Optimal Scheduling of Plugin Electric Vehicles Considering Seasonal Uncertainty

Project report submitted for the partial fulfilment of the requirements for the degree of

BACHELOR OF TECHNOLOGY

Submitted by

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West Bengal
2024

CERTIFICATE

This is to certify that project report on "**Optimal Scheduling of Plugin Electric Vehicles Considering Seasonal Uncertainty**" is submitted in partial fulfilment of the requirement for the degree of Bachelor of Electrical Engineering by the following students.

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We would like to take this opportunity to extend our gratitude to the following revered persons without whose immense support, completion of this project would not have been possible. We are sincerely grateful to our advisor Prof. (Dr.) Sourav Das of the Electrical Engineering department, IEM Kolkata, for his/her constant support, significant insights and for generating in us a profound interest for this subject that kept us motivated during the entire duration of this project. We would also like to express our sincere gratitude to Prof. Dr. Satyajit Chakrabarti (Director, IEM), Prof. Dr. Arun Kumar Bar (Principal, IEM) and Prof. Dr. Subhajit Kar, HOD of Electrical Engineering Department and other faculties of Institute of Engineering & Management, for their assistance and encouragement. Last but not the least, we would like to extend our warm regards to our families and peers who have kept supporting us and always had faith in our work.

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ABSTRACT

In the era of globalization, Electric Vehicle (EV) smart charging is grabbing attention because it may put impact on the distribution network. This smart charging includes the coordination of Grid to Vehicle (G2V) and Vehicle to Grid (V2G). This scheduling is strongly correlated with the EV driving cycles, which includes daily mileage of EV, its each trip length for rides, its All-Electric Range, Battery capacity and so on. How the battery capacity of EV highly dependent on the specific density of the battery. This may differ due to the change in ambient temperature. Hence, it is very obvious that due to the seasonal changes, the battery may behave in different manner. Hence, the scheduling pattern for each EV may differ. In this paper, the variation of the charging coordination and its related variation in cost of charging has been observed. Moreover, to optimize the cost of charging, a recent soft computing technique has been applied. Later, a general conclusion has been made regarding the selection of season for better charging coordination.

Keyword: Charging scheduling, Electric Vehicles, seasonal uncertainty, Optimization, Vehicle to Grid (V2G), grid to vehicle (G2V)

Table of Contents

Chapter 1: Introduction

1.1 About Electric Vehicles: National and International Scenario

1.1.1 National Scenario (India):

- **EV Market Growth**: Indian EV market is gaining speed with the help of incentives from the government through its Faster Adoption and Manufacturing of Hybrid and Electric Vehicles (FAME) program. The size of the EV market was at USD 3.2 billion in 2022 and is expected to be at USD 14.5 billion by 2030.
- **EV Sales**: As many as 1 million EVs were sold in 2023 in India. Two-wheelers top the sales followed by electric cars and buses. Popular models include Tata Nexon EV, MG ZS EV, BYD Atto 3.
- **Charging Infrastructure**: India has a target of setting up over 46,000 EV charging stations by 2030. However, the infrastructure is still evolving, and challenges like uneven geographical distribution exist. India sets a target of more than 46,000 EV charging stations by 2030, but the infrastructure still needs to develop and work through issues such as uneven geographical distribution.

1.1.2 International Scenario:

- **Global EV Market**: The global EV market exceeded 10 million units in 2023, led by China (60% market share), Europe, and the USA.
- **Policies and Incentives**: Countries like Norway have achieved over 80% EV penetration due to aggressive policies, tax benefits, and subsidies.
- **Key Players**: Tesla, BYD, Volkswagen, and Hyundai are leading global EV manufacturers. Notable models include Tesla Model 3, BYD Dolphin, and VW ID.4.

1.2 Charging Scheduling

Charging scheduling involves managing when and how electric vehicles are charged to optimize energy usage, minimize grid impact, and reduce costs for users.

1.2.1 Correlation between EV and Charging Scheduling:

- **Grid Impact**: Unscheduled charging can lead to peak load problems, grid instability, and higher electricity costs.
- **Battery Health**: Proper scheduling ensures optimal charging patterns, reducing battery degradation.
- **User Needs**: Smart scheduling meets the energy demands of EV users without compromising their driving needs.

1.2.2 G2V (Grid-to-Vehicle):

In G2V mode, energy flows from the grid to the EV for charging. Smart scheduling ensures that EVs are charged during off-peak hours when electricity tariffs are lower.

1.2.3 V2G (Vehicle-to-Grid):

In V2G mode, EVs act as energy storage devices, sending power back to the grid during peak hours. This helps stabilize the grid and reduces overall energy costs.

1.3 Impact of Seasons on Charging Scheduling

Seasons significantly influence EV driving patterns and charging requirements due to variations in weather conditions:

1.3.1 Summer: Increased use of air conditioning leads to higher energy consumption, requiring more frequent charging. Charging stations may experience peak demand.

1.3.2 Winter: Heating systems consume significant energy, reducing range. Batteries are also less efficient in cold temperatures, necessitating more charging.

1.3.3 Monsoon: Slower traffic and adverse road conditions may lead to lower energy consumption per kilometer but longer charging durations due to reduced vehicle speeds.

Optimal scheduling must consider these seasonal impacts to ensure efficient charging and grid stability.

Chapter 2: Literature Survey

Some literature surveys have been conducted to explore the opportunities and challenges posed by Vehicle-to-Grid (V2G) technologies. In paper [2], the authors analysed the potential of V2G to stabilize power grids and support the integration of renewable energy sources. However, the study primarily focused on the technical feasibility of V2G without delving into its economic impact. This limitation restricts the scope of understanding regarding the full implications of large-scale adoption of V2G technology. The absence of economic considerations makes it difficult to fully assess the financial and infrastructure challenges associated with implementing V2G on a wide scale.

In paper [4], Yilmaz and Krein (2013) reviewed the effects of V2G on distribution systems and utility interfaces. They emphasized the importance of proper scheduling to avoid overloading the grid, which is essential for maintaining grid stability. While their study provided valuable insights into the technical challenges, it lacked comprehensive strategies for managing simultaneous Grid-to-Vehicle (G2V) and V2G operations. This creates a gap in understanding how to effectively integrate charging and discharging systems without compromising either grid efficiency or vehicle performance.

In paper [7], the authors proposed coordinated charging strategies for Plug-In Hybrid Electric Vehicles (PHEVs) to reduce system losses. Their work focused mainly on G2V operations and did not explore the potential of V2G applications. Although their research contributed to the understanding of energy efficiency in PHEV charging, it did not address the role of V2G in minimizing system losses. This highlights an area for further exploration, as the potential of V2G to contribute to grid stability and energy savings has yet to be fully examined.

In paper [9], the authors examined the financial viability of V2G technology, focusing on its potential to generate revenue through ancillary services, such as frequency regulation and grid support. While their study highlighted the economic potential of V2G, it lacked practical implementation details for scaling V2G technology. This gap suggests the need for further research into the real-world feasibility of monetizing V2G capabilities. Without concrete implementation frameworks, the broader economic benefits of V2G remain uncertain.

In paper [12], the authors developed scheduling algorithms aimed at optimizing resource allocation for PEV charging in shared parking lots. While their work laid the groundwork for efficient scheduling, it did not incorporate dynamic electricity pricing or grid constraints—both of which are crucial for maximizing the benefits of V2G. The absence of these factors leaves room for further refinement of scheduling strategies to better align with grid demands and improve the overall efficiency of energy distribution.

In paper [13], the authors presented a stochastic optimization strategy for scheduling PEVs in a manner that minimized load variance in regional grids. Their approach effectively smoothed out load curves and reduced strain on the grid. However, the study did not address the costs associated with battery degradation in V2G operations, which is a critical factor for the long-term sustainability of the technology. This oversight indicates that further research is needed to balance grid benefits with the impact on vehicle batteries, as prolonged use of V2G could lead to significant battery wear and reduced lifespan.

2.1 Drawbacks of Existing Studies

One of the key drawbacks is the primary focus on the technical feasibility of V2G, often without addressing its economic impact. This limitation makes it difficult to fully assess the financial and infrastructure challenges that come with large-scale implementation of V2G technology. Without considering the economic factors, it becomes challenging to evaluate the real costs and potential revenue generation from V2G systems. Another issue is the lack of comprehensive strategies for managing both Grid-to-Vehicle (G2V) and V2G operations simultaneously. This gap leaves uncertainty about how to integrate both systems effectively without compromising grid efficiency or vehicle performance.

Furthermore, many studies fail to explore the potential benefits of V2G applications, particularly in minimizing system losses, which restricts their relevance to modern energy systems that demand more dynamic two-way energy flows. Another drawback is the absence of practical implementation details for scaling V2G technology. While its economic potential is often discussed, the lack of concrete frameworks makes it difficult to assess its real-world feasibility and profitability. Additionally, several studies do not incorporate dynamic electricity pricing or grid constraints in their scheduling algorithms, which are crucial for optimizing V2G operations. This oversight makes the proposed solutions less adaptable to the complexities of modern energy markets and grid demands.

Lastly, a significant gap is the failure to address the costs associated with battery degradation in V2G operations, which is a critical concern for the long-term sustainability of the technology. Prolonged use of V2G could lead to significant wear on vehicle batteries, reducing their lifespan and affecting both vehicle owners and the broader economic viability of V2G systems.

Chapter: 3: Work Done 1

3.1 Motivation:

The motivation for our project comes from the increasing need for efficient EV integration within the power grid. As EVs become more popular, effective charging strategies are required to prevent excessive load on the distribution network. Traditional charging stations and scheduling strategies do not adequately account for:

- **Active Power Loss Minimization**: Existing literature mostly installs EV charging stations without focusing on active power loss reduction in the network.
- **Geographic Constraints**: Some studies consider geographic factors, but without analyzing driving patterns and load uncertainties.
- **Uncontrolled Charging**: Many studies lack optimized charging schedules, leading to increased peak loads and inefficient use of grid resources.

This project addresses these gaps by optimizing the location and scheduling of EV charging, minimizing power losses, and taking into account EV driving patterns across seasons.

3.2 Objective:

- **Optimal Scheduling of EV Charging**: Develop a charging schedule that considers grid-to-vehicle (G2V) and vehicle-to-grid (V2G) modes to reduce overall charging costs while considering seasonal driving patterns and battery lifecycle constraints.

3.3 <u>Problem Formulation:</u>

The problem formulation includes defining the objective functions, energy equations, and constraints to optimize both the placement and scheduling of EV charging stations.

3.3.1 Objective Function:

- Minimize total charging cost:

$$min(C) = \sum(C_{charging} + C_{discharging}) \tag{3.1}$$

where:

- $C_{charging}$ represents the cost of charging in G2V mode.
- $C_{discharging}$ accounts for the cost savings in V2G mode.

3.3.2 Energy Equations:

- Battery degradation cost for each kilowatt-hour (kWh) charged or discharged:
- $C_{degradation}$= α × E × DOD × L
  where:
  - α is the cost coefficient.
  - *E* is the total energy discharged by the EV.
  - *DOD* is the depth of discharge.
  - *L* is the battery lifecycle at a particular DOD.

3.3.3 Constraints

- **Battery Constraints**:
  Battery State of Charge (SOC) must be within limits:
  $SOC_{min} \leq SOC \leq SOC_{max}$

- **Power Constraints**:
  Charging power cannot exceed the maximum rated power for the charging station.
- **Seasonal Driving Pattern Constraints**:
  Distance and energy consumption are constrained based on seasonal driving patterns (e.g., higher consumption in winter due to heating).
- **Grid Constraints**:
  Ensure that the grid load remains within safe operational limits to avoid overloading during peak hours.

3.4 **<u>Solution Strategy</u>:** Differential Evolution (DE) Algorithm

Differential Evolution (DE) is a metaheuristic optimization algorithm that is effective for complex, non-linear problems. It is particularly suitable for optimizing the placement and scheduling of EV charging stations due to its ability to handle multiple objectives and constraints.

Differential Evolution Algorithm Steps:

1. **Initialize Population**: Generate an initial population of candidate solutions. Each solution includes possible charging station locations and charging schedules.
2. **Mutation**: For each solution (target vector), create a mutant vector by combining three randomly selected, different vectors from the population. The mutation formula is

   $$V_i = X_a + F.\,(X_b - X_C) \qquad (3.2)$$

   where:
   - V_i is the mutant vector for individual i
   - X_a ,X_b and X_c are randomly selected individuals.
   - F is the scaling factor, a constant that controls the amplification of differential variations.
3. **Crossover**: Combine the mutant vector with the target vector to create a trial vector. For each component of the vector:

   $$U_i = \begin{cases} V_i\,;\ if\ rand\ < C_r \\ X_i\,;\ otherwise \end{cases} \qquad (3.3)$$

   Where:
   - U_i is the trial vector.
   - C_r is the crossover probability.
4. **Selection**: Evaluate the fitness of the trial vector and compare it to the target vector. If the trial vector has a lower cost (or better fitness), it replaces the target vector in the next generation.
5. **Repeat**: Continue mutation, crossover, and selection steps until a termination criterion (such as a maximum number of generations or minimum cost threshold) is met.

DE Algorithm Pseudocode:

```
Initialize population with random candidate solutions
Evaluate fitness of each solution

while termination criterion not met do
   for each solution Xi in population do
      Select three random solutions Xa ,Xb and Xc
      Create mutant vector

                    Vi = Xa + F. (Xb − Xc)

      Create trial vector Ui by crossover of Vi and Xi
      Evaluate fitness of trial vector Ui

      if fitness (Ui) < fitness (Xi) then
         Replace Xi with Ui
      end if
   end for
end while
Return best solution found
```

In paper [14] by R. Storn and K. Price introduces the Differential Evolution (DE) algorithm. It explains how DE is designed for optimizing nonlinear and non-differentiable continuous functions. The study highlights the algorithm's simplicity and effectiveness, with step-by-step descriptions of its mutation, crossover, and selection mechanisms, making it a foundational work in the field of evolutionary computation.

In paper [15] extends DE to address multiobjective optimization problems. It incorporates "speciation," a technique to handle multiple peaks in the objective space, ensuring diverse and robust solutions while respecting constraints. The research emphasizes applications in engineering and other fields requiring optimization across multiple conflicting objectives

This DE algorithm can be applied to optimize the placement and scheduling of EV charging stations, considering factors like seasonal variations in EV driving patterns, grid constraints, and energy costs.

3.5 Input Data & Test Cases:

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

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

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.

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

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 NO 3. 1: This table shows the mean and standard deviation values considered for all the driving cycles for three seasons

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
	FirstTrip 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 NO 3.2 : 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%

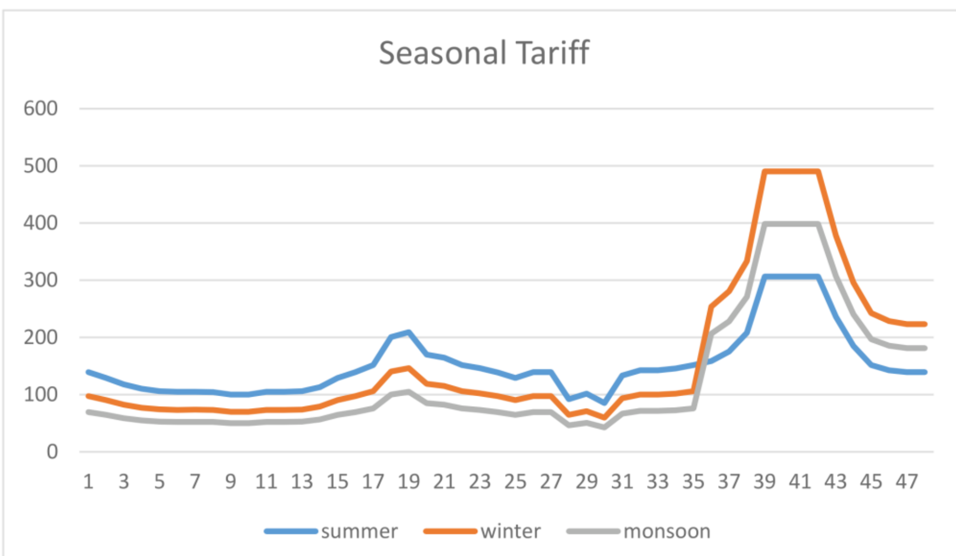


Fig. 3.1 : Seasonal Tariff

From the figure Fig 3.1, we can infer the following key points:

Seasonal Impact on Tariff: Tariffs vary significantly across the three seasons. The **summer tariff** shows a steady increase due to higher energy demand, likely driven by cooling needs. In contrast, the **winter tariff** exhibits a steep rise, indicating heavy grid usage, potentially due to heating requirements. The **monsoon tariff**, while lower initially, increases steadily, reflecting moderate energy demands but may include grid reliability adjustments during adverse weather conditions.

Energy Demand and Cost Correlation: The steep rise in tariffs, especially in winter, suggests that increased energy consumption directly impacts pricing. For EV charging, this emphasizes the importance of optimal scheduling to mitigate costs.

Optimal Charging Opportunities: **Monsoon** offers the most cost-effective charging periods due to lower tariffs, whereas **winter** requires strategic scheduling to avoid peak rates. Summer tariffs, though rising, allow for better predictability in planning.

These insights highlight the significance of incorporating seasonal variations into EV charging strategies, ensuring economic efficiency and grid stability.

3.6.1 For Summer:

High Battery Capacity (HBC)

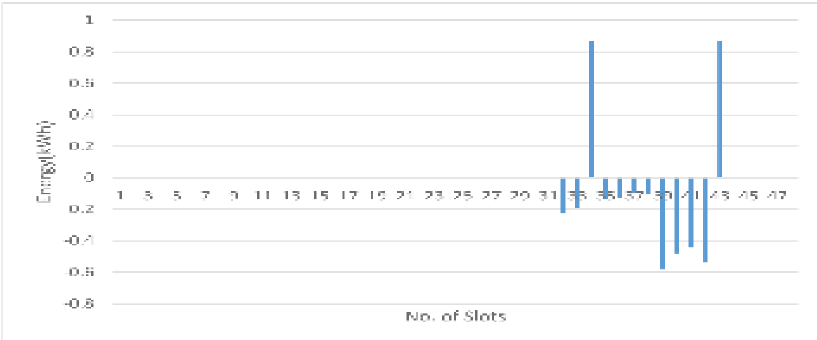


Fig. 1a. Energy Exchange of HBC set of vehicles for 48 slots

Here we can see the energy exchange between grid and vehicle for 48 slots during summer.

The vehicles are undergoing more V2G(discharging) than G2V(charging) even when the tariff rate is high (as we can see from 3.5)

Low Battery Capacity (LBC)

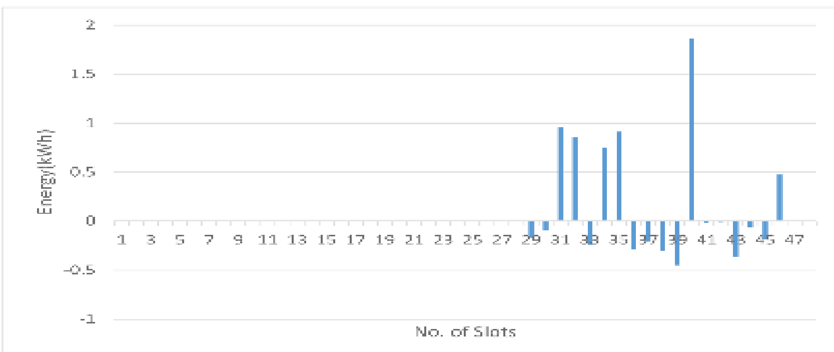
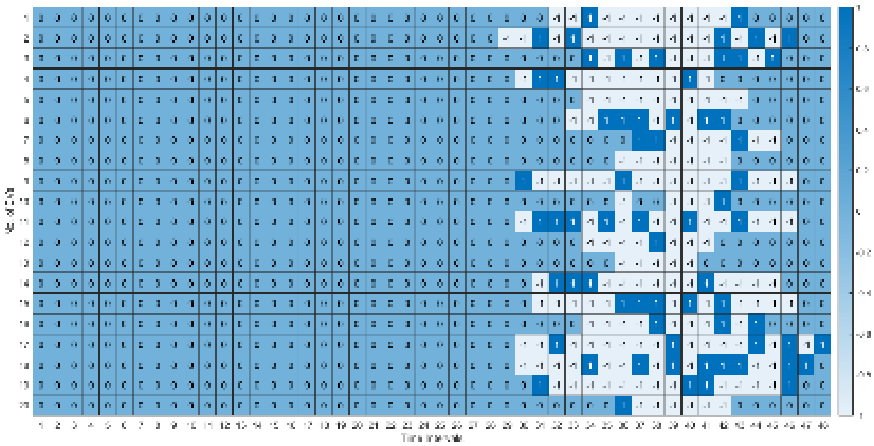
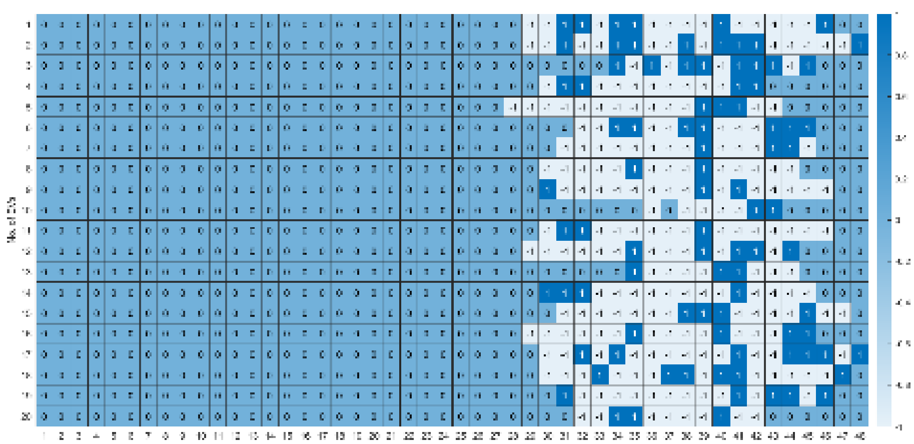


Fig. 1b. Energy Exchange of HBC set of vehicles for 48 slots

Here we can see the energy exchange between grid and vehicle for 48 slots for LBC during summer.

The vehicles are undergoing more G2V(charging) than V2G(discharging).

High Battery Capacity (HBC)

 **Fig. 2a.**. Charging Strategy for HBC set of vehicles considering G2V + V2G	In this charging strategy we can see white spaces are more which shows discharging and the dark blue spaces are less which shows charging.
Low Battery Capacity (LBC)	
 **Fig. 2b.** Charging Strategy for LBC set of vehicles considering G2V + V2G	In this charging strategy we can see dark blue spaces are more which shows charging and the white spaces are less which shows discharging.
High Battery Capacity (HBC)	

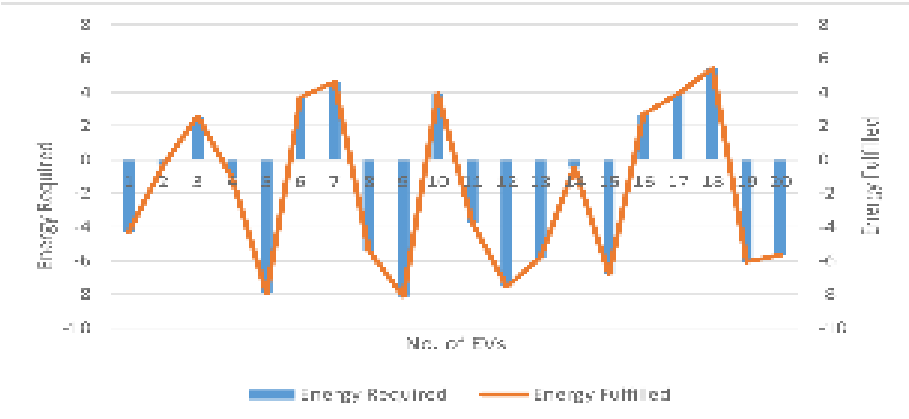


Fig. 3a. Energy Requirement Fulfilment of HBC set of vehicles

We can see from the figure that the energy required by the vehicles has been completely fulfilled with the charging strategies developed for HBC during summer.

Low Battery Capacity (LBC)

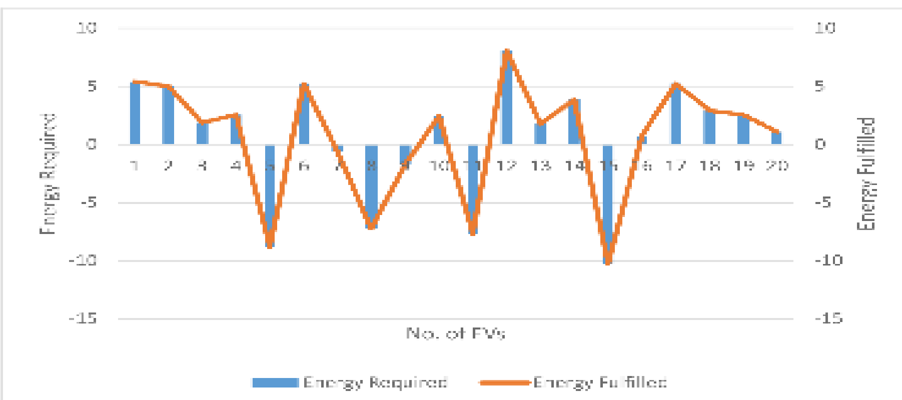


Fig. 3b. Energy Requirement Fulfilment of LBC set of vehicles

We can see from the figure that the energy required by the vehicles has been completely fulfilled with the charging strategies developed for LBC during summer.

3.6.2 For Monsoon

High Battery Capacity (HBC)

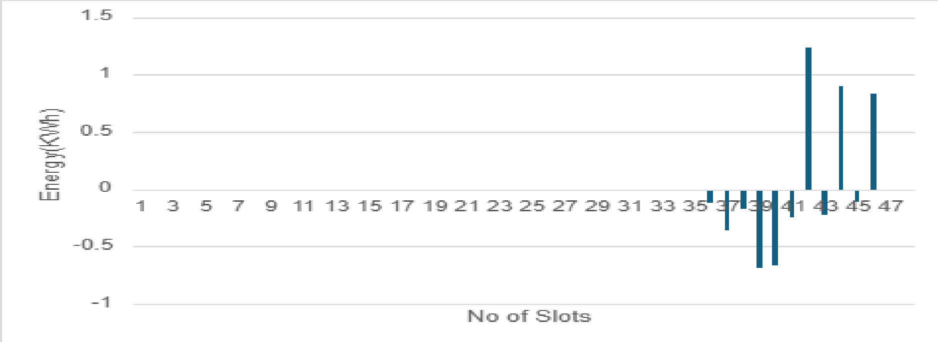


Fig. 1a. Energy Exchange of HBC set of vehicles for 48 slots

Here we can see the energy exchange between grid and vehicle for 48 slots during monsoon

The vehicles are undergoing more V2G(discharging) than G2V(charging) even when the tariff rate is high(as we can see from Fig 3.5)

Low Battery Capacity (LBC)

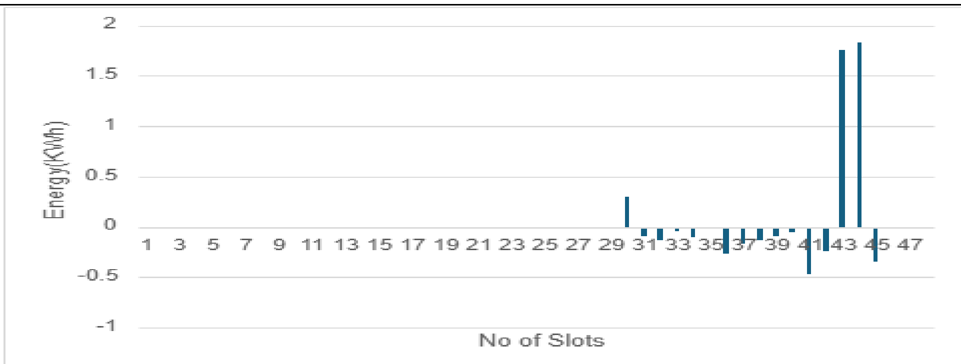


Fig. 1b. Energy Exchange of LBC set of vehicles for 48 slots.

Here we can see the energy exchange between grid and vehicle for 48 slots for LBC during monsoon.

The vehicles are undergoing more G2V(charging) than V2G(discharging).

High Battery Capacity (HBC)

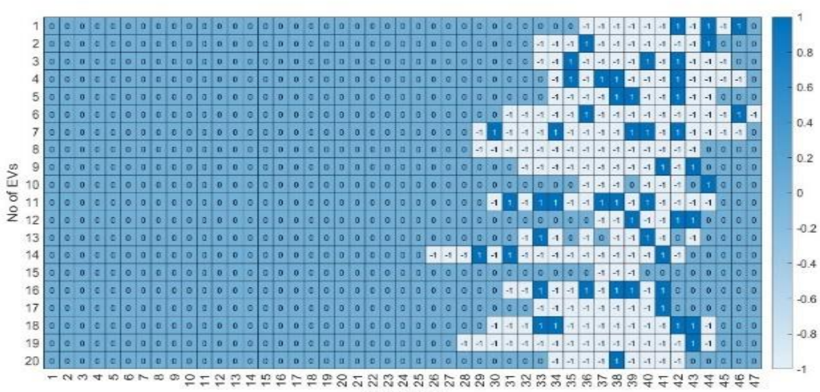


Fig. 2a. Charging Strategy for HBC set of vehicles considering G2V + V2G

In this charging strategy we can see white spaces are more which shows discharging and the dark blue spaces are less which shows charging.

Low Battery Capacity (LBC)

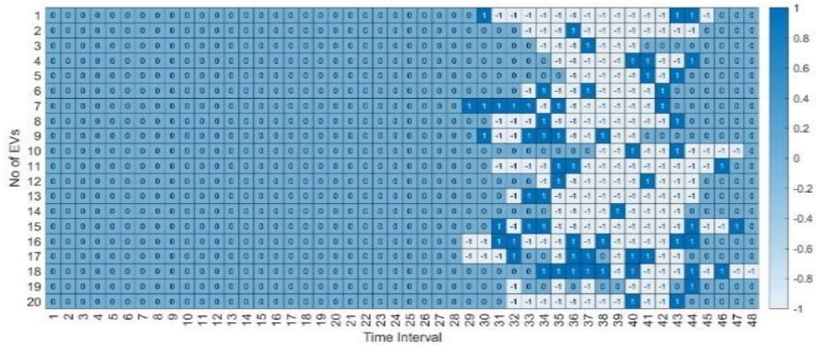


Fig. 2b. Charging Strategy for LBC set of vehicles considering G2V + V2G

In this charging strategy we can see dark blue spaces are more which shows charging and the white spaces are less which shows discharging

High Battery Capacity (HBC)

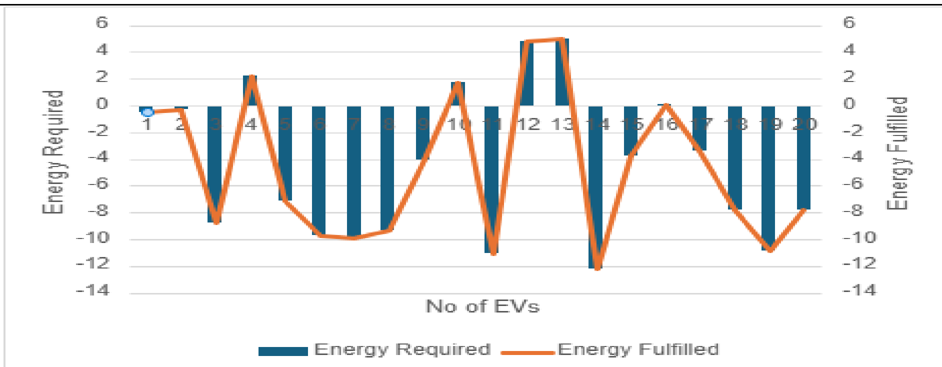


Fig. 3a. Energy Requirement Fulfilment of HBC set of vehicles

We can see from the figure that the energy required by the vehicles has been completely fulfilled with the charging strategies developed for HBC during monsoon.

Low Battery Capacity (LBC)

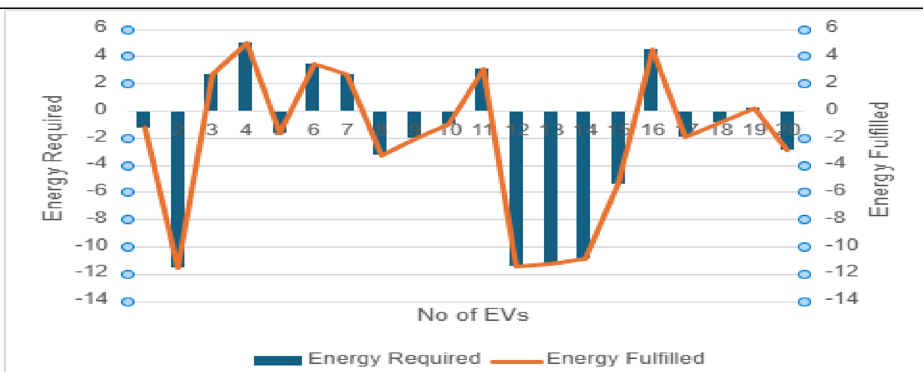


Fig.3b.Energy Requirement Fulfilment of LBC set of Vehicles

We can see from the figure that the energy required by the vehicles has been completely fulfilled with the charging strategies developed for LBC during monsoon.

3.6.2 For Winter

High Battery Capacity (HBC)

Fig. 1a.. Energy Exchange of HBC set of vehicles for 48 slots.

Here we can see the energy exchange between grid and vehicle for 48 slots during winter.

The vehicles are undergoing more V2G(discharging) than G2V(charging) even when the tariff rate is high (as we can see from fig 3.5)

Low Battery Capacity (LBC)

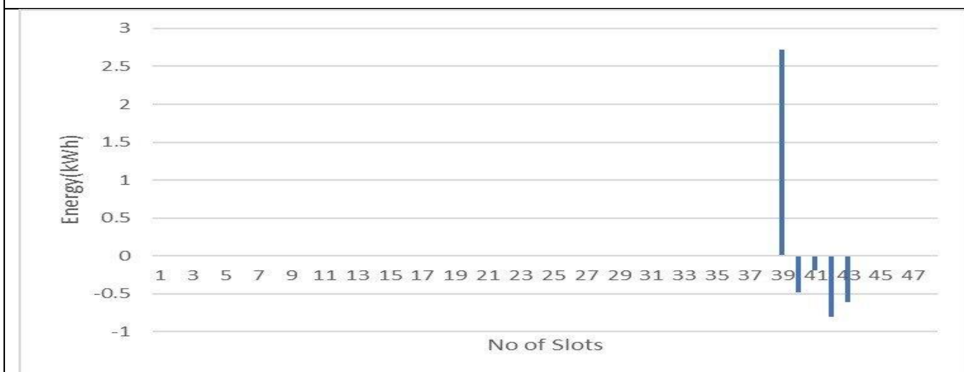


Fig. 1b. Energy Exchange of LBC set of vehicles for 48 slots

Here we can see the energy exchange between grid and vehicle for 48 slots for LBC during winter.

The vehicles are undergoing more G2V(charging) than V2G(discharging).

High Battery Capacity (HBC)

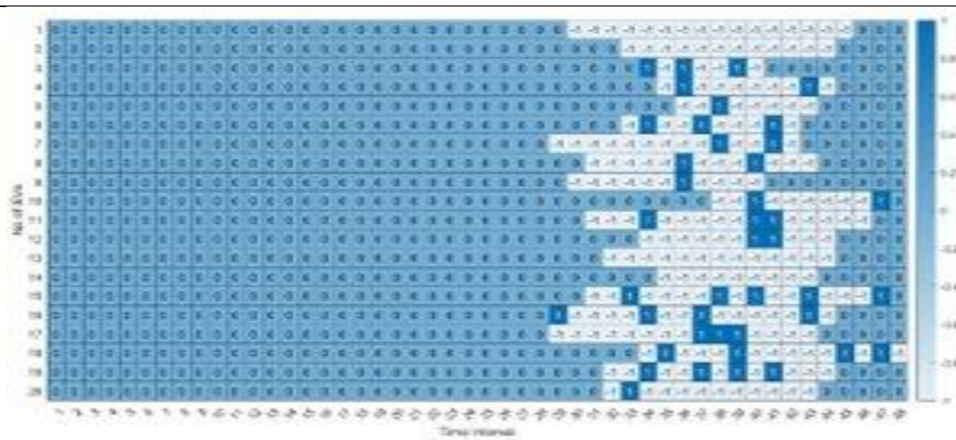


Fig. 2a. Charging Strategy for HBC set of vehicles considering G2V + V2G

In this charging strategy we can see white spaces are more which shows discharging and the dark blue spaces are less which shows charging.

Low Battery Capacity (LBC)

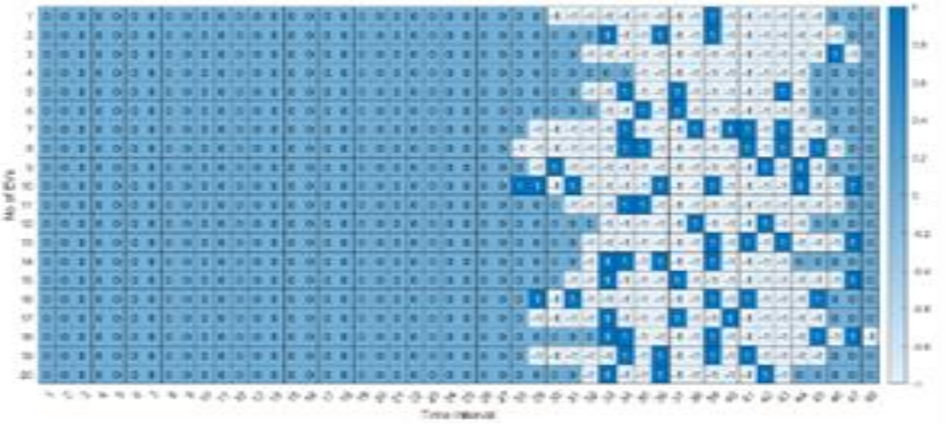
<table>
<tr><td>

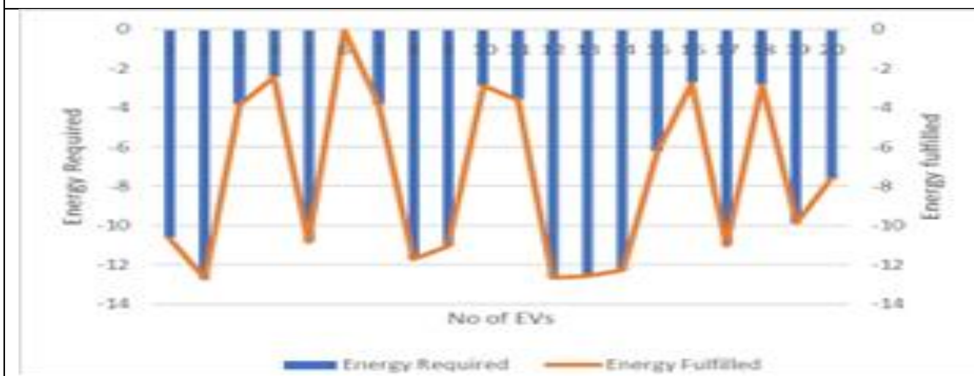
Fig. 2b. Charging Strategy for LBC set of vehicles considering G2V + V2G</td><td>In this charging strategy we can see dark blue spaces are more which shows charging and the white spaces are less which shows discharging</td></tr>
<tr><td colspan="2">High Battery Capacity (HBC)</td></tr>
<tr><td>

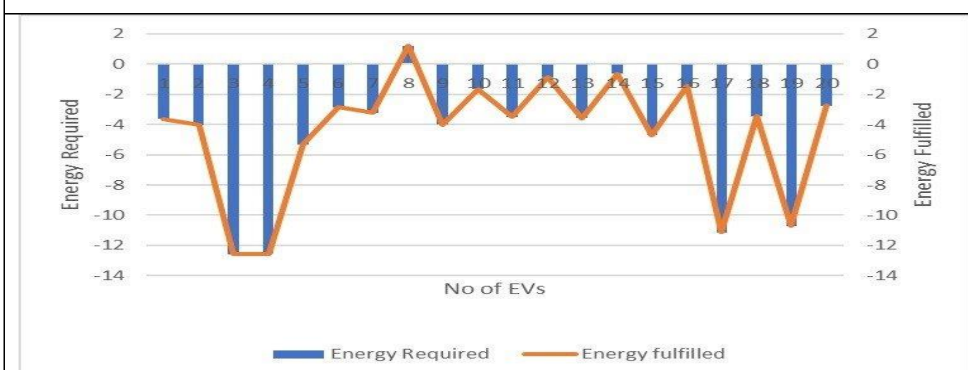
Fig. 3a. Energy Requirement Fulfilment of HBC set of vehicles</td><td>We can see from the figure that the energy required by the vehicles has been completely fulfilled with the charging strategies developed
for HBC during winter.</td></tr>
<tr><td colspan="2">Low Battery Capacity (LBC)</td></tr>
<tr><td>

Fig. 3b. Energy Requirement Fulfillment of LBC set of vehicles</td><td>We can see from the figure that the energy required by the vehicles has been completely fulfilled with the charging strategies developed for LBC during winter.</td></tr>
</table>

Comparison(from graphs)

- From the above graphs we can observe the vehicle undergoes maximum discharging in case of HBC even when we have higher tariff rates
- Secondly among three seasons, maximum V2G is seen in case of winter, followed by monsoon and summer.

3.7 .**Results & Discussion**:

Table No 3.3 Profit or Loss observed for 3 different seasons for HBC and LBC

Seasons	HBC	LBC
Summer	-1.3511	2.2226
Monsoon	-1.2108	0.1271
Winter	-3.5168	1.366

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.

Chapter 4: Conclusion

This project presents a comprehensive approach to optimize the allocation and scheduling of electric vehicle (EV) charging, considering the techno-economic perspectives of grid-to-vehicle (G2V) and vehicle-to-grid (V2G) operations. Through the analysis of seasonal driving patterns, the study addresses the challenges of uncontrolled EV charging, grid instability, and battery degradation. The following key conclusions can be draw. Seasonal variations significantly influence EV driving patterns and energy consumption, necessitating adaptive charging schedules for summer, monsoon, and winter scenarios. Optimized Scheduling: The proposed scheduling framework successfully minimizes charging costs while ensuring grid stability, especially under dynamic electricity pricing. Integrating battery degradation costs into the model ensures longer battery life, reducing overall costs for EV owners. The implementation of V2G strategies and optimal charging station placement enhances grid stability and reduces peak loads**.** By addressing these challenges, this project provides a pathway for efficient EV integration into existing power systems, supporting both energy providers and users in the transition toward sustainable mobility.

Chapter 5: Future Scope

Future research will focus on optimizing the placement of charging stations in distribution systems while ensuring smart charging schedules that minimize energy losses, enhance load balancing, and accommodate the integration of renewable energy sources.

Chapter 6: References

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