



Development of an ILP model for optimal site selection and sizing of electric vehicle charging station using GA: a case study of Tehran

Morteza Mollajafari^{1*}, Alireza Rajabi Ranjbar¹, Shayegan Shahed Haghighi²

¹ Vehicle Electrical and Electronic Research Lab, School of Automotive Engineering, Iran University of Science and Technology, Tehran, Iran

² School of Automotive Engineering, Iran University of Science and Technology, Tehran, Iran.

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ABSTRACT

The development and adoption of Electric Vehicles (EVs) appears to be an excellent way to mitigate environmental problems such as climate change and global warming exacerbated by the transportation sector. However, it faces numerous challenges, such as optimal locations for EV charging stations and underdeveloped EVs charging infrastructure among the major obstacles. The present study is focused on the location planning of charging stations in real cases of central and densely populated districts of Tehran, the capital of Iran. In order to achieve this goal, this paper attempts to validate the results of a previous study in another country. Secondly, by employing preceding principals in accordance with relevant information collected from the car parking and petrol stations in the regions of study, a five-integer linear program is developed based on a weighted set coverage model, considering EV users' convenience, daily life conditions, and investment costs, and finally optimally solved by a genetic algorithm under various distribution conditions; normal, uniform, Poisson and exponential, to specify the location and number of EV charging stations in such a way that EV drivers can have access to chargers, within an acceptable driving range.

*Corresponding Author :Morteza Mollajafari

Email Address: mollajafari@iust.ac.ir

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1. Introduction

Environmental problems such as air pollution and global warming are having a serious impact on people's lives. Vehicle emissions producing unwanted greenhouse gases (GHG); are one of the main causes of air pollution resulting in climate change and global warming.

Air pollution occurs at dangerously high levels in many parts of the world and poses a significant environmental risk to human health. There are nearly 6.5 million premature deaths each year worldwide due to poor air quality, and an estimated 3 million people die from exposure to air pollution [1]. Meanwhile, global warming is increasing human mortality from heat stress, disease and natural disasters, while displacing viable agriculture, damaging ecosystems and animal habitats, and reducing water supplies [2]. Furthermore, the energy crisis caused by the exhaustion of the fossil resources is also becoming an urgent issue. Global crude oil (including biofuels) demand averaged about 91 million barrels per day in 2020 falling from 99.7 million barrels per day in 2019 and is projected to increase to 101.2 million barrels per day in 2023. Leaving the remaining technically recoverable crude oil resources available for only about 60 years [3-4].

As one of the largest emitters of greenhouse gases, the transport sector plays an important role in all of these aspects. In addition, the transport sector accounts for over one third of the global demand for oil as the biggest oil consuming sector worldwide, mainly due to reliance on petroleum based transport fuels such as gasoline and diesel used in ICEVs (conventional Internal Combustion Engines) [5]. Global transport-related CO₂ emissions have surged over the past 50 years, increasing by almost 80 percent in between 1990 and 2019 up from just 2.8 billion GtCO₂ in 1970 [6]. According to the latest statistics, global CO₂ emissions in 2019 were equivalent to about 4976 (billion metric tons of carbon dioxide). The transport sector accounted for 17% of emissions in 2019, making it the second largest source of GHG emissions in the world after the electricity and heat sector [7]. Passenger vehicles were the largest source of emissions from the transport Automotive Science and Engineering (ASE)

sector at 41% in 2019, followed by medium and heavy trucks at 22% [8]. However, in 2020, global travel restrictions due to the COVID-19 outbreak reduced transport-related emissions by about 12% compared to the previous year.

Iran's oil consumption was reported at 1,689.960 Barrel/Day in December 2021. This represents an increase from the previous number of 1,672.799 Barrel/Day in December 2020, making the country 12th oil consumer in the world [9-10]. Meanwhile, OPEC reports that Iran's crude oil production in 2019 was 2,392,000 Barrel/Day, putting it in 7th place among the world's oil producers [11]. Additionally, Iran is almost totally dependent on fossil fuels as a primary energy source used in transport, energy and other sectors. In the most recent Global Climate Risk Index (CRI) data available for 2019 and from 2000 to 2019, which Analyzes and ranks countries and regions based on the impact of climate-related extreme weather events (storms, floods, heat waves, etc.), Iran ranked 18 between all countries in 2019 and placed 97 in between 2000-2019 which indicates the growing impact of climate change over past years [12]. These data show that Iran's economy and energy relies heavily on oil and that the country is severely threatened by climate change.

Growing concerns about climate change, oil depletion and supply reliability are forcing countries to adopt precautionary measures and strategies to slow the worsening impacts. Greenhouse gas emissions are expected to double by 2050 if no initiatives are taken to address this problems [13]. A promising approach to alleviate these impacts is to modify transport sector in terms of finding alternatives for fossil fuel usage as motor spirits and reduce (GHG) emission to achieve de-carbonization and adopt cleaner technologies in vehicles [14]. Electrifying transportation by developing electric vehicles seems to be a favorable way to reach this end [15].

EVs use electric motors powered by rechargeable batteries [16] instead of traditional vehicles with internal combustion engines that consume fossil fuels and emit gases such as carbon monoxide (CO), nitrogen oxides (NO_x),

particulate matter (PM) and volatile organic compounds (VOC) [17-18]. EVs use electricity provided from power grid and if the power generation process uses renewable energy sources (RESs) such as solar (using collectors, panels and etc.) [19], wind or other kinds of renewables instead of coal and oil, it can be eco-friendly and green [20]. Recent findings also show that multiple EV features improve driving safety. EVs typically have a lower center of gravity, which makes them less likely to tip over. Moreover, the risk of large fires and explosions is low, and the structure and durability of the EV body improves safety in crashes, making EV products safer [21]. Additionally, EVs bring further benefits to the power system, such as voltage and frequency regulation, backup for renewable intermittency, and peak shaving [22-24]. Also, EV has 30% more pedestrian traffic safety risk as compared to conventional vehicles under high ambient sound level, whereas at the low ambient sound level, EV has a 10% higher safety risk for pedestrians [25]. For these reasons, it is clear that EVs can completely outperform ICEVs. Widespread adoption of electric vehicles will therefore certainly help solve key Environmental problems and improve economical oil dependency in Iran.

Reaping these benefits will first require specific policies to be put in place to overcome certain market barriers that are slowing the EV adoption process, including technological, financial and behavioral. In addition to these barriers, installation of charging stations all over the places helps broaden the scale of adoption. If customers accept EVs but are unable to charge freely due to a severe lack of infrastructure, public support will be completely reversed [26]. Thus, one of the main concerns is overhauling the existing infrastructures. To achieve viability of constructing EVCS (Electric Vehicle charge stations), determining optimal size and location of EVCS with help of several Optimization-based strategies is needed. This further lead to economic benefits for investors, government and people. It also helps alleviate the first concern when buying an EV: fear of distance and charging ability (known as range of anxiety) [27] and provide authorities with a better

overview of EV-oriented development plans and regulatory introductions, especially in developing countries like Iran, which currently do not have clear plans for the development of EVs in society. Unlike developed countries, which have already started improving infrastructure with the latest technology by focusing on developing various forms of efficient electric transport, building new transmission systems and efficient charging mechanism [28-29]. Along this line, many recent research efforts have investigated the deployment and optimization of EV charging stations, some of which are presented in Table (1) [30-41].

Table 1: Related Works

Category	Related Works
Deployment of Electric Vehicles Charging Stations (EVCS)	(Chen et al., 2013) [30], (Zhu et al., 2016) [31], (Erbaş et al., 2018) [32], (Genevois & Kocaman 2018) [33], (Wang et al. 2019) [34]
EVCS Location Selecting	(Chen et al., 2013) [30], (Zhu et al., 2016) [31], (Efthymiou et al., 2017) [35], (Frade et al., 2011) [36], (Baouche et al., 2014) [8], (Li et al., 2018) [37]
EVCS Location Selecting and Sizing	(Sadeghi-Barzani et al., 2014) [38], (Mozafar et al., 2017) [39], (Wang et al., 2018) [40], (Bouguerra & Bhar Layeb, 2019) [41]

The present work seeks to determine the optimal size and location of EVCS within the central and densely populated districts of Tehran, capital of Iran by first validating the result of previous research by (Bouguerra & Bhar Layeb, 2019) [41] and then employ the same principals for our case study.

The paper is organized into several sections. Section 1 presents an introduction that describes a brief history of EVs and their current status. EV technologies are introduced in Section 2, concentrating mainly on the power train, battery, Automotive Science and Engineering (ASE)

and charging of the batteries. A modeling approach to choosing a charging station and the impacts of EV deployment are explained in Section 3. The fourth section describes the obtained results and their validation. EV deployment in smart grids in the future and research gaps and limitations in the present EV field are presented in Section 5.

2. Material and Method

2.1. Material

Our optimization is an integer linear programming model written programmatically in a Matlab environment as script files. three evolutionary Algorithm is used in these models,' Genetic Algorithm (GA),' 'Particle Swarm Algorithm (PSO),' and 'Ants Colony Algorithm (ACO).' A Lenovo laptop Thinkpad edge with the following specifications was used to execute the codes: CPU: Core i3 2.53 GHz RAM: 4 GB.

2.2. Method

The objective is to locate electric vehicle charging stations based on five integer programming models; each model contains specific decision variables, associated objective functions, and real-world constraints.

Due to the increased use of EV, the energy demand for EV is also expected to increase; Each charging station usually has three types of chargers. Table 2 shows these charging levels categorized by power level, charging time, and vehicle technology according to the J1772 standard.

The SAE J1772 standard covers the general physical, electrical, functional, and performance requirements for the conductive charging of EVs and PHEVs in North America [43].

Level 1 charging is the slowest type of EVC using standard 120V AC household outlets rated at 15 or 20A. This is the most convenient way to charge electric vehicles at home. It does not require any additional infrastructure.

Level 2 charging scheme is generally considered the most prevalent design for private Automotive Science and Engineering (ASE)

and public facilities. At this level, private systems require a single-phase 240 V AC source with a power of 40 A, while public installations require a three-phase 400 V AC connection with a power of 80 A.

Table 2: Different Types of Charging Stations [44]

Level Types	Typical Use	Expected Power Levels	Charging Time	Vehicle Technology
Level 1	Charging at Home or Office	1.4 kW for 12A,	11-36 h	PHEVs of 5 to 15 kWh
		1.9kW for 20A	4-11 h	EVs of 16 to 50 kWh
Level 2	Charging at Private or Public Outlets	19.2 kW for 80 A	2-3 h	PHEVs of 5 to 15 kWh EVs of 16 to 30 kWh
Level 3	Commercial, Similar to filling stations	50kW 100kW	0.4-1 h 0.2-0.5 h	EVs of 20 to 50 kWh

Level 3 or DC fast charging is the most appropriate for commercial or public charging facilities, as they can deliver an experience similar to a commercial filling station. Depending on the size and type of EV battery, fast charging can reach 80% in about 10–15 minutes [45-46].

Information on the use of electric car chargers in America, Europe, and China has been extracted and estimated until 2030 as shown in Figure. 1[47]. As a result, it can be concluded that the use of DC fast charging batteries has been considered, and an attempt has been made to use these batteries more extensively. Therefore, only fast charging stations are considered in this article.

2.2.1. Data interpretation

This study identifies potential EVCS charging locations based on locations with high population densities during peak daily hours. Candidate locations for EV charging stations are existing gas stations and parking lots within the area included in the study. Geographic data is collected by Google Maps@. For details of possible locations, see Appendix I . Figure 2

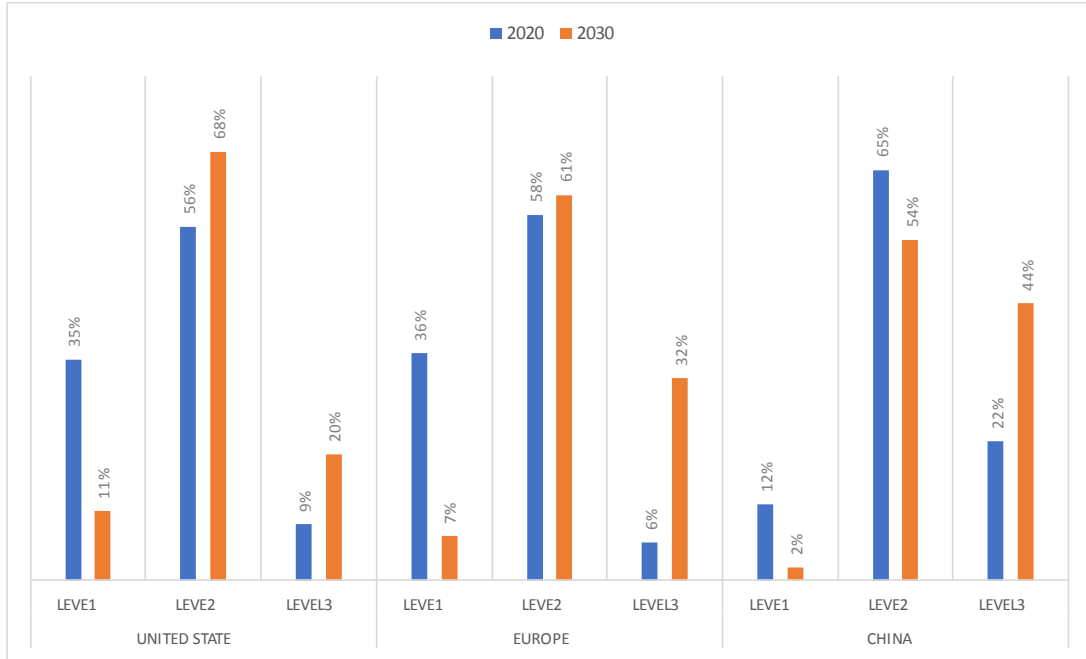


Figure 1: Energy demand by charging model [47]

shows that 19 parking lots (P location icon) and 16 gas stations (station icon) were identified. Each station's Cartesian distance is annotated as

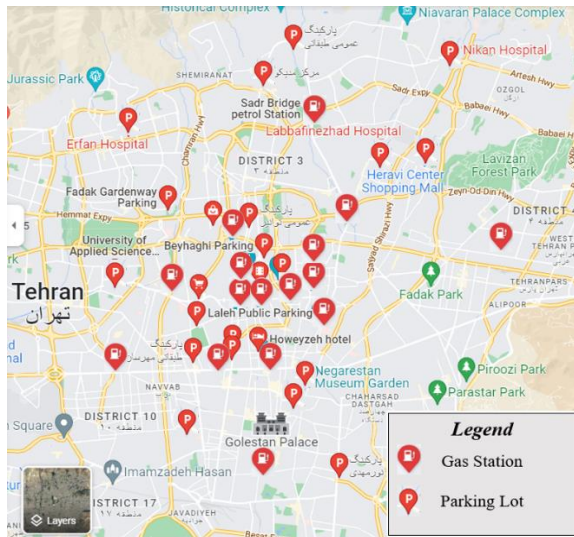


Figure 2: Potential locations for EVCS locations

$d_{i,j}$ ($i, j \in V$), representing the distance between locations i and j . A matrix of distances can be found in Appendix II.

A parking lot is selected based on the daily demand, capacity, and population density around the construction site. Moreover, the majority of the designated areas are among the most populated during the day, so electric cars are expected to be in high demand in these areas [48].

The demand for each station is modeled based on Bouguerra and Bharlayeb's work for Tunis City [42]. According to this model, each target location's demand will be considered 13. Furthermore, we generate 35 random numbers based on four distributions: the uniform distribution, the normal distribution, the Poisson distribution, and the exponential distribution. By using these different distributions, we can make the demand more realistic. Each number represents the demand for a candidate location. Poisson distributions are the most commonly used distributions for this kind of problem [49]. Also, the total number of demands was considered to be about 4000.

2.2.2. Symbol and variables Explanation

A set of variables defined in Tables 3 and 4 has been used to describe the models in this article. Each variable in Table 2 is selected in a binary Automotive Science and Engineering (ASE)

manner, such as whether or not an EVCS is set up and whether the vehicle is charged there. Other variables are defined in Table 3, including distances between locations and opening costs of EVCS, etc.

Table 3: Binary Variable Description

Number	Binary Variable	Description
01	x_i	takes value 1 for the installed charging station and 0 otherwise.
02	$\alpha_{i,j}$	takes value 1 if $d_{i,j} \leq R$, and 0 otherwise
03	γ_{ij}	takes value 1 if the electric vehicles of location (i) are charged in location (j)

3. Analysis

In this study, five linear programming models are used, as in the work of Seifeddine Bouguerra and Safa Bharlayeb. Model 1 only considers the location of EVCS. The second model adds a charging station's opening cost to the objective function. The third objective function incorporates charger installation costs. A consideration for access money will be included in the next model. Model 5 takes into account all previous models. In other words, as will be fully explained in the following, each model completes the previous one. As a final step, different distributions are used for more realistic conditions in the last model. The difference between model 5 and model 6 is only in their demand.

In addition, different algorithms such as GA, PSO, and ACO are used in the Tehran models, and their efficiency has been investigated. The models assume each car is charged at only one station, and daytime charging is considered only for EV users.

Table 4: Others Variable Description
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Number	Variable	Description
01	R	pre-fixed coverage radius
02	d_{ij}	distance between locations (i) and (j)
03	f_i	infrastructure opening cost
04	c_i	maximal number of charger that could be installed
05	u_i	per unit price of installing one charger
06	m_i	number of vehicles potentially using location i
07	n_i	number of chargers to be installed in location i

Note: The values of f_i and c_i are given in Appendix I.

3.1. Complementary Equations

Here are the relationships that will be used in the following sections.

φ is introduced as maximum number of parked electric vehicles powered and charged by one charger and calculated as:

$$\varphi = \lambda * S^t \gamma \tag{1}$$

Where λ is the number of electric vehicles that can be charged per hour and is set to 3 EV per hour, and S^t is the total charger service time is set to 12 hours per day.

ϕ is introduced as the walking cost and shown the estimated value of the owner vehicle for each walked kilometer and calculated as:

$$\phi = \frac{W^h}{W^s} \tag{2}$$

Where W^h is the average hourly wage for electric vehicle owners that's equal to \$17 per

hour and W^s is the walking speed which is assumed as 5km/h. Furthermore, the cost of installing the charger (u_i) is set at \$56000 [42].

3.2. ILP models for location decisions only

The first class of Integer Linear Programming (ILP) models describes NP-hard set covering problems. NP is a class of decision problems whose answers are nondeterministic and polynomial time. In other words, NP is the class of decision problems where the 'yes'-answer has a polynomial time certificate [50].

M1 and M2 are defined based on the NP-hard modeling. Each EVCS location will be illustrated using a binary variable; as is seen in sections M1 and M2, all the variables in these models will be defined based on decisions.

3.2.1. M1

The first model is introduced as follows:

Table 5: M1 Model

Model	Equation	functional constraint	constraint description
1	$Minimize \sum_{i \in V} x_i$	(01) $\sum_{i \in V} \alpha_{i,j} x_i \geq 1, \forall j \in V$	Accessibility coverage radius for EV users
		(02) $x_i \in \{0, 1\}, \forall j \in V$	Restrictions on x variables

Based on the first model, the objective function representing the total number of installed stations is minimized. This model may be helpful when station locations are the only factor that matters, and the price isn't an issue.

3.2.2. M2

Considering the costs of setting up a charging station is imperative, so f_i ($i \in V$) is introduced as a size-independent cost of opening a station in each potential location i . In other words, it refers to converting a parking lot or gas station to a EVCS, specifically, equipment and administrative costs.

With a pre-fixed accommodation capacity, size-dependent costs become invariant, and the optimization model should only minimize opening costs. In this way, the second model can be stated as follows:

Table 6: M2 Model

Model	Equation	functional constraint	constraint description
2	$Minimize \sum_{i \in V} f_i x_i$	(01) $\sum_{i \in V} \alpha_{i,j} x_i \geq 1, \forall j \in V$	Accessibility coverage radius for EV users
		(02) $x_i \in \{0, 1\}, \forall j \in V$	Restrictions on x variables

3.3. ILP models for location and sizing decisions

The appropriate size of charging stations is determined by a second family of ILP models. Aside from the cost of building the station, this section also discusses the cost of installing chargers in the station and the number of them, as well as the amount of time people waste tending to charge EVs, according to their income.

3.3.1. M3

The model is estimated based on the parking lot's capacity, the charger's installation cost, and the number of electric vehicles charging. Hence, the variable n_i is defined as the number of chargers installed at a specific location, and the variable $y_{i,j}$ determines whether the car will be charged at the desired location. As a result, the third model is presented in table 7.

3.3.2. M4

As EV owners often travel from one place to another to charge their vehicles, it is also pertinent to consider users' travel costs, so access costs will also be considered in the following. Considering walking as a traveling

Table 7: M3 Model

Model	Equation	functional constraint	constraint description	
3	Minimize $\sum_{i \in V} (f_i x_i + u_i n_i)$	01	$\sum_{i \in V} y_{i,j} = 1, \forall i \in V$	Assignment of all EV to a charging station.
		02	$y_{i,j} \leq x_j, \forall i, j \in V$	EV could be charged in location $j \in V$
		03	$x_i \leq n_i \leq c_i x_i, \forall i \in V$	If station is selected then at least one charger is installed
		04	$\sum_{i \in V} m_i y_{i,j} \leq n_j \phi, \forall j \in V$	Total charging EV vehicle should not exceed its available service chargers
		05	$d_{i,j} y_{i,j} \leq R, \forall i, j \in V$	Assignment ev vehicle to charging station with tolerance Radius limitation
		06	$x_i \in \{0,1\}, \forall j \in V$	Integrality constraint
		07	$y_{i,j} \in \{0,1\}, \forall j \in V$	Integrality constraint
		08	$n_i \in IN, \forall i \in V$	Non-negativity of integer

Table 8: M4 Model

Model	Equation	functional constraint	constraint description	
4	Minimize $\sum_{i \in V} u_i n_i + \phi \sum_{i \in V} m_i \sum_{i \in V} d_{i,j} y_{i,j}$	01	$\sum_{i \in V} y_{i,j} = 1, \forall i \in V$	Assignment of all EV to a charging station.
		02	$y_{i,j} \leq x_j, \forall i, j \in V$	EV could be charged in location $j \in V$
		03	$x_i \leq n_i \leq c_i x_i, \forall i \in V$	If station is selected then at least one charger is installed
		04	$\sum_{i \in V} m_i y_{i,j} \leq n_j \phi, \forall j \in V$	Total charging EV vehicle should not exceed its available service chargers
		05	$d_{i,j} y_{i,j} \leq R, \forall i, j \in V$	Assignment EV vehicle to charging station with tolerance Radius limitation
		06	$x_i \in \{0,1\}, \forall j \in V$	Integrality constraint
		07	$y_{i,j} \in \{0,1\}, \forall j \in V$	Integrality constraint
		08	$n_i \in IN, \forall i \in V$	Non-negativity of integer

means, ϕ is introduced in section 3.1. Therefore, m4 is presented in table 8.

3.3.3. M5

All previous objective functions are considered in this model, including the construction of total stations. M5 complements the previous models, as mentioned earlier. Table 9 presents the M5.

4. Results

The main paper focused on the models defined based on the genetic algorithm and with constant demand. First, the results extracted from Tunisia city are validated, and in addition, we examine the effects of using two other optimization algorithms. Finally, different distributions will be discussed for Tehran city.

Table 9: M5 Model

Model	Equation	functional constraint	constraint description	
		01	$\sum_{i \in V} y_{i,j} = 1, \forall i \in V$	Assignment of all EV to a charging station.
		02	$y_{i,j} \leq x_j, \forall i, j \in V$	EV could be charged in location $j \in V$
		03	$x_i \leq n_i \leq c_i x_i, \forall i \in V$	If station is selected then at least one charger is installed
5	Minimize $\sum_{i \in V} (f_i x_i + u_i n_i) + \phi \sum_{i \in V} m_i \sum_{j \in V} d_{i,j} y_{i,j}$	04	$\sum_{i \in V} m_i y_{i,j} \leq n_j \phi, \forall j \in V$	Total charging EV vehicle should not exceed its available service chargers
		05	$d_{i,j} y_{i,j} \leq R, \forall i, j \in V$	Assignment EV vehicle to charging station with tolerance Radius limitation
		06	$x_i \in \{0,1\}, \forall j \in V$	Integrality constraint
		07	$y_{i,j} \in \{0,1\}, \forall j \in V$	Integrality constraint
		08	$n_i \in IN, \forall i \in V$	Non-negativity of integer

4.1. Previous Study Validation

The p-value is used to validate the results. In statistics, a p-value is used to test a hypothesis against observed data. P-values indicate the likelihood that the observed result will occur if the null hypothesis is true. A lower p-value indicates a greater statistical significance of the practical difference [51].

Results for the validation are given in Table 10. Only the genetic algorithm results are validated. Due to m3, m4, and m5 models, with their assumptions, it is expected that $m4+m3 > m5$. However, none of the setup costs support this scenario, and the M5 results are statistically significant. Hence, the differences in validation data can be explained by different assumptions from what they say in the paper.

Results show that there is less than a 5% difference between the data obtained by the genetic algorithm. As a result of the random nature of GAs, differences have increased to 10% in some cases. However, this difference has increased by over 50% in the other two algorithms, indicating that they are inadequate for the given problem. Therefore, the genetic algorithm is the most logical option for choosing the right EVCS location.

4.2. Location planning of EVs charging stations in Tehran

This section evaluates the feasibility of building electric vehicle charging stations in Tehran based on the locations selected in section 2. Moreover, different demands have been analyzed to determine how effective algorithms are in real-world scenarios. The genetic algorithm was the most effective for this problem, so only the GA was used to optimize for Tehran city. The results of the EVCS are presented in table 11 and 12. The setup costs and number of chargers are shown in figures 3 and 4.

5. Conclusion

As one of the world's most polluted cities, Tehran must rely on clean energy daily. Vehicles powered by electric motors can be considered as a possible solution for transportation. This article investigates the feasibility of building electric vehicle charging stations in Tehran's high-traffic areas using five integer linear programming models. Three optimization algorithms have been used for this purpose. The analysis results show that the genetic algorithm is the most effective method for solving this kind of problem. In addition, Figure 6 shows the trend of charging setup costs the type of distribution. This shows the

Table 10: Results of validation and efficiency testing of different algorithms

Model	R (km)	Control			GA			PSO			ACO			P Value
		NS	NC	Cost	NS	NC	Cost	NS	NC	Cost	NS	NC	Cost	
M1	0.2	27	-	\$54,579	28	-	\$56,501	28	-	-	35	-	\$70052	0.077494
	0.4	17	-	\$34,763	17	-	\$34,219	24	-	-	24	-	\$47719	
	0.6	11	-	\$22,059	11	-	\$22,005	21	-	\$42,550	19	-	\$38147	
	0.8	10	-	\$20,082	10	-	\$19,953	17	-	\$34,117	15	-	\$30630	
	1	8	-	\$16,303	8	-	\$16,030	14	-	\$28,266	15	-	\$30565	
	1.2	8	-	\$16,303	8	-	\$16,543	15	-	\$30,295	15	-	\$29941	
	1.4	8	-	\$16,042	8	-	\$16,066	17	-	\$33,982	12	-	\$23766	
	1.6	8	-	\$16,229	9	-	\$18,288	17	-	\$34,848	11	-	\$22678	
	1.8	8	-	\$16,229	8	-	\$16,066	15	-	\$29,557	13	-	\$26411	
	2	8	-	\$16,229	9	-	\$18,498	17	-	\$33,762	11	-	\$21810	
M2	0.2	27	-	\$53,903	28	-	\$55,738	26	-	-	28	-	\$56,169	0.098928
	0.4	17	-	\$33,553	17	-	\$33,558	25	-	-	20	-	\$40,265	
	0.6	11	-	\$21,311	10	-	\$19,586	18	-	\$36,018	16	-	\$31,523	
	0.8	10	-	\$19,419	10	-	\$19,496	18	-	\$35,033	16	-	\$32,680	
	1	8	-	\$15,958	8	-	\$15,932	16	-	\$31,762	11	-	\$21,713	
	1.2	8	-	\$15,958	8	-	\$15,871	16	-	\$32,282	12	-	\$23,708	
	1.4	8	-	\$15,958	8	-	\$16,085	15	-	\$29,757	15	-	\$29,691	
	1.6	8	-	\$15,958	9	-	\$17,367	16	-	\$31,575	15	-	\$30,546	
	1.8	8	-	\$15,958	9	-	\$17,439	14	-	\$27,156	14	-	\$27,878	
	2	8	-	\$15,958	9	-	\$17,882	17	-	\$33,799	11	-	\$21,953	
M3	0.2	27	30	\$1,733,903	28	31	\$1,791,630	21	-	-	28	-	-	0.074039
	0.4	17	22	\$1,265,553	18	23	\$1,323,644	19	23	\$1,326,616	21	24	\$1,386,381	
	0.6	11	18	\$1,029,311	11	18	\$1,029,371	17	21	\$1,209,828	15	23	\$1,317,891	
	0.8	10	17	\$971,475	10	17	\$971,770	23	24	\$1,389,039	16	22	\$1,264,087	
	1	8	16	\$912,042	8	17	\$967,908	18	22	\$1,267,369	16	21	\$1,207,488	
	1.2	8	16	\$912,042	8	16	\$911,984	16	21	\$1,207,501	15	22	\$1,262,241	
	1.4	8	16	\$912,042	9	16	\$914,443	14	21	\$1,203,189	14	20	\$1,148,007	
	1.6	8	16	\$911,958	9	16	\$914,240	18	20	\$1,155,393	15	21	\$1,206,521	
	1.8	8	16	\$911,958	10	17	\$971,756	14	20	\$1,147,349	17	21	\$1,209,559	
	2	8	16	\$911,958	9	17	\$969,889	19	21	\$1,213,818	14	21	\$1,203,855	

M4	0.2	29	30	\$840,023	31	31	\$864,695.2 0	26	-	-	31	31	\$875,098	0.055568
	0.4	20	22	\$616,092	19	22	\$623,347.9 0	23	26	\$757,926	24	25	\$736,057	
	0.6	14	18	\$504,156	13	18	\$568,693.3 3	19	22	\$667,222	19	22	\$669,319	
	0.8	12	17	\$476,183	11	17	\$489,485.8 2	16	21	\$656,403	21	22	\$662,947	
	1	9	16	\$448,258	12	17	\$451,991.3 5	19	21	\$649,870	19	22	\$680,370	
	1.2	9	16	\$448,251	11	17	\$448,280.7 6	17	21	\$673,666	18	21	\$657,049	
	1.4	9	16	\$448,251	9	16	\$448,280.7 6	15	21	\$657,855	20	22	\$687,549	
	1.6	9	16	\$448,251	9	16	\$448,280.7 6	20	22	\$681,419	14	21	\$681,329	
	1.8	9	16	\$448,251	10	17	\$448,280.7 6	15	21	\$671,084	18	21	\$669,148	
2	9	16	\$448,251	9	16	\$448,280.7 6	16	21	\$670,358	22	23	\$688,849		
M5	0.2	27	30	\$33,812.2 94	30	31	\$904,969	28	31	\$906,117	28	-	-	2.90987 E-07
	0.4	17	22	\$24,682.6 59	19	22	\$669,739	22	24	\$725,0119	24	25	\$752,838	
	0.6	11	18	\$20,078.8 42	12	18	\$583,713	17	19	\$609,992	20	23	\$714,723	
	0.8	10	17	\$18,953.3 01	12	17	\$567,112	21	22	\$680,169	15	21	\$672,143	
	1	8	16	\$17,798.1 15	10	17	\$573,480	13	19	\$644,131	17	21	\$686,109	
	1.2	8	16	\$17,798.1 15	9	16	\$571,596	17	20	\$663,939	15	21	\$686,117	
	1.4	8	16	\$17,798.1 15	9	16	\$557,843	15	19	\$624,579	15	21	\$695,992	
	1.6	8	16	\$17,798.1 15	8	16	\$575,127	17	20	\$653,663	16	22	\$701,921	
	1.8	8	16	\$17,798.1 15	10	17	\$578,629	14	18	\$591,728	20	22	\$707,989	
2	8	16	\$17,798.1 15	11	17	\$564,488	15	19	\$629,955	18	22	\$719,619		

Note: *NS=Number of Stations, **NC= Number of Chargers, ***Control=Tunisia Result
****P is Statically Significant if $p < 0.05$

Table 11: Tehran M1-M4 Results

R	M ₁		M ₂		M ₃			M ₄		
	NS*	Cost	NS	Cost	NS	NC**	Cost	NS	NC	Cost
0.2	28	\$59856	28	\$59275	28	29	\$1683336	29	29	\$817619.8
0.4	19	\$40658	19	\$40238	19	24	\$1384238	22	24	\$693693.6
0.6	12	\$25335	12	\$25497	13	18	\$1035467	16	19	\$580916.6
0.8	7	\$15270	7	\$14761	7	15	\$854799	8	15	\$516732.4
1	6	\$12588	6	\$12158	6	14	\$796155	8	15	\$526333.3
1.2	4	\$8427	4	\$8496	5	14	\$794437	6	14	\$519046.8
1.4	4	\$8575	4	\$7971	4	13	\$736348	4	13	\$536405.6
1.6	4	\$8645	4	\$8009	4	13	\$736072	4	14	\$556102.8
1.8	3	\$6265	3	\$6030	3	13	\$734330	4	13	\$548966
2	2	\$3971	2	\$3918	2	13	\$731918	3	13	\$575754.8

Note: *NS=Number of Stations, **NC= Number of Chargers

Table 12: Tehran M5 Results

R	M5											
	Uniform			Normal			Poisson			Exponential		
	NS	NC	Cost	NS	NC	Cost	NS	NC	Cost	NS	NC	Cost
0.2	28	100	\$2828225	27	333	\$2618654.4	28	94	\$2660213	28	97	\$2744137.4
0.4	19	82	\$2315926	19	85	\$2399708.2	19	82	\$2315790	19	87	\$2455713.1
0.6	13	75	\$2114436	13	77	\$2170831.5	13	71	\$2002508	13	72	\$2030270.1
0.8	8	57	\$1606323	9	62	\$1747223.7	8	59	\$1662345	8	62	\$1746393.1
1	7	51	\$1438092	7	54	\$1521620.8	7	50	\$1409608	7	54	\$1521579.7
1.2	5	48	\$1352329	5	49	\$1380369.7	5	46	\$1296204	5	51	\$1436074.5
1.4	4	43	\$1211396	4	44	\$1239503.7	4	39	\$1099407	4	45	\$1267420.3
1.6	4	38	\$1071448	4	41	\$1155575	4	33	\$931727.6	4	39	\$1099661.3
1.8	4	38	\$1071695	4	43	\$1011889.8	4	32	\$904465.4	4	29	\$820434.88
2	4	33	\$933306.7	4	34	\$960580.84	4	29	\$820821.8	4	29	\$820900.12

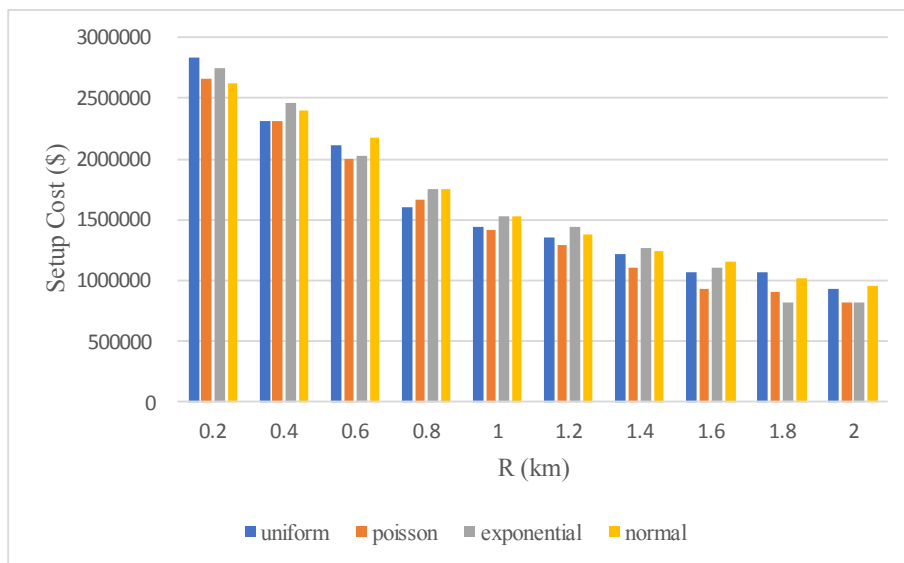


Figure 3: M5 setup cost of EVCS for various demands distribution

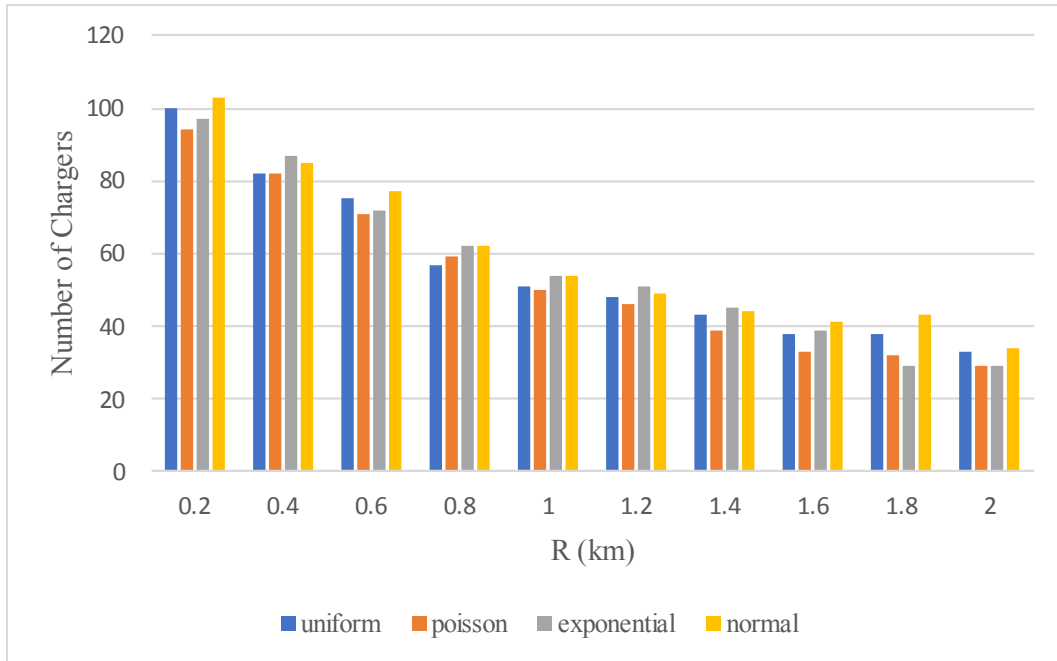


Figure 4: M5 number of chargers in EVCS for various demands distribution

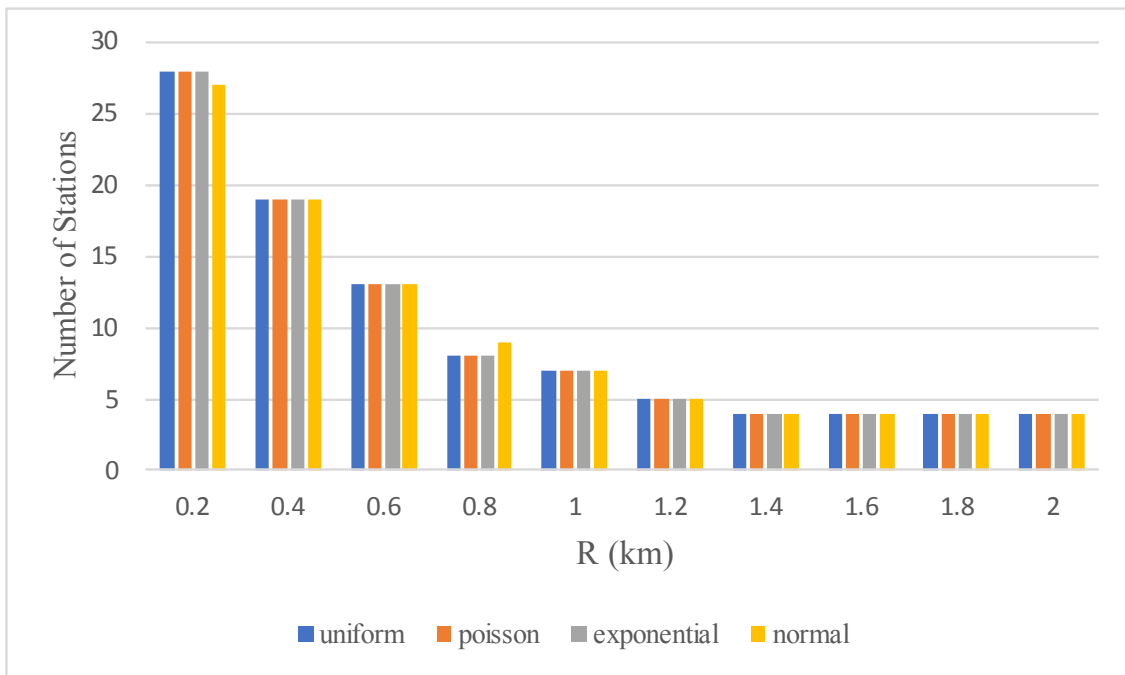


Figure 5: M5 number of stations for various demands distribution

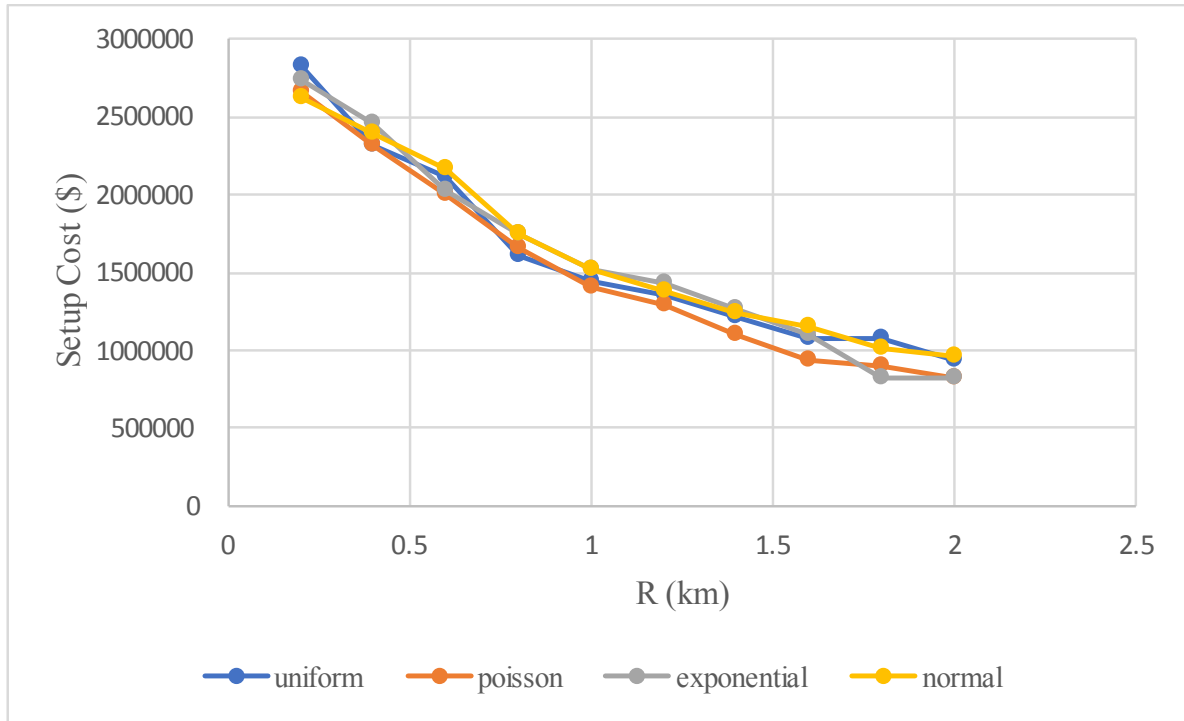


Figure 6: Trend of EVCS setup costs for various demands distributions

5. Conclusion

For various distributions. There are specific processes for optimizing all distributions. It can be concluded that the results are independent of algorithm's efficiency since it can handle any distribution in the real world. On the other hand, the estimated costs for different models using different distributions were quite close to those in the review articles in section 1.

The results of the exact location selection of charging stations for various distributions are available. Nonetheless, Table 13 only contains results for the Poisson distribution, which is closest to reality.

6. Further Study

This article investigated different distributions of demand in the target area. In contrast, the fast and medium demand, followed by the type of charger, was not analyzed. In addition, the formation of the queue was not addressed, so these two crucial issues can be further explored in future studies. Furthermore, the distances

between places were calculated using latitude and longitude components, and it would be appropriate to consider urban accessibility in future studies. Although the M5 model presents two goals: reducing the costs of setting up the station and reducing the costs for the customer walking to the station, future studies should consider multi-objective optimization. After many years, EV still have no place on Tehran's streets, despite the widespread use of EV in developed countries. Therefore, future studies can examine the existing challenges and opportunities for Tehran city.

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Table 13: M5 selected locations with Poisson distribution

Locations	State for each radius
1 Pakistan Gas Station	✓-----
2 Mirzaye Shirazi Gas Station	✓-----
3 Shahid Mofateh Gas Station	✓✓---✓---
4 Ferdowsi Petrol Station	✓-----
5 Shariati Park Gas Station	✓-✓-----✓
6 Baharestan Gas Station	✓✓✓✓✓✓---
7 Sohrevardi 133 Gas Station	✓✓✓✓✓✓-✓---
8 Yousef Abad Gas Station	✓✓-----
9 Gisha Gas Station	✓✓✓✓✓✓-----
10 Sei Gas Station	✓✓-----
11 Bahar Shiraz 155 Gas Station	✓✓-----✓✓-
12 Khorramshahr Gas Station	✓✓✓-----
13 Vesal Gas Station	✓✓-----
14 No. 235 Petrol Station	-----
15 No. 135 Gas Station	-----
16 Zartosht Gas Station	✓✓-----
17 Beheshti Parking	-✓-✓✓-----
18 Azadi Cinema Parking	✓-✓-----
19 Millennium Parking	✓✓✓-----
20 No. 114 Public Parking	-----
21 A .University of Tehran Parking	✓✓-✓-----
22 B .University of Tehran Parking	--✓-----
23 Hafez Public Parking	✓-----
24 Nur Public Parking	✓-----
25 Vali Asr Public Parking	✓-----
26 Ghezel Ghaleh Public Parking	✓✓✓-----
27 Fadak Gardenway Parking	-----
28 Abbaspour Public Parking	-----
29 Mehrun Public Parking	✓-----
30 Pardis Public Parking	✓✓✓-----
31 Beyhaghi Parking	✓✓-----
32 Howeyzeh Hotel Parking	✓-----
33 Medico Plus Center Public Parking	✓✓✓✓✓✓✓✓✓✓
34 University of Applied Science and Technology Public parking	✓✓✓✓✓✓✓✓✓✓
35 Laleh Public Parking	✓✓✓✓✓✓✓✓✓✓

Note: ✓ means location is chosen in the state of radius.

Appendix I*EV Charging Station Location Characteristics*

Index (i)	Type	Designation	Longitude	Latitude	Parking capacity (ci)	Opening cost(fi)
1	Gas Station	Pakistan Gas Station	51.42301	35.73024	6	2175
2	Gas Station	Mirzaye Shirazi Gas Station	51.41762	35.72212	10	2238
3	Gas Station	Shahid Mofateh Gas Station	51.428	35.72351	12	2224
4	Gas Station	Ferdowsi Petrol Station	51.41902	35.70392	6	2300
5	Gas Station	Shariati Park Gas Station	51.44434	35.72657	10	1953
6	Gas Station	Baharestan Gas Station	51.43487	35.69504	11	2275
7	Gas Station	Sohrevardi 133 Gas Station	51.43567	35.72831	12	2118
8	Gas Station	Yousef Abad Gas Station	51.40522	35.74315	7	1939
9	Gas Station	Gisha Gas Station	51.38251	35.72813	8	2331
10	Gas Station	Sei Gas Station	51.41126	35.73389	6	2043
11	Gas Station	Bahar Shiraz 155 Gas Station	51.44622	35.72314	10	1911
12	Gas Station	Khorramshahr Gas Station	51.43712	35.73731	6	2301
13	Gas Station	Vesal Gas Station	51.40048	35.70281	8	2113
14	Gas Station	No. 235 Petrol Station	51.41271	35.70239	8	2199
15	Gas Station	No. 135 Gas Station	51.38966	35.71753	10	2032
16	Gas Station	Zartosht Gas Station	51.40835	35.71961	12	2290
17	Parking Lot	Beheshti Parking	51.41869	35.7261	460	2043
18	Parking Lot	Azadi Cinema Parking	51.41617	35.7281	200	2002
19	Parking Lot	Millennium Parking	51.39794	35.74782	243	2231
20	Parking Lot	No. 114 Public Parking	51.41291	35.74797	240	2248
21	Parking Lot	A .University of Tehran Parking	51.3948	35.70795	250	2052
22	Parking Lot	B .University of Tehran Parking	51.39483	35.707	50	2274
23	Parking Lot	Hafez Public Parking	51.41136	35.71279	400	2076
24	Parking Lot	Nur Public Parking	51.40567	35.70805	150	1915
25	Parking Lot	Vali Asr Public Parking	51.4118	35.75097	350	2012
26	Parking Lot	Ghezel Ghaleh Public Parking	51.39302	35.72429	150	2298
27	Parking Lot	Fadak Gardenway Parking	51.41088	35.7506	50	2040
28	Parking Lot	Abbaspour Public Parking	51.4113	35.7471	50	1977
29	Parking Lot	Mehrsun Public Parking	51.39044	35.70367	300	2230
30	Parking Lot	Pardis Public Parking	51.40701	35.71233	450	1928
31	Parking Lot	Beyhaghi Parking	51.41602	35.73884	700	2085
32	Parking Lot	Howeyzeh Hotel Parking	51.41559	35.70658	40	2046
33	Parking Lot	Medico Plus Center Public Parking	51.41151	35.74594	20	2149
34	Parking Lot	University of Applied Science and Technology Public parking	51.41456	35.70167	30	2179
35	Parking Lot	Laleh Public Parking	51.39186	35.71564	50	2122

Appendix II
Distance table in kilometers

Table with 36 columns (index 1-35) and 36 rows (index 1-35). Each cell contains a numerical distance value representing kilometers between the corresponding stations. The table is symmetric, with the diagonal elements representing 0 km.