Charging scheduling of Electric Vehicles(V2G-G2V) incorporating Real Time Tariff considering Smart Grid

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By

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DECLARATION

We hereby certify that the work, which is being presented in the report/thesis, entitled V2G and G2V charging scheduling using multilevel optimisation, in fulfillment of the requirement for the award of the degree of Bachelor of Technology and submitted to the institution is an authentic record of my/our own work carried out during the period May-2024 to July-2024 under the supervision of Dr. Avadh Kishor . We also cited the reference about the text(s)/figure(s)/table(s) from where they have been taken.

Dated: **Signature of the candidate**

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Dated: **Signature of supervisor**

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Harsh Sharma

Abstract

Abstract: The distribution system's load demand is rising as a result of the automotive industry's recent adoption of electric cars (EVs). It is necessary to enhance charging management in order to handle this load requirement. Even yet, it takes an EV several hours to fully charge. The promotion of electric cars (EVs) over conventional automobiles is heavily reliant on reducing energy consumption and charging times. Prior to meeting the energy requirement, it is important to take into account how the itineraries may impact the EV's energy usage. This article treats the task of matching appropriate charging stations (CS) to specific electric vehicles (EVs) as an optimisation issue.The correct assignment of CS, a linear optimisation problem, is covered in the first section, and the charge scheduling problem is covered in the second. Henry gas solubility optimisation is integrated with dynamic charing rates to reduce the overall daily cost incurred by the CS operator. The robustness of HGSO along with the dynamic charing rates is evaluated and confirmed using the Wilcoxon signed rank test.

Keywords: *Charging stations (CS), distribution system, electric vehicle (EV), optimizations,Real time tarrif(RTT),Electric vehicle supply equipment(EVSE).*

Contents

List of Figures

List of Tables

List of Acronyms

EV	Electirc Vehicle
CS	Charging Station
CSO	Charging Station Operator
G2V	Grid to Vehicle
V2G	Vehicle to Grid
HGSO	Henery Gas Solubility Optimisation
ILPP	Integer Linear Programming Problem
PEM	Point Estimation Method
ORV	Output Random Variable
IRV	Input Random Variable
RTT	Real Time Tarrif
PEV	Plug in Electric Vehicles
SOC	State of Charge
WSRT	Wilcoxon Signed Rank Test
DOD	Battery's deapth of Discharge
ETL	Ensuing Trip Length

1

Introduction

This chapter offers an overview of the subject matter by presenting background information on need of EVs

1.1 Introduction

In this age of globalization, the usage of internal combustion (IC) engine vehicles has a massive negative impact on the environment. The problems with fossil fuel-powered vehicles (FFPVs) are as follows:

Fossil fuels are a scarce resource. Spilling of oil may be hazardous. It is very expensive nowadays. Therefore, in recent times, due to the cheaper rate of electricity and zero pollution features, Electric Vehicles (EVs) are gaining significant attention. EVs are much more reliable and require less maintenance than FFPVs. EVs also offer quiet and smooth driving features. Among various types of EVs, Plug-in Electric Vehicles (PEVs) are particularly favored, as they are more reliable and efficient than pure EVs.

A huge deployment of EVs requires a robust charging infrastructure to meet the charging demands of EVs smoothly and smartly. Intelligent charging management and scheduling are the two key solutions to such a problem. At an early stage, simple scheduling was performed by considering various driving cycle attributes, such as arrival time, departure time, daily mileage, and first trip distance, as shown in [1], where the attributes are deterministic in nature. Researchers are now focusing on improving these factors to enhance EV performance further. However, every new technology comes with its challenges that researchers must address. EV drivers often face anxiety about "when" and "where" to charge their vehicles. Therefore, it is important to identify the "appropriate" charging station (CS). To address this challenge, many researchers have proposed various methods, though most of them consider only distance as the key factor to identify the optimal CS for vehicles [2].

In [3]–[5], Wu et al. proposed a quick charging solution by increasing the charging current and voltage. Some studies have used ultracapacitors to reduce charging time, designating them as suitable for quick CS [6]. However, to identify an adequate CS, the availability of free charging slots at the CS is the most important factor to consider. Therefore, this factor is incorporated into this article, along with other factors such as minimal battery energy consumption and shortest distance, to identify an adequate CS.

Once the relevant CS is assigned to the corresponding vehicles, charging scheduling becomes the next key challenge. Moreover, managing EV charging optimally is always a great challenge. Many authors have focused on the methodology of EV charging using the Grid-to-Vehicle (G2V) mode. How the surplus energy of the EV can be utilized for the betterment of the grid is another major concern, which introduces Vehicle-to-Grid (V2G) technology. For charging scheduling purposes, some authors have proposed a window optimization technique suitable for online applications due to its continuous update of the information pattern. This technique determines the optimal scheduling with minimal charging cost [7].

In [8], considering various driving patterns, it has been shown that due to high pricing during the daytime and offering lower tariffs at night, EV owners are encouraged to charge their EVs during the night. In [9], an energy management scenario was established considering three types of traffic conditions, with the main objective of increasing the fuel economy of PEVs by integrating traffic information.

In [10], an autonomous distributed V2G control scheme was used, where EVs can be utilized as spinning reserves for the grid. In [11], the proposed charging strategy allows EVs to operate either in the V2G mode or in G2V mode while at the CS.

The major limitation of these articles is that PEVs have been operated either in G2V mode or in V2G mode while at the CS during a particular time. Some studies operated PEVs in G2V mode continuously for a certain duration and then again in V2G mode continuously for a certain duration, where frequent switching between G2V and V2G modes is missing [10]–[12].

However, in this article, it is demonstrated that the proposed Dynamic Stochastic Charging Optimization (DSCO) algorithm can handle both G2V and V2G modes of operation efficiently after a certain interval (at least 30 minutes), which differs from the concepts adopted by previous studies, potentially resulting in a more profitable scenario for both Charging Station Operators (CSOs) and EV owners.

In [12], fixed charging rates were considered, which are not economical for CSOs since electricity prices may vary due to the grid's generation and demand mismatches, making the electricity tariff dynamic. Therefore, in this article, dynamic charging rates have been used so that CSOs can control and vary the charging rates according to the Real-Time Tariff (RTT) at different intervals, making the operation more economical.

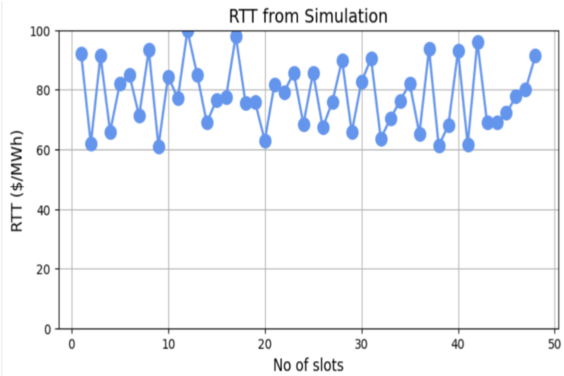

Figure 1.1: Real Time Tariff

From the critical literature survey [11]–[12], it has been observed that previous articles have used fixed data of driving cycles to perform charging scheduling. However, these attributes are often uncertain in nature, and fluctuations in these values are possible, making it critical to consider these uncertainties for better charging scheduling. Hence, in this article, the uncertainty related to driving cycles has been handled using the 2m-Point Estimation Method (PEM).

Previous articles have not considered 2m-PEM to handle probabilistic driving patterns. Different probabilistic methods, such as Monte Carlo Simulation (MCS), approximate methods [18], truncated Taylor series expansion method , and the discretization method [20], have some major limitations when handling many uncertain variables. Scientist H. P. Hong developed an efficient and modified 2m-PEM method for probabilistic analysis, which is computationally moderate and can deal with many uncertainties in less time [10]. It uses deterministic routines to handle stochastic frameworks, has less computational complexity, and is efficient enough to handle a large number of uncertainties. One more advantage is that at the end of the optimization problem, the best solution set obtained represents the mean value of the objective function, not the actual value of the objective function. The mean value is used because the present problem deals with a large number of uncertain variables. Hence, it is always better to use the mean value than the best value when dealing with the randomness of uncertain variables related to the driving cycle.

The proposed DSCO approach can be divided into two major parts. The first part of DSCO deals with building up mathematical problem formulations for selecting the "appropriate" CS, dealing with the uncertainties related to driving cycles by applying 2m-PEM, and the combined charging scheduling of the EVs. The second part of DSCO tackles the minimization of the total daily price incurred by CSOs by appropriately combining various optimization techniques.

The key contributions of this article are as follows:

Appropriate CS has been selected based on battery energy consumption required to reach the CS and the availability of slots. Both G2V and V2G modes of operation after a certain interval have been considered and handled by the proposed DSCO. Dynamic charging rates have been considered during scheduling, as they are more economical than fixed charging rates. Various uncertain attributes of driving cycles used in DSCO are stochastic in nature and have been critically handled by 2m-PEM. The performance of 2m-PEM has been compared with the conventional MCS method.

1.2 Motivation

The rapid proliferation of Electric Vehicles (EVs) presents both a remarkable opportunity and a substantial challenge. While EVs offer a sustainable alternative to traditional internal combustion engine vehicles, the transition to an electric vehicle-dominated landscape necessitates the development of sophisticated charging infrastructure and management systems. The success of EV integration into the grid hinges on optimizing the charging process to balance the demands of EV owners and the capacity of the grid, while simultaneously minimizing costs.

Current methodologies for managing EV charging primarily focus on either Grid-to-

Vehicle (G2V) or Vehicle-to-Grid (V2G) modes, often neglecting the dynamic interplay between these modes that can be leveraged for more efficient energy utilization. Additionally, most existing approaches do not adequately account for the inherent uncertainties in driving cycles, which can significantly impact the effectiveness of charging schedules. The complexity of these challenges is further compounded by the dynamic nature of electricity tariffs, which fluctuate in response to grid demand and supply conditions.

To address these multifaceted issues, this research is motivated by the need to develop a comprehensive solution that not only optimizes the selection of charging stations (CS) based on multiple factors but also effectively manages the stochastic nature of driving cycles. The proposed Dynamic Stochastic Charging Optimization (DSCO) approach aims to fill the gaps left by existing methods by integrating the 2m-Point Estimation Method (PEM) for handling uncertainties and adopting dynamic charging rates that align with real-time tariff changes.

The ultimate goal of this research is to create a more resilient and adaptive EV charging framework that can efficiently balance the needs of EV owners, Charging Station Operators (CSOs), and the power grid. By enabling frequent switching between G2V and V2G modes and accounting for uncertainties in driving patterns, DSCO not only enhances the reliability and economic feasibility of EV charging but also contributes to the broader objective of sustainable energy management. This innovation is poised to make a significant impact on the future of smart grid technology and electric mobility.

2

A Review on Charging Scheduling

Electric Vehicle (EV) charging scheduling has emerged as a critical area of research and development due to the rapid growth of the EV market. Effective scheduling is essential for managing the increased load on the electrical grid, minimizing charging costs, and ensuring the sustainability of energy sources. This review covers various existing methods for EV charging scheduling, discussing their advantages, limitations, and the contexts in which they are most effective.

2.1 Centralized vs. Decentralized Scheduling

2.1.1 Centralized Scheduling

In centralized scheduling, a central authority (such as a utility company or a central server) manages the charging of multiple EVs. The central authority has access to all relevant data, including grid load, energy prices, and the charging needs of individual vehicles. The main advantage of centralized scheduling is the ability to optimize charging across a large fleet of vehicles, balancing the load on the grid and minimizing costs.[6] However, centralized systems can suffer from scalability issues, as the computational complexity increases with the number of vehicles. Additionally, centralized systems are vulnerable to single points of failure and require robust communication infrastructure.

2.1.2 Decentralized Scheduling

Decentralized scheduling allows individual EVs or charging stations to make autonomous decisions based on local information. This approach reduces the complexity and scalability issues associated with centralized systems and can be more resilient to failures.[9] However, decentralized systems may struggle to achieve global optimization, potentially leading to suboptimal use of grid resources. Hybrid approaches that combine centralized and decentralized elements have also been proposed to balance these trade-offs.

2.2 Static vs. Dynamic Scheduling

2.2.1 Static Scheduling

Static scheduling involves pre-determined charging plans that do not change based on real-time conditions. This approach is simpler to implement and can be effective in environments with predictable demand and supply patterns.[3] However, static scheduling does not adapt to changes in grid load, energy prices, or the availability of renewable energy sources, which can result in inefficiencies.

2.2.2 Dynamic Scheduling

Dynamic scheduling adjusts charging plans in real-time based on current grid conditions, energy prices, and other factors. This approach is more flexible and can lead to significant cost savings and better grid management. Dynamic scheduling is particularly valuable in integrating renewable energy sources, as it can adjust charging times to coincide with periods of high renewable energy production. The main challenges of dynamic scheduling include the need for continuous communication and the complexity of real-time decision-making algorithms.

2.3 Time-Based Scheduling

Time-based scheduling methods focus on optimizing charging based on specific time intervals, often aligned with time-of-use (TOU) electricity pricing. The goal is to schedule charging during off-peak hours when electricity prices are lower and grid demand is reduced. This approach can lead to significant cost savings for consumers and helps in load leveling. However, it requires accurate forecasting of energy prices and grid demand, and it may not fully account for the availability of renewable energy.

2.4 Priority-Based Scheduling

Priority-based scheduling assigns different levels of priority to EVs based on factors such as battery state of charge, departure time, and user preferences. High-priority vehicles are charged first, ensuring they are ready when needed, while lower-priority vehicles are charged later. This method is particularly useful in environments with limited charging infrastructure or during peak demand periods. However, it can be challenging to determine and manage priorities, especially in scenarios with many vehicles and diverse user needs.

2.5 Vehicle-to-Grid (V2G) Integration

V2G integration involves using EVs as distributed energy storage systems, where vehicles can discharge electricity back to the grid during peak demand periods. Scheduling in V2G systems is more complex, as it must consider both the charging needs of the vehicle and the potential benefits of discharging electricity back to the grid. V2G scheduling can provide significant benefits to grid stability and energy cost reduction, but it requires sophisticated algorithms and reliable communication infrastructure. Additionally, V2G can accelerate battery degradation, which needs to be carefully managed.[5]

2.6 Optimization-Based Scheduling

Many scheduling methods are based on optimization techniques that aim to minimize costs, reduce charging time, or maximize the use of renewable energy. Common optimization methods include:[3]

2.6.1 Linear Programming (LP) and Mixed-Integer Linear Programming (MILP)

These are used to solve scheduling problems by finding the optimal allocation of charging resources. LP and MILP are powerful tools but can be computationally intensive, especially for large-scale problems.[8]

2.6.2 Heuristic and Metaheuristic Algorithms

Techniques such as Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization are used to find near-optimal solutions in complex and large-scale scheduling problems. These methods are particularly useful when the problem space is too large for exact optimization methods.[7]

2.6.3 Game Theory

In scenarios with multiple EV owners or competing objectives, game theory can be used to model and solve scheduling problems. This approach helps in understanding the interactions between different players and finding equilibrium strategies that balance individual and collective goals.

2.7 Machine Learning and AI-Based Scheduling

With advancements in artificial intelligence, machine learning algorithms are increasingly being applied to EV charging scheduling. These methods can learn from historical data to predict energy demand, price fluctuations, and user behavior, enabling more accurate and adaptive scheduling. AI-based methods can also handle the complexity of integrating renewable energy sources and V2G systems. However, they require large datasets for training and can be computationally demanding.

2.8 Challenges and Future Directions

While significant progress has been made in EV charging scheduling, several challenges remain:

2.8.1 Scalability

As the number of EVs increases, scheduling methods must scale to handle larger fleets without compromising performance.

2.8.2 Integration with Renewable Energy

Scheduling methods need to be more effective in integrating renewable energy sources, balancing the variability of these sources with the charging demands of EVs.

2.8.3 User Preferences

Personalizing scheduling to meet individual user preferences while still optimizing for cost and grid stability is a complex challenge.

2.8.4 Cybersecurity

As EV charging systems become more connected, ensuring the security and privacy of scheduling systems is critical.

EV charging scheduling is a multifaceted problem that requires balancing the needs of consumers, grid operators, and the environment. Existing methods offer various approaches, each with its own strengths and limitations. Future developments will likely focus on improving scalability, enhancing integration with renewable energy, and leveraging advanced technologies such as AI to create more adaptive and efficient scheduling systems. As the EV market continues to grow, effective scheduling will play a crucial role in ensuring the sustainability and reliability of electric transportation.

3

Problem Statement based on Identified Research Gaps

This chapter explains the formulation of the problem that this thesis addresses, as well as it outlines the thesis objectives.

3.1 Problem Formulation

The proliferation of Electric Vehicles (EVs) presents significant challenges to the existing power grid infrastructure. As the number of EVs increases, so does the demand for electricity, particularly during peak hours, which can strain the grid. Moreover, the charging behavior of EVs is highly uncertain, influenced by factors such as driver habits, arrival and departure times at charging stations (CS), and real-time electricity tariffs (RTT). These uncertainties make the task of scheduling EV charging and discharging (Vehicle-to-Grid, V2G) highly complex.

3.1.1 Challenges

- Selection of Appropriate Charging Station (CS):

  Battery Energy Consumption: Identifying the most energy-efficient CS for each EV, based on the distance to the CS and the EV's battery level.
  Availability of Charging Slots: Considering the real-time availability of charging slots at each CS to avoid unnecessary delays for EV owners.

- Optimization of Charging and Discharging:

  Minimizing Costs: The objective is to minimize the cost incurred by the Charging Station Operators (CSO) while charging the EVs, considering dynamic electricity prices.
  Maximizing Efficiency: Efficient utilization of available charging slots and resources to serve the maximum number of EVs with minimum waiting time.
  Balancing Grid Load: Preventing grid overload by scheduling EV charging during off-peak hours and utilizing V2G technology during peak hours.

- Dynamic and Stochastic Nature of the Problem:

  Uncertainty in Arrival and Departure Times: EVs do not arrive at or depart from CSs at fixed times, which makes scheduling their charging/discharging activities challenging.

Variability in Driving Cycles: The amount of charge required by an EV can vary significantly depending on its driving cycle, which is influenced by factors like traffic conditions, distance traveled, and driving habits.

Fluctuating Electricity Prices: Real-time tariffs (RTT) vary throughout the day based on supply and demand, requiring the charging scheduling algorithm to be adaptive.

3.2 Thesis Objective

- Development of DSCO Framework: Create a Dynamic Stochastic Charging Optimization (DSCO) framework to efficiently schedule EV charging and discharging, minimizing costs for Charging Station Operators (CSOs) and optimizing grid resource use.

- Enhancement of HGSO Algorithm: Integrate an enhanced Henry Gas Solubility Optimization (HGSO) algorithm with real-time tariff (RTT) adjustments and dynamic pricing, enabling superior optimization of EV charging schedules compared to traditional methods.

- Real-World Evaluation and Implementation: Assess the DSCO algorithm's performance against conventional techniques like HGSO and Gurobi using simulations and real-world data, and explore its practical deployment in smart grid environments.

4

Proposed Methodology

This chapter provides a comprehensive discussion of the methodology employed in the project, including the mathematical operations and optimisation models that were implemented.

4.1 Problem Formulation

The primary goal of the Dynamic Stochastic Charging Optimization (DSCO) framework is to minimize the total cost incurred by Charging Station Operators (CSOs) while ensuring efficient utilization of grid resources. The problem is modeled as an optimization problem, with the objective function representing the total cost and constraints related to grid capacity, EV charging requirements, and operational parameters.

4.1.1 Objective Function

The objective function in the DSCO framework is designed to minimize the total cost C_{total} for CSOs, which is composed of three primary components:

$$\text{Minimize } C_{\text{total}} = C_{\text{energy}} + C_{\text{operation}} - R_{\text{V2G}}$$

- **Energy Cost (C_{energy})**: This represents the cost associated with the electricity consumed by EVs during the charging process. The energy cost is dependent on the amount of energy required to charge the vehicles and the electricity prices, which can vary over time.

  $$C_{\text{energy}} = \sum_{t=1}^{T} P_t \cdot E_t$$

  Where:

  - P_t is the price of electricity at time t.
  - E_t is the energy consumed at time t.
  - T represents the total number of time slots in the scheduling period.

- **Operational Cost ($C_{\text{operation}}$)**: This cost includes all the expenses incurred in maintaining and operating the charging stations. These expenses may include maintenance costs, staff salaries, equipment depreciation, etc.

$$C_{\text{operation}} = \text{Fixed Cost} + \sum_{t=1}^{T} \text{Variable Cost}_t$$

Where:

- Fixed Cost represents constant operational costs that do not vary with time or energy usage.
- Variable Cost includes costs that may vary depending on factors like the number of EVs being charged, usage of equipment, etc.

- **Revenue from V2G Operations ($R_{\mathbf{V2G}}$)**: V2G technology allows EVs to discharge electricity back to the grid, generating revenue for CSOs. The revenue depends on the amount of energy sold back to the grid and the prevailing electricity prices.

$$R_{\text{V2G}} = \sum_{t=1}^{T} P_t \cdot E_t^{\text{V2G}}$$

Where:

- E_t^{V2G} is the energy discharged to the grid at time t.
- P_t is the price of electricity at time t.

4.1.2 Constraints

To ensure that the optimization problem is realistic and adheres to operational limits, several constraints are imposed:

- **Energy Demand Constraint**:

$$E_{\text{required}} \leq E_{\text{available}}$$

This constraint ensures that the total energy required to charge all the EVs at the station does not exceed the available energy supply. This is critical for maintaining grid stability and avoiding overloading the grid.

- E_{required}: Total energy required by all EVs.
- $E_{\text{available}}$: Total energy available for charging at the station.

- **Grid Capacity Constraint**:

$$P_{\text{grid}}^{\text{total}} \leq P_{\text{grid}}^{\text{max}}$$

This constraint ensures that the total power demand at any given time does not exceed the maximum capacity of the grid. It prevents scenarios where the grid could be overloaded due to excessive power demands from multiple charging stations.

- $P_{\text{grid}}^{\text{total}}$: Total power demand at the station.
- $P_{\text{grid}}^{\text{max}}$: Maximum allowable power from the grid.

- **Time Window Constraint**:

$$t_{\text{arrival}} \leq t_{\text{charge}} \leq t_{\text{departure}}$$

This constraint ensures that charging or discharging of EVs only occurs within their specified time window. It is crucial for ensuring that EVs are ready for use by their owners when needed.

- t_{arrival}: The time at which the EV arrives at the charging station.
- t_{charge}: The time at which the EV starts charging.
- $t_{\text{departure}}$: The time at which the EV departs from the charging station.

- **Real-Time Tariff (RTT) Constraint**:

$$\text{RTT}_t \cdot P_t \leq \text{RTT}_{\text{max}}$$

This constraint ensures that the cost associated with energy consumption at any time does not exceed a predetermined maximum limit. The RTT fluctuates based on grid demand, and this constraint helps prevent charging at times when electricity is prohibitively expensive.

- RTT_t: Real-Time Tariff at time t.
- RTT_{max}: Maximum allowable cost per unit time.

- **State of Charge (SoC) Constraint**:

The SoC of an Electric Vehicle (EV) at any time t must be within a predefined range to ensure battery health and meet operational requirements. This can be mathematically formulated as:

$$\text{SoC}_{\text{min}} \leq \text{SoC}_t \leq \text{SoC}_{\text{max}} \quad \forall t \in [t_{\text{arrival}}, t_{\text{departure}}] \tag{4.1}$$

Where:

- SoC_t is the state of charge at time t.
- SoC_{min} is the minimum allowable state of charge to avoid deep discharging, typically set to preserve battery life.
- SoC_{max} is the maximum allowable state of charge, often set to avoid overcharging and potential battery damage.
- t_{arrival} is the arrival time of the EV at the charging station.
- $t_{\text{departure}}$ is the departure time of the EV from the charging station.

The SoC at any time $t + 1$ can be updated based on the charging or discharging power applied during time t as follows:

$$\text{SoC}_{t+1} = \text{SoC}_t + \frac{P_t \cdot \Delta t}{C_{\text{battery}}} \tag{4.2}$$

Where:

- P_t is the charging (positive) or discharging (negative) power at time t.
- Δt is the time interval between successive charging/discharging events.
- C_{battery} is the total capacity of the EV's battery.

This constraint ensures that the SoC remains within the safe operating limits during the entire charging and discharging cycle, thus optimizing battery life and performance.

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4.2 Incorporation of 2m-PEM (Probabilistic Element Method)

In the context of electric vehicle (EV) charging scheduling, uncertainties such as EV arrival times, departure times, and energy requirements play a crucial role. These uncertainties can significantly affect the efficiency of the charging process and the associated costs. To address these challenges, a probabilistic approach is essential. The 2m-PEM (Probabilistic Element Method) is employed to effectively handle these uncertainties and ensure that the optimization process is robust and reliable.

4.2.1 Uncertainty Modeling

In the DSCO framework, each uncertain parameter, such as the arrival time t_{arrival}, departure time $t_{\text{departure}}$, and required energy E_{required}, is modeled as a random variable with a known probability distribution. The 2m-PEM approach is utilized to transform these probabilistic parameters into deterministic equivalents, which can be seamlessly integrated into the optimization process.

4.2.2 Stochastic Optimization

The objective function and constraints in the DSCO framework are reformulated to incorporate the expected values of these probabilistic parameters. This reformulation allows the optimization process to consider the mean behavior of the system rather than relying on exact values, which may vary due to the inherent uncertainties.

The reformulated objective function is expressed as:

$$\text{Minimize } \mathbb{E}[C_{\text{total}}] = \mathbb{E}[C_{\text{energy}}] + \mathbb{E}[C_{\text{operation}}] - \mathbb{E}[R_{\text{V2G}}]$$

Where $\mathbb{E}[\cdot]$ denotes the expected value operator. The expectation operator ensures that the optimization process accounts for the average or expected behavior of the uncertain parameters, leading to a more robust solution.

4.2.3 H.P. Hong's 2m-PEM Method

The 2m-PEM method, developed by H.P. Hong, is a probabilistic approach that efficiently handles uncertainties in complex systems. It is particularly advantageous when dealing with large numbers of uncertain variables, as it balances computational efficiency with accuracy.

4.2.3.1 Mathematical Implementation of 2m-PEM

The 2m-PEM method works by approximating the probabilistic behavior of the uncertain parameters using a small number of deterministic samples. These samples are chosen to represent the entire probability distribution of the uncertain variables. The method then calculates the mean value and variance of the objective function based on these samples.

Let $\mathbf{X} = \{X_1, X_2, \ldots, X_n\}$ be the set of uncertain variables, where each X_i follows a known probability distribution. The 2m-PEM method approximates the expected value of a function $f(\mathbf{X})$ as follows:

$$\mathbb{E}[f(\mathbf{X})] \approx \sum_{i=1}^{m} w_i \cdot f(\mathbf{X}_i)$$

Where:

- $\mathbf{X}_i$ are the deterministic samples of the random variables.
- w_i are the corresponding weights associated with each sample.
- m is the number of deterministic samples used in the approximation.

The weights w_i and the deterministic samples $\mathbf{X}_i$ are carefully chosen to ensure that the approximation accurately reflects the underlying probability distributions of the uncertain variables. Typically, these samples are chosen at the mean and points that capture the variance and higher moments of the distribution.

4.2.3.2 Application to DSCO Framework

In the DSCO framework, the 2m-PEM method is applied to the uncertain parameters such as t_{arrival}, $t_{\text{departure}}$, and E_{required}. The objective function is then evaluated using the deterministic equivalents of these parameters, allowing for the optimization of the expected total cost $\mathbb{E}[C_{\text{total}}]$.

By incorporating the 2m-PEM method, the DSCO framework achieves a balance between computational efficiency and accuracy, making it feasible to handle a large number of uncertain variables without significantly increasing the complexity of the optimization problem.

4.3 Henry Gas Solubility Optimization (HGSO) Algorithm

To solve the optimization problem, the Henry Gas Solubility Optimization (HGSO) algorithm is employed. HGSO is inspired by the solubility of gases in liquids, where the optimization process is analogous to the dissolution and diffusion of gas particles. The algorithm is applied to both the assignment of Electric Vehicles (EVs) to Charging Stations (CSs) and the scheduling of EV charging operations.

4.3.1 HGSO Implementation

4.3.1.1 Assignment Phase

In the assignment phase, HGSO is used to allocate EVs to CSs such that the overall cost is minimized while satisfying constraints such as grid capacity and energy demand.

- **Initialization:**

$$X = \{X_1, X_2, \ldots, X_N\} \tag{4.3}$$

  where each X_i represents a potential assignment solution of EVs to CSs, initialized randomly.

- **Fitness Evaluation:** The fitness of each solution X_i is evaluated based on the total cost function:

$$F(X_i) = C_{\text{total}}(X_i) = C_{\text{energy}}(X_i) + C_{\text{operation}}(X_i) - R_{\text{V2G}}(X_i) \tag{4.4}$$

- **Dissolution Process:** The solutions are adjusted based on the dissolution process, modeled as:

$$X_i(t+1) = X_i(t) + S \cdot (X_j(t) - X_i(t)) \cdot r \tag{4.5}$$

  where S is the solubility coefficient, r is a random number, and X_j is a solution with better fitness.

– **Solubility Coefficient Update:** The solubility coefficient is updated to balance exploration and exploitation:

$$S = S_{\min} + (S_{\max} - S_{\min}) \cdot e^{-\alpha \cdot t} \tag{4.6}$$

where α is a constant, and t is the iteration number.

– **Termination:** The process is repeated until a convergence criterion is met or the maximum number of iterations is reached.

4.3.1.2 Scheduling Phase

In the scheduling phase, HGSO optimizes the charging and discharging schedule for each EV at the assigned CS, considering real-time tariff (RTT) data.

– **Initialization:**

$$Y = \{Y_1, Y_2, \ldots, Y_N\} \tag{4.7}$$

where each Y_i represents a potential scheduling solution for EVs at a specific CS.

– **Fitness Evaluation:** The fitness of each schedule Y_i is evaluated considering the total cost and V2G revenues:

$$F(Y_i) = C_{\text{energy}}(Y_i) + C_{\text{operation}}(Y_i) - R_{\text{V2G}}(Y_i) \tag{4.8}$$

– **Dissolution Process:** The scheduling solutions are updated using:

$$Y_i(t+1) = Y_i(t) + S \cdot (Y_j(t) - Y_i(t)) \cdot r \tag{4.9}$$

– **Solubility Coefficient Update:** The solubility coefficient is updated similarly:

$$S = S_{\min} + (S_{\max} - S_{\min}) \cdot e^{-\alpha \cdot t} \tag{4.10}$$

– **Termination:** The process continues until convergence or the maximum number of iterations.

4.3.2 Pseudo-Code for HGSO

```
Begin
    Initialize population of solutions X (for assignment) and Y (for scheduling)
    while (termination criteria not met) do
        for each solution X_i in X do
            Evaluate fitness F(X_i)
            for each pair (X_i, X_j) do
                Update X_i based on dissolution process
            end for
            Update solubility coefficient S
        end for
        for each solution Y_i in Y do
            Evaluate fitness F(Y_i)
            for each pair (Y_i, Y_j) do
                Update Y_i based on dissolution process
            end for
            Update solubility coefficient S
        end for
    end while
    Output the best solution for X and Y
End
```

4.4 Real-Time Tariff (RTT) Integration

The DSCO framework integrates Real-Time Tariff (RTT) data into the scheduling decisions to dynamically adjust charging and discharging operations based on current electricity prices.

4.4.1 RTT-Based Decision-Making

The RTT data is used to decide the mode of operation (G2V, V2G, or idle) for each EV at each time slot:

– **High RTT:** Prefer V2G mode to sell energy back to the grid at higher prices.

– **Low RTT:** Prefer G2V mode to charge the EVs at lower costs.

– **Medium RTT:** Operate in an idle state if neither charging nor discharging is economically favorable.

The mode decision can be mathematically represented as:

$$\text{Mode}(t) = \begin{cases} \text{V2G} & \text{if } \text{RTT}(t) > \text{RTT}_{\text{high}} \\ \text{G2V} & \text{if } \text{RTT}(t) < \text{RTT}_{\text{low}} \\ \text{Idle} & \text{otherwise} \end{cases} \tag{4.11}$$

4.5 Scheduling and Decision-Making

The scheduling and decision-making process within the DSCO framework is a critical component that ensures optimal operation of the charging infrastructure. This process dynamically adjusts the charging and discharging schedules of EVs in real-time, based on the EVs' arrival and departure times, energy requirements, and Real-Time Tariff (RTT) data. The key elements of this process include Slot Allocation, Mode Decision, and the generation of the Final Schedule.

4.5.1 Slot Allocation

Slot allocation is the first step in the scheduling process. It involves determining which time slots are available for charging or discharging each EV, based on their arrival and departure times. This is crucial for ensuring that EVs are charged within their available time windows, without exceeding grid capacity or other operational constraints.

Mathematically, the available charging slots for each EV i are defined as:

$$\text{Slot}_i = \left\{ t \mid t^i_{\text{arrival}} \leq t \leq t^i_{\text{departure}} \right\} \tag{4.12}$$

Here, t^i_{arrival} and $t^i_{\text{departure}}$ represent the arrival and departure times of EV i, respectively. The set Slot_i includes all time slots t during which EV i can be charged or discharged. This allocation ensures that each EV is only considered for charging or discharging during its valid time window.

4.5.2 Mode Decision

Once the available slots are determined, the next step is to decide the mode of operation (G2V, V2G, or Idle) for each EV at each time slot. The mode decision is based on several factors, including the current RTT, the energy stored in the EV's battery, and the energy required to meet the EV's charging goals.

The mode decision can be expressed as:

$$\text{Mode}_i(t) = \begin{cases} \text{V2G} & \text{if } \text{RTT}(t) > \text{RTT}_{\text{high}} \text{ and } E^i_{\text{stored}}(t) > 0 \\ \text{G2V} & \text{if } \text{RTT}(t) < \text{RTT}_{\text{low}} \text{ and } E^i_{\text{required}}(t) > 0 \\ \text{Idle} & \text{otherwise} \end{cases} \tag{4.13}$$

In this formulation:

- V2G (Vehicle-to-Grid): EVs discharge energy back to the grid. This mode is preferred when the RTT is high, making it economically beneficial to sell energy.
- G2V (Grid-to-Vehicle): EVs charge from the grid. This mode is chosen when the RTT is low, allowing EVs to charge at a lower cost.
- Idle: EVs neither charge nor discharge. This mode is selected when neither charging nor discharging is advantageous based on the current RTT.

The decision process for each EV ensures that the most cost-effective operation mode is selected at each time slot, balancing the need to meet energy requirements with the goal of minimizing costs.

4.5.3 Final Schedule Generation

The final step in the scheduling process is to generate the overall schedule for all EVs, which minimizes the total operational cost while satisfying all system constraints, such as grid capacity, energy demand, and individual EV requirements.

The objective is to minimize the total cost function:

$$\min \sum_{i=1}^{N} [C_{\text{energy}}(Y_i) + C_{\text{operation}}(Y_i) - R_{\text{V2G}}(Y_i)] \tag{4.14}$$

Subject to the following constraints:

- **Grid Capacity Constraint:** The total power demand at any time must not exceed the grid's maximum capacity:

$$\sum_{i=1}^{N} P_i(t) \leq P_{\text{grid max}} \quad \forall t \tag{4.15}$$

- **Energy Demand Constraint:** The energy required by each EV must be met within the available time slots:

$$E^i_{\text{required}} \leq E^i_{\text{available}} \quad \forall i \tag{4.16}$$

- **Operational Constraints:** Other constraints include ensuring that EVs are charged or discharged only within their allocated slots and that the mode decision is followed based on the RTT.

The final schedule is generated by solving this optimization problem, ensuring that all EVs are charged or discharged optimally, with respect to the available grid resources and RTT conditions.This scheduling process is dynamically updated in real-time as new RTT data becomes available, or as EVs arrive or depart, ensuring that the system continuously operates in an optimal manner.

4.5.4 WORKFLOW

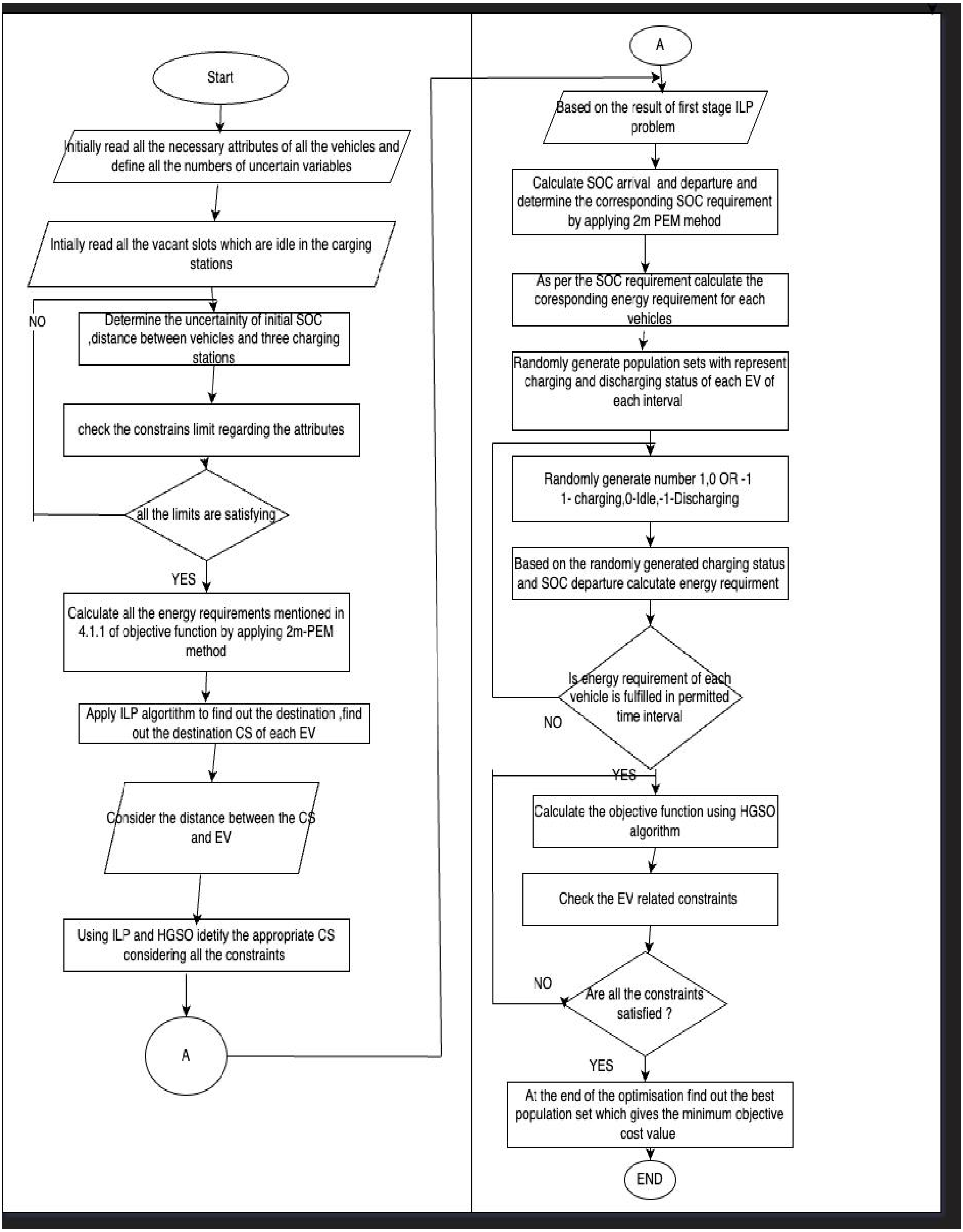

Figure 4.1: Workflow

5

Experiment and Results

The contents of this chapter encompass the description of the experiment set-up that was employed in the project, as well as a detailed account of the outcomes and results that were obtained.

5.0.1 Analysis of DSCO Framework

The tables provide a detailed evaluation of the DSCO (Dynamic Smart Charging Optimization) framework, focusing on how it manages EV assignments, charging schedules, and adapts to real-time tariffs (RTT) to optimize charging operations.

5.0.1.1 Dataset for Electric Vehicles and Charging Stations

This table provides the foundational data for the DSCO framework, detailing the initial and target states of charge (SOC), energy requirements, and assignments of EVs across three charging stations.

Table 5.1: Dataset for 15 Electric Vehicles and 3 Charging Stations

EV ID	**Arrival Time**	**Departure Time**	**Energy Consumption (kWh)**	**Assigned Charging Station**	**Initial SOC (%)**	**Target SOC (%)**
EV1	08:00 AM	12:00 PM	15	CS1	30	80
EV2	09:30 AM	01:30 PM	20	CS1	40	90
EV3	07:45 AM	11:45 AM	12	CS2	35	85
EV4	10:00 AM	02:00 PM	25	CS3	25	75
EV5	06:30 AM	10:30 AM	10	CS1	50	95
EV6	08:15 AM	12:15 PM	22	CS2	20	70
EV7	07:00 AM	11:00 AM	17	CS3	45	85
EV8	09:00 AM	01:00 PM	14	CS1	30	80
EV9	07:30 AM	11:30 AM	18	CS2	40	90
EV10	08:45 AM	12:45 PM	21	CS3	50	100
EV11	10:15 AM	02:15 PM	11	CS1	35	85
EV12	07:15 AM	11:15 AM	28	CS2	25	75
EV13	06:45 AM	10:45 AM	13	CS1	30	80
EV14	08:30 AM	12:30 PM	16	CS2	45	85
EV15	09:45 AM	01:45 PM	24	CS3	50	90

5.0.1.1.1 Key Insights:

- **Efficient EV Assignment:** The DSCO framework strategically assigns EVs to charging stations based on arrival/departure times, initial SOC, and energy needs. This ensures optimal use of the limited charging slots, avoiding bottlenecks and ensuring timely charging for all vehicles.
- **SOC Management:** The framework carefully manages the initial and target SOC, ensuring that each EV reaches its target before departure. This highlights DSCO's ability to handle diverse charging needs efficiently.
- **Energy Consumption:** By accurately accounting for the energy needs of each EV, DSCO optimizes resource allocation, preventing overcharging and ensuring efficient energy use across all stations.

5.0.1.1.2 Contextual Analysis:

- **Resource Allocation:** The DSCO framework optimizes the use of limited charging slots, ensuring that all EVs receive adequate charging within their available time windows, despite resource constraints.
- **Prioritization:** EVs with lower initial SOC and earlier departure times are prioritized, demonstrating the framework's ability to efficiently manage charging schedules under tight constraints.

5.0.1.2 EV Charging Schedule with Modes and RTT

This table outlines the charging schedules for each EV, segmented into 30-minute intervals, and shows how the DSCO framework dynamically adjusts charging modes (G2V, V2G, or Idle) based on real-time tariffs (RTT).

Table 5.2: Scheduing of EVs

Station	EV ID	Time Slot	Charging Mode	RTT
Station 1	EV1	08:00 - 08:30	G2V	0.18
		08:30 - 09:00	G2V	0.20
		09:00 - 09:30	Idle	0.35
		09:30 - 10:00	V2G	0.45
		10:00 - 10:30	G2V	0.25
		10:30 - 11:00	G2V	0.30
		11:00 - 11:30	G2V	0.27
		11:30 - 12:00	Idle	0.40
Station 1	EV2	09:30 - 10:00	G2V	0.15
		10:00 - 10:30	G2V	0.18
		10:30 - 11:00	V2G	0.42
		11:00 - 11:30	G2V	0.20
		11:30 - 12:00	Idle	0.38
		12:00 - 12:30	G2V	0.35
		12:30 - 01:00	Idle	0.40
		01:00 - 01:30	V2G	0.42
Station 2	EV3	07:45 - 08:15	G2V	0.12
		08:15 - 08:45	G2V	0.14
		08:45 - 09:15	Idle	0.28
		09:15 - 09:45	V2G	0.43
		09:45 - 10:15	G2V	0.15
		10:15 - 10:45	G2V	0.20
		10:45 - 11:15	Idle	0.35
		11:15 - 11:45	V2G	0.42

Station	EV ID	Time Slot	Charging Mode	RTT
Station 3	EV4	10:00 - 10:30	G2V	0.18
		10:30 - 11:00	G2V	0.20
		11:00 - 11:30	Idle	0.25
		11:30 - 12:00	V2G	0.30
		12:00 - 12:30	G2V	0.22
		12:30 - 01:00	Idle	0.28
		01:00 - 01:30	G2V	0.35
		01:30 - 02:00	V2G	0.45
Station 1	EV5	06:30 - 07:00	G2V	0.20
		07:00 - 07:30	G2V	0.22
		07:30 - 08:00	Idle	0.30
		08:00 - 08:30	V2G	0.42
		08:30 - 09:00	G2V	0.18
		09:00 - 09:30	Idle	0.35
		09:30 - 10:00	G2V	0.15
		10:00 - 10:30	V2G	0.45
Station 2	EV6	08:15 - 08:45	G2V	0.18
		08:45 - 09:15	Idle	0.32
		09:15 - 09:45	V2G	0.50
		09:45 - 10:15	G2V	0.21
		10:15 - 10:45	Idle	0.35
		10:45 - 11:15	G2V	0.19
		11:15 - 11:45	V2G	0.45
		11:45 - 12:15	Idle	0.30

Station	EV ID	Time Slot	Charging Mode	RTT
Station 3	EV7	07:00 - 07:30	G2V	0.14
		07:30 - 08:00	G2V	0.16
		08:00 - 08:30	Idle	0.30
		08:30 - 09:00	V2G	0.41
		09:00 - 09:30	G2V	0.17
		09:30 - 10:00	Idle	0.28
		10:00 - 10:30	G2V	0.15
		10:30 - 11:00	V2G	0.42
Station 1	EV8	09:00 - 09:30	G2V	0.18
		09:30 - 10:00	G2V	0.20
		10:00 - 10:30	Idle	0.35
		10:30 - 11:00	V2G	0.42
		11:00 - 11:30	G2V	0.20
		11:30 - 12:00	Idle	0.28
		12:00 - 12:30	G2V	0.30
		12:30 - 01:00	V2G	0.45
Station 2	EV9	07:30 - 08:00	G2V	0.18
		08:00 - 08:30	G2V	0.20
		08:30 - 09:00	Idle	0.35
		09:00 - 09:30	V2G	0.45
		09:30 - 10:00	G2V	0.22
		10:00 - 10:30	Idle	0.28
		10:30 - 11:00	G2V	0.18
		11:00 - 11:30	V2G	0.50

Station	EV ID	Time Slot	Charging Mode	RTT
Station 3	EV10	08:45 - 09:15	G2V	0.17
		09:15 - 09:45	G2V	0.18
		09:45 - 10:15	Idle	0.35
		10:15 - 10:45	V2G	0.42
		10:45 - 11:15	G2V	0.20
		11:15 - 11:45	Idle	0.35
		11:45 - 12:15	G2V	0.30
		12:15 - 12:45	V2G	0.45
Station 1	EV11	10:15 - 10:45	G2V	0.20
		10:45 - 11:15	Idle	0.28
		11:15 - 11:45	V2G	0.42
		11:45 - 12:15	G2V	0.30
		12:15 - 12:45	Idle	0.38
		12:45 - 01:15	G2V	0.20
		01:15 - 01:45	Idle	0.35
		01:45 - 02:15	V2G	0.42
Station 2	EV12	07:15 - 07:45	G2V	0.18
		07:45 - 08:15	Idle	0.32
		08:15 - 08:45	V2G	0.50
		08:45 - 09:15	G2V	0.21
		09:15 - 09:45	Idle	0.35
		09:45 - 10:15	G2V	0.19
		10:15 - 10:45	V2G	0.45
		10:45 - 11:15	Idle	0.30

Station	EV ID	Time Slot	Charging Mode	RTT
Station 3	EV13	06:45 - 07:15	G2V	0.20
		07:15 - 07:45	Idle	0.28
		07:45 - 08:15	V2G	0.35
		08:15 - 08:45	G2V	0.18
		08:45 - 09:15	Idle	0.38
		09:15 - 09:45	G2V	0.30
		09:45 - 10:15	Idle	0.35
		10:15 - 10:45	V2G	0.42
Station 2	EV14	08:30 - 09:00	G2V	0.22
		09:00 - 09:30	Idle	0.30
		09:30 - 10:00	V2G	0.35
		10:00 - 10:30	G2V	0.18
		10:30 - 11:00	Idle	0.28
		11:00 - 11:30	G2V	0.15
		11:30 - 12:00	V2G	0.45
		12:00 - 12:30	Idle	0.38
Station 3	EV15	09:45 - 10:15	G2V	0.20
		10:15 - 10:45	Idle	0.32
		10:45 - 11:15	V2G	0.42
		11:15 - 11:45	G2V	0.30
		11:45 - 12:15	Idle	0.38
		12:15 - 12:45	G2V	0.20
		12:45 - 01:15	V2G	0.45
		01:15 - 01:45	Idle	0.38

5.0.1.2.1 Key Insights:

- **Dynamic RTT Adaptation:** The DSCO framework adjusts charging operations in real-time, switching between G2V and V2G modes to capitalize on favorable RTTs, thereby optimizing cost and grid stability.
- **Mode Flexibility:** The schedule reflects the flexibility of the DSCO framework, as it alternates between charging, discharging, and idle states to maximize efficiency and minimize costs.

5.0.1.2.2 Contextual Analysis:

- **Cost Efficiency:** The integration of RTT in decision-making allows DSCO to minimize charging costs and maximize potential revenue from V2G operations, enhancing the economic feasibility of the system.
- **Grid Support:** By dynamically adjusting the charging mode in response to RTT, DSCO not only optimizes individual charging sessions but also contributes to overall grid stability.

This analysis underscores the effectiveness of the DSCO framework in managing EV charging schedules under varying conditions, optimizing resource use, and dynamically responding to real-time economic signals.

5.1 Comparison of Standard HGSO and DSCO

This section presents a comparative analysis of the standard Henry Gas Solubility Optimization (HGSO) algorithm and the enhanced version, HGSO + Real-Time Tariff (RTT). The addition of RTT data into the optimization process aims to improve the scheduling performance by considering real-time energy costs.

5.1.1 WSRT Test Results

The table below summarizes the results of the comparison between the two algorithms across several test cases. The metric used for comparison is the total cost, which reflects the efficiency of the charging schedule.

Table 5.3: Comparison of Standard HGSO and DSCO Algorithms

Algorithm	TC1a	TC1b	TC1c	TC1d	TC1e	TC1f
Standard HGSO	202.0	217.5	185.0	194.0	209.5	221.0
DSCO	182.5	190.0	174.0	180.5	189.5	200.0

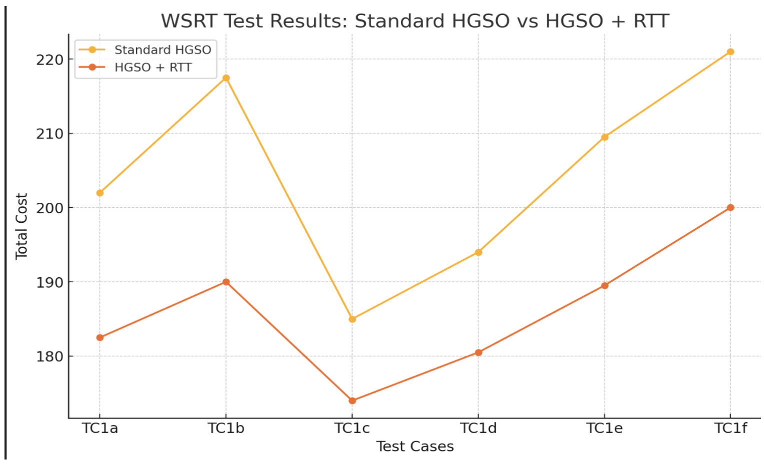

Figure 5.1: Standard HGSO vs DSCO Algorithm

5.1.2 Analysis and Discussion

The results in Table 5.3 clearly show that the DSCO algorithm outperforms the standard HGSO in all test cases. The incorporation of Real-Time Tariff (RTT) data allows the algorithm to optimize the charging schedule more effectively by considering energy cost fluctuations. This leads to a significant reduction in total cost, with improvements ranging from approximately 8% to 15%.

The enhanced performance of DSCO can be attributed to its ability to dynamically adjust the charging/discharging times of the EVs, taking advantage of lower energy costs and avoiding peak pricing periods. The standard HGSO, while effective, does not account for these real-time cost variations, leading to less optimal scheduling outcomes.

6

Conclusions and Future Scope

This chapter of the report is dedicated to the conclusion and future scope. This section presents a thorough summary of the principal discoveries and understandings attained through the research conducted in the preceding sections.

6.1 Conclusions

The DSCO (Dynamic Scheduling and Charging Optimization) framework offers a comprehensive solution to the challenges faced by Charging Station Operators (CSOs) in managing Electric Vehicle (EV) charging processes. By integrating advanced optimization techniques like the Henry Gas Solubility Optimization (HGSO) algorithm, probabilistic modeling with the 2m-PEM approach, and real-time adjustments based on electricity tariffs, the framework successfully minimizes operational costs while ensuring grid stability and efficient resource utilization. The DSCO framework demonstrates its potential to significantly enhance the efficiency and economic viability of EV charging infrastructure, addressing both current and future demands of the growing EV market.

6.2 Future Scope

DSCO framework opens up several avenues for future research and development. One potential direction is the integration of renewable energy sources, such as solar or wind power, into the charging process, further reducing dependency on the grid and enhancing sustainability. Additionally, the framework could be expanded to incorporate vehicle-to-vehicle (V2V) energy transfer, allowing for more flexible and distributed energy management. There is also room for improvement in the predictive modeling of EV behavior, using advanced machine learning techniques to better anticipate energy demands and optimize scheduling. Finally, as the EV landscape evolves, the DSCO framework could be adapted to accommodate new technologies, such as wireless charging and autonomous vehicle fleets, ensuring its continued relevance and effectiveness.

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