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Optimal Placement of Plug-in Electric Vehicles Fast-Charging Stations Using Geographic Information System and Considering Power Distribution Network Indexes: A Case Study in Kabul

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ABSTRACT

Concerning the increasing application of plug-in electric vehicles (PEVs), planning PEV fast-charging stations (PEVF-CS) has become an important research topic. Regarding the reactive power compensation capability, the optimal planning of PEVF-CS reduces voltage deviation and power loss in the distribution network. Also, one of the basic requirements for expanding electric transportation is the optimal placement of accessible PEVF-CSs, considering the geographic information data. Therefore, the optimal placement of PEVF-CS requires attention to different geographical criteria and power distribution network constraints. In this sense, this paper aims to propose an approach that integrates the Geographic Information System (GIS) technique, Multi-Criteria Decision-Making (MCDM) method, and Mixed-Integer Nonlinear Programming to find the optimal location of a PEVF-CS in Kabul city. The first stage is decision analysis based on the GIS technique and the MCDM approach. The second stage is suitability analysis of the power distribution network constraints to improve power quality. This paper considers ten different suitability criteria, and the Technique for Order Preference Similarity to Ideal Solution (TOPSIS) is applied to rank the different candidate locations. The analysis identified Junction 4 as the optimal choice and demonstrated a significant 3.6% reduction in power loss during peak hours, decreasing from 1071 kW to 1032 kW. These results demonstrate the effectiveness of our approach in optimizing PEVF-CS placement to enhance power quality and reduce the power loss.

NOMENCLATURE

AHP	Analytic hierarchy process.
EV	Electric vehicle.
GIS	Geographic information system.
MINLP	Mixed-integer nonlinear programming model.
MCDM	Multi-criteria decision-making.
PEV	Plug-in electric vehicle.
PDN	Power distribution network.
PEVCS	Plug-in electric vehicle charging station.
PEVF-CS	Plug-in electric vehicle fast-charging station.
TOPSIS	Technique for order preference similarity to ideal solution.
WLC	Weighted linear combination.
S^s	Set of reference bus.
S^{line}	Set of lines in DN.
i,j	Index of buses in DN.
t	Index of time.
$G_{i,j} - B_{i,j}$	Line conductance and susceptance.
C^{Volt}	Penalty factor for voltage deviation ($).
C_t^{Ploss}	Penalty factor for power loss ($/kWh).
C_i^u	Grid connection and AC/DC converter costs ($/MVA).
$P_{i,t}^l - Q_{i,t}^l$	Active/reactive power consumption of loads.
$P_{i,t}^{Fcs}$	Active power consumption of PEVF-CS.
P_t^{loss}	Power loss.
$P_{i,j,t}^{line} - Q_{i,j,t}^{line}$	Active/reactive power of lines.
$P_{i,t} - Q_{i,t}$	Active/reactive power generation.
$S_i^{Fcs} - Q_{i,t}^{Fcs}$	Apparent/reactive power of PEVF-CS.

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$V_{i,t}$	Voltage magnitude.	All electrical quantities are stated per unit (PU).
$\delta_{i,t}$	Voltage angle.	

I. Introduction

Environmental pollution resulting from burning fossil fuels, combined with the depletion of fossil energy resources, has compelled societies to focus more on transportation systems as significant consumers of these fuels. One effective way to decrease greenhouse gas emissions and dependency on fossil fuels is through the expansion of electric transportation. Advances in battery technology have significantly promoted the adoption of electric vehicles (EVs). Some researchers predict that EV production will soon overcome traditional vehicle production in the automotive industry. Additionally, improvements in rectifier design now enable EVs to function as mobile power sources and reactive power compensators [1]. One essential factor in expanding and promoting EVs is the availability of refueling infrastructure, specifically charging stations. Adequate and accessible charging stations accelerate the adoption of electric vehicles within transportation networks and contribute to their global proliferation. Therefore, the problem of determining the optimal location of charging stations has attracted more attention. In planning plug-in electric vehicle charging stations (PEVCS), mitigating adverse impacts on the Power Distribution Network (PDN) is crucial. Voltage stability, reliability, power loss, and power quality are pivotal concerns due to the potential harm from high EV penetration, which can affect grid performance [2, 3]. Various studies have addressed these challenges through optimization models for site selection and sizing of charging stations.

References [4, 5] propose models considering PDN constraints in optimizing PEVCS placement and sizing. Reference [4] integrates costs for distribution expansion, EV stations, voltage regulation, and protective devices into the objective function, preserving problem sensitivity and ensuring a global minimum through convex preservation. The results highlight the importance of voltage regulation and necessary upgrades to protection devices under high recharging demand. Reference [5] determines the optimal location and size of PEVCS in a PDN while maintaining stability conditions. The study analyzes the impact of PEVCS on the PDN by examining active and reactive power losses, power flow, and voltage deviation. Simulation results on the IEEE 33 bus distribution system indicate that up to 200 EVs can be charged without violating network constraints, and adding distributed generators, preferably renewable, is necessary to meet high EV demand while mitigating environmental pollution. Reference [6] proposes mixed-integer linear programming to optimize the sizing and placement of EVCSs in a real distribution system. The objective is to minimize the number of stations while meeting EV owners' needs and PDN constraints.

Using real EV charging data from a Turkish distribution network, the study validates the model's effectiveness through various case studies. It highlights potential cost reductions in installation and infrastructure upgrades while suggesting future research should focus on managing peak power impacts and utilizing ancillary services from EVs in distribution systems. However, these studies do not consider driver convenience in urban areas, which is crucial for EV adoption.

Reference [7] introduces a novel approach using stochastic power flow analysis to optimize the siting and sizing of PEVCSs, focusing on addressing uncertainties in power systems, such as load fluctuations and EV integration impacts. The model aims to maximize PEVCS investment returns by minimizing average wait times and charging distances prioritizing driver convenience. Additionally, it enhances system voltage stability through dynamic system voltage stability (DSVS) indices, demonstrating improved service quality even under high EV penetration scenarios. Reference [8] addresses the location planning of urban PEVCS and battery-swapping stations, considering user behavior and aiming to minimize total costs, maximize user satisfaction, and reduce energy consumption in route to stations. A multi-objective planning model is developed and solved using YALMIP/CPLEX, dynamically analyzing key parameters to determine optimal station locations. The results balance charging and battery-swapping pressures, ensuring even distribution and full utilization of facilities, thereby alleviating user anxiety and promoting EV adoption. These efforts demonstrate the importance of integrating technical and economic considerations in planning PEVCSs to sustain PDN performance. Yet they neglect the station's ability to compensate for voltage drop and power loss within the power network. In [9], a new model is introduced for optimal PEVF-CS siting and sizing, considering PEVF-CSs as power line conditioners to improve power quality and address traffic congestion by strategically placing stations. Reference [10] proposes a GIS-based method and a genetic algorithm for estimating charging demand and determining the optimal locations for charging stations. The primary goals of this study are to decrease investment costs and present an appropriate geographic distribution of charging stations. Additionally, the study investigates various aspects of electric vehicles by modeling electric and parallel hybrid vehicles in MATLAB/Simulink software. However, optimal planning for charging stations is a multi-criteria evaluation problem, with various conflicting criteria influencing the process. The recent studies mentioned above do not address geographical limitations, which are crucial in planning PEVF-CSs. The model needs to account for geographical barriers that could affect the practical suitability of the identified optimal charging station locations.

Furthermore, many studies have examined placing charging stations as the MCDM or the Analytical Hierarchy Process (AHP) for locating PEVCSs [11-15]. Reference [11] employed the fuzzy AHP to determine optimal placing EV charging stations in Ankara, Turkey. Their methodology included four stages: criteria identification, scoring the availability of EV charging station sites, criteria weighting through expert input, and ranking proposed sites using AHP. Meanwhile, in another study [12], AHP and FAHP methods are used to calculate criteria weights, with AHP initially determining weights that are subsequently averaged in the FAHP method. The study focused on accessibility, environmental impact, and economic considerations, including 13 sub-criteria, to identify optimal charging station locations within Istanbul, Turkey. In [16], an integrated strategy is proposed for ranking optimal locations and determining the number of charging stations in the Kadikoy and Ataşehir districts of Istanbul, Turkey. The methodology involves selecting alternatives based on different criteria utilizing the AHP method and ranking them by the TOPSIS method. Subsequently, the number of charging stations is optimized to maximize profitability using the LINGO tool. However, the paper does not introduce a new spatial siting solution. In [17], the study calculates criteria weights using the AHP method and prioritizes alternative locations using PROMETHEE and VIKOR methods for MCDM. Results indicate that the southeast of the European side and the southwest of Anatolian in Istanbul are most suitable for PEVCS deployment. Reference [18] analyzes critical factors in selecting optimal charging station locations in Greece, highlighting the importance of transportation hubs and parking lots over land usage. Public service criteria are comparatively less significant in location planning. Reference [14] identified optimal locations for EV charging stations in Upper Silesia and Dabrowa Basin, Poland. Their methodology is more straightforward than previous studies [12, 13], focusing on assessing and siting a limited number of off-road charging stations. However, to our knowledge, existing literature still needs to introduce a methodology to address the spatial sitting problem of EV charging points while simultaneously considering both geographical conditions and power constraints. It's important to note that PEVCSs can provide reactive power compensation through their power electronic converter, benefiting power networks, yet research still needs to integrate these parameters concurrently.

This paper addresses the optimal location for fast-charging stations in Kabul City, Afghanistan, to facilitate the transition from gasoline to electric vehicles and ensure proper geographic distribution. While some studies in Afghanistan have used MCDM methods for various purposes such as assessing the feasibility of wind energy for hydrogen production in Badakhshan [19], prioritizing locations for wind energy-based hydrogen production [20], and evaluating potential geothermal energy projects [21] none have focused on planning PEVF-CSs in Afghanistan, particularly in Kabul, the capital and largest city. Moreover, GIS-based studies have only focused on the optimal location of charging stations according to the proximity criterion to power transmission lines. However, by adding the PDN constraints and power quality issues, the optimal location of PEVF-CSs can be achieved from both the PDN and GIS aspects. Therefore, this paper addresses determining the optimal location for PEVF-CSs to satisfy the geographic criteria and power quality indexes as a distinguished feature. Improving the power quality of the PDN and finding an accessible location for placing PEVF-CSs are the two main goals of this paper. The paper is organized as follows: The next section presents the methodology for explaining all processes. The third section presents the results and discussion. Finally, the paper is concluded in section four.

II. Methodology

This paper proposes the integration of the GIS-based MCDM approach and a mathematical model for finding suitable locations of PEVF-CS. In this regard, the workflow of this study is shown in Fig. 1. This figure describes different steps in the proposed approach.

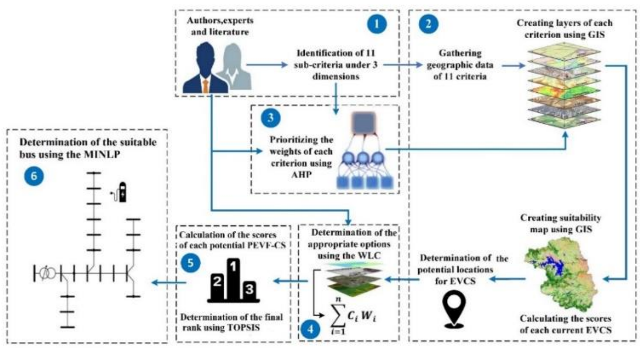

Fig. 1. The workflow of this study

In the first step, the essential criteria that affect the suitable location of PEVF-CS are chosen. In the second step, the geographic data of each criterion is gathered, and suitability layers for each criterion are produced using GIS-based analysis. The related data for each criterion is collected from different sources for spatial analysis. The GIS-based MCDM approach is implemented using the AHP and weighted linear combination (WLC) methods. In the following, the alternatives are ranked with the TOPSIS method. Also, QGIS software is used to analyze the GIS data. Finally, the most suitable alternative is analyzed as power network constraints. The proposed MINLP is used for selecting the optimal bus for connection of the PEVF-CS.

A. *Analysis of the evaluation attributes*

This paper considers eleven criteria to select the suitable location of PEVF-CS. Indeed, the criteria that affect the PEVF-CS location are chosen. Also, the criteria related to statistical data have been omitted due to the limited access to Kabul City's statistical data and the expense of preparing questionnaires to estimate some statistical data. In this study, eleven criteria have been extracted using various sources. The determined criteria are divided into three groups (Fig. 2).

Fig. 2. Criteria architecture of the PEVF-CS siting problem

1) Population density

The necessity for charging stations is more remarkable in areas with more population density than in other areas. For this reason, population density is used as a criterion to determine the candidate areas. In this paper, the raster layer of the Kabul population for 2020 is used [22]. A site with a high population density will be more suitable for placing PEVF-CS.

2) Shopping malls

Shopping malls can be considered as an evaluation factor for finding a suitable location for PEVF-CS. Placing PEV-FCS near shopping malls can cover a significant part of the demand for refueling. Google Maps has been used to determine the location of shopping malls and produce the shapefile layer of shopping malls.

3) Roads

In the transportation network, electric vehicles travel on the roads. Therefore, roads play a key role in determining the optimal location for installing charging stations. This study omits local streets, and just the main streets are considered. Places close to the roads are regarded as more suitable locations. The shapefile layer of roads is extracted from Ref. [23].

4) Income rate

The income rate factor can be considered in the PEVF-CS location selection. The income rate criterion is used as a determinative criterion in the TOPSIS method. A location with a high-income rate will be more suitable.

5) Transportation stations

However, these centers are located in high-traffic areas of the city. Therefore, places near these centers are more suitable for installing charging stations. The map layer of transportation stations is extracted using Google Maps and Ref. [23].

6) Park areas

Urban parks are green spaces used for recreation in cities. Many citizens visit these areas daily for exercise and recreation. Therefore, parks are one of the criteria that influence the optimal planning of charging stations. In other words, electric cars parked near parks can benefit from being changed by PEVF-CSs. The park map layer is produced using Google Maps and Ref. [23].

7) Green space

Green space has been chosen as an environmental factor to select the optimal location for installing charging stations. Green space layering was generated using Google Maps and Ref. [23]. Places far from green spaces are more suitable for installing charging stations.

8) Slope

The land slope can affect the location where charging stations are installed. The cost of placing PEVF-CS in high-slope areas is much higher than in low-slope areas. Since Kabul is located between mountains and rough plains, this criterion must be considered. The raster layer of elevation is extracted from Ref. [23], and the slope analysis tool of the QGIS software produces the raster layer of the slope. If the location has a low slope, it will be suitable.

9) Land values

Land value is an economic factor that can affect the suitable location selection of PEVF-CS. The land value criterion is used in the TOPSIS method for ranking alternatives. The land value is obtained from field research. The low-value land is more suitable for installing PEVF-CS.

10) Fuel stations

Fuel stations are one of the first places considered for the installation of PEVF-CS. Many studies considered fuel stations candidates for installing charging stations [24]. Since fuel stations are usually located in suitable places in terms of the transportation network and regional traffic, the places close to them can be suitable places to install the PEVF-CS. The map layer of petrol stations is extracted using Google Maps and Ref. [23].

11) Substations

PEVF-CSs should be installed near power lines with significant electrical demands. Since charging stations will encounter high power demands, proximity to high-voltage feeders is necessary to find the optimal location for placing PEVF-CS. On the other hand, the distribution network cannot accept charging stations as there is high electricity demand in each feeder, so with the recommendation of experts of Breshna Electric Company [25], eleven junctions are identified as suitable locations for the map layer of substations.

B. Kabul City

Kabul, the capital and the largest city of Afghanistan is located in the east of the country. Kabul with a population of about 5 million [26] is located between the coordinates 34° 31′ 31″ North and 69° 10′ 42″ East and at an altitude of 1.8 km from the sea level [27]. Fig. 3 shows the geographical location of Kabul city. Replacing gasoline cars with electric cars can be one of the appropriate solutions to reduce air pollution in Kabul city. The expansion of electric vehicles in Kabul requires determining the optimal location of PEVF-CSs according to effective criteria. Therefore, in this study, the optimal location of a PEVF-CS in Kabul is investigated using the GIS-based MCDM approach.

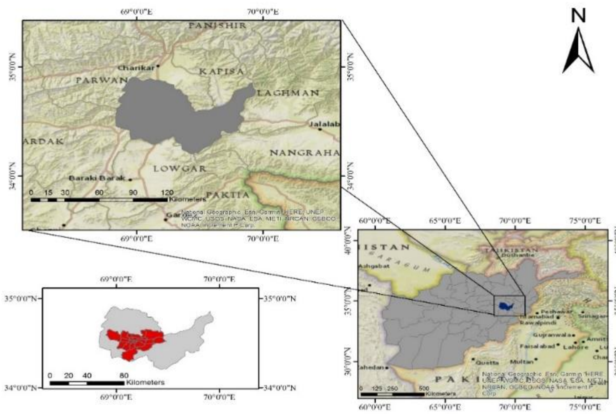

Fig. 3. Geographical area of the case study (Kabul City).

C. The analytic hierarchy process (AHP)

This study uses a GIS-based MCDM approach to find suitable locations for placing PEVF-CS. We first extracted maps related to critical criteria used in our research to analyze the optimal location for charging stations in Kabul's suburbs. These criteria include distance from power posts, population density, and road accessibility. We prepared distance maps for each criterion using the Proximity tool in QGIS software. After creating these distance maps, our next step was to evaluate and standardize them. The evaluation involved assigning values based on the desirability of each criterion's distance from the ideal placement. For example, shorter distances to power posts received higher desirability values per meter unit. Standardization ensured that the range of values across all criteria was consistent and comparable. This process is carried out using the Reclassify by Table tool in QGIS, following the guidelines specified in Table 1. Ultimately, this valuation and standardization process led to the production of merit maps for each criterion, illustrating the suitability of different areas for charging station locations. Fig.4 depicts these merit maps, displaying the spatial distribution of optimal criteria for siting charging stations in Kabul's suburbs. The AHP method uses the criteria that are essential for the decision-making process.

A detailed mythology of the AHP method can be found in [28]. Each criterion's superiority and value are compared by creating a pairwise comparison matrix. Finally, the weight of each criterion is determined. This process is done using Expert Choice software. The compatibility rate or ratio (CR) used to evaluate the precision of pairwise comparison must be computed. In the AHP method, CR signifies the level of compatibility in comparisons and provides insight into the accuracy of valuation made through pairwise comparisons. Pairwise comparisons are acceptable when their CR value is less than 0.1. If the CR exceeds 0.1, it is necessary to revisit the pairwise comparison matrix until the CR falls within the acceptable range [12, 29]. In this study, the CR is measured at 0.09, indicating that the judgments are reliable and acceptable. Consequently, the criteria can be weighted based on these reliable judgments. According to Fig. 5, the criteria of roads, petrol stations, and substations have the highest weight, respectively.

In this study, the PEVF-CS siting is determined using the MCDM approach, incorporating the WLC method to assign appropriate weights to different layers. The WLC method is the most common in MCDM analysis. This technique is also called the scoring method. After determining the weight of the criteria, the weight of each criterion is multiplied by the value of that attribute, and a final value is obtained as the new weight of the alternative [28].

D. Technique for order preference by similarity to ideal solution (TOPSIS)

Alternative locations or points are found using MCDM-based location selection studies. These alternatives are ranked according to two criteria, land value, and income rates.

TABLE 1 ATTRIBUTE CLASS INTERVALS AND SCORES [12]

Criterion	Population density					
Score	5	4	3	2	1	0
Limits (1000/Km^2)	33<	23-32	17-22	10-16	<9	-
Criterion	Shopping malls					
Score	5	4	3	2	1	0
Limits (m)	<250	250-500	500-750	750-1000	1000<	-
Criterion	Roads					
Score	5	4	3	2	1	0
Limits (m)	<250	250-500	500-750	750-1000	1000<	-
Criterion	Transportation stations					
Score	5	4	3	2	1	0
Limits (m)	<250	250-500	500-750	750-1000	1000<	-
Criterion	Fuel stations					
Score	5	4	3	2	1	0
Limits (m)	<250	250-500	500-750	750-1000	1000<	-
Criterion	Park areas					
Score	5	4	3	2	1	0
Limits (m)	<250	250-500	500-750	750-1000	1000<	-
Criterion	Green areas					
Score	5	4	3	2	1	0
Limits (m)	300<	250-300	200-250	150-200	100-150	<100
Criterion	Slope					
Score	5	4	3	2	1	0
Limits (degree)	<5	5-10	10-15	15-20	20-25	25<

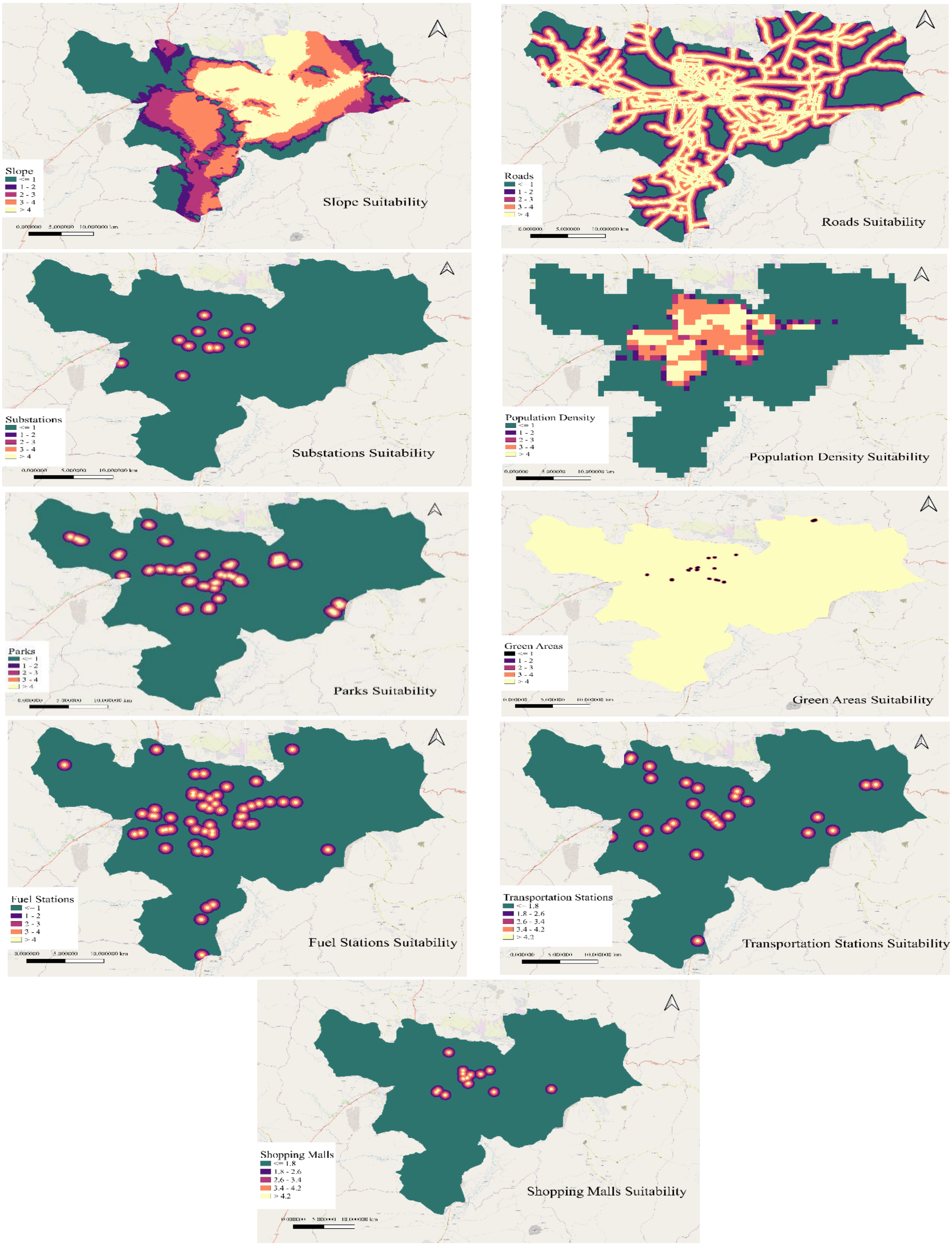

Fig. 4. Suitability maps for different criterion

Fig. 5. Weights of different criteria

The TOPSIS method is used to prioritize the optimal locations. In this method, each alternative's land cost and income rate are considered decisive criteria. First, the decision matrix is formed according to the alternative's land value and income rate. Next, the decision matrix is normalized, and the distances from each alternative to the worst and best conditions are calculated. High land value and high-income rate of points are the worst and best conditions, respectively. Finally, the similarity to the worst and the best conditions according to their distance are defined. A detailed methodology of TOPSIS can be found in [30]. Equations (1) and (2) illustrate the distance of each alternative from the best and worst alternatives.

$$S_i^* = \sqrt{\sum_{j=1}^{n}(V_{i,j} - V_j^*)^2} \tag{1}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}(V_{i,j} - V_j^-)^2} \tag{2}$$

Where j represents the desired criterion and i shows the alternative. S_i^* and S_i^- indicate the distances of i_{th} alternative from the best and worst solutions, respectively. $V_{i,j}$ is the performance of the i_{th} alternative concerning criterion j and V_j^* is the best value for the j_{th} criterion among all alternatives. V_j^- also shows the worst value of the j_{th} criterion among all alternatives. Equation (3) calculates the similarity index of each alternative.

$$C_i^* = \frac{S_i^-}{S_i^* + S_i^-} \tag{3}$$

$\boldsymbol{C_i^*}$ represents the similarity index. The range of $\boldsymbol{C_i^*}$ is between zero and one. The closer $\boldsymbol{C_i^*}$ is to one, the more similar the alternative is to the best solution. In other words, the alternative with the highest $\boldsymbol{C_i^*}$ is ranked first, and the alternative with the lowest $\boldsymbol{C_i^*}$ is ranked last.

E. Examination of junctions using a mathematical model

The GIS-based MCDM approach is analyzed considering the constraints of the DN. On the other hand, the PEVF-CS can compensate for reactive power using its power electronic converter. Therefore, placing the PEVF-CS in a suitable bus can enhance the voltage profile and decrease the power loss [9]. This study investigates the optimal location of the PEVF-CS obtained from the GIS-based MCDM approach according to power quality indexes. In other words, using the constraints of the DN and minimizing network power loss and voltage deviation, the optimal location (bus) for placing the PEVF-CS in the DN has been obtained.

As discussed, this study addresses the optimal location for placing the PEVF-CS to reduce network power loss and voltage deviation. According to equation (4), the objective function includes the penalty cost for voltage deviation and power loss.

$$\begin{aligned} F = (C^{Volt} \times \sum_t \sum_i (1 - V_{i.t})) \\ + \sum_t (C_t^{Ploss} \times P_t^{loss}) \\ + \sum_i (C_i^u S_i^{FCS} x_i) \end{aligned} \tag{4}$$

$V_{i,t}$ and P_t^{loss} represent bus voltage and network power loss, respectively. C^{Volt} and C_t^{Ploss} show the penalty cost for voltage deviation and power loss, respectively, and x_i is a binary variable that indicates the installation of PEVF-CS in bus i.

DN constraints are modeled with AC power flow [31]. In this study, the optimal location of the PEVF-CS has been determined considering the capability of reactive power compensation by the PEVF-CS. The constraints of the DN are as follows.

$$\begin{aligned} P_t^{loss} = \sum_{i,j} 0.5 \times G_{i,j} \\ +\big((V_{i,t})^2 + (V_{j,t})^2 \\ - 2V_{i,t}V_{j,t}\cos\big(\delta_{i,t} - \delta_{j,t}\big)\big) \end{aligned} \quad \forall t \tag{5}$$

$$P_{i,j,t}^{line} = \frac{(V_{i,t})^2}{Z_{i,j}}\cos(\theta_{i,j}) - \frac{V_{i,t}V_{j,t}}{Z_{i,j}}\cos(\delta_{i,t} - \delta_{j,t} + \theta_{i,j}) \quad \forall (i,j)\epsilon S^{line}, t \qquad (6)$$

$$Q_{i,j,t}^{line} = \frac{(V_{i,t})^2}{Z_{i,j}}\sin(\theta_{i,j}) - \frac{V_{i,t}V_{j,t}}{Z_{i,j}}\sin(\delta_{i,t} - \delta_{j,t} + \theta_{i,j}) \quad \forall (i,j)\epsilon S^{line}, t \qquad (7)$$

$$P_{i,t} - \sum_i P_{i,t}^l + \sum_i (P_{i,t}^{FCS}) * x_i = = \sum_{j\in S^{line}} B_{i,j} P_{i,j,t}^{line} \quad \forall i,t \qquad (8)$$

$$Q_{i,t} - \sum_i Q_{i,t}^l + \sum_i (Q_{i,t}^{FCS}) * x_i = = \sum_{j\in S^{line}} B_{i,j} Q_{i,j,t}^{line} \quad \forall i,t \qquad (9)$$

$$\sqrt{(P_{i,t}^{FCS})^2 + (Q_{i,t}^{FCS})^2} \leq S_i^{FCS} \quad \forall i,t \qquad (10)$$

$$-\overline{P_{\iota,t}} \leq P_{i,t} \leq \overline{P_{\iota,t}} \quad \forall i \in S^s, t \qquad (11)$$

$$-\overline{Q_{\iota,t}} \leq Q_{i,t} \leq \overline{Q_{\iota,t}} \quad \forall i \in S^s, t \qquad (12)$$

$$0.9 \leq V_{i,t} \leq 1.05 \quad \forall i,t \qquad (13)$$

$$-\frac{\pi}{2} \leq \delta_{i,t} \leq \frac{\pi}{2} \quad \forall i,t \qquad (14)$$

Equation (5) shows the active power loss. Equations (6) and (7) show the line power between the network buses in each time. Equations (8) and (9) lead to the balance of active and reactive power in each bus and time interval, respectively. Equation (10) calculates the apparent power of the PEVF-CS in bus i. Equations (11) to (14) express the permissible limits of network variables, where $\overline{P_{\iota,t}}$ and $\overline{Q_{\iota,t}}$ show maximum active and reactive power generation.

III. Results and Discussion

In this study, the optimal location of PEVF-CS in Kabul city is determined using GIS-based MCDM and MINLP method. The results of each part are discussed separately.

A. The GIS-based MCDM approach

This study uses the WLC method and nine suitability layers to identify six optimal locations for installing PEVF-CS. Fig. 6 shows the suitable locations resulting from the WLC method. This figure shows that these six places are close to junctions 2, 3, 4, 5, 7, and 12. Fig. 7 shows the satellite images of these six junctions. Therefore, it is expected that if a PEVF-CS is installed in each of these places, it will be supplied by these junctions. Table 2 also shows the scores of these six places. Also, the optimal locations near junctions 4, 2, and 7 have the highest scores.

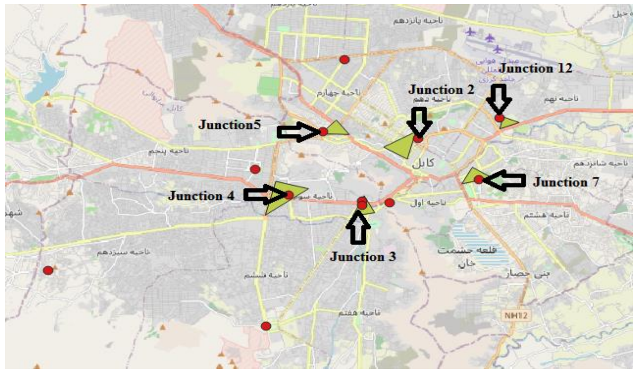

Fig. 6. Suitable locations for placing PEVF-CSs

In the following examination of alternative ranking, the TOPSIS method is used to identify the best location for installing the PEVF-CS. The decision matrix D_{ij} of the six candidate locations for placing PEVF-CS is obtained by considering land value criteria. The decision matrix is given by (15).

$$D_{ij} = \begin{bmatrix} 3 & 1800 \\ 3 & 1650 \\ 5 & 1800 \\ 2 & 2000 \\ 2 & 1850 \\ 4 & 1700 \end{bmatrix} \qquad (15)$$

In this matrix, column 1 represents the criteria value, and column 2 represents the corresponding values for alternative land. It should be noted that the weights of the criteria are considered equal. Using the TOPSIS method, six alternatives are ranked, and their closeness to the ideal solution is shown in Table 3.

TABLE 2 SUITABLE LOCATIONS FOR PLACING PEVF-CS

Suitable location	Junction 2	Junction 3	Junction 4	Junction 5	Junction 7	Junction 12
score	4.289	4.012	4.673	4.073	4.183	3.881

TABLE 3 THE SIMILARITY OF ALTERNATIVES TO THE IDEAL SOLUTION

Alternative	Junction 4	Junction 12	Junction 3	Junction 2	Junction 5	Junction 7
C_i^*	0.909	0.668	0.35	0.332	0.1168	0
Rank	1	2	3	4	5	6

According to the two criteria of land price, three optimal locations near junctions 4, 12, and 3 are selected in terms of priority. The places around junction 4 are the most similar to the ideal solution. However, which bus at junction four should be the optimized place for the PEVF-CS connection? In other words, regarding DN constraints, which bus is the best for connecting a PEVF-CS? Therefore, the suitable bus for placing the PEVF-CS is investigated according to the DN constraint.

B. MINLP method

Using the MCDM approach, Junction 4 is the optimal area for installing the PEVF-CS, with the highest score and priority percentage. Junction 4 has 162 buses (Fig. 8). The distribution network line and bus data have been presented in [32]. The bus voltage and power loss of the 162-bus network during 24 hours are shown in Fig. 9 and 10, respectively. According to the power flow analysis, the minimum voltage and maximum loss of PDN are 0.85 pu and 1071 kW. In such a condition, placing PEVF-CS as a new demand and line conditioner device is sensitive. At peak hour (13), bus 114 (the worst bus) has the lowest voltage with a value of 0.85. The number of electric vehicles is assumed to be 250, 5 percent of the number of taxis in Kabul [33]. The power consumption is assumed to be 0.15 kWh/km, and the driving range is 100 km. The traffic flow during the day is presented in [34].

This study implements the mixed-integer non-linear model in GAMS software to place PEVF-CS and to improve the power quality in junction 4. Due to the constraints of the PDN, bus 4 is chosen as the optimal bus to connect the PEVF-CS. Fig. 11 shows the voltage of PDN after placing the PEVF-CS. Also, a comparison of the voltage of bus 114 (the worst bus) is shown in Fig. 12 for two cases: before and after placing the PEVF-CS. The power loss before and after placing PEVF-CS is shown in Fig. 13, as the results show that all PDN bus voltages increase between 1.8 and 2.07 percent.

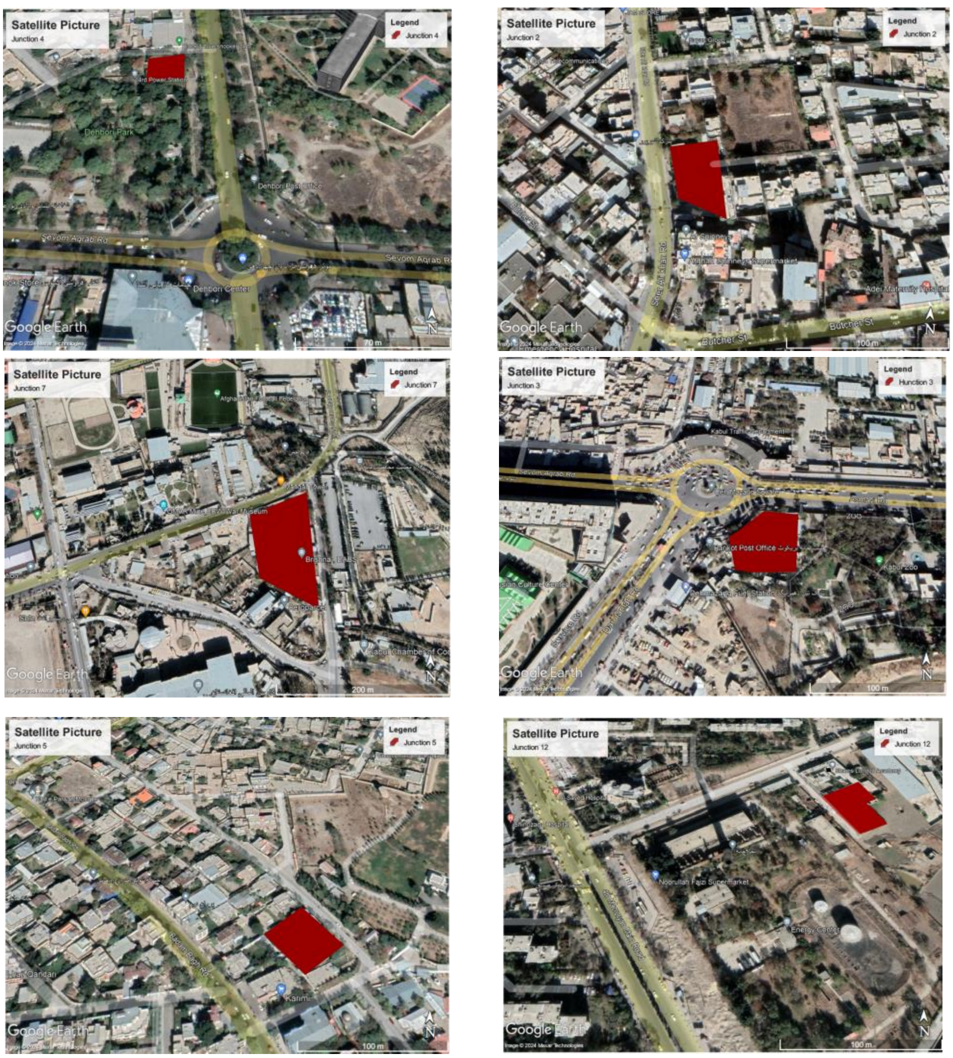

Fig. 7. The satellite pictures of the suitable junctions

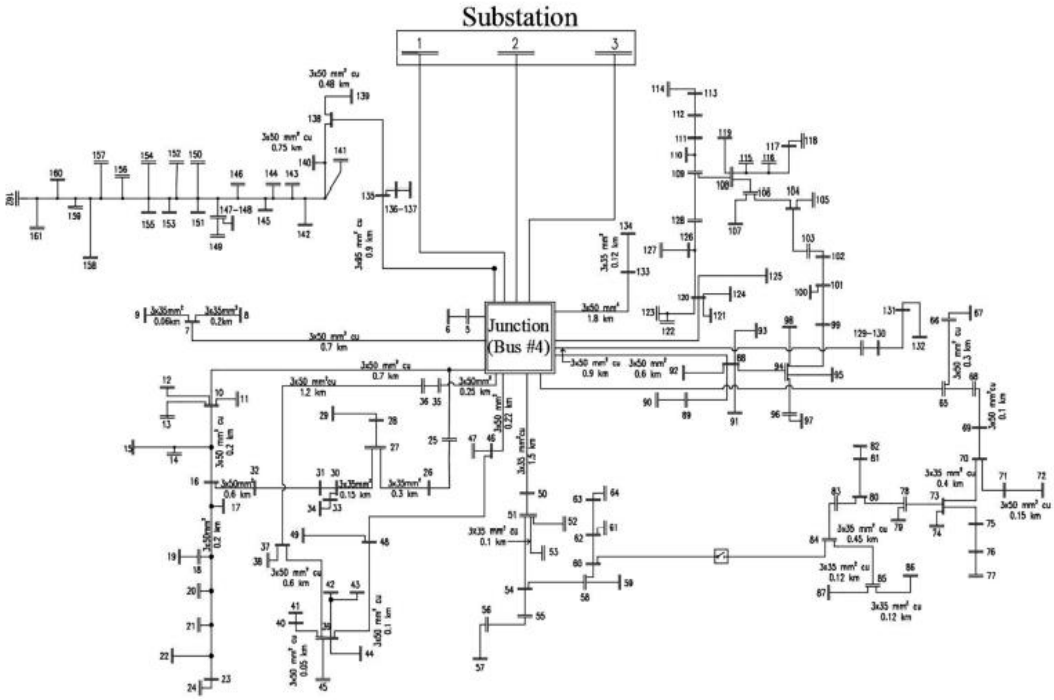

Fig. 8. Distribution network model (junction 4)

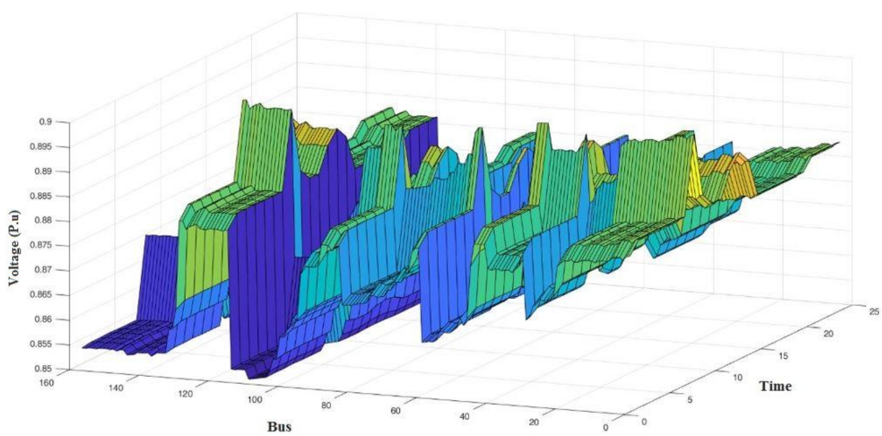

Fig. 9. Voltage profile of the DN before placing PEVF-CS

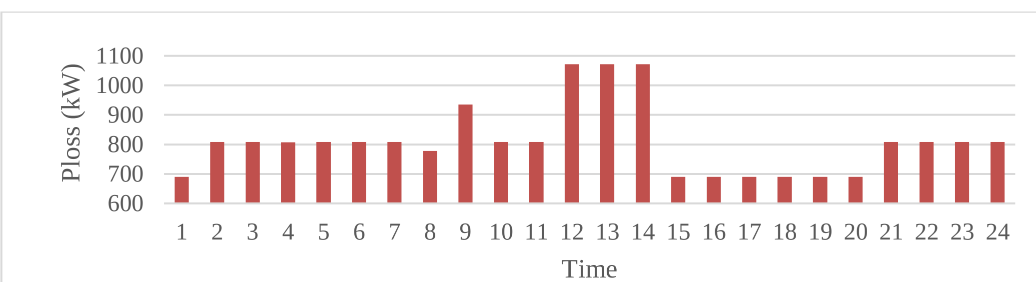

Fig. 10. Power loss before placing PEVF-CS

In addition, there is a 3.6% reduction in power loss during peak hours, decreasing from 1071 to 1032 kW. In other words, the power loss is significantly reduced, and the voltage profile improves after placing PEVF-CS. The PEVF-CS injects 850 kVAR at peak demand. The apparent power of the PEVF-CS is obtained equal to 1345 kVA. Fig. 14 shows the changes in active power consumption and reactive power generation of the PEVF-CS during 24 hours.

IV. Conclusion

This study addresses the critical need for optimal PEVF-CS locations in Kabul City, Afghanistan, during a global shift toward sustainable transportation. Integrating GIS tools, MCDM methods, and the MINLP model aims to balance geographic suitability with PDN constraints and power quality considerations. The research seeks to enhance infrastructure planning to support electric vehicle adoption and sustainable urban development in Kabul. Criteria such as population density, road accessibility, income rates, and proximity to essential facilities are analyzed using GIS tools. The AHP is applied for criteria weighting, while the TOPSIS ranks alternative locations. Subsequently, the MINLP model selects Junction 4 as the optimal area for PEVF-CS installation within the PDN, demonstrating significant improvements in voltage stability and power loss reduction during peak hours. Future studies could incorporate additional criteria, such as PEV distribution patterns, to enhance the proposed approach and improve result accuracy. Furthermore, considering the stochastic nature of PEV behavior and uncertainties in real-world conditions like weather and demand fluctuations would enhance the model's robustness. While this study focused on optimizing a single PEVF-CS in Kabul City, future research will expand to optimize multiple charging stations across urban networks, which is essential for scaling electric vehicle adoption strategies.

In conclusion, this research enhances the efficiency of PEVF-CS deployment and offers valuable insights into sustainable urban infrastructure planning. By using advanced decision support tools, such as GIS-based MCDM and MINLP modeling, this study promotes electric vehicle adoption. It enhances grid reliability in Kabul City, supporting its transition towards a sustainable urban future.

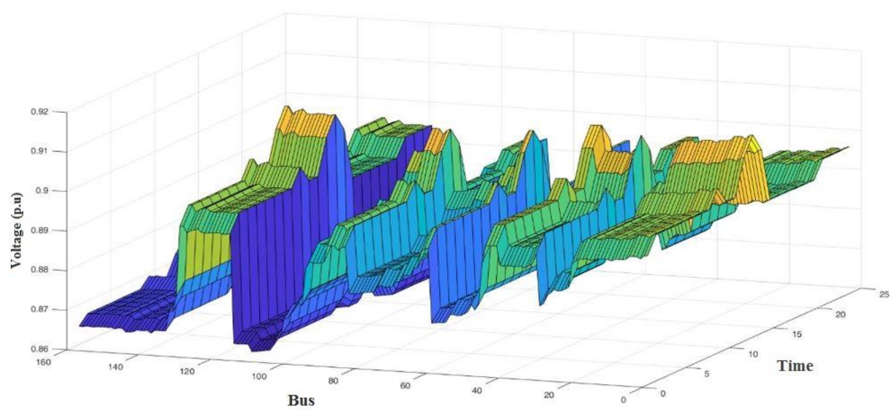

Fig. 11. The voltage profile of DN after placing the PEVF-CS

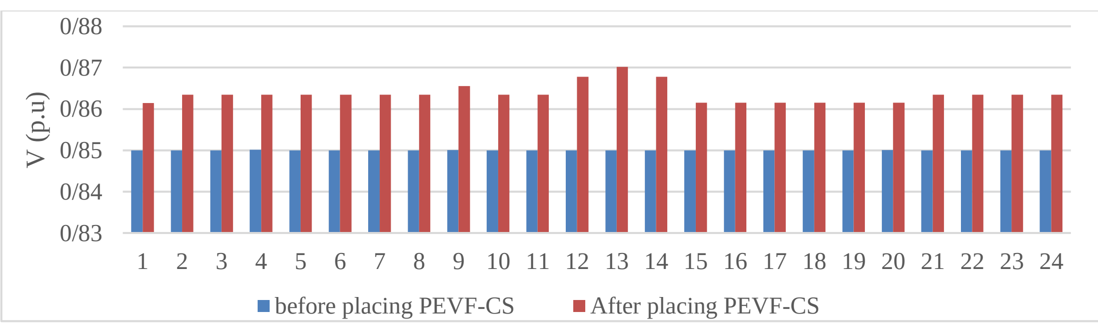

Fig. 12. The voltage of bus 114 before and after placing the PEVF-CS

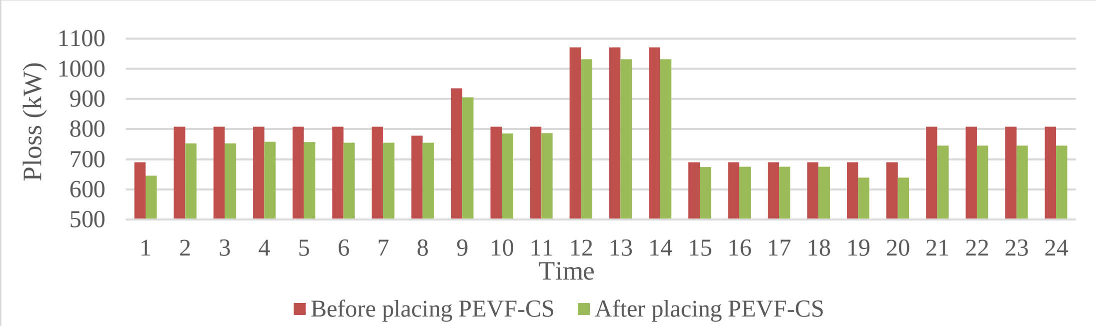

Fig. 13. The power loss before and after placing PEVF-CS

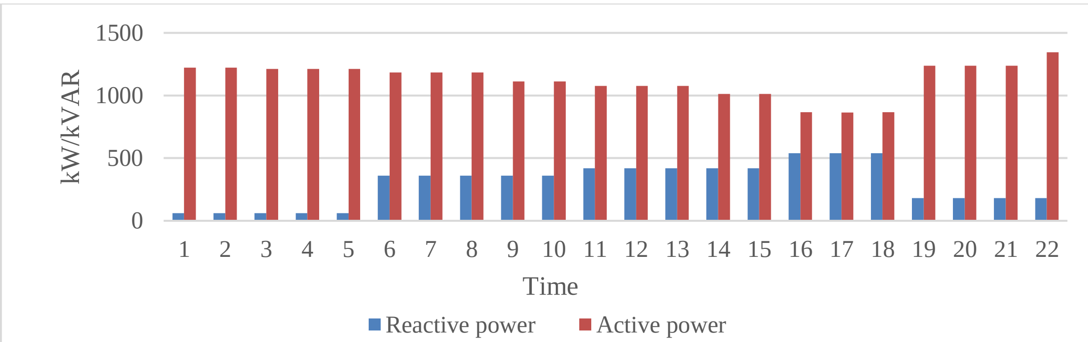

Fig. 14. Active power consumption and reactive power generation of the PEVF-CS during 24-hours

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