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Article

Grid to Ground: A Transportation Problem Approach to Evcharging Infrastructure

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Abstract: Since electric vehicles (EVs) are being used more and more quickly, there is a strong need to develop charging infrastructure. This research investigates how we use the transportation problem—a usual linear programming problem—to arrange EV charging stations in an optimal manner. In this way, the model hopes to lower fuel use and the distance needed for delivering power by guiding generation points to areas near charging stations and linking future charging centres to regional destinations. Using this approach helps city planners and decision-makers speed up EV use and develop future-oriented transportation systems at a lower cost. Since more people are using electric cars, we need to focus quickly on building convenient EV charging systems in both growing urban and rural areas. This paper uses the classical transportation problem, a method from linear programming, to improve the way EV charging stations are placed and distributed. When regional needs, setup costs and grid capacity are taken into account, the model suggests an efficient, data-based way for both policymakers and urban planners to support and build EV infrastructure and support sustainable, smart cities.

Keywords: Sustainable, Operational, Optimization, Efficiency, Logistics.

INTRODUCTION

Lots more people are buying electric vehicles because of a global trend toward sustain ability, higher fuel charges and new developments in clean energy. Because EVs are now used in both city and country areas, it's more important than ever to have dependable and easy access to charging stations. If strategy is lacking, it's likely charging stations will end up being unused or used unfairly and there will be more delays, especially in areas where infrastructure is limited. As a consequence, more ways are needed that will rely on data and save costs to help decide where to build EV charging stations. This paper looks at the transport problem, a traditional linear programming tool, for optimizing the design of EV charging infrastructure. To reduce the price and distance, the model maps power supply centres as sources and potential charging locations as destinations. As well as keeping costs low, the approach focuses on giving everyone equal access, so that charging networks expand at a suitable pace for the demands in the region. Since the model uses real world information such as set-up costs, rates of electric vehicle adoption and grid usage, it can be applied easily around the world. Results from this research support efforts to make urban and rural transportation systems smarter and more environmentally friendly. It allows policymakers, urban planners and utility providers to plan approaches, quickly set up EV infrastructure and help achieve clean energy and sustainability.

1.1 Motivation for the study: Since transport is a leading cause of greenhouse gas emissions, moving to electric vehicles (EVs) can greatly help the environment and make travel more sustainable. Even with plenty of EVs on the roads, adoption won't be successful unless charge points are available. As cities expand and rural areas become more modern, it is becoming more and more difficult to charge your car in many areas. A lack of accessible charging points in many places leads to gaps that stop people from using EVs and promote only limited growth. Meanwhile, erroneous sites for stations may cause them not to function properly, raise stress on the power grid and result in extra expenditure for infrastructure. To handle these issues, infrastructure strategy should use data to find solutions that consider cost, how easily people can access it and how efficient the grid is. This widely applied logistics tool provides a promising structure to deal with this challenge. The way it improves delivery from power supply centres to charging sites is comfortable with how EV networks are set up. This research is aimed at building a useful, expandable approach that helps guides decision-making by planners, utilities and policymakers about EV charging installations. This research uses linear programming to support a transportation ecosystem that is fairer, more efficient and better for the environment

1.2 Contribution of the Study: This study introduces a number of ground breaking ideas to the field of sustainable transportation planning and infrastructure optimization.

(i)Implementation of the Transportation Problem in EV infrastructure: The authors apply the classical transportation problem—a linear programming model—to the process of planning where to place EV charging stations. It offers a planned system for allocating electricity from power centres to charging stations. (ii) Infrastructure planning that saves money: Because of the model, costs and kilometres travelled are kept to the lowest level possible to support efficient networks for electric vehicles. (iii) More access to healthcare for the public: The addition of regional needs and unique locations helps the study meet EV charging demand in all sections of society, including areas less served by these stations. (iv)A Tool for Making Decisions with Data: Because of the framework, urban planners, utility providers and policymakers now have a practical method for making decisions. It helps develop infrastructure for upcoming energy use and increasing use of electric vehicles. (v)How easy it is for the business to adjust to change and grow. Due to its flexibility, the model can be tailored to different places and mixes of energy which makes it a helpful choice for all areas increasing their EV infrastructure. (vi)Support for the United Nations Sustainable Development Goals (SDGs). The report supports global goals by stimulating the growth of sustainable forms of transportation, affecting SDG 11 and SDG13.

REVIEW OF LITERATURE

Latpate and Kurade (2022) present a multi-objective multi-index transportation model specifically tailored for crude oil logistics. The study employs the fuzzy Non-dominated Sorting Genetic Algorithm II (NSGA-II) to handle the inherent uncertainty and vague ness in transportation parameters such as costs, demands, and supply levels. Complementing this approach, Mahan et al. (2025) develop a multi-objective optimization model using goal programming to design a multi-period blood supply chain network. Their model integrates uncertainty in supply and demand, while also incorporating social considerations, such as equity in healthcare access. This study stands out for its holistic perspective, accounting not only for operational efficiency but also for ethical dimensions of resource allocation. Bassam, Samson, and Leslie (2025) conducted a comprehensive experimental and numerical investigation into the aerodynamic behaviour of a flexing wing with active camber design. Their study addresses the limitations of traditional fixed-wing configurations by introducing a flexible aerodynamic surface that can adjust its camber dynamically. In contrast, Bhatia and Rana (2020) apply a linear programming model to optimize crop allocation in the agricultural sector. Their study formulates an objective function to maximize profit based on constraints like land availability, labour, water, and crop-specific requirements. The model aids in determining the best combination of crops that a farmer should cultivate to ensure optimal use of resources while maximizing returns. Shalini, Polasi, and Lakshmi (2023) present a compelling study that utilizes the Analytic Hierarchy Process (AHP) to facilitate decision-making in the selection of organic food farming systems. Wang et al. (2025) investigate the fuel reactivity-controlled auto ignition (FRCA) and the associated combustion characteristics in a supersonic combustor by examining the impact of various turbulence models. The study employs advanced computational fluid dynamics (CFD) simulations to analyse how different turbulence modelling approaches—such as k-ε, k-ω, and Reynolds Stress Models (RSM)—influence the ignition delay, combustion efficiency, and flame stability. Shalini and Polasi (2024) explore the application of goal programming models integrated with R programming to address the problem of acreage allocation—that is, how to optimally assign available land to different crops or uses based on multiple, often conflicting goals. Several studies have explored the application of optimization techniques, such as linear programming and goal programming, in solving complex decision-making problems across various domains. Heydari et al. (2018) utilized linear programming to predict the required amount of fertilizers for agricultural products based on an optimum cropping pattern. Their research demonstrated how optimization models could enhance resource allocation in the agricultural sector, ensuring efficiency and sustainability in production. Jagtap and Kawale (2017) addressed a Multi-Dimensional Multi-Objective Transportation Problem using goal programming. Their study contributed to the field by proposing a structured method to handle multiple conflicting objectives simultaneously, which is highly relevant in transportation and logistics planning. The goal programming approach proved effective in optimizing costs, time, and other vital factors. Kaur, Rakshit, and Singh (2018) presented a novel method to solve multi-objective transportation problems. Their approach emphasized the importance of balancing different objectives in transportation systems and offered improved solutions over traditional methods. This research highlighted the growing need for adaptable and efficient models to address the complexities in real-world logistics.

METHODOLOGY

The approach in this research has been systematized to be applicable within the transportation problem framework in order to optimize the location and amount of charging facilities for EV drivers. The approach can be summarized as follows:

3.1 Problem Definition and Modelling (i)

Sources and Destinations: Power supply centres (referred as grid hubs hereafter) are considered as sources; whereas, potential EVCS sites are treated as destinations. Each source has a rated power capability and each destination has a rated power requirement determined from the expected EV usage and regional factors.(ii)Decision Variables: The quantity of power (or number of chargers) transported from each source to each destination is the key decision variable to be determined.(iii)Objective Function: The main goal is to minimize the total transportation cost, which can include: The cost of transmitting power over distances, Installation and operational costs at charging stations, Possible penalties for unmet demand or overloading grid hubs.(iv)Constraints: Supply Constraints: Power dispatched from each source should not exceed its capacity. Demand Constraints: Power delivered to each destination must satisfy or closely meet its demand. Capacity and Accessibility Constraints: Charging station locations may have physical or regulatory limits on the number of chargers installed. Grid Capacity Limits: Ensure the local grid can handle the power flow without instability.

3.1.1 Data Collection

- Power Supply Data: Gather data on power generation capacity, grid hubs, and their locations.
- Demand Estimation: Project regional EV adoption rates using demographic, eco nomic, and transportation data to estimate charging demand per site.
- Cost Parameters: Include transmission cost per unit distance, installation and maintenance costs, and any other operational expenses.
- Geographical Data: Use GIS data to calculate distances between sources and destinations and to identify feasible charging station sites.

3.2 Mathematical Formulation: When using an Objective Function, supply constraints and demand constraints, mathematical formulation can be performed.

3.3 Solution Approach: Using common specialized transportation algorithms to find the best solution. Study how your system responds when scenarios are altered by demand, finances or rules about grid resistance.

3.4 Analysed sensitivity and validation in my model research: Compare results from the model to the already available information on charging stations or pilot project results. Explore the effects of demand, changes in prices and grid capacity on the optimal answers obtained

3.5 Implementation Guidelines: The model's results guide the team in recommending steps for rolling out charging stations. Compatibility with stakeholder needs and regulations helps to make a project successful. This way of working helps to make sure EV charging works well, is driven by data and can be changed to fit the needs and costs of the setting

4 Mathematical Formulation

Objective Function:

$$\text{Minimize } Z = \sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}x_{ij} \qquad (1)$$

Subject to:

Supply Constraints (each source can't send more than available):

$$\sum_{j=1}^{n} x_{ij} \le s_i \quad \forall i = 1, 2, \ldots, m \qquad (2)$$

Demand Constraints (each site receives required number of panels):

$$\sum_{i=1}^{m} x_{ij} \ge d_j \quad \forall j = 1, 2, \ldots, n \qquad (3)$$

Non-negativity:

$$x_{ij} \ge 0 \quad \forall i, j \qquad (4)$$

Where:

- x_{ij} : amount of power transported from source i to destination j
- C_{ij} : transportation cost per unit from source i to destination j
- s_i : supply capacity of source i
- d_j : demand at destination j

5. NUMERICAL PROBLEMS SET UP (1) (2) (3) (4) A utility company is trying to meet the energy demands of 6 EV charging stations using the least amount of money by distributing electricity through its 5 supply centres. Power from5centres has to be distributed to 6 locations where EV charging stations are placed. All supply centres have a max power output and all EV stations use that same Check total supply and demand: • Total supply = 1200 + 1000 + 1400 + 1100 + 1300 = 6000 kW • Total demand = 900 + 700 + 800 + 600 + 900 + 1100 = 5000 kW Since total supply > total demand, add a dummy destination D7 with demand = 1000 kW (to balance). Cost from each source to D7 = 0

This complex transportation problem solved by using the North-West Corner method for initial feasible solution, then improve it via the MODI method (also called UV method) to minimize total cost.

Initial table Feasible Solution using North-West Corner Method

Source \ Destination	D_1	D_2	D_3	D_4	D_5	D_6	D_7 (dummy)	Supply
S_1	7	9	3	4	8	6	0	1200
S_2	6	4	7	5	6	7	0	1000
S_3	8	5	6	4	7	5	0	1400
S_4	9	7	4	3	5	6	0	1100
S_5	5	6	8	7	4	3	0	1300
Demand	900	700	800	600	900	1100	1000	6000

Initial Feasible Solution Allocation Table

Source \ Destination	D_1	D_2	D_3	D_4	D_5	D_6	D_7 (dummy)	Supply Left
S_1	900	300	0	0	0	0	0	0
S_2	0	400	600	0	0	0	0	0
S_3	0	0	200	600	600	0	0	0
S_4	0	0	0	0	300	800	0	0
S_5	0	0	0	0	0	300	1000	0

5.1 Optimal Transportation Plan using MODI Method Here's the optimal allocation (minimizing total cost): Total Minimum Transportation Cost: Rs. 20,800

Source	D_1	D_2	D_3	D_4	D_5	D_6	D_7 (Dummy)	Supply
S_1	0	0	800	400	0	0	0	1200
S_2	300	700	0	0	0	0	0	1000
S_3	0	0	0	0	0	400	1000	1400
S_4	0	0	0	200	900	0	0	1100
S_5	600	0	0	0	0	700	0	1300
Demand	900	700	800	600	900	1100	1000	6000

5.2 Comparison of the results 9:

This solution is obtained using the MODI method, starting with a VAM-based feasible solution and then optimizing. Total Transportation Cost using North-West Corner Rule: Rs.29,800. This is not optimal and significantly higher than the MODI solution of Rs.20,800. Compared to the optimal solution via the MODI method (Rs.20,800), this is Rs.9,000 higher, indicating: The North-West method does not minimize cost. It's only a starting point for further optimization (e.g., with MODI or Stepping Stone).

- As the current solution is optimal, we use the MODI method to evaluate (it's not).
- Identify opportunities to reallocate shipments to lower-cost cells.
- Iterate until all unused cells satisfy the optimality condition (i.e., no negative opportunity costs).

Summary of the transportation problem distribution of electric vehicle (ev) charging stations.

Metric	Value
Method Used	North-West Corner
Feasible?	✓ Yes
Optimal?	× No
Total Cost	Rs. 29,800
Optimal Cost (MODI)	Rs. 20,800
Cost Difference	Rs. 9,000 (↑)

5.3 Conclusion: Distribution Optimization for EV Charging Stations This transportation problem effectively models a real-world logistics challenge faced by a utility company: distributing electric power from multiple power supply centres to a network of EV charging stations at minimum cost

Insights:

- The North-West Corner Method, while simple and fast, ignores transportation costs, leading to a feasible but cost-inefficient solution.
- The MODI Method (Modified Distribution Method) starts with a basic feasible solution and iteratively improves it by identifying opportunity costs and reallocating shipments to lower-cost routes.
- The MODI method reduced total distribution cost by Rs.9,000, or nearly 30% compared to the initial North-West allocation

Metric	Value
Method Used	North-West Corner Rule (Initial)
Initial Total Cost	Rs. 29,800
Method Used for Optimization	MODI (UV) Method
Optimal Total Cost	Rs. 20,800
Cost Savings Achieved	Rs. 9,000 (↓ 30%)
Feasible Solution	✓ Yes
Optimal Solution	✓ Achieved

Practical Implications: A plan that is feasible may not always be the least expensive choice. The model is adaptable to systems with multiple sources and destinations, and also to real-time factors such as prices, energy losses from distance, and infrastructure problems. Artificial Intelligence models assist in making decisions for utility companies, supporting better resource organization and sustainability.

Final Summary: The significance of this case is evident by revealing that efficient EV and infrastructure planning relies on the combination of transportation modelling and the MODI approach. When modelled well, it allows effective analysis of supply, demand, and price. Ensuring all EV stations are reliably connected keeps them operational, conserves energy resources, and helps companies reduce distribution expenses. Optimal Distribution of Electricity to EV Charging Stations: This study on optimizing electricity distribution from power supply centers to EV charging stations provides several practical and strategic benefits, particularly for utility companies, city planners, and sustainability initiatives.

- Cost Efficiency: Minimizes the cost of distribution. Using the MODI method cut transportation costs by Rs.9,000 compared with the previous best allocation. This elevates profit levels for the company. A decrease in energy delivery costs means a business can earn more without changing its costs or service quality for customers.
- Utilizing Resources Optimally: Prevents power wastage at supply centers by ap plying a system that decides power plant contributions based on cost-efficiency. It controls overloading or under-utilization and distributes load across centers to avoid resource strain and energy waste

Scalability and Flexibility: The model is designed to scale with additional charging stations and power sources. It can quickly adapt to real-world changes such as new demand patterns, pricing adjustments, or outages.

- Promoting Sustainability and Green Transportation: Helps support the adoption of electric vehicles by guaranteeing accessible charging. Proper electricity distribution reduces power loss, indirectly lowering reliance on fossil fuel generation and carbon emissions.
- Informed Decision-Making: Enables utility companies and planners to make data driven decisions regarding investments and balancing electricity demand. Identifies high-cost routes or locations for targeted improvements.
- Automation and Smart Grids Integration: Algorithmic allocation provides a solid foundation for integrating into automated energy management software and smart grid technologies.
- Real-Time Optimization: The approach can be used in real time by adjusting to dynamic changes in energy demand, prices, and grid availability.

5.4 Validation of the Transportation Model: It is important to check the integrity of the model for transportation. Checking validation provides proof that the model represents the truth about the world we live in. (i) Make survey our supplies are equal to your needs for demand: Validated: There are 6000 kW of total supply. Together, all demand plus that for the dummy destination adds up to 6000 kW. A fair approach to transportation makes it possible to use transportation systems that use MODI. (ii) Constraint Satisfaction: Validated: In both feasible and optimal allocations, all supply and demand constraints are being respected. All services are handled within the limits of capacity and demand. (iii)Non-Negativity Check: Validated: All the initial and optimal solutions have all xij values greater than or equal to zero. No negative rejections by both physical and mathematical standards.

5.5 Sensitivity Analysis It examines what happens to the best solution and the total cost if the main inputs (such as costs and supplies) are adjusted. It is very important for a company's ability to adjust its operations.

A. Sensitivity to the Cost Coefficients (Cij) Objective: Check how tiny changes in costs affect what is the best decision. Get the MODI solution and use the opportunity cost matrix it gives as a guide. When opportunity cost for a non-basic variable is positive, reducing that cost can make it available for allocation. The cell is degenerate when cost sensitive = 0 and means that any increase in cost leads to shut down. If opportunity cost for any cell is negative, the decision is not still the best option. When fuel requirements or repairs affect transportation costs, firms might need to move resources. Recommendation: Find out which cells are critical (they have zero opportunity cost) and pay attention to how their costs change.

B. Adjusting to changes in the number of products available Maintenance results in S3 dropping from 1400kW to 1000kW. Total supply is 5600, but demand stays at 6000 →It's not possible. Somehow the model will need to be changed: consume less energy, buy more from elsewhere or distribute the energy differently. Solution: Try increasing power purchases from outside or carrying out load shedding or just rerun the model now that the capacities are updated. We should either keep a spare supply or organize an alternative source should there be an outage.

C. Sensitivity to Demand Changes: Changes in demand are sensed by managers and affecting decisions are made to respond.

Scenario: Outcomes if the number of loads on D6 jumps from 1100kWto1300kWThe new demand is still within the supply of energy available. If you raise the demand, running the model again would show a new arrangement of suppliers. It has been observed that S5 to D6 is already used as a route, with a cost of 3. You should expect rates to go up except when low-cost routes have excess capacity. In places where EV stations are most needed (e.g., urban centres), several low-price pipelines should be connected. Recognizing that destination is a dummy diversifies the results. Whenever it falls to us in the future: Demand is equal to supply, so the dummy node can be dropped. If total demand is greater than what is supplied, a penalty can be created by adding an extra source with a very high cost. 5.6 Final Conclusion with Validation & Sensitivity Insights The transportation model is sound and can be used, because it also reflects the MODI approach and was successfully optimized. Cost optimization team could save Rs.9,000 which is a great amount (30%). Sensitivity analysis finds that the cost coefficients, S3's capacity and D6's demand are the most sensitive — they should be watched closely. The model can now be used as the foundation for a system that guides utility decisions in real time. Smart grid technologies will be used. Demand response that takes place immediately

CONCLUSION

This study not only addresses a technical logistics problem but also contributes to the broader goals of cost control, sustainability, infrastructure efficiency, and customer satisfaction. As electric vehicles become mainstream, such models will be critical tools for managing energy infrastructure smartly and sustainably. Societal benefits of the study: When electricity distribution is optimized for EV charging stations, many social advantages result. Also, by keeping charging stations running will allow more people to use electric vehicles which helps reduce air pollution. In addition, the design decreases power waste during transmission, helping make resource use more efficient. Discovering cost-effective ways to produce EVs could reduce charges for charging, making eco-friendly travel less expensive for people. On top of that, a well-balanced distribution system means the service is not often interrupted and outages are unlikely for EV users. The study also encourages environment-friendly urban growth by merging energy and transport systems and planning in a smart way. Thanks to advanced optimization, utility management is driving advancements such as smart grids and

systems for real-time energy use which are good for everyone in society. Besides, well-designed EV charging infrastructure helps economic growth by offering work opportunities in fields such as planning, computer programming, system maintenance and energy usage. Cities that upgrade their energy distribution systems need more skilled experts, creating more jobs and improving the economy where people live. Moreover, when charging is easy and stations are reliable, it motivates more people to get into electric vehicles, lowers the country's use of fossil fuels and increases national energy security. When we make transportation cleaner and strengthen infrastructure, optimization helps both the community and each individual live a healthier and eco-friendlier life. Acknowledgements The authors would like to thank the editor and the anonymous reviewers for providing enlightening comments and useful suggestions. Their helpful ideas made this article clearer, improved its writing and made it effective

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