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Reactive Power Optimization Using Firefly Algorithm for Dispersed Electric Vehicles Charging Stations in Radial Distribution System

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WHAT IS ALREADY KNOWN ON THIS TOPIC:

- *Electric Vehicle Charging Station (EVCS) along with Distributed Generators are integrated for balancing the load growth in radial Distribution System.*
- *Reactive power compensating devices can also be placed centrally at designated buses for voltage control services to improve grid performance considering the several inequalities, posing both the technical and economic challenges.*

WHAT THIS STUDY ADDS ON THIS TOPIC:

- *This work demonstrates that placing reactive power compensating units directly at EVCS locations is more effective than relying solely on centralized utility-based solutions.*
- *It introduces the use of the Firefly Algorithm to determine optimal compensation values and placement, validated through IEEE 14-bus and 30-bus systems, ultimately improving voltage profiles and enhancing grid capacity.*

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ABSTRACT

Electric vehicle charging stations (EVCSs) in the distribution system are attracting more attention these days. Several technical and economic issues are associated with their management and the overall power drawn from the grid. Reactive power compensation has also been identified as a key operational consideration when using such systems. While utility-based reactive power units can be operated within the system, reactive power compensating units commissioned by EVCS owners can help address issues such as expanded line loading capacity, reserved capacity, installed capacity, and increased line losses. While optimization methods such as genetic algorithms and particle swarm optimization have been proposed, their practical implementation in large-scale systems remains underexplored. As the number of EVCSs in the distribution network grows, the number of compensating units involved will increase, necessitating advanced optimization techniques to determine the appropriate rating for each EVCS at the charging station. The Firefly Algorithm, developed using MATLAB software, is employed to tackle this optimization problem. This work presents five cases that provide a line-by-line update on the proposed approach for identifying the role of reactive power compensating units in conjunction with EVCSs. The results are validated using the IEEE 14-bus and 30-bus systems. By addressing reactive power compensation challenges, the study contributes to reducing energy losses and ensuring a stable power supply. These advancements support the broader goal of sustainable energy transition and the widespread adoption of electric vehicles (EVs), ultimately fostering environmental conservation and energy equity.

Index Terms— Distribution system, electric vehicle charging station (EVCS) management, Firefly Algorithm (FA), reactive power compensation, voltage indices

I. INTRODUCTION

Electric vehicle charging stations (EVCSs) in existing distribution systems are an emerging area of research due to their various technical, financial, and social challenges [1–5]. Many researchers have focused on aspects related to utility benefits or requirements [6–8]. However, end users are also a critical component of such systems, as they are the ultimate beneficiaries and key stakeholders [9]. Therefore, EVCSs must align their daily operations with the needs of both utilities and end users.

Among the several technical issues, the reactive power demand of EVCS for customers and charging station loads is a significant research area [10,11]. Reactive power independent EVCS could help in meeting both requirements and reducing the financial burden on the grid. In traditional power system structures, distribution networks were electrified by central power plants. However, the integration of renewable energy resources is transforming conventional distribution systems into modern power systems.

The incorporation of renewable-based power stations into existing distribution networks highlights the role of renewable-based distributed generators (DGs) in radial distribution systems (RDSs) to accommodate load expansions. Several machine learning-based studies are available that demonstrate the methods for integrating DGs into the network. Methods for optimal DG placement to minimize power losses are proposed in ref. [12]. Whale optimization, considering techno-economic analysis for DG placement, is presented in ref. [13]. Suresh et al. proposed optimal allocation using the Dragonfly algorithm to maximize benefits in distribution networks [14]. Ali suggested a method using a Genetic Algorithm with various cost parameters [15]. The placement of EVCS in RDS is also relevant to load expansion research. Public–private partnerships for EVCS commissioning in distribution networks can be indulged through proper location selection and identification. Transient search optimization for this purpose is developed in ref. [16]. Electric vehicle charging stations designed for commercial use, where multiple electric vehicle (EV) units can be charged simultaneously, are discussed in ref. [17]. Load profiles are intermittent and subject to both real and reactive power demands from the grid. Voltage sensitivity factor (VSF) and voltage stability indices (VSIs) are used for estimating the distribution network conditions for forecasting load burden scenarios and their impacts. To mitigate these load demands, reactive power sources must be added to RDS to avoid overloading the grid. Several reactive power compensators, such as fixed capacitor banks, movable capacitor banks, SVC, and DSTATCOM, have been proposed for RDS in various papers [18–20].

According to CIGRE (*The International Council on Large Electric Systems*) and North American Electric Reliability Corporation (NREC) standards, reactive power management should be addressed as a local issue and considered a routine operational service type. Reactive power compensation could also be integrated with EVCS as a mandatory service, with customers potentially paying a modified tariff that includes the costs associated with reactive power setups at EVCS. To offset this tariff increase, the savings from reduced grid demand due to local reactive power management at EVCS could be passed on to customers. Most of the available studies focus either on load flow analysis for reactive power procurement and electric vehicle placement or on grid-isolated microgrid models with reactive power compensation analysis. However, very few works analyze radial distribution networks connected to EVCSs with STATCOM as a reactive power compensator. Additionally, the optimization of STATCOM reactive power is typically performed using classical tuning methods. This paper proposes the Firefly Algorithm (FA) as an advanced, machine-learning-based tuning method, offering several advantages over classical approaches, as highlighted in the literature. The major contributions of this paper are as follows: 1) development of a MATLAB code to estimate power losses, voltage indices, and voltage profiles using the backward-forward sweep method for load flow analysis, 2) utilization of an iterative approach that incorporates all constraints to determine the optimal placement of distributed generation in a radial distribution system, 3) application of an error minimization technique with MATLAB iterations to identify the requirements for utility-based reactive power compensation, and 4) employment of the FA for optimization to determine the appropriate rating for reactive power units at each EVCS in a radial distribution system.

Therefore, this paper presents a Firefly-based machine learning algorithm to identify the required reactive power sources at proposed EVCSs to maintain voltage profiles within acceptable limits at each bus. Voltage indices and voltage profiles on RDS are used to develop an optimization function, which is utilized for the iterative processes involved in this proposed Firefly-based machine learning algorithm. The results, in terms of voltage profile (with and without reactive power requirements), are compared across various scenarios: independent RDS, RDS with proposed DG at the most sensitive bus, RDS with DG and proposed EVCSs at designated buses, RDS with compensating unit at DG bus and EVCSs at designated buses, and RDS with proposed DG and EVCSs with distributed reactive power compensating sources at each EVCS. The comparison also includes the reactive power requirements for these different setups.

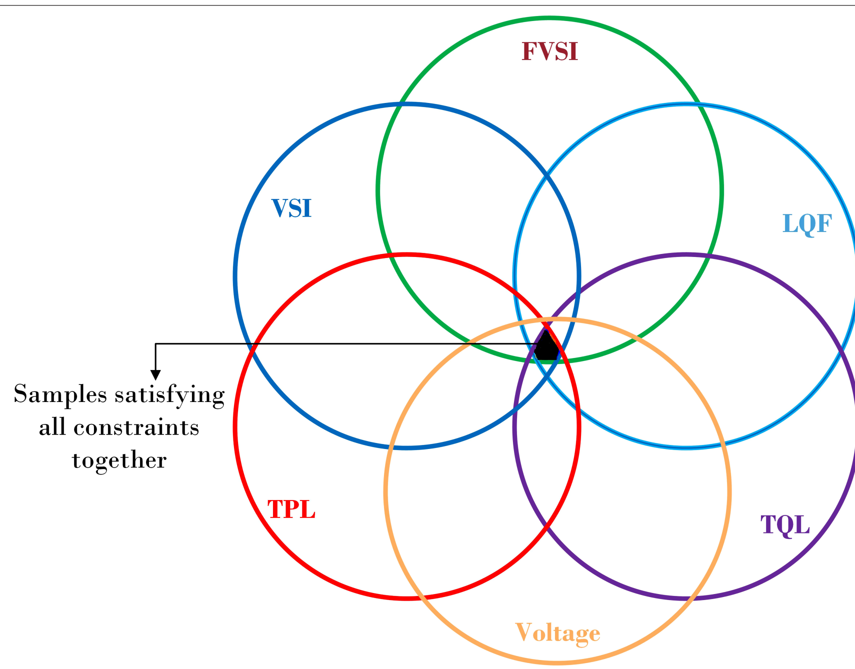

Fig. 1. Distributed generator size and location investigation using all constraints simultaneously.

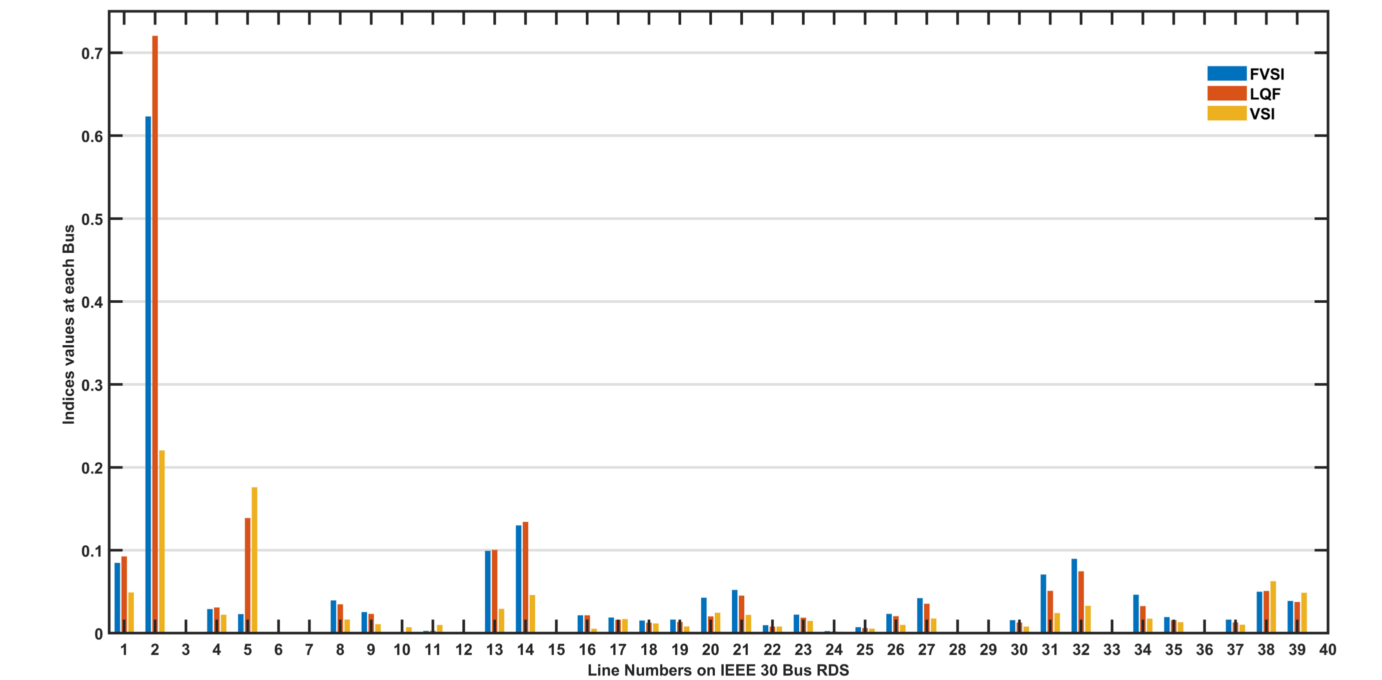

Fig. 2. Investigation of most vulnerable line in RDS using Fast Voltage Stability Index, voltage Stability Index, and Line Quality Factorsimultaneously in IEEE 30 Bus radial distribution systems.

II. INVESTIGATION FOR THE MOST SENSITIVE BUSES

In RDS, the overall network performance can be evaluated through the performance of the most sensitive bus. The load flow studies for the existing network can be done using the backward–forward sweep method [21]. Load flow analysis includes constraints like the real and reactive power balance equations as in (1) and (2):

$$P_i = Pg_i - Pl_i = V_i \sum_{j=1}^{n} V_j \left[G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j) \right] \quad (1)$$

$$Q_i = Qg_i - Ql_i = V_i \sum_{j=1}^{n} V_j \left[G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j) \right] \quad (2)$$

Pg_i and Qg_i club the DGs and reactive power compensators' power generations and Pl_i and Ql_i club the several loads, particularly EVCS load too. The total real and reactive power losses in the distribution system can also be expressed as equality constraints:

$$TPL = \sum_{j=1}^{n} (Pg_i - Pl_i) \quad (3)$$

$$TQL = \sum_{j=1}^{n} (Qg_i - Ql_i) \quad (4)$$

The study also includes inequality constraints to establish the operating boundaries for the network. This includes generation limits as in (5) and (6), voltage and load angle limits as in (7) and (8), and power factor limits as in (9).

$$Pg_i \in \left[Pg_i^{min}, Pg_i^{max} \right] \quad (5)$$

$$Qg_i \in \left[Qg_i^{min}, Qg_i^{max} \right] \quad (6)$$

$$V_i \in \left[V_i^{min}, V_i^{max} \right] \quad (7)$$

TABLE I. INDICES PERFORMANCE AROUND MOST SENSITIVE LINE OF IEEE 30 BUS WITH DIFFERENT RATING DISTRIBUTED GENERATOR PLACEMENT SCHEME

S. No.	VSI with DG at Bus 8	VSI with DG at Bus 13	FVSI with DG at Bus 8	FVSI with DG at Bus 13	LQF with DG at Bus 8	LQF with DG at Bus 13
1.	0.1868	0.2200	0.6648	0.6222	0.6218	0.7190
2.	0.1635	0.2196	0.6312	0.6212	0.6205	0.7177
3.	0.1534	0.2174	0.6138	0.6148	0.6138	0.7093
4.	0.1632	0.2194	0.6300	0.6207	0.6193	0.7170
5.	0.1841	0.2172	0.6545	0.6143	0.6127	0.7086
6.	0.2182	0.2197	0.7123	0.6215	0.6171	0.7180
7.	0.2545	0.2170	0.7764	0.6139	0.6107	0.7081
8.	0.2925	0.2191	0.8536	0.6197	0.6020	0.7158
9.	0.3396	0.2164	0.9767	0.6122	0.6076	0.7059
10.	0.3810	0.2185	1.0908	0.6181	0.6003	0.7136

DG, distributed generator; FVSI, Fast Voltage Stability Index; LQF, Line Quality Factor; VSI, Voltage Stability Index.

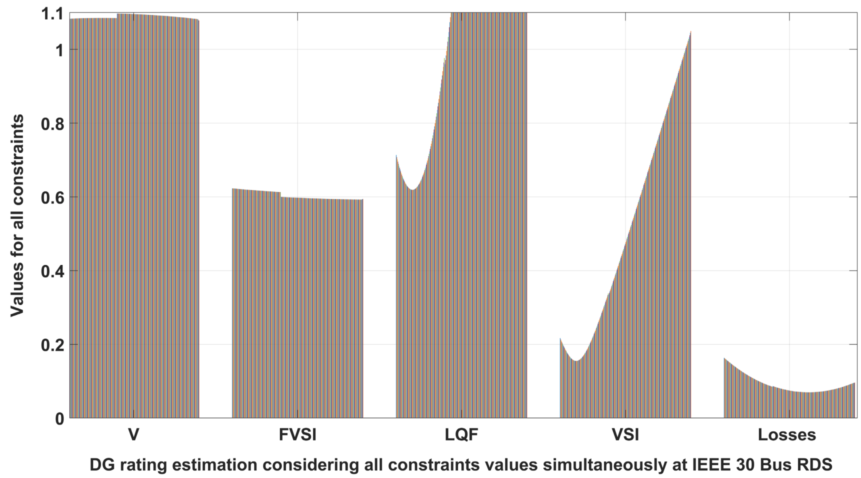

Fig. 3. Investigation of distributed generator size in RDS using all constraints simultaneously on IEEE 30 Bus radial distribution systems.

$$\delta_i \in \left[\delta_i^{min}, \delta_i^{max}\right]. \tag{8}$$

$$pf_i \in \left[pf_i^{min}, pf_i^{max}\right] \tag{9}$$

By obtaining the bus parameters through a load flow study, the most vulnerable bus using stability indices can be identified and DG can be placed on it to improve the system performance in terms of voltage and power loss profiles. Voltage Stability Index (VSI), Fast Voltage Stability Index (FVSI), and Line Quality Factor (LQF) are identified as some indices for the same in ref. [22].

Fast Voltage Stability Index, LQF, and VSI can be formulated with load flow study parameters. The critical loading can be allowed until the threshold values of VSI, LQF, and FVSI equal to unity. However, the complement values, i.e., close to 0, of these three are more preferable for a stable distribution system.

$$FVSI_{ij} = \frac{4Z_{ij}^2 Q_j}{V_i^2 X_{ij}} \tag{10}$$

$$LQF_{ij} = \frac{4X_{ij}\left(Q_j + \frac{P_j^2 X_{ij}}{V_i^2}\right)}{V_i^2} \tag{11}$$

$$VSI_{ij} = \frac{4X_{ij}}{V_i^2}\left(\frac{P_j^2}{Q_j} + Q_j\right) \tag{12}$$

Line losses and voltage profile are also considered using the least error iteration concept in the same work for identifying the most appropriate DG size and its location in RDS. The selection of DG size at the most sensitive bus using all these constraints together can be explained as the intersection of all these satisfying condition sets together, as shown in Fig. 1.

Mathematically, these satisfying conditions for voltage and indices sets are

$$V_j \in \left[0.9, 1.1\right] \tag{13}$$

$$FVSI_j \in \left[0, 1.0\right] \tag{14}$$

$$VSI_j \in \left[0, 1.0\right] \tag{15}$$

$$LQF_j \in \left[0, 1.0\right] \tag{16}$$

III. ROLE OF REACTIVE POWER AT BUSES WITH ELECTRIC VEHICLE CHARGING STATIONS

Voltage profile at each bus can be maintained by providing adequate reactive power compensators. In available studies, it is suggested that the utility must provide leading reactive power sources to maintain the voltage profile and impose penalties on end users who are drawing power below the specified power factor.

An iterative procedure to maintain the voltage profile by providing adequate reactive power at the DG bus is suggested in ref. [23]. Reactive power in samples can be examined using the backward–forward sweep method in load flow studies [21, 24, 25]. For defined iterative samples of reactive power with 0 as the minimum value sample and slack bus reactive power amount as the maximum value sample, the RDS can be examined and evaluated for the best possible sample of reactive power with the DG bus. Mathematically, reactive power at each iteration would be

$$Qcom_k = Qcom_{min} + \frac{k}{\sum(\forall k)}\left(Qcom_{max} - Qcom_{min}\right) \tag{17}$$

The optimization problem with a single variable of reactive power requirement at DG bus can be mathematically optimized using a single variable optimization problem. The fitness function for this can be expressed for ΔV as the change in voltage at each bus with reference case values as

$$\varepsilon = \min\left[\sum_{j=1}^{n} \left|\Delta V\right|\right] \tag{18}$$

To reduce the reserved capacity and installed capacity, and even to suppress the overburden on distribution lines, reactive power management at charging stations is suggested. Distribution systems with number of EVCS should maintain their reactive power on their own by mounting additional reactive power units at respective charging stations. However, this reactive power management at each station is complex because of the multi-variable optimization involved through load flow studies and hence requires a machine learning optimization problem to tackle such mathematical problems.

IV. SCOPE AND ROLE FOR FIREFLY ALGORITHM IN PROPOSED WORK

As described in the previous section, machine learning optimization is developed to investigate the accurate rating of reactive power compensating units at every EVCS so that the overall burdens on the distribution network can be suppressed. This will also assist commercial EVCS investors in making their energy consumption tariffs free from low power factor penalties. For *N* number of EVCSs in RDS, the rating of respective *N* number of reactive power compensators can be optimized using an optimization technique. Though traditional optimization techniques such as linear and mixed-integer, convex, quadratic, and non-linear programming are also suggested in many papers, these approaches become more complex and give local optimum and time-consuming results in multi-variable-based optimizations.

A nature-inspired Metaheuristic Approach can be used to achieve globally optimum, more accurate, and fast results. A swarm intelligence FA is developed for this multi-variable optimization problem. Fireflies, as nature-inspired species, produce short and rhythmic brightness through bioluminescence [26, 27]. The FA is applied due to its superior ability to handle complex, nonlinear optimization problems. Compared to classical optimization methods, which includes integral square error, integral absolute time error, integral square time error, and integral absolute error methods, FA has faster convergence, reduced computational complexity, and robustness in finding global optima in multidimensional search spaces. These features make it particularly suitable for optimizing reactive power compensation and other parameters in EVCS networks. This phenomenon can be correlated with the illumination concept of light waves. At any instant *t*, the movement of a firefly at location *x* attracted to another firefly at location *y* is determined by

$$d_x^{t+1} = d_x^t + \beta_0 e^{-\gamma r_{xy}^2}\left(d_y^t - d_x^t\right) + \alpha \epsilon_i^{\,t} \tag{19}$$

Parameter $\beta_0 e^{-\gamma r_{xy}^2}\left(d_y^t - d_x^t\right)$ evaluates the attraction-related correlation between the two species, and the randomization effect in species movement is evaluated using the term $\alpha \epsilon_i^{\,t}$. The proposed algorithm works to identify the optimum rating of every reactive power compensator associated with each EVCS. Pseudo-code for developing the algorithm for this proposed work is as follows:

Step 1: Identify the number and rating of EVCS connected with RDS.

Step 2: Formulate the corresponding reactive power compensation rating.

$Q \in \left(Q_1, Q_2, ..Q_N\right)$ Step 3: Initialize the reference value for all *Qs*.

Step 4: Select the inequality constraints with every *Q*.

$Q_{min} \le \forall Q \le Q_{max}$

Step 5: Develop a fitness function.

$\varepsilon = \sum_{j=1}^{n} \left|\Delta V\right|$ Step 6: Initialize population number.

Step 7: Start with this population number and rank all fireflies.

Step 8: Find the best solution if the criterion is satisfied and stop.

Step 9: Else, return to step 6 for the next population number through the iteration process.

V. METHODOLOGY DISCUSSION WITH IEEE 30 BUS RADIAL DISTRIBUTION SYSTEMS

The proposed work is established for the standard IEEE 14 and 30 Bus systems. The standard bus data carries parameters in sequence as bus no, voltage, load angle, real power generation, reactive power generation, real load power, reactive load power, max reactive power limit, minimum reactive power limit, and finally bus type. Similarly, the standard line data carries parameters in sequence as from bus number to bus number, resistance of line, reactance of line, susceptance at line end, and finally transformer tap position. The work is carried out in sequence and is presented in their corresponding subsection.

A. Coding and Testing of Backward–Forward Sweep Method

For the real and reactive power balance equations with equality and inequality constraints as presented by the mathematical equations in preceding sections, a load flow study is developed using the backward–forward sweep method. This generates the reference data of the RDS system. The study is done for IEEE 14 as well as 30 Bus RDS. However, this section mainly focuses on the IEEE 30 Bus system. The results of the IEEE 14 Bus RDS are also presented in the next section.

B. Identification of Most Vulnerable Bus in Radial Distribution Systems

With the data obtained in Subsection V(A), FVSI, LQF, and VSI indices are used to identify the most vulnerable bus of the system. Mathematical expressions for these indices have already been discussed in the last section.

IEEE 30 bus RDS system has 41 lines. Each line's performance based on these indices is shown in Fig. 2. It can be observed that

TABLE II. PROPOSED ELECTRIC VEHICLE CHARGING STATIONS FOR TESTING THE PROPOSED METHODOLOGY WITH IEEE 30 BUS SYSTEM

S. No.	Bus No.	EVCS Rating (MW)
1	3	21
2	13	17
3	15	18
4	27	25

EVCS, electric vehicle charging station.

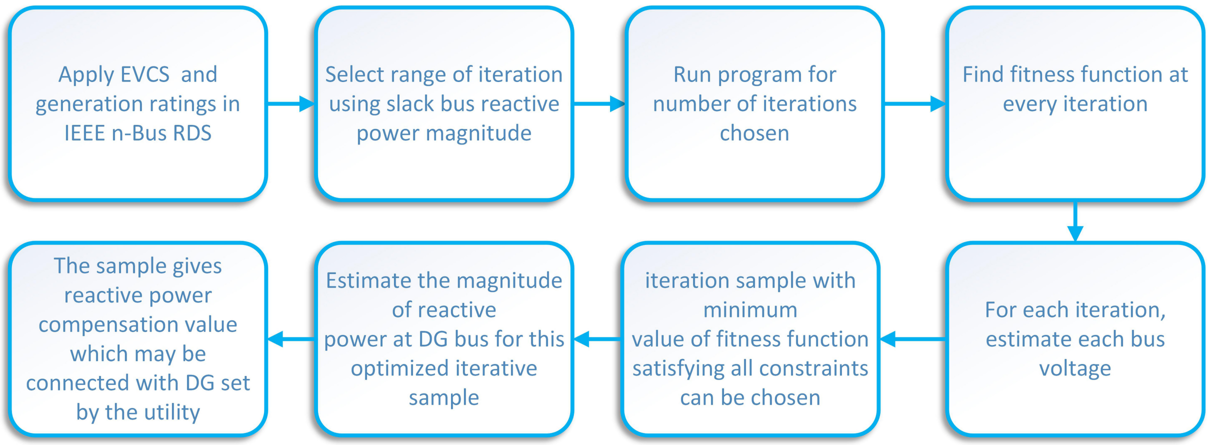

Fig. 4. Algorithm for identifying utility-based reactive power compensating unit at distributed generator Bus.

Line 2, which is connected with Bus 8 and 13, is showing all indices close to unity and so requires more attention. However, DG can be installed with either of the buses connected with this Line 2. The next step is to find the more vulnerable bus between these two buses, 8 and 13.

As these indices provide information about the lines connected between different buses. Therefore, the appropriate bus for DG commissioning can be identified through a reverse evaluation. For this, slack bus real power data is divided into ten samples, and DG equivalent to these ratings is placed on Bus 8. Data for FVSI, VSI, and LQF are collected for all ten samples. The same is done for Bus 13. The performance of Bus 8 and 13 is compared, as shown in Table I.

From the data tabulated in Table I, it can be observed that Bus 8 is more sensitive for DG placement schemes, and so, Bus 8 must be considered more sensitive than Bus 13 in the IEEE 30 Bus RDS.

C. Estimation of Distributed Generator Rating for Radial Distribution Systems

In IEEE 30 Bus RDS, Bus 8 has been identified for placing DG, and now this section deals with the size calculation of DG. Another iterative procedure is developed using MATLAB codes, which takes samples from 0 to the highest value, equal to the slack bus real power value. For all samples, six parameters are evaluated as presented in Fig. 1. The most favorable sample satisfying all the constraints together is chosen. Real power calculated using load flow analysis is found to be approximately 239 MW at the slack bus and

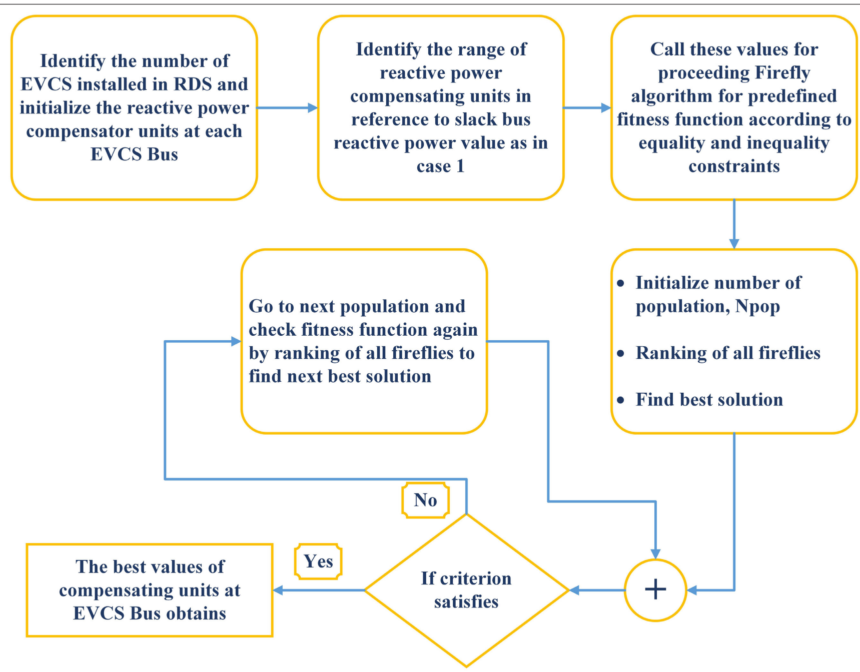

Fig. 5. Flowchart to describe the Firefly algorithm adopted for estimating the reactive power compensating units by the electric vehicle charging stations owner at their specific buses in radial distribution system.

TABLE III. THE PARAMETERS SETTING USED FOR FIREFLY ALGORITHM

Parameters	Values
Maximum iteration	20
Population size (number of fireflies)	25
Mutation coefficient (α)	0.01
Least attractive factor (β_0)	2
Light absorption coefficient (γ)	1
Randomness reduction factor ($\in$)	0.98
Equality and inequality constraints	As in Fig. 1
Fitness function	As in (18)

so 240 samples are chosen for the iteration purpose of tentative DG size. Fig. 3 represents voltage, FVSI, LQF, VSI, and losses samples through the iterative procedure [22]. It has been discussed that DG would be selected based on the conditions satisfying all the constraints together, and so, 90 MW DG is proposed by this analysis at the eighth Bus.

D. Electric Vehicle Charging Stations Placements in Radial Distribution Systems

The placement of EVCS in RDS depends on several technical and financial considerations. Several studies have been conducted to identify the EVCS size and locations. In this work, it is assumed that a number of EVCS are placed on RDS so that multi-variable optimization can be tested and validated. The bus number selections may also have a separate scope of research; however, this work is being limited by the selection of buses for EVCS placements. Therefore, four random EVCS are placed at bus numbers 3, 13, 15, and 27 to test the proposed methodology. Table II gives the EVCS rating considered to test the proposed model. It is also important to mentioned here that all EVCS are assumed to be operated with 0.9 lagging power factor.

E. Reactive Power Management with Distributed Generator

As proposed in refs. [9, 17, 28, 29], reactive power can be managed at the DG bus location and EVCS may be charged as a commercial load. In the case of reactive power demand, EVCS owner may be penalized

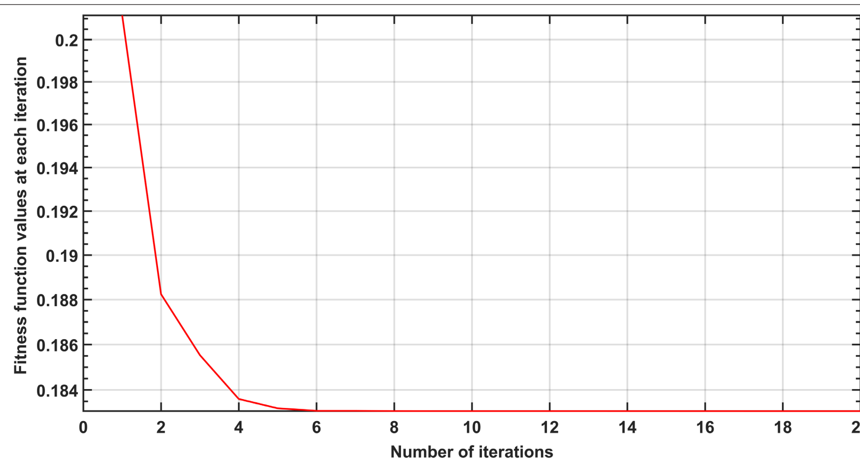

Fig. 6. Convergence curve for optimizing fitness function with multivariable constraints at IEEE 30 Bus radial distribution system.

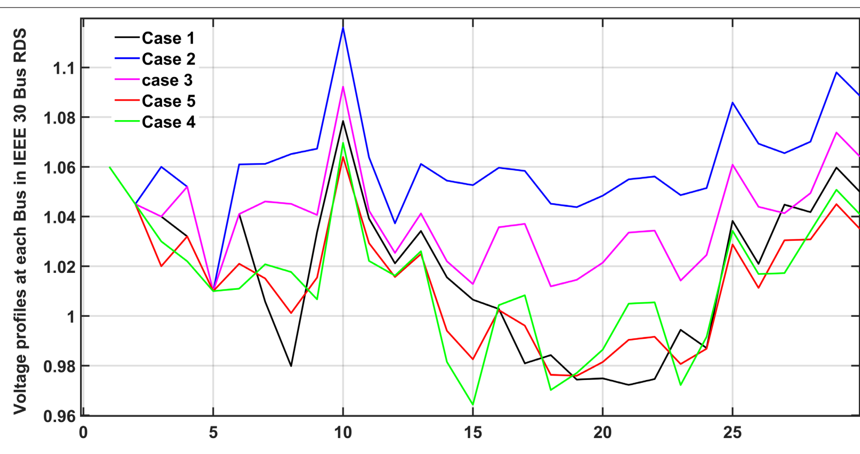

Fig. 7. Voltage profiles at each Bus of IEEE 30 Bus radial distribution system in all five cases.

TABLE IV. MAGNITUDE OF VOLTAGE PROFILES AT EACH BUS OF IEEE 30 BUS RADIAL DISTRIBUTION SYSTEMS IN ALL FIVE CASES

Voltage Profile at Each Bus in Different Cases					
Bus	**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 5**
1	1.0600	1.0600	1.0600	1.0600	1.0600
2	1.0450	1.0450	1.0450	1.0450	1.0450
3	1.0400	1.0600	1.0400	1.0200	1.0300
4	1.0320	1.0520	1.0520	1.0320	1.0220
5	1.0100	1.0100	1.0100	1.0100	1.0100
6	1.0410	1.0610	1.0410	1.0210	1.0110
7	1.0058	1.0612	1.0461	1.0151	1.0208
8	0.9798	1.0651	1.0451	1.0012	1.0177
9	1.0338	1.0673	1.0407	1.0154	1.0067
10	1.0784	1.1160	1.0923	1.0640	1.0697
11	1.0392	1.0638	1.0424	1.0293	1.0221
12	1.0212	1.0373	1.0254	1.0157	1.0162
13	1.0342	1.0612	1.0412	1.0249	1.0260
14	1.0155	1.0544	1.0220	0.9940	0.9815
15	1.0065	1.0526	1.0128	0.9826	0.9643
16	1.0028	1.0596	1.0357	1.0024	1.0044
17	0.9809	1.0584	1.0371	0.9961	1.0083
18	0.9843	1.0451	1.0119	0.9763	0.9702
19	0.9744	1.0438	1.0145	0.9759	0.9771
20	0.9749	1.0484	1.0214	0.9815	0.9864
21	0.9723	1.0550	1.0336	0.9904	1.0049
22	0.9746	1.0561	1.0343	0.9916	1.0055
23	0.9944	1.0486	1.0142	0.9807	0.9722
24	0.9871	1.0515	1.0245	0.9868	0.9916
25	1.0383	1.0858	1.0609	1.0288	1.0342
26	1.0209	1.0693	1.0439	1.0113	1.0169
27	1.0448	1.0655	1.0413	1.0305	1.0173
28	1.0418	1.0701	1.0494	1.0308	1.0341
29	1.0597	1.0980	1.0738	1.0450	1.0508
30	1.0489	1.0876	1.0631	1.0340	1.0398

to recover this additional MVA required due to a poor lagging power factor load. The rating of the centralized reactive power compensation unit held by utility can be evaluated using an iterative process that keeps the voltage profile near the reference case, as discussed in Section V(A). The algorithm, as shown in Fig. 4, adopted for this iterative process is based on the least voltage deviation from the reference case.

This proposed iterative procedure evaluates the size of the reactive power compensator that would be the optimum solution for placing it at the DG Bus. In this IEEE 30 Bus system, a DG of 90 MW with a 0.9 lagging power factor at Bus number 8 and four EVCS, as mentioned in Table II, evaluates reactive power compensating units of 18.6614 MVAR at Bus 8 (with the DG set of 90 MW and 0.9 lagging power factor).

F. Reactive Power Management at Electric Vehicle Charging Stations Bus as Proposed Study

In Section V(E), reactive power management is discussed at DG Bus, which would be governed by the utility. Though the utility is charging for surplus MVA asked by the EVCS owner, this solution still has gaps in securing reserve capacity, additional generating unit installation, and losses in the line. As all international regulatory bodies are at the same level of concern for reactive power management that it must be resolved at the local end. So reactive power compensators are mandatorily suggested with the EVCS unit. These reactive power compensators will not only manage the reactive power at the EVCS but also work to balance the voltage in the RDS. As the number of reactive power compensators increases in RDS, the iteration process suggested in Subsection V(E) may not be effective, and so, natural-inspired machine learning optimization technique may work satisfactorily for this case. The FA is proposed for this work. The FA has already been explained conceptually in Section IV. This section describes how this algorithm is developed for the proposed work. The flowchart for the same is presented in Fig. 5.

With the parameters set as in Table III with IEEE 30 Bus RDS, DG and EVCSs conditions the same as described in the Subsections V(C) and V(D), this algorithm optimizes the fitness function. The convergence curve demonstrating the fitness of FA is presented in Fig. 6. The reactive power units proposed for this EVCS loading on RDS are 36.9278 MVAR, 11.7519 MVAR, 0 MVAR, and 0 MVAR at bus numbers 3, 13, 5, and 27, respectively. It can also be observed that reactive power compensating units may not be necessary if rating and bus conditions are under the scope of stability.

G. Voltage Profile Comparisons for All the Cases

From Subsections V(A) to V(F), different cases have been discussed. Now all the cases are being brought together in this section to analyze the working of our proposed structure. All the cases are recapitulated here below:

Case 1*:* IEEE standard n-Bus RDS profile.

Case 2*:* IEEE standard n-bus with DG placement.

Case 3: IEEE standard n-bus with DG and EVCSs placement.

Case 4: IEEE standard n-bus with DG and EVCSs placement having utility-based compensation at same bus of DG.

Case 5*:* IEEE standard n-bus with DG and EVCSs placement, having EVCSs' owner-based compensation at same bus of EVCS.

All five cases profiles are compared on the same window to understand the system performance in each case and therefore, the voltage profile improvement with the final proposed Case 5. Fig. 7 gives the voltage comparison for each case. The Case 1 voltage profile (in the black line) is the base value voltage profile. The Case 2 voltage profile (in the blue line) shows the maximum DG

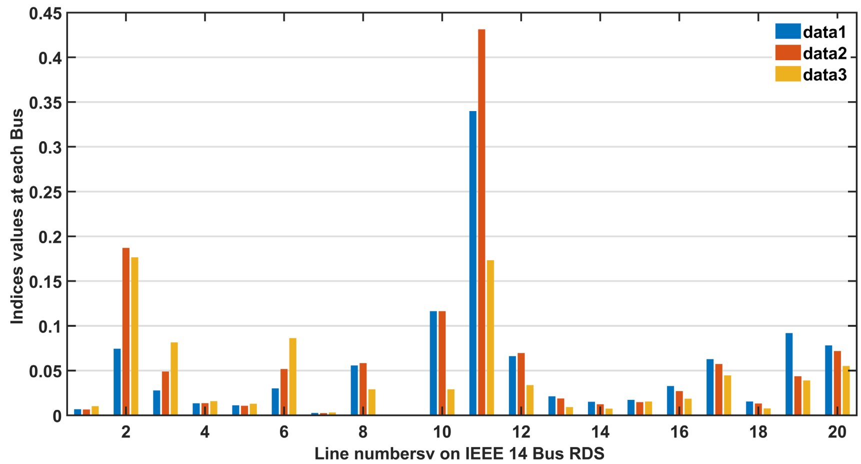

Fig. 8. Investigation of most vulnerable line in radial distribution system using Fast Voltage Stability Index, Voltage Stability Index, and Line Quality Factor simultaneously in IEEE 14 Bus radial distribution system.

rating that can be imposed on the IEEE 30 Bus system by following the Fig. 1 limits always. It can be observed that the voltage at almost each bus is within the voltage deviation range of ±10%. The Case 3 voltage profile (in the magenta line) represents the voltage drop due to the proposed additional EVCS at four buses in the distribution system. However, the voltage is still away from the standard voltage performance as given in Case 1. For Case 4, gives the utility established procedure as discussed in Subsection V(E) and the voltage profile (in the green line) can be seen, which is very close to the Case 1 profile. However, the owner-based reactive power compensation has more versatile usefulness compared to utility-based reactive power compensation and hence case 5 voltage profile (in the red line) is presented finally, which gives voltage levels very close to the standard voltage profile of Case 1. Therefore, the nature-inspired FA for reactive power compensation units' installation along with EVCS bus validation is proven through this work. Table IV also provides the numerical data of Fig. 7 for readers' better understanding and conceptualizations.

TABLE V. INDICES PERFORMANCE AROUND MOST SENSITIVE LINE OF IEEE 14 BUS RADIAL DISTRIBUTION SYSTEM WITH DIFFERENT RATING DISTRIBUTED GENERATOR PLACEMENT SCHEME

S. No.	VSI with DG at Bus 4	VSI with DG at Bus 9	FVSI with DG at Bus 4	FVSI with DG at Bus 9	LQF with DG at Bus 4	LQF with DG at Bus 9
11.	0.1726	0.1304	0.3385	0.3381	0.4290	0.3775
12.	0.1718	0.0969	0.3371	0.3363	0.4268	0.3456
13.	0.1711	0.0837	0.3357	0.3347	0.4247	0.3347
14.	0.1704	0.0986	0.3343	0.3332	0.4226	0.3443
15.	0.1698	0.1318	0.3330	0.3318	0.4206	0.3738
16.	0.1691	0.1729	0.3317	0.3306	0.4186	0.4228
17.	0.1685	0.2171	0.3305	0.3294	0.4167	0.4909
18.	0.1679	0.2629	0.3293	0.3284	0.4149	0.5778
19.	0.1673	0.3075	0.3281	0.3254	0.4131	0.6772
20.	0.1657	0.3541	0.3250	0.3246	0.4084	0.7997

DG, distributed generator; FVSI, Fast Voltage Stability Index; LQF, Line Quality Factor; VSI, Voltage Stability Index.

VI. RESULTS VALIDATION WITH ANOTHER IEEE 14 BUS RADIAL DISTRIBUTION SYSTEMS

The results obtained in Section V are tested and trained using the proposed methodology on the IEEE 30-Bus RDS. To further validate the findings, the IEEE 14-Bus system RDS is also analyzed, and the results for each case are presented to reaffirm the effectiveness of the proposed approach.

IEEE 14 Bus system standard data is used as Case 1. To obtain the most suitable bus for DG location, the same procedure as in Subsection V(B) is adopted and it confirms that the IEEE 14 Bus system has 20 lines, and Line number 11, which is connected with Buses 4 and 9, is most vulnerable. This result is investigated with voltage in dices as shown in Fig. 8. Now, out of these two buses, the next problem statement is to identify one bus for DG placement. For this same iterative procedure discussed in Subsection V(B) tests bus performance with different DG ratings on each bus and concludes that Bus 9 as most vulnerable bus of the RDS, and DG must be installed on it. Table V also validates to this.

The next Subsection V(C) describes the procedure for estimating DG rating. In the IEEE 10 Bus RDS, by following the same procedure, Fig. 9 is developed, which identifies the 58 MW DG should be placed at Bus number 9 in this case.

In the next step, EVCSs are commissioned on the IEEE 14 Bus system. Four random EVCS are placed at bus numbers 3, 5, 7, and 11 to test the proposed methodology. Table II gives the EVCS rating considered to test the proposed model. It is also important to mentioned here that all EVCS are assumed to be operated with 0.9 lagging power factor.

With DG and EVCS installation on RDS, the voltage profile will be affected, and therefore reactive power compensation is mandatory to supersede the effect of these variations. In Case 4, a utility-based

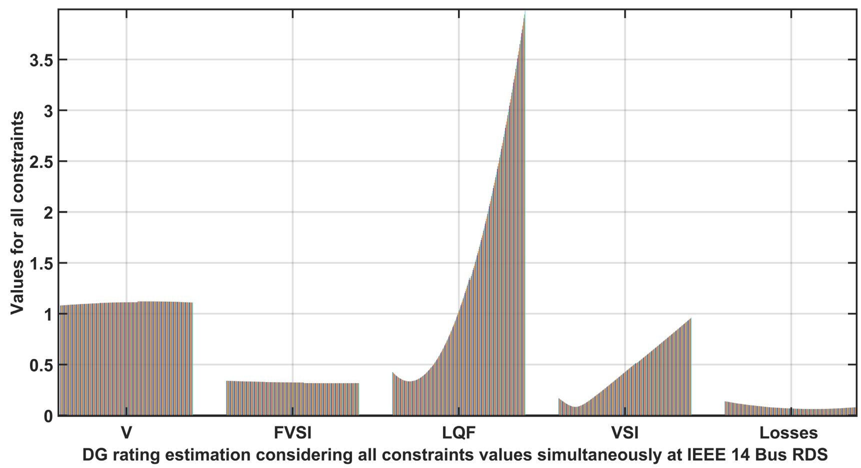

Fig. 9. Investigation of distributed generator size in radial distribution system using all constraints simultaneously at IEEE 14 Bus radial distribution system.

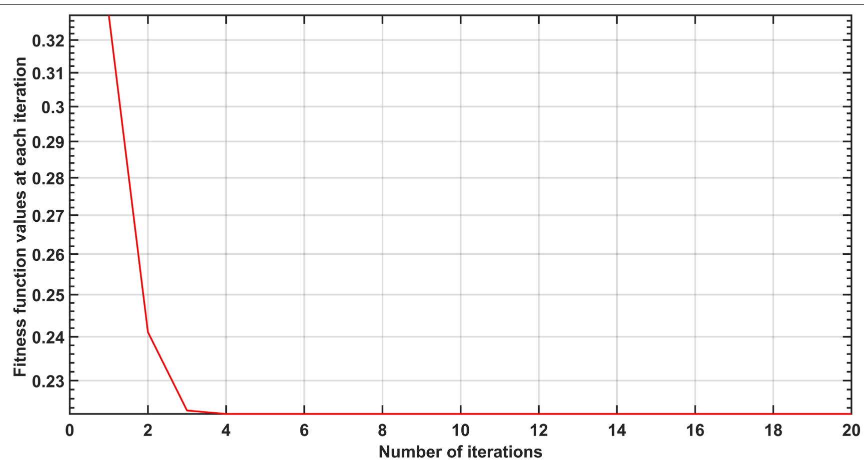

Fig. 10. Convergence curve for optimizing fitness function with multivariable constraints at IEEE 14 Bus radial distribution system.

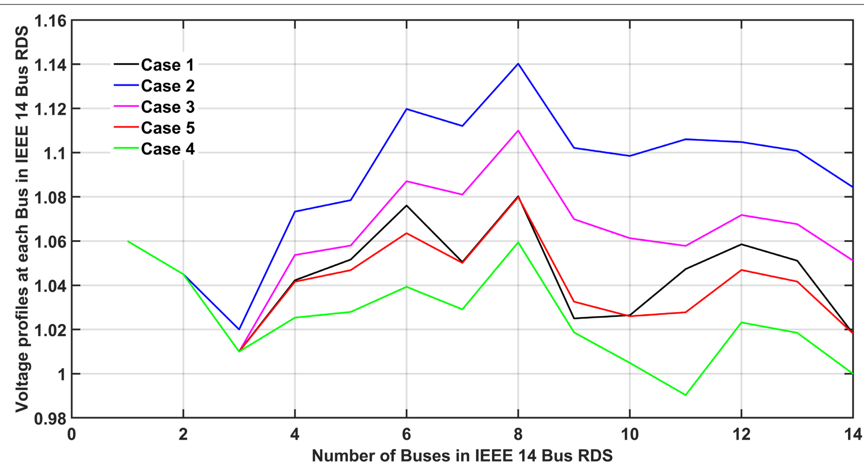

Fig. 11. Voltage profiles at each Bus of the IEEE 14 Bus radial distribution system in all five cases.

TABLE VI. PROPOSED ELECTRIC VEHICLE CHARGING STATIONS FOR TESTING THE PROPOSED METHODOLOGY WITH IEEE 14 BUS SYSTEM

S. No.	Bus No.	EVCS Rating
1	3	11 MW
2	5	18 MW
3	7	17 MW
4	11	15 MW

EVCS, electric vehicle charging station.

reactive power unit of 12.5548 MVAR would be required. However, through the proposed work with the same parameters setting for the FA as shown in Table III, the reactive power units are proposed. For this EVCS loading on RDS, reactive power compensating units of 11.1283 MVAR would be required at Bus 5 only. Here, it validates that reactive power compensating units may not be necessary if rating and bus conditions are under the scope of stability. The convergence curve demonstrating the fitness of FA is also presented in Fig. 10 for the IEEE 14 Bus RDS, and Fig. 11 represents the voltage profiles comparison for the IEEE 14 RDS with all five cases. The results validate the proposed work technically for both the RDS Bus structure.

VII. CONCLUSION

The load demand on the national grid is increasing exponentially, and the integration of EVCSs further contributes to this surge. To alleviate the pressure on the existing grid, various measures are being implemented at different levels, including reactive power management at the local end. This study demonstrates that procuring reactive power at the EVCS owner's end is more effective than relying solely on utility-based solutions. Additionally, machine learning-based approaches may play a very important role in deciding the optimal value of reactive power compensation. The FA is proposed for the same in the paper, including the important voltage indices for implanting the charging station at the most suitable location.

The proposed approach is tested and validated using the IEEE 14-bus and IEEE 30-bus RDS. In the IEEE 14-bus system, the 9th bus was identified as the most vulnerable, and a 58 MW distributed generation (DG) unit was commissioned. Similarly, in the IEEE 30-bus system, the 8th bus was identified as the most vulnerable, and a 90 MW DG unit was installed. Four EVCSs were located at buses 3, 5, 7, and 11 in the IEEE 14-bus system and at buses 3, 13, 15, and 27 in the IEEE 30-bus system.

To improve the voltage profile, reactive power compensating units were analyzed both with a centrally located DG and individually at the EVCS buses. The results indicate that the voltage profile improves more significantly when the compensating units are placed directly at the EVCS locations. These findings were consistently validated across both test systems. By managing reactive power (MVAR) locally through each EVCS, this approach not only enhances reactive power management at the local level but also increases the overall power capability of the grid, thereby helping to meet demand more effectively at the utility level.

This study may be further expanded to explore new algorithms for determining reactive power compensation alongside the establishment of charging stations. It can also be extended to include a Simulink model-based integrated study for the same proposals, such as controller tuning, ancillary service provisions, and power pricing.

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