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A new deployment method for electric vehicle charging infrastructure

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Abstract: The fast depletion of fossil fuels, climate change, and global warming have become major worldwide problems and alternatives for conventional transportation have been actively researched in the last decade. Compared to available conventional vehicles, electric vehicles have a leading position due to their environmentally friendly transportation. Recent electric vehicle penetration brings the necessity of a high number of charging stations, which are considered to be established in community areas such as shopping centers, hospitals, commercial areas, university campuses, residential areas, and streets. Deployment planning of charging stations is very important for driver expectations and social and economic impacts of electric vehicles. In this regard, optimizing the number of charging stations and their locations is very important for wide-scale use of electric vehicles. Including a new criterion into the existing charging station planning methods is difficult. Due to their structural characteristics, a new flexible planning model of charging stations is needed. In the new model, the queue theory and the analytic hierarchy process are used together to develop a mathematical model for both optimizing the number of charging stations and choosing the best charger locations in a selected region. A case study is performed to show the suitability of the proposed model for finding the optimum location and number of charging stations by evaluating survey data, which reflects drivers' habits within a university campus.

Key words: Electric vehicle, charging station, charging infrastructure planning, decision making, optimization

1. Introduction

The depletion of oil reserves as well as growing environmental concerns in the world have led to the use of alternative energy-based technologies for many applications. In this context, many studies investigated the possibility of using electric vehicles (EVs) for road transport [1–3]. The energy storage systems of the EVs need to be replenished or charged periodically via charging stations (CSs) at home, at work, at shopping centers, and even on streets. Thus, CS infrastructure is one of the most important parts of the EVs and provides rapid adoption of EVs in the market.

Before the mass deployment of EVs, CS planning should be ready for such a massive infrastructure conversion. Accordingly, many researchers have studied CS sizing, location, and impact on the power grid. Tang et al. combined the weighted Voronoi diagram (WVD) and particle swarm optimization to optimize the CS location [4]. Heng et al. proposed a nonlinear multiobjective planning model, which considers the type of CS, drivers' behavior, distribution of charging demand, sustainable development of EVs, distribution network, traffic flow, and municipal planning [5]. Ip et al. provided a two-step model. The first step of the study was the road traffic model and the respective demands into a hierarchy of clusters, in a natural and automatic manner.

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The second part of the model was composed of applied optimization through using linear programming for site planning considering the investment cost [6]. Long et al. used graph theory for optimal location sitting, sizing, and economic modeling of CSs in a selected area [7]. Frade et al. considered the CS deployment plan with maximum covering model for Lisbon [8]. Liu investigated different charging infrastructure deployment strategies in Beijing, China [9]. Sweda and Klabjan provided a case study in CS deployment for the Chicagoland area. In that study, an agent-based decision method was used to enable deployment of CSs for residential users of EVs [10]. Xi et al. studied optimum allocation of charging units considering the maximum use of private EVs in central Ohio [11]. A mixed-integer linear programming model was developed by Kim and Kuby for optimizing the location of refueling stations in the shortest way [12]. He et al. evaluated optimal deployment of commercial CSs in metropolitan areas to maximize social welfare. In that study, they used a static game theory utilized to study the communications, such as availability of public CSs, destination selections of plug-in hybrid electric vehicles (PHEVs), and prices of electricity [13]. Shaoyun et al. studied the CS planning problem in an urban area. In that paper, the road network structure, vehicle flow information, distribution system structure, capacity constraints, etc. are considered for optimal deployment of CSs minimizing the user wastage cost of reaching the CS and investment costs of the power line with the WVD. Each CS capacity was determined by queuing theory (QT) [14]. Another study on electric vehicle charging station planning involved a mathematical model using QT to optimize the quantity of an off-board charger in a station [15]. Although the mentioned studies consider many different methodologies, it is difficult to include new criteria in an existing structure. In CS planning, the traffic data, parking area, driver behavior, economic considerations, power grid conditions, etc. can be considered. Implementing driver behavior as a new criterion into the existing structure of CS planning, which considers the traffic data and power grid condition, is more complex. Thus, in this study, a new model is proposed to find out the optimum locations and numbers of CSs. The proposed method provides easy implementation of new decision criteria compared to existing planning methods.

In this regard, a new CS deployment planning model considering both the optimum location selection and CS quantity determination is proposed in this study. For that purpose, a combined QT-analytic hierarchy process (AHP) model is used for determining an optimal number of chargers as well as convenient locations in a predefined area. Many CS planning criteria can be easily integrated into the problem using AHP. Besides, many parameters including minimum investment cost, waiting time, minimum service time, and optimal operating service of CSs can be optimized simply by QT. Compared with existing CS planning methods, the combination of QT and AHP approaches provides flexibility of CS infrastructure planning while increasing the accuracy of the planning target in modeling. For the performance evaluation of the proposed model, a case study in a campus area of Yıldız Technical University, İstanbul, Turkey, is conducted.

The paper is organized as follows: Section 2 describes the system and explains the proposed methodology. Section 3 presents the case study results derived from the proposed model. Finally, the whole study is discussed and conclusions are presented in Section 4.

2. System description and methodology

In the whole CS planning, each CS should be established in a location considering the energy requirement level and driving habits as main parameters for decision making. This structure can be considered as an optimization problem with relevant minimization objectives and techno-economic limitations. Thus, optimization methods for multicriteria decision making should be applied to CS planning. The proposed model in this regard consists of a combined QT-AHP structure and block diagram of the proposed algorithm as shown in Figure 1. The following subsections provide the details of the proposed model.

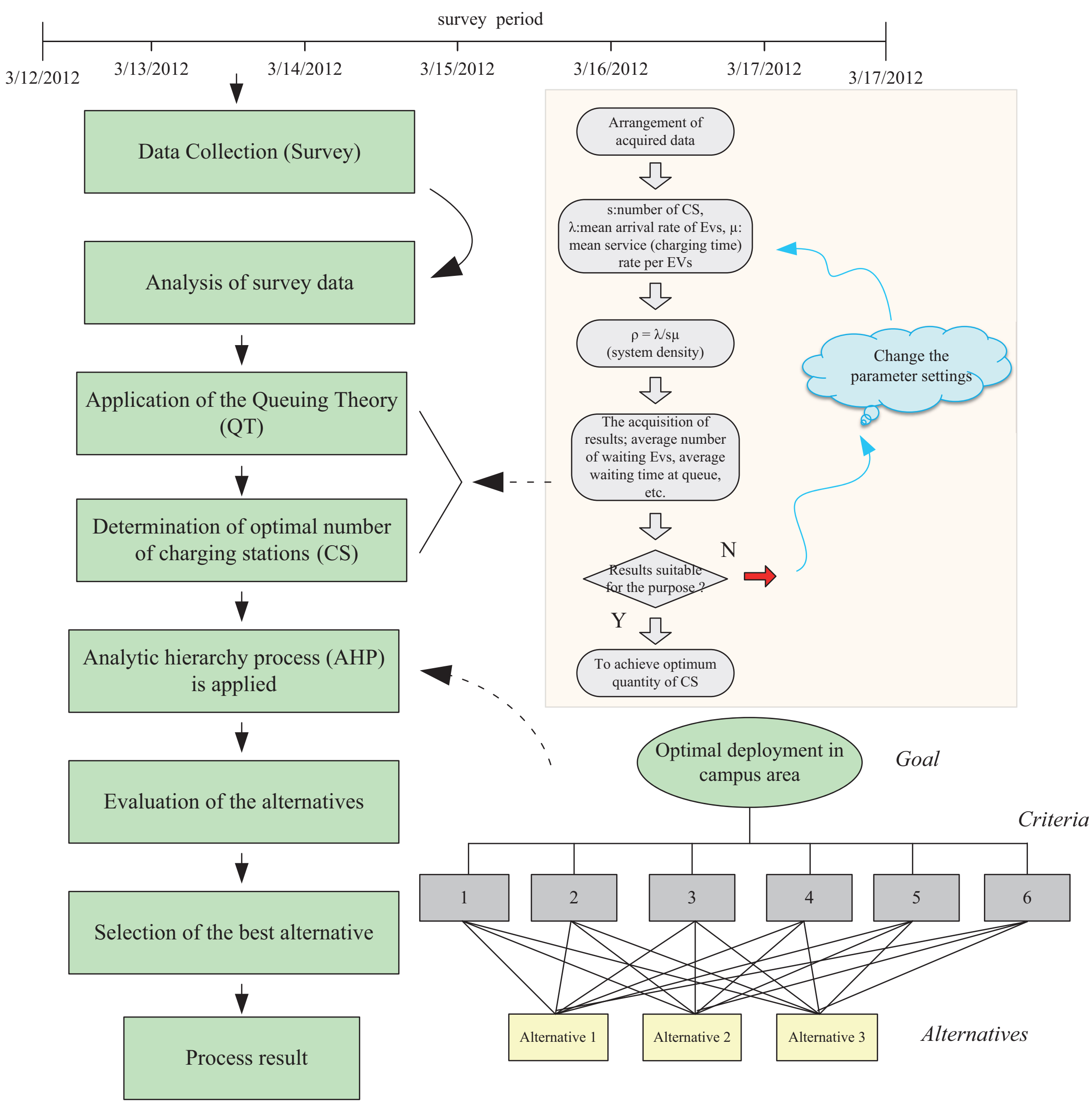


Figure 1. Block diagram of the proposed algorithm.

2.1. Queuing theory

As a widely used theory for stochastic processes, QT is employed for handling the stochastic structure of the charging requests and differences of the drivers' behavior. EV charging requirements are similar to Poisson flow, and entrance of drivers (customers) must be a negative exponential distribution [15]. Full charging of EVs takes a long time, so the average waiting time of EVs at CS queues should be minimized. For this purpose, QT is used in this paper.

QT is used widely in daily life and has solved a real-life queue problem with mathematical modeling [16,17]. Like gasoline stations, a CS is a service system for each customer. Minimum waiting time in the queue for each EV has to be arranged by the charging service. CSs have some important characteristics, such as: a) the charging service has a random characteristic due to drivers' behavior, b) the battery state of charge (SoC) for EVs is different because of the drivers' behavior and charging time is different for that reason, and c) every charging unit works at the same efficiency and their service capacities are constant [15,18].

Different types of queues can be modeled considering the number of servers, number of queues, and number of phases [19]. In this study, CS service can be modeled as the single-phase, single-line, and multiple-service desk of the QT model (M/M/s). Some assumptions are needed to create the model. These assumptions are: a) every EV reaches the CS individually and independently, and b) EVs access the CS by Poisson process and move out with exponential distribution.

The mentioned QT (M/M/s) model is given in the following equations [20]. System density can be expressed as:

$$\rho = \frac{\lambda}{s\mu}, \tag{1}$$

where λ is expressed as the average rate of EVs, $\rho = \frac{\lambda}{s\mu} s$ is the number of chargers, μ is the average rate of charging time, and ρ is the system density. Here, λ and μ are calculated from statistical data. The idle probability of the CS is expressed as:

$$\underset{0}{P} = \left[\left(\sum_{n=0}^{s-1} \frac{(\lambda/\mu)^n}{n!} \right) + \frac{(\lambda/\mu)^s}{s!} \left(\frac{1}{1-\rho} \right) \right]^{-1}, \tag{2}$$

where P_0 is the idle probability of the CS. The number of waiting EVs in the queue is expressed as:

$$L_q = \frac{P_0 (\lambda/\mu)^s \rho}{s!(1-\rho)^2}, \tag{3}$$

where L_q is the number of waiting EVs. Waiting time in the queue is expressed as:

$$W_q = \frac{L_q}{\mu}, \tag{4}$$

where W_q is the waiting time. Total waiting time (service and waiting) in the queue is expressed as:

$$W = W_q + 1/\mu, \tag{5}$$

where W is the average waiting time in the queue. Total number of waiting and charging EVs is expressed as:

$$L = \lambda W, \tag{6}$$

where L is the number of average total EVs. The steady-state probability is expressed as:

$$P_n = \begin{cases} \frac{(\lambda/\mu)^n}{n!} P_0; n \leq s \\ \frac{(\lambda/\mu)^n}{s! s^{n-s}} P_0; n > s \end{cases}, \tag{7}$$

where P_n denotes the steady-state probability of the whole number of EVs, and n is a total number of (charging and waiting) EVs in a given time. In this system, inequality of $\frac{s\mu}{\lambda} > 1$ must be maintained at all time. Otherwise, the queue increases continuously.

QT is used to decide on an optimum number of CSs for providing minimum waiting time in the queue considering the above mathematical formulations. After QT study, AHP is used for determining the optimum location of the specified number of CSs.

2.2. Analytic hierarchy process

In the CS planning process, using QT alone is not sufficient for comprehensive planning of CS deployment in a selected area. The deployment process can be considered as a multiobjective decision-making problem since it is affected by criteria. There are many techniques used to deal with multiobjective decision-making problems. AHP is one of the most commonly used methods for decision making, which was created by Saaty [21]. AHP is utilized in a wide variety of multiobjective decision-making applications [22,23]. Objectives, criteria, subcriteria levels, and alternatives are derived from AHP and used in every hierarchical model. It is a common solution method for complex, difficult to understand, and unstructured problems. AHP is founded on basic principles of the creation of hierarchies, determination, and logical and numerical consistencies [24].

The decision-making process of AHP mainly consists of five steps:

a) First, creating a model that defines relations between essential criteria of a problem.

b) Second, arranging a subgroup of problems and making a hierarchy among them.

c) Third, the expression of the hierarchy should give reasonable numbers to compare the hierarchy among itself.

d) Specifying the alternative decision and defining the priority of criteria, which were achieved from previous phases.

e) Finally, results are analyzed for decision making.

Generally, it is required to develop an evaluation matrix for comparing criteria. For this purpose, a pairwise comparison matrix, A, is defined and can be expressed as:

$$A = (a_{ij})_{m\times m}, \tag{8}$$

were a_{ij} indicates the ratio of the ith weight criterion to the jth weight criterion, and m is the number of criteria. It is necessary to scale the ratio level from 1 to 9 for decisions as shown in Table 1 [24].

Table 1. The fundamental scale of absolute numbers for AHP.

Number of rating	Verbal judgment of preferences
1	Equally
3	Moderately
5	Strongly
7	Very
9	Extremely
2, 4, 6, 8	Medium value above pairwise comparison

The second step of AHP finds the priority matrix that shows the degree of importance. Comparing the matrix presents the priority rank criteria in regular formation. Weight criteria (b_{ij}) are obtained from columns of the compared matrix considering Eq. (8):

$$b_{ij} = \frac{a_{ij}}{\sum\limits_{i=1}^{m} a_{ij}}. \tag{9}$$

Numbers of m column vectors are combined in matrix form, and B matrix is created as:

$$B = [b_{ij}]_{m\times m}. \tag{10}$$

The B matrix can be used to determine the weight between each criterion:

$$w_i = \frac{\sum_{j=1}^{m} b_{ij}}{m}. \tag{11}$$

Eq. (11) can be used to obtain the weight and acquire the W column vector, which is called a priority vector. The realistic results of AHP depend on the consistency ratio of criteria. AHP suggests a process to measure the consistency of these comparisons. Coherence ratio (CR) provides a consistency test for comparisons. CR calculation is based on the comparison of the eigenvalue ($\lambda_{\max}$) and number of criteria. $\lambda_{\max}$ can be expressed as;

$$\lambda_{\max} = \frac{\sum_{i=1}^{m}\left[(\sum_{j}^{m} a_{ij}\times w_j)/w_i\right]}{m}. \tag{12}$$

After calculating $\lambda_{\max}$, the consistency index (CI) can be computed as:

$$CI = \frac{(\lambda_{\max} - m)}{m-1}. \tag{13}$$

CR is described as the ratio of the CI and a random index (RI), which is given in Table 2 [25].

$$CR = \frac{CI}{RI} \tag{14}$$

If CR $\leq$ 0.1, judgments of decision makers (such as infrastructure planners or experts) are satisfied and the results are usable. Otherwise, pairwise comparison of matrix A should be changed. Consequently, the decision matrix multiplies the pairwise matrix to find the global weight of each alternative.

Table 2. Arithmetic mean of random matrix consistency indexes.

n	1	2	3	4	5	6	7	8	9	10	11
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51

2.3. Combined model of QT-AHP

In optimization of CS deployment planning, first, a step-by-step structure is considered by applying QT and then AHP with the relevant results obtained from QT steps. For the first step of the proposed structure, some assumptions are made in order to apply the QT method on the campus area: a) EVs form a single queue and arrival time is different for each EV, and b) EVs have a Poisson characteristic (drivers' behavior is different and independent). In addition, other assumptions mentioned previously in Section 2.1 are noted for the idealization of the problem of the queue waiting times such that they will not lead to separations and all vehicles will enter the queue. All calculations are made based on the M/M/s-QT model. We get a different number of chargers corresponding to different charging times under a variety of scenarios. This is due to the fact that different vehicle brands utilize different battery and charger technologies, which causes the charging time of the battery to be different in each case. Different scenarios are adopted to show that the proposed model can perform effectively in different conditions. In this study, calculations are made to reduce the number of vehicles in the queue and the waiting time. Table 3 shows the required number of chargers under different service (charging) times (where s is the number of chargers, W_q is waiting time in the queue (in minutes), and L_q is the average number of waiting EVs). The aim of this part of the study is to minimize the average number of waiting EVs in the queue.

Table 3. The results with different charging (service) times and 5% EV penetration rate.

	5% Electric vehicle penetration rate		
Charging (service) time (h)	s (number of chargers)	Wq (min)	Lq (number of waiting EVs)
3**	18	33.9507	2.8292
	19	14.5347	1.2112
	20	6.8863	0.5738
	21	3.4311	0.2859
	22	1.7481	0.1456
6*	33	11.6078	9.5506
	34	53.8688	4.4890
	35	28.4099	2.3674
	36	16.0116	1.3343
	37	9.3909	0.7825

*Scenario 1.
**Scenario 2.

After obtaining the optimal number of chargers, AHP is used to determine optimum locations of chargers in the campus area. AHP is applied in three steps: the first step is the determination of the criteria and alternatives, the second step is to calculate the weights of alternatives, and the third step is to analyze the results using the best alternative that has a higher weight value.

In this study, six criteria are selected to meet the needs of drivers and power grid:

i) *Number of parking areas that have charging unit(s):* This criterion is used to determine the priority (weight) of parking areas in the selected areas. In the AHP modeling criterion, "$\boldsymbol{f_1}$" is defined as the change in the number of CSs among alternatives, shown in Table 4.

ii) *Walking distance:* Distance is very important for drivers to choose parking lots. If the distance between the parking area and office buildings is greater than 500 m, many drivers do not want to use that parking area [26]. Criterion "$\boldsymbol{f_2}$" is defined in Figure 2 and is used for preparing the pairwise comparison matrix.

iii) *Distance between power substations and parking areas:* This criterion, "$\boldsymbol{f_3}$", is important to reduce the investment cost and to increase the power quality.

iv) *Density:* Population and usage density, "$\boldsymbol{f_4}$", are the main parameters of the CS deployment in a selected area. For example, if a parking area is near a high population with high traffic density, then more charging units are required in that parking area.

v) *Expandability:* It is very important to meet charging requests in the future. In order to meet a charging request, transformer capacity and parking capacity are the main factors of this criterion. This criterion, "$\boldsymbol{f}_{\mathbf{5}}$", will help to understand further expansion potential of parking areas for future planning.

vi) *Accessibility:* Drivers prefer to reach CSs easily. This criterion, "$\boldsymbol{f}_{\mathbf{6}}$", will give accessible CSs on the campus.

Table 4. Survey results and specifications of parking areas.

Parking area	Capacity	Occupancy rate (%)	Average parking time (h)	Distance to substations (m)
P1	85	24.57	5.06	TR2-86
P2	150	32.46	5.78	TR1-51
P3	76	46.47	5.52	TR2-181
P4	110	43.25	5.68	TR5-96
P5	150	46.25	5.29	TR5-192
P6	220	31.47	5.63	TR6-108
P7	15	16.48	4.84	TR6-382
P8	35	57.38	5.47	TR7-215
P9	34	2.47	4.89	TR7-35
P10	180	1.9	4.56	TR8-122
P11	50	31.76	6.8	TR2-306

Based on each criterion the algorithm determines where and how many charging units should be located in the parking area.

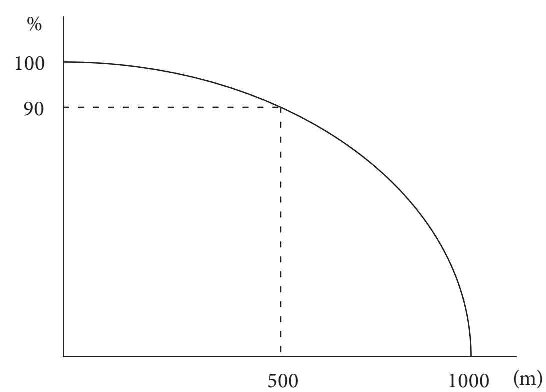


Figure 2. Interest rates of parking habits within walking distance.

2.4. Case study

Yıldız Technical University (YTU) is the 3rd oldest university of Turkey, which was founded in 1911. YTU has 10 faculties and more than 23,000 students. Additionally, YTU has approximately 1500 academic staff and the main research areas of the university are electrics, electronics, and machinery. The Davutpaşa Campus is the biggest campus of YTU, which is 131 ha. For evaluating the performance of the proposed methodology, a case study for Davutpaşa Campus of YTU in Turkey is conducted. Many studies have been performed on home charging (stations) units in the literature, mostly in the United States. However, in İstanbul, EVs can be charged in the daytime in public CSs because of the physical conditions of the city, and most drivers park their vehicles on streets randomly, in contrast to night charging in the United States. Thus, EV owners can charge their vehicles on streets, in shopping centers or working areas, etc. In this context, this study suggests an optimal solution considering the drivers' requests during working hours in campus-based working areas.

A selected campus overview, parking areas, and substations are shown in Figure 3. First of all, the average vehicle density is obtained using a survey for each hour between 0700 and 1900 hours. Figure 4 shows the vehicle density of campus for 1 week. Only weekdays are evaluated in the analysis because of the small number of vehicles during weekends. The mean value of vehicle density for 5 days (from Monday to Friday) is 1102.2 vehicles/day. Besides, hourly average vehicle density is 91.85 vehicles/h, and it is used for deciding the optimal number of CSs in the campus area considering 5% penetration rate of EVs as a case scenario. In this study, each parking area is analyzed for 1 month to make high-accuracy decisions. Parking capacity, usage density, distances to substations, and nearest faculty buildings are considered for the analysis and summarized in Table 4.

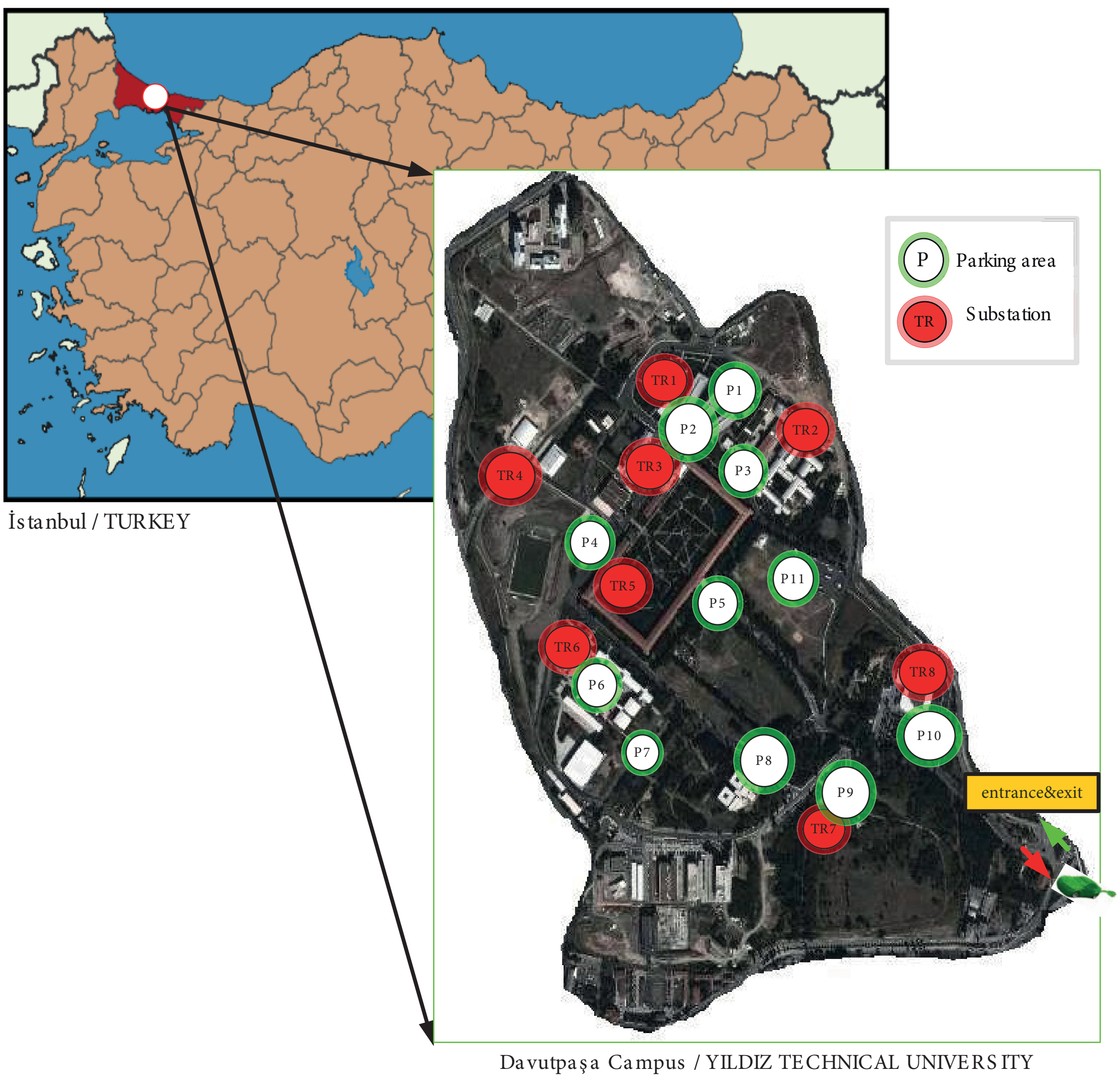


Figure 3. Parking areas and substations of Davutpaşa Campus.

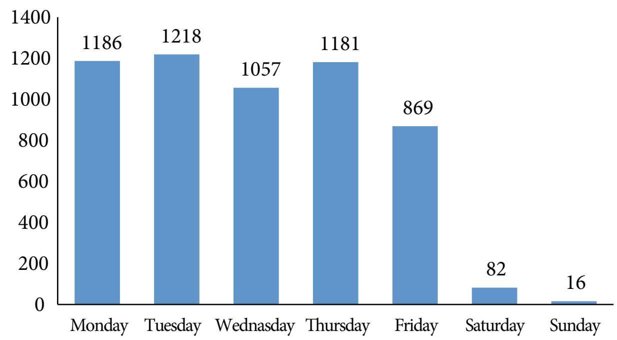


Figure 4. Survey result of vehicle density for 1 week in campus area.

The calculation-based assessments are presented for CS deployment planning for the Davutpaşa Campus case. According to the survey results, average parking time of vehicles is about 6 h. Our purpose is to minimize the average number of waiting EVs in the server queue. When the average number of waiting EVs (Lq) is less than 1, the simulation will be stopped. First, we consider the 6-h charging (service) time as a first scenario given in Table 3. As is clearly shown in Figure 5, when the number of chargers reaches 37, the simulation is stopped. Thus, 37 chargers are deployed. The main priorities to form the alternatives in the first scenario are chosen as density (traffic, population) and accessibility. Charging units can be deployed in parking areas either randomly or based on some criteria. Here, the number of charging units is chosen considering density and accessibility as the main criteria. Accordingly, three alternatives, given in Table 5, are considered to calculate their weights. First of all, the comparison matrix A_1 is built up with the pairwise comparison of each criterion. The criterion weights are obtained by such questions as "which criterion is much/more important than others?" [24].

Table 5. Proposed alternatives for Scenario 1 (37 charging units are allocated between parking areas).

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
Alternative 1	3	4	5	5	5	3	2	4	2	0	4
Alternative 2	4	5	5	4	4	4	3	3	2	1	2
Alternative 3	1	5	5	4	5	3	3	3	3	2	3

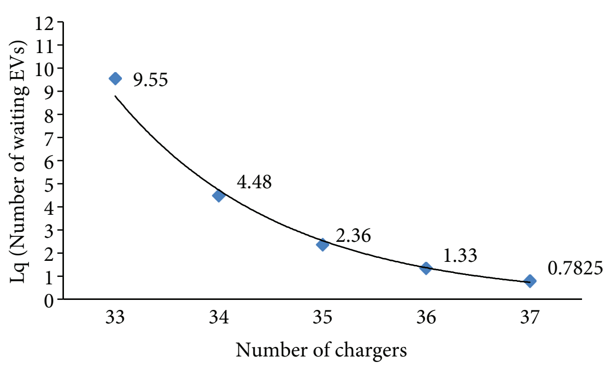


Figure 5. Changing of average waiting time (Lq) in the queue.

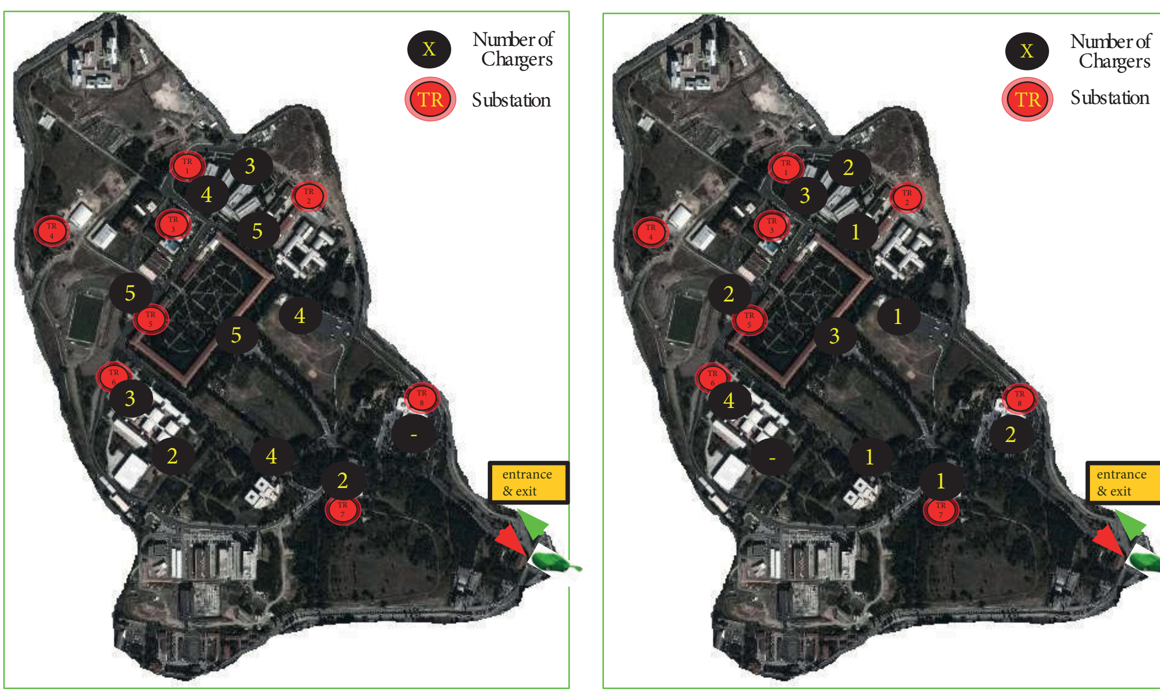
The A_1 matrix is decided (according to Section 2.2 considering Table 1) as follows.

$$A_1 = \begin{array}{c|cccccc} & \mathbf{f_1} & \mathbf{f_2} & \mathbf{f_3} & \mathbf{f_4} & \mathbf{f_5} & \mathbf{f_6} \\ \hline \mathbf{f_1} & 1 & 1/3 & 1/2 & 1/7 & 1 & 1/7 \\ \mathbf{f_2} & 3 & 1 & 1 & 1/5 & 1 & 1/5 \\ \mathbf{f_3} & 2 & 1 & 1 & 1/5 & 1 & 1/5 \\ \mathbf{f_4} & 7 & 5 & 5 & 1 & 5 & 1 \\ \mathbf{f_5} & 1 & 1 & 1 & 1/5 & 1 & 1/5 \\ \mathbf{f_6} & 7 & 5 & 5 & 1 & 5 & 1 \end{array}$$

The normalized eigenvector of matrix A_1 is computed as W_1 = [0.0475 0.0849 0.0769 0.3608 0.0690 0.3608]. This vector indicates criterion weights "f_1", "f_2", "f_3", "f_4", "f_5", and "f_6", respectively. According to Eq. (12), we also get the eigenvalue, $\lambda\max_1$, as 6.1006. Consequently, the consistency ratio (CR_1) is calculated as 0.0162 and this value is smaller than 0.1; thus, matrix A_1 satisfies the consistency test. After that, AHP results, shown in Table 6, present the total weights of each alternative. The weight value of alternative 1 is higher than the others, so it is selected as the best alternative. Optimal deployment of chargers according to alternative 1 is illustrated in Figure 6a.

Table 6. The weight of the alternatives for Scenario 1.

	f1	f2	f3	f4	f5	f6	Total weights
Alternative 1	0.0068	0.0121	0.0132	0.2097	0.0281	0.2097	0.4796
Alternative 2	0.0204	0.0364	0.0213	0.0395	0.0182	0.0395	0.1754
Alternative 3	0.0204	0.0364	0.0424	0.1116	0.0227	0.1116	0.3450



a) Scenario 1 (37 chargers)

b) Scenario 2 (20 chargers)

Figure 6. Optimal deployment of chargers for Davutpaşa Campus.

In the second scenario, charging (service) time is set to 3 h to minimize the number of EVs in a queue considering the first five criteria. Additionally, the minimum investment cost, which is related to the third criterion (***f3***), is taken into account as a main priority. In this case, 20 chargers, as given in Table 3, are sufficiently deployed considering the average number of waiting EVs (Lq), which is less than 1. Different alternatives shown in Table 7 have been created with specified priority. The comparison matrix A_2 for the second scenario is decided as follows.

Table 7. Proposed alternatives for Scenario 2 (20 charging units are allocated between parking areas).

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
Alternative 1	1	2	3	3	3	2	1	3	0	0	2
Alternative 2	2	3	1	2	3	4	0	1	1	2	1
Alternative 3	2	3	3	2	2	2	1	2	1	0	2

$$
\mathrm{A}_2 = \begin{array}{c|ccccc}
 & \mathbf{f_1} & \mathbf{f_2} & \mathbf{f_3} & \mathbf{f_4} & \mathbf{f_5} \\
\hline
\mathbf{f_1} & 1 & 1 & 1/7 & 1/3 & 1/3 \\
\mathbf{f_2} & 1 & 1 & 1/7 & 1/3 & 1/3 \\
\mathbf{f_3} & 7 & 7 & 1 & 5 & 5 \\
\mathbf{f_4} & 3 & 3 & 1/5 & 1 & 1 \\
\mathbf{f_5} & 3 & 3 & 1/5 & 1 & 1
\end{array}
$$

The normalized eigenvector is computed as $\mathrm{W}_2 =$ [0.0610 0.0610 0.5662 0.1559 0.1559]. It indicates the criterion weights "f_1", "f_2", "f_3", "f_4", and "f_5", respectively. According to Eq. (12), we obtain the eigenvalue $\lambda\max_2$ as 5.094. The consistency radio (CR_2) is calculated as 0.0210, which is smaller than 0.1, and thus matrix A_2 satisfies the consistency test. Table 8 shows the total weights of each alternative. In that table, the weight of alternative 2 is higher than others, so it is selected as the best alternative. Optimal deployment of chargers according to alternative 2 is illustrated in Figure 6b. Other alternatives can also be considered since the proposed model provides an easy implementation of new criteria into the existing CS planning.

Table 8. The weight of the alternatives for Scenario 2.

	f1	f2	f3	f4	f5	Total weights
Alternative 1	0.0122	0.0181	0.1029	0.0840	0.0780	0.2953
Alternative 2	0.0244	0.0100	0.3088	0.0255	0.0390	0.4077
Alternative 3	0.0244	0.0329	0.1544	0.0463	0.0390	0.2970

3. Conclusion and future work

In this paper, a new planning method for EV charging infrastructure is proposed. QT and AHP methods are used to develop a combined model to optimize the number of CSs and to choose their optimal locations in the selected region. A case study is performed to show the applicability of the proposed model in a university campus.

CS infrastructure planning is an important issue with the rapid increase in the number of EVs. Optimum planning of CSs provides many significant advantages for sustainable growth of the alternative transport sector. In this study, the proposed model was successfully applied to the case of charging infrastructure planning on the Davutpaşa Campus of YTU in İstanbul, Turkey. The results show the effectiveness of the new planning method and the feasibility of the proposed combined model of QT-AHP considering different objectives, such as a minimum number of waiting EVs, different service (charging) times, and minimum investment cost.

Both economic and environmental issues of CS infrastructure planning in a campus area considering the smart grid concept will be presented as a future work. Additionally, CS infrastructure planning will be extended to whole city of İstanbul using the proposed model.

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