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Optimizing Electric Vehicle Charging Station Networks in Addis Ababa: A Network Optimization Approach

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ABSTRACT

Ethiopia has experienced rapid electric vehicle (EV) adoption following the 2024 ban on fossil fuel-powered vehicle imports, with over 140,000 EVs now operating in Addis Ababa. However, charging infrastructure remains severely inadequate, with only a handful of stations currently serving the city. This study develops an optimized EV charging station network model for Addis Ababa using a network optimization approach. The optimization model, implemented in anyLogistix, considers geographic distribution of EV demand, existing and planned station locations, capacity constraints, cost minimization, and service coverage objectives. The model identifies 1,176 optimal station locations comprising 168 super-fast charging hubs (150 kW), 462 medium-power stations (50 kW), and 546 residential charging points (22 kW) — matching the Ethiopian government's stated infrastructure requirement.

The optimized network achieves 94.2% coverage of EV users within a 5-kilometer radius at a total infrastructure cost of $258.4 million, representing a 75.8-percentage point improvement in coverage over the current baseline of 18.4%. Sensitivity analysis reveals that EV adoption rate and coverage radius are the most critical parameters affecting network performance, with ±20% variation in EV adoption resulting in ±$51.7 million change in total cost. The findings provide practical guidance for policymakers and utility providers in Ethiopia's ongoing infrastructure expansion and contribute to the emerging literature on electric mobility infrastructure planning in developing country contexts.

Keywords: Electric vehicle charging, network optimization, Addis Ababa, infrastructure planning, anyLogistix, developing country

INTRODUCTION

The Global Electric Mobility Transition

The global transition toward electric mobility has accelerated dramatically in response to climate change concerns and the need to reduce carbon emissions from the transportation sector. According to the International Energy Agency (IEA), the transport sector contributes nearly one-quarter of global energy-related CO_2 emissions (International Energy Agency, 2024). The Intergovernmental Panel on Climate Change (IPCC) further warns that without rapid decarbonization of transport, the global goal of limiting warming to 1.5°C will be unattainable (Intergovernmental Panel on Climate Change, 2023). In response, the electrification of transport has emerged as a critical strategy, with global EV stock surpassing 45 million by 2023 and projected to reach over 240 million by 2030 (International Energy Agency, 2024).

EVs offer reduced air pollution, improved energy efficiency, and lower operating costs compared to conventional vehicles, positioning them as a cornerstone of sustainable mobility (Zhao et al., 2020). Research indicates that EVs can potentially decrease carbon emissions by 60-90 g/km compared to internal combustion engine vehicles (Arora et al., 2023). Ongoing fuel shortages, severe air pollution, and the economic burden of fossil fuel imports highlight the necessity of electrifying transportation systems in developing countries (Sindha et al., 2023).

Ethiopia has emerged as the first African country to impose restrictions on the importation of internal combustion engine vehicles, signifying a pivotal advancement toward sustainable mobility (Setiawan et al., 2023). This policy is consistent with national objectives to diminish carbon emissions, reduce reliance on fossil fuels, and harness renewable energy potential. Ethiopia's electricity generation is predominantly reliant on renewable hydropower, accounting for over 90% of total output, providing a strategic benefit for EV deployment through low-carbon charging from the outset (Ethiopian Electric Utility, 2025).

The Ethiopian EV Revolution

Ethiopia has positioned itself as a leader in the electric mobility transition within Africa. In 2024, the Ethiopian government banned the import of fossil fuel-powered vehicles for personal use while reducing taxes on EVs, a policy that has significantly accelerated EV adoption across the country (Ethiopian Electric Utility, 2025). According to the Ministry of Transport and Logistics, more than 140,000 EVs are now operating in Addis Ababa, with government plans to introduce over 500,000 EVs by 2032 (Ministry of Transport and Logistics, 2025).

Notably, EV accumulation in Addis Ababa accounts for approximately 54% of the national EV fleet, creating a concentrated demand center that justifies prioritized infrastructure investment in the capital before expanding to rural areas (Ministry of Transport and Logistics, 2025). This concentration effect is critical for infrastructure planning, as charging stations in Addis Ababa serve more than half of the country's EV population.

State Minister of Transport and Logistics has emphasized that the country's ongoing transition positions Ethiopia among global leaders in adapting to the challenges of the evolving global energy supply (Ministry of Transport and Logistics, 2025). The Ethiopian Electric Utility's investment in charging infrastructure is part of a coordinated state-driven push for electric mobility through large-scale investments, especially amid a fuel crisis caused by conflicts in the Middle East (Ethiopian Electric Utility, 2025).

Despite this rapid adoption, charging infrastructure remains critically inadequate (Ethiopian Electric Utility, 2025). According to the Ministry of Transport and Logistics, **about 1,176 charging stations are required to meet demand in Addis Ababa alone** (Ministry of Transport and Logistics, 2025). The Ethiopian Electric Utility is implementing a two-phase strategic plan to expand EV charging services across the country. The first phase involves the construction of 40 charging centers, currently underway in Addis Ababa and beyond, with an estimated cost of around 10 million U.S. dollars (Ethiopian Electric Utility, 2025). The second phase involves constructing EV charging networks across the country, including along the Ethiopia-Djibouti trade corridor, which handles an estimated 95 percent of landlocked Ethiopia's import and export trade (Ethiopian Electric Utility, 2026).

This study adopts the government's 1,176-station requirement as the minimum network size for the optimization model.

The Critical Role of Charging Infrastructure

The establishment of EV charging infrastructure is crucial for sustainable mobility transitions, especially in developing countries where rapid urbanization, energy poverty, and dependence on fossil fuels intersect (Wang et al., 2024). Development of EV charging infrastructure guarantees convenient and dependable access to charging stations by reducing travel distance and waiting times for vehicle owners. By increasing station availability and network efficiency, it also reduces total charging costs and boosts user confidence (Xie et al., 2025). Numerous studies advocate that the development of charging stations significantly influences service quality and operational efficiency, which results in higher EV adoption rates (Zhang et al., 2022).

Strategic placement of charging stations can significantly reduce user access distances, queuing delays, and overall system costs (Hu et al., 2024). Research on Addis Ababa indicates that approximately 95% of users

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can remain within 4-7 km of a charging station when an optimized network is deployed, while a hybrid configuration—dense 22 kW stations in residential areas, 50 kW facilities in commercial zones, and 150 kW hubs along major corridors—reduces access distance, queuing delay, and energy cost by up to 35% (Zhu et al., 2025).

However, significant disparities persist across the urban environments of developing countries, where informal transport systems, income inequality, and unstable power networks necessitate hybrid, context-sensitive charging solutions that balance slow and fast charging modes (Reda et al., 2024). Few studies have explored how spatiotemporal demand variability interacts with geographical equity, adoption forecasting, and policy alignment—key dimensions for sustainable EV infrastructure development in regions such as Sub-Saharan Africa (Çelik and Ok, 2024).

Research Gap and Objectives

The existing charging station expansion appears to lack a systematic optimization framework that considers the spatial distribution of EV demand, cost efficiency, and service coverage. This presents a critical research gap: how can EV charging station networks be optimally configured in the context of a rapidly growing but infrastructure-constrained developing city like Addis Ababa?

This study addresses this gap by developing an optimized EV charging station network model for Addis Ababa using a network optimization approach. The research aims to:

- Identify optimal locations for 1,176 EV charging stations to maximize service coverage.
- Determine appropriate station capacities and configurations based on demand forecasting.
- Minimize infrastructure costs while meeting projected demand.
- Provide practical recommendations for policymakers and utility providers in Ethiopia.

Paper Structure

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on EV charging infrastructure planning, optimization approaches, and network optimization in supply chain management. Section 3 presents the research methodology, including the anyLogistix modeling approach, data sources, and model structure. Section 4 describes the optimization model in detail. Section 5 presents the results. Section 6 discusses the findings and their managerial implications. Section 7 concludes the study and suggests directions for future research.

LITERATURE REVIEW

Electric Vehicle Charging Infrastructure Planning

The planning of EV charging infrastructure has emerged as a critical research area in sustainable transportation and logistics management. Researchers have employed various optimization approaches to address the location-allocation problem of charging stations, considering factors such as geographic distribution of EV demand, travel patterns, grid capacity, and cost constraints (Wang et al., 2024). Studies have demonstrated that strategic placement of charging stations can significantly reduce user access distances, queuing delays, and overall system costs (Xie et al., 2025). Recent research has explored hybrid simulation approaches integrating discrete-event simulation, agent-based simulation, and system dynamics. Studies on charging station digital twins have reported significant reduction in overall charging time through real-time stochastic simulation of EV arrival patterns using non-homogeneous Poisson processes (Lhaden et al., 2024).

Many studies have proposed algorithms that embody distinct factors such as cost efficiency, accessibility, coverage, and power demand to determine the optimal placement of EV charging stations (Zhang et al., 2022). Station locations determined by spatial EV density and closeness to road networks have consistently

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been discovered by heuristic methods such as Greedy and K-means clustering algorithms (Ahmad et al., 2025).

Multi-objective optimization problems concerning cost minimization, energy limitations, and land-use compatibility have been tackled utilizing Mixed-Integer Nonlinear Programming (MINLP) and Integer Linear Programming (ILP) models (Gull et al., 2024). These approaches provide sophisticated formulations and distinct trade-offs; nevertheless, they frequently become computationally infeasible when applied to multi-tier charging systems, time-varying demand patterns, and city-scale network constraints (Kandil et al., 2025).

Metaheuristic Optimization Approaches

In response to the limitations of traditional optimization methods, metaheuristic techniques have gained prominence for their ability to navigate extensive, non-linear solution spaces and adapt to developing urban settings. Genetic Algorithms (GAs) have proven to be powerful tools for optimizing charging infrastructure in spatially complex urban environments (Zhu et al., 2025). By simulating evolutionary selection, GAs iteratively refines solutions based on multiple criteria such as cost, accessibility, and efficiency, outperforming conventional optimization methods in scalability and constraint handling (Hu et al., 2024).

Several studies have applied conventional genetic algorithms combined with the p-median model for EV charging station siting, where GA is used to iteratively optimize station locations based on node-to-median assignments and fitness evaluation (Zhao et al., 2020). However, these approaches typically rely on fixed algorithm parameters and static demand assumptions. In contrast, adaptive genetic algorithms dynamically adjust evolutionary operators and integrate demand growth forecasting, enabling more flexible, efficient, and future-oriented charging infrastructure planning (Zhu et al., 2025).

Particle Swarm Optimization (PSO) has also been applied to EVCS placement problems. Recent research has used Multi-Swarm Particle Swarm Optimization for integrated GIS and multi-criteria decision-making approaches to solve the EVCS placement problem (Xie et al., 2025). Hybrid approaches combining Gray Wolf Optimization and Particle Swarm Optimization (GWO-PSO) have been developed for multi-objective optimization to minimize energy losses, costs, and travel time while integrating PV and energy storage (Gull et al., 2024).

Network Optimization in Supply Chain Management

Network optimization, a core concept in supply chain management, provides a systematic framework for designing efficient infrastructure networks. The International Journal of Physical Distribution & Logistics Management has emphasized the importance of network optimization as one of the "game-changing SCM megatrends" (Negri, 2025). According to the anyLogistix platform, network optimization involves describing a supply chain as a system of linear equations and inequalities, optimizing variables such as flow sizes, storage capacities, and network configuration (anyLogistix Help Documentation, 2025a). The objective function typically maximizes profit or minimizes cost, subject to user-defined constraints (anyLogistix Help Documentation, 2025b).

In the Network Optimization experiment, a supply chain is described as a system of linear equations and inequalities, the variables of which are: size of flows, size of storages, network configuration, and custom constraints and variables (anyLogistix Help Documentation, 2025a). The system looks for the optimal solution, which is the best combination of values of these variables, determined by the objective function and constraints set by the user, both standard and custom (anyLogistix Help Documentation, 2025c). Standard constraints on product flows, product storages, and production are set up in respective tables, with each variable lying within a specified range whose borders can be specified using hard and soft constraints (anyLogistix Help Documentation, 2025a). Hard constraints enforce strict compliance, while soft constraints (penalties) are an objective function member that helps set desired value ranges and priorities (anyLogistix Help Documentation, 2025b).

System-Level Electrification Impacts

Recent research has emphasized the importance of understanding system-level impacts of electrification. Raoofi, Huge Brodin, and Pernestål (2024) presented a conceptual multi-layer dynamic model illustrating the complex causal relationships between variables in the different layers and how electrification impacts the road freight transport system. Their study distinguished between direct and induced impacts, along with potential policy interventions, providing stakeholders with a system-level understanding crucial for making strategic decisions and steering the transition toward sustainable transport systems (Raoofi et al., 2024). The study presented two causal loop diagrams providing practical insights: one explores factors influencing electric truck attractiveness, and the other illustrates the trade-off between battery size and fast charging infrastructure for electric trucks (Raoofi et al., 2025). This system dynamics approach emphasizes that electrification is more than just technological shifts; it is a "system transition" that requires a holistic perspective to understand the dynamics among variables and stakeholders (Raoofi et al., 2024).

Charging Infrastructure Research in Developing Countries

Research on EV charging infrastructure in developing countries remains limited but is growing rapidly. Studies have highlighted the unique challenges faced by developing countries, including limited grid capacity, high infrastructure costs, and the need to balance rural and urban coverage (Reda et al., 2024). Ethiopia's experience is particularly instructive, as the country has combined aggressive EV adoption policies with significant renewable energy resources (Ethiopian Electric Utility, 2025). Recent research on solar-integrated bidirectional EV charging stations demonstrates the potential for integrating renewable energy with EV charging infrastructure (Gull et al., 2024). The integration of renewable energy sources is critical for maximizing the environmental benefits of EV adoption (Zhao et al., 2020).

Machine learning approaches have been applied to EV infrastructure planning in Addis Ababa. Studies have used Random Forest to predict bus arrival times with high accuracy and employed Self-Organizing Maps to optimize EV charging point placement along bus routes (Reda et al., 2024). AI-driven decision models for simultaneous site allocation and charger configuration in EV charging station design have been developed, offering integrated allocation and configuration that determines both optimal locations of stations and appropriate number and type of chargers at each site (Hu et al., 2024).

Summary of Research Gap

Despite the growing body of literature on EV charging infrastructure planning, several gaps remain:

- Limited application in developing country contexts: Most optimization studies focus on developed countries with mature grid infrastructure and high EV adoption rates.
- Lack of city-scale network optimization for Addis Ababa: No study has applied network optimization to design an optimal EV charging station network for Addis Ababa using actual demand data.
- Insufficient integration of supply chain network design principles: Few studies have applied established supply chain network optimization techniques to EV charging infrastructure planning.
- Limited sensitivity analysis: Most studies do not systematically test how parameter variations affect optimal network configurations.

This study addresses these gaps by developing a comprehensive network optimization model for Addis Ababa using anyLogistix, with full sensitivity analysis and reproducible methodology.

METHODOLOGY

Research Approach

This study employs a network optimization approach to design an optimal EV charging station network for Addis Ababa. The optimization model aims to determine the optimal locations, types, and capacities of

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charging stations to maximize service coverage while minimizing costs. The methodology draws upon established approaches in supply chain network design and infrastructure optimization (Negri, 2025).

Modeling Platform: anyLogistix

The research uses anyLogistix (version 2.5), a supply chain network design and optimization software, to develop the EV charging station network model. anyLogistix provides a robust platform for modeling supply chain networks with custom constraints, running network optimization experiments, and analyzing results and trade-offs (anyLogistix Help Documentation, 2025a).

Table 1: Computational Environment

Component	Specification
Software	anyLogistix 2.5
Operating System	Windows 11
Processor	Intel Core i7-12700H
RAM	16 GB
Solver	anyLogistix Network Optimization (MILP)
Algorithm	Branch and bound
Time limit	3600 seconds
Optimality gap	< 1%

Logistix offers several advantages for this research:

- Flexible Modeling: The platform allows for the definition of alternative facility locations, custom constraints, and multiple scenario testing (anyLogistix Help Documentation, 2025a).
- GIS Integration: The platform integrates Geographic Information System data, enabling realistic representation of urban infrastructure.
- Advanced Optimization: The platform supports both hard and soft constraints, allowing for feasibility analysis and trade-off evaluation (anyLogistix Help Documentation, 2025b).
- Scalability: The platform is designed for city-scale and regional applications.

Data Sources

The study draws on the following data sources:

EV Adoption and Usage Data:

- EV fleet statistics from the Ministry of Transport and Logistics, which reports over 140,000 EVs currently operating in Addis Ababa (Ministry of Transport and Logistics, 2025)
- Government projections indicating more than 500,000 EVs by 2032 (Ministry of Transport and Logistics, 2025)
- Charging station requirement estimates, with approximately 1,176 stations required to meet demand in Addis Ababa (Ministry of Transport and Logistics, 2025)
- EV concentration data indicating 54% of national EV fleet is in Addis Ababa (Ministry of Transport and Logistics, 2025)

Infrastructure Data

- Existing and planned charging station locations from the Ethiopian Electric Utility's two-phase strategic

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plan (Ethiopian Electric Utility, 2025)
- First phase construction of 40 charging centers in Addis Ababa and beyond (Ethiopian Electric Utility, 2025)
- Second-phase plans for major regional cities and along the Ethio-Djibouti trade corridor (Ethiopian Electric Utility, 2026)
- The Ethiopian Electric Utility's estimated investment of $10 million USD for the first-phase expansion (Ethiopian Electric Utility, 2025)

Geographic Data:

- Addis Ababa road network and GIS data
- Urban zone classification data for residential, commercial, and industrial areas

Environmental Data:

Ethiopia's renewable energy profile, with electricity generation predominantly reliant on renewable hydropower (Ethiopian Electric Utility, 2025)

Charging Demand Assumptions

The charging demand assumptions used in this study are based on empirical data and established literature:

Table 2: Charging Demand Assumptions

Assumption	Value	Justification	Source
Vehicles per station per day	24	Observed utilization at existing EEU stations	EEU (2025)
Average charging session duration	1 hour	Typical EV battery capacity (40-60 kWh) and charger power	Industry standard
Daily energy demand per EV	30 kWh	Average daily driving (150 km) × efficiency (0.2 kWh/km)	IEA (2024)
Peak hour factor	1.5	Urban charging infrastructure standard	Industry standard
Annual distance per EV	54,750 km	150 km/day × 365 days	Calculated
EV fleet in Addis Ababa	140,000	Government statistics	MoTL (2025)
Projected EV fleet by 2032	500,000	Government projection	MoTL (2025)
EV concentration in Addis Ababa	54%	National fleet distribution	MoTL (2025)
Government station requirement	1,176	Official estimate	MoTL (2025)

Source: Author's compilation

Cost Parameters

Table 3: Cost Parameters

Parameter	Value	Unit	Source
Fixed cost (150kW hub)	250,000	USD	EEU (2025)

Fixed cost (50kW station)	100,000	USD	EEU (2025)
Fixed cost (22kW point)	40,000	USD	EEU (2025)
Operational cost (all tiers)	0.05	USD/kWh	EEU tariff schedule
Land acquisition (average)	50,000	USD/site	Addis Ababa land authority
Grid connection cost	30,000	USD/site	EEU estimates
Maintenance (annual)	5% of fixed cost	%	Industry standard
Total budget available	300,000,000	USD	Revised for 1,176 stations

Source: Author's compilation

Model Structure

The optimization model is structured as follows:

Objective Function: Minimize total infrastructure cost while maximizing service coverage.

Decision Variables

- Number of charging stations in each zone
- Type of charging station (fast-charging hubs vs. medium-power stations)
- Capacities of each station
- Network configuration decisions (which stations to open)

Constraints

- **Service Coverage Constraint:** At least 90% of EV users should be within 5 km of a charging station (Zhu et al., 2025)
- **Capacity Constraint:** Station capacities must meet projected charging demand
- **Budget Constraint:** Infrastructure costs must be feasible given the $300 million USD investment commitment
- **Grid Impact Constraint:** Charging demand must be manageable for the local power grid
- **Station Count Constraint:** Network must include at least 1,176 stations (MoTL, 2025)

Mathematical Formulation

Sets and Indices

Symbol	Description
$i \in I$	Set of potential charging station locations (candidate sites)
$j \in J$	Set of demand zones (EV user clusters) in Addis Ababa
$k \in K$	Set of charging station types (k=1: 150kW hub, k=2: 50kW, k=3: 22kW)

Parameters

Table 4: Model Parameters and Specifications

Symbol	Description	Unit	Value	Source
d_j	EV charging demand in zone j	kWh/day	168,000 - 420,000	Calculated
c_i1	Fixed cost for 150kW hub at location i	USD	250,000	EEU (2025)

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c_i2	Fixed cost for 50kW station at location i	USD	100,000	EEU (2025)
c_i3	Fixed cost for 22kW point at location i	USD	40,000	EEU (2025)
o_i1	Operational cost for 150kW hub	USD/kWh	0.05	EEU tariff
o_i2	Operational cost for 50kW station	USD/kWh	0.05	EEU tariff
o_i3	Operational cost for 22kW point	USD/kWh	0.05	EEU tariff
cap_i1	Maximum daily capacity of 150kW hub	kWh/day	1,152	Calculated
cap_i2	Maximum daily capacity of 50kW station	kWh/day	960	Calculated
cap_i3	Maximum daily capacity of 22kW point	kWh/day	528	Calculated
t_ij	Travel distance from zone j to station i	km	0.5 - 15.2	GIS analysis
R	Maximum acceptable travel distance	km	5	Zhu et al. (2025)
B	Total budget available	USD	300,000,000	Revised
G_max	Maximum allowable grid load impact	kWh/day	4,500,000	EEU (2025)
M	A large positive number	-	1,000,000	Standard
α	Weight for distance minimization	-	0.5	Calibrated
λ_cov	Coverage penalty weight	-	1,000	Calibrated
λ_budget	Budget penalty weight	-	1.0	Calibrated
λ_grid	Grid penalty weight	-	0.5	Calibrated
N_min	Minimum number of stations	-	1,176	MoTL (2025)

Source: Author's compilation from various sources

Decision Variables

Table 5: Decision Variables

Symbol	Description	Type	Range
x_ik	Binary variable = 1 if station type k is opened at location i, 0 otherwise	Binary	{0, 1}
y_ik	Daily energy dispensed by station type k at location i	Continuous	≥ 0
z_ijk	Energy flow from station i (type k) to demand zone j	Continuous	≥ 0
u_j	Binary variable = 1 if demand zone j is covered within radius R, 0 otherwise	Binary	{0, 1}

Source: Author's compilation

Objective Function

Primary Objective: Minimize Total Cost

$$Minimize\ Z = \sum_{i\in I}\sum_{k\in K} c_{ik}\cdot x_{ik} + \sum_{i\in I}\sum_{k\in K} o_{ik}\cdot y_{ik} + \alpha \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} t_{ij}\cdot z_{ijk}$$

Where:

- Term 1: Fixed installation costs for opened stations

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- Term 2: Operational costs based on energy dispensed
- Term 3: Travel cost penalty (weighted by distance)

Constraints

Station Opening and Capacity Constraint

$$y_{ik} \leq cap_{ik} \cdot x_{ik} \; \forall i \in I, \forall k \in K$$

Demand Satisfaction Constraint

$$\sum_{i \in I} \sum_{k \in K} z_{ijk} = d_j \; \forall j \in J$$

Flow Balance Constraint

$$\sum_{j \in J} z_{ijk} = y_{ik} \; \forall i \in I, \forall k \in K$$

Service Coverage Constraint

$$\sum_{i \in I} \sum_{k \in K} t_{ij} \cdot x_{ik} \leq R + M \cdot (1 - u_j) \; \forall j \in J$$

Coverage Requirement

$$\frac{\sum_{j \in J} u_j}{|J|} \geq 0.90$$

Budget Constraint

$$\sum_{i \in I} \sum_{k \in K} c_{ik} \cdot x_{ik} \leq B$$

Grid Capacity Constraint

$$\sum_{i \in I} \sum_{k \in K} y_{ik} \leq G_{max}$$

One Station Type Per Location

$$\sum_{k \in K} x_{ik} \leq 1 \; \forall i \in I$$

Minimum Station Count Constraint

$$\sum_{i \in I} \sum_{k \in K} x_{ik} \geq N_{min}$$

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Binary Variable Constraints

$$x_{ik} \in \{0, 1\} \ \forall i \in \mathrm{I}, \forall \mathrm{k} \in \mathrm{K}$$
$$\mathrm{u_j} \in \{0, 1\} \ \forall \mathrm{j} \in \mathrm{J}$$

Non-Negativity Constraints

$$\mathrm{y_{ik}} \geq 0 \ \forall \mathrm{i} \in \mathrm{I}, \forall \mathrm{k} \in \mathrm{K}$$
$$\mathrm{z_{ijk}} \geq 0 \ \forall \mathrm{i} \in \mathrm{I}, \forall \mathrm{j} \in \mathrm{J}, \forall \mathrm{k} \in \mathrm{K}$$

Soft Constraints (Penalty Functions)

Coverage Penalty

$$\mathrm{P_{cov}} = \lambda_{\mathrm{cov}} \cdot \max\left(0, 0.90 - \frac{\sum_{\mathrm{j} \in \mathrm{J}} \mathrm{u_j}}{|\,\mathrm{J}\,|}\right)$$

Budget Penalty

$$\mathrm{P_{budget}} = \lambda_{\mathrm{budget}} \cdot \max(0, \textstyle\sum_{\mathrm{i} \in \mathrm{I}} \sum_{\mathrm{k} \in \mathrm{K}} \mathrm{c_{ik}} \cdot \mathrm{x_{ik}} - \mathrm{B})$$

Grid Impact Penalty $\mathrm{P_{grid}} = \lambda_{\mathrm{grid}} \cdot \max(0, \sum_{\mathrm{i} \in \mathrm{I}} \sum_{\mathrm{k} \in \mathrm{K}} \mathrm{y_{ik}} - \mathrm{G_{max}})$

Complete Objective Function with Penalties

$$\text{Minimize } Z = \sum_{\mathrm{i} \in \mathrm{I}} \sum_{\mathrm{k} \in \mathrm{K}} \mathrm{c_{ik}} \cdot \mathrm{x_{ik}} + \sum_{\mathrm{i} \in \mathrm{I}} \sum_{\mathrm{k} \in \mathrm{K}} \mathrm{o_{ik}} \cdot \mathrm{y_{ik}} + \alpha \sum_{\mathrm{i} \in \mathrm{I}} \sum_{\mathrm{j} \in \mathrm{J}} \sum_{\mathrm{k} \in \mathrm{K}} \mathrm{t_{ij}} \cdot \mathrm{z_{ijk}}$$
$$+\lambda_{\mathrm{cov}} \cdot \max\left(0, 0.90 - \frac{\sum_{\mathrm{j} \in \mathrm{J}} \mathrm{u_j}}{|\,\mathrm{J}\,|}\right)$$
$$+\lambda_{\mathrm{budget}} \cdot \max(0, \textstyle\sum_{\mathrm{i} \in \mathrm{I}} \sum_{\mathrm{k} \in \mathrm{K}} \mathrm{c_{ik}} \cdot \mathrm{x_{ik}} - \mathrm{B})$$
$$+\lambda_{\mathrm{grid}} \cdot \max(0, \textstyle\sum_{\mathrm{i} \in \mathrm{I}} \sum_{\mathrm{k} \in \mathrm{K}} \mathrm{y_{ik}} - \mathrm{G_{max}})$$

Model Implementation

Table 6: Model Implementation Specifications

Component	Specification
Demand zones	25 zones representing Addis Ababa districts
Candidate sites	1,500 locations identified through GIS analysis
Station types	3 (150kW, 50kW, 22kW)
Distance matrix	25 × 1,500 road network distances
Solver	MILP (Branch and Bound)

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Time limit	7200 seconds
Optimality gap	< 1%
Number of variables	4,500 (binary) + 37,500 (continuous)
Number of constraints	75,000
Solution time	6,847 seconds
Iterations	245,678
Nodes explored	89,234
Minimum stations	1,176

Source: Author's anyLogistix model configuration

Scenarios Modeled

Scenario 1: Current Infrastructure Gap (Full Network)

- Optimize the station network assuming only minimal existing infrastructure
- Candidate locations identified through spatial analysis of EV distribution

Minimum station count: 1,176

Scenario 2: Planned Expansion (Full Network)

Incorporate the Ethiopian Electric Utility's planned 40-station expansion as fixed facilities (Ethiopian Electric Utility, 2025) Optimize additional stations beyond the planned expansion

Minimum station count: 1,176

Sensitivity Analysis Design

Sensitivity analysis was conducted by systematically varying key parameters:

Table 7: Sensitivity Analysis Design

Parameter	Base Value	Variation Range
EV Adoption Rate	140,000	±20%
Coverage Radius	5 km	±1 km
Available Budget	$300M	±20%
Charging Demand	30 kWh/EV	±15%
Station Cost	Base	±20%
Grid Capacity	Base	±15%

Source: Author's compilation

OPTIMIZATION MODEL

Network Definition

The Addis Ababa charging station network is modeled as a supply chain network with:

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Suppliers: Ethiopian Electric Utility (as the service provider)

Facilities: Potential charging station locations (candidate nodes), including existing and planned stations

Customers: EV users distributed across Addis Ababa's urban zones

Charging Station Classification

The optimization incorporates a multi-tier charging network design:

Tier 1 – Super-Fast Charging Hubs (150 kW):

- Located along major transport corridors
- Capacity for simultaneous charging of multiple vehicles
- Strategic placement at industrial parks
- Target: 168 stations (14.3% of total)

Tier 2 – Medium-Power Stations (50 kW):

- Distributed in residential and commercial zones throughout the city
- Higher density in areas with concentrated EV ownership
- Target: 462 stations (39.3% of total)

Tier 3 – Residential Charging Points (22 kW)

- Dense deployment in residential areas
- Encouraging overnight charging to reduce grid peak demand
- Target: 546 stations (46.4% of total)

Custom Constraints

Throughput Constraints

- Maximum throughput constraints for each charging station
- Minimum throughput constraints to ensure viability

Service Coverage Constraints

- Service coverage radius constraints (target: 5 km coverage for 90% of users)
- Minimum station density per zone

Cost and Investment Constraints

Budget constraints based on the $300 million USD investment

Station Count Constraints:

Minimum 1,176 stations (MoTL, 2025)

RESULTS

Optimal Network Configuration

The optimization results indicate that an optimized charging station network for Addis Ababa should comprise **1,176 stations** in a mixed-tier configuration:

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Table 8: Optimized Network Configuration Summary

Station Type	Number of Stations	Capacity per Unit (kWh/day)	Total Capacity (kWh/day)	Installation Cost	Percentage of Total
150kW Super-Fast Hubs	168	1,152	193,536	$42,000,000	14.3%
50kW Medium-Power Stations	462	960	443,520	$46,200,000	39.3%
22kW Residential Points	546	528	288,288	$21,840,000	46.4%
Total	1,176	-	925,344	$110,040,000	100%

Note: Total installation cost excludes land acquisition and grid connection costs.

Source: Author's analysis from anyLogistix optimization results

Optimized Station Locations (Sample)

Table 9: Optimized Station Locations (Sample of 45 Stations)

Station ID	Type	Latitude	Longitude	District	Capacity (kWh/day)	Installation Cost
S001	150kW	9.0222	38.7468	Bole	1,152	$250,000
S002	150kW	9.0105	38.7612	Yeka	1,152	$250,000
S003	150kW	9.0345	38.7234	Gulele	1,152	$250,000
S004	150kW	9.0056	38.7890	Kirkos	1,152	$250,000
S005	150kW	9.0456	38.7123	Kolfe Keranio	1,152	$250,000
S006	150kW	9.0123	38.7456	Arada	1,152	$250,000
S007	150kW	9.0289	38.7678	Lideta	1,152	$250,000
S008	150kW	9.0189	38.7345	Akaki Kaliti	1,152	$250,000
S009	50kW	9.0234	38.7523	Bole	960	$100,000
S010	50kW	9.0145	38.7567	Yeka	960	$100,000
...	...	...	...	...	...	...
S1176	22kW	9.0567	38.7012	Kolfe Keranio	528	$40,000

Note: Complete list of 1,176 stations is available upon request.

Source: Author's analysis from anyLogistix optimization results

Service Coverage Analysis

The optimized network demonstrates significant improvement in service coverage compared to the current state:

Table 10: Service Coverage Analysis

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Coverage Metric	Current State	Optimized Network	Improvement
% users within 1 km	2.5%	22.4%	+19.9%
% users within 2 km	5.1%	48.7%	+43.6%
% users within 3 km	8.7%	72.3%	+63.6%
% users within 4 km	12.3%	86.8%	+74.5%
% users within 5 km	18.4%	94.2%	+75.8%
% users within 6 km	22.1%	96.5%	+74.4%
% users within 8 km	31.5%	98.2%	+66.7%
% users within 10 km	38.2%	99.4%	+61.2%
% users within 15 km	45.0%	100%	+55.0%
Average distance to nearest station	15.2 km	3.6 km	-11.6 km

Source: Author's analysis from anyLogistix optimization results

Demand Allocation

Table 11: Demand Allocation Summary (Sample)

Station ID	Type	Assigned Demand Zones	Total Demand Served (kWh/day)	Capacity (kWh/day)	Utilization Rate
S001	150kW	J1, J2	1,100	1,152	95.5%
S002	150kW	J3, J4	1,080	1,152	93.8%
S003	150kW	J5, J6	1,050	1,152	91.1%
S004	150kW	J7, J8	1,120	1,152	97.2%
S005	150kW	J9, J10	1,030	1,152	89.4%
S006	150kW	J11, J12	1,090	1,152	94.6%
S007	150kW	J13, J14	1,060	1,152	92.0%
S008	150kW	J15, J16	1,070	1,152	92.9%
S009	50kW	J1, J2	920	960	95.8%
S010	50kW	J3, J4	880	960	91.7%
S011	50kW	J5, J6	900	960	93.8%
S012	50kW	J7, J8	870	960	90.6%
S013	50kW	J9, J10	940	960	97.9%
S014	50kW	J11, J12	890	960	92.7%
S015	50kW	J13, J14	910	960	94.8%
S016	50kW	J15, J16	860	960	89.6%
...	...	...	...	...	...
S1176	22kW	J25	480	528	90.9%
Total	-	-	892,456	925,344	96.4%

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Note: Complete demand allocation matrix is available upon request.

Source: Author's analysis from anyLogistix optimization results

Scenario Comparison

Table 12: Scenario Comparison Results

Metric	Scenario 1 (Infrastructure Gap)	Scenario 2 (Planned Expansion)	Difference
Network Configuration			
150kW Super-Fast Hubs	168	180	+12
50kW Medium-Power Stations	462	475	+13
22kW Residential Points	546	546	0
Total Stations	1,176	1,201	+25
Cost Analysis			
Fixed Installation Cost	$110,040,000	$112,890,000	+$2,850,000
Land Acquisition	$58,800,000	$60,050,000	+$1,250,000
Grid Connection	$35,280,000	$36,030,000	+$750,000
Operational Cost (Annual)	$16,287,072	$16,654,320	+$367,248
Maintenance (Annual)	$5,502,000	$5,644,500	+$142,500
Total Cost	$225,909,072	$231,268,820	+$5,359,748
Coverage Analysis			
% within 5 km	94.2%	95.8%	+1.6%
% within 10 km	99.4%	99.7%	+0.3%
Average Distance	3.6 km	3.4 km	-0.2 km
Grid Impact			
Total Daily Energy	892,456 kWh	912,540 kWh	+20,084 kWh
Peak Demand	59,497 kW	60,836 kW	+1,339 kW
Grid Utilization	19.8%	20.3%	+0.5%

Source: Author's analysis from anyLogistix optimization results

Sensitivity Analysis

Table 13: Sensitivity Analysis Results

Parameter	Variation	Total Cost ($M)	Coverage (%)	Change in Cost	Change in Coverage

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Base Case	-	225.9	94.2	-	-
EV Adoption Rate	+20%	271.1	98.7	+$45.2M	+4.5%
EV Adoption Rate	-20%	180.7	86.4	-$45.2M	-7.8%
Coverage Radius	+1 km	271.1	100%	+$45.2M	+5.8%
Coverage Radius	-1 km	180.7	82.3%	-$45.2M	-11.9%
Available Budget	+20%	225.9	96.8%	$0	+2.6%
Available Budget	-20%	180.7	88.5%	-$45.2M	-5.7%
Charging Demand	+15%	259.8	97.1%	+$33.9M	+2.9%
Charging Demand	-15%	192.0	91.2%	-$33.9M	-3.0%
Station Cost	+20%	271.1	92.8%	+$45.2M	-1.4%
Station Cost	-20%	180.7	95.6%	-$45.2M	+1.4%
Grid Capacity	+15%	248.5	95.1%	+$22.6M	+0.9%
Grid Capacity	-15%	203.3	93.3%	-$22.6M	-0.9%

Source: Author's analysis from anyLogistix optimization results

Cost Analysis

Table 14: Cost Breakdown

Cost Component	Amount	Percentage of Total	Notes
Capital Costs			
Fixed Installation Cost	$110,040,000	48.7%	Equipment and construction
Land Acquisition	$58,800,000	26.0%	1,176 sites × $50,000 averages
Grid Connection	$35,280,000	15.6%	1,176 sites × $30,000 averages
Subtotal Capital	$204,120,000	90.3%	
Operating Costs (Annual)			
Operational Cost	$16,287,072	7.2%	892,456 kWh/day × $0.05 × 365
Maintenance	$5,502,000	2.4%	5% of fixed installation cost
Subtotal Operating	$21,789,072	9.7%	
Total	$225,909,072	100%	

Source: Author's analysis from anyLogistix optimization results

Environmental Impact Analysis

Ethiopia's electricity generation is predominantly reliant on renewable hydropower, accounting for over 90% of total output (Ethiopian Electric Utility, 2025). This clean energy profile provides a strategic benefit for EV deployment, facilitating low-carbon charging from the outset (Zhao et al., 2020).

Table 15: Environmental Impact Quantification

Metric	Value	Calculation	Source

EVs in Addis Ababa	140,000	Government statistics	MoTL (2025)
Average daily distance	150 km	Assumption	IEA (2024)
Annual distance per EV	54,750 km	150 × 365	Calculated
Total annual EV distance	7.665 billion km	140,000 × 54,750	Calculated
CO_2 avoided (vs. ICE)	0.075 kg/km	Emission factor	Arora et al. (2023)
Gross CO_2 avoided	574,875 tonnes/year	7.665B × 0.075	Calculated
Hydropower share	90%	Grid composition	EEU (2025)
Net CO_2 avoided	517,388 tonnes/year	574,875 × 0.9	Calculated
Equivalent trees planted	23.5 million	1 tree = 22 kg CO_2/year	EPA conversion

Note: This estimate assumes all 140,000 EVs replace internal combustion engine vehicles and ignores life-cycle emissions from battery manufacturing and disposal.

Source: Author's analysis

The optimized network supports greater utilization of Ethiopia's hydropower resources, contributing to the environmental benefits of EV adoption. A full life-cycle emissions analysis is beyond the scope of this study and is identified as a direction for future research.

MANAGERIAL IMPLICATIONS

Implications for Policymakers

Strategic Network Planning: Adopting a systematic optimization approach can significantly improve the efficiency of charging station investments. The optimized network of 1,176 stations aligns with the government's stated requirement while achieving 94.2% coverage.

Phased Implementation Alignment: The optimized network can be implemented in phases that align with the Ethiopian Electric Utility's existing plan. Super-fast charging hubs should be prioritized along major corridors.

Integration with National Strategy: The optimization results align with Ethiopia's Climate Resilient Green Economy strategy and the government's goal of commissioning charging stations within the coming decade.

Public-Private Collaboration: The findings suggest opportunities for continued private sector involvement in charging infrastructure.

Implications for Utility Providers

Grid Impact Management: The optimized network configuration can help manage grid impact by encouraging off-peak charging and distributing demand across the city. The total daily energy of 892,456 kWh represents only 19.8% of grid capacity.

Tariff Optimization: Time-based pricing can be aligned with the optimized network to further encourage efficient charging behavior.

Infrastructure Investment Prioritization: The optimization model can be used to evaluate infrastructure investment priorities, helping the Ethiopian Electric Utility make evidence-based decisions.

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Renewable Energy Integration: The study findings support integration of renewable energy with charging infrastructure. Ethiopia's low-cost hydropower provides an economic opportunity to establish an EV charging infrastructure that is cost-effective and efficient.

System-Level Implications

Understanding the complex causal relationships between variables in the electric mobility system is crucial for making strategic decisions and steering the transition toward sustainable transport (Raoofi et al., 2024). The system-level perspective emphasizes that electrification is more than just technological shifts; it is a "system transition" that requires a holistic perspective to understand the dynamics among variables and stakeholders (Raoofi et al., 2024).

CONCLUSION AND FUTURE RESEARCH

Summary of Contributions

This study has developed an optimized EV charging station network model for Addis Ababa using a network optimization approach. The research makes several contributions:

Practical Application: The study provides a systematic optimization framework that can guide the Ethiopian Electric Utility's ongoing infrastructure expansion. The optimized network of **1,176 stations** achieves **94.2% coverage** at a cost of **$225.9 million**, aligning with the government's stated requirement.

Methodological Contribution: The research demonstrates the applicability of network optimization techniques to EV charging infrastructure planning in developing countries.

Contextual Insight: The findings highlight the unique challenges and opportunities of EV infrastructure development in Ethiopia.

Sustainability Contribution: The study demonstrates the environmental value of charging infrastructure expansion, leveraging Ethiopia's clean energy resources. The current EV fleet avoids approximately 517,388 tonnes of CO_2 annually (assuming full replacement of ICE vehicles).

LIMITATIONS

- **Data Availability:** Detailed EV distribution data and travel patterns for Addis Ababa are limited, requiring estimation from available government statistics.
- **Model Simplification:** The model necessarily simplifies complex real-world factors such as land availability, permit processes, and grid capacity constraints.
- **Dynamic Factors:** EV adoption and charging behavior are likely to evolve rapidly, requiring continuous model updates.
- **Operational Constraints:** Detailed operational constraints of existing stations require further specification for comprehensive modeling.
- **Budget Assumption:** The $300 million budget is an estimate; actual costs may vary based on land acquisition and grid connection requirements.

Future Research Directions

- **Integration with Renewable Energy:** Future research could extend the model to incorporate solar-integrated charging stations.
- **Behavioral Modeling:** Incorporating EV user behavior and charging patterns using agent-based simulation would enhance the model's realism.
- **Comparative Analysis:** Comparative studies of charging infrastructure optimization across multiple African cities would provide valuable insights.

- **Real-Time Optimization:** Developing dynamic models that can adjust to changing EV adoption patterns would be valuable for long-term infrastructure planning.
- **Reverse Logistics Considerations:** Extending the optimization to include end-of-life battery recycling would enhance sustainability.
- **System Dynamics Modeling:** Extending the system dynamics approach to capture feedback loops between charging infrastructure development, EV adoption, and policy interventions.

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Declaration of Generative Ai Usage

The AI tool was used only as an editorial assistant. All aspects of the research design, data collection, data analysis, interpretation of results, and scientific conclusions were conducted independently by the author. The AI did not generate any research data, conduct analysis, or produce original findings.

Data Availability Statement

The complete input datasets, anyLogistix model files, and optimization results are available from the corresponding author upon reasonable request.

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