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Research Article

Optimal Location Placement of Electric Vehicle Fast Charging Station in Distribution Network Using Genetic Algorithm

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***Abstract*— In recent times, as the number of electrical vehicle (EV) became increased, many researches has been done on finding the optimal placement of Electrical Vehicle Charging Stations (EVCS). EV research has become one of the most fascinating, interesting, intriguing and exciting field areas in transportation system due to its low CO_2 emission, lower energy consumption and high efficiency. It also has lower maintenance costs compared to normal internal combustion engine vehicles. Inappropriate placement of EVCS lead to under-utilization, grid strain, traffic and safety concerns, limited accessibility, environmental and zoning issues. In this study, Genetic Algorithm (GA) based approach model for electrical distribution network are developed to find best placement of Electrical Vehicle Fast Charging Station (EVFCS). Model has been developed to optimize the placement location of EVFCS in the power distribution network. The distance from each proximity area to EVFCS is considered as objective function of problem formulation and constructed for the acquired model. In this research, the power loss cost of distribution network, fixed installation cost and the line cost of EVFCS are analyzed. The duration time for EVCS is determined and the optimal time is identified. The results obtained demonstrate that the optimization technique employed significantly reduces operating costs and power losses. The study was conducted using three different EV brands with varying battery capacities, evaluated based on their respective charging times.**

Index Terms— **Distribution network, Electrical vehicle fast charging station, Genetic algorithm, Optimal location.**

I. INTRODUCTION

Due to the environmental effects of internal combustion engine-powered vehicles and the usage of fossil fuels, EV are becoming increasingly essential in the automotive industry. For these reasons, efforts to lower pollution and greenhouse gas emissions are being coordinated by the public and commercial sectors [1-3]. However, the dearth of EVCS is one of the biggest issues fostering EV popularity grid. The opportunities and problems associated with EV charging stations were investigated. The study stressed that the location of EV charging stations is crucial and should not be disregarded [4]. Along with battery management systems and charging techniques for lithium-ion batteries, they also examined a number of technologies. It is possible to use a genetic algorithm to solve the problem of figuring out the best Transformer Substation (TS) workload and location while taking in to consideration the limitations on how the TS and other components of the urban distribution network can fit together [5]. Transformer failures as a function of age and condition were studied using the sequential Monte-Carlo simulation. The best approach to proactive transformer replacement and sparing in a transmission system will weigh the expenses of replacing and buying spares against the expense of having transformers out of commission and potential for load decrease [6]. The charging requirement of EVs is developed using a probabilistic load modeling approach and test system for voltage profile and convergence properties approach is created by altering the conventional IEEE 33 bus system [7], [8]. During EV charging, the distribution system's power loss rises, and voltage falls to meet the increased power demand. In the study, the IEEE 33 node radial distribution network's EV charging station allocation is developed and three regions have been created within the distribution network to provide charging facilities using Whale Optimization Algorithm (WOA) and Grey Wolf Optimization (GWO) techniques [9]. The distribution infrastructure may be harmed by both high electrical power needs and rapid EV population growth. Research suggests that by 2030, the production of EVs could reduce CO_2 emissions by 28% [10]. Using a geographic information system, the study produced a geographical map for Istanbul's traffic density and the locations of the current EV charging stations. The genetic

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algorithm was used to assess the charging demand satisfaction scenario of the current charging stations and to identify the city's top charging inquiry spots [11]. To choose the best site in the province of Ankara, a study was conducted using multi-criteria decision-making techniques and the study identified the weighted and merged using the Fuzzy Analytical Hierarchy Method [12]. Using infrastructure of the distribution company, HV/LV distribution feeders and substations were chosen for the Istanbul/VANIKOY zone. Using technical data, the best optimal value of EVFCS and consequences of various short circuit types on the electrical distribution network were examined [13]. Using an algorithm developed based on Haversine formulas, the current and voltage values on the LV side at selected short circuit points of the optimally located fast charging stations are investigated [14]. It presents the case for the optimal siting of fast charging stations, in particular based on economic benefits and grid effects. In addition, energy supply from renewable energy sources and the benefits of V2G technology are also presented [15]. Considering the variable network parameters in the Radial Distribution Network (RDN) and using the Loss Sensitivity Factor (LSF) approach, the optimal placement of the EVCS was determined with the goal of minimizing network losses. The optimal placement was performed using the Arithmetic Optimization Algorithm (AOA), and the obtained locations were compared with those from the Particle Swarm Optimization (PSO) and Harris Hawks Optimization (HHO) algorithms [16]. To determine the optimal locations for EVCS, a hybrid optimization method combining MATPOWER's computational speed with a meta-heuristic optimization algorithm based on an extended ant colony, serving as the Energy Management System (EMS) of the microgrid, was employed. The identified locations were generated by positioning them at various points within the microgrid, considering energy savings [17]. A method has been developed to distribute charging demand for optimal EVCS placement, considering not only drivers' preferences and available charging stations but also the installation costs [18]. A hybrid algorithm, based on an improved model of the genetic algorithm and conventional particle swarm optimization, is used to determine the optimal placement of charging stations in the distribution network of Allahabad, one of the smart cities in India. Simulation studies on a real-time system have demonstrated improvements in the voltage profile and overall quality using the aforementioned technique [19]. It considers installation costs as well as penalties for violating grid constraints as criteria for charging station placement. To determine the optimal locations, the best features of two efficient algorithms Chicken Swarm Optimization (CSO) and the Teaching-Learning-Based Optimization (TLBO) algorithm are combined. The results of this hybrid algorithm are compared with those of other algorithms used to solve this problem [20]. A new Pigeon-Based Recursive Deep Network (DbRDN) application is designed to analyze load and line data and determine the optimal location for connecting an EVCS to the distribution grid system, which initially operates with a combination of hybrid wind, solar, and hydroelectric resources [21]. A demand forecasting model based on supervised learning, combined with a Deep Q-Network (DQN) reinforcement learning (RL) algorithm, is applied to identify optimal locations for charging stations using traffic data and points of interest (POIs) for specific counties in New York State [22]. When modeling, it allows parameter values to be tailored more specifically to user groups rather than to the entire population. Furthermore, in this system, which employs advanced discrete choice models, a highly flexible framework has been created, enabling decision-makers to design solutions tailored to their specific problems and available data sources [23]. We designed optimal charger placement strategies in Texas to minimize travel time by analyzing congestion and charging time scenarios using a real-time transportation and charging station datasets [24]. This study compiles optimization techniques, including various objective functions for determining optimal locations, and incorporates the constraints that must be considered when planning the placement [25]. The Forward and Backward Scanning Methodology (FBSM), combined with GA optimization and load flow analysis, is used to scale and optimize EVCSs in a distribution network with distributed PV/BESSs [26]. A new algorithm for determining the optimal EVCS connection nodes, based on Monte Carlo simulation and considering various numbers and configurations of EVCSs, has been implemented and tested in a low-voltage network using real data, taking into account both the traffic model and network modeling [27]. Mixed Integer Linear Programming (MLP) techniques were used to determine the optimal locations for the stations, considering user accessibility and investment costs [28]. The Chicken Swarm Optimization (CSO) algorithm, which minimizes power losses, the average voltage deviation index, and harmonic distortion effects, is used to determine the optimal locations for charging stations in the radial distribution network. Simulations are conducted on IEEE standard 33-bus radial distribution test systems [29]. The optimal siting of EVCSs is achieved through a novel demand forecasting approach, which transforms demand into a weighted neighborhood average and applies regular regression [30]. To minimize power loss and voltage fluctuations in the distribution system, it is recommended to determine the optimal allocation of charging station algorithms with varying capacities using stochastic optimization techniques at strategic locations. This approach enhances the efficiency, reliability, and scalability of the charging infrastructure [31].

When the above-mentioned literature review is examined, the majority of the research simply got the best optimal location by optimizing either installation cost or line cost of the distribution network. In this research, finding the best optimal location of EVFCS from VANIKOY to UMRANIYE geographical area by considering constraint problem, giving priority for transformers proximity to construct the network with lowest cost. More over model has been developed to optimize location of EVFCS in the power distribution network. The power loss cost, initial installation cost of EVFCS and the cost transmission line from EVFCS to correlated transformers are analyzed. Random EVs charging state of charge is modeled and duration of time for EV charging is determined. By developing GA to the closest official institutions, transformers, transportation, petrol stations, shopping malls, normal charging stations, main road,

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parking lot, the best charging station locations are determined in the selected distribution network.

II. MATERIAL AND METHODOLOGY

A. Distribution network data

This study selected sub-feeders from a 380/34.5 kV, 125 MVA transformer supplying the Umraniye district in Istanbul, within the AYEDAS service area. Four 1600 kVA HV/LV transformers, three 1000 kVA feeders, and one additional 1600 kVA transformer from the 154/34.5 kV, 125 MVA transformer feeding the Beykoz district were integrated into a semi-ring network via a coupling breaker. As shown in Fig.1, the single-line diagram modeling one- and three-phase EVFCS units are connected to these sub-feeders [13]. The study uses proximity areas as input data to determine the best location for an EVFCS. These include areas that are close to parking lot, main road, official institution, transformer, transportation, gas station, shopping mall, and regular charging stations are as shown in Table I. An assessment has been made based on distance criteria according to the transformer locations on Google Maps obtained from the distribution company.

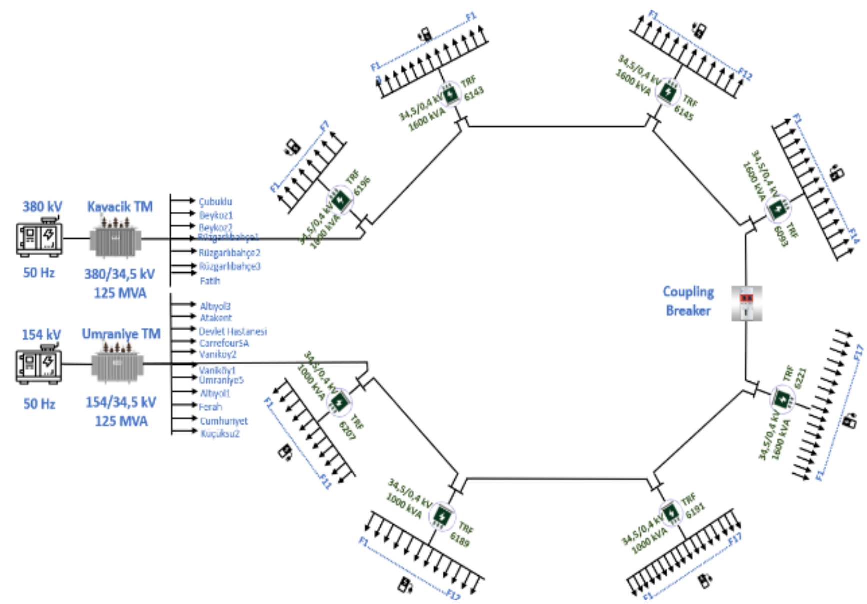

Fig. 1. Single line diagram of the distribution network [1]

Table I. Charging stations coordinate data under proximity area [1]

EVFCS No.	Phase Type	Connected Transformer No	Nearest Transformer (Lat, Lon)	Nearest Shopping Mall (Lat, Lon)	Nearest Main Road (Lat, Lon)	Nearest Petrol Station (Lat, Lon)	Nearest Parking Lot (Lat, Lon)	Nearest Transportation Station (Lat, Lon)	Nearest Official Institution (Lat, Lon)	Nearest Normal EVFCS (Lon, Lon)
1	1/3	6196	41.096871 29.091761	41.100107 29.092649	41.087264 29.093720	41.094707 29.091190	41.094448 29.091959	41.095950 29.091920	41.097126 29.090889	41.095451 29.086329
2	3	6143	41.096871 29.091761	41.100107 29.092649	41.087264 29.093720	41.094707 29.091190	41.094448 29.091959	41.095950 29.091920	41.097126 29.090889	41.095451 29.086329
3	3	6143	41.096871 29.091761	41.100107 29.092649	41.087264 29.093720	41.094707 29.091190	41.094448 29.091959	41.095950 29.091920	41.097126 29.090889	41.095451 29.086329
4	1/3	6143	41.095381 29.091441	41.096110 29.091826	41.089722 29.092866	41.094707 29.091190	41.094465 29.092016	41.094751 29.089318	41.094964 29.091592	41.095451 29.086329
5	1/3	6145	41.095382 29.091456	41.095495 29.088766	41.090328 29.093477	41.094707 29.091190	41.094465 29.092016	41.095833 29.091874	41.094900 29.091787	41.095451 29.086336
6	3	6093	41.100205 29.088785	41.100094 29.088810	41.090261 29.093148	41.096613 29.087185	41.094448 29.091959	41.099265 29.088321	41.099791 29.090730	41.095451 29.086329
7	3	6093	41.100205 29.088785	41.100094 29.088810	41.090261 29.093148	41.096613 29.087185	41.094448 29.091959	41.099265 29.088321	41.099791 29.090730	41.095451 29.086329

8	1/3	6093	41.100205 29.088785	41.100094 29.088810	41.090261 29.093148	41.096613 29.087185	41.094448 29.091959	41.099265 29.088321	41.099791 29.090730	41.095451 29.086329
9	1/3	6221	41.094042 29.083742	41.094536 29.085907	41.089461 29.089987	41.094707 29.091190	41.093637 29.089722	41.092794 29.083343	41.092688 29.083276	41.095451 29.086329
10	3	6221	41.094042 29.083742	41.094536 29.085907	41.089461 29.089987	41.094707 29.091190	41.093637 29.089722	41.092794 29.083343	41.092688 29.083276	41.095451 29.086329
11	3	6221	41.094042 29.083742	41.094536 29.085907	41.089461 29.089987	41.094707 29.091190	41.093637 29.089722	41.092794 29.083343	41.092688 29.083276	41.095451 29.086329
12	1/3	6191	41.093653 29.079635	41.098745 29.075859	41.092564 29.084925	41.094707 29.091190	41.092827 29.083366	41.093941 29.079458	41.092495 29.076059	41.095451 29.086329
13	1/3	6189	41.090284 29.077828	41.086865 29.082522	41.092166 29.081385	41.081239 29.076829	41.082896 29.068689	41.088968 29.078119	41.090728 29.079886	41.080235 29.078768
14	1/3	6207	41.088351 29.075812	41.084618 29.077625	41.091764 29.072680	41.081239 29.076829	41.082896 29.068689	41.087720 29.076065	41.087882 29.075892	41.082627 29.066668
15	3	6207	41.088351 29.075812	41.084618 29.077625	41.091764 29.072680	41.081239 29.076829	41.082896 29.068689	41.087720 29.076065	41.087882 29.075892	41.082627 29.066668
16	3	6207	41.088351 29.075812	41.084618 29.077625	41.091764 29.072680	41.081239 29.076829	41.082896 29.068689	41.087720 29.076065	41.087882 29.075892	41.082627 29.066668

B. EV demand profile

As the input data, the EV demands are first modeled. The types of EVs that has minimum, average and maximum battery capacity and EV's battery's state of charge is taken in the research. The first phase is choosing the minimum, average and maximum EVs battery from various data. In this study some information data on electric car is taken in the light of the factory data of vehicles of different brands to test the FCS in how much time they charge EVs is as shown in Table II. Three different brand models are chosen to test the duration time of EVFCS. Based on the battery capacity Citroen, Opel and Audi are the minimum, average and the maximum capacity values respectively.

Table II. Data's of EVS battery capacity [2]

Brand	Model	Capacity of battery (kWh)	Battery Type
Citroen	C-Zero	15	Li-ion
Opel	Ampera -e	58	Li-ion
Audi	e-Tron	95	Li-ion

C. Matlab profile

The MATLAB platform was used to perform analysis and optimization techniques with the global optimization toolbox and its GA function. Additionally, system design and simulation were conducted using the MATLAB Simulink platform. The simulation data was sourced from the distribution company holding operational rights for the region.

D. Electric fast charging station and batteries

This study because of their extended cycle life, high Since they take a much less time to charge than traditional chargers, electric fast charging stations are essential to the broad adoption of EVs. In this study, the stations are designed to provide high-power DC charging, between 15 and 480 kW, which allows EV batteries to reach 90% capacity in less hour. One of the main issues that EV customers have is range anxiety, which is addressed by this quick and effective charging procedure. Lithium-ion batteries were selected for energy density, and quick charging speed.

E. Formulation problem

The genetic algorithm-based optimization model was developed to determine the strategic placement of EVFCS units by minimizing the total Manhattan distance to key proximity points such as shopping malls, main roads, petrol stations, parking lots, transportation hubs, and official institutions. This ensures both energy efficiency and user accessibility. All parameters used in the cost model including fixed installation cost, line installation cost, and power loss cost have been clearly defined, and the cost calculation steps are now presented in a structured manner. The model has been designed to accommodate various EV brands and battery capacities. Charging duration is calculated based on the state of charge, specifically from 20% to 90%, and results are presented in minutes for practical relevance.

The Objective is to minimize the total cost of the distribution network by evaluating the total distance in the fitness function. In this study, we use the GA Manhattan distance calculation to determine the distance. The total distance is the objective formulation of this study.

The Manhattan distance is given by Equation (1) [3]

$$d(L_{EVFCS}, P_{ci}) = |lat_{EVFCS} - lat_i| + |lon_{EVFCS} - lon_i| \quad (1)$$

Where,

$L_{EVFCS} = [lat_{EVFCS}, lon_{EVFCS}]$ Be the coordinates of the EV fast charging station location. Latitude and longitude respectively.
$P_{ci} = (lat_i, lon_i)$ is coordinates of proximity area $i$for eight data system.
$d(L_{EVFCS}, P_{ci})$ is the Manhattan distance from EVFCS to proximity data.

The optimization of total distance indirectly minimizes the total cost in Equation (2):

$$C_{total} = C_{installation} + C_{powerloss} \tag{2}$$

Where,
C_{total}, is the total cost
$C_{installation}$ is installation cost of EVFCS
C_{loss} is power loss cost of the distribution network

Installation cost

1. Line cost:
The network line costs from EVFCS to transformer in the selected region in Equation (3).

$$C_{line} = C_{rd} \cdot \sum_{i=1}^{n} d(L_{EVFCS}, T_i) \tag{3}$$

Where,
C_{line} is line cost.
$T_i = [lat_{ti}, lon_{ti}]$ is Coordinates of transformer,
C_{rd}: cost rate per distance unit for installation cost.
$L_{EVFCS} = [lat_{EVFCS}, lon_{EVFCS}]$ Be the coordinates of the EV fast charging station location. Latitude and longitude respectively.

2. Initial cost
The cost that expense due to EVFCS, land rental and connector is given in Equation (4) [4].

$$C_{inital} = N_{EVFCS}\big(C_{fix} + A_{EVFCS} \cdot ND \cdot C_{lan} + C_n \cdot C_{dev}\big) \tag{4}$$

Equation (4) is general initial for 16 EVFCS. However, only for 8 EVFCS there is additional expense for 1 phase connector.

Where,
$C_{initial}$ is the initial cost for EVFCS, land rental and connector.
N_{EVFCS} is the number of EVFCS in the selected region
C_{fix} is fixed cost of each EVFCS
A_{EVFCS} is proposed required area for each EVFCS
$ND$is number of days for proposed planning,
C_{lan} is land rental cost per m^2per day
C_n is the number of connector
C_{dev} is Development cost of the connector

Some assumptions in the study
- ✓ 4x185 YAVV-NAYY aluminum cable 20 USD per meter
- ✓ The power loss for almunim cable is 0.114 kW per meter
- ✓ Each EVFCS has 5 connectors. for 3 phase EVFCS
- ✓ Required area for each EVFCS is 100 m^2
- ✓ Electric connector for 1 phase EVFCS is 30 \$. [34, 35] This is additionally for 8 EVFCS and each has Five 1 phase connector.

Finally in Equation (5) the installation cost is the sum of line cost and initial cost.

$$C_{installation} = C_{line} + C_{initial} \tag{5}$$

Power loss cost: The power loss cost of the distribution network is given by Equation (6).

$$C_{loss} = E_{re} \cdot T \cdot L_{rd} \cdot \sum_{i=1}^{n} d(L_{EVFCS}, T_i) \tag{6}$$

Decision variables are represented
C_{loss} is power loss cost of the distribution network
L_{rd} is rate per distance unit for power loss.
E_{re} is electricity rate per kWh
T is operating hours for the EVFCS
$T_i = [lat_{ti}, lon_{ti}]$ is coordinates of transformer

The total optimization problem is defined in Equation (7) by summing the break down cost:

$$min_x\, C_{total} = C_{rd} \cdot \sum_{i=1}^{n} d(L_{LVFCS}, T_i) + N_{EVFCS}\big(C_{fix} + A_{EVFCS} \cdot ND \cdot C_{lan} + C_n \cdot C_{dev}\big) + E_{re} \cdot T \cdot L_{rd} \cdot \sum_{i=1}^{n} d(L_{LVFCS}, T_i) \tag{7}$$

Where,
C_{total} is total optimization cost (objective function)
C_{rd} is road-related (distance-dependent) cost coefficient
L_{EVFCS} is location of the EV Fast Charging Station
T_i is location of demand node (i-th proximity area/load point)
$d(L_{EVFCS}, T_i)$ is distance between EVFCS and demand node T_i
n is total number of demand nodes
N_{EVFCS} is number of EV Fast Charging Stations to be installed
C_{fix} is fixed installation cost of one EVFCS
A_{EVFCS} is area requirement (or area factor) of the EVFCS
ND is network density (or demand factor of the grid)
C_{lan} is land cost
C_n is network cost coefficient
C_{dev} is development/infrastructure cost.
E_{re} is energy-related cost (e.g., losses, consumption).
T is time horizon of the analysis
L_{rd} is road length (or cost per road distance)

$\sum_{i=1}^{n} d(L_{LVFCS}, T_i)$ is total distance from EVFCS to all demand nodes.

x is the total distance from each EVFCS to all proximity data. To find the total cost, the number of parameters is as shown in Table III [4].

Table III. Parameters used in the study [4]

Parameters Name	Value
Capacity of FCS	480 kW
Operating Hours FCS	24 Hours
Fixed cost of EVFCS	21900 $
Cost of connector	109.5 $
Connector Capacity	96 kW
Electric price	0.11 $/kW
Number of days	365 days
Land rental	0.1$ per m^2 per day

Charging duration for EVs:
One of the crucial factors used to characterize a batteries condition is its state of charge. It displays relative number between 0 and 1 that represents the battery's current power to capacity ratio. We generalize charging length time of EVs as a function of important charging process parameters in order to model it. These consist of the battery's capacity, charging power, and state of charge. Equation (8) defines the charging time period [5].

$$D_{t(i)} = \frac{B_{capa} \cdot (0.9 - SOC)}{P_{cha(i)}} \tag{8}$$

Where,
$D_{t(i)}$ is charging duration time for vehicle i (in hours)
B_{cap} is battery capacity of the EV (in kWh)

In this research the final target SOC is taken 0.9 to increase the EVs battery span life.

$P_{cha(i)}$ is Electricity provided by the fast-charging station for charging (in kW). In this study the EVFCS provide sufficient energy for EVs.

F. Optimization algorithm

In order to reduce overall costs, this optimization seeks to identify the best location for EV fast charging station (EVFCS) with in a distribution network. Three primary factors are taken into account by the total cost function: the initial cost of installation, cost of transmission lines from the EVFCS to the corresponding transformers and distribution network loss power outages. The optimal location of EVFCS is obtained through GA optimization technique.

GA process for EVFCS location optimization.

1. *Initialization:*
A starting population of 500 candidate solutions (possible EVFCS locations) randomly chosen by GA. These values are subject to the bounded value.

2. *Fitness Evaluation:*
The fitness of each random candidates is computed using the Manhattan distance calculation function. The total distance for one randomly chosen candidate (EVFCS) is calculated by GA from the point chosen to all proximity data.

3. *Selection*:
From process two that has lower total distance are selected. Parents are the randomly individual location of EVFCS that has best fitness value. These selected individuals are used to create new EVFCS location (offspring)

4. *Crossover:*
Using GA, pairs of selected EVFCS value exchanges and one take others attributes of their coordinates to produce the best fitted locations (offspring). In the study 0.8 is taken.

5. *Mutation:*
Changing slightly the values of offspring coordinates without violating the constraint. In mutation process the GA wants to maintain the diversity to improve the fitness.

6. *Termination:*
Until a termination requirement 1000 or tolerance function 0.00005 limit is satisfied, the GA keeps going through this cycle. In the study it stops in 51 generation. In the study, GA based work flow for finding optimal location of EVFCS is as shown in Fig. 2.

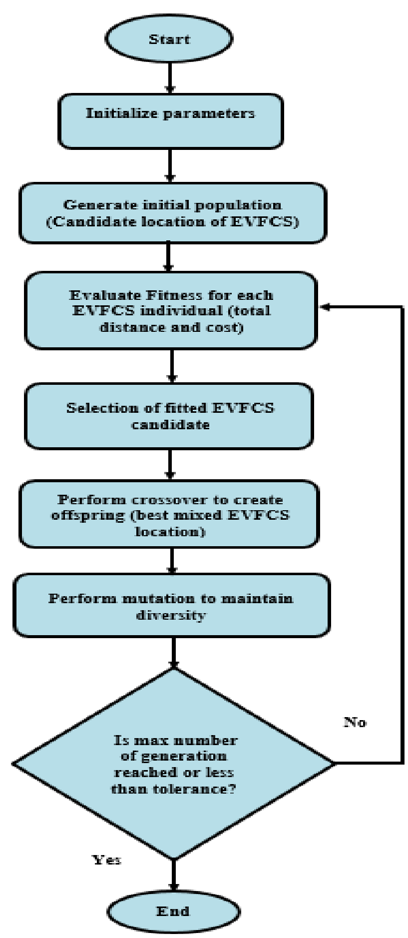

Fig. 2. GA based flowchart for optimal location of EVFCS

G. *Computational Process*

In this research to implement the optimization algorithm the following procedures were used.

- ✓ Locating areas of proximity and entering their coordinates into MATLAB.
- ✓ Determining GA parameters (such as population size the number of candidates of EVFCS that are randomly chosen and iteration count).
- ✓ Examining optimization outcomes and choosing the optimal solution

III. RESULTS AND FINDINGS

In a distribution network, we identified the best place for EVFCS using the suggested genetic algorithm-based optimization technique. The proposed optimization considered factors such as proximity to the transformer, official institutions, transportation, petrol stations, shopping malls, normal charging stations, main road, parking lot and the impact of installation costs and power loss on the distribution network. As shown in Table IV, it indicates the optimal location for the EVFCS.

Table IV. Optimal location of EVFCS

EVFCS No	Phase Type	Transformer Connected No	Latitude location	Longitude Location
1	1/3	6196	41.095950	29.091813
2	3	6143	41.095950	29.091820
3	3	6143	41.095950	29.091823
4	1/3	6143	41.094964	29.091465
5	1/3	6145	41.095382	29.091501
6	3	6093	41.099265	29.088785
7	3	6093	41.099265	29.088787
8	1/3	6093	41.099265	29.088787
9	1/3	6221	41.094042	29.085917
10	3	6221	41.094041	29.085969
11	3	6221	41.094042	29.086059
12	1/3	6191	41.093941	29.079740
13	1/3	6189	41.088968	29.078156
14	1/3	6207	41.087720	29.075816
15	3	6207	41.087720	29.075822
16	3	6207	41.087719	29.075824

These findings underscore the effectiveness of GA in solving complex multi-objective optimization problems for distribution networks. By minimizing the total distance from each EVFCS to all proximity area, the best optimal location values are obtained. In the study, by running genetic algorithm several times, several optimal locations are obtained. The algorithm considers priority for the distance from transformer to EVFCS. Finally, the lower distance value optimal point is selected in the study. The genetic algorithm displays the best fitness value as shown in Table V.

Table V. Best total distance and transformer to EVFCS distance fitness value

EVFCS	Transformer Connected No.	Distance from transformer to EVFCS (m)	Best total distance fitness (m)
1	6196	106.88	2869.79
2	6143	107.48	2869.79
3	6143	107.78	2869.79
4	6143	48.44	1760.39
5	6145	3.80	1820.83
6	6093	104.67	3690.52
7	6093	104.78	3690.52
8	6093	104.79	3690.52
9	6221	182.51	2888.99
10	6221	186.87	2888.99
11	6221	194.38	2888.99
12	6191	40.87	4177.91
13	6189	174.02	5211.07
14	6207	70.56	4602.20
15	6207	71.08	4602.20
16	6207	71.36	4602.20

As shown in Table V, the distance of the EVFCS to the transformer does not exceed 200 m as a result of GA findings, which reveals that the cross-section of the cable used is suitable according to the current carrying capacity and the load profile of the EVFCS.

In the study, 16 EVFCS locations are obtained. For each EVFCS the best fitness function is obtained. However here, as a test for the first EVFCS GA fitness vs generation graph is as shown in Fig. 3.

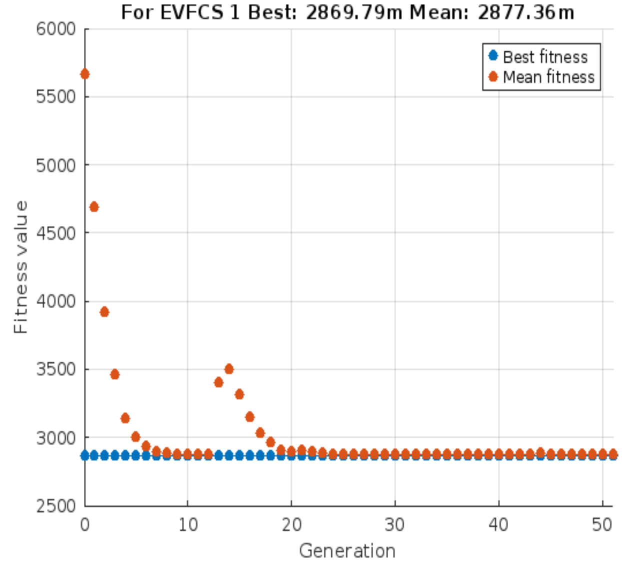

Fig. 3. EVFCS 1 best distance fitness value

Together with the cost breakdown (installation, and power loss), the final result gives the EVFCSs best coordinates. This option guides the most economical site for EVFCS installation in the specified area by representing the optimal trade-off based on the goal function.

This GA-based method is ideally suited for actual EVFCS placement since it successfully strikes a compromise between demand density considerations and installation and operating expenses. The result of detailed cost breakdown is obtained as shown in Table VI. In this study out of 16 EVFCS 8 of them are both 1 phase and 3 phase.

Table VI. Break down cost

NO of EVFCS	Fixed installation cost ($)	Line cost ($)	Power loss cost ($)	Total cost ($)
1	26247.5	2137.6	32.2	28417.3
2	26097.5	2149.7	32.3	28279.5
3	26097.5	2155.7	32.4	28285.7
4	26247.5	968.9	14.6	27231.0
5	26247.5	76.0	1.1	26324.7
6	26097.5	2093.5	31.5	28222.5
7	26097.5	2095.6	31.5	28224.6
8	26247.5	2095.9	31.5	28375
9	26247.5	3650.3	54.9	29952.7
10	26097.5	3737.5	56.3	29891.3
11	26097.5	3887.6	58.5	30043.6
12	26247.5	817.5	12.3	27077.3
13	26247.5	3480.5	52.4	29780.4
14	26247.5	1411.3	21.2	27680.0
15	26097.5	1421.7	21.4	27540.5
16	26097.5	1427.4	21.5	27546.3
The total sum cost for 16 EVFCS 452872.4				

In the study for three different EVs brand model that are distinguished based on their battery magnitude capacity, the EVs charging duration time is conducted and the result is obtained as shown in Table VII.

Table VII. Duration of charging time for three different model based on their battery capacity from 20% to 90%

Brand	Model	Battery Capacity (kWh)	Duration Time (Minutes)
Citroen	C-Zero	15	6.563
Opel	Ampera –e	58	25.375
Audi	e-Tron	95	41.563

IV. CONCLUSION

Generally, in this research the model evaluates different proximity areas with their occupancy rates and distribution network configurations using a genetic algorithm to determine the best optimal point. In the end, it chooses locations that strike a balance between cost-effectiveness, network requirements, and user needs. This method optimizes placement for accessibility and operational efficacy, supporting effective EV infrastructure planning. Because of network line and power loss expenses are reduced, the optimization technique reduces overall cost by determining the optimal distance in the fitness function. The Manhattan distance from transformer to EVFCS and each EVFCS to all proximity data's are analyzed. In the study the GA achieved convergence with single best location of EVFCS and it stops in the 51 generation because of the average change in the fitness value is less than the tolerance. Results show that the optimization technique significantly reduces power loss and operational costs. This approach guarantees economical placement while preserving accessibility to important areas. In the study, the charging duration time of three different battery capacity EVs to fill from 20% to 90% are obtained. The duration time for minimum, average and maximum battery capacity of EVs are 6.563, 25.375 and 41.563 minutes respectively. Future research might cover dynamic traffic patterns, integrating EVFCS with dynamic load analysis and expanding the scope of the study. In general, this framework encourages the construction of sustainable EV charging infrastructure and reduces the total expense. The effectiveness of the proposed optimization technique in reducing operating costs and power losses has been emphasized. The model's applicability to various EV brands and battery capacities, along with its ability to realistically estimate charging durations, has been highlighted as a practical contribution to infrastructure planning. Furthermore, the advantages of the proposed approach in terms of energy efficiency, system reliability, and scalability have been framed within a strategic context.

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