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YILDIZ TECHNICAL UNIVERSITY
MECHANICAL FACULTY
DEPARTMENT OF INDUSTRIAL ENGINEERING

Demand Prediction and Placement Optimization Model for Electric Vehicle Charging Stations in istanbul

19069608 Muhammed Talha Gedikli
20069910 Gizem Mum
20069935 Muhammad Harits Aqila Fredyan

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ABSTRACT

In recent years, a transformative shift in automotive preferences towards Battery Electric Vehicles (BEVs) has gained momentum, driven by their environmental advantages and economic efficiency compared to traditional Internal Combustion Engine cars.

This project focuses on Istanbul, Turkey's most populous city, where transportation demands are high. The primary aim is to predict the future demand for electric vehicles in Istanbul and propose a model for optimizing the distribution of new charging stations across the city. This initiative seeks to decrase the range anxiety among EV users by strategically locating charging infrastructure.

The research employs a forward-looking methodology, projecting the number of EVs in Istanbul's districts over the next 30 years. A tailored mathematical model, incorporating the S-curve structure to represent the adoption rate of EVs, will be developed. This model considers factors such as SEGE scores, reflecting the developmental status of each district, to refine projections. The temporal span is divided into six periods, each lasting five years from 2020 to 2050. Through this comprehensive analysis, optimal locations for electric charging stations in Istanbul will be identified at the conclusion of each period, offering a holistic strategy to alleviate range anxiety and foster sustainable growth in EV adoption.

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BEV Battery Electrical Vehicle

CDF Cumulative Distribution Function

EV Electric Vehicle

ICE Internal Combustion Engine

MCSP Maximum Coverage and Shortest Path

MIP Mixed Integer Programming

ND Normal Distribution

SL Saturation Level

TUIK Turkish Statistical Institute

1 Introduction

In recent years, there's been a big change in how people think about cars. More and more people are interested in using Battery Electric Vehicles (BEVs) because they help reduce pollution and are cheaper to run than regular cars with internal combustion engines (ICE). According to some studies, the global share of EVs is projected to reach 70% by 2050 .This shift is mainly because of the environmental problems linked to traditional fuels and their unpredictable prices.

However, even with better technology and batteries in cars, there's still a big issue – there aren't enough places to charge these electric vehicles. The distribution of EV charging stations is sparse in most regions. Because of this, EV owners and potential buyers frequently worry about whether the vehicle will have sufficient charge to travel to their trip destinations or an intermediate charging station. On the other hand, given the high cost of building a charging station and currently low number of EVs, charging station operators would only want to place stations where demands for charging are high. This results in a situation where the charging station density is concentrated near city centres, rapidly decreasing while moving outwards [1] and will create range anxiety for EV users.

1.1 Aim of the Project

Istanbul is Turkey's most crowded city, with a high demand for transportation. This project is an attempt predict the demand of electric vehicle in istanbul in the next years and suggests a model to improve the distribution of new charging stations in Istanbul so as to mitigate the range anxiety of EV users.

1.2 Electric Vehicles

Electric vehicles (EVs) represents a shift in the automotive industry, offering a sustainable and eco-friendly alternative to traditional internal combustion engine vehicles. Unlike conventional cars that rely on gasoline or diesel, EVs are powered by electricity stored in rechargeable batteries. This change from fossil fuels reduces carbon emissions and mitigates air pollution. Beyond environmental benefits, advantages of electric vehicles extends to reduced operating costs, lower maintenance requirements and advanced technology.

Technological breakthroughs, particularly advancements in battery technology, have been essential on enhancing the practicality, range, and overall features of electric cars.

EVs come in various forms, including battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and hybrid electric vehicles (HEVs), each offering unique combinations of electric.

1.3 History of Electric Vehicles

The history of electric vehicles dates back to the late 1820s and 1830s when crude electric carriages were first invented. Practical, commercially available electric vehicles appeared during the 1890s. However, the high cost, low top speed, and short-range of battery electric vehicles, compared to internal combustion engine vehicles, led to a worldwide decline in their use as private motor vehicles in the early 20th century.

Electric vehicles have continued to be used for loading and freight equipment and for public transport – especially rail vehicles. Interest in electric and alternative fuel vehicles in private motor vehicles increased due to growing concern over the problems associated with hydrocarbon-fueled vehicles, including damage to the environment caused by their emissions; the sustainability of the current hydrocarbon-based transportation infrastructure; and improvements in electric vehicle technology [2]

1.4 Battery Electric Vehicles

Battery electric vehicles (BEVs) are the type of vehicles that do not contain a combustion engine and are powered by an electric motor which uses only a battery (usually a Li-ion battery) as its energy source. Batteries of these vehicles can be recharged externally by plugging in a charging station or simply a power outlet. BEVs usually are high efficiency cars with zero tailpipe emission which exterminates the environmental concerns for users.

Recently, this encouraged many car manufacturers to promise changing their entire production line from combustion engine vehicles to BEVs until 2050 .Since there is only one way to empower the BEV, one of the crucially important parameters is distance coverage of the model. Range also is another parameter for customers to make decision on whether to buy it or not. In the recent models, ranges differ between 95 to 695 kilometers which is a huge interval. However, with the purpose of the customer to buy one of those, any model of BEV can be appropriate to afford. [3]

2 Demand Prediction for Districs of Istanbul

Istanbul stands as Turkey’s most populous city, grappling with substantial transportation demands. Electric Vehicles (EVs) emerge as a highly promising solution for sustainable and efficient mobility. Studies suggest that the global share of EVs is anticipated to reach 70% by 2050 [4]. This section endeavors to forecast the number of EVs across Istanbul's districts over the next three decades, employing a mathematical model developed subsequently. The objective is to identify optimal locations for electric charging stations in Istanbul at the conclusion of each five-year period, dividing the timeframe into six segments from 2020 to 2050. The starting year is set as 2020 to synchronize with the target years.

Estimating the number of EVs in Istanbul and its districts involves applying methods that consider the diffusion of new technologies, specifically EVs. The S-curve structure, elucidated later, models the adoption rate of EVs over time. SEGE scores, indicative of each district's development level, influence the S-curve and EV projection. Subsequent sections will delve into more details about these methods.

2.1 Projections of Total Cars

The initial task involves estimating the number of vehicles in Istanbul and its districts for each period, commencing with the total number of vehicles in Turkey based on TÜİK data. Utilizing the constant ratio of Istanbul's population to Turkey's population at 18.7%, we project the total number of vehicles in Istanbul for subsequent periods by multiplying this ratio with the number of vehicles in Turkey. To project the number of vehicles in Turkey for future periods, the constant average growth rate of 3.5% observed in the last five years is employed.

The process ensures the estimation of total vehicles in Turkey for the upcoming six periods. Subsequently, these figures are multiplied by the population ratio of Istanbul to Turkey, resulting in the estimated total number of vehicles in Istanbul for the future periods. Verification of these estimates against İBB's population projections adds a layer of consistency. Table 2.1 provides an overview of the anticipated number of vehicles in Turkey and Istanbul for the forthcoming periods.

Period	**1**	**2**	**3**	**4**	**5**	**6**
Turkey	15 829 201	18 806 223	22 343 137	26 545 245	31 537 649	37 468 983
İstanbul	2 952 761	3 508 091	4 167 863	4 951 720	5 882 997	6 989 422

Table 2.1: Total number of cars in Turkey and Istanbul

The subsequent step involves estimating the number of vehicles in each district of Istanbul, employing a similar method. The population ratio of each district within Istanbul is calculated and assumed to be constant over time. For instance, the ratio for Maltepe is computed as Maltepe's population (528,544) divided by Istanbul's population (15,937,951). Table 2.2 showcases the population ratios for selected districts. Multiplying these ratios by the projected number of vehicles for Istanbul yields the estimated number of vehicles in each district for each period. Table 2.3 presents the projections for some selected districts, chosen for visualization and illustration purposes in this report. The subsequent steps involve estimating the number of EVs in each district using the S-curve, SEGE scores, and these projections.

District	Multiplier
Beşiktaş	%1.10
Fatih	%2.31
Maltepe	%3.32
Küçükçekmece	%5.08
Çekmeköy	%1.86

Table 2.2: Selected district's population multipliers

District / Period	1	2	3	4	5	6
Beşiktaş	32 457	38 561	45 813	54 429	64 666	76 828
Fatih	68 220	81 050	96 293	114 403	135 920	161 482
Maltepe	97 921	116 337	138 217	164 212	195 096	231 787
Küçükçekmece	149 872	178 059	211 547	251 333	298 601	354 760
Çekmeköy	54 851	65 167	77 423	91 984	109 284	129 837

Table 2.3: Total number of cars in selected districts

2.2 Adaptation of a New Technology

The subsequent phase involves estimating the total number of EVs in each district, necessitating a detailed analysis of the adoption and assimilation of new technology. The Technology Adoption Life Cycle, conceptualized by Everett Rogers, categorizes users based on their adaptation to new technology. The stages in this model include Innovators, Early Adopters, Early Majority, Late Majority, and Laggards (refer to Figure 2.1). The adaptability of users to new technologies follows a normal distribution, often referred to as the S-shaped curve, depicting how the adoption of innovation evolves over time [8].

The S-shaped curve encompasses three phases: a slow start, a rapid growth, and a slow decline. The slow start initiates with a small group of innovators and early adopters embracing the new technology. Rapid growth ensues when the technology is adopted by a larger group of early and late majority users, influenced by social norms and peer pressure. The slow decline transpires when the technology gains acceptance among the final group of laggards, who exhibit greater resistance to change. This curve effectively illustrates the adoption processes of various innovations and technologies.

The saturation level (SL) denotes the maximum level reached by the S-curve, serving as a pivotal concept in the adoption process of new technology. It signifies the peak of the curve and the proportion of the technology adopted by the total potential user base [9]. The saturation level aids in determining when the adoption process will plateau and the extent of technology adoption. For instance, the widespread availability of wireless internet today indicates that this technology has reached its saturation level, embraced by nearly everyone.

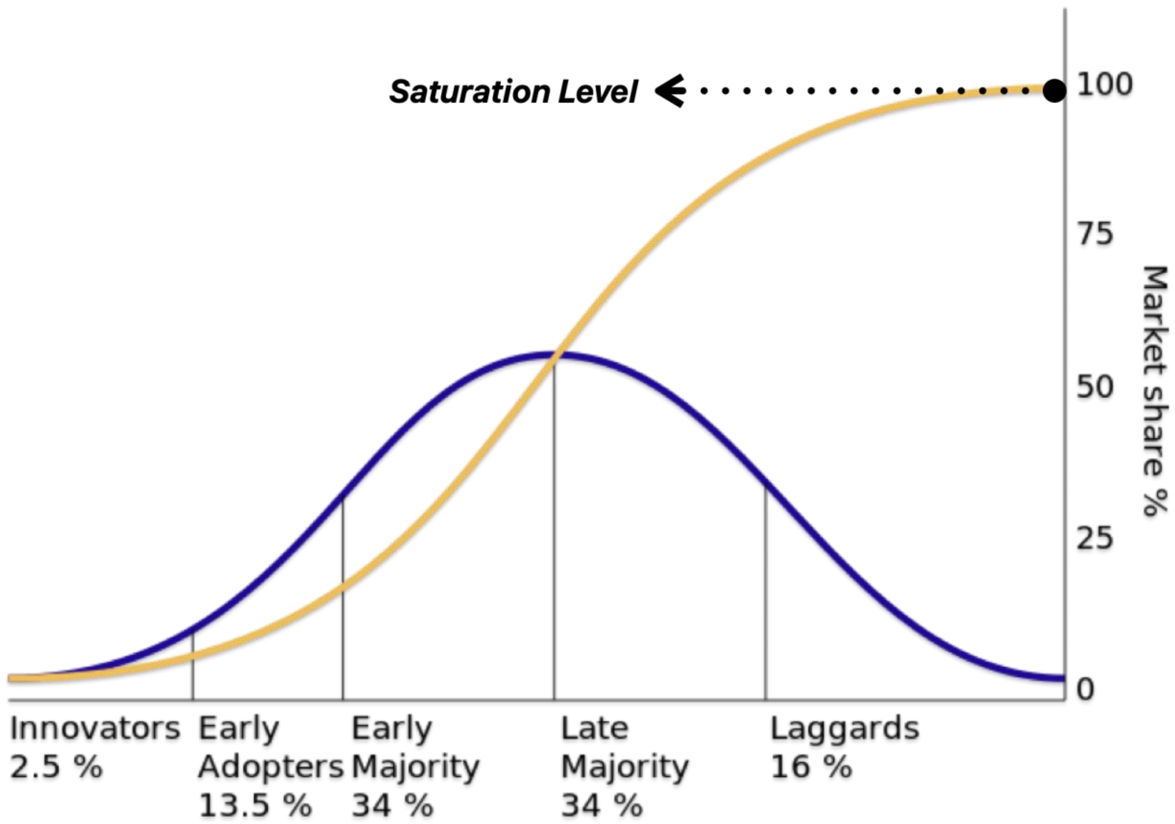

Figure 2.1: Diffusion of innovators and SL

In this context, the assumed EV ratio of districts by the end of 2050 serves as the saturation level. Based on our literature review, it is estimated that 70% of the total vehicles globally will be electric by the end of 2050 [4]. We employ this ratio as the saturation level for Istanbul's districts, assuming that 70% of the total vehicles in each district will be electric by the conclusion of 2050.

2.3 Projections of EVs

The determination of the shape of the S-curve for estimating the number of EVs in districts is crucial, considering that the ratio of EVs to all vehicles varies between developed and less developed districts [7]. The SEGE report of 2022 [2] becomes instrumental in assessing the development levels of Istanbul's districts.

The SEGE report is an analytical study that evaluates and compares the socio-economic development of districts in Turkey. Employing 56 variables across 8 dimensions, the study calculates index scores and rankings for districts, categorizing them into 6 development stages. A higher score corresponds to a higher development level for the district. These scores will be utilized to shape the S-curves, assuming that a district's higher SEGE score implies a faster progression towards the saturation point. Table 2.4 provides the SEGE scores for the selected districts.

The initial step involves utilizing the cumulative distribution function (CDF) of the normal distribution to outline the S-curve. The CDF of the normal distribution yields the probability of a value being at or below a certain point. Python is employed for calculating penetration values of districts and drawing the S-curves. This analytical approach ensures a nuanced representation of the adoption dynamics of EVs in each district based on their respective SEGE scores.

The S-Curve of a district can be characterized by the Cumulative Distribution Function (CDF) of a normal distribution [10]. The CDF of a normal distribution, also known as the Gaussian distribution, is expressed by the formula:

$$F(x) = \frac{1}{2}[1 + erf(\frac{x-\mu}{\sigma\sqrt{2}})]$$

where:

- $F(x)$ is the cumulative distribution function,
- *erf* is the error function,
- x is the point up to which the distribution is considered,
- μ is the mean of the distribution,
- $\sigma$is the standard deviation of the distribution.

District	Score	Score-normalized
Beşiktaş	5.940	0.838
Fatih	4.226	0.564
Maltepe	2.685	0.319
Küçükçekmece	2.161	0.235
Çekmeköy	1.450	0.122

Table 2.4: Selected district's SEGE scores

In our context, to define the S-Curve with a mean value between 0 and 1 (equivalent to 1 - normalized score of the district) and a standard deviation of one, these values are substituted into the formula. For instance, if the mean value is 0.5, the formula becomes:

$$F(x) = \frac{1}{2}[1 + erf(\frac{x-0.5}{\sqrt{2}})]$$

This expression generates the S-Curve of the district, as defined by the CDF of a normal distribution with a mean of 0.5 and a standard deviation of one. Adjusting the mean value within the range of 0 to 1 allows for the creation of different S-Curves. The S-Curve is graphically represented by plotting $F(x)$ against x to visualize the cumulative distribution.

In Python, we implemented the S-curve using the CDF function from the module <*scipy.stats.norm*> to calculate the Cumulative Distribution Function of the normal distribution. This function returns the CDF value at a given point, which represents the y-axis value of the S-curve.

To create the S-curve, we generated an array of x values representing the periods, where these x values serve as the x-axis values of the S-curve. Subsequently, for each x value, we computed the corresponding CDF value and stored these values in an array. These CDF values indicate the penetration values of a district in a specific period.

District / Period	1	2	3	4	5	6
Beşiktaş	0.01531	0.12262	0.43565	0.79898	0.96697	0.99773
Fatih	0.00743	0.0755	0.33142	0.71362	0.94109	0.99483
Maltepe	0.00367	0.04638	0.24794	0.62514	0.90642	0.9898
Küçükçekmece	0.00285	0.03878	0.22214	0.5929	0.89158	0.98729
Çekmeköy	0.002	0.03019	0.18997	0.54855	0.86907	0.98308

Table 2.5: Penetration values of selected districts

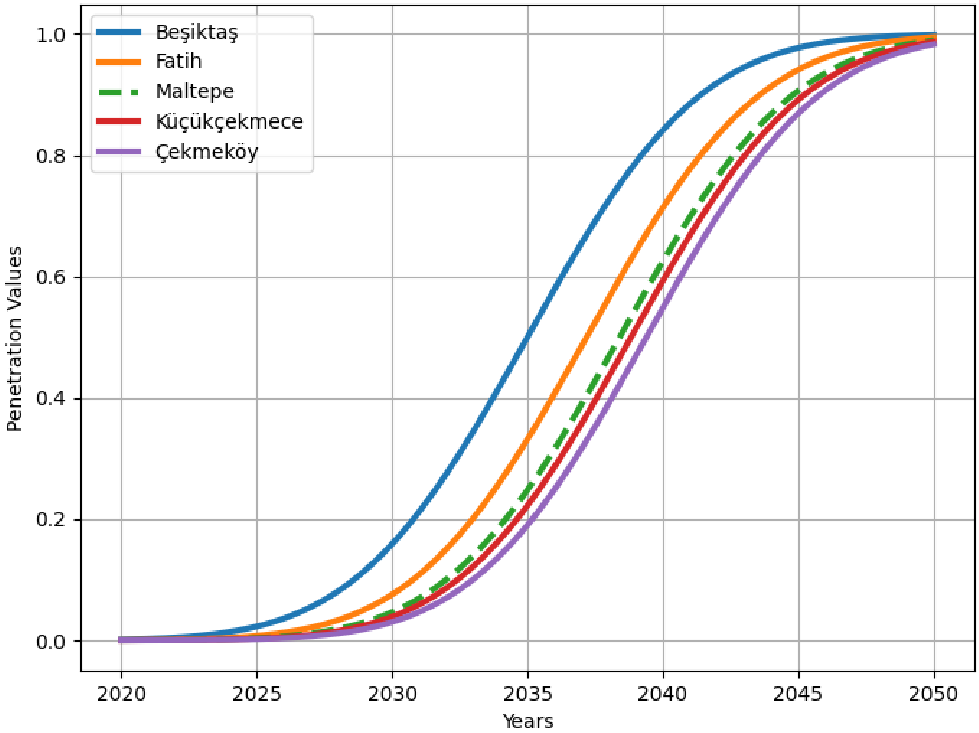

Figure 2.2: S-curves of districts

The plotting function from the module *<matplotlib.pyplot>* was then utilized to plot the x values (time/period values) against the CDF values (penetration values), resulting in the visual representation of the S-curve. Figure 2.2 illustrates the S-curves of selected districts, and Table 2.5 displays their penetration values at the end of each period.

After estimating the total number of vehicles, penetration values, and saturation level (SL) for future periods, the subsequent step involves estimating the number of EVs in districts. This calculation is performed by multiplying relevant values. For instance, to estimate the number of EVs in Maltepe at the end of the third period (end of 2035), the penetration value for Maltepe at that time (0.24794), the total number of vehicles in Maltepe for that year (171,714), and the SL value (0.7) are multiplied. This calculation yields the number of EVs in Maltepe at the end of 2035 as 29,802. Table 2.6 provides estimates of the number of vehicles for future periods in the selected districts. To observe the disparity between the growth of the total number of vehicles and the results of the EV projections using the S-curve, Figures 2.3 and 2.4 offer visual comparisons.

District / Period	**1**	**2**	**3**	**4**	**5**	**6**
Beşiktaş	348	3 310	13 971	30 442	43 771	53 657
Fatih	355	4 284	22 339	57 148	89 539	112 453
Maltepe	252	3 777	23 989	71 859	123 787	160 596
Küçükçekmece	299	4 834	32 895	104 311	186 359	245 175
Çekmeköy	77	1 377	10 296	35 320	66 483	89 348

Table 2.6: Total number of EV of selected districts

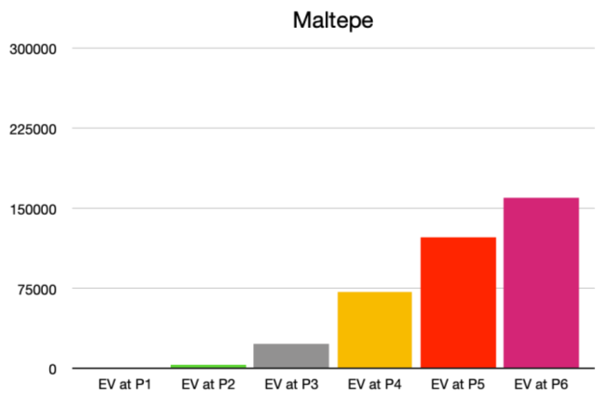

Figure 2.3: Total number of EV in Maltepe for each period

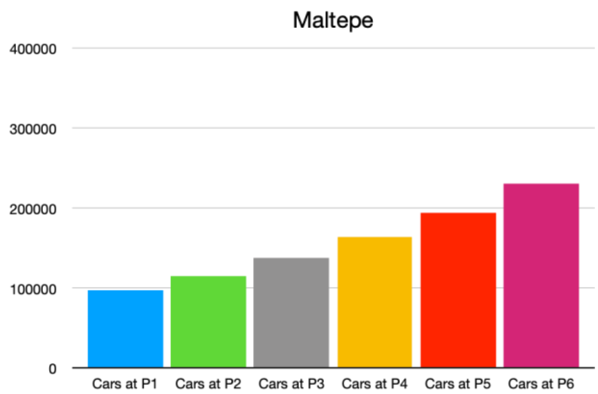

Figure 2.4: Total number of cars in Maltepe for each period

3. Location Selection Model

3.1 Literature Review

3.1.1 Node-based models

Node-based models consider demand coming from nodes in a traffic network and also place charging stations at the nodes of the network. Such models are commonly used for real-world facility location problems. Typically, node-based models compute the distance between two nodes as their shortest path in a graph. Node-based models aim to optimally locate facilities while complying with given constraints.

Set cover problem is one of the node based models.The set cover problem aims to locate the minimum charging stations so that all EVs can be served. Each candidate charging facility node is assumed to be able to support a set of demand points, which is the problem input. It implicitly implies that facility capacity is limited[11].

Maximal cover problem are whereas the set cover problem satisfies all demand nodes, the maximal cover problem assumes that some demand nodes may not be covered. The other setting is similar to the set cover problem, where each candidate facility can accommodate a predetermined set of demand nodes. The goal is to place a fixed a number of charging stations to satisfy the maximum points with the EV charging need[12].

3.1.2 Arc-based models

Arc-based charging models assume that the demands are correlated from arcs in a transportation network. In the context of this optimization model, an "arc" refers to a directed edge or connection between two nodes in the transportation network. Each node represents a location or point in the network, and arcs define the possible paths or routes between these nodes. For example, if you have nodes representing different locations on a map (e.g., districts), the arcs would represent the roads or routes connecting these cities.

Considering a highway network, node based charging models place EV charging stations at intersections. Whereas, arc-based charging models may place EV charging stations along in the middle of a highway. For large transportation network, arc-based models can be more realistic. Due to the mileage limit of EVs, it may not be feasible to place charging station at nodes, as EVs can be out of electricity in the middle of a trip. A transportation network usually has more arcs than nodes. These factors make arc-based charging models more complex and difficult than node-based models.

3.2 Proposed Model

The Maximum Coverage and Shortest Path Problem (MCSP) is a complex arc based optimization challenge associated with transportation networks, particularly in the context of Electric Vehicle (EV) refuelling infrastructure. The problem involves finding an optimal solution that addresses two main objectives: achieving maximum coverage of nodes and determining the shortest path between a start and end node.

Here's a breakdown of the key components and considerations:

1. **Network Representation:**
    - The transportation network is represented as a map with numerous nodes, each denoting a specific location.
    - There is a designated start node and an end node, defining the origin and destination of the transportation route.
2. **Coverage Definition:**
    - The objective is to draw a line connecting the start and end nodes in such a way that it covers all nodes in the network.
    - A node is considered covered if it either lies directly on the drawn line or falls within a specified distance from the line.

3. **Charging Stations and EV Refuelling:**
    - Charging stations are planned to be strategically placed along the drawn line.
    - An Electric Vehicle (EV) owner residing on the line or within the specified distance from it should have access to these charging stations for refuelling.

MCSP involves finding a solution that simultaneously maximizes the coverage of nodes in the transportation network and minimizes the distance of the drawn line. The introduction of charging stations adds an additional layer of complexity, transforming the problem into a multi-objective optimization task with considerations for both coverage and station placement. This type of problem is commonly tackled using optimization algorithms and mathematical modelling techniques to arrive at an optimal or near-optimal solution.

$$max\ w \sum_{k=2} a_k\ y_k - \ (1-w) \sum_i \sum_j d_{ij}\, x_{ij} \qquad (3.1)$$

subject to (3.2)

$$\sum_{j \in N_1} X_{1j} = 1$$

$$\sum_{j \in N_n} X_{jn} = 1$$

$$\sum_{i \in N_j} X_{ij} - \sum_{i \in N_j} X_{1j} = 0 \quad , \forall j, (j \neq 1)$$

$$\sum_{i \in N_j} \sum_{j \in S_k} X_{ij} - y_k \geq 0 \, , \forall k$$

$$X_{ij},\, y_k \ \in \ \{0, 1\}, \forall i, j, k$$

i and *j* are generic indices representing starting and ending nodes in the transportation network
k is used as an index to represent specific nodes associated with EV charging stations
w: Weight parameter.
s : Maximum coverage distance.
x_{ij}: Binary decision variable, i.e. 1 if arc (i,j)is included in the path, otherwise 0.
y_k: Binary decision variable, i.e. 1 if EV refueling demand at point k is met, otherwise 0.
a_k : EV refueling demand at node k.
d_{ij}: Interval between demand point i and j.
N_j: Set of neighboring nodes of node j.
S_k: EV charging demand points that are within the specified coverage distance s from established XFC station k.

Table 3.1 Decision variables, sets and parameters

The model denotes node 1 and n as start and end nodes respectively. To enforce node 1 to be in the selected path, one of its incident links must be included in the path. It also applies to node n. The first two constraints are their mathematical representations.

If a node is included in the selected path, then one incoming incident link and one outgoing incident link must be included in the path, which is represented by the third constraint. Demand at node k is satisfied, when there is one charging station placed within its reachable distance. Is is mathematically represented by the fourth constraint.

In the objective function, $\sum_{k=2} a_k \ y_k$ represents the number of covered demand nodes, $\sum_i \sum_j d_{ij} \ x_{ij}$ computes the aggregated travel distance, and w is the weight parameter. By adjusting w, the objective function balances maximal covering and shortest path[13].

Conculison

For the successful implementation of this model within the scope of the project, it is essential to introduce a time constraint into the objective function, taking into account the demand projections outlined in section 2. This adjustment ensures that the model's optimization process is not only informed by the sconsiderations of node coverage and station placement but also dynamically responsive to the evolving demands over time. By integrating dynamic demand the objective function, the model becomes more robust and aligned with the project's goal of adapting to changing electric vehicle demand patterns, thereby enhancing its practical utility and strategic value.

This new implementation, incorporating a time constraint into the objective function, represents a significant enhancement to the existing model and can be considered as a distinct project phase. As part of this evolved project, references will be given to acknowledge that this project will be a foundation to the next phase.

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