Meta Heuristic Algorithm Based Multi Objective Optimal Planning of Rapid Charging Stations and Distribution Generators in a Distribution System Coupled with Transportation Network

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Abstract. *The application of Electric Vehicles (EVs) is increasing in many countries, causing many researchers to focus on EV Rapid Charging Station (RCS) related issues. The optimal planning of RCS considering only distribution networks is not a reliable approach. Moreover, the RCS location should be convenient to the EV user in a given EV driving range and the performance of the distribution system. In this paper, a multi-objective approach for optimal planning of RCS and Distributed Generators (DG) in a distributed system coupled with a transportation network is analyzed. The proposed optimal planning method aims to achieve reduced active power loss, EV user costs, and voltage deviation for effective RCS and DG planning. The approach includes the analysis of the test system with the base case, solo planning of RCS, planning of DGs with fixed RCS, and simultaneous optimal planning of RCS and DGs. Daily load variation at buses and hourly charging probability of EVs have been used in the analysis. IEEE 33 bus distribution system superimposed with a 25-node transportation network is considered the test system. Rao 3 algorithm is applied for optimization, and the results have been compared with PSO and JAYA algorithms.*

Keywords

Distributed Generator, distribution system, electric vehicle, Rao 3 algorithm, Rapid Charging Station.

1. Introduction

Greenhouse gas emission, depletion of fossil fuels, and growing oil prices are favouring the choice of EVs for transportation [1]. The deployment of 20 million Electric Vehicles (EVs) globally was a promising beginning to reduce greenhouse gas emissions by 2020. Such a global deployment of EVs will replace 62 % of fleet vehicles by 2050 [2]. Although EVs have several advantages, they also have the drawback of low driving range. The charging time and limited driving range of EVs are the major reasons for the slow expansion of EVs [3]. Installing proper charging infrastructure can mitigate the problem of low driving range. There are three charging methodologies, among them level 1 and level 2 take a few hours for charging while DC rapid charging takes 15–20 minutes for charging [4]. So the deployment of RCS can make the customers switch to EVs as RCS can quickly charge. However, the growth of the EV population creates a negative effect on power sector [5]. The placement of RCS at improper locations can further enhance the harmful impact on the distribution system that alters the healthy operating conditions of the power system [6].

The RCS hurts the distribution system. In the literature, most of the authors concentrated on the minimization of power loss and voltage deviation as objectives to support distribution systems in the presence of charging stations. In [7], minimization of investment cost, connection cost, total cost of losses, and Demand Response (DR) cost were used as objectives for placing RCS optimally. The concept of an incentive-based demand response program was used to achieve the objective. For the best positioning of charging stations and distributed generators, the author in [8] used hybrid grey wolves and the particle swarm optimization method. The authors of [9] proposed a methodology for scheduling EV in both V-G and G-V modes in the presence of DG to reduce network power loss and enhance the voltage profile. In [10], the authors have proposed a two stage approach for optimal planning of Distributed Generators (DGs), Shunt Capacitors (SCs) and charging stations with grass-hopper optimization based fuzzy multi-objective technique. The optimal planning of DGs and SCs have been done in the first stage and the planning of CS is done in the second stage.

The above literature considered electrical networks only as a test system. However, considering of only electrical networks for charging station placement is not a credible approach. As there is a requirement for placing Rapid Charging Stations (RCS) along urban roads to increase the utilization of EVs, there is a necessity to consider the road network along with electrical network.

Very few authors have considered both electrical and road networks for optimal planning of charging stations. The author of [11] proposed a method for positioning and sizing the Fast Charging Station (FCS). In addition, to reducing power loss and waiting times, FCS positioning is done as efficiently as possible to compensate for reactive power. In [12], the best site for Charging Stations (CS) was determined by minimizing power loss and EV energy loss incurred during the trip to CS. The queuing theory was employed by the author to capture the dynamic behavior of CS serviceability. In [13], [14], [15], and [16], authors formulated the multi objective problem for optimal planning of charging stations. In [13], optimal planning was done with the goals of reducing voltage variation and power loss, maximization of EV flow supplied by the fast-charging station with confirming the impact of service radius and waiting time on planning. In [14], the authors applied meta-heuristic algorithms to solve the problem to reduce energy loss, voltage deviation and to minimize the land cost to support maximum EVs with low establishment cost. Minimization of the VRP (Voltage deviation, Reliability, and Power loss) index, installation and operation cost, and improving accessibility index was considered for optimal planning of charging stations in [15]. In [16], the authors used the NSGA algorithm for the simultaneous placing and sizing of FCS. Minimization of investment cost, energy losses, waiting time for charging, and maximization of captured traffic flow are considered for optimal planning.

In [17], the author used a heuristic technique for optimal planning of DGs and D-statcom. Voltage Stability Index (VSI) was considered for optimal planning of D-statcom and Loss sensitivity factor is used for optimal planning of DGs. In [18], the author used multi-objective bat algorithm for optimal planning of DGs, here maximization of voltage sensitivity index is used for optimal placement and the minimization of total active power loss is used for optimal sizing of DGs. In [17] and [18], the authors placed DGs in the Distribution System (DS) for improving the performance of DS.

In the literature, authors in [7] considered only DS for RCS planning and authors in [8], [9] and [10] planned RCS and DGs on DS only. Authors in [11], [12], [13], [14], [15], and [16] considered coupled network for planning, and yet only RCS is optimally planned. However, optimal planning of RCS and DGs has to be done on superimposed network of electrical network and road network. Because EV users always choose the closest RCS to charge their vehicles, considering the road network is crucial for effective planning. Even when RCS is positioned at the optimal locations, their presence would increase power loss and voltage deviation. In this regard, DG integration is a feasible solution to address the aforementioned issues. Hence, in this paper, both the electrical network and the road network were taken into consideration while determining the best location for RCS and DGs. In addition to the other two goals of minimizing active power loss and voltage deviation, the placement also considered customer convenience through the minimization of EV user costs. Mostly in literature, authors used the grey wolf optimization algorithm, grass hopper optimization algorithm, chicken swarm optimization, and their hybrid forms for finding optimal solutions. However, most algorithms are parameter dependent and require better tuning of parameters for finding optimal and accurate solutions. In this paper, the authors used parameter less novel Rao 3 algorithm for obtaining the optimal solutions.

The main contributions of this paper are listed below.

- The optimal placement and sizing of RCS and DGs have been done on the superimposed electrical and road network. Integration of DGs in a distribution system counters the negative effects caused by the presence of RCS.
- Minimization of Electric vehicle energy loss for travelling from the current position to the charging station location is adequately dealt with.
- The analysis takes into account different load types, their variation over 24 hours, and the probability of daily hourly EV charging.

- For getting the best RCS and DG locations and sizes in a superimposed network, three cases are taken into consideration: case 1 is optimal RCS planning alone; case 2 is optimal DG planning with case 1's fixed RCS locations and sizes; and case 3 is concurrent optimal RCS and DG planning.
- For the goal of tackling an optimization issue, the novel Rao 3 algorithm is chosen, and the solutions are compared with those obtained using the PSO and JAYA algorithms.

The organization of the remaining paper is as follows: DG modelling and objective function formulation are explained in Sec. 2. Section 3. explains Rao 3, Jaya algorithms, and flow chart of implementation of Rao 3 algorithm for solving the problem. Results are discussed in Sec. 4. , followed by conclusions in Sec. 5.

2. Problem Formulation

2.1. DGs Modeling

PV or PQ modelling can be used to model distributed generators. In this paper, PQ (negative load model) mode has been taken for modelling DGs. Here the quantities that are emphasized real power output (P_{dg}) and power factor ($p.f$). Reactive power output (Q_{dg}) can be calculated from the relation governing real power, reactive power, and power factor as shown in Eq. (1). Eq. (2) and Eq. (3) show the calculation of real effective load ($P_{effectiveload}$) and reactive effective load ($Q_{effectiveload}$) at distribution buses, respectively.

$$Q_{dg} = P_{dg} \tan(\cos^{-1}(pf)), \tag{1}$$

$$P_{effectiveload} = P_{load} - P_{dg}, \tag{2}$$

$$Q_{effectiveload} = Q_{load} - Q_{dg}. \tag{3}$$

2.2. Multi Objective Function (MOF)

In this paper, the minimization of active power loss, EV user cost and voltage deviation were considered for optimal planning of charging stations and DGs. Here the weighted multi-objective formulation was done with equal weights.

$$MOF = \min(w_1 APLRI + w_2 MVDRI + w_3 EVUCI). \tag{4}$$

In Eq. (4) w_1, w_2, and w_3 are weights between [0,1] and the sum of these weights needs to be 1. In this paper, equal weights are considered for all individual objectives.

1) Active Power Loss Reduction Index (APLRI)

Power flow in a distribution system causes active Power loss (Ploss). The addition of Rapid Charging Stations (RCS) to the distribution system puts more strain on the network, resulting in higher power losses and voltage magnitude degradation of buses. Further, the placement of RCS at improper places increases losses abnormally and alters the healthy voltage profile. Usually, RCS is considered as the load at the power distribution substation. Mathematically, the load due to EVs at i^{th} RCS (CS^i_{load}) is calculated as per Eq. (5). The connectors at i^{th} RCS ($CS^i_{connectors}$) and the capacity of i^{th} RCS ($CS^i_{capacity}$) are calculated using Eq. (6) and Eq. (7), respectively. Power losses can be reduced by minimizing the Active Power Loss Reduction Index (APLRI). Here APLRI (Eq. (8)) is the ratio of daily Ploss after the placement of CS or DG or both, to the daily Ploss before the placement of both.

$$CS^i_{load} = N^{iCS}_{ev}, \tag{5}$$

$$CS^i_{connectors} = \max(P_{evc}) N^{iCS}_{ev}, \tag{6}$$

$$CS^i_{capacity} = CS^i_{connectors} R_c, \tag{7}$$

$$APLRI = \frac{\sum_{t=1}^{24} P^{fcs/dg}_{loss}}{\sum_{t=1}^{24} P_{loss}}. \tag{8}$$

2) EV User Cost Index (EVUCI)

Electric vehicle user has a choice to select the nearest RCS to charge their EV. This decision not only helps the user but also reduces the energy loss from travelling to the RCS. Consider m possible charging station locations and q charging demand nodes which belong to road network nodes. The selection of RCS in optimal planning is done by the calculation of the distance between q^{th} demand node to all available RCS and is stored in **D** matrix with the order of $[q, z]$ $z \in m$. After comparing the distances of q^{th} demand node to all RCS, EVs present at the demand node are assigned to the nearest RCS and the corresponding distance is stored in **DD** matrix. Here **DD** matrix has the order of $[q, 1]$.

$$\mathbf{D} = \begin{bmatrix} d_1c_1 & d_1c_2 & \dots & d_1c_z \\ d_2c_1 & d_2c_2 & \dots & d_2c_z \\ \vdots & \vdots & \vdots & \vdots \\ d_qc_1 & d_qc_2 & \dots & d_qc_z \end{bmatrix}, \quad \mathbf{DD} = \begin{bmatrix} \min() \\ \min() \\ \vdots \\ \min() \end{bmatrix}, \tag{9}$$

d=$[d_1, d_2, \ldots, d_q]$ is the set of demand points, c=$[c_1, c_2, \ldots, c_m]$ is the set of charging nodes belonging to road network nodes. EV user cost can be calculated from Eq. (10). Here $Nev(i)$ is total number of EVs at i^{th} RCS, EC is the energy consumption of EVs and P_e is the electricity price.

$$EVusercost = \sum_{n=1}^{q} DD(i)Nev(i)ECP_e. \tag{10}$$

Calculating the distance from q^{th} demand node to all m charging nodes and choosing the longest distance among them offers the maximum distance that an EV customer must travel from the q^{th} demand node. $DD_{\max}$ is the result of forming a **DD** matrix for maximum distances. The values of maximum EV user loss cost and EV user cost index are given by the Eq. (11) and Eq. (12).

$$EV_{usercost}^{\max} = \sum_{n=1}^{q} DD_{\max}(i)Nev(i)ECP_e, \tag{11}$$

$$EVUCI = \frac{EVusercost}{EV_{usercost}^{\max}}. \tag{12}$$

3) Maximum Voltage Deviation Reduction Index (MVDRI)

Loading the distribution system with RCS can cause a deviation of voltage beyond its limits. The AC load flow gives the value of the voltage at each bus. The maximum voltage deviation ($VD_{\max}$) can be calculated using Eq. (13).

Maximum voltage deviation:

$$VD_{\max} = \max(1 - v(i)), \quad i = 1, 2, 3, \ldots, N_{distnodes}. \tag{13}$$

MVDRI refers to the ratio of maximum voltage deviation over the day with the integration of RCS/DG or both to the maximum voltage deviation over the day without the integration of both RCS and DG. It is calculated as follows:

$$MVDRI = \frac{\sum_{t=1}^{24} VD_{\max}^{RCS/DG}, t}{\sum_{t=1}^{24} VD_{\max}, t}. \tag{14}$$

2.3. System Constraints

Each RCS must have atleast one charging connector to supply the EVs, and Eq. (15) support this constraint. Eq. (16) and Eq. (17) are the real reactive power balance constraints, respectively in the system. Integration of RCS alters the voltage profile, so there is a need to check voltage limits in optimal planning. Eq. (18) adds the voltage limits as a constraint. Each DG has maximum and minimum capacity limits (Eq. (19)), and the maximum total capacity supplied by all DGs($P_{DG}^{T,\max}$) is a user-defined quantity and should be less than the minimum total real power consumption throughout a day (Eq. (20)).

$$CS_{connector}^{i} \geq 1 \quad i = 1, 2, \ldots, z(numberof\ RCS), \tag{15}$$

$$P_{sub} + \sum P_{dg} = P_D + \sum P_{RCS} + P_{loss}, \tag{16}$$

$$Q_{sub} + \sum Q_{DG} = Q_D + Q_{loss}, \tag{17}$$

$$|V_{\min}| \leq |V_n| \leq |V_{\max}| \quad n = 1, 2, \ldots, N_{bus}, \tag{18}$$

$$P_{dg}^{\min} \leq P_{a,dg} \leq P_{dg}^{\max}, \quad a = 1, 2, \ldots, N_{DG}, \tag{19}$$

$$\sum_{a=1}^{N_{DG}} P_{a,DG} \leq P_{DG}^{T,\max} < \min(P_{n,D}). \tag{20}$$

Here P_{sub} and Q_{sub} are the substation real power and reactive power respectively. P_D, Q_D, P_{loss} and Q_{loss} are real power demand, reactive power demand, real power loss and reactive power loss in a taken test system. Here RCS are considered as only real power loads, it is (P_{RCS}) equal to CS_{load}^{i}. $V_{\min}$, $V_{\max}$, $P_{dg}^{\min}$ and $P_{dg}^{\max}$ are the voltage minimum limit, voltage maximum limit, DGs minimum real power limit and DGs maximum real power limit respectively. $P_{DG}^{T,\max}$ is the maximum limit of total active power supplied by all DGs. $P_{n,D}$ real power demand at n^{th} node of the distribution system.

3. Algorithm

3.1. Raos 3 Algorithm

Rao 3 algorithm was proposed by Rao in 2020 [19]. The algorithm is easy to understand and has the advantage of metaphor-less and few algorithm-specific parameters. The principle behind this algorithm is random interaction between the candidate solutions, and the candidate solutions move towards the best solutions and away from the worst solutions in the optimization process. This algorithm is a population-based technique and updates equations in each iteration as shown below.

$$\begin{aligned} X_{i,j,k}^{'} &= X_{i,j,k} + r1_{j,k}(X_{j,best,k} - |(X_{j,worst,k})|) + \\ &+ r2_{j,k}((|X_{i,j,k} or X_{r,j,k}|) - (X_{r,j,k} or X_{i,j,k})). \end{aligned} \tag{21}$$

Here $X_{i,j,k}^{'}$ is the updated solution of i^{th} candidate, j^{th} variable in k^{th} iteration. $X_{i,j,k}$ is the solution of i^{th} candidate,

j^{th} variable in k^{th} iteration, $r1$, $r2$ are random values between [0,1]. $X_{j,best,k}$ is the best value of j^{th} variable of X in the k^{th} iteration. $X_{j,worst,k}$ is the worst value of j^{th} variable of X in the k^{th} iteration. $X_{r,j,k}$ randomly selected r^{th} candidate, j^{th} variable in k^{th} iteration. The flowchart of the Rao 3 algorithm for optimal planning is shown in Fig. 1.

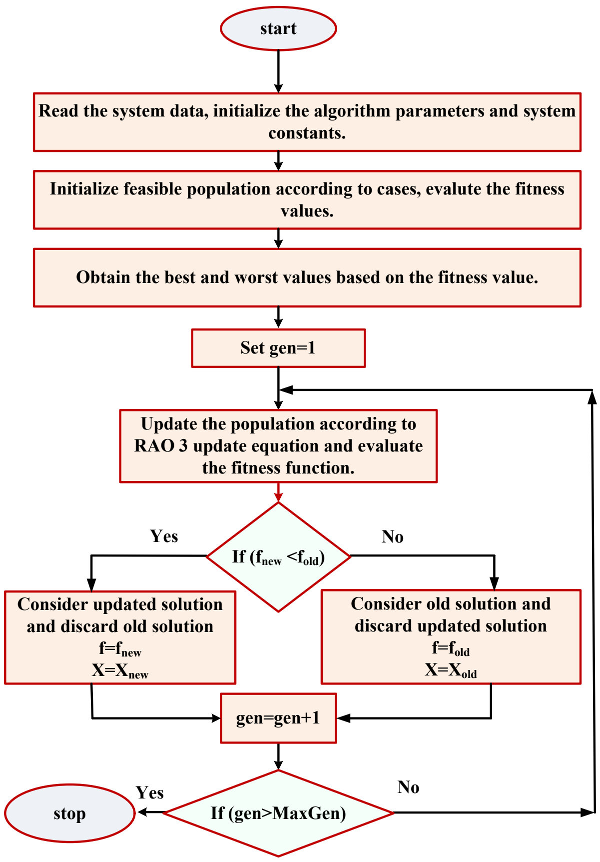

Fig. 1: Flowchart for implementation of Rao 3 algorithm.

$$\mathbf{L}_{cspop} = \begin{bmatrix} X_{1,1} & X_{1,2} & \dots & X_{1,z} \\ X_{2,1} & X_{2,2} & \dots & X_{2,z} \\ \vdots & \vdots & \vdots & \vdots \\ X_{pop,1} & X_{pop,2} & \dots & X_{pop,z} \end{bmatrix}, \quad (22)$$

$$\mathbf{L}_{dgpop} = \begin{bmatrix} Y_{1,1} & Y_{1,2} & \dots & Y_{1,n} \\ Y_{2,1} & Y_{2,2} & \dots & Y_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ Y_{pop,1} & Y_{pop,2} & \dots & Y_{pop,n} \end{bmatrix}, \quad (23)$$

$$\mathbf{S}_{dgpop} = \begin{bmatrix} S_{1,1} & S_{1,2} & \dots & S_{1,n} \\ S_{2,1} & S_{2,2} & \dots & S_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ S_{pop,1} & S_{pop,2} & \dots & S_{pop,n} \end{bmatrix}. \quad (24)$$

$\mathbf{Init}_{cspop} = [\mathbf{L}_{cspop}]$ is the matrix used for optimal planning of only RCS (Case 1). This matrix consist of feasible locations of RCS in a distribution system. $\mathbf{Init}_{dgpop} = [\mathbf{L}_{dgpop}, \mathbf{S}_{dgpop}]$ is the matrix consisting of randomly initialized feasible locations and the corresponding size of DGs used in order to plan DGs in the distribution system optimally (Case 2). $\mathbf{Init}_{csdgpop} = [\mathbf{L}_{cspop}, \mathbf{L}_{dgpop}, \mathbf{S}_{dgpop}]$ is the matrix that consists of RCS location, DG location and the corresponding DG size. It is utilised to plan RCS and DGs at the same time to get the best results (Case 3). Here X indicates the location of RCS, Y indicates the location of DG and S indicates the size of the DG.

3.2. Jaya Algorithm

Rao proposed the Jaya algorithm [20], which is a population-based meta-heuristic algorithm. The premise of this algorithm is that the solution to an optimization problem goes towards the global best solution while avoiding the worst solution. It has the advantage that it requires only the common control parameters which are: population size and maximum iterations, and it does not require any algorithm-specific parameter setting.

The modified value of k^{th} candidate i^{th} variable in j^{th} iteration is obtained using the Eq. (25) given below:

$$\begin{aligned} x'_{k,i,j} &= x_{k,i,j} + r1_{i,j}(x_{best,i,j} - x_{k,i,j}) + \\ &-r2_{i,j}(x_{worst,i,j} - x_{k,i,j}). \end{aligned} \quad (25)$$

Here $x'_{k,i,j}$ is the modified k^{th} candidate, i^{th} variable in j^{th} iteration, $x_{k,i,j}$ is the present k^{th} candidate, i^{th} variable in j^{th} iteration. $r1$, $r2$ are the random values between 0 and 1 i.e. [0 1]. $x_{best,i,j}$ is the best solution of i^{th} variable among all candidates in j^{th} iteration. $x_{worst,i,j}$ is the worst solution of i^{th} variable among all candidates in j^{th} iteration. If the objective value yield by the modified $x'_{k,i}$ is better than $x_{k,i}$, then the modified candidate solution is accepted in each iteration. Acceptable solutions are kept in each iteration, and subsequent searches are based on the solutions in the following iteration. When the termination criteria are met, the final optimal solutions are achieved.

4. Simulation Results and Analysis

Superimposed IEEE 33 bus electrical system and 25 node road network were treated as test system [15], as shown in Fig. 2. All the buses in IEEE 33 bus test system were segregated as 17 residential load buses, 9 industrial load buses and 5 commercial load buses shown in Tab. 1. Bus data and line data were taken from [21]. The hourly load at various buses vary according to the load patterns (in p.u.) as shown in Fig. 3. The data regarding road network was taken from [22], and 1 km per unit was considered. Superimposed nodes of the distribution network and road network were taken from [15], which are represented in Tab. 3.

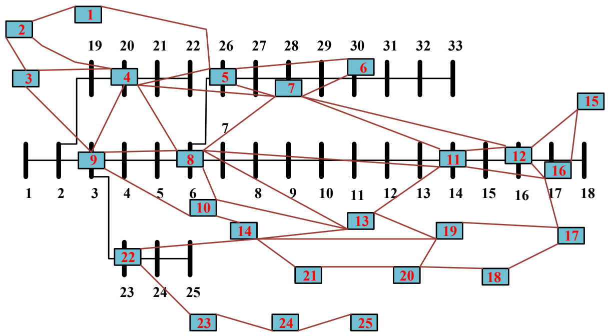

Fig. 2: Super imposed IEEE 33 bus distribution system with 25 node road network.

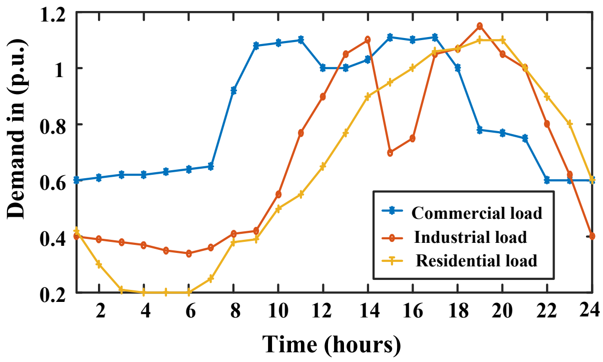

Fig. 3: Plot of different types of load patterns.

Tab. 1: Identification of types of load buses.

Residential loads	Commercial loads	Industrial loads
2, 3, 5, 6	4, 11, 12, 18	22, 26, 27, 28
7, 8, 9, 10	19	29, 30, 31, 32
13, 14, 15, 16	–	33
17, 20, 21, 23, 24	–	–

Tab. 2: Electric vehicle technical parameters.

Parameter	Value
Total number of EVs (N_{TEV})	238
Connector rating (R_c) (kW)	96
EV battery capacity (P_b) (kWh)	50
Energy Consumption (EC) (kWh·km^{-1})	0.219
Electricity Price (P_e) (\$·MWh^{-1})	87.7

The total assumed EV population at road network nodes was 238, and were allowed to charge at selected charging stations according to the probability of EV charging shown in Fig. 4. Table 4 gives the assumed number of EVs present at the nodes of the road network. In this work, all 25 road network nodes were considered demand nodes. For all optimization algorithms, 100 maximum generations and 30 population size are considered. For the PSO algorithm inertia constants $C_1 = C_2 = 2$ are considered. Simulations were carried out on PC with windows 10 operating system, 4 Gb ram, and MATLAB 2014b software.

Tab. 3: Coupling of the road network nodes (R_n) with the distribution network nodes (D_n).

D_n	R_n	D_n	R_n
03	09	20	04
06	08	23	22
14	11	26	05
16	12	28	07
17	16	30	06

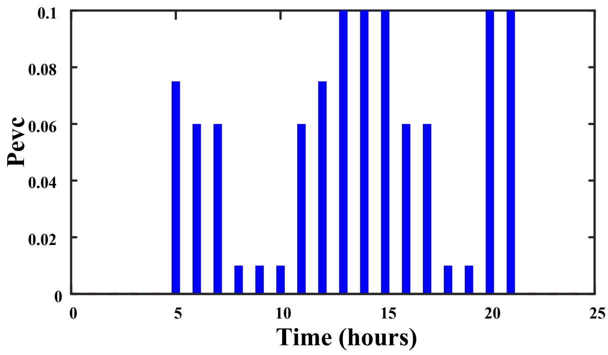

Fig. 4: Variation of Electric Vehicle charging probability.

In this paper, the analysis was done by considering the base case, case 1, case 2, and case 3.

- Base case: In this case, the load flow was done on the distribution system without the integration of RCS and DG to find daily active power loss and maximum voltage deviation.
- Case 1: In this case, optimal placement and sizing of RCS is done on the superimposed network to minimize the EV user cost, active power loss and voltage deviation.
- Case 2: The load due to the charging stations from case 1 is added to the current load at the corresponding distribution bus in case 2. In this system, optimal placement and sizing of DGs are done to minimize the EV user cost, active power loss and voltage deviation.
- Case 3: In this case, concurrent placement and sizing of RCS and DGs are done to minimize the active power loss, EV user cost and voltage deviation.

Tab. 4: Assumed EVs present at road network nodes.

R_n	EVs	R_n	EVs	R_n	EVs	R_n	EVs	R_n	EVs
1	5	6	8	11	3	16	15	21	9
2	9	7	15	12	3	17	8	22	12
3	13	8	6	13	10	18	6	23	15
4	8	9	4	14	12	19	7	24	5
5	5	10	15	15	15	20	15	25	15

4.1. Base Case

The test system consists of IEEE 33 bus distribution system. As it is radial and has a high R/X ratio, the feed forward and backward sweep load flow algorithm was used for load flow study. In the base case, the distributed load flow study was simulated without the integration of RCS and DGs into the test system by considering hourly load patterns of different load types over 24 hours.

It was observed that the load flow led to daily active power loss of 2811 kW and daily maximum voltage deviation of 1.5816 (p.u.). The lowest voltage of 0.8968 (p.u.) was observed at 18^{th} node in 17^{th} hour. Voltage profile over 24 hours is as shown in Fig. 5

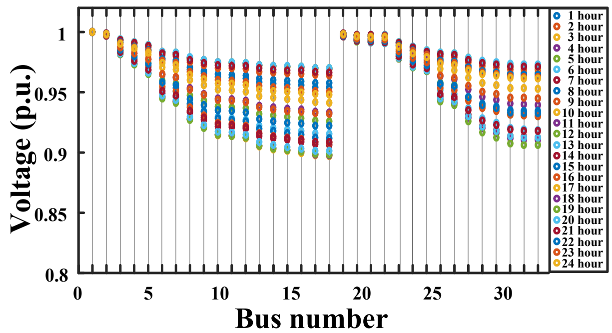

Fig. 5: Distribution system voltage profile in base case.

4.2. Case 1: Optimal Planning of RCS

Case 1 deals with the optimal placement and sizing of RCSs. The placement was done based on the following assumptions:

- The superimposed nodes are considered for RCS placement.
- RCS can be placed at 3 buses and it is observed that placement at more than 3 buses makes the system unstable.

In case 1, RCS was optimally planned. In optimal planning, primarily all EVs were distributed among the initialized RCS locations to minimize EV user costs by selecting the nearest RCS. After adding the RCS load, the distribution load flow algorithm is applied to the test system to find Ploss and MVD. To minimize the considered multi-objective function various algorithms are applied. It is observed from Tab. 5 that, distribution system performance is affected by RCS installation. Daily active power loss increased by 19.5 %, 12.1 %, and 9.73 % compared with the base case Ploss, obtained using PSO, JAYA, and Rao 3 algorithms, respectively. The presence of RCS is also witnessed with the increased value of MVD (1.6120 (p.u.)) in comparison with base case MVD (1.5816 (p.u.)). Here Rao 3 algorithm gave the least MVD compared to the other two algorithms. The system's minimum voltage was 0.8949 (p.u.), which appeared at the 18^{th} bus in the 17^{th} hour using the Rao 3 algorithm, as shown in Fig. 6.

Tab. 5: Comparison of various algorithms for optimal allocation of RCS in case 1.

Parameter	PSO	JAYA	Rao 3
CS locations	23,20,30	23,20,26	20,23,3
EVs	129,50,59	144,76,18	105,114,19
Connectors	13,5,6	14,8,2	11,11,2
Size (kW)	1248,480,576	1344,768,192	1056,1056,192
Ploss (kW)	3359.8	3151.8	3084.6
EVUC ($)	34.0335	36.1270	36.3383
MVD (p.u.)	1.6608	1.6271	1.612
APLRI	1.1952	1.1212	1.0973
EVUCI	0.3643	0.3867	0.3890
MVDRI	1.0501	1.0288	1.0193
MOF	0.8690	0.8447	0.8343
Time (sec)	250.4	169.3	155.6

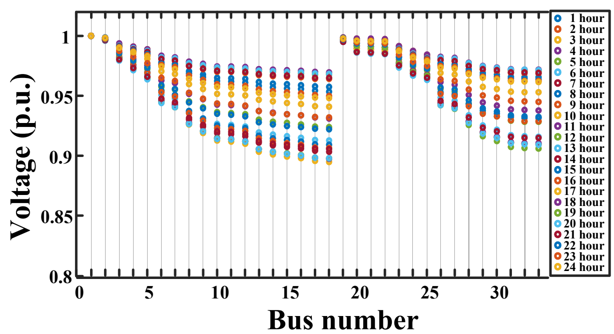

Fig. 6: Distribution system voltage profile in case 1.

RCS placement caused, the downfall of system minimum voltage from 0.8968 (p.u., base case) to 0.8949 (p.u.). EVUC is 36.3383 $ with Rao 3 algorithm which is high among EVUC of PSO and JAYA algorithms. However, the overall objective function value of 0.8343 by the Rao 3 algorithm is the lowest in comparison with the JAYA algorithm (0.8447) and PSO algorithm (0.8690). Rao 3 algorithm took less time for evolution compared to PSO and JAYA algorithms. To counter the effects caused by RCS installation in the distribution system DGs are installed.

4.3. Case 2: Optimal Planning of DGs

Installing DGs in the distribution system reduces power loss and improves voltage profile. Renewable type DGs of size 5 kW–1 MW are considered for integration. It has been observed that integration of three DGs in a distribution system outperforms integration of single DG or two DGs. It's also been observed that adding more than three DGs to a distribution system doesn't significantly increase performance. As a result, three DGs were considered in this study. The hourly total real load demand on the system, which includes RCS load and the hourly charging probability of EVs, is depicted in Fig. 7. According to this plot, the minimum real power load demand of 1420.8 kW appeared at the 4^{th} hour. As a result, the total real power injection by all DGs is limited to less than or equal to 1400 kW (<1420.8) according to the constraint Eq. (20).

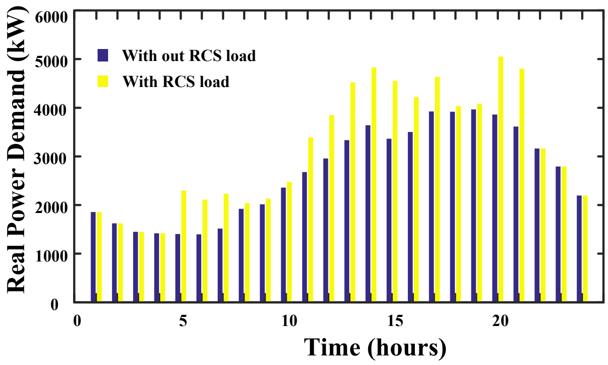

Fig. 7: Plot of hourly varying load demand with and with out RCS load.

Tab. 6 shows the optimal placements, DG sizes, and numerous technical observations. When compared to the base case, active power loss was reduced to 38.42 % in case 2. This reduction was aided by the insertion of DGs in the distribution system. The PSO and JAYA algorithms reduced active power loss by 40.06 % and 39.45 %, respectively, but the optimal placements and sizes of DGs obtained by the Rao 3 algorithm reduced active power loss to the maximum in comparison with the other two algorithms. The maximum voltage deviation with the Rao 3 algorithm was 0.5215 (p.u.), which is higher than the 0.5151 (p.u.), 0.5162 (p.u.) of the PSO, and JAYA algorithms, respectively.

Furthermore, as compared to 0.3718 of PSO and 0.3699 of JAYA, the Multi-Objective Function (MOF) with the Rao 3 algorithm was 0.3675, which was the lowest value. The voltage profile at all buses throughout the day is depicted in Fig. 8, with the DGs placed at optimal locations and sizes using the Rao 3 algorithm. A minimum voltage of 0.9626 (p.u.) appeared at the 30^{th} bus in the 19^{th} hour, according to Fig. 8. The lowest voltage at the 18^{th} bus improved from 0.8968 (p.u. base case) to 0.9627 in the 17^{th} hour (p.u.). The placement of DGs in the proper locations is responsible for this improvement. When compared to the PSO and JAYA algorithms, Rao 3 produced efficient outcomes in the shortest time.

Tab. 6: Comparison of various algorithms for optimal allocation of DGs in case 2.

Parameter	PSO	JAYA	Rao 3
DGs locations	15,33,5	33,15,8	33,15,12
Size (kW)	609,784,5	793,554,52	773,429,196
Ploss (kW)	1126.3	1108.9	1080
EVUC ($)	36.3383	36.3383	36.3383
MVD (p.u.)	0.5151	0.5162	0.5215
APLRI	0.4007	0.3945	0.3841
EVUCI	0.3890	0.3890	0.3890
MVDRI	0.3257	0.3264	0.3297
MOF	0.3718	0.3699	0.3675
Time (sec)	274.2	136.1	130.5

4.4. Case 3: Concurrent Optimal Planning of RCS and DGs

In this case, the Rao 3 algorithm was used to plan RCS and DGs at the same time. RCS location, DG location, and DG size make up the initialization matrix. The system was examined for improved overall objective function once these two were added. Tab. 7 shows the optimal results by the various algorithms. The Rao 3 algorithm was shown to generate a better MOF of 0.3441. The daily active power loss was 1079.2 kW, or 38.39 % of the base active power loss. In comparison to the PSO and JAYA algorithms, the Maximum Voltage Deviation (MVD) was 0.5960 (p.u.), which was the lowest of the values. With the Rao 3 algorithm, EV user cost of an electric vehicles was 25.3715 $, which is cost - effective when compared to the 42.3306 $ and 31.1142 $ for PSO and JAYA, respectively.

The system's voltage profile is shown in Fig. 9, with the RCS and DGs placed simultaneously using the Rao 3 algorithm. At 16^{th} bus in 20^{th} hour, the system's minimum voltage is 0.9518 (p.u.). The voltage improved from 0.8968 (p.u., base case) to 0.9629 (p.u.) at the 18^{th} bus in the 17^{th} hour. When compared to the other two algorithms, the Rao 3 algorithm takes less time to simulate and produce optimal results.

We know from Tab. 8 that, daily active power loss is gradually reduced from case 1 to case 3. Though the maximum voltage deviation is slightly higher in case 3 compared to case 2, EVUC and overall objective function are the smallest of all cases (case 1 and case 2) in case 3. Based on these findings, it can be inferred that using the Rao 3 algorithm to plan RCS and DGs concurrently (case 3) generated the best outcomes.

Tab. 7: Comparison of various algorithms for concurrent optimal allocation RCS and DGs in case 3.

Parameter	PSO	JAYA	Rao 3
CS locations	20,28,16	23,20,6	16,20,23
EVs	44,112,82	104,40,94	67,73,98
Connectors	4,11,8	10,4,9	7,7,10
Size (kW)	384,1056,768	960,384,864	672,672,960
DGs locations	13,11,30	14,31,30	31,11,17
Size(kW)	514,69,791	569,461,151	615,389,395
Ploss (kW)	1271.9	1219.2	1079.2
EVUC ($)	42.3306	31.1142	25.3715
MVD (p.u.)	0.8192	0.6714	0.5960
APLRI	0.4525	0.4337	0.3839
EVUCI	0.4531	0.3331	0.2716
MVDRI	0.5179	0.4245	0.3768
MOF	0.4745	0.3971	0.3441
Time (sec)	298.8	160.1	148.06

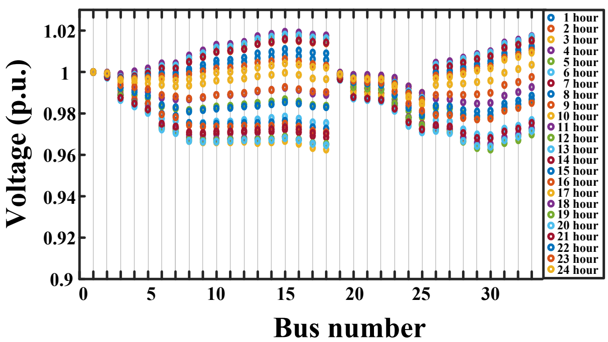

Fig. 8: Distribution system voltage profile in case 2.

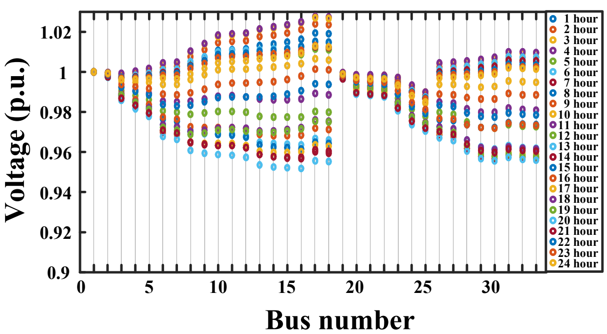

Fig. 9: Distribution system voltage profile in case 3.

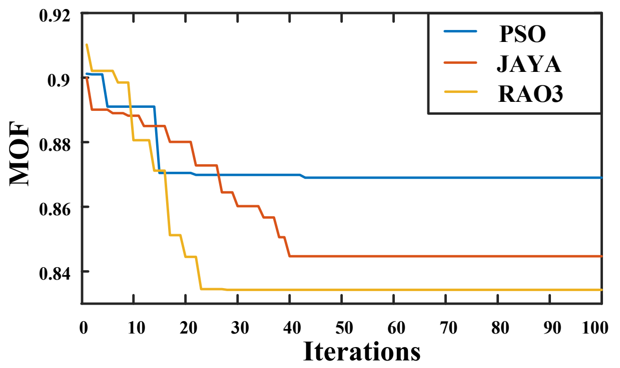

Fig. 10: Convergence characteristics by various algorithms in case 1.

Tab. 8: Comparison of Ploss, MVD, and EVUC in various cases by Rao 3 algorithm.

Parameter	Base case	Case 1	Case 2	Case 3
Ploss (kW)	2811	3084.2	1080	1079.3
MVD (p.u.)	1.5816	1.6120	0.5215	0.5960
EVUC ($)	–	36.3383	36.3383	25.3715
MOF	–	0.8343	0.3675	0.3441

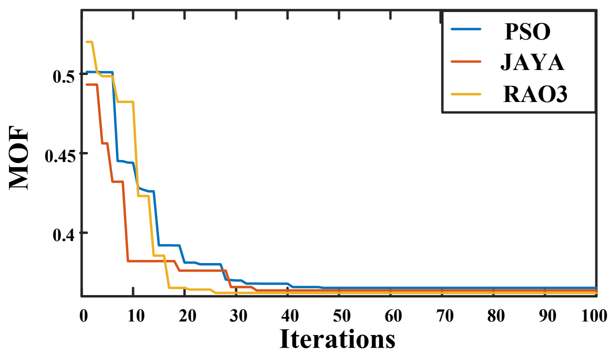

Fig. 11: Convergence characteristics by various algorithms in case 2.

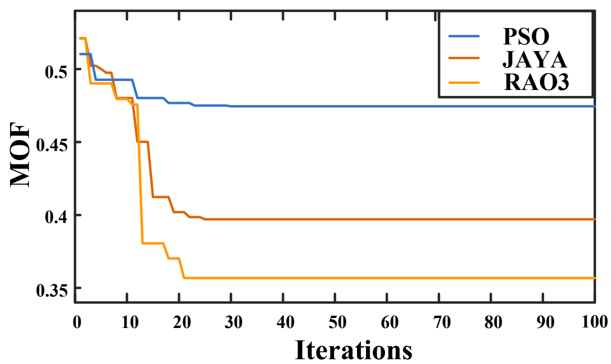

Fig. 12: Convergence characteristics by various algorithms in case 3.

5. Conclusion

Adopting electric vehicles for road transport is a feasible way to reduce greenhouse gas emissions. Although, RCS promotes EV sales, it can harm the distribution system by increasing power loss and voltage deviation. It is important to consider EV user behaviour for RCS planning when installing charging stations. To address these issues, this paper presents a concise planning of RCS and DG to reduce power loss, voltage deviation, and EV user cost on a coupled network. The optimal RCS planning is analysed and compared for the following scenarios: i) RCS alone, ii) Optimal DG planning with the prior RCS outcomes. iii) Concurrent planning of RCS and DGs. The proposed RCS planning is implemented by considering daily EV charging probability and load patterns. The use of the metaphasorless Rao 3 algorithm can ensure faster convergence with better performance for the optimal planning of RCS and DGs simultaneously. Random interactions between candidate solutions and the ability to move candidate solutions towards the best optimal solution and away from the worst solution of the Rao 3 algorithm outperform PSO and Jaya algorithms. Future research could include adding reactive power support by the capacitor placement in the test system and analysing the distribution system performance of such a system.

Author Contributions

V.V. performed the analytic calculations, numerical simulations and writing. V.C. supervised the project and contributed to the design and implementation in addition to writing and editing. Both V.C. and V.K. authors contributed to the final version of the manuscript.

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