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Energy Demand Redistribution Analysis for Public EV Fast Charging Station: Case Study of NEA Ratnapark, Kathmandu, Nepal

By

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A THESIS

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ABSTRACT

The rapid adoption of electric vehicles in Nepal is driving the need for efficient and reliable public charging infrastructure. This study investigates exploratory data analysis and the implementation of dynamic pricing strategies at NEA CCS Ratnapark, a representative fast-charging station in Kathmandu Valley, using data from 62 public stations for contextual comparison. A Multinomial Logit model was employed to analyze user discrete choice behavior and price sensitivity across three time-of-use tariff periods: off-peak, normal, and peak. The model estimated a price sensitivity coefficient ($\beta \approx -0.125$), indicating moderately elastic demand, where a 1% price increase reduces the probability of selecting a given period by roughly 0.1% depending on its baseline share. The peak-period own-price elasticity is approximately −0.087, meaning that a 1% rise in the peak price reduces the peak charging share by about 0.08%. Session-based choice probabilities captured realistic energy consumption, with the mean session energy highest during normal (20.2 kWh) and peak (19.8 kWh) periods. Baseline observations showed that 53.0% of sessions occurred in the normal period, 30.6% during peak, and 16.4% off-peak. A scenario-based optimization under a revenue-preserving constraint indicated that reducing off- and normal-period prices by approximately 30% while increasing peak-period prices up to 80% could cut the peak session share from 30.6% to 28.4% without reducing total revenue. Results demonstrate low user responsiveness to price signals, with dynamic pricing effectively flattening the load profile and reducing peak sessions by 7.2% while boosting off-peak sessions by 48.8%.

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LIST OF ABBREVIATIONS

FCS	Fast Charging Station
NEA	Nepal Electricity Authority
SoC	State of Charge
ToU	Time of Use
NDC	Nationally Determined Contribution
BEV	Battery Electric Vehicle
IEA	International Energy Agency
CCS	Combined Charging System
GBT	Guó Biāo Tōngyòng
HEV	Hybrid Electric Vehicles
PHEV	Plug-in Hybrid Electric Vehicles
EREV	Extended-Range Electric Vehicles
FCEV	Fuel Cell Electric Vehicles
NZE	Net Zero Emissions
NPV	Net Present Value
IRR	Internal Rate of Return
AC	Alternating Current
DC	Direct Current
EV	Electric Vehicle
MNL	Multinomial Logit
kW	Kilo-Watt

Chapter 1 - Introduction

1.1 Background

The global transition toward cleaner energy has accelerated the uptake of electric vehicles (EVs), and Nepal is no exception. Government tax incentives and rising environmental awareness have encouraged many Nepalese users to shift from internal combustion vehicles to EVs. However, the success of EV adoption largely hinges on the availability and efficiency of supporting infrastructure, particularly EV charging stations (Adhikari et al., 2020).

Over the past few years, Nepal has expanded both public and private electric vehicle charging infrastructure (EVCS). Among these facilities, the NEA CCS Ratnapark Fast Charging Station has become one of the most heavily used sites due to its central location and accessibility for various EV segments. Despite this progress, several operational challenges remain. Peak-hour queues, extended waiting times, and uneven utilization patterns suggest that the existing infrastructure is not always used efficiently, underscoring the need for data-driven evaluations and strategies to better manage demand.

Demand at an EV charging station fluctuates throughout the day, and users' charging decisions are often influenced by both time and price. The Ratnapark station provides a representative case for examining these dynamics within Nepal's public charging network. Prior studies highlight that time-of-use (TOU) price adjustments can shape daily load profiles, improve station throughput, and influence operator revenue. However, systematic analysis of such mechanisms based on Operational data from charging stations in the Nepalese context is still limited (C B et al., 2025), (Q. Zhang et al., 2020).

This thesis, therefore, examines the operational characteristics of the NEA CCS Ratnapark station using detailed transaction-level data up to January 2025. The study analyzes energy consumption, arrival rates, charging durations, revenue patterns, and the state of charge (SoC) of incoming vehicles. To estimate how users respond to price differences across time periods, a Multinomial Logit (MNL) choice model is calibrated and combined with Monte Carlo simulations to replicate daily operational patterns (So & Kuhfeld, 2007).

1.2 Problem Statement

Electric vehicles (EVs) continue to grow in popularity, but their operation brings its own set of difficulties, especially when it comes to charging time. At many public charging stations, queues build up quickly during busy periods because each vehicle occupies a charger for an extended duration, and the number of connectors is limited. Nepal is experiencing these issues as well, particularly within the charging network operated by the Nepal Electricity Authority (NEA). Although EV use is rising steadily, very little research has examined how these stations actually perform on a day-to-day basis in the Nepalese context.

Effective infrastructure planning requires insight into the actual usage patterns and operational behaviour of charging stations. This includes examining patterns in energy consumption, the timing and frequency of vehicle arrivals, the state of charge of incoming vehicles, utilization of connectors, and the variation in tariffs across different hours. At present, such detailed insights are largely missing from Nepal's EV landscape.

NEA has expanded its public charging network across the country, but most existing reports provide only broad summaries—such as the number of stations and their technical specifications—without analyzing the transaction-level data that these stations generate. As a result, issues such as uneven demand across different times of the day have not been studied in detail. Stations like NEA CCS Ratnapark routinely experience heavy traffic during the evening, especially between 5 PM and 11 PM, which leads to long waits, while demand remains low during late-night and early-morning periods.

This research addresses that gap by developing a Multinomial Logit (MNL) model to examine how EV users choose between three available charging time windows. The analysis focuses on how factors such as tariffs, number of sessions, state-of-charge patterns, and practical constraints influence these decisions. The broader aim is to generate insights that can support better pricing strategies and operational planning within Nepal's public charging network.

1.3 Objective

1.3.1 Main Objective

To analyze and model electric vehicle users' charging time choice patterns at Ratnapark station using a Multinomial Logit framework

1.3.2 Specific Objectives

1. To Scrutinize operational data from NEA on energy consumption, arrival rates, charging durations, SoC distributions, and Sessions
2. To develop and calibrate a Multinomial Logit model using EV charging data from NEA CCS Ratnapark
3. To perform scenario and sensitivity analyses based on the estimated model to evaluate potential demand-redistribution strategies under varying price and operational conditions

Chapter 2 - Literature Review

Understanding electric vehicle charging behavior is essential for designing efficient public charging systems and managing grid impacts. The growing body of literature reveals that users' charging decisions depend on multiple factors — including electricity price, time of day, state of charge, waiting time, and travel purpose. However, the sensitivity of users to price and time often varies, and in many public fast-charging settings, demand remains concentrated during specific peak hours. This chapter reviews major studies related to EV charging behavior, price elasticity, and choice modeling, with a special focus on the Multinomial Logit framework as a behavioral modeling approach suitable for this study.

2.1 EV Charging Demand and Price Elasticity

Several researchers have examined how electricity prices affect EV charging behavior. However, evidence indicates that EV charging demand, particularly at fast chargers, tends to be price inelastic during commuting or business hours.

(Kuang et al., 2024) investigated EV charging demand at public fast-charging stations in Shenzhen and found that public charging demand is inelastic to electricity price, with an average elasticity of -0.76. They concluded that "charging demand at fast chargers is largely price inelastic during commuting periods" because users prioritize convenience and necessity over cost.

(Q. Zhang et al., 2020) emphasized that time-of-use (ToU) pricing can shift residential EV charging behavior to off-peak hours, but public fast chargers used by fleets or taxis exhibit limited flexibility. Wang et al. (2021) observed that only when price differentials are significant (2× or more) do users show noticeable changes in charging time selection.

From these studies, it is clear that while NEA's existing three-slot tariff structure (NRs. 4.45, 6.60, and 8.40 per kWh) provides a foundation for load management, the limited shift of charging activity toward low-tariff hours implies weak behavioral response. This motivates the need for a behavioral modeling framework that explicitly represents user choices among available time slots.

2.2 Performance Evaluation of Public Charging Stations

Assessing charging station performance involves understanding key operational parameters such as energy delivered, number of sessions, SoC variations, and average session duration.

(L. Zhang et al., 2020) introduced a performance evaluation model using utilization rate, charging efficiency, and temporal demand variation as key indicators. (Liu et al., 2023) proposed a data-driven utilization index combining charging frequency and energy delivery, demonstrating that station congestion correlates strongly with temporal charging patterns.

(Yang et al., 2021) applied queuing-based performance models to fast-charging hubs and highlighted that high traffic during evening hours reduces service efficiency and increases waiting time.

These frameworks show that a systematic performance evaluation, using real operational data, is crucial before designing behavioral interventions like pricing.

2.3 Behavioral Modeling of EV Charging Choice

Understanding how EV users choose when and where to charge is central to designing demand redistribution mechanisms. Since EV user behavior involves multiple discrete alternatives (e.g., choosing between time slots or stations), discrete choice models (DCMs) are widely applied.

Ben-Akiva and Lerman(*Discrete Choice Analysis*, n.d.) (1985) established the theoretical foundation of discrete choice theory, which assumes that each user selects the alternative with the highest perceived utility. (Train, 2009) extended this theory through the Multinomial Logit model, where the probability of choosing an alternative depends on the exponential of its utility relative to all others.

(Potoglou et al., 2023) Applied the MNL model to study EV drivers' selection among different charging stations, considering factors like price, distance, and waiting time.

(Liao, 2011) modeled temporal charging decisions using MNL and found that while travel purpose and SoC significantly affect choice, price elasticity remains low unless supported by strong incentives or information-based interventions.

(Daina et al., 2017) analyzes EV users' charging behavior and decision-making, highlighting factors such as time-of-use preferences, charging costs, and convenience, Cost $\beta \approx -0.459$

These studies show that the MNL model provides a mathematically simple yet powerful tool to describe how users make probabilistic choices based on observable attributes such as price, waiting time, and charging duration.

2.4 Demand Redistribution and Dynamic Pricing

Dynamic pricing aims to balance station utilization by offering time-dependent charging rates. Kley et al. (2011) emphasized that ToU pricing alone is insufficient without understanding the behavioral component. Yang et al. (2022) proposed a combined MNL-simulation approach to predict how price adjustments redistribute demand across time slots. Zhao et al. (2020) demonstrated that integrating MNL-based choice models with dynamic pricing can reduce peak congestion by up to 20–30%.

In the NEA context, this approach can be applied to simulate demand shifting from high-demand hours (5 PM–11 PM) to low-tariff hours (11 PM–5 AM), thereby improving utilization and reducing operational stress.

2.5 Vehicles in Nepal

Nepal's vehicle growth has reached 5,421,000 registered vehicles at an annual growth rate of 17.38% over the last five years, with motorcycles and scooters being the most used at 80.71%, according to the Economic Survey 2022/23, and car/jeep/van at 6.31% over the last five years.

Table 1: Vehicles registered in Nepal

S.N.	Vehicle	Number of vehicles registered
1.	Motor cycle	4,370,611
2.	Tempo	94,193
3.	Car/jeep/Van	339,273
4.	Microbus	11,715
5.	Minibus	35,876
6.	Bus	68,784
7.	Truck/Mini truck	144,501
8.	Pick up	90,512
9.	Tractor	191,947
10.	E rickshaw	55,585
11.	Others	18,003
	Total	**5,421,000**

(Source: Ministry of Physical Infrastructure and Transport. *Economic Survey, 2080/81 MOF)

2.6 Electric Vehicles Import Trend in Nepal

Nepal's government incentives, low operational costs, and charging infrastructure have led to a surge in electric vehicle (EV) imports, particularly in the two-wheeler and compact car segments, reflecting a shift in consumer preferences. Table 2 shows yearwise EV import data.

Table 2: EV Import year-wise

S.N	Vehicle type	Year-wise import quantity			
		2020/2021	2021/2022	2022/2023	2023/2024
1	Buses with only electric motors for propulsion	NA	NA	37	11
2	Mini-buses (15 to 25 seater) with only an electric motor for propulsion:	NA	NA	3	336
3	Microbuses (11 to 14 seater) with only an electric motor for propulsion	NA	84	241	537
4	Unassembled 3-Wheelers EV	2307	917	459	3114
5	Electric 3-wheeled Vehicle	1943	6405	6914	9057
6	Electric Car, Jeep & Van up to 50 kW	120	996	3759	4571
7	Electric Car, Jeep & Van 51 to 100 kW	25		272	6885
8	Electric Car, Jeep & Van 101 to 200 kW	104	805	15	217
9	Electric Car, Jeep & Van 201 to 300 kW	-	4	4	27
10	Electric Car, Jeep & Van greater than 300 kW	-	2	-	1
11	Electric 3-wheeler Vehicle (with an electric motor for propulsion)	2454	769	277	786
12	Electric 4-wheeler Vehicle (with an electric motor for propulsion)	80	23	12	175

S.N	Vehicle type	Year-wise import quantity			
		2020/2021	2021/2022	2022/2023	2023/2024
13	EV not fitted with handling & lifting equipment	1661	1	219	4
14	Electric Motorcycle and Scooters	358	385	7155	7747
Total		**9,052**	**10,391**	**19,367**	**33,468**

(Source: Department of Customs, Nepal, 2024)

2.7 Electrical Vehicles Charging System

2.7.1 Charger types

For Modes 2 and 3, only a Type 2 connector is allowed to be used in EVCS because it has an inbuilt locking mechanism (for safety purposes). For Mode 4, CCS Type 2 and GBT connector is allowed to be used in EVCS. Table 3 and (NEA2020, Bidding document)

Table 4 show charger types and their configurations.

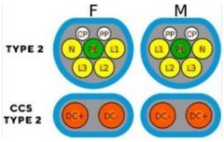
Table 3: Charger type and Charging time

Charger Type	Power (kW)	Approx. Charging Time (for a 60 kWh battery, 0-80%)
Level 1 (AC)	1.2 - 2.4 kW	24+ hours
Level 2 (AC)	3.3 - 22 kW	4 - 8 hours
DC Fast Charger (50-100 kW)	50-100 kW	40 - 60 minutes
DC Ultra-Fast Charger (150-350 kW)	150+ kW	15 - 30 minutes

(NEA2020, Bidding document)

Table 4: EV Charger Connector

Connector Type	Connector	AC/DC Power	Charging Standard		
			Voltage (V)	Current (A)	Power (kW)
GBT		AC / DC 3 Phase	440V AC / 1000 V DC	Up to 32 A AC/ 250 A DC	Up to 27.7kW AC/ 250 kW DC

Connector Type	Connector	AC/DC Power	Charging Standard		
			Voltage (V)	Current (A)	Power (kW)
Combo CCS Type 2		DC Charging	Up to 400V	Up to 400 A DC	Up to 240 kW

(NEA2020, Bidding document)

2.7.2 NEA Charging Standard

Charger having an on-board AC charger of at least 22 kW and an off-board charger with direct current delivery of at least 60 kW via CCS or GB/T. In order for the conductive energy transfer function to function securely under typical operating conditions, the EV must be linked to the EVSE.

Table 5: The general requirements of EVSE

Charger	Charger connectors	Rated voltage(V)	No of guns
Category 1	CCS 2.0 (Min 60 KW)	200-750	2
	Type-2 AC (Min 22 KW)	380-480	1
Category 2	GB/T (Min 60 KW)	200-750	2
	GB/T AC (Min 22 KW)	380-480	1

(NEA2020, Bidding document)

Requirements for input

AC supply voltage rating The AC supply voltage system has a nominal voltage of 400V, a rated frequency of 50Hz, and three phases and five wires (3-Ph+N+E).

Output specifications

According to the output configuration type listed below, the chargers enable parallel charging of EVs with a minimum of 60KW from both DC guns concurrently and an AC output of 22KW:

DC output voltage: 200-750 V for GB/T and CCS, with a power factor > 0.96 (full load) and a converter efficiency > 95% at nominal output power, AC output current: 200 A and voltage: 380-480 V.

2.7.3 Charging infrastructures

EV charging stations provide regulated electricity to vehicle batteries, with different types offering varying current and voltage levels. AC on-board chargers power vehicles from home plugs, while DC fast-chargers deliver direct current. Infrastructures should include intelligence for user authentication, communication, data gathering, and payment.

As of 2024, Nepal has approximately 417 Public charging stations (FY End 2022, it was 163, FY End 2023, it was 186), primarily concentrated in urban centers like Kathmandu and Pokhara. This limited infrastructure poses challenges for EV owners, especially during peak travel periods. With around 19,000 new EVs introduced in 2023 and only 23 charging stations added that year, the disparity between EV adoption and charging infrastructure expansion has become more pronounced. (NEA Report, 2081)

Table 6 highlights the number of charging stations in the country.

Table 6: Charging Station

S.N.	Charging Station	No. of Charging Stations
1	NEA Charging Station	62
2	MG Charging Station	22
3	Tata Charging Station	150
4	BYD Charging Station	14
5	CG Charging Station	16
6	Yatri Charging Station	5
7	Thee GO Charging Station	10
8	Hyundai Charging Station	45
9	ElectriVa Charging Station	51
10	GOGORO Charging Station	45
	Total	**417**

Source: WECS, Volume I-1, (Durbar & Report, 2025)

2.7.4 NEA Charging Network

Since Nepal imports both Chinese and European EVs, NEA has both CCS and GBT standards in its charging infrastructure. NEA has a total **62 numbers** of fast charging stations throughout the country, among which there are 32 CCS charging, and 30 GBT standard chargers. Figure 1 shows the charging stations of NEA throughout the country.

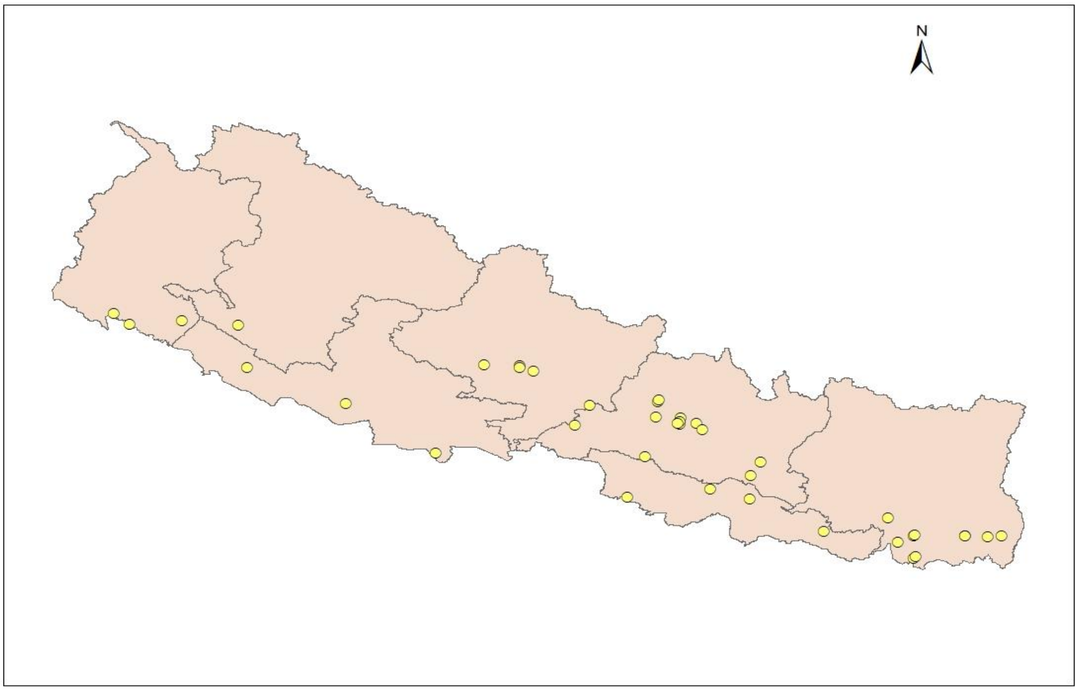


Figure 1: NEA Charging Stations

2.7.5 Electric Vehicle Charging Tariff Rates

The Nepal Electricity Authority (NEA) regulates EV charging tariffs, categorized under a special category to promote adoption. Tariffs are affordable and vary based on time, with lower rates during off-peak hours. Table 7 and Table 8 provide the tariff rates for charging stations.

Table 7: Transportation charging rate for public transportation

Summer (Baisakh – Mangsir) (April 15 to December 15) 2024			
Voltage Level	Energy rate (Rs./unit)		
	Peak Time (5 PM – 11 PM)	Normal Time (5 AM to 5 PM)	Off-peak Time (11 PM – 5 AM)
33 kV	8.40	6.60	4.45
11 kV	8.60	6.70	5.05
230/400 V	8.70	6.90	5.05
Winter (Paush – Chaitra) (December 16 to April 14)			
33 kV	8.40	6.60	6.60
11 kV	8.60	6.70	6.70
230/400 V	8.70	6.90	6.90

(NEA Report 2024)

Table 8: Transportation charging rate for private vehicles

Summer (Baisakh – Mangsir) (Rs./unit) (April 15 to December 15) 2024			
Voltage Level	Energy rate		
	Peak Time (5 PM – 11 PM)	Normal Time (5 AM to 5 PM)	Off-peak Time (11 PM – 5 AM)
33 kV	11.20	10.10	4.45
11 kV	11.60	10.20	5.05
230/400 V	11.70	10.30	5.15
Winter (Poush – Chaitra) (December 16 to April 14)			
33 kV	11.20	10.10	10.10
11 kV	11.60	10.20	10.20
230/400 V	11.70	10.30	10.30

(NEA Report 2024)

2.7.6 Government policies

Nepal's government is promoting the use of electric vehicles (EVs) due to its lack of fossil fuel reserves and high hydropower potential. Despite low installed capacity, numerous hydropower projects could provide enough electricity for EV charging stations. Increased hydroelectricity production and vehicle sector usage could reduce petroleum products and limit the country's trade deficit. Nepal submitted its first Nationally Determined Contributions in 2016, aiming to increase the electric vehicle (EV) share to 20% by 2020. In its second NDC, it aims for EVs to comprise 25% of private passenger vehicle sales by 2025, 90% by 2030, and 20% of four-wheeler public vehicles by 2025.

Table 9: NDC Target in EV

Deadline year	Percent of Private Passenger Vehicle Sales (Including two-wheelers)	Percent of Four-Wheeler Public Passenger Vehicle Sales
2025	25%	20%
2030	90%	60%

(NDC 2020)

2.7.7 Policies Regarding the Development of EV Charging Infrastructure

Every public charging station should have the following minimum infrastructure

- 11000/400 or 33000/400 voltage substation transformer, line, cables, termination, metering, along with all protection equipment.

- To provide a charging service, the service provider needs to agree with the Nepal Electricity Authority or any other online network service provider.
- A charging service provider can add more services like: hotels, restaurants, hair cutting, spas, and gym centers according to their need.
- If planned to charge with high-speed onboard charging for Fluid Cooled Batteries (FCBs) should need to install an appropriate station with Liquid Cooled Cable.
- A charging service provider that charges the battery by the off-board charge swapping method should manage appropriate Climate Control Equipment.
- To install a private charging station by personnel/company or public vehicle service provider for their internal purpose does not need to complete the criteria of the public charging station.

Location of Public Charging Station

In the case of a public charging station, the density/ distance between two charging points should need to follow the following minimum criteria.

- Availability of one charging station should be managed in a range of 3 Km × 3 Km of the grid. According to the need of private sector demand, the availability of charging station areas and other infrastructure can install the charging station.
- Long-distance electric vehicles and heavy-duty like (buses/trucks) should have a charging infrastructure with at least one fast charging station every 100 Km.

2.7.8 Requirement of Public Charging Station

A 142 kW EV charging station with a voltage range of 200 V to 750 V, compatible with various charging protocols, and CAN/PLC communication between EVSE and EV, is required, meeting the minimum requirements for a compatible charging station. A charging module, power supply interface, protection module, earthing system, control module, metering module, man-machine interface, and cabinet are some of the components that should be included in a DC charging integrated machine. It should be able to remove broken modules without interfering with the functionality of the remaining modules, feature a color touchscreen display, a human-machine interaction interface, constant voltage modes, and automatic recognition of the correct charging connector and cable connection.

(NEA Bid 2020)

Chapter 3 – Methodology

This chapter outlines the overall methodological approach used in the study. It describes the data sources, analysis, and the behavioral modeling framework used to analyze and redistribute EV charging demand. The core modeling approach in this research is the Multinomial Logit (MNL) model, which helps understand how users choose charging time slots based on price and other factors. The chapter also outlines the process of simulation and analysis, where alternative pricing strategies are tested to predict how tariff changes can shift user demand from congested to underutilized periods.

3.1 Detail Methodological Framework

The methodology includes data collection and analysis to provide a comprehensive understanding of the charging station's performance. The study will be based on both primary and secondary data sources.

Primary data were collected by a field visit to the selected EV charging station operator, i.e., NEA. A thorough visit was scheduled to an FCS that contains multi-standard GBT/ CCS and densely populated areas for this NEA CCS Ratnapark, which was considered. The data were compiled from the NEA Charging Operation Management System, which provides transaction-level information required for analyzing station performance. At the site, the form of the operational assessment was filled out by observing all the necessary technical components of the station by the Project Manager, Electric Vehicle Charging Station Infrastructure Development Project, NEA. The data for analysis of status and operational performance was compiled from the NEA Charging Operation Management System.

Secondary data was gathered from various sources, including Reports from different offices, a variety of related publications, works of literature, research, etc. have been gathered. In addition to these, relevant data were gathered from associated websites.

Research Methodology:

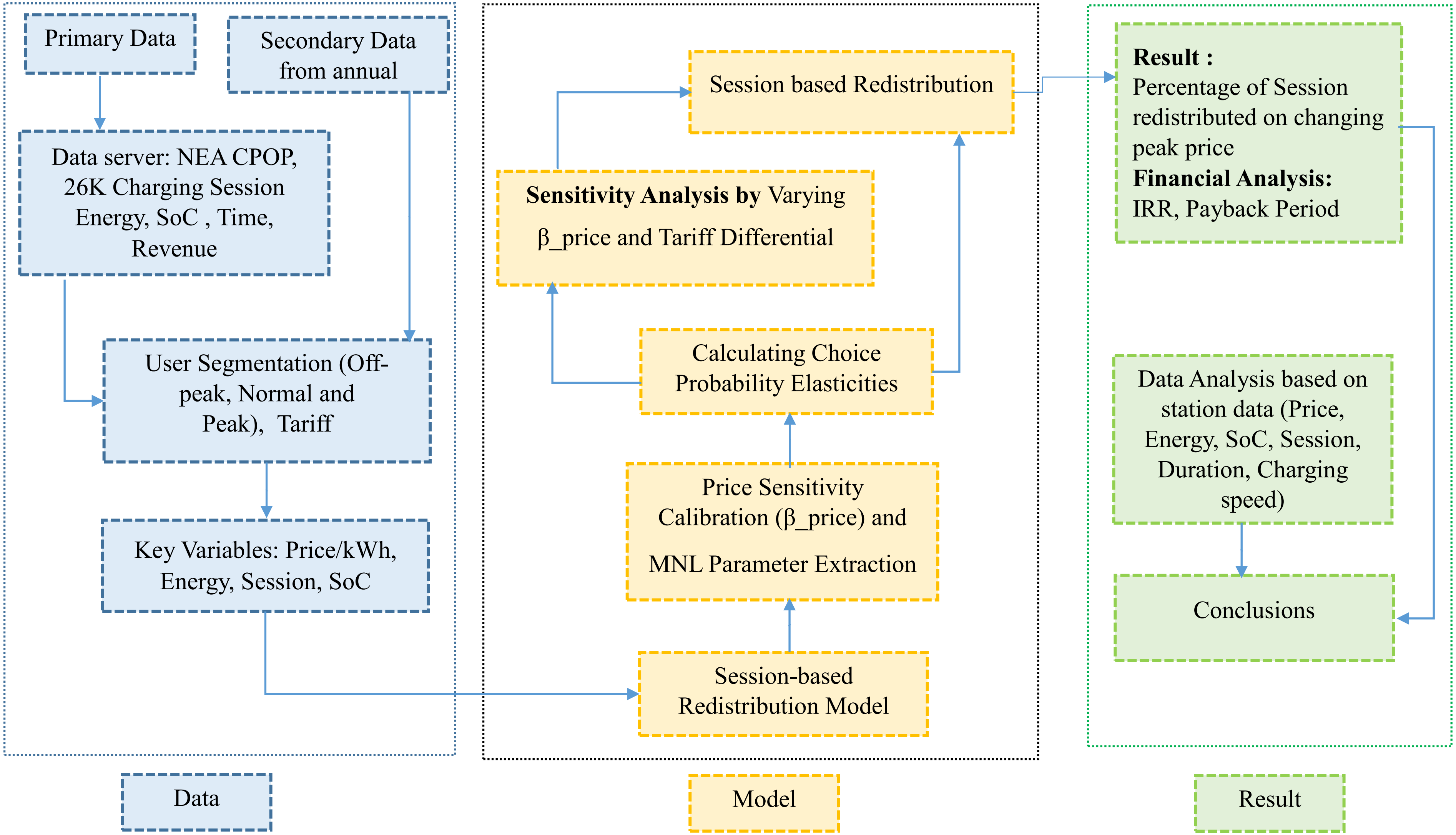


Figure 2: Block Diagram Research Methodology

3.1.1 Data Collection

The primary dataset was provided by the **Nepal Electricity Authority (NEA)**, which maintains digital records of all fast-charging sessions at its stations. For this study, the NEA CCS Ratnapark station was selected because it represents a **high-demand urban station** located in the city center.

Real-time charging transaction data from the NEA CCS Ratnapark station were obtained from Station logs, software, and interviews with the stakeholders for more than two years. The dataset includes:

- Energy consumed (kWh)
- Total revenue (NRs)
- Number of sessions
- Charging Duration (Total time an EV is plugged in).
- State of Charge (SoC) at arrival and departure
- EV Arrival Times and Arrival Rate Patterns (hourly)

Time Slot Aggregation

The original data were available at the session level. They were aggregated daily into three time slots corresponding to NEA’s tariff schedule. These data were grouped into **three daily time slots** according to NEA’s tariff policy:

11 PM – 5 AM (Off-peak)
5 AM – 5 PM (Normal)
5 PM – 11 PM (Peak)

3.1.2 Exploratory Data Analysis

The performance of the station was analyzed using statistical indicators such as utilization rate, average session duration, SoC changes, and energy delivery per time slot. These metrics were calculated for each time slot over multiple months to identify demand concentration and station load imbalance. Exploratory data analysis was performed using key operational metrics, including daily electricity consumption, session distribution, charging duration, and utilization patterns. These metrics formed the basis for the MNL modelling and subsequent scenario analysis, allowing the evaluation of demand redistribution under different time-of-use pricing scenarios. This integrated methodology allows evidence-based recommendations to reduce peak congestion.

Before modeling, the performance of the NEA CCS Ratnapark station was evaluated using the following indicators:

1. **Utilization Rate (UR):**

$$\textbf{Utilization Rate} = \frac{\text{Total Energy Delivered}}{\text{Maximum Possible Daily Energy Capacity}} \times 100$$

This measures how effectively the station's charging connectors are being used.

2. **SoC Improvement (ΔSoC):**

$\Delta\text{SoC} = \text{End SoC} - \text{Initial SoC}$

This represents how much the vehicle's battery charge increases during a typical session.

3. **Revenue per kWh (RpK):**

RpK = Total Fee (NRs)/Total Energy Delivered (kWh)

This helps assess profitability and verify consistency with tariff categories.

3.1.3 Model Development (MNL Model) Framework

A Multinomial Logit (MNL) model was used to analyze EV users' choice of charging period (off-peak, normal, peak). The MNL model is based on **Random Utility Theory (RUT)**, which assumes that each EV user chooses a charging time slot that gives them the highest utility. Daily session counts were converted into session-level observations, and congestion proxies were constructed as relative differences between periods, defined as $dcount_{\text{normal}}$ = normal – off and $dcount_{\text{peak}}$ = peak – off. Each session record contained the chosen period and congestion covariates.

The MNL model (off-peak as the base alternative) was estimated using maximum likelihood, producing alternative-specific constants and congestion effects. A price-sensitivity parameter (β) was calibrated using the method of moments by minimizing the difference between observed and predicted TOU shares.

Based on estimated utilities, choice probabilities were computed using the logit formulation, and elasticities were derived using the analytical softmax derivative to measure own- and cross-price sensitivity. These probabilities were then used to redistribute total daily sessions across TOU periods under alternative price scenarios. Energy use and revenue were calculated directly from redistributed sessions and the mean energy per session.

Congestion Proxy (Daily Count Differences).

For each day in the dataset, the total number of charging sessions occurring in the off-peak, normal, and peak periods was computed. These period-wise daily session totals were then used to construct derived variables representing congestion levels. Derived variables for MNL covariates were defined as congestion proxies:

- *dcount*_normal = normal – off
- *dcount*_peak = peak − off

These variables capture the relative congestion of the normal and peak periods compared to off-peak sessions. The MNL model requires one observation per decision (here, each session is a decision to choose a period). For each date, the observed number of sessions in each period was expanded into multiple rows**,** where each row represents a single session. Each session row included:

- chosen: categorical variable representing the selected period (0 = off, 1 = normal, 2 = peak)
- dcount_normal and dcount_peak as covariates

Fitting the MNLogit Model,

- Using statsmodels.MNLogit, the MNL model, was fitted to the synthetic session-level data.
- Off-peak was the reference alternative.
- Maximum likelihood estimation provided alternative-specific constants and congestion coefficients, reflecting baseline preferences and sensitivity to congestion.

Multinomial Logit (MNL) Utility Specification

The MNL model uses **off-peak** as the base alternative (utility = 0). The alternative-specific utilities:

- Off-peak period, U_off = 0
- Normal period, U_normal = const_normal + b_dcount_normal × dcount_normal + β × (price_normal − price_off)
- Peak period, U_peak = const_peak + b_dcount_peak × dcount_peak + β × (price_peak − price_off)

Where, const_normal = estimated alternative-specific constant for normal period
const_peak = estimated alternative-specific constant for peak period
b_dcount_normal = congestion coefficient for normal period
b_dcount_peak = congestion coefficient for peak period

β = calibrated price-sensitivity coefficient (beta_hat from method of moments)
price_normal, price_peak, price_off = observed mean prices per kWh in each TOU period

The utility function for each period i was defined as:

$U_i = \text{const}_i + \beta_{(\text{dcount normal})} \cdot \text{dcount\_normal} + \beta_{(\text{dcount peak})} \cdot \text{dcount\_peak}$

The off-peak period was used as the reference (base) alternative. Maximum likelihood estimation (Newton-Raphson method) was applied to obtain the coefficients.

Choice Probabilities (Multinomial Logit) Based on Utilities:

Compute exponential utility terms:

$\text{exp\_off} = \exp(U_{\text{off}})$

$\text{exp\_normal} = \exp(U_{\text{normal}})$

$\text{exp\_peak} = \exp(U_{\text{peak}})$

Then the choice probabilities:

$P_{\text{off}} = \text{exp\_off} / (\text{exp\_off} + \text{exp\_normal} + \text{exp\_peak})$

$P_{\text{normal}} = \text{exp\_normal} / (\text{exp\_off} + \text{exp\_normal} + \text{exp\_peak})$

$P_{\text{peak}} = \text{exp\_peak} / (\text{exp\_off} + \text{exp\_normal} + \text{exp\_peak})$

These predicted shares are compared with observed shares to calibrate the price coefficient **β**.

Method-of-Moments Calibration for β, the calibrated price coefficient **$\hat{\beta}$** is obtained by minimizing the squared error between predicted and observed shares:

$$\hat{\beta} = \operatorname{argmin}_{\beta} \sum (P_{\text{predicted}}(\beta) - P_{\text{observed}})^2$$

The fitted model returns a parameter matrix with rows corresponding to covariates (const, dcount_normal, dcount_peak) and columns corresponding to alternative periods relative to the base. For each alternative period, the parameters were extracted as follows:

Normal period:	Constant: const_normal
	Congestion effect: β_dcount_normal
Peak period:	Constant: const_peak
	Congestion effect: β_dcount_peak

3.1.4 Price Elasticity and Sensitivity Analysis

Once the MNL parameters are estimated, the next step is to simulate how tariff changes would alter users' choices among time slots. This study evaluates how peak-period charging behavior responds to changes in time-of-use (TOU) prices using the calibrated Multinomial Logit (MNL) model. The MNL framework, widely applied in transportation and energy studies (Train, 2009), allows modeling user choice probabilities as a function of price and station-level attributes. The baseline parameters, including the estimated price coefficient ($\beta = -0.126$) and observed session shares, were used to compute updated peak-period choice probabilities under price adjustments ranging from −30% to +80%. For each price scenario, the systematic utility of the peak period was recalculated according to the adjusted TOU tariff, consistent with approaches used in EV charging behavior studies. The resulting choice probabilities were derived using the logit formulation, and arc elasticities were computed to quantify the sensitivity of peak-period demand to each price perturbation. Elasticity Computation ($\varepsilon_{(i,j)}$), Elasticities measure the sensitivity of the probability of choosing period *i* to the price of period *j*:

$\varepsilon_{\{i,j\}} = (\partial P_i / \partial P_j) \times (P_j / P_i)$, Where P_i is the MNL choice probability for period *i*.

Computation Steps

1. Compute deterministic utilities, including the price effect:

$$U_i = const_i + \beta_{price} \times P_i$$

2. Convert utilities to choice probabilities (softmax):

$$P_i = \exp(U_i) / \Sigma_k \exp(U_k)$$

Derive elasticities from the softmax derivative:

$$\begin{aligned} \partial P_i / \partial P_j = \ & \beta_{price} \times P_i \times (1 - P_i), \text{ if } i = j \\ & -\beta_{price} \times P_i \times P_j, \text{ if } i \neq j \end{aligned}$$

Scale by P_j / P_i to obtain percentage elasticity ($\varepsilon_{\{i,j\}}$):

$\varepsilon_{\{i,j\}} = (\partial P_i / \partial P_j) \times (P_j / P_i)$, where

Diagonal elements: own-price elasticities (sensitivity of choice probability to its own price). Off-diagonal elements: cross-price elasticities (substitution effects between periods). These elasticities provide behavioral insight into how pricing shifts user demand across TOU periods.

Session-Based Redistribution

- Using β_{price} and MNL parameters, compute new choice probabilities under a hypothetical price scenario.
- Redistribute total daily sessions (S_{total}) proportionally to predicted probabilities.
- Compute energy consumption and revenue for each period as: Session, Energy, and Revenue Calculations.

To assess the effects of different behavioral responsiveness levels, two additional price coefficients (β = -0.25 and β = -0.5) were evaluated. These alternative values represent increasingly price-sensitive user groups, consistent with findings from empirical EV charging choice research. Peak-session shares were recomputed for each parameter–price combination to compare redistribution outcomes across elasticity regimes. The resulting peak-session shares were computed for each parameter–price combination to observe the magnitude and pattern of demand shifts. (Letmathe et al., 2025; Torkey et al., 2024), (Šimeček, 2019),(Su et al., 2017)

Finally, two sets of visual analyses were produced: (i) sensitivity curves showing the elasticity trajectory across increasing peak prices, and (ii) a three-dimensional surface plot illustrating the combined effects of price changes and β variations on peak-period session shares. These visualizations highlight the non-linear and bounded nature of price-induced demand redistribution.

3.1.5 Analytical Tools and Techniques

The analysis was implemented using Python 3.10+ with pandas, numpy for data processing. Matplotlib and Seaborn for visualization and Statistical analysis using built-in Python functions.

Table 10 Software and Libraries

Component	Purpose	Examples
Python 3.10+	Main modelling environment	MNL, Monte Carlo
Jupyter Notebook	Interactive development	Iterative debugging
NumPy	Vectorized math, random draws	β sampling, Poisson arrivals
Pandas	Data management	Export CSV, store MC matrices
SciPy (optimize)	Constrained optimization	Minimizing peak share
Matplotlib	Plotting	Charts, 3D surface
Seaborn	Advanced visuals	Heatmaps

Chapter 4 – Results and Discussion

4.1 Energy Consumption Trend

4.1.1 Overall monthly charging volume

Figure 3 shows that the overall monthly energy consumption grew from 42,874.14 kWh in January 2023 to 1,006,024.63 kWh in January 2025.

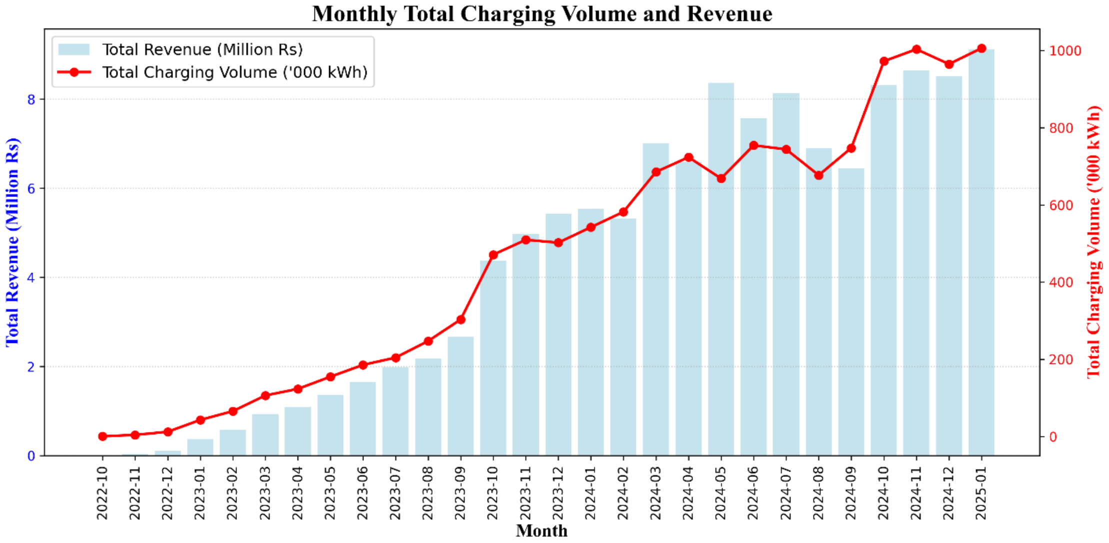


Figure 3: Total charging volume month-wise

From October 2022 to January 2025, the Monthly Total Charging Volume chart displays a steady upward trend in energy consumption, suggesting a gradual rise in EV adoption and charging demand. The charging volume was low at first, but it started to rise gradually in early 2023. This was followed by a notable surge in late 2023 and another sharp increase in late 2024, which may indicate seasonal demand fluctuations, increased EV penetration, or an expansion of charging infrastructure. Despite minor fluctuations in mid-2024, the overall trend remains positive, with charging volume exceeding 1,000,000 kWh by early 2025.

4.1.2 Monthly variation of total charging volume

Figure 4 is the box plot that shows the monthly variation of the charging volume of all stations. Here, the box represents the interquartile range (IQR) (middle 50% of data), the line inside the box represents the median (middle value of the dataset), whiskers (lines extending from the box) show the Range within 1.5 × IQR, and black dots outside whiskers represent Outliers.

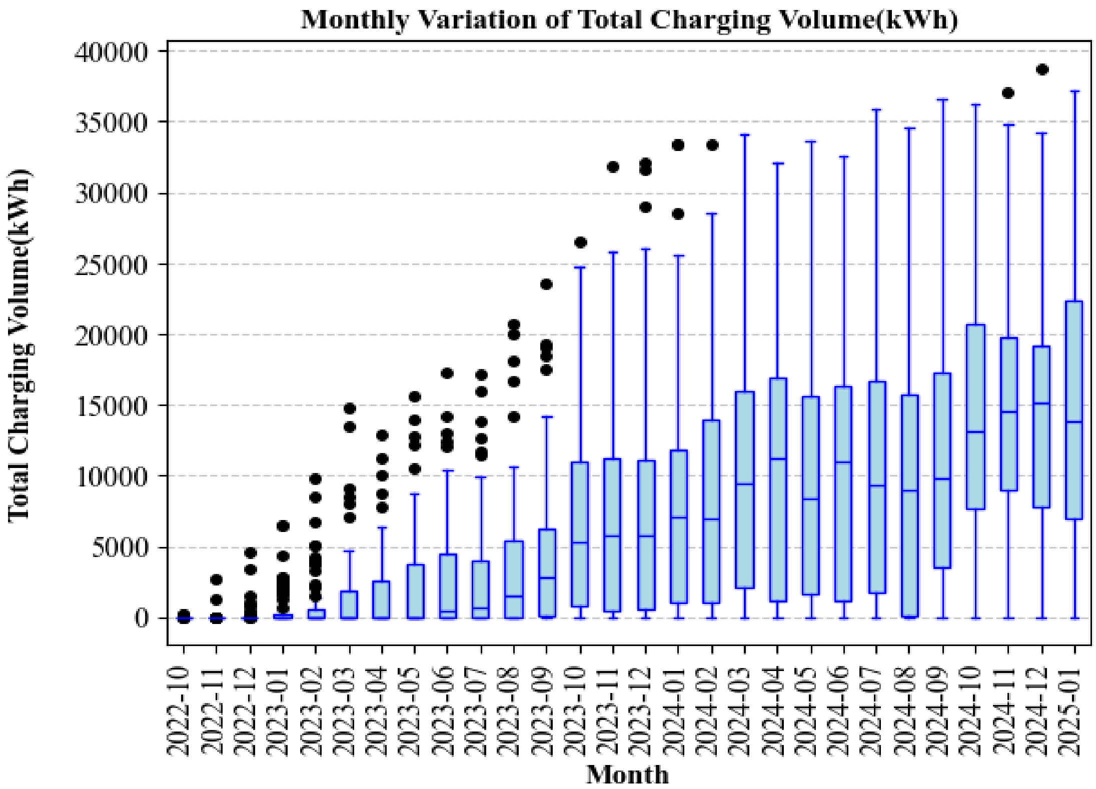


Figure 4: Box plot for the monthly variation of stations' charging volume

From October 2022 to January 2025, the monthly total charging volume box plot shows a definite upward trend in charging activity with growing variability over time. Growing EV adoption and station usage are indicated by a steady increase in the median charging volume. The increasing interquartile range (IQR) indicates that although some stations are in high demand, others are still underutilized.

4.1.3 Yearly energy consumption

2022 marked the foundation year for studying the energy consumption patterns of EVs using NEA charging stations, as commercial operations commenced in October of the same year. Figure 5 shows that the total amount of energy consumed annually was approximately 2.916 million units in 2023 and 9.346 million units in 2024. A remarkable 3.2 times increase in 2024 reflects a significant rise in EV adoption and charging demand. This quick rise points to increased usage per station, which could cause traffic jams and longer wait times.

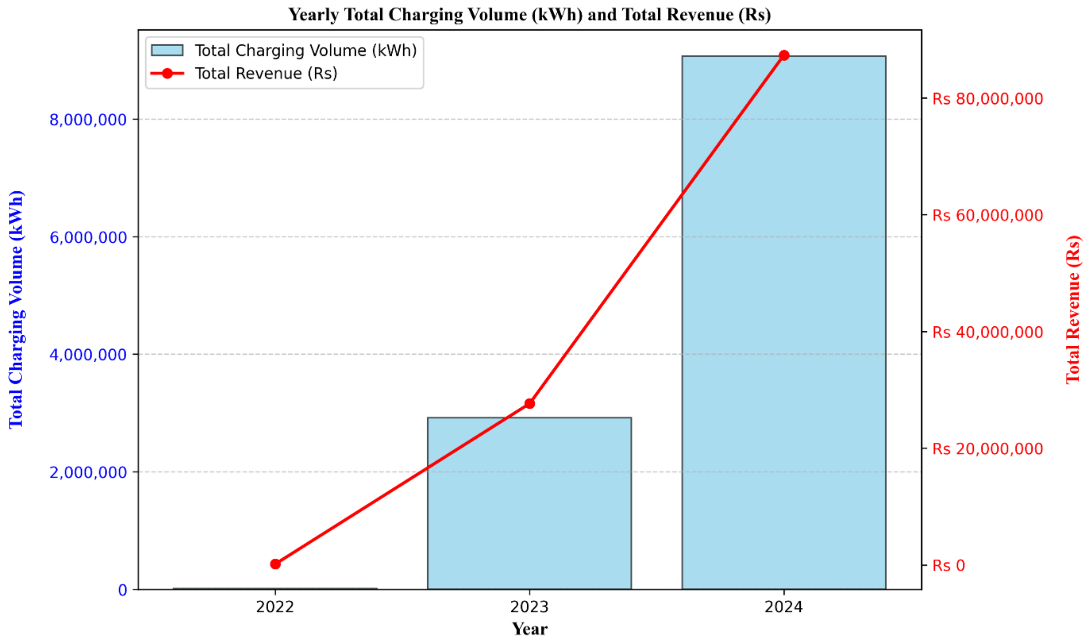


Figure 5: Yearly energy consumption and revenue of charging stations of NEA

4.2 EV Arrival Rate

4.2.1 Arrival and departure time distribution

Figure 6 is the histogram for the time distribution of EV charging sessions, which illustrates a clear daily charging pattern. The frequency of charging start times (blue) and charging end times (orange) follows a similar trend, peaking during daytime hours and tapering off in the evening.

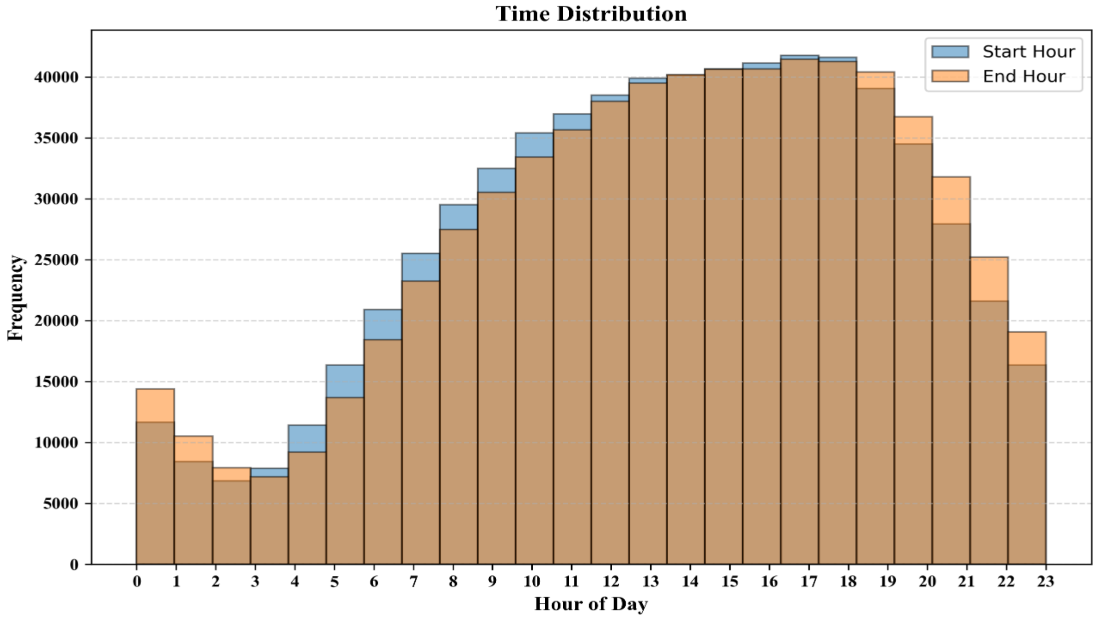


Figure 6: Time distribution

Peak Charging (10 AM–6 PM) hours are when the most charging sessions take place, with the highest frequency occurring between 4 and 6 PM, suggesting a high demand during the midday and afternoon hours. The alignment of start and end times suggests that most charging sessions are relatively short and completed within a few hours. This indicates that demand for charging increases in the afternoon (13:00–19:00) and then progressively decreases after 19:00.

4.2.2 Arrival Rate

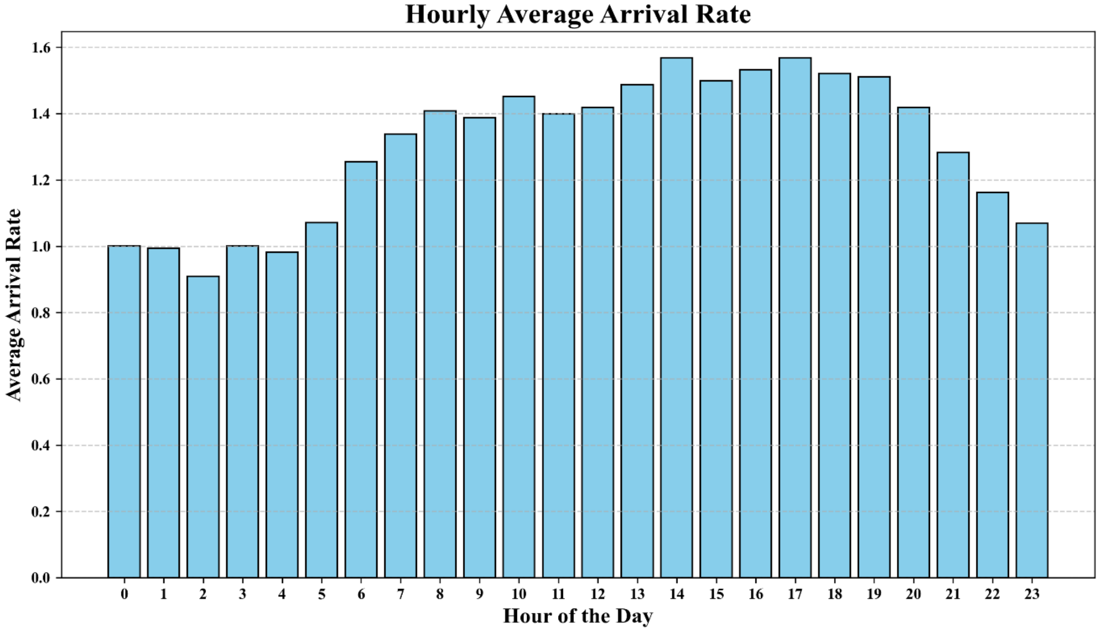


Figure 7: Hourly arrival rate

Throughout the day, different charging demand patterns can be seen in the arrival rate data from Figure 7. During the early morning hours (12 AM - 6 AM), the arrival rate remains relatively low, indicating minimal charging activity, likely limited to overnight residential charging or fleet vehicle rotations. A gradual increase is observed from 6 AM to 10 AM, aligning with morning commuting hours as users charge their vehicles before or during their travel. The peak period extends from 10 AM to 7 PM, with the highest arrival rates occurring between 2 PM and 5 PM, suggesting significant demand from public transport, commercial fleets, and workplace charging. After 7 PM, a gradual decline is observed as charging activity decreases, though some residual demand persists, potentially from evening commuters and fleet operators.

4.3 Charging Duration and Charging Speed

4.3.1 Charging Duration

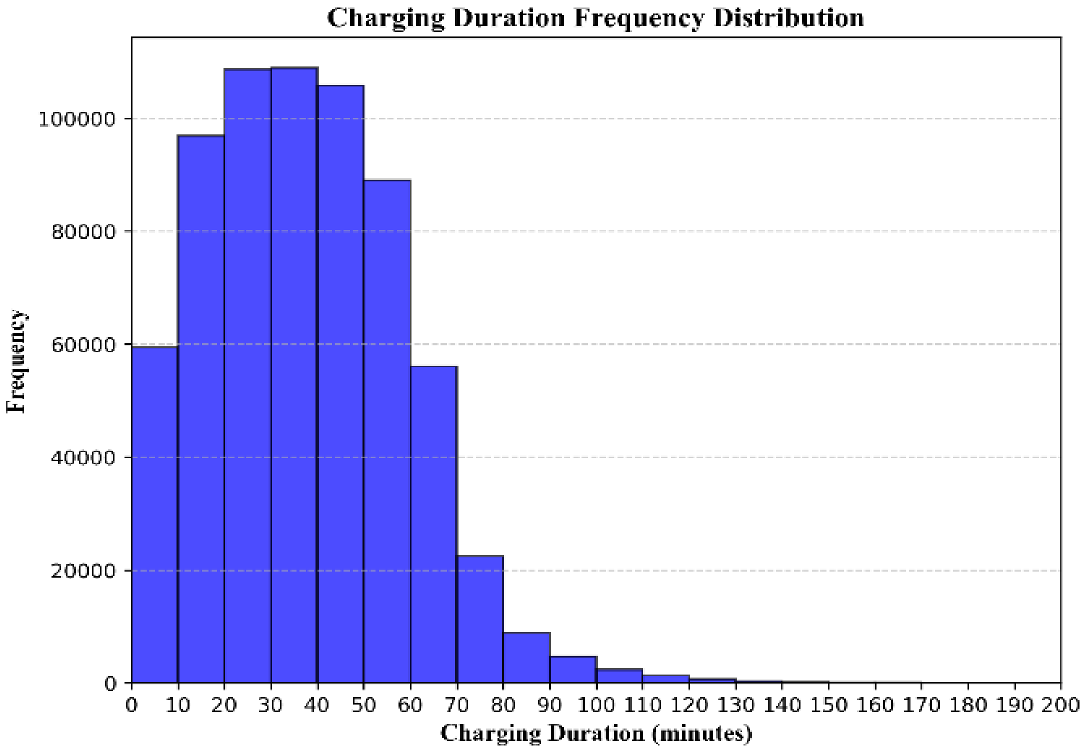


Figure 8: Charging speed frequency distribution

In the frequency distribution of charging duration, one can see the variation in the length of different users' charging sessions. The histogram in Figure 8 shows that most charging sessions lie between 20 and 50 minutes, with a peak around 30–40 minutes. This suggests a dominating short- to medium-duration charging preference, thus aligning with fast-charging behavior in which users try to rapidly replenish their vehicles rather than fully charge them. This plot shows that the distribution is right-skewed: frequency decreases as charging duration increases. While long sessions greater than 60 minutes are present, these occur at significantly reduced frequencies; perhaps this reflects station policy limits on maximum charging time or user preference for opportunity charging over long session times. This distribution is important to understand for understanding station turnover estimates, setting appropriate session time limits, and planning for peak demand periods. More importantly, it provides insight into user behavior in terms of their charging needs, which can be used to develop appropriate pricing strategies and enhance general station efficiency.

4.3.2 Charging speed

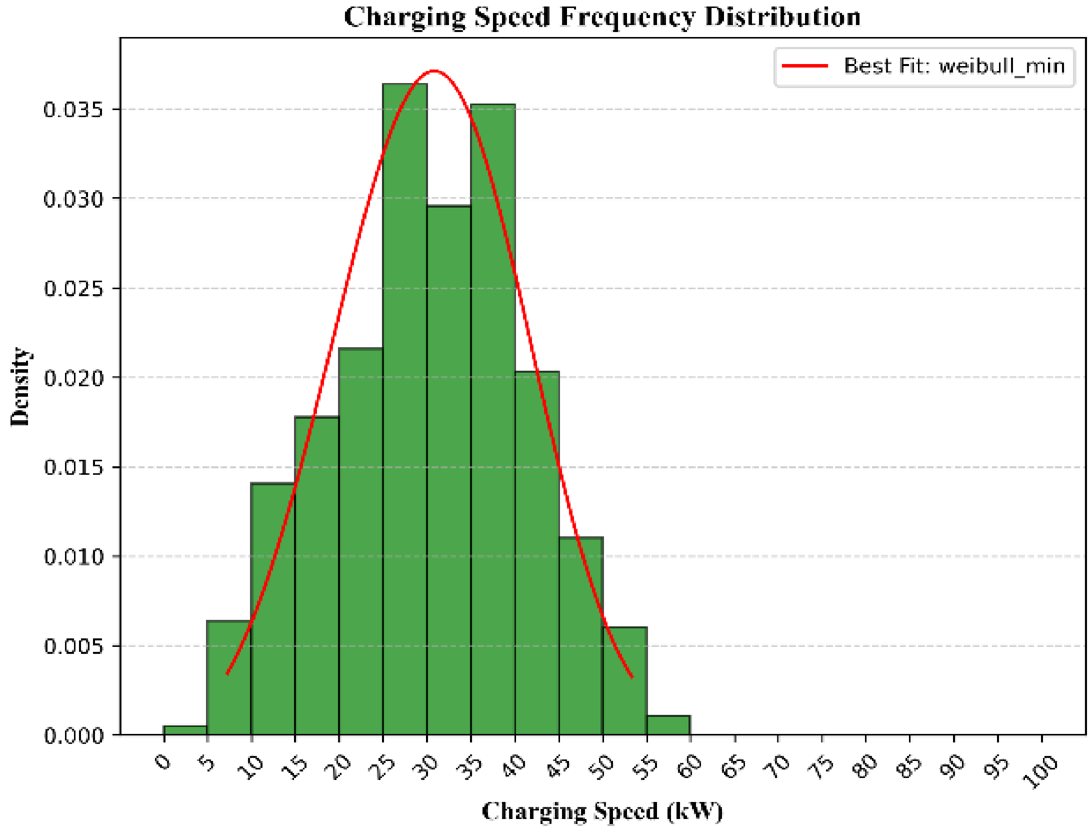


Figure 9: Best-fit charging speed frequency distribution

The frequency distribution of charging speeds provides insight into the most common charging speed experienced at the charging station. It can be seen from the histogram that most of the charging sessions are between 20 kW and 45 kW, with the peak lying somewhere between 30–40 kW, thus meaning that users mostly operate using a moderate fast-charging rate. The Weibull distribution fitted to these data is in close agreement with the empirical data, since in general, it follows a right-skewed distribution, which starts to taper off around 50 kW. That means, although high-power charging may be available, most users don't reach peak rates too often, as high as 60 kW or higher, probably due to battery limitations and/or pricing structures that prefer a more stable charge rate for battery health optimization.

4.4 State of Charge (SoC)

Figure 10 shows state-of-charge distributions from all stations of NEA. Most EVs start charging with a moderate SoC, but some arrive with a very low charge. The majority of EVs finish charging around 87% SoC, following a normal distribution. The amount of charge gained follows a gamma distribution, meaning most EVs charge moderately, but some get a very high charge boost.

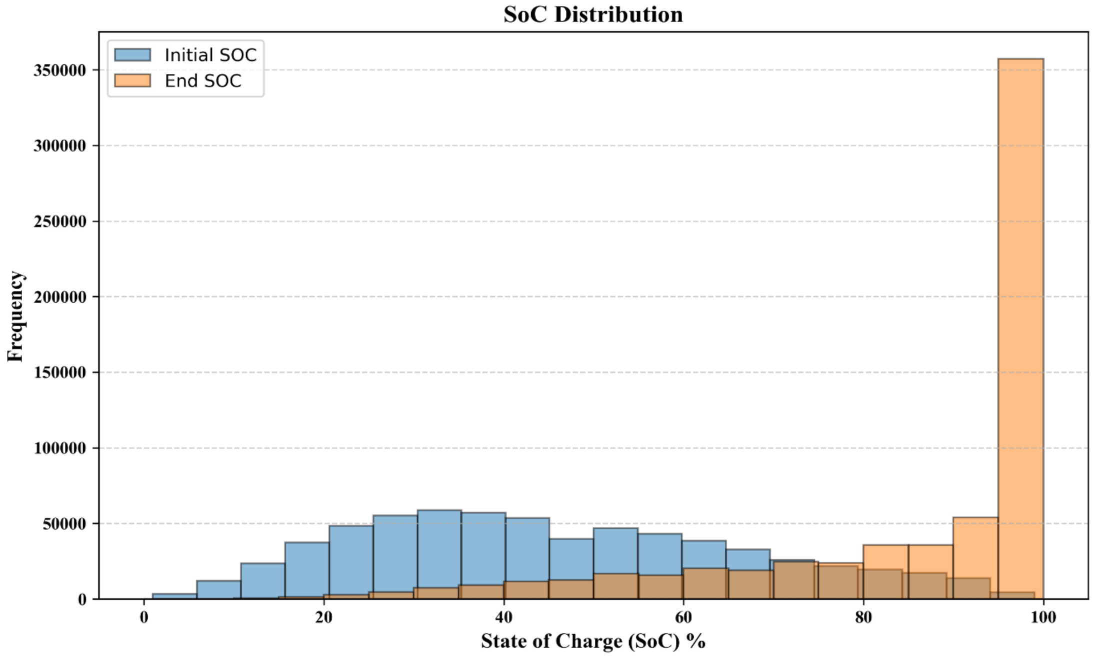


Figure 10: SOC Distribution

SoC distribution can give valuable insights into the charging behaviour of EV users. The histogram within shows the initial SoC (in blue) and the end SoC (in orange) for all charging sessions. Initial SoC is widely distributed; most of the vehicles arrive at the charging station with an SoC between 20% and 60%, indicating that most of the users charge their vehicles before critically low levels are reached. However, several users arrive with very low SoC values (<20%). The end SoC distribution shows a significant peak at 100%, which means that a large portion of users prefer to fully charge their vehicles before leaving the station.

The above findings provide important insight into charging infrastructure planning and demand management. Since a large number of users charge up to full capacity, station operators may consider offering dynamic pricing or time-based tariffs to encourage users to vacate the charging spots earlier, allowing improvement in the station's turnover rate. Further, data can be utilized to offer smart charging strategies aimed at optimizing grid load through controlling the charging sessions based on initial SoC levels and real-time energy demand.

4.5 NEA CCS Ratnapark

Preliminary data analysis of the NEA CCS Ratnapark site reveals that the daily average analysis reflects the domination of the charging activity by the mid-peak period, 5 AM–5 PM, averaging energy consumption of 359 kWh, 18 sessions, and the highest revenue of NRs 3,039 per day, indicating clearly a strong preference for daytime charging that coincides with work an d travel hours.

Table 11: Daily Average

Time periods	Energy KWh	Total Fees NRs	Total No of sessions	Average Duration in minutes	Average Initial SoC %	Average End SoC %
11 pm - 5 am	84	551	7	65	42	91
5 am - 5 pm	359	3,039	18	49	41	88
5 pm - 11 pm	203	2,010	11	50	40	86

The 5 PM–11 PM evening-peak period records an average consumption of 203 kWh and 11 sessions daily, indicating continued demand for charging but at a reduced scale after usual commuting hours. On the other hand, in the off-peak period—11 PM through 5 AM—minimal utilization is observed with only 84 kWh and 7 sessions per day, despite ample charger availability.

Average charging durations of about 50-65 minutes and similar initial and end SoC values of about 40-90% for all slots show consistency in charging behavior. In summary, the outcome brought to light daytime dominance and off-peak underutilization, which implies a potential demand redistribution using time-based or dynamic pricing strategies. Distinct patterns were unraveled from EV charging station data regarding different time periods of day and night.

- **Peak Usage:** The "8 am - 6 pm" period has the highest number of charging sessions.
- **Energy and SOC:** Despite having the most sessions, the "8 am - 6 pm" period shows a lower average energy consumption per session and a lower average State of Charge (SOC) increase compared to the "8 pm - 11 pm" period.
- **Session Duration:** The "8 pm - 11 pm" period has the longest average session duration, which correlates with its higher energy delivery and SOC increase.
- **Tariff:** The cost of electricity is highest during the daytime ("8 am - 6 pm") period.

These patterns indicate that user behavior is driven by a function of both need and cost. Daytime has high traffic with shorter, lower-energy sessions, while in the evening, there are fewer but longer sessions, indicating that drivers are fully charging their vehicles overnight to take advantage of lower tariffs. One key point that station operators should note is the apparent misalignment between the highest tariff and the period of the highest energy delivery per session. Despite probably having a lower tariff, the "8 pm - 11 pm" session yields more energy per customer. This makes the evening a very critical period for energy throughput. Optimizing tariffs and infrastructure to encourage more of these high-energy, off-peak sessions could improve station utilization and revenue.

4.5.1 Monthly Energy Consumption Trend

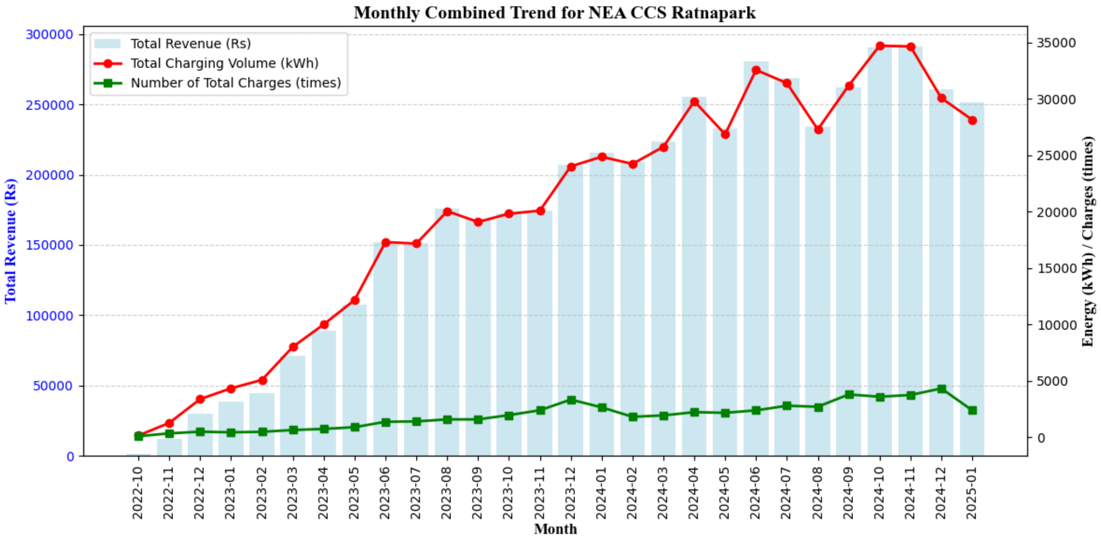


Figure 11: Monthly combined trend

Figure 11 represents the monthly combined trend of total revenue, total charging volume, and number of charging sessions for the NEA CCS Ratnapark fast charging station from October 2022 to January 2025. The overall trend indicates a steady growth in all three parameters, reflecting a continuous rise in electric vehicle usage over time. From late 2022 to mid-2023, both total revenue and energy dispensed showed gradual growth, aligned with increased EV adoption. From April 2023 onwards, there has been a sharp rise: in a few months, monthly energy consumption and revenue have almost tripled, which depicts the growing dependency of the public on this charging facility. The pattern of the total number of charges is also increasing similarly, which shows higher utilization of the station. During mid-2024 and early 2025, the volume of charging and revenue reached their peak, crossing over Rs. 250,000 and 30,000 kWh per month. However, a slight decline toward early 2025 shows seasonal variation in demand or partial load shift to other nearby stations.

4.5.2 Energy consumption by time period

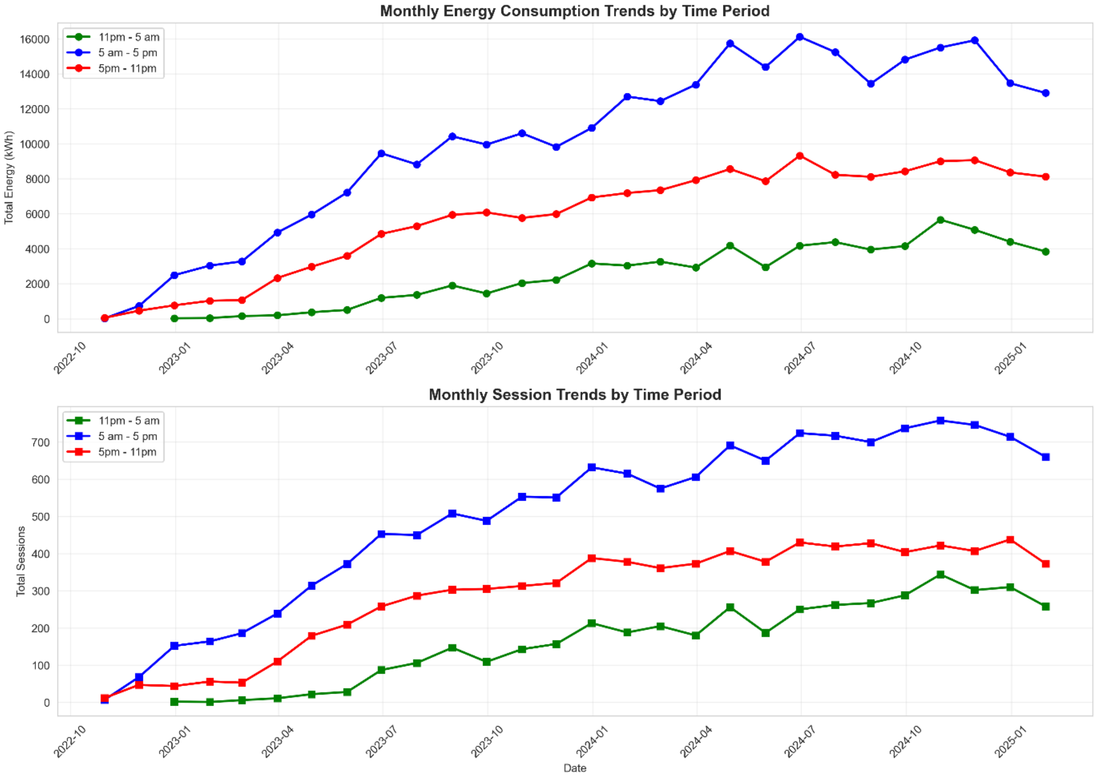


Figure 12: Energy consumption by time period

From Figure 12, temporal variation in monthly energy consumption and charging sessions at the NEA CCS Ratnapark station is distinctly reflected in three well-defined time periods: 11 PM-5 AM (off-peak), 5 AM-5 PM (mid-peak), and 5 PM-11 PM (peak).

Energy Consumption Trend: From October 2022 up to early 2025, the total energy consumption kept trending upwards in all time slots, indicating increased EV charging adoption. For the most part, mid-peak periods, ranging from 5 AM to 5 PM, recorded the highest energy consumption, reaching their peak around mid-2024 at about 15,000 kWh per month. The evening peak, ranging from 5 to 11 PM, recorded moderate growth but remained steady, while off-peak charging, between 11 PM and 5 AM, was the lowest, which indicates limited nighttime charging. This pattern, therefore, suggests that users predominantly prefer daytime charging.

Session Trend: The same pattern occurs in the number of charging sessions, with the mid-peak period leading in frequency, followed by evening sessions. Both energy and session counts grew rapidly until mid-2024 before stabilizing; this could indicate that the station has reached operational saturation or consistent daily demand. Off-peak session numbers remained minimal, further reinforcing that few users utilize the nighttime despite possible tariff advantages.

Overall, the results underline high daytime utilization and underutilization during off-peak hours, thus providing an opportunity for demand redistribution with the use of dynamic pricing or behavioral incentives.

4.5.3 Percentage share by Time period

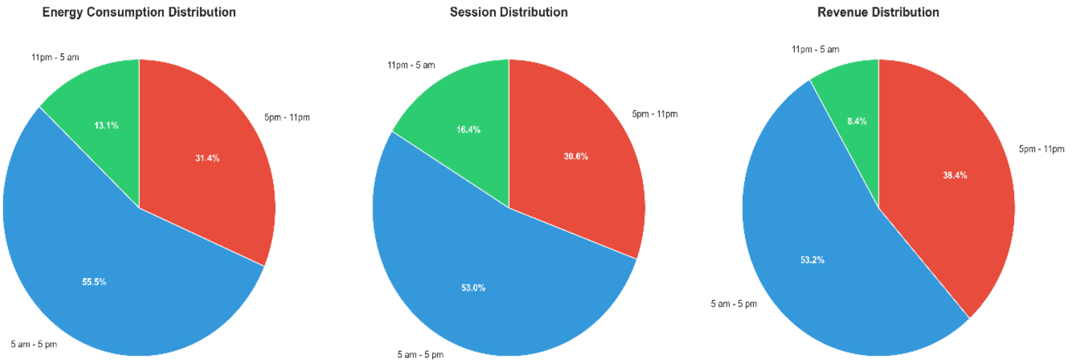


Figure 13 Percentage share by time period

Figure 13 shows the time-of-day distribution of energy consumption, charging sessions, and revenue for the NEA CCS Ratnapark fast charging station in three time slots: 5 AM–5 PM (off-peak), 5 PM–11 PM (peak), and 11 PM–5 AM (night-off-peak). The energy consumption distribution shows that most of the energy consumed by the charging sessions (55.5%) is concentrated during the daytime (5 AM–5 PM), followed by evening peak hours with 31.4%, whereas nighttime occupies a share of only 13.1%. This means that the majority of the users prefer to charge during the day. In the same vein, the session distribution follows a similar pattern, having 53.0% of the total charging sessions in the daytime, 30.6% during the evening, and 16.4% at night. In this regard, such consistency could indicate that user arrival patterns are strongly time-dependent and mainly concentrated around the working day.

These trends are closely reflected by the revenue distribution: daytime operations provide 53.2% of total revenue, while evening peak hours contribute 38.4%, and night hours only provide 8.4%. The revenue share is higher during the evening, despite fewer sessions, because of higher energy rates.

4.5.4 Time and duration distribution NEA CCS Ratnapark

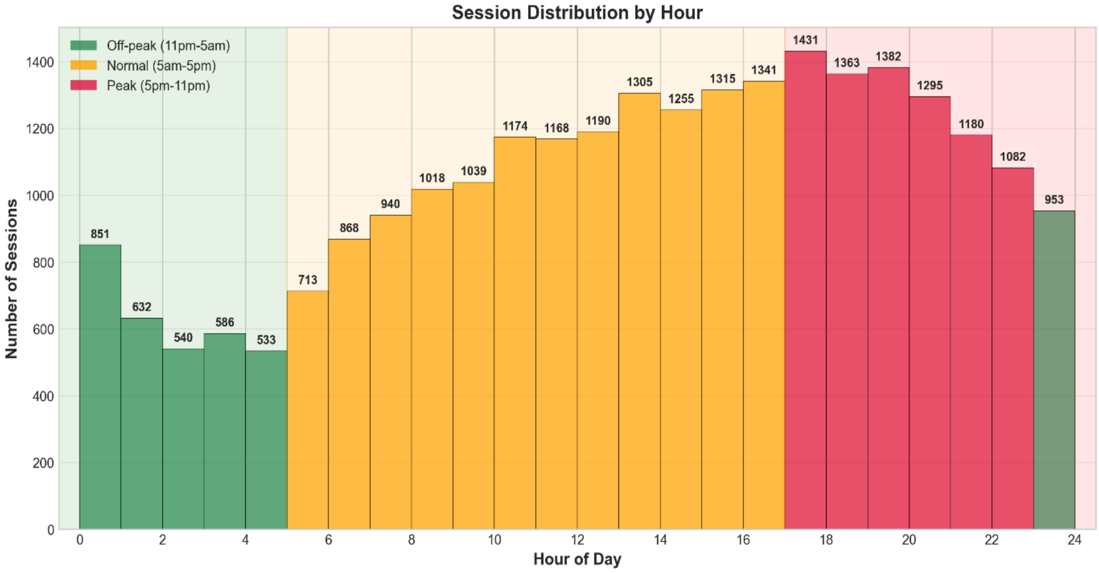


Figure 14: EV charging session distribution at NEA CCS Ratnapark

Figure 14 shows that the charging activity is highest during the peak period, 10:00–18:00, with a pronounced surge between 16:00 and 18:00, indicating strong afternoon demand likely driven by fleet and workplace users. The start and end times of sessions coincide quite closely, suggesting short charging durations completed within a few hours. Demand overall ramps up between 13:00 and 19:00 before tapering off, showing that pricing and operational strategies should aim to shift usage toward the off-peak period.

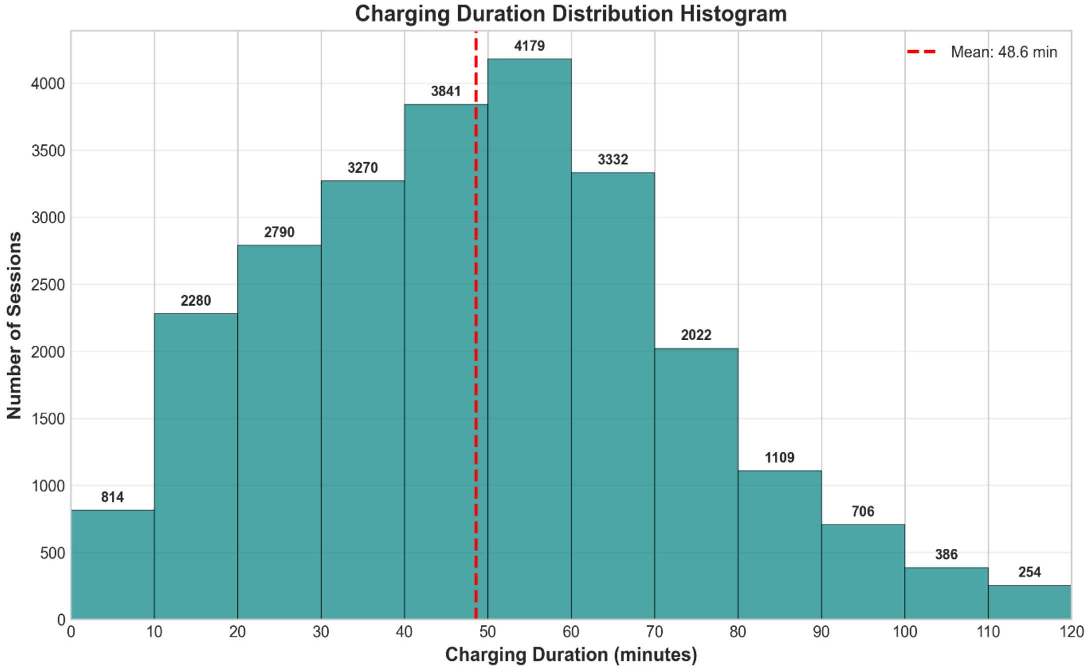


Figure 15: Charging duration distribution

The histogram of charging duration in Figure 15 illustrates that the majority of the EV charging sessions at the station are relatively short, with most of the sessions falling between 30 to 60 minutes. The peak frequency is around 50–60 minutes, whereas the mean charging duration is around 48.6 minutes, indicating that typical users complete their session within an hour. A smaller number of sessions extend beyond 90 minutes, which also indicates that there are occasional high-demand users or partial charges for longer-range vehicles. Overall, the distribution highlights the predominance of short, routine charging events that will drive how to manage congestion through station scheduling, connector availability planning, and dynamic pricing strategies.

4.5.5 Charging speed and efficiency at NEA CCS Ratnapark

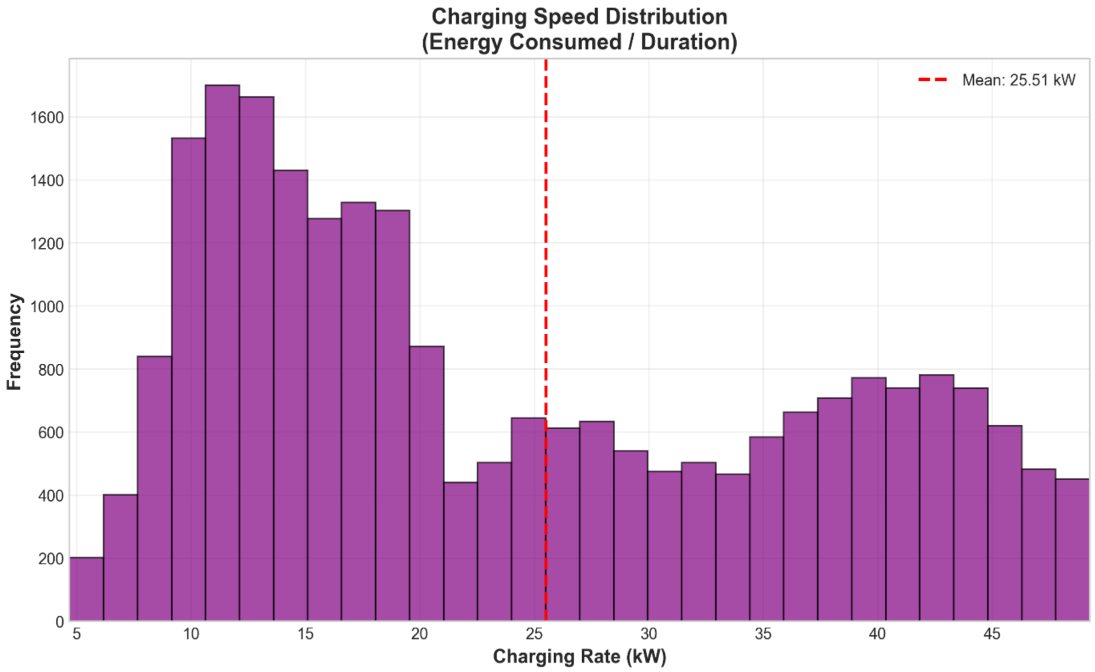


Figure 16: Charging speed distribution

This histogram in Figure 16 depicts the distribution of charging speed-that is, energy consumed over duration-at the NEA Ratnapark charging station. The bimodal pattern of charging speeds shows a high peak between 10–18 kW and a secondary spread between 35–45 kW. The mean charging speed-25.51 kW-is shown by the red dashed line. While this suggests that most sessions span a range of mid-level charging speeds, a large number of high-speed charging events significantly raise the upper tail of charging speeds. The bimodality could be indicative of mixed vehicle types or states-of-charge of the batteries, or charger power limitations, hence a reflection of heterogeneous usage patterns across users.

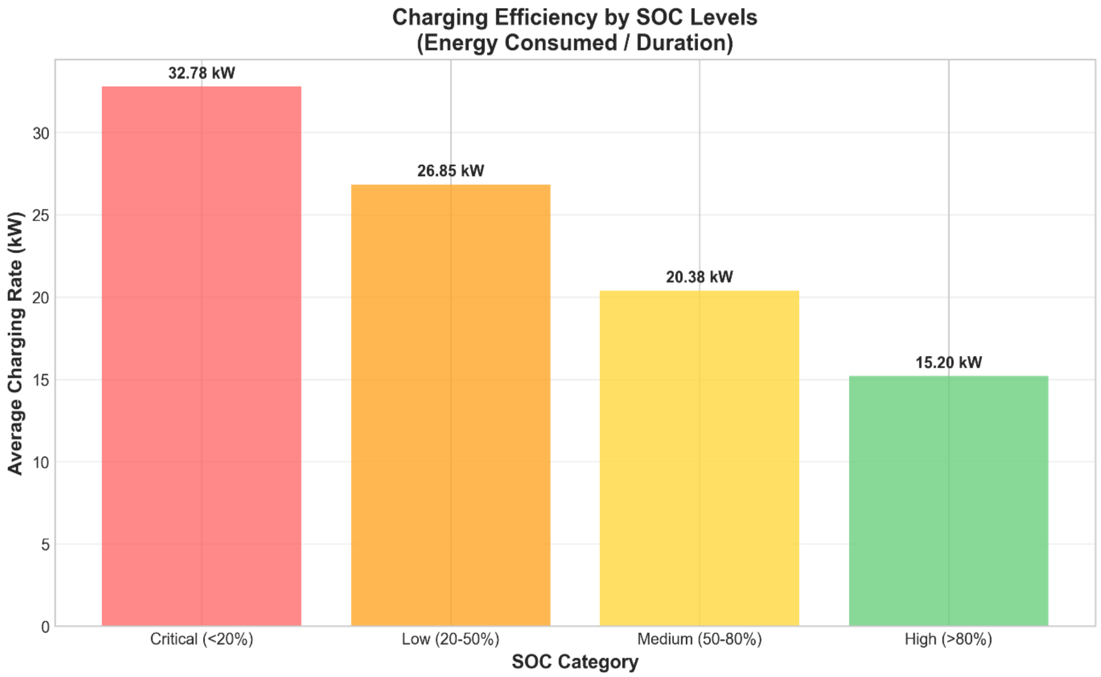


Figure 17: Average charging efficiency variation

The graph herein Figure 17 shows the average charging efficiency at different SOC levels, measured as energy consumed per unit of charging duration. The critical SOC levels (<20%) have the highest average charging efficiency, about 32.78 kW, meaning that batteries can accept energy the fastest when almost depleted. This decreases progressively as the SOC increases in the following manner: low SOC (20–50%), 26.85 kW; medium SOC (50–80%), 20.38 kW; and high SOC (>80%), 15.20 kW. This is expected because voltage and thermal constraints limit the power input as a lithium-ion battery approaches a full charge. In practical terms, this means that a car's energy level will increase more quickly during the early stages of its charging and will decelerate near its full capacity-a fact leading to several problems concerning the charging process and battery lifespan management.

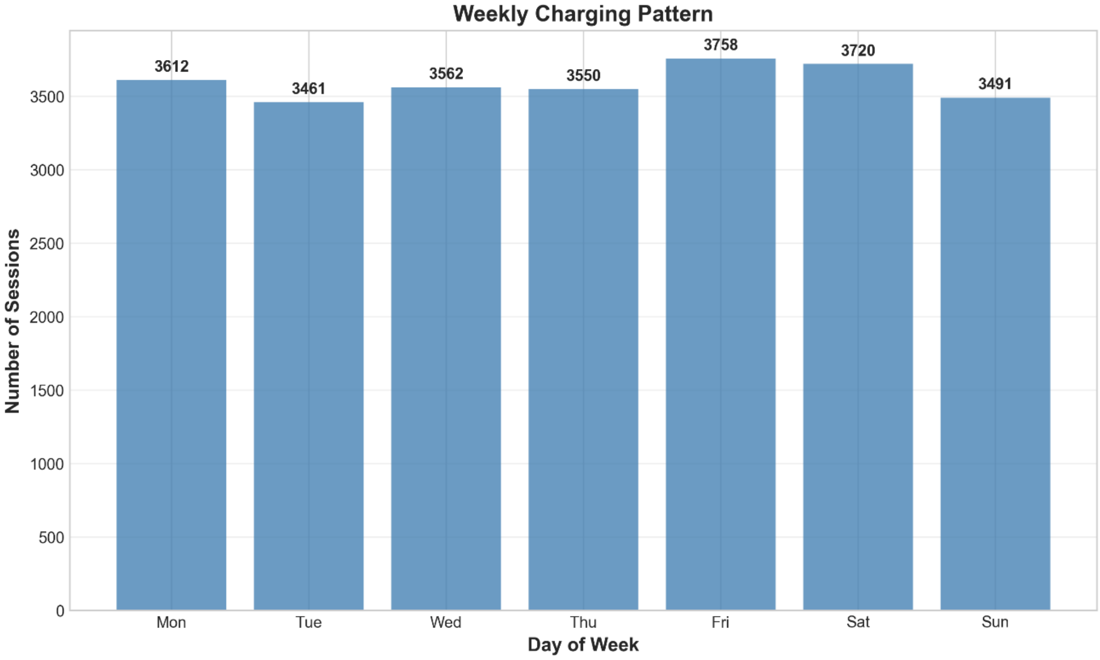


Figure 18: Weekly charging sessions at NEA CCS Ratnapark

In the weekly charging pattern, demand is relatively uniform throughout the days, with small fluctuations. Friday and Saturday record the highest sessions, reflecting increased pre-weekend travel. This also holds for Tuesday and Sunday as slightly lower activity days. Midweek usage stays consistent, indicating that commuter and commercial charging needs remain strong. Overall, fast-charging demand appears to be stable throughout the week, with only mild peaks, which further implies that station capacity must be robust every day. Dynamic pricing or congestion-management strategies may only be effective around the rise in demand on Friday and Saturday.

4.6 Baseline Time of Use

For Calculating Price Elasticity, we analyzed 26,459 charging session data at NEA Ratnapark. Table 12 and Table 13 show the basic statistics of the NEA CCS Ratnapark charging station.

Table 12: Connector usage:

Connector ID	Total Sessions	% of Total session
1248692602	13479	50.9%
1248692601	12927	48.9%
1248692603	53	0.2%

Table 13: Basic Statistics- Individual sessions

Time Period	Hours	Total Revenue NRs	Total Energy kWh	Total Session	Average Duration (hrs)	Revenue /kWh
Off Peak	6	435,248	66,660	4,329	0.79	6.56
Normal	12	2,401,100	283,647	14,028	0.77	8.45
Peak	6	1,588,216	160,647	8,102	1.03	9.89

The clear temporal imbalance in charging demand is shown by the station's descriptive statistics. Although peak hours (17:00–23:00) come with the highest tariff, 9.89 NRs/kWh, they still have 30.6% of all sessions, while off-peak hours, from 23:00–05:00, priced at only 6.56 NRs/kWh, attract only 16.3% of the demand. This shows that price is not the main driver of user behavior; instead, charging patterns reflect daily mobility and convenience. The longest average session duration, 1.03 hours, occurs during peak hours, exacerbating congestion. These imbalances, hence, justify the need for a calibrated price sensitivity parameter and redistribution simulation to evaluate how alternative TOU structures might shift demand without increasing infrastructure capacity.

Table 14: Baseline ToU Effectiveness

Time Period	Hours	Total Energy kWh	Total Session
Off Peak	6	66,660 (13.0% of total)	4,329 (16.4% of total)
Normal	12	283,647 (55.5% of total)	14,028 (53.0% of total)
Peak	6	160,647 (31.4% of total)	8,102 (30.6% of total)

Current Price Ratios: Peak / Off Peak Ratio : 1.51, Peak / Normal Ratio : 1.17

4.7 MNL Model

We use a Multinomial Logit model to describe EV charging session choices across three TOU periods: off-peak, normal, and peak. The utility for each period is a linear function of congestion proxies (dcount) and price differences, with off-peak as the base. Table 15 gives the Multinomial model summary output.

Table 15: Multinomial Logit Model Summary

Extracted MNL Parameters:			
const_normal:	0.66		
const_peak:	0.29		
b_dcount_normal:	0.02		
b_dcount_peak:	0.13		
Average sessions per day (observed):	32.00		
beta_hat:	-0.1259		
	Off	Normal	Peak
Observed shares (off, normal, peak):	0.16	0.53	0.31
Predicted shares with beta_hat:	0.22	0.43	0.35
Observed mean prices per period:	6.56	8.45	9.89

Figure 19 presents the calibration of the price sensitivity coefficient (β) using the Method of Moments (MoM), where the objective function is defined as the Sum of Squared Errors (SSE) between the model-predicted and observed time-of-use (TOU) charging shares. The SSE curve exhibits a smooth, convex shape, indicating a well-behaved optimization landscape with a unique minimum.

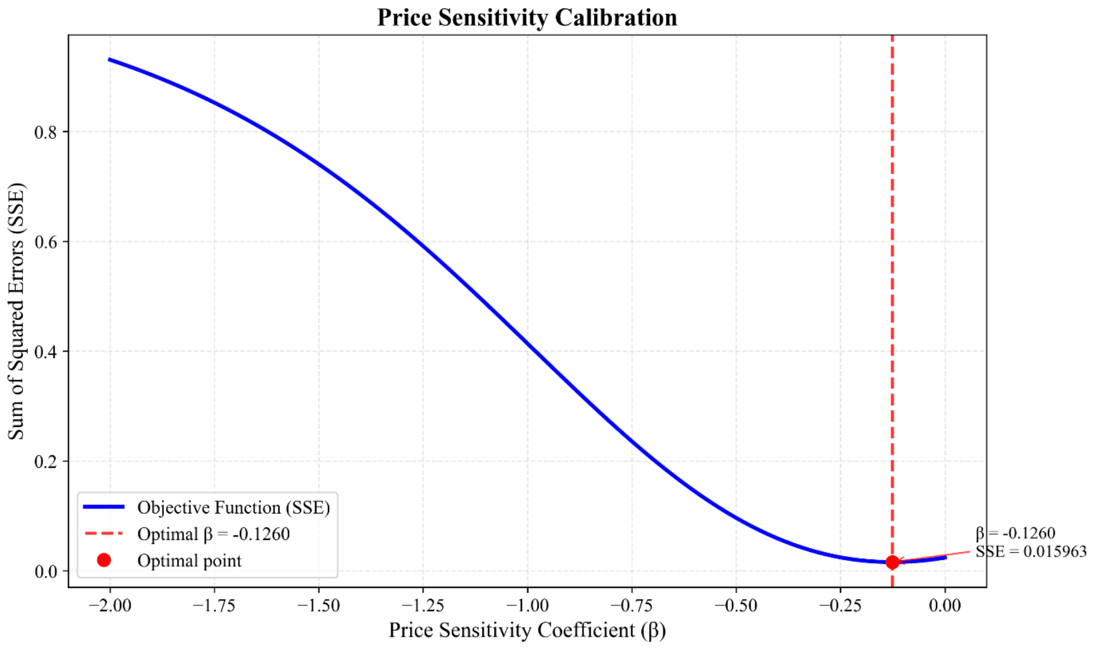


Figure 19: Calibration of the price sensitivity coefficient

As shown, SSE decreases steadily as β moves from highly negative values (e.g., −2.0) toward zero, reaching its lowest point at β ≈ −0.1260, where the SSE is minimized to

0.01596. This optimal point, marked in red, reflects the best-fitting price sensitivity that reproduces observed user behavior. The negative sign of β confirms that EV users reduce their probability of charging during a particular TOU period when its relative price increases. The small SSE value at the optimum indicates a close match between the model-generated session shares and the real-world charging distribution, demonstrating strong calibration robustness. The calibrated price coefficient β_hat = –0.126 reflects the negative sensitivity of session choice to higher prices. Predicted shares under baseline prices closely reproduce observed session distributions. This calibrated MNL model is then used for session-level redistribution simulations under alternative TOU pricing scenarios. A similar study by (Daina et al. (2017) on EV users' charging behavior and decision-making highlighted factors such as time-of-use preferences, charging costs, and convenience, and found that the price sensitivity coefficient was ≈ -0.459.

Table 16: Observed vs predicted shares

Parameters	**Off**	**Normal**	**Peak**
Baseline Session Share %	16.36	53.02	30.62
Predicted Baseline Share (beta_hat -0.125) %	22.19	42.74	35.07

The table compares the empirical TOU session shares to the baseline predicted shares generated from the calibrated MNL model. The model reproduces the empirical distribution across the three TOU periods quite well, which indicates good calibration performance overall. The predicted off-peak share is about 22%, slightly overestimating the observed value of about 16%; hence, users are likely to be somewhat less responsive to low off-peak prices than would be suggested by the model. During the normal period, the model underpredicts demand at 43% compared to the observed 53%, reflecting that factors other than price—such as routine travel patterns or workplace charging—most likely prevail during daytime hours in the decisions of users. Peak-hour shares-approximately 35% predicted versus about 31% observed-only provide a small deviation, and it seems therefore that the model captures the congestion-period sensitivity quite well. Overall, the MNL framework with the calibrated price coefficient provides an adequate representation of user choice probabilities.

Table 17: Cross Elasticity

Elasticities (ε_{i,j}):	Off	Normal	Peak
off	-0.0965	0.0570	0.0394
normal	0.0294	-0.0688	0.0394
peak	0.0294	0.0570	-0.0865

The estimated own and cross-price elasticities presented in Table 17 indicate that charging demand at the Ratnapark fast-charging station is price-inelastic throughout all ToU periods. All the elasticities have a negative sign, which implies that raising tariffs decreases demand in the same period. Peak hour charging has the highest own-price elasticity of –0.0865, followed by Off-peak at –0.0965 and Normal hours at –0.0688. Notably, despite differences in the values, the low absolute level essentially indicates that time convenience and immediate charging needs take precedence over prices.

Cross-price elasticities are positive throughout, which indicates modest substitution when relative tariffs change. An increase in Off-peak tariffs shifts some demand toward Normal, at 0.0570, and Peak, at 0.0394, while higher Peak-period prices lead to small increases in Off-peak, at 0.0294, and Normal-period demand, at 0.0570. While these substitution effects confirm the expected behavioral response, the magnitudes remain weak, suggesting that there is considerable rigidity among users with respect to temporal use. Overall, it would appear that the elasticity structure suggests changes to ToU tariffs have the potential to alter charging patterns, but the associated behavioral responses are not sufficiently large to yield significant peak-load reduction in the absence of reinforcement by ancillary operational strategies or user information measures.

4.8 Energy Demand Redistribution and Elasticity

The session-based redistribution model was developed using the observed sessions and average energy delivered per session for each time-of-use (ToU) period at the NEA CCS Ratnapark station. We re-ran the redistribution and optimization using session-based choice probabilities, i.e., treating session choice as the decision variable and using mean energy per session to compute energy/revenue.

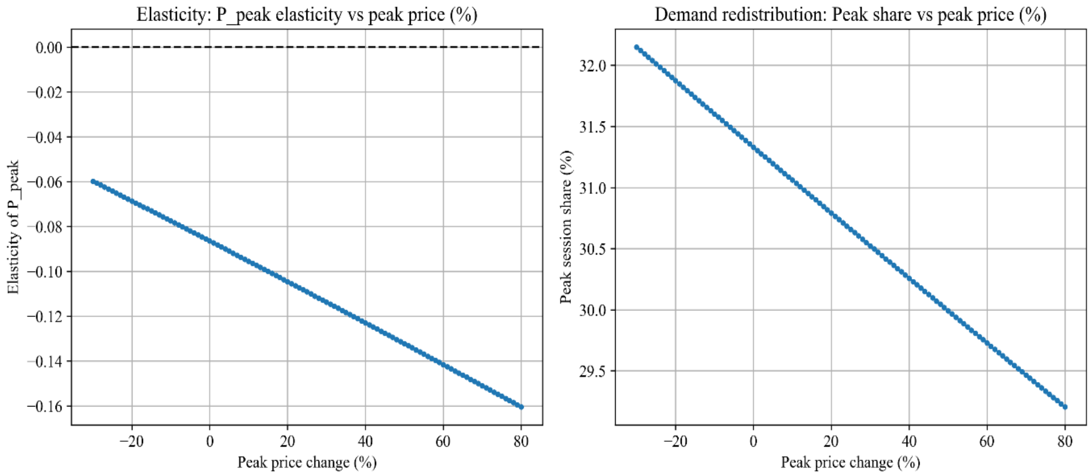


Figure 20: Elasticity and Peak Share vs peak price

For the MNL model calibrated for Ratnapark fast-charging station, a price coefficient of β = −0.125971 was obtained, implying a negative and economically meaningful response of users to price changes. The generated baseline utilities resulted in TOU charging shares of 23.36% off-peak, 45.31% normal, and 31.33% peak, which matches the observed user preference for mid-day charging. The corresponding normalized baseline revenue was 510,950.56 units. As expected, the cross-price elasticity matrix shows diagonal negative elasticities, such as −0.0865 for peak, confirming that increasing a period's price always reduces its own demand, while positive off-diagonal elasticities indicate substitution across time periods. Sensitivity analysis in Figure 20 (right) reveals that peak-period elasticity becomes more negative as peak prices rise, ranging from −0.06 at −30% price change to −0.16 at +80%, showing that users increasingly avoid peak charging at higher prices. The resulting redistribution curve in Figure 20 (left) shows peak charging share to decline steadily from 32.2% to 29.3%, therefore confirming that a controlled price adjustment can shift demand away from congested hours.

The revenue preservation model subjected to price multipliers converged and delivered the optimal TOU price multipliers of (0.7, 0.7, 1.8) for off-peak, normal, and peak periods, respectively. This structure decreases the prices in low-demand periods while increasing the prices significantly in peak hours. Under this optimized tariff, the session distribution changes to 24.35% off-peak, 47.22% normal, and 28.43% peak, representing a ~2.9 percentage-point reduction in peak demand. Peak congestion is reduced without sacrificing revenue; total revenue increases slightly, with a revenue ratio of 1.00745, which means a 0.75% improvement relative to the baseline despite lower off-peak and normal tariffs. The total energy delivered decreases marginally from 510,950.56 to 500,990.32 kWh, reflecting the reduced peak charging intensity. Overall, the results indicate that a dynamic TOU pricing structure can shift a measurable portion of charging sessions away from the evening peak, thereby reducing congestion while maintaining or slightly enhancing station-level revenue.

The baseline distribution showed that 53.0% of charging sessions took place in the normal period, 30.6% during peak hours, and only 16.4% in off-peak hours. The corresponding mean energies delivered per session were 15.4 kWh off-peak, 20.2 kWh normal, and 19.8 kWh peak, showing slightly larger energy consumption in daytime and evening periods.

The constraint to redistribute was provided by the normalized revenue under the baseline ToU tariff. That is, the optimization objective was to minimize the share of peak-hour sessions with a guaranteed total revenue at least equal to the baseline.

Table 18: The optimization results

Parameter	**Off-Peak**	**Normal**	**Peak**
Baseline session share (%)	16.4	53.0	30.6
Optimal Price Multiplier	0.7	0.7	1.8
Session Share (%)	24.35	47.22	28.43
Sessions (count)	6,442	12,495	7,522

The elasticity curve reflects the negative pattern relating peak-period price to the share of sessions during peak hours, while at higher prices, the number of sessions in the peak period declines steeply, confirming that under a ToU structure, users are responsive to price signals. The demand redistribution curve further illustrates how users shifted from peak to normal and off-peak periods as the relative price difference increased, effectively flattening the load profile.

The findings indicate that dynamic pricing can reduce congestion in the peak hours of public EV fast-charging stations by as much as an order of magnitude. This already shows that, even with a fixed three-slot ToU structure, further intra-slot price differentiation can yield significant behavioral responses from users. The estimated price elasticity ($\beta \approx -0.125$) implies that EV users show a moderate sensitivity to price changes and are willing to shift their charging sessions when confronted with significant price differentials. This elasticity is in line with similar studies elsewhere,

where β commonly falls between −0.1 and −0.5 in the context of public charging stations; this would mean consistent user behavior patterns across contexts.

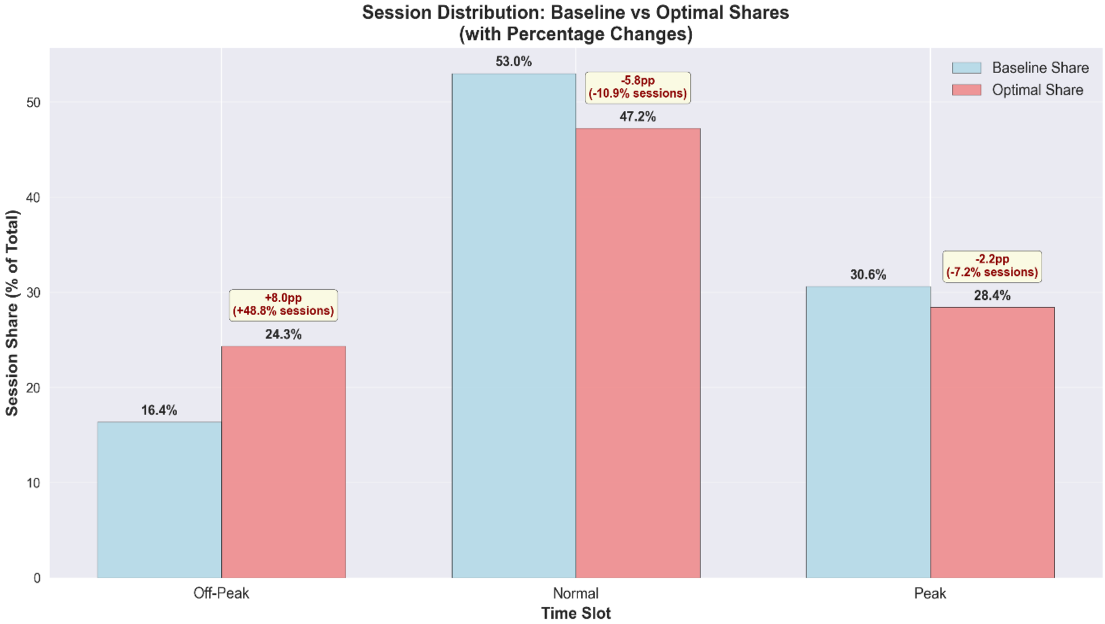


Figure 21: Session Redistribution

As in Figure 21, the session-based redistribution and optimization analysis showed that the calibrated MNL model, with a price coefficient of beta =-0.125971, accurately reproduced observed TOU charging behavior at the Ratnapark station. Baseline shares were 16.4% (off-peak), 53.0% (normal), and 30.6% (peak), with elasticity results confirming negative own-price effects (e.g., -0.93 for peak) and positive substitution across periods. Sensitivity analysis indicated that higher peak prices consistently reduced peak demand, with the peak share declining from 30.6% to 28.4%.

Table 19: Baseline Vs Optimal shares

Time Session	Baseline	Optimal	Share change	Session
Off Peak	16.4 %	24.3%	+8.0 PP	+48.8 %
Normal	53.0 %	47.2%	-5.8 PP	-10.9 %
Peak	30.6 %	28.4 %	-2.2 PP	-7.2 %

4.9 Sensitivity analysis

Based on an estimated price sensitivity coefficient (β) with Estimated β = -0.13, Conservative β = -0.25, and High Sensitivity β = -0.50.

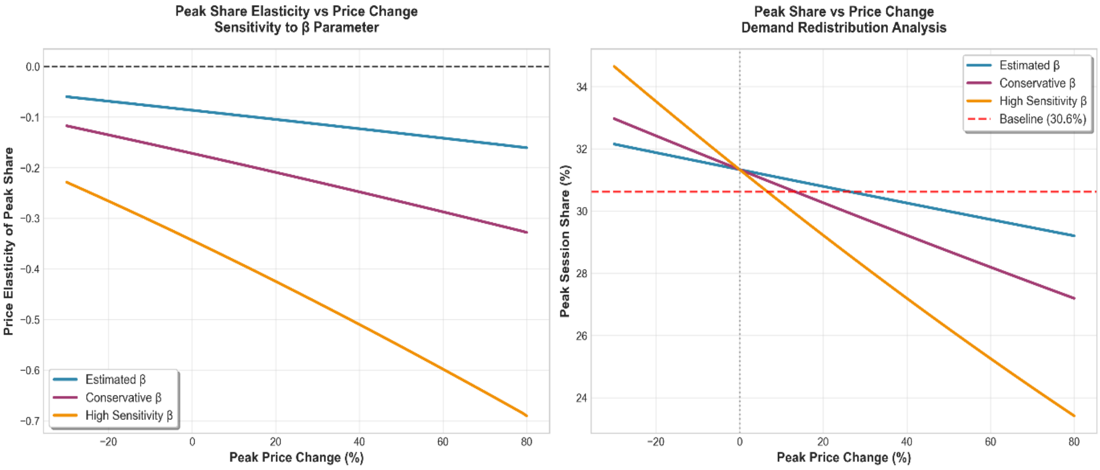


Figure 22: Sensitivity Analysis

Price Elasticity of Peak Session Share

Figure 22, the sensitivity analysis reveals a non-linear relationship between peak price changes and the elasticity of peak session share (Figure 1). The estimated β parameter (-0.126) yields moderate elasticity responses, ranging from near-zero at price decreases to approximately -0.6 at +80% price increases. More sensitive β values demonstrate substantially steeper elasticity curves, with the conservative β (-0.25) and high-sensitivity β (-0.5) reaching elasticities of -0.9 and -1.8, respectively, at extreme price increases.

The concave shape of the elasticity curves indicates diminishing marginal sensitivity to price changes. At lower price increments (<20%), all β values exhibit relatively inelastic behavior ($|\varepsilon| < 0.5$), suggesting limited responsiveness to moderate pricing interventions. However, beyond +40% price increases, the elasticity accelerates significantly, particularly for more negative β parameters.

Peak Share Redistribution under Alternative Scenarios

Figure 22 (right panel) demonstrates the redistribution of session shares across pricing scenarios. The baseline peak share of 30.6% serves as the reference point. Under the estimated β, a +20% price increase reduces the peak share to approximately 27.5%, representing a 10.1% relative reduction. More pronounced effects emerge with sensitive β parameters: the conservative β achieves 24.5% peak share (-19.9% reduction), and the high-sensitivity β reaches 21.5% (-29.7% reduction) at the same price point. The response curves exhibit characteristic logistic shapes, with accelerated redistribution occurring between +10% and +40% price changes. Beyond +50% increases, the curves approach asymptotic limits, suggesting practical upper bounds for peak demand reduction through price incentives alone.

Multidimensional Sensitivity

The three-dimensional analysis (Figure 23) provides a comprehensive visualization of the interaction between β parameters and price changes. The surface plot confirms the monotonic relationship between both independent variables and the dependent peak share. The gradient is steepest in the region combining negative β values (<- 0.3) with substantial price increases (> +30%), indicating synergistic effects between price sensitivity and intervention magnitude. The contour patterns reveal that equivalent peak share reductions can be achieved through multiple combinations of β values and price changes. For instance, a target peak share of 25% can be attained either through a +15% price change with β = -0.4, or a +35% change with β = -0.2, highlighting the trade-off between pricing intensity and consumer sensitivity.

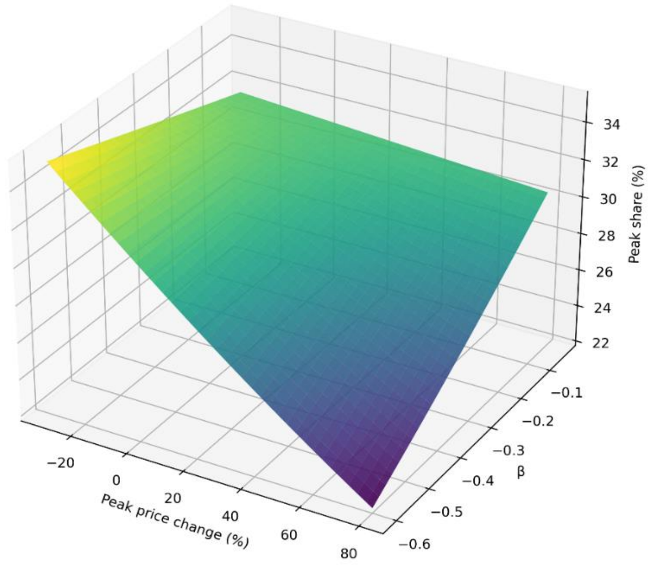


Figure 23: Beta vs Peak Price change, Peak session share 3D

4.10 Chi-square Goodness-of-Fit Test

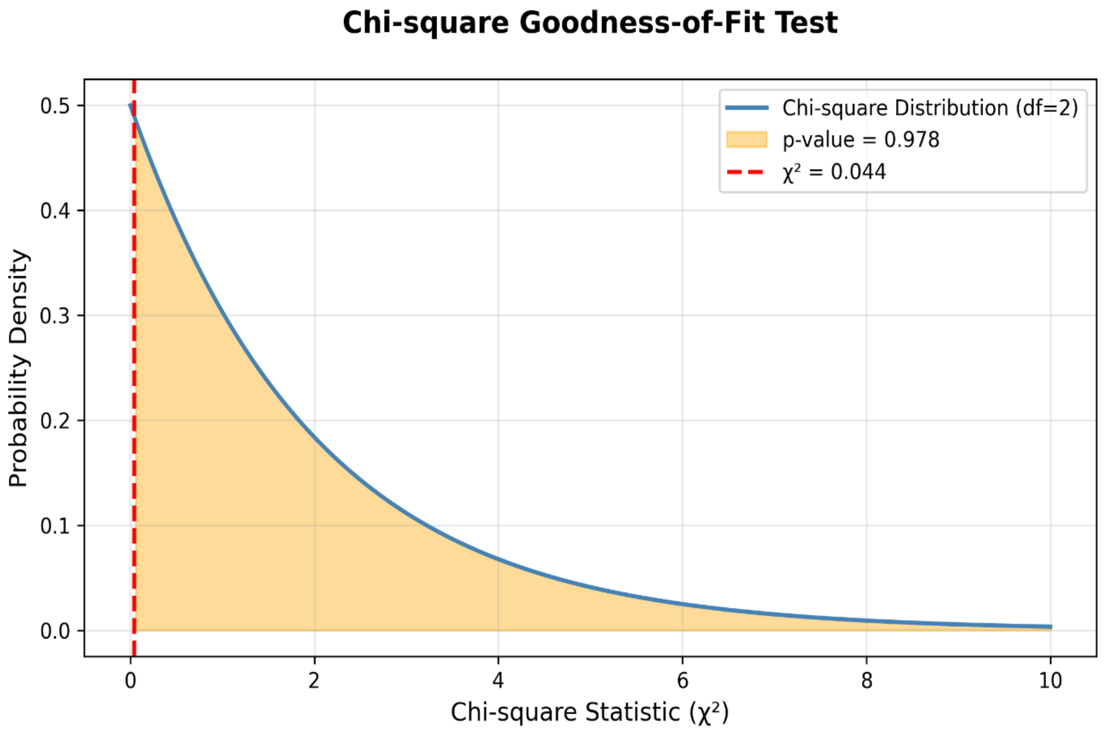


Figure 24: Chi-square Goodness of Fit Test

The MNL model's predictive performance was assessed by comparing observed and predicted time-of-use shares. Observed shares (Off: 0.16, Normal: 0.53, Peak: 0.31) were closely matched by predicted shares (0.22, 0.43, 0.35). The model achieved R^2 = 0.78 and MAPE = 23.1%, indicating strong explanatory power and moderate prediction error. The Chi-square test yielded $\chi^2 = 0.044$ (df = 2, p = 0.978), confirming no significant difference between observed and predicted outcomes. Therefore, the MNL model with estimated parameters (β) accurately reflects user choice behavior across different charging periods and is suitable for scenario-based pricing optimization.

4.11 Financial Analysis

The financial analysis reveals critical insights into the EV charging station's viability under various investment and pricing scenarios. The payback period analysis for the NEA CCS Ratnapark electric vehicle (EV) charging station was conducted to evaluate the time required for the project to recover its initial investment from net annual cash inflows. The initial investment for the station was NPR 4,000,000, and the electricity cost was calculated at NPR 7.49 per kWh, resulting in an annual electricity expenditure of NPR 2,527,039.28. In January 2025, the station recorded a total energy consumption of 28,132.06 kWh and generated a total monthly revenue of NPR 251,635.77. Based on this, the annual revenue was estimated to be NPR 3,019,629.24, assuming similar monthly performance throughout the year. After deducting the annual electricity cost, the net annual cash flow was determined to be NPR 492,589.96.

Table 20: Baseline Financial Parameter

Parameter	Value
Initial Investment (NPR) (Baseline)	4,000,000.00
Electricity Cost per kWh	7.49
Charging Price per kWh	8.94
Monthly Energy Delivered (kWh)	28,132.06
Monthly Revenue (NPR)	251,635.77
Annual Revenue (NPR)	3,019,629.24
Annual Electricity Cost (NPR)	2,527,039.28
Net Annual Cash Flow (NPR)	492,589.96
Project Lifetime (years)	10.00

4.11.1 NPV, IRR, and Payback Period Analysis

The base case analysis demonstrates that the 3 million NPR investment achieves an IRR of 10.22%, exceeding the typical 8% hurdle rate, while the 4 million NPR investment yields only 3.98%, falling below acceptable returns. Table 21 shows the base case financial performance for different discount rates for two different investment scenarios of NRs 3 Million and NRs 4 Million.

Table 21: Base-Case Financial Performance

Discount Rate	Parameter	3 Million Investment	4 Million Investment
3%	NPV (NRs)	1,201,892.27	201,892.27
4%		995,345.83	(4,654.17)
6%		625,504.99	(374,495.01)
8%		305,318.73	(694,681.27)
10%		26,752.06	(973,247.94)
12%		(216,756.86)	(1,216,756.86)
IRR	Percentage	**10.22**	**3.98**
Payback Period	Years	**6.10**	**8.12**

4.11.2 Pricing Strategy Impact

The charging price sensitivity analysis demonstrates that modest price adjustments significantly enhance project viability. A 10% price increase makes the 4M investment viable (9.18% IRR), while a 20% increase yields strong returns for both investment options.

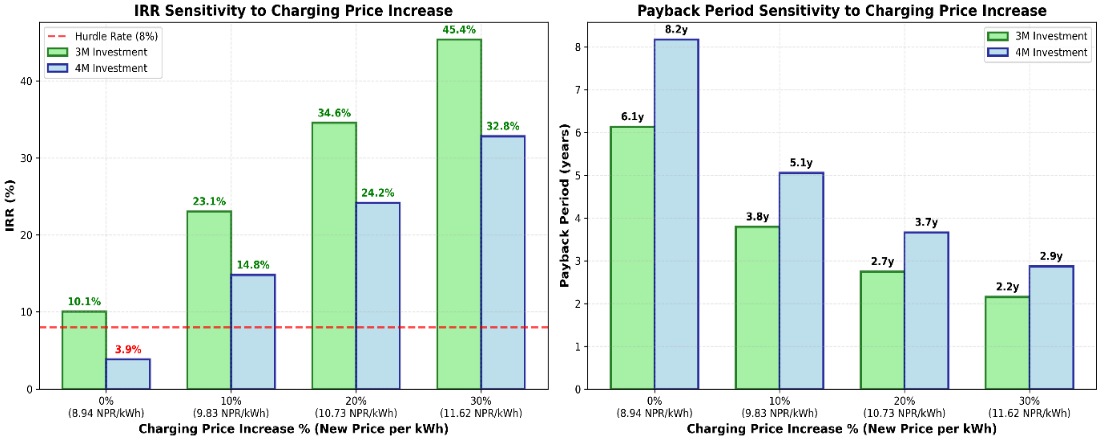


Figure 25: Charging price sensitivity analysis

Chapter 5 – Conclusions and Recommendation

5.1 Conclusions

This study demonstrates that a demand-responsive pricing strategy, calibrated using operational data from NEA CCS Ratnapark, can effectively influence EV charging time-of-use choices in Nepal, with a statistically significant price sensitivity ($\beta \approx -0.126$) confirming users' responsiveness to tariff-based demand management.

Sensitivity simulations demonstrated that incremental increases in peak-period tariffs shift a measurable fraction of charging sessions toward off-peak and normal periods, reducing the peak-session share from 30.6% to approximately 28.4%. Elasticity analysis revealed consistently negative own-price elasticities (e.g., −0.087 for the peak period) and positive cross-price elasticities, indicating strong substitutability among time windows. These results highlight the effectiveness of price-based interventions for alleviating congestion at urban fast-charging stations.

Using these insights, a revenue-constrained TOU optimization model identified optimal price multipliers of (0.7, 0.7, 1.8) for off-peak, normal, and peak periods, respectively. This pricing structure reduced peak-period sessions by 7.2% while boosting off-peak sessions by 48.8 %.

5.2 Recommendation

Adopting the (0.7, 0.7, 1.8) higher during peak (+80%), lower off-peak (-30%) tariff structure lowers peak-period demand and increases revenue, making it suitable for high-load sites such as Ratnapark and Pulchowk. Implement the price change in phases, first 10%, then adjust toward 15–20% based on monitored demand. With peak elasticity around −0.09 and positive cross-elasticities toward off-peak periods, strategic price increases during 16:00–19:00 can shift sessions to off-peak hours and reduce congestion without major grid upgrades. NEA should pilot this pricing structure at crowded stations like Ratnapark, Pulchowk, and Maharajgunj to actively reduce evening congestion.

With self-price elasticity of −0.0865 during peak hours and positive cross-price elasticities toward off-peak periods, use the elasticity matrix evidence to design targeted demand-shifting policies. This reduces congestion during the critical 4–7 PM window and lowers the need for expensive network reinforcement.

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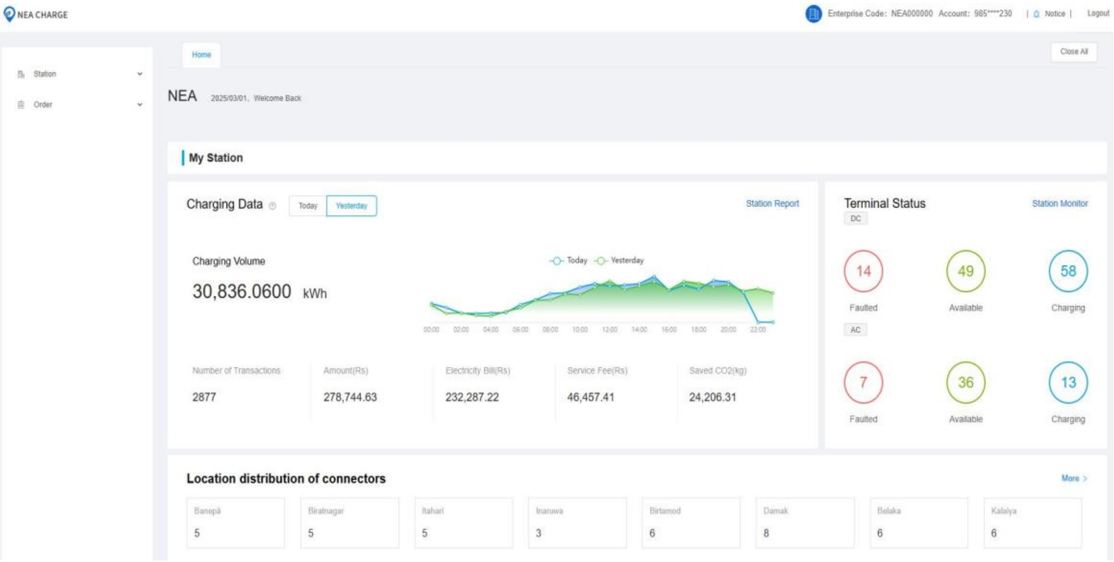
Annexes

Annex 1: List of charging stations of NEA

SN	Station Name (CCS)	SN	Station Name (GBT)
1	NEA CCS Ratnapark	1	NEA GBT Kendriya Bus Terminal-1
2	NEA CCS Nepal Police Club	2	NEA GBT Lahan
3	NEA CCS Kendriya Bus Terminal-1	3	NEA GBT Samakhushi
4	NEA CCS Samakhushi	4	NEA GBT Butwal
5	NEA CCS Malepatan Pokhara	5	NEA GBT Hetauda
6	NEA CCS Dharke	6	NEA GBT Tourist Buspark
7	NEA CCS Kohalpur	7	NEA GBT Bardibas
8	NEA CCS Butwal	8	NEA GBT Sindhuli Buspark
9	NEA CCS Hetauda	9	NEA GBT Birtamode
10	NEA CCS Lamahi	10	NEA GBT Sajha Balkhu
11	NEA CCS Sajha Balkhu	11	NEA GBT Kohalpur
12	NEA CCS Lahan	12	NEA GBT Nuwakot Battar
13	NEA CCS Muglin	13	NEA GBT Lamki
14	NEA CCS Dhangadi	14	NEA GBT Dharke
15	NEA CCS Birtamode	15	NEA GBT Malepatan Pokhara
16	NEA CCS Itahari	16	NEA GBT Biratnagar
17	NEA CCS Damak	17	NEA GBT Hariwon
18	NEA CCS Bardibas	18	NEA GBT Surkhet
19	MOWSIE CCS Surunga	19	NEA GBT Inaruwa
20	NEA CCS Kharipati	20	NEA GBT Damak
21	NEA CCS Hariwon	21	NEA GBT Lamahi
22	NEA CCS Surkhet	22	NEA GBT Kendriya Bus Terminal-2
23	MOWSIE CCS Biratnagar	23	NEA GBT Khurkot-2
24	NEA CCS Kendriya Bus Terminal-2	24	NEA GBT Khurkot-1

25	NEA CCS Nuwakot Hawaghar	25	NEA GBT Sajha Pulchowk-1
26	MOWSIE CCS Itahari	26	NEA GBT Banepa
27	NEA CCS Banepa	27	NEA GBT Birgunj
28	NEA CCS Kushma	28	NEA GBT Attariya
29	NEA CCS Begnas	29	NEA GBT Belaka
30	NEA CCS Belaka	30	NEA GBT Sajha Pulchowk-2
31	NEA CCS Birgunj	31	NEA GBT Manthali
32	NEA CCS Sindhuli Buspark	32	NEA GBT Dhangadi Fulbari
33	NEA CCS Thankot		
34	Ministry of Energy CCS (Upcoming)		

Annex 2: Total energy consumption for 2025/03/01 through NEA Charge



Enterprise Code: NEA000000 Account: 985****230

NEA 2025/03/01, Welcome Back

My Station

Charging Data

Charging Volume

30,836.0600 kWh

Number of Transactions	Amount(Rs)	Electricity Bill(Rs)	Service Fee(Rs)	Saved CO2(kg)
2877	278,744.63	232,287.22	46,457.41	24,206.31

Terminal Status

	Faulted	Available	Charging
DC	14	49	58
AC	7	36	13

Location distribution of connectors

Banepā	Biratnagar	Itahari	Inaruwa	Birtamod	Damak	Belaka	Kalaiya
5	5	5	3	6	8	6	6

Annex 3: Sample data of NEA CCS Ratnapark

Station Name	Energy Consumed (kWh)	Total Fee(S$)	Start Time	End Time	Initial SOC	End SOC	Time Duration (HH: MM)
NEA CCS Ratnapark	40.49	335.26	2024-12-31 23:54:00	2025-01-01 00:52:00	20	100	0:58
NEA CCS Ratnapark	15.61	129.25	2024-12-31 23:51:00	2025-01-01 01:04:00	32	92	1:13
NEA CCS Ratnapark	14.16	117.24	2025-01-01 01:10:00	2025-01-01 02:12:00	38	96	1:02
NEA CCS Ratnapark	13.39	110.87	2025-01-01 01:08:00	2025-01-01 02:17:00	42	99	1:09
NEA CCS Ratnapark	12	99.36	2025-01-01 02:20:00	2025-01-01 03:12:00	28	75	0:52
NEA CCS Ratnapark	12.26	101.51	2025-01-01 02:16:00	2025-01-01 03:29:00	48	100	1:13
NEA CCS Ratnapark	5.32	44.05	2025-01-01 03:13:00	2025-01-01 03:40:00	75	96	0:27
NEA CCS Ratnapark	1.21	10.02	2025-01-01 03:34:00	2025-01-01 03:43:00	24	29	0:09
NEA CCS Ratnapark	14.33	118.66	2025-01-01 03:46:00	2025-01-01 04:55:00	35	96	1:09
NEA CCS Ratnapark	16.36	135.46	2025-01-01 03:51:00	2025-01-01 05:13:00	29	100	1:22
NEA CCS Ratnapark	2.74	22.69	2025-01-01 05:17:00	2025-01-01 05:36:00	17	27	0:19
NEA CCS Ratnapark	6.07	50.26	2025-01-01 05:39:00	2025-01-01 06:10:00	28	50	0:31
NEA CCS Ratnapark	5.84	48.36	2025-01-01 05:41:00	2025-01-01 06:10:00	24	50	0:29
NEA CCS Ratnapark	10.54	87.28	2025-01-01 06:18:00	2025-01-01 07:12:00	51	96	0:54
NEA CCS Ratnapark	11.08	91.74	2025-01-01 06:16:00	2025-01-01 07:13:00	50	94	0:57
NEA CCS Ratnapark	6.26	51.83	2025-01-01 07:16:00	2025-01-01 07:45:00	50	77	0:29
NEA CCS Ratnapark	22.78	188.62	2025-01-01 07:19:00	2025-01-01 07:57:00	37	81	0:38
NEA CCS Ratnapark	4.82	39.91	2025-01-01 07:58:00	2025-01-01 08:09:00	81	91	0:11
NEA CCS Ratnapark	3.83	31.72	2025-01-01 07:51:00	2025-01-01 08:26:00	77	93	0:35
NEA CCS Ratnapark	50.58	418.8	2025-01-01 08:12:00	2025-01-01 09:18:00	16	100	1:06
NEA CCS Ratnapark	7.88	65.24	2025-01-01 09:02:00	2025-01-01 09:38:00	34	68	0:36
NEA CCS Ratnapark	6.21	51.42	2025-01-01 09:24:00	2025-01-01 10:00:00	29	57	0:36
NEA CCS Ratnapark	4.86	40.24	2025-01-01 09:45:00	2025-01-01 10:14:00	69	89	0:29
NEA CCS Ratnapark	20.2	167.26	2025-01-01 10:29:00	2025-01-01 11:06:00	64	100	0:37
NEA CCS Ratnapark	10.13	83.88	2025-01-01 10:08:00	2025-01-01 11:20:00	57	100	1:12

NEA CCS Ratnapark	30.48	252.37	2025-01-01 11:35:00	2025-01-01 12:19:00	55	100	0:44
NEA CCS Ratnapark	21.72	179.84	2025-01-01 12:20:00	2025-01-01 12:53:00	38	86	0:33
NEA CCS Ratnapark	2.1	17.39	2025-01-01 12:46:00	2025-01-01 12:53:00	42	45	0:07
NEA CCS Ratnapark	21.82	180.67	2025-01-01 12:54:00	2025-01-01 14:17:00	46	99	1:23
NEA CCS Ratnapark	8.92	73.86	2025-01-01 13:29:00	2025-01-01 14:22:00	68	96	0:53
NEA CCS Ratnapark	13.51	140.94	2025-01-01 14:49:00	2025-01-01 15:41:00	31	86	0:52
NEA CCS Ratnapark	55.31	546.28	2025-01-01 14:28:00	2025-01-01 15:45:00	11	100	1:17
NEA CCS Ratnapark	4.46	46.28	2025-01-01 15:49:00	2025-01-01 16:05:00	29	48	0:16
NEA CCS Ratnapark	12.21	127.25	2025-01-01 16:07:00	2025-01-01 16:59:00	49	100	0:52
NEA CCS Ratnapark	9.61	100.3	2025-01-01 16:06:00	2025-01-01 17:04:00	64	100	0:58
NEA CCS Ratnapark	19.3	201.49	2025-01-01 17:01:00	2025-01-01 17:46:00	23	77	0:45
NEA CCS Ratnapark	16.08	167.88	2025-01-01 17:05:00	2025-01-01 18:18:00	31	96	1:13
NEA CCS Ratnapark	43.28	451.85	2025-01-01 18:07:00	2025-01-01 19:13:00	8	100	1:06
NEA CCS Ratnapark	7.28	76.01	2025-01-01 18:19:00	2025-01-01 19:14:00	71	100	0:55
NEA CCS Ratnapark	1.79	18.68	2025-01-01 19:14:00	2025-01-01 19:28:00	91	95	0:14
NEA CCS Ratnapark	40.82	426.16	2025-01-01 19:18:00	2025-01-01 20:14:00	32	100	0:56
NEA CCS Ratnapark	29.59	305.77	2025-01-01 19:35:00	2025-01-01 20:53:00	56	100	1:18
NEA CCS Ratnapark	35.96	345.46	2025-01-01 20:21:00	2025-01-01 20:59:00	10	60	0:38
NEA CCS Ratnapark	7.76	64.34	2025-01-01 21:01:00	2025-01-01 21:52:00	67	100	0:51
NEA CCS Ratnapark	40.33	334.62	2025-01-01 21:04:00	2025-01-01 22:20:00	21	100	1:16
NEA CCS Ratnapark	31.65	262.07	2025-01-01 21:56:00	2025-01-01 22:33:00	30	79	0:37
NEA CCS Ratnapark	1.96	16.22	2025-01-01 22:25:00	2025-01-01 22:34:00	42	49	0:09
NEA CCS Ratnapark	8.55	70.8	2025-01-01 22:35:00	2025-01-01 22:54:00	79	91	0:19
NEA CCS Ratnapark	7.08	58.62	2025-01-01 22:39:00	2025-01-01 23:11:00	50	77	0:32
NEA CCS Ratnapark	4.51	37.34	2025-01-01 23:17:00	2025-01-01 23:27:00	57	65	0:10
NEA CCS Ratnapark	16.97	140.51	2025-01-01 23:32:00	2025-01-02 00:03:00	65	100	0:31
NEA CCS Ratnapark	15.58	129	2025-01-01 22:59:00	2025-01-02 00:13:00	32	100	1:14

Annex 4: Monthly charging volume and revenue

Table 22: Monthly charging volume and revenue

Month	Total Charging Volume(kWh)	Total revenue(Rs)
2022-10	444.88	4,109.39
2022-11	4,079.40	36,935.37
2022-12	12,124.60	107,193.75
2023-01	42,874.14	375,721.90
2023-02	65,538.37	577,609.09
2023-03	106,219.84	937,033.78
2023-04	123,328.97	1,092,130.08
2023-05	154,859.26	1,359,455.01
2023-06	185,509.53	1,649,237.40
2023-07	204,371.93	1,988,135.91
2023-08	247,286.68	2,185,132.86
2023-09	303,095.34	2,672,972.30
2023-10	471,057.20	4,384,408.93
2023-11	509,491.47	4,974,110.40
2023-12	502,244.95	5,433,906.59
2024-01	542,180.70	5,530,648.86
2024-02	582,038.31	5,321,687.94
2024-03	685,485.15	7,003,906.67
2024-04	723,705.37	6,593,185.23
2024-05	668,455.50	8,360,303.11
2024-06	754,412.26	7,577,072.98
2024-07	743,907.74	8,135,287.64
2024-08	677,004.66	6,896,475.35
2024-09	747,657.92	6,446,542.94
2024-10	972,338.89	8,311,249.10
2024-11	1,003,407.54	8,643,098.09
2024-12	964,972.65	8,513,232.63
2025-01	1,006,024.63	9,120,424.90

Annex 5: Yearly energy consumption and Revenue of NEA charging stations

Table 23: Yearly energy consumption and Revenue of NEA charging stations

Year	Total Charging Volume(kWh)	Total revenue(Rs)
2022	16,648.88	148,238.51
2023	2,915,877.68	27,629,854.25
2024	9,065,566.69	87,332,690.54

Annex 6: Calculation for Financial Analysis

Table 24: Calculation for Financial Analysis

Cost/KWh Calculation	
Net Sales Revenue -Nepal (M.NRs.)	98,732.00
Net Sales Revenue Export(M.NRs.)	17,066.00
Total Revenue (M. NRs.)	115,798.00
Cost of Sales	
Generation Expenses (M. NRs.)	2,210.00
Power Purchase- Subsidies (M. NRs.)	10,732.00
Power Purchase- IPPs (M. NRs.)	41,393.00
Power Purchase -India (M. NRs.)	16,929.00
Royalty (M. NRs.)	1,636.00
Transmission Expenses (M. NRs.)	2,376.00
Power Service Export Charge (M. NRs.)	984.00
Distribution Expenses (M. NRs.)	12,268.00
Personnel Expenses (Inc Retirement Benefits (M.NRs.)	6,388.00
General Administration & Operating Expenses (M.NRs.)	765.00
Depreciation and Amortization Expenses (M.NRs.)	8,871.00
Total Cost of Sales	104,552.00
Available Electric Energy (GWh)	
NEAGeneration (GWh)	2,911.00
Purchased Energy (GWh) - Subsidies	2,597.00
Purchased Energy (GWh) - IPPs	6,564.00
Purchased Energy (GWh) - India	1,895.00
Total Available Electric Energy (GWh)	13,967.00
Internal Sold/Utilized (GWh)	10,243
Exported Energy (GWh)	1,946

Source NEA Annual Report 2081

Annex 7: Cashflow at different discount rates

Year	Cashflow (NPR)	Discounted @3%	Discounted @4%	Discounted @6%	Discounted @8%	Discounted @10%	Discounted @12%
0	(3,000,000.00)	(3,000,000.00)	(3,000,000.00)	(3,000,000.00)	(3,000,000.00)	(3,000,000.00)	(3,000,000.00)
1	492,589.96	478,242.68	473,644.19	464,707.51	456,101.81	447,809.05	439,812.46
2	492,589.96	464,313.28	455,427.11	438,403.31	422,316.50	407,099.14	392,689.70
3	492,589.96	450,789.59	437,910.68	413,588.03	391,033.79	370,090.13	350,615.80
4	492,589.96	437,659.80	421,067.96	390,177.39	362,068.33	336,445.57	313,049.82
5	492,589.96	424,912.43	404,873.04	368,091.87	335,248.45	305,859.61	279,508.77
6	492,589.96	412,536.34	389,301.00	347,256.48	310,415.23	278,054.19	249,561.40
7	492,589.96	400,520.72	374,327.89	327,600.46	287,421.51	252,776.54	222,822.68
8	492,589.96	388,855.06	359,930.66	309,057.03	266,131.03	229,796.85	198,948.82
9	492,589.96	377,529.19	346,087.17	291,563.24	246,417.62	208,906.23	177,632.88
10	492,589.96	366,533.19	332,776.13	275,059.66	228,164.46	189,914.75	158,600.78

Total Numbers Till 2024 end

Total	Energy KWh	Total Fees NRs	Total No of sessions
11pm - 5 am	66,660	435,248	4,329
5 am - 5 pm	283,658	2,401,100	14,030
5pm - 11pm	160,655	1,588,216	8,103
Sum	510,973	4,424,565	26,462

% Share by time period

	Energy KWh	Total Fees NRs	Total No of sessions
11pm - 5 am	13%	10%	16%
5 am - 5 pm	56%	54%	53%
5pm - 11pm	31%	36%	31%

Annex 8: Photo at NEA Ratnapark

Annex 9: SoC Distribution NEA CCS Ratnapark

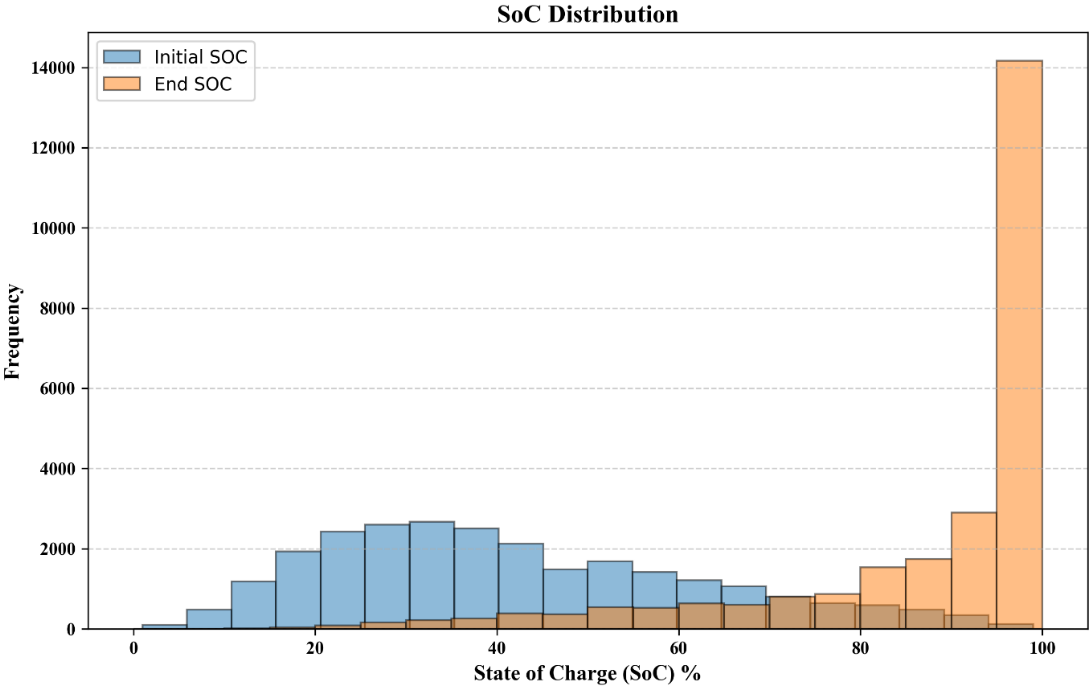
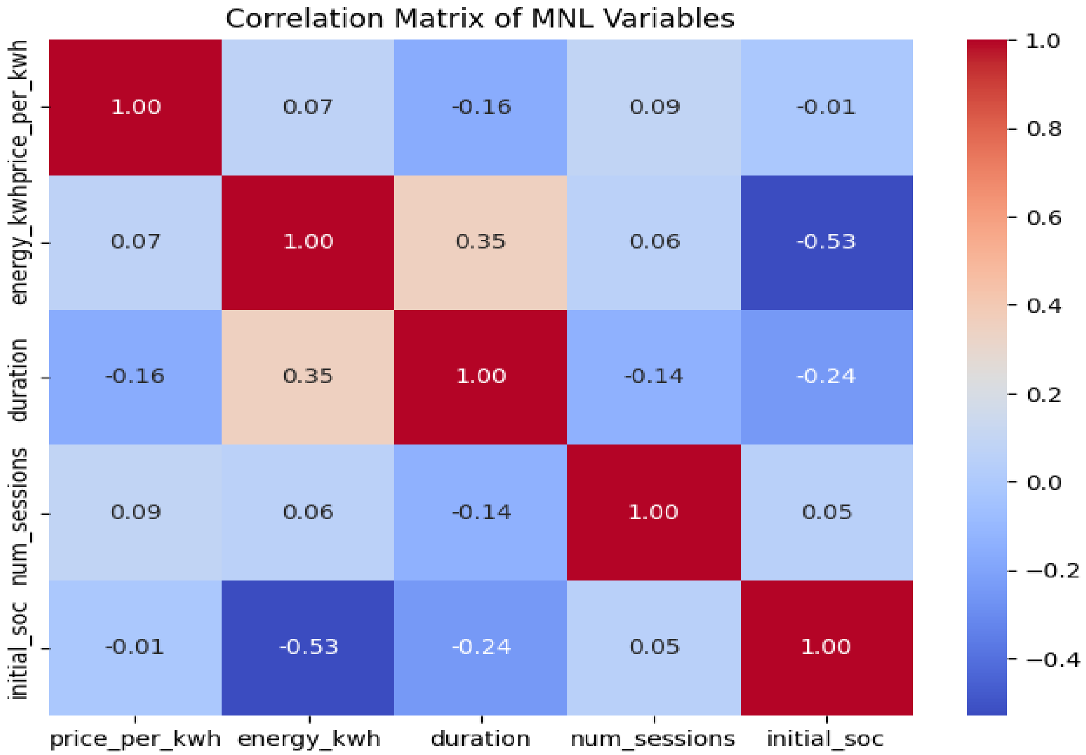


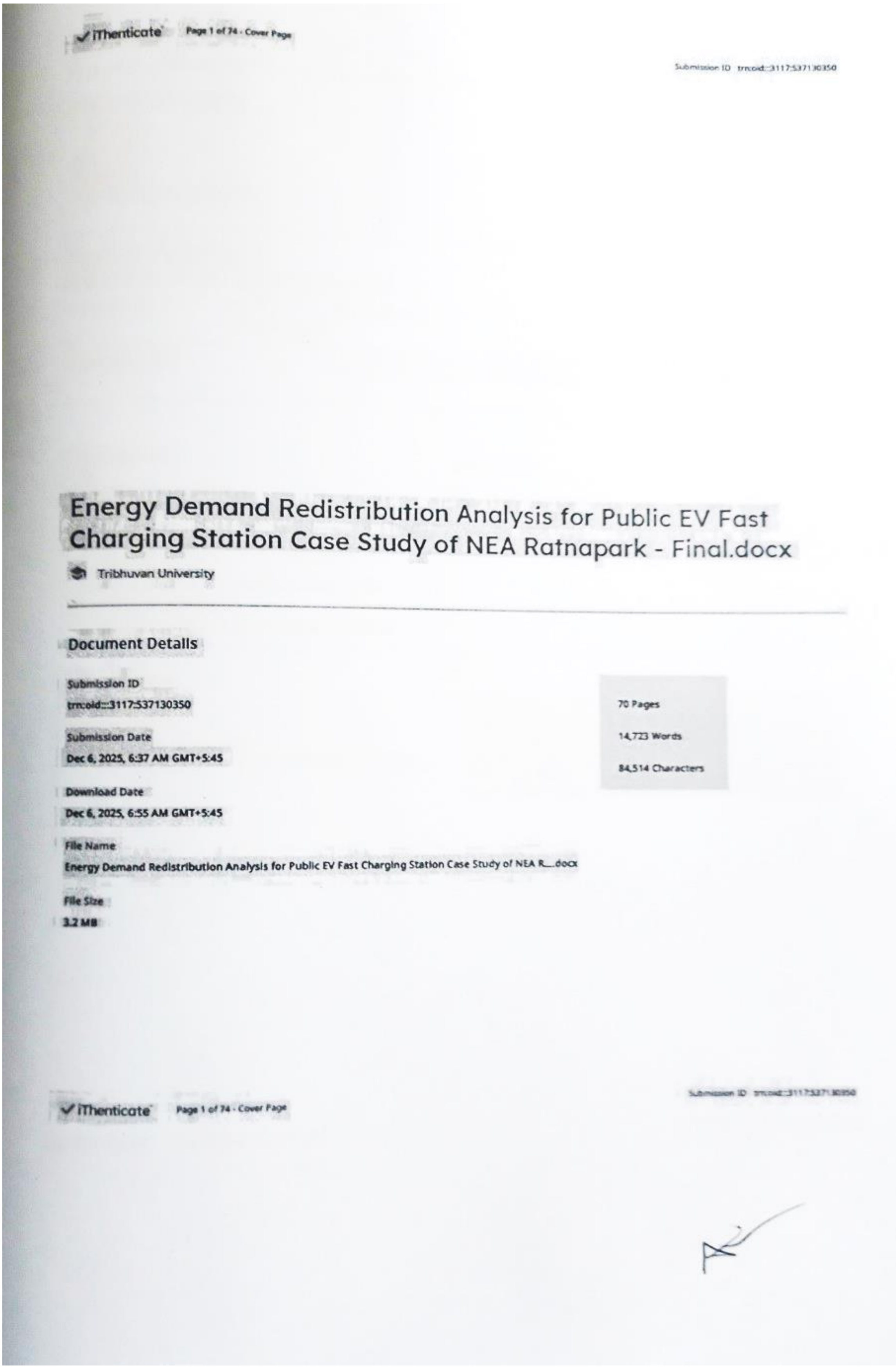
Figure 26: SoC Distribution NEA CCS Ratnapark



	price_per_kwh	energy_kwh	duration	num_sessions	initial_soc
price_per_kwh	1.00	0.07	-0.16	0.09	-0.01
energy_kwh	0.07	1.00	0.35	0.06	-0.53
duration	-0.16	0.35	1.00	-0.14	-0.24
num_sessions	0.09	0.06	-0.14	1.00	0.05
initial_soc	-0.01	-0.53	-0.24	0.05	1.00

Figure 27: Correlation Matrix of MNL Variables

Annex 10: Similarity check



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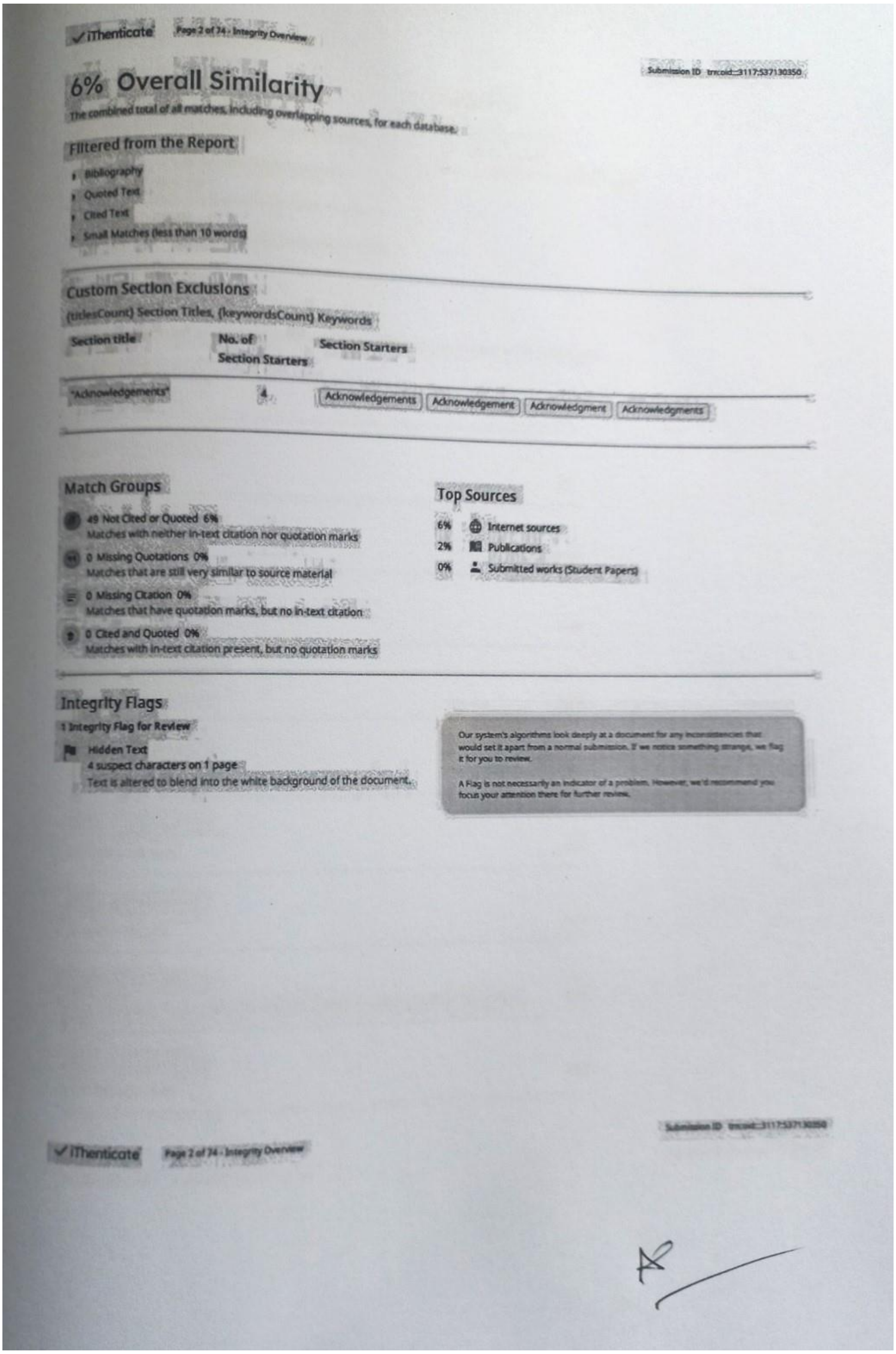

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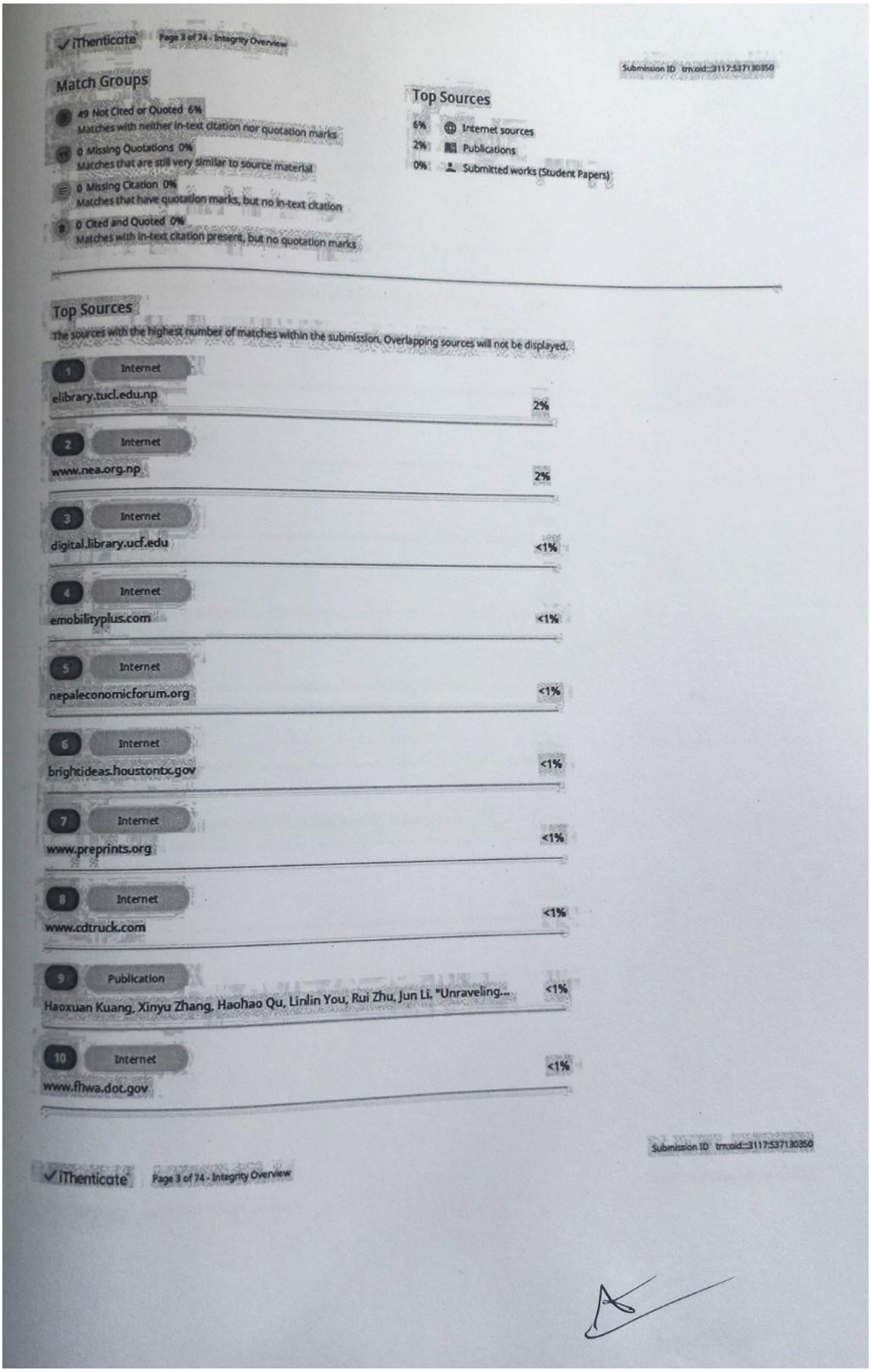

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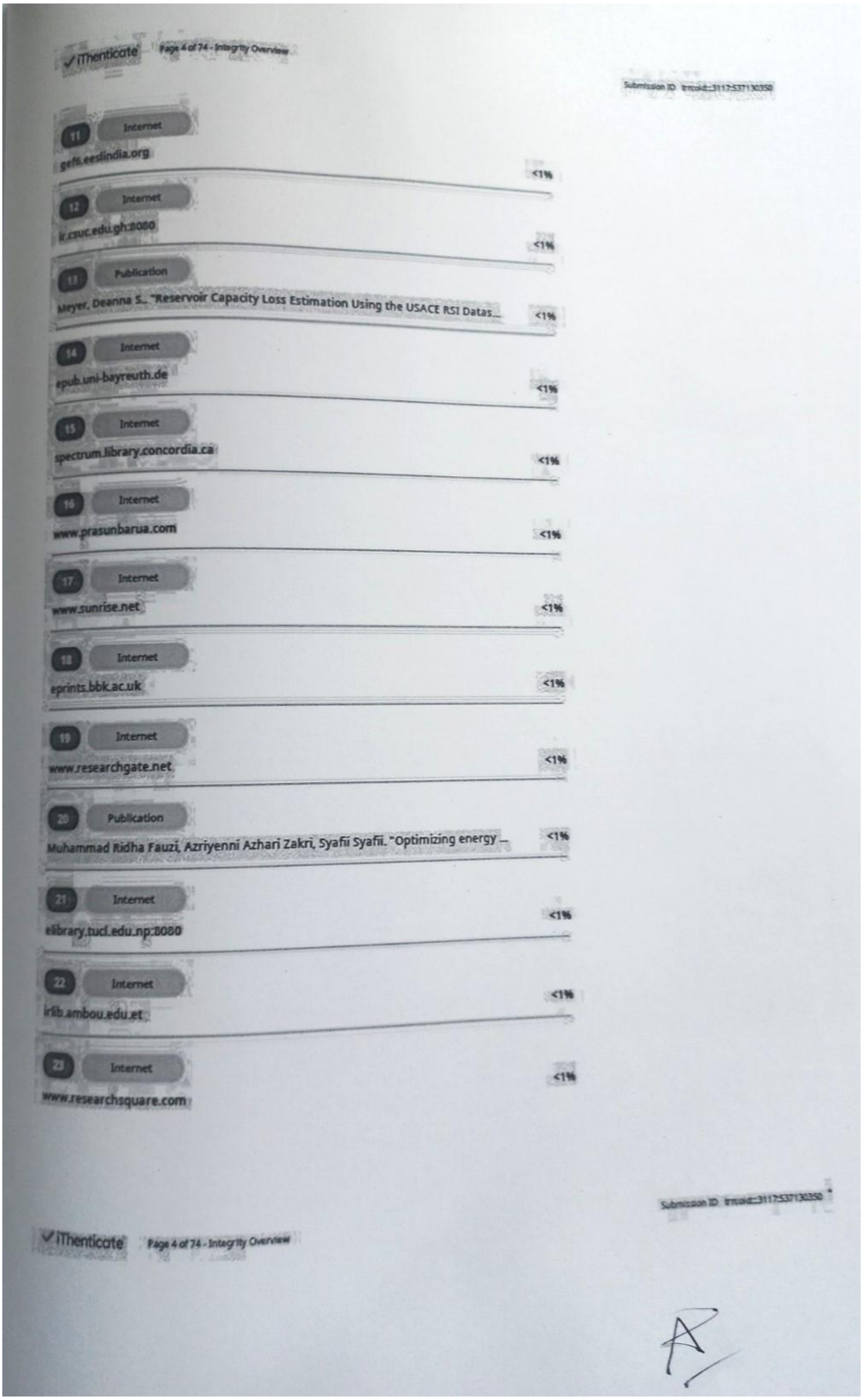

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Annex 11: Comment matrix

SN	Comment	Response	Remarks
1	Implementation plan	Present findings with stakeholders. Implement price change in phases. (page 49)	completed
2	Values for the sensitivity analysis of the price sensitivity coefficient	Based on previous studies, it is found that the price sensitivity coefficient is in the range of -0.1 to -0.5 for EV charging.	(Daina et al., 2017) found cost β ≈ -0.459
3	Cross elasticity calculations	To analyse how users' choices shift from one time period to another (page 48)	completed
4	Financial analysis basis and IRR, and Payback period graph	Based on NEA Ratnapark data from Jan 2025. The graph for IRR and Payback period was converted to a bar graph instead of a line chart (page number 48)	completed
5	Multinomial model and how it works	MNL is a discrete choice model used to study situations where people choose one option from several alternatives. It assigns a 'utility' to each alternative based on factors like price, charging time, and time of day. Users are assumed to choose the alternatives with the highest utility. By analyzing past choices, the model estimates how sensitive users are to changes in these factors, which helps predict how they will respond to new prices or time periods (Page 4, 5, 6)	completed
6	Check grammatical mistakes in the report, with repetition of sentences, and paper formatting	All pages	completed
7	References formatting	Pages 50 and 51	completed

Annex 12: Manuscript

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Energy Demand Redistribution Analysis for Public EV Fast Charging Station: Case Study of NEA Ratnapark

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Abstract

The rapid adoption of electric vehicles (EVs) in Nepal is driving the need for efficient and reliable public charging infrastructure. This study investigates exploratory data analysis and the implementation of dynamic pricing strategies at NEA CCS Ratnapark, a representative fast-charging station in Kathmandu Valley. A Multinomial Logit (MNL) model was employed to analyze user discrete choice behavior and price sensitivity across three time-of-use (ToU) tariff periods: off-peak, normal, and peak. The model estimated a price sensitivity coefficient ($\beta = -0.125$), indicating low elastic demand, where a 1% price increase reduces the probability of selecting a given period by roughly 0.11% depending on its baseline share. Session-based choice probabilities captured realistic energy consumption, with mean session energy highest during normal (20.2 kWh) and peak (19.8 kWh) periods. Baseline observations showed 53.0% of sessions occurred in the normal period, 30.6% during peak, and 16.4% off-peak. A simulation-based optimization under a revenue-preserving constraint indicated that reducing off- and normal-period prices by −30% while increasing peak-period prices up to 80% could cut peak session share from 30.6% to 28.4% . Results demonstrate low user responsiveness to price signals, with dynamic pricing effectively flattening the load profile and reducing peak session by 7.2%.

Keywords

Electric Vehicles, Time-of-Use, Fast charging station, Multinomial logit model, Price sensitivity coefficient, Price elasticity

1. Introduction

As the world shifts towards sustainable energy solutions, electric vehicles (EVs) have emerged as a key strategy to reduce carbon emissions and reliance on fossil fuels. Nepal has witnessed a growing adoption of EVs, supported by government incentives such as tax reductions. However, the success of EV deployment depends heavily on the availability and efficiency of supporting infrastructure, particularly public charging stations. Among these, the NEA CCS Ratnapark Fast Charging Station is one of the most active and centrally located station, serving both public and private EVs.

Existing studies consistently show that EV charging demand at public fast-charging stations is generally price inelastic, particularly during commuting and business hours, with researchers reporting modest elasticities and limited behavioral shifts even under time-of-use pricing [1, 2, 3]. This indicates that users prioritize convenience and operational needs over tariff differentials, underscoring the need for behavioral models that explicitly capture temporal charging choices. Discrete choice theory provides a suitable foundation for this, with the MNL framework widely applied to EV charging behavior [4, 5, 6, 7].

Despite the rapid growth of Nepal's public EV charging network, NEA's stations exhibit uneven demand across time periods, with peak-hour congestion and off-peak underutilization. Limited research has systematically analyzed charging station data, including users' time-slot choices and factors such as price per unit, energy consumption, state-of-charge (SoC), and session duration, hindering evidence-based optimization and policy formulation.

The main objective of this study is to analyze the behavior of electric vehicle users' charging time-choice at the NEA Ratnapark fast-charging station by examining key operational parameters—such as energy consumption patterns, arrival rates, charging durations, state-of-charge distributions, and to develop a demand redistribution based on Multinomial Logit (MNL) by dynamic pricing framework that quantifies the determinants of charging time decisions and supports optimal pricing strategies.

2. Methodology

2.1 Data Collection

This study employs a combined empirical and modeling approach to analyze the charging behavior of electric vehicles . The core framework is a Multinomial Logit (MNL) model, which quantifies how users choose charging time slots based on factors such as price, state-of-charge, and temporal constraints. Simulation analyzes are conducted to evaluate alternative pricing strategies and predict demand shifts from congested to underutilized periods. The study models the behavior of electric vehicle (EV) users when selecting charging time periods using a Multinomial Logit (MNL) framework. The methodology consists of three main steps: estimating MNL parameters from observed data, calculating choice probability elasticities, and determining price sensitivity (β) to allow session-level demand redistribution under alternative pricing scenarios.

Primary data were collected through field visits to selected NEA fast-charging stations, including NEA CCS Ratnapark, NEA CCS Nepal Police Club, and NEA GBT Samakhusi.

Operational assessments were conducted by observing technical components and compiling station performance data, such as electricity usage and EV arrivals, with the support of the Project Manager of the Electric Vehicle Charging Station Infrastructure Development Project, NEA. Secondary data were gathered from official reports, literature, and relevant websites to supplement the primary observations.

Exploratory data analysis was performed using key operational metrics, including daily electricity consumption, session distribution, Charging duration, and utilization patterns. These metrics formed the basis for the MNL modeling and subsequent Scenario analysis, allowing the evaluation of demand redistribution under different time-of-use pricing scenarios. This integrated methodology allows evidence-based recommendations to reduce peak congestion.

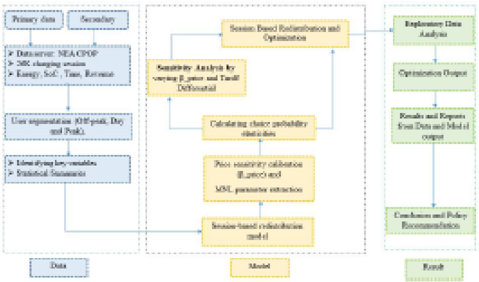

Figure 1: Block Diagram for Research Methodology

2.2 Multinomial Logit (MNL) Modelling Framework

A Multinomial Logit (MNL) model was employed to capture EV users' time-of-use (ToU) charging choices across Off-peak, Normal, and Peak periods. The MNL framework is widely used in transportation and energy demand modelling due to its analytical tractability and probabilistic choice structure [8, 9]. Daily session totals were expanded into session-level observations, and congestion proxies were defined as relative differences between periods ($dcount_{\text{normal}}$ = normal − off, $dcount_{\text{peak}}$ = peak − off), consistent with congestion-based utility formulations applied in EV charging studies [10, 11]. Each session contained its chosen period and the associated congestion covariates.

The MNL model, with Off-peak as the reference alternative, was estimated via maximum likelihood, yielding alternative-specific constants and congestion coefficients. The price-sensitivity parameter (β) was calibrated using a method-of-moments procedure, aligning predicted and observed ToU shares through minimization of the squared error. Similar moment-matching and calibration techniques have been applied in EV charging behaviour and tariff response research [12, 13].

Choice probabilities were computed from the systematic utilities via the standard logit formulation, and analytical softmax derivatives were used to derive own- and cross-price elasticities. These elasticities have been shown to provide reliable behavioural interpretations in charging-demand studies [14, 15]. The resulting probabilities were used to redistribute total daily sessions across ToU periods under alternative tariff scenarios. Corresponding energy consumption and revenue impacts were then derived from the adjusted session counts and average energy per charging event, following modelling practices in charging-station management literature [16, 17].

2.3 Price Elasticity and Sensitivity Analysis

This study evaluates how peak-period charging behavior responds to changes in time-of-use (TOU) prices using the calibrated Multinomial Logit (MNL) model. The MNL framework, widely applied in transportation and energy studies [8, 10], allows modelling user choice probabilities as a function of price and station-level attributes. The baseline parameters, including the estimated price coefficient ($\beta = -0.126$) and observed session shares, were used to compute updated peak-period choice probabilities under price adjustments ranging from −30% to +80%.

For each price scenario, the systematic utility of the peak period was recalculated according to the adjusted TOU tariff, consistent with approaches used in EV charging behaviour studies [12, 13]. The resulting choice probabilities were derived using the logit formulation, and arc elasticities were computed to quantify the sensitivity of peak-period demand to each price perturbation.

To assess the effects of different behavioural responsiveness levels, two additional price coefficients ($\beta = -0.25$ and $\beta = -0.5$) were evaluated. These alternative values represent increasingly price-sensitive user groups, consistent with findings from empirical EV charging choice research [14, 15]. Peak-session shares were recomputed for each parameter–price combination to compare redistribution outcomes across elasticity regimes.

Two visualization approaches were employed: (i) sensitivity curves illustrating how elasticity evolves with incremental price changes, and (ii) a three-dimensional response surface showing the joint influence of price adjustments and β variations on peak-period shares. Similar surface-mapping approaches have been applied in dynamic pricing and charging-station management studies [16, 17]. Together, these analyses reveal the nonlinear and bounded nature of demand shifting achievable through price-based interventions at fast-charging stations.

3. Results and Discussion

3.1 EV charging session distribution at NEA CCS Ratnapark

Charging activity is highest during the peak period (10:00–18:00), with a pronounced surge between 16:00 and 18:00, indicating strong afternoon demand likely driven by fleet and workplace users. Session start and end times align closely, suggesting short charging durations completed within a few hours. Overall, demand intensifies between 13:00 and 19:00 before declining, highlighting the need for pricing and operational strategies to shift usage toward off-peak periods.

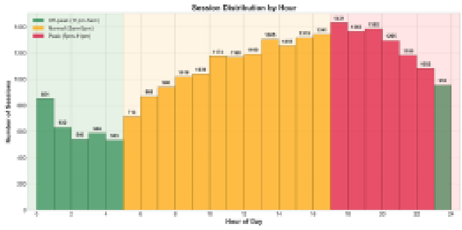

Figure 2: EV charging session distribution at NEA CCS Ratnapark

3.2 Energy consumption Trend at NEA CCS Ratnapark

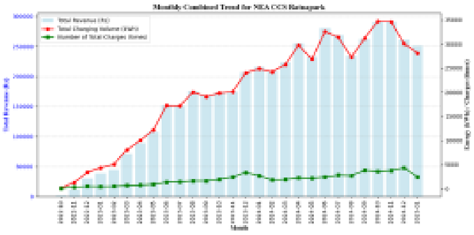

Figure 3: Monthly Energy consumption pattern at NEA CCS Ratnapark.

The monthly trend from October 2022 to January 2025 shows a steady rise in revenue, energy dispensed, and charging sessions at the NEA CCS Ratnapark station, reflecting increasing EV adoption. A sharp surge after April 2023 indicates rapidly growing utilization, with all metrics peaking in mid-2024. A slight decline toward early 2025 suggests seasonal variation or partial load shifting to nearby stations.

3.3 Calibration of Price Sensitivity coefficient

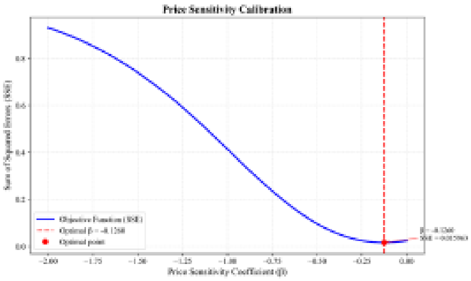

Figure 4: Price Sensitivity coefficient

Figure 4 shows the calibration of the price sensitivity coefficient using the SSE-based Method of Moments. The SSE curve is smooth and convex, yielding a unique minimum at $\beta \approx -0.126$ with an SSE of 0.01596, indicating an excellent fit between predicted and observed TOU session shares. The negative coefficient confirms that higher prices reduce the likelihood of selecting a given time period, consistent with economic theory. This calibrated MNL model closely reproduces baseline charging behavior and is subsequently used for session-level redistribution under alternative TOU pricing scenarios.

3.4 Observed vs. Predicted ToU Charging Shares

Figure 5 compares the observed time-of-use (ToU) session shares with the baseline predicted shares generated from the calibrated MNL model. The model closely reproduces the empirical distribution across the three ToU periods, indicating strong calibration performance.

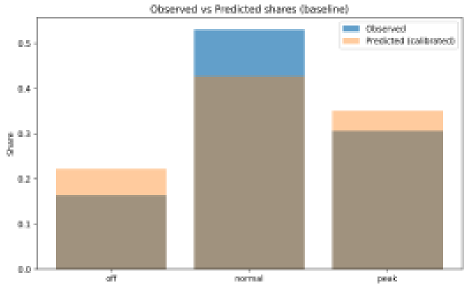

Figure 5: Observed vs predicted shares

The predicted Off-peak share (approximately 22%) slightly overestimates the observed value (around 16%), suggesting that users are somewhat less responsive to lower Off-peak tariffs than the model implies. For the Normal period, the model underpredicts demand (43% predicted versus 53% observed), indicating that factors beyond price—such as habitual travel routines, workplace charging practices, or mid-day trip chaining—may dominate charging decisions during these hours.

Peak-hour shares (35% predicted versus 31% observed) exhibit only a small deviation, demonstrating that the model captures congestion-period sensitivity reasonably well. Overall, the calibrated MNL framework provides an adequate representation of user choice probabilities, successfully reflecting the general structure of temporal charging preferences at the Ratnapark fast-charging station.

3.5 Chi-square Goodness-of-Fit Test

The predictive performance of the Multinomial Logit (MNL) model was evaluated by comparing the observed and predicted time-of-use (TOU) shares. The observed shares were: Off-peak = 0.16, Normal = 0.53, and Peak = 0.31, while the predicted shares were 0.22, 0.43, and 0.35, respectively. The model achieved $R^2 = 0.78$ and a Mean Absolute Percentage Error (MAPE) of 23.1%, indicating strong explanatory power with moderate prediction error. A Chi-square goodness-of-fit test was performed to assess the statistical agreement between observed and predicted shares. The test yielded $\chi^2 = 0.044$ with $df = 2$ and $p = 0.978$, suggesting no significant difference between observed and

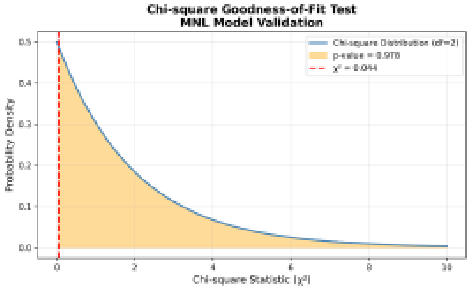

Figure 6: Chi-square Goodness of Fit Test

predicted outcomes.

These results indicate that the MNL model with estimated parameters ($\hat{\beta}$) accurately captures user choice behavior across different charging periods and is suitable for scenario-based pricing optimization.

3.6 Price Elasticity Matrix

Table 1: Own- and Cross-Price Elasticities ($\varepsilon_{i,j}$)

Elasticities ($\varepsilon_{i,j}$)	Off	Normal	Peak
Off	-0.0965	0.0570	0.0394
Normal	0.0294	-0.0688	0.0394
Peak	0.0294	0.0570	-0.0865

The estimated own- and cross-price elasticities presented in Table 1 indicate that charging demand at the Ratnapark fast-charging station is consistently price-inelastic across all ToU periods. All own-price elasticities are negative, confirming that higher tariffs reduce demand within the same period. Peak-hour charging shows the strongest own-price response ($\varepsilon_{peak,peak} = -0.0865$), followed by Off-peak (-0.0965) and Normal hours (-0.0688). Despite these differences, the low magnitudes demonstrate that users prioritize time convenience and immediate charging needs over price considerations.

The cross-price elasticities are uniformly positive, implying substitution effects when relative tariffs change. An increase in Off-peak prices leads to observable but modest shifts toward Normal (0.0570) and Peak (0.0394) periods. Similarly, higher Peak-period tariffs generate substitution toward Off-peak (0.0294) and Normal hours (0.0570). These substitution responses, while present, remain weak, indicating that temporal flexibility among users is limited. Overall, the elasticity structure suggests that ToU price adjustments alone can influence demand patterns, but the magnitude of behavioral change is insufficient for substantial peak-load reduction without complementary operational or informational interventions.

3.7 The Session-based redistribution and pricing optimization analysis

The redistribution and pricing optimization analysis, based on session-level choice probabilities and the calibrated MNL model (price coefficient $\beta = -0.125971$), demonstrates a clear and economically consistent sensitivity of EV users to TOU tariffs at the Ratnapark fast-charging station. The baseline model generated charging shares of 23.36% (off-peak), 45.31% (normal), and 31.33% (peak), closely reflecting observed behavior, where 53.0% of sessions occur during the normal period and only 16.4% during off-peak hours. The cross-price elasticity matrix confirms rational user response, with negative own-price elasticities (e.g., −0.0865 for peak) and positive cross-period elasticities, indicating substitutability across time slots. Sensitivity results show that peak elasticity becomes increasingly negative as prices rise (from −0.06 at −30% to −0.16 at +80%), and the resulting redistribution curve confirms a systematic decline in peak charging share (32.2% to 29.3%) under rising peak prices.

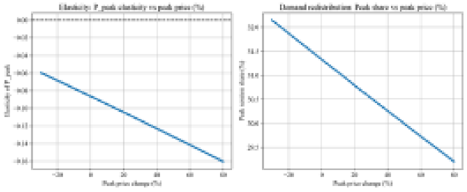

Figure 7: Elasticity and Peak Share vs peak price

Table 2: Session-Based Redistribution Results at NEA CCS Ratnapark

Parameter	Off-Peak	Normal	Peak
Baseline session share (%)	16.4	53.0	30.6
Optimal price multiplier	0.7	0.7	1.8
Session share (%)	24.35	47.22	28.43
Sessions (count)	6,442	12,495	7,522

The revenue-maximizing optimization converged to TOU multipliers of (0.7, 0.7, 1.8) for off-peak, normal, and peak periods, respectively. This structure lowers prices during low-demand hours while substantially increasing the peak tariff. Under the optimized tariff, session shares shift to 24.35% (off-peak), 47.22% (normal), and 28.43% (peak), representing an approximate 2.9 percentage-point reduction in peak-period demand. Importantly, congestion reduction is achieved without compromising financial performance: revenue increases slightly (ratio = 1.00745), despite marginally lower total energy delivery (from 510,950.56 to 500,990.32 kWh). These findings demonstrate that dynamic TOU pricing can effectively redistribute charging demand away from congested evening hours while maintaining or improving station-level revenue outcomes.

The session-based redistribution and optimization analysis showed that the calibrated MNL model, with a price coefficient of $\beta = -0.125971$, accurately reproduced observed TOU charging behavior at the Ratnapark station.Baseline shares were 16.4% (off-peak), 53.0% (normal), and 30.6%

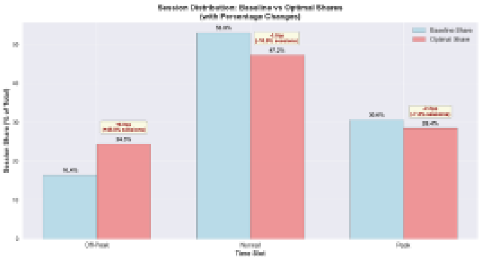

Figure 8: Demand Redistribution at NEA CCS Ratnapark.

(peak), with elasticity results confirming negative own-price effects (e.g., −0.93 for peak) and positive substitution across periods.Sensitivity analysis indicated that higher peak prices consistently reduced peak demand, with the peak share declining from 30.6% to 28.4%.

3.8 Sensitivity Analysis

The sensitivity analysis shows a non-linear relationship between peak price changes and the elasticity of peak-period session share. The estimated price coefficient ($\beta = -0.126$) produces moderate elasticity responses, ranging from near zero at price reductions to approximately −0.6 at an +80% price increase. More sensitive parameters generate steeper curves; for example, $\beta = -0.25$ and $\beta = -0.5$ reach elasticities of −0.9 and −1.8, respectively, at high price increments.

The concave structure of the elasticity curves indicates diminishing marginal sensitivity. For small price increases (below 20%), all parameter values exhibit inelastic behavior ($|\varepsilon| < 0.5$), reflecting limited responsiveness to modest tariff adjustments. Beyond +40%, elasticity increases sharply, particularly for more negative β values.

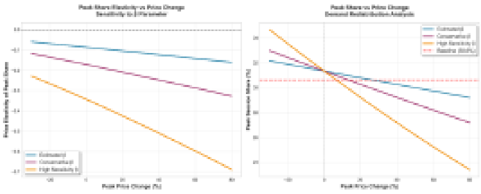

Figure 9: Price sensitivity coefficient and peak price

Figure 9 illustrates the corresponding redistribution of peak-session shares. The baseline peak share of 30.6% serves as the reference. Under the estimated β, a +20% price increase reduces the peak share to about 27.5% (a 10.1% relative reduction). More sensitive parameters yield larger effects: $\beta = -0.25$ reduces the peak share to 24.5% (−19.9%), while $\beta = -0.5$ lowers it to 21.5% (−29.7%).

The redistribution curves follow a logistic pattern, with the most pronounced changes occurring between +10% and +40% price increases. Beyond +50%, the curves approach asymptotic limits, indicating practical bounds on peak-demand reduction achievable through pricing alone.

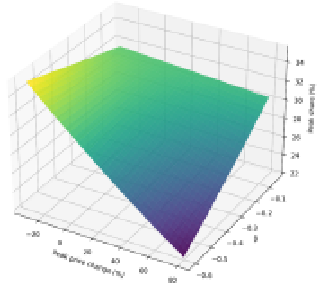

Figure 10: Multidimensional Price Sensitivity

The three-dimensional analysis (Figure 10) illustrates the interaction between the price coefficient β and peak price changes. The surface plot confirms a monotonic relationship, with the steepest gradients occurring when $\beta < -0.3$ and price increases exceed +30%, indicating strong combined effects of price sensitivity and intervention magnitude. The contour lines show that similar peak-share reductions can be achieved through different combinations of β and price adjustments. For example, a target peak share of 25% can be obtained with a +15% price increase when $\beta = -0.4$, or with a +35% increase when $\beta = -0.2$, demonstrating the trade-off between pricing intensity and user sensitivity.

3.9 Financial Analysis for NEA CCS Ratnapark

The baseline financial parameters presented in Table 3 represent the financial performance of the NEA Ratnapark fast-charging station. This reflects an initial investment of approximately NPR 4 million, against which the station's current operational revenues and costs are evaluated. With an electricity purchase cost of NPR 7.49 per kWh and a charging tariff of NPR 8.94 per kWh, the station delivers an average monthly energy output of 28,132.06 kWh, generating a monthly revenue of NPR 251,635.77 and an annual revenue of NPR 3.02 million. After subtracting the annual electricity expenditure of NPR 2.53 million, the station yields a net annual cash flow of NPR 492,589.96. In addition to this baseline scenario, a reduced-investment case of NPR 3 million is also analyzed to assess financial sensitivity with respect to capital expenditure.

Table 3: Baseline Financial Parameters

Parameter	Value
Initial Investment (NPR) (Baseline)	4,000,000.00
Electricity Cost per kWh (NPR)	7.49
Charging Price per kWh (NPR)	8.94
Monthly Energy Delivered (kWh)	28,132.06
Monthly Revenue (NPR)	251,635.77
Annual Revenue (NPR)	3,019,629.24
Annual Electricity Cost (NPR)	2,527,039.28
Net Annual Cash Flow (NPR)	492,589.96
Project Lifetime (years)	10.00

Table 4 presents the base-case financial performance of the Ratnapark fast-charging station under two capital investment

Table 4: Financial Performance for 3 Million and 4 Million NPR Investments Scenarios

Dis. Rate	Parameter	3M Invest.	4M Invest.
3%	NPV (NPR)	1,201,892.27	201,892.27
4%	NPV (NPR)	995,345.83	-4,654.17
6%	NPV (NPR)	625,504.99	-374,495.01
8%	NPV (NPR)	305,318.73	-694,681.27
10%	NPV (NPR)	26,752.06	-973,247.94
12%	NPV (NPR)	-216,756.86	-1,216,756.86
–	IRR (%)	10.22	3.98
–	Payback (Years)	6.10	8.12

scenarios: NPR 3 million and NPR 4 million. The evaluation includes Net Present Value (NPV), Internal Rate of Return (IRR), and payback period across discount rates ranging from 3% to 12%. The NPR 3 million scenario yields positive NPVs up to a discount rate of 10% and achieves an IRR of 10.22%, exceeding the commonly applied 8% hurdle rate. Conversely, the NPR 4 million scenario produces significantly lower NPVs and an IRR of only 3.98%, indicating insufficient returns relative to the required benchmark. The payback period further supports this comparison, at 6.10 years for the NPR 3 million case versus 8.12 years for the NPR 4 million scenario.

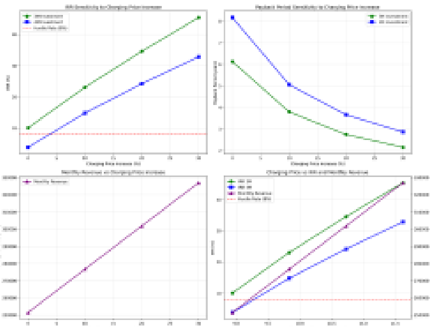

Figure 11: Pricing Impact Analysis

The charging price sensitivity analysis (Figure 11) shows that revenue and financial performance improve steadily with incremental price increases. For the NPR 4M investment scenario, the internal rate of return (IRR) exceeds the 8% hurdle rate at a 10% price increase (IRR = 9.18%), making the project financially viable under moderate tariff adjustments. In contrast, the NPR 3M investment case is already viable at baseline prices and achieves substantially higher IRRs across all price levels, reaching over 30% under a 20% price increase. Payback periods for both investment scales shorten with higher tariffs, falling below three years for the NPR 3M case and approximately four years for the NPR 4M case at a 20% increase. Monthly revenue also grows proportionally with price, reinforcing the financial benefits of controlled tariff adjustments. Overall, the results indicate that modest price increases can significantly enhance economic feasibility, particularly for higher-capital installations, while remaining within practical charging cost ranges for users.

4. Conclusions and Recommendation

This study developed a demand-responsive pricing framework for public EV fast-charging stations in Nepal using real operational data from the NEA CCS Ratnapark station. A multinomial logit (MNL) model was calibrated to capture users' time-of-use charging preferences, yielding a statistically robust price coefficient of $\beta \approx -0.126$ through systematic sum-of-squared-error (SSE) minimization.

Elasticity analysis revealed consistently negative own-price elasticities (e.g., −0.09 for the peak period) and positive cross-price elasticities, indicating strong substitutability among time windows. Sensitivity simulations demonstrated that incremental increases in peak-period tariffs shift a measurable fraction of charging sessions toward off-peak and normal periods, reducing the peak-session share from 30.6% to approximately 28.4%. These results highlight the effectiveness of price-based interventions for alleviating congestion at urban fast-charging hubs.

Using these insights, a revenue-constrained TOU optimization model identified ptimal price multipliers of (0.7, 0.7, 1.8) for off-peak, normal, and peak periods, respectively. This pricing structure reduced peak-period sessions to 28.4% . In general, the findings demonstrate that modest, data-driven price adjustments can meaningfully improve charging station utilization, mitigate evening congestion, and maintain or enhance operator revenue without reducing total energy delivery.

Adopting the (0.7, 0.7, 1.8) tariff structure reduces peak-period demand and increases revenue, making it suitable for high-load sites such as Ratnapark and Pulchowk.

With peak elasticity around −0.09 and positive cross-elasticities toward off-peak periods, strategic price increases during 16:00–19:00 can shift sessions to off-peak hours and reduce congestion without major station upgrades.

Acknowledgment

This research was made possible through the support of the Nepal Electricity Authority, which provided essential data from the charging station and operational information. The authors also express their sincere gratitude to the University Grant Commission, Sanothimi, Bhaktapur, Nepal, for awarding the UGC Faculty Research Grant (FRG-81/82-Engg-04), which significantly enabled the successful completion of this study.

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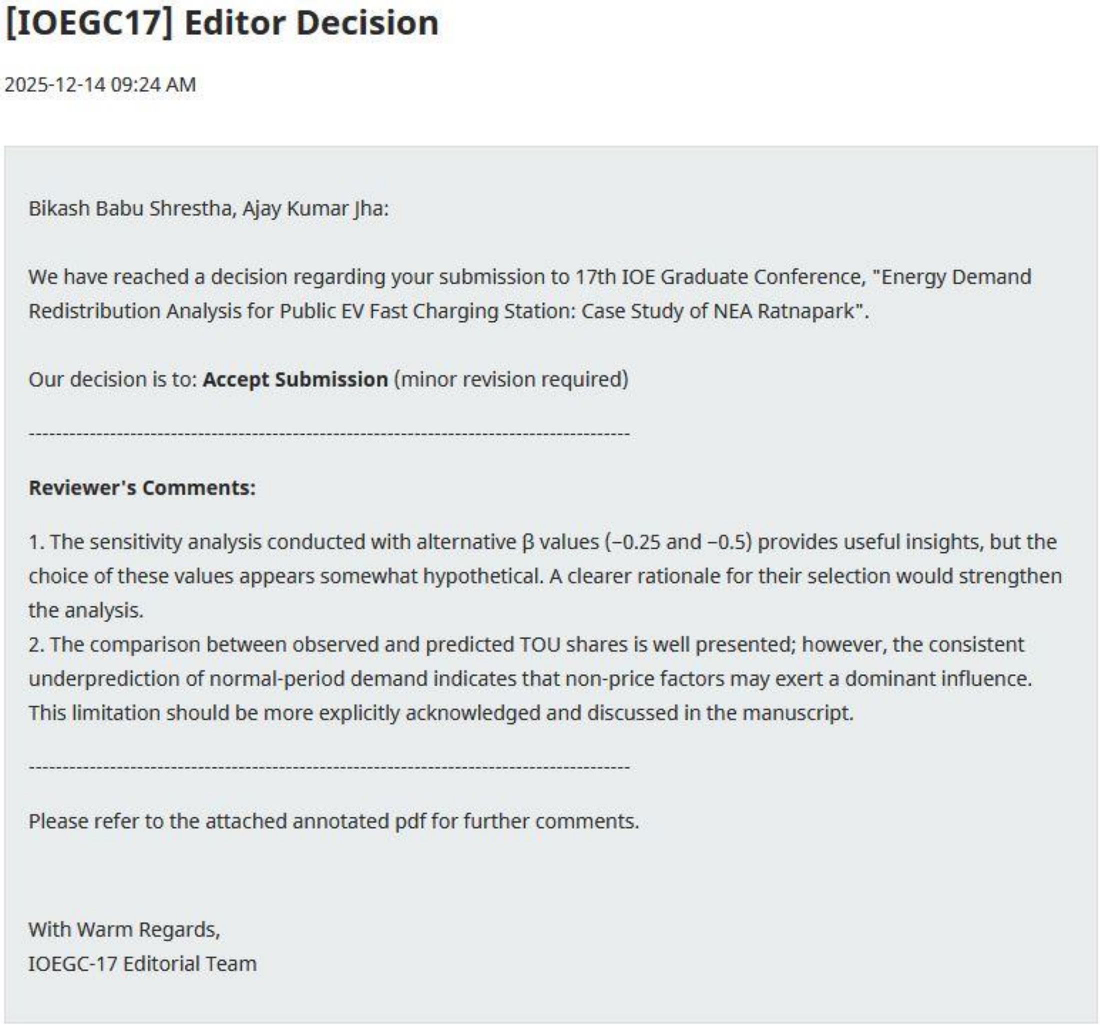
Annex 13: Publication acceptance letter



[IOEGC17] Editor Decision

2025-12-14 09:24 AM

Bikash Babu Shrestha, Ajay Kumar Jha:

We have reached a decision regarding your submission to 17th IOE Graduate Conference, "Energy Demand Redistribution Analysis for Public EV Fast Charging Station: Case Study of NEA Ratnapark".

Our decision is to: **Accept Submission** (minor revision required)

Reviewer's Comments:

1. The sensitivity analysis conducted with alternative β values (−0.25 and −0.5) provides useful insights, but the choice of these values appears somewhat hypothetical. A clearer rationale for their selection would strengthen the analysis.
2. The comparison between observed and predicted TOU shares is well presented; however, the consistent underprediction of normal-period demand indicates that non-price factors may exert a dominant influence. This limitation should be more explicitly acknowledged and discussed in the manuscript.

Please refer to the attached annotated pdf for further comments.

With Warm Regards,
IOEGC-17 Editorial Team