Optimal planning and utilisation of existing infrastructure with electric vehicle charging stations

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Abstract
In order to address the increased demand for utility with the adoption of electrification in the transport sector, infrastructure development plays an important role. This research helps in planning the optimum utilisation of the existing infrastructure. The planning of electric vehicle (EV) infrastructure is analysed by considering various loads such as (1) static (2) dynamic and (3) heuristic on balanced radial distribution system (BRDS). The introduction of electric vehicle charging station (EVCS) into BRDS increases the total losses. The optimised reconfiguration helps in reducing the losses and ensures increased reliability of the system. The major objective of this process is to minimise both the real power loss and the reliability index energy not supplied of the radial distribution system (RDS) with the placement of charging stations. The planning is accomplished with a single-step process in which the optimum location of the EVCS along with reconfiguration of BRDS is done using the multiple objective particle swarm optimisation (MOPSO). The performance of the BRDS with the proposed method is elaborated under three scenarios with three internal cases. The proposed methodology is validated through simulation for a three feeder IEEE 16 bus BRDS considering various load scenarios using MATLAB.

1 | INTRODUCTION

Sudden adaptation of EVs in transportation instead of the commercial internal combustion engine (ICE) based vehicles can reduce air pollution and the dependency on fossil fuels. The distribution grid should be capable of supplying power at regular intervals of time. Because of the lower specific energy of the EV batteries, electric vehicle charging stations (EVCS) cannot be erected just like the fuel filling stations. Proper infrastructure is required to place the EVCS in the distribution grid, which will have less impact on the power grid. The placement of EVCS and the number of charging units is also crucial for deciding the size of EVCS in the distribution network. The impact of EVCS on the distribution system is analysed using losses and bus voltages of the system called load flows. The radial nature of the distribution network is not suitable for computational studies using commercial load flow algorithms. So, a special algorithm is needed to study the behaviour of radial distribution networks. Due to the dynamic nature of the load, the algorithm must be updated to find the system performance with less computation time. However, for this type of large distribution networks, fast decoupled load flow [1] is used. The computational complexity of fast decoupled load flow is high due to its Jacobean matrix. Therefore, the familiar forward/backward sweep load flow [2] is used to analyse the system where it is mandatory to have a flat voltage profile at starting. But, a branch incidence matrix (BIM) based load flow can analyse the system with any bus as starting bus accomplishing any voltage profile. Hence BIM-based load flow is chosen for this study.

The sudden inclusion of EVCS to the existing grid system causes serious power quality issues such as electrical harmonics, poor power factor, voltage instability and imbalance. These issues reduce the capacity of distribution equipment like cables, conductors, transformers, switchgears etc., and also increase the distribution loss affecting the efficiency of the system. The system’s distribution branches carry huge current while charging the EVs, which has a significant impact on the generation and transmission systems [3, 4]. The impact on the distribution system depends on many factors [5] like charging methodologies, density of the vehicles at respective charging stations etc. The
effect of EVCS on the distribution grid is analysed and validated through experimental studies [6].

Searching for a low sensitivity voltage bus for the optimal location of the charging station is studied in [7]. But, this method of searching also fails in finding the optimum location of EVCS on a large RDS. The genetic algorithm [8] is primarily used to locate the EVCS optimally without considering losses and conductor thermal limits. This way of locating the EVCS affects the stability as well as reliability of the distribution system with grid connectivity. Hence, the researchers include the constraints like limits on voltage, current and reliability indices for optimal location of the charging stations. The placement of charging stations will include an additional cost for their erection and hence, in [9] authors have considered minimisation of the cost along with the reduction of losses. The methodology of finding the optimal location of EVCS is extended with game theoretical framework [10]. The impact of the EVCS can be verified by reliability indices. If the reliability indices are beyond the constraints, then necessary compensating techniques [11] should be implemented in the distribution network to improve these indices. In [12], the placement of EVCS is examined by using data mining methods for roads. The density of the EVs on the roads plays a vital role in estimating the need of a charging station. The optimum number and location of charging stations nearer to highways is also significant for the consumers.

The charging current for the EV is always real since the power rating of the batteries is in kW. Therefore, the EVCS connected to the radial bus system is modelled as an additional real power load at the buses [13]. In [14], the charging profile of EV batteries is modelled as an exponential function which resembles the charging behaviour and thereby improving the load factor of the system. The planning of charging and discharging behaviour of EV batteries is necessary for successful load management in distribution networks. In the utility management, the charge scheduling of EVs at off-peak hours of the load curve and discharging of EV batteries during peak hours of the distribution system makes the system more sustainable for all types of loads [15]. In [16], different charging priorities are followed for charging the multiclass EVs based on certain conditions. Higher priority is given to the EVs with a lack of power and least priority is given to the EVs which have sufficient power. This algorithm is applied to a real distribution network at Stackelberg which has a micro grid in its distribution system. The major limitation of EVs that make them lag in the competition with commercial or ICE vehicles is its charging time. In [17], the role of ultrafast charging stations (UFCS) is introduced in the urban sectors, which makes EVs lead the competition with fossil-fuel vehicles. But, this work also includes the planning of renewable energy resources management with UFCS in smart cities.

The definition of green transportation is that the impact of EVCS to the distribution grid is compensated by using renewable resources like photo-voltaic systems and wind farms [18]. The conversion of a normal power grid to smart grid [19] is by monitoring the grid at every discrete interval throughout the day. Grid has to take its own decisions with respect to change in loads like charging of EVs, faults etc. In [19], the behaviour of smart grid with respect to charging of EVs is detailed on a 24 h basis. The investigation on the optimal location of EVCS with and without reconfiguration is discussed in [21]. In [22], reconfiguration is adopted to the radial distribution network for reducing the losses. The renewable sources are included in the system to further reduce the losses. But the usage of the renewable supply to the load is controlled by a stochastic approach with the help of prediction of the loads with model predictive control (MPC) [22]. Reconfiguration of the distribution network reduces the losses of the system without erecting compensating devices like distributed generators (DGs) and capacitors. The inclusion of EVs in the distribution network increases system losses and reduces the voltage stability and reliability. This impact is reduced by reconfiguration of the distribution network and incorporation of distributed generators (DGs) [23]. Interestingly, [24] detailed the impact of EVCS on transmission systems which is controlled by using the voltage source converter (VSC).

With the latest developments in technologies, the distribution network operates with robust algorithms for protection, load scheduling, load forecasting etc. This type of distribution network is called a smart distribution network or smart grid. The charging schedule of EVs via grid called as grid to vehicle (G2V) and the discharging schedule during peak loading known as vehicle to grid (V2G) are the new trends in the load curve of the distribution networks. The effect of these behavioural changes needs to be considered for its efficient working. In [25], the EVs charging schedule and reconfiguration of distribution network took as two optimisation stages intending to minimise the real power losses. In [26, 27], the impact of EVCS on a RDS is tested on large-scale distribution system and a practical distribution system by considering the installation cost of EVCS.

From the literature, it is understood that there is a requirement to find the optimum size and location of EVCS distributed among various buses in the RDS and study the impact of reconfiguration under various load scenarios. In this study the RDS is analysed with the following three types of loads: (1) static (2) dynamic and (3) heuristic. The impact of EVCS on reliability of BRDS is also analysed based on customer reliability indices. There are not much literature discussing on three feeder IEEE 16 bus distribution systems with larger load capability to optimally locate the EVCS. This paper proposes a methodology for investigating the optimal placement of EVCS to minimise both the real power losses and ENS. The minimisation of losses improves the voltage profile along with reconfiguration of RDS. Thus, the optimal location of EVCS is achieved through a multiple objective function via a heuristic algorithm named multi objective particle swarm optimisation (MOPSO) considering various load scenarios.

The key contributions of this research work are:

1) Adoption of the non-linear behaviour of EVCS under various load scenarios of RDS.
2) Optimal placement of EVCS with optimal capacity on a RDS considering static, dynamic and heuristic loads.
3) Analysing the impact of EVCS on RDS with static, dynamic and heuristic loads.
4) Minimising the impact of high capacity EVCS on RDS by splitting the same into two EVCS at optimum locations along with reconfiguration.

5) Optimising the reliability of reconfigured RDS with EVCS.

6) Validating the study via a 16 bus RDS which has three feeders.

2 | PREAMBLE

Due to the fast development of enormous energy storage technologies, the use of EV increases proportionately year by year. This paper describes the impact of incorporating EVCS on the RDS and reduces the losses by optimal reconfiguration of the system, which is analysed via distribution load flow. This section introduces certain important terminologies to explain the proposed methodology.

2.1 | Distribution load flow

The load flow is the analysis of the distribution or transmission system to calculate the voltage of each bus (voltage profile), current flowing through each branch, real and reactive power losses. Branch incidence matrix (BIM) based load flow is used to analyse the RDS by using the equations from (1) to (14). Majority of load flows are started with flat voltage profile, but this load flow can analyse the system without flat voltage assumption. BIM is a vital part of this load flow, which is used to convert bus currents into branch currents. The complete analysis of the RDS using the proposed methodology is briefed using a small sample distribution network as shown in Figure 1. The BIM of the sample distribution system is shown in Table 1.

Let $V_{bus}$ be the bus voltage and $I_{bus}$ be the bus current in p.u. The bus current is calculated from the apparent power $S_b$ and voltage of the bus as in (1). The apparent power $S_b$ is calculated from the available data of real power $P_b$ and reactive power $Q_b$. The branch current, $I_{branch}$, is calculated from the bus incidence matrix (K) and $I_{bus}$ as per (2). The branch apparent power $S_{br}$ can be calculated from the bus apparent power $S_b$, the branch incidence matrix $K$ and the losses in the branch $L_{br}$ as given in (4).

$$I_{bus} = \frac{S_b^*}{V_{bus}} \quad (1)$$

$$I_{branch} = [K]^{-1}I_{bus} \quad (2)$$

$$S_b = K[S_{br} - L_{br}] \quad (3)$$

$$S_{br} = K^{-1}S_b + L_{br} \quad (4)$$

A new variable $\beta$ [14] is introduced, which is the product of apparent power ($S_{ab}$) and impedance ($Z_{ab}$) of a particular branch. This variable helps in formulating the receiving end voltage. Let $V_a$ and $V_b$ be the bus ‘a’ and bus ‘b’ voltages and $I_{ab}$ be the branch current.

$$\beta_{ab} = S_{ab}Z_{ab}^* \quad (5)$$

$$\beta_{ab} = V_a(V_a^* - V_b^*) \quad (6)$$

From (5)

$$S_{ab} = P_{ab} + jQ_{ab} = \beta_{ab}V_{ab}^* \quad (7)$$

From (6)

$$V_b = V_a - \frac{\beta_{ab}^*}{V_a^*} \quad (8)$$

Receiving end voltage = sending end voltage - drop across the branch. Hence, from (6) and (7)

$$I_{ab} = (\frac{\beta_{ab}^*}{V_a^*})Y_{ab} \quad (9)$$

$$S_{ab} = S_{bus} - I_{ab} \quad (10)$$

where,

$L_{ab}$ is losses in branch ‘ab’.

Total losses of the system $L_{loss}$ is given by:

$$L_{loss} = \Sigma L_{br}^* \quad (11)$$

where,

$$L_{br}^* = S_{br}^{2re} - V_{b}^{-1}I_{b}^* \quad (12)$$

| Branch | 1b | 2b | 3b | 4b | 5b | 6b |
|--------|----|----|----|----|----|----|
| 1b     | 1  | −1 | 0  | 0  | −1 | 0  |
| 2b     | 0  | 1  | −1 | −1 | 0  | −1 |
| 3b     | 0  | 0  | 1  | −1 | 0  | 0  |
| 4b     | 0  | 0  | 0  | 0  | 1  | 0  |
| 5b     | 0  | 0  | 0  | 0  | 0  | 1  |
| 6b     | 0  | 0  | 0  | 0  | 0  | 1  |
The specified apparent power at bus ‘b’ is given by $S_{bc}^{\text{spec}}$. The receiving end apparent power at the branches is given by:

$$S_{rec}^{ab} = S_{rec}^{ba} - L_{loss}$$

Max($I_{rec}^{ab}$) $\leq$ 0.0001  \hspace{1cm} (13)

Max($L_{r}^{ab}$) $\leq$ 0.0001 \hspace{1cm} (14)

### 2.2 Modelling of electric vehicle charging station

To study the impact of EVCS on the RDS the exact charging profile of the charging stations need to be incorporated. There are two techniques by which EV batteries are charged. They are: (a) fast charging and (b) slow charging. In fast charging a large DC current (say two to three times the rated current) is injected into the battery so that it takes less time to reach full charge at the cost of life of the battery, whereas in slow charging a healthy current (say less than the rated current) is used to charge the EV. In this work, slow charging stations are considered, which takes 5 h to attain 100% state of charge (SoC) of EV battery. A Li-ion battery is considered here which is charged using constant current–constant voltage method. The charging profile of the battery is as shown in Figure 2.

#### Constant current mode ($0 < t < t_1$):

A constant current is drawn from the bus to charge the battery to attain the 80% of rated voltage ($V_{\text{rated}}$). By this time interval $t_1$, SoC of the battery reaches only about 10% as shown in Figure 2.

#### Constant power mode ($t_1 < t < t_2$):

Once 80% of $V_{\text{rated}}$ is reached the voltage is maintained further to reach 100% SoC and to maintain power constant. The current exponentially decays to zero as soon as SoC reaches 100%. This is attained at $t_2$. So, from $t_1$ to $t_2$ the EVCS acts as a constant power load as is visible from the Figure 2.

#### Constant SoC mode ($t_2 < t < t_m$):

At $t_2$, the battery attains 100% SoC at rated voltage with a minimal value of current. In order to disconnect the EV from the charging station the battery current need to be nearly zero. This is expected to happen at $t_m$.

\[
P_{ev}(t) = \begin{cases} P_{ev}^{\text{max}}(1 - \exp(-\frac{\alpha}{t_2})) & \text{if } 0 < t \leq t_2 \\ P_{ev}^{\text{max}} \frac{t_2-t}{t_m-t_2} & \text{if } t_2 < t \leq t_m \\ 0 & \text{otherwise} \end{cases} \hspace{1cm} (15)\]

where, $\alpha > 0$

The reactive power offered by EV is calculated as:

$$Q_{ev}(t) = P_{ev}(t) \tan(\phi_{ev}) \hspace{1cm} (16)$$

where, $\phi_{ev}$ is the power angle of the EV battery. As SoC is dependent on instantaneous real power of EV, SoC is expressed as:

$$\text{SoC}(t+1) = \text{SoC}(t) + P_{ev}(t) \Delta(t) \hspace{1cm} (17)$$

where, $\Delta(t)$ is the sampling time.

The charging behaviour of EVCS in RDS is analysed by dividing the day into 96 samples, which has each sample of 15 min as the charging time of the EV battery is assumed as 5 h. Hence, each charging including disconnection from the grid corresponds to 20 samples. The real power profile of EVCS described by (15) and (16) is as shown in Figure 3. Here, in this study, the power factor of EVCS is assumed as 0.958 lag during charging.

### 2.3 Reconfiguration of the radial distribution system

Reconfiguration is the process of changing the topology of the distribution system without disturbing its radial nature. It is one of the economical methods to reduce system losses without incorporating any compensating devices into the system. The major challenge involved here is to select the number of tie-line switches, which depends on the number of loops in the RDS.

Figure 4 shows the single line diagram of IEEE 16 bus BRDS where the tie-line switches are represented with dotted lines. 

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**FIGURE 2** Charging behaviour of EV battery at RDS.

**FIGURE 3** Real power profile of EV battery in a day during charging at EVCS.

Therefore, the instantaneous value of real power is expressed as:

\[
P_{ev}(t) = \begin{cases} P_{ev}^{\text{max}}(1 - \exp(-\frac{\alpha}{t_2})) & \text{if } 0 < t \leq t_2 \\ P_{ev}^{\text{max}} \frac{t_2-t}{t_m-t_2} & \text{if } t_2 < t \leq t_m \\ 0 & \text{otherwise} \end{cases} \hspace{1cm} (15)\]

where, $\alpha > 0$
where as the sectionalised switches are represented with solid lines. The three tie-line switches form three individual loops in the system likely connecting the path externally between, 1. Feeder I - Feeder II, 2. Feeder II - Feeder III and 3. Feeder III - Feeder I. The reconfiguration of the system is achieved by opening/closing either the tie-line switch or sectionalised switch in each loop as shown in Figure 4. Here, there are 13 sectionalised switches and 3 tie-line switches. So totally $16 \times C_3$ combinations need to be analysed to identify minimum losses at the BRDS to ensure optimum reconfiguration. This indicates the requirement of analysing 560 combinations via analytical approach. Hence, to minimise the complexity in the analysis adoption of a heuristic algorithm helps. Here, a loop matrix (LM) is used to select the switch in each loop. The LM for the given problem is formulated as:

$$\text{LM} = \begin{bmatrix} 2 & 5 & 8 & 9 & 0 \\ 7 & 11 & 14 & 0 & 0 \\ 3 & 4 & 16 & 15 & 13 \end{bmatrix}$$

where, each element of the LM is the open or closed position of the branch number of the system.

The constraints for the formulation of LM are:

1. The opened switch should not
   a) affect the radial nature of the original BRDS,
   b) be a common path between the loops,
   c) be idle at any part of the original system.

2. The size of each matrix row should be the same. So, if the number of branches is less in any loop then, zeroes are padded.

Branches 1, 6 and 12 are not selected as they disconnect the source from the system. Branch 10 is also not selected as this disconnect the bus 10 from the system making it idle. Thus, formed LM contains 12 branches. This leads to analysing only $12 \times C_3$ combinations (i.e. 220) for finding the optimised path for reconfiguration. Hence, 30% of the effort gets reduced via use of heuristic approach.

### 2.4 Reliability of radial distribution system

According to Electric Power Research Institute (EPRI), the most commonly analysed customer based reliability indices [5] are:

1) System Average Interruption Frequency Index (SAIFI)
2) System Average Interruption Duration Index (SAIDI)
3) Customer Average Interruption Duration Index (CAIDI)
4) Energy not supplied (ENS).

The indices are calculated as follows:

$$\text{SAIFI} = \frac{\text{Total number of customers interrupted}}{\text{Total number of customers served}}$$  \hspace{1cm} (18)

$$\text{SAIDI} = \frac{\text{Sum of customer's minutes of interruption}}{\text{Total number of customers served}}$$  \hspace{1cm} (19)

$$\text{CAIDI} = \frac{\text{Sum of customer's minutes of interruption}}{\text{Total number of customers interrupted}}$$  \hspace{1cm} (20)

$$\text{ENS} = \text{Sum of energy not supplied at each point}$$  \hspace{1cm} (21)

In the above equations, the number of customers served at each bus is considered as the total load of the bus. The indices are varying according to the variations in the load.

### 2.5 Multi-objective optimisation

Though the planning of power systems is done to ensure minimising power outages and interruptions, there can be a direct or indirect impact of these on the utility and its customers. Implementation of utilities like EVCS to the existing distribution system will increase both the losses and ENS of the system. The impact of EVCS can be reduced by optimal reconfiguration of the system and optimal placement of EVCS. The reduced impact of EVCS to the system will ultimately ensure a minimum reliability index on ENS. Hence, here the problem formulation directs to a multi-objective optimisation technique to calculate the global optimum values for both the losses and ENS. Thus, the objective function for G(Y) is:

Minimise $G(Y)$

which otherwise means minimise $(I_{loss}(Y), ENS(Y))$

Subject to

$U_i \leq Y \leq L_i$, with $i = 1, 2, \ldots, m$

where, $U_i$ and $L_i$ are the upper and lower boundaries of the function Y.

$m$ is the maximum number of buses and branches of the system.

$L_{loss}(Y)$ is the total losses of the system and is represented as:

$$L_{loss} = \sum_{a=1}^{n} \sum_{b=1}^{n} \text{Real} (V^*_a - V_b) I_{ab}^* ) \quad \forall \ a \neq b$$  \hspace{1cm} (22)
ENS (Y) is the energy not supplied and is represented as:

\[ ENS = \sum_{k=1}^{n} UN_k \cdot P_k \]  

(23)

where,

- \( UN \) is the unavailability rate (h/year)
- \( n \) is the total number of buses.
- \( P \) is the real power of the bus.

Let \( A = (a_1, a_2, a_3, \ldots a_m) \) and \( B = (b_1, b_2, b_3, \ldots, b_m) \) be the solutions for the objective function \( G(Y) \) where, vector \( A \) dominates vector \( B \) if and only if, the fitness value of vector \( A \) is less than or equal to the fitness value of vector \( B \) in all the ‘n’ objective space and the objective function value of vector \( A \) is less than that of the the objective function value of vector \( B \) in at least one of the ‘n’ objective space as formulated in (24) and (25).

\[ G(A) \leq G(B) \quad \forall a \]  

(24)

\[ G(A) < G(B) \quad \forall a \]  

(25)

Solution \( A \) is considered as a non-dominated Pareto optimal solution if it is not dominated by any other solutions. No better solutions than \( Y \) exist in the particular problem. However, similarly good solutions may exist, dependent on user perception. A solution \( B \), which is an element of \( Y \), is called Pareto-optimal if and only if, there does not exist a solution \( B \), which is an element of \( Y \), which dominates any solution \( A \) as formulated in (26).

\[ \nexists B \in Y | G(B) > G(A) \]  

(26)

The Pareto optimal set is defined by a set of solutions that fulfill (24) and (25), while at the same (26) holds true. The collective fitness values obtained from these solutions are known as the Pareto front or trade-off surface.

3 | PLACEMENT OF EVCS ALONG WITH RECONFIGURATION FOR AN EXISTING RDS USING MOPSO

According to literature [1, 6, 7] and [29], multi-objective particle swarm optimisation (MOPSO) provides a simple computation methodology in finding the nearest optimal solution. The major step in any optimisation technique is to initialise the searching agents like particles in PSO with required dimensions. In this work, the particles are initialised with combinations of tie-line switches and number of buses for EVCS locations. To find \( G(Y) \), the objective for the MOPSO with the proposed methodology is to minimise both the losses and ENS to attain optimal placement of EVCS along with reconfiguration which is given as follows:

\[ \text{Minimise } L_{loss} = \sum_{a=1}^{n} \sum_{b=2}^{n} \text{Real} \left( (V_a - V_b) I_{ab}^* \right) \quad \forall a \neq b \]  

(27)

Subject to

\[ 0.95 < V_a < 1.05. \]  

\[ 0.95 < I_{ab} < 1.05. \]

If the load is maintained constant at 1 p.u then the placement of EVCS will not affect the minimum and maximum constraints of bus voltage and branch current. The minimum constraints for the branch current are applicable for vehicle to grid (V2G), which is shown in Figure 5. In V2G, vehicle supplies energy to the grid, injects a current opposite to the grid current. Thus, the net current through the distribution branches reduce. This reduction in the branch currents need to be greater than the minimum constraint of current for maintaining the stability of the distribution system.

But while considering grid to vehicle (G2V), the electric power is supplied to the vehicle from the grid. If a larger capacity EVCS is connected to BRDS then the current drawn by the system from the grid need to be less than the maximum constraint of the branch current for maintaining the stability of RDS.

Thus, justified the constraints on current to ensure the thermal stability and reliability of the system during bidirectional flow of current through the branches.

The impact of EVCS on RDS is successfully studied by considering EV battery charging behaviour. A lot of literature exists to discuss the impact of charging stations on distribution system, but the literature mainly focuses on including the EVCS as additional load to the system, cost analysis by erecting the EVCS etc. In this work the static load is also discussed to know the variation of voltage, real and reactive power losses with respect to charging behaviour of EV along with dynamic load and heuristic load. To validate the proposal the performance of the RDS is studied under the following scenarios using PSO. The parameters used for PSO are given in Table 2.

| S. no. | Parameter | Value |
|--------|-----------|-------|
| 1      | Generations | 100   |
| 2      | Particles  | 50    |
| 3      | Maximum inertia | 0.9   |
| 4      | Minimum inertia | 0.2   |

FIGURE 5 Modelling of EVCS at connected bus of BRDS.
The size of the particle matrix depends on dimension of the problem and population size of the algorithm. The dimension of the optimisation algorithm changes according to the type of the load. For static and dynamic loads, the dimension of the algorithm depends on the number of tie-line switches and bus number of EVCS locations. However, for heuristic load the dimension of the algorithm depends additionally on the total number of buses. Although, this research work considers 16 bus system, it uses less dimensions for static and dynamic loads whereas more dimensions for heuristic load. Thus, the same methodology is applicable to higher bus systems.

To study the performance of the RDS, optimal placement of EVCS is furnished along with reconfiguration. The algorithm for placing EVCS along with optimal reconfiguration of RDS is given in Table 3. The flowchart for the above methodology is shown in Figure 6. The system is evaluated for its performance in terms of voltage profile, real power losses and reactive power losses. In this study, a charging station of capacity 32kW of each charge point with dynamic charging behaviour with power factor of 0.958 [14] is added with time-varying load of RDS.

The charging behaviour of EVCS in RDS is analysed by dividing a day into 96 samples, which has each sample of 15 min as the charging time of the EV battery is assumed as 5 h. In static load, the 96 samples of the day is constant, whereas it is varying w.r.t load curve for dynamic load. However, with the heuristic load the 96 samples of the day are varying heuristically in every 15 min at each bus of the system.

4 RESULTS AND DISCUSSION

The proposed scheme is validated by implementing them on to the standard IEEE 16 bus RDS whose single line diagram referred in Figure 4 consists of three feeders each supplied with the same voltage. Therefore, buses 1, 2 and 3 always maintain the same voltage and are at 1.0 p.u. Feeder 1, 2 and 3 are zero load buses directly connected to the substation. The base voltage in kV and base MVA for the buses are assumed as 23 kV and 100 MVA respectively. To reconfigure the RDS, the switches 5, 11 and 16 need to be opened in the basic load flow. The total real and reactive power on the BRDS is 28.7 MW and 5.9 MVAR respectively as shown in Table 4. The real power loss of the actual BRDS (without reconfiguration and without placement of EVCS) is 511.435 kW. Further, reconfiguration via branches 7, 9 and 16 optimised using BIM load flow reduces the losses to 466.230 kW.

With the placement of EVCS, the losses increase. Hence the study is extended to know the impact of increased capacity EVCS at single location as well as distributed location of reduced capacity EVCS on the BRDS as mentioned below:

Case 1: Single charging station of 3.2 MW placed at optimal location.
Case 2: Single charging station of 4.8 MW placed at optimal location.
Case 3: Two charging stations of 3.2 MW and 1.6 MW placed at optimal locations.

| Case | Charging Capacity | Location |
|------|-------------------|----------|
| 1    | 3.2 MW            | Optimal  |
| 2    | 4.8 MW            | Optimal  |
| 3    | 3.2 MW and 1.6 MW | Optimal  |

In this work, the capacity of each charging point is 32 kW and hence 3.2 MW supports 100 charging points and 1.6 MW supports 50 charging points. Therefore, a total of 150 charging points with an installed capacity of 4.8 MW is optimally placed by splitting this into two EVCS having capacities 3.2 and 1.6 MW each. The actual installed capacity of load on the RDS is 28.5 MW as shown in Table 4. Generally any system will be
FIGURE 6  Flow chart of optimal placement of EVCS along with reconfiguration using MOPSO

designed to accommodate an installed capacity of 120% of the rated value. Thus, here 20% additional load of 28.5 MW can be installed to the system without affecting thermal aspects and stability. Here, in this study 150 charging points are considered as the maximum capacity of EVCS which is well within these limits. The total current drawn from the grid increases with the placement of EVCS compared to the existing RDS. Let ‘1’ be the total current drawn from the existing RDS. The optimisation constraint on current conveys that the limits for the current need to be ‘0.95 1’ to ‘1.05 1’ even with placement of EVCS. Since the total branch current is exceeding this limit, placing a single unit of high capacity is not advisable. This encourages splitting of EVCS into two or more charging stations at different locations increasing the reliability of the system.

The optimal placement of EVCS along with reconfiguration is verified with analytical method and tabulated in Table 5 to illustrate the losses and ENS of 16 bus BRDS considering case 1. The Table 5 shows that fourth bus is the most optimal bus for placing the EVCS with respect to losses of the system and reliability indices. However, the analytical approach is not suitable for situations like higher bus system and placement of EVCS at multiple locations. Hence PSO is used for optimal placement of EVCS along with reconfiguration for both minimum losses and ENS of the system. Though, ENS is minimum at thirteenth bus the losses are found to be minimum at fourth bus. Considering the combined objective to minimise both ENS and losses, the optimum location is obtained as the fourth bus.

Also, it is very much essential to understand the reliability of the system and most representative reliability indices for a RDS like SAIFI, SAIDI, CAIDI and ENS are optimised for various load conditions. SAIFI indicates how often the average customer experiences a sustained interruption during a predefined period of time and is expressed as interruptions per year. SAIDI indicates duration of these interruptions over a year. CAIDI is an indication of duration of interruptions per frequency of occurrence (h/f). ENS gives a measure of total unserved energy of the system and is expressed in MWh/yr. The impact of reconfiguration on reliability is also analysed and optimised in this study. The placement of EVCS increases the load on the system; hence, there can be an interruption of power for the customers during the charging period of EVs. The reliability of the system deteriorates with an increase in the above mentioned indices. Among these cases, case 2 is the worst case where a high capacity single EVCS is located into the RDS along with existing loads. Hence, this case gives the maximum deviation in the indices compared to other two cases.

Now, to validate the scheme the RDS is operated under various load conditions like static, dynamic and heuristic loads. In this study, the available load on the system throughout the day is assumed to be acquired at a rate of 4 samples/h (i.e. 96 samples/day). The charging time of EV is considered as 5 h which is equal to 20 samples duration. Hence, the EV is connected for 18 samples duration to charging station and disconnected at the twentieth sampling instant.

4.1 Static load

The load on the system is constant throughout the day and assumed to be acquired at a rate of 4 samples/h (i.e. 96 samples/day). The load profile of EVCS is as shown in Figure 3. The losses of the system under various cases including with and without reconfiguration of the system are illustrated in Figure 7. The losses are maximum when the battery is energised and losses are minimal when the EV is disconnected from the charging station and is observed within the limit of losses with reconfiguration of RDS.

The placement of EVCS has increased the losses on the RDS and the losses are maximum during case 2 where, a large capacity (i.e. 4.8 MW) EVCS is placed on the BRDS. Instead of single
TABLE 4  Load data of IEEE 16 bus RDS

| Bus no. | Active power (MW) | Reactive power (MVAR) | Bus no. | Active power (MW) | Reactive power (MVAR) | Bus no. | Active power (MW) | Reactive power (MVAR) |
|---------|------------------|----------------------|---------|------------------|----------------------|---------|------------------|----------------------|
| 1       | 0                | 0                    | 8       | 4.0              | 2.7                  | 13      | 1.0              | 0.9                  |
| 2       | 0                | 0                    | 9       | 5.0              | 3.0                  | 14      | 1.0              | -1.1                 |
| 3       | 0                | 0                    | 10      | 1.0              | 0.9                  | 15      | 1.0              | 0.9                  |
| 4       | 2.0              | 1.6                  | 11      | 0.6              | 0.1                  | 16      | 2.1              | -0.8                 |
| 5       | 3.0              | 1.5                  | 12      | 4.5              | 2.0                  |         |                  |                      |
| 6       | 2.0              | 0.8                  |         |                  |                      |         |                  |                      |
| 7       | 1.5              | 1.2                  |         |                  |                      |         |                  |                      |
| Total   | 8.5              | 5.1                  | Total   | 15.1             | 8.7                  | Total   | 5.1              | -0.1                 |

TABLE 5  The losses and ENS at each bus of IEEE 16 bus BRDS with the placement of EVCS via case 1 using analytical method

| EV Bus No | $EN_{max}$ (MWh/yr) | Loss (kW) | UN (h/day) |
|-----------|----------------------|-----------|------------|
| 4         | 121.04               | 560.2244  | 1.75       |
| 5         | 137.04               | 612.0349  | 6.75       |
| 6         | 125.84               | 621.1153  | 3.25       |
| 7         | 137.04               | 640.6763  | 6.75       |
| 8         | 121.68               | 662.7495  | 1.95       |
| 9         | 126.16               | 772.095   | 3.35       |
| 10        | 125.84               | 625.1836  | 3.25       |
| 11        | 132.24               | 625.1415  | 5.25       |
| 12        | 132.56               | 833.5801  | 5.35       |
| 13        | 117.04               | 565.3734  | 0.5        |
| 14        | 128.24               | 608.3938  | 4          |
| 15        | 128.88               | 613.7138  | 4.2        |
| 16        | 132.72               | 632.8314  | 5.4        |

large capacity EVCS, two distributed EVCS has reduced losses as well as improved the voltage profile as illustrated via case 3 in Figures 7 and 8 respectively. The variations in the load affect the voltage profile of the buses nearer to thirteenth bus in case 3. Since, the loads at fourteenth, fifteenth and sixteenth buses are lower than fourth, fifth and sixth buses, the voltages at fourth, fifth and sixth buses are lower than that at fourteenth, fifteenth and sixteenth buses as shown in Figure 8. The minimum voltage profile is at bus 12 and is approximately 0.971 p.u.

In cases 1 and 2, a single EVCS is considered and is optimally placed at fourth bus whereas, in case 3 two separate EVCS of capacity 3.2 MW and 1.6 MW are optimally placed at fourth and thirteenth buses respectively as shown in Figure 9.

For this static load, the study confirms that the indices are minimum for the original RDS without EVCS (Table 6). Under this scenario, the indices convey that approximately four interruptions each of duration 5.6 h occur over a year in the system. The customers are facing an interruption of 1.4 h duration. In total, the system is not serving energy equal to 115 MWh/yr which is 0.04% of the total energy supplied to the loads. With the placement of EVCS the percentage maximum deviation in these indices are found to be within 12% only whereas, with reconfiguration an improvement in indices could be observed.

FIGURE 7  Total losses of the 16 bus BRDS under different cases for static load.

FIGURE 8  Voltage profile at each bus of the 16 bus reconfigured BRDS with and without EVCS.


TABLE 6  Percentage maximum deviation of reliability indices for 16 bus system with EVCS placement and reconfiguration with static load

| Cases                        | SAIFI (inter./yr) | % ΔSAIFI (max) | SAIDI (h/yr) | % ΔSAIDI (max) | CAIDI (h/inter.) | % ΔCAIDI (max) | ENS (MWh/yr) | % ΔENS (max) |
|-----------------------------|-------------------|----------------|--------------|----------------|------------------|----------------|--------------|--------------|
| RDS without EVCS            | 3.92              | —              | 5.60         | —              | 1.42             | —              | 115.00       | —            |
| EVCS without reconfiguration (case 2) | 4.30      | 10.26          | 6.26         | 11.79          | 1.45             | 2.11           | 126.80       | 10.26        |
| EVCS with reconfiguration (case 2) | 4.20      | 7.60           | 6.13         | 9.46           | 1.45             | 2.11           | 123.00       | 6.96         |

FIGURE 9  Single line diagram of reconfigured 16 bus radial bus system with optimally placed EVCS at fourth and thirteenth buses.

FIGURE 10  Dynamic load profile of 16 bus system without EVCS.

The maximum deviation lies within 10% even for the worst case 2 as mentioned in Table 6. In case 2 the indices are high because a single high capacity 4.8 MW EVCS is optimally located at fourth bus. The reliability of the system is improved by splitting 4.8 MW EVCS in to two EVCS of size 3.2 MW and 1.6 MW and locating them at two different buses: fourth and thirteenth bus.

4.2  Dynamic load

In reality, the load on the system varies throughout the day as shown in Figure 10 without considering EVCS. This dynamic load data for 16 bus RDS is referred from [28]. The inclusion of EVCS increases the load on the RDS along with the existing load. But, for every 20 samples that is, 5 h, EV battery is charged fully and disconnected from the system, which is shown in Figure 3. The losses of the system under various cases are illustrated in Figure 11. For every 20 samples, a dip in the real power losses can be observed corresponding to all the cases considered. The losses are maximum at sixty-sixth sample as the EVCS is acting as an additional load along with the available maximum load on the system and losses are minimum at twentieth sample, because EVCS is disconnected from the charging station. The minimum losses are found to be within the least value corresponding to reconfiguration.

The algorithm places the EVCS optimally at fourth bus as this is the less voltage-sensitive bus closer to feeder 1 and substation under this dynamic load for cases 1 and 2. The voltage profiles of the reconfigured system with EVCS connected and disconnected at every bus are shown in Figure 12. The buses 4, 5, 6, 7 and 11 are influenced with the inclusion of EVCS located at fourth bus and the voltage profiles are improved in every 5 h i.e, twentieth sample when EV is disconnected. In cases 1 and 2 single EVCS need to be placed and the system behaves alike but, with inferior indices and voltage profile for case 2. In case 3 the two EVCS of capacity 3.2 MW and 1.6 MW are optimally placed at fourth and thirteenth buses respectively as shown in Figure 13 with reduced losses and improved voltage profile. The variations in the load affect the voltage profile in case 3 and the buses nearer to the thirteenth bus are affected similar to the observations and discussions in the static load scenario. Even in this scenario, the minimum voltage profile is at bus 12 and is improved to 0.985 p.u.
TABLE 7  Percentage maximum deviation of reliability indices for 16 bus system with EVCS placement and reconfiguration for dynamic load

| Cases                                         | SAIFI (inter./yr) | %ΔSAIFI (max) | SAIDI (h/yr) | %ΔSAIDI (max) | CAIDI (h/int.) | %ΔCAIDI (max) | ENS (MWh/yr) | %ΔENS (max) |
|----------------------------------------------|-------------------|---------------|--------------|---------------|----------------|---------------|--------------|-------------|
| RDS without EVCS                             | 3.92              | —             | 5.60         | —             | 1.42           | —             | 115.00       | —           |
| EVCS without reconfiguration (case 2)         | 4.30              | 10.26         | 6.26         | 11.79         | 1.45           | 2.11          | 126.80       | 10.26       |
| EVCS with reconfiguration (case 2)            | 4.20              | 7.60          | 6.13         | 9.46          | 1.45           | 2.11          | 123.00       | 6.96        |

In cases 1 and 2 the single EVCS considered is optimally placed at fourth bus whereas, in case 3 the two separate EVCS of capacity 3.2 MW and 1.6 MW are optimally placed at fourth and thirteenth buses respectively as shown in Figure 13. The reliability indices coincide with those obtained with static load and are tabulated in Table 7.

4.3  | Heuristic load

The load on the system is varying randomly throughout the day and the p.u distribution of load is as shown in Figure 14. The losses of the system under various cases are illustrated in Figure 15. The losses are maximum at forty-third sample for the specified load along with EV and losses are minimum at fortieth sample as EV is disconnected from the charging station. Here also the minimum losses are found to be within the least value corresponding to reconfiguration.

In this scenario also algorithm places the EVCS at the least voltage sensitive buses, fourth and thirteenth for case 3 as illustrated in Figure 16. The variations in the load affect the voltage profile as shown in Figure 17 and the buses nearer to thirteenth bus are affected in a similar way as observed in the previous scenarios. The minimum voltage profile is at bus 12 and is found to be 0.96 p.u, which is also the least among all scenarios.

For this heuristic load, the number of interruptions over the year is about 3 with less duration which is lower compared to...
that observed in other scenarios. Also, there is an improvement seen for the ENS as in Table 8. However, the customer indices are the best in this scenario as the load is optimally distributed over the day.

5 CONCLUSION

Green transportation is one of the smart solutions for reducing carbon emissions globally. Electric Vehicles play a crucial role in green transportation. But, abrupt adoption of EVs need charging infrastructure along with existing RDS. The introduction of charging infrastructure affects the power quality in terms of reduced voltage, increased branch currents and increased power losses. The use of compensating devices such as distributed generators, capacitors, D-STATCOM etc. are also not a smart solution because they reduce the losses at the cost of an added burden to the power engineer by increasing the maintenance and thermal instability.

This paper examines the incorporation of EVCS into the existing balanced RDS without using extra compensating devices. The EVCS are successfully located at optimal locations in the existing distribution grid via reconfiguration. The optimal reconfiguration and location of EVCS is carried out using the most successful bio-inspired heuristic algorithm, MOPSO.

The proposed method is validated with standard three feeder IEEE 16 bus BRDS considering three types of loads with increase in capacity of EVCS. The impact of EVCS is analysed by modelling the charging behaviour of EV battery. The charging time of the battery at EVCS is considered as 5 h. Hence the entire day is divided into 96 samples, so the charging process of the EV battery is monitored and easily disconnected once it reaches its 100% SoC. The capacity of each charging point is considered as 32 kW. Hence 3.2 MW EVCS serves for 100 charging points, 1.6 MW EVCS serves for 50 charging points and 4.8 MW serves for 150 charging points. Optimal placement of EVCS onto the existing BRDS has increased the losses due to increase in capacity of the charging infrastructure. The reliability indices also change according to the variation in the load with EV battery charging. But, by distributing the infrastructure, the losses decrease with optimal placement of EVCS in two different feeders with deterioration in the voltage profile along with higher branch currents. The objective of choosing each scenario is not only to minimise the losses but also, to illustrate the improvement in the voltage profile, thermal stability and system reliability. The simultaneous process of optimally placing EVCS along with reconfiguration shows minimum losses and improved system reliability. Thus, the proposed scheme gives the optimal solution for improving the electric transportation infrastructure without using external compensating devices.

Further, the algorithm can also be extended by modelling the fast charging stations. When EVCS is operated during heavy load conditions of load curve, DGs need to be implemented to flatten the load curve with respect to distribution grid. In future, all these schemes can be extended to practical unbalanced radial distribution systems.
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