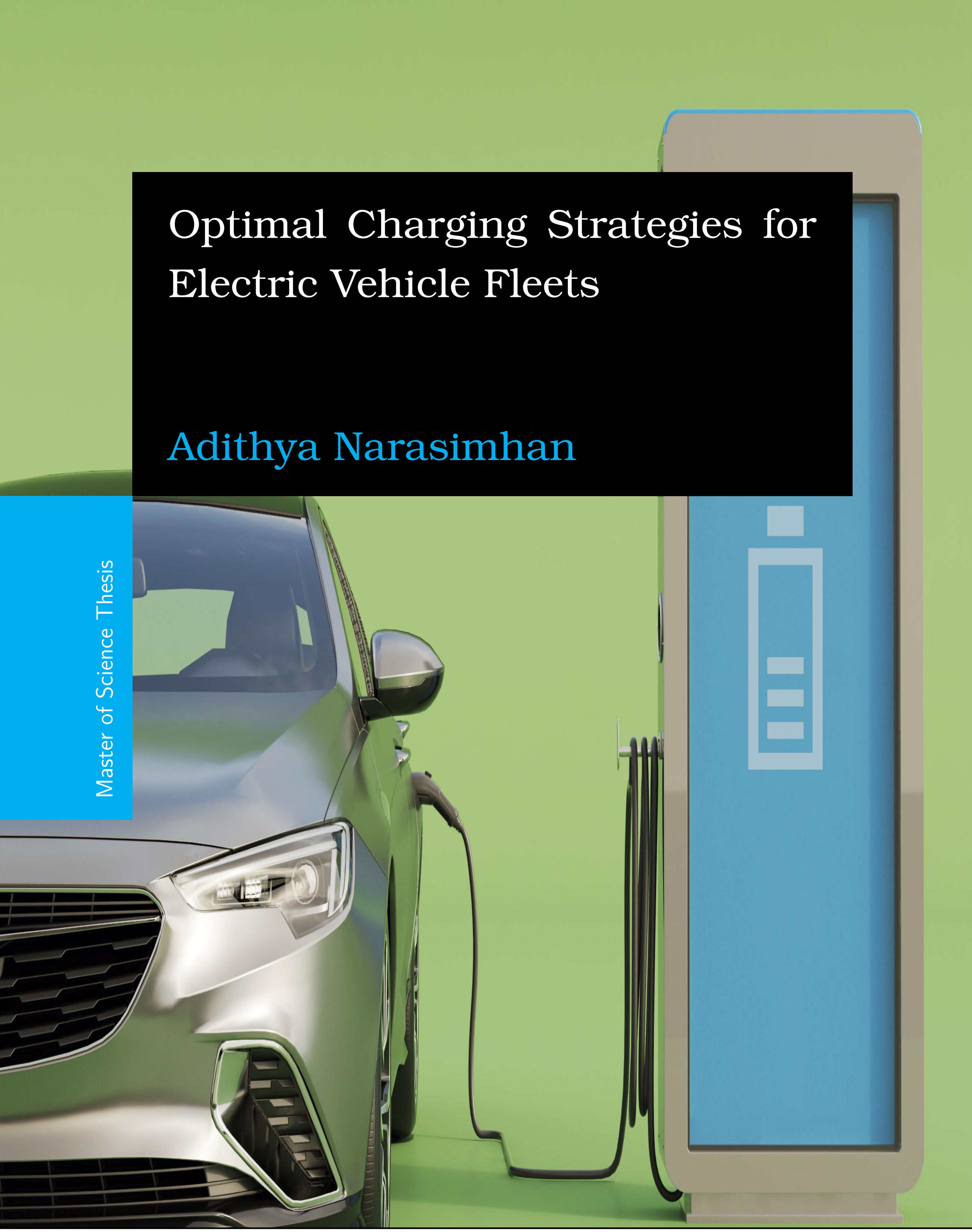

Optimal Charging Strategies for Electric Vehicle Fleets

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Master of Science Thesis

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Optimal Charging Strategies for Electric Vehicle Fleets

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Abstract

Electric vehicles are a fast-growing market in the automotive sector. In addition, the widespread use of renewable energy to power electric vehicles makes them sustainable, with considerably low greenhouse gas emissions. As a result, service providers are switching to fleets of electric vehicles to promote environmental sustainability. However, unlike conventional vehicles, EVs require unique infrastructure to charge them. This leads to some technical and economic challenges. Therefore, intelligent charging strategies are needed to charge EV fleets optimally.

The thesis primarily focuses on minimizing the energy and battery degradation costs for a fleet operator using different charging strategies. To accomplish this objective, a joint optimization technique is used to solve the problem. The method used is an optimal exchange problem that works by clearing market constraints. Specifically, an ADMM-based distributed charging problem is used for charging the EV fleet. The algorithm is implemented for different charger power levels for the different strategies to analyze the difference in energy and battery degradation costs. Furthermore, a variable charger allocation method is proposed to charge the EV fleet.

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Acknowledgments

"You have a right to perform your prescribed duties, but you are not entitled to the fruits of your actions."- Srimad Bhagvaad Gita.

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Chapter 1

Introduction

Driven by the need to mitigate the climate crisis, the world is devising ways to reduce the use of fossil fuels and adopt sustainable and green energy. Fossil fuels are one of the main threats to the earth's environment as they contribute to many greenhouse gases (GHG) emissions [3]. These emissions are majorly released by the transport sector which is currently the largest benefactor of greenhouse gases globally. Thus, a broad-scale adoption of electric vehicles could bring significant changes to the transportation's environmental footprint [6]. Furthermore, the European Union (EU) promotes the increase of renewable and carbon-free energy resources and design complimentary policies for the electrification of the transport sector [30]. These green policies have helped electric vehicles (EVs) to become a key player in the mobility sector. [8].

EVs have been present since the invention of the electric motor around 150 years back. In the late 1920s and 1930s, electric motor vehicles were used more than IC engine vehicles. However, around 1930, the electric vehicle was no longer used as internal combustion engines became more developed and mass-produced at a reasonable cost. Also, EVs could not exploit long-distance traveling during the 1930s, along with poor infrastructure for charging and unreliable electricity transmission [20]. Recently, battery technology has considerably improved, allowing EVs to travel greater distances with a single charge. Despite the technological advancements, there are still several hindrances to the high penetration of EVs. Increasing EV penetration will have system-scale impacts and interactions in the electricity generation, transmission, distribution, and demand side management sectors, the resources, technologies, and wastes associated with energy storage and batteries [6]. Another fundamental limitation is the battery's composition, which is prone to degradation each time the EV charges. Therefore, optimal fleet charging strategies are adopted to lessen the impact of the degradation

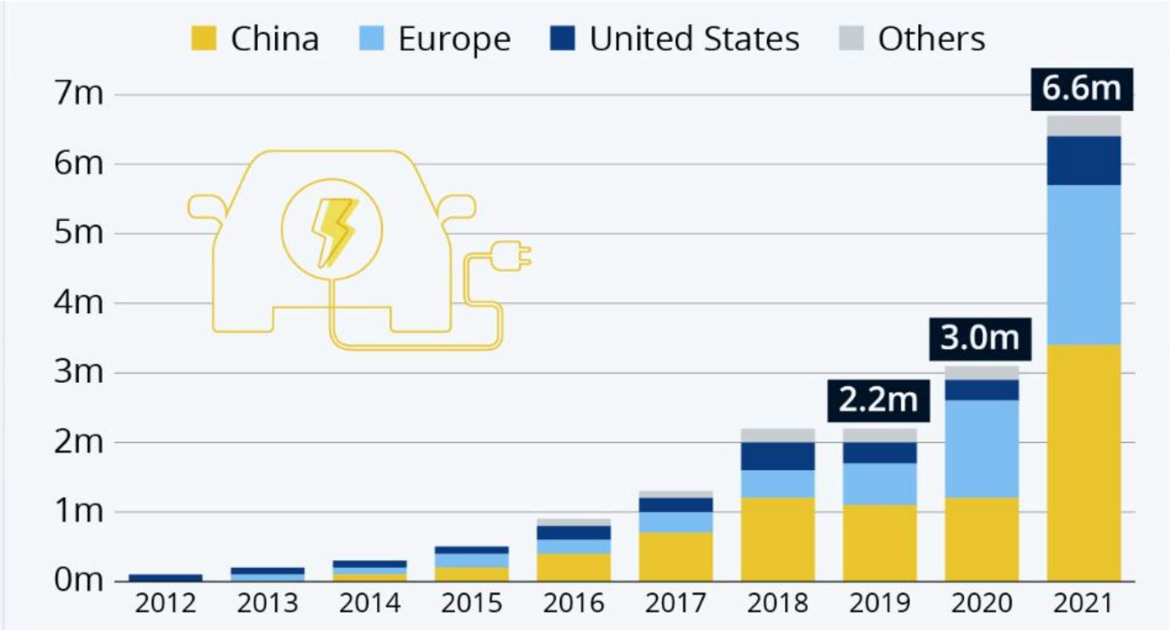


Figure 1-1: Global EV Market Demand
[28]

problem. [9].

In this thesis, the primary focus is on optimal fleet charging strategies for EVs. Many service providers like GO Sharing, DHL, and Albert Heijn are investing in EVs because of government incentives and policies to develop green businesses. In such business models, the service provider or fleet operator manages a fleet of EVs. The fleet operators are mostly interested in reducing their Total Cost of Ownership (TCO). It includes depreciation cost throughout the ownership of the EVs, the cost of maintenance, battery purchase, taxes, and cost of charging. Therefore, optimal fleet charging will significantly benefit fleet operators by reducing energy costs and battery degradation.

1-1 EV Fleet Charging Problem

With an increase in the fleet size of service providers, optimal charging strategies are needed. This thesis aims at solving a fleet charging problem for a fleet operator. There are two different aspects considered for fleet providers.

1. Operational Aspects: Operational aspects deal more with optimizing factors like load regulation, frequency regulation, and battery degradation.
2. Cost Aspects: Cost aspects are optimization based on reducing costs for aggregators or users for charging the EVs.

In this thesis, only the cost aspect is considered. The control objective to be optimized is to reduce the cost of charging a fleet of EVs for a fleet operator. In literature, two major control architectures are described to solve the fleet charging problem: centralized and decentralized charging.

Centralized EV architecture employs a centralized mechanism to obtain the EV profiles for charging from all the vehicles. The fleet of vehicles is then optimized based on the EV profile and grid constraints by the central controller, as shown in figure (1-2).

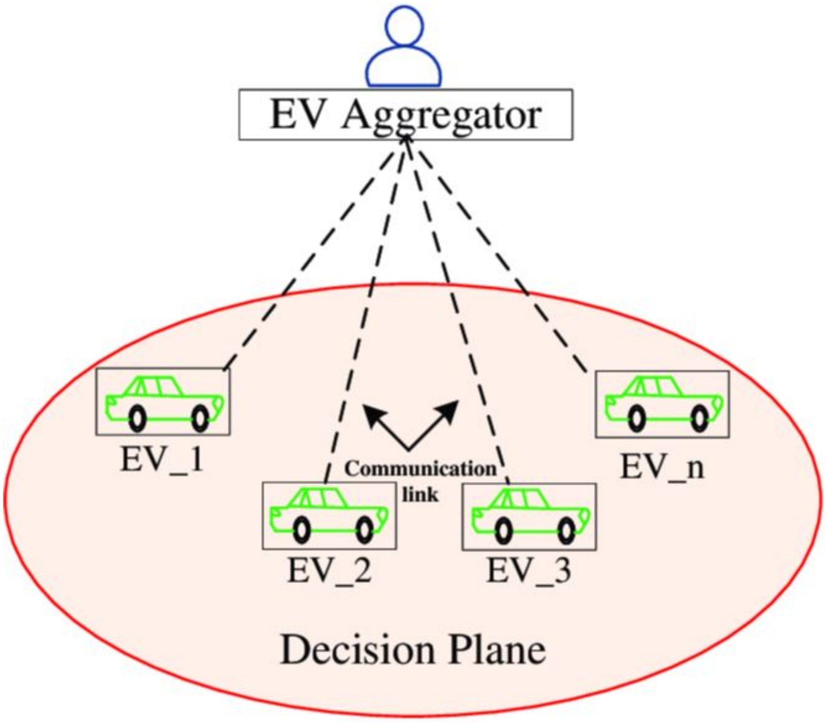


Figure 1-2: Centralized Control Architecture

Esmaili et al. [10, 35, 36], develop various centralized charging methods for different optimization problems like reducing power loss, minimizing system cost, and adjusting power frequency. In, [8], a hierarchical scheme is employed for charging the EV station loads in the distribution network to minimize energy costs. In [27], a dynamic programming optimization method of charging the fleet is proposed based on the forecast of the load information. However, in the papers mentioned above, the charging patterns of the EV are not considered. Qi et al. [14, 23], employ a horizon control-based method to mitigate uncertainties in dynamic charging cases. Furthermore, the problem's length increases with the number of EVs. Therefore, implementing a practical centralized approach becomes difficult.

The second control architecture is decentralized control. Each EV acts independently in a decentralized control architecture to solve a problem, as shown in figure (1-3).

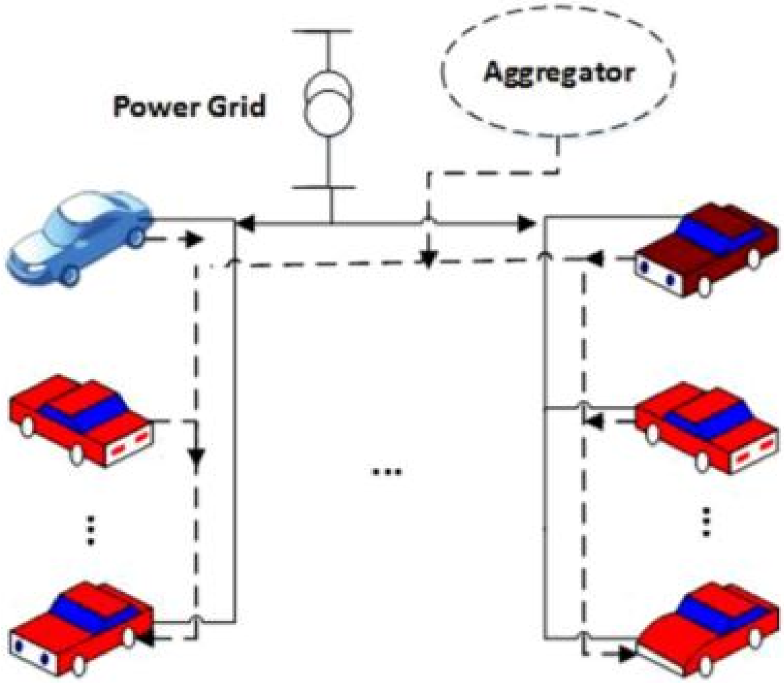


Figure 1-3: Decentralized Control Architecture

The EVs are independent decision-makers and make decisions for their more minor optimization problems in size than the entire fleet. Therefore, it is also referred to as indirect control. In decentralized control, EV users can control their charging patterns employing various techniques [7,16,30,31,34,37]. The information on the schedule of one vehicle is not available to others. Therefore, decentralized charging control does not comply with optimal charging regimes due to this lack of information at individual layers. However, since the primary problem is divided into sub-problems that reduce complexities by a major solution tier, decentralized control is highly scalable in practical applications. Yang et al. [34] focus on charging EV stations based on renewable energy and distribution networks. Cao et al. [7] proposed a concept that uses the forecast of price signals to charge the vehicles. In [4,26,31], decentralized charging frameworks are used based on a game theoretic approach. Among the two control architectures, decentralized control suits the thesis problem as it is scalable and computationally tractable for larger fleets.

For the control objective taken, different approaches were compared through an extensive literature review. We can broadly divide the approaches into three categories. First is heuristic algorithms which are majorly based on concepts found in nature. The advantage of heuristic algorithms is that a system model is not required to solve the problem. They aim to achieve high-quality results for the optimization they try to solve but cannot always attain the exact solution in every case with certainty. Also, they are easy methods to implement and are flexible for different problem fits [32]. Two major heuristic algorithms can be used for the fleet charging problem. The first is a genetic algorithm [2, 12, 22, 33] and the second one is particle swarm optimization [4, 19, 21]. However, as the length of the problem increases, its complexity increases, making it difficult to solve it numerically. The second approach is a game theory-based approach. The focus of the game theory is the game that is played, which acts as a model for an interactive situation among the individual rational players [4, 19, 21]. The key to game theory is that one player's payoff is contingent on the strategy implemented by the other player. The game identifies the players' identities, preferences, and available methods and how these strategies affect the outcome. Depending on the model, various other requirements or assumptions may be necessary. The game theoretic approach is a decentralized control method and is very effective if the game is designed perfectly with the role of all players mentioned with certainty. However, there are some drawbacks. For example, once a game is chosen for the problem, it cannot be alternated, making it inflexible. Furthermore, if the game chosen is inappropriate, obtaining a nash equilibrium is problematic.

Therefore, the final method researched is the distributed control method. Distributed control is a form of decentralized control. Distributed optimization is used for the control and coordination of distributed systems. It is used to parallelly compute solutions for problems as the information and processing are shared among the agents. The scalability of the solvers is improved using traditional rationale. Global optimization is obtained through local interactions, and computations [5]. There are many distributed control algorithms, but ADMM is majorly researched and implemented in this case. ADMM is suitable for coordinating many processes, substantially solving individual problems to solve a more significant problem. Furthermore, ADMM is helpful for large-scale optimization, as in this case, where the fleet of electric vehicles will increase over the years. Khaki et al. [18,38] propose ADMM as a method to increase scalability and reduce the computational burden for scheduling the EV charging in distribution grids. Although ADMM is primarily used for separable functions, in [11,13,39] ADMM is used to solve a non-separable function with coupling constraints for vehicle charging. Furthermore, ADMM achieves faster convergence. For the research question in the literature, Jose et al. [25] can be implemented that uses decentralized control on ADMM to solve the valley filling and minimal cost charging problem for a fleet of electric vehicles. ADMM algorithm is apt to solve more significant problems that require faster convergences. The advantage of ADMM is that the algorithm is highly robust and supports decomposition. Furthermore, the optimality achieved is asymptotic, and few iterations are required to achieve the desired results for any optimization problem. Therefore, it is highly recommended for convex problems where agents must cooperate. However, all algorithms have specific cons. To implement ADMM, the cost function and constraints to be optimized have to be convex. Since the convergence occurs fast, there are chances that the solution obtained is not precisely accurate. In the next section, we discuss the different charging methods of the battery.

1-2 Battery Charging Methods

The battery of an electric vehicle is the most critical component that determines the range of the car and how long it takes to recharge. Different battery capacities are considered based on the type and size of the cars. In addition, electric vehicle range depends on factors like temperature, speed, driving patterns, and road conditions [8].

Electric Vehicles have three types of charging techniques:

1. **Conductive Charging:** In conductive charging, the electric vehicle (EV) connector and charge inlet are in direct contact. The charging is done using a standard electrical unit or a charging station.
2. **Inductive Charging:** The charging is done using electromagnetic fields. The charge is transferred in the form of energy using couplers from the charging station to an electrical unit. This energy stored in the electrical unit is used to charge the EVs.
3. **Changing Battery:** This technique removes the discharged battery from the car and replaces it with a fully charged battery.

Conductive charging is the most commonly used method of charging. It is cheap compared to changing batteries frequently and has minimal power losses due to direct contact charging, unlike inductive charging. Therefore, in this thesis, we only focus on conductive charging [9].

1-2-1 Conductive Charging

Charging Levels

Charging levels are classified into various levels based on the amount of power used for charging, and the time the car takes to charge.

Home Charging: In this charging, the EV is connected to the most common electrical network. The EV has an onboard charger to receive energy from an AC supply.

Fast AC Charging: Fast AC charging uses a 7kW (32 A) single-phase or 21kW three-phase supply to charge the EVs. A separate AC supply is dedicated to this charging. The vehicles are equipped with onboard chargers capable of accepting the charge from the dedicated AC supply, which is present at private or public locations.

Fast DC Charging: In this charging, usually, the supply given is around 50kW or higher. With a DC charging supply, the battery of EVs can be charged from 0 to 80% within 20 minutes. Therefore, separate DC equipment is required to provide energy from an off-board charger to the Electric Vehicle (EV) in private or public locations.

1-3 Research Question

The main problem addressed in the thesis is the cost minimization of a fleet of electric vehicles is for a fleet operator. The fleet operators mainly deal with two major costs: energy costs and the battery degradation costs. There is always a trade-off between the energy costs and the battery degradation costs in the fleet charging problem and this thesis addresses this trade-off by formulating a joint optimization problem. Therefore, the goal of the thesis is to reduce the total incurred costs paid by the fleet operators by optimally solving the problem for various power level chargers using different charging strategies. Simulation studies are designed for the various power level chargers and the best strategy is anlaysed.

Chapter 2

Preliminaries

This chapter discusses the basics of the ADMM fleet charging problem.

2-1 ADMM

In this section, we look at the ADMM method. The ADMM algorithm combines the decomposability of the dual ascent with the convergence properties of the method of multipliers. ADMM is a convex optimization algorithm usually used for solving separable functions. However, it can also optimize fairly non-smooth convex functions. Furthermore, the generalized problem formulation given in [5] can be applied to most problems.

$$\begin{aligned} \min \;\; & f(x) + g(z) \\ \text{st.} \;\; & Ax + Bz - c = 0 \end{aligned} \tag{2-1}$$

where, the variables $x \in \mathcal{R}^l$, $z \in \mathcal{R}^n$. The functions f and g are convex. The functions are subject to a linear equality constraint where $A \in \mathcal{R}^{p*l}$, $B \in \mathcal{R}^{p*n}$ and $c \in \mathcal{R}^p$. The method of multipliers is adopted. Therefore the augmented lagrangian is taken as:

$$L_\rho(x, y, z) = f(x) + g(z) + y^T(Ax + Bz - c) + \frac{\rho}{2}||Ax + Bz - c||_2^2 \tag{2-2}$$

where L_ρ is the augmented lagrangian. The iterations needed to solve the problem are given as follows [5]:

$$\begin{aligned} x^{k+1} &= \text{argmin}_x\, L_\rho(x, z^k, y^k) \\ z^{k+1} &= \text{argmin}_z\, L_\rho(x^k, z, y^k) \\ y^{k+1} &= y^k + \rho(Ax^{k+1} + Bz^{k+1} - c) \end{aligned} \tag{2-3}$$

where $\rho > 0$. The ADMM algorithm resembles the dual ascent and method of multipliers very closely. In the method of multipliers, the lagrangian is minimized in conjunction with the two primal variables. However, in ADMM, the variables x and z are updated alternating or sequential, accounting for the alternating direction term [5]. It can be viewed as a Gauss-Seidel iteration over the variables x and z instead of a joint minimization. This separation of the two variables is necessary to decompose the functions f and g. The variable y is then updated using the next states x^{k+1} and z^{k+1}. The following section illustrates a straightforward solution to solve the ADMM exchange problem.

2-2 ADMM Formulation

The EV fleet charging is considered an exchange problem in the thesis. The solution to the sharing problem is explained in this section. The sharing problem in equation (3-6) has a shared objective g which is an indicator of the set $\{0\}$. The components of vector x_i represent the quantity of a commodity that is exchanged among N agents [5]. Therefore, the exchange problem given in equation (3-6) is reformulated as follows [5]:

$$\begin{aligned} \underset{x_i, z_i}{\text{minimize}} \quad & \textstyle\sum_{i=1}^{N} f_i\left(x_i\right) + g(z) \\ \text{subject to} \quad & x_i = z_i \;\; i = 1, 2 \ldots N \end{aligned} \tag{2-4}$$

where,

$$g_z = 0 \;\text{ if } \sum_{i=1}^{N} z_i = 0 \tag{2-5}$$

Looking at equation (2-4) and equation (3-6), we can say that both the formulations are the same. Therefore, to solve the problem, we first define an augmented Lagrangian function [24].

$$L_\rho = \sum_{i=1}^{N} f_i(x_i) + g(z_i) + y_i^T(x_i - z_i) + \frac{\rho}{2}||x_i - z_i||_2^2 \tag{2-6}$$

where ρ is the penalty parameter of the augmented term. The augmented term introduces a penalty onto the primal variables x and z by taking the square of the Frobenius norm.

$y = [y_1, y_2 \dots y_N]^T$ is the vector of Lagrangian variables. The function is minimized over the primal variables x_i and z_i and maximized over the Lagrangian variables y_i.

$$\max_{y} \min_{x,z} L_\rho(x, z, y) \tag{2-7}$$

The Lagrangian equation (2-6) is solved as in equation (2-8)

$$\begin{aligned} x^{k+1} &= \min_{x} L_\rho(x, z^k, y^k) \\ z^{k+1} &= \min_{z} L_\rho(x^{k+1}, z, y^k) \\ y^{k+1} &= \max_{y} L_\rho(x^{k+1}, z^{k+1}, y) \end{aligned} \tag{2-8}$$

The terms are then expanded by substituting the lagrangian function in equation (2-6). The term x shows the initial value vector of the commodity x, and x^{k+1} is the updated value vector of the commodity.

$$\begin{aligned} x_i^{k+1} &= \min_{x_i} f_i(x_i) + y_i^k \left(x_i - z_i^k\right) + \frac{\rho}{2} \left\|x_i - z_i^k\right\|_2^2 \\ z^{k+1} &= \min_{z} g(z) - y^{kT} z + \frac{\rho}{2} \left\|x^{k+1} - z\right\|_2^2 \\ y^{k+1} &= \max_{y} y^T \left(x^{k+1} - z^{k+1}\right). \end{aligned} \tag{2-9}$$

So, the equations (2-9) are solved iteratively. First, the update of x is computed by minimizing the Lagrangian function. Then, the z update is computed with the updated x variable. Finally, we maximize the variable y with updates of x and z. So, solving these iterations, we arrive at the following formulation, which gives the same solution as the exchange problem in equation (3-6).

$$\begin{aligned} x_i^{k+1} &= \min_{x_i} f_i(x_i) + y_i^k x_i + \frac{\rho}{2} \left\|x_i - x_i^{k+1} + \bar{x}^{k+1}\right\|_2^2 \\ y_i^{k+1} &= \bar{y_i}^k + \rho \bar{x}^{k+1} \end{aligned} \tag{2-10}$$

In equation (2-10), $\bar{x}^{k+1} = 1/N \sum_{i=1}^{N} x_i^{k+1}$ and $\bar{y}^{k+1} = 1/N \sum_{i=1}^{N} y_i^{k+1}$ are the averages. Next, there is a scaled version of the equation (2-10). In the scaled version we consider a variable u=y_i/ρ. Therefore, rewriting the formulation of equation (2-10) we get:

$$\begin{aligned} x_i^{k+1} &= \min_{x_i} f_i(x_i) + \frac{\rho}{2} \left\|x_i - x_i^k + \bar{x}^k + u^k\right\|_2^2 \\ u_i^{k+1} &= \bar{u_i}^k + \bar{x}^{k+1} \end{aligned} \tag{2-11}$$

The mathematical solution to the ADMM exchange problem is solved using the above equations. Finally, the optimality and stopping criteria for the ADMM method are illustrated in the next section.

2-3 Optimality and Stopping Condition

Optimality in ADMM is achieved when the primal feasibility and dual feasibility are obtained, which is given as [5]:

$$\begin{aligned} Ax^* + Bz^* - c = 0 \\ 0 = \nabla f(x^*) + A^T y^* \\ 0 = \nabla g(z^*) + B^T y^* \end{aligned} \tag{2-12}$$

where ∇ represents the gradients of the functions f and g.

The residuals obtained using the optimality conditions are related to the bounds on the objective suboptimality of the current point. The residuals for the primary and dual feasibility are given as follows [5]:

$$\begin{aligned} r^{k+1} &= Ax^{k+1} + Bz^{k+1} - c \\ s^{k+1} &= \rho A^T B(z^{k+1} - z^k) \end{aligned} \tag{2-13}$$

The residuals obtained for the primal and dual feasibility are small; therefore, the suboptimality is also tiny. Therefore, the termination criterion is that the residuals must be smaller than some value which is represented as:

$$||r^k||_2 \leq \epsilon^{pri} \quad ||s^k||_2 \leq \epsilon^{dual} \tag{2-14}$$

where $\epsilon^{pri} > 0$ and $\epsilon^{dual} > 0$ are called the feasibility tolerances.

The following section discusses the charging strategies implemented in the thesis.

2-4 Charging Methods

This section explains the two charging methods implemented in the thesis: greedy and minimal energy charging.

2-4-1 Greedy Charging

In this strategy, as the name suggests, the EVs try to charge the battery to its maximum capacity each time for the next trip. The assumption is that the EV is connected to the grid each time it stops driving. This strategy is currently being used in the real world.

2-4-2 Minimal Energy Charging

Minimal energy charging is the more thoughtful strategy, where each time the EV is connected, it tries to charge the EV battery with the minimal amount of energy required for the next trip. This strategy can significantly reduce the charging costs of individual EVs and might be a better option.

Chapter 3

Optimal EV Fleet Charging

3-1 Cost Minimization Problem

The problem considered in this thesis is a fleet charging problem devised as a joint optimization problem. There are two components in EV fleet charging: the aggregator and the EVs. The aggregator wants to minimize the cost of charging the fleet using the price of energy from the grid, whereas the individual EVs want to minimize their degradation costs. In this thesis, a private fleet operator wants to minimize the total cost. However, there is always a trade-off between the aggregator's perspective and the EV's perspective of charging. Therefore, a joint optimization problem is formulated [24]. The parameters for the optimal fleet charging problem are shown in table [3-1]:

Variable	Variable Description	Type
T	Time Horizon	T $\in \mathcal{Z}$
x_a	Fleet charging profile for the day	$x \in \mathcal{R}^T$
x_i	Charging profile of vehicle i for a day	$x \in \mathcal{R}^T$
$f_a(x_a)$	Cost function of aggregator	Convex function
$f_i(x_i)$	Cost function of EV i	Convex function
$\mathcal{X}_a$	Constraint set of aggregator	Convex set
$\mathcal{X}_i$	Constraint set of EV i	Convex Set
η	Trade-off parameter	$\eta \in \mathcal{R}$
N_e	Number of EV present	$N_e \in \mathcal{Z}$

Table 3-1: Parameters for fleet optimization problem

The minimization problem is given as follows [24]:

$$\begin{array}{ll} \underset{x_a, x_i}{\text{minimize}} & f_a\left(x_a\right)+\eta \sum_{i=1}^{N_e} f_i\left(x_i\right) \\ \text{subject to} & x_a=\sum_{i=1}^{N_e} x_i \\ & x_a \in \mathcal{X}_a \\ & x_i \in \mathcal{X}_i ; \quad i=1, \ldots, N_e \end{array} \tag{3-1}$$

The optimization variable x is the charging power. Therefore, x_a is the power profile of the entire fleet per time slot for a day. x_i is the power profile of the individual EV for the day.

Now, let us consider that if $x_i(t) > 0$, the car is charging at time t. Similarly, if $x_i(t) < 0$, it is considered discharging at time t. The same consideration can be taken for the aggregated EV profile x_a. So, the problem is reformulated considering the number of EVs and the aggregator combined. The aggregator and the EVs are considered agents:

$$N = N_e + 1 \tag{3-2}$$

The aggregator is considered the N^{th} agent. Intuitively looking, the aggregator spends energy to charge the cars and can be considered discharging energy.

$$x_N = -x_a \tag{3-3}$$

The cost function of the N^{th} agent is given as:

$$f_N\left(x_N\right)=f_a\left(-x_N\right) \text{ if } -x_N \in \mathcal{X}_a \tag{3-4}$$

Since the aggregator is the N^{th} agent, and the EVs are agents from {1 . . . N-1} and the cost function for the EVs is given as:

$$f_i\left(x_i\right)=\eta f_i\left(x_i\right) \text{ if } x_i \in \mathcal{X}_i \tag{3-5}$$

The fleet charging problem can therefore be rewritten as an exchange problem:

$$\begin{array}{ll} \underset{x_i}{\text{minimize}} & \sum_{i=1}^{N} f_i\left(x_i\right) \\ \text{subject to} & \sum_{i=1}^{N} x_i=0 \end{array} \tag{3-6}$$

The exchange problem considers N agents exchanging a common goal under an equilibrium constraint [5]. The variables $x_i \in R^T$, i=1 $\ldots N$. f_i is the cost function of subsystem i. The formulation of the exchange problem is discussed in the preliminary work. The following section illustrates the distribution model used for EV fleet charging.

3-2 Distributed EV Aggregation Model

In this section, the exchange problem is redefined in terms of the fleet charging problem. The working model is shown in fig (3-1)

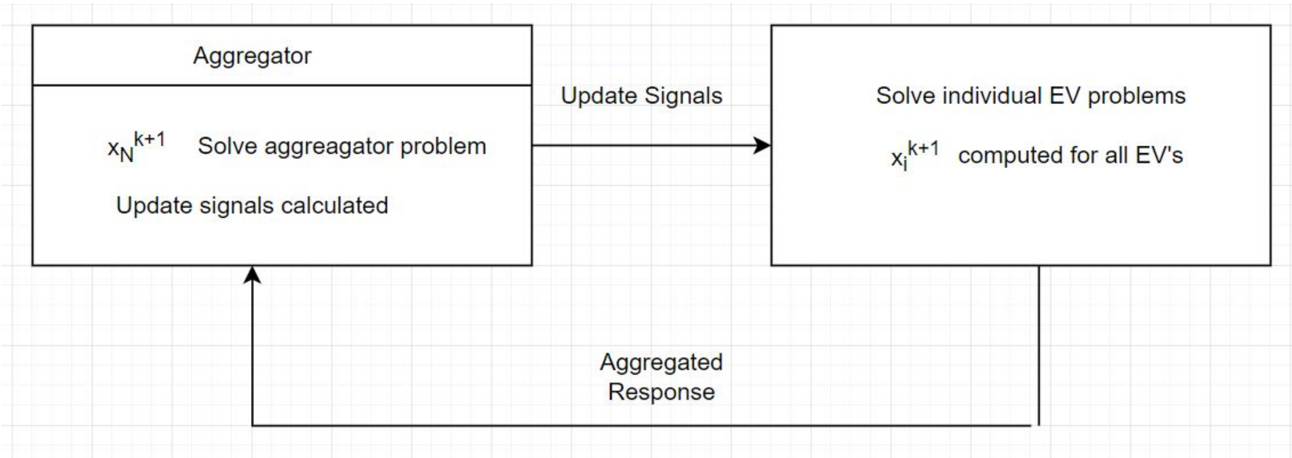


Figure 3-1: EV framework

The grid operator determines the energy prices sent to the aggregator. However, in this case, the fleet operator is the aggregator. The EV Aggregator model then updates the Lagrangian price vector y based on the constraints and sends the scaled price along with the aggregated charging profile to the EVs. At each iteration step k, the EVs and the EVA solve their sub-problems independently. The incentive signals are updated continuously with each iteration (the scaled price signal $\bar{u_i}$ and the updated average profile of all EV's $\bar{x_i}^k$) [25].

3-3 Optimization model for optimal fleet charging problem

The optimal EV management problem in figure (3-1) solves the aggregator and individual EV problems separately. Nevertheless, they are connected through update signals and the exchange problem constraint mentioned in equation (3-6). Therefore, the formulation is given as follows: For each EV i=1,2 . . . N-1 [25]:

$$x_i^{k+1} = \begin{array}{ll} \text{minimize} & \eta f_i\left(x_i\right) + \frac{\rho}{2}\left\|x_i - x_i^k + \bar{x}^k + u^k\right\|_2^2 \\ \text{subject to} & x_i \in \mathcal{X}_i \end{array} \tag{3-7}$$

For the aggregator:

$$x_N^{k+1} = \begin{array}{ll} \text{minimize} & f_a\left(x_N\right) + \frac{\rho}{2}\left\|x_N - x_N^k + \bar{x}^k + u^k\right\|_2^2 \\ \text{subject to} & x_N \in \mathcal{X}_a \end{array} \tag{3-8}$$

The coordinator, which is also the aggregator here:

$$\begin{aligned} \bar{x}^{k+1} &= x_N^{k+1} + \frac{1}{N_e}\sum_{i=1}^{N_e} x_i^{k+1} \\ u^{k+1} &= u^k + \bar{x}^{k+1} \end{aligned} \tag{3-9}$$

where, $u_i^k = \frac{y_i^k}{\rho}$. y_i^k is the lagrangian multiplier associated with the price vector. ρ stands for the penalty term in the augmented lagrangian function. The incentive signals from the aggregator denote the average power mismatch of each iteration. The exchange ADMM problem is viewed as a general equilibrium problem with a price adjustment process [1]. So, each EV agent wants to minimize its power consumption x_i to minimize individual cost $f_i(x_i)$. adjusted by a cost $y_i^T x_i$.

3-4 EV Optimisation Model

Batteries are a crucial component of an EV. Lithium batteries are prime candidates for EVs because of their high power density and higher cycle life [29]. Even though they have a good life cycle, the degradation of lithium batteries is one of the significant problems that EV fleet owners face. The different charging methods are explained in section (1-2-1). The more the batteries charge and discharge, the more they degrade. Currently, the research on improving battery life is extensive. In this thesis, we try to use a model that depicts the aging cost of an EV battery with the optimization variable as the power drawn from the chargers.

The power rating of a charger determines how fast the EV charges. If the charger power is high, the faster it charges. Therefore, to model this, a quadratic relation is considered. The battery degrades with the square of the power it charges over time. Therefore, the cost function of the EVs in equation (3-7) is given by [25]:

$$\begin{aligned} f_i(x_i) = \min_{x_i} \alpha ||x_i||_2^2 \\ \underline{R_i} \leq A_i x_i \leq \bar{R}_i \\ \underline{S_i} \leq B_i x_i \leq \bar{S}_i \\ \underline{x_i} \leq x_i \leq \bar{x}_i \end{aligned} \tag{3-10}$$

Variable	Variable Description	Type
T	Number of Time Slots	Scalar
c_i	Number of times connected to grid	Scalar
T_{c_i}	Number of time slots connected	Scalar
α	Battery Depreciation parameter	Scalar
x_i	Charging Profile of vehicle i for the day	Vector $\in \mathcal{R}^T$
A_i	Connection Matrix	Matrix $\in \mathcal{R}^{c_i \times T}$
$\underline{R}$	Minimal Energy Required	Vector $\in \mathcal{R}^{c_i}$
$\bar{R}$	Maximal Energy Required	Vector $\in \mathcal{R}^{c_i}$
B_i	Progressive Input Matrix	Matrix $\in \mathcal{R}^{T_{c_i} \times T}$
$\underline{S_i}$	Minimal State of battery	Vector$\in \mathcal{R}^{T_{c_i}}$
$\bar{S_i}$	Maximal State of battery	Vector$\in \mathcal{R}^{T_{c_i}}$
$\bar{x_i}$	Maximum Charger Power	Vector $\in \mathcal{R}^T$
$\underline{x_i}$	Minimum Charger Power	Vector $\in \mathcal{R}^T$

Table 3-2: Parameters for aggregator problem

The first inequality $\underline{R_i} \leq A_i x_i \leq \bar{R}_i$, sets bound on the minimum energy required by the EV for each time it is connected. The energy required depends on the EV's driving profile and charging strategy. The second constraint, $\underline{S_i} \leq B_i x_i \leq \bar{S}_i$, determines the state equation of the EV battery. It guarantees that the state of the battery is kept on an operational level for each time slot. It determines the energy that can be put into or removed from the battery. The last constraint, $\underline{x_i} \leq x_i \leq \bar{x_i}$ determines the minimum and maximum power that is drawn.

The optimization of the individual EVs is based on their personal goals and the incentive signal. The scaled variable u can be considered the energy price that the aggregator defines for the EVs. The mean value of the optimization variable x represented by $\bar{x}$ can be considered a social cost caused by the EVs not cooperating to achieve global convergence. Individual EV optimization takes these prices into account. The individual EV optimization model is given as follows:

$$x_i^{k+1} = \eta \min_{x_i} \alpha ||x_i||_2^2 + \frac{\rho}{2} ||x_i - x_i^k + \bar{x}^k + \bar{u}^k||_2^2 \tag{3-11}$$

$$s.t. \;\; \underline{R_i} \leq A_i x_i \leq \bar{R}_i$$

$$\underline{S_i} \leq B_i x_i \leq \bar{S}_i$$

$$\underline{x_i} \leq x_i \leq \bar{x_i}$$

3-4-1 Battery Model

Battery models are highly non-linear and, therefore, not convex. The choice of the objective function strongly depends on the optimization algorithm [15]. In this case a convex objective function is required; therefore, we consider a linear model for the battery.

The primary states of the battery are the SOC and the temperature. In this case, we ignore the temperature and solely focus on the SOC. SOC is the amount of charge available in the battery divided by the nominal capacity of the battery C_{nom} (Ah) [25]. The voltage for operating is taken as V_{nom}.

The SOC state equation is given as follows:

$$SOC = \eta \frac{I}{C_{nom}} \tag{3-12}$$

where η is the efficiency and I [A] is the current flowing through the battery. Another way to interpret it is the State of Energy (SOE).

$$SOE = \eta \frac{IV_{nom}}{E_{nom}} \tag{3-13}$$

where E_{nom} is the nominal energy content of the battery. If we discretize this equation, it can be written as:

$$SOE(k+1) = SOE(k+1)\eta \frac{I(k)V_{nom}}{E_{nom}} \Delta t \tag{3-14}$$

Here, we take P=$V_{nom}I$.

$$SOE(k+1) = SOE(k+1) + \eta \frac{P(k)}{E_{nom}} \Delta t \tag{3-15}$$

Now, we consider $x^k = P^k$ as our optimization variable. The state equation can be reformulated as

$$SOE(k+1) = SOE(k+1) + \frac{\eta \Delta t}{E_{nom}} x^k \tag{3-16}$$

Multiplying this equation with E_{nom}

$$E(k+1) = E(k) + \eta \Delta t x^k \tag{3-17}$$

The state of the battery can be defined in terms of a minimum and maximum bound for each time step and is given by:

$$\frac{E_{min}(k+1) - E(k)}{\eta \Delta t} \leq x^k \leq \frac{E_{max}(k+1) - E(k)}{\eta \Delta t} \tag{3-18}$$

This generally defines the state of the battery. It defines the energy consumed by the battery. Therefore, the state constraints can be defined as:

$$\underline{S} \leq Bx \leq \bar{S} \tag{3-19}$$

The other constraint is the charging requirements which depend on the charging strategy. Using the equation (3-17) is written as:

$$\frac{\underline{\underline{E_{req}}} - E^{tc-1}}{\eta \Delta t} \leq x^k \leq \frac{\bar{E}_{req} - E^{tc-1}}{\eta \Delta t} \tag{3-20}$$

This is then rewritten as:

$$\underline{R} \leq Ax \leq \bar{R} \tag{3-21}$$

The final constraint is the minimal and maximal power that can be drawn from the grid and is given as:

$$\underline{x} \leq x \leq \bar{x} \tag{3-22}$$

The definitions for the parameters B, $\underline{S}$, $\bar{S}$, A $\underline{R}$, $\bar{R}$, $\underline{x}$, $\bar{x}$ depends on the driving profile and constraint formulation which is explained in the next section.

3-4-2 Driving Profile and Constraint Formulation

In this case, EVs have complete knowledge of the driving profile required for each trip for the entire optimization period. For the sake of simplicity, let us ignore the EV indexes for now. The driving profile is defined as a row vector d $\in R^T$, where an element of this vector d is 0 if the EV is not connected and 1 if the EV is connected to the grid at time slot T. The number of times the EV is connected to the grid is defined by c. With this, the amount of energy required for the trips can be defined in the vector $E_{req} \in R^c$.

The definition of the variables B, $\underline{S}$, $\bar{S}$, A, R, $\underline{x}$ and $\bar{x}$ depends on the driving profile and the charging strategy that the EV follows. Based on these variables, constraints are devised to solve the optimization problem. However, first, let us look at some assumptions that are taken.

- The time slots taken are in one-hour intervals.

- Each time the vehicle is connected to the grid, it charges else, we take the car is driving.

Based on the driving profile and charging methods, the constraints are devised and presented in the following sections.

Power Level Constraints

The constraint determines the minimum and maximum energy that can be taken from the grid as mentioned in equation (3-11). This is determined by multiplying the driving vector for each EV by the power drawn by each vehicle based on its charger type at a particular time.

$$\underline{x}_i = d_i \cdot^* \underline{x_i} \tag{3-23}$$

$$\bar{x}_i = d_i \cdot^* \bar{x}_i \tag{3-24}$$

where d is the driving vector and x_{min} and x_{max} and the minimum and max power that can be drawn from a charger by an EV.

There are different variations of driving profile vectors that can be considered for each EV. For example, a driving vector for 1 EV can be given as follows:

$d =$	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0

The driving vector above can have different variations based on the driving profile. Similarly, the power drawn by the EV from a charger is given by x_{min} and x_{max}

The minimum power taken can be 0, which is the EV is not charging for that particular time.

$x_{min} =$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The maximum power that can be drawn is restricted by the type of charger used by the EV. For example, if the EV uses a 16kW charger, the maximum power bound is 16 kW.

$x_{max} =$	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16

Energy Demand Constraints

This constraint determines the minimum energy that must be given to the EV before the next trip. Therefore, it is given by the formula:

$$\underline{R_i} \leq A_i x_i \leq \bar{R_i} \tag{3-25}$$

where, A is the connection matrix, and $\underline{R_i}$ and $\bar{R_i}$ is the lower and upper bound on the amount of energy required before the next travel. The connection matrix depends on the number of times the EV connects to the grid and the time horizon of the optimization.

Case 1

If we take c=1 and T=24, i.e., the car is connected to the grid once with a time horizon of 24 hrs.

$$A = \begin{array}{|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|}\hline 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ \hline \end{array}$$

$$\underline{R} = \bar{R} = \frac{E_{req}}{\eta \Delta t} \tag{3-26}$$

where R is the amount of energy that must be put into the vehicle for the next trip. η is the charger efficiency, and Δt is the difference between charging slots. This case is also called home charging, where the EV tries to charge the required amount in one charge.

Case 2

If we take c=2 and the T=24, the car is connected to the grid twice with a time horizon of 24 hrs. The upper and lower limit for the energy bounds $\underline{R}$ and $\bar{R}$ are separately defined based on the charging strategy.

- Greedy Charging: In greedy charging, as stated, it charges the battery each time it gets connected to the grid. In this case, it is connected twice; therefore, the battery charges to the energy requirement needed for that trip each time.

$$A = \begin{array}{|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|}\hline 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ \hline \end{array}$$

$$\underline{R} = \bar{R} = \frac{1}{\eta \Delta t} \begin{bmatrix} E_{req1} \\ E_{req2} \end{bmatrix} \tag{3-27}$$

- Minimal Energy Charging: In minimal energy charging, it tries to minimize the amount of energy put into the battery by considering both trips together.

$$A = \begin{array}{|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|}\hline 0&0&0&0&0&0&0&0&0&0&1&1&1&1&0&0&0&0&0&0&0&0&0&0\\ \hline 0&0&0&0&0&0&0&0&0&0&1&1&1&1&0&0&0&0&0&0&1&1&1&1\\ \hline \end{array}$$

$$\underline{R} = \frac{1}{\eta \Delta t} \begin{bmatrix} E_{req1} + E_{req2} - E_{bat} \\ E_{req1} + E_{req2} \end{bmatrix} \tag{3-28}$$

$$\bar{R} = \frac{1}{\eta \Delta t} \begin{bmatrix} E_{req1} \\ E_{req1} + E_{req2} \end{bmatrix} \tag{3-29}$$

Battery State Constraints

The third and final constraint defines the minimal and maximal energy that is allowed or can be taken from the battery. It also defines the dynamics of the battery. The formula is given as follows:

$$\underline{S}_i \leq B_i X_i \leq \bar{S}_i \tag{3-30}$$

where B is, the input matrix and $\underline{S}$ and $\bar{S}$ are the minimal and maximal states. The input matrix B depends on which time slots the EV charges. The EV charges at 8-time slots; therefore, the input matrix has eight rows with 24-time slots. An example of an input matrix for the driving vector (3-4-2) is given as follows.

$$B = \begin{array}{|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|}\hline 0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&0&0&0\\ \hline 0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&1&0&0&0&0&0\\ \hline 0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&1&1&0&0&0&0\\ \hline 0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&1&1&1&0&0&0\\ \hline 0&0&0&0&0&1&0&0&0&0&0&0&0&0&0&0&0&1&1&1&1&0&0&0\\ \hline 0&0&0&0&0&1&1&0&0&0&0&0&0&0&0&0&0&1&1&1&1&0&0&0\\ \hline 0&0&0&0&0&1&1&1&0&0&0&0&0&0&0&0&0&1&1&1&1&0&0&0\\ \hline 0&0&0&0&0&1&1&1&1&0&0&0&0&0&0&0&0&1&1&1&1&0&0&0\\ \hline \end{array}$$

The input matrix is taken as a progression of the summation of the power variables at particular time slots. The bounds for both charging strategies are given as follows:

$$\underline{S} = \begin{bmatrix} E_{req1} - E_{bat} \\ E_{req1} - E_{bat} \\ E_{req1} - E_{bat} \\ E_{req1} - E_{bat} \\ E_{req1} + E_{req2} - E_{bat} \\ E_{req1} + E_{req2} - E_{bat} \\ E_{req1} + E_{req2} - E_{bat} \\ E_{req1} + E_{req2} - E_{bat} \end{bmatrix} \tag{3-31}$$

$$\bar{S} = \begin{bmatrix} E_{req1} \\ E_{req1} \\ E_{req1} \\ E_{req1} \\ E_{req1} + E_{req2} \\ E_{req1} + E_{req2} \\ E_{req1} + E_{req2} \\ E_{req1} + E_{req2} \end{bmatrix} \tag{3-32}$$

where E_{bat} is the battery capacity that can be used. In the following section, the aggregator model is explained.

3-5 EV Aggregator Optimization Model

The aggregator's goal is to minimize the overall cost of charging the entire fleet of vehicles. These requirements can come from a third party interested in such EV behavior, e.g., a fleet operator in this case. A price-based approach is implemented for the control of the EV fleet in this thesis.

In a price-based optimization, the goal is to optimize the fleet of EVs such that their aggregated EV behavior incur minimal costs under certain constraints imposed on the minimum and maximum aggregated power for the given time horizon. Therefore, the cost function of the aggregator problem in equation (3-8) is given as:

$$f_a(x_a) = \min_{x_a} \; p^T x_a \tag{3-33}$$

$$s.t. \;\; \underline{x_a} < x_a < \bar{x_a}$$

Variable	Variable Description	Type
T	Number of Time Slots	Scalar
p	Electricity price profile	Vector $x \in \mathcal{R}^T$
x_a	Fleet Charging profile for a time in the day	Vector $x \in \mathcal{R}^T$
$\underline{x_a}$	Aggregated maximum energy fed-back to grid	Vector $\in \mathcal{R}^T$
$\bar{x_a}$	Aggregated maximum consumption	Vector $\in \mathcal{R}^T$

Table 3-3: Parameters for aggregator problem

where p is the price of electricity in (€/kWh). The constraints are the limits on minimum and maximum power that can be given back to the grid to be taken from the grid, respectively. Therefore, in the ADMM framework, the optimization problem for the aggregator is as follows:

$$\begin{aligned} x_a^{k+1} = \min_{x_a} \ -p^T x_a + \frac{\rho}{2}||x_a - x_a^k + \bar{x}^k + \bar{u}^k||_2^2 \\ s.t. \quad -\underline{x_a} \geq x_a \geq -\bar{x}_a \end{aligned} \tag{3-34}$$

In the next section, the stopping criteria formulation for the EV fleet charging.

3-6 Stopping Criteria

As we define in our preliminary work of the ADMM method, the stopping criteria for ADMM are given by the primal r^k feasibility and dual feasibility s^k [5]. The formulation taken in this case is given as follows [25]:

$$r_i^k = \bar{x}_i^k \tag{3-35}$$

$$s_i^k = -\rho N(x_i^k - x_i^{k-1} + (\bar{x}_i^{k-1} - \bar{x}_i^k)) \tag{3-36}$$

$$\begin{aligned} ||r_i^k||_2 \leq \epsilon_i^p \\ ||s_i^k||_2 \leq \epsilon_i^d \end{aligned} \tag{3-37}$$

The convergence is satisfied only when both the primal variable r and dual variable s are lower than the tolerance threshold.

3-7 ADMM Algorithm

In this section, the pseudo-code for the ADMM algorithm is shown.

Algorithm 1 EV ADMM

```
Initialization ρ, y_i^k, x_i^k, x_a^k, ϵ_i^p, ϵ_i^d
k = 0                                                  ▷ Iteration steps
while (3-37) not true do                               ▷ Check for Convergence
    for all i=1:N_e do
        Solve individual EV optimisation problems using (3-7)
    end for
    Solve the EV Aggregator optimization problem using (3-8)
    update x̄^{k+1} and y_i^{k+1} using (3-9)           ▷ New Incentive Computed
    Compute r^k by (3-35) and s^k by (3-36)
    if (3-37) true then
        break loop
    else
        do the default actions
    end if
    Send x̄^{k+1} and y_i^{k+1} to EV's                 ▷ Incentive sent to EV's
    k=k+1                                              ▷ Update iteration number
end while
```

Chapter 4

Battery Degradation

The battery degradation directly relates to the power taken by EV according to equation (3-10). However, the battery degradation also depends on external and internal factors like temperature, depth of discharge (DOD) and c-rate, charging, discharging, and time [17]. Battery degradation is, therefore, a non-linear process. The battery degradation model can be classified into theoretical and empirical models. Theoretical degradation models usually depend on the loss of lithium ions and other active materials. These models provide detailed explanations of the various degradation mechanisms and how they are affected by the use and condition of the battery. Empirical models are formulated based on experimental data. The empirical models are specifically designed for a particular application that cannot be used for another application [29]. Therefore, in the thesis, we try to estimate the degradation constant α through an empirical model that depends on the c-rate. C-rate is considered the bridging variable because we can indirectly relate it to power. Degradation of a battery is the capacity loss that occurs over time. The function form of the life model of a battery is taken from [29] as follows:

$$Q_{loss} = B \cdot \exp[\frac{-31700 + 370.3 * Crate}{RT}](A_h)^z \tag{4-1}$$

where Q_{loss} is the percentage of capacity loss, B is the pre-exponential factor, R is gas constant, T is the absolute temperature, and z is the power law factor.

The exponent term in the function shows that it follows the Arrhenius power law. For higher charging rates, as mentioned in [29], it is observed that the power factor remained relatively constant, and the value was found to be 0.55. However, the pre-exponential factor B decreased with increasing C-rates. Then if we compute the capacity loss based on the experimental data from [29], we can observe the following trend.

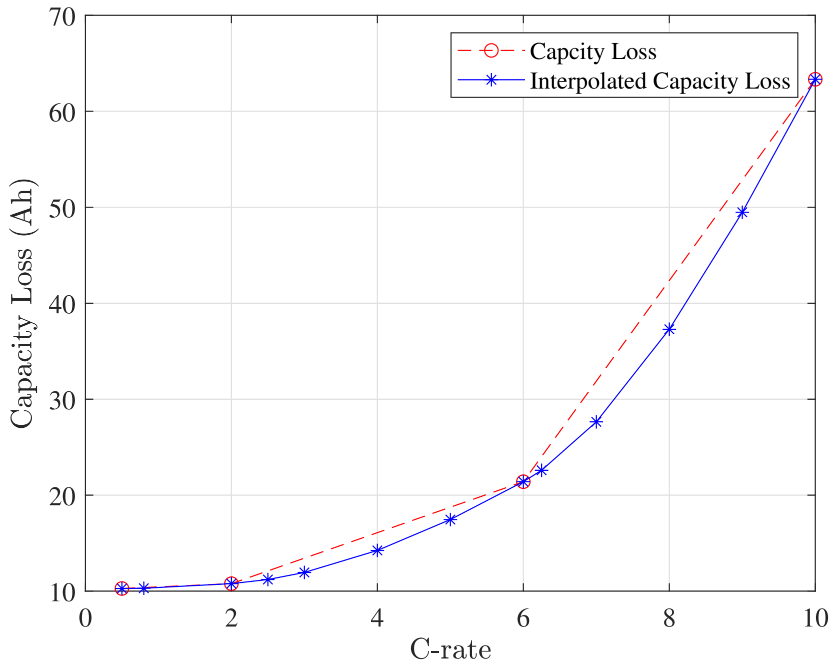


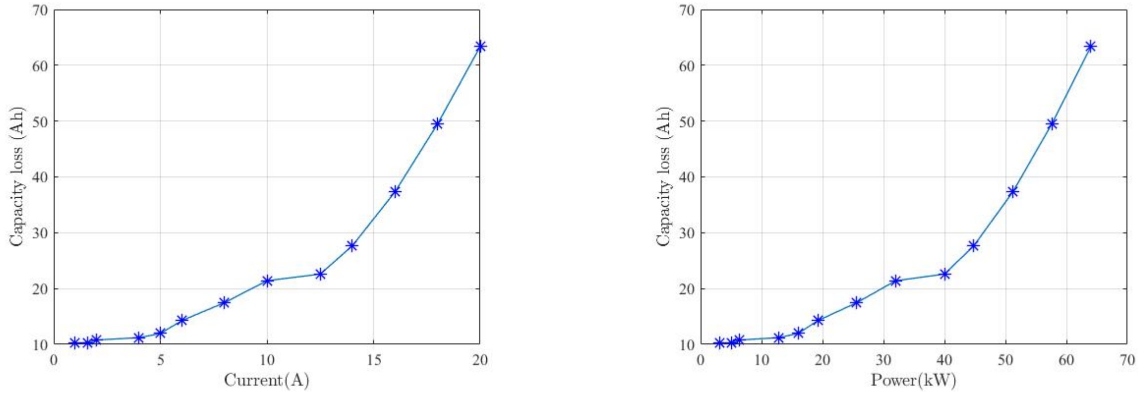
Figure 4-1: Capacity Loss vs. C rate

In figure (4-1), the red line is the capacity loss computed using equation (4-1) at 0.5C, 2C, 6C and 10C. The value of the capacity loss shows an exponential increase as the C rate increases. The blue line shows the interpolated values at various C rates, which also follow the same trend.

The c rate of the battery is usually measured as the time the battery takes to charge and discharge. For example, a graphite-LiFePO4 battery cell with a rated capacity of 2 Ah and discharge current of 2A for a C rate of 2C is considered. So, the battery discharges 2A of current in 30 minutes. Now, we can see that the C rate and current are linked, and the relation is given as follows:

$$Crate = \frac{I_{dis}}{C_{rated}} \tag{4-2}$$

The current flowing through the cell while charging can be computed using equation (4-2). Therefore, the power put into the battery can be found by the current passing through it. Power is the voltage multiplied by current. Therefore, we multiply the current obtained by the battery's nominal voltage to calculate the power.



(a) Capacity Loss vs. Current **(b)** Capacity Loss vs. Power

Figure 4-2: Capacity loss vs. Current and Power

Plots (4-2a, 4-2b) both show a greater amount of capacity loss with increase in power and current. So, this thesis implements four charger ratings like 5kW, 16kW, 25kW, and 40kW. Therefore, we use this model to try a fit to the EV optimization model equation (4-1) to determine a degradation constant α from it.

The model is fit using the curve fitting toolbox in MATLAB. First, we need to provide the toolbox with values, and then we provide it with the regression equation to which we want to fit the data. The equation to be fitted is given as follows:

$$f(P) = \alpha.P^2 + b \tag{4-3}$$

where P is the power taken by the charger. The toolbox automatically fits the data, and the unknown constant α is predicted.

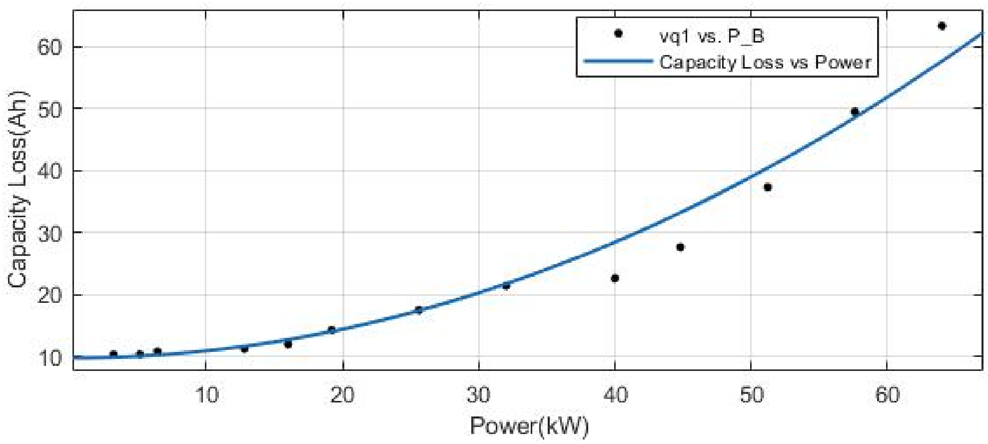


Figure 4-3: Measured data vs. Fitted Data

In figure (4-3), the black points are the computed data points, and the blue line is the fitted line for equation (4-3). The constant α obtained for all the power values after the fit is 0.017 €$/kWh$.

Chapter 5

Simulation Studies

This chapter presents a simulation study for the optimal fleet charging problem discussed in chapter 3. The fleet charging problem tries to minimize the aggregator and degradation costs.

5-1 Simulation Setup

In our simulation setup for case one, we consider a fleet of 40 EVs managed by a single fleet operator. The maximum distance an EV travels in a single day is around 300 km. As an EV consumes around 0.45-0.65 kWh of energy to drive a distance of 1 km, the maximum distance corresponds to an energy requirement of 250 kWh. To consider the extent of uncertainty in the driving tasks an EV is supposed to perform, we randomly generate a uniform distribution of 100 energy demand profiles for EVs in the range of 1 to 250 kWh. Furthermore, we consider different power charging levels in the simulation. The power ratings of the four chargers are 5kW, 16kW, 25kW, and 40kW.

However, for the second case, the EVs are connected to the grid twice. The simulation setup has the same fleet size. However, in this case, the two individual energy requirements are generated. Therefore, we consider a maximum energy range of 125kWh each time. In this case, we implement two charging strategies at four different power levels and analyse associated costs to gain insights for finding a favorable strategy for the fleet operators.

The aggregator optimization given in equation (3-8) optimizes the aggregator energy based on the energy price of the day. The energy price profile for a day is shown in figure (5-1).

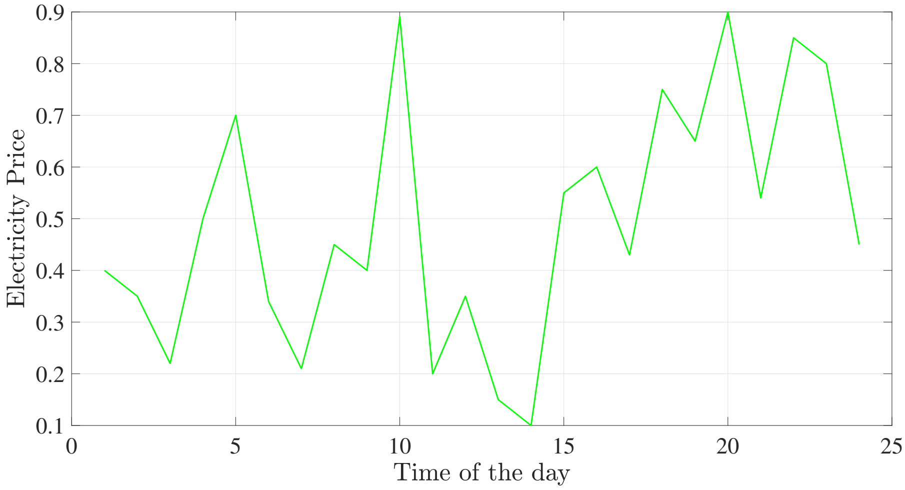


Figure 5-1: Energy Price for the day

5-2 Night-time charging

The EVs managed by a fleet operator mostly drive during the day and return to the EV hub at night. Therefore, night charging refers to a case when the EVs are connected to the grid overnight. The EVs are connected to the grid only once. In this case, the only charging method possible would be a greedy one. The definition of the greedy charging method is explained in Chapter 2. The EVs are connected to the grid for 8 hours, as shown in the driving profile (5-2). When an EV connects to the grid, the energy required for the next trip must be provided in a single charge.

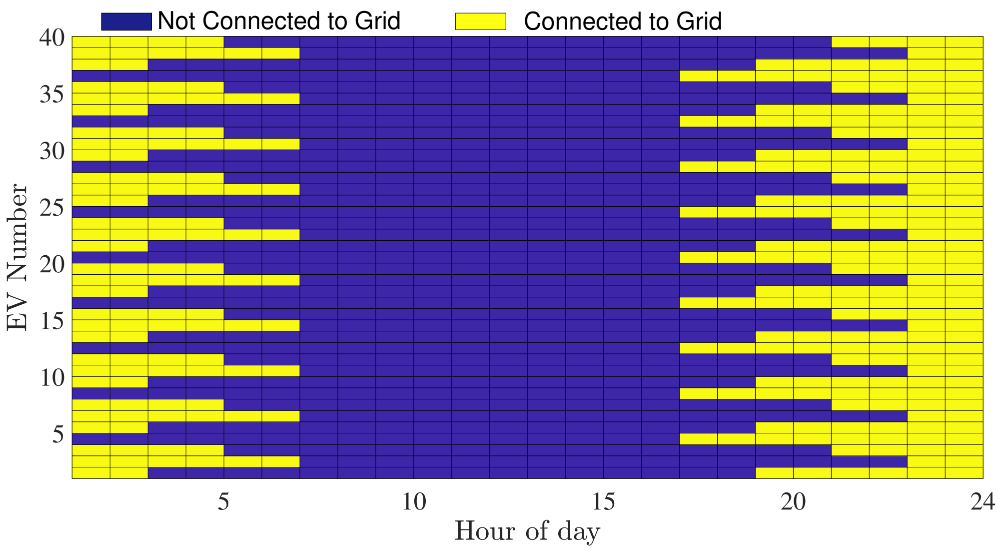


Figure 5-2: Driving Profile for Night Charging

5-2-1 Constant Power Level Charging

In this section, we run simulations for the 100 randomly generated energy demand scenarios and charge EVs using the four different power level chargers that are 5kW, 16kW, 25kW, and 40kW.

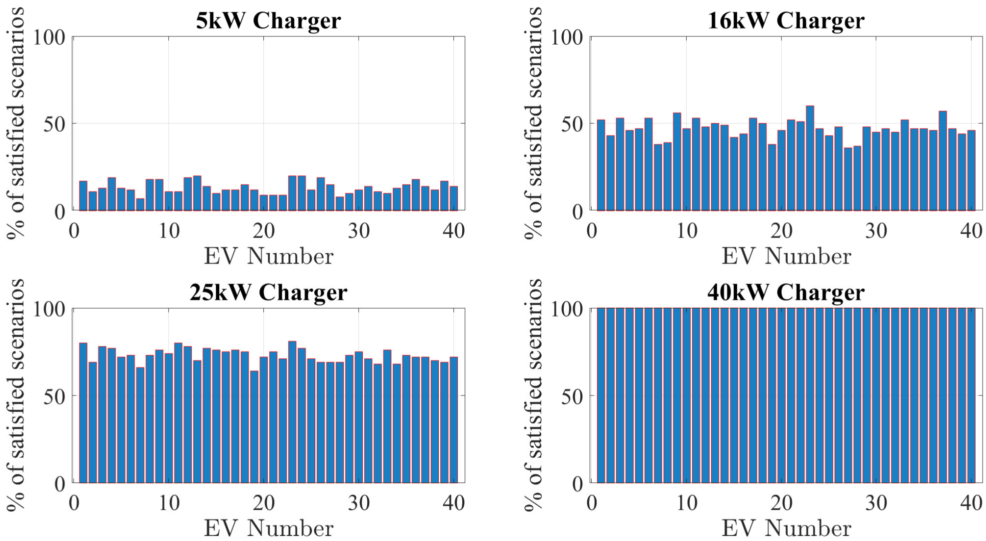


Figure 5-3: Percentage of Satisfied Scenarios for different charger types

In figure (5-3), the percentage of satisfied scenarios of the individual EVs are shown for the various chargers. For example, taking the 5kW charger, only 7-20% of the energy demand scenarios are satisfied by the individual EVs. This is because a 5kW charger can only provide a maximum of 40kWh for 8 hours. Therefore, it shows that almost 80-90% of scenarios have an energy requirement greater than 40kWh, and a 5kW charger does not satisfy the requirements. Furthermore, with higher charger powers like 16kW and 25kW, a 20-60% increase in the satisfied scenarios is observed. Here, only a 40kW charger satisfies energy demand for 100% of the scenarios. This analysis alone suggests that using the highest power level charger can better fulfill the expected demand safely. However, this is much costlier in terms of battery degradation, which is analyzed next.

To compare the degradation and aggregator costs, we now consider a scenario where all chargers satisfy the energy requirements. In this case, the energy requirement is assumed to have a maximum range of 40kWh for all EVs. The simulation is then run, and the results are observed.

The figure (5-4) shows the degradation cost incurred by individual EVs based on the charger type. As expected, the charger power rating relates directly to the battery degradation. For example, if we consider EV numbers 7, 8, and 31, there is an apparent increase in degradation

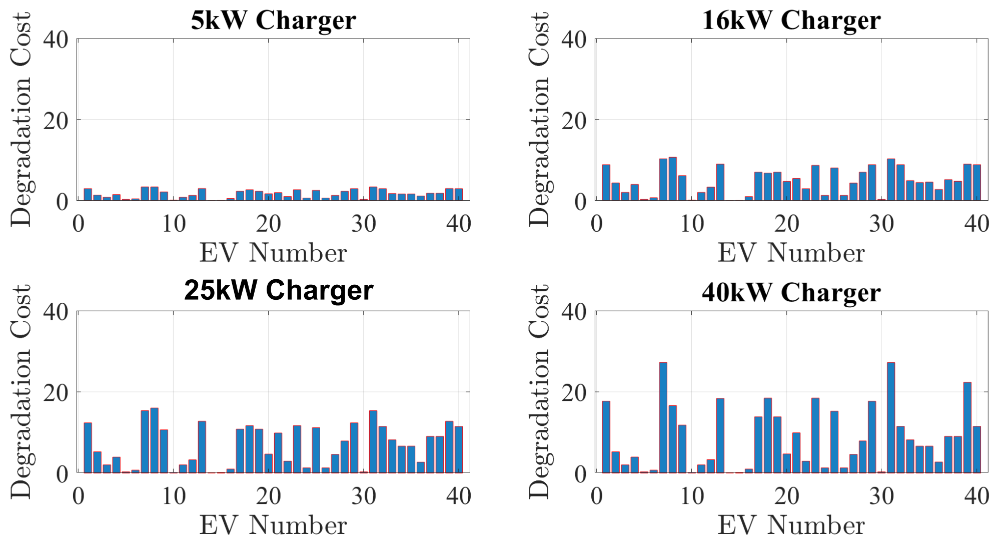


Figure 5-4: Degradation Cost of EVs for different chargers

based on the charger used. This is because even though the energy requirement is the same, the amount of energy put into the EV at a particular time differs. Therefore, if more energy is put into the EV at a particular time to charge faster, the more it degrades. The entire degradation cost of the EV fleet is presented in the table (5-1). Interestingly, as the higher power level chargers can put more energy during the period of lower energy price, the incur lower cost to an aggregator. However, due to much higher battery degradation the total cost of charging with the high power chargers is high.

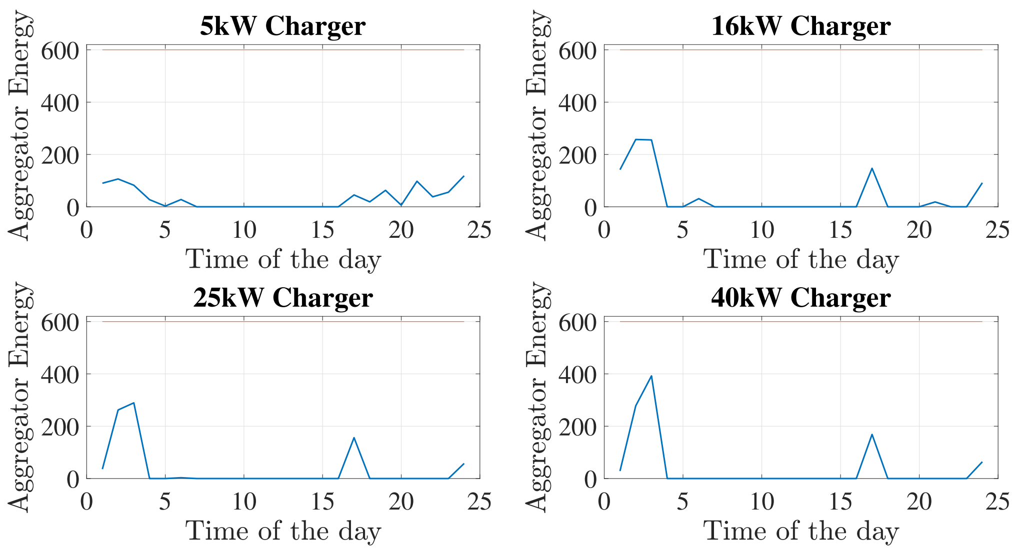


Figure 5-5: Aggregator Energy Demand for EVs using different chargers

The figure (5-5) shows the aggregator energy demand for the EV fleet for the entire optimization period. We assume that the maximum energy that the grid can provide at any hour is around 600kWh. The aggregator charges the EVs to minimize the energy price. Therefore, it tries to minimize charging at high prices. We note that between 07:00 till 16:00 the EVs are not connected to the charging stations. Here, from 00:00 till 02:00, the energy prices are low, as shown in figure (5-1), thus maximum energy is consumed. Consequently, if the charger has a higher power rating, it can put more energy at lower price to reduce the aggregator costs significantly. It is also important to note that if a lower power charger can fulfill the demand for an energy requirement, it puts less stress on the grid, making it favorable for grid operators in case of high EV penetration. The aggregator cost for the fleet is shown in table (5-1).

Charger Power	Fleet Degradation Costs	Aggregator Costs	Total Costs
5kW	70.50 €	379.49 €	450 €
16kW	201.30 €	328.15 €	529.45 €
25kW	281.47 €	264.07 €	545.54 €
40kW	356.69 €	296.55 €	653.25 €

Table 5-1: Cost Incurred for fleet using various chargers

The term fleet degradation refers to the battery degradation of all the EVs in the fleet. Furthermore, aggregator cost is the price paid for using energy from the grid. The table (5-1) shows the fleet degradation, aggregator, and total costs incurred by the fleet. Furthermore, the cost of degradation for a lower rating charger, like a 5kW charger, is the least, whereas for a 40kW charger is the most. However, if we look at the aggregator cost, it is different. The aggregator costs seem to decrease with a higher power because, a higher power charger can put more energy at cheaper energy price times. Nevertheless, the 5kW charger is the most suited overall, resulting in the lowest costs compared to the other three chargers.

5-2-2 Variable Power Level Charging

In section (5-2), we observed that using a lower-rating charger fares better for cases when the energy demand is not high. Therefore, in this case, a variable charger allocation is implemented for the 100 energy demand scenarios to help reduce the degradation and aggregator costs. Finally, we compare it with the 40kW charger case that satisfies all the energy demand scenarios.

The aggregator energy demand is plotted in figure (5-6). The aggregator demand is based on the energy price. Therefore, energy is added at periods when the energy price is low. First, from 07:00 to 16:00, no energy is added as the EV is considered driving which is given in the driving profile (5-2). The rest of the time, the EVs are connected to the grid. During those

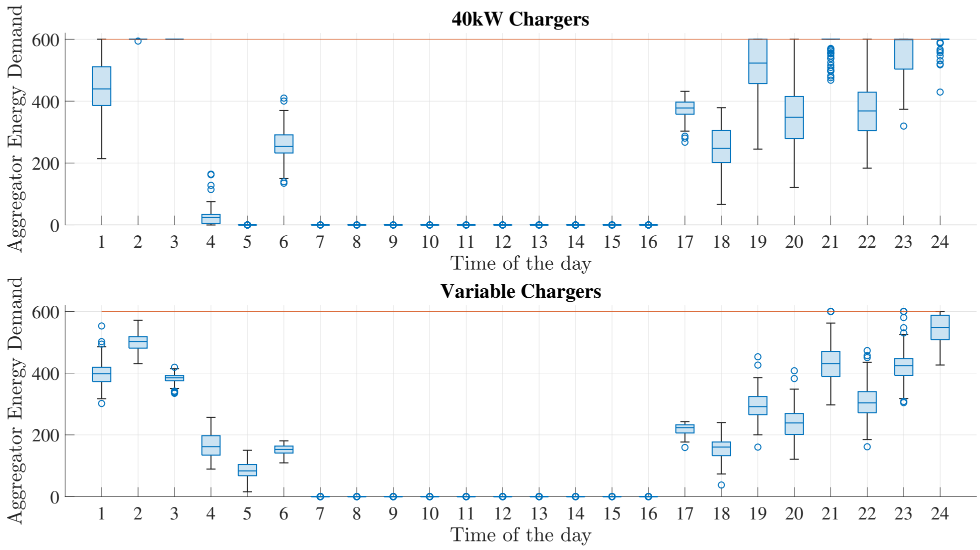


Figure 5-6: Aggregator Energy Demand

times, the EVs try to put maximum energy at times 00:00, 01:00, 02:00, and 21:00. This is because, at those times, the energy price is low, and the aggregator tries to minimize the cost. However, if we compare the 40kW chargers and the variable chargers, we observe that the 40kW charger has more freedom to charge at the time when the price is low. Therefore, it can reduce the aggregator costs as low as possible.

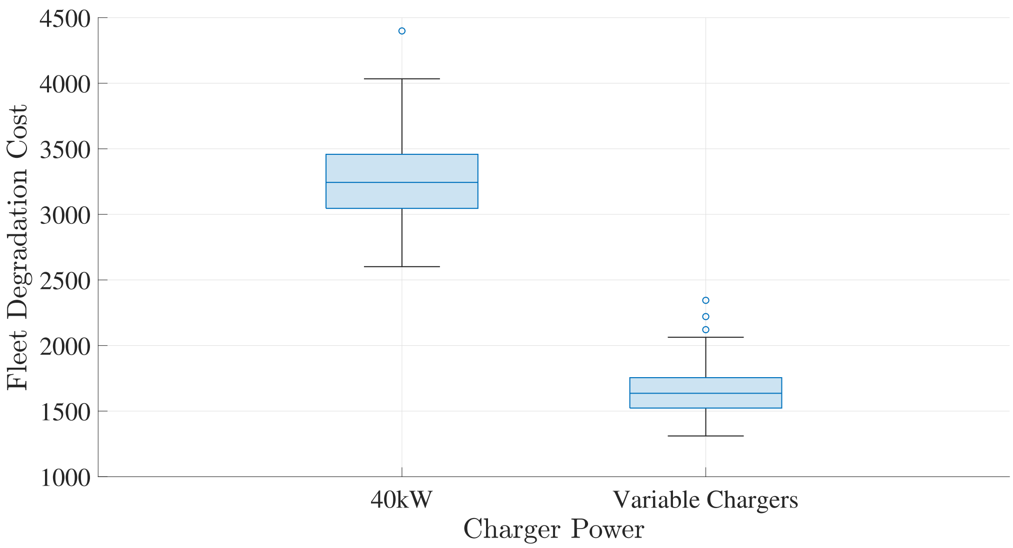


Figure 5-7: Fleet Degradation Cost for different energy scenarios

In figure (5-7), the fleet degradation cost is computed for the 40kW chargers and the variable chargers' case. The fleet degradation of the 40kW chargers is considerably higher than the variable charger cases. This is because the charger assigned in the variable charger case is based on the energy requirement. For example, if the energy requirement is above 40kWh and less than 128kWh, 16kW can satisfy the requirement. The results also show that a lower-rating charger will lower degradation costs. Therefore, the variable charger case is the more suitable case among the two as it reduces the degradation cost of the fleet significantly.

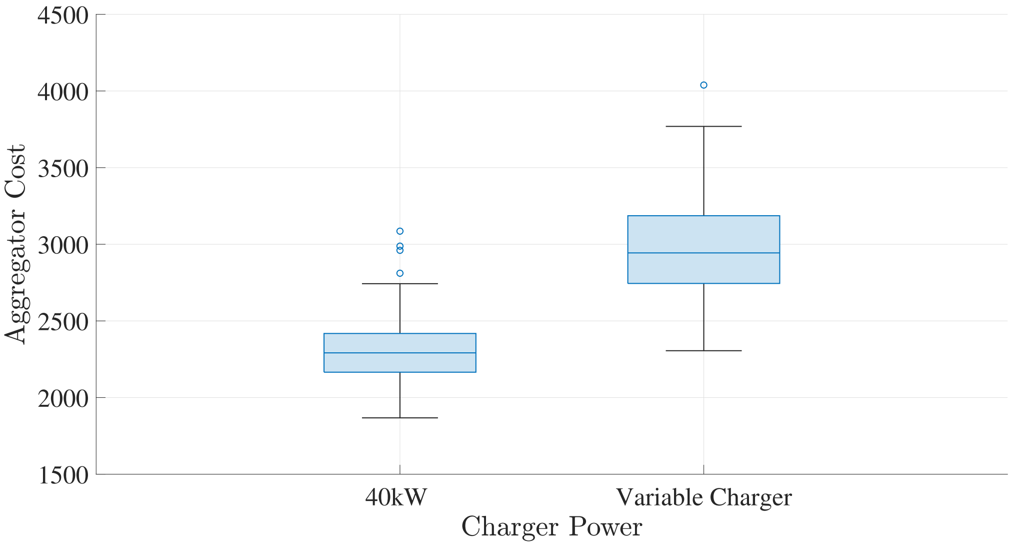


Figure 5-8: Aggregator Costs for different energy scenarios

The aggregator cost for the entire fleet is plotted in (5-8). Unlike the degradation cost, the aggregator cost for the variable charger case is larger than the 40kW chargers. As seen in figure (5-6), the aggregator demand for the variable charger is greater than the 40kW charger cases. Therefore, it results in higher costs.

Finally, the total cost incurred by the fleet is shown in figure (5-9). The total cost is the sum of the degradation and aggregator costs. Now, even though the aggreagtor cost of the 40kW is better compared to the variable chargers, the degradation cost incurred is considerably high. Therefore, the total cost incurred from the variable chargers is less than the 40kW chargers.

From the above simulation results, it is good to assume that using different power level chargers based on the energy demand is better than using chargers of the same power level. The total cost incurred is significantly reduced. Therefore, the variable power charging approach is better suited in this case, when the EVs are connected to the grid only once.

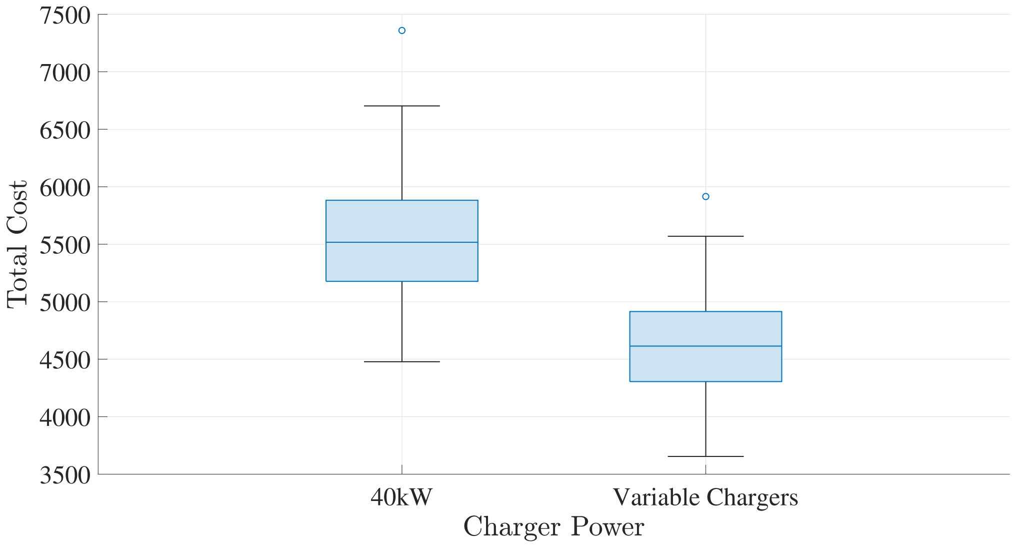


Figure 5-9: Total Cost of the fleet for different energy scenarios

5-3 Day-Night Charging

Day-Night charging is a case where EVs are connected to the grid twice. The simulation setup is the same as in section 5-1. The driving profile of the 40 EVs is shown below in figure (5-10). Furthermore, in this case, two different charging strategies; greedy charging and minimal energy charging are implemented. The charging strategies are explained in Chapter 2.

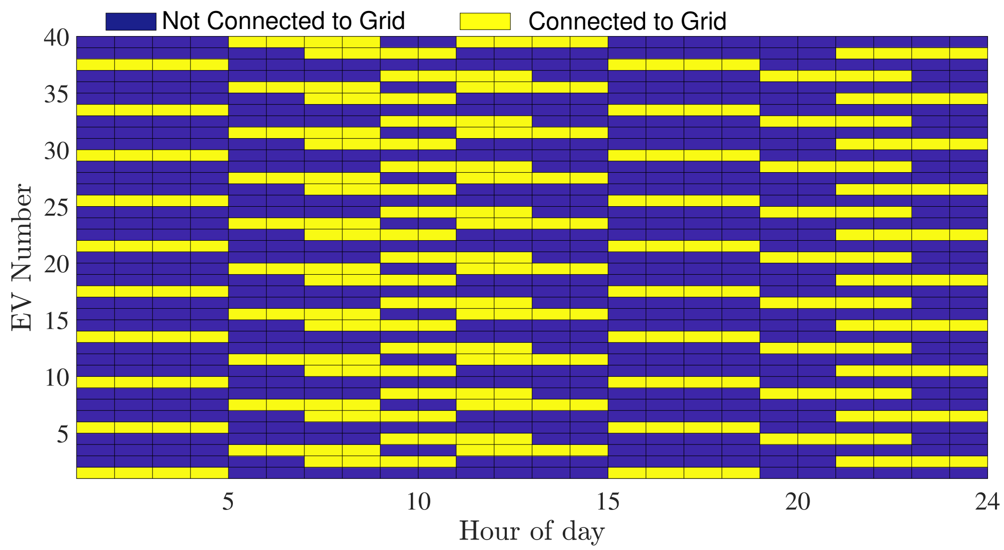


Figure 5-10: Driving Profile of the EVs

5-3-1 Constant Power Level Charging

The simulation is run using a constant power level charger for 100 randomly generated energy demand scenarios. The four charger power levels are a 5kW, 16kW, 25kW and 40kW. Two charging strategies are implemented for each power level charger: greedy charging and minimal energy charging. In figure (5-11), the percentage of satisfied scenarios for the individual EVs using greedy charging is presented for the entire day.

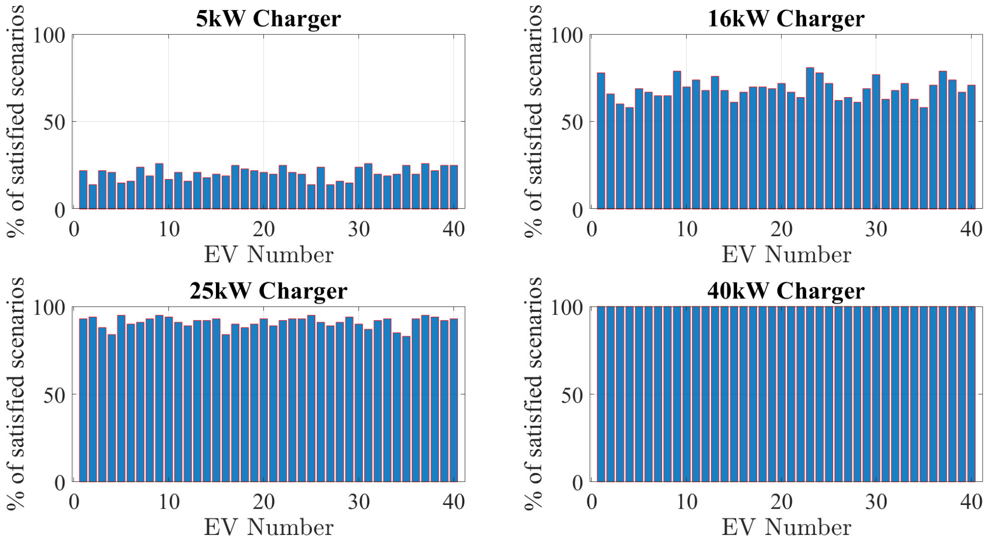


Figure 5-11: Percentage of satisfied scenarios using greedy charging

A 5kW charger satisfies around 14-26% of the energy requirement scenarios. However, the rest of the 74-86% of the time, the 5kW charger does not satisfy the energy requirements of the EVs. Next, the 16kW charger is taken. This charger satisfies about 58-81% of the scenarios. This makes only 19-42% of the scenarios unsatisfied. Then for a 25kW charger, the scenarios satisfied are about 83-95%. Finally, the 40kW charger satisfies 100% of the time for all 100 scenarios.

Second, the simulation is run for all the charger types using the minimal energy charging method. In figure (5-12), the percentage of satisfied scenarios for the individual EVs is presented for the entire day.

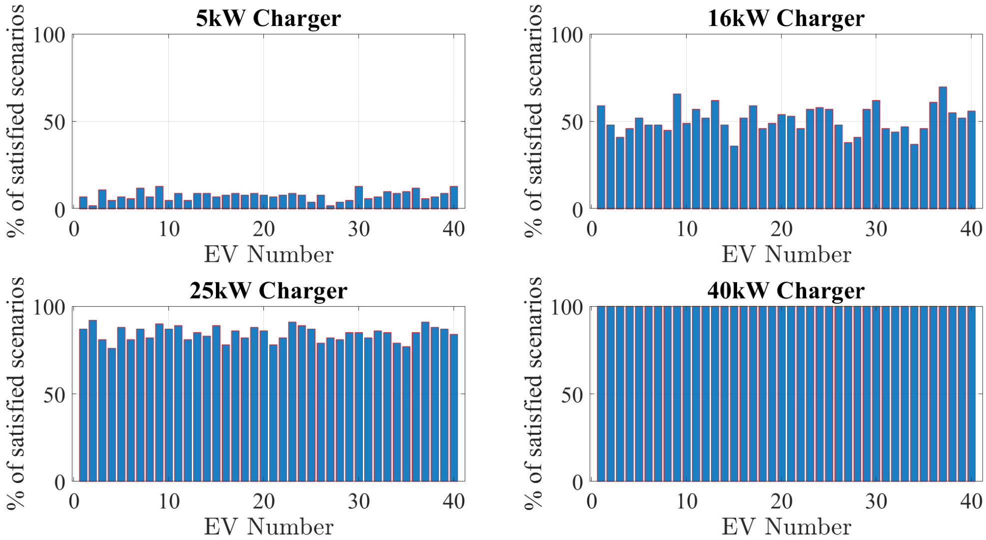


Figure 5-12: Percentage of satisfied scenarios using minimal energy charging

For example, taking the 5kW charger, only 2-13% of the scenarios are satisfied by the individual EVs. A 5kW charger can only provide a maximum of 40kWh for 8 hours. Therefore, it shows that almost 87-98% of scenarios have an energy requirement greater than 40kWh, and a 5kW charger does not satisfy the requirements. However, the 16kW charger satisfies 36-70% of the scenarios. However, 43-64% of the scenarios remain unsatisfied. Furthermore, the 25kW charger satisfies almost 76-92% of the scenarios. However, there remains 8-24% of the scenarios are unsatisfied. Finally, if we look at the 40kW charger, it satisfies 100% of the scenarios in each case.

In the analysis, the minimal charging case satisfies fewer cases than the greedy charging case. This is because, with greedy charging, the energy is put into the EV is each time it connects to the grid. It charges to the full capacity of the battery. However, with minimal energy charging, the energy put is minimal to satisfy the next trip. However, the analysis alone suggests to use a higher power level charger to safely fulfill all the energy requirements. Nevertheless, this will be much costlier in terms of battery degradation which we analyze next.

To compare the degradation and aggregator costs, we now consider a scenario where all the chargers satisfy the energy requirements. in this case, we consider an energy requirement such that the maximum range of energy is 5kW. Then, the simulation is run for all the chargers for both charging strategies, and the results are observed.

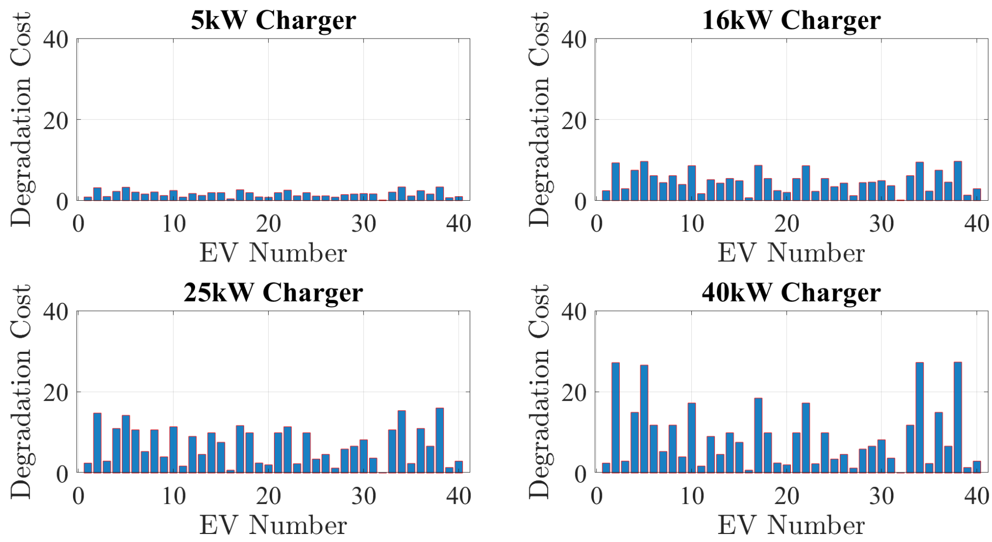


Figure 5-13: Degradation Cost of EVs using greedy charging for different chargers

The figure (5-13) presents the degradation costs of the individual EVs using a greedy charging method for the various charger types. As the charger power increases, the degradation cost increases for specific EVs in the fleet can be observed. The reason is that EV degradation depends on the amount of power put in at a particular time. If the EV draws more power at a particular time, more degradation cost it incurs. The degradation cost of the fleet is given in table (5-2)

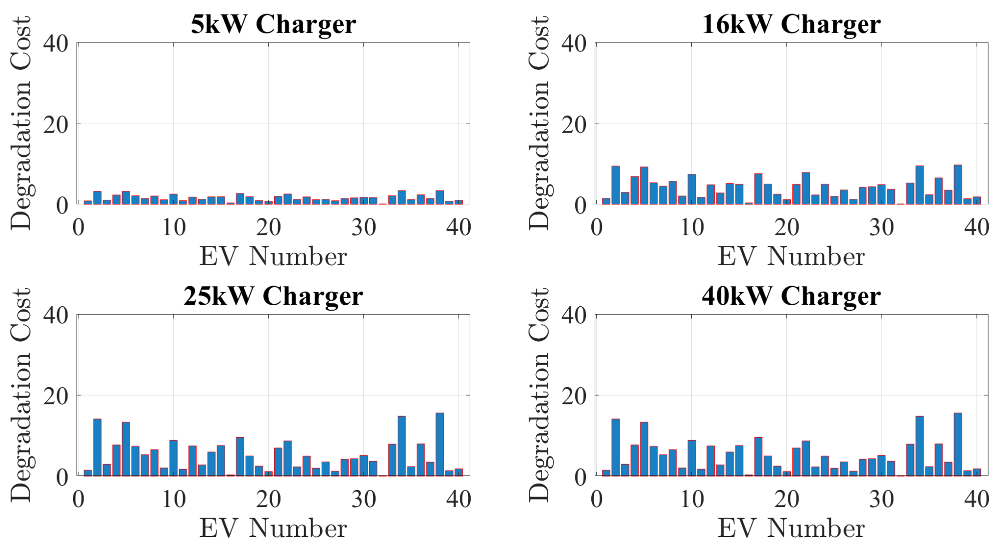


Figure 5-14: Degradation Cost of EVs using minimal energy charging for different chargers

The figure (5-14) presents the degradation costs of the individual EVs using a minimal energy charging method for the various charger types. Similar to the greedy charging case, degradation costs are higher when the charger power is higher. However, if we compare the greedy charging and the minimal energy case, minimal energy has a lower degradation cost. Therefore, the least degradation cost is when a 5kW charger is used with minimal energy charging, whereas the maximum cost is using a 40kW charger with greedy charging. The degradation cost of the fleet is given in table (5-3)

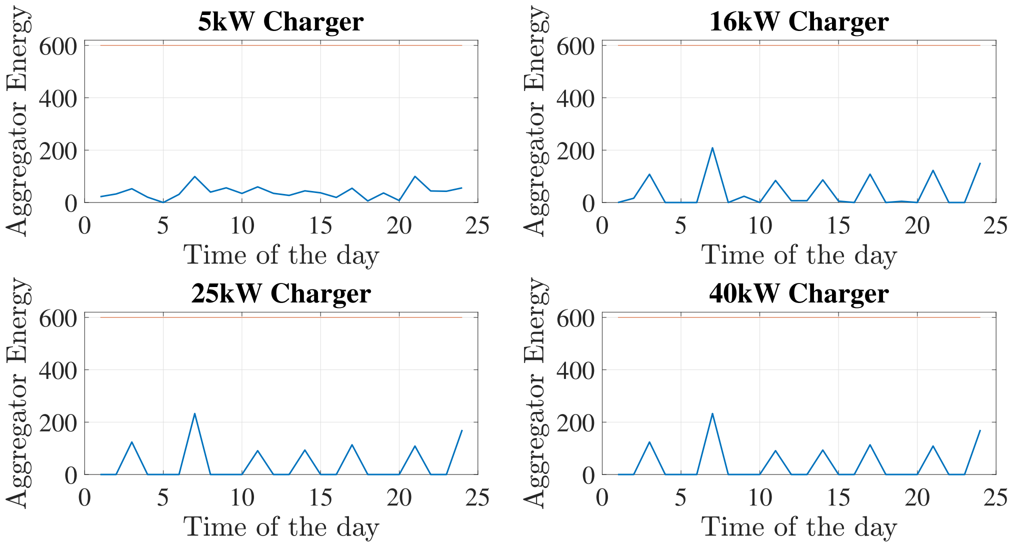


Figure 5-15: Aggregator Energy Demand using greedy charging for EVs using different chargers

The figure (5-15) shows the aggregator demand of the EVs using greedy charging for different chargers. The lower power chargers, like 5kW, can only provide up to 5kWh energy in an hour. However, higher power level chargers like 25kW and 40kW can put energy in a particular time. So, if we observe the figures, the EVs try to put the maximum energy at periods 02:00, 06:00, 11:00, and 14:00 when the energy price (5-1) is meager. Furthermore, the amount of energy depends on when the EV is connected to the grid. The aggregator cost incurred is shown in table (5-2).

Charger Power	Fleet Degradation Costs	Aggregator Costs	Total Costs
5kW	69.50 €	418.42 €	487.92 €
16kW	195.93 €	298.70 €	494.63 €
25kW	281.60 €	287.94 €	569.54€
40kW	359.43 €	287.93 €	647.36 €

Table 5-2: Cost Incurred for fleet using greedy charging for various chargers

The table (5-2) shows the degradation cost, aggregator cost, and the total cost incurred by the fleet using a greedy charging method. In this case, the energy is added each time it connects to the grid. In the table (5-2), the 5kW charger is the most effective in terms of degradation among the three as it yields the lowest cost overall. However, if the aggregator costs are seen, the 40kW charger has the least cost. However, a 40kW charger incurs a higher overall cost due to its degradation; therefore, a 5kW is the most effective charger.

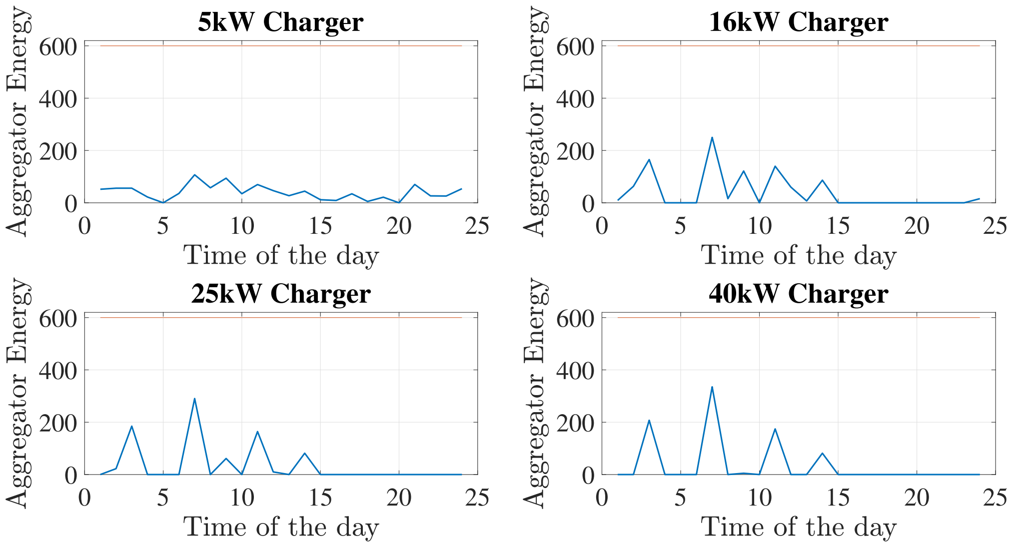


Figure 5-16: Aggregator Energy Demand using minimal energy charging for EVs using different chargers

The figure (5-16) shows the aggregator demand of the EVs using minimal energy charging for different chargers. The aggregator demand, in this case, reduces the aggregator cost even further compared to the greedy charging case. The figure shows that more energy (5-1) is put at 02:00, 06:00, 11:00, and 14:00 to reduce the aggregator costs. The aggregator costs are shown in table (5-3).

Charger Power	Fleet Degradation Costs	Aggregator Costs	Total Costs
5kW	67.51 €	380.92 €	448.43 €
16kW	175.37 €	236.08 €	411.45 €
25kW	217.03 €	178.74 €	395.77 €
40kW	504.96 €	131.09 €	636.05 €

Table 5-3: Cost Incurred for fleet using minimal energy charging for various chargers

The table (5-3) shows the degradation cost, aggregator cost, and total incurred costs using a minimal charging method. Compared to the greedy charging case, minimal energy charging has lower incurred costs in total. However, in this case, the 25kW charger yields the best result. Even though the degradation cost incurred by the 25kW charger is relatively high, the aggregator costs are meager, making the overall cost lower. Furthermore, even the 16kW charger has a lower overall cost. It differs only by 15 €.

Now, in both cases of greedy charging and minimal energy charging, the aggregator demand is quite less for the lower power chargers. This is very beneficial for a grid operator when there is a higher penetration of EVs in the grid as it puts less strain on the grid. Furthermore, in this case, where the EVs are connected to the grid twice minimal energy charging strategy makes a better strategy for charging the EVs. It results in lower total cost in comparison to the greedy charging method.

5-3-2 Variable Power Level Charging

In section (5-3-1), we observed that lower rating chargers have lower degradation costs but high aggregator cost. However, higher rating chargers have lower aggregator costs but higher degradation. Now, in this case a variable charger allocation is implemented to reduce the degradation and aggregator costs. We then compare the results with the 40kW charger case that satisfies all the energy demand scenarios.

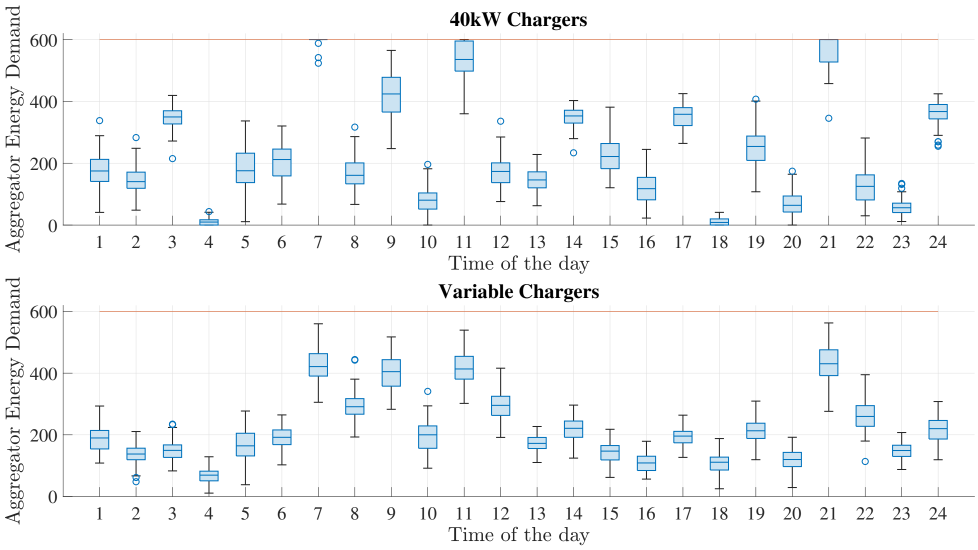


Figure 5-17: Aggregator EV Demand using greedy charging

The aggregator demand for the greedy charging method is plotted in figure (5-17). Now, we can see that the aggregated energy in the 40kW charger case is higher in comparison to the variable charging case. This is because 40kW chargers can put more energy at times when the energy price is cheap. This shows that the aggregator cost for the 40kW chargers should be lower than the variable power charger case.

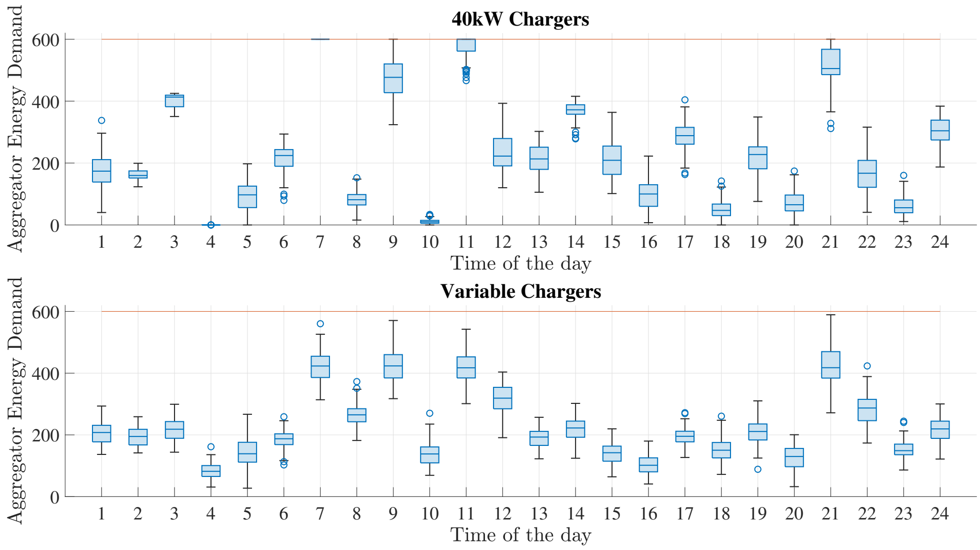


Figure 5-18: Aggregator EV Demand using minimal energy charging

The aggregator demand for the minimal energy charging method is plotted in figure (5-18). Now, this case we again see that the aggregator energy for the 40kW charger is higher than the variable charger case. Also, when we compare the greedy charging and minimal energy charging case, the minimal energy charging has a higher aggregator demand than the greedy charging.

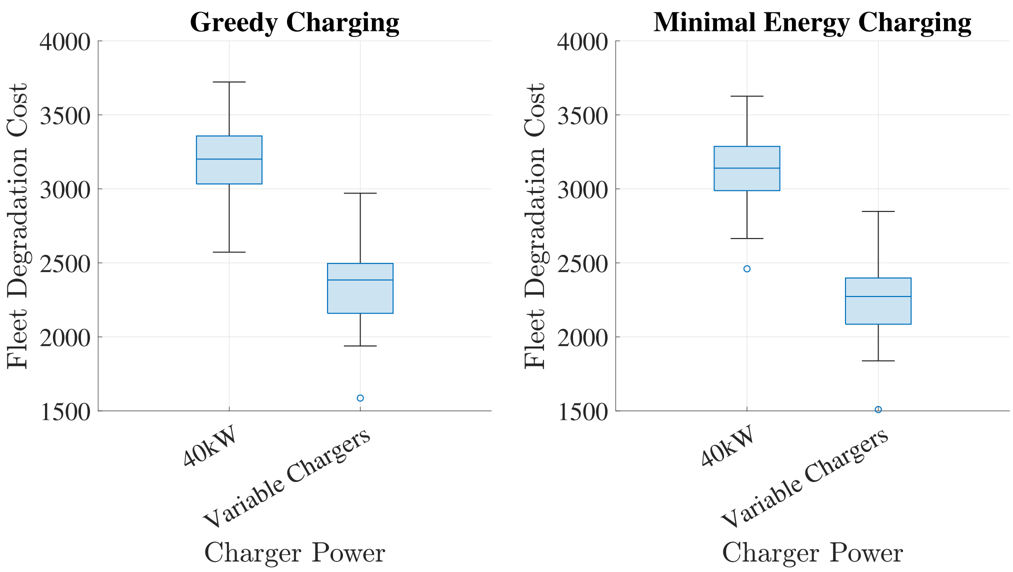


Figure 5-19: Fleet Degradation cost

The degradation costs for the entire fleet is shown in figure (5-19) for both the charging strategies. The minimal energy charging is better compared to greedy charging in both cases.

However, the variable charger case has lower degradation compared to the 40kW charger. The lower degradation accounts to the fact that in a variable charger case, we use lower rating chargers to satisfy the energy demand that are within the scope for the charger. Overall, the variable charger case with minimal energy charging has the lowest fleet degradation costs whereas the greedy charging with the 40kW chargers has the highest degradation.

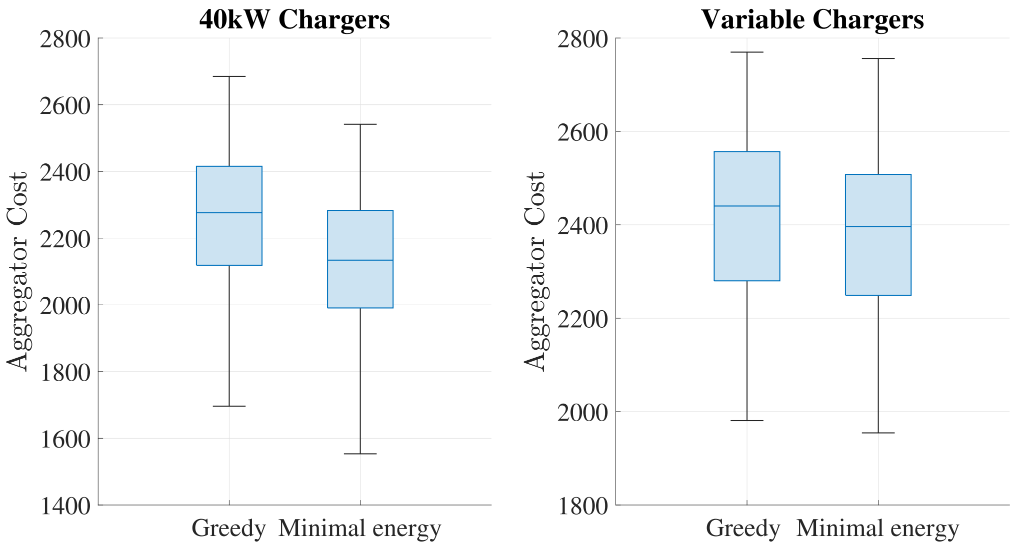


Figure 5-20: Aggregator cost

The aggregator costs for the fleet are shown in figure (5-20) for the greedy and minimal energy charging strategy. Unlike, the degradation costs, the aggregator costs for the 40kW charger are lower compared to the variable charger case. If we observe, figure (5-17),(5-18), the energy put at at cheaper energy prices are higher in the 40kW charger case. Therefore, the aggregator costs incurred using 40kW chargers will be lower than the variable charger case. Furthermore, the minimal charging case with the 40kW charger results in the lowest aggregator costs whereas the variable charger case using greedy charging has the highest aggregator cost.

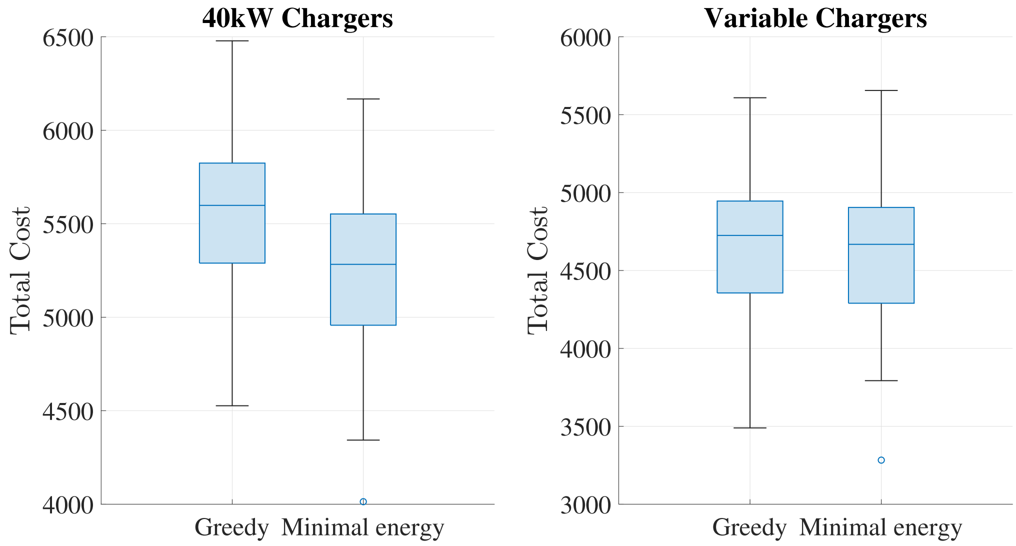


Figure 5-21: Total Cost

Finally, the total cost for the fleet is computed as shown in figure (5-21). Interestingly, we observe that total cost incurred by the variable chargers in both the charging methods is lower than the 40kW chargers. Even though the aggregator costs of the 40kW chargers are lower, the degradation costs are considerably higher. Therefore, the total cost incurred increases for a 40kW charger. Furthermore, if we see the minimal energy charging with the variable charger case results in the least overall costs than the greedy charging variable charger case. The best case among the four is the minimal energy charging with variable charger whereas the worst case is a greedy charging case with 40kW chargers.

Chapter 6

Conclusion and Future Work

6-1 Conclusion

In this thesis, we formulate optimal EV fleet charging as a convex optimization problem [25] to minimize the cost of charging the fleet, considering energy and battery degradation costs. We solve the resulting optimization via an ADMM-based algorithm. For modelling battery degradation, we utilize a non-linear empirical battery model [29] to identify a battery degradation constant. The empirical model mainly depends on the c-rate, which directly relates to the power level of the charger. Therefore, we construct a relation between capacity loss and power, and then the obtained values are fitted into the EV degradation model to predict a constant battery degradation factor. The simulation studies are designed to analyze and obtain a charging strategy to minimize the cost of charging for a fleet operator.

The simulation results concluded that lower power chargers did not satisfy the energy requirements for most scenarios. However, as the charger power level increases, a higher percentage of scenarios are satisfied. Therefore, the simulation was run for a feasible case where all power level chargers satisfied the energy requirements to compare the aggregator and battery degradation costs. For the feasible case, it is observed that using lower power chargers always benefits the fleet, resulting in lower degradation costs. Furthermore, it is essential to note that the aggregator demand is low with lower power chargers. This implies that even if there is higher penetration of EVs in the grid, it will not affect the grid. However, there is a trade-off concerning the aggregator costs. Similarly, fleet operators can use higher-level power chargers to reduce aggregator costs. Nevertheless, this results in considerably higher degradation costs for the fleet.

Therefore, the concept of variable charger allocation is presented, giving the best solution among all the simulation cases. The variable charger allocation allocates chargers based on the energy requirement of the EVs and, therefore, reduces aggregator and battery degradation costs. Furthermore, considering the two charging strategies that were implemented: minimal energy charging was the better strategy than greedy charging. Minimal energy charging only charges for the energy required for the next trip. This significantly reduces the battery degradation costs resulting in lower total incurred costs. Finally, it can be inferred that using such intelligent methods to charge the EVs help reduce the TCO for the fleet operators.

6-2 Future Work

In this thesis, we use the aggregator model as a price-based model, i.e., the aggregator tries to minimize energy costs. However, the aggregator model can be altered based on the requirement. For example, two other alternate aggregator models can be a valley filling and direct coupling model to support the grid operation. We also note that the process of battery degradation is highly non-linear and depends on many factors like temperature, c-rate, DOD, charging, and time.

Currently, we only consider a quadratic function that depends on the power drawn from the chargers and is only an approximation of the battery degradation. However, as battery degradation constitutes a considerable cost for EVs, a promising future direction can be to incorporate more sophisticated degradation models and design optimization methods to handle the resulting cost function. Furthermore, the problem can incorporate dynamic pricing schemes for the electric prices and uncertainties associated with the constraints, for example, including uncertainty in driving profile based on driver behavior or integrating delay in fleet arrival.

Appendix A

ADMM: Convergence

In this chapter, the convergence criteria for the ADMM method is discussed in detail. One assumption on the function f and g is made and one assumption on the problem is considered.

Assumption 1: The (extended-real-valued) functions f : $R^n \to$ R $\cup \{+\infty\}$ and g : $R^m \to$ R $\cup \{+\infty\}$ are closed, proper, and convex.

The assumption is expressed compactly using epigraphs. The function f satisfies assumption 1 if and only if its epigraph

$$\text{epi}\, f = \{(x, t) \in \mathbf{R}^n \times \mathbf{R} \mid f(x) \leq t\} \tag{A-1}$$

is a nonempty convex set.

The meaning of Assumption 1 is that the x-update and z- update can be are solvable. There exist a x and z not necessarily unique, that minimizes the augmented Lagrangian. It is also important to note that the function f and g are considered as non differentiable functions and assume value of $+\infty$.

Assumption 2: The unaugmented Lagrangian L_0 has a saddle point.

Explicitly, there exist (x^*, z^*, y^*) not necessarily unique, for which

$$L_0(x^*, z^*, y) \leq L_0(x^*, z^*, y^*) \leq L_0(x`z`y^*) \tag{A-2}$$

holds for all x,y,z.

Considering assumption 1, it follows that $L_0(x^*, z^*, y^*)$is finite for any saddle point (x^*, z^*, y^*). This implies that (x^*, z^*) is a solution to (3.1), so $Ax^* + Bz^* = c$ and f$(x^*) \leq \infty$, g$(z^*) \leq \infty$. It also implies that y^* is dual optimal, and the optimal values of the primal and dual problems are equal, i.e., that strong duality holds. Note that we make no assumptions about A, B, or c, except implicitly through assumption 2.

A-1 Convergence

The ADMM iterations satisfy the following conditions considering the assumptions 1 and 2:

- Residual convergence. $r^k \to 0$ as $k \to \infty$, i.e., the iterates approach feasibility.
- Objective convergence. $f\left(x^k\right) + g\left(z^k\right) \to p^\star$ as $k \to \infty$, i.e., the objective function of the iterates approaches the optimal value.
- Dual variable convergence. $y^k \to y^\star$ as $k \to \infty$, where $y^\star$ is a dual optimal point.

Appendix B

Simulation Environment

B-1 MATLAB

The simulation environment used is MATLAB. The optimization toolbox of MATLAB was used to solve the problem. The **fmincon** function is used to solve the aggreagtor and EV problems. The optimization technique used was interior-point in the fmincon function. The simulation parameters are given below as follows:

B-2 Simulation Parameters

EV Parameters		
Parameter	Description	Value
E_{bat}	Battery Capacity	50kWh
α	Battery degradation constant	0.017 kW/h
N_e	Number of EV's in Fleet	40
c	Number of times connected to grid	{1,2}
η_{ch}	Charging efficiency	0.91
T	Time period	24

Table B-1: EV parameters

Price Based Parameters		
Parameter	Description	Value
ρ	Penalty factor	0.001
γ	Trade-off parameter	1
ϵ_p	Primal Convergence tolerance	1
ϵ_d	Dual Convergence tolerance	1
λ	Factor for ρ updation	0.001
μ	Factor for ρ updation	0.01
$\bar{x_a}$	Maximum Power taken from grid	600 kW
$\underline{x_a}$	Minimal Power given back to grid	0

Table B-2: Price based parameters

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