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Optimizing Charging Station Locations for Public Transport Route Coverage in Kathmandu Valley

by

Purushartha Khatiwada

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Head
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Pulchowk Campus, Institute of Engineering
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The undersigned certify that they have read and recommended to Institute of Engineering for acceptance, a thesis entitled **“Optimizing Charging Station Locations for Public Transport Route Coverage in Kathmandu Valley”** submitted by Purushartha Khatiwada in partial fulfillment of the requirement for degree of Master of Science in Transportation Engineering.

....
Supervisor: Dr. Rojee Pradhananga
Assistant Professor
Institute of Engineering

....
Co-Supervisor: Hemant Tiwari
Transportation Specialist
Asian Development Bank

....
External Examiner: Bhimarjun Adhikari
Joint Secretary
Ministry of Physical Infrastructure and
Transport

....
Program Co-Ordinator: Anil Marsani
M.Sc. in Transportation Engineering
Department of Civil Engineering

Date: ....2082/01/09........................

ABSTRACT

The major transportation related challenges, such as fossil fuel depletion, air pollution, and low energy efficiency of fossil fuel vehicles, have driven the development of electric vehicle technology. However, one of major hindrances for adoption of electric vehicle technology in public transportation is the lack of charging infrastructure and their proper planning especially in cities like Kathmandu Valley. This research focuses on identifying feasible zones for the placement of charging infrastructure and subsequent assessment of optimal charging location maximizing the public transport route coverage for public transport vehicles. K-means clustering is used to group boarding and alighting points, with the cluster centroids serving as initial feasible locations. Raster analysis is then performed to assess the suitability of these areas. The Analytical Hierarchy Process (AHP) assigns appropriate weights to various criteria in the Multi-Criteria Decision Analysis (MCDA). The analysis reveals that most locations are feasible, as they fall within highly to moderately suitable regions, determined through suitability mapping by merging raster data. The most viable locations are in commercial, public, or residential areas that are well-connected to roads and urban facilities. Once feasible locations are identified, they are used in the Maximum covering problem. This model aims to minimize the number of charging stations while maximizing route coverage. It optimizes the number of charging stations and determines which routes can be electrified based on accessibility to charging stations within the battery mileage limit. The results indicate that property acquistion costs for charging stations are lower with higher battery mileage, whereas lower battery mileage leads to higher property acquistion costs and fewer routes covered within the battery range. This model can be effectively applied in various transportation planning fields.

Keywords: Multi-criteria Decision Analysis, Analytical Hierarchy Process, K-Means Clustering, Quantum Geographical Information System, Maximum Covering Problem

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Name: Purushartha Khatiwada

Roll No: 079MsTrE016

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GIS	Geographical Information System
MCDA	Multi Criteria Decision Analysis
AHP	Analytical Hierarchy Process
KV	Kathmandu Valley
DB-SCAN	Density-Based Scanning
EV	Electric Vehicles
CPLEX	Complex Linear Programming Expert
ADB	Asian Development Bank
EVCS	Electric Vehicle Charging Station
QGIS	Quantum Geographical Information System
SSE	Squared Sum of Errors
DEM	Digital Elevation Model
SQL	Structured Query Language
FLP	Facility Location Problem
NEA	Nepal Electricity Authority
JICA	Japan International Cooperation Agency
MoPIT	Ministry of Physical Infrastructure and Transport

CHAPTER 1: INTRODUCTION

1.1 Background

The major challenges faced by transportation systems include fossil fuel depletion, air pollution, and low energy efficiency of conventional fossil fuel vehicle technology (He et al., 2019). According to the 2018 National Action Plan for Electric Mobility by the Global Green Growth Institute, the sharp rise in automobiles and motorbikes led to a 22% increase in greenhouse gas (GHG) emissions between 2007 and 2013. Worsening air quality is responsible for over 9,000 deaths annually in Nepal (JICA, 2019). Due to this there are initiatives from the government to reduce air pollution by management of wastages, unmaintained vehicles and industries. Adoption of Electric Vehicles (EVs) is one of the solutions to these problem especially inside Kathmandu Valley. To address this pressing issue, Government of Nepal introduced the National Action Plan for Electric Mobility in 2017 to promote a shift toward clean and sustainable transportation through EVs. The target was set to increase the share of EV by 20% by 2020. In line with this target, authorities announced plans to deploy 300 electric buses for public transport.

Many urban transportation issues are linked to public transit, as it comprises a significant portion of urban vehicle fleets. Adopting alternative propulsion technologies, such as battery-electric bus systems, is essential for reducing exhaust emissions in public transportation (Kunith et al., 2016). One of the primary obstacles to electrifying public transport is the limited driving range of electric buses compared to conventional diesel buses. Therefore, the strategic placement of charging stations is critical to ensuring the smooth operation of electric public transport systems. Charging infrastructure is ideally located near high-demand routes or stops to minimize additional travel costs for vehicles. In Nepal, there are initiatives for placement of charging stations for EVs across the country. A major achievement in this effort was the launch of 51 EV charging stations on September 6, 2023. The major challenges in placing EV charging stations in Kathmandu Valley include limited land availability, high installation costs, power grid capacity constraints, and unclear policy guidelines. Additionally, issues such as traffic congestion, slow EV adoption in public transport, and the need for standardized charging infrastructure further hinder the expansion of charging networks.

Several studies have explored the optimal placement of charging stations using mathematical optimization techniques. Limited research has focused on using clustering approaches to determine charging station locations. Cluster analysis is a type of unsupervised learning that includes various methods, such as the partition-based K-means clustering algorithm, hierarchical clustering techniques (both agglomerative and divisive), and the density-based DB-SCAN algorithm, among others (Li et al., 2022). K-means clustering is a widely used method in traffic flow prediction and identifying high-demand areas; however, it is rarely applied to charging location problems. The K-means clustering technique can be highly effective in identifying charging locations, particularly for public transportation. The cluster centers can serve as optimal locations for placing facilities such as charging stations. Before determining the cluster centers, it is essential to optimize the number of clusters to ensure maximum coverage and accessibility. In K-means clustering, the most common approach for optimizing cluster numbers is the elbow method, which minimizes the sum of squared errors. Once the errors are minimized, increasing the number of clusters further does not significantly improve coverage.

Various criteria must be considered before determining the placement of charging infrastructure. One of the key factors is land use, as it influences both land acquisition costs and availability. Infrastructure accessibility, such as proximity to major roads and highways, is another crucial criterion, as it determines how easily the locations can be accessed. Additionally, environmental factors, including proximity to rivers and vegetation, help assess potential adverse impacts on natural resources. A widely used approach for identifying feasible locations for charging infrastructure is Multi-Criteria Decision Analysis (MCDA). Supported by the Analytical Hierarchy Process (AHP) in GIS, MCDA assigns weights to different criteria, helping construct suitability maps and evaluate potential locations for charging stations.

The use of electric vehicles in the Kathmandu Valley began in 1993 as a response to the region's severe air pollution problem (Paudel et al., 2019). Air pollution is a major issue due to the heavy reliance on conventional fossil fuel vehicles, which emit harmful gases. One of the key solutions to reducing air pollution from conventional vehicles is the adoption of green infrastructure, such as the integration of an electric vehicle system. There is no proper route planning in Kathmandu and we can witness all type of vehicles plying on all routes in Kathmandu. As a result, buses operate on roads ranging from very narrow streets to wide arterial roads. This variation poses a significant challenge in placing charging infrastructure along roadsides, like petrol stations. Consequently, accommodating fast-charging stations as roadside facilities is particularly difficult in densely built areas like Kathmandu Valley.

1.2 Statement of the Problem

Kathmandu Valley faces severe air pollution due to rapid motorization, increased vehicular emissions, and industries. Among the major contributors, the transportation sector plays a significant role in degrading air quality. To mitigate this issue, the government has initiated policies promoting green vehicles, particularly electric public transport. However, the transition to electric mobility comes with several challenges that need to be addressed for successful implementation. A major barrier to the adoption of electric vehicles for public transportation is the lack of efficient charging infrastructure. Identifying key locations for this infrastructure is challenging, as it requires consideration of various criteria for effective placement. Charging stations must be strategically located near high-demand areas to ensure accessibility from major bus routes, minimizing additional travel costs. Nepal's topography presents challenges, including steep slopes and deep valleys formed by rivers. To minimize environmental impacts, it is essential to place charging infrastructure away from steep terrain and rivers. Petrol stations serve as key hubs for hybrid models that combine petroleum and electricity. Therefore, charging stations can be located near these existing facilities. The main challenge in Kathmandu Valley lies in the central core areas and cultural heritage sites, where the placement of charging stations could disrupt the landscape. To mitigate this, suitable locations should be chosen away from the core and cultural heritage sites. Additionally, remote areas, while less central, are often covered with dense vegetation, which must also be preserved. Proper site selection through careful planning is essential to ensure effective charging infrastructure placement in Kathmandu.

Placing EV charging stations for public transport in Kathmandu Valley presents several challenges. Limited land availability makes it difficult to find suitable locations, especially in dense urban areas where space is already constrained. High installation costs, including infrastructure development and grid connection expenses, further hinder expansion. The valley's power grid faces capacity constraints, raising concerns about whether it can support widespread electrification of public transport. Additionally, the absence of clear policy guidelines creates uncertainty for investors and operators. Traffic congestion complicates access to charging stations, potentially leading to operational delays. Slow adoption of electric buses and the lack of standardized charging infrastructure add to the complexity, making it difficult to establish a seamless and efficient charging network for Kathmandu's public transport system.

1.3 Research Objectives

The major objective of the study is to optimize charging station locations for maximizing public transport route coverage inside Kathmandu Valley. The specific objectives considered are:

a. To find the probable locations of the charging locations
b. To determine optimum charging locations and suggest feasible routes for the electrification of conventional public vehicles maximizing the route coverage

1.4 Scope of the Study

The scope of the study can be divided into the following:

1. Focusing on the boarding and alighting stops collected through the survey of various routes of public transportation around Kathmandu valley. Utilizing the stops in clustering techniques to establish the cluster centers as the feasible locations of the charging infrastructures.
2. Utilization of the various vector and raster data collected through different sources to map factors such as slope, proximity to rivers, proximity to roads, proximity to vegetation, power substation, land use mapping, etc., converting all vector data into raster if necessary.
3. Involving the survey of various experts related to the locations of charging stations, which involved a survey about various criteria of mapping. Following this survey, checking the consistency of the surveyed data and establishing the weights of various criteria of mapping such that they can be merged into one map.
4. Involving mapping of various suitability maps for environmental criteria, infrastructure accessibility criteria, and land use criteria using the weights obtained from AHP.

5. Involving the development of the optimization function to optimize the number of charging locations among the feasible locations such that the maximum coverage of the routes can be obtained through minimum placement of the facilities.

1.5 Limitations of the Study

The project report is prepared under the following limitations:

- The study is focused on the public transport routes within the Kathmandu valley and does not consider public transport connecting to other districts.
- The clustering techniques of K-means clustering are utilized as other clustering techniques, such as Hierarchical clustering, are also available.
- The weighting of the suitability mapping focuses on the judgement of a limited number of experts.
- The suitability mapping did not involve risk criteria such as landslides and earthquakes.
- The network maximum covering problem focuses on only the distance and capacity as major criteria to electrify the routes and optimize the locations of the infrastructures, respectively.

1.6 Organization of Report

The chapters of the report are organized as follows:

Chapter 1: Introduction: It deals with the background of the study, problem statement, objectives of research, scope of study, and limitations of the study.

Chapter 2: Literature Review: It deals with the literature background on various topics such as set covering problems, clustering algorithms, analytical hierarchy process, multi-criteria decision analysis, etc.

Chapter 3: Methodology: It deals with methods of clustering, analytical hierarchy process, data collection, multi-criteria decision analysis, and the maximal covering problem that are being used in this study.

Chapter 4: Results and Analysis: This chapter deals with the analysis of various results of the methodology applied, as mentioned in Chapter 3.

Chapter 5: This portion provides the final conclusion and recommendations of the study.

CHAPTER 2: LITERATURE REVIEW

2.1 Clustering Approaches of Fixing Charging Locations

Clustering approaches have been utilized in only a few studies related to the optimal placement of charging stations. Li et al. (2022) proposed clustering algorithms to determine optimal locations for electric vehicle charging stations. Their study used taxi GPS data, analyzing dwell times based on vehicle trajectories to gasoline stations and parking locations. The research focused on five municipal districts in Qingdao, where the study area was divided into suitable grids, and multiple clustering methods were applied. The "multiple same" approach referred to the K-means clustering method, while the "multiple multi-type" approach used hierarchical clustering. The K-means clustering technique determined the optimal number of clusters using the elbow method, which resulted in four clusters whose centroids were selected as charging station locations. Additionally, agglomerative hierarchical clustering was performed on dwell point data based on location. The data was divided into four categories, each of which was further subdivided, resulting in a total of 12 categories. Each category was then clustered using weighted K-means clustering to obtain 12 cluster centroids. The study found that the weighted error was significantly smaller in hierarchical clustering compared to the K-means clustering approach.

Sánchez et al. (2022) proposed a mixed-integer programming model to determine the optimal locations for charging stations for freight vehicles while considering a routing problem with time windows. The model accounted for key factors such as state of charge, battery capacity, and vehicle dynamics. The study aimed to minimize four objective functions: total driven distance, the number of electric vehicles (EVs) required, the number of charging stations, and overall monetary costs. The major constraints included freight flow along arcs, route definitions, the state of charge of vehicles, and vehicle travel times. To refine potential site selection, K-means clustering was applied to divide the study area into small zones. The centroids of these clusters were designated as potential charging station locations, while the clusters themselves were regarded as customer sites. The mathematical model was solved using CPLEX 20.1, and simulations were conducted using Python 3.8. The results indicated that the number of EVs required was influenced by customer time windows and freight demand. Additionally, minimizing the number of EVs and charging stations led to an increase in travel distance. Furthermore, reducing the number of EVs resulted in a higher demand for charging stations.

Abdullahi et al. (2024) proposed a methodology to minimize the distance between charging locations and high EV-demand areas while considering energy efficiency and redundancy. Their approach incorporated various factors, including charging demand, energy consumption, population density, and existing stations, to determine optimal charging station locations. Data points were iteratively reassigned, updating centroids to balance coverage and accessibility. The study highlighted K-means clustering as an effective tool for charging station placement, reducing the likelihood of locating stations in low-demand areas. It emphasized the importance of establishing a sustainable EV charging network with a limited number of strategically placed charging stations.

2.2 Optimization Modeling Related to Setting Problems

These studies primarily focused on developing optimization functions with constraints to determine the optimal locations for charging stations. A vast body of literature exists in this field, with most studies emphasizing the placement of fast-charging stations within the network.

Kunith et al. (2016) developed a mixed-integer linear programming model to determine the optimal placement of fast-charging stations and the required battery capacity for public transport lines. The optimization function considered battery costs, power grid costs, and infrastructure costs. The model was applied to Berlin's public transport network, which included 17 bus lines and 134 buses. Energy consumption was analyzed under varying route, bus, and traffic conditions. A scenario analysis was conducted based on factors such as climate, charging power, and operational conditions. The results highlighted differences across scenarios and revealed a trade-off between infrastructure investment and battery capacity. Additionally, the study identified optimal station placement locations, minimizing the number of charging stations while determining the appropriate charger sizes for different locations.

Liu et al. (2018) developed a spatiotemporal optimization model for deploying battery electric vehicles, focusing on minimizing bus and charging infrastructure costs while maintaining existing routes and schedules. Their transit deployment strategy was applied to the Utah Transit Authority network in the United States, which included 332 fixed and flexible routes. The study incorporated both overnight (depot) charging and on-route charging strategies. For shorter routes—111 buses with a mileage of 62 miles or less—overnight charging was recommended, utilizing four designated garages. Meanwhile, 221 routes were assigned on-route charging, requiring the installation of 36 charging stations at strategic locations along these routes.

Chaudhary et al. (2021) formulated a vehicle routing problem to determine the optimal placement of charging stations along the radial road network of Pokhara. A genetic algorithm was employed to solve the optimization model, and the impact of EV station installation was analyzed across various parameters, including voltage stability, power loss, and reliability index. The results indicated that while voltage fluctuations and power loss increased after installation, the reliability index remained unchanged.

Frade et al. (2011) investigated the optimal placement of electric charging stations in a high-density area of Lisbon, Portugal, characterized by a strong concentration of population and employment. The study identified the area as suitable for slow-charging stations, as vehicles remained parked for extended periods, often up to 24 hours. The optimization function was based on the maximum covering problem, aiming to maximize charging demand. Daytime and nighttime demand were modeled using regression analysis, with employment density representing daytime demand and residential population representing nighttime demand. The results demonstrated the model's effectiveness in infrastructure planning for EV charging stations.

Yu et al. (2024) developed a network-based set covering location problem that accounted for the coverage of both nodes and arcs within the network. The study focused on optimizing charging infrastructure for electric trucks in Norway. The optimization model aimed to minimize charging infrastructure costs while ensuring adequate station coverage through defined constraints. A case study was conducted in Northern Norway, considering two coverage distance scenarios: 150 km and 130 km. The results indicated that for a 150 km coverage distance, the model proposed two charging stations, whereas reducing the coverage distance to 130 km necessitated an additional station. The study suggested that the model could be further enhanced with more reliable data and by integrating shared charging stations for multiple vehicle types.

2.3 Suitability Mapping Using GIS and Analytical Hierarchy Process

Yomralioglu et al. (2020) utilized Geographic Information Systems (GIS) and the Analytical Hierarchy Process (AHP) to determine optimal charging station locations in Istanbul, Turkey. Fuzzy AHP was employed to calculate the weights of two key criteria: environmental impact and accessibility. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method was then applied to rank potential locations and identify the most suitable sites for charging station placement.

Kayaa et al. (2020) employed similar methods of Geographic Information Systems (GIS) and the Analytical Hierarchy Process (AHP) to determine optimal charging infrastructure locations in Turkey. The study focused on environmental and urbanity criteria and conducted a sensitivity analysis to assess variations in the weightings. To test the consistency of the results, the PROMETHEE and VIKOR methods were used.

Ward (2016) employed GIS and the Analytical Hierarchy Process (AHP) to identify optimal fast charging station locations in the Dutch environment. The study primarily considered urban factors such as proximity to roads, parking lots, shopping malls, power substations, and power loss. AHP was used to calculate the weights for these criteria, enabling the combination of raster layers to create a final suitability layer. The paper also included a sensitivity analysis to evaluate the reliability of expert knowledge on the relevant criteria. The results showed that the placement of fast charging stations largely followed busy city areas. Based on the suitability scores, 10 key locations were identified for optimal placement, with 5 located inside the city and 5 outside.

2.4 Set Covering Problems Using GIS

These problems primarily involved set covering problems, which were mostly solved using GIS. The key focus of these studies was on optimizing the coverage range of the charging stations before determining their final placement.

Vansola et al. (2022) formulated a maximum coverage problem for NCT-Delhi, focusing on maximizing the coverage of charging stations. The study divided the area into various zones, and the distance matrix between the zones was generated using GIS. Mixed traffic conditions, including two-wheelers, three-wheelers, four-wheelers, and commercial vehicles, were considered, and different penetration rates were used to estimate charging demand. With a 3 km coverage range, 62 feasible charging station locations were identified. However, when the coverage range was reduced by 1 km, the number of feasible charging locations increased by 72%.

2.5 Related Studies in the Study Area

The Kathmandu Valley has been selected as the study area for this research. There have been very few studies related to the optimal placement of charging infrastructure in Nepal, particularly within Kathmandu Valley. As mentioned earlier in the set covering problems, some studies outside the valley have addressed the placement of such infrastructure. However, no studies have been conducted regarding the placement of charging stations within Kathmandu Valley. In 2015, Chaudhary et al. (2015) conducted a study on the suitable locations for fire-fighting stations within Kathmandu Metropolitan City using the Group Decision Making Process. The study considered four key criteria for suitability mapping: distance from rivers, land cover, distance from roads, and population density. The results indicated that only 13.46% of the land within the city was deemed suitable for fire-fighting station placement.

2.6 Summary of the Literature Review

This summary highlights the growing trend of studies focused on the placement of charging infrastructure worldwide. Research has mainly concentrated on the placement of fast-charging stations, with optimization functions being developed to determine optimal locations, such as placing chargers at bus stops along public transport routes. In Nepal, while some studies on charging infrastructure placement have been conducted, they remain limited in number. Furthermore, there is a lack of literature addressing the feasible placement of charging infrastructure specifically for public transportation. No studies have been conducted within Kathmandu Valley regarding the placement of charging stations for electric vehicles (EVs), though research on the location of firefighting stations within the valley has been done. Studies outside the Kathmandu Valley, such as in Pokhara, have looked at charging infrastructure placement, but there are no studies specifically addressing the charging infrastructure for public transportation in Nepal. Given the significant potential for solving transportation challenges in Kathmandu Valley through the promotion of electric vehicles, proper placement of charging stations for public transport could address the critical issue of which routes should be electrified using electric vehicles. Therefore, there is a clear need for conducting a study to determine the optimal locations for charging infrastructure for public transport within Kathmandu Valley.

CHAPTER 3: METHODOLOGY

3.1 Research Methodology

The research methodology is illustrated in Figure 3.1 below. The first phase involves data collection, where various types of data are gathered, including GIS-related data and survey data. GIS data related to routes and boarding/alighting points is used for clustering and identifying feasible charging station locations in relation to public transport demand areas. Decision criteria is established for suitability mapping, and both raster and vector data is collected. The vector data is converted into raster format as needed. The Analytical Hierarchy Process (AHP) is employed, for which an expert survey will be conducted. A consistency check is necessary to assess the reliability of the survey data. This will help determine the weights required for merging the raster layers. Once the weights are established, they are applied to generate the final suitability maps, which will highlight the importance of various areas. The feasible locations generated from the clustering process are then incorporated into the optimization model, aimed at minimizing the number of charging stations while maximizing the coverage of public transport routes. Input data, such as vehicle fleet information and daily trip data from operator surveys, as well as government land cost data from municipal guidelines, are used in the optimization model. Based on the importance of areas indicated by the suitability maps and the locations of feasible charging stations, penalty costs and capacity constraints are set within the optimization model to achieve the best placement strategy for the charging infrastructure.

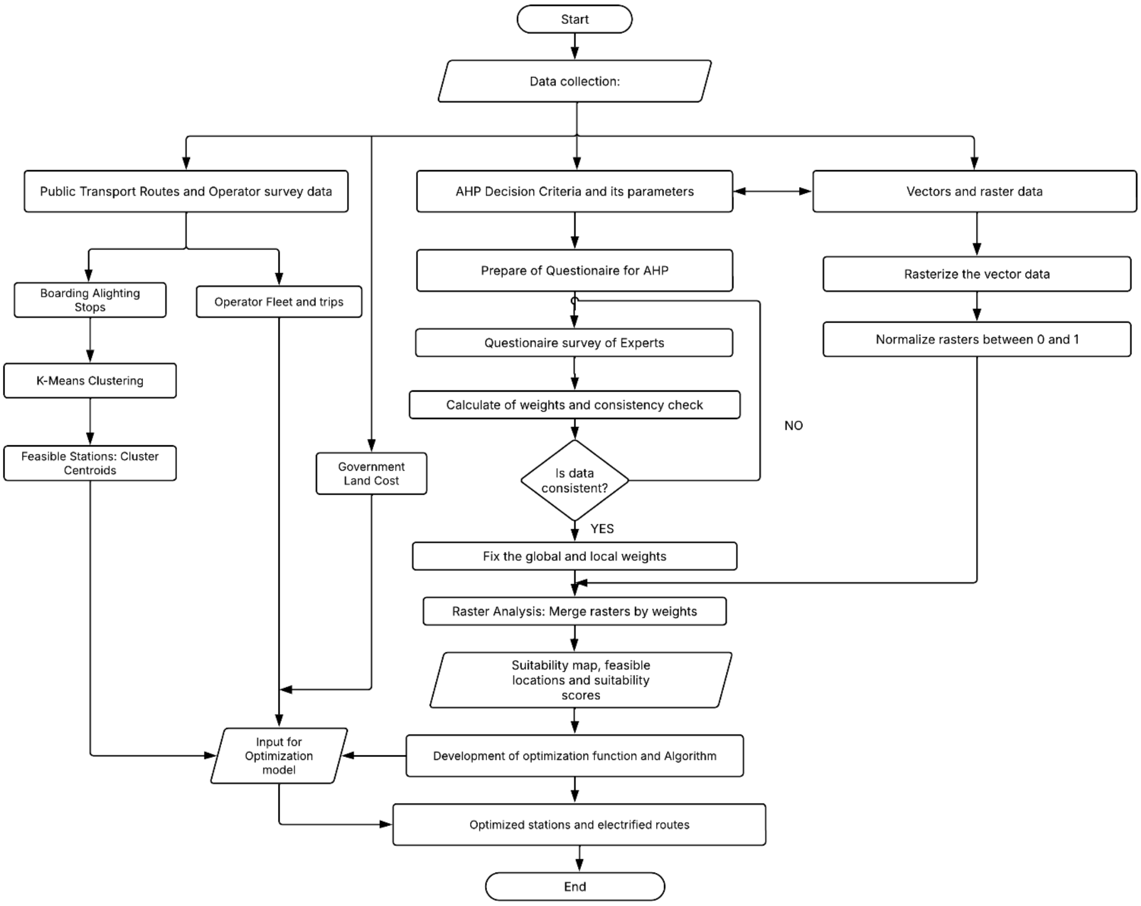

Figure 3. 1: Methodology

3.2 Study Area

The Kathmandu Valley has been chosen as the study area for this research. The public transport services in the valley are primarily operated by private operators, and Sajha yatayat is the only running in cooperative model with government share. The public transport network within the valley follows a radial route pattern, with the Ring Road at the center and routes radiating outward to the edges of the valley. The Ring Road, which is 27 km long, encircles the valley and connects major commercial centers. These centers are predominantly located inside the Ring Road, while the outer areas of the Ring Road are largely residential. Buses primarily operate from suburban areas towards the main urban commercial areas. The public transport routes follow the Ring Road and the roads inside it, as the highest demand for transport is concentrated in these areas. The terminals are situated farther from the city center, where most residential areas are located. The public transport system is busiest during the morning and evening peak hours. In total, 130 routes will be considered for this study, with boarding and alighting stops of passengers taken into account, as shown in Figures 3.2 and 3.3. Since there is no specific database on public vehicle routes inside Kathmandu Valley, this study considers 130 routes as identified by a survey recently conducted by Asian Development Bank (ADB). The study will focus solely on the routes within the Kathmandu Valley.

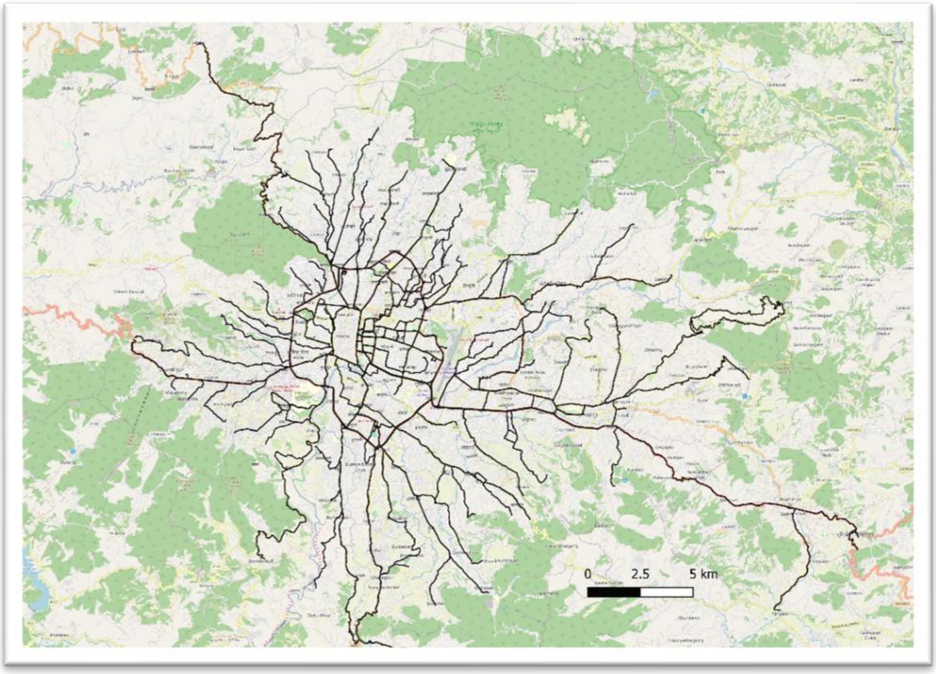

Figure 3. 2: Routes Considered for Study Area

3.3 Data collection

The various data related to clustering, AHP, raster analysis, and the set covering problem are collected in the data collection phase. The major data related to the research are explained below:

3.3.1 Public Transport Routes and Operator Survey Data

This study utilizes data from the routes and boarding and alighting stops collected under the Asian Development Bank's (ADB) Sustainable Urban E-Mobility Project (SUEP). A total of 133 boarding and alighting surveys were conducted across 128 routes in the Kathmandu Valley (KV), as shown in Figures 3.2 and 3.3. Additionally, 5 surveys were conducted for the second mode of public transport operating on five of the routes. The boarding and alighting stop data were gathered as secondary data from the ADB research committee. The data were extracted as GIS files using Python, and QGIS was employed to map the points. The operator survey data, which includes information about each public transport route, was also sourced from the same ADB project, specifically from the second phase. During this phase, a questionnaire survey was conducted to gather information from operators within the Kathmandu Valley. A total of 35 operators were surveyed. The data related to bus fleets and the trip rate per day for various routes are utilized in this research, sourced directly from the ADB project.

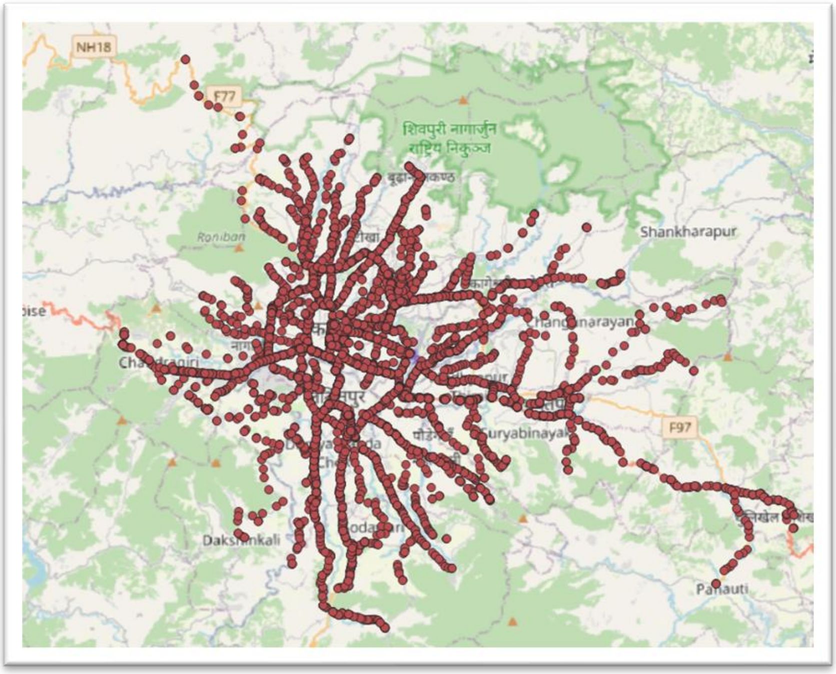

Figure 3. 3: Boarding and Alighting Stops for Public Transport Routes

3.3.2 Analytical Hierarchy Process Decision Criteria and Its Parameters

The Analytical Hierarchy Process (AHP) is a decision-making tool used to assign weights to various criteria, which are then used to merge multiple layers, such as raster files in this study. In this case, AHP will help assign weights to the different criteria necessary to combine the raster files effectively. To determine the most suitable decision criteria, several research papers relevant to this field, as shown in Table 3.2, were reviewed. Based on the insights gathered from these studies, the decision criteria were selected and their parameters were either adopted from existing literature or modified to better suit the local context of the Kathmandu Valley. The various decision criteria, along with their explanations, are presented in Table 3.1. These criteria will guide the suitability mapping process for the placement of charging stations.

Table 3. 1: Decision Criteria With Explanation

Criteria	Sub criteria	Explanation
Environmental	Proximity to the river	EVCS should be away from the rivers, considering the adverse effect on the water
	Proximity to vegetation	EVCS should be away from the vegetation, considering the adverse effect on vegetation
	Slope of the land	EVCS should be in an area that is flat (not more than a 7% slope)
Infrastructure Accessibility	Proximity to petrol stations	EVCS should be near the petrol stations to use the hybrid models with petroleum
	Proximity to power substation	EVCS should be near the power substation, considering the charging requirement
	Proximity to major roads	EVCS should be near the main roads, considering accessibility
	Proximity to EV charging stations	EVCS should be away from the current charging stations, considering coverage
Land use	Public	Easily available lands held by the government
	Commercial	Commercial use and very high-cost land
	Residential	Used for residential purposes, cheaper than commercial
	Industrial	Used for industrial purposes
	Agricultural	Used for agricultural purposes (loss of fertile agricultural land)

After establishing the decision criteria, the next step is to define their parameters. For instance, for the proximity to rivers, the parameter specifies the maximum allowable distance beyond which construction is not feasible. Similarly, for the slope criteria, the maximum slope allowed for construction is defined. For proximity to roads, the suitable distance within which a charging station can be located is determined.

The parameters for each criterion are chosen based on the specific context of the study area, as follows:

Proximity to rivers, **vegetation**, and **existing EV charging stations**: The minimum distance is set to 500 meters. This distance ensures that the charging stations are as far as possible from these features, thereby minimizing any potential environmental or regulatory issues.

Proximity to major roads and **petrol stations**: The maximum distance is set to 500 meters. This ensures that charging stations are easily accessible for vehicles, and also accounts for the hybrid model, where electric vehicles may still need to interact with conventional fuel stations.

Slope: A maximum slope of 25% is chosen. This is the steepest slope at which construction is deemed feasible for infrastructure.

Proximity to power stations: The distance is limited to 4,000 meters. This ensures that the charging stations can be easily connected to the electrical grid for a reliable power supply. The parameters for these criteria were derived from previous research and studies relevant to infrastructure planning. The sources of these parameters are summarized in Table 3.2 below, providing a clear reference for their selection.

Table 3. 2: Decision Criteria and Citation

Criteria	Sub criteria	Source
Environmental	Proximity to river	(Priefer et al., 2022)
	Proximity to vegetation	(Priefer et al., 2022)
	Slope of the land	(Yomralioglu et al., 2020)
Infrastructure Accessibility	Proximity to petrol stations	(Yomralioglu et al., 2020)
	Proximity to power substation	(Ward, 2016)
	Proximity to major roads	(Priefer et al., 2022)
	Proximity to EV charging stations	(Ward, 2016)

3.3.3 GIS Data Related to Decision Criteria

The vector and raster data were collected from various sources to support the decision criteria for raster analysis. The vector data, including information on rivers, vegetation, land use, and roads, were obtained from the Kathmandu Valley Physical Development Plan project. Data on power substations and petrol stations were extracted from OpenStreetMap using QGIS. The vector data for existing EV charging stations was sourced from Google Maps. The DEM data was downloaded from the USGS website, covering the required area. Slope data was derived from the DEM using the Slope Analysis tool in QGIS.

3.3.4 Government Land Rates:

The cost of government land is essential for penalizing locations with high land values in the optimization model. Land prices within Kathmandu Valley can be found in various municipal guidelines. The government land rates are obtained from the *Minimum*

Evaluation Guidelines issued by the Department of Land Management and Archives for each municipality. These rates are provided in Nepalese Rupees (NRs) per square meter.

3.4 K-means Clustering

Clustering analysis is an unsupervised learning technique in machine learning. Various clustering methods exist, including K-means clustering, DBSCAN, and hierarchical clustering (Li et al., 2022). This report focuses on the K-means clustering technique. K-means clustering partitions data into *K* clusters based on the distance from centroids, using the Euclidean distance as the metric. It is particularly useful for geographical clustering. The K-means algorithm operates in two phases: the first phase randomly assigns initial centroids, while the second phase assigns each data point to the nearest centroid based on Euclidean distance (Sanchez et al., 2022).

The Euclidean distance between the centroid and the data point can be represented in equation 3.1.

$$d(x_i, C_j) = \sqrt{\left(\sum_{k=1}^{n} (x_{ik} - C_{jk})^2 \right)} \qquad (3.1)$$

Where,

$\mathrm{d}(\mathrm{x_i}, \mathrm{C_j})$ = Euclidean distance between data point ($\mathrm{x_i}$) and centroid ($\mathrm{C_j}$)

$\mathrm{x_i} = (\mathrm{x_{i1}}, \mathrm{x_{i2}}, \dots, \mathrm{x_{in}})$ = Coordinates of data point (i)

$\mathrm{C_j} = (\mathrm{C_{j1}}, \mathrm{C_{j2}}, \dots, \mathrm{C_{jn}})$ = Coordinates of centriod (j)

$\mathrm{x_{ik}}$ = Value of the $\mathrm{k^{th}}$ feature of data point (i)

$\mathrm{C_{jk}}$ = Value of the $\mathrm{k^{th}}$ feature of centroid (j)

The next step in K-means clustering is to determine the optimal number of clusters using an appropriate method. Several techniques are available for this, including the elbow method and the Silhouette Score method. This research focuses on the elbow method.

3.4.1 Elbow Method

The elbow method determines the optimal number of clusters based on the sum of squared errors (SSE), as shown in Equation 2. The process begins by assuming trial values for the number of clusters (*K*). Initially, *K* is set to 1, and SSE is calculated. The value of *K* is then incremented by 1 in each iteration, and the SSE is computed for each clustering, as described in Equation 3.2.

$$SSE = \sum_{i=1}^{n} \sum_{j=1}^{k} (x_i - C_j)^2 \qquad (3.2)$$

Where,

SSE = Sum of Squared Errors, a measure of the total variance within clusters.

n = Total number of data points.

k = Number of clusters (centroids)

x_i= Data point i

C_j= centroid of cluster j

$(x_i - C_j)^2$ = Squared Euclidean distance between data point x_i and centroid C_j

The SSE values calculated for different cluster numbers are used to plot a graph of cluster number versus SSE, commonly known as the elbow plot. This plot helps identify the optimal number of clusters. The graph below illustrates the relationship between the cluster number (*K*) and inertia for clustering the boarding and alighting points in this research.

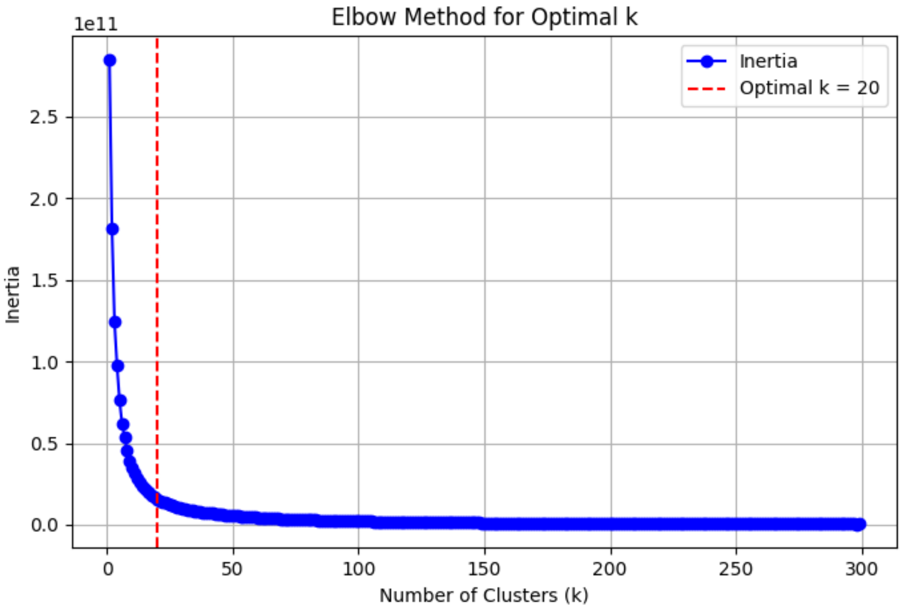

Figure 3. 4: Elbow Plot

As observed in the plot, the SSE decreases significantly as the number of clusters increases. At a certain cluster number, the SSE reaches its lowest point and remains relatively stable beyond that. The point where the curve bends or shows the first sharp decline is known as the *elbow point*, indicating the optimal number of clusters, as shown in the plot.

In this research, the elbow method is applied to determine the optimal number of clusters. The boarding and alighting points are plotted in QGIS 3, and the K-means clustering plugin tool is used. Using the built-in Python 3 environment in QGIS, K-means clustering is performed for K values ranging from 1 to 300. The Python code for this process is provided in Annex-IV. The code extracts SSE values for 300 clustering iterations and plots the curve to identify the optimal cluster number. Once the optimal number of clusters is determined, K-means clustering is performed again. The Mean Coordinates tool in QGIS is then used to extract cluster centroids, which are considered feasible charging locations based on accessibility.

In the K-means clustering dialog, the input layer is set as the vector file containing boarding and alighting points. After running the clustering process, a new attribute, *cluster ID*, is added to the dataset. For centroid calculation, the newly clustered point file is used as the input layer, with cluster ID assigned as the unique identifier. This process generates a unique centroid for each cluster. The resulting centroid point file is then created, which gives feasible charging locations.

3.5 Analytical Hierarchy Process

The Analytical Hierarchy Process (AHP) is a linear weighting method used to evaluate both qualitative and quantitative criteria. It was developed by Saaty in 1977 (Tang et al., 2013) and has been widely applied in various fields, including transportation planning, infrastructure projects, and Multi-Criteria Decision Analysis (MCDA). In this research, MCDA is used to analyze multiple criteria for raster analysis. However, before applying the process, it is essential to determine the weights for the raster data. The weighting process involves a pairwise comparison of the selected criteria using a predefined scale. First, the identified criteria are systematically broken down into sub-criteria. Then, pairwise comparisons are conducted at each hierarchical level—starting with the main criteria and proceeding step by step through their respective sub-criteria.

3.5.1 Pairwise Comparison

For pairwise comparison, a pairwise comparison matrix is constructed. In this study, the matrix is developed for the main criteria: Environmental, Infrastructure Accessibility, and Land Use. Similar matrices are then created for the sub-criteria within each main criterion.

Saaty provides a standardized scale for pairwise comparisons, ranging from 1 to 9. As the values increase, the relative importance of one criterion over another strengthens. 1 indicates equal importance, 3 indicates moderate importance, 5 indicates strong importance, 7 indicates very strong importance, and 9 indicates extreme importance. 2,4,6, and 8 are values between 1 and 3, 3 and 5, 5 and 7, and 7 and 9, respectively. This scale is shown in Table 3.4.

An example of a pairwise comparison matrix is shown in *Table 3.3*. The values in the matrix are derived from responses in a questionnaire survey. The rows are compared with the columns, and the goal is to determine the cell values in the pairwise comparison matrix based on these comparisons. For each pair, a scale value from 1 to 9 is assigned if the priority of the row criterion is higher than that of the column criterion. If the priority of the row is weaker than that of the column, the reciprocal of the corresponding value from 1 to 9 is used. When comparing the same criterion, the value is always 1. It is also important to note that the values above the diagonal in the matrix are reciprocals of those below the diagonal. Therefore, the values below the diagonal can be easily determined by taking the reciprocal of the values above the diagonal, and vice versa.

Table 3. 3: Pairwise Comparison Matrix

Environmental criteria	Proximity to river	Proximity to vegetation	Slope of the land
Proximity to river	1	0.167	0.25
Proximity to vegetation	6	1	0.2
Slope of the land	4	5	1

Table 3. 4: Saaty Scale for Pairwise Comparison

Scale Value	Definition	Explanation
1	Equal Importance	Two criteria contribute **equally** to the objective.
2	Weak or Slight	Intermediate value between **equal** and **moderate** importance.
3	Moderate Importance	One criterion is slightly more important than the other, based on experience or judgment.
4	Moderate Plus	An intermediate value between **moderate** and **strong** importance.
5	Strong Importance	One criterion is strongly favored over the other.
6	Strong Plus	An intermediate value between **strong** and **very strong** importance.
7	Very Strong Importance	One criterion is significantly more important than the other.
8	Very Strong Plus	An intermediate value between **very strong** and **extreme** importance.
9	Extreme Importance	The evidence overwhelmingly favors one criterion over the other.

3.5.2 Questionnaire Survey of Experts

The pairwise comparison is conducted through a questionnaire survey with experts in the field of charging station placement. A sample of the questionnaire used for the survey is provided in ANNEX-I. The survey involved four experts specializing in charging station placement within Kathmandu Valley. Two of the experts are from the Nepal Electricity Authority (NEA), while the other two work in the private sector. The questionnaire includes questions designed to gather data for each cell value in the pairwise comparison matrix. Gathering input from experts across various sectors ensures more reliable data and weights for the raster analysis. The survey results from the four experts are presented in ANNEX-II.

3.5.3 Analysis of Survey Data and Consistency Check

Before performing the consistency check of the data, the survey data from the various experts need to be combined or normalized. The cell values of the normalized matrix are obtained by calculating the mean of the corresponding cell values from all experts. The mean can be either the geometric mean or the arithmetic mean. In this research, the geometric mean is used to compute the normalized matrix. Once the normalized matrix is obtained, it is essential to conduct a consistency check using a statistical process to ensure the reliability of the data.

For the consistency check, various statistical parameters can be used as given by Saaty. The various parameters for the consistency check can be given below.

a. Principal Eigenvalue (λ_{max}):

   It is the largest eigenvalue of the pairwise comparison matrix. In an ideal situation, its value is equal to the number of criteria. The deviation from the ideal value makes the data more inconsistent.

b. Consistency index (CI):

   It is the measure of the data deviating from the ideal consistency. It gives how much the data has deviated from perfect consistency. It is given as:

$$\mathrm{CI} = \frac{\lambda_{max} - n}{n-1} \qquad (3.3)$$

c. Random Index (RI):

   Random index is the expected value of the consistency index when the values of the cells are randomly assigned. The value of RI depends on n and is given by a polynomial curve equation. For different values of n, the RI is given in Table 3.5.

Table 3. 5: Random Indices

Number of Criteria (n)	Random Index (RI)
1	0
2	0
3	0.58
4	0.9
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49

d. Consistency Ratio (CR):

The actual consistency is measured by the *consistency ratio* (CR), which is the ratio of the *consistency index* (CI) to the *random index* (RI). If the consistency ratio is less than 0.1, the data is considered consistent and unbiased. However, if the consistency ratio is greater than 0.1, the data is deemed biased, and the survey may need to be repeated to revise the cell values until consistency is achieved.

$$\mathrm{CR} = \frac{CI}{RI} \qquad (3.4)$$

The consistency check must be performed for each pairwise comparison matrix, including the main criteria and each sub-criterion. In this research, the consistency check is conducted for four tables. It is ensured that the data in all tables are consistent through separate statistical checks for each table. The results of the consistency checks and the process are provided in the *Results and Analysis* chapter.

3.5.4 Weights Calculation

Once the consistency of the data is verified, the weights obtained from the consistency check tables are fixed as the final weights, provided that all the tabular data are consistent. The weights derived are for the main criteria, which are global variables, and for each sub-criterion, which are local variables. The weights in the criteria tables represent global weights, while the weights in the sub-criteria tables represent local weights. To calculate the global weights for each sub-criterion, the local weight is multiplied by the global weight of the corresponding criterion to which it belongs. The weight calculation and consistency check process are detailed in ANNEX-III.

3.6 Multi-criteria Decision Analysis (MCDA)

Multi-Criteria Decision Analysis (MCDA) is a set of methodologies used to evaluate and rank alternatives based on multiple, often conflicting, criteria. It is widely applied in various fields, including transportation planning. The GIS-based Analytical Hierarchy Process (AHP) is particularly useful for solving hierarchical and complex problems (Yomralioglu et al., 2020). Given its effectiveness in such applications, the GIS-based AHP method is highly suitable for use in the placement of EV charging stations.

The MCDA used in this research is a GIS-based method that involves raster analysis of the various criteria previously established. The data are initially obtained in either vector or raster form; however, these forms of data do not directly represent the criteria and sub-criteria required for the analysis. Therefore, certain modifications and analyses must be conducted to transform the data into the necessary raster files for further processing.

3.6.1 Conversion to Necessary Raster Files

The vectors obtained can be easily converted into raster format using the rasterization tool in QGIS. In this tool, the vector file (point, line, or polygon layer) is selected in the input tab, and the specifications for the conversion of pixels into the raster are provided. In this research, georeferenced pixels with a width and height of 10 meters each were used. After running the tool, the raster corresponding to the vector file is generated. For slope analysis, the DEM data obtained during data collection is already in raster format. The DEM covers a large area in a square shape, so it needs to be clipped using a vector mask layer. The input layer is selected as the downloaded raster, and the mask layer is a vector polygon file. In this case, the mask layer is a polygon file representing Kathmandu Valley. After running the tool, the clipped DEM file corresponding to the shape is obtained. This clipped layer is then reprojected to the required projection system (EPSG:102306 in this case). The reprojected DEM is used to perform the slope analysis.

After running the slope analysis, the slope raster is obtained. The proximity raster can then be generated using a tool in QGIS for the rasterized files obtained earlier. The proximity distance is specified for the raster whose proximity raster is to be calculated. As mentioned in Section 3.3.2, the proximity distance is selected as fixed. For example, for major roads, this distance is set to 500 meters. After running the tool, the proximity distance raster is generated.

3.6.2 Normalization of Raster Files

The raster files obtained are not uniform in value range. For example, the slope raster obtained varies from approximately 0 to 150, while the proximity raster has values based on the proximity distance provided. For instance, for major roads, the raster pixel values vary from 0 to 500, and for power substations, the values range from 0 to 4000. To address this, we need to normalize the raster files to the same unit, converting all raster files to values between 0 and 1. In QGIS, there are two methods to normalize the raster: using the raster calculator or reclassifying by table. During reclassification, the maximum value limit is divided into four regions: Very Suitable, Suitable, Moderately Suitable, and Unsuitable. The "Very Suitable" region is given a value of 1, representing the lightest pixels, and as the values decrease, the color darkens. The "Unsuitable" region, with the lowest values, is assigned a value of 0, representing the darkest pixels. The slope raster after reclassification can be seen in Figure 3.5. The various reclassified regions for different sub-criteria are listed in the tables below.

Table 3. 6: Reclassified Regions for Roads and Petrol Stations

Distance (m)	Criteria
<125	Very suitable
125-250	Suitable
250-500	Moderate
>500	Unsuitable

Table 3. 7: Reclassified Region for Power Substations

Distance (m)	Criteria
<1000	Very suitable
1000-2000	Suitable
2000-4000	Moderate
>4000	Unsuitable

Table 3. 8: Reclassified Region for Rivers, Vegetations and EV Charging Stations

Distance (m)	Criteria
<125	Unsuitable
125-250	Moderate
250-500	Suitable
>500	Very suitable

Table 3. 9: Reclassified Region for Slope

Slope (%)	Criteria
0-7	Very suitable
7-12	Suitable
12-25	Moderate
>25	Unsuitable

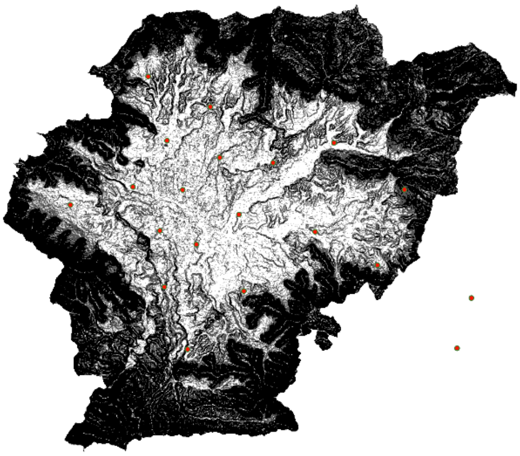

Figure 3. 5: Slope Reclassified

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3.6.3 Suitability Mapping

After obtaining all the normalized raster files, the weights obtained through AHP are applied to generate the suitability maps for each global criterion. The local weights are used to calculate the raster files for the global criteria. The Environmental criteria, Infrastructure Accessibility criteria, and Land Use mapping are achieved by merging the individual raster files. The raster files can be merged using the raster calculator in QGIS, which utilizes SQL. Next, by applying the global weights, the raster files for the global criteria are merged into one single raster file. This results in a raster file with values ranging from 0 to 1. The obtained raster is then divided into four regions: Very Suitable, Suitable, Moderately Suitable, and Unsuitable, as described in this research. Following this, the stations identified from the clustering analysis are compared with the suitability map. Stations that fall within the "Unsuitable" regions are disregarded, while the remaining stations are selected for the subsequent optimization process.

3.7 Facility Location Problem

A Facility Location Problem (FLP) is formulated when there is a need to optimally place a set number of facilities to serve a set of demand points while minimizing costs or maximizing service coverage. It is particularly relevant in transportation planning and the placement of charging stations. This type of problem encompasses various subproblems, each focusing on optimizing different criteria such as minimizing costs, travel distances, or maximizing service coverage. The establishment of optimal charging station locations falls under classic facility location problems, such as the p-median problem, p-center problem, and covering location problems (Yu et al., 2024). The p-median problem is a type of problem where the goal is to minimize the total weighted travel distance, considering the limitations on the number of facilities that can be opened. In contrast, the p-center problem minimizes the maximum travel distance from a customer to their nearest facility. The covering location problem is divided into two types: the set covering problem and the maximum covering problem. The set covering problem aims to minimize the number or cost of facilities required to cover all demand nodes, while the maximum covering problem seeks to maximize coverage using a limited set of facilities. The maximum covering problem is particularly useful in applications like public transportation planning, where it can help optimize the locations of bus stops or charging stations, fire stations, cell towers, and other facilities.

3.7.1 Development of Optimization Model

The optimization function involves the development of a maximal covering problem with minimization of penalty costs for charging stations and maximizing route coverage with capacity constraints. The model is as below:

Maximize:

$$Z_1=\sum_{i \in R} y_i \tag{3.5}$$

Minimize:

$$Z_2=\sum_{j \in S} P_j x_j \tag{3.6}$$

Subjected to:

$y_i=1$ if $\sum_{j \in S1} x_j * \left((2 * d_{ij} + L_i) \leq B\right)$, for all $i \in R$

and $\sum_{i \in R} N_{ij} \leq C_j * x_j$, for all $i \in R$ and $j \in S_1$ (3.7)

$\sum_{i \in R} N_{ij} \leq \sum_{j \in s1} C_j * x_j$ (3.8)

$\sum_{j \in S} x_j >= 0$ for all $j \in S$, (3.9)

$\sum_{j \in h} x_j = 0$ for all $j \in h$, h is subset of S (3.10)

$y_i=\{0,1\}$ for all $i \in R$ (3.11)

$x_j=\{0,1\}$ for all $j \in S$ (3.12)

Where,

x_j = Binary variable if the location is selected as charging station

S = Total number of feasible locations for charging station

S_1 = Number of installed stations (subset of S)

B =Total range of full charge battery

h= Set of stations in core areas

y_i = Binary variable indication a route/terminal is electrified or not

C_j = Capacity of location for a station (installed number of chargers)

L_i = Length travelled during the trips during the day i

h is a subset of S

N_i = Total number of buses in route i

P_j = Property acquisition cost for selection of location j

R =Total number of routes

d_{ij}= Shortest distance from the terminal of route i to the jth station

The formulation of the objective function involves two functions. The first function maximizes the number of routes which are covered while the second function minimizes the property acquisition costs associated with the installation of charging stations, given in equations 3.5 and 3.6, respectively. The property acquisition cost can be found by the land costs. Equation 3.7 gives the electrification condition. The routes are electrified if two conditions are satisfied, one if the distance travelled during the day during trips and trips made to and from charging stations are within battery mileage range. Second, if the first condition is satisfied, whether the maximum capacity of the selected location of the charging station is exceeded. If any of the conditions is not satisfied, the route will not be considered feasible for the electrification of electric vehicles. Equation 3.8 gives the general condition that the total number of buses should be equal to or less than the total capacity of the stations. 3.9 gives that the number of charging stations installed should be more than or equal to 1. Equation 3.10 sets the criteria to not select the stations in core areas. Equations 3.11 and 3.12 establish x and y as binary variables related to charging locations and feasible routes for the electrification of conventional vehicles, respectively.

3.7.2 Solution Algorithm:

The algorithm preparation involves methods to solve the linear programming model constructed above. The optimization function consists of two contrasting objectives: maximizing route coverage to electrify conventional vehicles and minimizing penalty costs related to the installation of charging stations. A heuristic approach using a genetic algorithm is employed to solve the problem. To combine these two objectives into a single function, weights are introduced to ensure that one function does not dominate the other. The decision on the weights is based on the range of values each objective produces. To align both objectives within the same range, the weights are set as powers of ten. By combining the two functions in this manner, a balanced solution can be achieved.

$$Z = \alpha \sum_{i \in R} y_i + \beta \sum_{j \in S} P_j x_j \tag{3.12}$$

The value of α is set to 0.01, and the value of β is set to -0.00001, ensuring that both objectives attain values within a similar range. The goal is to maximize the combined function. Once the optimization problem is formulated, the genetic algorithm is used to solve it as follows:

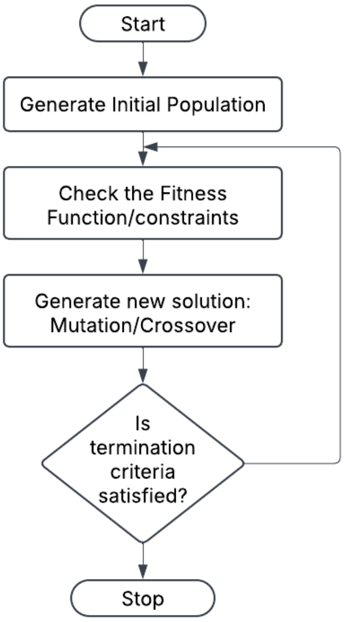

Figure 3. 6: Genetic Algorithm

Initially, the genetic algorithm generates a solution. The solution consists of the stations to be installed, which are represented as 1, and uninstalled stations as 0. Hence, the set will be of 18 values for the solution as there are 18 feasible locations. For this initial solution, the functional values and constraints are checked as shown above in 3.7.1. Then, the following methods are used for generating new solutions:

Selection: The selection involves the selection of the parent solution for crossover or mutation in the next generation. Fifty individuals are randomly selected, and the individual with the highest optimization function value is chosen for the next generation.

Crossover: The new solution is generated with the exchange of two genes from two parent solutions or individuals.

Mutation: One or more genes are randomly flipped to make a new solution.
After the break criteria are reached, the algorithm breaks and gives the optimal solution.

The terminals of each route represent the routes themselves, with various route attributes encoded into the file. The terminals are identified in QGIS by running the tool to extract specific coordinates, from which the start of the line segment can be determined. Once the routes are identified, they can be merged into a single file or layer, and this merged route file is used to locate the start terminals. The length of the routes in the merged route layer can be calculated using the raster calculator, and this attribute is then copied to the start terminal point layer. The fleet of vehicles and the number of trips per day can be manually input into the start terminal layer. Using the raster calculator, the total distance traveled by the fleet performing all trips in a day is calculated by multiplying twice the number of trips by the route length. After gathering all the necessary data in the start terminal point layer, it is input into the charging stations point layer, which was obtained earlier through K-means clustering. In the charging stations point layer, attributes such as maximum capacity, location-specific data, and land cost are input. The land cost per square meter can be collected from municipality guidelines for various local levels. The maximum capacity is set higher for locations with lower land costs and those farther from the core area. The property acquisition cost of installation for each charging station is calculated by dividing the land cost by the suitability score. An attribute indicating whether a location is in a core area is also created, helping to exclude core areas from the charging station installation. The suitability score is derived from raster analysis to determine the type of region. The property acquisition cost of installing a charging station is then determined by the following formula:

$$P_j = \frac{L}{S} \tag{3.13}$$

Where, L = Land cost in NRs per square meter

S = Average suitability score as given in raster analysis final map

The final property acquisition cost is measured in NRs per square meter. By incorporating the suitability score into the property acquisition costs, a balance is maintained between the land cost of the areas and the suitability of the region. For calculating distances, a road map layer is used, and a distance matrix is generated in QGIS from the start terminal layer to the charging station layer. After preparing the necessary data in QGIS, a program is written in Python 3 to access the data using the Geopandas module, and the DEAP module is utilized to perform the genetic algorithm as described in ANNEX-IV. The generated code uses a mutation probability of 0.2 and a crossover probability of 0.7. Following the methods outlined in section 3.7.2, new solutions are generated, and the best solution is optimized in each iteration. The maximum number of iterations is set to 100. Once the stopping criteria are met, the best solution is provided. The best solution is the one with the maximum functional value, as defined in equation 3.12. The output files are saved in the form of a charging station point layer, indicating the installed stations and their respective capacities. Additionally, another output file contains the start terminals, with an attribute indicating which terminals are covered. This attribute can be copied to the merged route layer, allowing for the separation of covered routes. Finally, the covered routes are mapped in QGIS.

CHAPTER 4: RESULTS AND DISCUSSIONS

4.1 Feasible Locations Through Clustering

The K-means clustering method uses the elbow technique to cluster the boarding and alighting points, as shown in Figure 3.3. The Elbow plot, depicted in Figure 3.4, reveals the optimal number of clusters as 20. This plot is generated using Matplotlib in Python 3. Based on this, the optimal cluster number, k=20, is plotted, and the centroids are identified. The final results of the clustering and the corresponding centroids are shown in Figure 4.1. These cluster centroids are considered feasible locations for placing charging stations for public transportation.

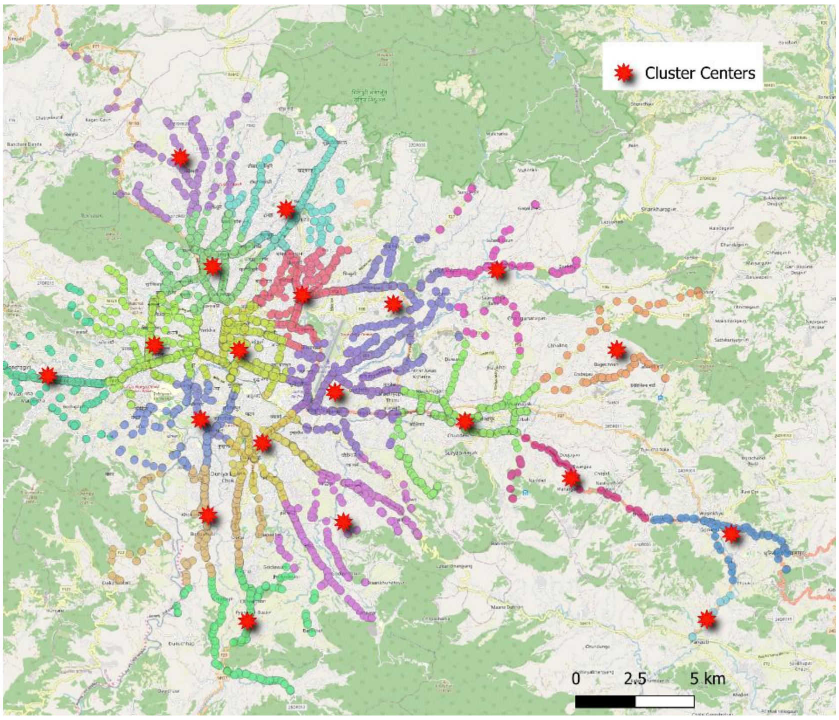

Figure 4. 1: K-means Clustering(K=20) with Centroids

The figure shows that six points are located near the core of the Kathmandu Valley. The stations in these areas cannot have large capacities, as they are situated in regions with significant cultural and ethnic residences, which makes it difficult to acquire. Additionally, commercial and public lands are located here, making them very expensive. Two of the spots are located near Dhulikhel, outside the Kathmandu Valley, and these will therefore be excluded. Four of the spots are located near residential areas, away from the core. These locations can accommodate larger capacities, as the land cost is lower compared to core areas. However, the land costs in these regions are still relatively high. The remaining eight spots are located farther away, around agricultural and industrial areas. The land costs in these areas are the lowest, but access to these lands is limited, and the availability of urban facilities is minimal.

4.2 Feasibility Maps for Various Criteria

The various feasibility maps are generated with each criterion and sub-criterion corresponding to each criterion. The feasibility maps are normalized maps for each sub-criterion as mentioned in Chapter 3. Figure 4.2 gives the feasibility map of the slope.

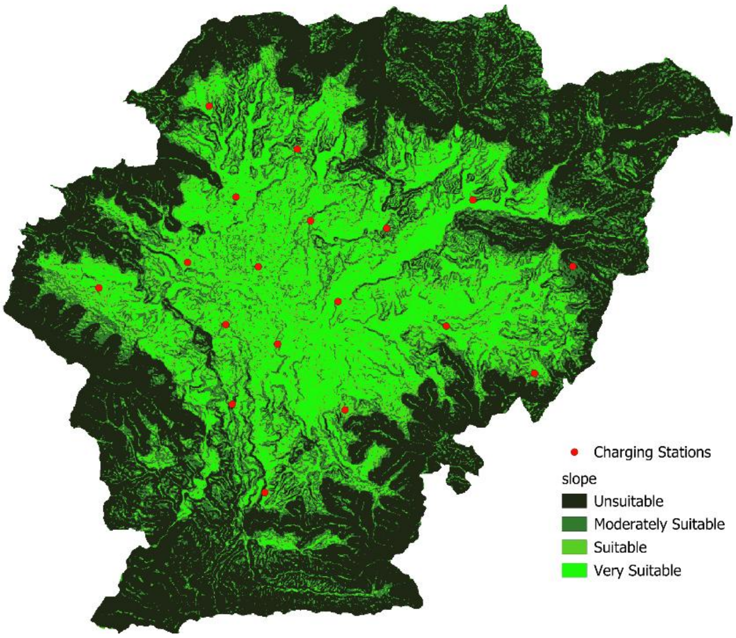

Figure 4. 2: Feasibility Map of Slope

As shown in the figure, all the spots are located within areas that have a slope of 25% or less. One spot is located in a 12-25% slope area, while the other spots are situated in areas with slopes of less than 12%. Figure 4.3 illustrates the feasibility of proximity to rivers. Three spots are very close to the rivers, which may render them unsuitable for installation.

Four spots are located in very suitable regions, while the remaining points fall within moderate to suitable regions.

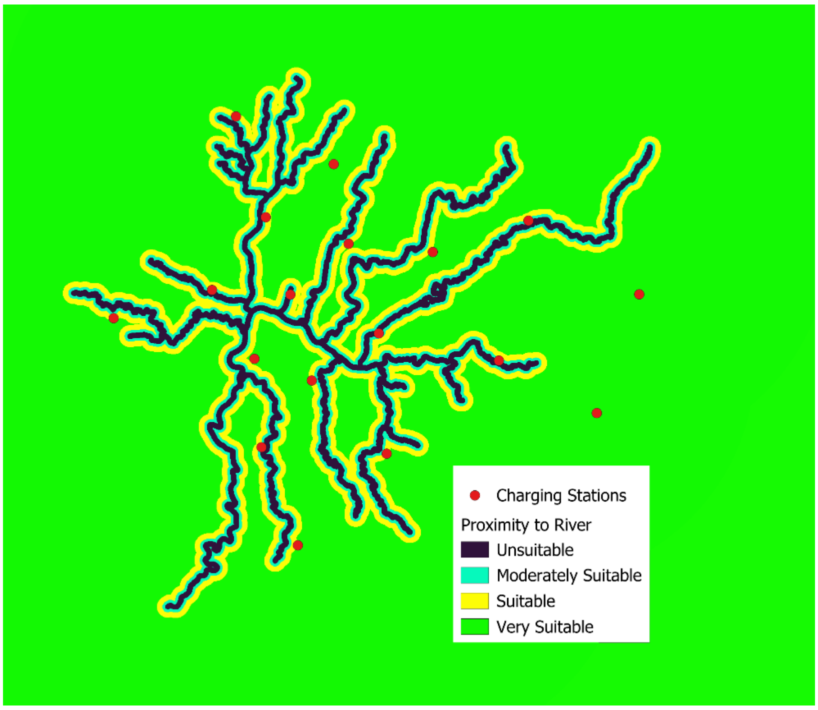

Figure 4. 3: Feasibility Map of Proximity to Rivers

Figure 4.4 shows the feasibility mapping of proximity to vegetation, with the proximity data provided in Table 3.8. The map highlights nine spots located in very suitable regions. All the spots fall within regions that range from moderately suitable to very suitable. Three of these very suitable regions are located outside the core area, while six are located within the core area, as these areas do not have forest cover. Figure 4.5 shows the feasibility mapping of proximity to major roads. This figure indicates that all the spots are highly accessible, as they all fall within suitable to very suitable regions. Figures 4.6 to 4.8 display the feasibility maps for proximity to existing EV charging stations, proximity to petrol stations, and proximity to power substations, respectively. The new charging stations should be located away from existing charging stations in order to ensure better coverage of the region.

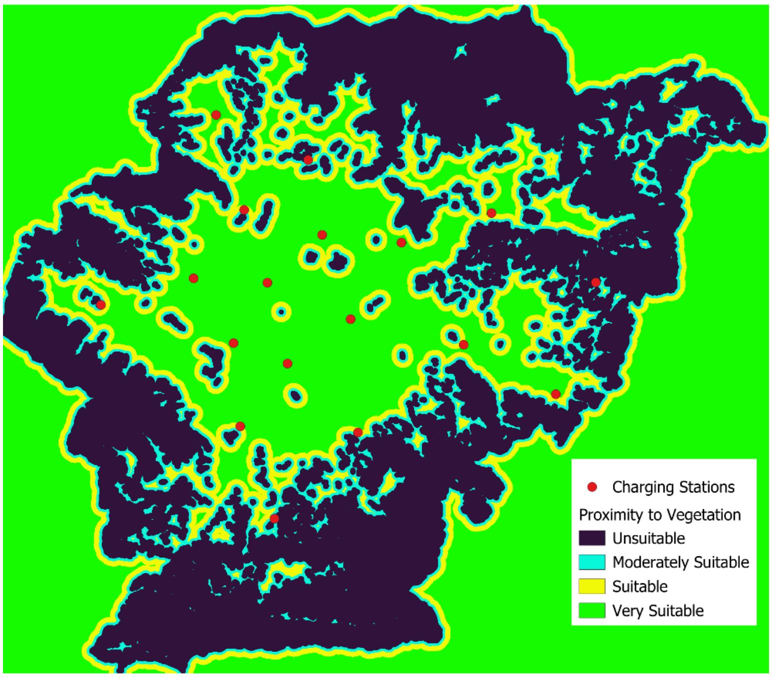

Figure 4. 4: Feasibility Map of Proximity to Vegetation

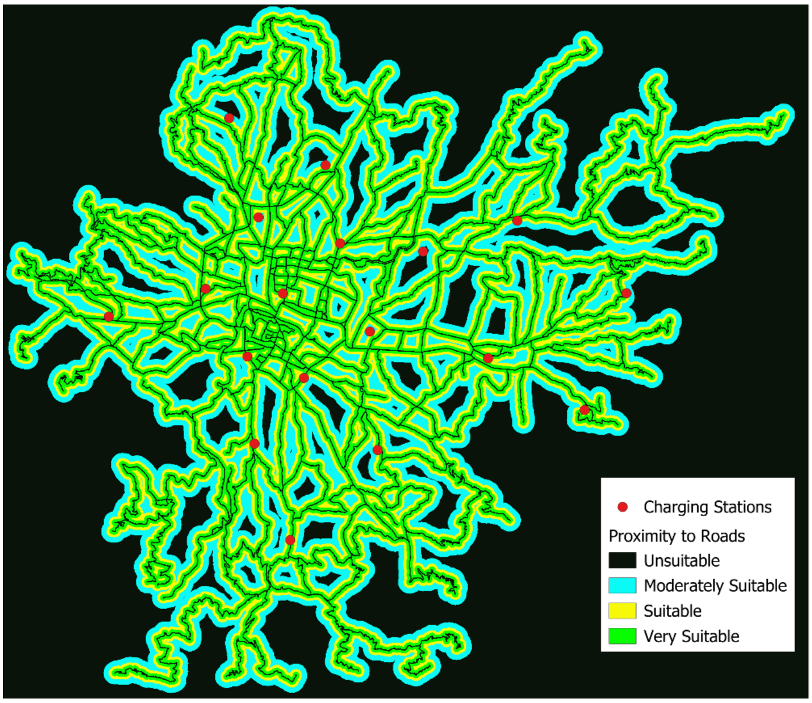

Figure 4. 5: Feasibility Map of Proximity to Roads

Figure 4.6 shows that all the spots are in very suitable to suitable locations, as shown. The proximity to petrol stations shows that all the spots are in very suitable to moderately suitable regions. The proximity to power substations shows that areas inside the core are in very suitable spots, while outside the core, the spots are in moderately suitable to suitable regions. This shows that major power substations are located near the core area of the study area.

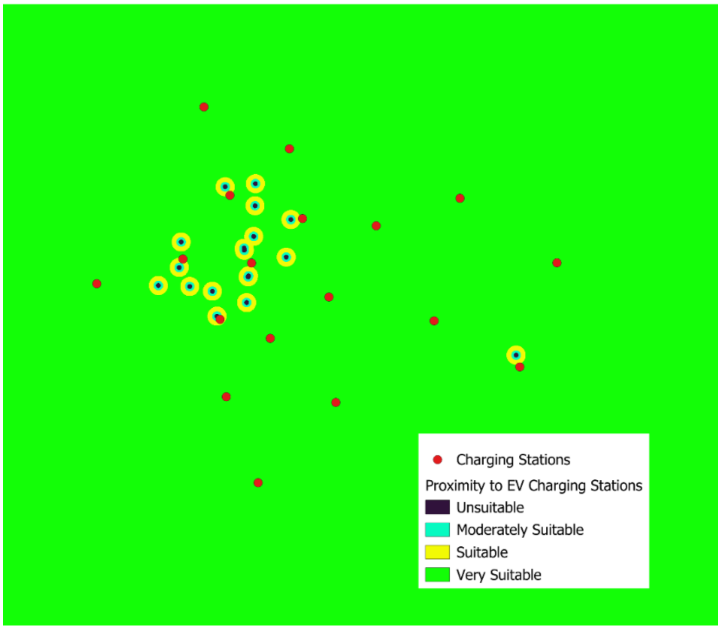

Figure 4. 6: Feasibility Map for Proximity to EV Charging Stations

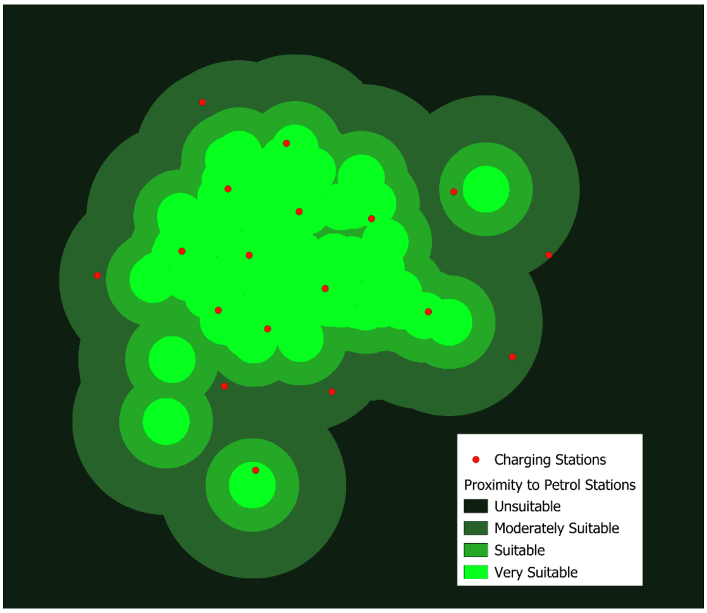

Figure 4. 7: Feasibility Map of Proximity to Petrol Stations

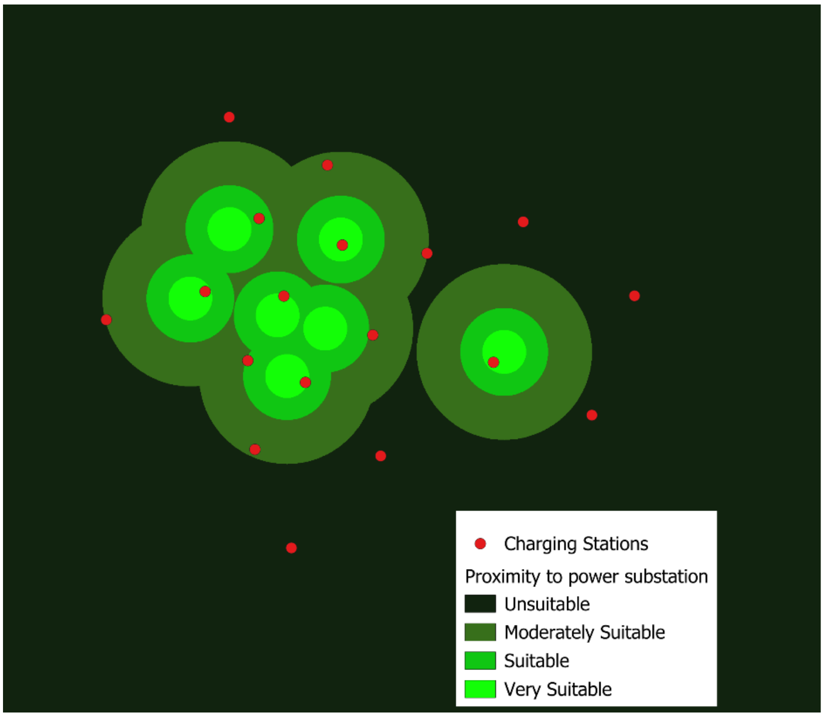

Figure 4. 8: Feasibility Map for Proximity to Power Substations

The land use rasterized map is shown in Figure 4.9. This map will be reclassified using specific weights to generate the suitability map of land use, which will be presented in the following sections.

Figure 4. 9: Land Use

4.3 Weights for Merging Raster

The weights for merging the raster files are determined using the Analytic Hierarchy Process (AHP), as described in Chapter 3. Before calculating the weights, a consistency check for the global criteria and their corresponding sub-criteria tables is essential. The pairwise comparison matrices, obtained from a questionnaire survey of four experts, are provided in ANNEX-II. The pairwise comparison matrix is normalized by taking the geometric mean of each cell value, as shown in Tables 4-1 to 4-4.

Table 4. 1: Pairwise Comparison for Global Criteria

Global pairwise	Environmental	Infrastructure Accessibility	Land use
Environmental	1.00	0.17	0.18
Infrastructure Accessibility	6.03	1.00	0.49
Land use	5.57	2.06	1.00

Table 4. 2: Pairwise Comparison for Environmental Criteria

Environmental criteria	Proximity to river	Proximity to vegetation	Slope of the land
Proximity to river	1.00	0.42	0.39
Proximity to vegetation	2.37	1.00	1.01
Slope of the land	2.53	0.99	1.00

Table 4. 3: Pairwise Comparison for Infrastructure Accessibility Criteria

Infrastructure Accessibility criteria	Proximity to petrol stations	Proximity to power substation	Proximity to major roads	Proximity to EV charging stations
Proximity to petrol stations	1.00	0.19	0.37	0.18
Proximity to power substation	5.20	1.00	0.49	0.49
Proximity to major roads	2.68	2.06	1.00	1.28
Proximity to EV charging stations	5.48	2.06	0.78	1.00

Table 4. 4: Pairwise Comparison for Land Use

Land use	Public	Commercial	Residential	Industrial	Agricultural
Public	1.00	1.86	2.00	1.68	1.68
Commercial	0.54	1.00	1.93	4.28	4.53
Residential	0.50	0.40	1.00	1.78	4.40
Industrial	0.59	0.17	0.49	1.00	1.07
Agricultural	0.59	0.17	0.18	0.78	1.00

Table 4.1 shows that the Environmental criterion is the least preferred, while the other two criteria are highly preferred.. The consistency check for each table is shown in ANNEX-III. It is observed that the tables for Global criteria, Environmental criteria, and Land use are consistent, as the Consistency Ratio (CR) is less than 0.1. However, the table for Infrastructure Accessibility criteria shows a CR greater than 0.1. Given that the CR value is just above 0.1, the table is considered fairly consistent. Therefore, we proceed to determine the weights for the criteria and sub-criteria.

Table 4. 5: Weights for Global Criteria

Criteria	Weights
Environmental	0.080
Infrastructure Accessibility	0.360
Land use	0.560

Table 4. 6: Weights for Local Criteria

Criteria	Global weights	Sub criteria	Local weights	Global weights
Environmental	0.08	Proximity to river	0.17	0.014
		Proximity to vegetation	0.412	0.033
		Slope of the land	0.418	0.033
Infrastructure Accessibility	0.36	Proximity to petrol stations	0.077	0.028
		Proximity to power substation	0.225	0.081
		Proximity to major roads	0.347	0.125
		Proximity to EV charging stations	0.351	0.126
Land use	0.56	Public	0.299	0.167
		Commercial	0.319	0.179
		Residential	0.196	0.110
		Industrial	0.101	0.057
		Agricultural	0.085	0.047

The local weights in Table 4.6 are used to generate suitability maps for each criterion, as shown in Table 4.5. The Environmental criterion is given the least priority by the experts, while Land Use holds the highest weight. Within the Environmental criterion, slope is considered the most important, as it can significantly impact construction costs as the slope increases. Proximity to vegetation is also an important factor, while proximity to the river is the least preferred. In the Infrastructure Accessibility criterion, proximity to roads is the most preferred factor by the experts. Proximity to existing EV stations and power substations also plays a major role, according to the experts. In the Land Use criterion, commercial lands are the most preferred, followed by public lands. Commercial lands are favored for their potential to provide better business opportunities, while public lands are considered easier to acquire compared to other land types. Agricultural lands are regarded as the least preferred by the experts.

4.4 Suitability Mapping

These local and global weights obtained above are used in suitability mapping. The various suitability maps are given below:

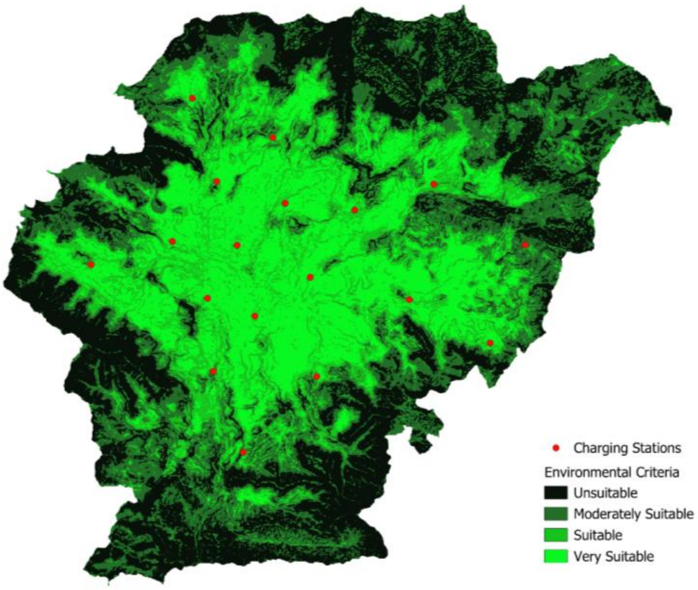

Figure 4. 10: Environmental Criteria

The values of the Land Use and Environmental criteria range from 0 to 1, where 0 represents dark pixels, indicating unsuitable regions, and 1 is represented by lighter pixels, indicating the most feasible regions. The suitability of an area increases as the pixels transition from darker to lighter. The values of the Infrastructure Accessibility raster range between 0.143 and 1. The Environmental raster highlights the most feasible regions within the core area, with areas becoming less feasible as one moves outward. This is due to the flatter terrain and the few forested regions within the core areas.

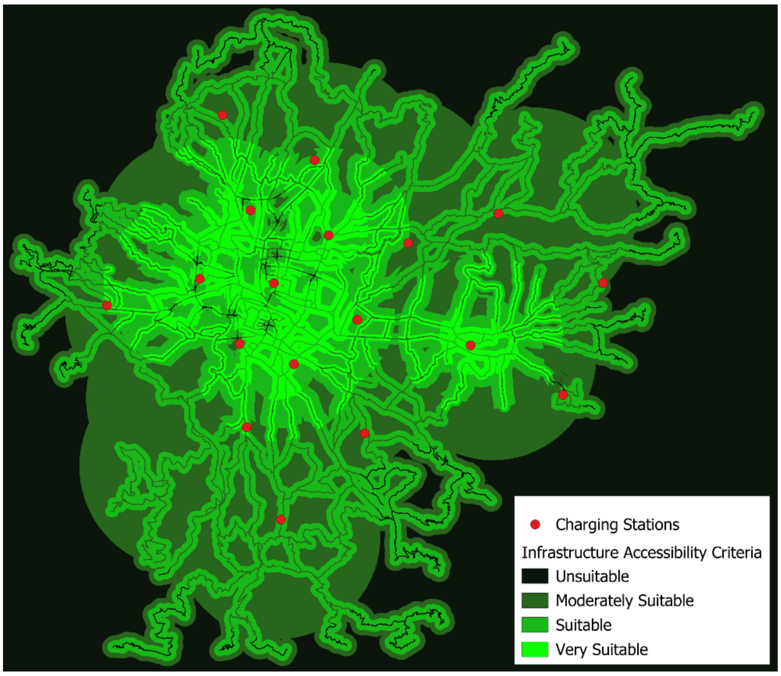

Figure 4. 11: Infrastructure Accessibility Criteria

The Infrastructure Accessibility raster also indicates that the most feasible regions are located within the core areas due to the availability of major urban facilities such as power substations, main highways, petrol stations, and other infrastructure. The major public lands are concentrated inside the core area of the valley, while lands farther from the core are primarily industrial or agricultural. Residential areas are found both inside the ring roads and farther from the core. The residential areas closer to the core are culturally rich, while those farther away tend to be new settlements, with a few exceptions. As the weights for public and commercial lands are higher than for other land uses, the raster shows that the most feasible regions are located within the core and areas near the core, with feasibility decreasing as we move outward. The areas near the ring roads and further from the core are predominantly residential and are considered fairly feasible.

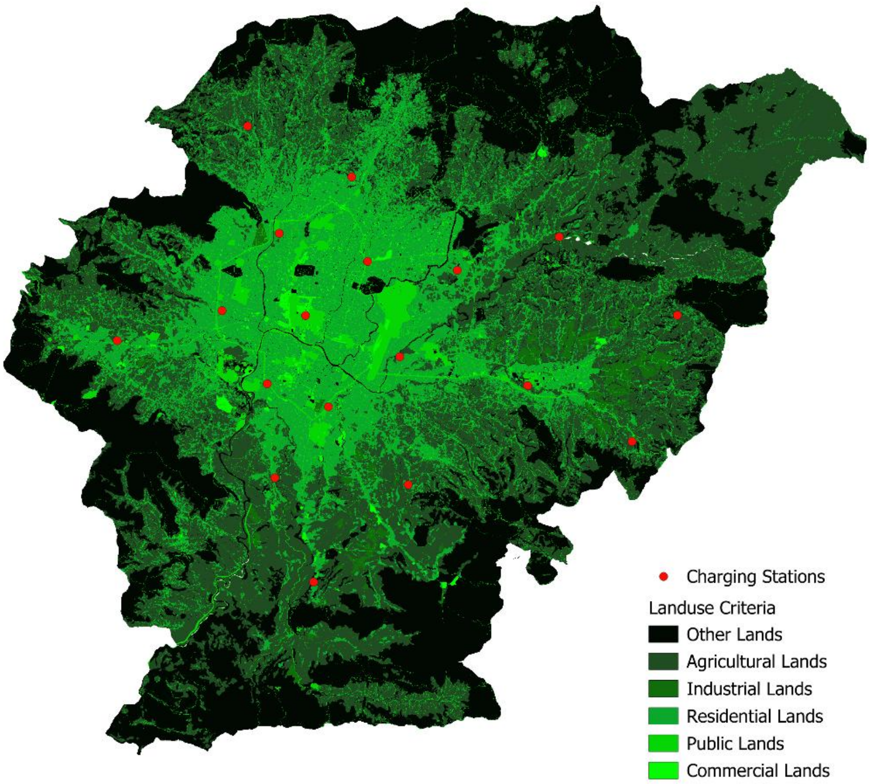

Figure 4. 12: Land Use Criteria

Finally, all the raster files of the global criteria are combined using the global weights, resulting in the final suitability map shown in Figure 4.13. The values of the final suitability map range from 0.1359 to 1, which are divided into four equal parts to generate four regions, as illustrated in Figure 4.13. As shown in Figure 4.14, the green regions are the most suitable. These areas are primarily public and commercial lands, and the high weights assigned to land use have a significant influence on the suitability mapping. The yellow regions are mostly residential, while the red regions represent agricultural or industrial lands. The most suitable regions are located inside the ring roads, close to urban facilities such as roads, petrol stations, and power substations. The least suitable regions, shown in black, are primarily forested areas with steep slopes. These regions are also poorly accessible to roads and other urban facilities.

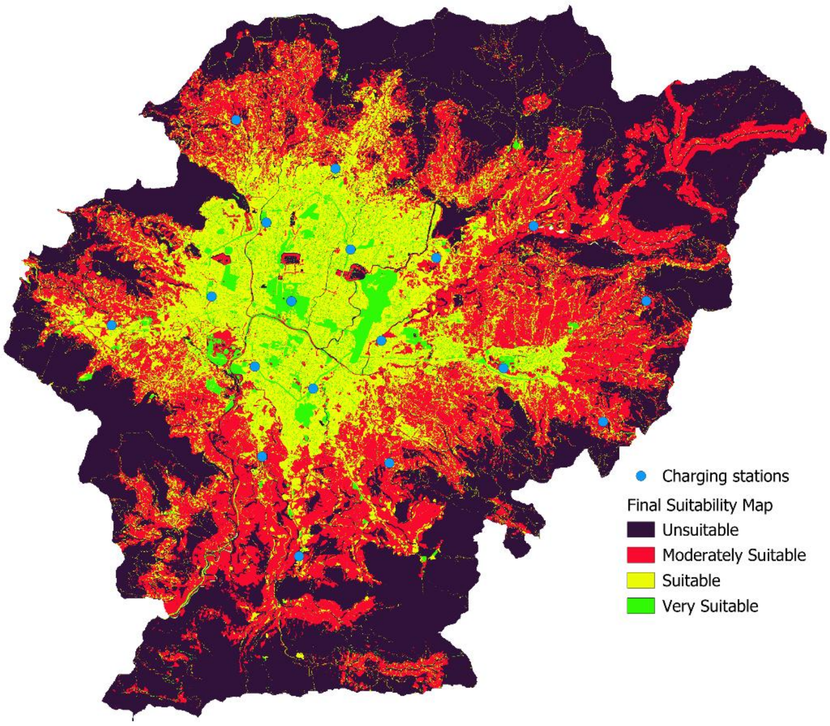

Figure 4. 13: Final Suitability Map

One of the feasible locations falls within the most suitable region, which are located in the core area. Five of the locations are in the yellow region inside the core area, predominantly residential areas. Seven other locations fall in the yellow region outside the core, while the remaining locations are in the red region. The red region consists of agricultural or industrial lands, which are relatively inexpensive. These areas are also fairly developed and have access to urban facilities.

4.5 Optimal Charging Locations:

The suitable locations, in terms of coverage and various feasible parameters, were generated in the previous sections through K-means clustering and suitability mapping. Each location represents the centroid of the formed clusters. These locations are spread across various areas within Kathmandu Valley. Each location point is denoted by its respective cluster ID, and the coordinates of these locations are presented in Table 4.7.

Figure 4.14 illustrates the locations of the points, categorized by the respective local levels they fall within.

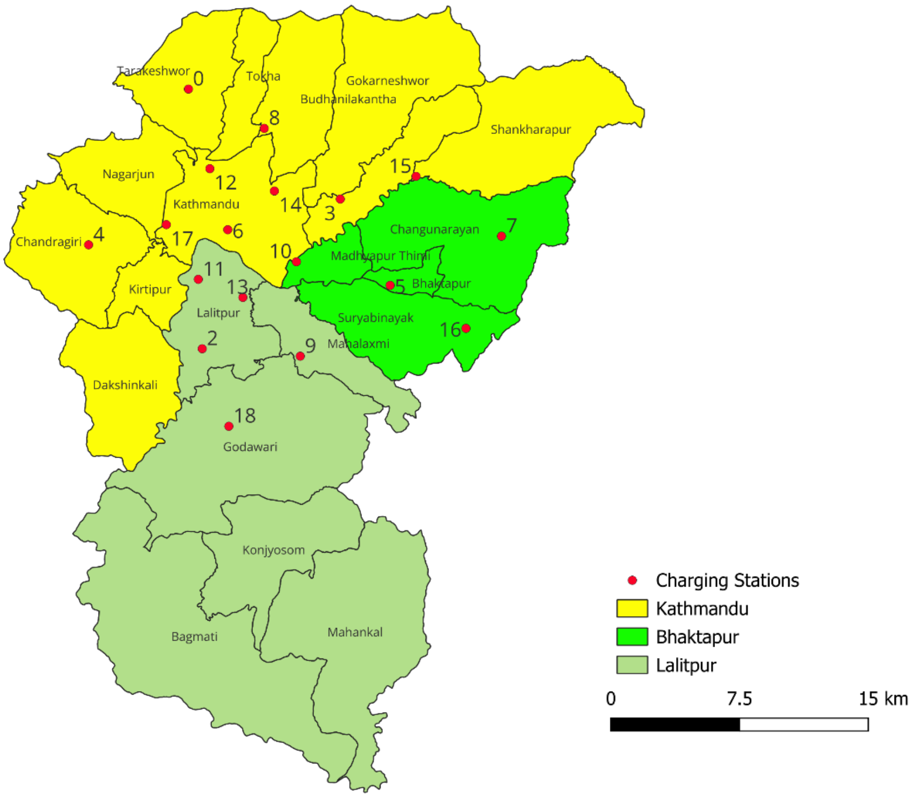

Figure 4. 14: Locations of Feasible Charging Stations

Based on the local levels where the points lie on the map, the land cost of the feasible locations is determined. The guidelines from the respective local levels are used to establish the land cost for the relevant locations. The government land rates, in NRs per square meter, are provided in Table 4.9. This land cost is then divided by the average suitability score to calculate the property acquisition cost of each location. The average suitability scores are derived from the range of scores provided in the suitability map in Section 4.4. The suitability scores and the corresponding average suitability scores are presented in Table 4.8.

Table 4. 7: Locations of Feasible Charging Stations

Cluster ID	X-Coordinates	Y-Coordinates	Local Level
0	627949.0	3073283.6	Tarkeshwor
2	629120.0	3058158.7	Lalitpur Metropolitan City
3	636955.6	3067084.7	Kageshwori Manohara
4	622349.7	3064059.7	Chandragiri
5	639981.8	3062123.7	Bhaktapur
6	630438.4	3065137.4	Kathmandu Metropolitan City
7	646403.9	3065150.4	Changunarayan
8	632420.9	3071100.4	Budanilkantha
9	634845.2	3057863.4	Mahalaxmi
10	634485.9	3063365.1	Madhyapur Thimi
11	628793.2	3062201.5	Lalitpur Metropolitan City
12	629309.3	3068673.7	Kathmandu Metropolitan City
13	631417.9	3061210.1	Lalitpur Metropolitan City
14	633101.5	3067461.3	Kathmandu Metropolitan City
15	641335.1	3068518.6	Shankharapur
16	644462.0	3059720.6	Suryabinayak
17	626852.3	3065348.4	Kathmandu Metropolitan City
18	630781.2	3053675.1	Godawari

Table 4. 8: Suitability Scores for Selected Locations

Region	Suitability Score	Average Score
Very Suitable	0.7854-1	0.89
Suitable	0.5687-0.7854	0.68
Moderately Suitable	0.3522-0.5687	0.46
Unsuitable	0.13559-0.3522	0.24

One location is considered to fall under the very suitable region, specifically the region with cluster ID 6. Twelve locations fall under the suitable region, and five locations are in the moderately suitable region. There are no locations falling under the unsuitable region. The property acquisition cost for each location is calculated using the formula provided in Equation 3.13.

Table 4. 9: Land and Property Acquisition Costs

Cluster Id	Land cost(NRs./Sq m)	Average suitability Score	Property Acquisition Cost (NRs/Sq. m)
0	34592	0.46	75200
2	27987	0.46	60841
3	44025	0.68	65030
4	66038	0.68	97545
5	110063	0.68	162575
6	136981	0.89	153394
7	22799	0.46	49563
8	40200	0.68	59380
9	21226	0.68	31353
10	44700	0.68	66027
11	75472	0.68	111480
12	121761	0.68	179854
13	76258	0.68	112641
14	121761	0.68	179854
15	28522	0.46	62004
16	73541	0.46	159872
17	138365	0.68	204380
18	37736	0.68	55740

There are areas where the traffic is very high, making it difficult to manage traffic and provide sufficient capacity for charging stations. Additionally, the land cost in these areas is significantly higher—ranging from 3 to 6 times higher than in other regions. These outliers are primarily found within the core areas of Kathmandu Valley. As a result, these areas are classified as core areas and must be excluded from the installation of charging stations. The optimization model aims to minimize the inclusion of these core areas as much as possible. The areas with cluster IDs 6, 11, 12, 13, 14, and 17 are classified as core areas due to their high land costs and their proximity to or location within the ring road, where traffic management is particularly challenging. The battery range for public transportation vehicles is set at 200 km. A total of 130 major routes are considered from the route data used in previous clustering analyses. The optimized locations for charging stations, considering the 200 km battery range, are shown in Figure 4.15.

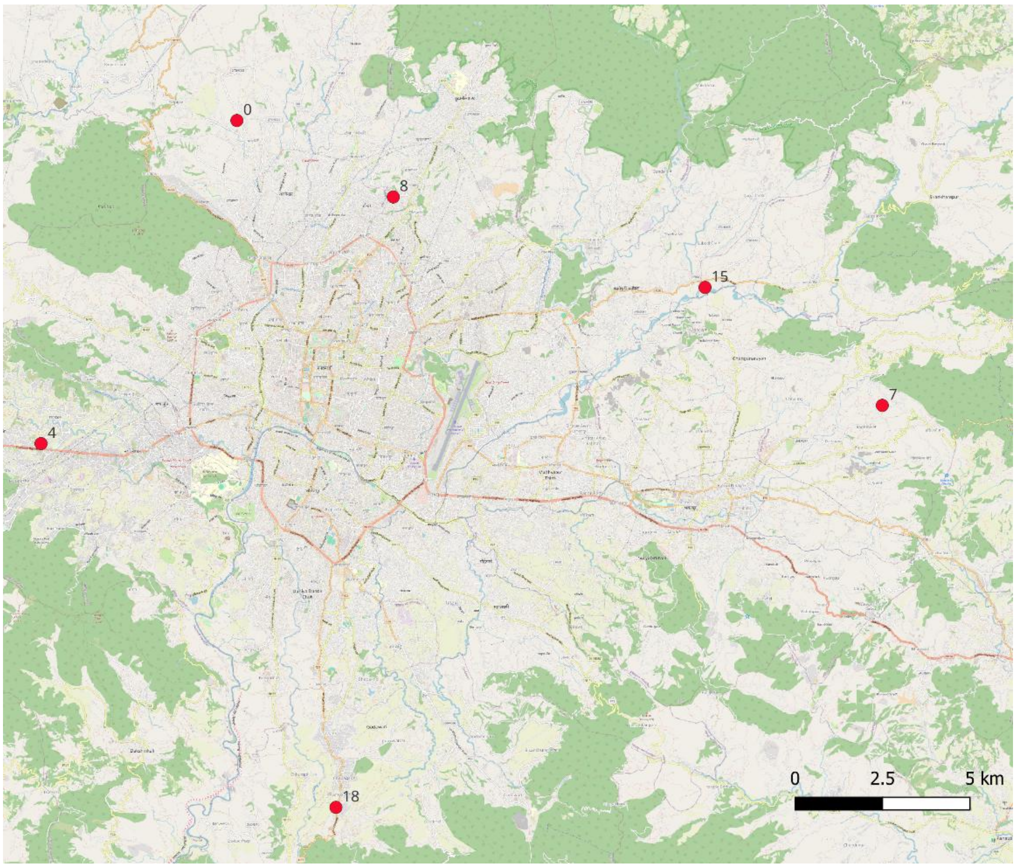

Figure 4. 15: Optimized Charging Stations (200 Km Battery Mileage)

The optimized charging station locations show that they are selected to be far from high-traffic zones and are situated in areas with low land costs. This ensures that the selected locations maintain a diverse spread, allowing for maximum coverage of routes. The northern area of Kathmandu Valley is identified as more suitable for the placement of charging stations because longer routes are predominantly located in the northern part, which provides optimal coverage for both the north and east sides of the valley. Additionally, there is one location each in the western and southern parts of the valley. The property acquisition cost function value, denoted as Z_2, for the 200 km battery range scenario is calculated as NRs. 399,432 per square meter of land. Among the selected locations, three fall under the "moderately suitable" category, while three others fall under the "suitable" category, reflecting a balance between feasibility and cost-effectiveness for the charging station placement.

4.6 Feasible Routes for Electrification of Vehicles:

The optimization model developed provides two key outcomes: the optimal locations of charging stations and the start terminals of routes that are covered. By copying the attributes from the start terminals to the routes line layer, the final set of routes that have been covered can be extracted. This process ensures that each vehicle, which covers the distance from the station to the terminal and completes its daily trips, returns to the charging station during the night for parking and charging. The vehicle is assumed to cover twice the distance between the charging station and the terminal, plus its daily trip distances, to account for both the outbound and return journeys. The optimized charging stations identified in section 4.5 are used to determine which routes are feasible for electrification based on coverage. Figure 4.16 and the table in ANNEX-V provide a detailed mapping and listing of these feasible routes in terms of their coverage distance. This approach ensures that the vehicle fleet's daily operation, including travel to and from charging stations, is accounted for, and the optimal locations for charging stations support the routes with sufficient coverage and efficient operation.

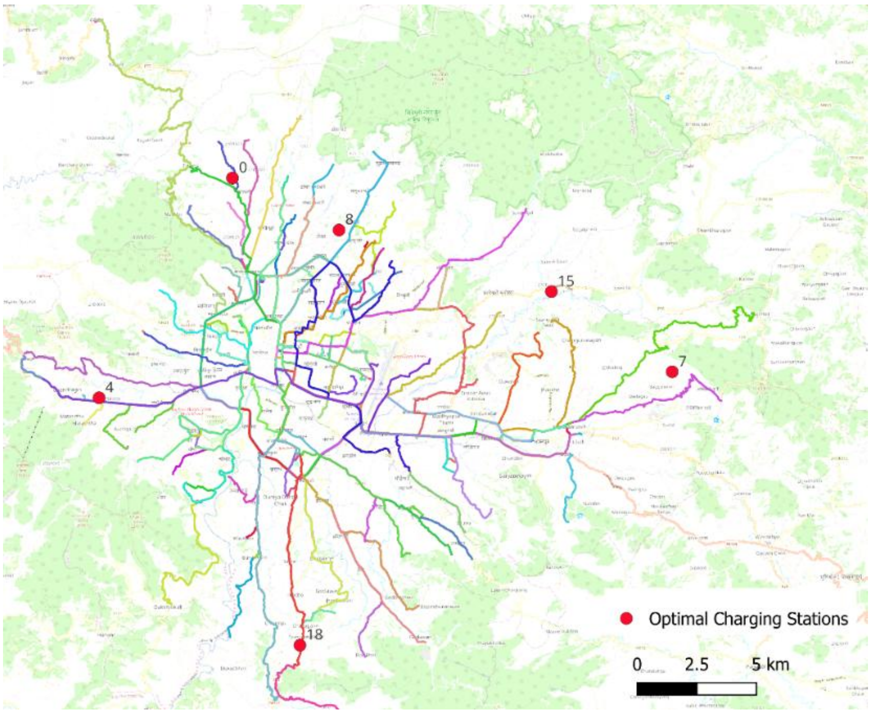

Figure 4. 16: Feasible Routes for Electrification (200 Km Battery Mileage)

The figure and table indicate that 121 routes are feasible for electrification, of which eight routes can be covered by vehicles from only one terminal. Additionally, six round-trip routes can reach charging stations within the battery range, while 107 routes allow vehicles to cover the distance to charging stations within the 200 km battery range from both terminals. Most of these routes are concentrated in the North and East, necessitating the installation of charging stations primarily in those areas. In contrast, only a few routes exist in the West and South, where a single station can cover both directions. The total vehicle count on these routes is 3,845. Assuming vehicles will park at the nearest charging station, if a station reaches full capacity, vehicles will opt for the next closest available station. The table below provides the charging station capacities for the 200 km battery range.

Table 4. 10: Capacity of Charging Stations

Cluster Id	Capacity (No. of installed chargers)
0	105
4	459
7	268
8	1785
15	196
18	1032
Total	3845

4.7 Sensitivity Analysis Considering Battery Range:

4.7.1 Battery Range 250 Km:

As the battery range increases, vehicles are able to travel longer distances to reach charging stations, resulting in a decrease in the number of charging stations required to cover the same number of routes. This is reflected in Figure 4.17, where the number of charging stations installed decreases. Each direction is covered by a single charging station, and with the increased battery range, more distant stations can be used, often in areas with lower land costs compared to central city locations. For the 200 km battery range, the optimal charging stations were selected farther from the city to minimize costs. However, due to the shorter battery range, a higher number of stations was necessary to maximize the coverage of routes. In contrast, with the 250 km battery range, vehicles can easily travel longer distances, leading to a reduction in the number of charging stations required to cover a similar number of routes. Notably, the number of routes covered in the 250 km range has increased compared to the 200 km range, even with fewer stations. Specifically, eight longer routes are covered in the 250 km range, compared to the 200 km range. Additionally, there are six routes with only one terminal covered, six round-trip routes, and 117 routes where both terminals are covered.

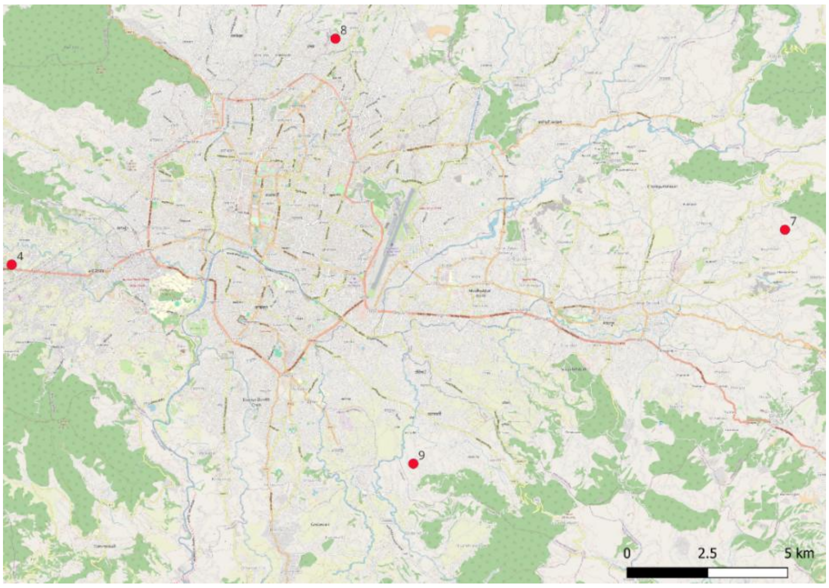

Figure 4. 17: Optimized Charging Stations (250 Km Battery Range)

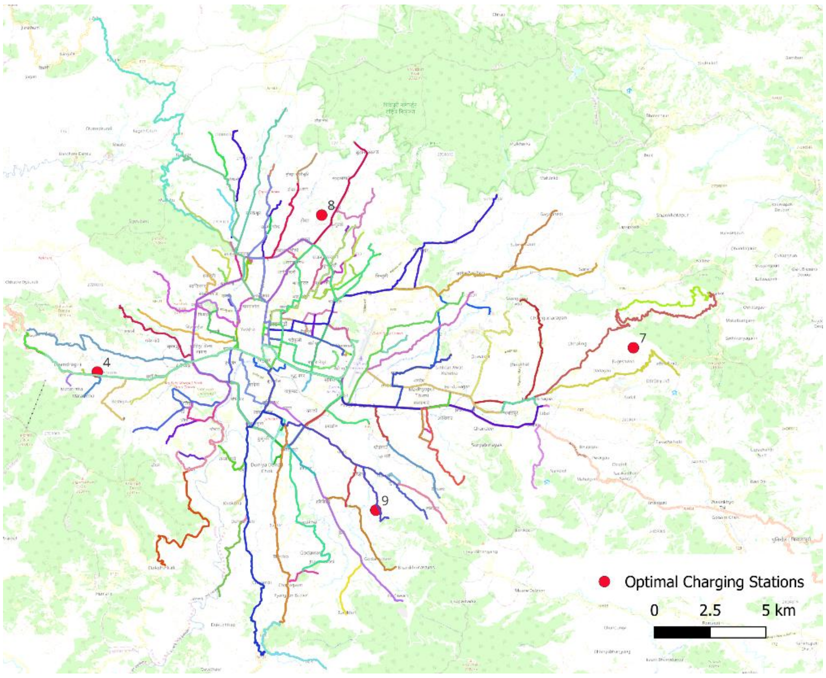

Figure 4. 18: Feasible Routes for Electrification (250 Km Battery Mileage)

The routes are maximally covered in the 250 km battery range with the fewest number of charging stations. As a result, the required capacity of the charging stations is higher than that for the stations used with the 200 km battery range. The table below shows the capacity of charging stations for the 250 km battery range. The capacities of the stations on the northern and southern sides are higher than those on other sides, likely due to the fact that the maximum number of routes are located in the northern and eastern areas of the valley, which are served by these stations. Since Station 7 is located far from the main routes, vehicles traveling on major east-side routes can instead opt for Station 9 to cover shorter distances. The feasible routes for the electrification of conventional vehicles with a 250 km battery range are provided in ANNEX-V.

Table 4. 11: Capacity of Charging Stations (250 Km Battery Mileage)

Cluster Id	Capacity(No. of installed chargers)
4	592
7	334
8	2000
9	1253
Total	4179

4.7.2 Battery Range 150 Km:

As the battery range decreases, vehicles can travel shorter distances, making it necessary to place charging stations closer to the terminals of the routes to ensure better coverage and accessibility. As a result, the charging stations are located closer to each other, though this often leads to higher land costs. In this case, the optimal number of stations has decreased compared to the 200 km battery range, but stations must be installed closer together, where land costs are higher, to provide better coverage. Stations 18, 9, and 5 offer maximum coverage for routes on the eastern and southern sides of the valley. Notably, Station 5, located in an area with higher land costs, is chosen to ensure better route coverage, but this also increases costs. Consequently, the stations are compelled to be installed closer to the core area. The number of routes covered by the 150 km battery range is the lowest among the three, and it comes with higher costs. The installed charging stations and the routes they cover are shown in Figures 4.19 and 4.20, respectively. The list of feasible routes for the electrification of conventional vehicles is provided in ANNEX-V.

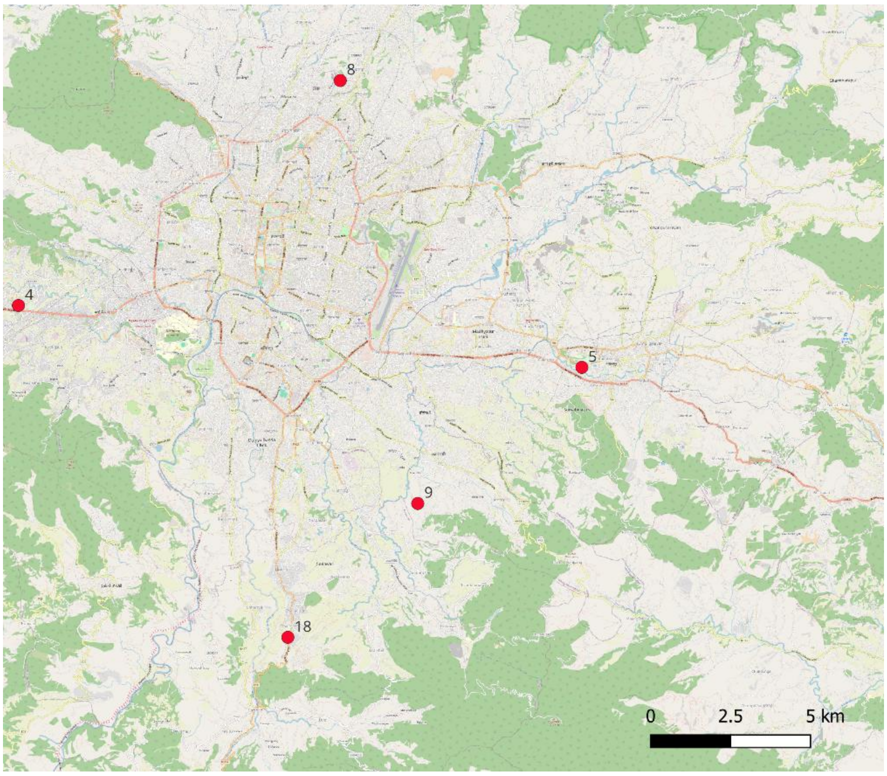

Figure 4. 19: Optimized Charging Stations (150 Km Battery Range)

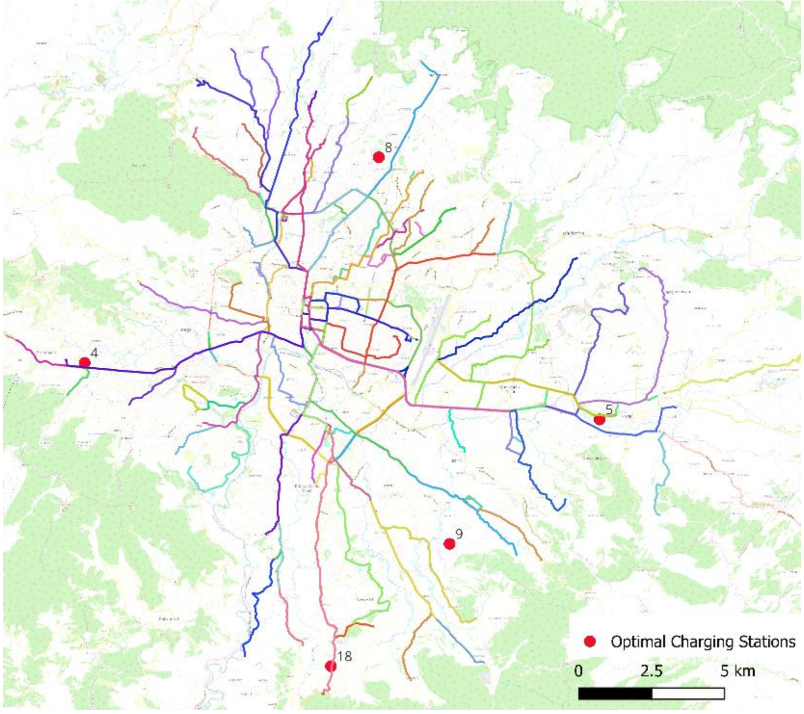

Figure 4. 20: Feasible Routes for Electrification (150 Km Battery Range)

Shorter routes are covered compared to those with higher battery ranges, leading to a decrease in the number of feasible routes for the electrification of conventional vehicles.

As a result, fewer routes are covered overall. Station 8 covers the maximum number of routes, while in the eastern and southern directions, three stations—Stations 18, 9, and 5—share the capacity to provide better coverage. The capacity for various stations with a 150 km battery range is provided in Table 4.12. The list of feasible routes for the electrification of conventional vehicles with a 150 km battery range is given in ANNEX-V. There are 15 routes, of which one has only one terminal covered, one is a round-trip route, and the remaining routes have both terminals covered.

Table 4. 12: Capacity for Charging Stations (150 Km Battery Mileage)

Cluster Id	Capacity
4	248
5	315
8	1362
9	634
18	264
Total	2823

4.7.3 Comparison of Various Scenarios

As seen in ANNEX-V, the total number of routes used as input is 130. The table below shows the total number of routes electrified for each battery range. The optimization function has two values: one is the maximized routes, which is given in terms of the terminals covered. Altogether, there were 254 terminals, counting both directions of the routes. Therefore, the optimization function values for various battery ranges are shown in Table 4.13. The optimized function is derived by using weights for both functions.

Table 4. 13: Routes Feasible for Electrification and Optimized Functions

Battery Range	Routes	Terminals (Z_1)	Property acquisition Cost (Z_2) (NRs/Sq. m)	Optimal Function (Z)
150	90	164	406592	-2.43
200	121	229	399432	-1.70
250	129	247	237841	0.09

The optimization function shows a significant increase from negative to positive as the battery range increases from 150 km to 250 km. This suggests that the cost per route covered is significantly higher for lower battery ranges, while this value decreases as the battery range increases. The cost per route covered reflects the cost of unit land required to cover one route for the electrification of conventional vehicles. The following table illustrates the cost per route covered. It shows that the cost per route covered is only 1,844 for the 250 km battery range, whereas it is 3,301 for the 200 km battery range, nearly double. This value is approximately 2.5 times higher for the 150 km battery range compared to the 250 km battery range.

Table 4. 14: Cost per Route Covered for Electrification

Battery Range	Cost per Route Covered (NRs./Sq. m/Route)
150	4518
200	3301
250	1844

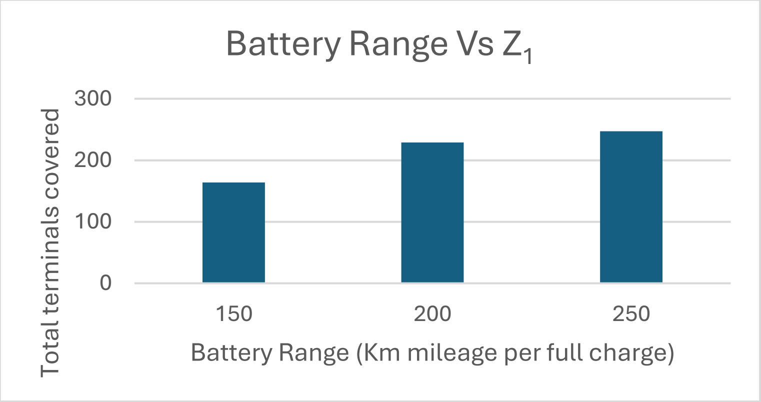

Figure 4. 21: Battery Range Vs Terminals Covered

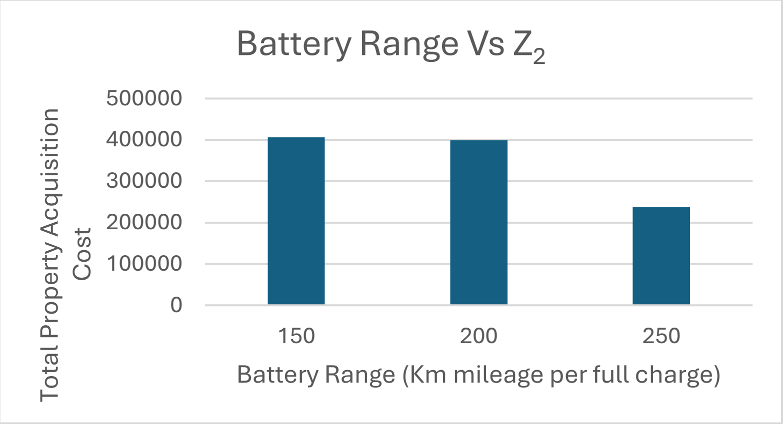

Figure 4. 22: Battery Range Vs Property Acquisition Costs

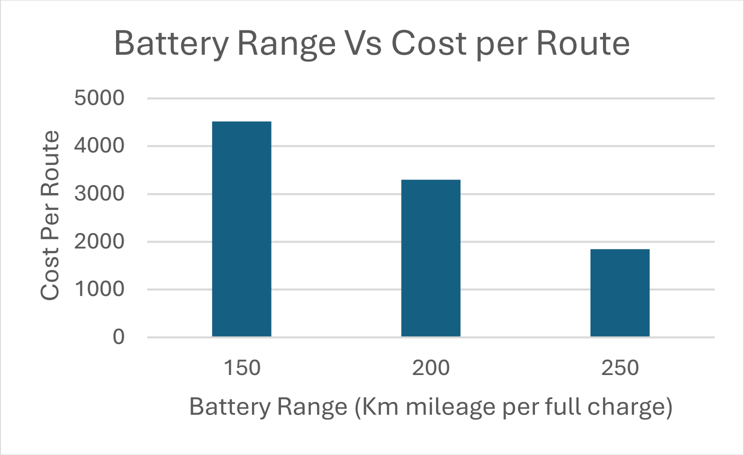

Figure 4. 23: Battery Range Vs Cost Per Route Covered

The comparison of various values is shown in the figures above. The number of routes covered increases significantly as the battery mileage increases. The penalty cost decreases slightly when the battery range increases from 150 km to 200 km, but it decreases significantly when the range is increased from 200 km to 250 km. The penalty cost per route covered continues to decrease significantly as the battery mileage increases.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The depletion of fossil fuels, air pollution, and low energy efficiency have necessitated the introduction of electric vehicles in Kathmandu Valley. Encouraging public transportation is crucial, but the adoption of electric vehicles in public transport is hindered by the lack of efficient charging infrastructure. This study aims to determine the optimal locations for charging stations for public vehicles in Kathmandu Valley using clustering, suitability mapping, and the maximal covering problem for optimization. The research applies K-means clustering to the boarding and alighting points of public transportation routes within the valley to identify potential locations for charging facilities. The K-means clustering method divides the data into 20 clusters, with the centroids considered as candidate charging station locations. A feasibility assessment of these locations is conducted using Multi-Criteria Decision Analysis (MCDA), incorporating environmental, urban, and land-use criteria.

The MCDA analysis employs the Analytical Hierarchy Process (AHP) to assign weights to various criteria and their corresponding sub-criteria. Raster analysis is performed, where raster files are normalized to values between 0 and 1. Key criteria include infrastructure accessibility factors, such as proximity to roads, power substations, and existing EV stations. Environmental criteria consider factors like slope, proximity to vegetation, and proximity to rivers. Finally, the set covering problem is applied to refine the feasible locations further and determine the optimal electrified routes, resulting in an optimized charging network. The maximum covering problem incorporates two key objectives: maximizing route coverage and minimizing the penalty costs associated with charging station installations. The model considers varying battery mileages, ranging from 150 km to 250 km.

The following are the main conclusions drawn from the analysis:

- The MCDA analysis identifies one highly suitable location for a charging station. Additionally, 12 locations are deemed suitable, while 5 fall within moderately suitable zones. 2 identified locations lie outside the Kathmandu Valley.

- The higher battery mileage reduces installation costs, as fewer charging stations are required. Conversely, lower battery mileage increases costs and results in fewer routes being covered due to limited accessibility.
- The property acquisition cost per route of the installment of charging stations decreases by 1.4 times when battery mileage is increased from 150 to 200 Km while it decreases by 1.8 times when mileage increases from 200 Km to 250 Km.

This study demonstrates that integrating clustering techniques, GIS-based multi-criteria decision-making methods, and the maximum covering optimization model offers an effective, data-driven approach to infrastructure planning. The findings highlight a systematic method for optimizing charging station placement, ensuring efficient electrification of public transportation. Furthermore, this approach can serve as a major inspiration for application in other urban areas facing challenges in public transport electrification due to the lack of adequate charging infrastructure.

5.2 Recommendations

Based on the findings of this research, several new possibilities for future studies and improvements emerge. The current MCDA analysis considered only three criteria—Environmental, Infrastructure Accessibility, and Land Use. However, incorporating more dynamic factors, such as population density and passenger demand, could provide better planning flexibility and adaptability to changes in demand and urban development. The optimization models could be further refined by integrating more parameters, such as travel time and real-time operational patterns of charging stations. By tracking the utilization of charging stations over time, more informed decisions can be made regarding the placement of new stations or the expansion of existing ones, ensuring that the infrastructure evolves in response to changing demand. Battery efficiency and discharging rates significantly impact the mileage of electric buses. An optimization model that accounts for these factors could improve the accuracy of the system's performance and reliability. Additionally, exploring the interaction between public vehicles and other vehicle types, incorporating private vehicles in hybrid share models for charging stations, and applying queueing theory to model service times at charging stations could further enhance the results and provide a more comprehensive understanding in future studies.

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ANNEX-I: Questionnaire for AHP

Sample Questionnaire:

Name:__________________

Organization:_____________________

Qualification:______________________

1. Which criteria is more important, Environmental criteria or Infrastructure Accesibility criteria and what is the score?
   Criteria: __________________________
   Score: ___________________________

2. Which criteria is more important, Land use criteria or Infrastructure Accessibility criteria and what is the score?
   Criteria: __________________________
   Score: ___________________________

3. Which criteria is more important, Land use criteria or Environmental criteria and what is the score?
   Criteria: __________________________
   Score: ___________________________

4. In Environmental Criteria, which sub-criteria is more important, slope or proximity to rivers and what is the score?
   Criteria: __________________________
   Score: ___________________________

5. In Environmental Criteria, which sub-criteria is more important, slope or proximity to vegetations and what is the score?
   Criteria: __________________________
   Score: ___________________________

6. In Environmental Criteria, which sub-criteria is more important, proximity to rivers or proximity to vegetations and what is the score?
   Criteria: __________________________
   Score: ___________________________

7. In Infrastructure Accessibility Criteria, which sub-criteria is more important, proximity to major roads or proximity to EV charging stations and what is the score?
   Criteria: ___________________________
   Score: ____________________________

8. In Infrastructure Accessibility Criteria, which sub-criteria is more important, proximity to major roads or proximity to Petrol stations and what is the score?
   Criteria: ___________________________
   Score: ____________________________

9. In Infrastructure Accessibility Criteria, which sub-criteria is more important, proximity to major roads or proximity to Power Sub stations and what is the score?
   Criteria: ___________________________
   Score: ____________________________

10. In Infrastructure Accessibility Criteria, which sub-criteria is more important, proximity to Petrol stations or proximity to Power Sub stations and what is the score?
    Criteria: ___________________________
    Score: ____________________________

11. In Infrastructure Accessibility Criteria, which sub-criteria is more important, proximity to Petrol stations or proximity to EV charging stations and what is the score?
    Criteria: ___________________________
    Score: ____________________________

12. In Infrastructure Accessibility Criteria, which sub-criteria is more important, proximity to Power sub- stations or proximity to EV charging stations and what is the score?
    Criteria: ___________________________
    Score: ____________________________

13. In Land use Criteria, which sub-criteria is more important, Public land use or Commercial land use and what is the score?
    Criteria: ___________________________
    Score: ____________________________

14. In Land use Criteria, which sub-criteria is more important, Public land use or Residential land use and what is the score?
    Criteria: ___________________________
    Score: ____________________________

15. In Land use Criteria, which sub-criteria is more important, Public land use or Agricultural land use and what is the score?
    Criteria: ___________________________
    Score: ____________________________

16. In Land use Criteria, which sub-criteria is more important, Public land use or Industrial land use and what is the score?
    Criteria: ___________________________
    Score: ____________________________

17. In Land use Criteria, which sub-criteria is more important, Commercial land use or Residential land use and what is the score?
    Criteria: ___________________________
    Score: ____________________________

18. In Land use Criteria, which sub-criteria is more important, Commercial land use or Agricultural land use and what is the score?
    Criteria: ___________________________
    Score: ____________________________

19. In Land use Criteria, which sub-criteria is more important, Commercial land use or Industrial land use and what is the score?
    Criteria: ___________________________
    Score: ____________________________

20. In Land use Criteria, which sub-criteria is more important, Residential land use or Industrial land use and what is the score?
Criteria: ___________________________
Score: ____________________________

21. In Land use Criteria, which sub-criteria is more important, Residential land use or Agricultural land use and what is the score?
Criteria: ___________________________
Score: ____________________________

22. In Land use Criteria, which sub-criteria is more important, Agricultural land use or Industrial land use and what is the score?
Criteria: ___________________________
Score: ____________________________

ANNEX-II: Pairwise Comparison Matrix for Various Experts

Expert I

Name: Pashupati Khatri
Qualification: MBA (Electrical Engineer, NEA)

Global Pairwise

Global Criteria	Environmental	Infrastructure Accessibility	Land use
Environmental	1	0.14	0.25
Infrastructure Accessibility	7	1	0.17
Land use	4	6	1

Local Pairwise

Environmental criteria	Proximity to river	Proximity to vegetation	Slope of the land
Proximity to river	1	0.17	0.25
Proximity to vegetation	6	1	0.2
Slope of the land	4	5	1

Infrastructure Accessibility criteria	Proximity to petrol stations	Proximity to power substation	Proximity to major roads	Proximity to EV charging stations
Proximity to petrol stations	1	1	0.2	0.17
Proximity to power substation	1	1	0.17	0.17
Proximity to major roads	5	6	1	1
Proximity to EV charging stations	6	6	1	1

Land use	Public	Commercial	Residential	Industrial	Agricultural
Public	1	4	4	4	4
Commercial	0.25	1	4	4	4
Residential	0.25	0.25	1	0.5	5
Industrial	0.25	0.25	2	1	0.33
Agricultural	0.25	0.25	0.2	3	1

Expert II

Name: Aasha Khanal
Qualification: Electrical Engineer (power system, NEA)

Global Pairwise

Global Criteria	Environmental	Infrastructure Accessibility	Land use
Environmental	1	0.11	0.13
Infrastructure Accessibility	9	1	2
Land use	8	0.5	1

Local Pairwise

Environmental criteria	Proximity to river	Proximity to vegetation	Slope of the land
Proximity to river	1	8	7
Proximity to vegetation	0.13	1	6
Slope of the land	0.14	0.17	1

Infrastructure Accessibility criteria	Proximity to petrol stations	Proximity to power substation	Proximity to major roads	Proximity to EV charging stations
Proximity to petrol stations	1	0.11	7	0.17
Proximity to power substation	9	1	9	9
Proximity to major roads	0.14	0.11	1	8
Proximity to EV charging stations	6	0.11	0.13	1

Land use	Public	Commercial	Residential	Industrial	Agricultural
Public	1	9	9	9	9
Commercial	0.11	1	7	7	7
Residential	0.11	0.13	1	5	5
Industrial	0.11	0.13	0.17	1	3
Agricultural	0.11	0.13	0.17	0.25	1

Expert III

Name: Bharat Sapkota
Qualification: Electronics Engineer (Green Infrastructures)

Global Pairwise

Global Criteria	Environmental	Infrastructure Accessibility	Land use
Environmental	1	0.14	0.17
Infrastructure Accessibility	7	1	0.17
Land use	6	6	1

Local Pairwise

Environmental criteria	Proximity to river	Proximity to vegetation	Slope of the land
Proximity to river	1	0.14	0.11
Proximity to vegetation	7	1	7
Slope of the land	9	0.14	1

Infrastructure Accessibility criteria	Proximity to petrol stations	Proximity to power substation	Proximity to major roads	Proximity to EV charging stations
Proximity to petrol stations	1	0.11	0.11	0.2
Proximity to power substation	9	1	0.11	0.11
Proximity to major roads	9	9	1	0.11
Proximity to EV charging stations	5	9	9	1

Land use	Public	Commercial	Residential	Industrial	Agricultural
Public	1	0.11	0.11	0.11	0.11
Commercial	9	1	3	3	5
Residential	9	0.14	1	1	5
Industrial	9	0.14	1	1	4
Agricultural	9	0.125	0.14	0.17	1

Expert IV

Name: Saurabh Agrawal
Qualification: Zeeva Internationals

Global pairwise

Global Criteria	Environmental	Infrastructure Accessibility	Land use
Environmental	1	0.33	0.2
Infrastructure Accessibility	3	1	1
Land use	5	1	1

Local Pairwise

Environmental criteria	Proximity to river	Proximity to vegetation	Slope of the land
Proximity to river	1	0.17	0.13
Proximity to vegetation	6.00	1	0.13
Slope of the land	8	8	1

Infrastructure Accessibility criteria	Proximity to petrol stations	Proximity to power substation	Proximity to major roads	Proximity to EV charging stations
Proximity to petrol stations	1	0.11	0.13	0.2
Proximity to power substation	9	1	0.33	0.33
Proximity to major roads	8	3	1	3
Proximity to EV charging stations	5	3	0.33	1

Land use	Public	Commercial	Residential	Industrial	Agricultural
Public	1	3	4	2	2
Commercial	0.33	1	0.17	4	3
Residential	0.25	6	1	4	3
Industrial	0.5	0.17	0.17	1	0.33
Agricultural	0.5	0.2	0.2	3	1

ANNEX-III: Weight calculations and Consistency Check for AHP

Global Pairwise: Calculation

Step I: Find the sum of each column

Table 1: Pairwise comparison

Global pairwise	Environmental	Infrastructure Accessibility	Land use
Environmental	1	0.17	0.18
Infrastructure Accessibility	6.03	1	0.49
Land use	5.57	2.06	1
sum	12.60	3.23	1.67

Step II: Divide each cell value by column sum

Global pairwise	Environmental	Infrastructure Accessibility	Land use
Environmental	0.08	0.05	0.11
Infrastructure Accessibility	0.48	0.31	0.29
Land use	0.44	0.64	0.60
sum	1	1	1

Now in the next table, each cell value is found by cell value in previous table divided by the corresponding column sum. For example, for cell value of environmental vs Infrastructure Accessibility i.e. 0.17 value, the value in next table is found by 0.17 divided by column sum i.e. 3.23 (0.17/3.23=0.05).

The table 2 is continued as given below.

Step III: Find eigen value and consistency check

Table 2: Calculation

Global pairwise	Environmental	Infrastructure Accessibility	Land use	Average weight	λ	λ_{max}	CI	RI	CR
Environmental	0.08	0.05	0.11	0.08	3.02	3.11	0.06	0.58	0.098
Infrastructure Accessibility	0.48	0.31	0.29	0.36	3.09				
Land use	0.44	0.64	0.60	0.56	3.11				

The each cell value is weight and the average weight is found by average of row weights. For example, for row 1, (0.08+0.05+0.11)/3=0.08. Then, the eigen value for each criteria or row is found. The eigen value for each row criteria can be found by matrix multiplication of row matrix of cell values of corresponding row in table 1 and column matrix of average weight in table 2 divided by corresponding weight.

For example, the eigen value for Environmental criteria is found as:
$\lambda=(1*0.08+0.17*0.36+0.18*0.56)/0.08 = 3.02$
Similarly, other eigen values are found. The maximum value among these values is λ_{max}.

Now, CI is calculated from the formula given in section 3.5.3. Here, the value of n is 3.
CI = (3.11-3)/(3-1) = 0.06

The random index for the value of n=3 is taken from table given in section 3.5.3.
Here, RI = 0.58

Then CR= CI/RI = 0.06/0.58 = 0.098 < 0.1, Hence the data is consistent and no further investigation needed.

Local Pairwise

The calculations for the local criteria are given below:

Environmental Criteria:

Environmental criteria	Proximity to river	Proximity to vegetation	Slope of the land
Proximity to river	1	0.42	0.39
Proximity to vegetation	2.37	1	1.01
Slope of the land	2.53	0.99	1
sum	5.90	2.41	2.41

Environmental criteria	Proximity to river	Proximity to vegetation	Slope of the land	Average weight	λ	λ_{max}	CI	RI	CR
Proximity to river	0.17	0.18	0.16	0.17	3.00	3.00	0.0004	0.58	0.0008<0.1
Proximity to vegetation	0.40	0.41	0.42	0.41	3.00				
Slope of the land	0.43	0.41	0.42	0.42	3.00				

Hence, the data is consistent and no further investigation required.

Infrastructure Accessibility Criteria:

Infrastructure Accessibility criteria	Proximity to petrol stations	Proximity to power substation	Proximity to major roads	Proximity to EV charging stations
Proximity to petrol stations	1.00	0.19	0.37	0.18
Proximity to power substation	5.20	1.00	0.49	0.49
Proximity to major roads	2.68	2.06	1.00	1.28
Proximity to EV charging stations	5.48	2.06	0.78	1.00
sum	14.35	5.31	2.64	2.95

Infrastructure Accessibility criteria	Proximity to petrol stations	Proximity to power substation	Proximity to major roads	Proximity to EV charging stations	Average weight	λ	λ_{max}	CI	RI	CR
Proximity to petrol stations	0.07	0.04	0.14	0.06	0.08	4.06	4.296	0.099	0.900	0.109
Proximity to power substation	0.36	0.19	0.18	0.16	0.22	4.30				
Proximity to major roads	0.19	0.39	0.38	0.43	0.35	4.23				
Proximity to EV charging stations	0.38	0.39	0.30	0.34	0.35	4.30				

CR=0.109> 0.1. This value is just above 0.1. Some revision may be required. But the research proceeds in as it can be tolerated.

Land use:

Land use	Public	Commercial	Residential	Industrial	Agricultural
Public	1.00	1.86	2.00	1.68	1.68
Commercial	0.54	1.00	1.93	4.28	4.53
Residential	0.50	0.40	1.00	1.78	4.40
Industrial	0.59	0.17	0.49	1.00	1.07
Agricultural	0.59	0.17	0.18	0.78	1.00
sum	3.23	3.60	5.60	9.52	12.68

The table for consistency check is given in next page

land use	Public	Commercial	Residential	Industrial	Agricultural	Average weight	λ	λ_{max}	CI	RI	CR
Public	0.31	0.52	0.36	0.18	0.13	0.30	5.35	5.35	0.09	1.12	0.08
Commercial	0.17	0.28	0.35	0.45	0.36	0.32	5.25				
Residential	0.15	0.11	0.18	0.19	0.35	0.20	5.24				
Industrial	0.18	0.05	0.09	0.10	0.08	0.10	5.11				
Agricultural	0.18	0.05	0.03	0.08	0.08	0.08	5.07				

Here, CR=0.09<0.1, Hence no further investigation required.

ANNEX-IV : Python Code

Python code for K-Means clustering and Elbow plot in QGIS:

First load the point file as named “stations”

Code:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from kneed import KneeLocator  # For finding the elbow point
from qgis.core import QgsProject, QgsVectorLayer
# Load the station layer
layer_name = "stations"
layer = QgsProject.instance().mapLayersByName(layer_name)[0]
# Extract coordinates from the layer
points = []
for feature in layer.getFeatures():
    geom = feature.geometry()
    if geom.isNull():
        continue
    x, y = geom.asPoint()
    points.append([x, y])
points = np.array(points)
# Run K-Means clustering for different values of k and store inertia values
inertia_values = []
k_values = range(1, 300)  # Adjusted to a reasonable range for better performance
```

```
for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(points)
    inertia_values.append(kmeans.inertia_)
# Use KneeLocator to find the optimal k
knee_locator = KneeLocator(k_values, inertia_values, curve='convex', direction='decreasing')
optimal_k = knee_locator.elbow
# Plot the elbow method graph
plt.figure(figsize=(8, 5))
plt.plot(k_values, inertia_values, marker='o', linestyle='-', color='b', label='Inertia')
plt.axvline(x=optimal_k, color='r', linestyle='--', label=f'Optimal k = {optimal_k}')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal k')
plt.legend()
plt.grid(True)
plt.show()
print(f"Optimal number of clusters: {optimal_k}")
```

Python code for Optimization of Charging Stations using Python 3.

```
import geopandas as gpd
import pandas as pd
import numpy as np
from deap import base, creator, tools, algorithms
import random

# Load data
charging_stations = gpd.read_file(r"Path to charging station file")
terminals = gpd.read_file(r"Path to terminals file")
distance_matrix = gpd.read_file(r"Path to distance matrix file")

# Parameters
BATTERY_RANGE = 200  # Km (change according to requirements)
alpha = 100  # Weight for maximizing terminal coverage
beta = 100000  # Weight for minimizing station penalties

# Ensure 'Core_Area' column exists in charging stations
if "Core_Area" not in charging_stations.columns:
    charging_stations["Core_Area"] = 0  # Default: Not a core area

# Create custom classes for individual and population
creator.create("FitnessMin", base.Fitness, weights=(1.0, -1.0))  # Maximize coverage, minimize penalty
```

```
creator.create("Individual", list, fitness=creator.FitnessMin)

# Initialize the toolbox
toolbox = base.Toolbox()

# Ensure core-area stations are never selected
def init_individual():
    return [0 if charging_stations.iloc[i]["Core_Area"] == 1 else random.randint(0, 1) for i in range(len(charging_stations))]

toolbox.register("individual", tools.initIterate, creator.Individual, init_individual)
toolbox.register("population", tools.initRepeat, list, toolbox.individual)

# Define the evaluation function
def evaluate(individual):
    total_coverage = 0
    penalty_cost = 0

    # Track capacity only for installed stations
    station_capacity_used = {
        station["CLUSTER_ID"]: 0 for j, station in charging_stations.iterrows() if individual[j] == 1
    }

    # Track which terminals are covered
```

```
    terminal_electrification_status = {terminal["id"]: 0 for _, terminal in terminals.iterrows()}


    for i, terminal in terminals.iterrows():
        terminal_covered = False
        fleet_size = terminal["Fleet"]


        # Get nearby stations sorted by shortest path
        available_stations = distance_matrix[
            distance_matrix["id"] == terminal["id"]
        ].sort_values(by="Shortest_path")


        for _, row in available_stations.iterrows():
            station_id = row["CLUSTER_ID"]


            # **Check if the station is installed**
            if station_id in station_capacity_used:
                shortest_path_distance = row["Shortest_path"]
                total_distance = terminal["Trip_length"] + 2 * shortest_path_distance


                # Ensure within battery range
                if total_distance <= BATTERY_RANGE:
                    station                    =charging_stations[charging_stations["CLUSTER_ID"]==
station_id].iloc[0]
                    max_capacity = station["Max_capacity"]
                    available_capacity = max_capacity - station_capacity_used[station_id]
```

```
                    if available_capacity > 0:
                        allocated_buses = min(fleet_size, available_capacity)
                        station_capacity_used[station_id] += allocated_buses
                        fleet_size -= allocated_buses

                        if fleet_size == 0:
                            terminal_covered = True
                            terminal_electrification_status[terminal["id"]] = 1
                            break

        if terminal_covered:
            total_coverage += 1

    # Compute penalty for selected stations
    for j, station in charging_stations.iterrows():
        if individual[j] == 1:
            penalty_cost += 100000 if station["Core_Area"] == 1 else station["Penalty"]

    # **Update only installed stations with capacity used**
    terminals["Electrified"] = terminals["id"].map(terminal_electrification_status)
    charging_stations["Capacity_Used"] = charging_stations.apply(
        lambda row: station_capacity_used.get(row["CLUSTER_ID"], 0) if individual[row.name] == 1 else 0,axis=1)
return total_coverage / alpha, penalty_cost / beta
```

w

```
def mutate(individual):
    # Flip a random bit (charging station selected or not), but **avoid core-area stations**
    index = random.randrange(len(individual))
    while charging_stations.iloc[index]["Core_Area"] == 1:
        index = random.randrange(len(individual))
    individual[index] = 1 - individual[index]
    return individual,

def crossover(ind1, ind2):
    # Single point crossover
    cxpoint = random.randrange(1, len(ind1) - 1)
    ind1[cxpoint:], ind2[cxpoint:] = ind2[cxpoint:], ind1[cxpoint:]

    # Ensure core-area stations are not selected
    for i in range(len(ind1)):
        if charging_stations.iloc[i]["Core_Area"] == 1:
            ind1[i] = 0
            ind2[i] = 0
    return ind1, ind2

# Register the genetic algorithm operations
toolbox.register("mate", crossover)
toolbox.register("mutate", mutate)
toolbox.register("select", tools.selTournament, tournsize=3)
```

```
toolbox.register("evaluate", evaluate)

# Create the population
population = toolbox.population(n=50)

# Run the genetic algorithm
def run_genetic_algorithm():
    # Set parameters for the evolutionary algorithm
    generations = 100
    crossover_prob = 0.7
    mutation_prob = 0.2

    # Record the statistics
    stats = tools.Statistics(lambda ind: ind.fitness.values)
    stats.register("avg", np.mean)
    stats.register("min", np.min)
    stats.register("max", np.max)

    # Run the algorithm
    algorithms.eaSimple(population, toolbox, cxpb=crossover_prob, mutpb=mutation_prob,
                        ngen=generations, stats=stats, halloffame=None, verbose=True)

    # Return the best individual
    best_individual = tools.selBest(population, 1)[0]
```

```
    return best_individual


# Run the GA and extract the results
best_individual = run_genetic_algorithm()


# Update the charging stations and terminals with the best individual
charging_stations["Installed"] = best_individual


# Save the output to the same file path and name
charging_stations.to_file(r"file path to save updated charging stations file"layer="optimized_charging_stations", driver="GPKG")
terminals.to_file( r"file path to save updated terminals file", layer="Electrified_terminals", driver="GPKG")
print("Optimization Complete!")
```

ANNEX-V: Route Information

Route Information of total routes assigned to optimization model

Name of the Route	Vehicle Mode	Fleet(no.)	Number of trips in a day	Route Length(Km)
Badikhel-Lagankhel	Microbus	50	6	10.23
Bagbazaar-Kamalbinayak	Bus	36	5	15.17
Bagbazaar-Saraswatikhel	Bus	36	5	13.42
Bagbazar-Changunarayan	Minibus	36	3	21.19
Bagbazar-Duwakot	Minibus	36	3	18.27
Bajrabarahi-Lagankhel	Microbus	50	6	9.32
Balaju bypass-Kakani	Bus	20	4	21.34
Balkot-Kalanki	Bus	40	4	12.47
Bhaktapur Buspark-Gongabu Bus park	Bus	38	4	20.56
Bhaktapur Sanothimi-Dudhpati	Bus	38	5	14.73
Bhaktapur(Dudhpati)-Lagankhel bus	Bus	36	5	13.47

Name of the Route	Vehicle Mode	Fleet(no.)	Number of trips in a day	Route Length(Km)
Bhaktapur Dudhpati-Lagankhel	Bus	36	5	16.77
Bhangal -Bhangal	Bus	20	3	30.99
Biruwa-Kalanki	Minibus	40	4	18.50
Bode-Gongabu	Bus	14	3	14.63
Boratar-NAC	Bus	12	11	7.70
Budanilkantha-Koteshwor	Bus	40	5	15.35
Budhanilkantha-Lagankhel	Bus	12	4	16.46
Budhanilkantha-Ratnapark	Bus	40	5	10.67
Bungamati-Lagankhel	Bus	36	5	6.89
Bungamati-Ratnapark	Minibus	40	6	10.26
Chappalkarkhana-NAC	Microbus	40	7	6.25
Chareli-Kamalbinayak	Bus	40	6	9.13
Chhampi-Lagankhel	Bus	36	5	10.26
Chunikhel-Ratnapark	Minibus	50	6	10.98

Name of the Route	Vehicle Mode	Fleet(no.)	Number of trips in a day	Route Length(Km)
Chyamasing-Kalanki	Minibus	36	4	20.93
Chyamasing-NAC	Bus	36	4	15.35
Chyamasing-Gongabu	Minibus	36	4	23.84
Dakshinkhali-Lagankhel	Minibus	40	4	19.27
Dallu- Lagankhel	Tempo	50	6	9.59
Dandathok- Lagankhel	Minibus	36	5	9.66
Dhitalchowk-NAC	Minibus	12	11	6.10
Dhungin-Lagankhel	Minibus	36	5	10.25
Doleswore-Jagati	Bus	40	8	3.46
Gagalphedi-NAC	Bus	10	6	18.05
Farsidol-Lagankhel	Bus	36	5	11.19
Godawari-Lagankhel	Microbus	50	6	7.40
Godawari-NAC	Bus	12	4	14.93
Gokarneswore-Kalanki	Microbus	40	5	18.25
Gokarneswore-Ratnapark	Microbus	40	6	9.94
Goldhunga- NAC	Minibus	18	4	10.02

Name of the Route	Vehicle Mode	Fleet(no.)	Number of trips in a day	Route Length(Km)
Gongabu- Bansbari	Bus	36	4	24.14
Gongabu-Kalanki	Bus	40	4	15.09
Gongabu-Lagankhel	Bus	12	4	14.28
Gongabu-Lagankhel	Minibus	20	6	10.66
Gongabu-Sinamangal	Bus	40	6	9.64
Gongabu-Ratnapark	Bus	20	6	8.37
Harharmahadev (manahara)-Haraharmahadev(manahara)	Bus	20	3	27.29
Hasantar-NAC	Microbus	12	7	15.18
Hattiban-Ratnapark	Microbus	50	6	8.98
Ichangu-Ratnapark	Microbus	12	7	11.61
Imadol-Ratnapark	Tempo	40	6	8.28
Ittakhel-Thali	Bus	40	4	26.89
Jalbinayak-Ratnapark	Minibus	12	8	10.10
Jamal-Lamatar	Bus	12	4	18.69
Jamal-Lele	Bus	12	4	21.36
Jharuwarashi-Lagankhel	Minibus	36	5	9.35
Jhor-NAC	Minibus	18	4	13.51

Name of the Route	Vehicle Mode	Fleet(no.)	Number of trips in a day	Route Length(Km)
Jitpurphedi-NAC	Minibus	18	4	12.53
Jorpati-Sankhamul	Tempo	30	6	7.88
Jorpati- NAC	Microbus	30	6	9.72
Kadaghari-Ratnapark	Microbus	24	4	10.86
Kalanki-Ratnapark	Microbus	60	6	4.88
Kalanki- Kalanki	Bus	24	6	28.34
Kalopul-Ratnapark	Tempo	40	8	6.64
Kamalbinayak-Nagarkot	Bus	8	6	14.83
Kapan Ratnapark	Tempo	40	6	9.03
Kapan-NAC	Bus	40	6	7.71
Kapan-Tikathali	Minibus	26	4	19.81
Kareswore- Ratnapark	Tempo	40	6	5.90
Kavresthali-NAC	Minibus	18	4	12.10
Khokana-Lagankhel	Minibus	36	5	6.15
Khokana-Ratnapark	Minibus	36	5	9.53
Kirtipur- NAC	Bus	40	6	8.95
Kirtipur-Lagankhel	Minibus	40	6	9.39

Name of the Route	Vehicle Mode	Fleet(no.)	Number of trips in a day	Route Length(Km)
Kittachaur-Lagankhel	Minibus	40	6	9.71
Koteswore Koteswore	Bus	24	6	27.41
Kritipur- NAC	Microbus	40	6	9.63
Lagankhel-Ratnapark	Microbus	50	6	5.95
Lagankhel- Lagankhel	Tempoo	18	5	12.66
Lagankhel-Lele	Minibus	36	6	15.12
Lagankhel-Lubhu	Minibus	36	6	10.31
Lagankhel-Sunakothi	Tempo	36	7	5.41
Lagankhel-Takhel	Minibus	36	6	10.04
Lagankhel- Tikabhairab	Minibus	36	6	14.51
Langol- NAC	Minibus	20	7	8.67
Machhegaun-NAC	Minibus	40	7	10.62
Machhegaun-NAC	Microbus	40	7	10.54
Machhegaun_Ratnapark	Tempo	40	6	8.35
Matatirtha-NAC	Bus	40	6	11.54
Milanchowk-NAC	Microbus	40	6	8.23

Name of the Route	Vehicle Mode	Fleet(no.)	Number of trips in a day	Route Length(Km)
Mulpani-NAC	Bus	36	4	13.48
Mulpani-Thankot	Bus	36	4	27.13
NAC-Gongabu	Bus	20	4	16.58
NAC-Dahachowk	Minibus	40	5	16.15
NAC- Kalanki Nagdhunga	Bus	60	6	14.96
NAC-Nakhipot	Microbus	50	6	8.79
NAC-Pandeychhap	Microbus	40	6	13.00
NAC-Panga	Minibus	36	7	9.78
NAC-Payutar	Minibus	18	4	8.44
NAC-Pushpalal Park	Minibus	36	7	11.98
NAC-Radheradhe	Microbus	36	5	11.73
NAC- Raniban bansthali bus	Bus	10	11	7.73
NAC-Ramkot	Microbus	12	11	16.61
NAC- Sanagaun	Minibus	38	6	14.38
NAC-Sankhadevi	Microbus	30	6	14.30
NAC-Sankhu	Bus	40	6	19.31
NAC- sundarbasti	Microbus	40	6	7.93

Name of the Route	Vehicle Mode	Fleet(no.)	Number of trips in a day	Route Length(Km)
NAC-Tarkeswore	Microbus	12	7	5.36
NAC- Thankot	Bus	33	6	13.23
NAC-Thankot	Microbus	50	6	11.43
NAC-Thimi	Microbus	30	8	10.56
NAC- Tinpipple	Minibus	18	4	11.54
NAC- Tokha bishnumati	Microbus	26	6	9.51
NAC- Tokha Chandeswori	Microbus	26	6	9.84
NAC-Tokha saraswati	Bus	32	6	8.10
NAC- Tokha bus	Bus	32	6	8.91
Nagdhunga-Budhanilkantha	Bus	18	4	23.28
Rammandir-Ratnapark	Tempo	40	6	9.32
Ratnapark tempoo-Swoyambu tempoo	Tempo	20	7	6.92
Ratnapark-Sankhamul	Microbus	40	6	4.40
Ratnapark-Sinamangal	Tempo	40	6	5.78

Name of the Route	Vehicle Mode	Fleet(no.)	Number of trips in a day	Route Length(Km)
Ratnapark Sitapaila	Tempoo	20	7	8.92
Ratnapark-Suryadarshan height	Microbus	24	6	6.63
Sundarighat-NAC	Microbus	40	6	18.90
Sundarijal- NAC	Bus	40	6	15.07
Tarkhagal-Thimi	Microbus	40	6	5.79
Tarkhagal-Thimi	Minibus	40	6	5.06
Thali-Thali	Minibus	100	6	32.86
Airport-Thankot	Bus	29	4	17.78
Total		4282		

Routes Assigned for 150 Km Battery Mileage:

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Badikhel-Lagankhel	Microbus	Both ways	50	6	10.23
Bagbazaar-Saraswatikhel	Bus	Both ways	36	5	13.42
Bagbazar-Changunarayan	Minibus	Both ways	36	3	21.19
Bagbazar-Duwakot	Minibus	Both ways	36	3	18.27
Bajrabarahi-Lagankhel	Microbus	Both ways	50	6	9.32
Balkot-Kalanki	Bus	Both ways	40	4	12.47
Bhaktapur Sanothimi-Dudhpati	Bus	Both ways	38	4	14.73
Bhaktapur(Dudhpati)-Lagankhel bus	Bus	Both ways	36	5	13.47

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Bode-Gongabu	Bus	One way	7	3	14.63
Budanilkantha-Koteshwor	Bus	One way	20	5	15.35
Budhanilkantha-Lagankhel	Bus	Both ways	12	4	16.46
Budhanilkantha-Ratnapark	Bus	Both ways	40	5	10.67
Bungamati-Lagankhel	Bus	Both ways	36	5	6.89
Bungamati-Ratnapark	Minibus	Both ways	40	6	10.26
Chappalkarkhana-NAC	Microbus	Both ways	40	7	6.25
Chareli-Kamalbinayak	Bus	Both ways	40	6	9.13
Chhampi-Lagankhel	Bus	Both ways	36	5	10.26
Chunikhel-Ratnapark	Minibus	Both ways	50	6	10.98
Chyamasing-NAC	Bus	One way	18	4	15.35
Dallu- Lagankhel	Tempo	Both ways	50	6	9.59
Dandathok- Lagankhel	Minibus	Both ways	36	5	9.66
Dhitalchowk-NAC	Minibus	Both ways	12	11	6.10
Dhungin-Lagankhel	Minibus	Both ways	36	5	10.25
Doleswore-Jagati	Bus	Both ways	40	8	3.46
Farsidol-Lagankhel	Bus	Both ways	36	5	11.19
Godawari-Lagankhel	Microbus	Both ways	50	6	7.40
Godawari-NAC	Bus	One way	6	4	14.93
Gokarneswore-Ratnapark	Microbus	Both ways	40	6	9.94
Goldhunga- NAC	Minibus	Both ways	18	4	10.02
Gongabu Bus Park-Bhaktapur Bus park	Bus	One way	19	4	20.56

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Gongabu-Kalanki	Bus	One way	20	4	15.09
Gongabu-NAC	Bus	One way	20	4	16.58
Gongabu-Lagankhel	Bus	Both ways	12	4	14.28
Gongabu-Lagankhel	Minibus	Both ways	20	6	10.66
Gongabu-Sinamangal	Bus	Both ways	40	6	9.64
Gongabu-Ratnapark	Bus	Both ways	20	6	8.37
Hattiban-Ratnapark	Microbus	Both ways	50	6	8.98
Imadol-Ratnapark	Tempo	Both ways	40	6	8.28
Jharuwarashi-Lagankhel	Minibus	Both ways	36	5	9.35
Jhor-NAC	Minibus	Both ways	18	4	13.51
Jitpurphedi-NAC	Minibus	Both ways	18	4	12.53
Jorpati-Sankhamul	Tempo	Both ways	30	6	7.88
Jorpati- NAC	Microbus	Both ways	30	6	9.72
Kadaghari-Ratnapark	Microbus	Both ways	24	4	10.86
Kalanki-Ratnapark	Microbus	Both ways	60	6	4.88
Kalopul-Ratnapark	Tempo	Both ways	40	8	6.64

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Kapan Ratnapark	Tempo	Both ways	40	6	9.03
Kapan-NAC	Bus	Both ways	40	6	7.71
Kareswore- Ratnapark	Tempo	Both ways	40	6	5.90
Kavresthali-NAC	Minibus	Both ways	18	4	12.10
Khokana-Lagankhel	Minibus	Both ways	36	5	6.15
Khokana-Ratnapark	Minibus	Both ways	36	5	9.53
Kirtipur- NAC	Bus	Both ways	40	6	8.95
Kirtipur-Lagankhel	Minibus	Both ways	40	6	9.39
Kittachaur-Lagankhel	Minibus	Both ways	40	6	9.71
Kritipur- NAC	Microbus	One way	20	6	9.63
Lagankhel-Ratnapark	Microbus	Both ways	50	6	5.95
Lagankhel- Lagankhel	Tempoo	Round	18	5	12.66
Lagankhel-Lubhu	Minibus	Both ways	36	6	10.31
Lagankhel-Sunakothi	Tempo	Both ways	36	7	5.41
Lagankhel-Takhel	Minibus	Both ways	36	6	10.04
Lamatar-Jamal	Bus	One way	6	4	18.69

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Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Langol- NAC	Minibus	One way	10	7	8.67
Machhegaun_Ratnapark	Tempo	Both ways	40	6	8.35
Matatirtha-NAC	Bus	Both ways	40	6	11.54
Milanchowk-NAC	Microbus	Both ways	40	6	8.23
Mulpani-NAC	Bus	Both ways	36	4	13.48
NAC-Nakhipot	Microbus	Both ways	50	6	8.79
NAC-Payutar	Minibus	Both ways	18	4	8.44
NAC-Radheradhe	Microbus	Both ways	36	5	11.73
NAC- sundarbasti	Microbus	Both ways	40	6	7.93
NAC-Tarkeswore	Microbus	Both ways	12	7	5.36
NAC- Tinpipple	Minibus	Both ways	18	4	11.54
NAC- Tokha bishnumati	Microbus	Both ways	26	6	9.51
NAC- Tokha Chandeswori	Microbus	Both ways	26	6	9.84
NAC-Tokha saraswati	Bus	Both ways	32	6	8.10
NAC- Tokha bus	Bus	Both ways	32	6	8.91
Panga-NAC	Minibus	One way	18	7	9.78
Pandeychhap-NAC	Microbus	One way	20	6	13.00
Rammandir-Ratnapark	Tempo	Both ways	40	6	9.32

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Ratnapark tempoo-Swoyambu tempoo	Tempo	Both ways	20	7	6.92
Ratnapark-Sankhamul	Microbus	Both ways	40	6	4.40
Ratnapark-Sinamangal	Tempo	Both ways	40	6	5.78
Ratnapark Sitapaila	Tempoo	Both ways	20	7	8.92
Ratnapark-Suryadarshan height	Microbus	Both ways	24	6	6.63
Tarkhagal-Thimi	Microbus	Both ways	40	6	5.79
Tarkhagal-Thimi	Minibus	Both ways	40	6	5.06
Thankot-NAC	Bus	One way	16	6	13.23
Thankot-NAC	Microbus	One way	20	6	11.43
Thimi-NAC	Microbus	One way	15	8	10.56
Total			2823		

Routes Assigned for 200 Km Battery Mileage:

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Badikhel-Lagankhel	Microbus	Both ways	50	6	10.23
Bagbazaar-Kamalbinayak	Bus	Both ways	36	5	15.17
Bagbazaar-Saraswatikhel	Bus	Both ways	36	5	13.42
Bagbazar-Changunarayan	Minibus	Both ways	36	3	21.19
Bagbazar-Duwakot	Minibus	Both ways	36	3	18.27
Bajrabarahi-Lagankhel	Microbus	Both ways	50	6	9.32

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Balaju bypass-Kakani	Bus	Both ways	20	4	21.34
Balkot-Kalanki	Bus	Both ways	40	4	12.47
Bhaktapur Buspark-Gongabu Bus park	Bus	Both ways	38	4	20.56
Bhaktapur Sanothimi-Dudhpati	Bus	Both ways	38	5	14.73
Bhaktapur(Dudhpati)-Lagankhel bus	Bus	Both ways	36	5	13.47
Bhaktapur Dudhpati-Lagankhel	Bus	One way	18	5	16.77
Bhangal -Bhangal	Bus	Round	20	3	30.99
Biruwa-Kalanki	Minibus	Both ways	40	4	18.50
Bode-Gongabu	Bus	Both ways	14	3	14.63
Boratar-NAC	Bus	Both ways	12	11	7.70
Budanilkantha-Koteshwor	Bus	Both ways	40	5	15.35
Budhanilkantha-Lagankhel	Bus	Both ways	12	4	16.46
Budhanilkantha-Ratnapark	Bus	Both ways	40	5	10.67
Bungamati-Lagankhel	Bus	Both ways	36	5	6.89
Bungamati-Ratnapark	Minibus	Both ways	40	6	10.26
Chappalkarkhana-NAC	Microbus	Both ways	40	7	6.25
Chareli-Kamalbinayak	Bus	Both ways	40	6	9.13
Chhampi-Lagankhel	Bus	Both ways	36	5	10.26
Chunikhel-Ratnapark	Minibus	Both ways	50	6	10.98
Chyamasing-Kalanki	Minibus	Both ways	36	4	20.93

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Chyamasing-NAC	Bus	Both ways	36	4	15.35
Chyamasing-Gongabu	Minibus	Both ways	36	4	23.84
Dakshinkhali-Lagankhel	Minibus	Both ways	40	4	19.27
Dallu- Lagankhel	Tempo	Both ways	50	6	9.59
Dandathok- Lagankhel	Minibus	Both ways	36	5	9.66
Dhitalchowk-NAC	Minibus	Both ways	12	11	6.10
Dhungin-Lagankhel	Minibus	Both ways	36	5	10.25
Doleswore-Jagati	Bus	Both ways	40	8	3.46
Farsidol-Lagankhel	Bus	Both ways	36	5	11.19
Godawari-Lagankhel	Microbus	Both ways	50	6	7.40
Godawari-NAC	Bus	Both ways	12	4	14.93
Gokarneswore-Kalanki	Microbus	Both ways	40	5	18.25
Gokarneswore-Ratnapark	Microbus	Both ways	40	6	9.94
Goldhunga- NAC	Minibus	Both ways	18	4	10.02
Gongabu-Airport	Bus	One way	20	4	15.09
Gongabu-Lagankhel	Bus	Both ways	12	4	14.28
Gongabu-Lagankhel	Minibus	Both ways	20	6	10.66
Gongabu-Sinamangal	Bus	Both ways	40	6	9.64
Gongabu-Ratnapark	Bus	Both ways	20	6	8.37
Harharmahadev (manahara)-Haraharmahadev(manahara)	Bus	Round	20	3	27.29
Hattiban-Ratnapark	Microbus	Both ways	50	6	8.98
Ichangu-Ratnapark	Microbus	Both ways	12	7	11.61

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Imadol-Ratnapark	Tempo	Both ways	40	6	8.28
Jalbinayak-Ratnapark	Minibus	Both ways	12	8	10.10
Jamal-Lamatar	Bus	Both ways	12	4	18.69
Jamal-Lele	Bus	Both ways	12	4	21.36
Jharuwarashi-Lagankhel	Minibus	Both ways	36	5	9.35
Jhor-NAC	Minibus	Both ways	18	4	13.51
Jitpurphedi-NAC	Minibus	Both ways	18	4	12.53
Jorpati-Sankhamul	Tempo	Both ways	30	6	7.88
Jorpati- NAC	Microbus	Both ways	30	6	9.72
Kadaghari-Ratnapark	Microbus	Both ways	24	4	10.86
Kalanki-Ratnapark	Microbus	Both ways	60	6	4.88
Kalanki- Kalanki	Bus	Round	24	6	28.34
Kalopul-Ratnapark	Tempo	Both ways	40	8	6.64
Kamalbinayak-Nagarkot	Bus	One way	4	6	14.83
Kapan Ratnapark	Tempo	Both ways	40	6	9.03
Kapan-NAC	Bus	Both ways	40	6	7.71
Kapan-Tikathali	Minibus	Both ways	26	4	19.81
Kareswore- Ratnapark	Tempo	Both ways	40	6	5.90
Kavresthali-NAC	Minibus	Both ways	18	4	12.10
Khokana-Lagankhel	Minibus	Both ways	36	5	6.15
Khokana-Ratnapark	Minibus	Both ways	36	5	9.53
Kirtipur- NAC	Bus	Both ways	40	6	8.95
Kirtipur-Lagankhel	Minibus	Both ways	40	6	9.39

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Kittachaur-Lagankhel	Minibus	Both ways	40	6	9.71
Koteswore Koteswore	Bus	Round	24	6	27.41
Kritipur- NAC	Microbus	Both ways	40	6	9.63
Lagankhel-Ratnapark	Microbus	Both ways	50	6	5.95
Lagankhel- Lagankhel	Tempoo	Round	18	5	12.66
Lagankhel-Lele	Minibus	Both ways	36	6	15.12
Lagankhel-Lubhu	Minibus	Both ways	36	6	10.31
Lagankhel-Sunakothi	Tempo	Both ways	36	7	5.41
Lagankhel-Takhel	Minibus	Both ways	36	6	10.04
Lagankhel- Tikabhairab	Minibus	Both ways	36	6	14.51
Langol- NAC	Minibus	Both ways	20	7	8.67
Machhegaun-NAC	Minibus	Both ways	40	7	10.62
Machhegaun-NAC	Microbus	Both ways	40	7	10.54
Machhegaun_Ratnapark	Tempo	Both ways	40	6	8.35
Matatirtha-NAC	Bus	Both ways	40	6	11.54
Milanchowk-NAC	Microbus	Both ways	40	6	8.23
Mulpani-NAC	Bus	Both ways	36	4	13.48
NAC-Gongabu	Bus	One way	20	4	16.58
NAC-Dahachowk	Minibus	Both ways	40	5	16.15
NAC- Kalanki Nagdhunga	Bus	Both ways	60	6	14.96
NAC-Nakhipot	Microbus	Both ways	50	6	8.79
NAC-Pandeychhap	Microbus	Both ways	40	6	13.00
NAC-Panga	Minibus	Both ways	36	7	9.78

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
NAC-Payutar	Minibus	Both ways	18	4	8.44
NAC-Pushpalal Park	Minibus	Both ways	36	7	11.98
NAC-Radheradhe	Microbus	Both ways	36	5	11.73
NAC- Raniban bansthali bus	Bus	One way	5	11	7.73
NAC- Sanagaun	Minibus	Both ways	38	6	14.38
NAC-Sankhadevi	Microbus	One way	15	6	14.30
NAC- sundarbasti	Microbus	Both ways	40	6	7.93
NAC-Tarkeswore	Microbus	Both ways	12	7	5.36
NAC- Thankot	Bus	Both ways	33	6	13.23
NAC-Thankot	Microbus	Both ways	50	6	11.43
NAC-Thimi	Microbus	Both ways	30	8	10.56
NAC- Tinpipple	Minibus	Both ways	18	4	11.54
NAC- Tokha bishnumati	Microbus	Both ways	26	6	9.51
NAC- Tokha Chandeswori	Microbus	Both ways	26	6	9.84
NAC-Tokha saraswati	Bus	Both ways	32	6	8.10
NAC- Tokha bus	Bus	Both ways	32	6	8.91
Nagdhunga-Budhanilkantha	Bus	One way	9	4	23.28
Rammandir-Ratnapark	Tempo	Both ways	40	6	9.32
Ratnapark tempoo-Swoyambu tempoo	Tempo	Both ways	20	7	6.92
Ratnapark-Sankhamul	Microbus	Both ways	40	6	4.40
Ratnapark-Sinamangal	Tempo	Both ways	40	6	5.78
Ratnapark Sitapaila	Tempoo	Both ways	20	7	8.92

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Ratnapark-Suryadarshan height	Microbus	Both ways	24	6	6.63
Sundarijal- NAC	Bus	One way	20	6	15.07
Tarkhagal-Thimi	Microbus	Both ways	40	6	5.79
Tarkhagal-Thimi	Minibus	Both ways	40	6	5.06
Airport-Thankot	Bus	One way	9	4	17.78
Total			3845		

Routes Assigned for 250 Km Battery Mileage:

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Badikhel-Lagankhel	Microbus	Both ways	50	6	10.23
Bagbazaar-Kamalbinayak	Bus	Both ways	36	5	15.17
Bagbazaar-Saraswatikhel	Bus	Both ways	36	5	13.42
Bagbazar-Changunarayan	Minibus	Both ways	36	3	21.19
Bagbazar-Duwakot	Minibus	Both ways	36	3	18.27
Bajrabarahi-Lagankhel	Microbus	Both ways	50	6	9.32
Balaju bypass-Kakani	Bus	Both ways	20	4	21.34
Bansbari-Gongabu	Bus	One way	18	4	24.14
Balkot-Kalanki	Bus	Both ways	40	4	12.47
Bhaktapur Buspark-Gongabu Bus park	Bus	Both ways	38	4	20.56
Bhaktapur Sanothimi-Dudhpati	Bus	Both ways	38	5	14.73

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Bhaktapur(Dudhpati)-Lagankhel bus	Bus	Both ways	36	5	13.47
Bhaktapur Dudhpati-Lagankhel	Bus	Both ways	36	5	16.77
Bhangal -Bhangal	Bus	Round	20	3	30.99
Biruwa-Kalanki	Minibus	Both ways	40	4	18.50
Bode-Gongabu	Bus	Both ways	14	3	14.63
Boratar-NAC	Bus	Both ways	12	11	7.70
Budanilkantha-Koteshwor	Bus	Both ways	40	5	15.35
Budhanilkantha-Lagankhel	Bus	Both ways	12	4	16.46
Budhanilkantha-Ratnapark	Bus	Both ways	40	5	10.67
Bungamati-Lagankhel	Bus	Both ways	36	5	6.89
Bungamati-Ratnapark	Minibus	Both ways	40	6	10.26
Chappalkarkhana-NAC	Microbus	Both ways	40	7	6.25
Chareli-Kamalbinayak	Bus	Both ways	40	6	9.13
Chhampi-Lagankhel	Bus	Both ways	36	5	10.26
Chunikhel-Ratnapark	Minibus	Both ways	50	6	10.98
Chyamasing-Kalanki	Minibus	Both ways	36	4	20.93
Chyamasing-NAC	Bus	Both ways	36	4	15.35
Chyamasing-Gongabu	Minibus	Both ways	36	4	23.84
Dakshinkhali-Lagankhel	Minibus	Both ways	40	4	19.27
Dallu- Lagankhel	Tempo	Both ways	50	6	9.59
Dandathok- Lagankhel	Minibus	Both ways	36	5	9.66
Dhitalchowk-NAC	Minibus	Both ways	12	11	6.10

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Dhungin-Lagankhel	Minibus	Both ways	36	5	10.25
Doleswore-Jagati	Bus	Both ways	40	8	3.46
Gagalphedi-NAC	Bus	Both ways	10	6	18.05
Farsidol-Lagankhel	Bus	Both ways	36	5	11.19
Godawari-Lagankhel	Microbus	Both ways	50	6	7.40
Godawari-NAC	Bus	Both ways	12	4	14.93
Gokarneswore-Kalanki	Microbus	Both ways	40	5	18.25
Gokarneswore-Ratnapark	Microbus	Both ways	40	6	9.94
Goldhunga- NAC	Minibus	Both ways	18	4	10.02
Gongabu-Kalanki	Bus	One way	20	4	15.09
Gongabu-Lagankhel	Bus	Both ways	12	4	14.28
Gongabu-Lagankhel	Minibus	Both ways	20	6	10.66
Gongabu-Sinamangal	Bus	Both ways	40	6	9.64
Gongabu-Ratnapark	Bus	Both ways	20	6	8.37
Harharmahadev (manahara)-Haraharmahadev(manahara)	Bus	Round	20	3	27.29
Hasantar-NAC	Microbus	Both ways	12	7	15.18
Hattiban-Ratnapark	Microbus	Both ways	50	6	8.98
Ichangu-Ratnapark	Microbus	Both ways	12	7	11.61
Imadol-Ratnapark	Tempo	Both ways	40	6	8.28
Ittakhel-Thali	Bus	One way	20	4	26.89
Jalbinayak-Ratnapark	Minibus	Both ways	12	8	10.10
Jamal-Lamatar	Bus	Both ways	12	4	18.69
Jamal-Lele	Bus	Both ways	12	4	21.36

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Jharuwarashi-Lagankhel	Minibus	Both ways	36	5	9.35
Jhor-NAC	Minibus	Both ways	18	4	13.51
Jitpurphedi-NAC	Minibus	Both ways	18	4	12.53
Jorpati-Sankhamul	Tempo	Both ways	30	6	7.88
Jorpati- NAC	Microbus	Both ways	30	6	9.72
Kadaghari-Ratnapark	Microbus	Both ways	24	4	10.86
Kalanki-Ratnapark	Microbus	Both ways	60	6	4.88
Kalanki- Kalanki	Bus	Round	24	6	28.34
Kalopul-Ratnapark	Tempo	Both ways	40	8	6.64
Kamalbinayak-Nagarkot	Bus	Both ways	8	6	14.83
Kapan Ratnapark	Tempo	Both ways	40	6	9.03
Kapan-NAC	Bus	Both ways	40	6	7.71
Kapan-Tikathali	Minibus	Both ways	26	4	19.81
Kareswore- Ratnapark	Tempo	Both ways	40	6	5.90
Kavresthali-NAC	Minibus	Both ways	18	4	12.10
Khokana-Lagankhel	Minibus	Both ways	36	5	6.15
Khokana-Ratnapark	Minibus	Both ways	36	5	9.53
Kirtipur- NAC	Bus	Both ways	40	6	8.95
Kirtipur-Lagankhel	Minibus	Both ways	40	6	9.39
Kittachaur-Lagankhel	Minibus	Both ways	40	6	9.71
Koteswore Koteswore	Bus	Round	24	6	27.41
Kritipur- NAC	Microbus	Both ways	40	6	9.63
Lagankhel-Ratnapark	Microbus	Both ways	50	6	5.95

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Lagankhel- Lagankhel	Tempoo	Round	18	5	12.66
Lagankhel-Lele	Minibus	Both ways	36	6	15.12
Lagankhel-Lubhu	Minibus	Both ways	36	6	10.31
Lagankhel-Sunakothi	Tempo	Both ways	36	7	5.41
Lagankhel-Takhel	Minibus	Both ways	36	6	10.04
Lagankhel- Tikabhairab	Minibus	Both ways	36	6	14.51
Langol- NAC	Minibus	Both ways	20	7	8.67
Machhegaun-NAC	Minibus	Both ways	40	7	10.62
Machhegaun-NAC	Microbus	Both ways	40	7	10.54
Machhegaun_Ratnapark	Tempo	Both ways	40	6	8.35
Matatirtha-NAC	Bus	Both ways	40	6	11.54
Milanchowk-NAC	Microbus	Both ways	40	6	8.23
Mulpani-NAC	Bus	Both ways	36	4	13.48
Mulpani-Thankot	Bus	One way	18	4	27.13
NAC-Gongabu	Bus	One way	20	4	16.58
NAC-Dahachowk	Minibus	Both ways	40	5	16.15
NAC- Kalanki Nagdhunga	Bus	Both ways	60	6	14.96
NAC-Nakhipot	Microbus	Both ways	50	6	8.79
NAC-Pandeychhap	Microbus	Both ways	40	6	13.00
NAC-Panga	Minibus	Both ways	36	7	9.78
NAC-Payutar	Minibus	Both ways	18	4	8.44
NAC-Pushpalal Park	Minibus	Both ways	36	7	11.98
NAC-Radheradhe	Microbus	Both ways	36	5	11.73
NAC- Raniban bansthali bus	Bus	Both ways	10	11	7.73

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
NAC- Sanagaun	Minibus	Both ways	38	6	14.38
NAC-Sankhadevi	Microbus	One way	15	6	14.30
NAC-Sankhu	Bus	Both ways	40	6	19.31
NAC- sundarbasti	Microbus	Both ways	40	6	7.93
NAC-Tarkeswore	Microbus	Both ways	12	7	5.36
NAC- Thankot	Bus	Both ways	33	6	13.23
NAC-Thankot	Microbus	Both ways	50	6	11.43
NAC-Thimi	Microbus	Both ways	30	8	10.56
NAC- Tinpipple	Minibus	Both ways	18	4	11.54
NAC- Tokha bishnumati	Microbus	Both ways	26	6	9.51
NAC- Tokha Chandeswori	Microbus	Both ways	26	6	9.84
NAC-Tokha saraswati	Bus	Both ways	32	6	8.10
NAC- Tokha bus	Bus	Both ways	32	6	8.91
Nagdhunga-Budhanilkantha	Bus	Both ways	18	4	23.28
Rammandir-Ratnapark	Tempo	Both ways	40	6	9.32
Ratnapark tempoo-Swoyambu tempoo	Tempo	Both ways	20	7	6.92
Ratnapark-Sankhamul	Microbus	Both ways	40	6	4.40
Ratnapark-Sinamangal	Tempo	Both ways	40	6	5.78
Ratnapark Sitapaila	Tempoo	Both ways	20	7	8.92
Ratnapark-Suryadarshan height	Microbus	Both ways	24	6	6.63
Sundarighat-NAC	Microbus	Both ways	40	6	18.90
Sundarijal- NAC	Bus	Both ways	40	6	15.07

Name of the Route	Vehicle Mode	Direction	Fleet(no.)	Number of trips in a day	Route Length(Km)
Tarkhagal-Thimi	Microbus	Both ways	40	6	5.79
Tarkhagal-Thimi	Minibus	Both ways	40	6	5.06
Thali-Thali	Minibus	Round	100	6	32.86
Airport-Thankot	Bus	Both ways	29	4	17.78
Total			4179		