Optimal Scheduling of Plugin Electric Vehicles Considering Seasonal Uncertainty

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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 charging schedules. One of the most critical yet often overlooked factors in PEV scheduling is seasonal variation, which directly influences both vehicle usage patterns and energy demand.

Seasonal changes affect driving cycles, as temperature shifts impact vehicle range, battery efficiency, and charging behaviour. In colder seasons, for example, PEVs often experience reduced battery performance and driving range, leading to increased charging frequency. Conversely, warmer seasons may extend driving range but also increase electricity demand due to air conditioning needs. These seasonal impacts create distinct patterns in energy consumption and vehicle utilization, challenging the grid to accommodate changing demands without risking stability or escalating costs.

This study presents a model designed to optimize PEV scheduling by accounting for seasonal uncertainties in driving cycles and charging behaviours. Employing stochastic optimization techniques, particularly differential evolution (DE), the model aims to minimize charging costs while enhancing the grid's ability to handle varying demand. The proposed scheduling strategy demonstrates how adaptive, season-aware planning can improve grid stability and economic efficiency, supporting the integration of PEVs under fluctuating seasonal conditions. This work offers valuable insights into resilient PEV integration, highlighting the importance of seasonal adaptability in advancing sustainable transportation.

1.1 Literature Survey related to the work:

The optimal scheduling of Plug-in Electric Vehicles (PEVs) in power systems has been extensively explored in recent literature, focusing on balancing demand, minimizing costs, and supporting grid stability. Researchers have primarily investigated methods for scheduling PEV charging to alleviate grid stress, integrate renewable energy, and reduce operational expenses. A common approach involves leveraging optimization techniques, with a particular emphasis on managing uncertainties related to energy demand and PEV charging behaviors. However, the effects of seasonal variations on PEV scheduling, including their influence on driving patterns and charging cycles, have been relatively underexplored.

- **Seasonal Impact on PEV Performance and Charging Patterns**

Several studies address the impact of environmental conditions on PEV performance, particularly focusing on how temperature variations affect battery efficiency and range. Research by Fathabadi (2017) highlights that PEVs suffer from decreased battery efficiency and range in colder temperatures, which, in turn, impacts their driving and charging cycles. Similarly, studies by Neubauer et al. (2014) demonstrate that winter conditions can increase energy consumption by as much as 30% due to factors like battery heating and reduced chemical performance at low temperatures. These studies emphasize the need for seasonally adaptive PEV scheduling models that can account for variations in vehicle performance and charging needs throughout the year.

- **Optimization Techniques for PEV Scheduling**

Optimization methods have been central to addressing the complexities of PEV scheduling, particularly in the context of managing demand and minimizing costs. Traditional techniques, such as linear programming (LP) and mixed-integer linear programming (MILP), have been widely used for deterministic scheduling of PEVs. However, these methods may struggle with the uncertainties that characterize seasonal and behavioral variations in PEV usage. Recent studies by Wang et al. (2019) and Luo et al. (2020) have introduced stochastic optimization and heuristic techniques like genetic algorithms (GA) and particle swarm optimization (PSO) to handle uncertainties in charging demands and grid supply constraints more effectively.

Differential Evolution (DE), a robust and adaptable optimization method, has also been applied in PEV scheduling research. Studies by Ali and Khalid (2018) demonstrate that DE is effective in handling multi-objective optimization problems, including the cost, charging time, and grid stability issues associated with high PEV penetration. DE's effectiveness in optimizing complex, multi-dimensional systems suggest it is well-suited for addressing the additional layers of seasonal variability in PEV scheduling.

- **Seasonal Scheduling Models**

Though limited in number, some studies have proposed season-specific scheduling frameworks for PEVs, considering how seasonal demand variations impact grid stability. For instance, studies by Zhou et al. (2021) introduce models that adjust PEV charging patterns based on seasonal demand peaks and troughs, demonstrating that season-aware scheduling can significantly reduce peak load pressures on the grid. This research suggests that seasonally adaptive scheduling could alleviate grid stress and reduce the need for costly energy storage or peaking power plants. However,most existing seasonal models are still rudimentary and do not account for how sea- sonal driving patterns affect PEV charging cycles, pointing to a gap that this study aims to address.

- **Driving Behavior and Seasonal Variability**

PEV driving behavior varies widely across seasons, influenced by factors such as weather, daylight hours, and seasonal travel trends. Research by Mersky et al. (2016) and Lee et al. (2018) finds that PEV usage increases in warmer months when commuting and leisure travel demand rises. In contrast, colder months often see reduced driving ranges and higher frequency of shorter trips, altering charging needs and timing. Seasonal driving trends underscore the necessity of models that can adapt to variations in both driving behaviour and battery performance.

- **Contribution to the Literature**

While previous studies provide valuable insights into PEV scheduling and optimization, few have systematically incorporated seasonal variability in both PEV performance and driving behavior. This research addresses this gap by developing a season-aware scheduling model that optimizes PEV charging cycles in response to fluctuations in seasonal driving patterns and battery performance. By leveraging differential evolution (DE), the proposed model offers a novel approach to minimizing operational costs and grid impacts under seasonal uncertainties, contributing a new dimension to PEV scheduling research. This work extends current methodologies by emphasizing adaptive scheduling as a crucial element in resilient and cost-effective PEV integration, particularly under fluctuating seasonal conditions.

Based on the provided paragraph, the contributions of the paper are as follows:

1. **Development of a Model for Optimal PEV Scheduling:** The paper pre- sents a model designed for the optimal scheduling of Plug-in Electric Vehi- cles (PEVs) that incorporates seasonal uncertainties to balance grid demands and improve energy efficiency.

2. **Consideration of Seasonal Factors:** The model accounts for seasonal variations such as temperature and daylight hours, which significantly impact electricity demand, supply, and PEV usage patterns.
3. **Mitigation of Demand-Supply Mismatches:** By incorporating seasonal variations, the model aims to mitigate the risks associated with demand-supply mismatches in the power system, promoting smoother grid opera- tions.
4. **Use of Differential Evolution (DE) for Optimization:** The study leverages stochastic optimization techniques, particularly differential evolution (DE), to achieve robust and adaptable PEV scheduling across different seasons.
5. **Cost Minimization of Charging:** The model is designed to minimize the cost of PEV charging under seasonal uncertainties, making the integration of PEVs more economically efficient.
6. **Enhanced Grid Stability and Reduced Reliance on Fossil Fuels:** Results from case studies show that the model enhances grid stability and reduces reliance on fossil fuel-based power sources by optimizing the timing and demand of PEV charging.
7. **Economic and Resilient Grid System Improvement:** The work contributes to the development of a resilient and cost-effective grid system by adapting to high PEV penetration under varying seasonal conditions, supporting sustainable energy system goals.

These contributions highlight the novel integration of seasonal adaptability in PEV scheduling, optimization techniques tailored for cost reduction, and the advancement of sustainable grid operation practices.

2 Problem Formulation

2.1 Minimizing the Total Cost of Charging by Considering Uncertainty in EVDriving Cycles

This objective focuses on developing a model that minimizes the overall cost associated with charging Plug-in Electric Vehicles (PEVs) by accounting for variations in driving cycles. The driving cycles of EVs are not constant; they fluctuate based on factors like daily commute patterns, travel frequency, and seasonal conditions. For instance, during colder months, battery efficiency may drop, reducing driving range and increasing the frequency and intensity of charging. Conversely, warmer months may extend the range but also increase usage, potentially impacting charging patterns. By incorporating these uncertainties into the scheduling model, the approach allows for dynamic adjustments in charging schedules that align with the actual usage pat- terns and driving needs. This not only reduces the total cost of charging by avoiding unnecessary charges during peak grid hours but also ensures that the charging process is more cost-effective and responsive to real-world driving behaviors. This type of adaptive scheduling, which anticipates and adjusts to fluctuations in EV driving cy- cles, helps optimize both energy use and costs over time.

2.2 Analyzing Charging Behavior Considering G2V and V2G Modes of Operation with Seasonal Uncertainty

This objective focuses on understanding and optimizing PEV charging and discharg- ing behavior under different seasonal conditions in two primary modes of operation:

- **Grid-to-Vehicle (G2V):** In the G2V mode, PEVs draw power from the grid for charging. The scheduling model takes into account the seasonal varia- tions in electricity demand and supply, adapting the timing and intensity of charging sessions based on seasonal load patterns. For example, in high- demand winter months, the model could schedule charging during off-peak hours to minimize costs and avoid straining the grid. Additionally, seasonal changes in EV driving cycles can affect when and how often G2V charging occurs, which must be factored into the scheduling process to optimizecharging times and reduce grid impact.
- **Vehicle-to-Grid (V2G):** In V2G mode, PEVs can discharge electricity back to the grid, acting as mobile energy storage units. This capability is valuable for stabilizing the grid during periods of high demand or low supply, which often vary with the season. For example, in summer months when energy demand may be high due to air conditioning use, V2G mode can discharge stored energy from PEVs back into the grid, helping balance demand without resorting to additional fossil-fuel generation. By analyzing V2G potential across seasons, the model identifies optimal times for discharging, thereby improving grid reliability and potentially generating revenue or savings for PEV owners.

Incorporating seasonal uncertainty into the analysis of G2V and V2G modes is essen- tial, as it allows the model to dynamically adapt to seasonal changes in both grid de- mand and PEV usage patterns. This holistic approach to charging and discharging behavior ensures that PEVs are integrated into the grid in a way that is economically efficient, grid-supportive, and adaptable to seasonal variations. By optimizing both G2V and V2G operations in response to seasonal shifts, the model enhances grid resilience and cost-effectiveness, promoting sustainable and flexible PEV integration.

3. Problem Formulation

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:

$$min(C) = \sum(C_{charaainaa} + C_{discharaainaa}) \quad (1)$$

where:

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

3.3.2 Energy Equations:

- Battery degradation cost for each kilowatt-hour (kWh) charged or discharged:

$$C_{deaaradation} = \alpha \times E \times DOD \times L \quad (2)$$

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:

$$SOC_{min} \leq SOC \leq SOC_{max} \quad (3)$$

- **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 Solution Strategy: 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

$$V_i = X_a + F.\,(X_b - X_C) \tag{4}$$

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:

$$U_i = \begin{cases} V_i;\ if\ rand < C_r \\ X_i\ ;\ otherwise \end{cases} \tag{5}$$

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 X_a ,X_b and X_c
    Create mutant vector

$$V_i = X_a + F.\,(X_b - X_C) \tag{6}$$

    Create trial vector Ui by crossover of V_i and Xi
    Evaluate fitness of trial vector U_i

    if fitness (U_i) < fitness (X_i) then
      Replace X_i with U_i
    end if
  end for
end while

In paper [14-16] 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 [17-19] 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.

4. 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. In the Table 1 and Table 2, the driving cycles attributes mean and standard deviation has been shown along with the penetration of EV for each of the test cases.

- **Daily mileage** represents the total distance a vehicle travels in a single day, commonly used for tracking fuel consumption, planning maintenance, and optimizing routes [21-23].
- **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 [24].
- **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.

- **Dynamic tariff:** In this paper, since the coordinated charging scheduling has been considered, hence, the dynamic tariff rate is required for the decision making regarding G2V or V2G mode of operation. In this regard, the tariff of summer, monsoon and the winter season has been extracted and shown in Fig. 1 [19]. Since, the EV driving cycles can be varied, hence, it is essential to consider the tariff of each season to check the feasibility of coordinated charging process which includes G2V and V2G mode of operation.

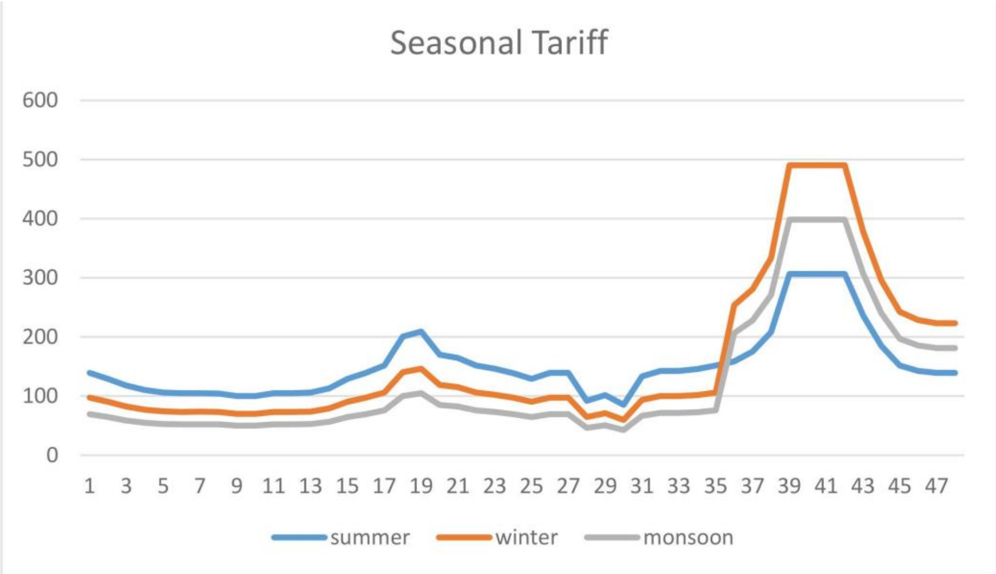

Fig. 1. Dynamic tariff for each season for coordinated charging scheduling

Table 1. This table shows the mean and standard deviation values considered for all the driving cycles for three seasons [20]

Season	Driving Cycle	Mean	Standard Deviation
Summer	Daily Mileage(km)	55	10
	First Trip Distance(km)	18	8.41
	Arrival Time(hrs)	16	1.2
	Departure Time(hrs)	22	1.2
Monsoon	Daily Mileage(km)	41	8
	First Trip Distance(km)	15	5.41
	Arrival Time(hrs)	16	1.2
	Departure Time(hrs)	22	1.2
Winter	Daily Mileage(km)	32	6
	First Trip Distance(km)	11	3.41
	Arrival Time(hrs)	16	1.2
	Departure Time(hrs)	22	1.2

Based on the above driving cycles, two test cases have been formed which are consist of BEV, PHEV 30 and PHEV 40. The two test cases have been designed in such a way that the test case one is dominated by the Higher Battery Capacity (HBC) EVs. On the other hand the Test case 2 is dominated by the lower battery capacity (LBC) EVs. Now how these two test cases will behave to the smart charging scheduling, has been observed for three seasons, such as summer, monsoon and winter respectively. The charging behaviors and its corresponding energy requirement and the satisfaction of energy requirement is possible or not through the charging scheduling or not, has been observed and shown in the next section.

Table 2. Percentage of type of vehicles taken for two test cases: HBC and LBC

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

4.1. Summer season

4.1.1. Charging Scheduling of HBC set of vehicles

In Fig. 2, 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. 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.

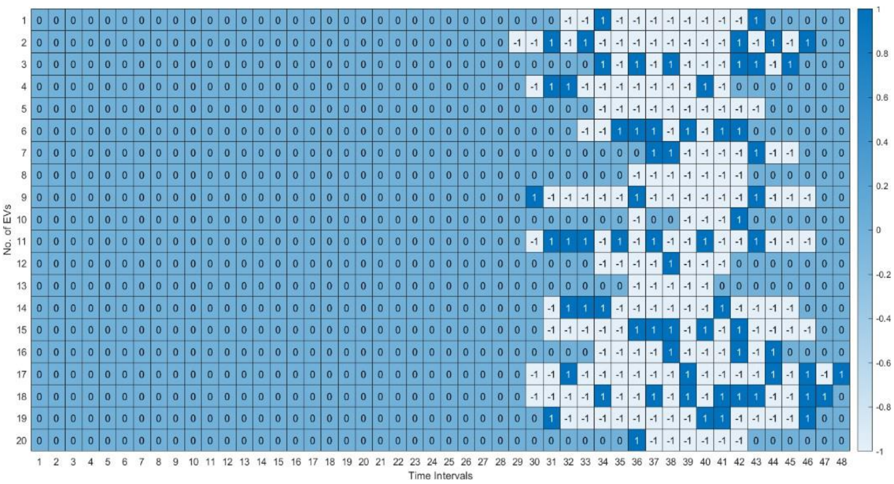

Fig. 2. Charging Strategy for HBC set of vehicles considering G2V + V2G

4.1.2. Charging Scheduling of LBC set of vehicles

In Fig. 3., 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.

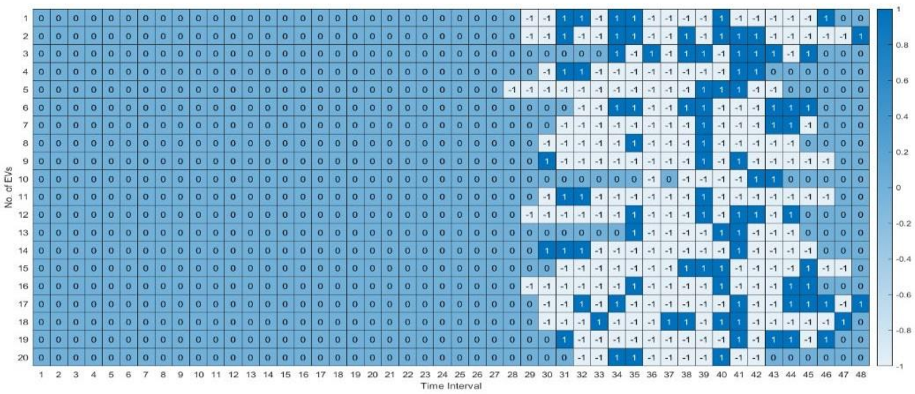

Fig. 3. Charging Strategy for LBC set of vehicles considering G2V + V2G

4.1.3. Energy requirement fulfilment of HBC set of vehicles

In Fig.4. 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.

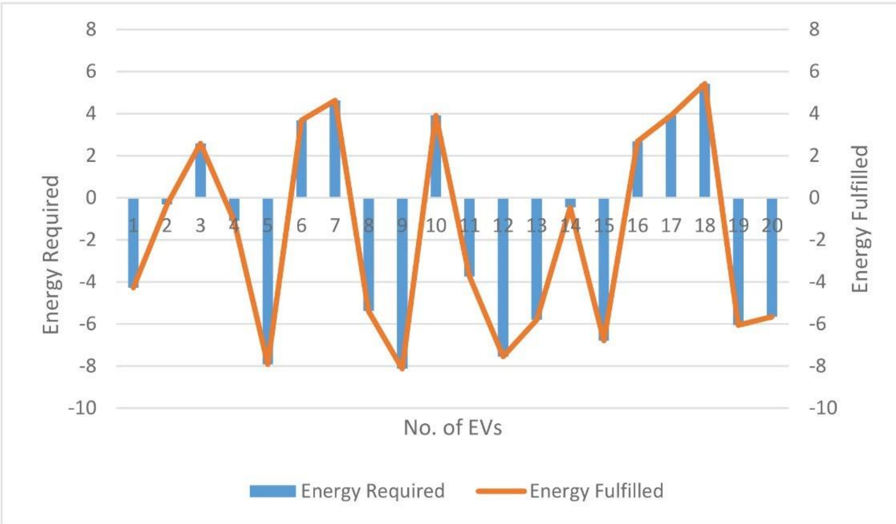

Fig.4. Energy requirement fulfilment of HBC set of vehicles

4.1.4. Energy requirement fulfilment of LBC set of vehicles

Fig.5. 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 in Fig. 3, it 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.

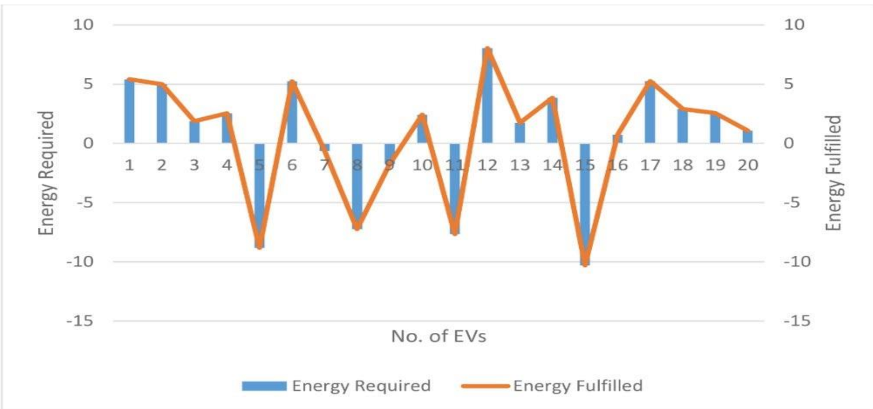

Fig. 5. Energy requirement fulfilment of LBC set of vehicles

4.2. Monsoon season

4.2.1. Charging Scheduling of HBC set of vehicles

In Fig.6, 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.

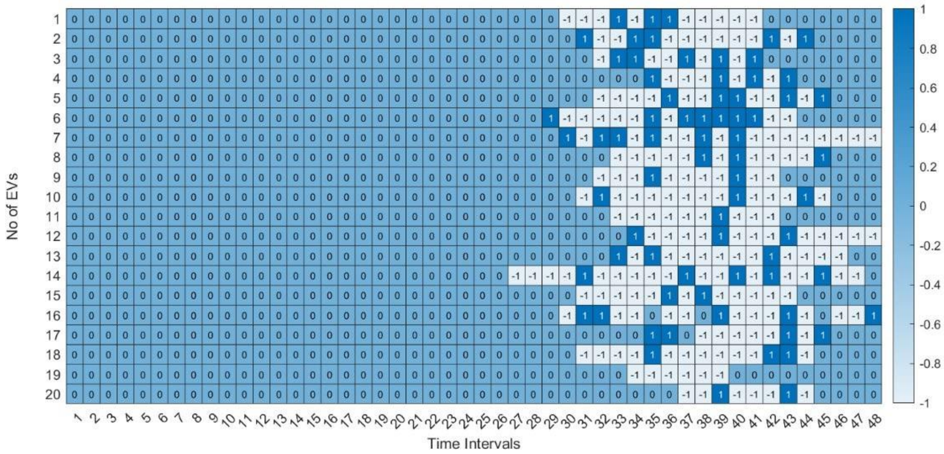

Fig. 6. Charging Strategy for HBC set of vehicles considering G2V + V2G

4.2.2. Charging Scheduling of LBC set of vehicles

In Fig.7, 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.

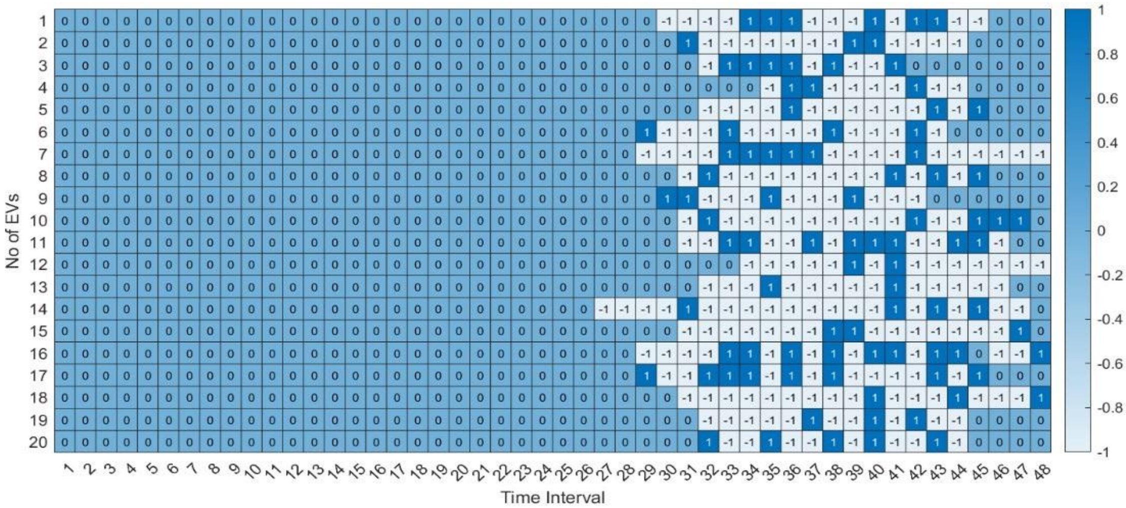

Fig. 7. Charging Strategy for LBC set of vehicles considering G2V + V2G

4.2.3. Energy requirement fulfilment of HBC set of vehicles

Fig.8. 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.

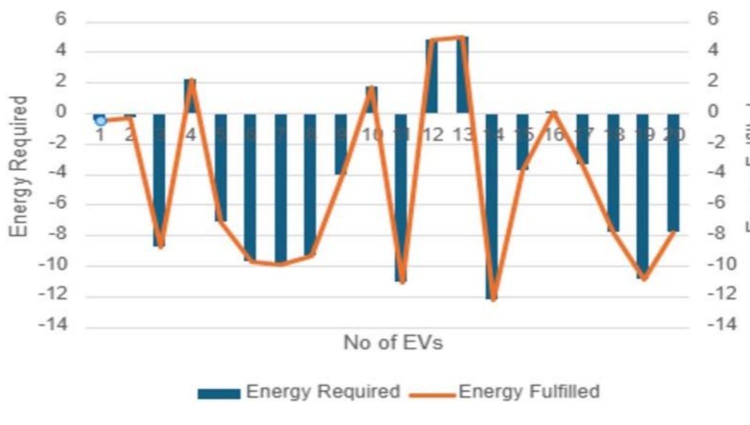

Fig. 8. Energy requirement fulfilment of HBC set of vehicles

4.2.4. 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. 9. demonstrates that the energy demand of the vehicles has been completely met using the charging strategies developed for LBC set of vehicles during monsoon.

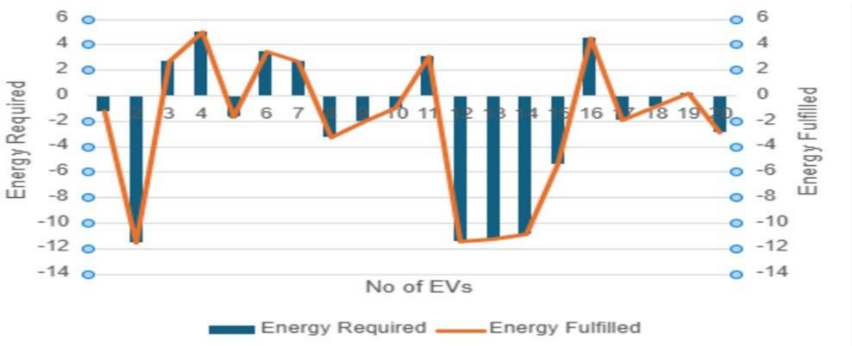

Fig. 9. Energy requirement fulfilment of LBC set of vehicles

4.3. Winter Season

4.3.1. Charging Scheduling of HBC set of vehicles

In fig 10. 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.

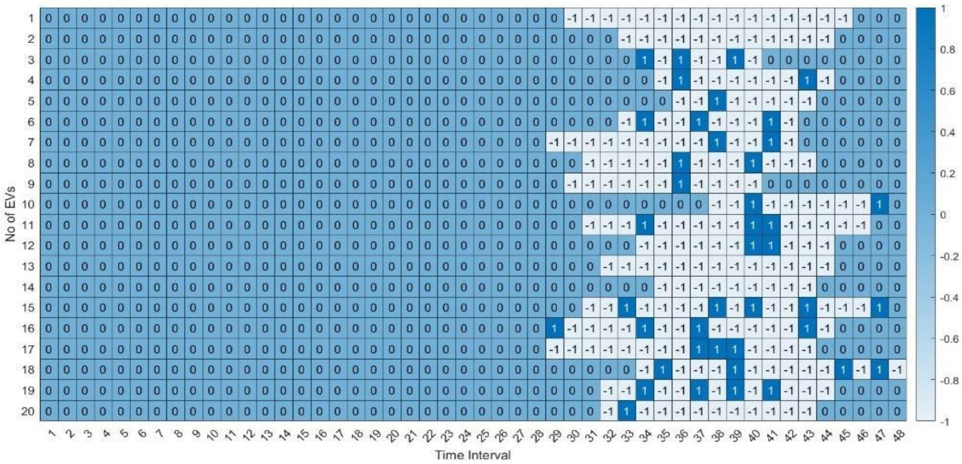

Fig. 10. Charging Strategy for HBC set of vehicles considering G2V + V2G mode

4.3.2. Charging Scheduling of LBC set of vehicles

In Fig.11, 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.

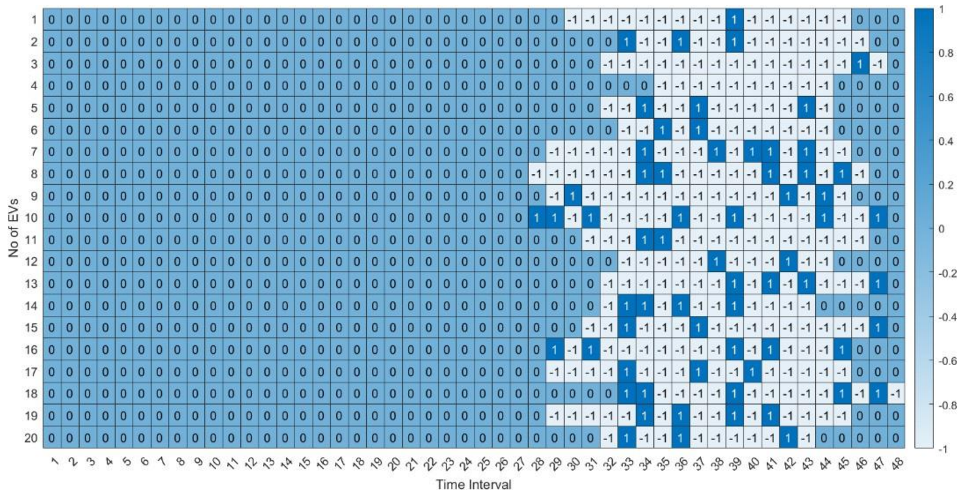

Fig. 11. Charging Strategy for LBC set of vehicles considering G2V + V2G

4.3.3. Energy requirement fulfilment of HBC set of vehicles

Fig. 12. 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

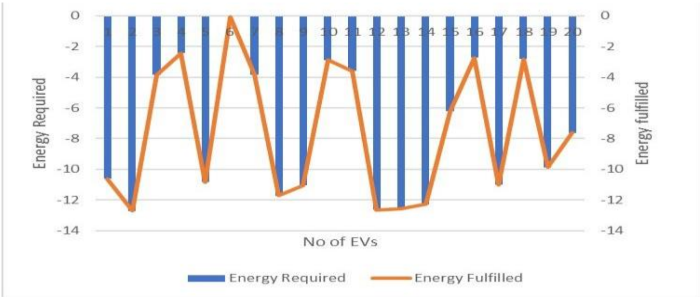

Fig. 12. Energy requirement fulfilment of HBC set of vehicle

4.3.4. Energy requirement fulfilment of LBC set of vehicles

Fig.3.4. demonstrates that the energy demand of the vehicles has been completely met using the charging strategies developed for LBC set of vehicles during monsoon.

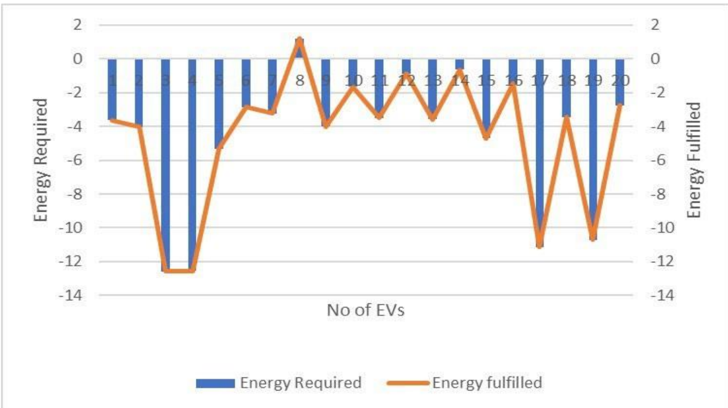

Fig.3.4. Energy requirement fulfilment of LBC set of vehicles

4.4. 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 more participation in V2G mode of operation, the profit is more.

Table 3. cost of charging for EVs for all three seasons.

SEASON	Cost for HBC EVs (S$)	Cost for LBC EVs (S$)
Summer	**-1.3511**	**2.2226**
Monsoon	**-1.2108**	**0.1271**
Winter	**-3.5168**	**1.3660**

5. 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.

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