BATTERY MANAGEMENT OPTIMIZATION AND LIFECYCLE IMPACT ANALYSIS FOR MICROGRID OPERATION WITH V2G IMPLEMENTATION

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THESIS SUBMITTED IN FULFILMENTOF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

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Battery management optimization and lifecycle impact analysis for microgrid operation with V2G implementation

Field of Study: **Electricity & Energy**

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BATTERY MANAGEMENT OPTIMIZATION AND LIFECYCLE IMPACT ANALYSIS FOR MICROGRID OPERATION WITH V2G IMPLEMENTATION

ABSTRACT

The electric power system has been transformed and evolved towards decentralized systems, which interact with each other and within the whole electrical system. In this way, microgrids are essential components to increase the reliability and efficiency of the power system. The critical issue in isolated microgrid is the energy demand balance in the presence of intermittent renewable energy sources. Energy storage systems are the adequate solution to balance the demand/supply issue and support the ancillary services such as voltage regulation and reserve requirement. However, due to high installation cost of storage system, their sizing is essential for optimized operation of microgrid. The first part of this work proposes energy management system to reduce the operating cost of isolated microgrid. The economic scheduling using firefly algorithm is implemented for the optimization of distributed energy sources and ascertain optimal size of energy storage while meeting the load demand. The efficacy of the optimization algorithm is compared with other metaheuristic techniques for economic and reliability indices such as cost of electricity and loss of power supply probability. In the second part, electric vehicles (EV) are incorporated as flexible load in the power system. The EVs charge coordination with vehicle to grid (V2G) technology is performed with respect to economic and technical perspective. The economic objectives encompass cost minimization and profit maximization whereas technical objectives constitute power loss minimization and peak load reduction. The EV users are certainly concerned for cost of battery replacement due to degradation with active participation in V2G energy exchanges. Therefore, battery degradation model is formulated for real time analysis by considering the depth of discharge at each time interval. The operating cost and V2G profit are analyzed with

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different penetrations of renewable power generation, EV battery capacity and travelling time. The results indicate that proposed energy management approach effectively reduced the operating cost, ensuring the reliability of the microgrid. Since battery sizes influence the operating cost, optimal battery size is calculated to have minimum cost of electricity and prolong the battery lifetime. The proposed method results in 50% cost reduction when compared with the conventional method. The proposed energy management approach is solved using firefly algorithm, artificial bee colony, harmony search algorithm and particle swarm optimization. It was found that firefly algorithm is robust and computationally effective. In addition, EV charge coordination improves the system performance, minimize the power losses and restricts grid overloading. The integration of renewable energy sources (RES) reduces the system cost and maximizes the profit for the EV users. The system losses and cost of electricity is minimum when the RES penetration is increased while different EV capacities yields minimum profit.

Keywords: Battery energy storage, electric vehicle, degradation cost, economic scheduling, charge coordination.

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ANALISA IMPAK PENGOPTIMUMAN PENGURUSAN DAN KITARAN HIDUP BATERI UNTUK OPERASI MIKROGRID DENGAN PELAKSANAAN V2G YANG OPTIMA

ABSTRAK

Sistem kuasa elektrik telah berubah dan berkembang ke arah sistem yang nyahpusat yang boleh berinteraksi antara satu sama lain dan juga di antara keseluruhan sistem elektrik itu sendiri. Oleh itu, mikrogrid adalah komponen penting untuk meningkatkan kebolehpercayaan dan kecekapan sistem kuasa. Isu kritikal dalam mikrogrid terpencil adalah keseimbangan permintaan tenaga di hadapan sumber tenaga diperbaharui yang tidak stabil. Sistem simpanan tenaga adalah penyelesaian yang sesuai untuk mengimbangi isu permintaan/bekalan tenaga dan menyokong perkhidmatan sampingan seperti peraturan voltan dan keperluan simpanan. Walau bagaimanapun, disebabkan kos pemasangan sistem simpanan tenaga yang tinggi, saiz kapasiti mereka adalah penting untuk menjalankan operasi mikrogrid yang optima. Bahagian pertama penyelidikan ini mencadangkan pengurusan tenaga untuk mengurangkan kos operasi mikrogrid terpencil. Penjadualan ekonomi menggunakan algoritma "firefly" dilaksanakan untuk pengoptimuman sumber tenaga dan saiz optima penyimpanan tenaga untuk mengurangkan fungsi kos sambil memenuhi permintaan beban tenaga. Keberkesanan algoritma pengoptimuman dibandingkan dengan teknik metaheuristik lain untuk pengukuran ekonomi dan kebolehpercayaan seperti kos elektrik dan kebarangkalian bekalan kuasa. Di bahagian kedua, kenderaan elektrik (EV) disambungkan sebagai beban fleksibel dalam sistem kuasa mikrogrid. Penyelarasan caj EV dengan teknologi kenderaan ke grid (V2G) yang dilakukan untuk tujuan ekonomi dan teknikal. Objektif ekonomi adalah merangkumi pengurangan kos dan keuntungan maksima, manakala untuk tujuan teknikal merupakan pengurangan kehilangan kuasa dan pengurangan beban puncak. Pengguna kenderaan elektrik amat prihatin terhadap kos penggantian bateri akibat

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kemerosotan bateri apabila terdapat penyertaan aktif dalam pertukaran tenaga V2G. Oleh itu, model degradasi bateri dirumuskan untuk analisa masa sebenar dengan mempertimbangkan kedalaman discas pada setiap selang masa. Kos operasi dan keuntungan V2G dianalisa dengan penetrasi yang berbeza ke sistem penjanaan kuasa yang boleh diperbaharui, kapasiti bateri EV dan perubahan waktu perjalanan. Hasil penyelidikan menunjukkan bahawa kaedah pengurusan tenaga yang dicadangkan boleh mengurangkan kos operasi mikrogrid disamping memastikan kebolehpercayaan mikrogrid. Oleh kerana saiz bateri mempengaruhi kos operasi, penentuan saiz bateri yang optima dihitung supaya kos elektrik adalah rendah dan jangka hayat bateri dipanjangkan. Didapati kaedah yang dicadangkan menurunkan kos sebanyak 50% jika dibandingkan dengan kaedah konvensional. Kaedah pengurusan tenaga diselesaikan dengan menggunakan kaedah-kaedah algoritma “firefly,” koloni lebah tiruan, algoritma carian harmoni, dan pengoptimuman gerombolan zarah. Hasil didapati algoritma ‘firefly’ adalah lebih kuat dan pengiraan yang berkesan. Di samping itu, kordinasi cas EV menambahbaikan prestasi sistem, mengurangkan kehilangan kuasa dan menyekat grid yang menyaratkan. Persepaduan sumber tenaga boleh diperbaharui (RES) dapat mengurangkan kos sistem dan memaksimakan keuntungan kepada pengguna EV. Kehilangan kuasa sistem dan kos elektrik adalah minima jika penembusan RES ditingkatkan disamping kapasiti EV menghasilkan keuntungan minima.

Kata kunci: Penyimpanan tenaga bateri, kenderaan elektrik, kos degradasi, penjadualan ekonomi, koordinasi cas.

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LIST OF ABBREVIATIONS

ABC	:	Artificial bee colony
AC	:	Alternating current
BEMS	:	Battery energy management system
BESS	:	Battery energy storage system
CAES	:	Compressed air energy storage
COE	:	Cost of electricity
CRF	:	Capital recovery factor
CVNN	:	Complex-valued neural network
DC	:	Direct current
DE	:	Diesel engine generator
DED	:	Dynamic economic dispatch
DER	:	Distributive energy resources
DG	:	Distributed generator
DOD	:	Depth of discharge
DSM	:	Demand side management
EENS	:	Expected energy not supplied
EIA	:	Energy information agency
ESS	:	Energy storage system
EV	:	Electric vehicle
FA	:	Firefly algorithm
FACTS	:	Flexible Alternating Current Transmission System
FC	:	Fuel cell
FiT	:	Feed in tariff
FRT	:	Fault ride through

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G2V	:	Grid to vehicle
GA	:	Genetic Algorithm
HESS	:	Hybrid energy storage system
HM	:	Harmony memory
HMCR	:	Harmony memory consideration ratio
HSA	:	Harmony search algorithm
ICE	:	Internal combustion engine
Li-Ion	:	Lithium ion
LOLE	:	Loss of load expectation
LPSP	:	Loss of power supply probability
LVRT	:	Low voltage ride through
MC	:	Maintenance cost
MILP	:	Mixed integer linear programming
MIP	:	Mixed integer programming
MT	:	Microturbine
MW	:	Megawatt
$NaNiCl_2$	:	Sodium nickel chloride
NaS	:	Sodium sulphur
NiCd	:	Nickel cadmium
NIST	:	National Institute of standards and technology
PAR	:	Peak average ratio
PHEV	:	Plug-in hybrid electric vehicle
PHS	:	Pumped hydro storage
PMU	:	Phasor management unit
PSO	:	Particle swarm optimization
PV	:	Photovoltaic

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RES	:	Renewable energy sources
RTTR	:	Real time thermal rating
SC	:	Super-capacitor
SMES	:	Superconducting magnetic energy storage
SOC	:	State of charge
T&D	:	Transmission and distribution
TCPD	:	Total cost per day
TOU	:	Time of use
UPS	:	Uninterruptable power supply
V2G	:	Vehicle to grid
VRFB	:	Vanadium redox flow battery
VSI	:	Voltage source inverter
WT	:	Wind turbine
ZnBr	:	Zinc Bromine

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CHAPTER 1: INTRODUCTION

1.1 Overview

In the last few decades, the world is seeing an unprecedented rise in its population with the resultant subsequent excessive power demand, both of which are the main operative factors behind global warming and carbon emissions. Unfortunately, the usage of fossil fuels still plays the major role in supplying energy for the power generation and transportation system. However, continual and inevitable depletion of fossil fuel resources in the recent years has put a serious pressure on governments and energy entrepreneurs to be responsible enough to move towards replenishment of energy through renewable energy sources (RES) (Jamshidi & Askarzadeh, 2018). The global renewable generation capacity amounted to 2,179 GW in 2017 with new installations for wind and solar accounting up to 85%. Figure 1.1 shows the renewable energy generation capacity from 2011-2017 with hydropower having the largest share of 1152 GW, wind and solar with capacities of 514 GW and 397 GW respectively in 2017 (IRENA, 2018). The increase in renewable energy generation is reducing the greenhouse emission by replacing fossil fuel consumption. However, the intermittent nature of RES is thwarting the stability of the power system in the economic sense. Hence, efficient controlled methods have become the order of the day to overcome the issues of voltage disturbances, frequency regulations and network security during the high penetration of the RES to meet the growing energy demand of the huge population (Kuang, Li, & Wu, 2011).

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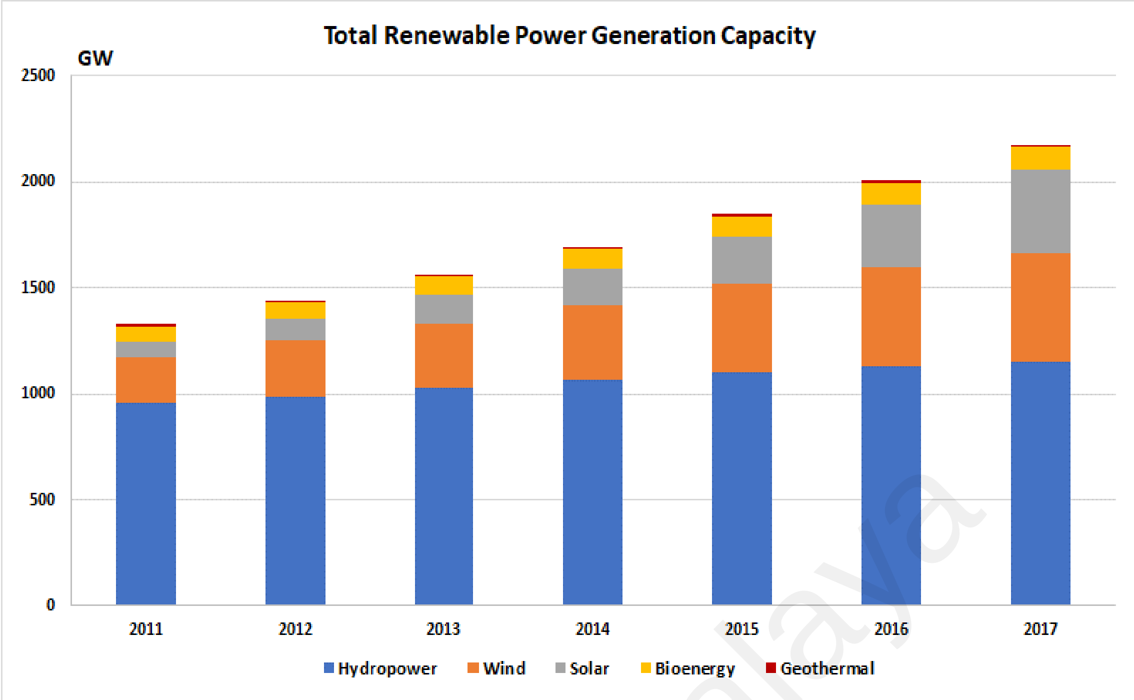

Figure 1.1: Total renewable power generation capacity, 2011-2017 (IRENA, 2018)

Microgrids have emerged as a platform to integrate distributive energy resources (DER), such as diesel engine generators (DE), wind turbine (WT), microturbine (MT), fuel cell (FC), solar photovoltaic (PV) panels and energy storage system (ESS) within a network to feed into the utility grid in a more orderly and manageable network. Over the past few years, ESS has become an essential component of the microgrid. ESS can reduce the power fluctuations caused by RES. In addition, ESS can store the energy during the periods of high-power generation and release it when the load exceeds the power generation capacity. ESS with high energy density and longer discharge time are utilized for the applications related to economic energy dispatch and peak shaving. On the other hand, a high power density ESS with a fast response capability is better suited for the voltage control and frequency regulation applications (Eyer & Corey, 2010; Fu et al., 2013).

The investment cost of ESS is the main hindrance for the installation of large energy storage to solve the supply/demand problem. However, an attractive solution is the use of electric vehicles battery which can provide ancillary services of energy arbitrage, load balancing and voltage regulation (Uddin, Jackson, et al., 2017). Electric vehicle (EV) is gaining popularity in recent times and this is evident through the soaring sales of EV. The advantages of EV over the conventional vehicles are the ability to run on the power generated locally, vehicle to grid (V2G) power transfer and reduction in CO_2 emission. To establish a clean and reliable energy system, large-scale adoption of EVs has been considered an effective solution to decarbonize the environment (Dong et al., 2018).

The ongoing research for new developments with the policy support for the investment in charging infrastructures is resulting in lower battery costs and higher EV production. International Energy Agency has predicted a massive increase in EV sales after 2020 reaching up to 220 million per year by 2035 (Falahati, Taher, & Shahidehpour, 2016). Figure 1.2 shows that expected sales of EVs can reach up to 400 million in 2040 with 35% sale of EVs in the market. Local and national authorities around the world are promoting the use of electric vehicles over the internal combustion engine (ICE) vehicles by providing incentives to consumers in tax exemption, cheap electricity tariff for overnight charging, free public parking and access to bus lanes (Bjerkan, Nørbech, & Nordtømme, 2016).

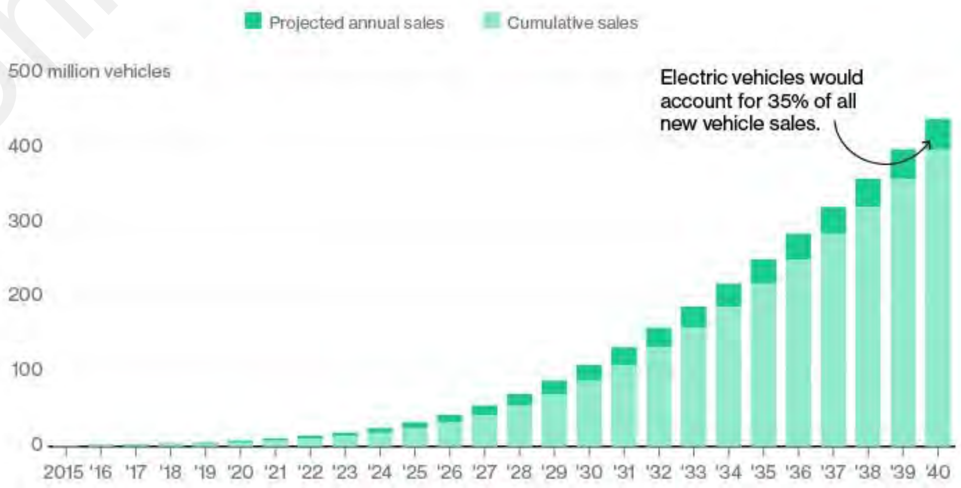

Figure 1.2: Global electric vehicles sale till 2040 (Randall, 2016)

EVs are the adequate candidate for demand side management (DSM), providing flexibility for time-dependent charging. Peak shaving and load shifting can be performed with smart charging techniques. Moreover, EVs are capable to feed the power back to the grid during high peak demands, reducing the electricity cost and earning profit for the consumers. EVs that are equipped with bidirectional converters are capable to connect the EVs to the grid, facilitating the charging of batteries at low demand period and discharging at high demand. This concept is referred as V2G. The V2G methods can be approached from economic and technical aspects. Economic strategies focus on EV owners profit maximization considering the impact of battery degradation, user availability and time of use (TOU) tariff. Whereas technical strategies support the system in performing voltage and frequency regulation, power balance, demand response and loss reduction.

The assessment of economic viability by V2G service should also consider the battery degradation cost for the financial profitability of the user as battery degrades with the V2G cycling and the age of the battery. Moreover, certain factors accelerate battery degradation such as deep discharges, high temperature and high current rate, which are referred to as aging stress factors. Hence, customer's revenue for energy arbitrage decreases with the addition of battery degradation cost. The studies in (Antúnez, Franco, Rider, & Romero, 2016; Czechowski, 2015; Uddin, Gough, Radcliffe, Marco, & Jennings, 2017) concludes that costs associated with battery lifetime outweigh the V2G profit.

1.2 Problem Statement

The optimal scheduling of microgrid to reduce the overall operating cost has been a serious concern for the researchers for many years. This includes the sizing of distributed generators in the microgrid. Energy storage in microgrid balances

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the power between generation and load, ensuring the frequency and voltage regulation. Battery energy storage systems (BESS) are best suited for power system applications due to their technical benefits and ability to provide both the power and the energy density. The operation and the scheduling of the BESS have been addressed by many researchers but the design and estimation of its optimal size to achieve a cost-effective system with minimum power losses is still in progress. In order to ensure the reliability, security and economic benefits of the microgrid, ascertaining an optimal size of BESS is indeed essential. The lifetime of the battery is an essential factor for the sizing of BESS. The lifetime of the battery is affected by two main factors, namely, 1) the lifecycle stating the number of charge and discharge cycles a BESS can sustain, and 2) the depth of discharge representing the amount of capacity used by a BESS. Over the years, the energy scheduling and optimal sizing of battery storage have been proposed by many researchers, by considering only the fixed value of battery lifetime. Many researchers have developed a battery degradation model and cost of battery degradation, while research on the integration of the developed model in the economic dispatch has not been conducted.

With the substantial growth in EV market, the utilities are concerned for the demand response programs to generate secure network with maximum economic benefits. Nevertheless, the electrical distribution system will face overloading effect without proper coordination of EV charging. Moreover, the high penetration of EV may result in increase of technical losses, higher peak demands and reduction in the voltage profile (Arias, Franco, Lavorato, & Romero, 2017). These negative impacts can be mitigated by metaheuristic techniques to solve charge coordination of EV. However, the cost of EV battery replacement due to degradation is of paramount concern for EV users that constitute the most important ingredient to achieve active participation in V2G energy exchanges. Besides, there is also concerns within the EV manufacturers pertaining to the state of warranty for batteries that participate in V2G system.

As such, the research in this project aims to study the economic power dispatch in V2G environment by incorporating the latest findings in battery degradation. The conventional synchronous generator economic dispatch problem with energy storage for isolated microgrid will first be taken as the basis for this study. Next, the presence of RES, centralized charge coordination and distributed V2G batteries power dispatches will be considered in the economic dispatch problem. Customarily, large majority of the decision-making in battery energy management system (BEMS) is simply based on the availability and deficit of renewable energy respectively to meet the demand (Azaza & Wallin, 2017; Borhanazad, Mekhilef, Ganapathy, Modiri-Delshad, & Mirtaheri, 2014; Ismail, Moghavvemi, & Mahlia, 2013). However, this project will propose methods to develop further optimized solution for BEMS by considering the battery degradation cost.

1.3 Research Objectives

The objective of this dissertation is to incorporate real-time battery degradation model in the economic dispatch problem to reduce the operating cost of the system and prolong the battery lifetime. In order to achieve this, the following objectives are defined:

1. To design the real-time battery degradation cost model for economic dispatch problem.
2. To develop the optimal battery sizing model for the economic scheduling of isolated microgrid.
3. To solve the real-time economic dispatch optimization problem in isolated microgrid.
4. To adapt the developed real time battery degradation cost model for electric vehicle charge coordination with V2G application.

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1.4 Scope of Study

Isolated microgrids are dependent on RES and portable units such as diesel generator and energy storage to maintain the balance between demand and supply. The integration of ESS to suppress the power fluctuations and minimize the technical losses has improved the reliability and power quality of microgrid. BESS amongst various storage technologies is mostly adopted for microgrid applications due to their ability to improve the operational strategies and reduce the operating cost. BESS optimal size with appropriate technology and effective scheduling of charging and discharging cycles maximizes the benefits of the microgrid. Generally, the BESS with larger size reduces the thermal generations and improves the microgrid performance but the high installation cost is the main barrier to deployment of large BESS. Therefore, optimal size with proper operational strategies and cost-benefit analysis is required to minimize the microgrid operating cost. Economic scheduling together with an optimal battery size is also significant for rural electrification schemes in small towns where the electrical grid is not available.

When EVs are treated as energy storage, EV charging increases the electrical load of the distribution network. The operation of the electrical distribution system is extremely affected with the high penetration of EVs and if the charging is uncontrolled, the additional EV load during peak period can challenge the reliability of the power system. On the contrary, the smart charging schemes for EV reduces the peak load and minimizes the technical losses and generation cost. Moreover, V2G technology provides ancillary services for power system such as spinning reserve and DSM.

Smart charging/discharging increases the customer's awareness towards energy usage and prolonging the battery lifetime. Effective battery scheduling avoids deep discharges and maximizes the profit for EV customer. When the battery state of charge (SOC) ranges

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between 40% to 60%, the battery lifetime is extended with V2G cycling (Uddin, Jackson, et al., 2017). Therefore, an effective mechanism with bidirectional power transfer inflates the revenues earned through V2G and prolongs the lifetime of the battery.

1.5 Thesis Outline

The thesis consists out of the following five parts: research objectives, background, methodology and theoretical framework, findings and results, and conclusion and future work. The thesis is organized as follows:

Chapter 2 includes a comprehensive review of different application and benefits of energy storage systems. The factors associated with the sizing of energy storage in microgrids are also discussed. In addition to this, various strategies implemented for economic dispatch are reviewed. This chapter also discusses the significance of charge coordination of electric vehicles in the power system. The chapter ends with an overview of optimization algorithms implemented in this thesis.

Chapter 3 describes the methodology for the proposed energy management strategy with optimal battery sizing in the isolated microgrid. The battery energy storage model together with other distributed energy source models is discussed. The framework for the economic scheduling of grid-connected network with electric vehicles is also presented.

Chapter 4 validates the proposed methodology and evaluates the performance of the proposed method with tradeoff methods in terms of performance measurement indices; the cost of electricity and loss of power supply probability. The operating cost and technical losses of the distribution network are analyzed for different cases of electric vehicle charge coordination with V2G technology. The EV user's profit in V2G considering the impact of battery lifetime degradation is also computed.

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Chapter 5 presents the overall conclusion of the research work and the possibility of the research impact on future technology. Finally, this chapter mentions the current limitation of the proposed work and provides the direction for further improvement in the future.

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CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Currently, the dominant source of energy for the power generation and transportation is fossil fuel. Most of the countries are depending upon imported fossil fuels, causing these countries to financial instability when the price of fossil fuel changes in the international market. According to the Energy Information Agency (EIA) report, a substantial increase in oil prices will be observed in the next two decades (EIA, 2016). As such, government and energy companies are taking steps to move towards the RES. Greenhouse gas emission will be reduced by replacing fossil fuels with RES. However, RES will present challenges when integrated with the existing power grid due to the former intermittent nature. As such, the battery is considered an important component to suppress the intermittent power delivery from RES. In contrast to the conventional grid, a modified electrical system is required to overcome the challenges of sustainable, economic and reliable electricity when installing RES at a higher level.

Smart grid provides the solution to revolutionize the electricity grid and improve the power delivery in an efficient manner. Smart grid transforms the current grid into one that functions more responsively, economically and cooperatively. The National Institute of the Standards and Technology (NIST) describes smart grid as a system with the capability to integrate communication and computing technologies as well as services into power system infrastructure (Bryson & Gallagher, 2012; Tuballa & Abundo, 2016). Figure 2.1 shows the transfer of electricity from the power plant generators to the customer end in a smart grid power system. The flow of electricity and communication between the generation, transmission and distribution utilities and the customer is also shown in the diagram. The generation part consists of fossil fuels generators, RESs and battery storage system. The data center unit manages the generation part remotely through its intelligent

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nodes installed at different locations. Phasor management units (PMU) are also installed inside the control center by which operator can measure grid stability in case of any fault. The customer section contains the intelligent building, electrical vehicles, household and batteries to store excess energy for later use as per customer requirement (Hassaine, Olías, Quintero, & Barrado, 2014). In a smart grid network, RESs are safely plugged into the grid and additional power is provided by the household distributed generation and battery storage. The smart grid will enable consumers to manage energy consumption and cost. This will benefit the utility companies through increasing security, reducing peak loads and lowering the operational costs (Al-Nasseri & Redfern, 2007; Driesen & Katiraei, 2008).

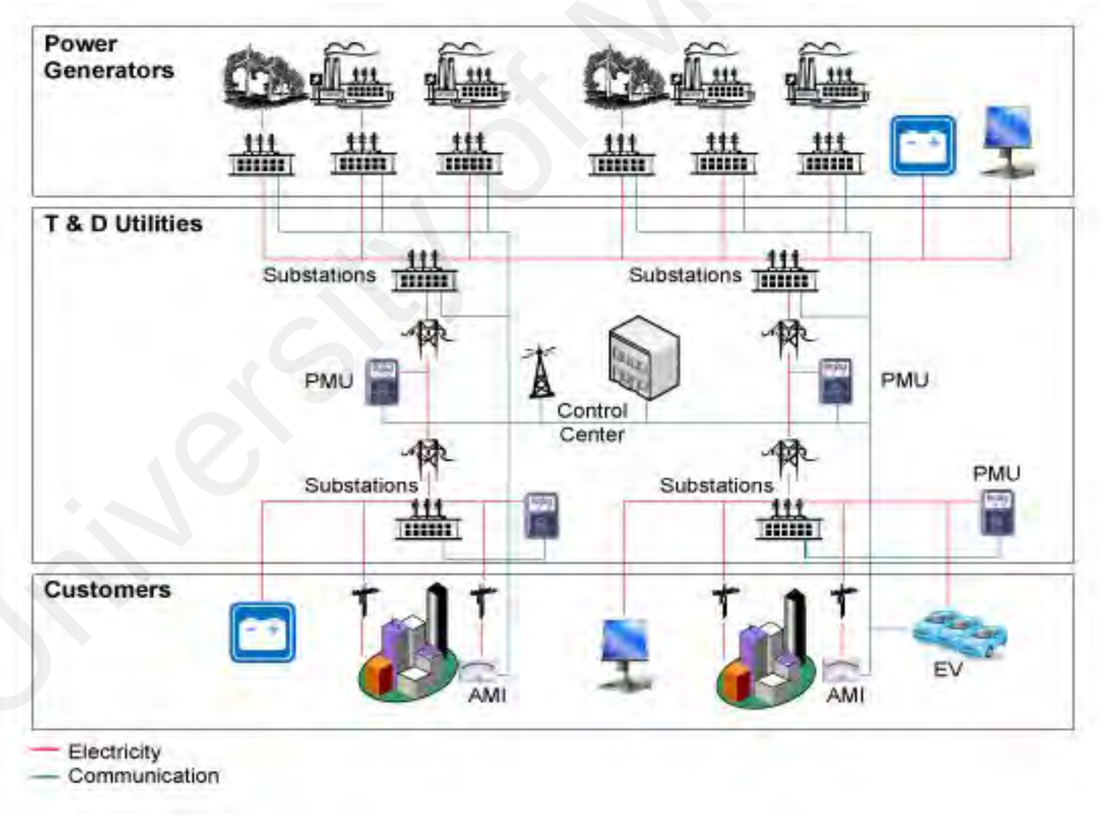

Figure 2.1: Flow of electricity in a smart grid system with a control unit and PMU (Hossain et al., 2016)

However, smart grid also brings upon many challenges when the integration of fuel cells, photovoltaic, wind energy and battery storage are considered (Amin, 2011; Hossain

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et al., 2016). The energy storage system (ESS) has a leading role in increasing the penetration of renewable energy sources due to its continuous support to the power grid in fulfillment of load demand in terms of regulating power system frequency and upgrading the transmission line capability. ESS minimizes the fluctuations of renewable energy and stores additional power when the generation is high so that the energy can be used during peak load hours (Vazquez, Lukic, Galvan, Franquelo, & Carrasco, 2010). ESS also improves the efficiency of the power system by mitigating grid congestion (Hasan, Hassan, Majid, & Rahman, 2013). In general, ESS can be classified into mechanical energy storage (pumped hydro storage, flywheel, compressed air energy storage), electrical energy storage (super-capacitors, superconducting magnetic energy storage), electrochemical energy storage (battery), chemical energy storage and thermal energy storage technologies (Gallo, Simões-Moreira, Costa, Santos, & dos Santos, 2016). Figure 2.2 shows the classifications of energy storage systems.

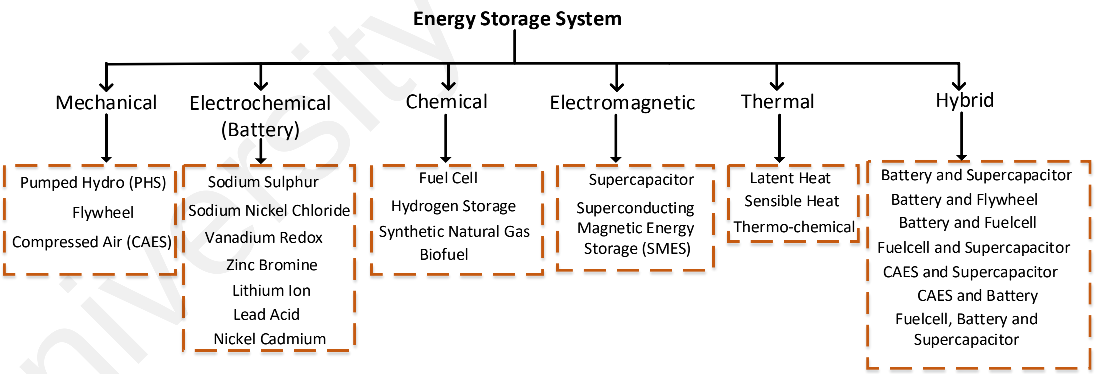

Figure 2.2: Classification of the energy storage system (Gallo et al., 2016)

2.2 Energy Storage System

Electrical energy storage and technologies that have the capability to reduce peaks and smooth the power are crucial elements of the future power system network. ESS can be the solution to fix the aging power grid, bridging the gap between the utilities and customer's demand. They have become a critical tool for increasing consumers comfort, reducing electricity bills and earning revenue.

Storage device allows the consumer to not only store energy for a longer duration of time but also to save the consumer's money by charging the storage devices during off-peak hours when the price is low and using them during peak hours (H. K. Nguyen, Song, & Han, 2015). This increasing importance of energy storage devices has forced researchers to put great effort into achieving high efficient and cost-effective storage device. However, there are many other factors associated with the energy storage devices such as energy storage capacity (MWh), power capacity (MW), device cost and maintenance cost. The charging and discharging process of storage devices requires adequate control strategies to perform the reliable operation of the grid even during the peak demand (Lindley, 2010; Thatte & Xie, 2012).

Microgrids are a small part of the power system that allows the smart grid to function properly. Microgrid plays a vital role in the integration of smart grid to the existing network, consisting of distributed energy resources and loads that are grid-connected or operated in islanded mode. They generally produce energy with renewable sources, making power system reliable, economical, clean and protected. ESS in microgrid is used to retain the power balance between the demand and generation, thus ensuring the regulation of frequency and grid voltage. Selection of different energy storage units, each having distinguished characteristics in power and energy, depends on the nature of power required and delivered, but the most commonly used in microgrid are super-capacitors (SC) and batteries. Super-capacitors have high power density and low energy density. SCs are used in applications to support the fast-transient power demands. In contrast, batteries have high energy density and low power density that can be active for longer durations and are used to support slow transient power demands. Hybrid energy storage

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system having both high energy and power density are deployed to support the slow and fast transients together (Dubal, Ayyad, Ruiz, & Gomez-Romero, 2015; Kollimalla et al., 2017).

Some benefits of energy storage system in microgrid and smart grid are presented as follows:

2.2.1 Peak Shaving

Peak shaving is a technique to reduce the consumption of electricity when the demand for electricity is at peak, usually during daytime in summer and night time in winters. Utility companies now have different pricing tariffs based on the demand at a different time, with high price during peak hours. This variable tariff has helped the utility companies to achieve economic dispatch during peak hours. The other viable option is to install storage devices and solar panels that may help in reducing power demand as these are effective during peak hours when the demand is high. Organizations with high electrical consumptions find peak shaving an attractive option due to its pricing.

A self-consumption energy generation technique for peak shaving is studied in (Luthander, Widén, Munkhammar, & Lingfors, 2016) where the community based centralized storage unit is analyzed to share power within the community. The self-consumption ratio rises for the case without storage unit compared to the case with the central storage unit. The storage unit is hardly used in winters due to low PV power production. However, the storage unit increases yearly revenue and reduces losses by changing from the individual household to a centralized unit. The extra revenue can be used for the community expenses and maintenance work.

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2.2.2 Home Energy Management

Battery storage is deployed in houses as a source to provide power supply during power interruptions. Batteries are often used with uninterruptable power supply (UPS) to protect the equipment during the times of high spikes or low voltages. Moreover, energy tariff implemented in many countries can help residential customers to store energy when the electricity price is low and then utilizing the stored energy during the high tariff period. A home energy management model is examined in (Shirazi & Jadid, 2017) to minimize the electricity price of the household by shifting the timings of the electrical and thermal appliances of the housing based on the electricity pricing value. The author discusses the home with self-energy generation and storage units, which interact with the main grid for the exchange of power. Within the home, energy consumption pattern examines the probability of activity and social random factors like weather and environment for the electrical and thermal household appliances. In addition, the energy scheduling problem is modeled as Mixed Integer Linear Programming (MILP) to get the optimal power dispatch. The optimal size for the storage device is obtained to enhance the supply and demand by saving the extra energy.

2.2.3 Load Levelling

Load leveling involves the process of storing energy when the system load is light and delivering the energy back during the high spikes of the load. Flexible Alternating Current Transmission Systems (FACTS) devices and battery energy storage system are examined by (Rafi, Hossain, & Lu, 2016) to mitigate the voltage rise and load leveling problem. The smart voltage source inverter (VSI) having the capability for the reactive power compensation using variable power factor is used for high penetration of PV in low-voltage (LV) network. The control method minimizes the communication between static synchronous compensator (STATCOM) and PV units. During the high PV penetration up to 30%, the overvoltage issues are mitigated using the proposed control method even at the farthest point from the distribution transformer. Thus, the control method is cost effective because the controller can be installed only at the critical points rather than installing at all the testing points with a conventional controller.

2.2.4 Power Fluctuations

The energy storage system has been very effective in reducing fluctuations by providing ancillary services during the intermittent nature of RES. However, with the rapid increase in load demand and penetration of renewable sources, the distribution system faces many challenges of power fluctuations, voltage stability and immense power losses (Hung, Mithulananthan, & Bansal, 2014; Omran, Kazerani, & Salama, 2011; Sugihara, Yokoyama, Saeki, Tsuji, & Funaki, 2013).

The authors in (Reihani, Motalleb, Ghorbani, & Saoud, 2016) proposes methods for smoothing the power fluctuations by using two load forecasting methods. Complex-Valued Neural Network (CVNN) to predict the 24-hour load data and series-parallel forecasting method to predict the load data of 20 minutes ahead. The primary objective is to achieve smoothing and peak shaving for which CVNN performs optimization technique to follow the state of charge trajectory of BESS. Distribution grid load curve experiences some unsuitable charging and discharging of BESS, which increases the complexities due to inaccurate forecasting. Thus, the series-parallel method performs smoothing of the load curve by dumping the load stochastic fluctuations due to high PV penetration.

2.2.5 Transmission and Distribution (T&D) upgrade deferral

Energy storages are deployed in the transmission system to defer the equipment upgrades of T&D due to an increase in power demand or to extend the life of T&D

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equipment. ESS provides economical alternatives to develop new infrastructure (substations and feeder) which poses challenges concerning local communities, future demand growth, capital investment and massive time requirement. The T&D system may require energy storage for a small portion of the year during the summer days when the demand exceeds the equipment's capacity. Thus, ESS is beneficial in increasing the equipment life provided that equipment operates under the rated capacity and temperature. This helps in reducing the ground faults incidents in the underground cables ("Energy Storage Association - Electrochemical Capacitors," ; Eyer & Corey, 2010).

2.2.6 Frequency regulation

Electric power system faces problems likes frequency deviations and voltage variations due to uncertainty in wind and PV output power depending on the location of installation, weather conditions and season of the year (Datta & Senjyu, 2013). The power fluctuations of these renewable sources in islanded mode may result in disconnection of a large area. The grid codes in European countries have been modified to provide dynamic grid support such as frequency control and fault ride through (FRT) during voltage sags. The ancillary service markets are providing system services like frequency regulation in many countries. The fast response time of BESS compared to other storage devices makes it a more effective way of supporting system frequency. Moreover. the charging and discharging operation of battery delivers the regulated power to grid in less than 20 milliseconds (Xu, Oudalov, Poland, Ulbig, & Andersson, 2014). The power block of the battery storage system includes converters, filter circuits and control system. The frequent change in active and reactive power supply improves the frequency control capability and delivers fast active power by implementing effective control strategy (Mercier, Cherkaoui, & Oudalov, 2009).

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2.2.7 Low Voltage Ride Through

Photovoltaic systems connected to the network are developing at a very fast pace and will soon be a large part of the power generation in some regions (Y. Yang & Blaabjerg, 2013). With more grid-connected PV systems in the medium voltage network, the higher penetration level in the grid will cause stability and reliability issues, particularly under voltage problem (Mirhassani, Ong, Chong, & Leong, 2015). Thus, grid codes are being released by the transmission system operators for PV sources that are connected to the low or medium voltage networks with Low Voltage Ride Through (LVRT) capability. Furthermore, grid codes require the injection of reactive current during such faults. The switching losses increase with the injection of reactive power; to compensate this, the system must draw active power. Moreover, the DC voltage falls in the system during the severe faults. The energy storage can support the voltage level to stabilize the system during such faults (Koutroulis & Blaabjerg, 2013; Obi & Bass, 2016; Shenoy, Kim, Johnson, & Krein, 2013; Y. Yang, Blaabjerg, & Wang, 2014).

2.2.8 Loss Minimization

The radial structure of the electrical distribution system and having large current to voltage ratio results in a high quantity of power losses in a distribution system. These power losses can be minimized by reconfiguration of the system like the optimal allocation of distributed generators, shunt capacitors and placement of RES (Brown, 2008; Rahmani-Andebili, 2017). The utility companies are intended to place the distributed generators e.g. PV system near to distribution load to reduce the power flow, minimize losses and provide stability to the system in terms of avoiding voltage disturbances. Power loss in each branch is the measure of the squared value of current flowing into the branch; energy storage shifts some of this current to low demand period, decreasing the resistive losses. The energy storage placement in the distribution system can also result in power loss minimization. The energy loss within the storage system due to power conditioning unit and internal resistance loss during the charge/discharge can be minimized by managing the efficiency of energy storage (Hien, Mithulananthan, & Bansal, 2013; Hung, Mithulananthan, & Bansal, 2013; Ochoa & Harrison, 2011; Tran & Khambadkone, 2013).

Ali Moeini in (Moeini, Kamwa, & de Montigny, 2016) discusses the power factor-based method to minimize the losses during charging and discharging. A multi-objective genetic algorithm technique is proposed to find the optimal tuning of power factor to save energy throughout the year. The power loss of the system can be decreased even during charging mode by allocating the energy storage appropriately.

2.2.9 Reliability Improvement

The variability in wind and solar power may deteriorate the reliability of the power system. Energy storage can provide the required reactive power to improve reliability by providing the voltage support. A charge/discharge schedule of BESS is designed in (Teng, Luan, Lee, & Huang, 2013) to reduce the line losses of the photovoltaic connected distribution system. The fast response time of BESS allows the charging/discharging to be scheduled on an hourly basis depending on the intermittent nature of PV and load variations. A mathematical model of the battery storage is implemented to determine the scheduling process using the genetic algorithm technique. The authors further emphasize that the battery scheduling can improve the reliability and provide voltage support to the system.

2.2.10 Reserve Application

Energy storage can provide reserve facility to respond to the forecast error of renewable resources. These reserves can be utilized to solve the contingency issue due to

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a rapid increase in the generation or sudden fall of load demand. The response time of the storage system for this kind of support is very fast and may last for some hours (Díaz-González, Sumper, Gomis-Bellmunt, & Villafáfila-Robles, 2012). The storage system balances the supply and demand of the electricity when the actual demand rises above the forecasted demand. Flow batteries due to their short response time and high capacity are heavily used for this application (Sasaki, Kadoya, & Enomoto, 2004).

2.2.11 Demand Response

The demand response programs have been deployed in large extent as the possible solution to overcome the unpredictability of RES. The demand response is defined as the change in the energy consumption by the consumer from the normal load as an incentive provided by the utility companies or change in price of electricity during on-peak hours to maintain the stability and reliability of the system (Brahman, Honarmand, & Jadid, 2015; Vlot, Knigge, & Slootweg, 2013). Energy storage due to its prominent features is the ideal candidate to manage the residential demand response where the demand and supply are controlled by households (Z. Wang, Gu, Li, Bale, & Sun, 2013). The benefits from the demand response programs are not limited to the consumers in term of saving bills, but they can be extended to utility companies where reliability is increased by modifying load shape and improving market performance (Siano, 2014).

A demand management response is studied in (Shakeri et al., 2017) where the primary objective is to provide the energy with relatively low price and without sacrificing human comforts. A control algorithm for the electricity demand response of a smart house is proposed. The algorithm uses local battery storage as an additional supplementary source to manage the electrical operation on basis of hourly electricity price. The algorithm charges the battery during off-peak hours and discharges during high demand hours. Furthermore, it manages the temperature of the room to optimize the electricity

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consumption if the total power consumption of the house exceeds the defined level. A daily reduction in electricity price is observed by deploying the storage device and managing the power consumption efficiently.

2.2.12 Electric/hybrid vehicles

Battery energy storage is extensively used in transportation applications to provide power such as electric and hybrid electric vehicles. BESS with high energy density and fast charging/discharging capability is well suited for EVs. Super-capacitors are also utilized in transportation during high power peaks for short durations when the BESS fails to deliver. The efficiency of the EV is increased by incorporating a hybrid energy storage system (e.g. combination of SC-battery), which stores the energy during braking. The phenomenon of regenerative braking energy is dominant in city buses. SC delivers this energy for acceleration purpose while the battery can be used for air-conditioning, heater or electronic appliances (Kouchachvili, Yaïci, & Entchev, 2018; Miller, 2016). Therefore, hybrid storage with high power and energy density and long calendar life can improve the performance of EV and increase their penetration in the market. However, the range of the EV is a major issue due to high time consumption in charging the energy storage. Thus, adequate charging infrastructure should be developed (Andwari, Pesiridis, Rajoo, Martinez-Botas, & Esfahanian, 2017).

Table 2.1 summarizes the benefits of energy storage with the specific characteristics and suitable technology preferred (Barton & Infield, 2004; de Boer & Raadschelders, 2007; Díaz-González et al., 2012; X. Luo, Wang, Dooner, & Clarke, 2015).

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Table 2.1: Overview of benefits with their characteristics

Benefits	Characteristics Power Requirement, Response time, Storage/discharge time	Energy storage technology
Peak Shaving	100 kW-100MW, seconds to minutes, 1-10 hour	Lead-acid, Li-Ion, VRFB, fuel cell, ZnBr, NaS, NiCd
Energy Management	< 1 MW, milliseconds to seconds, seconds, ~2-10 hour	PHS, NaS, ZnBr, VRFB, Li-Ion, flywheel
Load Levelling	More than 100MW, minutes, up to 10 hours	Lead-acid, SMES, Li-Ion, PHS, CAES, VRFB, ZnBr, fuel cell
Power fluctuations	Few hundred kW, milliseconds, few seconds	Flywheel, SMES, super-capacitor, VRFB
T&D upgrade deferral	10-100 MW, seconds, 1-10 hour	PHS, CAES, VRFB, fuel cell
Frequency Regulation	1-5 MW, milliseconds to seconds, few minutes to 1 hour	NaS, Lead-acid, $NaNiCl_2$, NiCd, ZnBr, super-capacitor
Low voltage ride through	< 10 MW, ~ milliseconds, few seconds to a minute	Lead-acid, $NaNiCl_2$, Li-Ion, NaS, super-capacitor
Loss Minimization	~100 MW, milliseconds, few seconds	SMES, NaS, ZnBr, VRFB, Li-Ion, flywheel
Reliability Improvement	~ 1 MW, milliseconds, few minutes to ~5 hour	Super-capacitor, SMES, lead-acid, VRFB, NaS
Reserve Application	1-100MW, few seconds, minutes to few hours	CAES, flywheel, VRFB, ZnBr, fuel cell, NiCd, PHS
Demand Response	< 1 MW, seconds, ~ 1-10 hours	Li-Ion, VRFB, ZnBr, flywheel, $NaNiCl_2$
Electric/hybrid vehicles	~ 50 kW, milliseconds, minutes to hours	Li-Ion, Lead-acid, super-capacitor, fuel cells

2.3 Hybrid energy storage

HESS is the combination of two ESSs in which one storage has high power density, high efficiency during transient, longer lifetime and fast response time, while the other storage provides high energy density having comparatively lower discharge rate (Bocklisch, 2016). The most commonly used HESS is battery having high energy density, reliability and modularity mixed with super-capacitor, which overcomes the battery deficiencies of low power density, low cycle life and increases the overall efficiency of

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the system. The hybrid energy systems can be connected in seven types of structures which are subdivided into two main categories of direct and indirect connection structures. DC-DC converters and DC-AC inverters are used to connect the batteries, super-capacitors and motors to the DC bus. In direct connection structures, the batteries and super-capacitor are directly connected to DC bus without any involvement of converters (DC-DC, DC-AC), whereas battery and super-capacitor are connected to converters and then to DC bus in indirect connection structures. Figure 2.3 shows direct and indirect connection structures. The main benefits of hybrid energy storage are cost reduction, increase in system efficiency, greater storage capacity and longer lifetime (Ostadi, Kazerani, & Chen, 2013; H. Wang, Wang, & Hu, 2017; H. M. Wang, 2014).

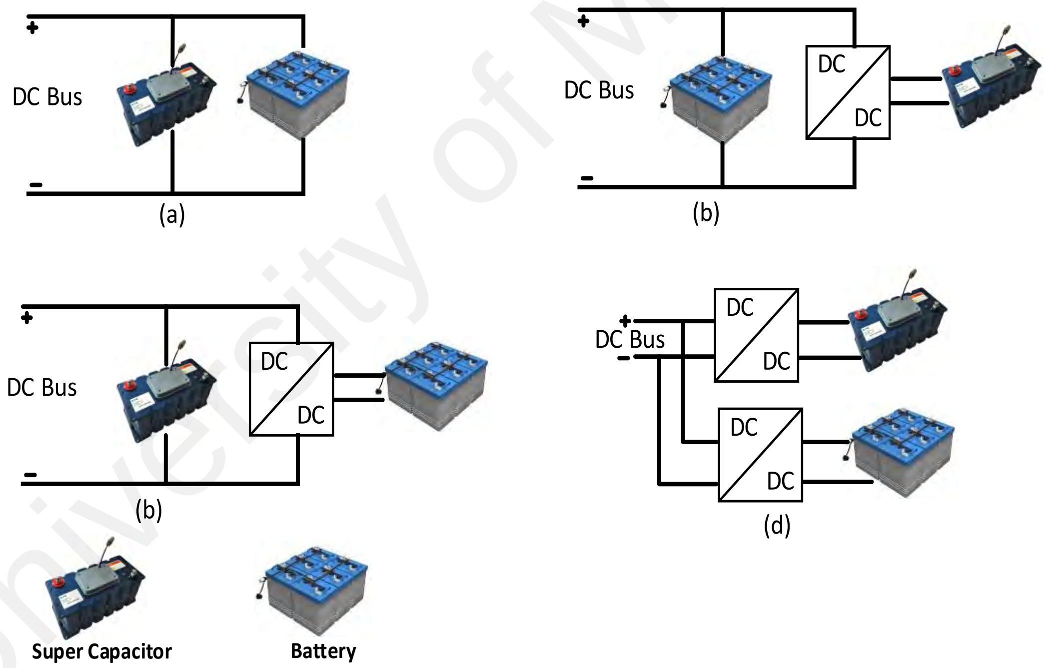

Figure 2.3: Schematic structures of hybrid ESS (a) direct connection, (b) (c) (d) indirect connections (H. Wang et al., 2017)

HESS applications have been reported in a number of literature, where a battery with super-capacitor hybrid storage and battery with fuel cell hybrid storage is applied in electric vehicles (Camara, Gualous, Gustin, & Berthon, 2008). Electric vehicles use HESS to meet the demands of high energy and high-power densities, and also due to the small size and weight of HESS. Hybrid storage is able to perform peak shaving and stress reduction on other storage devices and public grid. HESS is also used in renewable energy systems with battery/hydrogen combination and in solar parks (Alloui, Becherif, & Marouani, 2013; Shen, Jiang, Su, & Karimi, 2015; Song et al., 2015).

2.4 Sizing of Energy Storage System

To achieve maximum economic benefit from the storage system, optimal sizing is an important factor of the battery that should be known. The calculation for the optimal size of the battery is a complex task because the efficiency of the battery, its lifecycle and electricity tariff are all dependent on battery sizing. This task becomes more complicated when ESS is integrated with the RES that contains uncertainties, which has a direct impact on load demand and energy prices. Probabilistic and stochastic approaches have been reported in the literature for the sizing of BESS. The former is used when ESS is integrated with RES due to its fluctuating nature, while the latter is used when storage devices are connected with the load (Bayram, Abdallah, Tajer, & Qaraqe, 2017; Carpinelli, Mottola, & Proto, 2016; Hajipour, Bozorg, & Fotuhi-Firuzabad, 2015; Harsha & Dahleh, 2015).

2.4.1 Probabilistic methods

A probabilistic approach for the optimal sizing of ESS has been discussed in (Greenwood, Wade, Taylor, Papadopoulos, & Heyward, 2017) which takes into account demand variability, reliability and energy-power limits. The authors consider the energy storage system and real-time thermal rating (RTTR) to address the optimal sizing problem for the application of peak shaving in distribution networks. A reliability metric known as Expected Energy Not Supplied (EENS) has been used to quantify the appropriate size of ESS. Extension of RTTR in the sizing method provides greater benefits on the

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distribution network security of supply compared to ESS individually. However, the inclusion of RTTR increases the size of ESS and high energy to power is attained.

Hans Bludszuweit (Bludszuweit & Domínguez-Navarro, 2011) studied the cost-benefit analysis for ESS sizing to reduce the forecast uncertainty. The method estimates the uncertainty as a function of ESS size by studying the forecast error statistical patterns and state of charge (SOC) to quantify unused wind energy. Energy storage power and capacity can be reduced by having a small quantity of unused energy, whereas the inclusion of forecast error increases the size of energy storage. The study concludes that large energy storage capacity is required to reduce the forecast uncertainty.

In (Zarezadeh, Fakharzadegan, Ghorbani, & Fathabadi, 2015), a probabilistic approach for the optimal energy dispatch by considering the uncertainties of solar irradiance and consumer load has been discussed. Feed in Tariff (FiT) and time of use electricity tariff are taken into account for the consumers to decide the optimal PV array and battery size for the residual installations. The authors implement fuzzy method to conduct the long-term assessments of battery sizing. The result report that sizing of PV array and energy storage is independent with identical electricity buying and selling price. However, when the tariffs are different, simultaneous optimization for the battery and PV sizing maximizes the benefits of the system.

A reliability index known as loss of load expectation (LOLE) has been discussed in (Bahramirad, Reder, & Khodaei, 2012) that helps to curtail the microgrid operating cost by optimizing the battery size. The economic benefits of the microgrid are justified by providing power from ESS to local loads at a low price during peak periods and controlling excessive power generations. The mixed integer programming assesses the reliability criteria with high accuracy. The larger size of the battery (more than the optimal) results in the high operating cost of microgrid.

Another similar approach has been addressed in (Carpinelli et al., 2016) to optimize the total cost with energy prices, discount rate and load demand as input variables. The probability density functions of these random input variables are solved by Monte Carlo simulation for effective size of BESS. Furthermore, the authors also highlight the importance of TOU tariffs in battery sizing and allowing the customers to sell energy to the grid with beneficial rates. The analysis demonstrated the important link between the BESS size and energy price and the results showed that profit of installing BESS decreases with the increase in electricity tariff.

2.4.2 Stochastic Methods

A unit commitment approach for the sizing of energy storage in grid-connected and islanded mode is analyzed in (Chen, Gooi, & Wang, 2012). In grid-connected mode, the objective is to obtain a cost-effective solution for the microgrid with power being exported to the grid during low load periods. The proposed method takes the forecast error and uncertainties into consideration. The optimal BESS size reduces the total cost for the islanded microgrid and increases the total benefit in the grid-connected scenario. It is indicated that the lifetime of the battery can be increased with the limitation of charging and discharging rate.

Nguyen (T. A. Nguyen, Crow, & Elmore, 2015) discussed the vanadium redox flow battery (VRFB) in microgrid system to be effective in both modes with charging and discharging rates added as a constraint. Furthermore, the nonlinear charge/discharge efficiencies are considered as a function of voltage, stack efficiency and temperature. The independent ratings of power and energy make VRFB more flexible for the microgrid conditions. The dynamic programming-based unit commitment method is implemented to find the optimum size.

A heuristic method incorporating particle swarm optimization (PSO) is used to find the optimal size of BESS (Sukumar, Mokhlis, Mekhilef, Naidu, & Karimi, 2017). The mix-mode energy management strategy operates the microgrid at the lowest operating cost by integrating three different operating strategies. Linear programming and mixed integer linear programming methods are used to minimize the cost of microgrid under these strategies. The operating cost of microgrid in a day is reduced with an initial charge of battery to be taken as 100% at the start of the day. In addition to this, the immense availability of PV in summer affects the cost compared to winter.

In (Aghamohammadi & Abdolahinia, 2014), the energy storage size is determined for the frequency regulation services in an islanded microgrid. The overloading characteristic of BESS is implemented for a short time duration to control frequency, resulting in a quick response of battery to overcome the power mismatch. However, the authors did not consider the impact of lifetime degradation and economic drawbacks by overloading the BESS.

The genetic algorithm (GA) based method to determine the optimal battery size has been presented in (Fossati, Galarza, Martín-Villate, & Fontán, 2015). The proposed method uses the fuzzy expert system to regulate the power flow of energy storage. The GA method builds the knowledge base of the fuzzy rules and membership functions. A lifetime aging model predicts the lifetime and growth of the battery. The microgrid cost is also affected by the lifetime and sizing of the battery. However, deep discharges reduces the lifetime of battery storage.

2.5 Factors Affecting Sizing of Energy Storage

There are multiple factors which decide the size of energy storage. These factors are described in the sub-sections below.

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2.5.1 Battery degradation

The design consideration for the optimal sizing of BESS must undertake some key battery parameters and battery degradation is one of them. Apart from its rated life, there are other factors which deteriorate the battery capacity.

2.5.1.1 Depth of discharge:

The depth of discharge (DOD) represents the amount of capacity used by the battery relative to its total battery capacity. DOD is a major factor in the lifespan of the battery as it allows for deep charge/discharge cycles. Unlike sodium sulphur batteries which can bear 100% DOD, the lifetime of other battery chemistries will be severely impacted by DOD value. The optimal DOD should be selected to increase the efficiency and longevity of the battery. The relationship between the lifecycle and DOD is normally presented in a curve which varies across different battery types. A typical curve is shown in Figure 2.4 for the lithium-ion battery at 20^{o}C temperature.

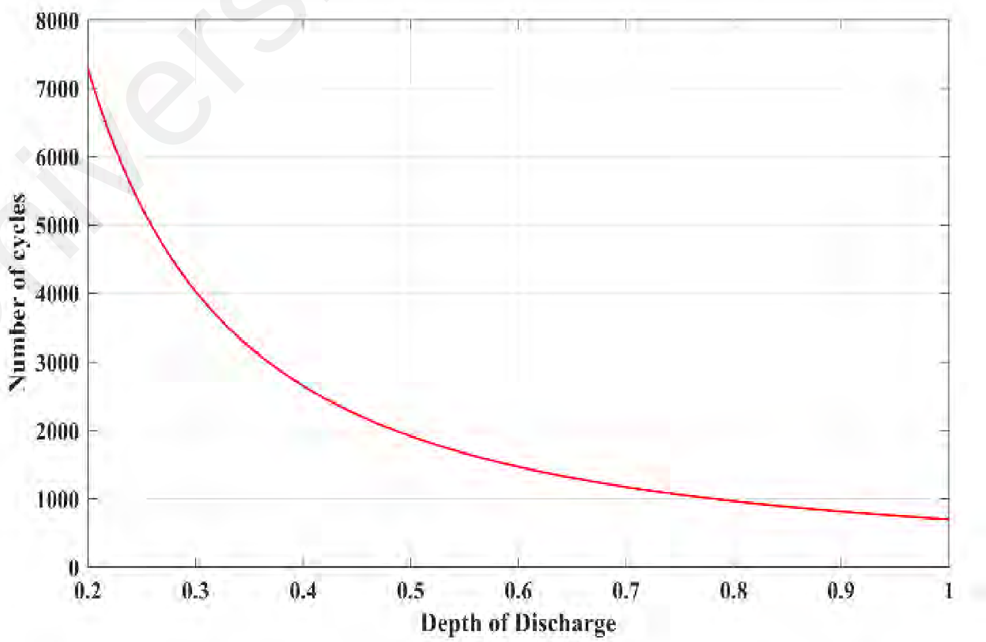

Figure 2.4: Lifecycle curve of Li-Ion battery for different depth of discharges (C. Zhou, Qian, Allan, & Zhou, 2011)

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2.5.1.2 Battery lifetime:

The lifetime of the battery is one of the most important factor in the cost operation of BESS. The number of lifecycles a battery can sustain in its entire life depends on the charging and discharging schedule of the battery. The lifetime degradation of the battery is affected by two main factors: the lifecycle aging reflecting the number of cycles the battery has accomplished, and the decrease in battery capacity (Ju & Wang, 2016; Smith, Earleywine, Wood, & Pesaran, 2012). The lifetime equation varies with the type of battery used. However, it can be extended with a proper selection of depth of discharge and cycle depth.

2.5.1.3 Temperature:

The degradation of the battery life is dependent on the ambient temperature by a phenomenon called capacity fading. It analyses the reduction in total battery capacity operating at a certain temperature after it experiences a particular number of charging and discharging cycles. This phenomenon has been observed at both high and low temperatures to evaluate their impact on the performance of the battery. The internal resistance of the battery increases at low temperature, whereas battery chemical reaction increases at high temperatures, which degrades the electrodes (Bandhauer, Garimella, & Fuller, 2011; Khawaja et al., 2017). The capacity fading percentage changes with the battery characteristics provided by the manufactures.

2.5.1.4 Charge and discharge current:

Another factor constituting the battery degradation is the charge and discharge currents. The high current during charging and discharging operation negatively affects the battery lifespan. The battery capacity also reduces when supplying large currents due to the

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increase in the internal resistance. Thus, charge and discharge power should be limited to specific values to avoid the damage of BESS.

2.5.2 Reliability

The reliability of microgrid is essential in determining the optimal size of energy storage. The reliability criteria should satisfy the reliability indices available in terms of generation adequacy and economic factors. Energy storage provides feasible solutions for satisfying the microgrid reliability levels efficiently. Load curtailment and load leveling are viable options to achieve the reliability indices in the microgrid.

2.5.3 Battery placement

Research into the optimal placement of BESS in a microgrid is still at its infancy. To minimize the losses and improve system stability, energy storage must be allocated appropriately. The optimum location may lead to a reduction in the energy purchased from the main grid, which decreases the cost of microgrid. The optimal storage location, which can support high penetration of RES is selected by performing tests for different scenarios.

2.6 Recycling of Batteries

Recycling of batteries is a process to reduce the disposal of batteries as a waste product. There are heavy toxic chemicals and materials within the battery and disposal of such elements as trash may increase environmental concerns and water pollution. Battery manufactures should be aware of the health hazards of battery waste and have their own recycling centers. Europe has been the leading market for recycling services, implementing major projects of energy conversion and growing awareness among the people to increase the demand for battery recycling process. North America is the second

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largest market followed by Asia Pacific region as a result of stringent governmental and environmental regulations ("Transparency Market Research-Published on 14-07-2016,").

Lead acid has the highest recycling market among all the battery storage due to the high demand for recovered materials. The high maturity level of lead-acid has retained its dominance in the market for centuries and will continue to lead the battery recycling market till 2021 ("Global Battery Recycling Market 2017-2021,"). On the contrary, other battery storages like Li-Ion, Ni-Cd and Ni-MH are less economical to recycle as energy storages, whereas flow batteries and Na-S, Na-$NiCl_2$ are not recyclable (May, Davidson, & Monahov, 2018; Sullivan & Gaines, 2010).

The recycling process of lead-acid is done by crashing the batteries and recovering the chemical contents. Lead, after refining, is again used for battery production, and other materials are recovered as scrap. Battery manufacturers are finding ways to give a second life to lithium batteries in other applications to overcome the dependency on lithium. However, the lithium recovered from the battery is in small proportion and inexpensive compared to cobalt and nickel (Heelan et al., 2016). Lithium batteries used in electric vehicles, when degraded with time, lose performance by reduction of 20% from its initial capacity. The average life of batteries for electric vehicles is 8 to 10 years but these batteries can be reused as storage for load balancing and other applications. Nickel metal hydride batteries used in hybrid vehicles are recycled to get nickel and iron. These elements go through electric arc furnace process to get ferro-nickel used in the stainless-steel industry (Gaines, 2014).

The high utilization and presence of domestic and international companies have increased the diversity in battery manufacturing. Low cost, less efficient and poor life batteries are also available in the market which has a bad impact on the socio-economic-health of society. Stringent laws and enforcement are urgently needed. More efforts are

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required from the recycling industry to expand the reusing of waste by offering motivating forces to the consumers.

2.7 Economic Dispatch

In electrical power systems, economic dispatch problem is considered to be one of the crucial decision-making processes for the reliable operation of the power system. The economic operation of a microgrid is essential for effective utilization of renewable energy and other distributed energy sources integrated within microgrid. Economic dispatch optimizes the power generation from distributed generators such that there is no mismatch between demand and generation. The objective of the economic dispatch problem is to optimize the overall cost of the system within the defined set of constraints.

Many classical techniques have been used in the literature (Bayón, Grau, Ruiz, & Suárez, 2012; Chauhan, Jain, & Verma, 2017; Zhigang Li, Wu, Zhang, Sun, & Guo, 2013; Palanichamy & Babu, 2008; Zhan, Wu, Guo, & Zhou, 2014) for the optimization of economic dispatch problem like linear programming, fast lambda iteration, interior point and other heuristic techniques. The complexity of the problem increases when dynamic dispatch is used to find the most optimal cost for the given period of time. The objective is to provide the power within the minimum cost at each hour of the time depending on the load demand. The static economic dispatch optimizes the generation of plants for a specific time period minimizing the overall cost, whereas dynamic dispatch plans the generation for the complete time period taking ramp constraints rate into account, which results in reliable operation (Benhamida, Ziane, Souag, Salhi, & Dehiba, 2013; P. Luo, Sun, Zhu, Wu, & Chen, 2016).

Dynamic economic dispatch (DED) reduces the overall operating cost and increases the total profit by coordinating and cooperating among other devices in the system.

Hence, DED is more suitable for microgrid operation comprising of storage devices and generators. Economic dispatch is a nonlinear optimization problem with different optimization strategies used to formulate the dynamic scheduling problem.

The authors in (Zhigang Li et al., 2013) solves the DED problem using Lagrangian relaxation method with the help of the central coordinator to communicate with all the generators. The quasi Newton method has been applied for updating multiplier to solve the dual problem of DED. The proposed method has been examined on the different distribution network, producing high computational efficiency.

Dynamic programming is implemented to solve the economic dispatch problem in (Shuai et al., 2018). The uncertainties of renewable power generation, electricity price and load are solved by Monte Carlo method. The dynamic programming can solve the discontinuous cost functions, but the computational time increases with the number of generating units. The proposed algorithm results in an optimal solution compared with other techniques, showing robustness in solving the intra-day optimization even with inaccurate forecast information.

The economic load dispatch problem of a hydropower plant with 26 turbines is solved by an improved genetic algorithm in (Shang et al., 2017). The performance of the algorithm is evaluated in terms of stability, computational time, and accuracy. The results show the effectiveness of the proposed method over the genetic algorithm in avoiding the running of turbines in vibration zones to ensure the safety of turbines. However, the stability of the algorithm is reduced when the number of generating units increases.

Wu in (Wu, Ding, Wu, Jing, & Zhou, 2016) has used mixed integer programming (MIP) approach to solve the non-convex economic dispatch problem by considering the value-point effect, power losses, operating zone and spinning reserve constraints. The two-phase optimization algorithm linearizes the non-smooth cost function and uses the encoding technique to convert the non-convex problem into a MIP problem in the first phase. The obtained solution generates the optimal value in the second stage when the power range of each unit is compressed. The proposed method is found effective for solving non-convex economic dispatch problems compared to metaheuristic approaches.

2.8 Electric Vehicle

In recent years, the transportation industry has begun to increase the production of electric vehicles due to increasing public awareness and political support. The reduction of greenhouse gas emissions and sustainable transportation system are the environmental benefits associated with the large-scale development of electric vehicles. Significant advancements in the battery storage technology, particularly in lithium ion and nickel-metal hydride (NiMh) enabled the adoption of hybrid and battery electric vehicles all over the world. This continuous development had stimulated the transportation manufacturers to introduce plug-in hybrid electric vehicle (PHEV) that can be recharged by the power grid.

The global oil consumption by transport industry is more than 50% and CO_2 emission by transportation is approximately 23% until 2013 (R. Zhang, Fujimori, Dai, & Hanaoka, 2018). EV can play major role in reducing oil consumption and gas emission, while providing clean energy. If renewable energy is used to charge the EV, CO_2 emissions are further reduced. Beside emission reduction, the advantages of EV include high energy efficiency, energy production by regenerative braking, low energy per km cost and less noise. EV batteries can store energy during the times of low energy price and release back to power grid during high electricity tariff, making revenue for EV owner. On the other hand, EVs are expensive compared to internal combustion engine vehicles due to high cost of battery storage. But with the decreasing cost of storage components, it is predicted that 2.7 million EVs will be on road by 2019 (Mao et al., 2017).

2.8.1 EV charging levels

The charging power levels reflect the amount of power, the time consumed, cost and effect on the grid. The availability of charging stations near the parking area reduces on-board charging requirement and cost. The charging cords, power outlets, vehicle connectors differ from vehicle to vehicle and region to region depending on voltage and frequency standards. The electric power research institute reports that mostly EV users charge their vehicles overnight. Generally, the EV charging can be categorized into three levels:

2.8.1.1 Level 1 charging

Level 1 provides the charging through the 120 V single phase household outlet. This is the slowest charging method and takes more than eight hours to charge for 40 miles of range. Level 1 charging is done overnight as the electricity rate is cheapest at night. This charging level is suitable for vehicles with small battery capacity or vehicles with a traveling range of maximum 40 miles per day. The charging connector for level 1 is shown in Figure 2.5.

Figure 2.5: Level 1 charger

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2.8.1.2 Level 2 charging

The charging equipment under level 2 charging requires 240 V, AC (single/three phase) either installed at home or public charging station. Level 2 chargers are most commonly available chargers at offices and parking lots, which can draw current at up to 80A (19.2 kW). EV owners prefer level 2 charging owing to its fast charging with about 70 miles of range per hour. The charging equipment for level 2 has standard EV connection plug that can fit into all electric vehicles except Tesla as they require an adapter. Figure 2.6 shows the level 2 charging device.

Figure 2.6: Level 2 charger

2.8.1.3 Level 3 charging

Level 3 equipment has the fastest charging capacity with 480V, DC that can add 50 to 90 miles in half hour. Tesla supercharges are even faster with charging capacity of 170 miles in 30 minutes. The charging equipment is installed mostly at highways, rest areas and charging stations used for longer trips. Different plug types are available for DC fast charging with most common protocol CHAdeMO, which is recognized internationally. Figure 2.7 shows the charging station powered by DC fast chargers for EV.

Figure 2.7: Charging station with DC fast chargers

2.8.2 EV charging strategies

2.8.2.1 Uncoordinated charging

In uncoordinated charging scheme, EV batteries are connected to charging station immediately and they continue to charge until the battery is fully charged. This charging scheme is most likely seen at home when EVs return home in the evening and the batteries are charged until midnight. The network load increases during the peak hours by simultaneous charging of multiple EVs which affects the power quality of the distribution system having voltage deviations and extra power losses. The EV charging load may lead to overloading of distribution transformers, reducing reliability and increasing the cost of the power grid.

2.8.2.2 Coordinated charging

The coordinated charging scheme reduces the peak load by charging the EV batteries at night time when the electricity demand is low. Utility companies offer a time of use tariff to charge the battery at off-peak periods. A coordinated charging system improves

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the reliability of the system and reduces the voltage deviations and transformer overloading. An aggregator sends the control signal to the connected EVs to continue or stop charging based on the capacity available in the distribution transformer.

The smart charging coordination to reduce the peak load and extra power losses has been proposed in (Suganya, Raja, & Venkatesh, 2017). The proposed method locates the optimal, midst and unfit sites for charging stations based on technical losses and voltage deviations. The distribution system can be divided into residential and commercial buses when simultaneous scheduling of EVs is established. The modified particle swarm optimization has been used to schedule the EV charging in both areas. The proposed method locates the charging station in an optimal site as a priority. However, EV user convenience and overloading of distribution transformer in the optimal site is also considered to find the charging station in other sites. Results showed that two area framework improves the performance of the system and provides flexibility in EV charging.

A charge coordinated problem of EV batteries has been solved in (Arias et al., 2017) to reduce the operational cost of the system. The proposed method has been implemented with three metaheuristic techniques: tabu search, greedy randomized adaptive and hybrid optimization algorithm. The impact of charging EVs under specific time period according to EV owner's preference is evaluated with three techniques, producing an optimal solution by using a hybrid optimization algorithm. Different EV penetrations are examined in the presence of distributed generators (DG) on a 449-node distribution network. The results show that charging of EV improves the voltage profile and minimizes the system losses when DG is integrated into the network.

An optimal scheduling algorithm with a decentralized controller is proposed in (Xing, Fu, Lin, & Mou, 2016) to schedule the charging and discharging of EV. The proposed

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method aims to flatten the demand curve as per consumer battery requirement. The optimal scheduling problem is formulated as a mixed discrete programming problem, which is solved by water-filling algorithm. The decentralized controller communicates with the aggregator after EV conducts local computation. The study recommends to retain the battery state of charge between 20% to 85% to extend the battery lifetime. The proposed algorithm reduces the computational burden in charging EVs to specific state-of-charge (SOC) compared to other mixed integer non-linear programming problems.

Nguyen in (H. N. T. Nguyen, Zhang, & Mahmud, 2015) performs the charging and discharging coordination of EV for G2V and V2G operation taking customers preference to charge up to defined SOC. The proposed method is to able to schedule the future charging request as per the customer's desire for the day ahead. The customer participation program improves the performance of the control algorithm in load shifting during peak periods. However, the authors have not taken the power losses into consideration during charging and discharging event.

A smart charging strategy to integrate EVs in the carpark is presented in (Mehta, Srinivasan, Khambadkone, Yang, & Trivedi, 2018) to reduce the cost and minimize the peak average ratio (PAR). The proposed method has been tested on 37 bus distribution system with maximum EV penetration by considering the technical constraints of the system. The study focuses on EV charging at workplace, hence charging to maximum SOC is avoided and EV battery is charged as per user's next trip details, which are based on present SOC, traveling distance and departure time. The analysis found that fast charging results in higher cost and PAR and reduces the EV penetration into the distribution system. Furthermore, a predefined boundary is allocated for charging/discharging of EV to reduce the battery degradation cost.

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The cost-benefit analysis for the optimal charging and discharging coordination of EV is proposed in (Z. Luo, Hu, Song, Xu, & Lu, 2013). The study addresses the issues of characterizing the charging pattern and computing the maximum charging load and available discharge capacity of EV battery. The two-stage optimization model minimizes the peak load with maximum EV load in the first stage and then reduces the fluctuation at the peak load in the second stage. The proposed method calculates the annual benefit from the savings earned through peak shaving whereby neglecting the battery degradation cost and taking fixed charging power of EVs. The case study has been performed for data collected from a region in China with different penetration levels expected for 2020 and 2030.

The economic dispatch of microgrid was optimized by developing a multi-agent system with different penetrations of EV (Lin et al., 2018). Three charging patterns; uncontrolled charging, rapid charging and smart charging together with V2G were analyzed in the presence of a gas turbine, chillers and photovoltaic system. The smart charging strategy shifts the EV charging load to valley period during peak time to improve the stability of the system. The V2G technology reduces the electricity supply from gas turbine when high penetration was considered. Hence, the microgrid operating cost was remarkably minimized with V2G availability compared with the uncontrolled charging. However, the proposed method had defined a potential limit for V2G in a specific time to avoid deep discharge depreciating battery lifetime.

Zhang in (H. Zhang, Hu, Xu, & Song, 2017) has developed a quantitative evaluation method for discharging PEV fleets by considering power and energy constraints of the PEVs. The proposed method develops aggregate queueing model to evaluate the available V2G capacity during real-time operations without identifying the charging and discharging durations. The difficulty in forecasting of charging demand due to the

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stochastic behavior of EV traveling is reduced to compute the available capacity for V2G. In addition, laxity-SOC based heuristic smart charging strategy is designed to perform a reliable operation for PEV charging and discharging. The uncertainty of reserve utilization is also considered during scheduling strategy by ensuring the profit maximization. The numerical analyses result in gaining the benefits from the reserves accumulated during energy scheduling of EV.

A stochastic optimization model for energy management in a microgrid using uncertain battery capacity of the EV parking lot is proposed in (Mortaz & Valenzuela, 2017) to minimize the total operating cost. The economic benefits of integrating the parking lot in the microgrid are analyzed by providing a free parking facility for EV owners and compensation for battery wear cost. Market price fluctuation, parking time, the uncertainty of battery capacity and EV arrival/departure are considered for the cost saving analysis. The proposed model is tested on 14 bus distribution system, and Benders decomposition algorithm is implemented to optimize the operating cost. The results show the increase in savings with high price fluctuation ratio and increase parking time for EV users.

A stochastic optimization method having a centralized control unit is proposed in (Tabatabaee, Mortazavi, & Niknam, 2017) for coordinated charging of PEV. The load flow based on unscented transform is formulated to model the uncertainties of renewable power and EV charging/discharging load. The operational cost accounts for the cost of charging EV, battery degradation cost for the discharging event and the cost of energy not supplied. The optimal solution is computed using a modified bat algorithm and the performance of the model is examined on the local distribution system. The simulation results showed a reduction in operational cost by V2G implementation, whereas the uncertainty effect increases the network cost.

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Lu in (Lu, Zhou, Yang, & Liu, 2018) proposed a multi-objective optimal dispatch of microgrid incorporating wind turbine, photovoltaic, diesel generators and microturbine. The Monte Carlo simulation is used to solve the uncertainties of EV arrival and departure. The proposed method performs peak shaving by charging the EVs during low price period to reduce the operating cost. The results reveal that coordinated charging with higher penetration of distributed generators minimizes the cost and load variance. However, weighting factor behaves as a trade-off between system cost and load fluctuation. The study finds V2G is not economical for EV owners due to battery degradation cost, but it improves the stability of the system by minimizing load variance.

The charge coordination problem of EV together with V2G technology in an unbalanced distribution system is solved in (Antúnez et al., 2016). The authors have taken random arrival and departure times and EVs state of charge upon arrival with different battery sizes to reduce the energy cost and optimize the operation of the distribution system. The proposed method schedules the optimal EV charging by considering the uncertainty of load while satisfying the voltage limits and minimizing the power losses. The results illustrate that V2G utilization in the distribution system is not economically beneficial as the lifetime of EV battery depreciates and cost of replacing the battery outstrips the benefits associated with V2G.

A novel bidirectional operation of EV in grid-connected and islanded mode is proposed in (Rodrigues, de Souza, & Ribeiro, 2018) for the three-phase unbalanced distribution system. The proposed method implements grid-to-vehicle (G2V) strategy based on the power availability of buses ensuring the grid operative conditions are satisfactory. If any failure leads the network to islanded mode, the reliability and security of the network are increased by V2G implementation. Furthermore, EV operation enables the mutual implication of G2V and V2G strategies with variable load and generation in a

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smart microgrid environment. The complexity of the proposed model is increased with the combination of both modes in an unbalanced real distribution network.

2.9 Optimization Algorithm

Optimization algorithms are significant to determine the optimal solutions for the economic power dispatch. Optimization techniques can be classified as heuristic and meta-heuristic techniques. The former are problem-dependent techniques and fails to find the global optimum solution whereas the latter provides the better solution near to global solution. Different metaheuristic optimization techniques have emerged over the past few years but convergence analysis for majority algorithms still remains unsolved. Stochastic approaches are preferred over deterministic approach due to their ability to solve the randomness in the algorithm. In this thesis, optimization techniques such as firefly (FA), particle swarm optimization (PSO), artificial bee colony (ABC) and harmony search algorithm (HSA) are evaluated to obtain the optimal solution with minimum computational cost.

2.9.1 Firefly Algorithm

The firefly algorithm (FA) analyzes the social behavior of flies and is similar to other meta-heuristic techniques. The algorithm was originally developed by Yang (X.-S. Yang, 2010) based on three main ideas:

1) The fireflies attract their mating partners.

2) The bright firefly gets attracted to brighter fireflies.

3) If the firefly cannot find brighter fireflies, then it will move randomly in the search space.

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Firefly is a population-based optimization algorithm and is distinguished from the other optimization techniques by adjusting the parameters, which have low dependency on the algorithm and appropriately identifying the search space. The above mentioned three ideas of firefly algorithm are explained in the mathematical form below:

2.9.1.1 Separation between fireflies

The distance between two mating fireflies in the search space is calculated as vector operation performed in Cartesian framework between the *i*th and *j*th firefly given by the expression:

$$r_{ij} = \left|Y_i - Y_j\right| = \sqrt{\sum_{D=1}^{s} (Y_{i,D} - Y_{j,D})^2} \tag{2.1}$$

where *r* is the distance between two fireflies, *s* is the dimension of the control vector, $Y_{i,D} / Y_{j,D}$ are the Dth dimensions of Y_i / Y_j fireflies respectively.

2.9.1.2 Attraction between firefly

The attraction of the fireflies decreases when the two mating fireflies move in the opposite direction and the separation between them increases. The attraction of the flies can be represented by the following expression:

$$\beta(r) = \beta_0 \times \exp(-\gamma r^m); \quad m \geq 1 \tag{2.2}$$

where $\beta(r)$ and β_0 represents the attractiveness when the fireflies are at the distance *r* and 0. γ is the coefficient of light absorbed by firefly and *m* is the number of fireflies taken as 2.

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2.9.1.3 Movement of the fireflies

The fireflies move towards brighter fireflies. The movement between the two fireflies, *j*th firefly (low intensity) towards the *i*th firefly (high intensity) is given by the mathematical expression:

$$Y_j(t) = Y_j + \beta_0 \times \exp(-\gamma r^m) \times (Y_i - Y_j) + v_j \qquad (2.3)$$

$$v_j = \delta(rand - 0.5) \qquad (2.4)$$

The first term of the Eq (2.3) shows the present position of *j*th firefly. The second term represents the intensity of brightness by which the *j*th firefly is attracted towards *i*th firefly. However, the last term v_j represents the movement of a *j*th firefly in the entire search space when it cannot find fireflies with more intensity. The randomization parameter δ is a constant value in the range of 0-0.5. The pseudo code of the firefly algorithm is shown in Figure 2.8.

Firefly Algorithm

```
Problem Definition : Objective function f(x)
Randomly generate an initial population of n fireflies
Fitness calculation of each firefly
while termination condition do
    for i= 1: N  do   (all fireflies)
        for j= 1: N do   (all n fireflies)
            if (fitness (yi) > fitness (yj))    then /* yi is more brighter than yj */
                Move yj firefly towards yi firefly
            end
            Vary attractiveness with distance r between fireflies
        end
    end
    Sort the fireflies and find the global best
end
```

Figure 2.8: Pseudo code of firefly algorithm

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2.9.2 Particle Swarm Optimization

PSO is an optimization technique that evaluates optimal parameters from complex search space based on the paradigm of swarm intelligence. The algorithm developed by Kennedy and Eberhart was initially modeled as the social behavior of animals like a flock of birds or school of fish. In PSO, the group of random particles is initiated to obtain the optimal parameters by updating generations. Each particle tracks its position within the search space at each iteration and the new position is obtained. The movement of particles is identified by two values $\mathrm{P_{best}}$ and $\mathrm{G_{best}}$. $\mathrm{P_{best}}$ is the particles best position in all iterations whereas $\mathrm{G_{best}}$ is the global best value of any particle in the search space (Kerdphol, Fuji, Mitani, Watanabe, & Qudaih, 2016). The particles update their velocity and new position based on the following equations;

$$v_{k+1} = w * v_k + \mathrm{c}_1 * \mathrm{r}_1 * \left(\mathrm{P_{best}} - \chi_k\right) + \mathrm{c}_2 * \mathrm{r}_2 * \left(\mathrm{G_{best}} - \chi_k\right) \tag{2.5}$$

$$\chi_{k+1} = v_{k+1} + \chi_k \tag{2.6}$$

where v_{k+1} and χ_{k+1} represents the updated velocity and position of the particle, w is the inertia weight, r_1 and r_2 are the random numbers ranging from 0 to 1 and $\mathrm{c}_1, \mathrm{c}_2$ are the acceleration constants. The advantage of PSO is fast computation and simplicity. However, with the multivariable components, the convergence accuracy decreases. Thus, hybrid optimization techniques including PSO and other metaheuristic algorithms can yield an optimal result with less computation time.

2.9.3 Artificial Bee Colony

ABC is another intelligent swarm-based optimization technique which stimulates the foraging behavior of honey bee colony. The mechanism of the algorithm is based on three

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fundamental components: food source, employed bees and unemployed bees, which are further classified as scout bees and onlooker bees (Sundareswaran, Sankar, Nayak, Simon, & Palani, 2015). At the starting phase, scout bees are the employed bees, which are trying to find the location of food source in search space given by

$$\chi_{j,k} = \chi_{j,k}^{\min} + \mathrm{r} * \left(\chi_{j,k}^{\max} - \chi_{j,k}^{\min} \right) \tag{2.7}$$

where $\chi_{j,k}^{\max}$ and $\chi_{j,k}^{\min}$ are the maximum and minimum values of the food source position in search space. The number of food sources is assumed to be half of bees colony, containing an equal number of employed bees and onlooker bees.

Employed bees are the ones, which are presently exploiting food source position. In order to find a better location for a food source, the following equation is used

$$\mathrm{P}_{j,k} = \chi_{j,k} + \zeta_{j,k} (\chi_{j,k} - \chi_{l,k}), \;\; j \neq l \tag{2.8}$$

where $\chi_{j,k}$ and $\chi_{l,k}$ are the food source locations in the search space and $\zeta_{j,k}$ is the random number ranging from -1 to 1. The reference position is denoted as *j*th position and *l* is the dimension of search space $l \in \{1, 2, \ldots.\mathrm{NE}\}$. When the employed bee finds a better position $\mathrm{P}_{j,k}$ than the reference position $\chi_{j,k}$, the candidate position is replaced with a better one.

Onlooker bees also try to find the food source location similar to employed bees but they look for the positions with more nectar available (fitness value) in the search space. The probability of food source position selected by onlooker bees is dependent on the amount of nectar and is calculated as fitness function, defined by

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$$\rho_j = \frac{fit_j}{\sum_{l=1}^{NE} fit_l} \tag{2.9}$$

The probabilistic fitness function locates the better food source position for onlooker bees and this step improves the performance of the algorithm in obtaining an optimal result.

However, if both the bees are not able to improve the food source position, then the food source reaches its maximum limit and is removed from the search space. The scout bees again find the new food source in replacement and its location is determined by Eq (2.7). Thus, the algorithm does not trap into local optima through this abandoning and searching mechanism. The advantage of the ABC algorithm is the robustness, flexibility and capability to explore local solutions with easiness. They can be applied to complex functions but when sequential processing is performed, the computational time increases.

2.9.4 Harmony Search Algorithm

Harmony Search is a different meta-heuristic technique which is inspired by artistic improvisation process of musicians searching for harmony state. The optimization solution vector in the algorithm is related to harmony in music, while a global search scheme can be compared with musician's improvisation. The algorithm stimulates the behavioral phenomenon of musicians where they search for perfect harmony state by repeating experiments, as the optimization process finds the better optimal value for the defined objective function (Khorram & Jaberipour, 2011). The optimization algorithm consists of three operational steps: randomly search, memory consideration and pitch adjustment.

Step 1: The Harmony Memory (HM) matrix is initialized containing elements of decision variables which are randomly generated from the search space as

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$$\chi_j^h = \ell_j + \gamma * (\upsilon_j - \ell_j) \quad (2.10)$$

where χ_j^h is the element of harmony memory, ℓ_j and υ_j represent the lower and upper boundary limits of the dimension and γ is the real number ranging between 0 and 1.

Step 2: The harmony memory is improvised with each of the uniformly random value chosen from the search space is not larger than harmony memory consideration rate (HMCR). HMCR is the rate of choosing the value from harmony memory, varying between 0 and 1

$$\chi_j^h = \chi_j^n \quad (2.11)$$

where χ_j^n is the selected harmony from memory.

Step 3: The elements improvised from memory consideration step are now further improvised with pitch adjustment rate (PRA). If the element is pitch adjusted, then they are modified with the following equation to generate a better harmony matrix

$$\chi_j^h = \begin{cases} \chi_j^h + \gamma * \beta\omega & \text{if } \gamma' < \text{PRA} \\ \chi_j^h & \text{otherwise} \end{cases} \quad (2.12)$$

where $\beta\omega$ is an arbitrary distance bandwidth, γ' and γ are the real numbers uniformly distributed between 0 and 1.

2.10 Summary

When designing a battery storage system in a microgrid system, several requirements have to be determined from the technical, economic and environmental point of views. In a microgrid application, combining renewable energy with battery energy storage

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systems improves the reliability and stability of the energy supply for extended periods. However, the high cost of battery storage is the main deterrent when designing a microgrid system.

To ensure the proper sizing of battery storage is economical for the microgrid, battery degradation factors such as depth of discharge, battery lifetime, temperature and charge/discharge current must be considered in the economic scheduling. Moreover, at the end of the battery life cycle, the disposal of batteries has become problematic in recent years. The heavy toxic chemical and materials have a negative impact on the environment. To reduce this impact, recycling and second use of batteries have been implemented by battery manufacturers. However, further policies and enforcement should be introduced to support safe battery disposal and recycling.

The charge coordination of electric vehicles is essential for peak shaving and load balancing in a power system network. The economic scheduling of EV battery with V2G technology increases the benefits for EV users. Different optimization techniques have been discussed to improve the system performance and obtain the optimal solution.

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CHAPTER 3: METHODOLOGY OF THE PROPOSED ENERGY MANAGEMENT SYSTEM

3.1 Introduction

In this chapter, the proposed methodology is divided into two phases in order to determine economic power dispatch by distributed generators and obtain the optimal size of energy storage. In the first phase, economic scheduling of BESS and the synchronous generator is obtained for the isolated microgrid. Subsequently, in the second phase, EVs are treated as energy storage and charging/discharging schedule of EVs are analyzed. The impact of battery degradation, which constitutes the major factor in the lifetime of energy storage is taken into consideration.

3.2 Economic scheduling of isolated microgrid

3.2.1 Overview

Distributed energy resources such as diesel generators, wind energy and solar energy can be combined within a microgrid to provide energy to the consumers in a sustainable manner. The integration of intermittent sources has brought instability problems for microgrid to balance demand and generation. In order to ensure a more secure and economical energy supply, the battery storage system is integrated within the microgrid.

Microgrids can be operated in the islanded mode as well as grid-connected mode, depending on the load conditions and electricity market price (Alsaidan, Khodaei, & Gao, 2017; Robert, Sisodia, & Gopalan, 2018), providing the potential to solve the existing power system problems of stability, reliability and demand response. Because of the limited reach of the utility grid, microgrids in islanded mode are more intended for the power balance as compared to the grid-connected mode. Therefore, reliable power sources like synchronous generator and energy storage are crucial elements to regulate

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voltage and frequency, and improve the stability of the system (Carta & Velázquez, 2011). In this study, the operating cost of an isolated microgrid is reduced by economic scheduling considering the optimal size of the battery. It has been reported in the literature that deep discharge shortens the lifetime of battery operation (Uddin, Dubarry, & Glick, 2018). Hence, real-time battery operation cost is modeled considering the depth of discharge at each time interval. Moreover, the proposed economic scheduling with battery sizing is optimized using the firefly algorithm (FA). The efficacy of FA is compared with other metaheuristic techniques in terms of performance measurement indices, which are the cost of electricity and loss of power supply probability.

3.2.2 Hybrid Microgrid Model

A hybrid microgrid system contains three subsystems: the power demand, the power generation, and the power distribution subsystem. These subsystems have a major impact on the cost of the microgrid system. They are dependent on climatic conditions and consumer services. The hybrid microgrid system is designed to improve the performance, reliability and achieve cost-effective system. Thereby, knowledge of all factors affecting the performance of the system and precise modeling of each component is essential for the design of a hybrid model.

In an isolated microgrid, wind and solar are the most common source of RES. Hence, this study includes wind, solar, diesel generator and energy storage as the DERs of the power generation subsystem with the load profile of the residential area as the demand subsystem and the microgrid itself is configured as the power distribution subsystem. The combination of different RESs improves the system efficiency and reduces the requirements of energy storage as compared to a single RES. The general schematic of the microgrid system containing the three subsystems is shown in Figure 3.1.

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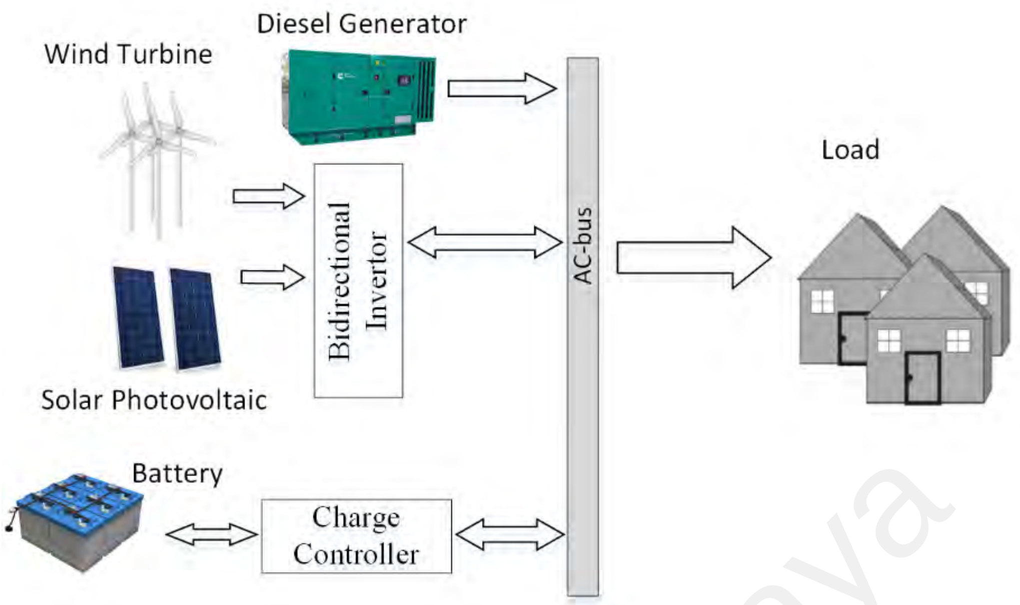

Figure 3.1: General schematic of hybrid microgrid

3.2.2.1 Wind Turbine Model

The power model of a wind turbine measures the power as a function of the hourly wind speed. The relation between the output power and the speed is given by the set of equations as (Mehmood et al., 2017):

$$P_t^w = \begin{cases} 0 & v_h \le v_{c,i} \ or \ v_h \ge v_{c,o} \\ P_{\max}^w * \dfrac{v_h - v_{c,i}}{v_{rt} - v_{c,i}} & v_{c,i} \le v_h \le v_{rt} \\ P_{\max}^w & v_{rt} \le v_h \le v_{c,o} \end{cases} \tag{3.1}$$

where $P_{\max}^w$ (kW) is the maximum power output of wind turbine (WT), v_h (m/s) is the speed of wind at hour *h*, v_{rt} (m/s) is its rated value whereas the cut-in speed and cut-out wind speed are shown by $v_{c,i}$ and $v_{c,o}$ respectively. The cost of power dissipated by the wind turbine in a particular day is the product of power dispatched and the initial cost IC_{WT} ($/kW) of wind turbine. The capital recovery factor (CRF) calculates the present

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value for the 24-hour analysis, taking interest rate (i_r) and projected lifetime (ly)into consideration.

$$C_{WT} = \left(\sum_{t=1}^{T} \mathrm{P}_w(t) \right) * \mathrm{I}C_{WT} * CRF \tag{3.2}$$

$$CRF = \frac{1}{365} \times \frac{i_r(1+i_r)^{ly}}{(1+i_r)^{ly} - 1} \tag{3.3}$$

3.2.2.2 Solar PV model

The power measured by solar photovoltaic array is dependent on the solar irradiation and the ambient temperature at each hour. The PV power is given by (Borhanazad et al., 2014)

$$\mathrm{P}_t^{pv} = \mathrm{P}_{rt}^{pv} * \frac{\mathrm{I}}{\mathrm{I}_{ref}} * \left[1 + \tau \left\{ \left(\mathrm{T} + (0.0256 * \mathrm{I}) \right) - \mathrm{T}_{ref} \right\} \right] \tag{3.4}$$

where P_t^{pv} (kW) is output power of the solar panel, P_{rt}^{pv} (kW) is maximum power at standard conditions, I is solar irradiation (W/m^2), I_{ref} is the solar radiation at standard temperature (I_{ref} = 1 kW/m^2), τ is 3.7x10^{-3} (1/^{o}C), T_{ref} is standard temperature taken as 25^{o}C, and T (^{o}C) is the ambient temperature of the solar panel. The cost of power dispatched by solar photovoltaic is dependent on the initial cost $\mathrm{I}C_{PV}$ (\$/kW) and power output defined as

$$C_{PV} = \left(\sum_{t=1}^{T} \mathrm{P}_{pv}(t) \right) * \mathrm{I}C_{PV} * CRF \tag{3.5}$$

3.2.2.3 Diesel generator

The diesel generator and energy storage are the secondary power generation sources for the microgrid when renewable energy cannot fulfill the required electricity demand. The conventional generator serves as a backup energy source and improves the system reliability by smoothing the power generation from the renewable energy source. The high cost of energy storage has captivated the attention of utility providers to utilize diesel generators in the microgrid. There are a total of three generators considered in this study. The cost of the generator in terms of power dispatch is expressed by (Modiri-Delshad, Kaboli, Taslimi-Renani, & Rahim, 2016)

$$C_{de} = \mathrm{F}_i\left(\mathrm{P}_{de,i}(t)\right) = a_i \mathrm{P}_{de,i}^2(t) + b_i \mathrm{P}_{de,i}(t) + c_i \tag{3.6}$$

where $\mathrm{F}_i\left(\mathrm{P}_{de,i}(t)\right)$ is the cost ($) of the *i*th generator at time *t*, $\mathrm{P}_{de,i}(t)$ is the power (kW) generated by the *i*th generator and a_i, b_i, c_i are the cost coefficients of the *i*th generators.

3.2.2.4 Battery Energy storage model

The BESS in a microgrid is used to avoid any power mismatch between the demand and generation. The selection of different battery energy storage units, each having its own distinguishing characteristics in power and energy, depends on the nature of the power required and the power delivered. The lithium-ion battery is used in this study as they are mainly used for storing wind and solar energy due to its high energy density among other battery technologies, long life cycle and high efficiency (Khorramdel, Aghaei, Khorramdel, & Siano, 2016; Torreglosa, Garcia, Fernandez, & Jurado, 2014). The proposed energy storage cost analysis is shown in Figure 3.2 for different values of power discharge and depth of discharge.

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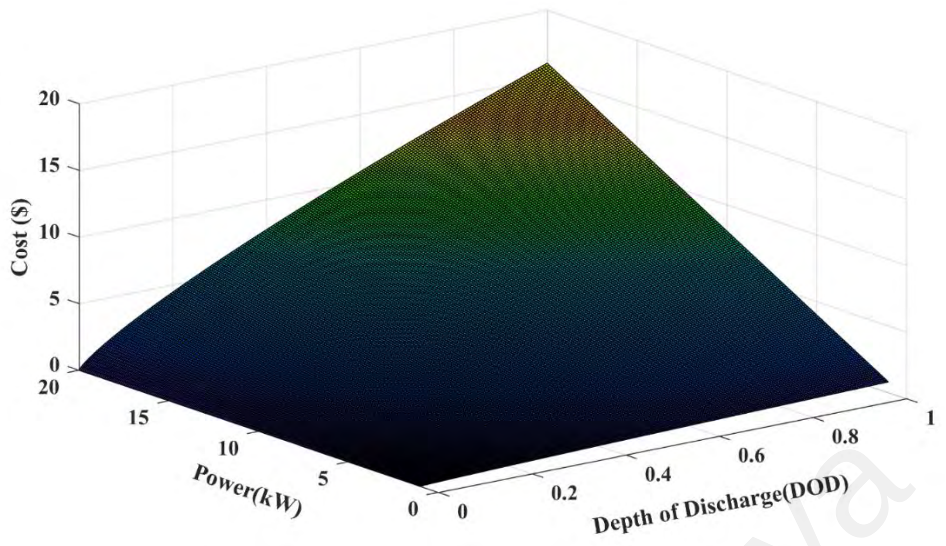

Figure 3.2: Cost of energy storage for different DOD and power discharge

The figure depicts that the cost of the energy storage increases when the DOD is high. Similarly, the cost is increased when the battery discharges more power. The increase in the discharge power results in decreasing the capacity of the energy storage and causes the DOD to be high. However, the continuous discharge from the energy storage at maximum DOD increases the cost of the energy storage to the maximum value. The cost of charging/discharging battery at any time interval as a function of battery power and DOD is formulated in Eq (3.10). The proposed model calculates the real time battery cost at each hour for the economic feasibility of battery scheduling. However, previous works by (Han, Han, & Aki, 2014; B. Zhou et al., 2016) have calculated the battery cost only at rated DOD. The proposed cost function of the battery storage during charge/discharge event is modeled by taking the cost model from (B. Zhou et al., 2016)

$$C_{BATT} = \frac{C_{batt,cap}}{\mathrm{E}_{batt,t} * l_c * DOD_{ref}} \tag{3.7}$$

The lifecycle of the lithium-ion battery is represented by an exponential function that depends on the DOD of the battery taken from (C. Zhou et al., 2011).

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$$l_c(DOD_{batt}(t)) = 850 * (DOD_{batt}(t))^{-1.4611} \quad (3.8)$$

DOD_{ref} is the constant value provided by the battery manufacturers as the rated DOD for the battery. However, in this study the real time value of DOD is considered for the lifecycle analysis. With the coefficients of battery charging and discharging efficiencies, the battery model can be written as

$$C_{BATT}(t) = \frac{C_{batt,cap}}{\mathrm{E}_{batt,t} * l_c(DOD_{batt}(t)) * \eta_{batt}^{ch} * \eta_{batt}^{dch}} \quad (3.9)$$

The proposed battery model for each charging and discharging event can be obtained by multiplying the power required by battery to charge and discharge in an event. The battery charging η_{batt}^{ch} and discharging η_{batt}^{dch} efficiency is considered same in this study and is equal to the efficiency of the battery.

$$C_{BATT}(t) = \frac{C_{batt,cap} * \mathrm{P}_{batt}(t) * \Delta t}{\mathrm{E}_{batt,t} * l_c(DOD_{batt}(t)) * \eta_{batt}{}^2} \quad (3.10)$$

where $C_{BATT}(t)$ is the cost of energy storage, $C_{batt,cap}$ is the capital cost of energy storage in \$/kW, $\mathrm{P}_{batt}(t)$ is the amount of power charged/discharged by battery at time *t*, $\mathrm{E}_{batt,t}$ represents the battery energy storage total capacity, $l_c(DOD_{batt}(t))$ is the number of cycles of energy storage due to change in depth of discharge at time *t* and η_{batt} is efficiency of the energy storage.

The battery DOD relation with the state of charge (SOC) is represented in Eq (3.11). The SOC represents the status of battery capacity at any time expressed by Eq (3.12) as

$$DOD_{batt}(t) = 1 - SOC_{batt}(t) \quad (3.11)$$

$$SOC_{batt}(t+1) = SOC_{batt}(t) + \frac{\mathrm{P}_{batt,ch}(t) * \Delta t * \eta_{batt}^{ch}}{\mathrm{E}_{batt,t}} - \frac{\mathrm{P}_{batt,dch}(t) * \Delta t}{\mathrm{E}_{batt,t} * \eta_{batt}^{dch}} \tag{3.12}$$

where $\mathrm{P}_{batt,ch}(t)$ is the amount of power delivered to charge the energy storage in a given time, $\mathrm{P}_{batt,dch}(t)$ is the amount of power discharged by energy storage, Δt is the time interval taken as 1 hour.

3.2.3 Problem Formulation

The energy management strategy in this study is implemented to obtain an optimal battery size and daily economic scheduling of microgrid. The capital cost of battery constitutes a major factor in calculating the battery size. The optimal BESS size is obtained when the sum of daily scheduling cost of the microgrid and BESS total cost per day (TCPD) is minimum. Hence, the objective function of the microgrid is the total operating cost given by the expression

$$OC = SC_D + TCPD_{BESS} \tag{3.13}$$

where

$$SC_D = Min \sum_{t=1}^{T} \left(\sum_{i=1}^{N} F_i \left(\mathrm{P}_{de,i}(t) \right) + C_{BATT}(t) \right) \tag{3.14}$$

$$TCPD_{BESS} = \left(CRF * C_{batt,cap} + \frac{MC}{365} \right) * E_{batt,t} \tag{3.15}$$

The scheduling cost for the day is the sum of the cost of three diesel generators dispatching power to fulfill the load demand and the cost of charging/discharging the battery storage. In this study, *N* is taken as three while the time period *T* is formulated as

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24 hours. The TCPD of battery storage is the function of battery capital cost and yearly maintenance cost accounted for the lifetime of battery. The optimal battery size will minimize the total cost of the microgrid. The energy management operation of the microgrid has been optimized by meeting the following constraints:

3.2.3.1 ESS Constraints

The battery charging and discharging energy is expressed in Eq (3.16) (Khorramdel et al., 2016). The battery discharges when P_{batt} is positive whereas negative P_{batt} indicates charging status of BESS. The associated constraint (3.17) limits the battery power to minimum and maximum value. The charging and discharging of the battery depends on the status of the battery power itself. The binary variable $\mu_{batt,st}$ states the operating status of the battery. The battery discharges only when $\mu_{batt,st}$ is 1 and charges when $\mu_{batt,st}$ is 0, avoiding the simultaneous charge and discharge event at any interval. The maximum amount of power charged and discharged by the battery storage during the time *t* is shown by $P_{batt,ch}^{\max}$ and $P_{batt,dch}^{\max}$ respectively. The battery capacity at each interval is within the minimum $E_{batt}^{\min}$ and maximum $E_{batt}^{\max}$ level.

$$E_{batt}(t+1)=\begin{cases} E_{batt}(t)-\dfrac{P_{batt,dch}(t)*\Delta t}{\eta_{batt}^{dch}} & \left(P_{batt}(t)>0\right) \\ E_{batt}(t)-P_{batt,ch}(t)*\Delta t*\eta_{batt}^{ch} & \left(P_{batt}(t)<0\right) \end{cases} \tag{3.16}$$

$$P_{batt}^{min}\le P_{batt}(t)\le P_{batt}^{max} \tag{3.17}$$

$$0\le P_{batt,dch}(t)\le P_{batt,dch}^{\max}*\mu_{batt,st} \tag{3.18}$$

$$-P_{batt,ch}^{\max}*(1-\mu_{batt,st})\le P_{batt,ch}(t)\le 0 \tag{3.19}$$

$$E_{batt}^{min} \leq E_{batt}(t) \leq E_{batt}^{max} \tag{3.20}$$

3.2.3.2 Diesel Generator Constraint

The power generated from the diesel generators must be within the upper and lower limits of each generator.

$$P_{de,i}^{min} \leq P_{de,i}(t) \leq P_{de,i}^{max} \tag{3.21}$$

3.2.3.3 Power Balance Constraint

The primary constraint in the power system is the balance of demand and supply. The microgrid must balance the power flow at each time step expressed by Eq (3.22)

$$P_{pv}(t) + P_{w}(t) + P_{batt}(t) + P_{de}(t) - P_{L}(t) = 0 \tag{3.22}$$

where $P_L(t)$ is the load of microgrid at time *t*.

3.2.4 Energy Management Strategy

The energy management strategy of the microgrid has a direct impact on the operational behavior of the system regardless of the grid-connected or isolated mode of operation. However, in the isolated mode the power generated from the distributed resources must satisfy the load demand for secure and reliable operation; otherwise, the system will face load shedding, which increases the cost in term of power losses. The unavailability of RESs at certain times of the day will force the diesel generator and battery storage to operate and dispatch optimal power. Moreover, excess power generation by renewable resources necessitates the charging of the battery. The extra energy after charging is dissipated into dump load to avoid overcharging of batteries. Thus, an efficient energy management strategy is proposed to dispatch the power at the

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lowest cost and reliably serve the load considering the technical constraints of the microgrid. The power strategy for economic scheduling in this study has been summarized in the following scenarios:

Scenario 1: Renewable energy sources are capable to provide sufficient energy to meet the load demand, and the battery is charged by the excess energy.

Scenario 2: This scenario is identical to scenario 1 with the exception that the battery is fully charged, and the extra energy generated by renewable sources is dissipated as a dump load.

Scenario 3: Renewable energy sources cannot satisfy the required load of the system. The algorithm will decide to run the diesel generators or discharge the battery depending on the required load and the cost accumulated in two distributed sources.

Scenario 4: The renewable sources energy generation is insufficient to satisfy the required load and depth of discharge of battery storage is high, with the result that the generator will dispatch the remaining power and to charge the battery to reduce the depth of discharge status.

3.2.5 Performance Evaluation Parameters

The reliability and economic evaluation of designed microgrid are significant factors to ensure optimum power dispatch. There are many key indicators to evaluate the economic benefits of microgrid such as net present cost, cost of electricity and break-even analysis method. The reliability of microgrid is technical criteria to avoid any power mismatch between generation and demand, resulting in load shedding of the microgrid.

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3.2.5.1 Cost of electricity

The cost of electricity (COE) is calculated as an indicator of the economic profitability of hybrid microgrid. The electricity cost is the ratio of the sum of the costs associated with solar photovoltaic (C_{PV}), wind turbine (C_{WT}) diesel generators (C_{de}) and the energy storage (C_{BATT}) to the total load of the day. The electricity cost is measured between all the power generation sources and load for the 24-hour analysis.

$$\mathrm{COE} = \frac{C_{PV} + C_{WT} + \sum_{t=1}^{T}\left(C_{de} + C_{BATT}\right)}{\sum_{t=1}^{T}\mathrm{P}_L} \tag{3.23}$$

3.2.5.2 Reliability Analysis

The reliability of the microgrid is measured by the statistical parameter loss of power supply probability (LPSP). The reliability parameter signifies the probability over the time horizon when the generation fails to satisfy the demand. This failure can be either due to the improper designing of the distributed energy resources, immediate drop in renewable energy or increase in power demand. LPSP can be calculated by either using time series data or by determining the energy accumulative effect over the total load. The latter technique has been used in this study, as shown by the expression

$$LPSP = \frac{\sum_{t=1}^{T}\left(\mathrm{P}_L - \mathrm{P}_{pv} - \mathrm{P}_w - \mathrm{P}_{batt,dch} - \mathrm{P}_{de}\right)}{\sum_{t=1}^{T}\mathrm{P}_L} \tag{3.24}$$

3.2.6 Framework of BESS sizing method

The proposed optimization algorithm dispatches the optimal power from the three diesel generators and the energy storage, depending on the cost equations of the respective

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DERs and the load demand at the specific hour. In addition, the proposed method also directs the diesel generators to charge the energy storage when the cost of the BESS per unit of energy is higher than the generator cost. The battery SOC is computed at the end of each hour after the algorithm takes the decision to charge or discharge the battery. The battery optimal size is calculated for the defined strategies so that the cost is minimal for the scheduling of the power resources, which will reduce the overall cost of the microgrid. The battery optimal size is selected from a range such that the lower value $\overline{\mathrm{E}_{l,t}}$ corresponds to the battery size in which there is no mismatch between the generation and load whereas the upper value $\overline{\mathrm{E}_{u,t}}$ sustains the maximum charge at each interval. The battery size range in this study is taken from 100 kWh to 250 kWh. The flowchart of the proposed energy management strategy together with the battery sizing method is shown in Figure 3.3.

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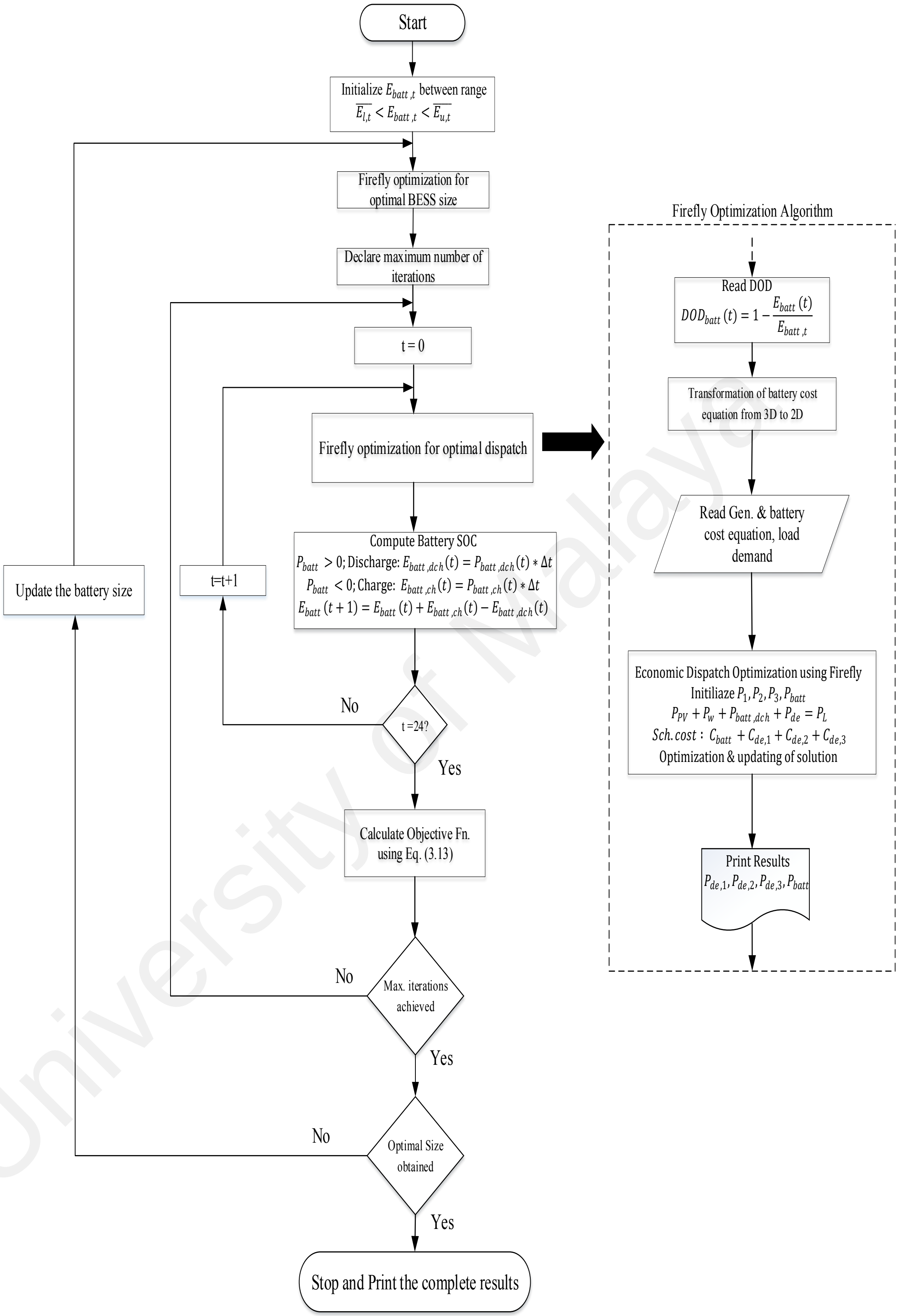

Figure 3.3: Framework for optimal battery sizing

3.3 Economic Scheduling of grid-connected network

3.3.1 Overview

With the growing concerns on the energy depletion and the reduction of CO_2 emission, electric vehicles have gained popularity in the transport sector due to the clean and reliable energy source. The EV benefits are not only associated with the automobile industry, but they can be treated as battery energy storage to reduce the power fluctuations from RES, provide energy arbitrage and earn extra revenue (Bessa & Matos, 2012; Hu, Zou, & Yang, 2016). However, the charging of EVs has imposed significant load in the electrical distribution system. Moreover, the high penetration of EV may result in the increase of technical losses, higher peak demands and reduction in the voltage profile (Arias et al., 2017). The stability of power network is disturbed with uncoordinated charging. This study aims to investigate the optimal EV coordination with V2G technology for the cost-benefit analysis. As such, the research into the V2G and battery energy management system had seen rapid progress in the last decade. The most important objective of these researches is to optimize cost savings, which can be achieved through peak shaving for the utility companies and the resultant saving is turned into cash incentives for the EV users. However, EV users are concerned about the battery replacement cost due to degradation with active participation in V2G exchange. Therefore, battery degradation cost is formulated for real-time analysis taking the depth of discharge at each time interval. The firefly algorithm is used to optimize the system cost. The performance of the proposed system is tested on a modified 33 bus distribution system in the presence of RESs. The impact of system cost and energy losses are analyzed for different RES penetration, RES location and EV capacities.

3.3.2 Modeling of grid-connected network

Figure 3.4 shows the grid-connected network to evaluate the performance of the proposed charge coordination method for EVs. The power network in this study includes modified IEEE 33 bus distribution system with residential houses and commercial buildings. The electric vehicles are incorporated in the distribution system, which are assumed to be travelling from home to workplace in the morning and return home in the evening. There are total of 320 EVs connected in the distribution system with 10 EVs at each bus except the bus1. The distribution system is integrated with wind turbine and solar photovoltaic as renewable power sources and EV battery as energy storage. The controller manages the entire communication of the network through its intelligent nodes. The detailed modeling of each component has been explained in section 3.2.2.

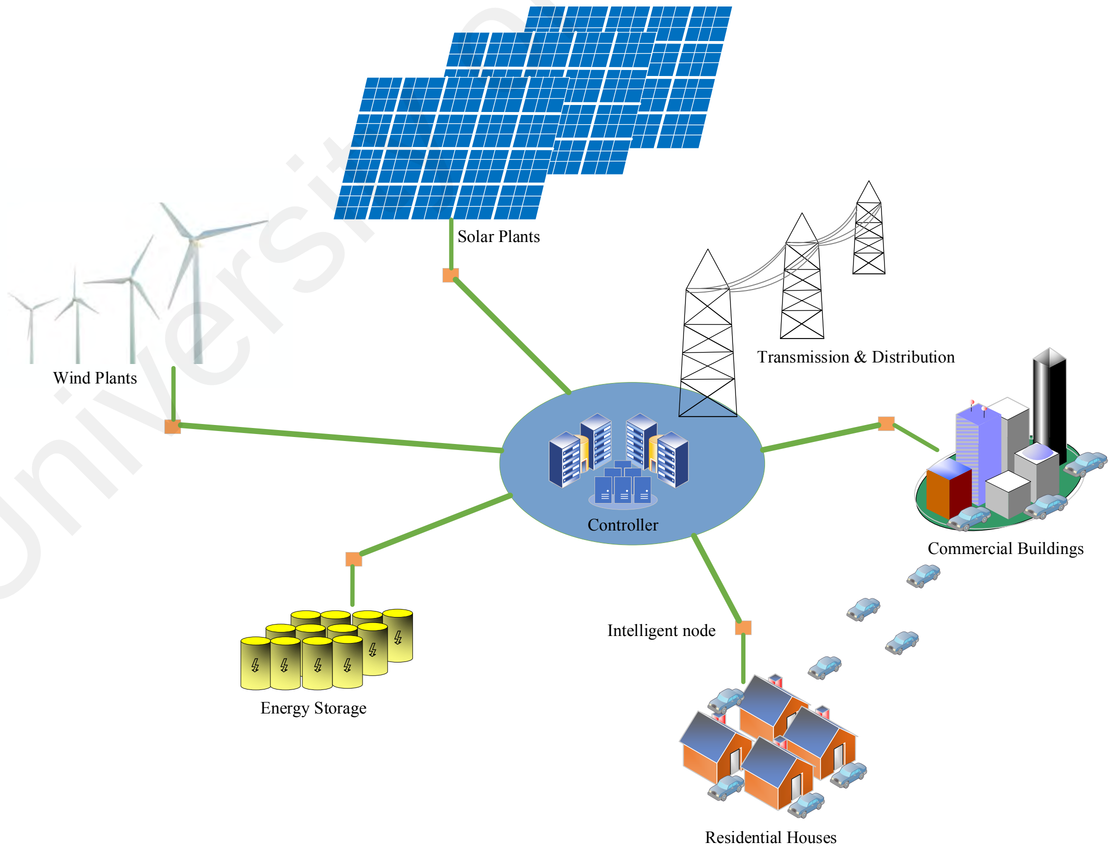

Figure 3.4: Schematic of grid-connected network

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3.3.3 Problem formulation

The incorporation of electric vehicles in the power grid improves the stability of the system as they can behave as energy consumer and energy providers during the low and high demand periods respectively. The electrical system faces issues like grid overloading and voltage deviation under uncoordinated EV charging. On the other hand, smart charging mechanism reduces the power difference between the peak and valley periods minimizing the system losses. The objective function considered for EV charge coordination is as follows:

$$Objective = Min. \sum_{h \in \Phi_t} \left(\mathrm{C}_h^{res} + \mathrm{C}_h^{com} + \mathrm{C}_h^{ev} + \mathrm{C}_h^{los} + \mathrm{C}_h^{b,d} \right) \tag{3.25}$$

where

$$\mathrm{C}_h^{res} = \sum_{rt \in \varphi_b} \mathrm{P}_{r,h}^{res} * \delta_{res} \tag{3.26}$$

$$\mathrm{C}_h^{com} = \sum_{rt \in \varphi_b} \mathrm{P}_{r,h}^{com} * \delta_{com} \tag{3.27}$$

$$\mathrm{C}_h^{ev} = \sum_{rt \in \varphi_b} \mathrm{P}_{r,h}^{ev} * \varepsilon_{ev} \tag{3.28}$$

$$\mathrm{C}_h^{los} = \sum_{sr \in \varphi_l} \mathrm{I}_{sr,h}^2 * \Re_{sr} * \lambda \tag{3.29}$$

$$\mathrm{C}_h^{b,d} = \frac{\mathrm{C}_{b,cap} * \mathrm{P}_h^{ev} * \Delta h}{\mathrm{E}_{cap}^{ev} * l_c(dod_h^b) * {\eta_b}^2} \tag{3.30}$$

In the above formulation, Eq (3.26) and Eq (3.27) are the costs of the residential and commercial loads respectively, Eq (3.28) is the cost of EV charging/discharging and Eq (3.29) shows the cost of power losses in the distribution network. It is to be noted that the cost of EV will be negative when discharging and positive if charging. I_{sr} is the bus current and $\Re_{sr}$ is the bus resistance associated for the power loss in the network, while λ is the cost parameter for losses. The variables δ_{res}, δ_{com} and ε_{ev} are the residential, commercial and EV electricity tariffs rate respectively. The battery degradation cost $C_h^{b,d}$ is shown in Eq (3.30), where $C_{b,cap}$ is the capital cost of energy storage, P_h^{ev} is the amount of power discharged by battery at hour *h*, Δh is the time interval taken as 1 hour in this study, E_{cap}^{ev} represents the electric vehicle battery capacity, dod_h^b is the battery depth of discharge status at hour *h*, $l_c(dod_h^b)$ is the number of cycles of battery storage and η_b is efficiency of the energy storage.

3.3.3.1 Active and reactive power constraints

$$\sum_{sr\in\varphi_l} P_{sr,h} + \sum_{r\in\varphi_b} P_{r,h}^{g} + P_{r,h}^{ren} = \sum_{rt\in\varphi_l} P_{rt,h} + \sum_{rt\in\varphi_b} P_{r,h}^{res} + \sum_{rt\in\varphi_b} P_{r,h}^{com} + \sum_{rt\in\varphi_b} P_{r,h}^{ev} + \sum_{rt\in\varphi_b} I_{rt,h}^{2} * \Re_{rt} \tag{3.31}$$

where $P_{sr,h}$ is the active power of branch sr, $P_{r,h}^{ren}$ is the renewable power (WT and PV) connected at bus *r*, $P_{r,h}^{g}$ is the generated power at bus *r*, $P_{r,h}^{res}$ and $P_{r,h}^{com}$ are the active residential and commercial loads connect at bus *r*.

$$\sum_{sr\in\varphi_l} Q_{sr,h} + \sum_{r\in\varphi_b} Q_{r,h}^{g} = \sum_{rt\in\varphi_l} Q_{rt,h} + \sum_{rt\in\varphi_b} Q_{r,h}^{res} + \sum_{rt\in\varphi_b} Q_{r,h}^{com} + \sum_{rt\in\varphi_b} I_{rt,h}^{2} * X_{rt} \tag{3.32}$$

where $Q_{sr,h}$ is the reactive power of branch sr, $Q_{r,h}^{g}$ is the generated power at bus *r*, $Q_{r,h}^{res}$ and $Q_{r,h}^{com}$ are the reactive residential and commercial loads connect at bus *r*.

$$\left|P_{sr,h}\right| \le V_{\max} * I_{\max} \tag{3.33}$$

$$\left|Q_{sr,h}\right| \le V_{\max} * I_{\max} \tag{3.34}$$

$$\mathrm{P}_{sr,h}^2 + \mathrm{Q}_{sr,h}^2 \le V_{r,h}^2 * \mathrm{I}_{sr,h}^2 \tag{3.35}$$

where $V_{r,h}^2$ is the voltage of bus r, $V_{\max}$ is the maximum voltage at bus, $\mathrm{I}_{\max}$ is the maximum branch current.

3.3.3.2 Voltage limit constraints

The voltage of the bus r at every hour should be within the maximum and minimum voltage level.

$$V_{\min}^2 \le V_{r,h}^2 \le V_{\max}^2 \tag{3.36}$$

3.3.3.3 EV power and its state of charge

$$\chi_{ch,h}^{ev} + \chi_{dch,h}^{ev} + \chi_{i,h}^{ev} = \chi_h^{ev} \tag{3.37}$$

$$\chi_{ch,h}^{ev} * \mathrm{P}_{ch,\min}^{ev} \le \mathrm{P}_{ch,h}^{ev} \le \chi_{ch,h}^{ev} * \mathrm{P}_{ch,\max}^{ev} \tag{3.38}$$

$$\chi_{dch,h}^{ev} * \mathrm{P}_{dch,\min}^{ev} \le \mathrm{P}_{dch,h}^{ev} \le \chi_{dch,h}^{ev} * \mathrm{P}_{dch,\max}^{ev} \tag{3.39}$$

$$\mathrm{E}_h^{ev} = \mathrm{E}_{h-1}^{ev} + \left(\chi_{ch,h}^{ev} * \mathrm{P}_{ch,h}^{ev} - \chi_{dch,h}^{ev} * \mathrm{P}_{dch,h}^{ev}\right) - \left(1 - \chi_h^{ev}\right) * \mathrm{E}_{trv,h}^{ev} \tag{3.40}$$

$$\mathrm{E}_{\min}^{ev} \le \mathrm{E}_h^{ev} \le \mathrm{E}_{max}^{ev} \tag{3.41}$$

where $\chi_{ch,h}^{ev}$, $\chi_{dch,h}^{ev}$ and $\chi_{i,h}^{ev}$ are the binary statuses for the charging, discharging and idle state of EV respectively. χ_h^{ev} represents the EV status when it is connected to the distribution system. $\mathrm{P}_{ch,h}^{ev}$ and $\mathrm{P}_{dch,h}^{ev}$ are the EV charging and discharging power, E_h^{ev} represents the present EV battery capacity at a specific time and $\mathrm{E}_{trv,h}^{ev}$ is the energy associated with EV traveling. The maximum charging and discharging power are

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specified by constraints (3.38) and (3.39), constraint (3.40) specifies the battery capacity at each hour for EV charging/discharging and traveling states, whereas the maximum and minimum SOC limit is defined by (3.41).

3.3.4 Performance Evaluation Parameters

3.3.4.1 Cost of electricity (COE)

The cost of electricity is calculated as same discussed in section 3.2.5.1. The COE for the grid-connected network is given by the expression

$$\mathrm{COE} = \frac{\sum_{h \in \Phi_t} \left(\mathrm{C}_h^{res} + \mathrm{C}_h^{com} + \mathrm{C}_h^{ev} + \mathrm{C}_h^{los} + \mathrm{C}_h^{b,d} \right)}{\sum_{h=1}^{24} \sum_{rt \in \varphi_b} \left(\mathrm{P}_{r,h}^{res} + \mathrm{P}_{r,h}^{com} \right)} \tag{3.42}$$

3.3.4.2 Profit for EV user

The EV users are concerned for the profit from V2G application. In this study, the cost for battery degradation is deducted from the EV users profit. Therefore, EV users prefer to discharge during high tariff periods only to get maximum profit. The profit equation is calculated as ratio of the amount of power exchanged through V2G ($\mathrm{P}_{\mathrm{V2G},h}$) to the total power discharged by EV.

$$\mathrm{Profit} = \frac{\left(\mathrm{P}_{\mathrm{V2G},h} * \varepsilon_{ev} \right) - \mathrm{C}_h^{b,d}}{\sum_{h=1}^{24} \mathrm{P}_{dch,h}^{ev}} \tag{3.43}$$

3.3.5 Framework of EV charge coordination with V2G application

It is seen that EV owners start charging their vehicles after returning to home during night time to the maximum state of charge (ratio of energy available in the battery to the maximum battery capacity). They are most likely to sell this power to the grid when the electricity tariff is high during day time. Commercial workplaces and parking lots are the best places to implement V2G and earn maximum profit as the vehicle is parked there for several hours. Thus, the utility grid must dispatch less power because these workplaces can act as generation sources to fulfill the load requirement. The framework methodology is explained in steps and the flowchart of the proposed method is shown in Figure 3.5.

Step 1: Interpret commercial and industrial load, wind and photovoltaic power production and EV state of charge status.

Step 2: Initialize charging power of EV and identify the number of EVs in charging mode as per each bus.

Step 3: Forward backward sweep load flow is executed for the distribution system with the network load and EV charging load. The power losses and bus voltages of the distribution system are computed.

Step 4: The algorithm fitness function is evaluated using Eq (3.31) and minimum operating cost is obtained for the objective function in Eq (3.25). The intensity and position of fireflies represents the optimal number of EVs charging within the defined set of constraints.

Step 5: If all the network constraints are satisfied, then the optimization updates the best solution and if any violation occurs then the EV charging load is reduced.

Step 6: The above cycle is repeated until the maximum iterations are executed and the time horizon is completed.

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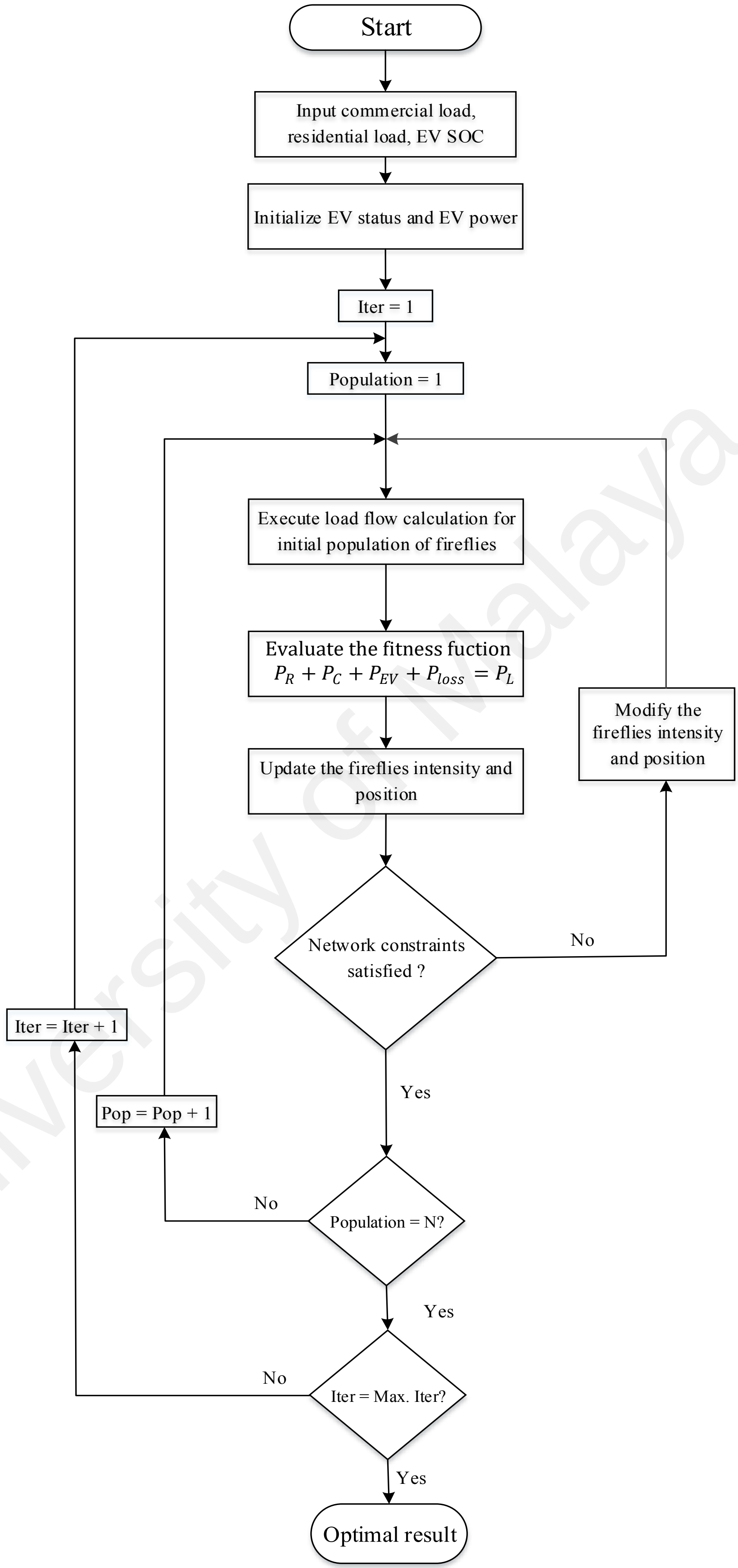

Figure 3.5: Framework for EV charging in distribution network

3.4 Summary

In this chapter, a new approach has been presented to schedule the energy resources in the microgrid considering optimal battery size. The microgrid is incorporated with diesel generator, renewable energy and the optimal size of energy storage to maximize the economic benefit and minimize the operational cost. The detailed modelling of microgrid components was studied for optimal power generation. The energy management strategy has been designed ensuring the reliability of the microgrid. Moreover, EV charge coordination to avoid grid overloading during peak hours has been presented. The optimal charging/discharging schedule will maximize the EV users profit by selling energy to the grid and minimize the power losses.

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CHAPTER 4: VALIDATION OF PROPOSED ENERGY MANAGEMENT SYSTEM

4.1 Introduction

In this chapter, the proposed energy management strategy with optimal battery sizing for the isolated microgrid is validated. The power losses and voltage profile of the distribution network are evaluated with the charge/discharge coordination strategy for electric vehicles. The impact of battery degradation cost to avoid deep discharges and to prolong battery lifetime is also validated for each of test system. Moreover, a comparative analysis is conducted to evaluate the effectiveness of the proposed algorithm.

4.2 Validation of economic scheduling and BESS sizing method for isolated microgrid

4.2.1 Test system for isolated microgrid

A typical low voltage microgrid with diesel generator and a battery storage as shown in Figure 4.1 is analyzed in this study to validate the performance of the proposed energy management strategies. The microgrid consists of 68 kW solar photovoltaic and 37 kW wind turbine system. The maximum capacity of diesel generators with their cost coefficients has been reported in Table 4.1 (Zhongwen Li, Zang, Zeng, Yu, & Li, 2016). The battery storage parameters such as capital cost, charging/discharging power limits and lifetime constitute major influence on the economic scheduling of energy storage. The energy storage parameters considered in this study are shown in Table 4.2. The parameters for the wind turbine and solar photovoltaic are represented in Tables 4.3 and 4.4 respectively (Chen et al., 2012).

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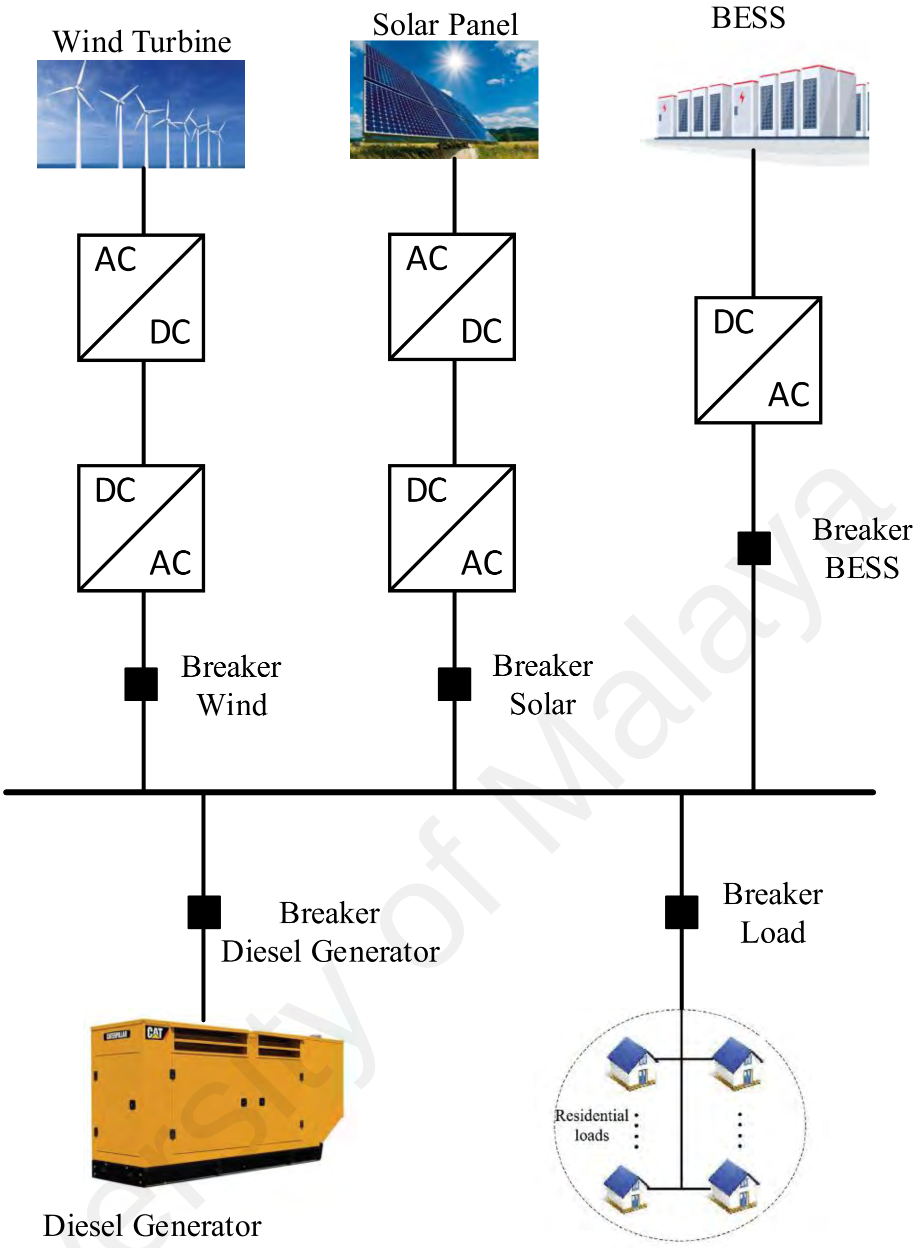

Figure 4.1: Low voltage microgrid

Table 4.1: Parameters of diesel generators

DG	a_i (\$/kW²)	b_i (\$/kW)	c_i (\$)	P_{min} (kW)	P_{max} (kW)
Diesel 1	0.0001	0.0438	0.3	0	40
Diesel 2	0.0001	0.0479	0.5	0	20
Diesel 3	0.0001	0.0490	0.4	0	10

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Table 4.2: Parameters of Energy Storage

Component Parameter	Value
Initial SOC (%)	75
$SOC_{batt}^{\max}$ (%)	90
$SOC_{batt}^{\min}$ (%)	15
Initial capital cost ($/kWh)	625
Maintenance cost ($/kWh)/year	25
Round-trip Efficiency (%)	90
Lifetime (years)	8
$P_{batt}^{\min}$ (kW)	10
$P_{batt}^{\max}$ (kW)	25
Interest rate (%)	6

Table 4.3: Parameters of Wind Turbine

Component Parameter	Value
Rated Power (kW)	37
Cut-in speed (m/s)	3
Cut-out Speed (m/s)	30
Rated speed (m/s)	12
Initial Capital cost ($/kW)	2000
Lifetime (year)	10
Interest rate (%)	6

Table 4.4: Parameters of Solar PV

Component Parameter	Value
Rated Power (kW)	68
Initial Capital cost ($/kW)	3000
Lifetime (year)	10
Interest rate (%)	6

The generation subsystem is designed to meet the peak load. However, intermittency of RESs and consumers' behaviors may affect the electricity cost and system reliability. A typical load profile of small residential area with the peak load of 163 kW has been

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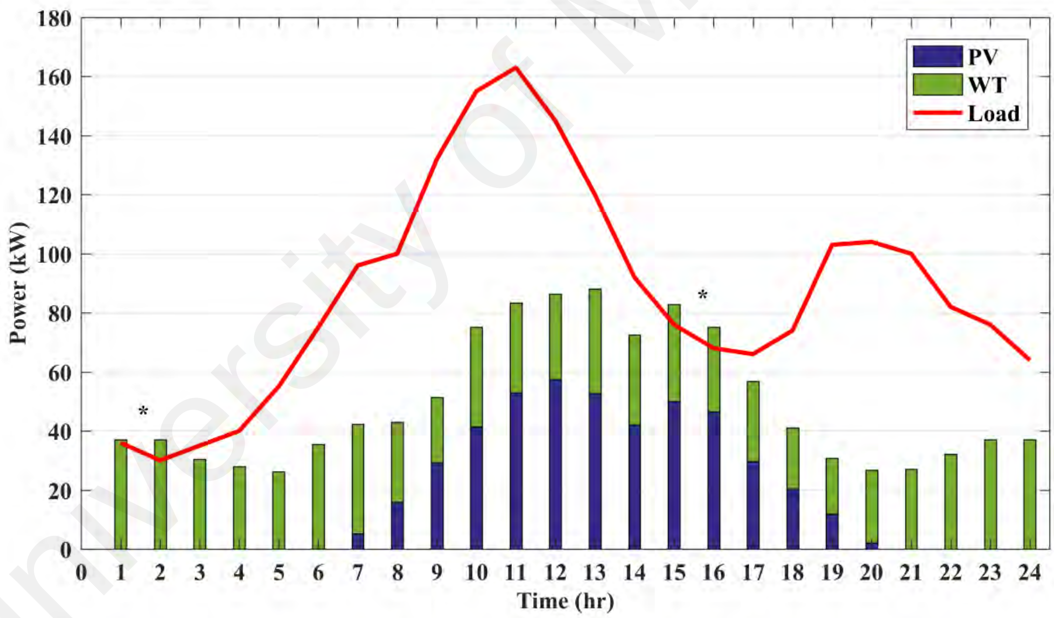
taken in this study. The microgrid load profile and renewable energy generation for each hour is shown in Figure 4.2. The load demand at most of the instances is higher than the combined wind and solar power generation. Thus, the generator and battery storage will be operated at these instances. However, there are certain instances when the renewable power generation is slightly higher than the load demand marked by * in the Figure 4.2. Hence, the surplus power will charge the energy storage and the generators remains in the idle state during these time intervals. The diesel generator will charge the battery storage when the cost of battery storage becomes higher than the diesel generator cost. The battery storage used in the microgrid operation is assumed to be initially charged at 75% SOC.



* excess energy to charge the battery

Figure 4.2: Renewable energy and load data for a day

4.2.2 Results for economic scheduling and battery sizing

The simulation results for the proposed energy management approach are analyzed for three cases discussed below. The proposed battery management strategy is compared with the conventional battery management strategy for cost benefit analysis and the effectiveness of different optimization algorithms is also discussed.

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4.2.2.1 Case A: Microgrid operation without BESS

The microgrid is operated without the energy storage. Thus, there will be no cost for the TCPD, and the objective function is restricted to the daily economic scheduling of the microgrid. The RESs and diesel generators must satisfy the load demand at all instances. However, there are some instances where the renewable and diesel generators cannot fulfil the required load; thus, there will be power mismatch between the generation and demand. This power mismatch will imbalance the system and will result in a power loss due to load shedding. The load shedding accounts for the penalty to be imposed increasing the scheduling cost of the microgrid. However, when the RES power is higher than the loads, the surplus power from the RESs will be dissipated as a dump load. Assuming the penalty factor for load shedding is 10 ($/kWh), the total operating cost of microgrid is calculated as $590. The microgrid distributed generators and load profile are shown in Figure 4.3. In this study, the accumulative sum of all the three diesel generators power dispatch has been considered for analysis.

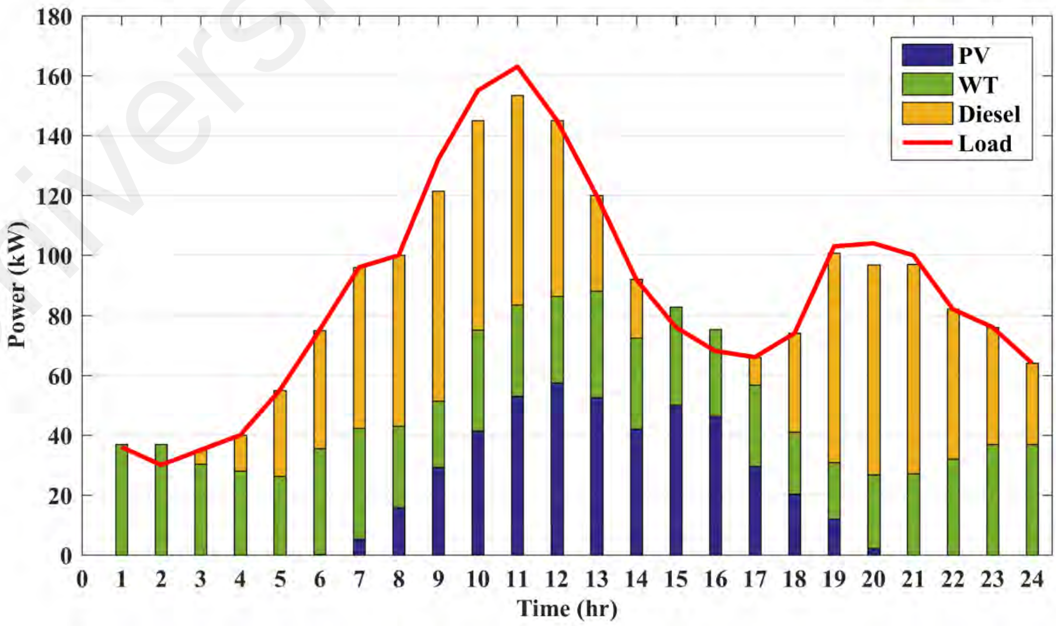

Figure 4.3: Microgrid operation without the battery storage

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4.2.2.2 Case B: Battery size of 100 kWh is added to microgrid

The renewable sources and diesel generator cannot meet the load demand at all instances; hence, the battery storage must be installed in the microgrid system. In this case, a battery size of 100 kWh is added to the system. The battery size is selected such that there is no mismatch between the generation and the load at any time of the day. The battery is discharged when the cost of battery is lower than generator cost and recharged when the battery operational cost increases due to high DOD value. This approach supports the microgrid during the fluctuations of RES and avoids load shedding. The microgrid scheduling cost for a day in this case is calculated as $281.37 whereas the battery TCPD is $ 70.90. The average per day cost of electricity in this case is computed as 18.44 (cents/kWh). Figure 4.4 shows the battery DOD curve for each time interval. It can be seen from the figure that during certain instances, the DOD becomes higher than 70%, which greatly impacts the cost of energy storage during discharge. Also, the battery charge at the end of the day is low, which may impact the operation for the next day. The power dispatch of all the DERs in the microgrid with battery size of 100 kWh is represented in Figure 4.5. The negative power shows that battery is charging during that instant. Therefore, during charging process the cumulative generation from distributed resources exceeds the load profile.

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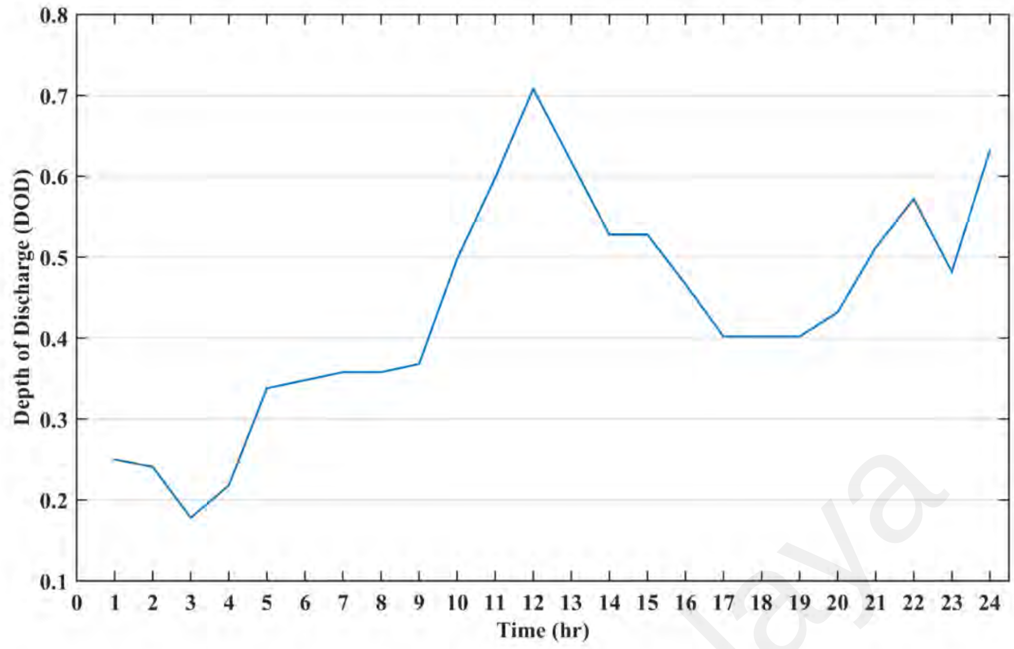

Figure 4.4: The depth of discharge status of battery for case B

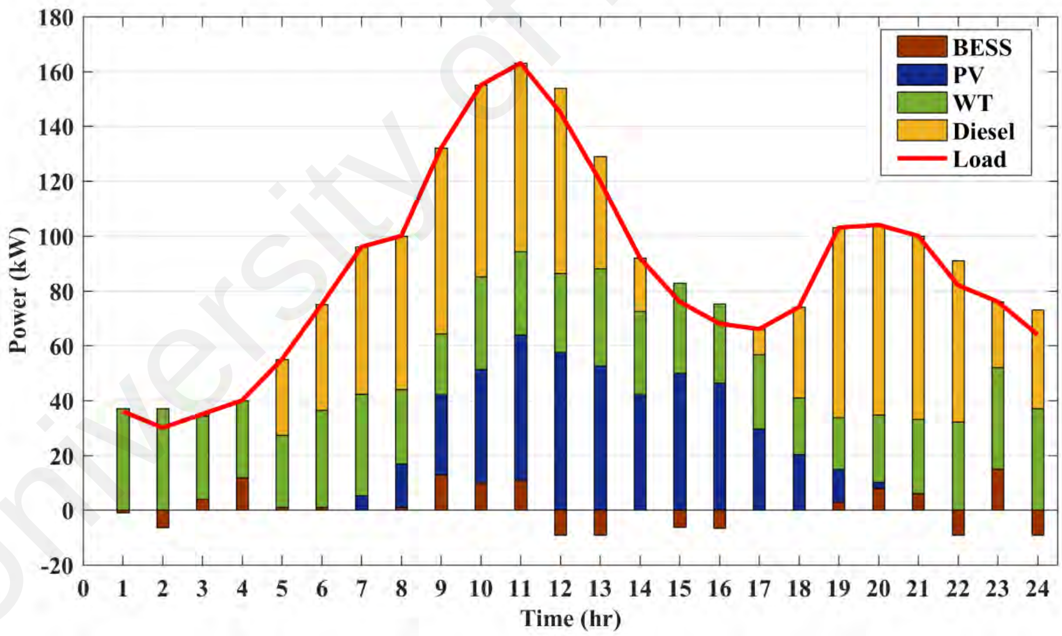

Figure 4.5: Operation of microgrid with all power generations and load for battery size of 100kWh

4.2.2.3 Case C: Optimal battery size is added to the microgrid

The optimal battery size for the microgrid operation is determined to produce a cost-effective system. The proposed algorithm computes the optimal battery size to minimize the OC of microgrid. The proposed method calculates the battery size to be 145.5 kWh.

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The daily operating cost for the optimal size is found to be $325.68. To validate the result of the proposed method, the microgrid OC has been computed for the battery size within the range of 100kWh - 250kWh, considering all the constraints of the distributed energy resources and the battery. Figure 4.6 shows the scheduling cost, TCPD and the overall OC for the different battery sizes. The optimum battery capacity for this system is recorded to be 145kWh, similar to that by the proposed method. The results show that the scheduling cost is high for smaller battery sizes, and as the size is increased the cost gradually reduces. This trend is followed until the battery size reaches up to 145kWh after which the scheduling cost increases again. The TCPD of battery is a linear curve which increases with the size of the battery. The OC for the microgrid shows a very small change in the cost until the battery size reaches 145kWh and continuously increases thereafter.

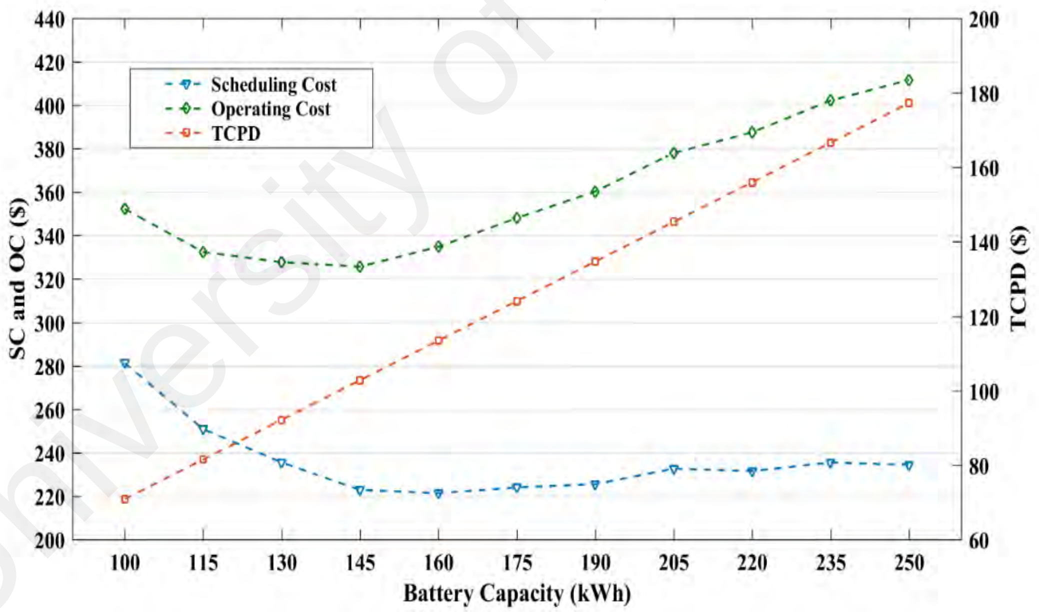

Figure 4.6: Microgrid operating cost for different battery sizes

The battery DOD for the entire time period is shown in Figure 4.7. It can be seen from the figure that during the initial hours, the battery is discharging and DOD value is increasing. At 06:00 the battery DOD has raised to 38%, at which level the battery cost rises, while the generator discharges more power and simultaneously charges the battery.

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After 09:00, the generator alone cannot fulfil the load demand; hence, the battery has to discharge in these instances to avoid load shedding. The DOD value at these instances increases and the battery discharges irrespective of the high cost. As soon as the high load period ends, the generator charges the battery again to ensure sufficient charge during the critical hours. The critical hours are considered as those hours when the renewable energy and diesel generator together cannot meet the load demand. Despite the high cost of the battery storage, it discharges power to fulfil the load demand. Thus, the battery is never depleted completely and avoids deep discharges, which prolongs the battery lifetime.

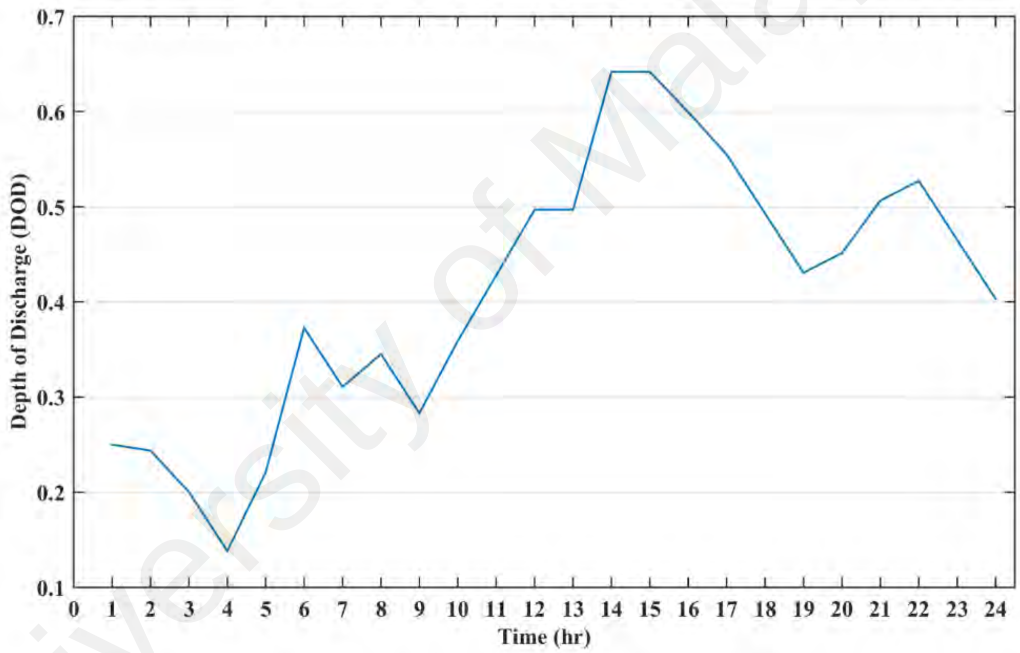

Figure 4.7: The depth of discharge status of battery for case C

The battery charging and discharging power analysis is shown in Figure 4.8. The battery discharging power is represented by a positive value whereas the negative value shows the charging process. The figure shows that most of the time the battery is discharging. The discharged power varies during these instances. The maximum discharge power in one-time sequence is set to 25kW. This is to avoid complete discharge of the battery storage in one interval so that the battery can be utilized during critical

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hours. The optimal power dispatch for the distributed sources and load profile are shown in Figure 4.9.

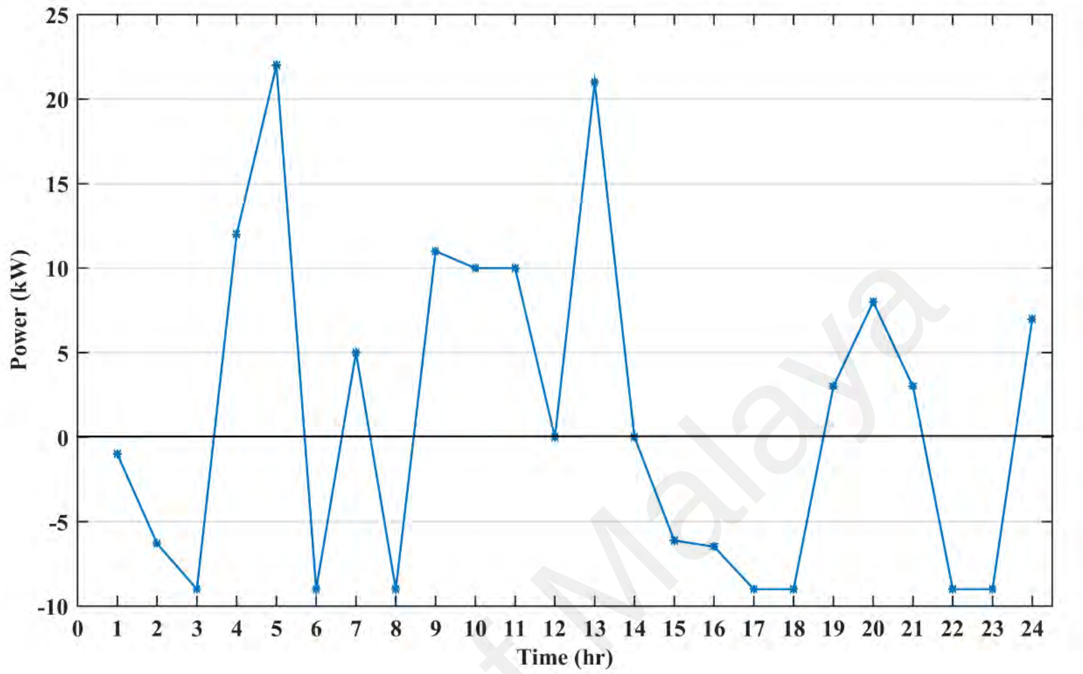

Figure 4.8: The battery charging and discharging power analysis

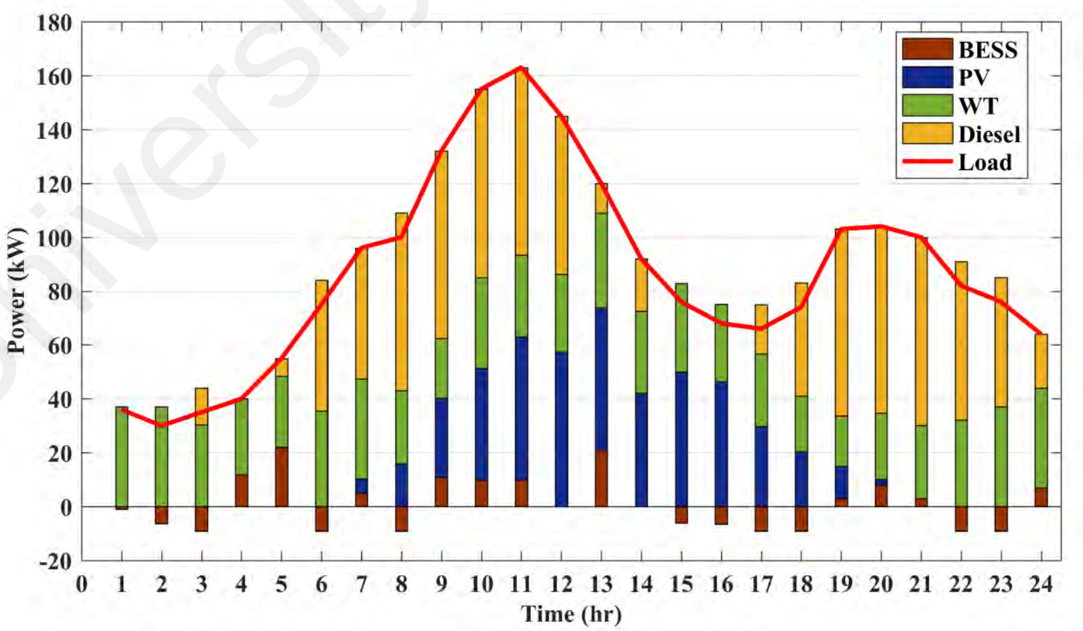

Figure 4.9: Operation of microgrid with all generations and load

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The optimal power dispatches for the above cases are tabulated in Table 4.5. The renewable power generation in all cases is identical, and the economic dispatch is performed for the power difference between the load and the renewable energy. The negative values in the BESS shows the charging schedule while the positive values represent the discharging schedule. Generator 1 dispatches more power due to it being the cheapest among the three generators, whereas generator 3 dispatches minimal power.

Table 4.5: Scheduling results of different cases at every hour

Time	Economic dispatch without BESS				Economic dispatch with 100kWh Battery size				Economic dispatch with optimal battery size			
(hr)	G1	G2	G3	BESS	G1	G2	G3	BESS	G1	G2	G3	BESS
1	0	0	0	0	0	0	0	-0.9	0	0	0	-0.9
2	0	0	0	0	0	0	0	-6.3	0	0	0	-6.3
3	4.6	0	0	0	0	0	0	4.6	13.6	0	0	-9
4	12	0	0	0	0	0	0	12	0	0	0	12
5	24.7	4	0	0	24	3.7	0	1	6.7	0	0	22
6	28.7	8.1	2.7	0	28.3	7.8	2.4	0	31.6	11.2	5.7	-9
7	33.4	12.8	7.5	0	33.4	12.8	7.5	0	38.6	8.5	1.6	0
8	34.5	14	8.5	0	34.1	13.7	8.2	0	38.3	17.7	10	0
9	40	20	20.6	0	39.1	18.5	10	13	40	19.6	10	11
10	40	20	19.9	0	40	19.9	10	10	40	19.9	10	10
11	40	20	19.6	0	39.6	19	10	11	40	19.6	10	10
12	35	14.6	9.1	0	39.1	18.6	10	-9	39.9	11.7	7.1	0
13	26.1	5.6	0.2	0	29.1	8.6	3.2	-9	10.9	0	0	21
14	19.5	0	0	0	15.4	2.3	1.8	0	6.2	10.3	3	0
15	0	0	0	0	0	0	0	-6.12	0	0	0	-6.12
16	0	0	0	0	0	0	0	-6.48	0	0	0	-6.48
17	9.2	0	0	0	9.2	0	0	0	18.2	0	0	-9
18	26.5	6	0.5	0	26.9	6.1	0	0	29.5	9	3.5	-9
19	39.6	19	13.6	0	39.9	19.3	10	3	39.9	19.3	10	3
20	40	20	17.2	0	39.9	19.3	10	8	39.9	19.3	10	8
21	39.9	19.3	13.7	0	38.7	18.2	10	6	40	19.9	10	3
22	32.1	11.7	6.1	0	35.1	14.7	9.1	-9	35.1	14.7	9.1	-9
23	28.5	8	2.5	0	0	20	4	15	31.5	11	5.5	-9
24	23.8	3.2	0	0	20.5	7	1.5	-9	16.3	7.4	3.3	7

The daily operating costs for the above defined cases are compared in Table 4.6. The operating cost is minimum with the optimal BESS size whereas TCPD is maximum in

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this case. The operating cost is high when battery storage is not included in the microgrid due to penalty of load shedding.

Table 4.6: Comparison of battery cost and microgrid operating cost for different cases

Cases	Daily Operating cost ($)	TCPD ($)
Without BES	590	-
100kWh battery size	352.27	70.90
Optimal battery size	325.68	102.80

The battery DOD curves for the different battery sizes are shown in Figure 4.10. The figure shows that DOD values for the optimal battery size of 145 kWh is lowest at most of the instances as compared to other battery sizes. The lifecycle and lifespan of the different battery sizes are tabulated in Table 4.7 by taking the average of the DOD. The optimal battery capacity results in longer lifetime in comparison to other battery capacities and the conventional method (Borhanazad et al., 2014). The lifetime of the battery storage is computed with the assumption that battery completes one cycle in a day as discussed in (Khawaja et al., 2017). Thus, the optimal size and the economic scheduling prolongs the battery lifetime and reduces the microgrid cost.

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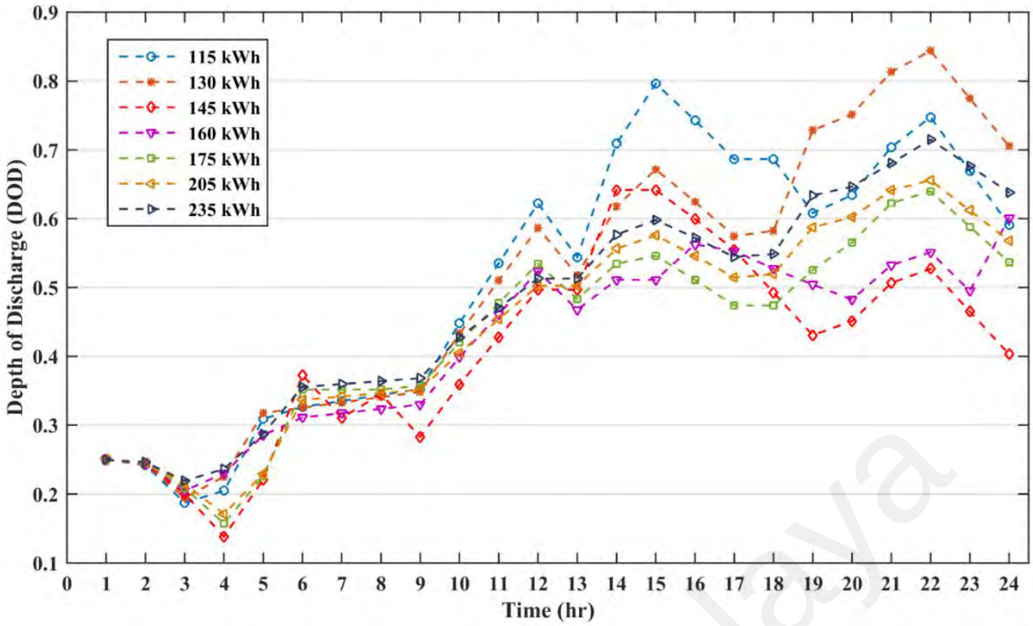

Figure 4.10: DOD curves of different battery sizes

Table 4.7: Lifetime analysis for different battery capacities

Battery capacities (kWh)	**Average DOD value (%)**	**Lifecycles (cycle)**	**Lifetime (year)**
115	51.15	2264	6.2
130	51.30	2254	6.2
145	40.08	3233	8.9
160	45.24	2709	7.4
175	43.47	2871	7.9
190	45.58	2679	7.3
205	44.71	2756	7.5
215	46.92	2568	7.0
235	47.67	2509	6.9
145 (Borhanazad et al., 2014)	54.55	2061	5.6

4.2.2.4 Comparison of proposed technique with the conventional technique

The effectiveness of the proposed method is verified by comparing it with other conventional methods (Borhanazad et al., 2014; Ismail et al., 2013) in which the battery storage discharges when the renewable resources fail to provide sufficient energy to meet the load. When the battery reaches minimum energy level, the diesel generator is turned on to charge the battery storage. This method reduces the lifetime of battery storage by continuously discharging to the minimum level. The authors in (Borhanazad et al., 2014) have used PSO to get the optimal power dispatch. The comparison is done by implementing the conventional method using the above-mentioned parameters, and the results are shown in Table 4.8. It is apparent from the table that the proposed method reduces the operating cost by 50% as compared to the conventional method. The battery depth of discharge status for the conventional method is shown in Figure 4.11, which depicts that the DOD is higher at most of the instances due to complete power discharge from the energy storage. Thus, the operating cost of the microgrid by using the conventional method is high as compared to the proposed method. The overall power generations and load for all the time intervals are plotted in Figure 4.12.

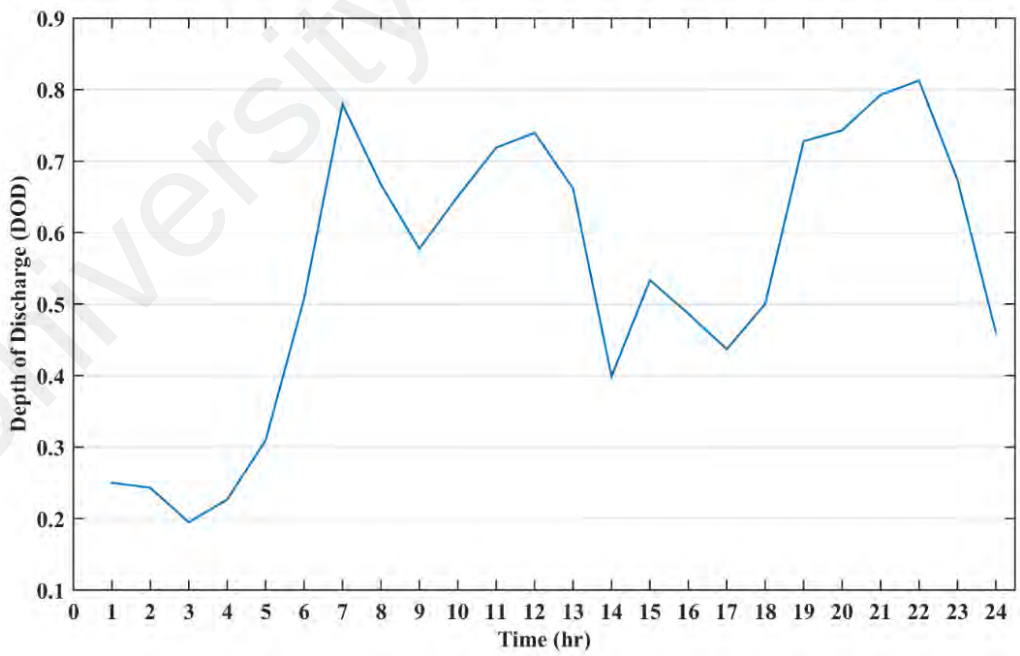

Figure 4.11: Battery depth of discharge status for the conventional method

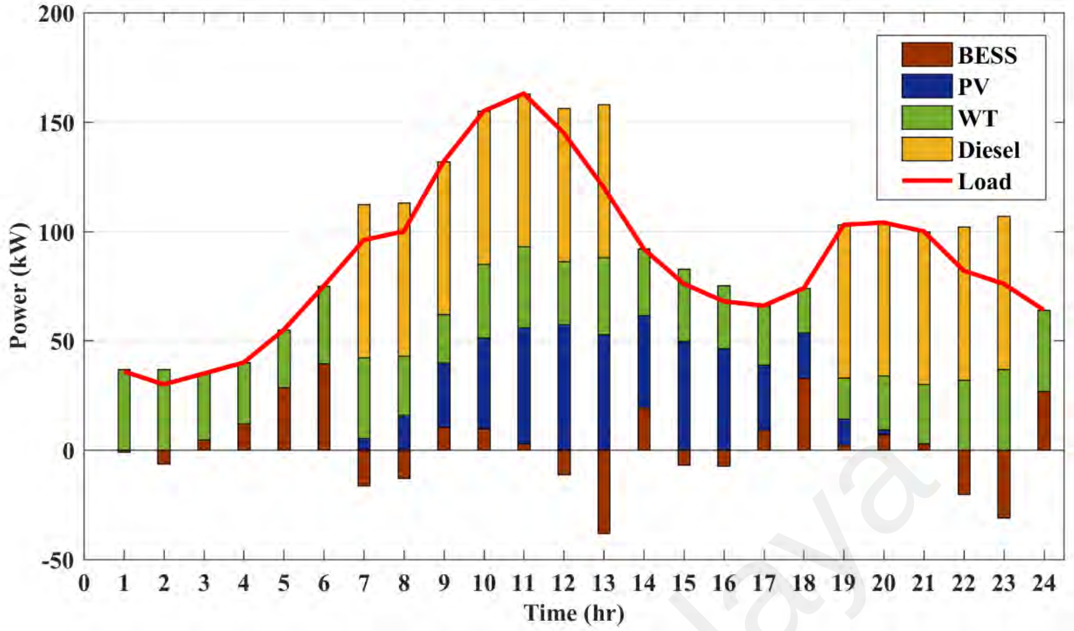

Figure 4.12: Microgrid operation with all the generations and load for the conventional method

Table 4.8: Comparison of proposed method with the conventional method

Method	Scheduling Cost ($)	Daily Operating Cost ($)	Average COE (cents/kWh)
Conventional method	557.09	659.90	31.65
Proposed Method	222.87	325.68	15.63

4.2.2.5 Comparison of proposed optimization algorithm with other algorithms

The robustness of the firefly algorithm (FA) is analyzed by implementing artificial bee colony (ABC), harmony search algorithm (HSA) and particle swarm optimization (PSO) for the proposed method and the results are reported in Table 4.9. The table shows that FA has the minimum operating cost with 0% LPSP. However, PSO and HSA are not capable to meet the load demand at all the instances resulting in the load shedding and has a higher LPSP ratio. The battery discharging cost is the ratio of the accumulated battery cost at all the instances in which the BESS is discharged to the sum of the power

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discharged by the BESS. The battery discharging cost of FA is minimum compared to other algorithms due to the fact that BESS does not discharge more power at high DOD values, thus reducing the scheduling cost of the microgrid. The battery DOD has been compared for all the algorithms and the results are shown in Figure 4.13. The results illustrate that FA has been capable of limiting the battery DOD to a low value to minimize the battery operational cost. The scheduling cost for the hourly analysis with the battery size of 145 kWh had been compared with the above-mentioned algorithms as in Figure 4.14. The figure clearly depicts that the cost at each hour by FA is comparatively lower than other algorithms, which reduces the overall operating cost of the microgrid.

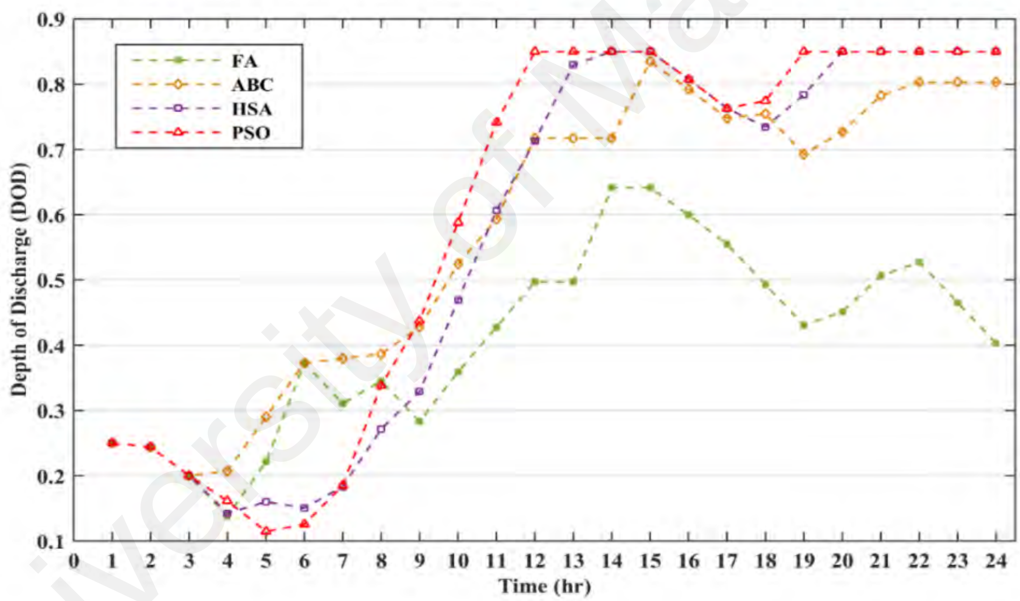

Figure 4.13: Depth of Discharge status for different optimization techniques

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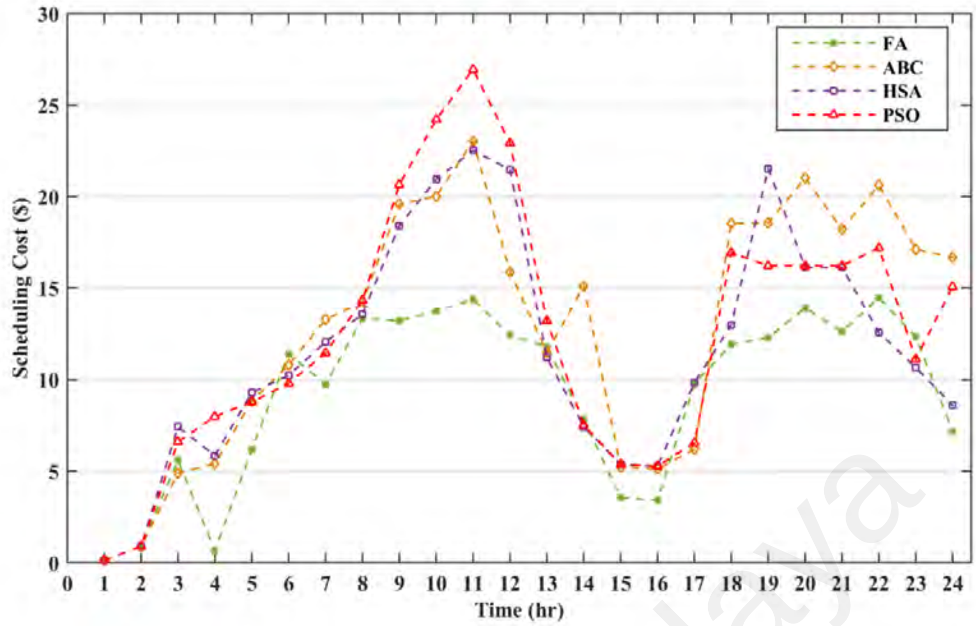

Figure 4.14: Hourly scheduling cost for different optimization techniques

Table 4.9: Comparison of different algorithms for the proposed method

Method	Daily Operating Cost ($)	Average cost of electricity (cents/kWh)	Average Battery Discharging Cost (cents/kWh)	Loss of Power Supply Probability (%)	Computational time (sec)
Artificial Bee Colony	393.10	18.86	39.24	0	265
Harmony Search Algorithm	383.34	18.40	37.00	37.5	225
Particle Swarm Optimization	404.46	19.41	38.02	25	250
Firefly Algorithm	325.68	15.63	22.13	0	195

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4.3 Validation of EV charge coordination with V2G application

4.3.1 Test system for grid-connected network

In this study, the proposed charging/discharging schedule of EV is tested on modified IEEE 33 bus medium voltage distribution network as shown in Figure 4.15 (Muhammad et al., 2018). The test system is connected to the 12.66 kV substation at bus 1. The buses from 2-15 are assumed as residential load buses whereas buses from 16-33 are taken as commercial load buses. Moreover, each bus in the distribution network can accommodate 10 EVs except the bus 1. The total load of the system is 3.78 MW (active load) and 2.35 MVAR (reactive load). The residential and commercial load of the system is shown in Figure 4.16. The line and load data of each bus of the distribution network is given in Appendix A. The residential and commercial hourly load of each bus is varied by adjusting the magnitude of the load data of the respective bus. For instance, residential active and reactive power at bus 2 for the complete day is represented by Figure 4.17. Three units of PV and WT are integrated in the distribution system. The number of EVs charged/discharged at each time period in the distribution system is 320. In addition, all the EVs are assumed to have the maximum capacity of 85kWh in order to model the system effectively. The maximum transformer capacity of distribution system is taken as 4.12 MW whereas the minimum bus voltage limit is set as 0.94 p.u. The average distance EV user travels is 34 km per day which constitutes 6 kWh of battery capacity as suggested by (Gough, Dickerson, Rowley, & Walsh, 2017; Gustafsson & Nordstrom, 2017). Therefore, it is assumed that EV battery discharges 3 kWh during travel from home to workplace and 3 kWh to return home. The parameters for EV battery are shown in Table 4.10.

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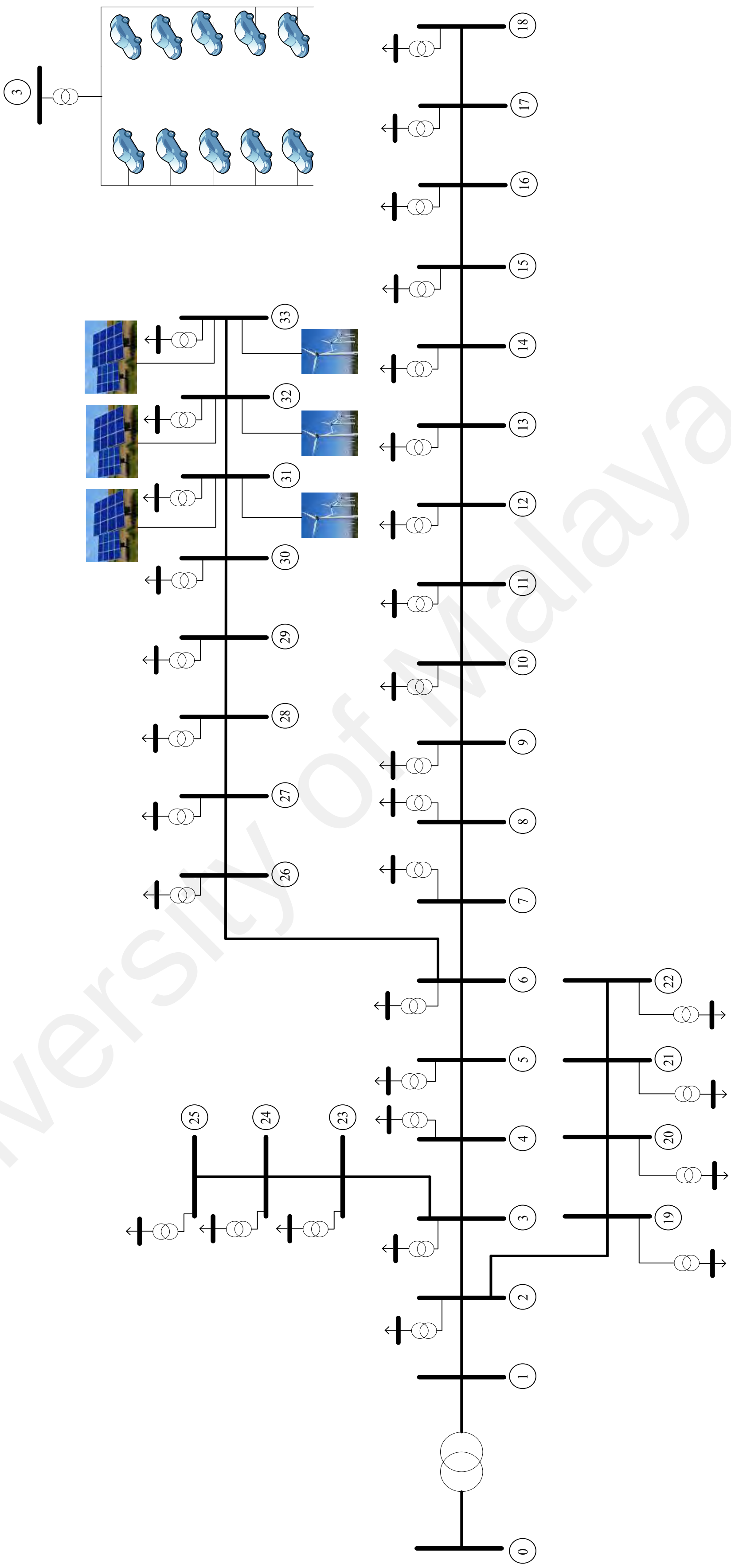

Figure 4.15: Modified IEEE 33 bus distribution system

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Figure 4.16 shows the commercial and residential load of one day. It can be observed that commercial load rises significantly from 07:00 in the morning. The peak load exists from 12:00 noon to 16:00 in the afternoon. On the other hand, peak load in residential sector is from 19:00 to 22:00. In addition, the residential load rises in the morning during 08:00-09:00. Therefore, the proposed method allows minimum EVs to charge during these peak hours such that distribution system may not face any overloading issue utilizing the maximum capacity of the power system.

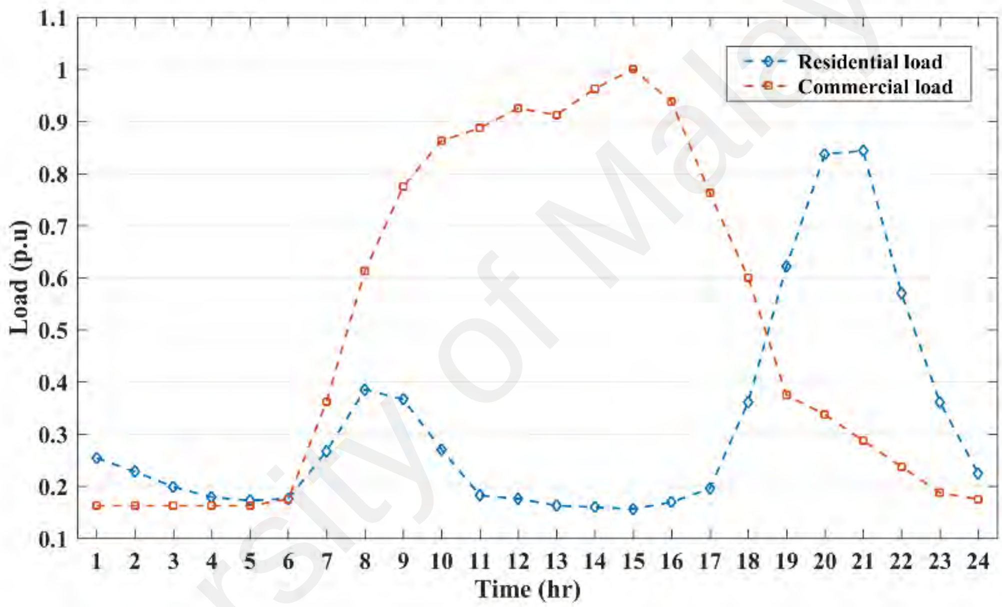

Figure 4.16: Residential and commercial load profile

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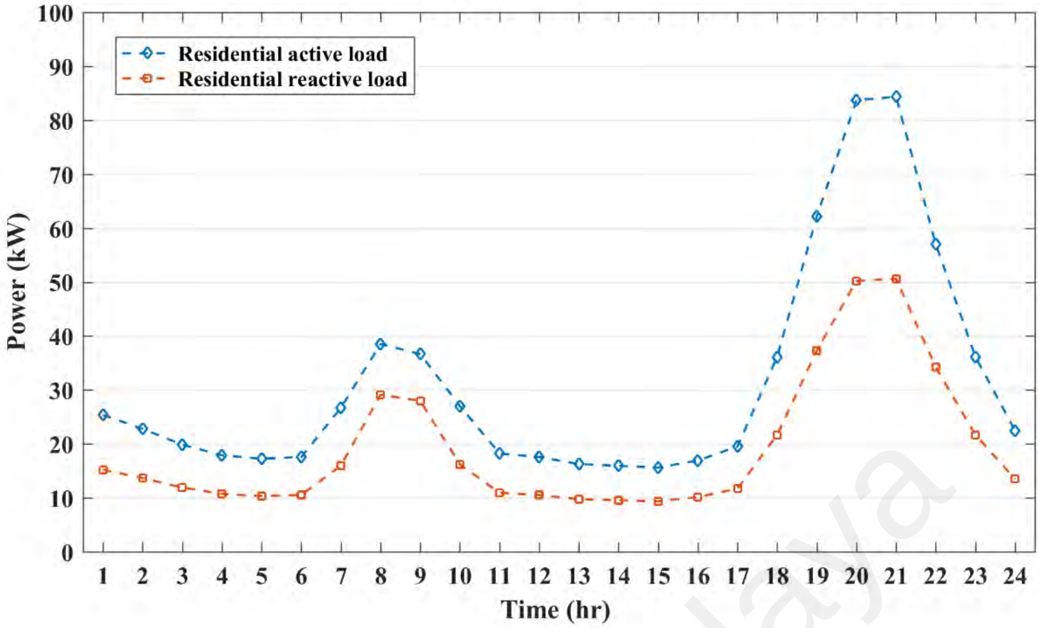

Figure 4.17: Residential active and reactive power of bus 2

Table 4.10: Parameters of EV

Component Parameter	Value
Battery Capacity (kWh)	85
SOC minimum/maximum limit (%)	20/100
$P^{ev}_{ch,max}$ (kW)	20
$P^{ev}_{dch,max}$ (kW)	8
Efficiency (%)	0.9

The solar irradiation and wind speed profiles are shown in Figure 4.18. It can be seen from the figure that the output power of PV is high at noon when solar irradiation is at peak whereas the output power is zero during night time. The solar irradiation in this study is recorded at University of Malaya, Wisma R&D for a summer day. The output power for WT varies with the speed of wind at each time interval and fluctuations are observed within the certain range (Chen et al., 2012). The hourly electricity price for the residential and commercial sector are shown in Figure 4.19. The commercial tariff is divided into three periods: peak, mid-peak and off-peak taken from Tenaga Nasional

Berhad (TNB) Malaysia whereas the residential tariff consists of peak and off-peak periods (Thoubboron, 2018). The electricity price is high during peak periods which provides an opportunity for the EV users to sell energy during these hours.

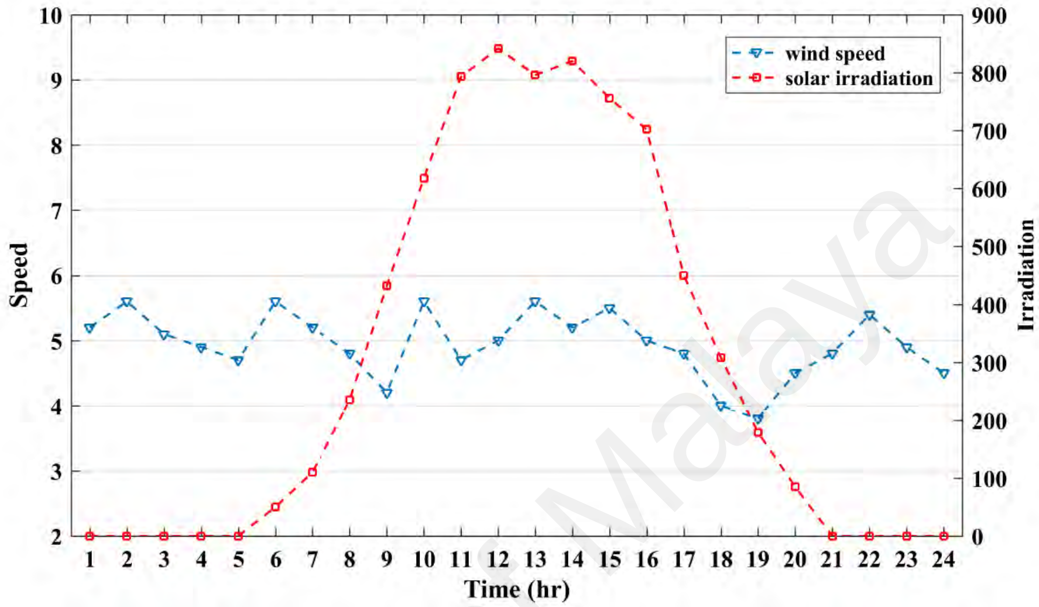

Figure 4.18: Solar irradiation and wind speed

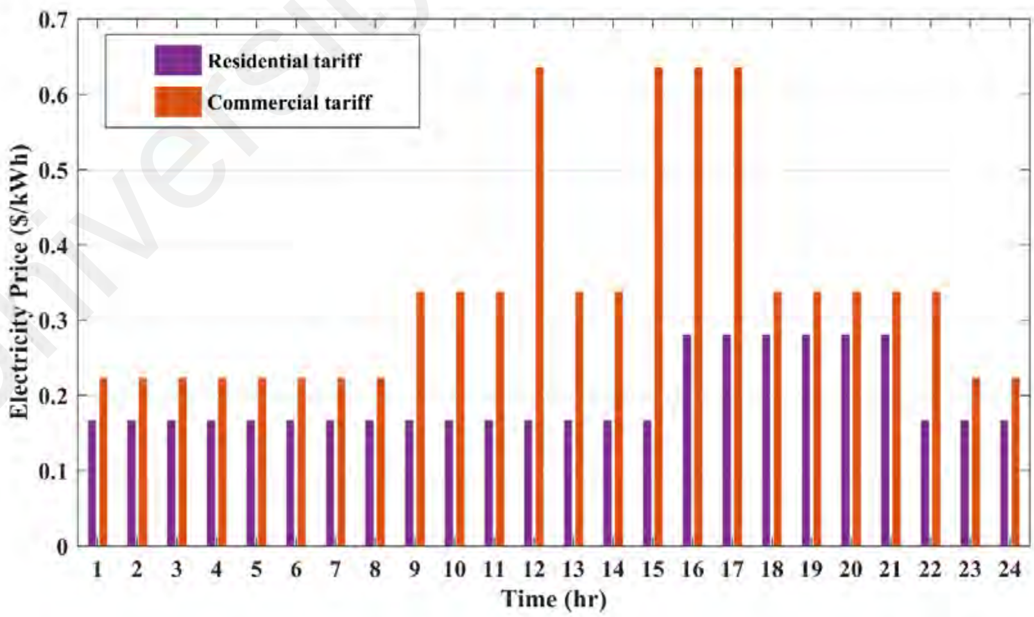

Figure 4.19: Residential and commercial electricity tariff

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The impact of coordinated charging/discharging of EV in the distribution system is analyzed by considering three scenarios. The power dispatch and the total operating cost is compared for each scenario. The scheduling scenarios are described as

Scenario1

In this scenario the load model is established under uncoordinated charging/discharging schedule of EVs. The electricity cost and system stability are analyzed when all the EVs start charging immediately after returning to home. This scenario serves as a reference case when investigating the effectiveness of algorithm.

Scenario 2

The coordinated charging/discharging schedule of EVs is modeled in this scenario. The load model ensures that bus voltage does not fall below the minimum voltage level. The electricity cost consumption in this scheduling scenario is analyzed and compared with the scenario 1.

Scenario 3

The impact of renewable energy (photovoltaic and wind turbine) is considered in this scheduling scenario. The electricity cost of the system with coordinated charging/discharging including the renewable energy is analyzed and the system stability is compared with other scenarios. The optimal location for the PV and WT system is located at buses 31, 32 and 33 based on previous work in (Rao, Ravindra, Satish, & Narasimham, 2013).

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4.3.2 Results for EV charge coordination with V2G application

The power profiles of EV charging and discharging under different scheduling scenarios is shown in Figure 4.20. The time period in this study starts from 19:00 after EV returns home in the evening till 18:00 on the next day. The EV travelling period in this study is considered from 8:00 – 9:00 in the morning and 18:00 – 19:00 in the evening when EV travels from home to workplace and workplace to home respectively. During uncoordinated charging, the charging power is high at the start of the time period. The charging power drops to zero after the EV is completely charged. Similarly, during the day time when the electricity tariff is high, all the EVs start discharging, which is represented by negative values in the figure. The battery degradation cost under this scenario increases due to continuous discharge even at high DOD. On the other hand, the charging power under scenario 2 and 3 is quite low when coordinated charging is performed. Unlike scenario 1, all the EVs are not connected to the charging station at 19:00 maintaining the voltage profile within limits whilst serving high residential load at this time. Moreover, the charging power is almost uniformly distributed over the night time, ensuring the distribution system is not overloaded. Similarly, when EVs start discharging during day time, the discharging power is low in scenario 3 compared to scenario 2. This is because the renewable energy generation is high during day time which reduces the overall load of the distribution system. EV owners considers incentives while discharging and if there is no profit in discharging, they are unwilling to discharge as the battery degradation cost increases with increase in discharge cycles.

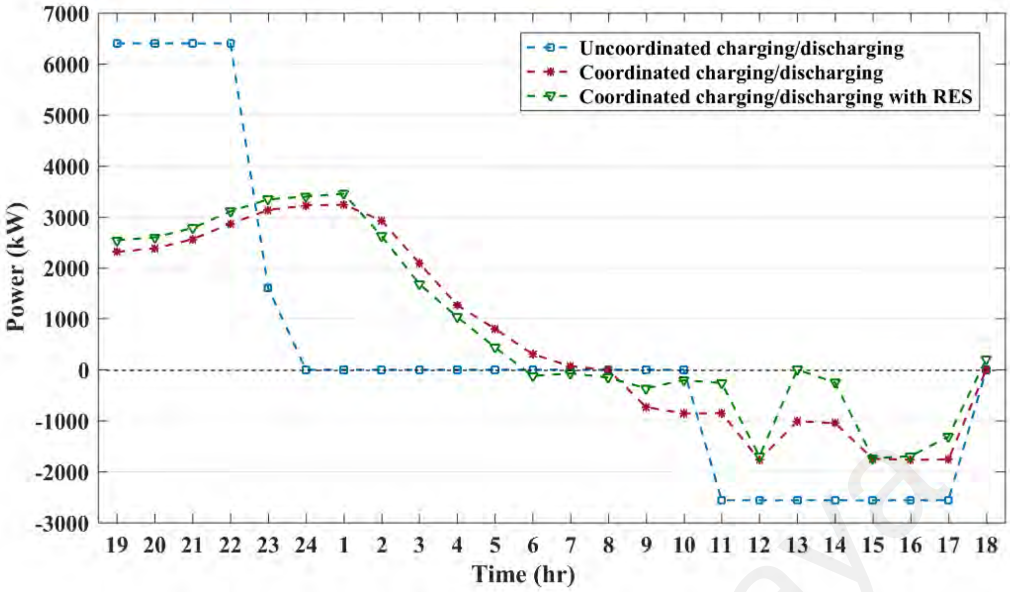

Figure 4.20: EV charging power for different scenarios

The minimum bus voltage of the weakest bus in the distribution system is shown in Figure 4.21 for all the scheduling scenarios. It is depicted from figure that the voltage level is violated when uncoordinated charging is performed. The bus voltage drops below 0.94 p.u. when EV starts charging from 19:00 to 22:00. The bus voltage remains within the voltage limit during coordinated charging in scenario 2 and 3.

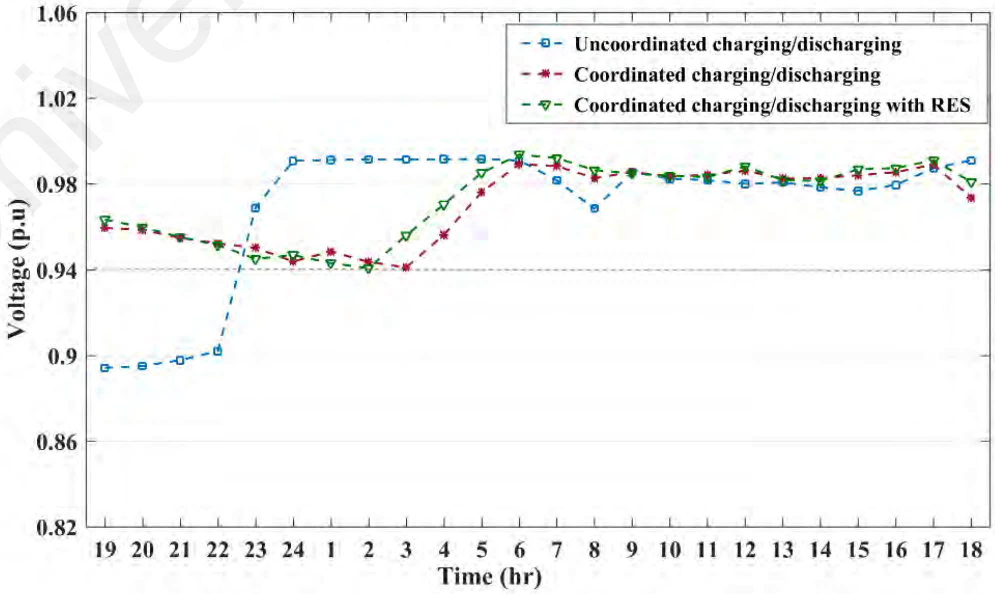

Figure 4.21: Voltage magnitude of the weakest bus

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The power generation profiles between the distribution system and the power grid is shown in Figure 4.22 for coordinated and uncoordinated scheduling. The peak load in uncoordinated scenario is twice as compared to coordinated scenarios because of high EV charging power in the evening when EVs return homes. Substantial power difference between charging and discharging creates stability issues in the distribution system. In the coordinated scenarios, the charging power does not increase above the maximum transformer capacity. Hence, the power difference is low, resulting improvement of the system stability. The power exchange in scenario 3 is less compared to scenario 2 due to the addition of RES, which decreases the operating cost of the system.

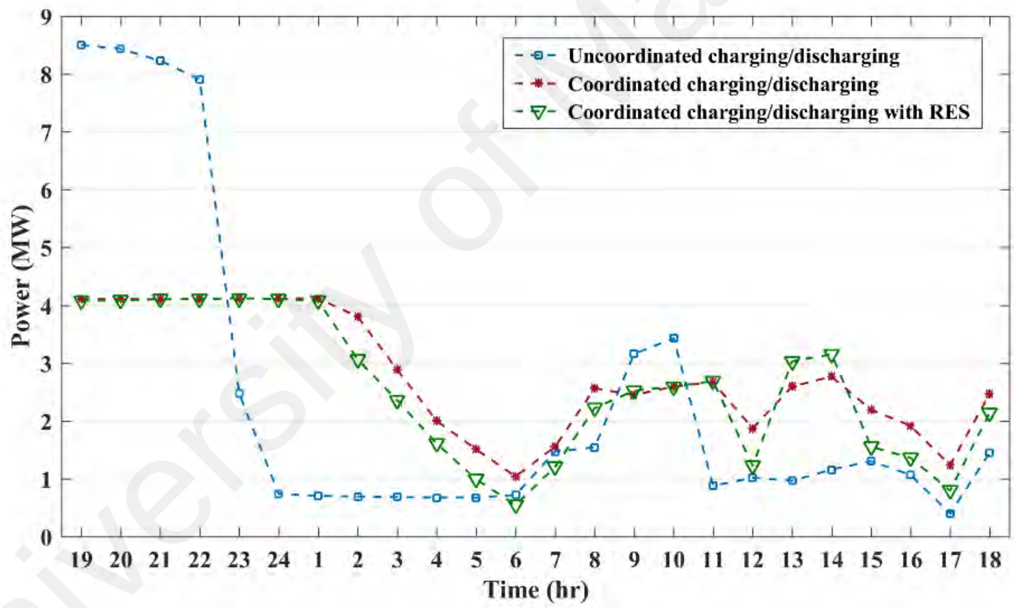

Figure 4.22: Power generation profile for different scenarios

It has been established that suitable incentives are requisite of encouraging EV owners to plug in their vehicles, in this regard the profit to EV owner under coordinated scheduling for scenario 2 and 3 is shown in Figure 4.23. The profit during uncoordinated charging scenario is not considered for comparison due to minimal profit as shown in Table 4.11. The profit of each EV owner varies depending on the charging and discharging power. The maximum profit of a single EV owner at each bus of the

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distribution system is represented in Figure 4.23. It can be observed that EV owners have high profit in scenario 3 when renewable energy is integrated in the system. However, Figure 4.20 shows that EV discharges more power in scenario 2 as compared to scenario 3. The battery degradation cost increases with high power discharge, reducing the profit for EV user. Hence, with integration of renewable energy, EV discharges less power during the times when the tariff is low making it an optimal scenario where the EV owners earn maximum profit and experience relatively less battery degradation.

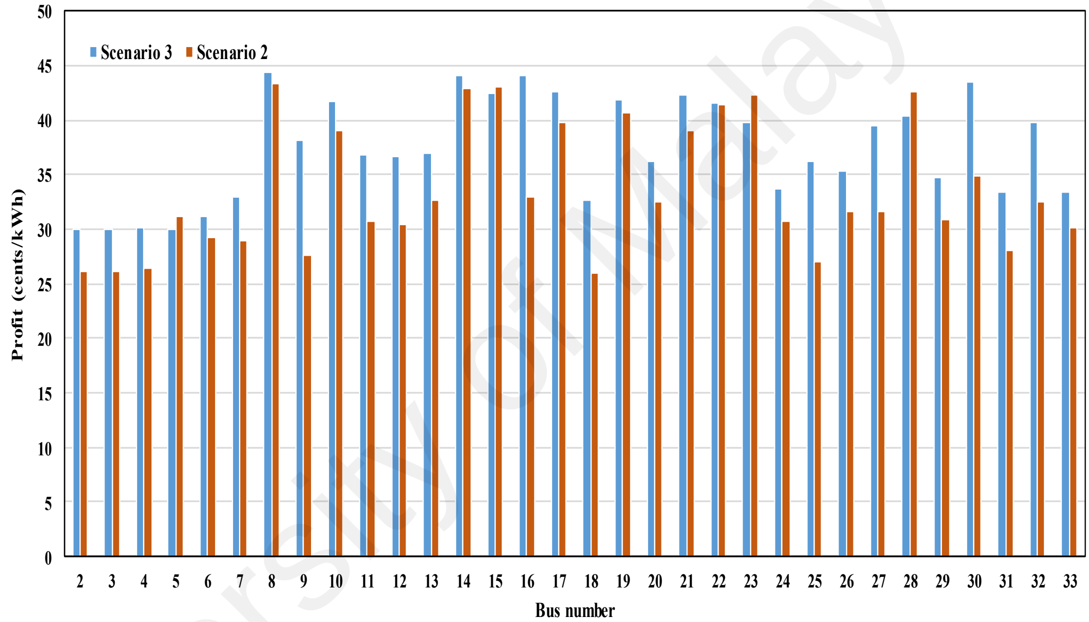

Figure 4.23: EV owner profit at each bus of network

The cost analysis for the V2G implementation under different scheduling scenarios is presented in Table 4.11. The total cost of the system when coordinated charging/discharging is performed with renewable energy integration is lowest compared to other scenarios. The cumulative profit of all EV users is also reported in the table. The profit is relatively low with uncoordinated scenario and increases when coordinated charging/discharging is applied. However, EV users have maximum profit with the integration of renewable energy to the system. This is because in scenario 3, load of the system of the system is minimized through energy generated from RES, due to which EV users do not discharge during the low tariff times. The average electricity cost for each of the scenario is also reported in Table 4.11. The COE is minimum in scenario 3 when coordinated charging discharging is analyzed with RES.

The maximum lifecycle of EV battery in all the above defined scenarios is also computed in Table 4.11. Battery lifecycle is highest in scenario 3 and lowest in uncoordinated scenario. With the assumption that battery performs one complete cycle each day, the lifetime (years) of the battery is dependent on the number of cycles the battery can sustain until it reaches its end of life. As reported in the table, the battery can last longer in scenario 3 due to minimal V2G exchange compared to scenario 2, saving the battery replacement cost for the system. To analyze the significance of V2G technology, the system cost for coordinated charging and coordinated charging with RES is also shown in the table. The cost of the system increases excessively when EVs are not allowed to discharge and EV owners cannot earn any revenue. However, due to no V2G the profit to EV user is zero and impact of battery degradation is not computed for this case.

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Table 4.11: System cost and profit for different scenarios

Scenarios	Cost ($)	Average Cost of Electricity (cents/kWh)	Cumulative EV Profit ($/kWh)	Lifecycle (cycle)	Lifetime (year)
Uncoordinated Charging Discharging	20741.43	43.08	23.85	2213	6
Coordinated Charging	25491.54	52.94	-	-	-
Coordinated Charging Discharging	19488.61	40.47	62.88	2788	7.6
Coordinated Charging with RES	22136.43	45.97	-	-	-
Coordinated Charging Discharging with RES	18231.52	37.86	68.35	3276	9

The electric vehicle charging schedule and system cost is examined for different cases of renewable energy integration in the distribution network.

4.3.2.1 Impact of Renewable energy penetration

To test the resilience of the distribution network, renewable energy (WT and PV) is increased by 30% for high RES penetration and is decreased by 30% for low RES penetration. The renewable energy penetration affects the charging / discharging schedule of EVs and the total cost of system. Table 4.12 reports the system cost and the cumulative profit by EV owners. The maximum lifecycle of single EV battery and its lifetime is also shown in Table 4.12. It can be seen from the table that cost of the system reduces with high penetration of renewable energy, earning more profit for EV owners. On the other hand, when the renewable energy penetration is low, cost of the system increases,

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reducing the profit of EV owner. The lifetime of battery storage also increases proportionally with the penetration of RE output. However, the system cost and EV profit for all cases of RE penetration is better than scenario 2 as shown in Table 4.11. The reduction in cost compared to scenario 2 is due to the fact that RE reduces the load of the distribution network during the day time and EV owner discharges only during the times when the profit is maximum.

Figures 4.24 to 4.29 shows the EV charging/discharging scheduling together with the total load, network losses and power supplied by grid. As defined in Eq (3.31), the sum of power generated at bus (grid power) and renewable power must balance the EV charging capacity, residential and commercial load and network losses. The load is the sum of residential and commercial load at each hour. The losses are minimum during certain hours when EV charging load is low. The negative power of EV shows V2G implementation to minimize the load of the system. Hence, the load exceeding the grid power during the day time is balanced by V2G.

The impact of RES penetration on EV charging/discharging when the penetration is 30% increased and decreased are shown in Figures 4.24 and 4.25 respectively. The charging power is high when the RES penetration is increased accommodating a greater number of EVs to charge and ensuring the maximum transformer capacity. This is because the RES provides excess power to minimize the load of distribution network. Moreover, during the day time when the PV power is at peak and the electricity price is low at 13:00-14:00, EV owners are reluctant to supply power to grid due to minimal profit. In fact, few of EV owners prefer to charge their battery so that they can sell power to grid during the high tariff period. However, with low RES penetration, EV users discharge less power during these hours to minimize battery degradation cost. The EV

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users are more concerned for the profit from V2G and that is why, despite of high load during 09:00-11:00, they are unwilling to discharge power due to low electricity tariff.

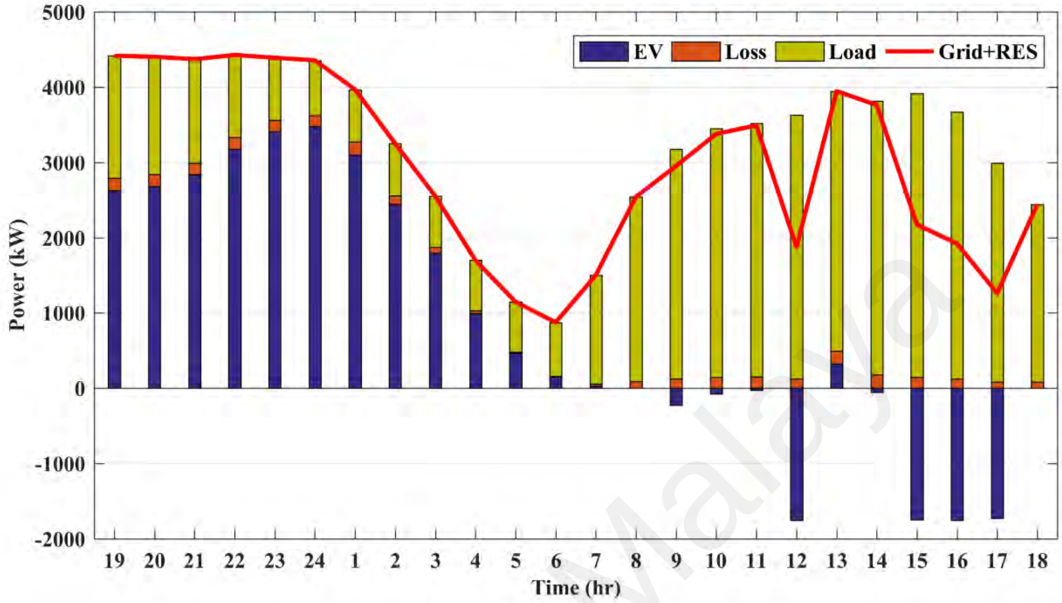

Figure 4.24: Optimal operation with EV charging/discharging schedule for higher RES penetration case

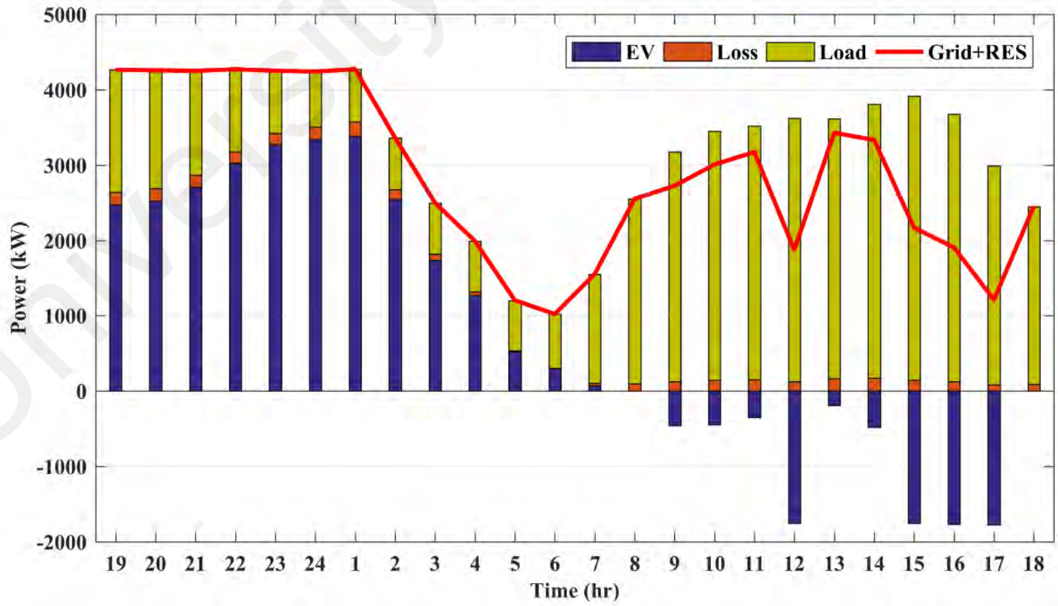

Figure 4.25: Optimal operation with EV charging/discharging schedule for lower RES penetration case

4.3.2.2 Impact of RES location in the distribution system

To investigate the impact of locations of RES, wind turbine and photovoltaic plants are located at different nodes of the distribution network as identified by (R. Li, Wang, & Xia, 2018). The load flow analysis is executed to calculate the system cost and total losses as shown in Table 4.12. It can be depicted from table that EV owners earn less profit compared to the base case reported in Table 4.11 when the DGs are connected at the end buses 31-33. The load generation balance graph with the EV charging/discharge schedule for renewable energy integrated at different locations of distribution network is shown in Figure 4.26.

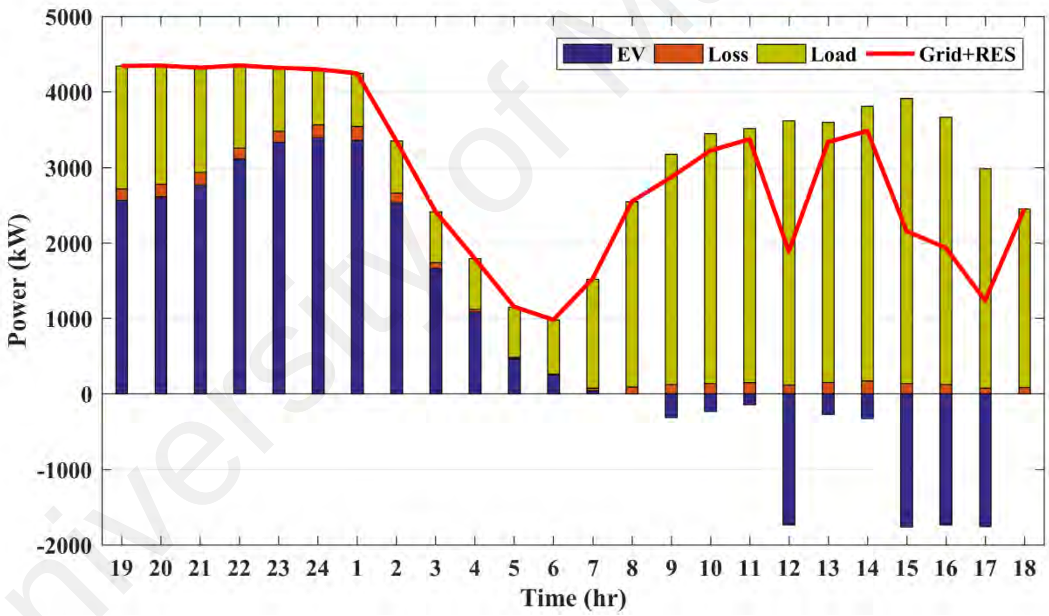

Figure 4.26: Optimal operation with EV charging/discharging schedule for different RES locations

4.3.2.3 Impact of different EV capacities

The cost of the system varies with different EV battery capacities. To analyze the impact of battery capacity, different models of EV are taken in to account. The analysis in this subsection considers 30% of Nissan Leaf 40 kWh, 30% of Chevy Bolt 60 kWh and 40% of Tesla Model X 100 kWh. The overall cost and losses are reduced as compared to

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the case in which all the EVs have 85 kWh battery because Nissan Leaf and Chevy Bolt require less power and time to fully charge. In addition, the profit to the EV owner is remarkably low because EV users with small battery capacity are not willing to sell energy to the grid as the financial gain of selling energy is low.

The EV charging schedule in Figure 4.27 for this case shows a decreasing trend due to different EV capacities. The 40 kWh Nissan Leaf and 60 kWh Chevy Bolt EV battery are charged within few hours to maximum SOC, reducing the charging load on the distribution network. Moreover, during the high tariff period, V2G exchange is low due to smaller battery capacities and consequently grid has to provide more power to balance the load. However, the degradation cost for these EV batteries increases with maximum discharge power compared to 100 kWh Tesla.

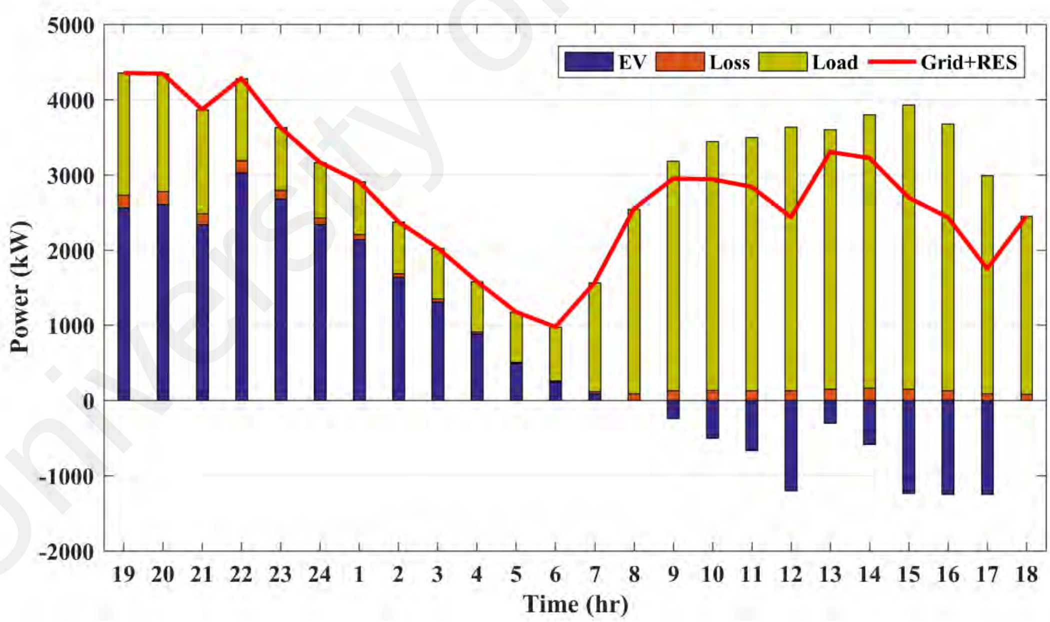

Figure 4.27: Optimal operation with EV charging/discharging schedule for different battery capacities

4.3.2.4 Impact of travelling distance

EV loses its energy when travelling and its battery degrades with high travelling distance. The driving distance in this subsection is assumed to be twice of the average distance EV travels (68 km/day). As expected, the system cost increases with the distance, and EV owners earn less profit because travelling distance increases battery degradation cost. In addition, EV needs to charge back again to sell energy to the grid. Figure 4.28 shows the charging/discharging power when EV travelling distance is extended.

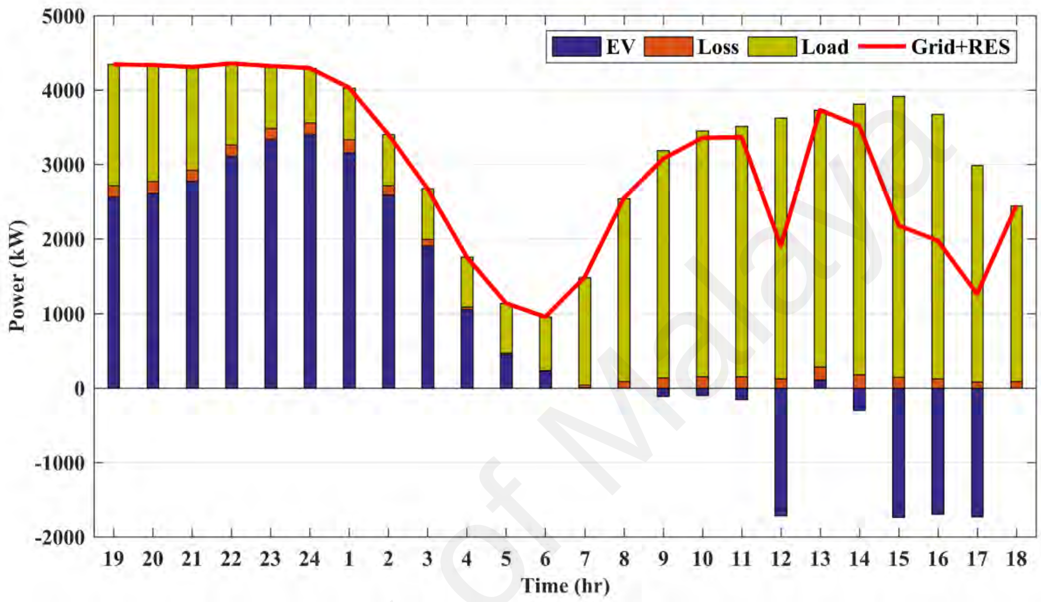

Figure 4.28: Optimal operation with EV charging/discharging schedule for extended travelling case

4.3.2.5 Impact of different travelling time

This study is conducted under the assumption that EVs travels from home to workplace at 08:00 and returns home at 7 pm (19:00). However, the travel-to-work time in Malaysia varies from 06:00 to 08:00 in the morning and return time varies from 17:00 to 18:00 in the evening. Therefore, in this subsection the impact of different travelling time is analyzed. It is assumed that 30% of EVs travel at 06:00, 30% travels at 07:00 and the rest 40% travels at 08:00 from home to workplace. On the way back from work, 60% of EVs travel at 17:00 and 40% travels at 18:00. The system cost increases with different travel times because there are only 40% of EVs available to discharge during peak hours. Thus, the total profit for EV owners also reduces. In the morning, when EVs reach early to

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workplace, most of EV owners are unwilling to sell energy due to low electricity tariff. The load generation balance graph with EV schedule for this case is shown in Figure 4.29. It is interesting to note that in this case the EVs are connected to distribution system throughout the day. The variations in travelling time allows few EV users to discharge their battery during 8:00 am after arriving workplace and charge at 18:00 when arrived home.

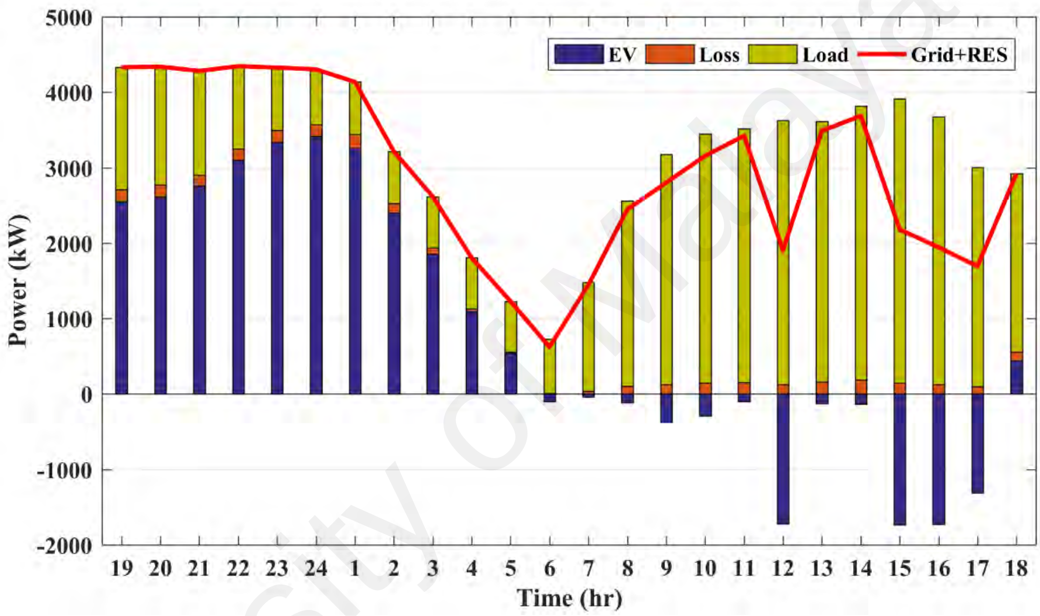

Figure 4.29: Optimal operation with EV charging/discharging schedule for different travel time

The network losses for total time horizon in each of the above defined cases are shown in Figure 4.30. The network losses are minimum in case 4 when EVs with different battery capacities are modelled. This is because the overall charging power in this case is low, minimizing the generation power exchanged between the grid and distribution system. The losses are also reduced in case 1 when the RES penetration is increased. However, the losses escalate when the RES penetration is decreased. Hence, the integration of RES reduces the system cost and total losses and maximizes the profit for EV owners.

Table 4.12: Cost analysis for different cases of scenario 3

S.No	Cases	Cost ($)	Average COE (cents/kWh)	Cumulative EV Profit ($/kWh)	Lifecycle (cycle)	Lifetime (year)
1	Coordinated Charging discharging with high RES penetration	16696.59	37.28	70.63	3614	10
2	Coordinated charging discharging with low RES penetration	18069.13	41.17	67.99	3093	8.4
3	Coordinated charging discharging with different renewable location	17515.85	39.10	65.52	3257	8.9
4	Coordinated charging discharging with different EV capacities	17417.74	39.82	31.85	2742	7.5
5	Coordinated charging discharging with long traveling distance	17559.26	40.54	46.01	3055	8.3
6	Coordinated charging discharging with different travel time	17660.16	39.35	58.06	3133	8.6

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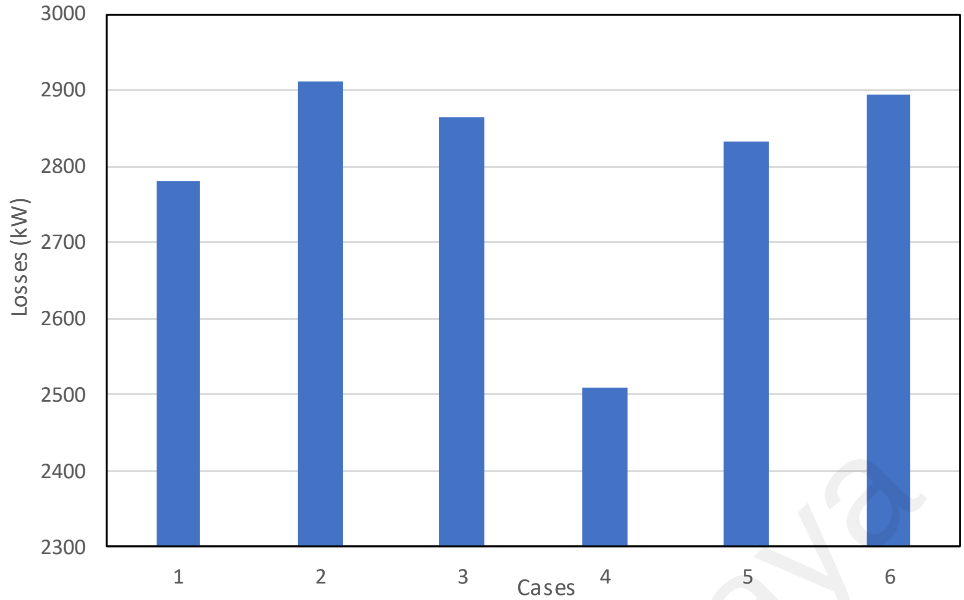

Figure 4.30: Network losses for different cases

4.4 Summary

In this chapter, the simulation results validate the proposed energy management strategy for optimal microgrid operation. The addition of energy storage in the microgrid increases capital cost, but also reduces the operating cost of the system. The proposed BESS sizing method is validated against the traditional tradeoff method and optimal BESS size is calculated. Moreover, the optimal size of the battery prolongs the lifetime of the storage system and it is significantly affected by the DOD. In addition, when battery electric vehicles are integrated into the distribution network, the coordinated charging of EVs improve the system performance and minimizes the operating cost. The impact of RES penetration, EV capacity, travelling time and distance has been investigated for battery lifetime analysis. Furthermore, firefly algorithm has been considered to attain the optimal dispatch and effectiveness of different optimization algorithms has been compared.

CHAPTER 5: CONCLUSION AND FUTURE WORK

5.1 Conclusion

The challenging issue of today's modern power system is the reliable and optimal generation of distributed sources. The complexity of the network increases when energy demand is subjected to non-linear load profile. Hence, energy management strategies are introduced to improve the stability and performance of the microgrid. The economic operation of distributed sources is essential for microgrid cost optimization.

The work in this research has been divided into two parts. In the first part, the optimal battery sizing and economic scheduling problem of isolated microgrid has been solved. The microgrid was incorporated with solar photovoltaic and wind turbine as renewable power generation, diesel generator and energy storage as backup sources to balance the electrical load of residential area. The objective of this research was to optimize the power dispatch from the generation sources by considering the power fluctuations of renewable sources, battery state of charge constraints, battery lifetime and capital cost. Thus, effective energy management strategies were developed to dispatch the power at the least cost, ensuring the reliability of the microgrid. The proposed method also evaluated the optimal size of energy storage for the economic operation of microgrid. The obtained result was validated with the traditional trade-off method and it was found that proposed battery sizing problem was accurate in evaluating the optimal BESS size. The results revealed that energy storage operation cost is high when the battery discharges more power. In addition, the high depth of discharge status of battery escalates the cost. Hence, efficient battery management approach was proposed for the economic scheduling. The battery storage was charged when the operating cost of energy storage exceeded the diesel generator cost. The aim was to limit the depth of discharge status to minimum level such that battery can provide backup energy during critical hours when the renewable energy power certainly drops.

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The economic dispatch and battery sizing problem was solved using firefly optimization algorithm. The results were compared with other optimization techniques like PSO, ABC and HSA. It was found that firefly was robust and computationally effective to determine the optimal dispatch of distributed sources. The performance measurement indices such as cost of electricity and loss of power supply probability were computed to compare the effectiveness of different optimization techniques. The efficiency of the proposed method was validated by comparing with other existing work. It was found that the microgrid operating cost was 50% reduced with the proposed method. In addition, the battery management strategy was able to prolong the battery lifetime with optimal BESS size. Thus, the obtained results validated that depth of discharge has significant impact on the economic scheduling of BESS.

In the second part, the impact of electric vehicles charge coordination with V2G technology was analyzed on the distribution network. The on-board batteries of EV were treated as energy storage to minimize the operating cost of the electrical power network. The proposed economic scheduling was validated on modified 33 bus distribution system with ten EVs connected at each bus and three wind turbine and photovoltaic systems. Three scenarios that involve economic scheduling: uncoordinated charging, coordinated charging and coordinated charging with RES were simulated with the residential and commercial load of the system. The real time battery degradation cost was modelled by considering the DOD at each time interval to maximize the profit for EV user through V2G. The obtained results illustrate that uncoordinated EV charging increased the peak load violating the constraints of the distribution network. In addition, coordinated charging improved the system performance, restricted grid overloading and minimized the power losses. The system cost showed remarkable savings with maximum profit for EV users when RES's were integrated into distribution network. The controlled charging mechanisms were proven to be effective in minimizing the power difference between peak and valley periods. Moreover, the battery degradation cost was minimal extending the battery lifetime.

The operating cost was analyzed for different cases of RES integration in the network. The total system cost was reduced with maximum profit for EV users when the RES penetration was increased. On the contrary, the power losses were minimum for different EV battery capacity case. The EV owners profit was low for this case due to minimal power sharing between EV and the grid.

5.2 Future work

As an extension to the work proposed in this study, some potential issues have not been addressed. These can be considered for the future research:

- The proposed energy management approach assumed renewable power generation and load profile to be forecasted for day ahead. The forecasting modules can be added into the study by considering the uncertainties of renewable power and load with real time simulations.
- The efficiency and emission cost of microgrid was not considered in this thesis, the optimization of microgrid with respect to efficiency and emission cost can be considered as a future aspect of this research.
- With regard to communication technologies for EV coordination, the centralized aggregation of EVs for providing a service in the amount of several MW requires thousands of vehicles and a stable low-latency communication with all of them. The use of real-time simulators such as OPAL-RT and RTDS where communication links can be emulated together with EVs could help addressing the quality of service for coordinating large fleets of EVs.
- For the provision of local grid support using EV load, the combination of active power solutions using the load of EV charging stations with other options such as

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reactive power from PV inverters have not been addressed. Furthermore, voltage support using EV load coordination, in cooperation with tap-changer transformer strategies can be addressed.

- The battery degradation factors such as capacity throughput, calendar ageing, temperature and charge current can be considered for the battery modeling with different usage cycles. Furthermore, effect of these battery degradation factors on different EV technologies can be addressed for profit maximization analysis as future research.

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LIST OF PUBLICATIONS AND PAPERS PRESENTED

Journal Papers

1. **Sufyan, M.**, Rahim, N. A., Aman, M. M., Tan, C. K., & Raihan, S. R. S. (2019). Sizing and applications of battery energy storage technologies in smart grid system: A review. *Journal of Renewable and Sustainable Energy, 11*(1), 014105. doi:10.1063/1.5063866 (Accepted)

2. **Sufyan, M.**, Rahim, N. A., Tan, C., Muhammad, M. A., & Raihan, S. R. S. (2019). Optimal sizing and energy scheduling of isolated microgrid considering the battery lifetime degradation. *PloS one*, *14*(2), e0211642 (Accepted)

3. **Sufyan, M.**, Rahim, N. A., Muhammad, M.A., Tan, C. K., & Raihan, S. R. S. Economic dispatch of active distribution network in the presence of electric vehicle and renewable energy sources. *IET Renewable Power Generation,* 2019 (Under Review)

Conferences

1. **M. Sufyan**, C. Tan, N. A. Rahim, S. R. Shaikh Raihan and M. A. Muhammad, "Dynamic Economic Dispatch of Isolated Microgrid with Energy Storage Using MIQP," *2018 International Conference on Intelligent and Advanced System (ICIAS)*, Kuala Lumpur, 2018, pp. 1-6.

2. Arshad, M.; **Sufyan, M.**; Aman, M.M.; Raihan, S.R.S.; Rahim, N.A.: 'Islanding detection technique based on rate of change of reactive power (dq/dt)', *IET International Conference on Clean Energy and Technology (CEAT 2018)* p. 57 (7 pp.)

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