Centre for Transportation and Logistics
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March 2023

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Abstract

Electric Vehicles (EVs) are expected to play a significant role in the reduction of global emissions originating from the transportation sector. Penetration of EVs has been shown to be a significant enabler for rapid adoption of EV technology among light-duty passenger vehicles. An analysis of contemporary EV charging technologies and charging mechanics is performed. The location of EV fast charging facilities in an urban transportation network is posited as a part of an existing body of research on facility location optimization.

A flow capturing facility location problem is formulated for identifying optimal locations of EV fast charging points in an urban transportation network. In the solution, vehicular traffic is allocated using a shortest path algorithm to optimally located charging stations. The weighted total supply chain costs consisting of operating costs (OC), travel costs (TC), and service costs (SC) is minimized. A concave service cost function is included to ensure adherence to preset service levels, which is then approximated as a set of linear constraints. A computationally efficient solution to the mixed integer linear programming (MILP) problem is obtained using IBM ILOG CPLEX.

The sensitivity of optimum facility count and computational time with increasing order of magnitude of operating cost is analyzed. Using a social equity approach, facility count and total costs are analyzed by restricting the maximum customer detour permitted within the model.

Keywords: Electric vehicles, DC fast charging, facility location optimization, urban transportation

Introduction

The transportation sector has emerged as one of the biggest contributors to global greenhouse gas (GHG) and CO_2 emissions in the 21st century. According to a report by the International Energy Association (IEA), the transportation industry contributed 37% of global CO_2 emissions from end-use sectors in 2021, and achieving the Net Zero Emissions target by 2030 will require a reduction in global roadways related emissions by a massive 35% from the 2021 levels[1]. Reduction of emissions from transportation is therefore a crucial factor in combating climate change. Since the 1990s, there has been an effort to calculate the total cost of transportation by including the social and environmental impact during computation (Greene and Jones, 1997). Adoption of greener technologies which reduce emissions has been unequivocally identified as the key enabler of reduction in adverse impact of transportation upon the environment (Geerlings, 1996; Gwilliam and Geerlings, 1994).

[1] https://www.iea.org/topics/transport

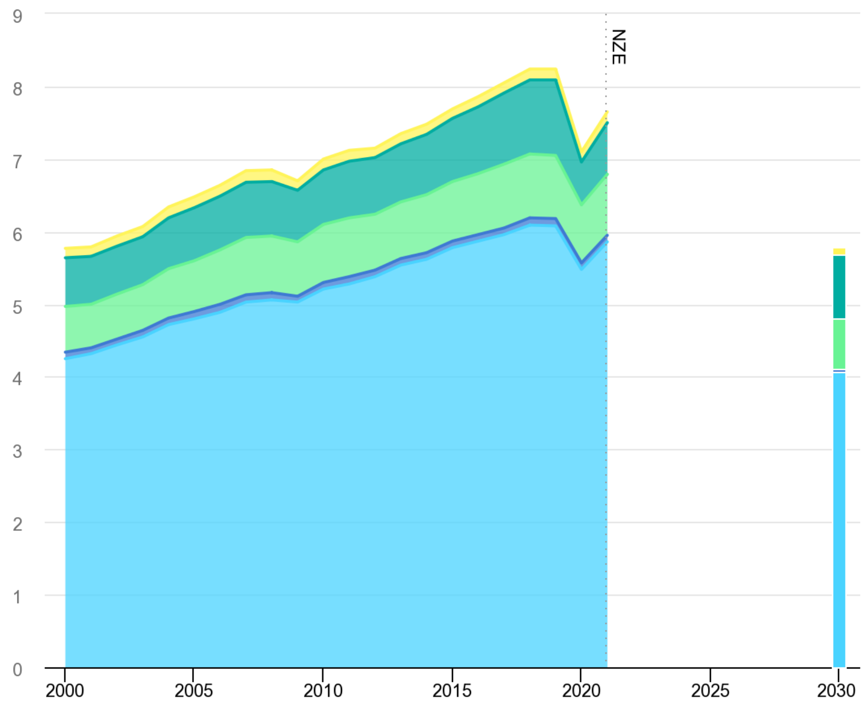


Fig. 1: Global CO_2 emissions from transport by sub-sector in the Net Zero Scenario, 2000-2030 (International Energy Agency 2021)

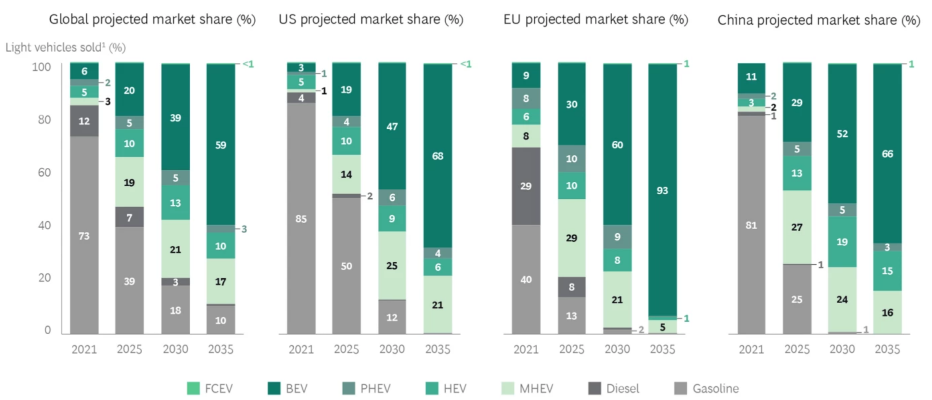
Beyond Internal Combustion: The Role of Alternative Fuel Vehicles

According to the US Environmental Protection Agency (EPA), the light-duty vehicle sector alone contributes 57% of total transportation emissions[2]. Over the past decade, there has been a growing call for shifting from internal combustion vehicles (ICVs) powered by petrol, diesel, methane, natural gas, etc, to alternative fuel vehicles (AFVs) (Günther et al., 2015; Reitz et al., 2020). The movement away from internal combustion driven transportation has been strengthened by both academics and

[2] https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions

industrial practitioners across the spectrum. Since the beginning of the millennium, researchers have been adding to the academic evidence in favor of the shift – electric vehicles (EVs) are potentially more fuel efficient than ICVs (Moriarty and Wang, 2017), incur lesser per kilometer running costs (Eaves and Eaves, 2004), and contribute to large public health benefits (Choma et al., 2020). On the other hand, a 2022 report by the Boston Consulting Group (BCG) highlighted the stringent and demanding environmental regulations in US & Europe and an increasing focus of automakers on electric vehicles as key contributors to a very rapid growth in battery operated EV sales in the developed economies[3].

Exhibit 1 - Battery Electric Vehicles Are Projected to Make Up 20% of Global Sales in 2025



Source: BCG analysis.

Note: FCEV = fuel cell electric; BEV = battery electric; PHEV = plug-in hybrid electric; HEV = full hybrid electric; MHEV = mild hybrid electric. Because of rounding, the percentage total for a particular year may not equal 100%.

¹Forecast includes cars, SUVs, and all other light vehicles except heavy vans.

Fig. 2: Electric Cars Are Finding Their Next Gear (Boston Consulting Group, 2022)

A few additional environmental benefits from increased EV adoption may be summarized as follows:

[3] https://www.bcg.com/publications/2022/electric-cars-finding-next-gear

- Renewable energy integration: Electric vehicles can help integrate renewable energy into the grid by charging during periods of excess renewable energy generation. This can help reduce the need for fossil fuel-based power generation and increase the penetration of renewable energy sources. Technologies such as vehicle-to-grid (V2G) selling has the potential to offset uncertainties in electricity demand and as a storage device hedging against energy shortage – thereby acting as a virtual power plant (Zhang et al., 2021).
- Zero tailpipe emissions: Tailpipe emissions contain harmful noxious pollutants such as carbon monoxide, nitrogen oxides, sulfur compounds, etc, which are difficult to capture within the limited size of individual combustion-fueled engines. Electrically operated vehicles do not have any tailpipe emissions; even for thermally generated power, plant-level emissions can be captured with much greater efficiency due to the benefits of technology and scale (Gustafsson et al., 2021).
- Lower lifecycle emissions: Even when taking into account the emissions generated from fossil fuel based power generation and battery production, electric vehicles have lower lifecycle emissions compared to gasoline or diesel vehicles (Gustafsson et al., 2021).
- Reduced noise pollution: Electric vehicles are much quieter than internal combustion engine vehicles, which can help reduce noise pollution in urban areas.

It is crucial to make note of the opinion among academics and practitioners that efforts to popularize EVs need to be supplemented with a shift towards electricity production from renewable sources (Álvarez Fernández, 2018; Sandy Thomas, 2012) and developing a sustainability & life cycle assessment framework for EVs (Faria et al., 2012; Ma et al., 2012; Towoju and Ishola, 2020). There exists a line of argument which raises concern about how EV technology's intended environmental benefits are greatly correlated with the methods of electricity generation, which in a lot of instances is still dependent on non-renewable sources. While the scrutiny regarding dirty sources of electrical power are perfectly legitimate, the following points are worth noting:

- Energy efficiency: Even when electrical power is generated from fossil fuel, the engineering processes used to generate electricity from fossil fuel are much more efficient as compared to the gasolene-dependent internal combustion cycles used in conventional vehicles. So even in the instances where the source of electricity is not a clean one, EVs provide a much cleaner alternative in terms of energy efficiency.
- Local pollution: EVs do not generate any localized pollution, as compared to internal combustion vehicles - a source of degradation in air quality in urban areas with high population density and traffic congestion.
- Movement towards cleaner electricity: The pace of migration towards clean energy is speeding up. Backed up by high-end R&D going into renewable energy generation at affordable costs, most countries have boosted efforts to make their economies less reliant on fossil fuel and non-renewable energy sources. India's clean energy capacity itself has increased by a whopping 396% in the past decade, with 40% of the total installed capacity coming from renewable sources[4]. The United States also generated 20% of its total electricity from renewable sources in 2021 - a significant proportion in view of the country's total energy consumption[5].

[4] https://www.investindia.gov.in/sector/renewable-energy
[5] https://www.eia.gov/tools

Market Penetration of EVs: Current state and challenges to adoption

EV adoption is still in the nascent phases in most of the emerging economies. Based on qualitative and empirical research conducted in India, Sweden, South Africa & China, the most significant barriers to widespread adoption of EVs are shortage of charging stations, unavailability of reliable electricity, lack of incentive programs, ignorance about advantages, high price points (Moeletsi, 2021; Patyal et al., 2021; Tarei et al., 2021; Vassileva and Campillo, 2017; Wang et al., 2017). The pace of adoption of EV technology has been comparatively faster in the public transportation system in India and other parts of the world. This could be accorded to the benefits of scale, investment, and predictability associated with public transport systems, and widespread support for modernizing public transport systems (Guno et al., 2021). Such momentum however has not been seen for private vehicles, which also happen to be a far larger contributor to transportation emissions (Nour et al., 2020).

The density and accessibility of public charging infrastructure has been empirically observed to have a strong influence on EV adoption patterns (Kumar et al., 2021; Narassimhan and Johnson, 2018). Along with financial incentives, charging infrastructure availability has been shown to be the most significant regressor behind a country's EV market share (Sierzchula et al., 2014). In an interesting study recently conducted on a specific urban context in Montreal, authors show that expanding the public charging network and increased awareness among potential EV adopters about the infrastructure availability can positively impact the shift towards EVs (Renaud-Blondeau et al., 2022). Increasing the penetration of the EV charging network assumes paramount importance, and therefore arises the question of optimally locating the charging points to maximize the benefit of both customers and charging service providers within the EV ecosystem. This brings the problem within scope of the well-known facility location optimization problem.

Mechanics of EV Charging

Designing the optimum charging infrastructure for EVs requires some understanding of the underlying mechanics of EV charging and its classifications. The Niti Aayog classifies EVs based on charging methods as follows[6]:

- Battery Electric Vehicles (BEVs): These vehicles are solely powered by an electric motor and are charged by plugging them into an external power source such as a charging station or a household outlet. They typically have larger battery capacities, require longer durations of charging, and also have a greater efficiency of operation.
- Plug-In Hybrid Electric Vehicles (PHEVs): These vehicles, also known as parallel hybrids, have both an electric motor and an internal combustion engine. They can be charged by plugging them into an external power source or by using the internal combustion engine to charge the battery while driving. They have greater reliability in terms of travel range, and shorter charging times.
- Hybrid Electric Vehicles (HEVs): These vehicles, also known as series hybrids, have an electric motor and an internal combustion engine, but the battery is only charged through regenerative braking, which converts some of the kinetic energy of the vehicle into electrical energy. These vehicles cannot be charged from the grid.

[6] https://e-amrit.niti.gov.in/types-of-electric-vehicles

- Fuel Cell Electric Vehicles (FCEVs): These vehicles use a fuel cell to generate electricity from hydrogen and oxygen, which is used to power an electric motor. They are typically refueled with hydrogen at specialized filling stations, and the source of mechanical energy comes from chemical conversion of the fuel.

A similar classification is required for the charging equipment used to refuel EVs. According to the US Department of Energy's Alternative Fuels Data Center (AFDC), the classification is done on the basis of charging rates[7]:

- Level 1 Charging: 5 miles of range per hour of charging through a standard 120 V AC plug
- Level 2 Charging: 25 miles of range per hour of charging through a 240V (residential) or 208V (commercial) AC plug
- DC Fast Charging: 100-200 miles of range per half hour of charging through specialized high capacity DC charging points

The private EV owner market can be broadly divided into two overlapping categories according to vehicle charging choices. BEV or PHEV owners have the option of charging their vehicles either at privately owned restricted-use plug-in points (at-home installations, office charging points, etc), or use the network of publicly available EV fast charging facilities. While the capital investment for setting up an at-home Level 1 or Level 2 charger might be out of budget for sections of the potential EV market, publicly available DC fast charging points fill this gap. Operated and maintained by EV manufacturers or the government, the public charging points are moving towards a pay-as-you-use

[7] https://afdc.energy.gov/fuels/electricity_infrastructure.html

model where the customer pays for the kWh-s of electrical power used (similar to paying for petrol or diesel fuel in terms of gallons or liters filled). Contingent upon the capacity of the charging ports, each recharge normally takes around 20 to 30 minutes of time. These public charging stations are typically unmanned parking slots with multiple plug outlets (ranging from 1 to up to 8 points in a single facility, depending upon size and capacity). Penetration of these fast charging stations within urban transportation networks is a key enabler behind widespread EV adoption.

Fig. 3: Shaping the future of fast-charging EV infrastructure (McKinsey & Company, 2021)

Studies conducted in Europe further strengthen the argument in favor of a robust public fast charging infrastructure as a lever for promoting EV adoption (Golab et al., 2022; Razmjoo et al., 2022; Schulz and Rode, 2022). A McKinsey study places the onus on both governments and EV makers to ensure that public charging infrastructure does not become a bottleneck for rapid adoption[8]. The spatial location of these charging facilities, especially in a busy urban transportation network, therefore emerges into relevance. This paper is motivated by the problem of locating public charging stations which optimizes the placement of the facilities while taking into account both service provider cost as well as customer convenience.

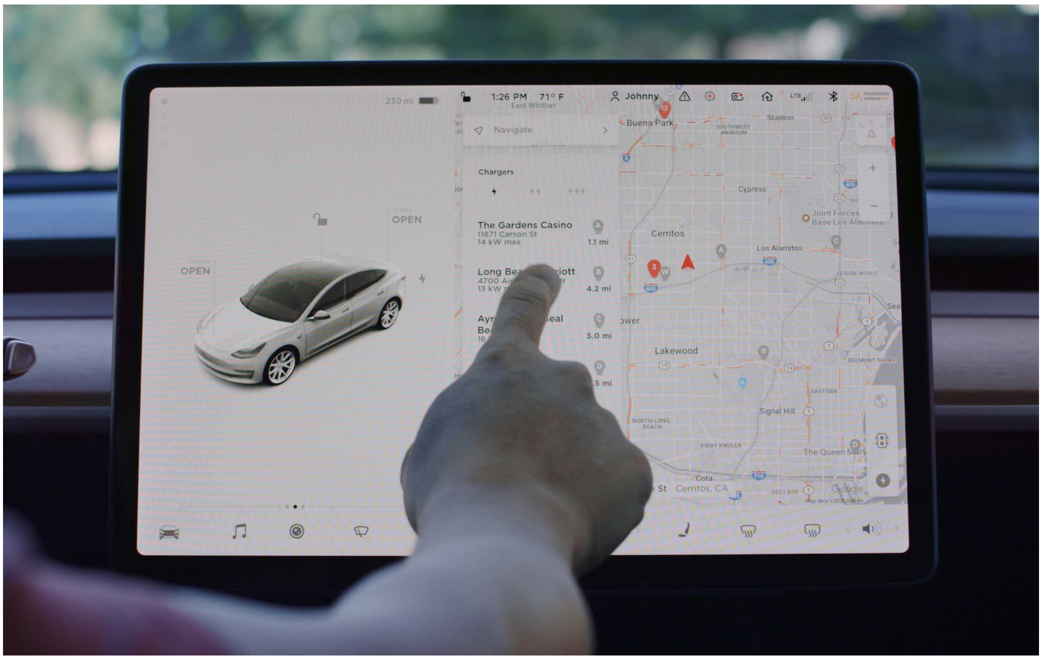


Fig. 4: Destination Charging (Tesla)

The Flow-Capturing Facility Location Optimization Problem

8 https://www.mckinsey.com/capabilities/operations/our-insights/shaping-the-future-of-fast-charging-ev-infrastructure

Academicians have been interested in the optimum facility location problem for multiple decades now. The objective of the problem is to design the geographical distribution of a marketplace which optimizes the performance of the entire supply chain based on one or more predetermined parameters. The final solution identifies the unique set of service facility locations which optimizes the performance of the marketplace. This problem is especially significant in setups where establishing the service facility requires significant fixed cost and operating investment, and therefore it is necessary to ensure optimized operating conditions by.establishing a limited number of facilities under resource restrictions.

The EV charging facility location problem is solved within a network structure consisting of discrete nodes and connecting edges. In an urban context, the nodes replicate major intersections and busy spots within the city, and the edges replicate the roads and interstates which connect the nodes among themselves. The candidate set refers to a set of predetermined nodes where facilities may be located – the "solution space" of the problem.

Much of the work in this type of flow-capturing facility location problem arises from mathematician Oded Berman's work in the early 1990s. Since the 1960s, most of the work in location optimization had been done from the perspective of "single-stop trips" (Hakimi, 1964) – visiting a bank, transferring finished goods from distributor's warehouse to a retail outlet, ambulance services, etc. Berman's work was among the earliest to break the assumption of single-stop trips. He proposed a model of capturing pre-existing customer traffic within a network, which is independent of the service facilities being optimized (Berman et al., 1992). Classic examples include refueling a vehicle, purchasing groceries from a local supermarket, etc. Berman also proved that optimality is necessarily achieved when all service facilities are located on the nodes, and not at any other point along an edge connecting two nodes. None of these activities merit single-stop trips, and in reality are mostly carried out on-the-go.

Berman's original model operated under extensive assumptions, which were gradually relaxed along the way. When multiple facilities lay on the same route, fractional services were allowed with exponentially decreasing flow captured. Requirement of traffic data availability was relaxed by using a Markov decision process to determine traffic volumes. Demand for the service, instead of being mapped to nodes, were instead mapped to the node-pair traffic instead (Hodgson, 1990; Hodgson and Rosing, 1992). Customer detouring was allowed in instances when no facility lies on the direct path, and a customer's propensity to avail a service by rerouting was considered to be inversely proportional to the detour distance (Berman et al., 1995a, 1995b). The cumulative detour distance for the entire population of customers was then used as a parameter for optimization (Li et al., 2022; Zockaie et al., 2016).

Mechanics of Customer Detouring - Social efficiency v/s Social equity

The mechanics of detouring become crucial while locating charging facilities. Following Berman's earlier work, authors allowed detours by the drivers from their shortest route which would allow them to refuel (Kim and Kuby, 2013). Other authors used a set covering method to calculate the number of facilities required for a given vehicle range without provision for detouring (MirHassani and Ebrazi, 2013; Wang and Lin, 2009; Wang and Wang, 2010). If the model allows customers to detour from their shortest path in order to reach the nearest uncapacitated recharging point, it is intuitively evident that it will bring down service provider costs since they can now set up fewer facilities and expect customers to take longer detours; however, more detouring will result in greater customer inconvenience (Kang and Recker, 2015, 2014).

Broadly, the aims of flow-refueling models may be categorized into two types - social efficiency approach and social equity approach (Lin and Lin, 2018). The p-maximal coverage model prioritizes social efficiency by fixing a number of facilities, which are located to minimize a measure of the total detour within the customer space. The p-center set covering models, on the other hand, set a cap on the maximum detour-related inconvenience faced by customers, and accordingly serve the customer set by allocating them to optimally located service facilities. This paper also analyzes the underlying dynamics of balancing the two approaches.

Problem Formulation

The spatial location of charging facilities in an urban transportation network is an NP-hard large scale combinatorial optimization problem where customer traffic is allocated to existing charging points. The complexity of the problem increases since the demand in the charging network originates not from static points on the Euclidean plane - a frequently analyzed variant of the location problem - but instead from pre-existing traffic flows in a city. This paper examines the specific subset consisting of privately owned light-to-medium duty passenger BEV market, and aims to create a fast and efficient algorithm for locating multi-point DC fast charging stations in urban transportation networks.

The problem of EV charging location optimization is formulated as a combinatorial optimization problem which uses mixed linear integer programming (MILP) methods to optimally solve an NP-hard problem. The problem is contextualized as follows:

- Transportation network: The network consists of nodes (representative of urban centers with a concentration of population) and undirected edges connecting the nodes (representative of roads and highways). The strength of an edge is represented by its length – the connecting distance between the nodes. Our study is conducted on a standard 25-node network used by Hodgson in his pioneering work in the 1990s.
- Pairwise traffic volumes: To each unordered origin-destination (OD) pair in the network, a finite traffic volume is mapped. Following the gravity based method, an OD pair traffic volume is directly proportional to the product of the population densities at both nodes, and inversely proportional to the square of the shortest connecting distance between them. In our study, the population densities are chosen from a uniform distribution with specified upper and lower limits.
- Set partitions and customer mapping: "Demand points" in the network are the undirected traffic between the OD pairs. For a network of n nodes, the cardinality of the demand set is $\binom{n}{2}$. The final output of the model partitions the demand points in the network, and every demand point is mapped to exactly one facility.
- Shortest distance paths: Mapping the customers between a node-pair OD to a facility at node at J assumes the customers will sequentially choose the shortest paths connecting O to J and J

to D. The well-known Dijkstra's shortest path algorithm is used to compute these distances within the model.

- Customer congestion: The total traffic mapped to each facility is calculated, and it contributes towards the total congestion at that facility. It is assumed that both the inter-arrival time of customers and the time taken by a customer to recharge follow an exponential distribution, and hence the arrival and charging rates are Poisson processes. A predetermined service level is set apriori, which requires the service provider to ensure a maximum limit on waiting times or queue lengths. Higher traffic allocation i.e. higher arrival rates will therefore need to be compensated by higher charging rate or greater number of service points.

The following components of the total supply chain cost are considered while formulating the objective function:

Service Provider Cost

Service provider cost has two components – facility operating costs and facility service costs.

I. Operating cost (OC): This component captures all costs which are independent of the traffic volume being catered to. Depending on the location of the candidate node, setting up a charging spot will have distinct operating costs. The variation in fixed cost is explained by differences in cost of real estate, power grid capacity, network externalities, etc. In this study, the impact of operating costs on the optimal solution is studied by progressively increasing their order of magnitude by powers of 10. For every simulation, facility operating costs are randomly generated from a uniform distribution within a 5% range of the set order of magnitude.

II. Service cost (SC): This component captures all costs which are positively correlated to the traffic volume. A minimum service level to all customers is ensured with a restriction on maximum waiting time and maximum queue length. With increasing traffic, economies of scale kicks in and results in a diminishing marginal cost of service. The resulting service cost function is concave in nature, and can be modeled using the commonly used square root staffing level principle based on Whitt's studies on congestion in multi-server queues (Whitt, 2004, 1992). Service cost for a traffic arrival rate of λ is expressed as $\theta \times k_1 \times \sqrt{\lambda} + k_2 \times \lambda$, where θ reflects the desired service level.

    This formulation results in a concave nonlinear service cost function, which we then linearize by choosing strategic cut-points over the functional domain. The domain is broken into distinct linear segments and the approximated linearized service cost is computed as a linear combination of the nearest set of cut-points.

It can be intuitively reasoned that the total service provider cost will be minimized when all the traffic within the network is forced to recharge at one single charging point. This ensures both minimum operating cost (since only one facility is active) and minimum service cost (since marginal cost of service will be minimum at the maximum possible traffic level.

Customer Cost

Customer cost consists of the costs borne by the EV owner which is proportional to the distance traveled by the vehicle.

I. Travel cost (TC): Travel cost is computed by multiplying the traffic-weighted sum of the total distance traveled by the population of customers within the network with the cost per unit traffic per unit distance. It can again be intuitively reasoned that the total customer cost will be minimized when every node-pair in the network has at least one charging point located directly on the shortest path connecting them, thus ensuring no customer has to detour from their desired shortest path.

Model Extensions

The following model extensions are proposed beyond the primary model:

I. Weighted sum of cost components: Relative importance of each cost component can be included by setting weights to each cost

II. Social equity considerations: Social equity can be prioritized by removing the travel cost from the objective function, and adding a constraint which restricts the maximum detour any customer is forced to take

III. Fixed facility problem: The number of facilities being opened can be fixed upfront and the locations determined accordingly

Results and Discussions

The mixed integer linear programming (MILP) model was solved using IBM ILOG CPLEX 12.10 and Boost 1.80 libraries. The problem was coded in C++ on Microsoft's Visual Studio 2022. Network visualizations were created using the *igraph* package in R.

Initializing the Problem

I. Hodgson's 25-node network was used to create the network using the Boost package. Based on the network structure, Dijkstra's shortest distance matrix is calculated upfront using Boost, which calculates every pairwise shortest connecting distance between node pairs.

II. Population densities were generated from a uniform distribution using a seeded random number generator in R

III. Common values of congestion constraints θ, k_1, and k_2 were taken from Venkateshan *et al.*, 2010

IV. Traffic flows and traffic cut-points were generated upfront before running the optimization

V. The shortest distance matrix was generated upfront using Dijkstra's method

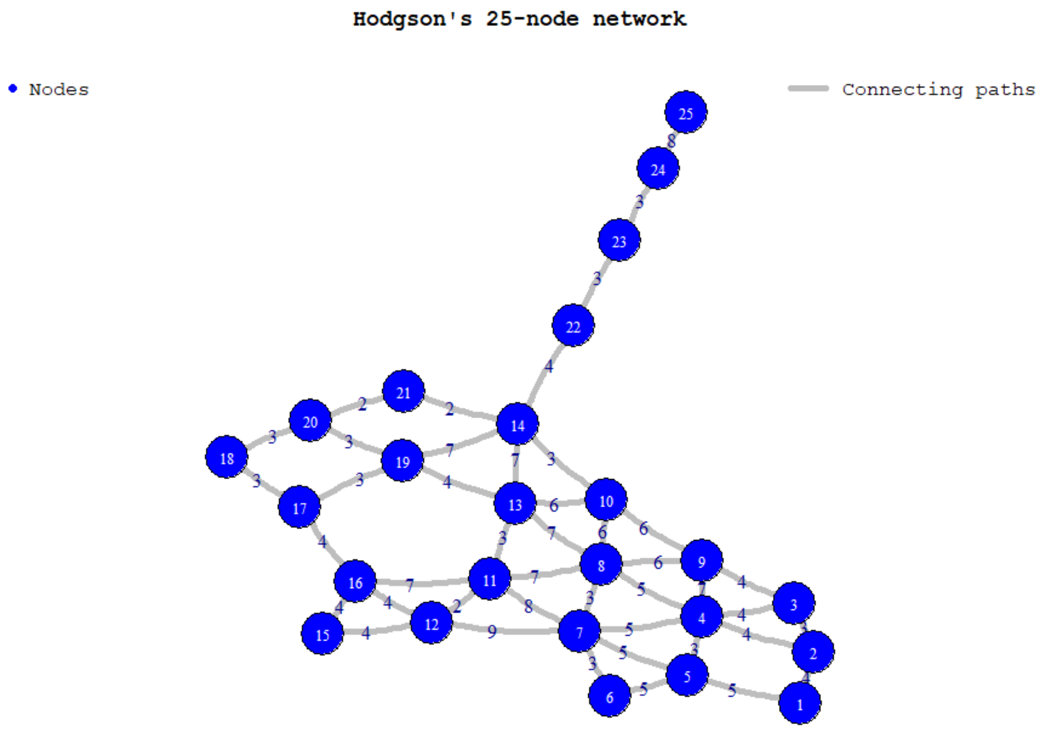


Fig. 5: Hodgson's 25-node network (1992)

The results shown in this paper are all derived from simulations run on artificially generated transportation network parameters. The relative magnitude of different network parameters is a crucial factor. While being implemented in the real world using transportation records and demographic data, the method of solving would remain identical to the one followed in this paper and simply the input parameters would reflect the actual conditions.

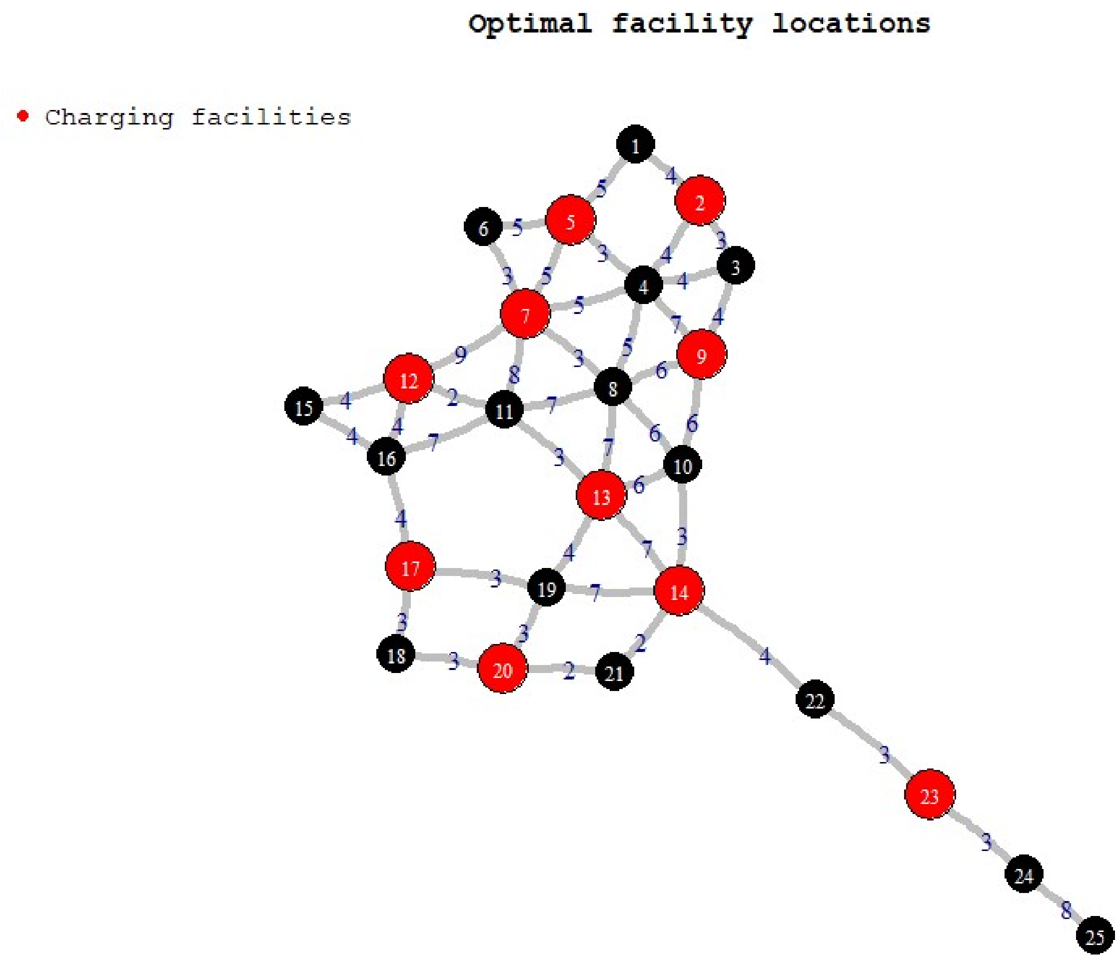


Fig. 6: A sample solution to the facility location problem

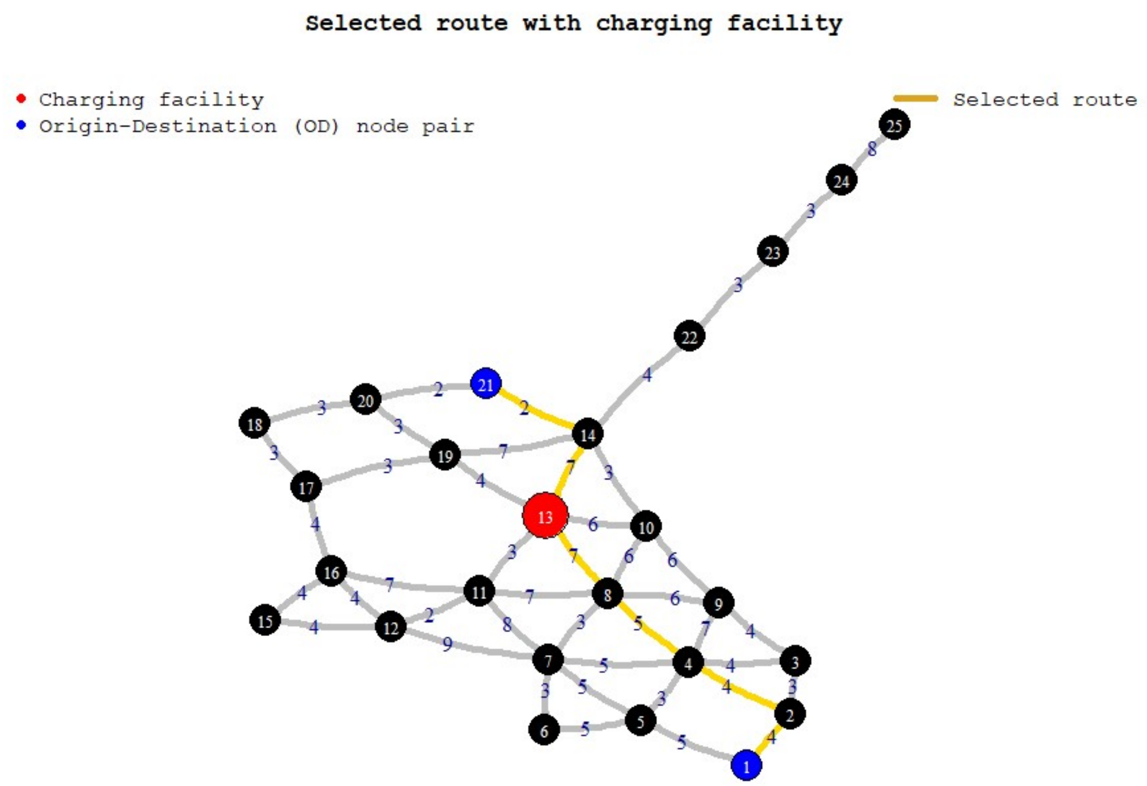


Fig. 7: Selected route with charging facility

Operating cost orders of magnitude (OOM) sensitivity analysis

Facility operating costs could be subject to some variability due to externalities such as real estate cost, network effects from nearby offline stores, electricity tariff, etc. The relative magnitude of facility cost influences the total number of charging points in the network.

The sensitivity of the optimal output to the scale of facility operating costs was tested. A set of operating costs were generated from a seeded random number generator from a uniform distribution with upper and lower bounds at $\pm 10\%$ of the selected OOM. At each level, the simulation was run with five different samples drawn at random from the same distribution. Beyond the topmost range reported in the table, the number of facilities drops down to 1, and further results are trivial in nature. It is also worth noting that the computational time requirement falls as the relative magnitude of operating cost increases. The summary results are reported in Table 1.

OOM	Mean Operating Cost	Median Facility Count	Mean Elapsed Time (s)
$U(10^1 \pm 10\%)$	141 ± 4.85	14	230.67 ± 109.132
$U(10^2 \pm 10\%)$	1391 ± 32.33	14	46.63 ± 15.198
$U(10^3 \pm 10\%)$	13853 ± 242.69	14	21.09 ± 5.666
$U(10^4 \pm 10\%)$	89514 ± 2416.37	9	10.19 ± 2.202
$U(10^5 \pm 10\%)$	292692 ± 7955.49	3	1.43 ± 0.307

Table 1. Sensitivity Analysis of Operating Cost OOM

Maximum allowable detour restrictions

In a variant of the problem using the social equity approach, only the service provider cost (OC + SC) was optimized while constraining the maximum detour customers are forced to take Δ_{max}. Starting from Δ_{max}, the restriction is incrementally relaxed until all customer traffic is directed through a single facility. Operating costs randomly generated from a $U(10^3 \pm 10\%)$ distribution. After restrictions on detour were sufficiently relaxed, the facility count dropped down to 1, and the algorithm selected the node with lowest operating cost within the network to locate the facility. These results reflect the significance of including a social equity parameter to prevent crowding out of non-centrally located customers or de-prioritization of customer convenience. An alternative way of achieving equity in EV charging services is by upfront fixing the number of facilities to be established, and accordingly optimizing the individual locations. The results are shown in Figure 5 and Table 2.

Maximum detour allowed Δ_{max}	**Facility Count**	**Service Provider Cost**	**Elapsed Time (s)**
0	14	71187.40	135.93
1	13	71051.60	225.81
2	14	70859.50	354.98
3	13	69785.70	156.77
4	11	67809.90	28.89
5	11	67749.30	33.57
6	7	63735.50	30.86
7	6	62771.80	29.44
8	5	61873.70	15.08
9	5	61837.80	21.32
10	4	60726.40	7.15
11	4	60725.50	9.06
12	4	60548.00	21.86
13	4	60507.30	40.79
14	3	59608.90	9.80
15	3	59517.80	22.50
16	3	59504.40	27.91
17	3	59503.90	39.25

18	3	59467.40	62.26
19	3	59463.50	77.46
20	3	59402.30	99.47
21	2	59401.80	83.50
22	2	58568.00	5.67
23	2	58456.10	4.17
24	2	58416.00	7.93
25	2	58415.40	10.25
26	1	57440.30	1.05

Table 2. Maximum Allowable Detour Restrictions

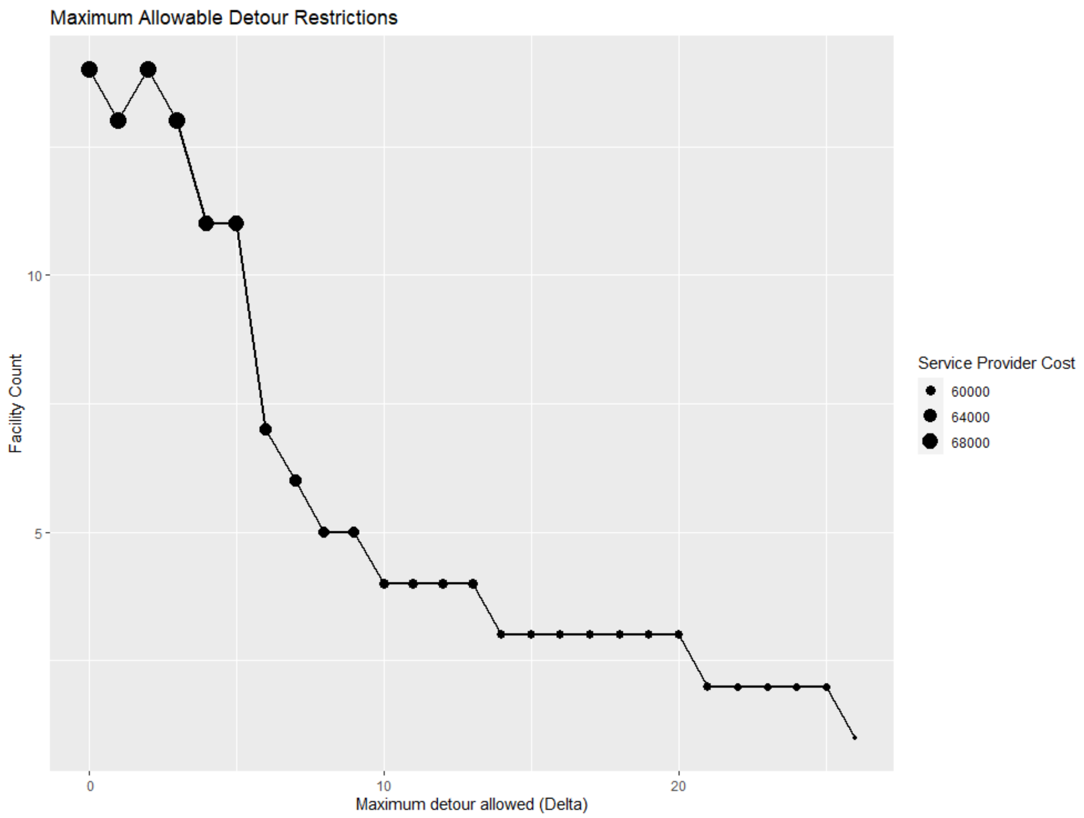


Fig 8. Maximum Allowable Detour Restrictions

Conclusion

This paper highlights the significance of fast charging infrastructure for faster EV adoption, and thereby their optimized positioning in an urban transportation network. We present a novel approach of dealing with flow capturing facility location problems. Pairwise traffic flow is mapped as a set of demand points, and economies of scale are imposed on stochastic facility congestion constraints. The concave service cost function is approximated into a set of linear constraint inequalities. The total supply chain cost consisting of operating cost (OC), travel cost (TC), and service cost (SC) is minimized. The preliminary results show how different orders of magnitude of facility operating costs impact the facility count and computational time, and how social equity constraints and relaxations impact customer detour.

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