of integrating more renewable sources and balancing the utility grid against the variable demands.

In this chapter, we firstly describe the historical background of power systems and their operations in Section 2.1. Distributed power systems and their existing problems are detailed in Section 2.2 to provide a clear understanding of the issues and techniques involved in this area. Section 2.3 describes the modifications needed in the traditional grid and provides the details of the transition from the traditional grid to a Smart Grid (SG). This section also points out how a SG system can overcome the problems encountered by a traditional distributed power system. A comparative analysis of the operational aspects of SG and a traditional grid is illustrated in Section 2.4. The ways of transforming a traditional grid into a SG has been described in

Section 2.5 with detailed information. Section 2.6 introduces the Gridable Vehicles (GVs) and their role as energy storage devices in the SG environment. Section 2.7 presents the existing research works around gridable vehicles and critically analyse their contributions and lacking. From the study of the existing literature, a number of areas have been identified that needed more research. A number of such areas have been specified to identify a list of research questions as presented in Section 2.8, and finally a conclusion has been made in Section 2.9 summarising the limitations of the current research that led to the research work of this thesis in filling in the identified research gaps.

2.1 Background

An electric power system is composed of electrical generators, transformers, transmission lines, distribution lines, and electronic components for supplying, transmitting, and distributing electric power to the consumer loads. The first power system designed by Thomas Edison in 1882, was a direct current system that was supplemented by the invention of the first transformer the same year for transferring electric power from a generating station to a distant consumer load. Several modifications and improvements have been made since then to make electric power system available for the general use of the consumers. By the end of the nineteenth century the electric power industry had expanded a lot, and thousands of power systems had been built by power companies across the world. Modifications and improvements in power systems continued in the twentieth century. Due to the development of a huge number of power systems by the first half of nineteenth century, the generation and transmission systems have come across many challenges to cope up with the rapid changes [9]. The second half of the nineteenth century has witnessed an enormous amount of developments that the power systems had to go through to be able to meet the requirements of the generation, transmission, and distribution sides. With the advancement of technology and the extent of services, power systems had to deal with contemporary issues such as high demand profile, reliability of service, power quality, and security threats in the twentieth century. Diversity of consumer loads and generating sources has further complicated the electrical networks leading to the adoption of grid management activities by the power industry. Information and communication technology has since been used to support the grid management activities in real life situations. As the adoption of distributed power systems has been the state-of-the-art in power systems operations, real-time monitoring and control systems have been an integral part of a power system by the end of the twentieth century [10]. In the last 25 years, the electricity grid has been modernized by the use of sophisticated communication, control and automation devices. In the last quarter of the twentieth century, excessive green house gas (GHG) emissions and the resulting climate change issues have created enormous pressure on the power industry to reduce such emissions from the electricity generation side. In addition to the contemporary environmental catastrophes, increased industrialisation and fuel price rises have forced the power industry to adopt environment-friendly, yet economic, generating sources. As a result, the current power systems have been modernized with the inclusion of a range of renewable energy sources to secure a cleaner and environment-friendly power industry [11]. Due to the technical overheads of integrating cleaner energy sources into the power systems, complexities have been added to the ways the power systems had been operating earlier. The management, monitoring, and control strategies had to be changed to accommodate the necessary changes to ensure a cleaner and sustainable power industry. While automatic meter reading were being used in the 1980s, advanced metering infrastructure (AMI) had evolved in the 1990s to provide the power systems operators with detailed real-time information on the load demands and network capabilities. Moreover, implementing demand response as well as demand side management have been made possible with the use of modern metering and communication infrastructure.

With the recent technological improvements in the way power systems are being managed and operated, expectations are rising towards handling grid level transactions in the real-time without compromising the economy. Existing electricity grid is now meant to operate more intelligently to perform real-time processes to comply with higher energy efficiency and sustainability standards, to convert the existing electricity grid to a "Smart Grid". The first reference to the term "Smart Grid" was made in [11] in 2005 to point toward a more intelligent and sustainable electricity grid with a two-way information and power transactions capability for the twenty-first century. The visible difference between a traditional electricity grid and a SG is in the ways the grids operate. A SG uses smart meters, advanced communication technologies, and other electronic devices to perform real-time computations and decision makings to explore the full potential of the two-way power transfer. The ultimate goal of a SG is to enhance the overall functionality of the power generation, transmission, and distribution stems to ensure a sustainable and environment-friendly power system.

A SG can be considered as a traditional electricity grid with some added functionalities to enable the grid to operate sustainably. With the inclusion of different types of generating plants and renewable energy sources, a SG operates like a distributed power system with additional capabilities. As an effort to understand the difference between a traditional distributed power system and a SG, the basic operational details of a distributed power system and its associated limitations are described in the following section.

2.2 Distributed power systems and their problems

Distributed power system is an architecture where a single power system can integrate sources and loads from different locations. Unlike a central power system, a distributed power system allocates the power requirements of the whole system to a number of smaller power processing units, which are located at different points of electricity generation and consumptions in the system, with a vision to transfer the power processing functionalities closer to the consumer sites [12]. To enable such power processing at the consumer sites, several basic structures of distributed power systems have been used by the power industry such as paralleling, cascading, source splitting, and load splitting [13].

The history of distributed power systems is not new. Before the early twentieth century, all power generating sources were located closer to the point of use thus comprising a small distributed power system providing electricity to the nearest consumers through DC power lines. Economies of scale enabled the power industry to install larger capacity power plants in the early twentieth century to encourage a shift towards a central power system, where all the consumer loads were supplied from a central point of generation to all different consumers [14]. This trend prevailed until the end of the twentieth century with the privilege of using economic alternating current transmission systems to supply power to distant consumers. As the demand for electricity production and supply increased, management and control of the power transmission and distribution systems have become more complex; a demand for both consumer and generation side automation and control system has risen. It was not until the recent advances of information and communication technologies by the late twentieth century that the power industry was convinced that moving back to the distributed systems would meet the industry requirements with reasonable efficiency and affordable economy. While the central power stations are still in action, power stations in different user locations are connected together to a common grid to form a truly distributed power system. Technology advances and operational requirements have made the integration of different sizes and types of generating stations possible to form a more efficient and economically viable distributed power system.

Distributed power system has been in place for several reasons. One of the main reasons includes reduction of line losses from the generating stations through the transmission and distribution lines to the end users. Another reason is maintaining the reliability of power system operation as a central generating station may pose unreliability in continuous operation for both technical and non-technical reasons. Distributed power systems offer scalability of the power system that allows the new entrepreneurs to build and operate their local small power stations with the help of latest technologies. Moreover, scalability enables the power system operators to match between the demand and supply of electrical energy in the present time, and to plan according to the future demand of the locality in question. A major benefit of using distributed power technologies is the ability of the system operators to manage and control the everyday operations and the maintenance services locally according to their specific needs [14]. More changes are taking place in the electricity infrastructure nowadays. Penetration of distributed generation is growing day by day due to the fact that electricity industry is moving towards an environment friendly paradigm and is welcoming diversified energy sources to increase energy efficiency and customer participation.

However, existing distributed power systems lack a number of functionalities and services to ensure a fully user-centric, economic, and environment-friendly power industry. With the vision of alleviating the limitations of the existing distributed power system and adding a lot more of the functionalities, a smarter distributed power system structure "Smart Grid" has been proposed by the researchers to integrate more user-centric power system services. The details of SG structure and its benefits are described in the following section.

2.3 SG and how SG can alleviate potential problems encountered by distributed power system

Emergence of a variety of generating sources and loads has necessitated the present day power industry to be able to deal with the unanticipated events generated by these electrical equipments. Moreover, growing requirements for customer-focused electricity industry has posed new challenges to the power system operators in delivering electrical power with highest level of reliability at a lowest possible price. However, the existing power systems are always subject to real-world variations due to communication, security, reliability, uncertainty, and economic parameters. Any of these parameters can destabilise an already stable existing power grid, leading to enormous consequences. Even though the traditional distributed power systems have some processing capabilities, and some capabilities to communicate between the generation and consumer side, they are unable to make real-time decisions in response to any disturbances or instabilities. In addition to that, increasing demand for reliable power supply at a lower price compels the electricity grid to attain more capabilities to effectively respond to the unanticipated events.

A "Smart Grid" has been envisioned as the next stage of existing electricity grid by adding the extra functionalities and capabilities, as mentioned in the previous section, to be able to respond to real-world events. Literature has described this improved grid as one which is smart and capable of self-healing in the events of a broad range of destabilizers [15]. To improve the reliability of power system, a SG architecture adds intelligence to the electric power transmission system by providing independent processors in each component of the electrical equipments. These processors are expected to be based on a robust operating system to act as independent agents to exchange information with each other, forming a large distributed computing environment [15]. This real-time processing platform along with the bi-directional communication systems are expected to transform the existing electricity grid into a true "Smart Grid".

To modernize the existing distributed energy system, many countries around the world have started to think about the limitations of the aged electricity grid and have determined some goals to achieve towards a future grid. The goals include [16]:

- cost-effective electricity production and delivery,
- providing consumers with updated information and means of control to interact with the system according to their choice,
- reduction of GHG emissions from the electricity sector by increasing theh use of renewable energy sources (RESs),
- enabling integration of the electric vehicles for reducing the use of mineral energy sources, and
- improving the quality and reliability of service.

With these goals in mind to modernise the existing grid, the future grid would be different than the existing grid and be called the SG. The major difference of a SG from the existing grid would be in the way the power distribution system operates in the new environment of increased load demands, ever changing customer expections, and sustainable power industry. Modernising the distribution network by introducing latest information and communication technologies can be instrumental in managing the consumer load variations as well as maintaining the economy of the power supply [17]. The changed grid would also be different in the way the power system equipments are used with the addition of a great number of advanced electronic devices and systems.

Table 2.1: Comparison between the existing grid and the SG (Intelligent Grid) [15].

Existing Grid	Intelligent Grid
Electromechanical	Digital
One-Way Communication	Two-Way Communication
Centralized Generation	Distributed Generation
Hierarchical	Network
Few Sensors	Sensors Throughout
Blind	Self-Monitoring
Manual Restoration	Self-Healing
Failures and Blackouts	Adaptive and Islanding
Manual Check/Test	Remote Check/Test
Limited Control	Pervasive Control
Few Customer Choices	Many Customer Choice

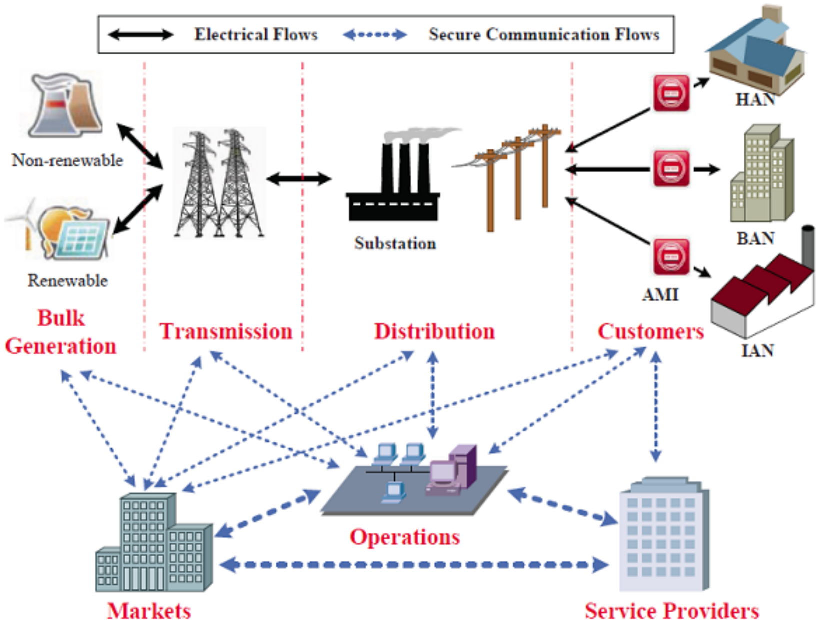

Figure 2.1: The NIST Reference Model [16] for SG.

A brief comparison between the existing grid and the SG has been described in Table 2.1 [17] where the SG has been labeled as 'Intelligent Grid'. In an effort to keep up with the new requirements and concepts in implementing the new grid paradigm, the electricity industry, research organizations and government bodies have taken different steps to make SG a reality. The U.S. National Institute of Standards and Technology (NIST) has provided a reference model of the SG as shown in Figure 2.1 [18], which has been widely accepted as a standard model for the different parts of an electricity grid where SG related works are in progress.

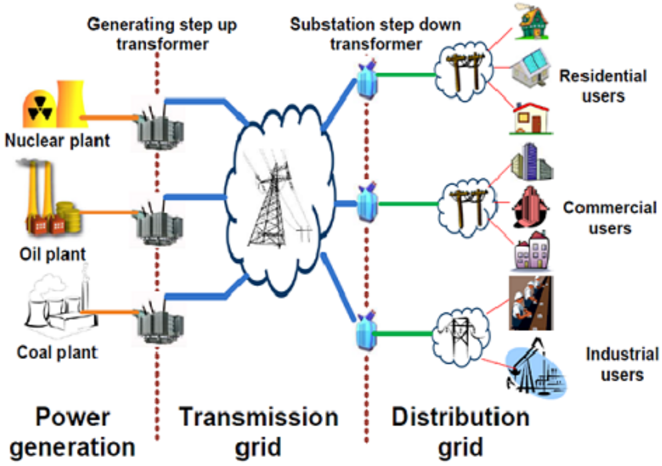

Figure 2.2: A typical representation of the traditional power grid [17].

Table 2.2: Domain and actors in the SG reference model [16].

Domain	Actors in the Domain
Customers	The end users of electricity. May also generate, store, and manage the use of energy. Traditionally, three customer types are discussed, each with its own domain: residential, commercial, and industrial.
Markets	The operators and participants in electricity markets.
Service Providers	The organizations providing services to electrical customers and utilities.
Operations	The managers of the movement of electricity.
Bulk Generation	The generators of electricity in bulk quantities. May also store energy for later distribution.
Transmission	The carriers of bulk electricity over long distances. May also store and generate electricity.
Distribution	The distributors of electricity to and from customers. May also store and generate electricity.

According to this reference model, SG has been divided into seven different domains, namely customers, markets, service providers, operations, bulk generation, transmission and distribution. Each of the domains has its own actors, which are devices, systems or programs to perform the functionality or task. Domains and their corresponding actors in that domain are represented in Table 2.2 [18].

2.4 SG as compared to the traditional grid

A traditional power grid has three subsystems, namely, generating sources, transmission grid, and distribution grid with the capability of unidirectional power transfer only from the source to the load. A typical representation of the traditional power grid is given in Figure 2.2 [19].

The two main features of the SG that distinguish it from the traditional electricity grid are using two-way flows of electricity and information, and integration of renewable energy sources. In traditional power system, central generating units fueled by mineral energy resources are the main source of power. These central units are of higher capacities so as to make it economic in energy production. The generated voltage is stepped up for transmission over long distances to the substations, where the power is again stepped down to a distribution level voltage. At the end user points, distribution voltage is stepped down again to the service level voltage. The whole process acts like a top-down system; the end user power is strictly determined by the central generating stations, which are rather invisible to the transmission or the distribution grid. In contrast, in the SG environment, distributed energy sources like the renewable energy sources are connected to the system at some points of the distribution grid and are capable of supplying power to the grid to be delivered to the user. In this concept, even the ultimate consumer may have a small energy source to participate in the total delivery system. As variable sizes of the generating unit are possible to be deployed, the utility grid has the option of choosing the smallest through to the largest power generator so as to meet its real-time demand. In this way, the consumers are able to communicate with the system operator according to their needs and can contribute to the grid operation. This makes the system more flexible in nature and improves the quality and reliability of the whole power system.

A 2002 study from the International Energy Agency [20] has shown that a power system with many reliable small generating units can operate with the same level of reliability and capacity margin as a system with equally reliable less number of large generating units. Although the proposition has been very simple, actual deployment of the renewable sources pose some difficulties. Research has shown that generation patterns of these clean energy sources do not match with the demand patterns [21]. Matching these two patterns is the key to the effective utilization of the renewable sources. Another research [22] depicted that considering the capital costs associated with the renewable sources, unit electricity cost from renewable sources is higher than that of a conventional thermal generator. A balance is thus required between the sustainability and costs of power system in this regard.

Another implication of the two-way communication system is the customer interaction with the supply side regarding their energy usage. In the real-world energy pricing system, energy prices go high and low at different hours in a day according to the load demand. With the advent of AMI, customers can see their real-time energy usage and piece-wise billing for individual appliances. They can also manipulate their energy usage by time scheduling the operation of some of their appliances. For example, if in a particular day, the energy price rises sharply at

1 pm, a customer can turn-off their air conditioning unit to get rid of the excess dollars and then turn it on when the prices go down the following hours. Moreover, the same consumer can benefit from supplying power from his/her own distributed generating unit at that particular hour of higher energy prices. Latest research reveal that use of AMI has made a really flexible way of communication between the consumer and energy supplier in the SG environment [23]. Realization of the full potential of the two-way communication would not have been possible otherwise.

The use of latest information and communication technology has made the two-way communication possible in the realization of SG benefits. In order for the utility be more reliable in terms of continuous supply of power, an independent system operator (ISO) must know the demand of the near future ahead of time so that he/she can reschedule the operation of different generating units. In doing this, if some excess energy is needed to be bought from other operators or the utility, the ISO should be able to make two-way communication through latest technology so that fast and secure communication is ensured. Considering the real-time operation of the SG, a 15 minutes ahead prediction is expected - the fastest computational and communication technology is thus a prime requirement.

2.5 Transforming the traditional grid into a SG

Three ways are being explored to make the new transformation to the SG:

2.5.1 Increasing penetration level of renewable energy sources

The first journey is to gradually increase the penetration level of renewable energy sources to significantly decarbonise the electricity industry. Both wind and solar power have been taking a significant share in the total renewable generation around the world. With new generation capacity installed in the European Union and United States in the recent years, wind energy seems to be the largest share holder of the generation industry [24]. One major problem of the RESs is their unreliability in continuous energy production in real time. Wind power depends on wind speed and solar power depends on solar insolation rate at a certain period of time. As both wind speed and solar insolation rate directly depend on the meteorological conditions of the generating site, energy production is highly variable from these renewable sources and the power system containing these sources suffer from unreliability of continuous supply. This intermittency in power production can lead to a substantial variation in power supply even within few minutes. Such frequent changes in wind and solar power production are a major challenge for the ISOs. Precise forecasting methods are extremely essential to cope up with this situation. Literature [25] shows that for a day-ahead forecasting, wind forecast errors are more than 10% of the capacity while for an hour-ahead forecasting, the error goes down to as less as 5% at the current stage. If more renewable energy sources are deployed to balance the distribution system, the system will be more likely to be unreliable in the real time. The U.S. Department of Energy has asserted in a literature [26] that with invariable system operating conditions, the grid operation will face no significant disturbances until renewable energy penetration, mainly wind, exceeds 20% of the total generation. Current pace of renewable deployment may exceed this limit within a short period of time. A definite example is the case of California, USA that targets to serve 33% of their retail load from renewable by 2020 [27]. Other such examples are easy to find as well. Therefore, limiting the penetration level will not serve the purpose of embracing SG technologies, rather than finding solutions for disturbances caused by these renewable sources.

2.5.2 Enabling demand response and use of information and communication technology

The second step towards SG encompasses customer interaction through advanced information and communication technologies. In the traditional power system, load demands are always passive elements and users do not have any influence on the load demand or pricing. In a sense, the end users cannot see the other side of the power system where the whole system is managed. On the other hand, the utility and the central management system cannot see the real-time energy usage and thus cannot take any measure against any event from the distribution side. The communication between the generation side and the distribution, and similarly consumer side is more or less blind in nature. The SG is meant to improve this information and communication system through advanced technologies. The vision is to accurately monitor, analyse, optimise and control the whole system from central utility locations to the transmission and distribution grids. The envisioned system is meant to work as a distributed automation system and is expected to deal with the interoperability of data exchanges and integration of existing and future devices, systems and applications [28].

Smart metering and demand response is one of the most important mechanisms used in the SG environment. Both the consumers and the utility can be benefited from using the smart meters as the meters gives real-time measure of the power usage. The end user can control their energy usage according to the real-time pricing and the utility can control the behaviour

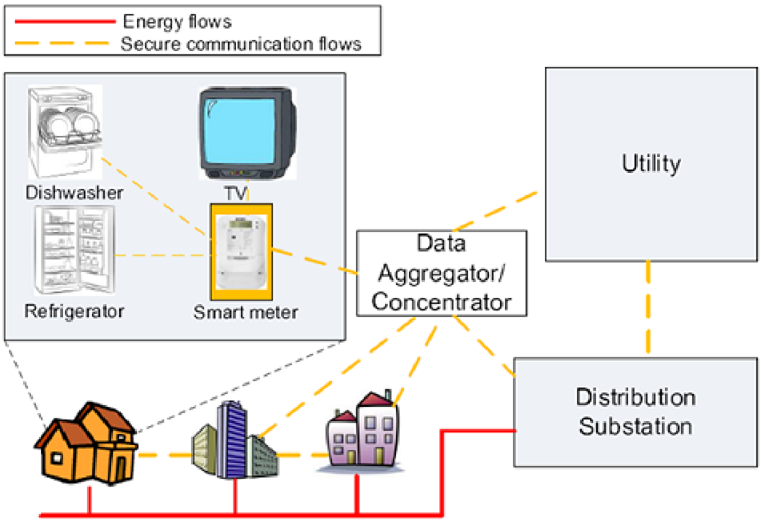

Figure 2.3: An example of smart metering structure [17].

of consumer appliances so as to reduce energy costs and unreliability of the entire system. Using AMI, two-way communication has been made possible, which led to the availability of real-time and on-demand information for improved operational efficiency and customer satisfaction. A smart meter can record energy consumption in intervals of as short as minutes and send this information to the central management system to assist with the billing and monitoring systems [29]. In addition, a smart meter can connect or disconnect a particular user appliance to control the energy usage of the user and to help stabilize the utility load demand [19]. One such metering structure is shown in Figure 2.3 [19] where the smart meter collects energy usage data from the appliances, and passes the command to control the appliances' energy usage if necessary. The data aggregator collects usage and/or control data from different buildings which can be further transmitted to the utility or the distribution substation. The smart meter can be communicated from the utility as well to control or manage the user load demand.

Demand response is a mechanism where the electricity users can manipulate and control their energy usage themselves in a response to real time energy pricing information available from the smart meters. End users can choose what appliances are to be kept on or off at a certain period of time as determined by the energy pricing at that particular period. Demand response has been made possible by deploying the smart meters and the two-way communication system. Increasing level of customer participation has been enabled by adopting these techniques, which are the basic elements of the SG. This advanced metering structure and communication technology is thus bringing about major changes in the structure of power system operation.

2.5.3 Using sufficient cost-effective and sustainable storage systems

The third step involves the use of storage energy systems to balance for the intermittency of the renewable energy sources in continuous energy production. Modeling the renewable energy sources is a difficult problem in integrating them in the SG with the other conventional generators. The variable nature of generation has made the forecasting system and resource scheduling a more complex problem. Understanding the long-term and short-term patterns of energy output from the renewables and their likely behaviour has become a new dimension of research [30]. One of the main fields of research in the SG deployment is the efficient and economic resource scheduling problem. With the renewable sources considered as compulsory sources, as they are meant for in the SG, a well analysed forecasting method may even fail to model the real-time energy production from the renewables leading to a failure of the efficient resource scheduling method. If at any time, resource scheduling fails to supply the load with required energy demand, the whole power system may be affected and incur a huge loss of money and reputation. Reliability from this perspective is thus of utmost importance. To address the possibility of potential blackouts or mismatch between the source and the load, different technologies have been proposed, such as efficient forecasting tools, demand control, fast start-up units and storage devices of any form [31]. Different electric energy storage technologies are available nowadays, such as flywheels, capacitors, compressed air, pumped hydro and batteries that can be used to balance the grid [32][33][34]. Costs and size of the storage devices dictate the choice of energy storage types. Among them, batteries have been proposed by many researchers as viable solution in the context of SG environment. Batteries are rather costly and the space requirement for the batteries is a real concern. Alternate solution to this energy storage problem is to use the Electric Vehicles (EVs) and the Plug-in Hybrid Electric Vehicles (PHEVs), with the capacity to charge/discharge from/to the utility grid, recently defined as 'Gridable Vehicles' by some research [2], as portable storage devices to instantly respond to the utility grid's need.

2.6 Gridable vehicles as cost-effective and clean storage devices

Real-time variations in generation and load demand has necessitated the inclusion of storage energy units to maintain power quality and service reliability in the SG. Although conventional battery storage are commonly in use, capital costs and space requirements add more to the energy price to be paid by the electricity consumers. Different types of storage energy sources have been in use for many years now in the quest for a cheaper and viable storage option, but none of them has been conclusively adopted as the most suitable one. In the meantime, the global community has emphasized on the urgency and necessity of reducing the overall GHG emissions from different industry sectors. Electricity and transportation sectors have been identified as two major sources of GHG emissions [8] so low emission and sustainable power and transportation industry alternatives have become a major concern. In line with this requirement of environment-friendly transportation sector, EVs and PHEVs have been introduced in the personal transport sector to get rid of the huge emission figures from the internal combustion engine vehicles. Shedding the dependence on mineral fuels as well as reducing GHG emissions have made these vehicles a choice of the age from the sustainability perspectives. Moreover, running costs of these electricity-fueled EVs and PHEVs have been identified as cheaper as compared to their mineral-fueled counterparts.

Although the primary purpose of introducing the EVs and PHEVs in the transportation sector was to reduce emissions and mineral resources consumptions, further use of these electricity-fueled vehicles has also been considered from the very beginning. Excessive capital cost of purchasing a new electric vehicle has reinforced the need for the vehicles to be able to maximize their return from any potential use other than the normal driving. Thinking this way, the electricity industry has considered the batteries of the EVs and the PHEVs as potential energy sources [2][35][36] that can store and drain electrical energy in the events of such needs. As the electric vehicles sit idle in the parking stations for the major portion of the daily hours, their batteries can be used to charge and discharge energy from and to the grid, respectively [37][38][39][40][41]. As a result, power system operators can save both a significant amount of capital cost for purchasing storage batteries and that of floor space, yet maintain their service reliability. At the same time, vehicle owners can earn a certain revenue by trading their battery energy with the system operators during the generation and load variation periods. With this business model, both vehicle owners and the power system operators can be benefited as determined by a mutual trading agreement. In addition to that, if considerable number of electric vehicles participate in the battery storage trading, the system operators can deal with a range of generation and load variations that would otherwise be dealt by starting a new thermal generator thus adding more costs and emissions to the entire power system.

A SG has been envisioned as an electricity grid with no disturbances, excellent power quality, maximum service reliability, and overall sustainability. To maintain these criteria of a SG, cheap, available and viable energy storage sources are very important. Given that the EVs and PHEVs can be used for power transactions between themselves and the grid, the batteries of these vehicles are in huge demand as storage devices to a SG. The principal purpose of using the gridable vehicles (GVs) (both EVs and PHEVs) in the SG environment is to improve reliability and sustainability in the electricity sector. As has been already mentioned, electricity and transportation sectors are the two major sources of greenhouse gas emissions. If both these sectors can be tied together towards a common goal of reducing carbon emissions, this will contribute significantly in achieving a sustainable energy and transportation system. The concept lies in using the GVs as distributed storage energy sources [35][40][41] to enable the utility grid to deploy significant level of RESs, provided the vehicles will be charged from the grid using the renewable sources. The resulting effect is that both the electricity and the transportation sector are using the RESs towards maximizing the RESs utilization, which will ultimately ensure overall sustainability of the power system. Another positive aspect of using GVs as storage devices is that the utility has the flexibility to source/drain power of as small as the capacity of one vehicle from/to the GVs as GVs are literally individual small storage devices. For example, the utility can store energy to the vehicles of the range from 15 kW through to 15 MW depending on utility's real-time condition.

2.7 Research on gridable vehicles

In recent time, researchers have contributed some useful ideas that establish the effectiveness of GVs in a SG environment. Efficient optimization techniques [2] have been developed to accommodate RESs and GVs in the utility grid. Reduction in emissions and costs has been made possible by adopting these innovative techniques. Research is being conducted on how to integrate PHEVs and EVs to the SG environment economically and reduce utility disturbances generated by load variations [35][36][37]. PHEVs and EVs, however, need electrical power for charging, which again is a significant source of cost and emission. If RESs can be used to charge GVs from the grid and since GVs are capable of discharging to the grid, cost and emissions can be significantly reduced.

Research is ongoing on different aspects of using the GVs in the SG environment. Purpose and technology for using GVs have been described in [35][5][6] from the load leveling, regulation, and reserve perspectives. Potential impacts of GVs' integration on demand, supply, generation, infrastructure, prices and emission levels in the near future have been discussed in [38][42] while impacts on electric power network components have been investigated in [39]. Although several works have been done on the frequency regulation applications, a leading research [40] proposed an optimal vehicle-to-grid aggregator for frequency regulation to measure optimal charging control for individual vehicle. Use of GVs in the vehicle-to-building mode under peak load and during outage condition have been proposed and demonstrated in [41]. The evolution of the technology trends and an analysis of the likely scenario for GVs integration into the grid over the next decade have been explored in [43]. This particular research has articulated the important issues which may affect GVs adoption, characteristics, capabilities and interaction with the utility grid. Charging profile and its effect on load has been addressed by a group of researchers [44][45][46] where different methods and algorithms of charging the GVs have been illustrated. Charging infrastructure has been discussed in [47]. GV battery technology and possible goals have been extensively analysed in [48][49][50] where efficiency and economy of the currently developed batteries have been described and future requirements for the batteries have been envisaged. Economic aspects of deploying large number of vehicles into the SG environment have been researched in [51] and [52].

Lately, research around the integration of gridable vehicles have been broadly divided into three major areas namely, GV charging methodologies and options, communication technologies between the grid and the GVs, and the various effects of GV integration into the SG. With the increasing focus on facilitating more GV integration as energy storage devices, charging load of the participating GVs has been a major concern now a days. Considering the large variations between forecast and realized behaviour of the individual customers, a multi-period, unbalanced load flow and rolling optimization method has been implemented in [53] to control the rate and times of EV charging over a 24-hour period. A study of the risk-aware day-ahead scheduling and real-time dispatch for EV charging has been done in [54] aiming to jointly optimize the EV charging cost and the risk of load mismatch between the forecast and real world EV loads. A decentralized and packetized approach to plug-in electric vehicle (PEV) charge management has been investigated in [55], where charging of PEVs is requested and accepted for time-limited periods. Economic benefits of a smart charging system have been benchmarked along with the proposal of a vehicle-to-grid (V2G) operational strategy of an EV in [56], in which the reduction of a charging cost has been claimed and established. A coordinated charging strategy of EVs has been described in [57] for congestion prevention in the grid by accommodating the services and constraints of the EV owners, fleet operators, and the system operators. Optimal charging of PEV has been studied on a proposed intelligent workplace parking garage in [58] that claims reduced cost and effect of EV charging on the utility grid. Contactless smart charging station has been studied in [59], whereas fast charging infrastructure based on Flemish mobility behaviour has been explored in [60]. Real time coordination of PEV charging has been described in [61] to minimise power losses and improve voltage profiles, while a fuzzy approch for online coordination of the same has been described in [62]. Smart load management of PEV in the distribution and residential network has been researched in [63] to minise losses and shaving peaks considering voltage regulation effects.

Although GV integration into the SG is a business issue between the electricity grid and the vehicles, communication technologies play an inevitable role in implementing the bi-directional information and energy transfer operations. Details of the communication technologies currently employed in the SG environment have drawn enough attention to the communication engineering researchers. For instance, a survey of the communication infrastructures for the SG systems is given in [64]. A detailed description of a smart information subsystem is given in [65]. A brief comparison of the different SG technologies is given in [66], along with a list of progresses made in Europe and the U.S..

Research on GV integration into the SG mainly focuses on the different types of effects, aspects and economy of such integration. Reliability of service and economy of the system operations have drawn more attention to date. While discharging the GVs to the grid, the state of health of the GV batteries has always been a concern. Measurement techniques for online battery state of health estimation has thus been studied with regard to the vehicle-to-grid applications in [67]. The impact of smart and fast charging of EVs on the battery state of health and degradation has been studied using sustainable energy in [68] to find out the possible down sides of using the vehicle batteries in the SG. A short duration real-time V2G capacity estimation algorithm has been proposed in [69] to support the implementation of smart energy storage system with GVs in the SG environment. Use of GVs as energy storage units has been investigated from different viewpoints. PHEV utilization and recharging price sensitivity model has been developed in [70] to determine the vehicles' charging load profiles depending on the driving patterns. To minimize the effects of source and load variations, a strategy has been proposed in [71] to optimize the demand response with EVs in a distributed system environment. Flattening of demand curve is claimed in this work as well as reducing the users' daily bills. User comfort has been considered as an important factor in jointly optimizing the scheduling of EVs and home energy system in [72]. Mathematical modeling has been proposed for evaluating the economic benefits of integrating the EVs into the SG in [73], whereas long-term impact of EVs on the generation portfolio has been quantified in [74] drawing a conclusion that the impact of EVs on the generation portfolio is a variable item depending on the dynamics of the underlying generation portfolio.

In literature, some ideas have been proposed to integrate RESs and GVs with vehicle to grid discharging capacity in the resource scheduling problems. However, only a limited number of papers [2][75][76][77] have described and solved the resource scheduling problem under the uncertainties posed by RESs and GVs. One major limitation of these works is the assumption that the probability of GVs' availability is 90% round the clock in a day and that all the available vehicles are candidate for discharging to the grid when needed. While GVs as loads solves a major problem of storing excess energy, GVs as sources in real-time introduces two major challenges: i) in real time, GVs are not likely to be available with a probability of 90% for 24 hours a day and ii) success of this concept depends on the adoption rate of GVs and the participation rate of GV owners in the grid discharge program. Vehicle owners and potential buyers are increasingly concerned over the battery lifetime and efficiency from the cost and range perspectives, which pose a major challenge towards improving the adoption and participation rates. Since GV batteries come with a fixed number of deep discharge cycles, which is a measure for their calendar lifecycle, owners may have strong reservations about their cars discharging to the grid except if there is a benefit in it for them.

From sustainability perspective, another major challenge includes: if vehicles are selected for discharging based on the price of energy only [2], this does not comply with the concept of maximizing RESs utilization. If all GVs can be charged from RESs, and maximum possible power can be supplied to the grid during the peak load period keeping average battery lifetime within consumer expectations, emissions and fuel costs can be significantly reduced. A model for supervised use of GVs as sources conforming to a satisfactory effective lifecycle is thus necessary for improving vehicle adoption and participation rates, which ultimately will make the vehicle integration into the SG a huge success.

The concept of GVs as distributed sources is dependent on many factors. Real-time availability of GVs determines the available power from GVs. In practical scenario, vehicles' availability for discharging is not always deterministic. The reasons include: i) GVs are dependent on the performance of their batteries and there is a big concern over frequent use of batteries as a source of power to the grid, which may lead to premature expiry of the battery, ii) drivers' behaviour are undeterministic and availability of GVs when needed, is dependent on drivers' co-operation. According to national renewable energy laboratory's (NREL) report [3][78], premature battery failure is one of the major issues that needs to be addressed for widespread use of GVs in the SG. The evening peak load period is evident during 4-9 pm, which coincides with the period when GV owners return home, making moving GVs unavailable for immediate discharge. A commercially available GV battery comes with around 3000 deep discharge cycles over a lifetime of 15 years. This puts a constraint on the maximum number of discharge cycle per day (i.e., 0.547 per day on average), which significantly reduces the number of vehicles available for discharging in a day. The number of battery discharges, charges, and state-of-charge control directly affects the battery life. As such, an intelligent model is required that plans vehicle's availability during the peak load periods and takes the real-time battery condition of all GVs into account while choosing vehicles for discharging so that average battery lifetime remains above a threshold and GV owners do not have to be alert about premature expiry of batteries.

Summarising the existing literature and ongoing works, the following areas have been identified as the ones requiring further research:

1. Given that battery lifetime and revenue issues are the major concerns for the GV owners in letting their GVs to participate in the grid discharge program, no concrete proposals have been made from the research community to specifically address these two issues to eradicate the associated anxieties.

2. Considering the nature of battery lifetime degradation, effective economic model has not yet been developed to ensure the realization of proper value for the energy discharged from the GVs.

3. While the lifetime of a GV is constrained by its battery lifetime in the automotive use, other potential applications of these batteries can be explored with a detailed usage-benefits analysis to convince both the operators and the owners to make a deal that would benefit both parties, yet maintaining the sustainability of the power system.

With a vision to address the above issues, a set of particular research questions has been developed as given in the following section, and efforts have been made to provide novel solutions to these problems in the subsequent chapters.

2.8 Research questions

The main research challenges in integrating the GVs into the SG environment both for charging/discharging from/to the grid which have not yet been addressed by other researchers are named in the following list:

1. Increasing the average lifetime of an individual vehicle or a fleet of vehicles, which are participating in the charging/discharging program, to reduce owners' anxiety over battery lifetime and convince the owners to continue participating.

2. Making a trade-off between the cost of vehicle energy and the energy supplied from them to the grid so that GV owners can benefit from discharging to the grid.

3. Modeling the car owners' behaviour for charging and discharging considering the mobility and purpose of the vehicle owners.

4. If battery second use can be a factor in reducing the cost of owning an electric or plug-in hybrid electric vehicles. Answer to this question will significantly affect the concept of energy storage system in a positive way.

5. Analysing and modeling the economic aspect of using the second life batteries in crucial application such as backup storage energy sources during generator maintenance operations and justifying the capital cost of buying the second life batteries.

2.9 Closing remarks

SG is a new concept to make the existing electricity grid more functional, cost-effective and sustainable. Deployment of renewable energy sources into the SG provides opportunities to make the power system economic and environment-friendly. Variation in continuous generation of power is ubiquitous in the renewable generating stations. Gridable vehicles have been chosen by the energy industry as a novel way of addressing the unreliability of continuous production from the renewable sources. While gridable vehicles are a viable choice for balancing the utility grid, concerns have been raised by the owners as to how long will the batteries last and if it is beneficial for them. Second life batteries and their capital costs have also come into the scene. From the grid's perspective, using the vehicles in a sustainable way while preserving owners' interests has become the priority. This research has identified some problems yet unexplored by other researchers in this field. An extensive effort will be made to solve the identified problems.

Chapter 3

Improving Reliability of SG and Battery Lifetime of Gridable Vehicles

As discussed in Chapter 2, availability of GVs to discharge to the grid at the required hours is an important issue to be addressed. Ensuring the GV availability at different hours in a day in proportionate with the load demand can resolve this issue. In this chapter, we propose an intelligent SG system model, which mitigates real-time unavailability of GV sources via an availability planning model. We also propose a GV selection model that prevents GV batteries from premature expiry due to their vehicle-to-grid operations and improves average battery lifetime of the GV fleet. This latter model uses real-time parameters, such as available lifetime, available depletion cycles, real-time internal impedance, capacity, and battery aging as inputs. Incorporating these two models into the resource optimization model reduces overall costs, enhance system reliability, and improve practical battery lifetime to enhance sustainability.

The rest of this chapter is organized as follows. Importance of GVs as storage units in the SG environment and the factors hindering the widespread integration of GVs are described in Section 3.1. To solve the real-time GV availability mismatch, Section 3.2 introduces an availability planning model. Section 3.3 presents the battery lifetime improvement model to address the owners' concerns over GV battery efficiency and lifetime. Optimization model for economic load dispatch using GVs as storage devices and employing our proposed models is discussed in Section 3.4. The employed optimization method, Particle Swarm Optimization (PSO), has been described in Section 3.5 along with the implementation details while the simulation set-up and results have been presented in Section 3.6. A comprehensive description of the benefits of using our proposed models have been given in Section 3.7, and a conclusion has been drawn in Section 3.8.

3.1 Importance of GVs as storage and their integration barriers in the SG

A SG system, along with conventional thermal generators, consists of: (i) RESs, mainly wind and solar sources to reduce the running costs and emissions from power generation; (ii) GVs, such as PHEVs and EVs to reduce emissions and help balance the grid while acting as loads, storage units and small sources; and (iii) an on-board GV interface system and a parking station computer system to communicate with all registered vehicles to collect real-time data about the vehicles' battery condition. RESs are considered as compulsory generation along with the thermal generators, while vehicles are seen as distributed storage devices to help balance loads. An optimization method is then used to generate an intelligent schedule for cost and emission reductions.

A representative objective function [2] for cost-emission optimization is given as:

$$\min \left(\sum_{i=1}^{N} \sum_{t=1}^{H} \left[w_c \left(FC_i \left(P_i \left(t \right) \right) \right) + w_e \left(\psi_i EC_i \left(P_i \left(t \right) \right) \right) \right] \right). \tag{3.1}$$

Two essential constraints of this model, providing load balancing, and adequate spinning reserves, are defined in Equations (3.2) and (3.3). With GVs as sources of energy, the load balance equation with reserve capacity [2] is given as:

$$\sum_{i=1}^{N} P_i^{max} \left(t \right) + P_{pv} \left(t \right) + \sum_{j=1}^{N_{V2G(t)}} \zeta P_{vj} \left(\Psi_{pre} - \Psi_{dep} \right) + P_{wind} \left(t \right) \geq D \left(t \right) + Losses + R \left(t \right). \tag{3.2}$$

and with GVs as loads or storage the load balance equation with reserve capacity [2] is given as:

$$\sum_{i=1}^{N} P_i^{max} \left(t \right) + P_{pv} \left(t \right) + P_{wind} \left(t \right) \geq D \left(t \right) + Losses + R \left(t \right) + \sum_{j=1}^{N_{V2G(t)}} \zeta P_{vj} \left(\Psi_{dep} - \Psi_{pre} \right). \tag{3.3}$$

From Equations (3.2) and (3.3), it is evident that power transfer to/from the GVs is the only determining factor for ensuring maximum utilization of RESs and achieving a load balance condition. A confirmed availability of GVs in the time of need and a high participation rate of GVs in the grid discharge program are thus necessary for successful implementation of a SG with RESs. However, in real-time, vehicles are not available in significant numbers when the grid needs them the most. Moreover, even if sufficient numbers of GVs are available at a particular hour, their owners may be reluctant to discharge to the grid due to concerns over battery lifetime.

Real-time availability of GVs determines the total available power from GVs. In a practical scenario, vehicle availability for discharging is not always deterministic because: i) driver behavior is non-deterministic and availability of GVs when needed, depends on drivers' co-operation, and ii) owners are always concerned about any premature expiry of their vehicle battery. According to a National Renewable Energy Laboratory's (NREL) report [3][78], premature battery failure has to be addressed to foster widespread use of GVs in the SG. As such, an intelligent model is required that plans vehicle availability during the peak load periods and takes the real-time battery condition of all GVs into account while choosing vehicles for discharging.

In the following three sections, we present the availability planning model (APM) of GVs, the battery lifetime improvement model (BLIM) and the optimization model which is used to simulate the benefits of our proposed models.

3.2 Availability Planning model (APM) for gridable vehicles

In real-time, vehicles arrive at the parking stations randomly to discharge power to the grid, which means that the number of vehicles available in real-time may not meet the requirements of the grid. An APM matches the number of vehicles and the real-time demand by accumulating them to discharge to the grid when the grid needs them the most.

In a day, we expect two peaks of demand as can be seen from the universal historical demand data [2]. Let us assume that the peak demand periods in a day are denoted by *pk1* and *pk2*. Based on load demand curves as suggested by relevant research articles, *pk1* and *pk2* as 9 am-4 pm and 4 pm-11 pm can be considered as realistic assumptions. *Peakpk1* and *Peakpk2* represent the time in the *pk1* and *pk2* periods where the system requires the maximum energy from sources. It is important to plan ahead and schedule GVs so that more GVs are available for discharging to the grid around *Peakpk1* and *Peakpk2* times. This is important

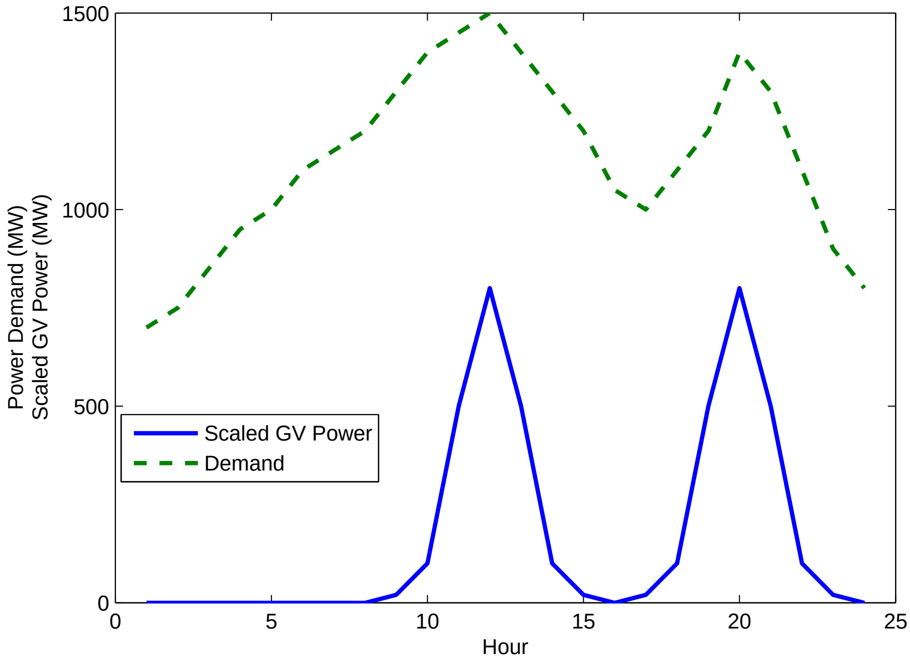

Figure 3.1: Availability planning of GVs at two peak load periods

because restrictions in terms of limited discharge cycles per day and long charging time allow only one complete discharge per day per GV. As universal demand curves follow two peaks in a day and the load distribution is more or less symmetric in these peak periods, we propose to use a Gaussian distribution model as illustrated in Figure 3.1 to schedule GVs' availability for discharging to the grid where the mean of each distribution are around the time (i.e., 12 pm and 8 pm) when the energy demand peaks. This distribution model provides the number of GVs that will be used for discharging energy to the grid at different hours of the peak periods.

To consider the real-time mobility of the vehicles for 24 hours per day, we introduce a mobility factor, m that will be different at different hours in a day. This mobility factor can be measured from the purpose of vehicles' use (i.e., private or commercial vehicles) and historical data of the transportation system. The number of vehicles on the road in a certain period is represented by this m, which is a percentage of the total registered vehicles. Therefore, an adjustment factor is necessary to correct for the mobility of planned GVs.

Number of vehicles scheduled for discharging during *pk1* and *pk2* can be given as:

$$N_{pk1} = \left(1 - m_1\right) N_{V2G}^{max} D_{pk1} / \left(D_{pk1} + D_{pk2}\right), \begin{cases} 0 \le m_1 < \quad 1 \end{cases} \tag{3.4}$$

$$N_{pk2} = (1 - m_2)\, N_{V2G}^{max} D_{pk2} / \left(D_{pk1} + D_{pk2}\right), \; \begin{cases} 0 \leq m_2 < \quad 1 \end{cases} \tag{3.5}$$

N_{pk1} and N_{pk2} number of GVs are distributed for discharging during the *pk1* and *pk2* periods using a Gaussian distribution. As such, the total number of scheduled GVs available for discharging in a time period $t_1 - t_2$ can be given as:

$$N_{pk1}\left(t_1 - t_2\right) = N_{pk1} \int_{t1}^{t2} \frac{1}{\sigma_{pk1}\sqrt{2\Pi}} e^{-\frac{\left(x-\mu_{pk1}\right)^2}{\sigma_{pk1}}} dx \tag{3.6}$$

$$N_{pk2}\left(t_1 - t_2\right) = N_{pk2} \int_{t1}^{t2} \frac{1}{\sigma_{pk2}\sqrt{2\Pi}} e^{-\frac{\left(x-\mu_{pk2}\right)^2}{\sigma_{pk2}}} dx \tag{3.7}$$

where μ_{pk1}, σ_{pk1} and μ_{pk2}, σ_{pk2} represent the mean and standard deviation during the *pk1* and *pk2* periods, respectively. The mean will be around the time when the demand is at its peak and standard deviation will follow the demand curve during the corresponding peak period.

Values of *pk1, pk2*, μ_{pk1}, σ_{pk1} and μ_{pk2}, σ_{pk2} will depend on operator's choice based on the historical demand curves, while values of m_1 and m_2 will depend on the drivers' behavior and/or purpose of the vehicles in the particular area.

An operator can select the values of these parameters in the real time to reflect the actual demand in the time of question. The operator also has the opportunity to tune these parameters in case the historical load demand data requires such tuning. This estimate of planned GVs at various hours in a day, when taken into account in the objective function as expressed in Equation (3.1), makes the system more reliable in real-time as all available vehicles under an operator are distributed over 24 hours a day following the daily forecasted load variations so that a good number of vehicles could be discharged to the grid during the peak hours. It would not have been the case if the distribution of the number of vehicles did not follow the load variations.

Vehicle scheduling for discharging to the grid would also account for the forecasting error for possible energy supplied by the RESs. A stochastic analysis with the RESs can enhance the balance of energy from RESs and GVs. A link between RESs and GVs can be easily established once we have historical data about the load variations and RESs production under a particular operator.

3.3 Battery lifetime improvement model (BLIM) of gridable vehicles

We model the overall battery condition of a fleet of GVs, in terms of their average effective available lifetime $EALT$ in real-time, which is given as:

$$EALT = \sum_{k=1}^{N_{V2G}(t)} \frac{LT_k}{N_{V2G}(t)} \tag{3.8}$$

where LT_k, represented in years, is modeled as a function of battery capacity, lifecycle already spent, total mileage spent, total deep cycle spent, and current internal impedance of the battery pack. Its mathematical representation is described below. We propose this model to maximize real-time $EALT$ subject to a constraint which meets a minimum threshold of battery lifetime. For example, consumers may want a battery to last at least 10 years before replacing it at a cost of up to USD 12000, depending on the battery type and size.

Articles on GV battery research [78][79][80][81][82] suggest that five parameters, namely, available lifecycle, available depletion cycle, aging, current impedance of the battery pack, and capacity affect the calendar life of a battery. Relationships between each of the parameters and the calendar lifecycle are described below.

3.3.1 Available lifetime

Available lifetime L of a battery represents its remaining lifetime in years. L is not an absolute measure as it also depends on the other four parameters. Research shows that as a battery ages, with the loss of power and capacity, its performance gradually decreases [78]. High temperatures, high currents, and high energy throughput are the major factors responsible for the deterioration of battery's electrical characteristics [79][80][81]. Thus the practical available lifetime will differ from the current value of available lifetime.

3.3.2 Available depletion cycles

As deep discharge is required for using vehicles as energy sources, available depletion cycle C is a clear indication of how many more times the battery can be fully discharged without affecting its lifetime. This measure depends on other factors including the temperature regime under which the battery was used. The practical number of available depletion cycle thus depends on other parameters.

3.3.3 Aging of a battery

Both calendar lifetime and depletion cycle losses affect the usable battery capacity. While depletion cycle life is a measure of losses when the battery is exercised, aging of a battery results in storage losses occurring when the battery is not used. Calendar lifetime of a battery is related to the age spent A by the Arrhenius equation [79] given as follows:

$$s_{loss} = 1.544 \times 10^{7} e^{-\frac{40498}{8.3143 T_k}} t_m \tag{3.9}$$

where T_k is the temperature in degree K and t_m is the age of the battery in months; s_{loss} is the percentage of the battery storage loss.

With aging, battery cells lose charge storing capacity which is visible at higher state-of-charge (SOC) values [78]. This is due to the fact that at lower SOC values, a battery gains more residual impedance that tend to reduce the conductivity inside the battery and hence reduce the charge storing capacity. The physical reason behind this is the loss of lithium ion inside the battery that is required to maintain the full conductivity of the battery cells. This process continues to repeat with time, both when the battery is in use or unused. The SOC values deteriorate with increasing depletion cycle numbers as the process of lithium ion loss continues. Experimental results for different depletion cycles illustrate that aged cells lose capacity to charge up to over 85% [78]. Depth-of-Discharge (DOD) is another factor that affects the storage capacity loss in batteries. Batteries are rated based on a standard DOD, which determines the allowable number of depletion cycles. If batteries are discharged at a higher DOD than that it is rated for, internal chemical structure of the battery experiences more stress and hence follows the processes resulting in a lithium ion loss, which is similar to aging. The ultimate effect is the faster rate of capacity degradation than the usual rate. The effect of aging in capacity loss should thus be taken into account when measuring the calendar life of a battery.

3.3.4 Current equivalent impedance of battery

As time progresses, batteries are used in different temperatures, currents, SOCs, and DODs, resulting in an irregular rate of capacity degradation [78]. The most significant factor behind this capacity degradation is the cumulative development of the combined equivalent impedance Z of all battery pack cells, which varies with time both when the battery is in use or idle. Z is a function of SOC and the number of depletion cycles [79]. The real-time measurement of Z indicates the existing capacity, which in turn leads to the battery's calendar lifetime.

3.3.5 Size (Capacity) of battery

A battery's final SOC varies within a range (i.e., SOC range=35-44%) specified by the manufacturer data. Final SOC of a battery of higher capacity is seen to be settled around the lower value of the SOC range [82], enabling them to supply power for longer duration before they reach the lowest SOC; which in turn saves some numbers of depletion cycles from what it was meant to spend. The opposite is true for the lower capacity batteries. Therefore, size (capacity) of a battery S can indicate lifecycle duration.

All five parameter (L, C, A, Z, S) values are collected from a vehicle in real-time and then converted into an equivalent battery calendar life in years. Each parameter is then given an weight factor to calculate the total weighted available lifetime. This is given by:

$$LT = w_L L_C + w_C C_C + w_A A_C + w_Z Z_C + w_S S_C \tag{3.10}$$

where

$$w_L + w_C + w_A + w_Z + w_S = 1. \tag{3.11}$$

The converted parameter values can be either positive or negative depending on their effect (reducing/increasing) on the weighted calendar lifetime. As higher age and impedance will decrease the overall battery lifetime, Equation (3.10) can be rewritten as:

$$LT = w_L L_C + w_C C_C + w_A\left(-A_C\right) + w_Z\left(-Z_C\right) + w_S S_C \tag{3.12}$$

The weight factors are selected according to the percentage of contribution of each parameter to the effective lifetime. For example, available lifetime L and available depletion cycle C have major contribution in determining the actual remaining lifetime of a battery. First, all registered GVs are passed through the real-time availability planning model (Equations (3.4) to (3.7)) and then parameters determining the battery lifetime are collected in real-time and effective available lifetime LT of individual vehicles is calculated. The $EALT$ of the fleet of vehicles is then calculated, using Equation (3.8), by averaging LT of all available vehicles. If this $EALT$ is greater than or equal to a threshold value T, the fleet of GVs is accepted for discharging to the grid, thus ensuring the available lifetime of the vehicle fleet exceeds T years. If $EALT$ is less than T, the system will remove n vehicles with least individual effective available lifetimes, from the fleet, until the new fleet of GVs gives an $EALT$ greater than T. Power supplied to the grid is then calculated by adding the power of all available vehicles in that fleet. A flowchart

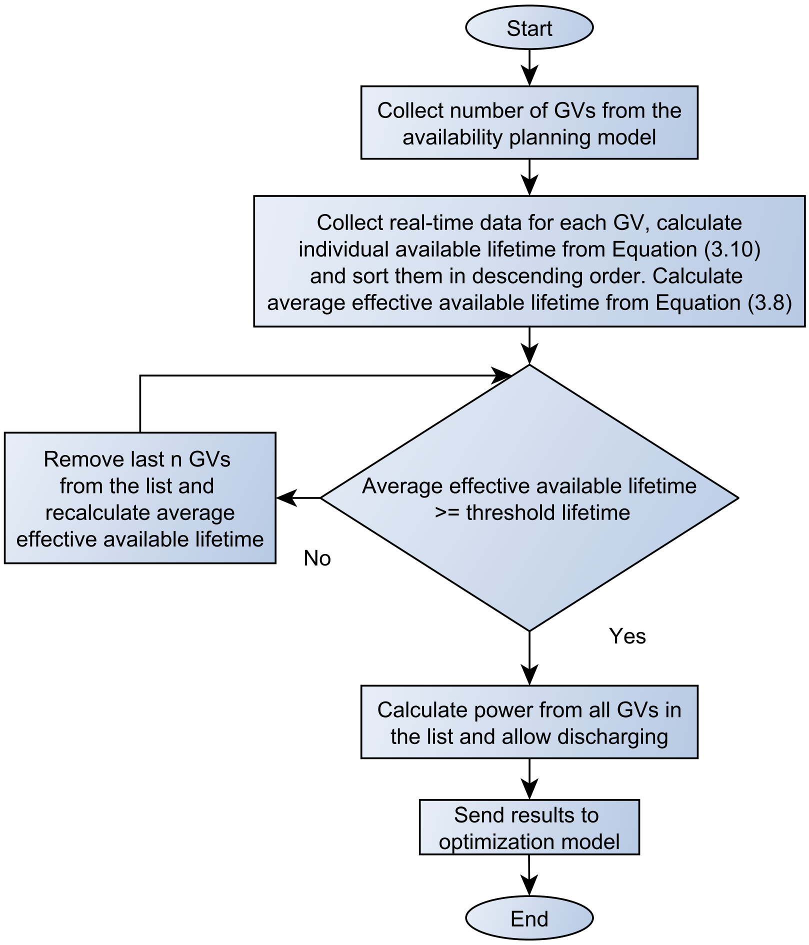

Figure 3.2: Flowchart for proposed BLIM for the batteries in a fleet of vehicles

of the BLIM is presented in Figure 3.2.

3.4 Optimization model for cost and emission reduction using the proposed APM and BLIM

Wind and solar energy are largely emission free and their operating costs are negligible. Fuel cost for a conventional thermal generator is expressed as a quadratic function of the unit's generated power as follows [2]:

$$FC_i\left(P_i\left(t\right)\right) = a_i + b_i P_i\left(t\right) + c_i P_i^2\left(t\right) \tag{3.13}$$

where a_i, b_i and c_i are positive fuel cost co-efficients of unit i at time t.

Emissions cost is expressed as another quadratic function of the unit's generated power as follows [2]:

$$EC_i\left(P_i\left(t\right)\right) = \alpha_i + \beta_i P_i\left(t\right) + \gamma_i P_i^2\left(t\right) \tag{3.14}$$

where a_i, β_i, and γ_i are emissions co-efficients of unit i.

In the SG, input power should meet the demand plus the system loss component. With GVs as sources in real-time, the load balance equation becomes [2]:

$$\sum_{i=1}^{N} P_i\left(t\right) + P_{pv}\left(t\right) + \sum_{j=1}^{N_{V2G(t)}} \zeta P_{vj}\left(\Psi_{pre} - \Psi_{dep}\right) + P_{wind}\left(t\right) = D\left(t\right) + Losses \tag{3.15}$$

With GVs acting as load or storage in real-time, the load balance equation becomes [2]:

$$\sum_{i=1}^{N} P_i\left(t\right) + P_{pv}\left(t\right) + P_{wind}\left(t\right) = D\left(t\right) + Losses + \sum_{j=1}^{N_{V2G(t)}} \zeta P_{vj}\left(\Psi_{dep} - \Psi_{pre}\right) \tag{3.16}$$

Adequate spinning reserves are considered for maintaining system reliability and the load balance equations which incorporate adequate spinning reserves are given by Equations (3.2) and (3.3).

Each thermal generator has a maximum and minimum power generation range, which is represented as:

$$P_i^{min} \leq P_i\left(t\right) \leq P_i^{max}. \tag{3.17}$$

Charging/discharging up to certain maximum/minimum level, to prevent battery failure, is given by:

$$\Psi_{min} P_{vj} \leq P_{vj}\left(t\right) \leq \Psi_{max} P_{vj}. \tag{3.18}$$

Number of vehicles that have been registered for charging/discharging from/to the grid, ${N_{V2G}}^{max}$ can take part during a predefined scheduling period.

$$\sum_{t=1}^{H} N_{V2G}\left(t\right) = N_{V2G}^{max} \tag{3.19}$$

Minimizing generation and emissions costs is considered as the objective of the SG; and load balance, reserve, power generation limit, charging/discharging limit are considered as the constraints.

The objective function for cost-emission optimization, therefore, is given by Equation (3.1) ; subject to Equations (3.2), (3.3), and Equations (3.15) - (3.19) constraints.

3.5 Particle Swarm Optimization (PSO)

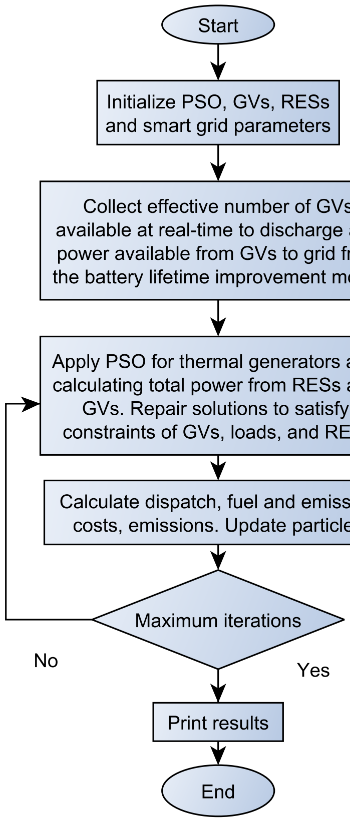

Figure 3.3: Flowchart for fuel and emissions costs minimization with RESs and GVs in the SG using our proposed models.

An efficient optimization method is required to minimize fuel and emissions costs in a system consisting of thermal generators, RESs, and GVs. Particle swarm optimization (PSO) is used in this study to create an intelligent schedule of the power sources and illustrate the effect of using the proposed models in the original scheduling to achieve cost and emissions reductions. Motivated by the social behavior of organisms, PSO [83] was first introduced by Kennedy and Eberhart in 1995. PSO provides a population-based search procedure in which each individual is called a particle, and is represented by its position (state) and velocity. Particles move within a multidimensional search space. While moving, each particle adjusts its position both according to its own experience and neighboring particles' experiences, thus making use of the best position discovered by itself and its neighbors. PSO is used throughout this thesis to deal with the combinatorial nature of comparatively large amounts of integer as well as continuous variables involved. Also, PSO provides a global optimal solution so is more suitable for solving optimisation problems of this nature. In PSO, the velocity and position of each particle are calculated iteratively as follows:

$$v_{pq}(k+1) = [v_{pq}(k) + c_1 r_1 (pbest_{pq}(k) - x_{pq}(k)) + c_2 r_2 (gbest_q(k) - x_{pq}(k))] \\ X \left[1 + \frac{-Range}{MaxIte}(Ite - 1)\right] \tag{3.20}$$

$$x_{pq}(k+1) = x_{pq}(k) + v_{pq}(k+1) \tag{3.21}$$

where velocity v, position x, accelerating parameters c_1 and c_2, random numbers r_1 and r_2, particle number p, problem dimension q and iteration index k are standard PSO terms [84]. A flowchart for minimizing fuel and emissions costs with RESs and GVs in a SG, using our proposed models, is given in Figure 3.3. If at hour t, the schedule is; $[P_1(t), P_2(t), \ldots, P_N(t), N_{V2G}(t), P_{pv}(t), P_{wind}(t)]^T$, then power supplied to/from vehicles is $\zeta N_{V2G}(t) P_{vj}$ $(\Psi_{pre} - \Psi_{dep})$. The sign of this expression will indicate whether it is a load or source; and the rest of the load demand, given by the expression; $[D(t) + \zeta N_{V2G}(t) P_{vj}$ $(\Psi_{pre} - \Psi_{dep}) - P_{pv}(t) - P_{wind}(t)]$ will be met from the conventional thermal units.

3.6 Simulation setup and results

Table 3.1: Generating unit capacity and coefficients

Unit	P^{min}(MW)	P^{max}(MW)	a ($)	b ($/MW)	c ($/MW^2)
1	100	500	240	7.0	0.0070
2	50	200	200	10.0	0.0095
3	80	300	220	8.5	0.0090
4	50	150	200	11.0	0.0090
5	50	200	220	10.5	0.0080
6	50	120	190	12.0	0.0075

Table 3.2: Generator emissions coefficients

Unit	α (ton/h)	β (ton/MWh)	γ (ton/MW^{2}h)
1	10.33908	-0.24444	0.00312
2	32.00006	-0.38132	0.00344
3	32.00006	-0.38132	0.00344
4	30.03910	-0.40695	0.00509
5	32.00006	-0.38132	0.00344
6	30.03910	-0.40695	0.00509

The system that we considered for simulation included conventional thermal generators, RESs, and GVs in a SG environment. It was assumed that GVs were charged from RESs as loads and discharged to the grid as power sources as far as possible. GVs that discharged to the grid were eligible to charge themselves at a subsidized rate throughout the month or year, depending on the operator's choice. The operator also had the choice of charging the vehicles for free at some specified hours in return of their discharged power to the grid during the peak hours. As such, cost of power from GVs was not considered in the calculation. An independent system operator (ISO) of a 6-unit system with 50,000 registered GVs was simulated in this study. Unit characteristics of the system were taken from [85] and are given in Table 3.1. Emissions coefficients were taken from [75] and are given in Table 3.2. For GVs, parameter values considered were: S = 15kW, H = 24 hours, minimum Ψ_{dep}= 40%, ζ = 85%, and vehicles' range of lifetime = 2-15 years and 2-12 years. For PSO, swarm size = 50, number of iterations = 1000, acceleration factor $c_1 = c_2 = 2$, $Range = 0.5$, emissions penalty factor ψ_i= 25 \$/ton, and weighting factors $w_c = w_e = 1$. PSO parameters have been selected on a trial and error process.

According to the proposed APM, we divided 50,000 registered vehicles into 20,000 and 30,000 between periods *pk1* (9 am-4 pm) and *pk2* (4 pm-11pm), respectively. Taking mobility factors m_1 as 0.2 and $m_2$as 0.3, we found the following availability planning V for the 24 hours in a day, where V = [0 0 0 0 0 0 0 0 16 336 2176 5456 5456 2176 336 37 441 2856 7161 7161 2856 441 21 0].

The number of planned available vehicles V has been given again in Table 3.3 against the hours of a day.

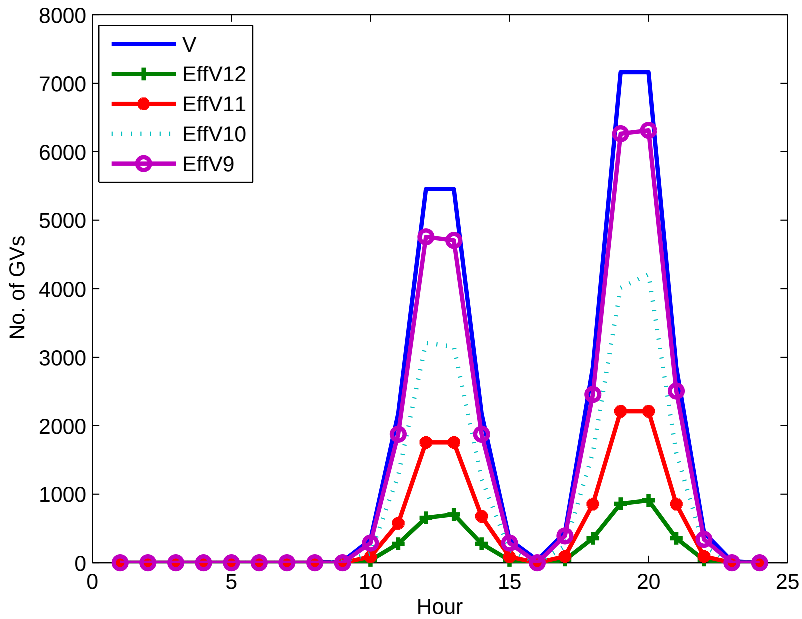

Figure 3.4: Number of real-time available vehicles and effective number of vehicles available to discharge (out of 50000) for w_L= 0.4, w_C = 0.4, w_A = 0.1, w_Z = 0.05 and w_S = 0.05, and lifetime range of 2 to 15 years.

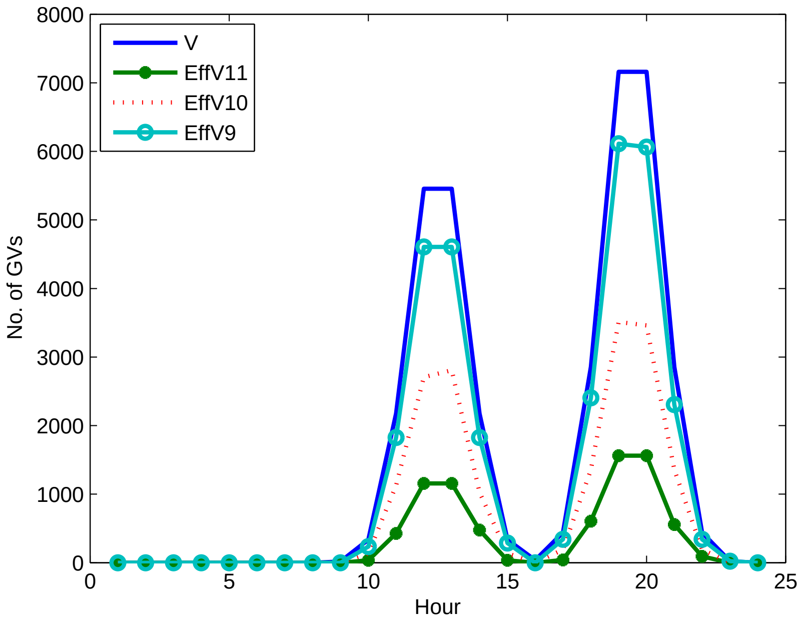

Figure 3.5: Number of real-time available vehicles and effective number of vehicles available to discharge (out of 50000) for $w_L = 0.3$, $w_C = 0.3$, $w_A = 0.1$, $w_Z = 0.2$ and $w_S = 0.1$, and lifetime range of 2 to 15 years.

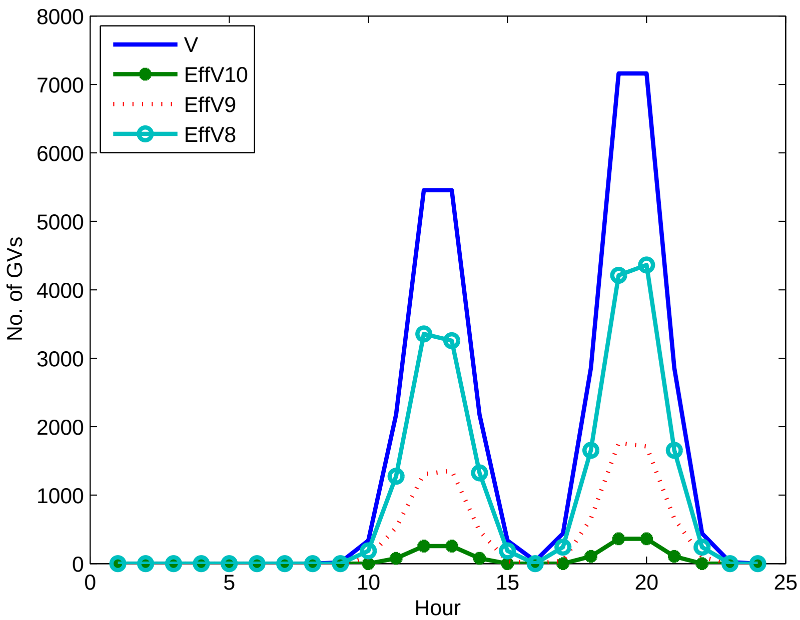

Figure 3.6: Number of real-time available vehicles and effective number of vehicles available to discharge (out of 50000) for $w_L = 0.4$, $w_C = 0.3$, $w_A = 0.1$, $w_Z = 0.1$ and $w_S = 0.1$, and lifetime range of 2 to 12 years.

The number of real-time vehicles available to discharge is derived from our proposed BLIM, depending on the threshold $EALT$ values. Figure 3.4 plots the effective number of vehicles available for discharging to the grid in real-time for different $EALT$ values while Figures 3.5 and 3.6 represent the same for different battery parameters where *EffV12*, *EffV11*, *EffV10* and *EffV9* represent the effective number of vehicles available to discharge for $EALT$ values of 12, 11, 10, and 9, respectively, and V represents the planned number of vehicles available in real time. It is evident in Figures 3.4, 3.5, and 3.6 that the effective number of vehicles is less than the available vehicles, which is also true for different combinations of battery parameter values. This means that not all available vehicles are eligible to discharge, thus providing the operator with a safety margin for battery status and ensuring a threshold $EALT$ value for the discharging vehicle fleet. Sparing ineligible vehicles from discharging enhances their battery lifetime and ensures a healthy $EALT$ value for the whole fleet.

The physical implication of this process is that the operator has a tool to determine which vehicles should discharge and which ones should not. As the vehicles with lower available lifetime are not allowed to discharge, the owners' concern over the lifetime deterioration from unsupervised discharging to the grid is automatically addressed by the operators. This is expected to bring enough confidence in the vehicle owners to allow their vehicles to participate in the grid discharge program.

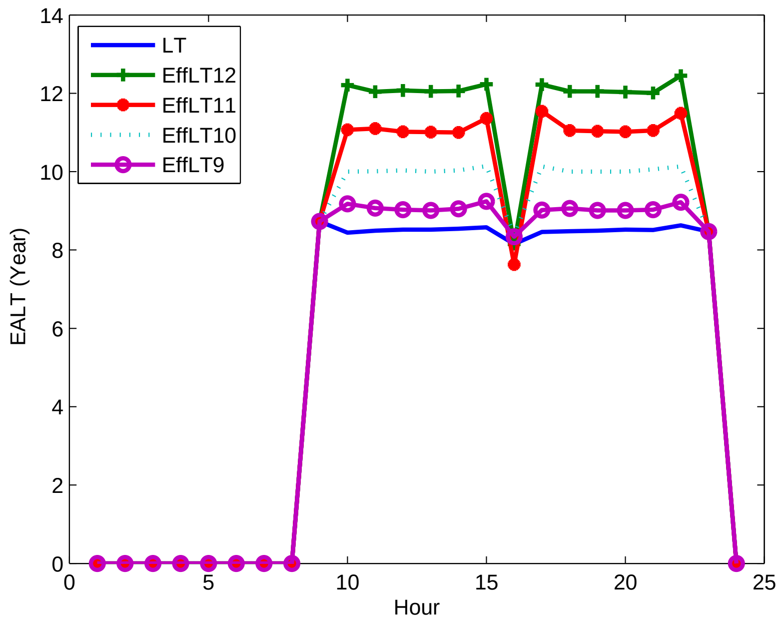

Figure 3.7: Lifetime saving of the fleet of available vehicles in real-time (corresponding to Figure 3.4) for $w_L = 0.4$, $w_C = 0.4$, $w_A = 0.1$, $w_Z = 0.05$ and $w_S = 0.05$, and lifetime range of 2 to 15 years.

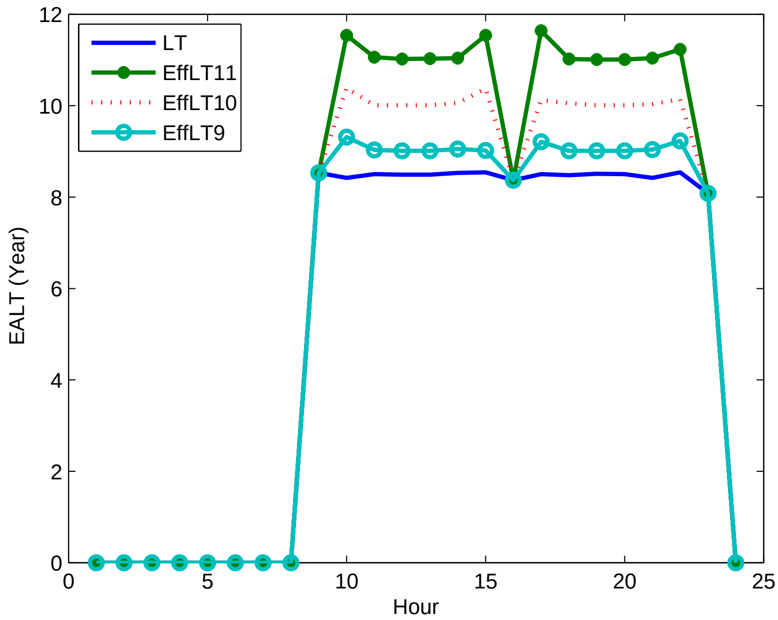

Figure 3.8: Lifetime saving of the fleet of vehicles available in real-time (corresponding to Figure 3.5) for $w_L = 0.3$, $w_C = 0.3$, $w_A = 0.1$, $w_Z = 0.2$ and $w_S = 0.1$, and lifetime range of 2 to 15 years.

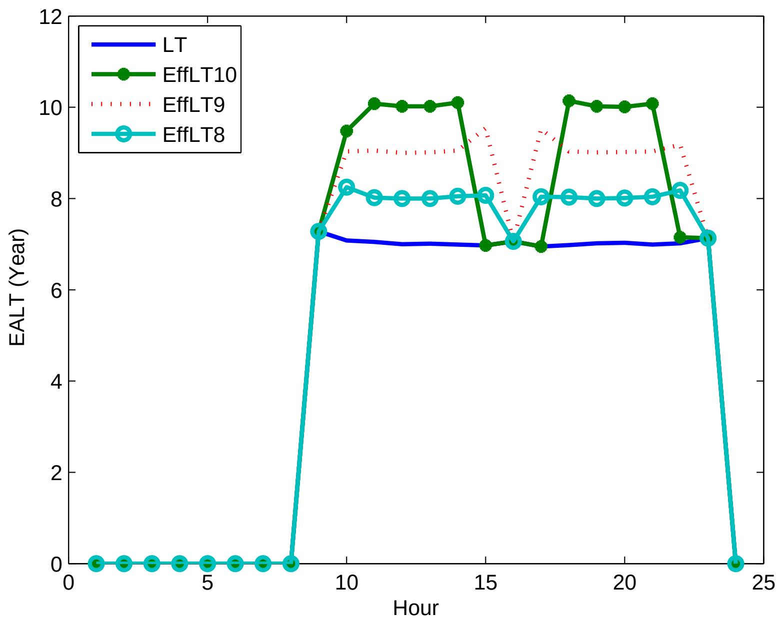

Figure 3.9: Lifetime saving of the fleet of vehicles available in real-time (corresponding to Figure 3.6) for $w_L = 0.4$, w_C= 0.3, $w_A = 0.1$, $w_Z = 0.1$ and $w_S = 0.1$, and lifetime range of 2 to 12 years.

Figure 3.7 provides effective average lifetime of the fleet of vehicles available to discharge to the grid in real-time for different threshold $EALT$ values. Figures 3.8 and 3.9 represent the same for different battery parameters where *EffLT12*, *EffLT11*, *EffLT10*, *EffLT9*, and *EffLT8* represent effective average lifetime of the fleet of vehicles available to discharge for threshold $EALT$ values of 12, 11, 10, and 9, and 8, respectively. LT represents the effective average lifetime of the fleet of planned number of vehicles available in real-time.

In Figure 3.7, LT = 8.5 (approx.), *EffLT12* = 12, *EffLT11* = 11, *EffLT10* = 10, and *EffLT9* = 9. Battery lifetime savings for different threshold lifetime values are given by (*EffLT12-LT*), (*EffLT11-LT*), (*EffLT10-LT*) and (*EffLT9-LT*), the values of which are approximately 3.5, 2.5, 1.5, and 0.5, in years, respectively. This means that the average LT of the GV fleet is 8.5 years, but the operator will want to only discharge vehicles with higher LT values, the average of which will exceed the threshold $EALT$. The operator will continue to spare the GVs with the lower LT values until the average LT value exceeds the threshold $EALT$. Doing that saves battery lifetime for the spared vehicles by the difference of LT and threshold $EALT$.

Similarly, in Figure 3.8, LT = 8.5 (approx.) and the lifetime savings for different threshold lifetime values are approximately 2.5, 1.5, and 0.5 years, respectively. In Figure 3.9, LT = 7.0 (approx.) and the lifetime savings for different threshold lifetime values are approximately 3.0, 2.0, and 1.0 years, respectively. In summary, the available lifetime of the entire vehicle fleet has been increased by up to 3.5 years, 2.5 years and 3.0 years for cases shown in Figures 3.7, 3.8, and 3.9, respectively. While battery lifetime is a major concern among the vehicle owners, this improvement in available lifetime will encourage greater participation rates of GVs in the SG systems.

To study the effect on cost and emissions reductions, these two models (APM and BLIM) have been incorporated into the economic load dispatch (ELD) problem. PSO has been used to calculate fuel and emissions costs for the economic dispatch. As vehicles are discharged at least once a day, they need to be charged on the same day to be available for the next day. If ${N_{V2G}}^{max}$ vehicles are to be charged, they must be distributed over the off-peak hours so that no artificial peaks are created. As such, load for charging the vehicles must be considered in the economic load dispatch problem. The vehicle charging distribution is more economically favourable if the charging is distributed over the period of surplus generation from the RESs. The greater the overlapping period of vehicle charging with the RESs surplus generation, the greater is the efficiency of the entire system. For example, wind energy is available in surplus amount from midnight till 6 am in the morning, though demand is low during this period. Therefore, using the energy produced during this period for charging as many GVs as possible represents ideal balancing in this context.

While charging the vehicles during off-peak hours, a priority must be set to indicate which GVs can charge in the daytime and which can charge at night. In order to make the charging schedule rational, GVs that discharge a threshold amount of energy during the peak hours should be given the highest priority while GVs that did not discharge on the same day would be given the lowest priority, so far as the charging time is concerned. Regardless, any GV can charge during a 24-hour period, but it may be during the lowest demand period. This priority will also be dictated by the amount of surplus RESs generation during off-peak hours. An intelligent coordination of the surplus RESs generation, consumer demand, and GV charging load can benefit consumers, GV owners and the operator.

As a specific solution to the GV charging distribution, all GVs are considered to be charged during a 24-hour period and thus the total energy required to achieve that is calculated. This required energy is distributed over the hours when the demand approximates the base load demand. Distribution of the GV charging load on individual hours would depend on the load demand, RESs generation, time-of-use pricing, generator parameters, balance between cost and emissions, and so on. An intelligent coordination of all these factors has been done as a test case, which gives us the following distribution of GV charging over a 24-hour period where V = [20668 13333 6666 0 0 0 0 0 0 0 0 0 0 0 0 0 1667 0 0 0 0 0 1000 6666].

For RESs, solar insolation, wind speed and demand data over 24-hour in a day have been taken from [2]. A $\pm 4\%$ error in forecasting power from wind and solar sources has been incorporated. Generated power from the solar and wind sources for 24 hours in a day has been taken for simulation purposes. Solar farm size = 40 MW, Wind farm size = 25.5 MW. Table 3.3 shows the demand, planned and available number of vehicles, taking into account mobility factors for the peak *pk1* as 0.2, and for the peak *pk2* as 0.3 in real-time in a typical day. The data is based on the assumption of a total number of 50,000 registered vehicles with Power from each vehicle being 6.375kW.

Resource scheduling has been done with vehicles as sources and loads or storage. Fuel and emissions costs in a SG system incorporating the proposed APM but not the BLIM used for GVs have been calculated first. The same is then calculated again with both our proposed APM and BLIM used. Fuel and emissions costs in the latter scenario is slightly higher than the former one. While the immediate monetary differences, through using our BLIM, seem relatively small, the broader impact of both of our models is substantial as discussed in the next section. The fuel and emissions costs results of the resource scheduling in the former scenario is given in Table 3.4 whereas Table 3.5 depicts the latter scenario.

Table 3.3: Demand and power available from available GV sources in real time for $EALT = 10$

Time (H)	Demand (MW)	Planned GVs (No.)	Parked GVs (No.)	Discharging GVs (No.)
1	700.00	0	0	0
2	750.00	0	0	0
3	850.00	0	0	0
4	950.00	0	0	0
5	1000.00	0	0	0
6	1100.00	0	0	0
7	1150.00	0	0	0
8	1200.00	0	0	0
9	1300.00	20	16	0
10	1400.00	420	336	136
11	1450.00	2720	2176	1126
12	1500.00	6820	5456	2856
13	1400.00	6820	5456	2956
14	1300.00	2720	2176	1176
15	1200.00	420	336	136
16	1050.00	50	37	0
17	1000.00	630	441	191
18	1100.00	4080	2856	1506
19	1200.00	10230	7161	3861
20	1400.00	10230	7161	3811
21	1300.00	4080	2856	1506
22	1100.00	630	441	191
23	900.00	30	21	0
24	800.00	0	0	0
Mobility factor for peak *pk1* is 0.2, and for peak *pk2* is 0.3.				

Note: Number of registered vehicles is 50,000 and each vehicle delivers 6.375 kW power.

3.7 Discussions and benefits of the study

Modeling the vehicles' practical availability is a crucial point to consider when GVs are taken as sources, as the number of available GVs in real time determines the remaining load demand to be dispatched by the thermal units, the cost and start-up time for which are major issues to be resolved. If the availability estimate is higher than the real-time availability; the probability of blackouts is very high, which is unacceptable. If the prediction is more accurate and close to the real-time value, the system can be run sustainably, even at the cost of committing a new thermal generator. The perfect fit would be to add a new RES, if available, so as to maximize the utilization of RESs. Our proposed APM ensures that GVs are distributed over 24 hours a day in a way that approximately follows the load demands over that period. Without such a planning model, an operator might use-up all available GVs at a certain hour, leaving no usable GVs at a later hour, thus affecting the reliability of the system.

Improving the GVs' battery lifetime is another crucial issue to encourage participation of

Table 3.4: PSO results for economic load dispatch schedule with the proposed APM but not the BLIM

Time (H)	Unit-1 (MW)	Unit-2 (MW)	Unit-3 (MW)	Unit-4 (MW)	Unit-5 (MW)	Unit-6 (MW)	Solar (MW)	Wind (MW)	GVs (MW)	Demand (MW)	Loss (MW)	Total Cost ($)
1	170.45	152.41	160.38	104.90	149.80	101.68	0.00	10.54	-131.76	700.00	18.40	17967.96
2	168.57	150.84	158.78	103.79	148.22	100.55	0.00	22.27	-85.00	750.00	18.02	17707.78
3	180.40	161.13	169.10	110.89	158.37	107.67	0.00	25.50	-42.50	850.00	20.56	19420.21
4	192.98	172.08	180.08	118.48	169.12	115.21	0.00	25.50	0.00	950.00	23.45	21362.12
5	204.41	182.05	189.89	125.38	178.87	120.00	0.00	25.50	0.00	1000.00	26.11	23158.92
6	231.45	200.00	213.21	141.58	200.00	120.00	0.00	25.50	0.00	1100.00	31.74	27092.55
7	255.29	200.00	233.61	150.00	200.00	120.00	0.09	25.50	0.00	1150.00	34.49	29286.39
8	273.87	200.00	249.47	150.00	200.00	120.00	17.46	25.50	0.00	1200.00	36.30	30849.98
9	323.11	200.00	291.20	150.00	200.00	120.00	31.45	25.50	+0.102	1300.00	41.36	35492.52
10	412.60	200.00	300.00	150.00	200.00	120.00	36.01	25.50	+2.142	1400.00	46.25	41653.34
11	450.69	200.00	300.00	150.00	200.00	120.00	38.06	25.50	+13.872	1450.00	48.13	44482.75
12	483.57	200.00	300.00	150.00	200.00	120.00	35.93	25.50	+34.782	1500.00	49.78	47122.42
13	377.49	200.00	300.00	150.00	200.00	120.00	36.78	25.50	+34.782	1400.00	44.56	39264.67
14	315.50	200.00	284.77	150.00	200.00	120.00	31.59	24.82	+13.872	1300.00	40.55	34755.51
15	279.80	200.00	254.51	150.00	200.00	120.00	9.70	20.74	+2.142	1200.00	36.89	31370.24
16	216.45	192.46	200.30	132.58	189.16	120.00	12.92	14.62	+0.2359	1050.00	28.73	24977.46
17	206.38	183.74	191.61	126.57	180.54	120.00	0.00	25.50	-7.8157	1000.00	26.53	23449.57
18	227.15	200.00	209.51	138.98	198.18	120.00	0.00	19.04	+18.207	1100.00	31.07	26604.74
19	257.80	200.00	235.79	150.00	200.00	120.00	0.00	25.50	+45.651	1200.00	34.74	29492.66
20	412.58	200.00	300.00	150.00	200.00	120.00	0.00	18.02	+45.651	1400.00	46.25	41651.89
21	330.81	200.00	297.67	150.00	200.00	120.00	0.00	25.50	+18.207	1300.00	42.19	36282.62
22	232.00	200.00	213.69	141.90	200.00	120.00	0.00	21.42	+2.811	1100.00	31.81	27145.82
23	189.01	168.64	176.51	116.10	165.69	112.80	0.00	0.00	-6.241	900.00	22.51	20731.18
24	174.46	156.00	163.98	107.34	153.32	104.12	0.00	2.55	-42.50	800.00	19.27	18552.13
Total fuel and emissions costs = $7,09,875.43												

Note: '+' and '-' signs for GV power stands for GVs as source and load, repectively.

Table 3.5: PSO results for economic load dispatch schedule with both the proposed APM and the BLIM (Vehicle's lifetime range = 2-15 years; $w_L = 0.4$, $w_C = 0.3$, $w_A = 0.1$, $w_Z = 0.1$ and $w_S = 0.1$; and threshold $EALT = 10$ years.)

Time (H)	Unit-1 (MW)	Unit-2 (MW)	Unit-3 (MW)	Unit-4 (MW)	Unit-5 (MW)	Unit-6 (MW)	Solar (MW)	Wind (MW)	GVs (MW)	Demand (MW)	Loss (MW)	Total Cost ($)
1	170.45	152.41	160.38	104.90	149.80	101.68	0.00	10.54	-131.76	700.00	18.40	17967.96
2	168.57	150.84	158.78	103.79	148.22	100.55	0.00	22.27	-85.00	750.00	18.02	17707.78
3	180.40	161.13	169.10	110.89	158.37	107.67	0.00	25.50	-42.50	850.00	20.56	19420.21
4	192.98	172.08	180.08	118.48	169.12	115.21	0.00	25.50	0.00	950.00	23.45	21362.12
5	204.41	182.05	189.89	125.38	178.87	120.00	0.00	25.50	0.00	1000.00	26.11	23158.92
6	231.45	200.00	213.21	141.58	200.00	120.00	0.00	25.50	0.00	1100.00	31.74	27092.55
7	255.29	200.00	233.61	150.00	200.00	120.00	0.09	25.50	0.00	1150.00	34.49	29286.39
8	273.87	200.00	249.47	150.00	200.00	120.00	17.46	25.50	0.00	1200.00	36.30	30849.98
9	343.08	200.00	270.75	150.00	200.00	120.00	31.45	25.50	0	1300.00	40.82	35568.62
10	413.94	200.00	300.00	150.00	200.00	120.00	36.01	25.50	+0.867	1400.00	46.31	41748.70
11	457.74	200.00	300.00	150.00	200.00	120.00	38.06	25.50	+7.1783	1450.00	48.48	45033.03
12	500.00	200.00	300.00	150.00	200.00	120.00	35.93	25.50	+18.207	1500.00	50.62	48608.80
13	394.23	200.00	300.00	150.00	200.00	120.00	36.78	25.50	+18.845	1400.00	45.36	40377.71
14	331.30	200.00	275.54	150.00	200.00	120.00	31.59	24.82	+7.497	1300.00	40.61	35123.94
15	294.98	200.00	240.34	150.00	200.00	120.00	9.70	20.74	+0.867	1200.00	36.63	31474.04
16	222.22	189.90	200.64	131.27	186.80	120.00	12.92	14.62	0	1050.00	28.61	24981.94
17	206.81	184.08	191.95	126.78	180.90	120.00	0.00	25.50	-9.4095	1000.00	26.61	23509.18
18	236.64	200.00	209.11	139.92	197.18	120.00	0.00	19.04	+9.6008	1100.00	31.41	26967.46
19	279.33	200.00	236.32	150.00	200.00	120.00	0.00	25.50	+24.614	1200.00	35.69	30515.74
20	435.03	200.00	300.00	150.00	200.00	120.00	0.00	18.02	+24.295	1400.00	47.35	43289.87
21	354.38	200.00	282.85	150.00	200.00	120.00	0.00	25.50	+9.6008	1300.00	42.20	36870.32
22	240.22	200.00	211.76	140.73	196.36	120.00	0.00	21.42	+1.2176	1100.00	31.70	27222.00
23	189.00	168.63	176.55	116.12	165.76	112.84	0.00	0.00	-6.375	900.00	22.52	20735.75
24	174.46	156.00	163.98	107.34	153.32	104.12	0.00	2.55	-42.50	800.00	19.27	18552.13
Total fuel and emissions costs = $7,17,425.14												

Note: '+' and '-' signs for GV power stands for GVs as source and load, respectively.

GVs into the grid discharge program. Unsupervised discharge could shorten GVs' battery lifetime and discourage owners from participating in the grid discharge program. Our proposed BLIM selects the GVs for discharging based on the remaining $EALT$ of the GV fleet, and spares GVs with least remaining LT from discharging; thus saving their battery lifetime for automotive use. If our model is not used, the GVs discharge to the grid at the cost of reducing their battery lifetime.

It can be noted from Tables 3.4 and 3.5 that although a total fuel and emissions costs of (\$7,17,425.14-\$7,09,875.43) = \$7,549.71 has been increased with our proposed BLIM used, it is insignificant compared to the minimum cost savings from the lifetime saving of the GVs. As an illustration, with our proposed BLIM used, a total of (36,926-19,452) = 17,474 GVs did not discharge. Considering a minimum of \$12000 per battery purchase cost and an average lifetime of 10 years, per day costing of using a GV becomes \$12000/(10*365) = \$3.29. So, saving at least 1 day of lifetime of those 17,474 non-discharging GVs will indirectly save \$3.29*17474 = \$5,743.56. This means that saving a lifetime of at least 2 days per vehicle will justify the excess cost. In practice, if our model is used continuously, the lifetime of GVs will improve in the scale of years, thus providing an economic justification for using our models.

To calculate the total cost savings by using our proposed BLIM in this case study, we use the actual data of the GVs considered in this optimization model. The average LT value of the GVs considered is 8.0 years (approx.) and the threshold $EALT$ value is 10 years, so a (10-8) = 2-year battery lifetime saving has been possible with our BLIM, thus saving a total of \$((12000/10)*2*17474) = \$41,937,600. This significant financial benefit complements the improved system reliability afforded by APM.

Table 3.6: Overall benefits of using our proposed models

Items	Without Our Proposed Models	With Our Proposed Models
GVs Availability for Discharging	Unplanned and unreliable	Reliable and follows load demands
Basis of Discharging	Non-Transparent	Objective; preserving a benchmark battery lifetime for the fleet of GVs
Effect on Battery Lifetime	Chances for premature expiry	Increasing automotive lifetime
Expected GV Participation Rate	Low due to battery lifetime concerns	High due to supervised discharging
Potential for RESs Integration	Low due to low participation rate	High due to high participation rate

If the conventional model is used to select the number of GVs to discharge, only a portion of the vehicles will be available at the peak hour and that does not ensure maximum RESs utilization. Moreover, as vehicles are selected randomly rather than based on their battery condition, the conventional model would not prevent premature battery failure. In contrast, our proposed models ensure maximum possible power discharge from the GVs, which in turn, facilitates maximum RESs integration. The models also keep the average lifetime of the whole vehicle fleet to a level acceptable to the operator or vehicle owners. The lifetime saving of the GV batteries will encourage owners to participate in the grid discharge program, which is a primary requirement for enabling RESs integration into the SG. A summary of the benefits of using our models is given in Table 3.6.

3.8 Conclusion

Reliability and sustainability are the two major concerns in integrating RESs and GVs in a SG environment. Achieving an appropriate balance in the SG, for various load conditions, requires RESs and GVs to be integrated intelligently in real time. In this chapter, we have proposed an availability planning model and a battery lifecycle improvement model to intelligently use GVs with RESs. The availability planning model ensures that sufficient number of GVs are present at the parking stations at different hours in a day so that they can discharge to the grid according to the real-time energy needs. This model also ensures GV energy are not used up at an hour of minor needs leaving the peaking hours in storage scarcity. A distribution model following the historical load demand under a certain operator is adopted to meet the operator's storage energy needs in a best possible way. The battery lifetime improvement model provides a way for the operators to convince the GV owners to allow their GVs to discharge at the grid's requests. This model requests energy only from the GVs that as a fleet maintain an acceptable average remaining lifetime and spares the GVs from discharging that do not fall into the group maintaining the expected remaining lifetime. As a result, the operators take care of the GVs' batteries for the GV owners thus relieving the owners form the worries of premature battery failure. Our simulation results show that using the proposed models in real-time enhances GVs availability as sources, which makes the system more reliable. The proposed models also improve the battery lifetime of the vehicle fleet by a significant margin. The improved battery lifetime of a GV fleet is expected to increase the adoption rate of GVs and participation rate of GVs in the grid discharge program, which ultimately will contribute to improved sustainability and better utilization of renewable energy sources.

Chapter 4

Gridable Vehicles as Energy Storage Devices from Owners' Perspectives

High cost of storage energy is a major concern for the grid operators in maintaining economic load dispatch. A variety of energy storage provisions have been proposed in the literature to flatten the cost [86], although achieving an acceptable cost of storage is still a very active area of research. A justification for using gridable vehicles (GVs) as storage devices has been provided in Chapter 3. This chapter investigates this issue from the GV owners' perspectives. GV owners are very much concerned over battery lifetime and cost effectiveness of the two-way power transfer. This issue reduces the participation rate of GVs in the vehicle-to-grid discharge program.

In this chapter, we present a system model, for GVs to act as distributed storage devices, which mitigates concerns over battery lifetime, and provides GV owners with a transparent cost-benefit analysis of their participation in the vehicle-to-grid discharge program. Such a model is expected to significantly increase the participation rate, and to create a valuable contribution towards the realization of a sustainable SG system.

4.1 System model for efficient and economic use of gridable vehicles (GVs)

The main contributions of of the research work described in this chapter are two-fold. First, we model the capacity degradation cost of a battery, based on its numbers of cycles that have already been spent, and include this in the cost of a single charging/discharging cycle of the

GV, at various stages of its lifetime. This model is then used to make a trade-off between the cost involved in a charging/discharging cycle, and the real-time power available from a GV; in order to decide whether it should discharge or not, and in what amount. Second, we develop an economic load dispatch model, where the objective function takes the cost of using the GVs' energy into account, in conjunction with the cost of fuel and emissions for thermal generators. By using these two models, we ensure a cost-effective use of the battery energy, which is expected to enhance the participation rate of the GVs.

4.1.1 Modeling capacity degradation and actual cost of using GVs as storage

Battery capacity degradation depends on a number of factors, such as spent depletion cycles, age, temperature at which it has been used, size and type, and battery chemistry. As the vehicles continue using the batteries, capacity degradation is believed to fall in two categories; namely cycling degradation and storage degradation. Research shows that these two broad categories of loss cover most of the factors concerning capacity degradation, and can be represented as a function of the number of spent cycles [87]. If the current cycle number of a battery is N_{cycle}, the capacity degradation as a percentage of the initial capacity, $CD_{remaining}$, can be given as in Equation (4.1), further details being described in the following sections.

$$CD_{remaining} = f(N_{cycle}) \tag{4.1}$$

The real-time energy available from a GV is justified against the current cycle number, to make a trade-off, so that a GV does not pay more in terms of its capacity degradation. The actual cost of GV energy consists of the capacity degradation cost, and the opportunity cost, both of which are described below. If this actual cost is beneficial with respect to the current energy pricing, a GV will discharge; otherwise the GV can deny discharging.

4.1.1.1 Capacity degradation cost

The capacity loss of batteries has been observed by many researchers. It is stated that the fraction of capacity loss can be measured per cycle of charging and discharging [88]. Degradation in current cycle number has thus been used in this study as one of the representative measure of the capacity losses during continuous cycling of batteries, as it has been shown on various experimental results [87]. In order to make a closer approximation of the conventional Li-ion battery capacity degradation trajectory, representative experimental results have been adopted

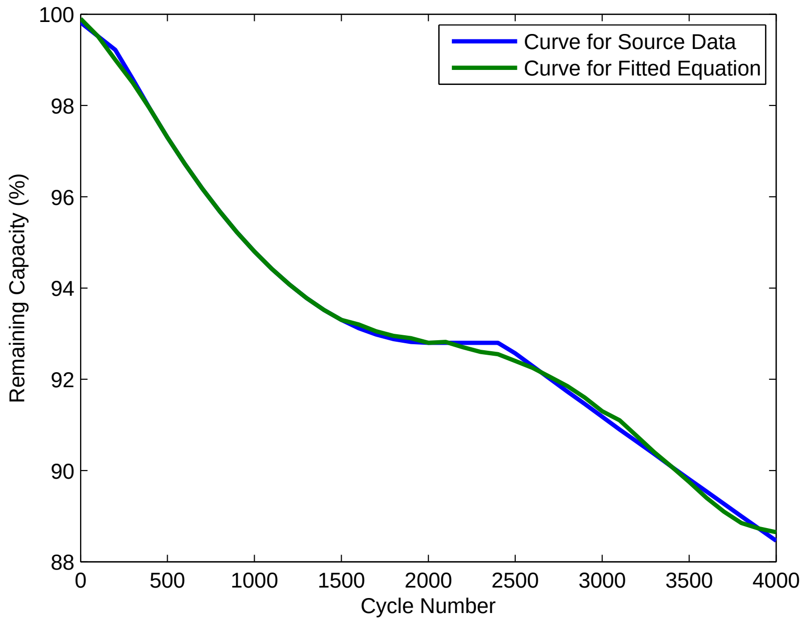

Figure 4.1: A plot of the total capacity fading of a battery against the number of cycles both from and the fitted Equation (4.7). The quality of the fit is given by R^2=0.9985.

[87] to demonstrate how to determine the capacity degradation from the current cycle number. Each vehicle is expected to charge and discharge only once a day, after giving consideration to both the battery lifetime issues and the charging-discharging time. In order to relate capacity degradation to cycle numbers, we use the experimental result graphs [87] showing capacity degradation during storage, and cycling against time and cycle numbers. Ultimate capacity fade is determined from the minimum of these two capacity fading effects [87]. Reformulating the graphs (cycle numbers in the X-axis) and assuming each battery will discharge at most once a day, we derive Equations (4.2) and (4.3).

For storage, the capacity fade equation becomes:

$$CD_{storage} = 2 \times 10^{-6} N_{cycle}^2 - 0.008 N_{cycle} + 100.8 \tag{4.2}$$

For cycling, the capacity fade equation becomes:

$$CD_{cycling} = 4 \times 10^{-8} N_{cycle}^2 - 0.003 N_{cycle} + 99.82 \tag{4.3}$$

Using 4,000 cycles as a benchmark [87], and taking the minimum value of capacity from Equations (4.2) and (4.3), we find Equation (4.4) and the corresponding fitted graph in Figure 4.1 (R^2= 0.9985).

$$CD_{remaining} = 2 \times 10^{-16} N_{cycle}^5 - 2 \times 10^{-12} N_{cycle}^4 + 5 \times 10^{-9} N_{cycle}^3 - 5 \times 10^{-6} N_{cycle}^2 - 0.0038 N_{cycle} + 99.961 \quad (4.4)$$

We use the battery internal management system records to find out the number of cycles already spent by the battery. Capacity degradation versus cycle number graph has been used in Figure 4.1 to find the capacity degradation at that particular cycle number. This information can now be used to calculate the real-time degradation as a percentage of the original capacity.

Costing for the degradation caused by the current charging-discharging cycle can be calculated using established battery performance data. As a battery cannot be used for vehicle-to-grid power transfer once the remaining capacity drops below 80% of the initial capacity, cost of the battery should be distributed to the range between 80% and 100% of the original capacity.

When using the GV batteries, the end-of-life (EOL) requirements of the batteries must also be addressed. When discharging the batteries, the state-of-charge (SOC) window should not cross a certain limit [89] to ensure the expected longevity and safety of the battery. Because of the EOL requirements of the battery, owners are always concerned about the depth-of-discharge (DOD) while discharging. The owners also look at the DOD range when selecting their weight factors for different cost items; as described in the following sections.

4.1.1.2 Battery opportunity cost

The cost to manufacture lithium-ion batteries depends on the time, size, and volume of the production run. Currently the opportunity cost is approximately \$1000/kWh [90][91]. Both opportunity and degradation cost are converted into a cost per cycle, and are then added together to find the per cycle charging-discharging cost. The cost per charging/discharging cycle, C_{cycle}, can thus be modeled as:

$$C_{cycle} = w_{opp} C_{opp} + w_{dgdn} C_{dgdn} \quad (4.5)$$

Weighting factors (ranging from 0 to 1) are selected by the owner, depending on the current cycle number and the DOD the batteries are required to operate up to. Before discharging a vehicle, an owner/owner's agent can look at this costing per cycle and corresponding battery capacity to analyze the revenue and battery lifetime.

If the current price of selling energy to the grid exceeds C_{cycle}, the GV may decide to

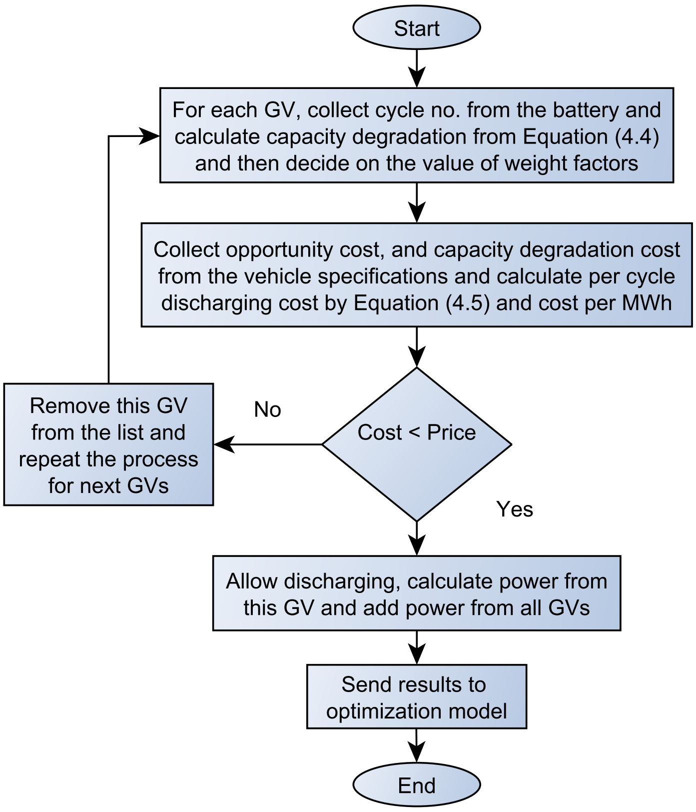

Figure 4.2: Flowchart for discharging decision by the owner of GVs in the SG using proposed model.

discharge; otherwise it should decline discharging. The flowchart for the decision making process is given in Figure 4.2. All the necessary parameters (including cost, and amount of energy from all the vehicles that discharge at a particular hour), are calculated to find the total cost of energy from the vehicles, $V_c(t)$ as follows:

$$V_c(t) = \sum_{s=1}^{N_{V2G-Dsch}(t)} E_s(t) p_s(t) \tag{4.6}$$

where E_s represents the amount of energy delivered from a GV in a cycle and p_s represents the price of unit energy for that GV.

4.1.2 Variation in per cycle charging/discharging cost and analysis of the vehicle-to-grid (V2G) economics

The cost of capacity degradation and consequently of per cycle discharging, changes according to the variation of the vehicle price, type of vehicle, and rate of discharge. Further, the cost of energy sold to the grid depends on the variation in the amount of energy actually sold, as this is directly related to the DOD, which ultimately affects the rate of capacity degradation per cycle. From previous research [87], we can relate the DOD to the cost per cycling of a battery. A DOD corresponding to discharge cycles of either less/more than that specified, require an adjustment factor of more/less than unity, respectively. The capacity degradation cost then becomes a direct product of the cost and the adjustment factor.

4.2 Optimization model for cost and emission reduction considering cost of vehicle energy

Wind and solar energy are largely emission free and their operating costs are negligible. Fuel cost for a conventional thermal generator is expressed as a quadratic function of the unit's generated power as follows [75]:

$$FC_i\left(P_i\left(t\right)\right) = a_i + b_i P_i\left(t\right) + c_i P_i^2\left(t\right) \tag{4.7}$$

where a_i, b_i and c_i are positive fuel cost co-efficients of unit i at time t.

Emissions cost is expressed as another quadratic function of the unit's generated power as follows [75]:

$$EC_i\left(P_i\left(t\right)\right) = \alpha_i + \beta_i P_i\left(t\right) + \gamma_i P_i^2\left(t\right) \tag{4.8}$$

where a_i, β_i, and γ_i are emissions co-efficients of unit i.

With GVs as sources in real-time, the load balance equation becomes:

$$\sum_{i=1}^{N} P_i\left(t\right) + P_{pv}\left(t\right) + \sum_{j=1}^{N_{V2G-Dsch}(t)} \zeta P_{vj}\left(\Psi_{pre} - \Psi_{dep}\right) + P_{wind}\left(t\right) = D\left(t\right) + Losses \tag{4.9}$$

With GVs acting as load or storage in real-time, the load balance equation becomes:

$$\sum_{i=1}^{N} P_i\left(t\right) + P_{pv}\left(t\right) + P_{wind}\left(t\right) = D\left(t\right) + Losses + \sum_{j=1}^{N_{V2G-Dsch}(t)} \zeta P_{vj}\left(\Psi_{dep} - \Psi_{pre}\right) \tag{4.10}$$

Adequate spinning reserves are considered for maintaining system reliability and the load balance equations which incorporate adequate spinning reserves are given below.

With GVs as sources of energy the load balance equation with reserve capacity is given as:

$$\sum_{i=1}^{N} P_i^{max}(t) + P_{pv}(t) + \sum_{j=1}^{N_{V2G-Dsch}(t)} \zeta P_{vj}(\Psi_{pre} - \Psi_{dep}) + P_{wind}(t) \geq D(t) + Losses + R(t) \tag{4.11}$$

and with GVs as loads or storage the load balance equation with reserve capacity is given as:

$$\sum_{i=1}^{N} P_i^{max}(t) + P_{pv}(t) + P_{wind}(t) \geq D(t) + Losses + R(t) + \sum_{j=1}^{N_{V2G-Dsch}(t)} \zeta P_{vj}(\Psi_{dep} - \Psi_{pre}) \tag{4.12}$$

Each thermal generator has a maximum and minimum power generation range, which is represented as:

$$P_i^{min} \leq P_i(t) \leq P_i^{max} \tag{4.13}$$

Charging/discharging up to certain maximum/minimum level, to prevent battery failure, is given by:

$$\Psi_{min} P_{vj} \leq P_{vj}(t) \leq \Psi_{max} P_{vj} \tag{4.14}$$

Number of vehicles that have been registered for charging/discharging from/to the grid, ${N_{V2G}}^{max}$ can take part during a predefined scheduling period.

$$\sum_{t=1}^{H} N_{V2G}(t) = N_{V2G}^{max} \tag{4.15}$$

Minimizing generation and emissions costs is considered as the objective of the SG; and load balance, reserve, power generation limit, charging/discharging limit are considered as the constraints.

The objective function for cost-emission optimization, therefore, is given by the below equation; subject to the above constraints.

$$\min\left(\sum_{i=1}^{N}\sum_{t=1}^{H}\left[w_c\left(FC_i\left(P_i(t)\right)\right) + w_e\left(\psi_i EC_i\left(P_i(t)\right)\right)\right] + V_c(t)\right) \tag{4.16}$$

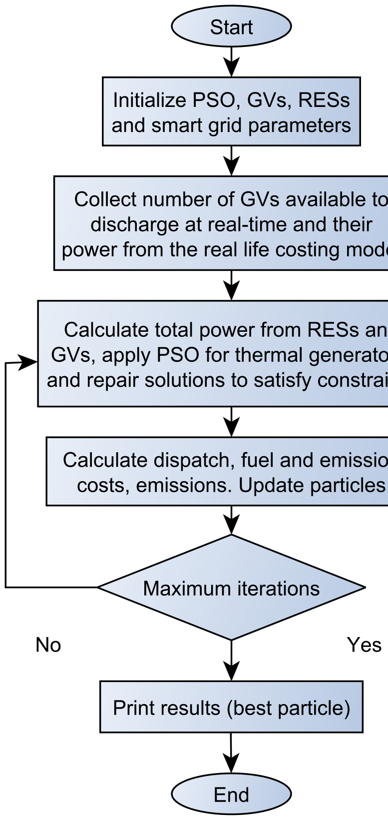

Figure 4.3: Flowchart for fuel and emissions cost minimization with RESs and GVs in the SG using proposed models.

4.3 Optimization method, simulation setup and results

An efficient optimization method is required to minimize fuel and emissions costs in a system consisting of thermal generators, RESs, and GVs. Particle swarm optimization (PSO) [83] is used to create an intelligent schedule of the power sources to justify the benefits of using our proposed cost models to achieve cost and emissions reductions. A basic description of PSO method is given in Chapter 3, Section 3.5. A flowchart for minimizing fuel and emissions costs with RESs and GVs in a SG, using our proposed models, is given in Figure 4.3. If at hour t, the schedule is; $[P_1(t), P_2(t), \ldots, P_N(t), N_{V2G\text{-}Dsch}(t), P_{pv}(t), P_{wind}(t)]^{\mathrm{T}}$, then power supplied to/from vehicles is $\zeta N_{V2G\text{-}Dsch}(t) P_{vj}\ (\Psi_{pre} - \Psi_{dep})$. The sign of this expression will indicate whether it is a load or source; and the rest of the load demand, given by the expression; $[D(t) + \zeta N_{V2G\text{-}Dsch}(t) P_{vj}\ (\Psi_{pre} - \Psi_{dep}) - P_{pv}(t) - P_{wind}(t)]$ will be met from the conventional thermal units.

The system described in this study includes thermal generators, RESs, and GVs in the SG environment. An on-board GV interface system and the parking station computer system communicate with all registered vehicles for collecting information on the vehicles' battery

Table 4.1: Generating unit capacity and coefficients

Unit	P^{min}(MW)	P^{max}(MW)	a ($)	b ($/MW)	c ($/MW^2)
1	100	500	240	7.0	0.0070
2	50	200	200	10.0	0.0095
3	80	300	220	8.5	0.0090
4	50	150	200	11.0	0.0090
5	50	200	220	10.5	0.0080
6	50	120	190	12.0	0.0075

Table 4.2: Generator emissions coefficients

Unit	α (ton/h)	β (ton/MWh)	γ (ton/MW^{2}h)
1	10.33908	-0.24444	0.00312
2	32.00006	-0.38132	0.00344
3	32.00006	-0.38132	0.00344
4	30.03910	-0.40695	0.00509
5	32.00006	-0.38132	0.00344
6	30.03910	-0.40695	0.00509

condition. This is how the owners will know the current rate of capacity degradation, and are able to decide if discharging will make revenue for them. GVs that discharge to the grid are eligible for charging at a subsidized rate for a period determined by the operator. An independent system operator (ISO) of a 6-unit system with 50,000 registered GVs has been simulated in this study. Unit characteristics of the system were taken from a relevant study [85] and are given in Table 4.1. Emissions co-efficients were taken from [75] and are given in Table 4.2. For GVs, the following parameter values were considered: GV battery capacity $S =$ 15kW, $H =$ 24 hours, minimum Ψ_{dep}= 40%, and ζ = 85%. For PSO, swarm size = 50, number of iterations = 1000, $c_1 = c_2 = 2$, $Range = 0.5$, ψ_i= 25 $/ton, and w_c= w_e= 1.

GVs arrive at parking stations randomly, so the number of GVs available may not meet the real-time requirement of the grid. Planning is thus necessary to provide a match between the number of GVs and the real-time demand. An availability planning model [92] does this matching by scheduling the GVs to discharge to the grid only when the grid needs them the most. The availability planning model provides a distribution of number of GVs that will discharge energy to the grid at different times throughout the peak periods.

In the availability planning model we divide the 50,000 registered vehicles into a group of 20,000 and a group of 30,000 for the two peak periods, *pk1* (9 am-4 pm) and *pk2* (4 pm-11pm), respectively. Mobility factors have been considered as described in Section 3.2. We have set the mobility factors m_1 and m_2 as 0.2 and 0.3, corresponding to *pk1* and *pk2*, respectively. We also assumed that around 0.2% of the GVs would not show up at all, giving us the proposed availability planning V_{disch} for each of the 24 hours of the day: V_{disch}=[0 0 0 0 0 0 0 0 16 336 2176 5456 5456 2176 336 37 441 2856 7161 7161 2856 441 21 0]. All GVs are assumed to be charged during each 24-hours period, and thus the total energy required to charge them is distributed over the hours when the demand is close to the base load demand. Economy of the charging load distribution over individual hours is dependent on the load demand, RESs generation, time-of-use pricing, generator parameters, and balance between cost and emissions. An intelligent coordination of all these factors has been performed, which gives us the following daily distribution of GV charging, where V_{chrg}= [20668 13333 6666 0 0 0 0 0 0 0 0 0 0 0 0 0 1667 0 0 0 0 0 1000 6666].

To study the effect of the proposed cost models with respect to cost and emissions reduction, these two models have been incorporated in the economic load dispatch (ELD) problem. PSO was used to minimise fuel and emissions costs for the economic dispatch. For RESs, solar insolation data, wind speed data, and generated power, and demand data over the 24-hour period have been taken from [75]. The Time-Of-Use pricing of energy (in \$/MWh) for a typical day is as follows [93]: from hours 7 to 17, price is 320.30; from hours 18 to 23, price is 332.00; and during all other hours, price is 145.90.

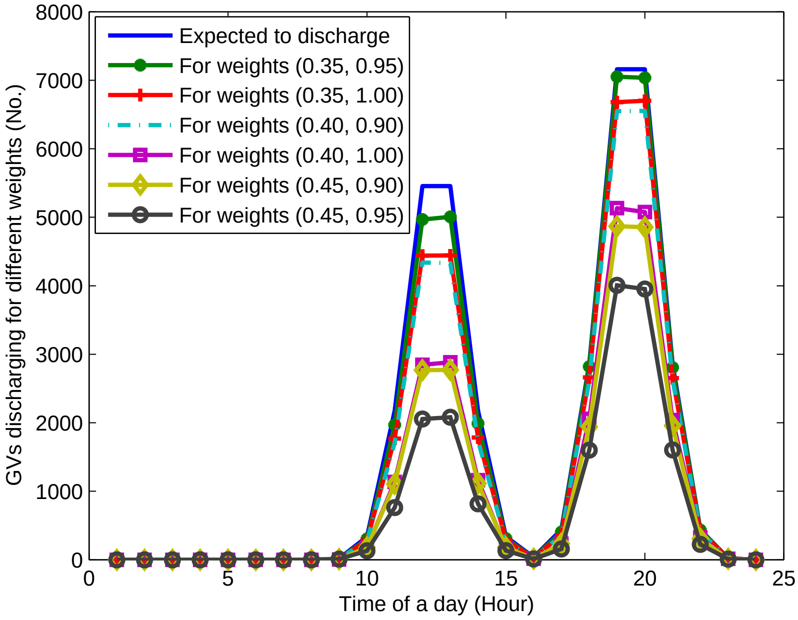

Figure 4.4: Number of discharging GVs at loss at different hours in a day for different weight factors (w_{opp}, w_{dgdn}) described in Equation (4.8).

For calculating per cycle charging-discharging costs, the opportunity cost has been taken

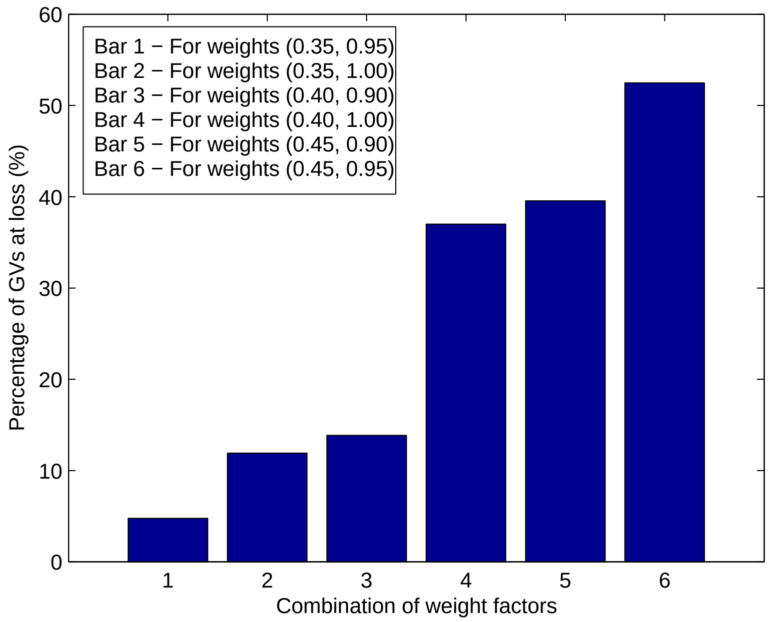

Figure 4.5: Percentage of discharging GVs at loss at different hours in a day for different weight factors (w_{opp}, w_{dgdn}) described in Equation (4.8), corresponding to Figure 4.4.

from the \$800-\$1200 per kWh range [90][91] (assuming a cycling capacity of around 4000 cycles). Capacity degradation cost is measured throughout the entire life of a battery until it is suitable for discharging to the grid. By taking battery costs from [90][91], capacity degradation cost for a 4000 cycle battery can be taken as \$6000-\$8000 throughout its discharging capacity lifetime. A random distribution of these costs has been considered, within the specified range, for all 50,000 vehicles.

Owners are free to choose the weighting factors in Equation (4.8) that best represent the cost of their vehicle's energy. Although vehicles discharge to supply the grid, they also discharge while being driven for everyday purposes, which accounts for a significant portion of the various cost items. Depending upon the situation, capacity degradation costs may account fully for each discharge cycle. A range of different weighting factors have been studied. From this study, the gross numbers of vehicles experiencing a loss, and the percentage with respect to the available vehicles have been calculated as shown in Figures 4.4 and 4.5. Figures 4.4 and 4.5 show that up to a 52.47% of vehicles can be in a loss condition, depending on the specific choices made by each owner. Even with a grid-friendly weight factor selection, which is unlikely to happen from the owners' perspective, at least 4.76% of the vehicles would be operating at loss.

To reflect the differences in weighting factor selection from different GV owners, the calculations have been performed again allowing the weighting factors to vary randomly within a

Table 4.3: PSO results for economic load dispatch scheduling with vehicle energy and costs considered without energy price checking

Time (H)	Unit-1 (MW)	Unit-2 (MW)	Unit-3 (MW)	Unit-4 (MW)	Unit-5 (MW)	Unit-6 (MW)	Solar (MW)	Wind (MW)	GVs (MW)	Demand (MW)	Loss (MW)	Total Cost ($)
1	170.45	152.41	160.38	104.90	149.80	101.68	0.00	10.54	-131.76	700.00	18.40	17967.96
2	168.57	150.84	158.78	103.79	148.22	100.55	0.00	22.27	-85.00	750.00	18.02	17707.78
3	180.40	161.13	169.10	110.89	158.37	107.67	0.00	25.50	-42.50	850.00	20.56	19420.21
4	192.98	172.08	180.08	118.48	169.12	115.21	0.00	25.50	0.00	950.00	23.45	21362.12
5	204.41	182.05	189.89	125.38	178.87	120.00	0.00	25.50	0.00	1000.00	26.11	23158.92
6	231.45	200.00	213.21	141.58	200.00	120.00	0.00	25.50	0.00	1100.00	31.74	27092.55
7	255.29	200.00	233.61	150.00	200.00	120.00	0.09	25.50	0.00	1150.00	34.49	29286.39
8	273.87	200.00	249.47	150.00	200.00	120.00	17.46	25.50	0.00	1200.00	36.30	30849.98
9	323.11	200.00	291.20	150.00	200.00	120.00	31.45	25.50	+0.102	1300.00	41.36	35524.14
10	412.60	200.00	300.00	150.00	200.00	120.00	36.01	25.50	+2.142	1400.00	46.25	42317.36
11	450.69	200.00	300.00	150.00	200.00	120.00	38.06	25.50	+13.872	1450.00	48.13	48783.07
12	483.57	200.00	300.00	150.00	200.00	120.00	35.93	25.50	+34.782	1500.00	49.78	57904.84
13	377.49	200.00	300.00	150.00	200.00	120.00	36.78	25.50	+34.782	1400.00	44.56	50047.09
14	315.50	200.00	284.77	150.00	200.00	120.00	31.59	24.82	+13.872	1300.00	40.55	39027.93
15	279.80	200.00	254.51	150.00	200.00	120.00	9.70	20.74	+2.142	1200.00	36.89	32034.26
16	216.45	192.46	200.30	132.58	189.16	120.00	12.92	14.62	+0.2359	1050.00	28.73	25050.59
17	206.38	183.74	191.61	126.57	180.54	120.00	0.00	25.50	-7.8157	1000.00	26.53	24321.10
18	227.15	200.00	209.51	138.98	198.18	120.00	0.00	19.04	+18.207	1100.00	31.07	32248.91
19	257.80	200.00	235.79	150.00	200.00	120.00	0.00	25.50	+45.651	1200.00	34.74	43644.59
20	412.58	200.00	300.00	150.00	200.00	120.00	0.00	18.02	+45.651	1400.00	46.25	55803.82
21	330.81	200.00	297.67	150.00	200.00	120.00	0.00	25.50	+18.207	1300.00	42.19	41926.79
22	232.00	200.00	213.69	141.90	200.00	120.00	0.00	21.42	+2.8114	1100.00	31.81	28017.35
23	189.01	168.64	176.51	116.10	165.69	112.80	0.00	0.00	-6.2411	900.00	22.51	20772.68
24	174.46	156.00	163.98	107.34	153.32	104.12	0.00	2.55	-42.50	800.00	19.27	18552.13
Total fuel, emissions, and GV energy costs = $7,82,822.56												

Note: '+' and '-' signs for GV power stands for GVs as source and load, respectively.

Table 4.4: PSO results for economic load dispatch scheduling with vehicle energy and costs considered after energy price checking

Time (H)	Unit-1 (MW)	Unit-2 (MW)	Unit-3 (MW)	Unit-4 (MW)	Unit-5 (MW)	Unit-6 (MW)	Solar (MW)	Wind (MW)	GVs (MW)	Demand (MW)	Loss (MW)	Total Cost ($)
1	170.45	152.41	160.38	104.90	149.80	101.68	0.00	10.54	-131.76	700.00	18.40	17967.96
2	168.57	150.84	158.78	103.79	148.22	100.55	0.00	22.27	-85.00	750.00	18.02	17707.78
3	180.40	161.13	169.10	110.89	158.37	107.67	0.00	25.50	-42.50	850.00	20.56	19420.21
4	192.98	172.08	180.08	118.48	169.12	115.21	0.00	25.50	0.00	950.00	23.45	21362.12
5	204.41	182.05	189.89	125.38	178.87	120.00	0.00	25.50	0.00	1000.00	26.11	23158.92
6	231.45	200.00	213.21	141.58	200.00	120.00	0.00	25.50	0.00	1100.00	31.74	27092.55
7	255.29	200.00	233.61	150.00	200.00	120.00	0.09	25.50	0.00	1150.00	34.49	29286.39
8	273.87	200.00	249.47	150.00	200.00	120.00	17.46	25.50	0.00	1200.00	36.30	30849.98
9	323.13	200.00	291.21	150.00	200.00	120.00	31.45	25.50	+0.0765	1300.00	41.36	35517.73
10	413.65	200.00	300.00	150.00	200.00	120.00	36.01	25.50	+1.1411	1400.00	46.30	42081.92
11	457.20	200.00	300.00	150.00	200.00	120.00	38.06	25.50	+7.6946	1450.00	48.45	47375.61
12	500.00	200.00	300.00	150.00	200.00	120.00	35.93	25.50	+18.443	1500.00	50.62	54302.50
13	394.13	200.00	300.00	150.00	200.00	120.00	36.78	25.50	+18.940	1400.00	45.35	46242.31
14	319.00	200.00	287.73	150.00	200.00	120.00	31.59	24.82	+7.7775	1300.00	40.92	37488.73
15	280.34	200.00	254.99	150.00	200.00	120.00	9.70	20.74	+1.1730	1200.00	36.95	31783.01
16	216.46	192.50	200.34	132.60	189.17	120.00	12.92	14.62	+0.1339	1050.00	28.74	25022.97
17	206.70	184.00	191.86	126.72	180.86	120.00	0.00	25.50	-9.0461	1000.00	25.50	23985.69
18	228.79	200.00	210.94	139.95	199.60	120.00	0.00	19.04	+13.056	1100.00	31.38	30864.90
19	265.27	200.00	242.13	150.00	200.00	120.00	0.00	25.50	+32.557	1200.00	35.46	40205.66
20	452.85	200.00	300.00	150.00	200.00	120.00	0.00	18.02	+33.029	1400.00	46.90	52848.47
21	333.81	200.00	300.00	150.00	200.00	120.00	0.00	25.50	+13.190	1300.00	42.50	40673.34
22	232.29	200.00	213.96	142.08	200.00	120.00	0.00	21.42	+2.1038	1100.00	31.85	27827.76
23	189.00	168.64	176.48	116.10	165.68	112.86	0.00	0.00	-6.2539	900.00	22.51	20769.16
24	174.46	156.00	163.98	107.34	153.32	104.12	0.00	2.55	-42.50	800.00	19.27	18552.13
Total fuel, emissions, and GV energy costs = $7,62,387.67												

Note: '+' and '-' signs for GV power stands for GVs as source and load, respectively.

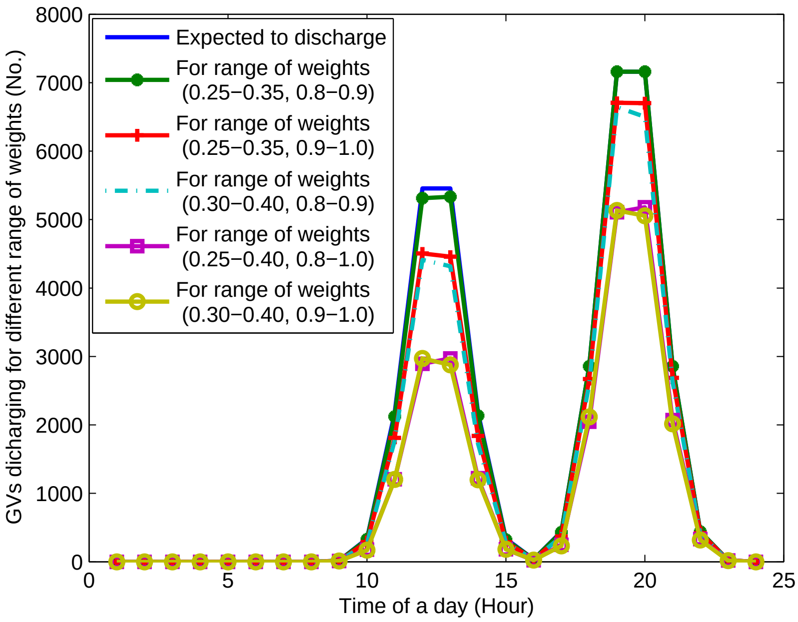

Figure 4.6: Number of discharging GVs at loss at different hours in a day for different ranges of weight factors (w_{opp}, w_{dgdn}) described in Equation (4.8).

certain range, and illustrated in Figures 4.6 and 4.7. Figures 4.6 and 4.7 show that even though different GV owners select a variety of weighting factors from within a given range, up to a 36.30% of vehicles can still be operating at a loss.

Resource scheduling has been performed with vehicles as sources, storage, and loads. Results for cost and emissions reduction in a SG system, incorporating the proposed availability planning model and the battery capacity degradation model, with real-world costing for wind, solar, and GVs are shown in Tables 4.3 and 4.4. As a likely real-world scenario, weighting factors representing the fourth bar in the bar chart of Figure 4.7 have been taken to select the number of discharging vehicles. Table 4.3 represents the economic load dispatch for a conventional SG model, and the planned availability distribution. Table 4.4 represents the same scenario for weighting factors of (0.25-0.40, 0.8-1.0) that leads to 35.85% of discharging vehicles operating at a loss, and hence being restricted from discharging.

As a result, 35.85% of the expected discharging vehicles have been saved from operating at a loss. The GV discharging distribution in this case is V=[0 0 0 0 0 0 0 0 12 179 1207 2893 2971 1220 184 21 248 2048 5107 5181 2069 330 19 0]. Signs for the GV energy in Tables 4.3 and 4.4 represent GVs as source (+) and load (-).

It is evident from Tables 4.3 and 4.4 that fuel and emissions costs have been reduced with our proposed models. As a considerable amount of power has been supplied from the vehicles,

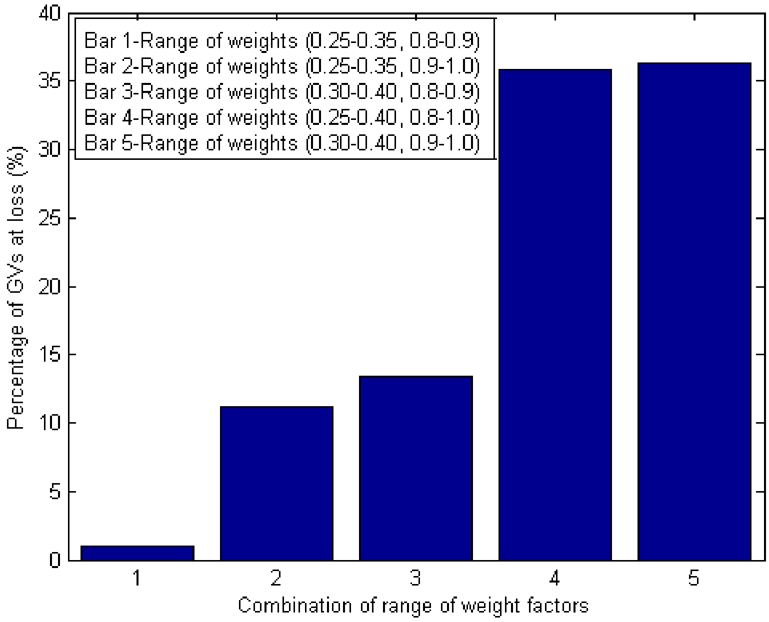

Figure 4.7: Percentage of discharging GVs at loss at different hours in a day for different ranges of weight factors (w_{opp}, w_{dgdn}) described in Equation (4.8), corresponding to Figure 4.6.

utilization of more renewable sources has been and would be possible, if it were available. Similar results with other combination of weighting factors justify the benefits of using our proposed models.

4.4 Discussions and benefits of the study

A summary of the benefits of using our model over a conventional model [2] are given in Table 4.5.

Table 4.5: Overall benefits of using our proposed model

Items	Conventional Model	Our Proposed Model
GVs at Loss	Up to 52%	Close to none
Expected GV Participation Rate	As low as 48%	Close to 100%
Total Cost	\$7,82,822.56	\$7,62,387.67
Potential for RESs Integration	Less	More
Basis of Discharging Decision	Non-Transparent	Transparent and Objective

For an ISO implementing V2G, total storage capacity potentially available from the GVs is dependent on the number of participating GVs and the effective discharging capacity of the GV batteries. Our proposed system model maintains the owners' confidence in their vehicles' operating conditions, as well as maintaining revenue outcomes against battery wear. At the same time, owners have the freedom to stop discharging to the grid should they be concerned that they are not earning any revenue, which would help provide an incentive to participate and remain in the grid discharge program. Because the individual owners are convinced of their revenue outcomes, the system operator can in turn be confident of the availability of a considerable number of GVs for discharge. As a result, both the vehicle owners and the system operator have their own freedom to choose any combination of buying and selling energy to/from the grid. Providing such a flexible arrangement will encourage more owners to participate in the grid discharge program, which is imperative if the GV integration is to be a success.

4.5 Conclusion

Using GV batteries as energy storage units for dealing with the variable RESs and loads in the SG environment has been an undesirable option for each individual operator. The low participation rate in the V2G discharge program has been a major concern in this perspective. The main obstacles being the owners' anxiety about battery lifetime, and concern over the ultimate benefit arising from using GVs as energy storage units. In this chapter, we have proposed a model that considers the issues associated with battery degradation and relevant costs, and have provided the owners of the GVs with a transparent tool for estimating the real-time cost of discharging to the grid, eradicating concerns that they will incur a loss over the long run. We have also proposed an economic load dispatch model that includes the cost of using GV energy in the objective function, along with the fuel and emissions cost of the thermal sources. Our proposed models will save discharging vehicles from experiencing a loss, which is expected to significantly increase V2G participation rate, to integrate more RESs, and ensure improved levels of sustainability. In addition, the models provide an assurance to the operators that GV energy is available, enabling them to deal with more variable generations and loads, and to maintain economic load dispatch with GVs.

Chapter 5

Second Use of Gridable Vehicle Batteries and the Economic Benefits

High cost of GV batteries is one of the major issues that concerns the owners in discharging their GVs to the utility grid. Second use of GV batteries can refund a portion of the initial battery cost if batteries in their second life can be used to serve other applications. In general, GV batteries are retired from their automotive life when they reach 70-80% of their initial capacity; however, they can still be used for other applications, requiring less power and energy content, in a second life [94]. Two important considerations, before using these retired GV batteries, are: i) whether the retired batteries are suitable for other applications from power and energy content perspectives, and ii) how long these batteries continue to serve other applications profitably. A model that provides these solutions is the goal of the research study presented in this chapter.

In this chapter, capacity degradation and the remaining energy of a GV battery at different operating cycles are quantified in both their automotive and second lives. Cost of battery energy both in automotive and second life is also modeled that informs the owners of the revenue potentials, especially from the second life use. Finally, an economic load dispatch model with the inclusion of second life revenue is developed to establish that using GV batteries in this way would earn extra revenue thus contributing to the initial buying price and encouraging more GV participation in the SG.

5.1 Modeling capacity degradation in automotive life and remaining capacity for second life batteries as storage

Battery capacity degradation depends on several factors, such as spent depletion cycles, age, operating temperature, size, type, and battery chemistry. The two most significant factors of capacity degradation are discharge cycling and storage loss. Every discharge cycle costs a fraction of the original capacity degradation regardless of the percent of depth-of-discharge (DOD) involved. Measuring the capacity loss per cycle is critical to estimating the residual capacity left in the battery after thousands of cycles already spent during the automotive life. Different researchers [87] have quantified the capacity degradation against the number of cycles spent according to a fixed DOD. However, in practice, no vehicle would have the same DOD in every discharge cycle regardless of driving profiles. The DOD can vary from 20% to 80%, which reveals that measuring capacity degradation for a fixed DOD is inadequate for determining the actual capacity degradation of a vehicle battery. To address this problem, battery capacity degradation is calculated in every discharge cycle for a DOD specific to that cycle. Let $CapD$ be the capacity degradation per cycle when the DOD is maximum, f_{DOD} be the factor for depth of discharge corresponding to DOD, f_{dsch_rate} be the multiplication factor for rate of discharge for a particular cycle. So, the percentage capacity degradation $Dgdn$ after CN automotive cycles is given by:

$$Dgdn_{CN} = \sum_{n=1}^{CN} \left(f_{DOD} \times f_{dsch-rate} \times CapD\right)_n \tag{5.1}$$

Another item of capacity degradation is the storage capacity loss which is an insignificant portion of the total capacity loss, yet countable given the range of years the batteries were in use. The third and final item is the operating temperature for the battery. Temperature effects are critical for capacity degradation, particularly when the vehicles are operated continuously for hours on the road and the battery temperature continues to vary with that of the environment. Combining all three factors of capacity degradation, the practical capacity degradation equation stands as:

$$Dgdn_{CN} = \left(\sum_{n=1}^{CN} \left(f_{DOD} \times f_{dsch-rate} \times f_{temp} \times CapD\right)_n + \left(f_{storage} \times Yr\right)\right) \times f_{temp} \tag{5.2}$$

where $f_{storage}$ stands for the degradation rate per year due to storage, Yr stands for number of years and f_{temp} represents the acceleration factor of capacity degradation due to temperature change. The modeling and/or quantification of all individual parameters in Equation (5.2) are described in the following paragraphs. From Equation (5.2), it is evident that determining the exact value of $CapD$ is very important for measuring the capacity degradation in each cycle at a specific DOD rate. $CapD$ is calculated by using Equations (5.3) and (5.4) as described below.

To implement our model in determining the actual capacity degradation of the batteries at the start of second life, the following fitted formula [87] has been used for measuring the capacity degradation with cycling.

$$Capacity_n = -4 \times 10^{-10} n^3 + 3 \times 10^{-6} n^2 - 0.008n + 100.37 \tag{5.3}$$

where $Capacity_n$ represents the remaining capacity in percent after being used for n automotive cycles. To calculate the capacity degradation for a particular number of discharge cycles, the difference in degradation between that particular cycle and the next cycle has been taken as follows:

$$CapD_n = Capacity_n - Capacity_{n-1} \tag{5.4}$$

For different DODs, the capacity degradation rates differ as well. Cycling capacity degrades at a linear rate with the change of DOD [87]. For illustration, cycling capacity degradation for 34% change of DOD is given by:

$$Capacity_{34\%DOD} = 100 - 0.0006n \tag{5.5}$$

whereas that for 51% and 68% change of DODs are respectively given by:

$$Capacity_{51\%DOD} = 99.89 - 0.0031n \tag{5.6}$$

and

$$Capacity_{68\%DOD} = 100 - 0.0055n \tag{5.7}$$

In order to model the capacity degradation rate at different DODs, the following equation has been proposed that fits the data presented in [87]:

$$Capacity_{d\%DOD} = 100 - (0.0006 + 0.00015 \times (d - 34)) \times n \tag{5.8}$$

where d represents the percentage DOD change for any particular discharge cycle. This equation is valid for DOD changes of 34% and above. As a close approximation to the above illustration, a direct multiplier of 0.025* d has been considered for the accelerated portion of the capacity degradation before or after 51% DOD. So the factor for DOD in Equation (5.2) would be given by Equation (5.9) and Equation (5.10) as the capacity degradation equation used in Equation (5.3) is derived for 51% DOD (and 20 degree Celsius temperature) only:

$$f_{DOD} = 1 + 0.025 \times (d - 51) \quad \Big\{ for \quad d \geqslant 51 \tag{5.9}$$

and

$$f_{DOD} = 1 - 0.025 \times (51 - d) \quad \Big\{ for \quad d < 51 \tag{5.10}$$

Recent research [95] on the effect of discharge C-rate with capacity degradation shows that if the C-rate does not exceed the maximum rating of the battery specification, discharge C-rate does not contribute to additional capacity fade, other than the ohmic heating, which can be taken into consideration with the temperature dependency of the degradation. It is known that batteries are often oversized, so EVs seldom discharge near the maximum battery rating.

The value of f_{dsch_rate} is taken as unity considering no significant variation in discharging C-rate and hence capacity degradation. This factor can be considered further in case C-rate deliberately exceeds the rated specifications. Capacity degradation for calendar storage is a phenomenon that degrades the battery capacity with aging even though the batteries are not in operation. It was established in [96] that battery efficiency decreases at a rate of 0.033 per year of storage so an additional factor for battery capacity degradation has also been considered. This loss should be added to the capacity loss due to cycling considering the DOD changes and temperature effects, which can be shown as:

$$CapD_{storage} = 0.033 \times Yr \tag{5.11}$$

Therefore, the degradation factor for storage can be given as:

$$f_{storage} = 0.033 \tag{5.12}$$

Effect of temperature on capacity degradation can be modeled with the Arrhenius equation [79][95] as follows:

$$\delta CapD\,(T) = \delta CapD_{reference} \times e^{-\frac{E_a}{R}\left(\frac{1}{T} - \frac{1}{T_{reference}}\right)} \tag{5.13}$$

where $\delta CapD_{reference}$ is the capacity fading rate under the reference conditions, R is the gas constant, E_a is the activation energy, T is the temperature and $T_{reference}$ is the reference temperature, both in Kelvin, and $\delta CapD(T)$ is the capacity fading rate at temperature T. So the factor for temperature effect is given by:

$$f_{temp} = e^{-\frac{E_a}{R}\left(\frac{1}{T} - \frac{1}{T_{reference}}\right)} \tag{5.14}$$

In our calculation, 20 degrees Celsius has been used as the reference temperature, activation energy has been taken as 78.06 Kmol/J, and gas constant is 8.3144621 J/Kmol. Considering the above descriptions, the parameters in Equation (5.2) are replaced by their corresponding values to determine the actual capacity degradation at a specific cycle.

5.2 Modeling capacity degradation and energy delivering capacity of second life batteries in practical applications

Prior to using the second life batteries as energy storage units for the grid services or other applications, capacity degradation rate and energy handling capacity in their second lives must be known to avoid potential disappointments. This is also essential for understanding the battery 'physiology', both from physical and chemical perspectives, to determine the second life duration of the batteries in a particular application. Given that the main purpose of using the second-hand batteries is to recover a portion of the initial battery cost, second life performance of the batteries must be quantified in terms of revenue earning potential. This is determined by their second life power and energy performance, regardless of any criteria in their automotive life.

A semi-empirical model for capacity degradation and the related energy handling capacity of the second-use batteries is proposed to measure their performance, and hence quantify the revenue potential from these batteries. Second life batteries will have less strength as compared to their first life. Three assumptions surrounding the capacity degradation and subsequent life time calculation for second life batteries warrant consideration:

1. The second life batteries would be used in a storage warehouse or shed where the environmental temperature would be the same as normal room temperature, so temperature related degradations are not of great concern.

2. The applications the second life batteries would serve require energy of various amounts

at different times and for different durations. It is therefore advisable that each battery only contribute a small amount of energy for a shorter duration,as a group of batteries will aggregate to serve any application.

3. According to the choices of owners, the energy storage warehouse will have batteries of different current delivering capacities. These batteries can then be grouped into low, medium, and high capacity batteries to match the energy demands of individual applications.

Based on these assumptions, capacity degradation of the second life batteries is quantified by starting from the endpoint of automotive life. Lifetime of the second life batteries must be determined to bolster the buyers' confidence in purchasing those batteries, even at a lower price. Considering the minimal impact of temperature on the capacity and separating the second life batteries of different current supplying capacity, Equation (5.2) is simplified for the second life as:

$$Dgdn_{CN_2} = \left(\sum_{n=1}^{CN_2} (f_{DOD} \times CapD)_n + (f_{storage} \times Yr) \right) \tag{5.15}$$

It may seem from the above equation that the rate of degradation of the second life battery would be less than that of first life, but this may not be the case due to the value of *CapD* in the second life. The manufacturer data supplied with a new battery provides information on the battery up to the end of their automotive life. Given that several studies [88] have identified the capacity degradation as the direct consequence of Lithium losses in the battery cells, *CapD* is likely to be higher in second life than in automotive life particularly as the rate of Lithium loss in the cells is believed to be higher as they age.

To reflect a real indication of this *CapD* value in the second life, the *CapD* rate is changed, which is a function of the number of cycles in the automotive life given by Equation (5.4), by adding the percentage of battery performance degradation of 3.3% per year [96] as an excess to the automotive life degradation. This 3.3% degradation is distributed throughout the year by distributing a 3.3/365 percent degradation per second life cycle.

To ascertain the remaining lifetime after the commencement of second life, a model is required that represents the progression of second use battery lifetime. Such an equation is modeled for estimating the remaining life of the second use batteries based on the battery chemistry and phenomenon of capacity degradation in real time.

CapSS and *CapES* are defined as the starting and ending point of the battery in the second life, respectively. *CapES* is the point after which the battery cannot reliably supply energy throughput to the load regardless of its remaining capacity. This is believed to be the "breakdown" or "threshold" point in the Li-ion battery life curve after which the rate of lithium loss is so significant as to make the battery unsuitable for further use [97]. Following equations are proposed to calculate *CapSS* and *CapES* :

$$CapSS = (100 - Dgdn_{CN}) \times Thru_{manf} \tag{5.16}$$

$$CapES = f_{threshold} \times Thru_{manf} \tag{5.17}$$

where $Thru_{manf}$ represents the manufacturer specified throughput capacity of a new battery before being used, and $f_{threshold}$ is the threshold point after which the battery cannot be reliably used for further discharge. The practical value of $f_{threshold}$ varies from 0.3 to 0.4 depending on the real time battery condition. A value of 0.3 is used throughout this study. Total throughput in the second life $Thru_2$ and estimated remaining lifetime of the usable second life battery $Life_2$ are given by:

$$Thru_2 = CapSS - CapES \tag{5.18}$$

$$Life_2 = \frac{Thru_2}{\sum\limits_{slc=1}^{k} (E_{Disch})_{slc}} \tag{5.19}$$

where E_{Disch} is the actual energy delivered from the battery at *slc*-th cycle of operation. This energy is a multiple of the power in watts and time in hours; power represents the current and the constant voltage rating of the battery (P = VI).

An important issue with both *CapSS* and *CapES* is that neither of these parameters is fixed for any two batteries as the battery's chemical properties determine these parameters. Statistical distributions for these parameters are thus worth considering. Two different Gaussian distributions can be used for these parameters, the mean and variance of which will be close to a real world representation. For the value of discharging current and discharge time, capacity vs. current data along with the time is taken to physically represent the second life battery capacities in grid's purposes. The energy content or throughput delivered per cycle or event of the second life battery use determines the number of cycles or events the individual battery can be used for. This can also be represented as a function of discharge throughput and the number of times they are used. So, the denominator in Equation (5.19) can be re-written as:

$$\sum_{slc=1}^{k} (E_{Disch})_{slc} = \sum_{slc=1}^{k1} (E_{LowDisch})_{slc} + \sum_{slc=1}^{k2} (E_{MediumDisch})_{slc} + \sum_{slc=1}^{k3} (E_{HighDisch})_{slc} \quad (5.20)$$

provided that

$$k = k1 + k2 + k3 \quad (5.21)$$

where $E_{LowDisch}$, $E_{MediumDisch}$ and $E_{HighDisch}$are energy parameters for discharging the batteries at lower, medium and higher rates and durations, respectively. Applying all the determining parameters in Equation (5.19), a lifetime range for the second life batteries is determined. Within that range, parameters can be set corresponding to the maximum and minimum possible lifetime of a second life battery that will ultimately provide reassurance to buyers of those batteries.

5.3 Maximum total throughput of a battery in both automotive and second life and cost contribution from the second life usage

The initial throughput capacity of a new battery as specified by the manufacturer is given by

$$Thru_{manf} = DOD_{manf} \times kWh_{manf} \times CN_{manf} \quad (5.22)$$

where DOD_{manf} is the manufacturer specified maximum DOD throughout the battery's automotive life, kWh_{manf} is the manufacturer specified energy throughput per cycle in kWh for maximum DOD, and CN_{manf} is the manufacturer declared number of cycles.

Total throughput of a battery is the sum of both automotive and second life throughput.

Automotive life throughput is given by

$$Thru_{auto} = DOD_{avg} \times kWh_{cycle} \times CN \quad (5.23)$$

where $Thru_{auto}$ is the total throughput already delivered during the battery's automotive life, DOD_{avg} is the average percentage of DOD throughout the battery's automotive life and kWh_{cycle} is the energy throughput per cycle in kWh for maximum DOD.

Throughput in the second life is given by Equation (5.18), which can be re-written as:

$$Thru_2 = DOD_{avg-2} \times kWh_{cycle-2} \times CN_2 \tag{5.24}$$

where $DOD_{avg\text{-}2}$, $kWh_{cycle\text{-}2}$, and CN_2 are the average DOD, energy throughput per cycle, and number of cycles operated in the second life, respectively.

Total throughput is thus given as:

$$Thru_{total} = Thru_{auto} + Thru_2 \tag{5.25}$$

Converting total throughput to financial measures, the initial cost of a battery can be justified and the contribution from the second life can be easily determined. Financial revenue from the automotive life Rev_{auto} can be calculated from the energy throughput and initial battery price in the following way:

$$Rev_{auto} = \frac{DOD_{avg} \times kWh_{cycle} \times CN}{DOD_{manf} \times kWh_{manf} \times CN_{manf}} \times Cost_{batt} \tag{5.26}$$

where $Cost_{batt}$ is the total initial cost of buying a new battery. Revenue in the second life depends on the remaining capacity of the battery, which will then be transferred to the net present value of the revenue earned after the automotive life. As capacity degradation in the automotive life increases, available energy throughput and consequent revenue earning in the second life decrease, and vice versa. For example, if the automotive life spends 6,000 cycles with an average DOD and degrades 25%, then the second life starts from 75% capacity and stops at 40% capacity at a different average DOD. But if the automotive life spends only 5,000 cycles with the same DOD and degraded 21%, the second life starts from 79% and is expected to deliver more throughput and more revenue from the second use.

Revenue in the second life is given by

$$Rev_2 = Thru_2 \times Rate_2 \tag{5.27}$$

where $Rate_2$ is the unit price of energy delivered in the second life.

Total revenue from the battery Rev_{total} is thus given by:

$$Rev_{total} = Rev_{auto} + Rev_2 \tag{5.28}$$

If Rev_{total} exceeds $Cost_{batt}$, a cost contribution from the second life use $Cost_{cntrb}$ is justified and is calculated as follows:

$$Cost_{cntrb} = Rev_{total} - Cost_{batt} \tag{5.29}$$

The motive for calculating the total revenue from both the automotive and second use of batteries is to demonstrate exactly at how many cycles in the automotive life a battery can start its second life and earn a revenue that ultimately contributes to the initial cost of the new battery and hence the battery energy.

5.4 Impact of cost recovery from second life battery use on cost and emission reduction

The only way to achieve the owners' confidence on the revenue outcome from their GVs is to provide them with some transparent information as to how vehicle-to-grid discharging can be beneficial to them, and in what financial amount. Using the vehicle batteries in their second life is a clear mean for earning extra revenue for the owners. This extra revenue can be seen as a recovery of initial battery purchase cost thus bringing down the battery price that in turn reduces the vehicle price. With a certain percentage of cost recovery from the second life use, energy price from a battery can be recalculated to a lower amount to ensure further opportunities to earn revenue from selling the battery energy. On the other hand, with a lower cost of battery energy, operators are in a better position to dispatch electrical loads to the ultimate consumers at a more affordable price. This way, the operators, the customers, and the GV owners are all benefited to make it a sustainable business case.

In the following subsections, an economic load dispatch model has been described and hence implemented to determine the exact monetary effect of the second use of GV batteries.

5.4.1 Proposed optimization model considering cost of vehicle energy

To demonstrate the effect of second life use of GV batteries, the economic load dispatch problem is implemented in a sustainable energy system by considering the cost contribution, to the battery energy cost, from their second life use. The power system optimization model used in this chapter is the same as that in Chapter 4, Section 4.2, except that the cost of vehicle energy is different due to the cost recovery from the second life use. The final optimization model is given below.

The system described in this chapter consists of thermal generators, RESs, and GVs. RESs are used as compulsory sources along with the thermal generators, while GVs are used as distributed storage devices to help balance loads. An optimization method is used to generate an intelligent schedule for cost and emission reduction. The economic load dispatch model formulated in this research is applied for a 24-hour period in a single day to illustrate the way of handling the load variations at different hours in a typical day.

As described above, the optimization model is similar to that in Chapter 4, Section 4.2, but the cost of battery energy is different. The total cost of energy from the vehicles will be less when the second use revenue from the batteries is considered. The reduced total cost of battery energy is denoted by $V_{c\text{-}2}$.

The objective function for cost-emission optimization considering the second use of vehicle energy, therefore, is given by the below equation; subject to the relevant constraints as described in Chapter 4, Section 4.2.

$$\min\left(\sum_{i=1}^{N}\sum_{t=1}^{H}\left[w_c\left(FC_i\left(P_i\left(t\right)\right)\right)+w_e\left(\psi_i EC_i\left(P_i\left(t\right)\right)\right)\right]+V_{c-2}(t)\right) \tag{5.30}$$

It is obvious from the above optimization model that the economy of the load dispatch will be influenced by the cost recovery from the second use of the GV batteries, establishing that alternate use of GV batteries is beneficial to the operators, GV owners, and the ultimate consumers.

5.4.2 Optimizing fuel and emissions costs

Particle swarm optimization (PSO) is used to create an intelligent power schedule to minimize fuel and emission costs in the system. PSO provides a population based search procedure where each individual called a particle, is represented by its position (state) and velocity. A brief description of PSO is given in Chapter 3, Section 3.5.

5.5 Simulation setup, results and discussions

The batteries considered in this simulation have 15 kWh capacity each. The manufacturer specified DOD = 80%, deep cycles allowed = 3,600, cost of battery = $12,000. To allow for maximum utilization of the battery in the automotive life, degradation has been allowed down to 70% of the original capacity (i.e., a total of 30% degradation in the automotive life) before retirement, while degradation down to 30% (i.e., a total of 70% degradation both in the automotive and second life) has been considered in the second life to maximize the second use of the battery energy. The initial charging-discharging capacity of a battery is considered 100%.

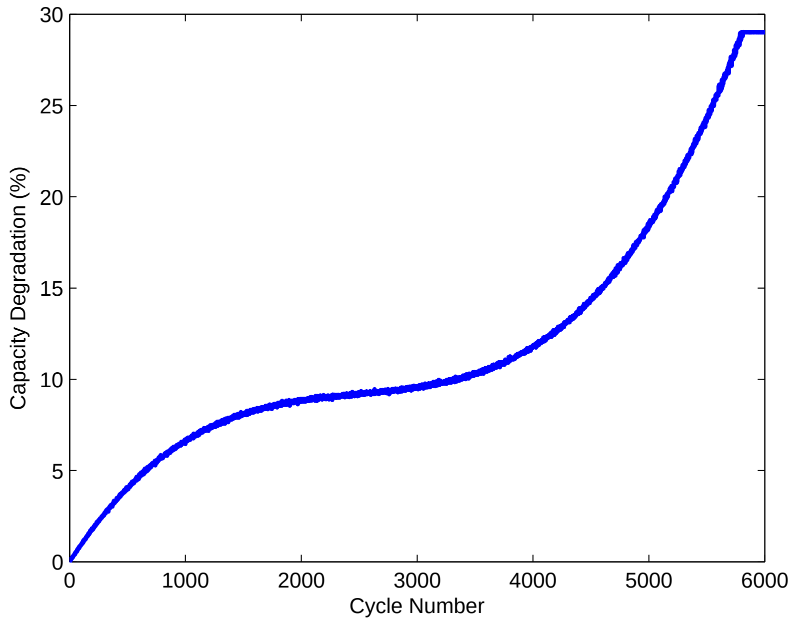

Figure 5.1: Cycle number spent in automotive life and corresponding capacity degradation curve considering the degradation due to both DOD and temperature variation. Average DOD = 59.99% and temperature variations from 20 to 60 degree Celsius.

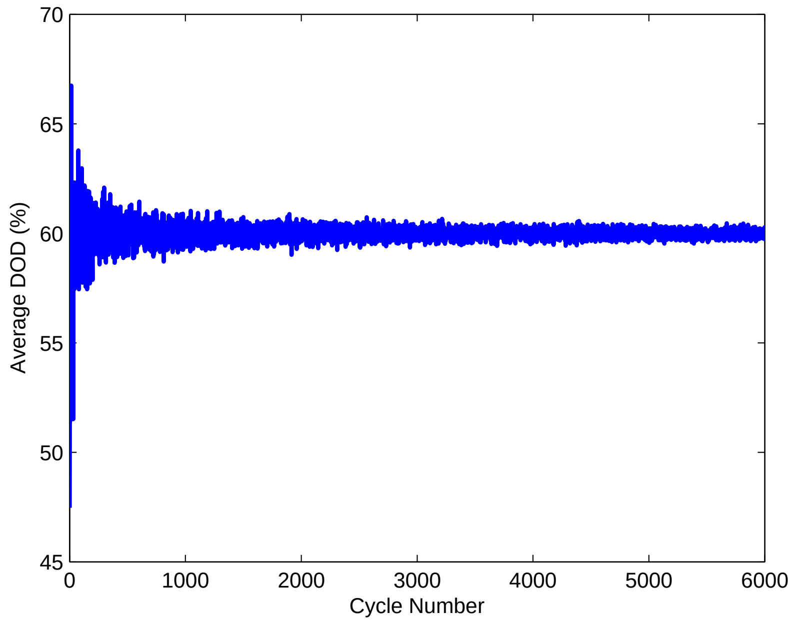

Figure 5.2: Cycle number spent in automotive life and corresponding average DOD allowing them to vary from 40 to 80 percent at random.

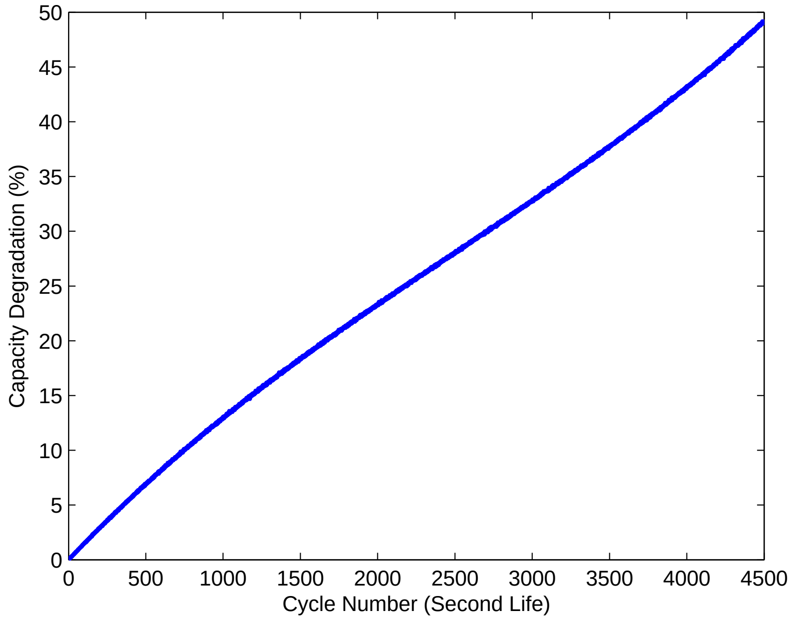

Figure 5.3: Cycle number spent in the second life and corresponding capacity degradation curve considering the degradation due to both DOD and temperature variation. Average DOD = 39.99% and temperature being fixed at 35 degree Celsius.

5.5.1 Capacity degradation and DOD changes

Capacity degradation in the automotive life for different number of cycles applied and DOD variations, as given by Equation (5.2) is shown in Figure 5.1.

Average change of DOD from the first through to the 6,000th cycle is 59.9923% (allowing them to vary from 40% to 80% at a uniform random distribution) as shown in Figure 5.2. The temperature variations have been allowed from 20 to 60 degree Celsius at a uniform random distribution. The simulation shows that capacity degrades up to 30% from the original capacity before reaching 6,000 cycles. More specifically, the capacity degrades up to 29.02% from the original capacity at the 5,821th cycle. As allowable degradation in the automotive life has been restricted to 30%, no further cycles have been simulated after this range. Capacity degradation in the second life, for different number of cycles spent and DOD variations, given by Equation (5.15) is shown in Figure 5.3.

Average change of DOD from the first through to the 4,500th cycle is 39.9945% (allowing them to vary from 30% to 50% at a uniform random distribution). The temperature has been kept fixed at 35 degree Celsius. The simulation shows that capacity degrades up to 50% of its second life starting capacity before reaching 4,500 cycles. As the allowable degradation in the automotive life has been restricted to 50%, no further cycles have been simulated after this

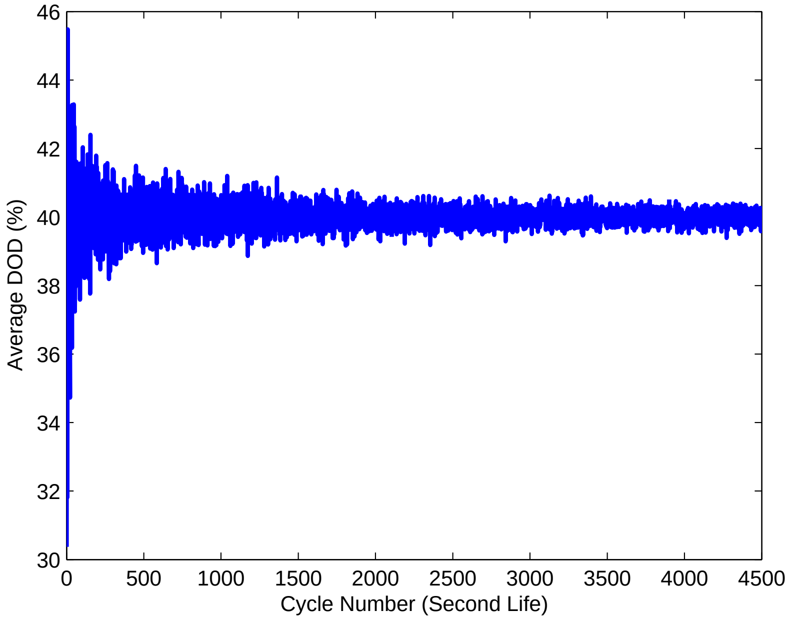

Figure 5.4: Cycle number spent in the second life and corresponding average DOD allowing them to vary from 30 to 50 percent at random.

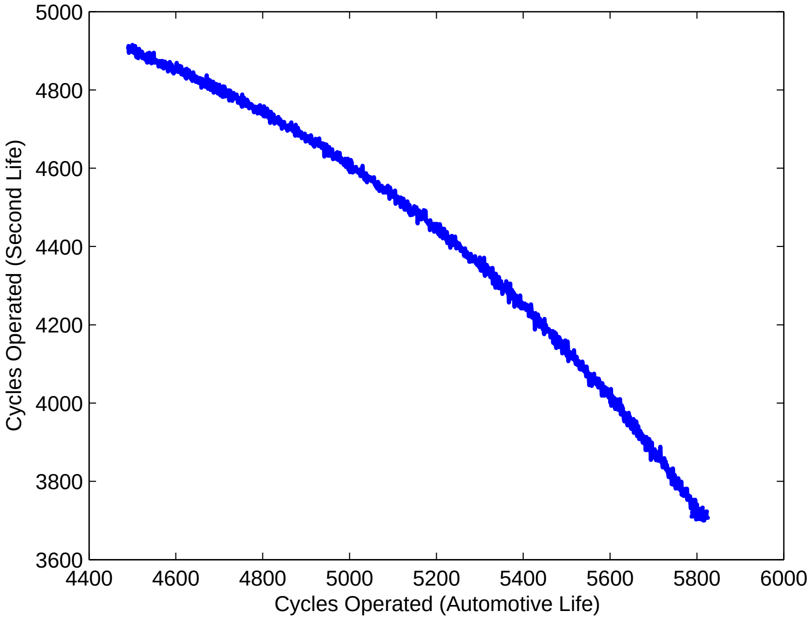

Figure 5.5: Cycle number spent in the automotive life vs corresponding cycle number spent in the second life that gives the maximum possible revenue within the allowable level of degradation in each stage.

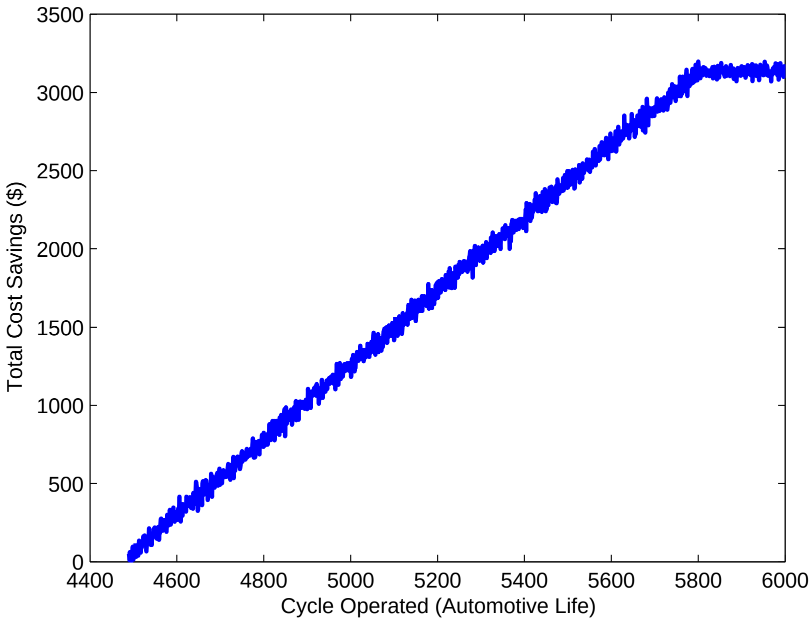

Figure 5.6: Cycle number spent in the automotive life vs total cost savings per battery from the use of second life within the allowable level of degradation in each stage.

range. The results are shown in Figure 5.4.

It is obvious from Figure 5.1 and 5.3 that degradation in the second life occurs at a further rate than that in automotive life. This is an expected outcome as the second life batteries are of less strength and energy capability. Similar conclusion can be drawn from Figure 5.2 and 5.4 regarding the average DOD over their entire lifetime. Average DOD in the second life settles well below that of the automotive life. Capacity degradation and DOD changes in Figures 5.1 to 5.4 have been obtained based on our modeling of such degradation, thus establishing the validity of our proposed models.

5.5.2 Number of cycles operated in both lives and corresponding revenue earnings

Considering the degradation both in the automotive and second life, the combination of the automotive and second life cycle numbers have been determined as shown in Figure 5.5. These cycle numbers have been constrained by the maximum allowable degradation level at each stage, which is in our case less than 30% in the automotive life and less than 70% as a summation of degradation both in the automotive and second life. The results, illustrated in Figure 5.5, show that cost contribution from the second life use starts from 4,490 automotive cycles regardless of the number of cycles in the second life. Before the 4,490th automotive cycles, the second life use still earns revenue, but total revenue from automotive and second life use does not exceed the battery purchase cost, which suggests that a battery should not retire from its automotive life before 4,490 cycles. Figure 5.5 also shows that the battery does not earn more revenue after 5,821 automotive cycles. Total contribution from the second use of batteries has been shown against automotive cycles spent in Figure 5.6, which suggests that a battery continues to earn revenue (measured both in automotive and second life combined) with increasing cycle number after 4,490 cycles till 5,821 automotive cycles.

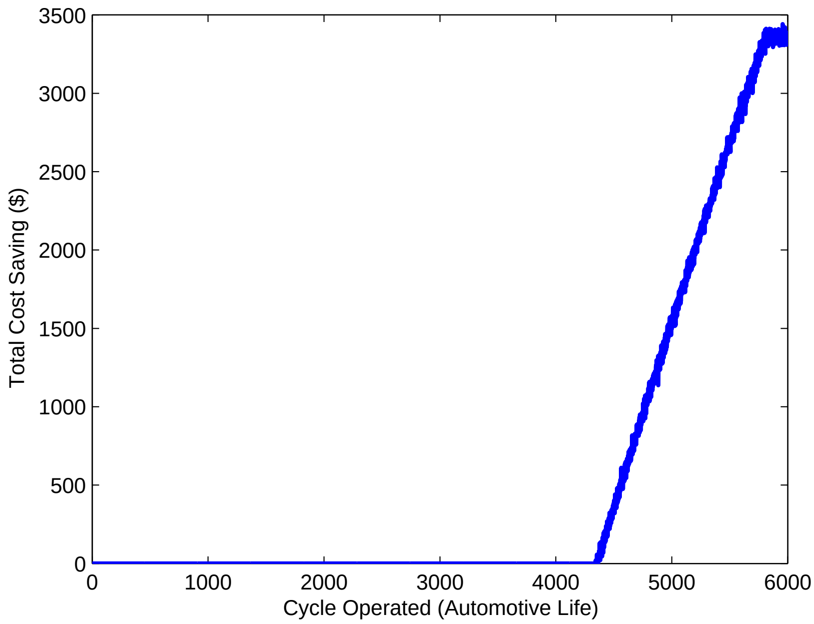

Figure 5.7: Cycle number spent in the automotive life vs total cost savings from the use of second life within the allowable level of degradation in each stage (Rate = \$37.5/MWh).

Cycle number where cost saving started and total cost saving were calculated on the basis of using the second life batteries only for regulatory purposes, at a minimum market price of \$27.50/MWh [98] energy capacity. Figure 5.5 suggests that cost saving starts at automotive cycle number 4,490 and stops after 5,821 cycles. Therefore, a battery can be operated up to 5,821 cycles in the automotive life before starting its second life. Provided that battery use in the automotive life earns more revenue than in second life, operating battery up to the maximum possible automotive cycle is the best possible option from the owner's perspective. Figure 5.5 also establishes a range of cycle numbers within which the battery can contribute to the initial buying price. This is a significant tool for the vehicle owners to decide when to start the second life according to their revenue requirements. Although the cost savings in this simulation has been calculated for using the second life battery for regulation purposes, a range of amount of cost savings can be established from simulation if the second life energy could be sold to other high demand applications. Basing on the demand and nature of applications for second use batteries, vehicle owners can optimize their revenue margin at any time. This revenue margin will encourage the existing owners to participate in the grid-discharge program and inspire new consumers to adopt a GV.

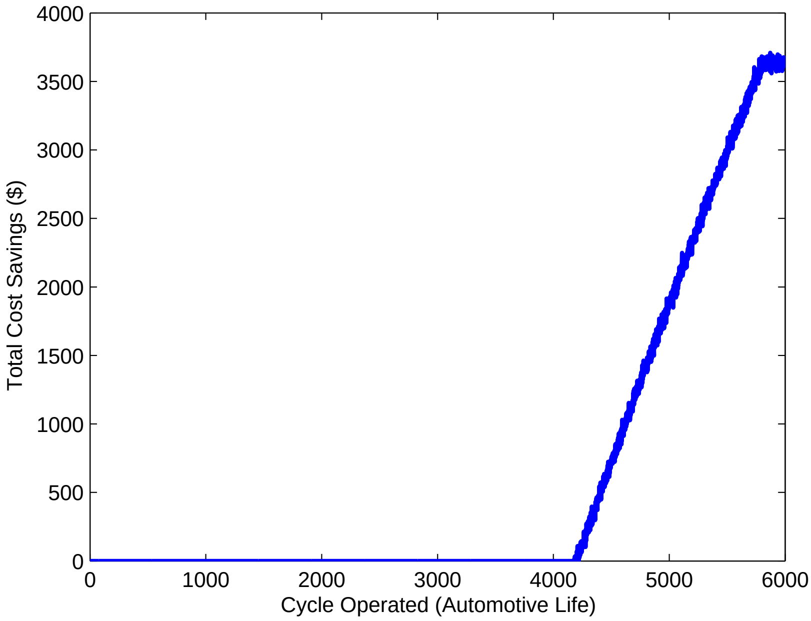

Figure 5.8: Cycle number spent in the automotive life vs total cost savings from the use of second life within the allowable level of degradation in each stage (Rate = \$50/MWh).

5.5.3 Sensitivity analysis of revenue figures

To verify the sensitivity of the cost saving with the value of regulation energy delivered in the second life, the regulation rate is changed to \$37.5/MWh and \$50.0/MWh to obtain the corresponding cost saving figures in Figure 5.7 and 5.8, respectively.

Figure 5.7 shows that total cost savings starts from 4,356 cycles in the automotive life and the amount of cost savings stalls after 5,821 cycles to around \$3,330, whereas in Figure 5.8, total cost savings starts from 4,186 cycles and the amount stalls to around \$3,640 after 5,846 automotive cycles.

It is thus confirmed that the starting of second life depends on, and is inversely related to, the energy selling price in the second life. The starting point for total cost savings also varies with the variation of battery buying price. The calculations presented up to now has been done considering the cost of battery as \$800/kWh capacity where cost savings started after 4,490

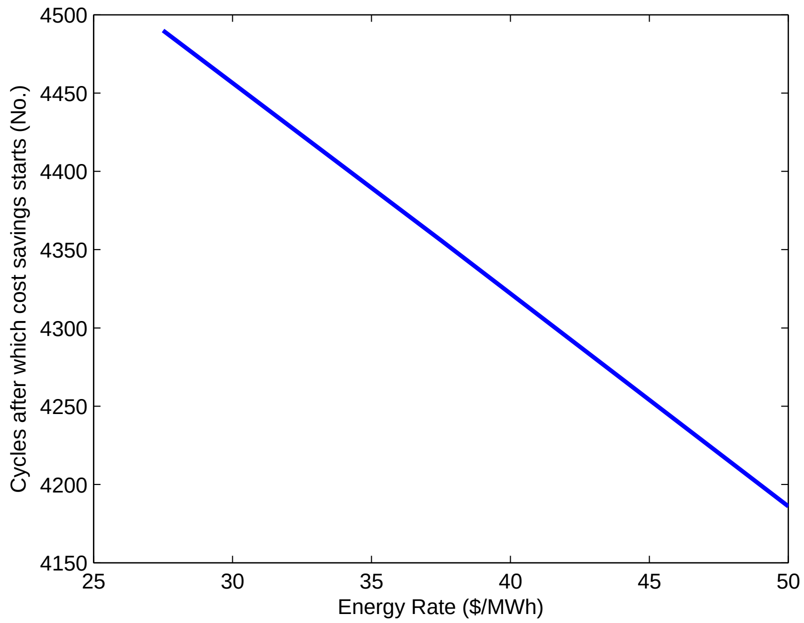

Figure 5.9: Cycle number in the automotive life after which total cost savings starts vs Energy Rate in the second life.

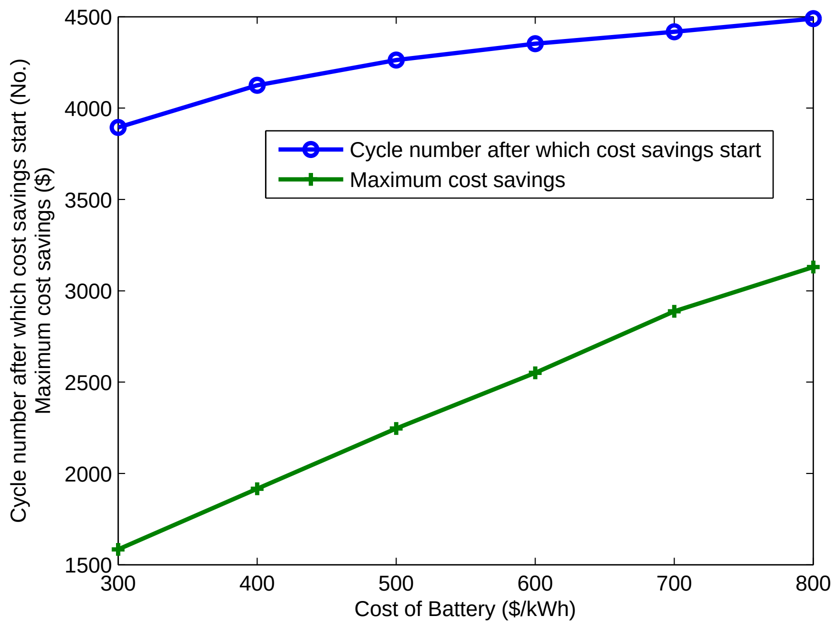

Figure 5.10: Cycle number in the automotive life after which total cost savings starts and maximum amount of cost savings vs cost of a new battery.

cycles and the maximum value amounted to around \$3,130. Figure 5.9 depicts the relationship of second life starting against energy price. Simulating the same situation for the battery cost of \$700, \$600, \$500, \$400, and \$300 per kWh capacity gives the cost savings starting point at 4,418, 4,353, 4,263, 4,125, and 3,894 cycles, respectively, where the maximum cost savings amounts to around \$2,888, \$2,551, \$2,246, \$1,916, and \$1,584, respectively (energy rate was fixed at \$27.5/MWh throughout the simulation). Figure 5.10 depicts the simulation results.

It is worth mentioning that with the decrease in cost of battery per kWh capacity, the amount of maximum cost saving decreases, but percentage of cost recovery increases. For instance, percentage of cost recovery is 26.08, 27.50, 28.34, 29.95, 31.93, and 35.20 for battery cost per kWh of \$800, \$700, \$600, \$500, \$400, and \$300, respectively. Figures 5.7 to 5.10 provides a clear understanding of the sensitivity criteria of the revenue figures from the second life use of a GV battery. For instance, with the increase in energy rate, revenue increases proportionately as shown in Figures 5.7, 5.8 and 5.9. This is due to the fact that with increased energy rate, cost savings starts early and continues for a wider range of cycles, thus contributing to a higher revenue figure. Another sensitivity criterion, as illustrated in Figure 5.10, is the initial battery price, which is expected to come down to a reasonable market price with mass production and technological advances [99]. While reduction in battery cost will lessen the financial burden for the GV owners in the near future, it will in no way discourage them to look for better revenue opportunities out of their purchased GVs. Revenue potential from second use of batteries thus remains as an ever demanding area to be explored that justifies this research as a necessary one. In order to account for the inflation rate and energy price increase with time, the net present value (NPV) of the cost savings is calculated to determine what amount of cost recovery is actually possible in regards to the current market prices. An annual energy price increase of 3% and inflation rate of 5% per year have been used and total lifetime of a battery is considered as 15 years to find the following multiplication factor in calculating NPV of the cost savings.

$$f_{NPV} = \frac{(1+0.03)^{15}}{(1+0.05)^{15}} = 0.75 \tag{5.31}$$

With this net-present-value factor applied, it can be concluded that at the NPV, percentage of cost recovery from the second use of GVs is 19.56 (i.e., 26.08*0.75), 20.63 (i.e., 27.50*0.75), 21.26 (i.e., 28.34*0.75), 22.46 (i.e., 29.95*0.75), 23.95 (i.e., 31.93*0.75), and 26.40 (i.e.,35.20*0.75) for battery cost per kWh of \$800, \$700, \$600, \$500, \$400, and \$300, respectively.

Table 5.1: Generator unit capacity and coefficients

Unit	P^{min}(MW)	P^{max}(MW)	a ($)	b ($/MW)	c ($/MW^2)
1	100	500	240	7.0	0.0070
2	50	200	200	10.0	0.0095
3	80	300	220	8.5	0.0090
4	50	150	200	11.0	0.0090
5	50	200	220	10.5	0.0080
6	50	120	190	12.0	0.0075

Table 5.2: Generator emission coefficients

Unit	α (ton/h)	β (ton/MWh)	γ (ton/MW^{2}h)
1	10.33908	-0.24444	0.00312
2	32.00006	-0.38132	0.00344
3	32.00006	-0.38132	0.00344
4	30.03910	-0.40695	0.00509
5	32.00006	-0.38132	0.00344
6	30.03910	-0.40695	0.00509

5.5.4 Load dispatch economy with second life use of GV batteries

In an effort to demonstrate the economy of load dispatch with the second use of GV batteries, the system considered includes thermal generators, RESs, and GVs in the SG environment. An on-board GV interface system and the parking station computer system are to communicate with all registered vehicles for collecting information on the vehicles' battery condition. GVs that discharge to the grid are eligible for charging at a subsidized rate all-round the month or year depending on the operator's choice. An independent system operator (ISO) of a 6-unit system with 50,000 registered GVs has been simulated in this study. Unit characteristics taken from [85], and emission co-efficients taken from [100] are given in Table 5.1 and 5.2, respectively. For GVs, vehicle battery capacity S=15kW, scheduling period H=24 hours, minimum departure charge=40%, system efficiency=85%. For PSO, swarm size=50, iterations=1000, acceleration parameters c_1= c_2=2, *Range*=0.5, ψ_i=25 $/ton, and w_c= w_e=1.

Considering a proposed availability planning model of the number of GVs, as mentioned in Chapter 4, Section 4.3, V for the 24 hours a day period, 50,000 registered vehicles are divided in 20,000 and 30,000 between two peak periods *pk1* and *pk2*, respectively. Vehicle mobility factors for the peaks *pk1* and *pk2* are taken as 0.2 and 0.3, respectively. The planning has been verified as suitable to make the SG reliable and sustainable, where V = [0 0 0 0 0 0 0 0 16 336 2176 5456 5456 2176 336 37 441 2856 7161 7161 2856 441 21 0]. The number of planned available vehicles V has been given again in Table 5.3 against hours of a day. Due to the freedom of GV

Table 5.3: Power from Solar and Wind sources, demand and GV energy data

Time (H)	Demand (MW)	Solar (MW)	Wind (MW)	Planned GVs (No.)	TOU price ($/MWh)	Discharging GVs (No.)
1	700.00	0.00	10.54	0	145.90	0
2	750.00	0.00	22.27	0	145.90	0
3	850.00	0.00	25.50	0	145.90	0
4	950.00	0.00	25.50	0	145.90	0
5	1000.00	0.00	25.50	0	145.90	0
6	1100.00	0.00	25.50	0	145.90	0
7	1150.00	0.09	25.50	0	320.30	0
8	1200.00	17.46	25.50	0	320.30	0
9	1300.00	31.45	25.50	16	320.30	16
10	1400.00	36.01	25.50	336	320.30	328
11	1450.00	38.06	25.50	2176	320.30	2098
12	1500.00	35.93	25.50	5456	320.30	5228
13	1400.00	36.78	25.50	5456	320.30	5239
14	1300.00	31.59	24.82	2176	320.30	2090
15	1200.00	9.70	20.74	336	320.30	317
16	1050.00	12.92	14.62	37	320.30	34
17	1000.00	0.00	25.50	441	320.30	418
18	1100.00	0.00	19.04	2856	332.00	2853
19	1200.00	0.00	25.50	7161	332.00	7142
20	1400.00	0.00	18.02	7161	332.00	7154
21	1300.00	0.00	25.50	2856	332.00	2851
22	1100.00	0.00	21.42	441	332.00	441
23	900.00	0.00	0.00	21	332.00	21
24	800.00	0.00	2.55	0	0	0
Solar farm size = 40 MW and Wind farm size = 25.5 MW.						

Number of registered vehicles is 50,000 and each vehicle delivers 6.375 kW power.

owners not to discharge to the gird for their specific selectivity criteria, a number of available vehicles would deny discharging and thus a selection model based on the time-of-use (TOU) energy pricing has been put in place to mimic the real-world situation that gives us the actual number of GVs discharging to the grid, as presented in column 7 of Table 5.3.

As a specific solution to the GV charging distribution, all GVs are considered to be charged during a 24-hour period and thus total energy required to charge them is calculated. This required energy is distributed over the hours when the demand is more or less close to the base load demand. Distribution of the GV charging load on individual hours depends on the load demand, RESs generation, time-of-use pricing, generator parameters, and balance between cost and emissions. An intelligent coordination of all these factors has been done as a test case, which gives us the following distribution of GV charging over a 24-hours period where $V =$ [20668 13333 6666 0 0 0 0 0 0 0 0 0 0 0 0 0 1667 0 0 0 0 0 1000 6666].

PSO has been used to calculate fuel and emission cost for the economic dispatch. For RESs

Table 5.4: PSO results for economic load dispatch scheduling with vehicle energy and costs considered without battery second use

Time (H)	Unit-1 (MW)	Unit-2 (MW)	Unit-3 (MW)	Unit-4 (MW)	Unit-5 (MW)	Unit-6 (MW)	Solar (MW)	Wind (MW)	GVs (MW)	Demand (MW)	Loss (MW)	Total Cost ($)
1	170.45	152.41	160.38	104.90	149.80	101.68	0.00	10.54	-131.76	700.00	18.40	17967.96
2	168.57	150.84	158.78	103.79	148.22	100.55	0.00	22.27	-85.00	750.00	18.02	17707.78
3	180.40	161.13	169.10	110.89	158.37	107.67	0.00	25.50	-42.50	850.00	20.56	19420.21
4	192.98	172.08	180.08	118.48	169.12	115.21	0.00	25.50	0.00	950.00	23.45	21362.12
5	204.41	182.05	189.89	125.38	178.87	120.00	0.00	25.50	0.00	1000.00	26.11	23158.92
6	231.45	200.00	213.21	141.58	200.00	120.00	0.00	25.50	0.00	1100.00	31.74	27092.55
7	255.29	200.00	233.61	150.00	200.00	120.00	0.09	25.50	0.00	1150.00	34.49	29286.39
8	273.87	200.00	249.47	150.00	200.00	120.00	17.46	25.50	0.00	1200.00	36.30	30849.98
9	323.16	200.00	291.21	150.00	200.00	120.00	31.45	25.50	+0.0383	1300.00	41.37	35508.11
10	413.43	200.00	300.00	150.00	200.00	120.00	36.01	25.50	+1.3515	1400.00	46.29	42131.39
11	456.70	200.00	300.00	150.00	200.00	120.00	38.06	25.50	+8.1664	1450.00	48.43	47482.84
12	497.97	200.00	300.00	150.00	200.00	120.00	35.93	25.50	+21.114	1500.00	50.51	54882.07
13	392.14	200.00	300.00	150.00	200.00	120.00	36.78	25.50	+20.834	1400.00	45.26	46694.54
14	318.74	200.00	287.50	150.00	200.00	120.00	31.59	24.82	+8.2429	1300.00	40.90	37606.13
15	280.28	200.00	254.87	150.00	200.00	120.00	9.70	20.74	+1.3388	1200.00	36.94	31825.98
16	216.48	192.49	200.31	132.60	189.15	120.00	12.92	14.62	+0.1530	1050.00	28.73	25028.15
17	206.70	184.03	191.90	126.74	180.82	120.00	0.00	25.50	-9.0843	1000.00	26.60	23975.26
18	228.30	200.00	210.51	139.68	199.20	120.00	0.00	19.04	+14.561	1100.00	31.29	31268.98
19	263.21	200.00	240.40	150.00	200.00	120.00	0.00	25.50	+36.146	1200.00	35.26	41146.52
20	422.11	200.00	300.00	150.00	200.00	120.00	0.00	18.02	+36.586	1400.00	46.71	53678.28
21	333.12	200.00	299.60	150.00	200.00	120.00	0.00	25.50	+14.216	1300.00	42.44	40929.55
22	232.23	200.00	213.88	142.04	200.00	120.00	0.00	21.42	+2.2759	1100.00	31.84	27873.87
23	189.95	168.65	176.55	116.06	165.76	112.81	0.00	0.00	-6.2794	900.00	22.52	20762.13
24	174.46	156.00	163.98	107.34	153.32	104.12	0.00	2.55	-42.50	800.00	19.27	18552.13
Total fuel, emissions, and GV energy costs = $7,66,191.84												

Note: '+' and '-' signs for GV power stands for GVs as source and load, respectively.

solar insolation, wind speed, and demand data over 24-hours in a day have been taken from [2]. Generated power from the solar source and the wind source for 24 hours in a day has been taken for simulation purpose. Table 5.3 shows the demand, amount of wind and solar energy considered [2][101], planned number of vehicles, and the real-time pricing of energy [93] in a typical day. For calculating per cycle charging-discharging costs, several recent studies [90][102][91] have been consulted and battery energy cost has been calculated as the total battery buying cost divided by the total energy throughput. For the batteries described in our study, per MWh battery energy cost would be ((12000*1000)/(0.8*15*3600))*1.08 = 300.00 dollars, where the multiplication factor 1.08 implies the overhead costs for maintaining the vehicles, batteries and the emission factors. Assuming that the vehicle owners have considered the cost recovery of using their batteries in the second life, the initial battery buying cost would be reduced by the amount of cost savings. Considering the NPV of the cost savings (Regulation Energy price of $27.5/MWh and cost savings of $3130), battery energy cost would be (((12000-(3130*0.75))*1000)/(0.8*15*3600))*1.08 = 241.3125 dollars.

Resource scheduling has been done with vehicles as sources, storage and loads. Results for cost and emission reductions, in a SG system incorporating the proposed availability planning model and real-world costing with wind, solar and GVs, are shown in Table 5.4 where the cost recovery from the second life use of the batteries has not been considered. Signs for the GV energy in Table 5.4 represent GVs as source (+) and load (-). Table 5.4 represents the total fuel and emissions costs when the battery energy price was set at $310/MWh so that the battery owner makes a profit of at least $10/MWh. Total fuel and emissions cost at this battery energy price is $7,66,191.84. If the second use of vehicle batteries are considered, the battery energy price drops to $251.3125/MWh (with $10/MWh profit as the battery energy cost is $241.3125/MWh), which changes the total fuel and emissions costs in hour 9 up to hour 16 and then hour 18 up to hour 22. Changing the battery energy price from $310/MWh to $251.3125/MWh gives a new total fuel and emissions costs of $7,56,507.02, thus saving a total of $9,684.82.

From economic perspectives, operators are reluctant to buy battery energy at a higher price. GV owners, on the other hand, are not happy to sell battery energy without a profit margin. Without considering the second life use of batteries, not many GV owners can see a profit margin thus leading to a non-participation in grid-discharging. When the second life revenue comes into account, estimated battery energy price reduces to a level that can earn profit from selling energy. This financial benefit would encourage more GV owners to participate in the grid-discharge program. With considerable amount of GVs participating as energy storage units in the SG will enable the operators to deal with more load and source variations. In particular, the operators will be able to integrate more RESs thus enhancing the overall sustainability of the SG.

5.6 Particular benefits of this study and their implications

For an ISO implementing vehicle-to-grid (V2G), total storage capacity potentially available from V2G depends on the number of GVs and the effective discharging capacity of the GV batteries. The useful energy storage capacity will be further determined by the GV owners' decisions as to what revenue the owner is agreed to sell the energy for and what ultimate revenue they earn for allowing their vehicles to help balance the utility grid. As a result, both the vehicle owners and the system operator have their own freedom of choosing any combination of buying and selling energy to/from the grid. The major achievement is that the vehicle owners have all the useful information needed to decide what and when to do with their GV batteries. Moreover, participation of more GV owners on the grid discharge program would bring down energy prices considerably and thus benefit both the power system operators and the consumers.

Table 5.5: Summary of benefits from our proposed models

Items	Without Second Use	With Second Use
GV profitability	Low	High
GV Participation Rate	Low	High
Total Cost	\$7,66,191.84	\$7,56,507.02
Potential for RESs Integration	Less	More
Basis of Discharging Decision	Non-Transparent	Transparent and Objective

A summary of the benefits of using our models is given in Table 5.5. The findings of this study can be scaled to meet the requirements of a larger grid if the whole grid considers integrating GVs in clusters in different distribution sites. For example, a large grid can define a specific number as GV requirement for a particular distribution site. This number can be different for different sites depending on their local demand, renewable energy variations, and central supply. In each distribution site, the operators can declare their real-time energy purchase price and hourly energy requirements that will allow the GV owners to decide on selling their GV energy. As individual distribution sites will manage their source and load variations separately, the central grid will require less computation and transaction complexities thus contributing to a stable grid.

In attracting the GV owners to sell their energy to the grid, the operators will have to offer a price that will enable the owners to make a profit. Because the owners are concerned about their battery capacity degradation, only a profit margin can encourage them to sell energy. In that circumstance, two things will impact the profitability of GV owners. The first one is the combination of the generating sources and the other one is the time-of-use pricing set by the operators. Generation mix impacts the real-time requirement of storage energy as different generation types have different variation profiles. Thermal and hydro-electric generating units can be pre-scheduled to minimize costs based on the day-ahead load profile. Starting time and cost of each unit will further determine the requirement for GV energy and its price. Time-of-use pricing plays an equal role in making profit for both operators and GV owners.

If the vehicle owner is free to choose whether to discharge or not and in what amount, considering their revenue outcome against the loss of battery utilizability, more owners will participate in the grid discharge program. This is a crucial requirement for making the GV integration a success. Providing a separate model to quantify the cost contribution from the second use of retired batteries is expected to encourage the owners towards bi-directional energy transactions.

5.7 Conclusion

Energy storage options with GVs have been considered with due consideration to the GVs' battery lifetime and their cost-effective use. Cost contribution from the second use of batteries has also been implemented towards contributing to the battery purchase cost. The proposed model gives both the owners and the system operator (on behalf of the electricity consumers) freedom to choose from options regarding whether to sell/buy and in what amount. An economic load dispatch model has been proposed that takes the second use cost contribution of batteries into account, yet maintains economic load dispatching. Providing a transparent model for cost contribution from the second use of batteries enhances the probability of vehicle owners' participation in the bi-directional power transfer.

Chapter 6

Gridable Vehicles and Second Life Batteries as Storage Backups During Short-Notice and Emergency Generating Unit Maintenance

As numerous generation and transmission assets, such as generators and transmission lines, in the SG system have already aged, well planned maintenance and operational scheduling is needed. Forced outages and short-notice/temporary maintenance of thermal units should also be considered as likely events. However, backup energy sources must replace these assets during the maintenance period. Using conventional storage (CS) devices for this purpose is feasible, but costly. Gridable vehicles (GVs) are an option as storage devices for this purpose. The high cost of GV batteries has necessitated approaches to cost recovery from using the retired GV batteries in various applications while research have shown the potential financial benefits from the second use [98]. Second life batteries (SLBs), disassembled from GVs after passing their automotive life, are another candidate for the same. Using SLBs as storage devices will also favor more integration of RESs as they too are subject to output variation that may have to be balanced with storage energy sources. Using GVs and SLBs for supplying backup energy during the maintenance/forced outage periods of thermal generators can save conventional storage energy costs and sustain power delivery. A system model that aggregates GVs and SLBs together in an intelligent way to provide backup during maintenance periods thus will benefit both operators and consumers. Such a system model is presented in this chapter to provide necessary and cost effective support to manage the maintenance works of the generation assets. Our simulation results suggest that using GVs and SLBs together can save up to 70% of storage energy costs and recover capital costs for the SLBs in only 1.5 years.

6.1 Overview of the proposed system model

Thermal generators are mechanical rotating devices requiring regular maintenance. Aged and overused thermal generators may require more frequent maintenance and overhauling during shutdown periods. Power system reliability is so important that operators are often forced to buy standalone storage energy sources; however, cost and space requirements of these storage are major concerns. Finding alternative energy storage sources at a reasonable cost and required reliability thus still remains an active area of research.

GVs and SLBs are suitable as storage devices from both economic and environmental sustainability perspectives. GV batteries can store energy during the off-peak hours and discharge the same at the peak hours. Capital costs for SLBs are much lower than that of conventional energy storage as SLBs are unsuitable for GVs, and might otherwise incur disposal costs. Using SLBs as lower capacity energy storage helps defer the battery disposal time by years thus favouring environmental sustainability. An intelligent system is required to ensure that GVs and SLBs can be aggregated to provide reliable, cost-effective storage. Modeling their aggregated performance is the principal purpose of the research work described in this chapter.

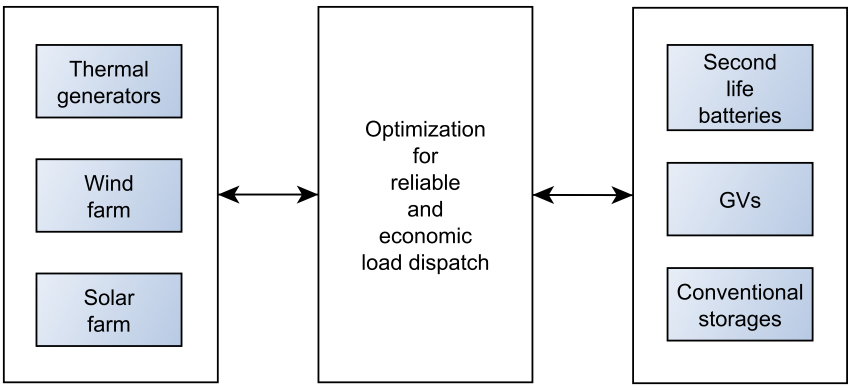

Figure 6.1: Schematic representation of the proposed system model.

In this chapter, we present a system model that uses GVs and SLBs as distributed energy resources to support implementing the economic maintenance schedule of the generation assets, and quantifying the associated financial savings relative to conventional storage devices. In our proposed system for the SG, thermal generators, RESs and storage devices are used to supply load and balance load variations. RESs are considered as essential for reducing emissions and running costs. GVs and SLBs are used as distributed storage devices while conventional battery storage are used as the last storage option. To deploy the available energy sources and storage devices cost-effectively, an intelligent energy source selection method is used to choose storage, along with an optimization method for scheduling power generation sources. Particle Swarm Optimization (PSO) is used to optimize costs and emissions in this study. A schematic model of our proposed system is given in Figure 6.1.

This chapter makes two main contributions. First, we model the energy cost of GV batteries and SLBs, and then coordinate these resources with the RESs to ensure appropriate grid planning. This model enables both the GV owners and the operator to trade-off the energy cost based on the real-time energy price, and backup energy required during a generator outage period. Second, we develop an economic load dispatch model for when a generating unit is off-line for maintenance purpose. The objective function for that model takes into account the cost of energy from SLBs, GVs, and CSs, in conjunction with the fuel and emission costs for thermal generators. This function is then re-evaluated with only the CSs costs, for relieving a generating unit for maintenance purpose, to determine the cost saving. These two models ensure economic management of generator maintenance works, and quantify the impact of using battery energy for this purpose.

6.2 Modeling energy cost of GV batteries and second life batteries (SLBs), and planning of battery energy use with renewable energy sources (RESs)

For laying-off a generation asset for maintenance works, sufficient storage energy needs to be available as backup, on a cost-effective basis. As GV batteries and SLBs continue to discharge to the grid, they tend to lose their useful life and capacity that their owners expect some compensation for.

Cost of energy from second life GV batteries depends on the end-of-life (EOL) condition and the market demand for such batteries. The cost of energy from SLBs, C_{slb}, is known in advance as the operators already have these batteries in hand. Usually, SLBs are cheaper and running costs of delivering energy form SLBs involves their recharging cost and battery condition monitoring cost.

GV batteries come with a specific number of deep discharge cycles, and the cost of GV battery is distributed over the number of deep discharge cycles. The cost per discharging energy unit from GVs, C_{GV}, will depend on the GV opportunity cost and the capacity degradation cost. Moreover, the availability of GV energy will depend on the real-time energy price C_{real} in the system. If the current unit price of energy exceeds C_{GV}, the GVs may decide to discharge; otherwise they should decline discharging. A trade-off then could be put in place to convince the GV owners to discharge to the grid, at a price agreed by both the GV owners and the operator.

A planning for using a right number of GVs and SLBs with RESs is important, because RESs too rely on the battery energy for balancing their variable generations. For instance, every operator schedules their thermal generating unit commitments based on forecasted data for the RES outputs, but this may differ from the real-time outputs so storage units meet any shortfalls to balance. For planning the use of battery energy with RESs, historical data for RESs and load demands is used and an appropriate distribution is used to ensure effective planning.

6.2.1 Modeling storage selection from GVs and SLBs

SLBs are owned by the operators and are always available to discharge provided they are charged themselves. Selection of these batteries for discharging will depend on the charging schedule and load demands at different hours. Being cheaper than any other storage options, using these batteries at the times of highest time-of-use (TOU) energy prices can ensure maximum economy for an operator. Historical data of such TOU pricing is consulted to plan the use of these batteries. A distribution of the total battery energy over a 24-hour cycle that takes account of the peak hours is used to determine the availability of these battery sources for grid discharging.

GV batteries are not always available for discharging due to two reasons: i) in real-time, vehicles are not available in significant numbers when the grid needs them the most. This is because driver behavior is non-deterministic and availability of GVs when needed depends on drivers' co-operation, and ii) even if sufficient number of GVs are available at a particular hour, their owners may be reluctant to discharge to the grid due to concerns over battery lifetime. Premature expiry of batteries is the reason behind that.

Real-time availability of GVs determines the total available power from GVs. A well considered selection model for GV batteries is thus important for allocating sufficient GVs, and their battery energy, at a particular hour of a day.

We use a GV selection model that takes into account the real-time battery condition and selects the GVs with a predetermined remaining lifetime while still maintaining a minimum average lifetime of the fleet of GVs under a particular operator as described in [92] as well as in Chapter 3, Sections 3.2 and 3.3. A portion of these selected vehicles are used for balancing the intermittency of the RESs, and the rest are used to discharge to the grid during generator outages.

6.2.2 Cost of energy from SLBs

SLBs are bought from the GV owners at a lower price. These batteries are aggregated in different combinations to supply the required energy according to the dynamically variable loads. While these batteries are always available for discharging, further capacity reduction and charging time and cost are the determining factors for their energy cost C_{slb}, which is calculated on a day-ahead basis. It is given by:

$$C_{slb} = \frac{C_{opp}\eta_{slb}}{Q} \times (1 + r_{slb}) \tag{6.1}$$

where C_{opp} is the opportunity cost per cycle, η_{slb} is the percent of initial capacity left in the SLB, r_{slb} is the margin of revenue in percentage for SLB, and Q is the recovery factor for SLB, valued between 5 and 10, depending on the market demand and suitability of these batteries.

6.2.3 Cost of energy from GVs

GV energy cost should account for both the opportunity cost and the capacity degradation cost. The latter depends on the number of discharge cycles a battery can efficiently operate up to and the depth-of-discharge (DOD) of the individual discharge cycles. If a battery worth a total of \$POB has N discharge cycles with d_{manf} DOD, then cost per kWh of energy C_{GV} from that battery at a DOD of d_{real} can be given by:

$$C_{GV} = \left(w_{opp}C_{opp} + w_{dgdn} \times \frac{POB}{N_{cycle}\left(1 \pm (d_{manf} - d_{real})\right) E_{cycle}} \right) \times (1 + r_{GV}) \tag{6.2}$$

where w_{opp} is the weight factor for C_{opp} and w_{dgdn} is the weight factor for C_{dgdn}, E_{cycle} is the energy discharged per cycle, and r_{GV} is the margin of revenue in percentage for GV. From the GV owners' perspectives, they may look forward to including a certain margin of revenue r in the C_{GV} for letting their GVs discharge to the utility grid.

Costing for the degradation caused by the current charging-discharging cycle can be calculated using established battery performance data. As a battery cannot be used for vehicle-to-grid power transfer once the remaining capacity drops below 80% of the initial capacity, cost of battery should be distributed to the range of 80% to 100% of the original capacity. Per cycle charging-discharging cost should therefore be calculated as a fraction of the whole 20% (i.e., 100%-80%) effective capacity of the vehicle-to-grid capable battery.

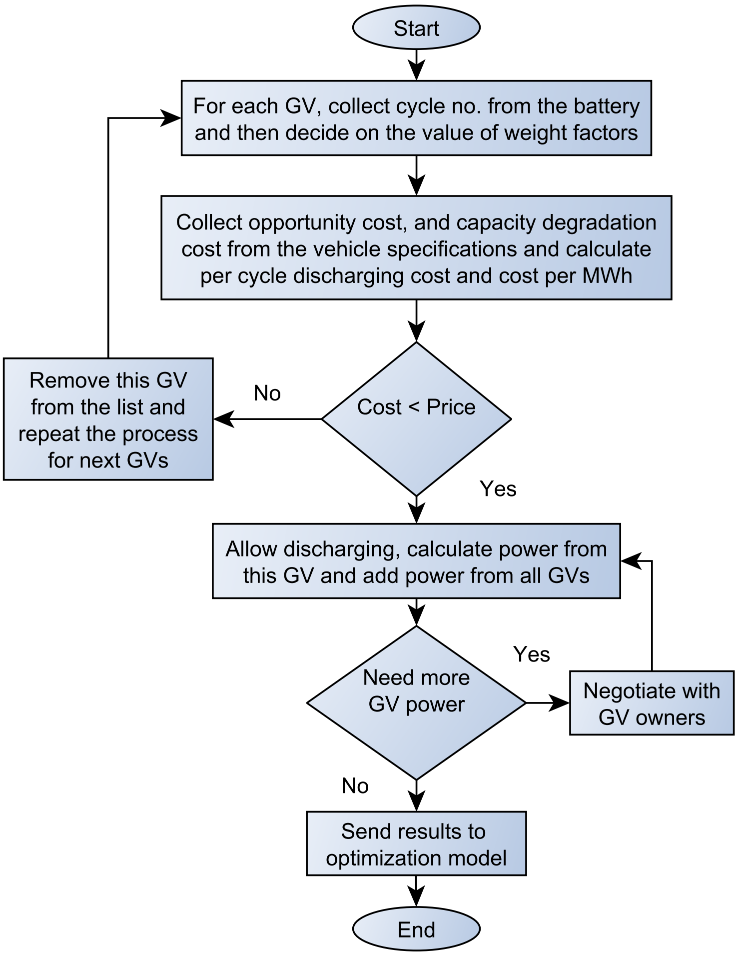

Figure 6.2: Flowchart for discharging decision by the owner of GVs in the SG using the proposed model.

EOL requirements of GV batteries must also be considered while discharging to the grid. Each battery has a specific number of deep discharge cycles, which in this study is estimated as 4000 over a lifetime of 13-15 years, depending on the manufacturer's specifications. When discharging the batteries, the state-of-charge (SOC) window should not cross a certain limit to ensure their safety and expected longevity [89]. The SOC window determines a battery's

DOD, which ultimately determines the actual energy it delivers. Because of the battery's EOL requirements, owners are always concerned about the DOD while discharging. The greater the DOD allowed, the shorter the expected battery lifetime. From this aspect, the owners also look at the DOD range when selecting their weight factors for different cost items; these are described below.

Weighting factors (ranging from 0 to 1) in Equation (6.2) are selected by the owner, depending on the current cycle number and the DOD at which the batteries are required to operate. Before discharging a vehicle, an owner/owner's agent can look at this costing per cycle and corresponding battery capacity to analyze the revenue and battery lifetime. If the current selling price of energy exceeds C_{GV}, the owners may decide to discharge; otherwise they should decline discharging. At this point a trade-off between the operator and GV owners can be puit in place if the operator needs more energy from GVs. The flowchart for the decision making process is given in Figure 6.2. An important point in this decision making process is the freedom enjoyed by both the GV owners and the grid operators in deciding on selling and buying the vehicle energy. At the same time, the GV owners are free to negotiate the price of battery energy based on their revenue expectations.

To improve the reliability of the power system, which is a measure of no possibility of blackouts due to the maintenance schedules of the thermal generating units, we propose to take additional measures. SLBs are always available, with the exception of their recharging time, but GVs are not always available and their state of charge condition and other lifetime factors affect the decision to discharge. With this variable storage device, a question of reliability is thus evident that leads to the inclusion of a minimum amount of CSs in the system even at a higher cost. This is worthwhile for maintaining the reliability of continuous energy supply from the system.

All necessary parameters (including cost, and amount of energy from all the vehicles that discharge at a particular hour) are calculated to determine the total cost of energy $V_c(t)$ from SLBs, GVs and CSs together as follows:

$$V_c(t) = \sum_{s=1}^{N_{GV}(t)} E_s(t) C_{GV}(t) + E_{slb} C_{slb} + E_{cs} C_{cs} \tag{6.3}$$

where E_s, E_{slb}, and E_{cs} are the amount of energy supplied from s-th GV, SLB, and CS respectively, and C_{cs} is the cost of unit energy from the CSs. This $V_c(t)$ will be included in the cost function for fuel and emissions cost reduction to ensure economic load dispatch with the storage energy sources as described in the following section.

6.3 Optimization model and method used for economic load dispatch during the maintenance period considering energy costs from GVs, SLBs, and conventional storage (CSs)

During the maintenance period of a thermal generating unit, total real-time load demand should be economically dispatched from the thermal generators, RESs, CSs, GV batteries, and SLB sources. Researchers have developed efficient optimization techniques [75] to accommodate RESs and GVs in the utility grid. However, these methods do not consider the real cost of CSs, GV energy and that of SLBs, in the objective function. In this study, we model that function considering the costs of energy from the SLBs, GVs, and CSs as described below.

Wind and solar energy are largely emission free and their operating costs are negligible. Fuel cost for a conventional thermal generator is expressed as a quadratic function of the unit's generated power as follows:

$$FC_i\left(P_i\left(t\right)\right) = a_i + b_i P_i\left(t\right) + c_i P_i^2\left(t\right) \tag{6.4}$$

where a_i, b_i and c_i are positive fuel cost co-efficients of unit i at time t.

Emissions cost is expressed as another quadratic function of the unit's generated power as follows :

$$EC_i\left(P_i\left(t\right)\right) = \alpha_i + \beta_i P_i\left(t\right) + \gamma_i P_i^2\left(t\right) \tag{6.5}$$

where a_i, β_i, and γ_i are emissions co-efficients of unit i.

With CSs, GVs, and SLBs as sources in real-time, the load balance equation becomes:

$$\sum_{i=1}^{N-1} P_i\left(t\right) + P_{pv}\left(t\right) + P_{CS} + \sum_{j=1}^{N_{GV}(t)} \zeta P_{vj}\left(\Psi_{pre} - \Psi_{dep}\right) + P_{SLB} + P_{wind}\left(t\right) = D\left(t\right) + Losses \tag{6.6}$$

where P_{CS} and P_{SLB} are the power output from CSs and SLBs, respectively. Number of thermal generating unit is considered (N-1) in this equation as one unit is off to maintenance.

With CSs, GVs, and SLBs acting as loads or storages in real-time, the load balance equation becomes:

$$\sum_{i=1}^{N-1} P_i\left(t\right)+P_{pv}\left(t\right)+P_{wind}\left(t\right)=D\left(t\right)+Losses+P_{CS}+P_{SLB}+\sum_{j=1}^{N_{GV}(t)} \zeta P_{vj}\left(\Psi_{dep}-\Psi_{pre}\right) \quad (6.7)$$

Adequate spinning reserves are considered for maintaining system reliability. Requirements for load balancing and adequate spinning reserves are given below.

With CSs, GVs, and SLBs as sources of energy, the load balance equation with reserve capacity is given as:

$$\sum_{i=1}^{N-1} P_i^{max}\left(t\right)+P_{pv}\left(t\right)+P_{CS}+P_{SLB}+\sum_{j=1}^{N_{GV}(t)} \zeta P_{vj}\left(\Psi_{pre}-\Psi_{dep}\right)+P_{wind}\left(t\right)\geq D\left(t\right)+Losses+R\left(t\right) \quad (6.8)$$

and with CSs, GVs, and SLBs as loads or storages, the load balance equation with reserve capacity is given as:

$$\sum_{i=1}^{N-1} P_i^{max}\left(t\right)+P_{pv}\left(t\right)+P_{wind}\left(t\right)\geq D\left(t\right)+Losses+R\left(t\right)+P_{CS}+P_{SLB}$$

$$+\sum_{j=1}^{N_{V2G-Dsch}(t)} \zeta P_{vj}\left(\Psi_{dep}-\Psi_{pre}\right) \quad (6.9)$$

Each thermal generator has a maximum and minimum power generation range, which is represented as:

$$P_i^{min}\leq P_i\left(t\right)\leq P_i^{max} \quad (6.10)$$

For GVs, charging/discharging up to certain maximum/minimum level, to prevent battery failure, is given by:

$$\Psi_{min}P_{vj}\leq P_{vj}\left(t\right)\leq \Psi_{max}P_{vj} \quad (6.11)$$

For SLBs, charging and discharging to certain maximum and minimum levels, respectively are ensured to prevent battery failure the same way, and are given by:

$$\Psi_{min(slb)}P_{SLBj}\leq P_{SLBj}\left(t\right)\leq \Psi_{max(slb)}P_{SLBj} \quad (6.12)$$

where $\Psi_{min(slb)}$ and $\Psi_{max(slb)}$ are the minimum and maximum levels of charge respectively,

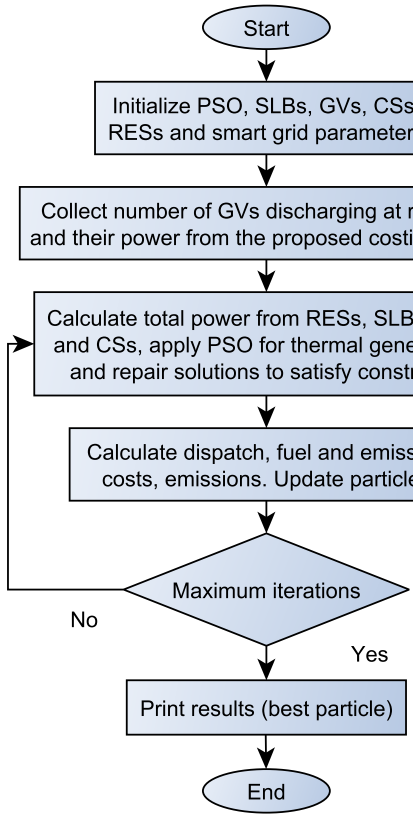

Figure 6.3: Flowchart for fuel and emissions cost minimization with RESs and GVs in the SG using the proposed models.

of the individual SLBs.

Number of vehicles that have been registered for charging/discharging from/to the grid, ${N_{GV}}^{max}$, can take part during a predefined scheduling period, where ${N_{GV}}^{max}$ is given as:

$$\sum_{t=1}^{H} N_{GV}\left(t\right) = N_{GV}^{max} \tag{6.13}$$

SLBs that are available for charging/discharging from/to the grid, ${N_{SLB}}^{max}$, can take part during a predefined scheduling period; and are given by:

$$\sum_{t=1}^{H} N_{SLB}\left(t\right) = N_{SLB}^{max} \tag{6.14}$$

Minimizing generation cost, emissions cost, and storage energy cost is considered as the objective of the SG; and load balance, reserve, power generation limit, charging/discharging limit are considered as the constraints.

The objective function for cost-emission optimization, including the cost for storage energy, therefore, is given by Equation (6.15); subject to the constraints in Equations (6.6) to (6.14).

$$\min\left(\sum_{i=1}^{N-1}\sum_{t=1}^{H}\left[w_c\left(FC_i\left(P_i\left(t\right)\right)\right)+w_e\left(\psi_i EC_i\left(P_i\left(t\right)\right)\right)\right]+V_c(t)\right) \tag{6.15}$$

Particle swarm optimization (PSO) [83] method is used to schedule the power intelligently towards minimizing fuel and emissions costs in a system consisting of thermal generators, RESs, SLBs, GVs, and CSs. The details of how the PSO works has already been described in Chapter 3, Section 3.5, and is not repeated in this chapter. The flowchart for the minimization of fuel and emissions costs for the described sytem in a SG, using our proposed models, is given in Figure 6.3.

If at hour t, the schedule is; $[P_1(t), P_2(t),\ldots, P_{N\text{-}1}(t), P_{CS}\ (t), P_{SLB}(t), N_{GV}(t), P_{pv}(t), P_{wind}(t)]^{\mathrm{T}}$, then power supplied to/from conventional storage, vehicles and SLBs is given by $P_{CS}\ (t)+P_{SLB}(t)+\zeta N_{GV}(t)P_{vj}\ (\Psi_{pre}\ \tilde{}\ \Psi_{dep})$. The sign of this expression will indicate whether the storage devices act as loads or sources; and the rest of the load demand, given by the expression; $[D(t)\ \pm\ \zeta N_{GV}(t)P_{vj}\ (\Psi_{pre}\ \tilde{}\ \Psi_{dep})+\ P_{CS}\ (t)+P_{SLB}(t)\ \text{-}\ P_{pv}(t)\ \text{-}\ P_{wind}(t)]$ will be met from the conventional thermal units. The '±' sign is used to mean that it would be a '+' when the storage devices act as sources and a '-'

when they are loads.

Table 6.1: Generating unit capacity and coefficients

Unit	P^{min}(MW)	P^{max}(MW)	a (\$)	b (\$/MW)	c (\$/MW^2)
1	100	500	240	7.0	0.0070
2	50	200	200	10.0	0.0095
3	80	300	220	8.5	0.0090
4	50	150	200	11.0	0.0090
5	50	200	220	10.5	0.0080
6	50	120	190	12.0	0.0075

Table 6.2: Generator emissions coefficients

Unit	α (ton/h)	β (ton/MWh)	γ (ton/MW^{2}h)
1	10.33908	-0.24444	0.00312
2	32.00006	-0.38132	0.00344
3	32.00006	-0.38132	0.00344
4	30.03910	-0.40695	0.00509
5	32.00006	-0.38132	0.00344
6	30.03910	-0.40695	0.00509

6.4 Simulation setup and generator maintenance schedule

The system described in this chapter includes thermal generators, RESs, CSs, GVs, and SLBs in the SG environment. An on-board GV interface system and a parking station computer system communicate with all registered vehicles for collecting information on the vehicles' battery condition. The same system communicates with the controller of SLBs to decide which SLBs will discharge when and for how long. A 6-unit system under an independent system operator (ISO) with 50,000 registered GVs and 50,000 SLBs has been simulated in this study. The simulation involves the situation in which only one of the thermal generators is off-line for maintenance purposes, thus leaving only 5 thermal units as operative. The total load is then optimally dispatched from these operative thermal units and the different battery storage sources. Unit characteristics and emission coefficients are taken from [85] and [75], respectively, and are given in Table 6.1 and 6.2. For GVs, following parameter values were considered: vehicle battery capacity S_{GV}=15 kW, H=24 hours, minimum Ψ_{dep}=40%, and ζ =85%. For SLBs, S_{slb}=10kW. For PSO, swarm size=50, iterations=1000, c_1= c_2=2, $Range$=0.5, ψ_i= 25 \$/ton, and w_c= w_e=1.

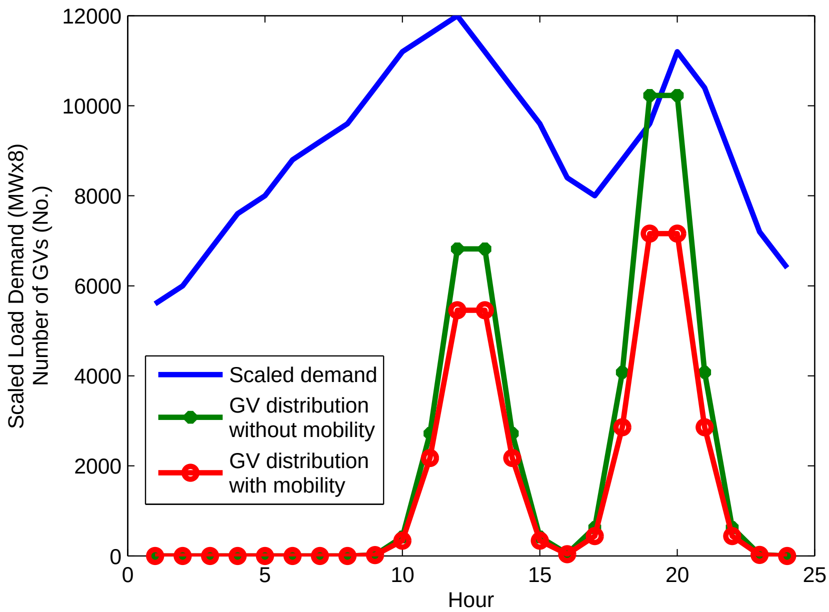

Figure 6.4: Load demands and GV discharging distribution.

SLBs are operators' own assets and are always available to discharge. GVs arrive at parking stations randomly, so the number of GVs available may not meet the grid's real-time requirement. Planning is thus necessary to provide a match between the number of GVs and the real-time demand. An availability planning model achieves this by scheduling the GVs to dis-

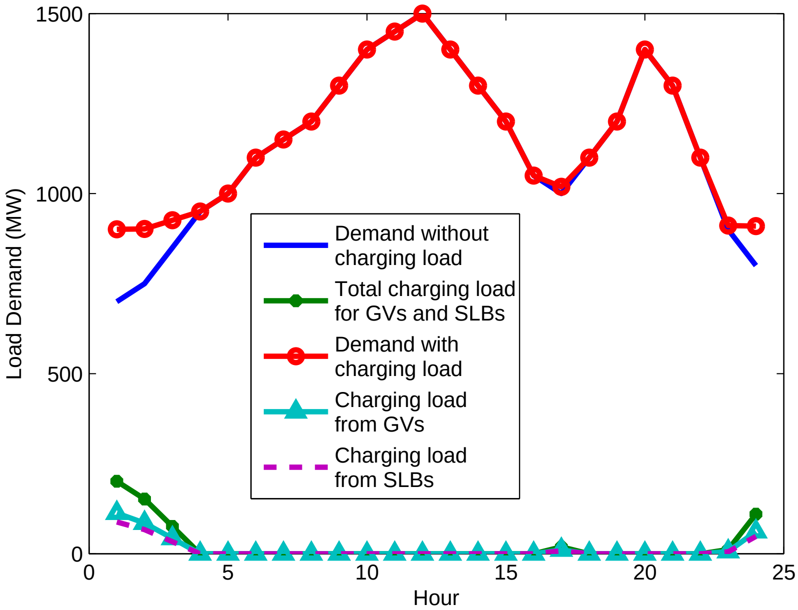

Figure 6.5: Hourly original load, recharging load, and combined load profile (charging each GV and SLB consumes 6.375 kW and 5 kW, respectively).

charge to the grid only when the grid has the greatest need for them.

As universal demand curves follow two peaks in a day (24 hours), and the load distribution is to some extent symmetric in these peak periods, we have used a Gaussian distribution model to schedule GVs availability for discharging to the grid, as shown in [92]. This distribution model provides the number of GVs that will discharge energy to the grid at different times throughout the peak periods.

In the availability planning model we divide the 50,000 registered vehicles into two groups of 20,000 and 30,000 for the two peak periods, *pk1* (9 am-4 pm) and *pk2* (4 pm-11pm), respectively. We have set the mobility factors m_1 and m_2 as 0.2 and 0.3, corresponding to *pk1* and *pk2*, respectively. We also assumed that around 0.2% of the GVs would not show up at all, giving us the proposed availability planning V_{disch} for each of the 24 hours of the day: V_{disch}= [0 0 0 0 0 0 0 0 16 336 2176 5456 5456 2176 336 37 441 2856 7161 7161 2856 441 21 0]. With this distribution, it may happen that real time demands are not met with only one generating unit being off-line for maintenance; steps should be taken to adjust the vehicle energy supply by dynamically changing the distribution of discharging vehicles. We propose using the Gaussian uniform distribution but with different distribution parameters approximating the variation in load changes. The load demand and the corresponding GV discharging distribution both with mobility of GVs considered, and not considered, are shown in Figure 6.4.

All discharging SLBs, GVs, and CSs (if used) are assumed to be charged during each 24-hour period, and thus the total energy required to charge them is distributed over the hours when the demand is close to the base load demand. The distribution of the charging load over individual hours depends on the load demand, RESs generation, time-of-use pricing, generator parameters, and balance between cost and emissions. Any operator could change this distribution according to their particular system requirements. An intelligent coordination of all these factors has been performed as a test case, which gives us the following distribution of GV and SLB charging over a 24-hour period, where V_{chrg}= [17668 13333 6666 0 0 0 0 0 0 0 0 0 0 0 0 0 1667 0 0 0 0 0 1000 9666]. The same distribution of charging of SLBs has been determined as economically acceptable, where battery charging distribution is B_{chrg}= [17668 13333 6666 0 0 0 0 0 0 0 0 0 0 0 0 1667 0 0 0 0 0 1000 9666]. This coordination has been done on the basis of keeping the total load demand close to the base load demands over 24 hours period, and ensuring that no artificial peak demand occurs due to these charging loads. The original consumer load, recharging load, and the modified/combined load (including recharging load) are shown in Figure 6.5.

The economic load dispatch (ELD) problem has been solved by using the proposed battery energy cost model and the GV and SLB discharging distributions. PSO was used to calculate fuel and emissions costs for the economic dispatch. For RESs, solar insolation data, wind speed data, and generated power and demand data, over the 24-hour period, were taken from [75]. The Time-Of-Use pricing of energy (in \$/MWh) considered for a typical day is as follows [93]: from hours 7 to 17, \$320.30; from hours 18 to 23, \$332.00; and during all other hours, \$145.90.

For calculating per cycle discharging costs, opportunity cost has been considered in the range of \$800-\$1200 per kWh [90][102][91] (assuming a cycling capacity of around 4,000 cycles). Capacity degradation cost is measured throughout the entire life of a battery until it is suitable for discharging to the grid. This is the real reduction in value of the vehicle in terms of its limited number of cycles and capacity. By taking battery costs from [90][102][91], capacity degradation cost for a 4000 cycle battery has been taken as \$6,000-\$8,000 throughout its discharging capacity lifetime. A random distribution of these costs has been considered, within the specified range, for all 50,000 vehicles.

As for selecting the weight factors in Equation (6.2), owners are free to choose the weighting factors that best represent the cost of their vehicle's energy. Although vehicles discharge to supply the grid, they also discharge while being driven for everyday purposes, which accounts for a significant portion of the various cost items. For example, an owner may logically divide the opportunity cost (for the initial investment and interests applicable for future years) between grid-discharging and usual driving. The proportion of each would be determined by the factors

Table 6.3: Demand and availability of GV sources in real time

Time (H)	Demand (MW)	Planned GVs (No.)	Parked GVs (No.)	Discharging GVs (No.)
1	700.00	0	0	0
2	750.00	0	0	0
3	850.00	0	0	0
4	950.00	0	0	0
5	1000.00	0	0	0
6	1100.00	0	0	0
7	1150.00	0	0	0
8	1200.00	0	0	0
9	1300.00	20	16	12
10	1400.00	420	336	179
11	1450.00	2720	2176	1207
12	1500.00	6820	5456	2893
13	1400.00	6820	5456	2971
14	1300.00	2720	2176	1220
15	1200.00	420	336	184
16	1050.00	50	37	21
17	1000.00	630	441	248
18	1100.00	4080	2856	2048
19	1200.00	10230	7161	5107
20	1400.00	10230	7161	5181
21	1300.00	4080	2856	2069
22	1100.00	630	441	330
23	900.00	30	21	19
24	800.00	0	0	0
Mobility factor for peak *pk1* is 0.2, and for peak *pk2* is 0.3.				

Number of registered vehicles is 50,000 and each vehicle delivers 6.375 kW power.

that suit the individual owners. Depending upon the situation, capacity degradation costs may account fully for each discharge cycle. The range of different weighting factors studied showed that only a portion of the available GVs are likely to discharge to the grid considering their revenue margins. For this study, a particular scenario has been simulated with weight factors w_{opp} and w_{dgdn} in the range of 0.25-0.40 and 0.8-1.0, respectively and yielded the number of GVs likely to discharge at real-time as shown in Table 6.3. The weighting factors w_{opp} and w_{dgdn} were allowed to vary randomly within these ranges to reflect the differences in weighting factor selection for different GV owners. Calculating all the parameters, cost of energy from discharging GVs was set at \$310/MWh. Cost of energy from SLBs were set at \$40/MWh considering the initial SLB purchasing cost recovery and lifetime issues. It is clear from Table 6.3 that not all available vehicles will discharge for grid's purpose, meaning a number of vehicles will be reluctant to discharge. At this point the negotiation from the operator's side starts and a group of GV owners agrees to discharge at a higher rate than others. The number of GVs and the price the operator negotiates depend on the real-time load condition and the availability of SLBs.

Table 6.4: Hourly maintenance schedule for generators

Unit	Hours on maintenance	Duration (Hours)	Priority
1	73-96	24	2
2	145-168	24	3
3	193-216	24	4
4	265-288	24	5
5	313-336	24	6
6	1-24	24	1

Maintenance schedule of the generators are finalised in consultation with the grid operators. It is assumed that the generator owners propose the maintenance schedule to the operators, who then assess the load demand and other generating sources, including GV batteries and SLBs to negotiate with the generator owners to review the maintenance schedule. The negotiated maintenance schedule is implemented with the help of other generating units and the battery energy. Individual generating units are scheduled for maintenance without affecting any other loads. As an illustrative example, the maintenance schedule in Table 6.4 was adopted after negotiation with the generator owners for the six generating units over a period of 14 days (336 hours).

The problem is formulated in such a way that maximum possible energy can be used from the SLBs first, and then from the GVs, either to compensate for the inoperative generator, if possible, or to support the running generators in meeting the load demands and ensuring enough reserve requirements. SLBs are already paid for, so maximizing their use is always cost-effective. It is considered that GV owners are already in a contract with the operators for recharging their GV batteries at a subsidized rate so maximizing the use of GV energy will also be cost-effective. For any energy requirement from the batteries, SLBs are used first, followed by the GV batteries.

Therefore, for any load requirement at a particular hour, the remaining generating units along with the SLBs are considered first for meeting the load demands and the reserve requirements. In case the demands are not met, GV battery energy is sought at an amount that satisfies those requirements.

In case those requirements are not met even with maximum available GV energy, extra storage energy is sought from CSs, even at a higher price, to enhance the power system's reliability. This step-by-step process of purchasing storage energy from different sources ensures economy of load dispatch based on the real-time load demands and reserve requirements.

6.5 Results and analysis

The results of our economic load dispatch simulation are given in Table 6.5. It is evident that in the event of forced outage or temporary maintenance of a generating unit, all the available energy from the SLBs has been utilized to partly provide the necessary backup energy. A total of 250 MW power was delivered for 1 hour duration, thus reducing the operator's costs as buying that much energy from the GV batteries or the conventional storages is more expensive. Considering the 6th unit down for maintenance purpose, total maximum thermal generating capacity of the system is 1,350 MW, so any load, including the line losses, above 1,350 MW, required extra storage energy from any of the available sources.

It should be noted that RESs are used first even before using the thermal generators. For example, in Table 6.5, when load was 1,400 MW at hour 10, more energy was needed even after using the RESs. Energy was first sought from the SLBs and the operator made a real-time decision on the number of SLBs to be deployed at any particular hour on the basis of amount of excess loads to be supplied at different hours in a day from the SLBs. 30 MW was required at that hour and was available, so other sources were not considered. Dispatch at hour 11 illustrates the full implementation of our proposed model when the load was 1,450 MW and the planned SLBs (by the operator) and GVs were unable to meet the total demand. The operator negotiated a higher rate of \$350/MWh with the owners of the remaining real-time available GVs leading to an additional supply of 6.18 MWh. A further shortage of 21.25 MWh had to be bought from CSs. In this particular case, in-house conventional storage has been avoided to save the operator from capital costs, and this remaining storage was bought from a third-party conventional storage battery source at a higher cost of \$400/MWh. Dispatch at all other hours was done the same way.

If SLBs and GVs were not integrated into the system and our proposed storage discharge model was not implemented, all required energy in excess of 1,350 MW would have been purchased from the conventional storage batteries, which are too costly. As a simple example of cost saving during a 24-hour period of operation, a total of 250 MWh from SLBs at a price of \$40/MWh, 78.11 MWh from GVs at regular price of \$310/MWh, and 18.30 MWh from GVs at negotiated rate of \$350/MWh have been used which would have otherwise been purchased from the cheapest possible conventional storage sources at a price of \$400/MWh. Therefore, a total saving of (250x(400-40)+78.11x(400-310)+18.30x(400-350))=\$97,944.90 has been achieved

Table 6.5: PSO results with SLB, GV and CS costs considered after energy price checking

Time (H)	Unit-1 (MW)	Unit-2 (MW)	Unit-3 (MW)	Unit-4 (MW)	Unit-5 (MW)	RESs (MW)	SLBs (MW)	GVs (MW)	Traded (MW)	CSs (MW)	Demand (MW)	Loss (MW)	Total Cost ($)
1	211.78	188.33	196.15	129.90	185.65	10.54	-88.34	-112.63	0.00	0.00	700.00	21.38	21243.51
2	209.01	185.91	193.75	128.24	183.32	22.27	-66.67	-85.00	0.00	0.00	750.00	22.27	20825.17
3	214.25	190.48	198.29	131.39	187.78	25.50	-33.33	-42.50	0.00	0.00	850.00	21.87	21623.05
4	220.34	195.73	203.51	135.02	192.98	25.50	0.00	0.00	0.00	0.00	950.00	23.09	22569.36
5	237.13	200.00	217.93	145.07	200.00	25.50	0.00	0.00	0.00	0.00	1000.00	25.63	24620.90
6	291.15	200.00	264.01	150.00	200.00	25.50	0.00	0.00	0.00	0.00	1100.00	30.66	29358.96
7	319.67	200.00	288.10	150.00	200.00	25.59	0.00	0.00	0.00	0.00	1150.00	33.36	32103.60
8	342.13	200.00	300.00	150.00	200.00	42.96	0.00	0.00	0.00	0.00	1200.00	35.09	34039.59
9	431.98	200.00	300.00	150.00	200.00	56.95	0.00	0.00*	0.00	0.00	1300.00	38.93	40031.54
10	499.30	200.00	300.00	150.00	200.00	61.51	+30.00	0.00*	0.00	0.00	1400.00	41.96	46974.47
11	500.00	200.00	300.00	150.00	200.00	63.56	+50.00	+7.70	6.18	21.25	1450.00	41.99	62602.17
12	500.00	200.00	300.00	150.00	200.00	61.43	+100.00	+18.44	12.12	0.00	1500.00	41.99	60651.18
13	490.32	200.00	300.00	150.00	200.00	62.28	+20.00	+18.94	0.00	0.00	1400.00	41.54	51328.81
14	432.55	200.00	300.00	150.00	200.00	56.41	0.00	0.00*	0.00	0.00	1300.00	38.96	40073.55
15	355.19	200.00	300.00	150.00	200.00	30.44	0.00	0.00*	0.00	0.00	1200.00	35.63	34825.55
16	261.59	200.00	238.88	150.00	200.00	27.54	0.00	0.00*	0.00	0.00	1050.00	28.00	26768.84
17	245.19	200.00	224.86	150.00	200.00	25.50	-8.34	-10.63	0.00	0.00	1000.00	26.59	25445.01
18	294.83	200.00	267.14	150.00	200.00	19.04	0.00	0.00*	0.00	0.00	1100.00	31.00	26699.79
19	360.35	200.00	300.00	150.00	200.00	25.50	0.00	0.00*	0.00	0.00	1200.00	35.85	35143.74
20	490.50	200.00	300.00	150.00	200.00	18.02	+50.00	+33.03	0.00	0.00	1400.00	41.55	56911.44
21	464.89	200.00	300.00	150.00	200.00	25.50	0.00	0.00*	0.00	0.00	1300.00	40.39	42569.91
22	293.47	200.00	265.99	150.00	200.00	21.42	0.00	0.00*	0.00	0.00	1100.00	30.88	29573.73
23	217.02	192.87	200.69	133.07	190.14	0.00	-5.00	-6.38	0.00	0.00	900.00	22.42	22052.26
24	216.03	192.03	199.81	132.45	189.30	2.55	-48.33	-61.62	0.00	0.00	800.00	22.22	21897.24
Total fuel, emissions, and storage energy costs = $8,32,933.37													

* GV power was available at this hour but the operator did not purchase power at this hour to ensure economic load dispatch.

Table 6.6: PSO results without SLB, but with GV and CS costs considered after energy price checking

Time (H)	Unit-1 (MW)	Unit-2 (MW)	Unit-3 (MW)	Unit-4 (MW)	Unit-5 (MW)	Solar (MW)	Wind (MW)	GVs (MW)	Traded (MW)	CSs (MW)	Demand (MW)	Loss (MW)	Total Cost ($)
1	189.72	169.20	177.06	116.62	166.77	0.00	10.54	-200.00	0.00	0.00	700.00	17.27	18050.87
2	192.38	171.47	179.34	118.21	169.07	0.00	22.27	-85.00	0.00	0.00	750.00	17.74	18416.56
3	205.91	183.27	191.04	126.34	180.68	0.00	25.50	-42.50	0.00	0.00	850.00	20.25	20362.04
4	220.34	195.73	203.51	135.02	192.98	0.00	25.50	0.00	0.00	0.00	950.00	23.09	22569.36
5	237.13	200.00	217.93	145.07	200.00	0.00	25.50	0.00	0.00	0.00	1000.00	25.63	24620.90
6	291.15	200.00	264.01	150.00	200.00	0.00	25.50	0.00	0.00	0.00	1100.00	30.66	29358.96
7	319.67	200.00	288.10	150.00	200.00	0.09	25.50	0.00	0.00	0.00	1150.00	33.36	32103.60
8	342.13	200.00	300.00	150.00	200.00	17.46	25.50	0.00	0.00	0.00	1200.00	35.09	34039.59
9	431.98	200.00	300.00	150.00	200.00	31.45	25.50	0.00*	0.00	0.00	1300.00	38.93	40031.54
10	500.00	200.00	300.00	150.00	200.00	36.01	25.50	+1.14	1.00	28.34	1400.00	41.99	60453.81
11	500.00	200.00	300.00	150.00	200.00	38.06	25.50	+7.69	6.18	64.56	1450.00	41.99	82926.04
12	500.00	200.00	300.00	150.00	200.00	35.93	25.50	+18.44	16.34	95.78	1500.00	41.99	106440.18
13	500.00	200.00	300.00	150.00	200.00	36.78	25.50	+18.94	10.78	0.00	1400.00	41.99	56198.10
14	432.55	200.00	300.00	150.00	200.00	31.59	24.82	0.00*	0.00	0.00	1300.00	38.96	40073.55
15	355.19	200.00	300.00	150.00	200.00	9.70	20.74	0.00*	0.00	0.00	1200.00	35.63	34825.55
16	261.59	200.00	238.88	150.00	200.00	12.92	14.62	0.00*	0.00	0.00	1050.00	28.00	26768.84
17	241.66	200.00	221.81	147.82	200.00	0.00	25.50	-10.63	0.00	0.00	1000.00	26.17	25079.36
18	294.83	200.00	267.14	150.00	200.00	0.00	19.04	0.00*	0.00	0.00	1100.00	31.00	26699.79
19	360.35	200.00	300.00	150.00	200.00	0.00	25.50	0.00*	0.00	0.00	1200.00	35.85	35143.74
20	500.00	200.00	300.00	150.00	200.00	0.00	18.02	+33.03	12.62	28.32	1400.00	41.99	75558.24
21	464.89	200.00	300.00	150.00	200.00	0.00	25.50	0.00*	0.00	0.00	1300.00	40.39	42569.91
22	293.47	200.00	265.99	150.00	200.00	0.00	21.42	0.00*	0.00	0.00	1100.00	30.88	29573.73
23	215.80	191.82	199.59	132.29	189.04	0.00	0.00	-6.38	0.00	0.00	900.00	22.17	21857.35
24	203.93	181.54	189.35	125.17	178.96	0.00	2.55	-61.62	0.00	0.00	800.00	19.87	20069.63
Total fuel, emissions, and storage energy costs = $9,26,791.24													

* GV power was available at this hour but the operator did not purchase power at this hour to ensure economic load dispatch.

using the SLBs and GVs, according to our proposed ways. The percentage of cost saving is significant, being \$97944.90/((250+78.11+18.3)*\$400)=70.69%.

To quantify the impact of not using the SLBs, we ran the simulations again without using the SLBs, yet otherwise using our proposed strategy. The results, given in Table 6.6, show that the fuel and emissions costs have increased by (\$9,26,791.24 - \$8,32,933.37) = \$93,857.87 for supplying the same load demand in a 24-hour period.

6.6 Discussions and benefits of the study

In providing backup energy for an off-line thermal generating unit, economy of dispatch is important. Cheaper storage devices, such as SLBs and GVs, can be used to supply that energy. SLBs can be scheduled by the operator in real-time according to the day long load demand. Being a cheaper source, SLBs can significantly reduce the pick-hour storage costs.

GV batteries can also be used for the same purpose ensuring real-time availability and owners' revenue outcomes while discharging to the grid. Our proposed GV energy cost modeling provides transparent information to the owners on the cost of their GV energy, based on which they can negotiate the energy price with the operators, and thus ensures that GVs benefit from discharging to the grid.

Ensuring economic load dispatch during the maintenance outage period is crucial for running a power system. Our proposed economic load dispatch model first tries to dispatch the load demand from the remaining thermal generators. If demand exceeds the capacity, a suitable supply is taken from the SLBs. Regular price GV energy is sought only when the operator specified SLB power cannot meet the demand of a particular hour. If the demand is still unmet, the operator negotiates with the other available GVs on a price. In case all GVs are exhausted, conventional storage sources from a third party are sought. This step-by-step process ensures maximum possible economy of power dispatch in real time.

It is appropriate to justify the capital cost of buying the SLBs for using as alternative energy sources. SLBs could be bought at 10% of the cost of equivalent new battery and be used for other revenue earning ancillary services [94][103]. An indicative maximum price can be only \$1000 for a 10 kW battery used in this study [99] thus leading to a cost of \$50,000,000 for 50,000 SLBs. From our simulation results in Tables 6.5 and 6.6, we can conclude that a single day use of SLBs can save a total of \$93,857.87 so using them for (50,000,000/93,857.87)=532.72 days (approximately 1.5 years) would justify the capital cost. SLBs in the current literature are expected to serve for around 10 years so the capital cost is strongly justified. It should be

Table 6.7: Overall benefits of the study

Items	Without Proposed Models	With Proposed Models
GV availability for discharging	Unplanned and unreliable	Reliable and negotiable
Basis of discharging decision	Non-Transparent	Objective and revenue-driven
Effect on economy	Less economic load dispatch	More economic load dispatch
Potential for risk reduction	Less due to no in-house storages	High due to cheaper in-house storages

noted that we have used \$40/MWh as the SLB energy cost and \$400/MWh as the conventional storage energy costs, both of which can be much higher in practical scenarios that would favor our proposition of the cost recovery time.

If the conventional model is used to select the number of GVs to discharge, only a portion of the vehicles will be available at peak hours, failing to ensure economic dispatch. Moreover, a conventional economic load dispatch model cannot ensure optimum economic dispatch during the unpredictable outages. In contrast, our proposed models would ensure maximum possible power discharge both from the SLBs and the GVs at a reasonable price, which in turn, ensures most economic load dispatch. The models also keep the power system reliable to the ultimate consumers by providing the necessary power at the necessary hours. A summary of the benefits of this study is given in Table 6.7.

6.7 Conclusion

Reliable and cost-effective storage energy resources are required to provide the necessary backup during a thermal generating unit's forced outages, short-notice shutdowns and regular maintenance periods. We have considered the energy storage options with SLBs, GVs, and CSs with due consideration to their cost-effective use in providing maintenance backups. We have also proposed an economic load dispatch model that includes the cost of using battery energy in the objective function along with the fuel and emissions costs from thermal sources to justify the economy of using battery energy as backup sources. This study suggests that using the SLBs and GVs in our proposed ways significantly reduces the storage energy costs. However, different types of electric vehicles will provide different results in terms of the energy cost reduction. The capital costs for SLBs are also justified. The proposed models will enable the system operators to economically schedule their energy resources and ensure a SG's reliability.

Chapter 7

Conclusion

This thesis deals with the integration of Electric Vehicles (EVs) and Plug-in Hybrid Electric Vehicles (PHEVs) into the SG environment along with the renewable energy sources. To ensure the viability of using the gridable vehicles (GVs), such as EVs and PHEVs, as distributed storage energy units, this thesis has reported several technical steps implemented in modeling, analysing and establishing the benefits of using GVs in the SG scenario. The following sections provide a general summary of the whole thesis and lists the contributions made in this thesis. Due to the high importance of this area of reserach, a list of future research directions is given in a separate section.

7.1 Thesis Summary

This thesis investigates different ways of integrating GVs into the SG environment in an effort to reduce the overall storage enrgy cost in the power system. GV integration issues have been looked into from both the GV owners' and the operators' perspectives. GV owners have concerns about the capital cost involved in adopting a GV as well as the lifetime deterioration issue from discharging to the grid. System operators, on the other hand, have concerns about the storge energy cost as well as reliability of the availability of such storages. This thesis has proposed technical models for using the GVs in an effective way, while ensuring the revenue outcome from such usage for the GV owners. The thesis has also proposed similar technical and business models for the system operators to ensure benefits for both themselves and the GV owners, yet offering a reliable power system. In addition, this thesis investigates the second life use of GV batteries along with their financial implications across the power system.

7.2 Thesis Contributions

On the basis of the different technical contributions described in the preceding chapters, the ultimate contributions of this thesis can be drawn in the following five main points:

- While EVs and PHEVs are viable sources of storage energy, their availability when needed is a major issue in balancing the demand for storage energy and the supply. Real-time availability pattern of such vehicles at the parking stations is unsuitable for meeting the exact demand of the storage energy. A match between the storage energy demand and supply is thus necessary to avoid possibilities of non-availability of vehicles at the time of highest demand. In this thesis, an availability planning model (APM) was implemented to distribute the number of vehicles discharging to the grid according to the demand pattern during a 24-hour period. This APM takes historical load demand data as input for identifying load variations so that the appropriate proportion of registered vehicles can be allocated for a particular period to meet the real-time load demand. To implement the APM, concurrent universal load demand curves have been studied and two peak demand periods have been identified in a 24-hour duration. Two Gaussian uniform distributions of different characteristics parameters have been used to follow this load pattern while balancing real-time storage needs and storage supply. Use of this APM has ensured the effective use of the vehicle energy as well as improving the reliability of the SG system in question.

- GVs are the owned assets of the general public, and because the GVs are still costly and depend on their batteries' capacity, GV owners are always worried about battery capacity loss and hence reluctant about discharging their GVs at the grid's requirements. An effective model is thus required to ensure protection of the owners' interests while discharging to the grid. This thesis developed and implemented a technical model, battery lifetime improvement model (BLIM), to calculate the average remaining lifetime of a fleet of vehicles, and to restrict the GVs with lower remaining lifetime from discharging thus saving their battery lifetimes for automotive use. In the implemented model, the operators, who set out a threshold remaining lifetime of the GV fleet before allowing them to discharge, are working to protect GV owners interests. The threshold remaining lifetime, being subject to change according to the requirement of the grid and the owners' choice, makes this model preferable for both operators and vehicle owners. By using this BLIM, if the owners have to retain their battery lifetime only for automotive use, they can offer to increase the threshold remaining lifetime of the vehicle fleet in consultation with the system operator. This two-way flexible technical model brings sufficient confidence in the vehicle owners to participate in the grid discharge program leading to a mutually beneficial outcome for both parties. The simulation results presented in this thesis indicate that the average lifetime of a fleet of vehicles can be improved by up to 3.5 years by using the proposed BLIM, for harnessing the GV energy to support the grid's purpose.

- Due to the high cost of GV batteries, GV owners are always concerned about the revenue earned from discharging their GV batteries to the grid and other appliances. At the minimum, the owners are concerned that they do not lose money by discharging their battery energy. Addressing this concern has two dimensions: overall revenue earned from discharging the GV batteries and quantifying the actual percentage of capacity degradation and the corresponding share of GV purchase cost in every discharge cycle. Given that every battery will have different chemical and physical compositions, quantifying the actual capacity degradation rate per discharging cycle is challenging. This thesis uses established experimental data for capacity degradation at different discharge cycles to model an empirical relationship between the capacity degradation and the number of discharge cycles. This relationship is then used to quantify the monetary value of the capacity degradation at every discharge cycle. The total cost of battery energy per unit is then modeled as a function of this capacity degradation cost and the battery opportunity cost. The ratio of each of these costs are determined by the business model and the revenue expectations of the vehicle owners. Weighting factors have thus been introduced for each of the cost items. A range of values for the weight factors has been used to investigate the effect of battery energy costs on the GV discharging decisions. Modeling the battery energy cost in this way provides the GV owners with a transparent capacity degradation and cost model for their battery energy leading to a satisfactory decision making process regarding discharging the battery energy to the grid or other appliances. The simulation results in this thesis show that using the proposed model ensures more GVs participating in the grid discharge program while ensuring economic load dispatch using the battery energy.

- User adaptability level for gridable vehicles are still lower than the market expectation due to the high opportunity cost. The cost of the battery is the main contributor to this higher cost. Consequently, vehicle owners are skeptical of the long term benefit from owning a gridable vehicle. Moreover, even if they adopt one, they are now concerned about the revenue outcome from grid discharging. Although research is ongoing to produce cheaper electric vehicles, there will be a delay before they are marketed. Currently, second use of vehicle batteries has been considered by researchers to recover a portion of the initial purchase cost of a GV. When retired from their automotive phase, GV batteries still retain at least 70% of their initial capacity that can be used for other low power applications. While potential applications for the second life batteries are being explored, an economic analysis of the second use of such batteries was performed in this thesis to establish the effect of using the second life batteries on the initial purchase cost recovery. To reflect the practical exposure of the batteries in both automotive and second life, this thesis considers and models the capacity degradation in each lives from technical perspectives, and then quantifies the monetary value of vehicle energy, in both lives, to identify the cost recovery from the second use. The simulation presented establishes that up to 19% of the initial battery purchase cost is recoverable from the second use while also ensuring economic load dispatch. This outcome is supportive of convincing the vehicle owners to discharge to the grid as well as encouraging general users to purchase a GV.

- Gridable vehicles such as EVs and PHEVs can provide small amounts of temporary energy storage for different purposes; and short-term energy needs at the peak demand period is a good example. Depending on the nature and frequency of demands generated for such storage sources, GV batteries can be used both in their automotive life and their second life for meeting the grid's emergency requirements as well as earning revenues for the GV owners. In this thesis a new area of application of the vehicle batteries, both automotive and second life ones, has been explored and an example system has been implemented. This new application is using the gridable vehicle batteries as backup energy storage during the routine generator maintenance period and/or short-time emergency generator shutdown periods. Because generator maintenance periods require backup energy to replace the off-line generators, economy of storage energy is of high interest to the system operators. Additionally, short-term emergency generator shutdowns are common. In both these cases, electric vehicle batteries are a good economic choice. Second use of retired GV batteries has made the energy storage even more affordable. This thesis has developed a system model to use the second life batteries and automotive batteries of GVs along with the conventional storage systems to provide sufficient and economic backup energy during generator maintenance and/or shutdown periods. Simulation results presented here suggest that using GVs and second life batteries (SLBs) together can save up to 70% of storage energy costs while the capital cost for second life battery purchase can be realized in only 1.5 years of continuous use.

7.3 Future works

The research work described in this thesis explored the key avenues towards effective integration of gridable vehicles into the SG environment. However, the following areas require further research:

- Although gridable vehicles are already being integrated into the SG environment, there is insufficient data regarding the practical movement and driving profile of the vehicles. In a few pilot projects, vehicle movement data and simulation set up are the key research outputs. Gathering detailed driving profile and movement data and corresponding changes in the vehicle and battery parameters would enable the existing research to reproduce practical cases of vehicle use. Further research to model the vehicle movement patterns and battery parameter changes in a large scale, real-world vehicle integration set up would be useful in closing this knowledge gap.

- The capacity degradation rate of a vehicle battery, with respect to real world drive cycles, has not been investigated in full scale but would provide more specific information about the battery lifetime and potential degradation rate patterns. Similar experiments, under different regional operators, would justify the validity of the degradation rates. Degradation data records after every 10 charging-discharging cycles should provide sufficient precision.

- Second life use of vehicle battery can recover a portion of the initial vehicle purchase cost. However, identification of further areas of use for the second life batteries is important for ensuring revenue earnings. Using these batteries for running domestic appliances would be a good way of widening the application range. A more efficient cost recovery model for the second use of vehicle batteries should be researched further.

- Charge and discharge scheduling of the GVs as well as SLBs is important in determining the economy and reliability of the bi-directional energy transfer system. Practical load demand and operator's choice are the decision making variables in setting a pre-determined charge and discharge schedule. Developing efficient charge and discharge scheduling algorithms is a demanding area still to be researched. A real-time goal for such scheduling may even require iterative algorithms to adjust for the real-time needs of the operators. Further research is necessary in this area to underpin a reliable power system.

- Charging and discharging rates affect the battery capacity degradation rate and hence the ultimate lifetime. Charging and discharging infrastructure in the parking stations and at the owners' homes is another determining factor in ensuring reliable energy transfer. Infrastructure establishment requires substantial funding, which is an extra burden for the power industry. Research on finding an optimum rate of such charging and discharging can ease this situation in the longer term.

- The social impact of using GVs and SLBs into the power industry is another important area for research. Both the owners and the general consumers have their own perceptions on the suitability of GVs and SLBs as acceptable energy storage devices. Determining the other factors, apart from revenue, that encourage the stakeholders to accept this new concept is worth further research, for example, environmental altruism.

Bibliography

[1] U. S. D. of Energy, "The Smart Grid: An Introduction," Contract No. DE-AC26-04NT41817, Subtask 560.01.04, Washington, DC 20585, Technical Report, 2008. 1

[2] A. Saber and G. Venayagamoorthy, "Plug-in vehicles and renewable energy sources for cost and emission reductions," *Industrial Electronics, IEEE Transactions on*, vol. 58, no. 4, pp. 1229–1238, April 2011. 1, 2.5.3, 2.6, 2.7, 3.1, 3.1, 3.1, 3.2, 3.4, 3.4, 3.4, 3.4, 3.6, 4.4, 5.5.4

[3] P. D. K. Parks and T. Markel, "Costs and emissions associated with plug-in hybrid electric vehicle charging in the Xcel Energy Colorado Service Territory," National Renewable Energy Laboratory, USA, Technical Report, 2007. 1, 2.7, 3.1

[4] E. P. R. Institute, "Comparing the benefits and impacts of hybrid electric vehicle options for compact sedan and sport utility vehicles," EPRI, Palo Alto, CA, Technical Report, July 2002. 1

[5] W. Su, H. Eichi, W. Zeng, and M.-Y. Chow, "A survey on the electrification of transportation in a smart grid environment," *Industrial Informatics, IEEE Transactions on*, vol. 8, no. 1, pp. 1–10, Feb 2012. 1, 2.7

[6] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid - the new and improved power grid: A survey," *Communications Surveys Tutorials, IEEE*, vol. 14, no. 4, pp. 944–980, Fourth 2012. 1, 2.7

[7] U. Madawala, P. Schweizer, and V. Haerri, "Living and mobility - a novel multipurpose in-house grid interface with plug-in hybrid BlueAngle," in *Sustainable Energy Technologies, 2008. ICSET 2008. IEEE International Conference on*, November 2008, pp. 531–536. 1.1

[8] R. R. W. S. Labatt, *Carbon Finance: The Financial Implications of Climate Change*. New Jersey: Wiley, 2007. 1.1, 2.6

[9] W. H. Kersting, *Distribution system modeling and analysis.* Boka Raton: CRC Press, 2006. 2.1

[10] C. W. Gellings, *The Smart Grid: Enabling energy efficiency and demand response.* Lilburn, GA 30047: The Fairmont Press, Inc, 2009. 2.1

[11] B. Roberts, "Capturing grid power," *Power and Energy Magazine, IEEE*, vol. 7, no. 4, pp. 32–41, July 2009. 2.1

[12] B. Mammano, "Distributed power systems," Texas Instruments, Dallas, Texas, USA, Technical Report, 1993. 2.2

[13] W. Tabisz, M. Jovanovic, and F. Lee, "Present and future of distributed power systems," in *Applied Power Electronics Conference and Exposition, 1992. APEC '92. Conference Proceedings, Seventh Annual*, February 1992, pp. 11–18. 2.2

[14] B. Owens, "The rise of distributed power," General Electric Company, Technical Report, 2014. 2.2

[15] S. Amin and B. Wollenberg, "Toward a Smart Grid: Power delivery for the 21st century," *Power and Energy Magazine, IEEE*, vol. 3, no. 5, pp. 34–41, September 2005. 2.3

[16] G. Arnold, "Challenges and opportunities in Smart Grid: A position article," *Proceedings of the IEEE*, vol. 99, no. 6, pp. 922–927, June 2011. 2.3

[17] H. Farhangi, "The path of the Smart Grid," *Power and Energy Magazine, IEEE*, vol. 8, no. 1, pp. 18–28, January 2010. 2.3, 2.3

[18] N. I. of Standards and Technology, "NIST framework and roadmap for Smart Grid interoperability standards, Release 1.0," U. S. Department of Commerce, Technical Report, 2010. 2.3, 2.3

[19] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart Grid - the new and improved power grid: A survey," *Communications Surveys Tutorials, IEEE*, vol. 14, no. 4, pp. 944–980, April 2012. 2.4, 2.5.2

[20] I. E. Agency, *Distributed generation in liberalised electricity markets.* Paris, France: OECD/IEA, 2002. 2.4

[21] A. Molderink, V. Bakker, M. G. C. Bosman, J. Hurink, and G. J. M. Smit, "Management and control of domestic smart grid technology," *Smart Grid, IEEE Transactions on*, vol. 1, no. 2, pp. 109–119, September 2010. 2.4

[22] K. B. H. Zareipour and C. A. Canizares, "Distributed generation: Current status and challenges," in *IEEE Proceeding of NAPS 2004*, February 2004. 2.4

[23] D. Hart, "Using AMI to realize the Smart Grid," in *Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE*, July 2008, pp. 1–2. 2.4

[24] P. Varaiya, F. Wu, and J. Bialek, "Smart operation of Smart Grid: Risk-limiting dispatch," *Proceedings of the IEEE*, vol. 99, no. 1, pp. 40–57, January 2011. 2.5.1

[25] P. I. R. W. Group, "Integration of wind production forecasting into day ahead and real-time scheduling and commitment," PJM, Audubon, PA 19403, Technical Report, 2013. 2.5.1

[26] U. S. D. of Energy, "20 percent wind energy by 2030: Increasing wind energy contribution to U.S. electricity supply," U. S. Department of Energy, Washington, DC 20585, Technical Report, 2008. 2.5.1

[27] D. Hawkins, J. Blatchford, and Y. Makarov, "Wind integration issues and solutions in california," in *Power Engineering Society General Meeting, 2007. IEEE*, June 2007, pp. 1–9. 2.5.1

[28] "IEEE draft guide for smart grid interoperability of energy technology and information technology operation with the electric power system (eps), and end-use applications and loads," *IEEE P2030/D7.0, July 2011*, pp. 1–121, August 2011. 2.5.2

[29] F. E. R. Commission, "Assessment of demand response and advanced metering, staff report," Federal Energy Regulatory Commission, Washington, DC 20426, Technical Report, 2011. 2.5.2

[30] C. Potter, A. Archambault, and K. Westrick, "Building a smarter smart grid through better renewable energy information," in *Power Systems Conference and Exposition, 2009. PSCE '09. IEEE PES*, March 2009, pp. 1–5. 2.5.3

[31] J. Smith, M. Milligan, E. DeMeo, and B. Parsons, "Utility wind integration and operating impact state of the art," *Power Systems, IEEE Transactions on*, vol. 22, no. 3, pp. 900–908, August 2007. 2.5.3

[32] J. Baker and A. Collinson, "Electrical energy storage at the turn of the millennium," *Power Engineering Journal*, vol. 13, no. 3, pp. 107–112, June 1999. 2.5.3

[33] J. Barton and D. Infield, "Energy storage and its use with intermittent renewable energy," *Energy Conversion, IEEE Transactions on*, vol. 19, no. 2, pp. 441–448, June 2004. 2.5.3

[34] J. Eyer and G. Corey, "Energy storage for the electricity grid: Benefits and market potential assessment guide," Sandia National Laboratories, California, USA, Technical Report, 2010. 2.5.3

[35] W. Kempton and J. Tomic, "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy," *Power Sources, Journal of*, vol. 144, no. 1, pp. 280–294, June 2005. 2.6, 2.7

[36] A. Affanni, A. Bellini, G. Franceschini, P. Guglielmi, and C. Tassoni, "Battery choice and management for new-generation electric vehicles," *Industrial Electronics, IEEE Transactions on*, vol. 52, no. 5, pp. 1343–1349, October 2005. 2.6, 2.7

[37] J. Tomic and W. Kempton, "Using fleets of electric-drive vehicles for grid support," *Power Sources, Journal of*, vol. 168, no. 2, pp. 459–468, June 2007. 2.6, 2.7

[38] S. W. Hadley and A. Tsvetkova, "Potential impacts of plug-in hybrid electric vehicles on regional power generation," Oak Ridge National Laboratory, Oak Ridge, TN, Technical Report, 2008. 2.6, 2.7

[39] S. Meliopoulos, J. Meisel, G. Cokkinides, and T. Overbye, "Power system level impacts of plug-in hybrid vehicles," Power Systems Engineering Research Center, PSerc Project T34 Final Report, Tempe, Arizona, Technical Report, 2009. 2.6, 2.7

[40] S. Han, S. Han, and K. Sezaki, "Development of an optimal vehicle-to-grid aggregator for frequency regulation," *Smart Grid, IEEE Transactions on*, vol. 1, no. 1, pp. 65–72, June 2010. 2.6, 2.7

[41] C. Pang, P. Dutta, and M. Kezunovic, "BEVs/PHEVs as dispersed energy storage for V2B uses in the Smart Grid," *Smart Grid, IEEE Transactions on*, vol. 3, no. 1, pp. 473–482, March 2012. 2.6, 2.7

[42] M. Yilmaz and P. Krein, "Review of the impact of vehicle-to-grid technologies on distribution systems and utility interfaces," *Power Electronics, IEEE Transactions on*, vol. 28, no. 12, pp. 5673–5689, Dec 2013. 2.7

[43] D. Tuttle and R. Baldick, "The evolution of plug-in electric vehicle-grid interactions," *Smart Grid, IEEE Transactions on*, vol. 3, no. 1, pp. 500–505, March 2012. 2.7

[44] K. Clement-Nyns, E. Haesen, and J. Driesen, "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid," *Power Systems, IEEE Transactions on*, vol. 25, no. 1, pp. 371–380, February 2010. 2.7

[45] K. Qian, C. Zhou, M. Allan, and Y. Yuan, "Modeling of load demand due to EV battery charging in distribution systems," *Power Systems, IEEE Transactions on*, vol. 26, no. 2, pp. 802–810, May 2011. 2.7

[46] E. Sortomme and M. El-Sharkawi, "Optimal charging strategies for unidirectional vehicle-to-grid," *Smart Grid, IEEE Transactions on*, vol. 2, no. 1, pp. 131–138, March 2011. 2.7

[47] M. Yilmaz and P. Krein, "Review of battery charger topologies, charging power levels, and infrastructure for plug-in electric and hybrid vehicles," *Power Electronics, IEEE Transactions on*, vol. 28, no. 5, pp. 2151–2169, May 2013. 2.7

[48] A. Pesaran, T. Market, H. Tataria, and D. Howell, "Battery requirements for plug-in hybrid electric vehicles: Analysis and rationale," in *presented at the 23rd International Electric Vehicle Symposium and Exposition (EVS-23), Anaheim, California*, December 2007. 2.7

[49] J. Cao and A. Emadi, "Batteries need electronics," *Industrial Electronics Magazine, IEEE*, vol. 5, no. 1, pp. 27–35, March 2011. 2.7

[50] H. Kim and K. Shin, "DESA: Dependable, efficient, scalable architecture for management of large-scale batteries," *Industrial Informatics, IEEE Transactions on*, vol. 8, no. 2, pp. 406–417, May 2012. 2.7

[51] J. Lassila, J. Haakana, V. Tikka, and J. Partanen, "Methodology to analyze the economic effects of electric cars as energy storages," *Smart Grid, IEEE Transactions on*, vol. 3, no. 1, pp. 506–516, March 2012. 2.7

[52] Y. Ma, T. Houghton, A. Cruden, and D. Infield, "Modeling the benefits of vehicle-to-grid technology to a power system," *Power Systems, IEEE Transactions on*, vol. 27, no. 2, pp. 1012–1020, May 2012. 2.7

[53] A. O'Connell, D. Flynn, and A. Keane, "Rolling multi-period optimization to control electric vehicle charging in distribution networks," *Power Systems, IEEE Transactions on*, vol. 29, no. 1, pp. 340–348, Jan 2014. 2.7

[54] L. Yang, J. Zhang, and H. Poor, "Risk-aware day-ahead scheduling and real-time dispatch for electric vehicle charging," *Smart Grid, IEEE Transactions on*, vol. 5, no. 2, pp. 693–702, March 2014. 2.7

[55] P. Rezaei, J. Frolik, and P. Hines, "Packetized plug-in electric vehicle charge management," *Smart Grid, IEEE Transactions on*, vol. 5, no. 2, pp. 642–650, March 2014. 2.7

[56] A. Schuller, B. Dietz, C. Flath, and C. Weinhardt, "Charging strategies for battery electric vehicles: Economic benchmark and V2G potential," *Power Systems, IEEE Transactions on*, vol. PP, no. 99, pp. 1–9, 2014. 2.7

[57] J. Hu, S. You, M. Lind, and J. Ostergaard, "Coordinated charging of electric vehicles for congestion prevention in the distribution grid," *Smart Grid, IEEE Transactions on*, vol. 5, no. 2, pp. 703–711, March 2014. 2.7

[58] T. Ma, A. Mohamed, and O. Mohammed, "Optimal charging of plug-in electric vehicles for a car park infrastructure," in *Industry Applications Society Annual Meeting (IAS), 2012 IEEE*, October 2012, pp. 1–8. 2.7

[59] K. Thirugnanam, T. Joy, M. Singh, and P. Kumar, "Modeling and control of contactless based smart charging station in v2g scenario," *Smart Grid, IEEE Transactions on*, vol. 5, no. 1, pp. 337–348, January 2014. 2.7

[60] N. Machiels, N. Leemput, F. Geth, J. Van Roy, J. Buscher, and J. Driesen, "Design criteria for electric vehicle fast charge infrastructure based on flemish mobility behavior," *Smart Grid, IEEE Transactions on*, vol. 5, no. 1, pp. 320–327, January 2014. 2.7

[61] S. Deilami, A. Masoum, P. Moses, and M. Masoum, "Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile," *Smart Grid, IEEE Transactions on*, vol. 2, no. 3, pp. 456–467, Sept 2011. 2.7

[62] A. Masoum, S. Deilami, A. Abu-Siada, and M. Masoum, "Fuzzy approach for online coordination of plug-in electric vehicle charging in smart grid," *Sustainable Energy, IEEE Transactions on*, vol. PP, no. 99, pp. 1–10, 2015. 2.7

[63] A. Masoum, S. Deilami, P. Moses, M. Masoum, and A. Abu-Siada, "Smart load management of plug-in electric vehicles in distribution and residential networks with charging stations for peak shaving and loss minimisation considering voltage regulation," *Generation, Transmission Distribution, IET*, vol. 5, no. 8, pp. 877–888, August 2011. 2.7

[64] Y. Yan, Y. Qian, H. Sharif, and D. Tipper, "A survey on Smart Grid communication infrastructures: Motivations, requirements and challenges," *Communications Surveys Tutorials, IEEE*, vol. 15, no. 1, pp. 5–20, January 2013. 2.7

[65] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart Grid; the new and improved power grid: A survey," *Communications Surveys Tutorials, IEEE*, vol. 14, no. 4, pp. 944–980, April 2012. 2.7

[66] M. Simoes, R. Roche, E. Kyriakides, S. Suryanarayanan, B. Blunier, K. McBee, P. Nguyen, P. Ribeiro, and A. Miraoui, "A comparison of Smart Grid technologies and progresses in Europe and the U.S." *Industry Applications, IEEE Transactions on*, vol. 48, no. 4, pp. 1154–1162, July 2012. 2.7

[67] M. Landi and G. Gross, "Measurement techniques for online battery state of health estimation in vehicle-to-grid applications," *Instrumentation and Measurement, IEEE Transactions on*, vol. 63, no. 5, pp. 1224–1234, May 2014. 2.7

[68] O. Camacho, P. Norgard, N. Rao, and L. Mihet-Popa, "Electrical vehicle batteries testing in a distribution network using sustainable energy," *Smart Grid, IEEE Transactions on*, vol. 5, no. 2, pp. 1033–1042, March 2014. 2.7

[69] K. Kumar, B. Sivaneasan, P. Cheah, P. So, and D. Wang, "V2G capacity estimation using dynamic EV scheduling," *Smart Grid, IEEE Transactions on*, vol. 5, no. 2, pp. 1051–1060, March 2014. 2.7

[70] P. Grahn, K. Alvehag, and L. Soder, "PHEV utilization model considering type-of-trip and recharging flexibility," *Smart Grid, IEEE Transactions on*, vol. 5, no. 1, pp. 139–148, January 2014. 2.7

[71] Z. Tan, P. Yang, and A. Nehorai, "An optimal and distributed demand response strategy with electric vehicles in the Smart Grid," *Smart Grid, IEEE Transactions on*, vol. 5, no. 2, pp. 861–869, March 2014. 2.7

[72] D. Nguyen and L. B. Le, "Joint optimization of electric vehicle and home energy scheduling considering user comfort preference," *Smart Grid, IEEE Transactions on*, vol. 5, no. 1, pp. 188–199, January 2014. 2.7

[73] R. Das, K. Thirugnanam, P. Kumar, R. Lavudiya, and M. Singh, "Mathematical modeling for economic evaluation of electric vehicle to Smart Grid interaction," *Smart Grid, IEEE Transactions on*, vol. 5, no. 2, pp. 712–721, March 2014. 2.7

[74] A. Shortt and M. O'Malley, "Quantifying the long-term impact of electric vehicles on the generation portfolio," *Smart Grid, IEEE Transactions on*, vol. 5, no. 1, pp. 71–83, Jan 2014. 2.7

[75] A. Saber and G. Venayagamoorthy, "Efficient utilization of renewable energy sources by gridable vehicles in cyber-physical energy systems," *Systems Journal, IEEE*, vol. 4, no. 3, pp. 285–294, September 2010. 2.7, 3.6, 4.2, 4.2, 4.3, 6.3, 6.4, 6.4

[76] A. Y. Saber and G. Venayagamoorthy, "Unit commitment with vehicle-to-grid using particle swarm optimization," in *PowerTech, 2009 IEEE Bucharest*, June 2009, pp. 1–8. 2.7

[77] A. Saber and G. Venayagamoorthy, "Resource scheduling under uncertainty in a Smart Grid with renewables and plug-in vehicles," *Systems Journal, IEEE*, vol. 6, no. 1, pp. 103–109, March 2012. 2.7

[78] M. Roscher, J. Assfalg, and O. Bohlen, "Detection of utilizable capacity deterioration in battery systems," *Vehicular Technology, IEEE Transactions on*, vol. 60, no. 1, pp. 98–103, January 2011. 2.7, 3.1, 3.3, 3.3.1, 3.3.3, 3.3.4

[79] O. Erdinc, B. Vural, and M. Uzunoglu, "A dynamic lithium-ion battery model considering the effects of temperature and capacity fading," in *Clean Electrical Power, 2009 International Conference on*, June 2009, pp. 383–386. 3.3, 3.3.1, 3.3.3, 3.3.4, 5.1

[80] G. Ning, B. Haran, and B. N. Popov, "Capacity fade study of lithium-ion batteries cycled at high discharge rates," *Journal of Power Sources*, vol. 117, no. 1, pp. 160–169, 2003. 3.3, 3.3.1

[81] D. U. Sauer and H. Wenzl, "Comparison of different approaches for lifetime prediction of electrochemical systems using lead-acid batteries as example," *Journal of Power Sources*, vol. 176, no. 2, pp. 534–546, 2008. 3.3, 3.3.1

[82] S. Neglur and M. Ferdowsi, "Effect of battery capacity on the performance of plug-in hybrid electric vehicles," in *Vehicle Power and Propulsion Conference, 2009. VPPC '09. IEEE*, September 2009, pp. 649–654. 3.3, 3.3.5

[83] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Neural Networks, 1995. Proceedings., IEEE International Conference on*, vol. 4, November 1995, pp. 1942–1948. 3.5, 4.3, 6.3

[84] Y. Del Valle, G. Venayagamoorthy, S. Mohagheghi, J.-C. Hernandez, and R. Harley, “Particle swarm optimization: Basic concepts, variants and applications in power systems,” *Evolutionary Computation, IEEE Transactions on*, vol. 12, no. 2, pp. 171–195, April 2008. 3.5

[85] Z.-L. Gaing, “Particle swarm optimization to solving the economic dispatch considering the generator constraints,” *Power Systems, IEEE Transactions on*, vol. 18, no. 3, pp. 1187–1195, August 2003. 3.6, 4.3, 5.5.4, 6.4

[86] Y. Makarov, P. Du, M. Kintner-Meyer, C. Jin, and H. Illian, “Sizing energy storage to accommodate high penetration of variable energy resources,” *Sustainable Energy, IEEE Transactions on*, vol. 3, no. 1, pp. 34–40, January 2012. 4

[87] K. Smith, T. Markel, and A. Pesaran, “PHEV battery trade-off study and standby thermal control,” in *26th International Battery Seminar and Exhibit,Fort Lauderdale, FL, USA*, March 2009. 4.1.1, 4.1.1.1, 4.1.1.1, 4.1.2, 5.1, 5.1, 5.1, 5.1

[88] R. Deshpande, M. Verbrugge, Y. Cheng, J. Wang, and P. Liu, “Battery cycle life prediction with coupled chemical degradation and fatigue mechanics,” *Journal of The Electrochemical Society*, vol. 159, no. 10, pp. 1730–1738, 2012. 4.1.1.1, 5.2

[89] J. Axsen, A. Burke, and K. S. Kurani, “Batteries for plug-in hybrid electric vehicles (PHEVs): Goals and the state of technology circa 2008,” ITS, Davis, CA, Technical Report, 2008. 4.1.1.1, 6.2.3

[90] S. G. Gondelach and A. Faaij, “Performance of batteries for electric vehicles on short and longer term,” *Journal of Power Sources*, vol. 212, pp. 111–129, April 2012. 4.1.1.2, 4.3, 5.5.4, 6.4

[91] O. V. Vliet, A. S. Brouwer, T. Kuramochi, M. V. Broek, and A. Faaij, “Energy use, cost and CO2 emissions of electric cars,” *Journal of Power Sources*, vol. 196, pp. 2298–2310, October 2010. 4.1.1.2, 4.3, 5.5.4, 6.4

[92] U. Kumar Debnath, I. Ahmad, D. Habibi, and A. Yousuf Saber, “Improving battery lifetime of gridable vehicles and system reliability in the Smart Grid,” *Systems Journal, IEEE*, vol. PP, no. 99, pp. 1–11, 2014. 4.3, 6.2.1, 6.4

[93] V. Government, “Victoria Government Gazette, no. S 226, 2012,” Victoria, Australia, Technical Report, 2012. 4.3, 5.5.4, 6.4

[94] J. Neubauer and A. Pesaran, “The ability of battery second use strategies to impact plug-in electric vehicle prices and serve utility energy storage applications,” *Journal of Power Sources*, vol. 196, pp. 10 351–10 358, June 2011. 5, 6.6

[95] L. Long and P. Bauer, “Practical capacity fading model for Li-Ion battery cells in electric vehicles,” *Power Electronics, IEEE Transactions on*, vol. 28, no. 12, pp. 5910–5918, December 2013. 5.1, 5.1

[96] V. Alimisis and N. Hatziargyriou, “Evaluation of a hybrid power plant comprising used ev-batteries to complement wind power,” *Sustainable Energy, IEEE Transactions on*, vol. 4, no. 2, pp. 286–293, April 2013. 5.1, 5.2

[97] Q. Zhang and R. White, “Capacity fade analysis of a Li-ion cell,” *Journal of Power Sources*, vol. 179, pp. 793–798, January 2008. 5.2

[98] V. Viswanathan and M. Kintner-Meyer, “Second use of transportation batteries maximizing the value of batteries for transportation and grid services,” *Vehicular Technology, IEEE Transactions on*, vol. 60, no. 7, pp. 2963–2970, September 2011. 5.5.2, 6

[99] J. Neubauer, A. Pesaran, B. Williams, M. Ferry, and J. Eyer, “A techno-economic analysis of PEV battery second use repurposed-battery selling price and commercial and industrial end-user value,” Detroit, Michigan, Technical Paper, 2012. 5.5.3, 6.6

[100] G. Li and X.-P. Zhang, “Modeling of plug-in hybrid electric vehicle charging demand in probabilistic power flow calculations,” *Smart Grid, IEEE Transactions on*, vol. 3, no. 1, pp. 492–499, March 2012. 5.5.4

[101] C. Liu, J. Wang, A. Botterud, Y. Zhou, and A. Vyas, “Assessment of impacts of PHEV charging patterns on wind-thermal scheduling by stochastic unit commitment,” *Smart Grid, IEEE Transactions on*, vol. 3, no. 2, pp. 675–683, June 2012. 5.5.4

[102] C. N. Shiau, N. Kaushal, C. T. Hendrickson, S. B. Peterson, J. F. Whitacre, and J. J. Michalek, “Optimal plug-in hybrid electric vehicle design and allocation for minimum life cycle cost petroleum consumption and greenhouse gas emissions,” *Journal of Mechanical Design*, vol. 132, pp. 1–11, 2010. 5.5.4, 6.4

[103] P. Wolfs, “An economic assessment of second use lithium-ion batteries for grid support,” in *Universities Power Engineering Conference, 2010 20th Australasian*, December 2010, pp. 1–6. 6.6

Appendix A: Parameters List - Chapter 3

Below are the list of parameter values considered in the simulations in Chapter 3.

PSO Parameters:

Swarm size = 50, number of iterations = 1000

$c_1 = c_2 = 2$, $Range = 0.5$, $\psi_i = 25$ \$/ton, and $w_c = w_e = 1$.

GV Parameters:

$S = 15$kW, $H = 24$ hours

Minimum $\Psi_{dep} = 40\%$, $\zeta = 85\%$

Vehicles' range of lifetime = 2-15 years and 2-12 years.

Power from each vehicle = 6.375 kW

Other Parameters:

Number of registerd vehicles = 50,000

Number of vehicles used during the period *pk1* (9 am-4 pm) = 20,000

Number of vehicles used during the period *pk2* (4 pm-11pm) = 30,000

Mobility factors $m_1 = 0.2$ and $m_2 = 0.3$

Appendix B: Parameters List - Chapter 4

Below are the list of parameter values considered in the simulations in Chapter 4.

PSO Parameters:

Swarm size = 50, number of iterations = 1000

$c_1 = c_2 = 2$, $Range = 0.5$, ψ_i= 25 \$/ton, and w_c= w_e= 1.

GV Parameters:

S = 15kW, H = 24 hours

Minimum Ψ_{dep}= 40%, ζ = 85%

Power from each vehicle = 6.375 kW

Weight factor w_{opp} for each vehicle is in the range of 0.25-0.40

Weight factor w_{dgdn} for each vehicle is in the range of 0.8-1.0

Opportunity cost range = $800 -$1200 per kWh of battery capacity

Capacity degradation cost range = $6000 - $8000 per lifetime of a battery

Total discharge cycles considered for a battery = 4000

Threshold charging-discharging capacity of battery = 80%

Other Parameters:

Number of registerd vehicles = 50,000

Number of vehicles used during the period *pk1* (9 am-4 pm) = 20,000

Number of vehicles used during the period *pk2* (4 pm-11pm) = 30,000

Mobility factors m_1 = 0.2 and m_2= 0.3

Appendix C: Parameters List - Chapter 5

Below are the list of parameter values considered in the simulations in Chapter 5.

PSO Parameters:

Swarm size = 50, number of iterations = 1000

$c_1 = c_2 = 2$, $Range = 0.5$, ψ_i= 25 \$/ton, and $w_c = w_e = 1$.

GV Parameters:

S = 15kW, H = 24 hours

Minimum Ψ_{dep}= 40%, ζ = 85%

Vehicles' range of lifetime = 2-15 years and 2-12 years.

Power from each vehicle = 6.375 kW

The manufacturer specified DOD = 80%

Deep cycles allowed = 3,600

Cost of battery = \$12,000

Allowable degradation to the automotive battery = 70% of the original capacity

Allowable degradation to the second life battery = 30% of the original capacity

The initial charging-discharging capacity of a battery is considered 100%.

Allowable DOD in the automotive life = 40% - 80%

Allowable DOD in the second life = 30% - 50%

Other Parameters:

Number of registerd vehicles = 50,000

Number of vehicles used during the period *pk1* (9 am-4 pm) = 20,000

Number of vehicles used during the period *pk2* (4 pm-11pm) = 30,000

Mobility factors $m_1 = 0.2$ and m_2= 0.3

Appendix D: Parameters List - Chapter 6

Below are the list of parameter values considered in the simulations in Chapter 6.

PSO Parameters:

Swarm size = 50, number of iterations = 1000

$c_1 = c_2 = 2$, $Range = 0.5$, ψ_i= 25 \$/ton, and w_c= w_e= 1.

GV Parameters:

S = 15kW, H = 24 hours

Minimum Ψ_{dep}= 40%, ζ = 85%

Power from each vehicle = 6.375 kW

For SLBs, S_{slb}=10kW

Weight factor w_{opp} for each vehicle is in the range of 0.25-0.40

Weight factor w_{dgdn} for each vehicle is in the range of 0.8-1.0

Other Parameters:

Number of registerd vehicles = 50,000

Number of vehicles used during the period *pk1* (9 am-4 pm) = 20,000

Number of vehicles used during the period *pk2* (4 pm-11pm) = 30,000

Mobility factors m_1 = 0.2 and m_2= 0.3

Number of registered SLBs = 50,000

Cost of energy from discharging GVs = \$310/MWh

Cost of energy from SLBs = \$40/MWh