Smart Charging Scheduling of EV based on Seasonal Uncertainty Considering Grid to Vehicle (G2V) and Vehicle to Grid (V2G) in presence of Renewable

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Thesis submitted for the partial fulfillment of

the requirements for the degree

of

BACHELOR OF TECHNOLOGY

ELECTRICAL ENGINEERING DEPARTMENT

INSTITUTE OF ENGINEERING & MANAGEMENT

MAULANA ABUL KALAM AZAD UNIVERSITY OF TECHNOLOGY,

WEST BENGAL

2025

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April 2025

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CERTIFICATE

This is to certify that the Thesis Report on **"Smart Charging Scheduling of EV based on seasonal uncertainty considering Grid to Vehicle (G2V) and Vehicle to Grid (V2G) in presence of renewable"** is submitted in partial fulfillment of the requirements for the degree of Bachelor of Mechatronic Engineering by the following students:

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Date: 09/04/25

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ACKNOWLEDGEMENT

I sincerely thank my project guide, Dr. Sourav Das, for his invaluable support, guidance, and encouragement throughout this project. I am also grateful to the faculty of the Electrical Department at the Institute of Engineering and Management, Kolkata, for their insights and constant support.

I extend my appreciation to my teammates for their collaboration and dedication, which contributed significantly to this project's success. Lastly, I am deeply grateful to my family and friends for their unwavering support, patience, and motivation throughout this journey.

Soumyadeep Bera

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Date: 09/09/25

DECLARATION OF ORIGINALITY AND COMPLIANCE OF ACADEMIC ETHICS

I hereby declare that this thesis **Smart Charging Scheduling of EV based on seasonal uncertainty considering Grid to Vehicle (G2V) and Vehicle to Grid (V2G) in presence of renewable** contains a literature survey and original project/research work carried out by me, the undersigned candidate, as part of my studies in the Department of Electrical Engineering.

All information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and regulations, I have fully cited and referenced all material and results that are not original to this work.

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I affirm that the work presented is original and all sources have been duly acknowledged.

Signature: Soumyadeep Bera

DEDICATION

We dedicate this thesis to Professor Dr. Sourav Das for his exceptional guidance and support, to our incredible team for their collaboration and encouragement, and to the Department of Electrical Engineering for fostering an environment of learning and growth.
Their contributions have all been vital to the success of our work.

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ABSTRACT

Electric Vehicles provide a sustainable substitute over standard internal combustion engine (ICE) vehicles because they cut down emissions and reduce reliance on fossil fuels. A total of 40 million electric car owners worldwide drove their vehicles by 2023 while future estimations predict a worldwide rise to 200-270 million electric vehicles during 2030.

PV systems linked to EV charging stations serve as an essential element for developing sustainable energy management systems. The charging infrastructure with PV powering reduces dependence on fossil-based electricity while supporting the Vehicle-to-Grid (V2G) capabilities for grid operators along with consumer advantages through dual flow mechanisms. The efficiency of PV-powered charging stations suffers from solar irradiance and energy demand fluctuations which requires optimized management systems to obtain optimal results.

The proposed analytical model presents an optimization solution for High Battery Capacity (HBC) and Low Battery Capacity (LBC) electric vehicle charging systems throughout the summer, monsoon, and winter time periods. The study analyzes realistic data to measure both PV energy involvement in EV charging requirements and it studies cost efficiencies for EV owners and station operators while investigating renewable energy-based charging system effectiveness. The research examines how PV energy production levels change based on seasons while examining their effect on prospective EV charging potentials. The research investigates solar power intermittency problems along with demonstrating why energy storage solutions are essential to handle supply-demand balance issues. Operation costs and financial incentives and return on investments are evaluated alongside each other in comparison for PV-integrated EV charging infrastructure.

Studies reveal that implementing adaptable charging methods yields the best results for enhancing PV system output. Higher solar irradiance levels during summer months produce higher quantities of photovoltaic energy which helps decrease power consumption from the electricity grid. Dynamic pricing methods along with optimized charging schedules and storage systems as per this framework improve the financial potential of PV-integrated charging stations. Every network of electric vehicle charging infrastructure needs to have PV systems incorporated because it enables sustainable mobility. The research demonstrates that strategic timing of renewable energy utilization depends on seasonal variations to achieve maximum effectiveness in EV charging operations.

Chapter-1

1. INTRODUCTION

Electric Vehicles (EVs) serve as vehicles run by electric power instead of conventional petroleum-based fuels such as gasoline or diesel. The power system in EVs consists of electric motors together with rechargeable batteries which provide a green transportation option to ICE vehicle users.

Electric Vehicles (EVs) play a crucial role in cutting greenhouse gas emissions and reducing dependence on fossil fuels, serving as a cleaner alternative to conventional internal combustion engine (ICE) vehicles. As of 2023, there were approximately 40 million electric cars on the road globally, a significant increase from previous years. This is expected to reach 200-270 million by 2030 [1].

The basic principle of EVs are simple as it contains very less power train and drive train components as compared to an Internal Combustion Engine (ICE) vehicles. An electric motor takes electrical energy to transform it into motion which powers the wheels thus acting as the main functional element in electric vehicles. The device stores electric energy within its lithium-ion battery pack that enables power for the motor operation. An integral component in any electric car system is the onboard charger which delivers its purpose by converting AC electricity from the power grid into the required DC energy needed for battery charging. The power electronics controller operates effectively to achieve control over battery and motor power flow which delivers best performance outcomes and energy utilization.

1.1. BENEFITS OF EVs

EVs offer several benefits over traditional fuel-based vehicles, including:

1.1.1. Environmental Benefits: Zero tailpipe emissions (in the case of Battery Electric Vehicles), leading to improved air quality and reduced carbon footprint. A study in the Journal of Cleaner Production shows that Battery Electric Vehicles (BEVs) produce zero tailpipe emissions, significantly reducing air pollution in urban areas and improving public health. Similarly, according to the IEA Report 2024, a BEV in India can reduce CO_2 emissions by up to 10 tons over its lifetime compared to an internal combustion engine vehicle [2].

1.1.2. Energy Efficiency: Higher energy conversion efficiency compared to ICE vehicles. For instance, an electric automobile uses 80% of its battery's energy to transmit electricity to the car as opposed to a gasoline-powered car using 14 to 26% of its energy [3].

1.1.3. Lower Operating Costs: The cost of electricity is generally lower than that of gasoline or diesel, making EVs more economical in the long run. For instance, the operational cost of an electric three-wheeler in India is approximately ₹0.54 per km, whereas its diesel counterpart costs around ₹3.75 per km, leading to substantial fuel savings.

1.1.4. Financial Incentives: Many states offer additional incentives such as rebates, tax credits, and discounted registration fees, making EV ownership more affordable. To accelerate EV adoption, the Government of India has introduced several financial incentives. Under the FAME (Faster Adoption and Manufacturing of Electric Vehicles) scheme, direct subsidies are provided to consumers, lowering the upfront cost of EVs. Furthermore, the Union Budget 2025-26 announced tax relief on critical minerals essential for EV manufacturing, such as lithium, cobalt, and nickel, reducing production costs and supporting local manufacturing. Additionally, reduced customs duties on EV components and tax incentives for buyers further contribute to affordability [4].

1.1.5. Job Creation: The transition to EVs is expected to drive economic growth, with estimates suggesting that it could create over 150,000 jobs in the U.S. by 2030 in manufacturing, infrastructure development, and renewable energy sectors. The EV market in India is projected to reach ₹20 trillion by 2030, potentially creating around 50 million jobs across the EV ecosystem [5].

1.1.6. Integration of renewable source with EVS: As per the features borne by an EV, in order to reduce the air pollution, only penetration of EV may not be an one step solution as to meet the EV energy demand, the thermal power station need to increase its generation by consuming more fuel. These may lead to air pollution anyhow. Hence, to make this technology zero carbon emission free, the integration of renewables are needed which may help to reduce the carbon emission and can make the EV technology green. The synergy between electric vehicles (EVs) and renewable energy plays a crucial role in reducing carbon emissions and promoting sustainable energy solutions. Tata Power is investing $14.3 billion in Rajasthan to develop 10 GW of renewable energy and expand EV charging infrastructure, supporting India's 500 GW clean energy goal by 2030 [6]. . Similarly, LG Energy Solution and JSW Energy are planning a $1.5 billion joint venture to establish a 10 GWh battery plant, enhancing EV adoption and renewable energy storage in India [7].

1.2. CHALLENGES IN EV

1.2.1. Seasonal Variation and cost of charging:
Despite these advantages, several challenges hinder the large-scale adoption of EVs. Among them, seasonal variations and scheduling costs pose significant issues for efficient energy management. Variations in temperature not only affect battery efficiency—leading to fluctuations in range and charging patterns—but also influence driving behavior and energy consumption patterns [8]. For instance, colder temperatures often reduce battery range and necessitate increased energy usage for heating, while extreme summer conditions elevate cooling demands, altering driving cycles [9]. These seasonal changes result in irregular energy demand, making it challenging to optimize EV charging schedules.

1.2.2. Uncertain Driving Pattern and seasonal influence:
Furthermore, the fluctuation in driving patterns due to seasonal impacts directly affects scheduling costs [10]. Increased or unpredictable demand during peak seasons can lead to higher electricity tariffs, while low-demand periods may create inefficiencies in grid utilization. This variability complicates the development of cost-effective charging strategies, impacting both EV users and grid operators.

1.2.3. Battery Technology:
The primary issue with battery technology involves lifespan deterioration as well as reduced battery life [11]. The lifespan of batteries decreases when users charge and discharge them regularly while operating within severe temperature environments which raises replacement expenses. The expensive nature of EVs coupled with battery technology continues to hinder mass adoption because battery prices have shown gradual reduction patterns.

1.2.4. Charging Technology:
The process of EV charging requires substantially increased duration compared to the gas vehicle gas-up procedure. Using DC fast chargers (Level 3) enables EVs to achieve an 80% charge within an hour although persistent charging will harm the battery performance. Charging at home through a standard outlet (Level 1) stretches from 8 to 20 hours but Level 2 charging significantly cuts this time to 4 to 8 hours. The extensive charging duration imposes challenges for users who depend on regular travel as it needs improved charging infrastructure coupled with better battery technologies to promote EV acceptance.

A detailed literature review on seasonal variations and scheduling costs has been provided in Chapter 2.

Based on the background study and literatures, the authors of these thesis can proposed the problem statement as follows:

1.3. PROBLEM STATEMENT

- Electric vehicle (EV) charging expenses depend on numerous uncertain factors like drive patterns and temperature changes together with power usage variations between seasons that impact charging services in both G2V and V2G modes. Regulatory strategies are fundamental to G2V charging because users will experience higher charging costs when charging during peak hours as well as use electricity inefficiently and experience more battery degradation due to nonregulated charging patterns. Higher electricity prices occur in extreme weather conditions because people increase their electric power consumption during summer air conditioning and winter heating seasons while these events affect EV battery performance. The operation of EV chargers during times of peak energy demand threatens to weaken the power grid while forcing an increase in the deployment of fossil fuel power plants to maintain system stability.
- Evolutionary power management by integrating Photovoltaic (PV) systems introduces additional requirements in the calculation of EV charging expenses. Because solar power generation produces intermittent results that vary based on weather conditions it creates a situation where EV drivers frequently need to get power from the electricity grid during periods without solar energy availability. Users of electric vehicles will experience higher expenses and decreased renewable integration advantages if they do not use an intelligent energy management system. The proper optimization of EV charging operations proves necessary to achieve lower expenses and improved power efficiency as well as stable power network operations.

1.4. OBJECTIVES

- This investigation aims to create an optimal EV charging approach that reduces charging expenses under simultaneous G2V and V2G operation conditions. The research includes analysis of driving cycle and seasonal variations because these elements determine charging expenses and available energy levels. Individual travel patterns through driving cycles shape battery discharge patterns and the number of charging cycles and temperature changes during different seasons affect both power rates and battery performance. The research targets design of an economical and energy-efficient charging system which maintains peak energy usage alongside power grid stability.

- In the second objective, the research aims to reduce EV charging expenses through optimized G2V and V2G operations which take into account driving cycle unpredictability and seasonal changes as well as PV system integration. Efficient solar power management requires perfect balancing of grid electricity with renewable energy sources so costs stay low and operation becomes more productive. A smart charging approach must be implemented to automate charging operations which will maximize the scheduling efficiency while mitigating reliance on grid electricity expenses and improving power consumption through GEV, V2G and P2V(PV TO VEHICLE) mode of operation.

1.5. ORGANIZATION OF THESIS

The thesis is structured into six chapters. **Chapter 1** provides an introduction to Electric Vehicles (EVs), discussing their advantages and the challenges they face. **Chapter 2** presents a literature survey, reviewing existing research on EV charging strategies and energy management. **Chapter 3** outlines the methodology used in the project, detailing the tools and techniques applied for charging scheduling analysis. **Chapter 4** focuses on the charging scheduling of EVs without using a photovoltaic (PV) system, analyzing the impact of different seasons—Summer, Winter, and Monsoon—as well as variations in battery capacity (high and low). **Chapter 5** extends this analysis by incorporating a PV system, evaluating its effects under the same seasonal and battery capacity conditions. Finally, **Chapter 6** concludes the thesis by summarizing the findings, highlighting key insights, and discussing the limitations of the study along with potential future research directions.

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Chapter-2

2. LITERATURE REVIEW

Various recent publications investigate the best possible scheduling method for Plug-in Electric Vehicles (PEVs) which aims to balance power requirements while controlling expenses and supporting grid stability. The main field of study for researchers consists of PEV charging schedule methods that help diminish grid pressure and incorporate renewable power while decreasing operational costs. The utilization of optimization methods represents a standard process where special attention exists for controlling PEV charging uncertainties as well as energy consumption variations. Research into PEV scheduling under seasonal conditions remains relatively limited because of the scarcity of investigation into driving patterns along with charging cycles modification

2.1. Seasonal Impact on PEV Performance and Charging Patterns

Multiple studies investigate how environmental elements influence PEV operation with special focus on how temperature fluctuations affect battery performance. [22] research shows that PEVs experience decreased efficiency and reduced range when operating in cold temperatures thus affecting their operational lifespan. [26] show through their research that winter environment raises overall energy use by 30% because of both battery heating requirements and declined chemical functionality at cold temperatures. The research proves that seasonal PEV scheduling methods require models which incorporate changing vehicle characteristics while handling different annual charging requirements.

2.2. Optimization Techniques for PEV Scheduling

The complexity of PEV scheduling requires optimization methods as its primary solution. The scheduling process focuses intensely on demand control and expense reduction in PEV operations. The industrial scheduling of PEVs makes extensive use of linear programming (LP) and mixed-integer linear programming (MILP) as traditional techniques. These optimization methods encounter difficulties when handling the unpredictable seasonal as well as behavioral PEV usage trends. The optimization method Differential Evolution (DE) serves as an adaptable robust approach which researchers now use to study PEV scheduling. The research by [21] shows that differential evolution techniques succeed in optimizing problems with multiple objectives which relate to PEV grid stability and charging cost and duration. Multiple variables present in complicated multi-dimensional systems indicate that DE proves successful for seasonal PEV scheduling problems.

2.3. Seasonal Scheduling Models

Certain research has offered limited methods to schedule PEVs based on seasons to manage grid stabilization across different periods. The works of [28] present models which modify PEV charging behavior to align with seasonal demand fluctuations to effectively lower grid peak load demands according to their research. The research indicates that scheduled EV charging according to seasonal adaptations helps decrease power grid pressure while lowering expenses for additional power storage or peak capacity plants. Most current seasonal models remain fundamental because they fail to integrate driving pattern variations within PEV charging cycles thus highlighting the research purpose to address this knowledge gap.

2.4. Driving Behavior and Seasonal Variability

PEV driving conduct continues to change throughout seasons because it responds to weather fluctuations as well as the variations in day length and seasonal travel patterns. [25] discovered that People Electric Vehicle adoption increases during warmer months because commuting and leisure travels become more frequent. Lower temperatures in winter create shorter drive distances together with more frequent short-length trips which affects how PEVs need to charge and when to do so. The way people drive along with battery performance variation makes it essential to develop models which can handle these seasonal changes.

2.5. Contribution to the Literature

Few studies examining PEV scheduling and optimization have integrated seasonal performance fluctuations of PEV vehicles together with seasonal driving habits into their analysis. Differential Evolution (DE) enables the proposed model to introduce a breakthrough solution for operational cost reduction linked with grid effects while handling seasonal uncertainties thus expanding PEV scheduling research. The proposed work builds existing methods by focusing on adaptive scheduling which plays a critical role for both cost-effective as well as resilient PEV integration dynamics during seasonal fluctuations.

This chapter provides a comprehensive review of the literature related to Electric Vehicles (EVs), Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) technologies, smart charging scheduling, seasonal impacts on EV usage, and the integration of photovoltaic (PV) systems for green EV charging. The review also explores the challenges and opportunities associated with incorporating V2G and renewable energy sources into EV charging infrastructure [12].

2.6. Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) Technologies

Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) technologies enable bidirectional energy flow between EVs and the power grid. These technologies play a crucial role in balancing grid demand, integrating renewable energy, and providing ancillary services [12].

2.6.1. V2G Technology

V2G allows EVs to discharge energy back to the grid during peak demand periods, acting as distributed energy storage systems. This capability can help stabilize the grid, reduce peak load, and provide financial incentives to EV owners.

- **Benefits of V2G** [13]:
    - **Grid Stability**: V2G can help balance supply and demand, reducing the need for additional power plants.
    - **Revenue Generation**: EV owners can earn money by selling excess energy back to the grid.
    - **Renewable Energy Integration**: V2G can store excess renewable energy and release it when needed, enhancing grid reliability.

- **Challenges of V2G** [13]:
    - **Battery Degradation**: Frequent charging and discharging can accelerate battery wear and tear.
    - **Infrastructure Requirements**: V2G requires advanced bidirectional chargers and communication systems.
    - **Regulatory Barriers**: Lack of standardized regulations and policies can hinder V2G implementation.

2.6.2. G2V Technology [14]

G2V refers to the traditional charging of EVs from the grid. While G2V is simpler to implement compared to V2G, it can strain the grid during peak demand periods if not managed properly.

2.7. Smart Charging Scheduling [15]

Smart charging scheduling optimizes the charging process by considering factors such as grid load, electricity prices, and renewable energy availability. This approach ensures efficient energy use and minimizes the impact of EV charging on the grid.

2.7.1. Key Features of Smart Charging

- **Load Balancing**: Smart charging distributes the charging load evenly to avoid grid congestion.
- **Time-of-Use Pricing**: Charging is scheduled during off-peak hours when electricity prices are lower.
- **Renewable Energy Integration**: Smart charging prioritizes the use of renewable energy sources, such as solar and wind, to charge EVs.

2.7.2. Benefits of Smart Charging

- **Reduced Grid Stress**: By avoiding peak demand periods, smart charging reduces the need for additional power generation.
- **Cost Savings**: EV owners can save money by charging during off-peak hours.
- **Environmental Benefits**: Smart charging promotes the use of renewable energy, reducing carbon emissions.

2.8. Seasonal Impact on EV Usage [16]

Seasonal variations significantly impact EV performance and charging patterns. Factors such as temperature, daylight hours, and driving conditions influence energy consumption and charging requirements.

2.8.1. Challenges in Summer season

- **Battery Overheating**: High temperatures can cause battery overheating, affecting performance and longevity.
- **Increased Cooling Load**: Air conditioning systems increase energy consumption, reducing the range.

2.8.2. Challenges in Monsoon season

- **Lower Range & Efficiency** – Waterlogged roads and humidity reduce battery performance, increasing energy use.
- **Charging Risks & Outages** – Flooded stations and power cuts disrupt charging, raising safety concerns.

2.8.3. Challenges in Winter season

- **Reduced Battery Efficiency**: Cold temperatures decrease battery efficiency, reducing the vehicle's range.
- **Increased Energy Demand**: Heating systems consume additional energy, further reducing the range.

2.9. EV Charging Scheduling Considering Photovoltaic (PV) Integration [17]

Integrating photovoltaic (PV) systems into EV charging infrastructure is essential for achieving green technology goals. PV systems generate clean energy from sunlight, reducing reliance on fossil fuels and minimizing environmental impact.

2.9.1. Benefits of PV Integration

- **Renewable Energy Source**: PV systems provide a sustainable and clean energy source for EV charging.
- **Reduced Grid Dependency**: By generating electricity on-site, PV systems reduce the load on the grid.
- **Cost Savings**: EV owners can save money by using solar energy instead of grid electricity.

2.9.2. Challenges of PV Integration

- **Intermittent Energy Supply**: Solar energy generation depends on weather conditions and daylight hours, making it intermittent.
- **Energy Storage Requirements**: To ensure a stable energy supply, PV systems often require energy storage solutions such as batteries.
- **High Initial Costs**: The installation of PV systems and energy storage solutions can be expensive.

2.10. Energy Sources: Grid and EV [18]

EVs can be charged from two primary energy sources: the grid and their own batteries. The bidirectional converter in Es allows them to operate in both G2V and V2G modes, making them versatile energy resources.

2.10.1. Grid as an Energy Source

- **Reliability**: The grid provides a reliable and consistent energy source for EV charging.
- **Environmental Impact**: Grid electricity often comes from fossil fuels, contributing to pollution unless renewable energy is integrated.

2.10.2. EV as an Energy Source

- **Bidirectional Capability**: Evs can discharge energy back to the grid, providing flexibility and grid support.
- **High Time Constant**: EV batteries have a high time constant, making them suitable for V2G applications.

2.11. Incorporating V2G with Smart Charging and PV Integration [19]

Incorporating V2G technology with smart charging and PV integration presents a promising solution for reducing grid load and promoting renewable energy use. However, this approach comes with challenges such as battery degradation, infrastructure requirements, and regulatory barriers.

2.11.1. Smart Charging with PV and V2G

- **Optimized Energy Use**: Smart charging ensures that Evs are charged using renewable energy whenever possible.
- **Grid Support**: V2G technology allows Evs to support the grid during peak demand periods.

- **Financial Incentives**: EV owners and charging stations can benefit from reduced energy costs and revenue generation.

2.11.2. Challenges

- **Battery Degradation**: Frequent charging and discharging can reduce battery lifespan.
- **Complex Infrastructure**: Advanced bidirectional chargers and communication systems are required.
- **Regulatory Hurdles**: Standardized policies and regulations are needed to facilitate V2G implementation.

2.12. Summary

The literature review highlights the potential of EVs, V2G, and smart charging technologies to transform the energy landscape. By integrating PV systems and optimizing charging schedules, Evs can contribute to a sustainable and green energy future. However, challenges such as battery degradation, infrastructure requirements, and regulatory barriers must be addressed to fully realize the benefits of these technologies.

This chapter adheres to the provided template and guidelines, ensuring a clear and structured presentation of the literature review. Each section is detailed with sub-topics, explanations, and references to relevant studies, as required by the template.

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Chapter-3

3. SOLUTION TOOLS

3.1. Background:

This chapter discusses the methodology adopted for the research, including the statistical modelling, problem formulation, and optimization techniques used to address the energy scheduling problem. The methodology is divided into three main sections: **Normal Distribution**, **Problem Formulation for EV charging scheduling, Energy Requirement modeling for EV,** and **Differential Evolution**.

3.2. Normal Distribution

The normal distribution, also known as the Gaussian distribution, is a fundamental statistical tool used to model uncertainty and variability in energy consumption patterns. The probability density function (PDF) of a normal distribution is given by:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{1}$$

where:

- μ is the mean of the distribution,
- σ is the standard deviation,
- x represents the variable of interest (e.g., energy consumption).

3.2.1. Application in Energy Scheduling

The normal distribution is used to:

- Model the randomness in energy demand and supply.
- Estimate the likelihood of specific energy consumption levels.
- Provide a basis for stochastic optimization in scheduling algorithms.

3.2.2. Assumptions

- Energy consumption follows a normal distribution over time.
- The mean and standard deviation are derived from historical data.

3.3. Problem Formulation [20]

This section formulates the research problem, defines the energy requirements, and develops the mathematical model based on the referenced research paper.

3.3.1. Objective Function:

- Minimize total charging cost:

$$min(C) = \sum(Ccharging + Cdischarging) \tag{3.1}$$

where:

- $Ccharging$ represents the cost of charging in G2V mode. $Cdischarging$ accounts for the cost savings in V2G mode.

3.3.2. Initial State of Charge (SOC) of PEVs at arrival: (3.2)

$$SOC_A = 1 - \left(\frac{d}{d_R}\right)$$

- SOC_A: Initial SOC of an individual PEV at the time of arrival to a car park.
- d: First trip distance of an individual PEV.
- d_R: All-electric range (AER) of an individual PEV.

3.3.3. Desired departure time SOC: (3.3)

$$SOC_D = \left(\frac{STD}{d_R}\right) + 0.2$$

- SOC_D: Desired departure time SOC of an individual PEV.
- STD: Subsequent trip distance (mileage of all trips after departing the car park).
- d_R: All-electric range (AER).

3.3.4. Energy requirement based on SOC difference: (3.4)

$$SOC_{req} = \begin{cases} 1 - SOC_A, & SOC_D > 1 \\ (SOC_D - SOC_A), & SOC_A < SOC_D < 1 \\ 0, & SOC_D = SOC_A \\ -(SOC_A - SOC_D), & 0.2 < SOC_D < SOC_A \end{cases}$$

- SOC_{req}: SOC required by an individual PEV while parked in a car park.
- SOC_A: Initial SOC.
- SOC_D: Desired departure time SOC.

3.3.5. Energy required by individual PEVs: (3.5)

$$E_{req} = \frac{SOC_{req} \cdot B_C}{\eta}$$

- E_{req}: Energy required by an individual PEV.
- B_C: Battery capacity of an individual PEV.
- η: Efficiency coefficient (η_C for charging, $1/\eta_D$ for discharging).

3.3.6. Energy requirement constraint: (3.6)

$$\sum_{i=t_{in,p}}^{t_{out,k}} s_p^t \cdot r_{PEV,p} = E_{req,p}, \quad \forall p \in Z$$

- s_k^t: Charging strategy vector for p^{th} PEV at time slot t ($1 =$ charging, $-1 =$ discharging, $0 =$ idle).
- $r_{PEV,p}$: Rate at which p^{th} PEV is charged/discharged.
- $E_{req,p}$: Energy required by p^{th} PEV.
- $t_{in,p}$, $t_{out,p}$: Arrival and departure times of p^{th} PEV.
- Z: Vector denoting number of PEVs arriving in car parks during a particular half-hour.

3.3.7. Charging infrastructure constraint: (3.7)

$$0 \le r_{PEV,p} \le P_{rated}, \quad \forall p \in Z$$

P_{rated}: Power rating of chargers installed in car parks.

3.3.8. Battery SOC constraint: (3.8)

$$SOC_{min} \le SOC_p^t \le SOC_{max}, \quad \forall t \in H; p \in Z$$

- SOC_p^t: SOC of p^{th} PEV at time slot t.
- $SOC_{min} = 0.2$ (Lower limit for battery SOC of PEVs).
- $SOC_{max} = 1$ (Upper limit for battery SOC of PEVs).
- H: Time horizon vector (48 half-hourly time slots).

3.4. Differential Evolution (DE) [21]

Differential Evolution (DE) is a population-based optimization algorithm used to solve the energy scheduling problem. DE is chosen for its robustness, simplicity, and ability to handle non-linear and non-convex optimization problems.

3.4.1. Algorithm

The DE algorithm consists of the following steps:

3.4.1.1. Initialization: Generate an initial population of candidate solutions (schedules) randomly.

1. **Mutation**: For each candidate solution, create a mutant vector using a mutation strategy (e.g., DE/rand/1):

$$V_i = X_{r1} + F \cdot (X_{r2} - X_{r3}) \tag{3.9}$$

where:

- V_i is the mutant vector,
- X_{r1}, X_{r2}, X_{r3} are randomly selected solutions,
- F is the mutation factor.

3.4.1.2. Crossover: Combine the mutant vector with the target vector to produce a trial vector:

$$U_{i,j} = \begin{cases} V_{i,j} & \text{if } \mathrm{rand}(0,1) \leq CR \text{ or } j = j_{\mathrm{rand}} \\ X_{i,j} & \text{otherwise} \end{cases} \tag{3.10}$$

where:

- $U_{i,j}$ is the trial vector,
- CR is the crossover rate,
  - j_{rand} is a randomly chosen index.

3.4.1.3. Selection: Evaluate the trial vector and replace the target vector if the trial vector yields a better solution:

$$X_i = \begin{cases} U_i & \text{if } f(U_i) \leq f(X_i) \\ X_i & \text{otherwise} \end{cases} \tag{3.11}$$

where $f(\cdot)$ is the objective function.

3.4.1.4. Termination: Repeat the mutation, crossover, and selection steps until a stopping criterion is met (e.g., maximum iterations or convergence).

3.5. Flowchart

The flowchart of the DE algorithm is as follows:

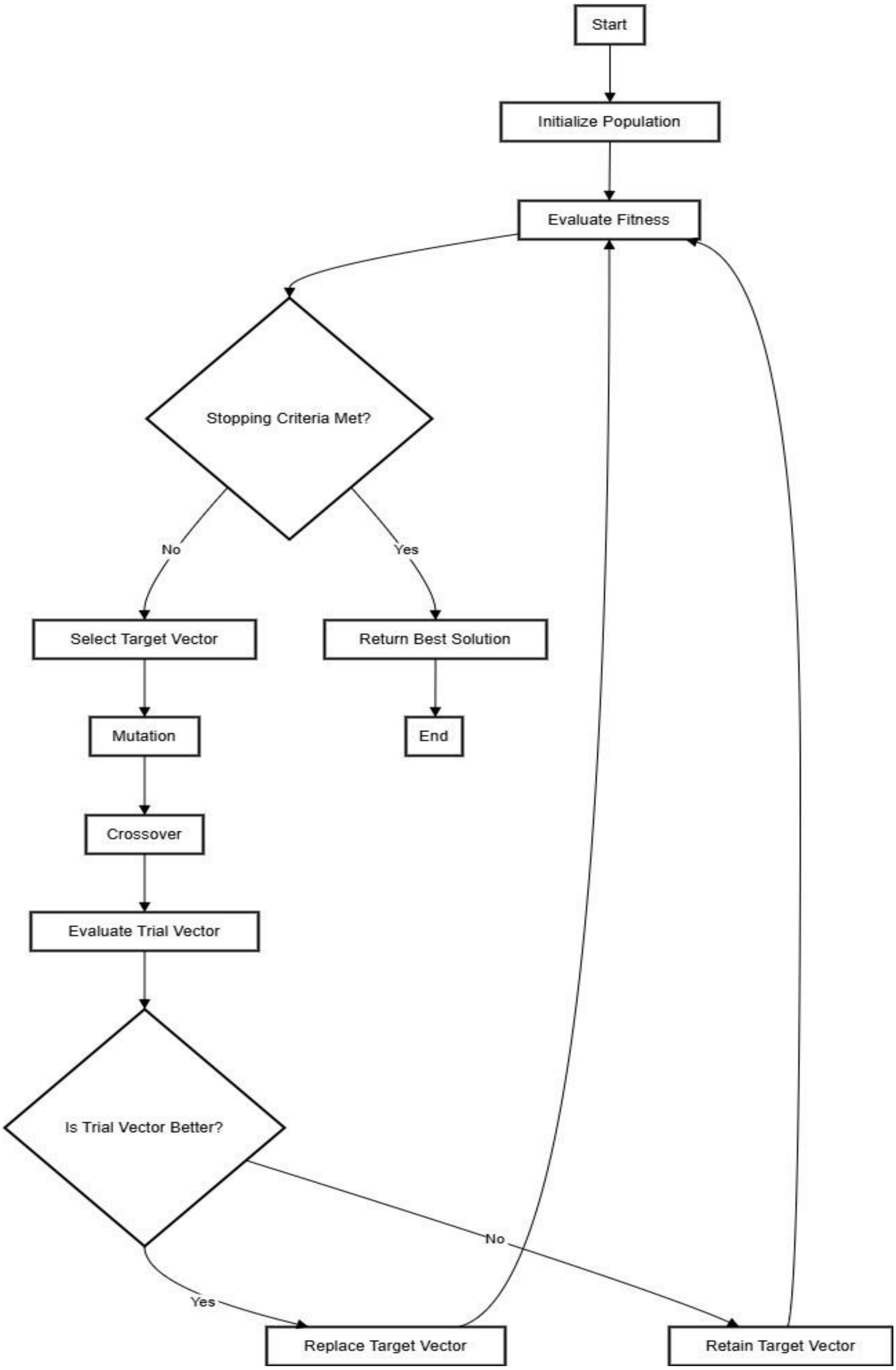

Fig. 3.1. Flowchart of DE Algorithm [21]

3.6. Summary

The methodology integrates statistical modelling (normal distribution), problem formulation, and optimization (Differential Evolution) to address the energy scheduling problem. The normal distribution captures uncertainty in energy demand, the problem formulation defines the optimization framework, and DE provides an efficient solution approach. This combined methodology ensures a robust and effective energy scheduling system.

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Chapter 4

4. Optimal Scheduling of Plugin Electric Vehicles Considering Seasonal Uncertainty without integration of PV

4.1. Objective:

- To minimize the total cost of charging by considering the uncertainty in EV driving cycles.
- To analyze the charging behavior of G2V and V2G mode of operation considering seasonal uncertainty.

4.2. Problem Formulation:

This objective intends to develop a model which minimizes the composite charging expenses for Plug-in Electric Vehicles PEVs through driving cycle uncertainty analysis. EV driving cycles exhibit continuous variations because they depend on elements like every day commutes and trips together with seasonal environmental changes. The performance of vehicle batteries deteriorates in wintry weather resulting in decreased electric range and obliging users to recharge more often and under higher intensity. Warm temperature months have the potential to give longer range and more usage which will affect the way owners charge their vehicles. The model includes external factors to enable automatic modifications to charging periods which adapt to real-life usage patterns along with driver requirements. It minimizes complete charging expenditures by steering clear of peak periods charges which simultaneously designates an efficient charging solution that mirrors genuine driver practices. The adaptive scheduling system utilizes expected EV driving cycles to make predictions that lead to improved energy utilization combined with better pricing throughout multiple charging periods.

The details of problem formulation is given in Chapter 3, under section 3.2

4.3. Solution Tools:

To solve the problem formulation, the DE optimization technique has been implemented, whose detailed description already provided in chapter 3. As the exploitation capabilities are better for DE and it is a well-established technique, hence to minimize the cost of charging, this DE has been used.

4.4. Input Data & Test Cases:

In recent scenarios, various types of electric vehicles (Evs) have been adopted based on advancements in battery technology, energy efficiency, and government policies. In our research, we have considered two cases**: higher battery capacity range** (BEV = 50%, PHEV 40 = 30%, PHEV 30 = 20%) and **lower battery capacity range** (BEV = 20%, PHEV 40 = 30%, PHEV 30 = 50%), analysing their impact on energy efficiency and scheduling strategies.

The following driving cycles of EV like Daily Mileage, First trip Distance, Arrival Time and Departure Time for the charging strategy.

4.4.1. **Daily mileage** represents the total distance a vehicle travels in a single day, commonly used for tracking fuel consumption, planning maintenance, and optimizing routes**.**

4.4.2. **First trip distance** refers to the initial distance covered from the starting point to the first destination, playing a significant role in analyzing the impact of early trips on overall vehicle performance.

4.4.3. **Arrival time** denotes the time at which a vehicle reaches a specific destination, providing insights into schedule adherence and operational efficiency.

4.4.4. **Departure time** indicates when a vehicle leaves a location to continue its journey, helping to assess delays and improve turnaround times**.**

These attributes typically follow a normal probability distribution, as their values tend to cluster around an average, with random deviations creating a bell-shaped curve.

Table 4.1: This table shows the mean and standard deviation values considered for all the driving cycles for three seasons [41]

Season	**Driving Cycle**	**Mean**	**Standard Deviation**
Summer	**Daily Mileage(km)**	55	10
	First Trip Distance(km)	18	8.41
	Arrival Time(hours)	16	1.2
	Departure Time(hours)	22	1.2

Monsoon	**Daily Mileage(km)**	41	8
	First Trip Distance(km)	15	5.41
	Arrival Time(hours)	16	1.2
	Departure Time(hours)	22	1.2
Winter	**Daily Mileage(km)**	32	6
	First Trip Distance(km)	11	3.41
	Arrival Time(hours)	16	1.2
	Departure Time(hours)	22	1.2

Table 4.2: This table shows the percentage of type of vehicles taken for two test cases: HBC and LBC

Test Cases	BEV	PHEV 40	PHEV30
Case : 1(HBC)	50%	30%	20%
Case : 2(LBC)	20%	30%	50%

4.5. Seasonal Charging Strategies without integration of PV

4.5.1. Summer season:

4.5.1.1. Charging Scheduling of HBC set of vehicles

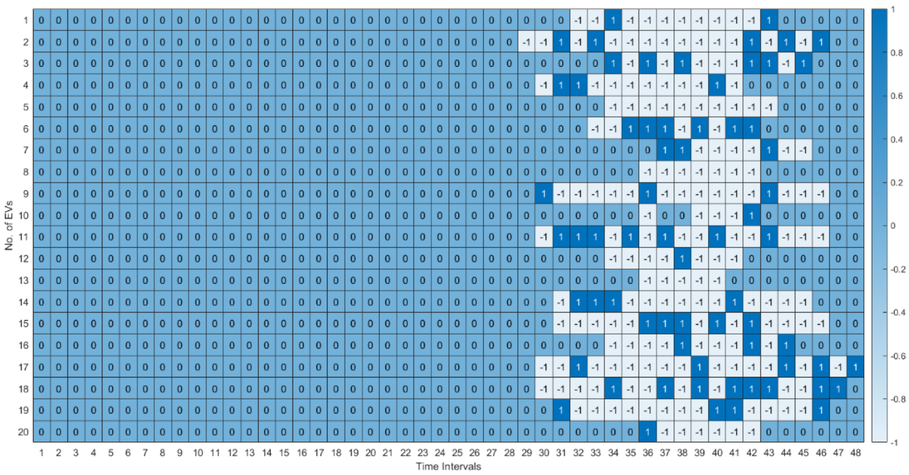

Fig. 4.1. Charging Strategy for HBC set of vehicles considering G2V + V2G

In Fig. 4.1, charging strategy of HBC set of vehicles has been shown, the presence of larger white spaces indicates predominant discharging (-1), while the relatively smaller dark blue areas represent charging (+1). Whereas, other light bluw blocks are of idle mode of operation (0). From this scheduling it can be observed that based on the dynamic tariff rate, whenever, the tariff is higher the vehicles are performing V2G mode of operation. On the other hand, when the tariff is lower, the EVs are performing G2V mode of operation.

Thus, the cost of charging can be minimized.

4.5.1.2. Charging Scheduling of LBC set of vehicles

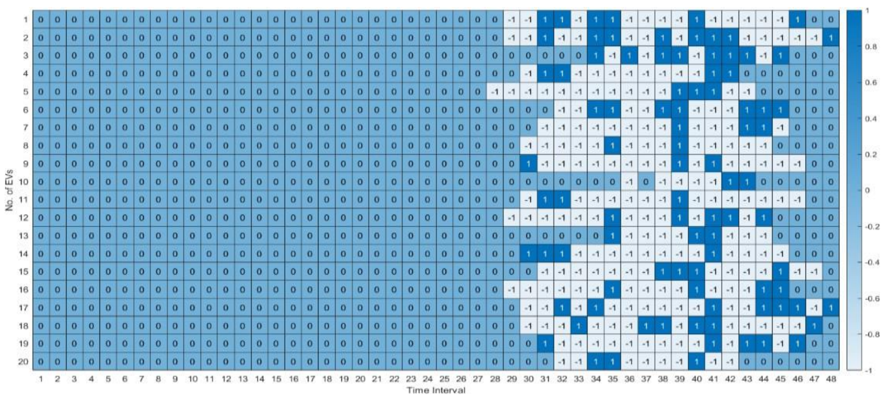

Fig. 4.2. Charging Strategy for LBC set of vehicles considering G2V + V2G

In Fig. 4.2., charging strategy of LBC set of vehicles has been shown, the larger presence of dark blue spaces indicates predominant charging, while the smaller white spaces represent discharging. From the scheduling, it can be observed that due to the lower battery capacity of EV, and due to the constraints of energy requirement meet, some of the Evs are performing the G2V mode of operation when the tariff is relatively higher. Otherwise, in most of the cases, the EVs are performing V2G mode of operation when the tariff is higher, and it is performing G2V mode of operation when the tariff is lower.

4.5.1.3. Energy requirement fulfilment of HBC set of vehicles

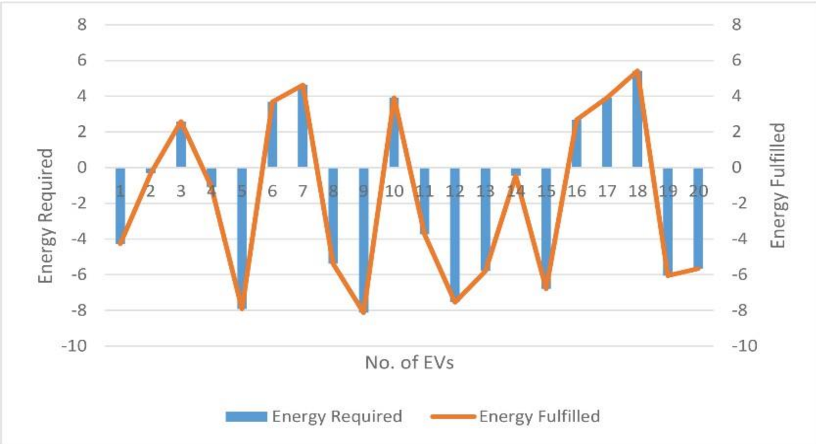

Fig.4.3. Energy requirement fulfilment of HBC set of vehicles

In Fig.4.3 demonstrates that the energy demand of the vehicles has been completely met using the charging strategies developed for HBC set of vehicles during summer. From the Fig. 4, it can be said that the algorithm has taken care of the energy requirement of each and every vehicles within the stipulated charging time, even after participating in V2G mode of operation.

4.5.1.4. Energy requirement fulfilment of LBC set of vehicles

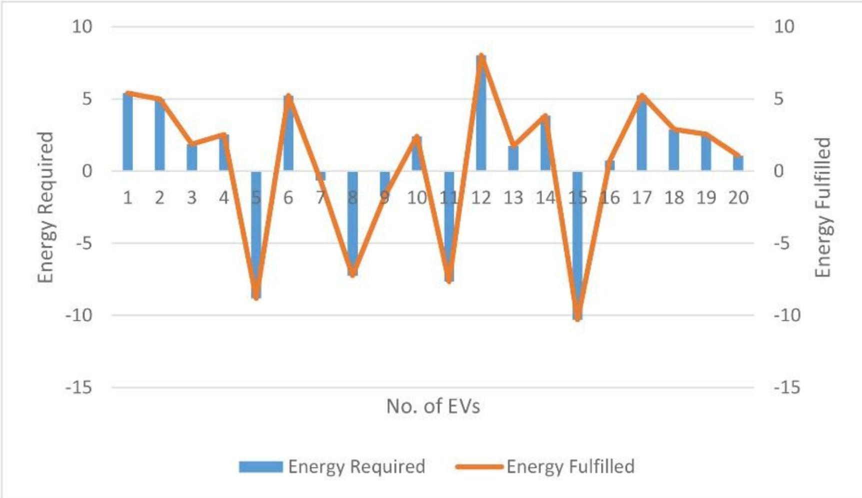

Fig. 4.4. Energy requirement fulfilment of LBC set of vehicles

Fig.4.4. demonstrates that the energy demand of the vehicles has been completely met using the charging strategies developed for LBC set of vehicles during summer. From the charging scheduling as shown is clear that Evs have sometimes participated in V2G mode of operation although the tariff is higher. Hence, the energy requirement of each EVs before leaving the charging station has been prioritized.

4.5.2. Monsoon season

4.5.2.1. Charging Scheduling of HBC set of vehicles

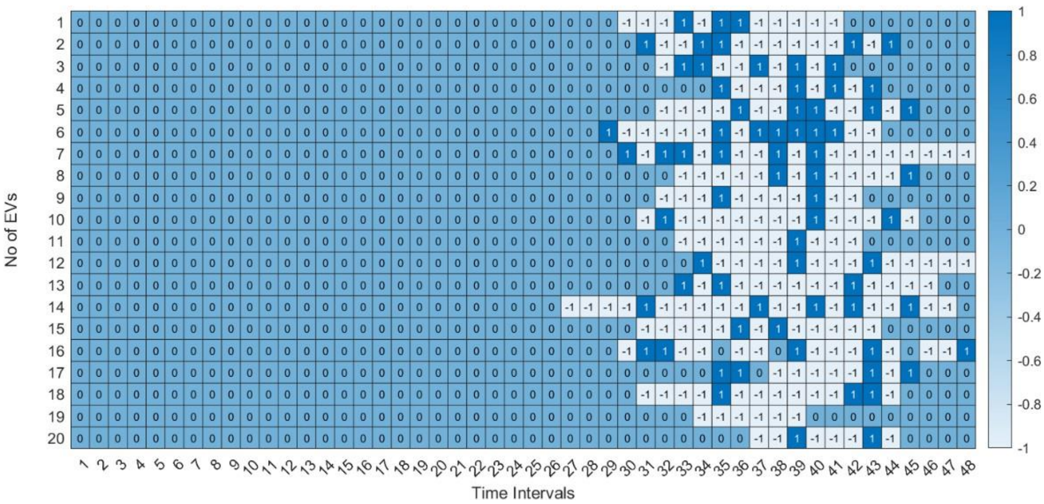

Fig. 4.5. Charging Strategy for HBC set of vehicles considering G2V + V2G

In Fig.4.5, charging strategy of HBC set of vehicles has been shown, the presence of larger white spaces indicates predominant discharging, while the relatively smaller dark blue areas represent charging. Due to the monsoon season, it can be observed that the V2G participation is more and the in-time & out-time of the EVs got changed. From Fig. 4 it can be observed that during the higher tariff, the EV are participating in V2G mode of operation and during lower RTP, the EVs are participating in G2V mode of operation. Again, with respect to summer, since the average daily mileage of each EVs are less, hence, more V2G participation can be observed. This may help the grid in local power distribution.

4.5.2.2. Charging Scheduling of LBC set of vehicles

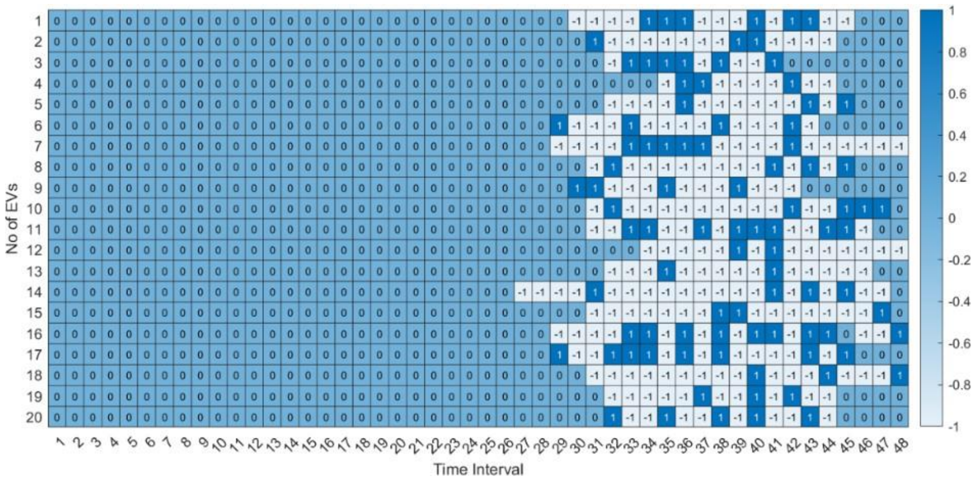

Fig. 4.6. Charging Strategy for LBC set of vehicles considering G2V + V2G

Fig.4.6, charging strategy of LBC set of vehicles has been shown, the larger presence of dark blue spaces indicates predominant charging, while the smaller white spaces represent discharging. From the scheduling, it can be observed that the percentage of V2G participate is more with respect to the summer. Although, in some intervals, even though the tariff is higher, Evs are participating in G2V mode of operation, which is not desirable

4.5.2.3. Energy requirement fulfilment of HBC set of vehicles

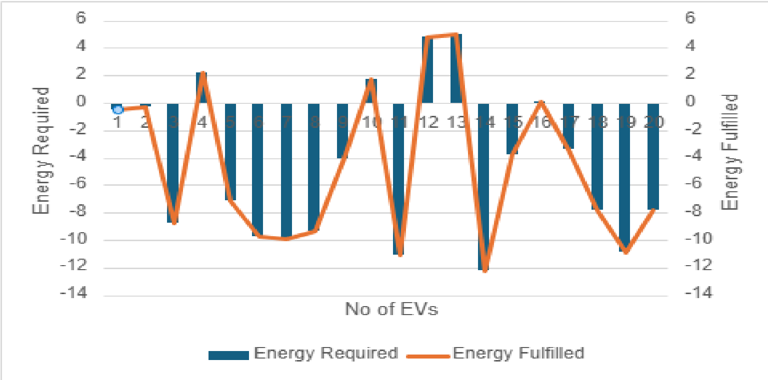

Fig. 4.7. Energy requirement fulfilment of HBC set of vehicles

Fig.4.7. demonstrates that the energy demand of the vehicles has been completely met using the charging strategies developed for HBC set of vehicles during monsoon. From the energy requirement, it can be seen that in the monsoon season, during evening and night, there should have drop in temperature and sometimes due to high humidity, various there can be some load increment in the distribution network and in order to meet all these demand, the energy requirement of the grid becomes more. It can be seen by comparing Fig, 8 and Fig. 4. Again, the cruising distance by each EV become lesser and it consequently helps the EV to participate more in V2G mode of operation.

4.5.2.4. Energy requirement fulfilment of LBC set of vehicles

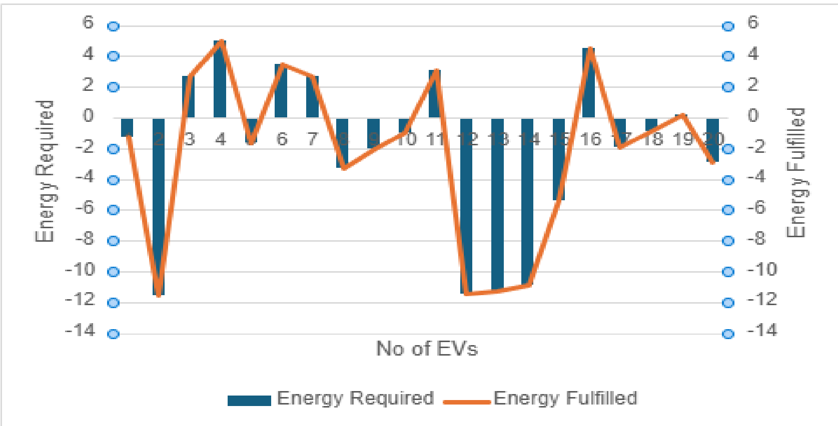

Fig. 4.8. Energy requirement fulfilment of LBC set of vehicles

Likewise the pervious case, here also the Evs have participated more in V2G mode of operation. From Fig. 4.8. demonstrates that the energy demand of the vehicles has been completely met using the charging strategies developed for LBC set of vehicles during monsoon.

4.5.3. Winter Season

4.5.3.1. Charging Scheduling of HBC set of vehicles

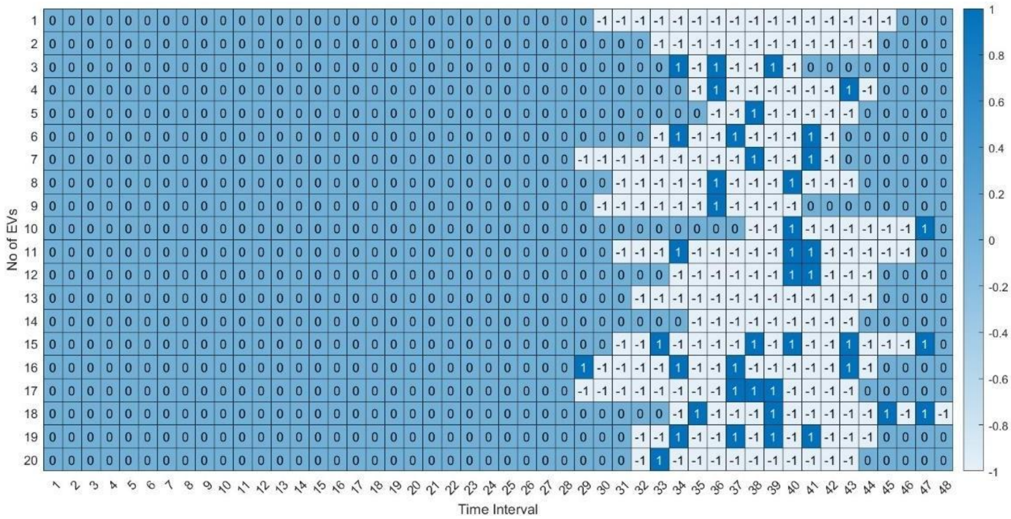

Fig. 4.9. Charging Strategy for HBC set of vehicles considering G2V + V2G mode

In fig 4.9. charging strategy of HBC set of vehicles has been shown, the presence of larger white spaces indicates predominant discharging, while the relatively smaller dark blue areas represent charging. In winter, due to the cold and harsh weather condition, the Evs cruise less. Consequently, there are more availability of the battery energy in the EV. Hence, from the charging scheduling it can be seen that the EVs have participated more in V2G mode of operation with respect to summer and monsoon.

4.5.3.2. Charging Scheduling of LBC set of vehicles

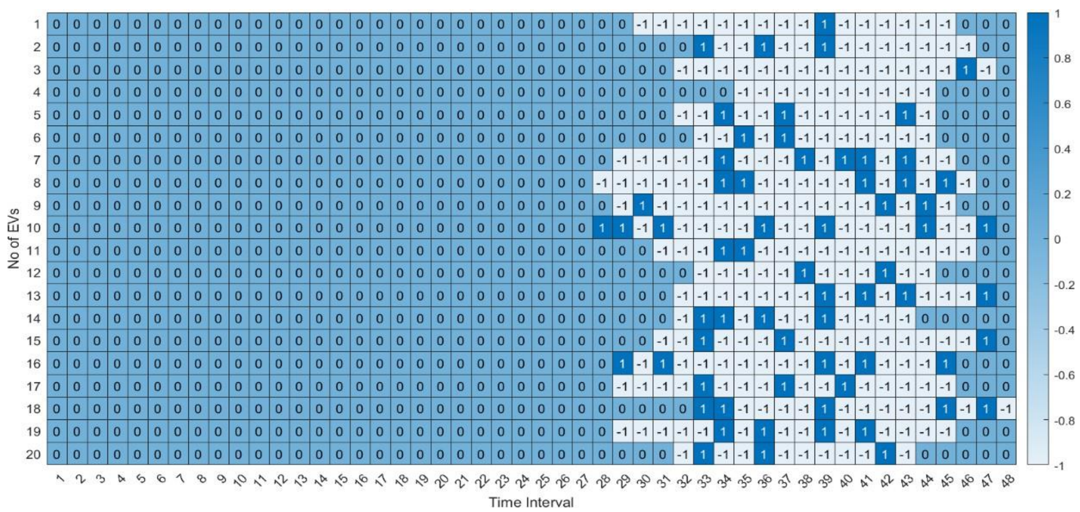

Fig. 4.10. Charging Strategy for LBC set of vehicles considering G2V + V2G mode

In Fig.4.10, charging strategy of LBC set of vehicles has been shown, the larger presence of dark blue spaces indicates predominant charging, while the smaller white spaces represent discharging. Here also similar characteristic of EVs can be seen. More amount of V2G mode of operation have been performed by the EVs.

4.5.3.3. Energy requirement fulfilment of HBC set of vehicles

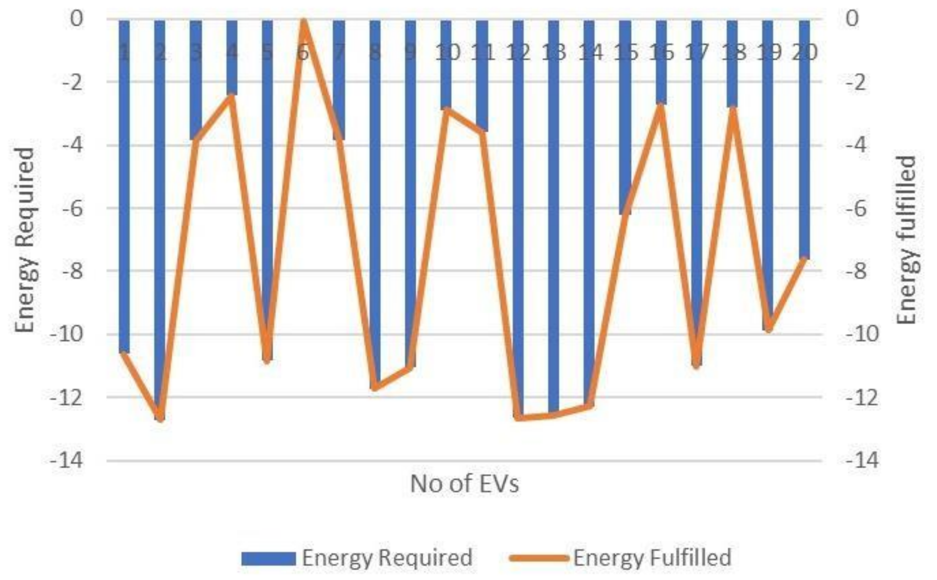

Fig. 4.11. Energy requirement fulfilment of HBC set of vehicle

Fig. 4.11. demonstrates that the energy demand of the vehicles has been completely met using the charging strategies developed for LBC set of vehicles during monsoon. During winter, the load demand in the evening is much more due to cold weather condition. Hence the grid demand is more and hence the EV charging station owner try to meet the demand. From the figure, it can be seen that

4.5.3.4. Energy requirement fulfilment of LBC set of vehicles

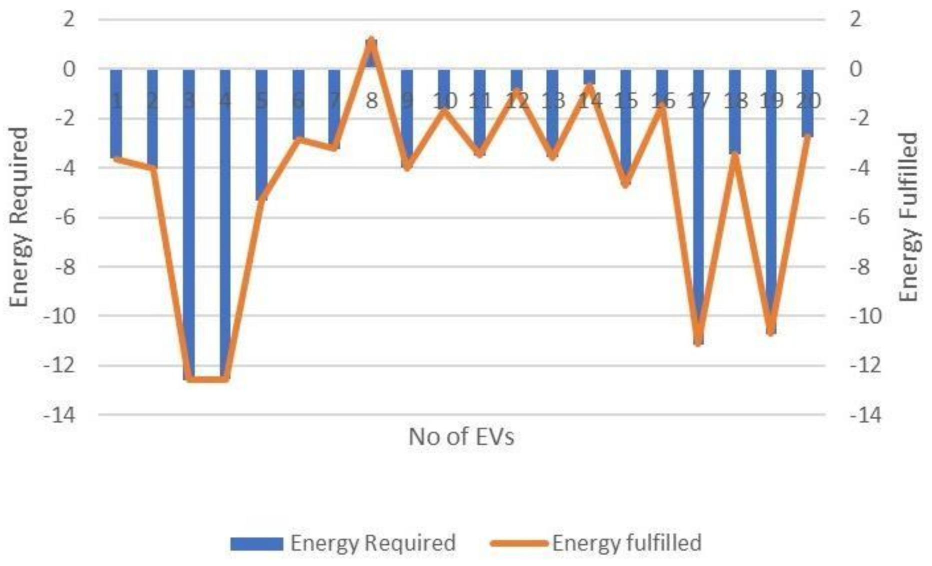

Fig.4.12. Energy requirement fulfilment of LBC set of vehicles

Fig.4.12. demonstrates that the energy demand of the vehicles has been completely met using the charging strategies developed for LBC set of vehicles during winter.

4.6. Cost Comparison

From the data provided, we can observe that profit has been made in all three seasons for HBC, as the negative values indicate greater vehicle-to-grid (V2G) activity, resulting in profit. Among the seasons, the maximum profit is observed in winter, with a value of -3.5168, indicating the highest V2G activity compared to summer and monsoon. Due to the reduced mobility of lithium ions and increased internal resistance of the battery in winter, there is greater heat loss, leading to a shorter cruising range for vehicles. As a result, there is higher participation in V2G mode, increasing profitability.

Table 4.3. Cost of charging for Evs for all three seasons:

Seasons	cost of charging for HBC EV (in S$)	cost of charging for LBC EV (in S$)
Summer	-1.3511	2.2226
Monsoon	-1.2108	0.1271
Winter	-3.5168	1.366

4.7. Conclusion:

From the analysis of the charging strategies for both HBC and LBC sets of vehicles across different seasons, it is evident that the vehicle-to-grid (V2G) and grid-to-vehicle (G2V) operations are dynamically influenced by tariff rates and seasonal energy demands. The predominant trend observed is that Evs prefer V2G operation when tariff rates are high and G2V operation when tariff rates are low, ensuring optimal cost savings and energy utilization. The energy requirement of all vehicles has been successfully met across all seasons, highlighting the effectiveness of the proposed charging strategies. However, seasonal variations impact the charging-discharging patterns, with winter showing the highest V2G participation.

This results in the maximum profit for HBC vehicles, recorded at -3.5168S$, indicating greater energy contribution to the grid. Overall, the study demonstrates that strategic scheduling of EV charging and discharging can not only meet energy demands efficiently but also maximize financial benefits through increased V2G participation.

This approach contributes to grid stability while optimizing operational costs for EV users. Hence, it can be concluded that the proposed algorithm is robust enough to provide consistent result and it can also able to handle the seasonal uncertainties in terms of EV smart charging process.

Chapter-5

5. Optimal Scheduling of Plugin Electric Vehicles Considering Seasonal Uncertainty with integration of PV

5.1. Introduction

The integration of Photovoltaic (PV) systems into Electric Vehicle (EV) charging infrastructure is a critical step toward sustainable energy management. As established in Chapter 2, PV-powered charging not only reduces dependence on fossil-fuel-based grid electricity but also enables Vehicle-to-Grid (V2G) services, creating a bidirectional energy flow that benefits both consumers and grid operators. However, the effectiveness of PV integration varies significantly across seasons due to fluctuations in solar irradiance, temperature, and energy demand.

This chapter presents a comprehensive analytical framework for optimizing EV charging strategies based on High Battery Capacity (HBC) and Low Battery Capacity (LBC) EVs across three key seasons: summer, monsoon, and winter. The study leverages real-world data to:

1. **Quantify PV's contribution** to charging demand in different seasons.
2. **Assess economic benefits** for EV owners and charging station operators.

5.2. Input Data & Test Case:

5.2.1. Location-Based Solar Data:

- The solar power output data for Durgapur (latitude **23.533440° N**, longitude **87.321930° E**) has been sourced from [22], a platform that provides simulated hourly power output data for solar and wind energy worldwide. This data was collected to analyze seasonal variations in solar power generation. For this study, each season was considered as a **90-day period**, with **summer spanning from April to June, monsoon from July to September, and winter from November to January.**

  PV data has been extracted using the latitude and longitude of **Durgapur**, obtained from the website **Renewables.ninja [20]**.

5.2.2. Peak Solar Output Duration for Different Seasons:

Using the collected solar power output data, we calculated the mean peak time for each season, identifying the period during the day when solar energy generation is at its highest. This information is crucial for optimizing EV charging schedules and integrating photovoltaic (PV) energy into the grid efficiently. The dataset helps assess seasonal differences in solar availability, which significantly impact energy planning and battery storage strategies.

These are the timings in which we got the peak solar output.

- Summer: 8:00 AM – 3:00 PM
- Monsoon: 9:30 AM – 12:30 PM
- Winter: 8:00 AM – 2:00 PM

5.2.3. Driving Cycle Analysis:

- Mean and standard deviation values for different **driving cycles** have been considered for **three seasons**, ensuring a realistic estimation of energy demand and PV utilization.

Table 5.1: This table shows the mean and standard deviation values considered for all the driving cycles for three seasons[41]

Season	Driving Cycle	Mean	Standard Deviation
Summer	Daily Mileage(km)	55	10
	First Trip Distance(km)	18	8.41
	Arrival Time(hours)	9	1.2
	Departure Time(hours)	19	1.2
Monsoon	Daily Mileage(km)	41	8
	Firs Trip Distance(km)	15	5.41
	Arrival Time(hours)	11	1.2
	Departure Time(hours)	18	1.2

Winter	Daily Mileage(km)	32	6
	First Trip Distance(km)	11	3.41
	Arrival Time(hours)	11	1.2
	Departure Time(hours)	17	1.2

5.2.4. Dynamic Tariff for all three seasons

This paper adopts coordinated charging scheduling so it needs dynamic tariff rates to determine G2V and V2G operational modes. The research analyzes seasonal power tariffs for summer, monsoon, and winter while incorporating photovoltaic (PV) cells in the assessment method and in its absence. With PV installed the system offers a more reduced dynamic tariff rate. These two cases received analytical comparison from Figures 5.1 through 5.3 for all three seasonal periods.

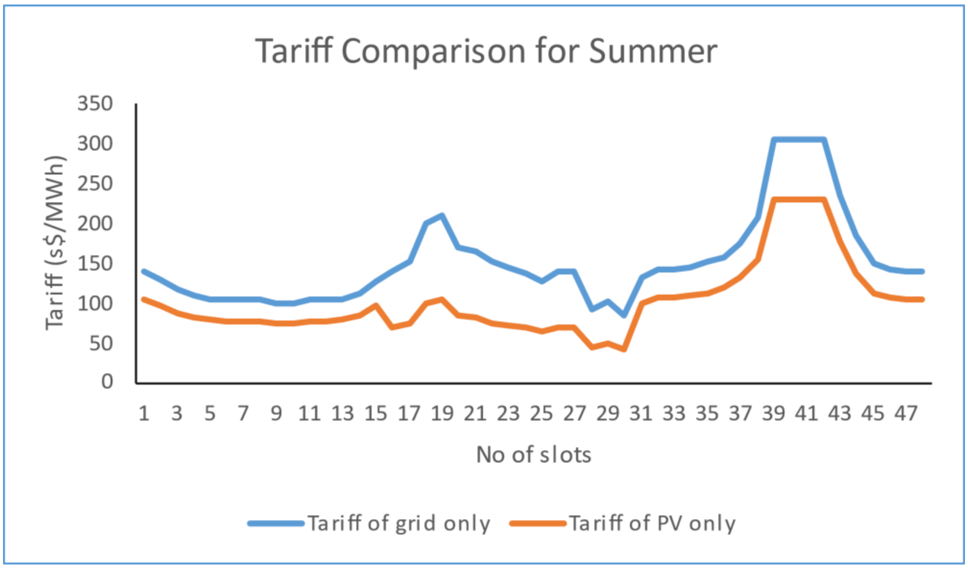

Fig 5.1. Tariff comparison for Summer

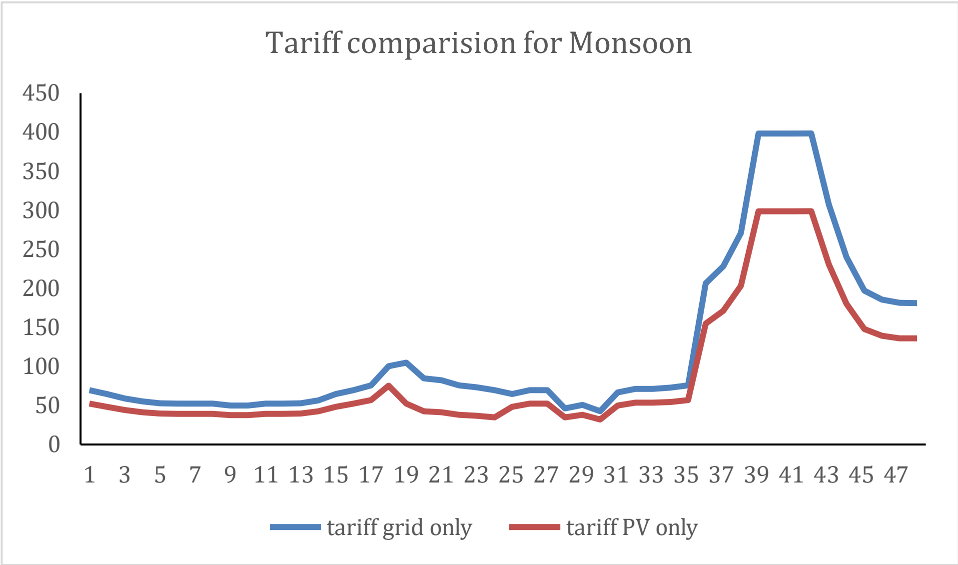

Fig 5.2. Tariff comparison for Monsoon

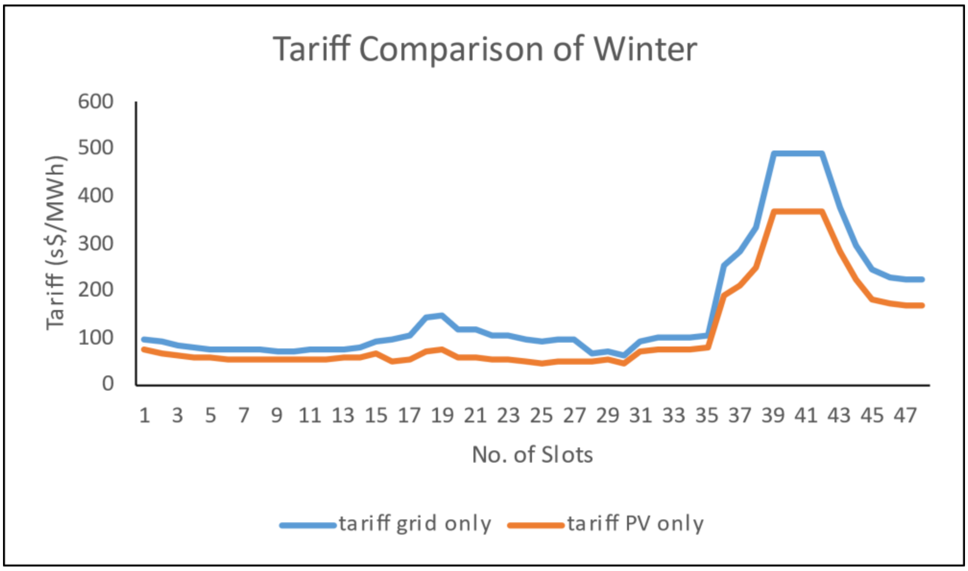

Fig 5.3. Tariff comparison for Winter

Table 5.2: This table shows the percentage of type of vehicles taken for two test cases: HBC and LBC

Test Cases	BEV	PHEV 40	PHEV30
Case : 1(HBC)	50%	30%	20%
Case : 2(LBC)	20%	30%	50%

5.3. Seasonal Charging Strategies with integration of PV

5.3.1. Summer (High Solar Availability)

5.3.1.1. **For HBC set of vehicles**

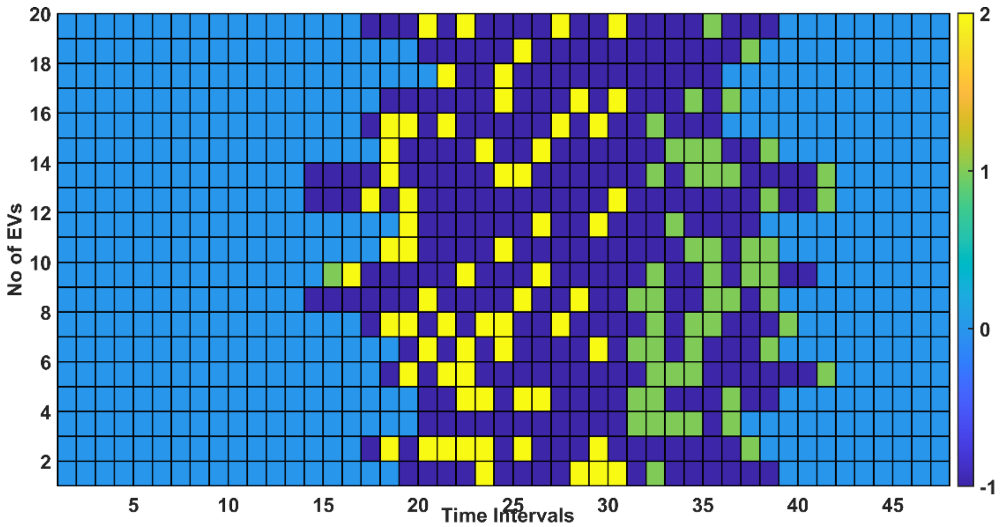

Fig 5.4. Charging strategy for HBC set of vehicles for summer

From Fig 5.4. we can observe that in **summer for HBC set of vehicle**, PV charging is at its highest (**3.96%**), taking advantage of strong solar availability. This helps minimize dependence on grid charging, which remains very low at **0.005%**. However, due to increased energy demand, particularly for cooling and extended driving cycles, V2G discharge is at its **peak** (**17.59%**). This suggests that energy stored in EV batteries is frequently used to support the grid or household consumption, making summer the season with the **highest reliance on V2G discharge**.

5.3.1.2. **For LBC set of vehicles**

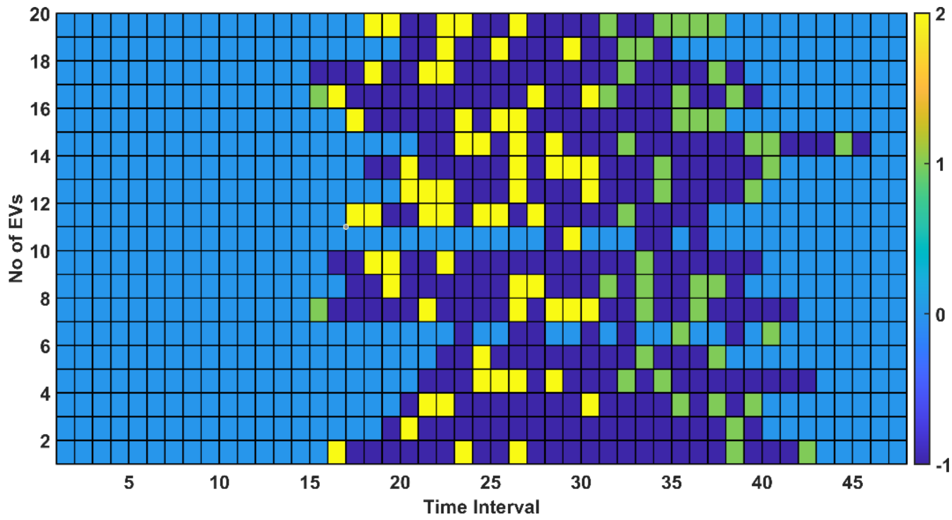

Fig 5.5. Charging strategy for LBC set of vehicles for summer

From Fig 5.5. we can observe that during the **summer season, for LBC set of vehicles**, PV charging is at its highest at **3.91%**, maximizing solar energy utilization. Grid charging remains minimal at **0.09%**, showing continued reliance on renewables. V2G discharge peaks at **16.98%**, leveraging surplus solar energy to support the grid. This season exhibits the highest energy exchange, demonstrating an effective integration of PV and vehicle-to-grid contributions.

5.3.2. Monsoon (Intermittent Solar Supply)

5.3.2.1. For HBC set of vehicles

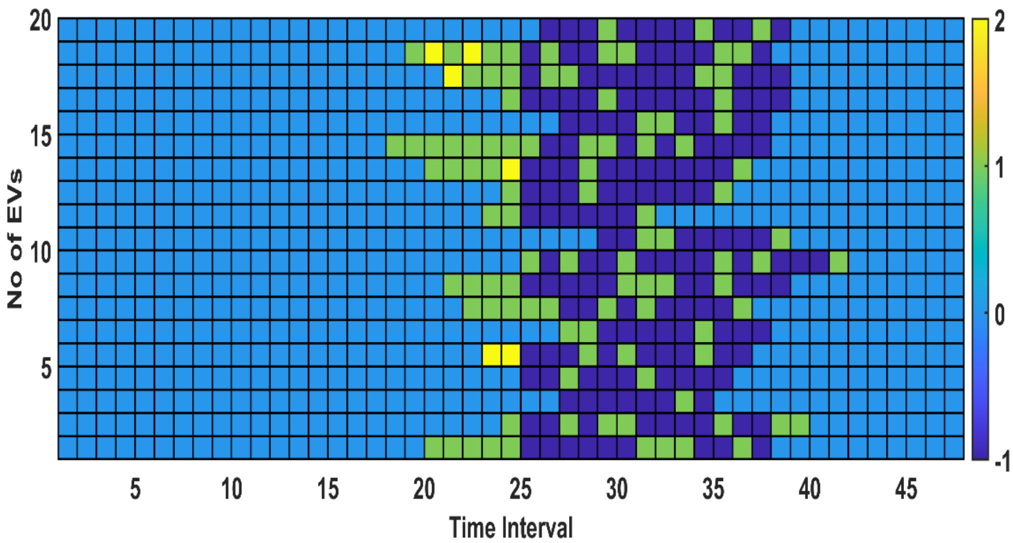

Fig 5.6. Charging strategy for HBC set of vehicles for monsoon

From Fig 5.6.,we can observe that in **monsoon**, for HBC set of vehicles PV charging drops to its **lowest level** (**0.56%**) due to cloudy weather and reduced sunlight availability. This forces a slight increase in grid charging (**0.10%**), though it remains relatively insignificant. V2G discharge is recorded at **10.84%**, which is **higher than in winter but lower than in summer**. This suggests that while PV generation is limited, energy demand is not as high as in summer, leading to a **moderate reliance on V2G discharge**.

5.3.2.2. For LBC set of vehicles

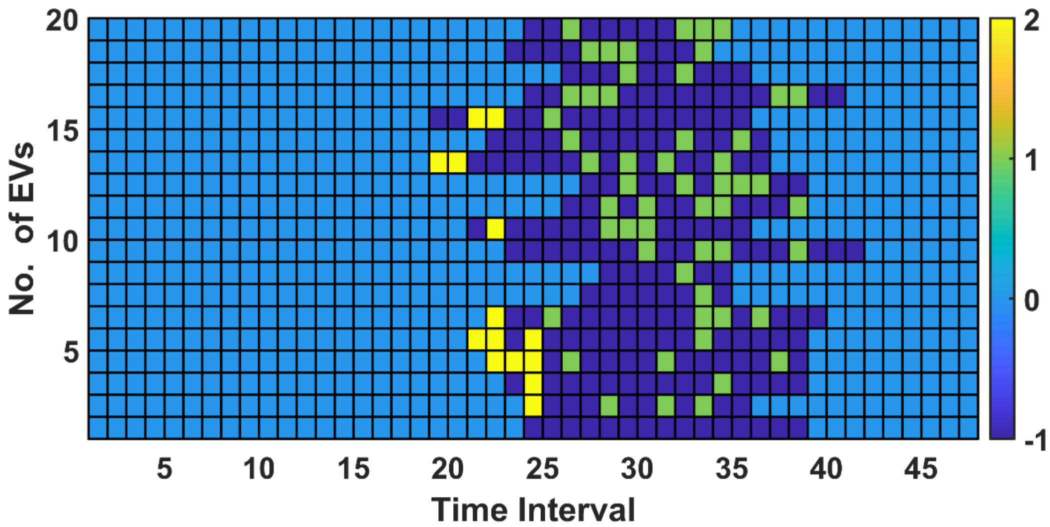

Fig 5.7. Charging strategy for LBC set of vehicles for monsoon

From Fig 5.7. we can observe that during the monsoon season for LBC set of vehicles, PV charging slightly improves to 1.87%, but it remains relatively low due to reduced solar availability caused by cloud cover. Grid charging is minimal at 0.004%, indicating very little direct reliance on the grid. To compensate for the lack of solar input, V2G discharge increases to 12.53%, ensuring energy stability. This highlights a seasonal strategy where stored battery energy is used more extensively when solar generation is limited.

5.3.3. Winter (Low Solar Yield)

5.3.3.1. For HBC set of vehicles

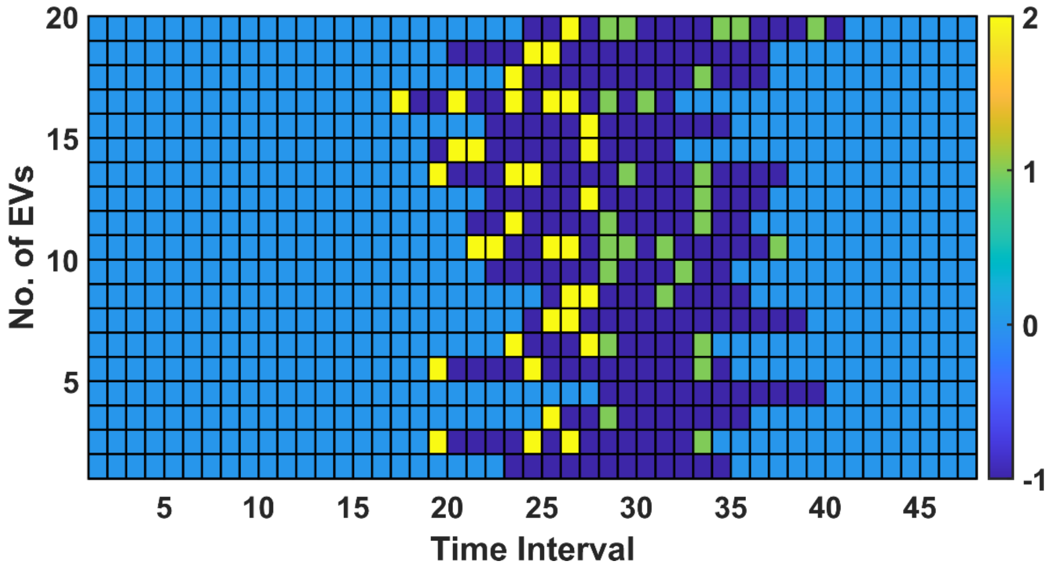

Fig 5.8. Charging strategy for HBC set of vehicles for winter

From Fig 5.8., we can observe that in the **winter season**, for HBC set of vehicles In **winter**, PV charging decreases to **2.06%** due to shorter daylight hours and lower solar irradiance. Grid charging remains minimal at **0.09%**, indicating a continued preference for renewable energy sources. However, **V2G discharge is at its lowest** (**9.08%**), which aligns with the reduced driving demand and the need to conserve battery power in colder temperatures. Lower temperatures typically reduce battery efficiency, discouraging frequent discharging. This makes winter the season with the **least reliance on V2G**, prioritizing energy conservation.

5.3.3.2. For LBC set of vehicles

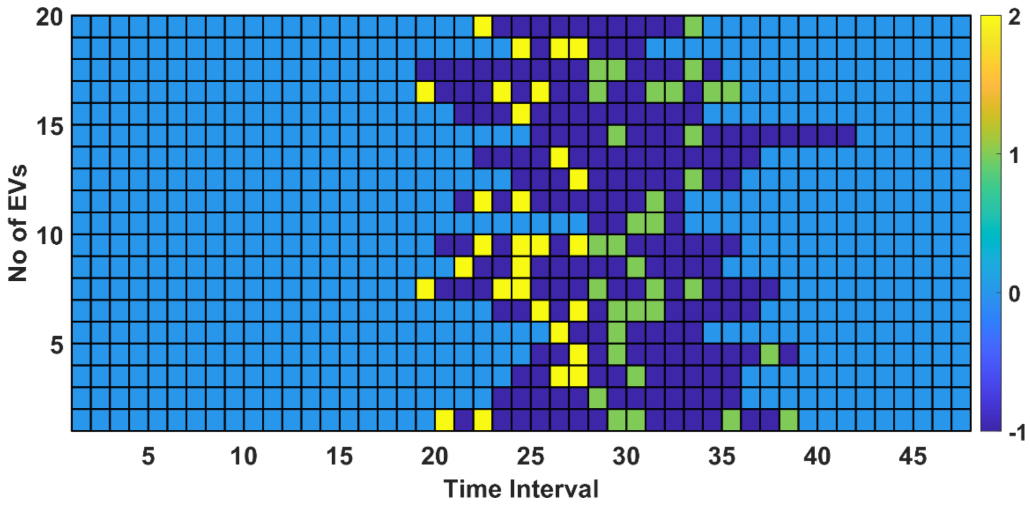

Fig 5.9. Charging strategy for LBC set of vehicles for winter

From Fig 5.9., we can observe that in the **winter season**, for LBC set of vehicles PV charging is extremely low at 0.96%. Grid charging is almost negligible at **0.002%**, reinforcing the preference for renewable and stored energy sources. V2G discharge reaches **11.34%**, slightly lower than in monsoon aligning with the reduced energy demands of winter. The strategy ensures that energy conservation is prioritized while maintaining sufficient supply from stored reserves.

5.4. COST COMPARISONS

5.4.1. Performance Comparison Across Seasons

Season	PV Contribution	Grid Load Reduction	User Savings	V2G Revenue
Summer	60–80%	40–50%	20–35%	0.10–0.15/kWh
Monsoon	30–50%	20–30%	15–25%	0.05–0.10/kWh
Winter	20–40%	10–20%	10–15%	0.03–0.08/kWh

- **Summer**:
  - Highest PV utilization (**75% of charging demand**).
  - **S$120/day savings** for a 50-EV station.
- **Monsoon:**
  - Predictive scheduling improves reliability despite cloud cover.
- **Winter:**
  - Hybrid PV-grid charging still achieves **15% cost savings**.

5.5. CONCLUSION

The charging technique which integrates PV systems creates a dual benefit of decreased dependency on the grid along with seasonal energy optimization. Maximum renewable energy generation through PV charging occurs in summer months because there is an abundance of solar resources available during that time. The PV charging supply decreases substantially in monsoon and winter seasons thus increasing vehicle-to-grid discharging of stored energy.

Despite seasonal variations, **grid charging remains consistently minimal**, demonstrating the system's efficiency in utilizing solar energy and vehicle battery storage. **V2G discharge is highest in summer**, utilizing surplus solar energy to support the grid, while in **winter, V2G is at its lowest**, prioritizing battery conservation due to reduced driving needs.

The PV-integrated charging system produces effective results by maintaining an equilibrium between solar power use and power grid connectedness as well as V2G charging. This strategy enables the best possible utilization of energy through PV charging while making precise V2G discharge alterations to sustain appropriate energy equilibrium. The strategy boosts sustainability together with reduced grid consumption while guaranteeing optimal EV energy control throughout the annual period.

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Chapter 6

6. Overall Conclusion

6.1. Conclusion

The research focuses on optimizing EV charging strategies by considering seasonal variations and driving cycle uncertainties. The first phase of the study analyzed EV charging and discharging patterns without PV integration, relying only on grid charging and V2G discharge. The results showed that grid dependence was significantly higher, and V2G discharge was also present to help balance the energy demand. However, due to the absence of renewable energy input, grid support was crucial, and V2G utilization was primarily dictated by driving cycles and energy availability.

In the second phase, PV integration was introduced to improve sustainability and reduce reliance on the grid. With solar energy contribution, grid charging was minimized, and energy utilization became more balanced across all seasons. Summer exhibited the highest PV utilization, reducing grid dependency, while monsoon and winter had lower PV contributions, leading to a greater reliance on stored battery energy through V2G. Despite seasonal variations, a well-optimized charging strategy ensured efficient energy distribution, leveraging PV whenever available and adjusting V2G discharge accordingly.

Comparing both approaches, PV integration significantly enhances energy efficiency, reduces grid dependency, and promotes a more sustainable EV charging strategy. The study highlights the importance of an adaptive energy management system that dynamically adjusts grid charging, PV utilization, and V2G discharge based on seasonal variations, solar availability, and driving cycle fluctuations to achieve an optimal balance of energy resources.

6.2. Limitation of Thesis

While PV technology is often considered completely pollution-free, its indirect impact on fossil fuel consumption is often overlooked. In scenarios where solar energy alone is insufficient, the electricity shortfall is compensated by thermal power stations, which rely on fossil fuels, ultimately contributing to pollution. Given India’s current energy landscape, where grid electricity still has a significant thermal power component, relying entirely on PV is not a robust solution. Therefore, a balanced approach that integrates PV with grid support is essential to ensure reliability while gradually transitioning toward cleaner energy sources.

Due to infrastructural constrains real time data of EV driving cycles based on seasonal variations are not available.

6.3. Future scope

Optimizing charging station placement is crucial for minimizing energy losses, improving grid efficiency, and ensuring sustainable EV integration. Future research directions include leveraging AI-driven optimization, renewable energy integration, dynamic load management, and economic feasibility studies. These advancements will contribute to a smart, efficient, and resilient EV charging infrastructure.

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PUBLICATIONS

[1] S.Das, S. Modi, S. Bera, R. Dutta "Optimal Scheduling of Plugin Electric Vehicles Considering Seasonal Uncertainty," International Conference on Recent Innovations in Energy Management and Renewable Resources, Springer LNEE, 2024 **(**IEMRE 2024) (**presented**)

[2] S. Das, S. Bera, S. Modi, R. Dutta, "Electric Aircraft Charging: Current Status, Evolving Trends, and Hurdles", IEEE North-East India International Energy Conversion Conference and Exhibition (**communicated**)


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Certificate Of Presentation

Optimal Scheduling of Plugin Electric Vehicles Considering Seasonal Uncertainty

Sourav Das[1*] and Soumyadeep Bera[1], Rupali Dutta[1] and Shruti Modi[1]

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Abstract. The optimal scheduling of Plug-in Electric Vehicles (PEVs) in power systems is crucial for balancing grid demands, enhancing energy efficiency, and supporting renewable integration. In this paper a model for the optimal scheduling of PEVs by incorporating seasonal uncertainties, which impact both energy generation and consumption patterns. Seasonal variations in temperature, daylight hours, create significant fluctuations in electricity demand and supply, posing challenges to effective PEV integration. This paper considers these seasonal factors in the scheduling process to mitigate the risks associated with demand-supply mismatches and reduce operational costs. By leveraging stochastic optimization techniques, i.e., differential evolution (DE), the proposed model ensures robust scheduling that minimizes cost of charging across different seasons. Results from case studies show that the model effectively enhances grid stability, reduces reliance on fossil fuel-based power, and achieves cost savings. This work provides insights into improving the resilience of grid systems in economic manner with high PEV penetration and varying seasonal conditions, thus contributing to the development of sustainable energy systems.

Keywords: Seasonal uncertainty, charging, G2V, V2G, scheduling, soft computing

1 Introduction

1.1 Background

The rapid growth of Plug-in Electric Vehicles (PEVs) in the transportation sector is reshaping the power grid's dynamics, offering potential benefits like reduced emissions and decreased reliance on fossil fuels. However, PEV integration into the grid requires careful planning to manage the substantial demand fluctuations that come with

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