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Transformer performance enhancement by optimized charging strategy for electric vehicles

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Abstract: Transformer efficiency and regulation, are to be maintained at maximum and minimum respectively by optimal loading, control, and compensation. Charging of electric vehicles at random charging stations will result in uncertain loading on the distribution transformer. The efficiency reduces and regulation increases as a consequence of this loading. In this work, a novel optimization strategy is proposed to map electric vehicles to a charging station, that is optimal with respect to the physical distance, traveling time, charging cost, the effect on transformer efficiency and regulation. Consumer and utility factors are considered for mapping electric vehicles to charging stations. An Internet of Things platform is used to fetch the dynamic location of electric vehicles. The dynamic locations are fed to a binary optimization problem to find an optimal routing table that maps electric vehicles to a charging station. A comparative study is carried out, with and without optimization, to validate the proposed methodology.

Key words: charging stations, electric vehicle, e-mobility, optimization, transformer efficiency, transformer regulation

1. Introduction

The demand and production of electric vehicles is increasing in the global market. This increasing trend creates many opportunities and challenges in various sectors like the power system, mechanical design, communication system, production, sales and services [1]. Unlike an internal combustion engine, wherein power is generated through the combustion of fuel; electric vehicles use electrical energy as a source of power. The power requirement for electric vehicle fleets is very high [2]. To meet this additional power demand, a sufficient source of power and associated infrastructure is to be deployed in the power system [3]. The e-mobility sector introduces numerous challenges to the power system, that needs to be addressed immediately [4]. The energy balance, utilization of the existing infrastructure and deployment of essential new infrastructure are the priorities in the power system. The physical components in the power system such as transformers, transmission lines, switchgear, generators and compensators are designed based on the installed load. The distribution network has to be now planned with consideration of electric vehicle fleets [5]. The additional burden caused by electric vehicles can be addressed either by infrastructural development or optimized utilization of existing infrastructure [6, 7].

In a power system, the transformers are the interface between the power grid and charging stations [8]. The efficiency of the transformer depends on the load. The transformer has maximum efficiency for the load which equates to the iron and copper loss. It is important to vary load in such a way that the efficiency of the transformer stays near the maximum point, so that loss and stress on the transformer is reduced [9]. Electric vehicle charging at a random charging station could lead to overloading, load shedding and instability in the power system. Charging at a random charging station will also result in economic loss and inconvenience for the customer [10, 11].

Uncertain loading on the transformer leads to increased electromagnetic stress and physical deformations. Optimization techniques and intelligence algorithms can be used to map electric vehicles to charging stations. The objectives considered are minimization, voltage deviation, charging cost in the distribution system [12]. The predicted load is embedded in the optimization problem to allocate electric vehicles to charging stations [13]. Optimal load flow is carried out by considering electric vehicle fleets to increase the stability of the system and to lower the charging cost [14, 15]. Distribution network reconfiguration is performed in case of uncertain electric vehicle loading and to decrease the switching cost and demand response charges [16, 17]. Distributed energy sources are strategically managed to minimize the unnecessary active power curtailments [18]. The impact of an electric vehicle load on the distribution transformer has to be analyzed for each discrete EV loading by considering customer requirements namely charging cost, travel time and travel distance [19–21].

In this work, distribution transformers connected to public charging stations are safeguarded by the strategic and optimized routing of electric vehicles considering both utility and consumer constraints. Utility and consumer factors are also considered while deriving the routing table, which results in optimal loading on the transformer. Efficiency and regulation increase and decrease respectively by the optimal loading on the transformer. Consumer benefited by the reduced travel time, distance and charging cost.

This paper is organized as shown below:

- Section 2 presents the interconnection of the system components, information flow and research process.
- Sections 3 and 4 present functional matrices and their corresponding weights to formulate the multi-objective optimization problem.
- Section 5 presents the mathematical model of the optimization problem consisting of objective functions and constraints.
- Section 6 presents the test system under consideration.
- Section 7 presents the proposed algorithm.
- Section 8 provides an optimized mapping of an electric vehicle with a charging station as a solution for the problem formulated in Section 5.
- Section 9 investigates and discusses the utility and consumer benefits.

2. Process and architecture

There are four stages in the proposed work, namely data collection, pre-processing, problem formulation and the solution of the optimization problem as shown in Fig. 1. Geolocation and electrical parameters are fetched from the electric vehicles, charging stations and distribution transformers. The distance, time and cost matrices are calculated using the collected data. The functional matrices are plugged into the optimization problem. The problem is solved using optimization technique to obtain the electric vehicle and charging station mapping.

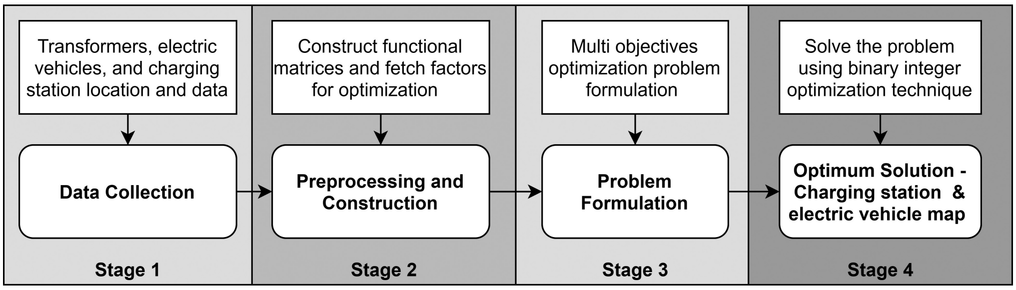

Fig. 1. Process diagram

The proposed architecture for the proposed method is shown in Fig. 2. Interconnection of physical entities, information flow and information technology infrastructures are shown in the figure. An algorithm is proposed to optimize physical distance, travel time, charging cost, efficiency and regulation, and developed as an application. Static information from electric vehicles, charging stations and transformers are pre-loaded in the application. The dynamic location of the electric vehicles is uploaded to the Internet of Things (IoT) platform from vehicle telemetry and fetched from the IoT platform to the proposed application. The application estimates

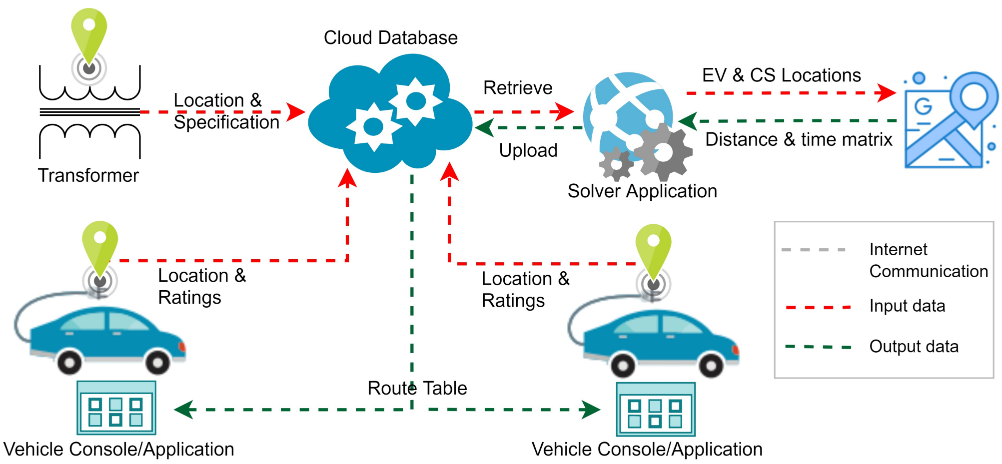

Fig. 2. Architecture

the routing table and uploads to the cloud database. The consumer is informed through listener service in the vehicle console. The application program runs at regular intervals of time to provide a customer and utility-centric routing table where time, cost, distance, the efficiency of transformers and regulations are optimal.

3. Functional matrices

Unique and novel functional matrices that are the matrix representation of specific parameters that relate the n number of electric vehicles and the m number of charging stations are proposed in this work. They are defined as follows: i is the index of a charging station and j is the index of an electric vehicle.

Distance Matrix

Distance Matrix (D): $D = d_{ij} \in \mathbb{R}^{m\times n}$. Element d_{ij} is the physical distance of the j^{th} electric vehicle to reach the i^{th} charging station. This distance is fetched from Google Maps distance/direction APIs by providing charging station and electric vehicle location as input.

Time Matrix

Time Matrix (T): $T = t_{ij} \in \mathbb{R}^{m\times n}$. Element t_{ij} is the travel time of the j^{th} electric vehicle to reach the i^{th} charging station. This time is fetched from Google Maps distance/direction APIs by providing charging station and electric vehicle location as input.

Cost Matrix

Cost Matrix (C): $C = c_{ij} \in \mathbb{R}^{m\times n}$. Element c_{ij} is the charging cost for the j^{th} electric vehicle at the i^{th} charging station. This cost is fetched from the Regional Time of Use (RToU) tariff database which is defined by distribution companies.

Efficiency Matrix

Efficiency Matrix (E): $E = \eta_{ij} \in \mathbb{R}^{m\times n}$. Element η_{ij} is the efficiency of the distribution transformer when loaded with the j^{th} electric vehicle alone at the i^{th} charging station along with the regular load. The deviation of efficiency with respect to the maximum point is to be minimized. The efficiency of the distribution transformer η is calculated by

$$\eta = \frac{kS\cos\phi}{kS\cos\phi + k^2 P_c + P_i}, \tag{1}$$

where: k is the ratio of current loading to the full load current, S is the transformer total power, ϕ is the angle between the voltage and current vector, P_c is the copper loss at the full load, P_i is the core loss.

Regulation Matrix

Regulation Matrix (R): $r_{ij} \in \mathbb{R}^{m\times n}$. Element r_{ij} is the regulation of the distribution transformer when loaded with the j^{th} electric vehicle alone at the i^{th} charging station along with the regular load. The regulation of the distribution transformer r is calculated by

$$r = k\left(U_r \cos\phi + U_x \sin\phi\right) + \frac{k^2}{200}\left(U_x \cos\phi - U_r \sin\phi\right)^2, \tag{2}$$

where U_r is the percentage resistance voltage at the full load and U_x is the percentage reactance voltage.

4. Weights for functional matrices

In this section, five factors with weights are proposed and defined, to be considered in the optimization problem. The weights have a value between 0 and 1. Individual weights are also considered for the n number of electric vehicles charging at the m number of charging stations.

Weight for Cost Matrix

$\beta_1 B' = \beta_1 b'_{ij} \in \mathbb{R}^{m\times n}$ is the weight for the Cost Matrix (C), where β_1 is the scalar value multiplied to all the elements in C and decided by the utility. b'_{ij} is the element in B' which indicates individual cost weight of the j^{th} electric vehicle charging at the i^{th} charging station. This factor is the weight for the $(ij)^{\text{th}}$ element in C and decided by a customer depending on the importance of cost of the customer. If distance and time constraints are less important to the customer then the customer would go for value 0. If, however, the cost is major criteria then the customer would go for value.

Weight for Distance Matrix

$\beta_2 B'' = \beta_2 b_{ij} \in \mathbb{R}^{m\times n}$ is the weight for the Distance Matrix (D), where β_2 is the scalar value multiplied to all the elements in D and decided by the utility. b_{ij} is the element in B'' which indicates individual distance weight of the j^{th} electric vehicle charging at the i^{th} charging station. This factor is the weight for the $(ij)^{\text{th}}$ element in D and decided by a customer depending on the traveling distance constraint of the customer.

Weight for Time Matrix

$\beta_3 B''' = \beta_3 b'''_{ij} \in \mathbb{R}^{m\times n}$ is the weight for the Time Matrix (T), where β_3 is the scalar value multiplied to all the elements in T. b'''_{ij} is the element in B''' which indicates individual time weight of the j^{th} electric vehicle charging at the i^{th} charging station. This factor is the weight for the $(ij)^{\text{th}}$ element in T and decided by a customer depending on the traveling time constraint of the customer.

Weight for Efficiency Matrix

$p_1 P' = p_1 p'_{ij} \in \mathbb{R}^{m\times n}$ is the weight for the Efficiency Matrix (E), where p_1 is the scalar value multiplied to all the elements in E. p'_{ij} is the element in P' which indicates individual efficiency weight of the j^{th} electric vehicle charging at the i^{th} charging station. This factor is the weight for the $(ij)^{\text{th}}$ element in E and decided by the utility.

Weight for Regulation Matrix

$p_2 P'' = p_2 p_{ij} \in \mathbb{R}^{m \times n}$ is the weight for the Regulation Matrix (R), where p_2 is the scalar value multiplied to all the elements in R. p_{ij} is the element in P'' which indicates individual regulation weight of the j^{th} electric vehicle charging at the i^{th} charging station. This factor is the weight for the $(ij)^{\text{th}}$ element in R and decided by the utility.

5. Multi objective optimization problem formulation

In the proposed work, electric vehicles must be directed to a particular charging station with the matrices and factors discussed in Sections 3 and 4. The problem is formulated as an integer optimization problem and solved using integer linear programming in the MATLAB® optimization toolbox (*intlinprog*). The objective is to get the best routing of electric vehicles to charging stations.

Problem statement

The problem is to find an optimal routing for each of the n electric vehicles to one of the m charging stations. The solution to be obtained is a matrix $[X]_{m \times n}$, where element x_{ij} is either 0 or 1. If the j^{th} electric vehicle is mapped to the i^{th} charging station then $x_{ij} = 1$. If the j^{th} electric vehicle is not mapped to the i^{th} charging station, then $x_{ij} = 0$.

Objective function

The objective function consists of five terms to account for cost, distance, time, efficiency and regulation for m charging stations and n electric vehicles.

- Cost objective function: $\min \sum_{i=1}^{m} \sum_{j=1}^{n} \beta_1 B'_{ij} c_{ij}$,
- Distance objective function: $\min \sum_{i=1}^{m} \sum_{j=1}^{n} \beta_2 B''_{ij} d_{ij}$,
- Time objective function: $\min \sum_{i=1}^{m} \sum_{j=1}^{n} \beta_3 B'''_{ij} t_{ij}$,
- Transformer efficiency objective function: $\min \sum_{i=1}^{m} \sum_{j=1}^{n} p_1 P'_{ij} \left|\eta_{i\,\max} - \eta_{ij}\right|$,
- Transformer regulation objective function: $\min \sum_{i=1}^{m} \sum_{j=1}^{n} p_2 P''_{ij} (r_{ij})$.

The overall objective function is given in (3).

$$\min \sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} x_{ij}\,, \tag{3}$$

where $f_{ij} = \beta_1 B'_{ij} c_{ij} + \beta_2 B''_{ij} d_{ij} + \beta_3 B'''_{ij} t_{ij} + p_1 P'_{ij} \left|\eta_{i\,\max} - \eta_{ij}\right| + p_2 P''_{ij} (r_{ij})$.

Constraints

Power limitation and physical restrictions are modelled as equality and inequality constraints. The constraints are:

– Electric vehicle constraint: An electric vehicle is allowed to charge at one charging station only. The electric vehicle constraint is given by

$$\sum_{i=1}^{m} X_{ij} = 1 \; \forall j \in R^n. \tag{4}$$

– Charging station constraint: The maximum number of electric vehicles which can be directed to any charging station is limited to n. The charging station constraint is given by

$$\sum_{j=1}^{n} X_{ij} \leq n \; \forall i \in R^m. \tag{5}$$

– Charging station power limit: The maximum number of electric vehicles mapped to any charging station is limited by the sanctioned load for the charging station. Cumulative power rating of all the electric vehicles assigned to a particular charging station should be less than the power limit of the charging station. The power limit constraint is given by (6) (where P_i^c is the power limit of the i^{th} charging station and P_{ij}^e is the power rating of the j^{th} electric vehicle mapped to the i^{th} charging station).

$$\sum_{j=1}^{n} P_{ij}^e X_{ij} \leq P_i^c \,. \tag{6}$$

– Control variable constraint: Mapping of electric vehicles to a charging station has to result in a binary outcome. The decision variable is either 0 or 1.

$$x_{ij} \in \{0,\ 1\}. \tag{7}$$

Output

The solution obtained is the $m \times n$ matrix with each element being 0 or 1 satisfying the constraints discussed above to minimize the objective function.

$$\text{Output matrix } (X): \;\; X = x_{ij} \in Z^{m \times n} : x_{ij} \in 0, 1\}. \tag{8}$$

It can be observed that the objective function and constraints are linear. Hence linear programming technique is used to solve this problem. Binary integer linear programming is used to obtain the optimal solution.

6. Case study

Input data

Ten electric vehicles, ten charging stations and five distribution transformers are considered to demonstrate the proposed method. The electric vehicle location, power rating and weights

Table 1. Electric vehicle specifications

EV	Latitude	Longitude	Power (kW)	B'	B''	B'''
E1	12.3199	76.6334	20	1	1	1
E2	12.3091	76.6442	18	1	1	1
E3	12.3155	76.6126	15	1	1	1
E4	12.303	76.6165	16	1	1	1
E5	12.3005	76.603	20	1	1	1
E6	12.2959	76.6376	15	1	1	1
E7	12.2886	76.6294	18	1	1	1
E8	12.3265	76.6127	16	1	1	1
E9	12.3316	76.6247	20	1	1	1
E10	12.3139	76.6588	15	1	1	1

considered in this work are shown in Table 1. E1, E2, …, E10 → electric vehicles. B', B'' and B''' are considered as 1 to portray equal significance to cost, distance and time concerns of electric vehicle users.

The charging station location, power limit, charging cost per unit and the distribution transformer association is shown in Table 2. C1, C2, …, C10 are the charging stations. DTC no. is a distribution transformer ID. In Table 2, charging stations C1 and C2 are connected to the distribution transformer whose ID is 1. Similarly, other records are to be interpreted.

Table 2. Charging station location and specification

EV	Latitude	Longitude	Power (kW)	Cost per unit (₹)	DTC no.
C1	12.32113	76.6357	20	5.00	1
C2	12.31055	76.64138	18	6.20	1
C3	12.31552	76.60822	15	5.50	2
C4	12.30521	76.60743	16	7.00	2
C5	12.29732	76.63475	20	6.50	3
C6	12.29384	76.62519	15	7.50	3
C7	12.32226	76.61568	18	6.75	4
C8	12.32239	76.62443	16	5.75	4
C9	12.31852	76.64883	20	5.25	5
C10	12.31392	76.65048	15	6.35	5

The location and electrical specifications of all the distribution transformers are shown in Table 3. DTC1, DTC2, . . . , DTC5 are distribution transformers. kVA and Z are the total power rating and percentage impedance of the distribution transformers. Power factor and voltage are measured values at a low-tension side when the load is connected.

Table 3. Distribution transformer location and specifications

DTC	Latitude	Longitude	kVA	Power factor	Voltage (V)	Z (%)†
DTC1	12.31681	76.63696	250	0.8	400	4
DTC2	12.31438	76.61405	250	0.85	404	4
DTC3	12.30231	76.62559	250	0.87	402	4
DTC4	12.31883	76.63023	250	0.79	405	4
DTC5	12.31761	76.64668	250	0.88	398	4

† Source: Low Voltage Transformers from https://library.abb.com/en

The Regional Time of Use (RToU) cost for the customer at various charging stations is fetched from Table 2. Let this vector be q. Hence the Cost Matrix is the arrangement of q vector n times. Therefore, $C = \left[q^T; q^T, \ldots, q^T\right]_{m\times n}$, where

$$q = [5\ 6.2\ 5.5\ 7\ 6.5\ 7.25\ 6.75\ 5.75\ 5.25\ 6.35]_{1\times m}.$$

The charging stations, transformers and feeders are immovable assets in the power system, whereas electric vehicles change their positions in the geographical space. The dynamic position of the electric vehicles is fetched from vehicle telemetry. The immovable asset locations are pre-loaded in the application. The challenge is to map electric vehicles and charging stations considering all the constraints. In Fig. 3, the location of feeders, distribution transformers, changing stations and electric vehicles are shown. The bubble size indicates power value.

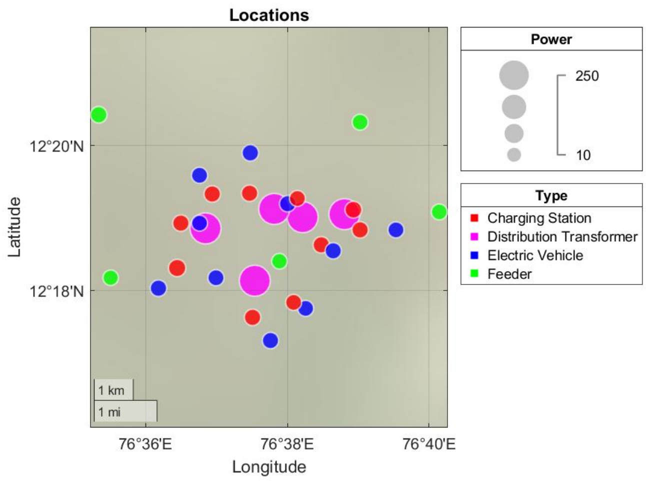

Fig. 3. Geo-spacial distribution of electric vehicles, charging stations, DTCs and feeders

Functional matrices of the case study

Distance Matrix API is one of the Google Maps APIs, which gives optimum or best distance and time for the given two locations. One can generate an API key to utilize services from Google. These services should be subscribed. The functional matrix can be constructed by any programming language such as Python. Python libraries namely google maps along with NumPy and Pandas are to be used to construct a functional matrix by feeding electric vehicles and charging station locations. The Distance Matrix for the case under consideration is shown in Table 4. This matrix is constructed on 23rd July 2020 05:57:02, using Google Maps API.

Table 4. Distance Matrix (in meters)

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10
C1	402	1732	3978	4412	3810	3803	2600	1509	2275	2931
C2	2704	619	5437	4431	2570	3528	3847	3498	2090	1469
C3	3904	4158	2163	2221	4717	3866	1140	2153	5590	5437
C4	4270	3843	2497	1491	2844	1993	2284	3297	5743	5122
C5	5832	5405	2524	1114	4061	3210	3845	4858	7305	6684
C6	3778	2002	5800	4794	451	1572	4921	4572	3918	3297
C7	5774	4222	5098	4008	1998	2113	5331	5282	6139	5518
C8	2702	3869	1674	3533	5946	4763	937	1762	4821	5148
C9	2023	3822	3478	4696	5900	5094	2100	1371	3488	4144
C10	3195	2428	6823	6578	4821	5675	5445	4936	1347	963

The Time Matrix for the case under consideration is shown in Table 5. This matrix is constructed on 23rd July 2020 05:57:02. The time estimation provided by Google Maps API is the travel time with the consideration of traffic density on that route.

Table 5. Time Matrix (in seconds)

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10
C1	74	210	599	569	484	474	359	237	364	484
C2	361	116	750	599	362	470	529	489	359	294
C3	561	562	395	357	709	557	216	400	847	838
C4	552	489	397	246	456	304	342	526	831	766
C5	720	657	377	186	601	449	510	694	999	934
C6	474	265	796	645	75	275	642	602	602	537
C7	805	598	866	661	346	353	816	791	936	871
C8	486	505	328	524	779	619	172	306	775	781
C9	316	552	619	731	826	736	379	253	530	650
C10	532	489	1106	1009	789	880	866	825	246	217

The Efficiency Matrix discussed in Section 3 is calculated and shown in Table 6. An element in this matrix is the efficiency of a transformer considering a specific EV load.

Table 6. Transformer Efficiency Matrix (in p.u)

	E1	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**	**E8**	**E9**	**E10**
C1	0.9853	0.9853	0.9861	0.9861	0.9868	0.9868	0.9862	0.9862	0.9866	0.9866
C2	0.9852	0.9852	0.9859	0.9859	0.9867	0.9867	0.9862	0.9862	0.9865	0.9865
C3	0.9852	0.9852	0.9860	0.9860	0.9867	0.9867	0.9862	0.9862	0.9865	0.9865
C4	0.9854	0.9854	0.9861	0.9861	0.9869	0.9869	0.9863	0.9863	0.9867	0.9867
C5	0.9852	0.9852	0.9859	0.9859	0.9867	0.9867	0.9862	0.9862	0.9865	0.9865
C6	0.9853	0.9853	0.9861	0.9861	0.9868	0.9868	0.9862	0.9862	0.9866	0.9866
C7	0.9852	0.9852	0.9860	0.9860	0.9867	0.9867	0.9862	0.9862	0.9865	0.9865
C8	0.9854	0.9854	0.9861	0.9861	0.9869	0.9869	0.9863	0.9863	0.9867	0.9867
C9	0.9852	0.9852	0.9859	0.9859	0.9867	0.9867	0.9862	0.9862	0.9865	0.9865
C10	0.9853	0.9853	0.9861	0.9861	0.9868	0.9868	0.9862	0.9862	0.9866	0.9866

The Regulation Matrix discussed in Section 3 is calculated and shown in Table 7. An element in this matrix is the regulation of a transformer considering a specific EV load.

Table 7. Transformer Regulation Matrix (in %)

	E1	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**	**E8**	**E9**	**E10**
C1	0.4712	0.4712	0.4490	0.4490	0.4564	0.4564	0.5090	0.5090	0.4405	0.4405
C2	0.4686	0.4686	0.4464	0.4464	0.4539	0.4539	0.5064	0.5064	0.4379	0.4379
C3	0.4647	0.4647	0.4426	0.4426	0.4500	0.4500	0.5026	0.5026	0.4340	0.4340
C4	0.4660	0.4660	0.4439	0.4439	0.4513	0.4513	0.5039	0.5039	0.4353	0.4353
C5	0.4712	0.4712	0.4490	0.4490	0.4564	0.4564	0.5090	0.5090	0.4405	0.4405
C6	0.4647	0.4647	0.4426	0.4426	0.4500	0.4500	0.5026	0.5026	0.4340	0.4340
C7	0.4686	0.4686	0.4464	0.4464	0.4539	0.4539	0.5064	0.5064	0.4379	0.4379
C8	0.4660	0.4660	0.4439	0.4439	0.4513	0.4513	0.5039	0.5039	0.4353	0.4353
C9	0.4712	0.4712	0.4490	0.4490	0.4564	0.4564	0.5090	0.5090	0.4405	0.4405
C10	0.4647	0.4647	0.4426	0.4426	0.4500	0.4500	0.5026	0.5026	0.4340	0.4340

7. Proposed algorithm

The algorithm to find the mapping of electric vehicles to charging stations is as follows.

Algorithm 1: Mapping of electric vehicle to charging station

Step 1: Load charging station, distribution transformer center (DTC) and Feeders' static data such as ratings and locations from the application database.

Step 2: Fetch dynamic location of electric vehicles from the cloud database.

Step 3: Load all the factors for optimization from the application database.

Step 4: Construct distance and time relational matrices using Google distance and direction APIs.

Step 5: Construct efficiency and regulation functional matrices by (1) and (2).

Step 6: Formulate the optimization problem.

Step 7: Solve the optimization problem using integer linear programming to get charging station and electric vehicle mapping.

Step 8: Perform element wise multiplication of solution and relational matrices to obtain actual parameters such as cost, distance and travel time of every electric vehicle; also the efficiency and regulation of all the DTCs.

8. Results

The test system defined by functional matrices in Section 6 is plugged in the problem formulation in Section 5 by using the MATLAB® integer linear programming (*intlinprog*) function. The solution is obtained and results are tabulated. The Euclidean mappings are shown using geoplot to visualize connectivity between an EV, CS and DTCs.

Optimized mapping table

The binary solution obtained from the mathematical model is shown in Tables 8 and 9. The table depicts the best charging station for the electric vehicle. Element $X(1,3) = X(\mathrm{C1}, \mathrm{E3}) = 1$ indicates that the 3$^{\text{rd}}$ electric vehicle is mapped to the 1$^{\text{st}}$ charging station. Element $X(1,1) = X(\mathrm{C1}, \mathrm{E1}) = 0$ indicates that the 1$^{\text{st}}$ electric vehicle is not mapped to the 1$^{\text{st}}$ charging station. An element in this matrix is either 0 or 1. All the electric vehicles are mapped to any one charging station. In Table 9, distance, time and cost per unit to reach a charging station is shown for all electric vehicles.

Table 10 gives summary of all the distribution transformer details where the electric vehicles mapped, power allocation, functional value, efficiency and regulation of all the distribution transformers are given.

Table 8. Optimized mapping of EV and charging station

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10
C1	0	0	1	0	0	0	0	0	0	0
C2	0	1	0	0	0	0	0	0	0	0
C3	0	0	0	1	0	0	0	0	0	0
C4	0	0	0	0	1	0	0	0	0	0
C5	0	0	0	0	0	1	0	0	0	0
C6	0	0	0	0	0	0	1	0	0	0
C7	0	0	0	0	0	0	0	1	0	0
C8	0	0	0	0	0	0	0	0	1	0
C9	1	0	0	0	0	0	0	0	0	0
C10	0	0	0	0	0	0	0	0	0	1

Table 9. Look-up table: electric vehicles and charging stations

Charging station	Electric vehicles	Power (kW)	Associated DTC	Distance (m)	Time (s)	Cost per unit (₹)
1	3	15	1	3904	561	5
2	2	18	1	619	116	6.2
3	4	16	2	2497	397	5.5
4	5	20	2	1114	186	7
5	6	15	3	451	75	6.5
6	7	18	3	2113	353	7.25
7	8	16	4	937	172	6.75
8	9	20	4	1371	253	5.75
9	1	20	5	2275	364	5.25
10	10	15	5	963	217	6.35

Table 10. Look-up table: electric vehicles, charging stations and DTCs

DTC no.	Charging stations	Electric vehicles	Power (kW)	Associated feeder	Objective function	Efficiency (%)	Regulation (%)
1	1, 2	3, 2	33	1	1.3421	98.985	0.6185
2	3, 4	4, 5	36	1	1.2573	98.988	0.61461
3	5, 6	6, 7	33	1	1.0766	98.947	0.68017
4	7, 8	8, 9	36	1	1.0584	98.761	0.96539
5	9, 10	1, 10	35	1	1.2634	98.986	0.60331

Euclidean mapping

The Euclidean mapping between electric vehicles and charging stations is shown pictorially in Fig. 4. Similarly, the Euclidean mapping between DTCs and electric vehicles is shown pictorially in Fig. 5. It shows the electric vehicle fleet loading on the distribution transformers.

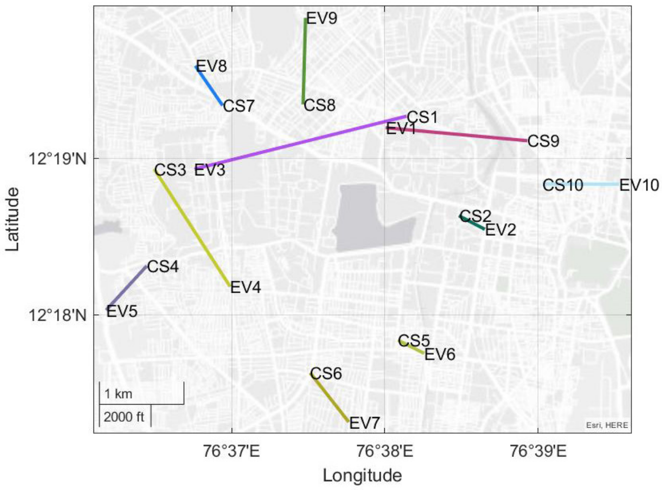

Fig. 4. Euclidean mapping of electric vehicles and charging stations

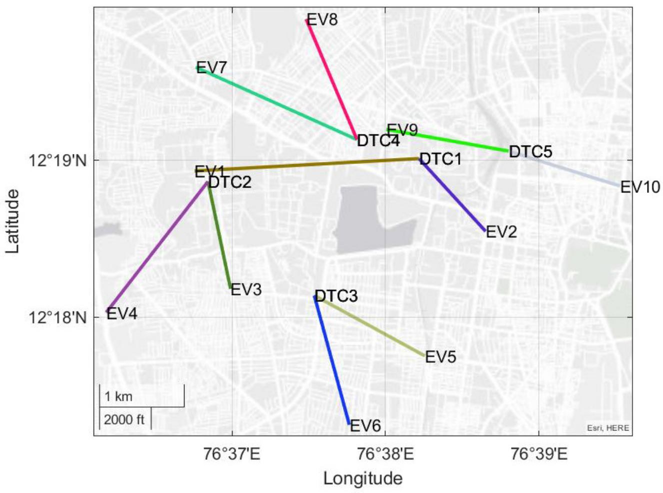

Fig. 5. Euclidean mapping of DTCs and electric vehicles

Comparison with random mapping

The proposed solution is validated by comparing objective function values of a random routing table. Random mapping, as shown in Table 11 is considered for the comparative study.

Table 11. Random mapping of EV and charging station

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10
C1	0	0	0	0	0	0	0	0	0	0
C2	0	0	0	0	0	0	0	0	0	0
C3	0	0	0	0	0	0	0	0	0	0
C4	0	0	0	0	1	0	0	0	0	0
C5	0	0	1	0	0	0	0	0	0	0
C6	1	0	0	0	0	0	0	1	0	0
C7	0	0	0	0	0	0	1	0	1	1
C8	0	0	0	0	0	1	0	0	0	0
C9	0	0	0	0	0	0	0	0	0	0
C10	0	1	0	1	0	0	0	0	0	0

Mean objective function value

The objective function values obtained for the optimized and non-optimized cases are shown in Table 12. It is evident from the table that the overall objective function value or a mean value of 1.1996 is much less compared to the mean value of 1.9267 of the non-optimized case. The overall objective function value is improved by 37.7381%. There is a marginal improvement in efficiency and a significant improvement in regulation.

Table 12. Random mapping of EV and charging station

Objective function	Without optimization	With optimization	Improvement (%)
Objective function value	1.9267	1.1996	37.7381
Transformer efficiency	98.875%	98.933%	0.0586
Transformer regulation	0.7403%	0.694%	6.2542
Cost	₹ 6.670	₹ 6.155	7.7211
Distance	3843.6 meters	1624.4 meters	57.7375
Time	571.1 seconds	269.4 seconds	52.8278

9. Discussions

In this section, the transformer performance enhancement for all distribution transformers and benefits for all electric vehicle users are discussed.

Transformer efficiency characteristics

The transformer efficiencies with and without optimization are estimated for each DTC. Loss is more for random mapping and less for the optimized system. The comparison results are shown in Fig. 6. It is evident from the figure that the mean value of efficiency is increased compared to the non-optimized system.

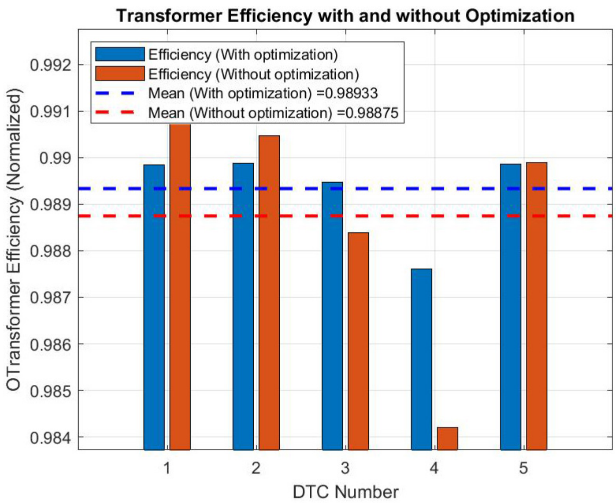

Fig. 6. Euclidean mapping of DTCs and electric vehicles

Transformer regulation characteristics

The transformer regulation with and without optimization is estimated for each DTC. Voltage droop is more for nonstrategic and less for the optimized system. Comparison results are shown in Fig. 7. It is evident from the figure that the mean values are much less compared to the non-optimized system.

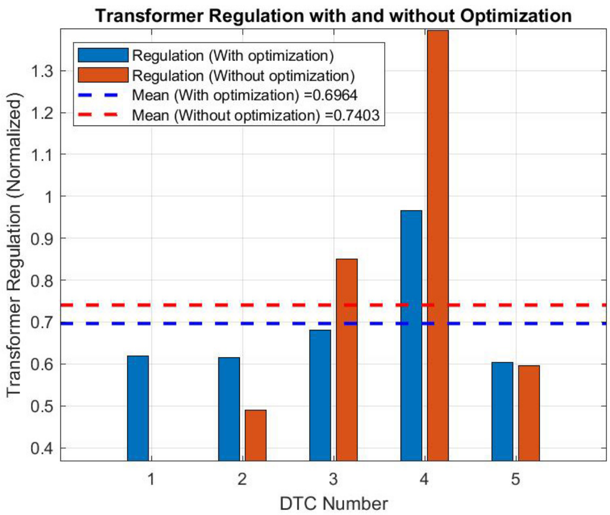

Fig. 7. Euclidean mapping of DTCs and electric vehicles

Time characteristics

It is highly essential to recommend an electric vehicle owner such a charging station that takes him less time to reach. Figure 8 shows that the mean value of time of travel is reduced drastically compared to the random system.

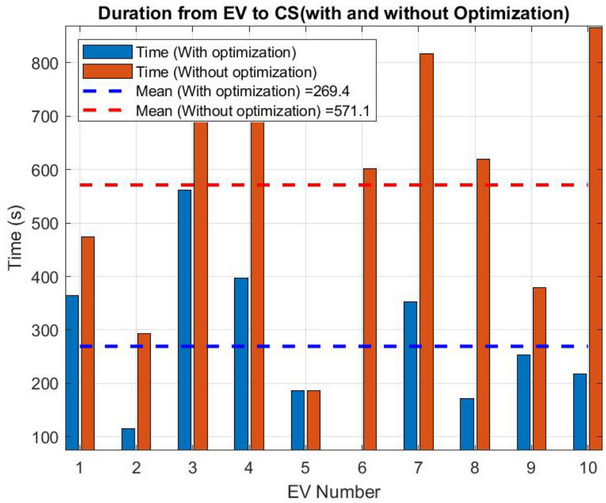

Fig. 8. Euclidean mapping of DTCs and electric vehicles

Distance characteristics

The algorithm recommends the nearest charging station to the customer. Figure 9 shows that the mean travel distance is reduced significantly compared to the random system. Reduction of distance consecutively saves time and cost.

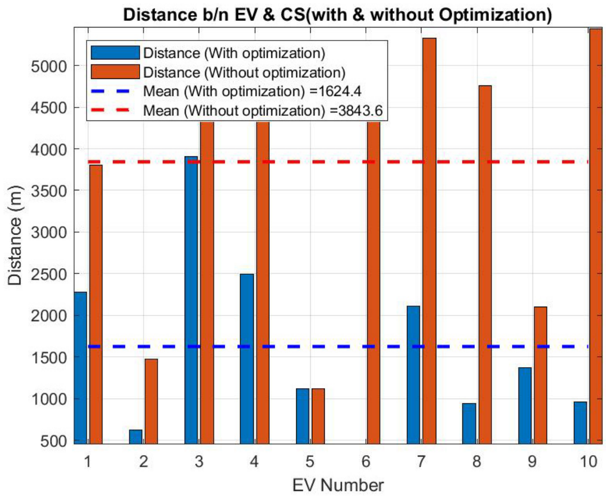

Fig. 9. Euclidean mapping of DTCs and electric vehicles

Cost characteristics

Figure 10 shows that the mean value of the customer cost per unit is less compared to the non-optimized system.

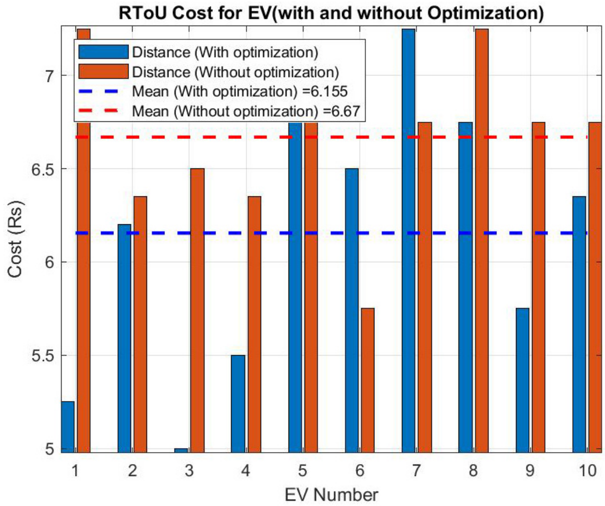

Fig. 10. Euclidean mapping of DTCs and electric vehicles

10. Conclusions

In this paper, a novel optimization methodology is proposed and validated to map an electric vehicle to a particular charging station. A multi-objective optimization problem is formulated with the consideration of five objectives, namely, the minimization of charging cost, distance of travel, time of travel, efficiency deviation and regulation in distribution transformers. The problem is solved using integer linear programming to obtain an optimal routing table. The proposed methodology is significantly benefited for both electric vehicle users and power supply utilities. The routing table ensures the optimal loading on the transformer, which eliminates excessive loss, faults due to overloading and peak demand penalties. The overall objective function value is improved by 37.73% in comparison with the non-optimized case. The transformer performance parameters namely, efficiency and regulation, are increased by 0.058% and decreased by 6.25%, respectively. The cost, distance and time parameters are decreased by 7.72%, 57.73% and 52.82%, respectively. The future scope of this research work is to upgrade the routing table by including additional constraints, namely the available space in charging stations and the SoC level of an electric vehicle.

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