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Research Article

Optimizing Resource Allocation for Enhanced Distribution System Performance Using Quokka Swarm Optimization

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Abstract:

The integrated optimization of charging station (CS) placement and distributed generation (DG) placement in distribution networks has been examined in this work. The aim is to improve system performance while incorporating the effects of load models and traffic congestion. Power distribution systems have become more complex due to the widespread adoption of electric vehicles (EVs) and the increasing penetration of DGs. To ensure power system stability, efficient resource utilization is essential. This paper proposes an integrated optimization model that combines DG allocation and CS placement using a Quokka Swarm Optimization (QSO) considering both traffic congestion and dynamic load profiles for realistic modelling. The proposed approach aims to minimize system losses, enhance voltage stability and mitigate the impact of traffic congestion on system performance. Simulations are performed with modified IEEE 69-bus radial distribution system. Proposed method for DG allocation and CS placement using QSO is compared with Grey Wolf Optimization (GWO) for analysis**.** The results show that optimal integration of DGs and CSs leads to a 48.23% reduction in active power losses (from 224.85 kW to 116.41 kW) and an improvement in the minimum bus voltage from 0.9101 p.u. to 0.9568 p.u. (over 5.15%,) under peak load and high congestion scenarios. These findings confirm that strategic coordination of DG and CS locations significantly enhances grid performance.

1. Introduction

Power system operation faces significant challenges as well as potential advantages due to the growing electrification of transportation and the incorporation of renewable energy sources into distribution systems. The popularity of EVs are predicted to grow over the next several years, which will increase electricity demand and possibly cause grid congestion, particularly during periods of peak load. On the other hand, the distribution of DGs, like wind turbines and solar photovoltaic (SPV) systems, combine challenges to improve grid stability and lessen dependency on conventional fossil fuel-based generation. To maximize the advantages and minimize the impact of EVs on distribution system (DS) performance, DGs and EV charging infrastructure must be integrated as best as possible.

1.1 Concepts and motivations

Innovations in EV technology and growing concerns about environmental sustainability are the primary motivating factors of the growing EV adoption trend. Because of this shift, the power system now faces both new opportunities and challenges particularly when it deals with integrating DG and EV charging infrastructure. Whenever these technologies are successfully integrated, the DS's dependability and efficiency can be significantly increased. One of the key issues in this integration involves incorporating traffic congestion and load model. Although load variation impacts the DS's functionality, traffic patterns have a direct impact on the demand for EV charging. Therefore, enhancing DS performance depends on the optimal placement of DG units and the allocation of EV charging stations. The objective of this research is to tackle these problems by designing a unified structure that enables optimal coordination. The inherent unpredictability in traffic flow and load variation compels the utilization of this approach.

1.2 Existing Work

The adoption of DG and EVCSs in electrical distribution networks has been widely assessed to improve resilience, efficiencies, and DS performance. A framework analyzing system reliability was proposed for the coordinated simultaneous placement of DG and EVCSs, using performance indices such as system average interruption frequency index and system average interruption duration index, by using an improved particle swarm optimization (IPSO) with grey wolf optimization (GWO) technique [1]. An optimized scheduling approach based on mixed-integer linear programming (MILP) incorporates demand side response and dynamic pricing, resulting in reduced energy costs and peak loads [2]. An EVCS placement methods have advanced to address urban mobility challenges. A two-layer optimization model that considers traffic congestion and electrical distribution system restriction has been developed to improve site selection and minimize power losses [3]. A multi objective strategies, using non-dominated sorting genetic algorithm II (NSGA II), have enhanced distribution system operations while considering future load demand growth [4]. Furthermore, probabilistic optimization techniques have been employed to handle uncertainties in EVs usage and renewable generation, leading to enhanced voltage stability and reduced energy losses [5].Recent studies have emphasized integrated planning that coordinate transportation systems with power system restrictions by employing a bi-level optimization. Case studies represented that considering traffic congestion along with grid limitations improves urban EVCS allocation [6]. Economic evaluations indicate that vehicle to grid (V2G) integration can help reduce electricity costs while increasing the flexibility of the electrical distribution network [7]. An optimization approaches using integer and mixed-integer methods have improved charging station placement by addressing location, charging demand, and accessibility constraints [8]. Adaptive strategies for EVCS deployment have been introduced to ensure that charging station placement considering both charging requirements and power system flexibility [9]. Extensive surveys have classified into planning methods, deterministic, stochastic, and hybrid approaches, highlighting the importance of multidisciplinary frameworks [10]. A time-varying traffic analysis has been utilized in electric vehicle path planning for city logistics, highlighting its importance in charging network development [11]. Design and operational frameworks for hybrid traffic patterns incorporating both electric and conventional fuel vehicles have integrated flexible demand considerations to support infrastructure development [12].A strategy integrating power system and load dispatch mechanisms was developed to optimize EVCS placement and design, adjusting the allocation methods with objectives of load distribution stability and improvement of distribution system efficiency [13]. A comprehensive model taking, network dynamics of transportation and power system restrictions was formulated to support the placement of fast charging stations for plug-in electric vehicle (PEVs), emphasizing the requirement for an improved infrastructure installation strategy [14]. Traffic responsive strategies have gained more attention. A space-time traffic model was used to support charging station placement, ensuring continuity with actual vehicle movement and congestion patterns [15]. Flexible traffic modeling techniques were used to support in the planning of highway EVCS infrastructure, allowing for flexible charging station allocation in response to fluctuating traffic conditions [16]. In micro grid strategic operational frameworks, demand-side management strategies contributed to enhanced multi objective optimization by balancing load distributions and reinforcing electric vehicle coordination [17]. Next generation traffic control systems also used to the strategic planning of EVCS. A dynamic traffic routing algorithm combined with adaptive traffic signal control, connected vehicle communication networks, was introduced to ease access urban traffic and enhance accessibility to EV chargers [18]. The power systems point of view, analytical methods for distributed generation planning were evaluated, emphasizing coordination with EV charging demands [19]. An extensive survey examined the interface between transport and power distribution system, introducing a future-oriented view on the strategic collaboration of EV charging services, taking both operational and structural strategies [20]. Allocation of D-STATCOMs in radial distribution systems under reconfiguration conditions for different load model. The research presented minimized power losses and improved voltage deviation, representing that appropriate placement of D-STATCOMs along with reconfiguration can contribute to conservation of energy [21]. Uncertainties in EV usage have been addressed in charging station placement strategies through stochastic optimization, aiming to reduce distribution losses and improve system reliability [22]. Moreover, recent innovations in optimization strategies have integrated nature-inspired algorithms like the Quokka Swarm Optimization. This metaheuristic strategy has represented strong performance in solving complex optimization problems, including those related to power systems and electric vehicle integration, by simulating the social patterns of quokka animals and exploring search spaces efficiently [23].

1.3 Novelties of Paper

The incorporation of traffic congestion problems in optimization model represents a key development. Traffic can be neglected in conventional research on the accessibility and use of charging stations. This strategy addresses the identified drawback by formulating optimization strategies that incorporate traffic flows, congestion conditions, and charging station placement to improve distribution system performance and reliability. Another important contribution is the development of a load model (LM) by incorporating dynamic load modeling into optimization frameworks. This methodology can better assess the impact of DG placement and EVCS allocation on distribution system performance under varying load conditions. These studies have focused on the synergies between DGs, EVs adoption, and distribution system operation. Researchers can maximize the utilization of renewable energy resources, minimize grid congestion, and promote the efficient integration of DGs and EVs nto the energy sectors and transportation. This integrated approach contributes to overall system resilience, sustainability, and cost-effectiveness. Novel optimization techniques, Quokka Swarm Optimization have emerged to address multiple conflicting objectives simultaneously. These objectives may include minimizing distribution system losses, improving voltage profile, voltage indexing, reducing greenhouse gas emissions, and enhancing distribution system reliability.

1.4 Organization of paper

Further this paper is organized as follows: Section 2 outlines the problem formulation for the proposed methodology, while Section 3 details the optimization technique applied. Section 4 shows the method's application to the modified 69-bus test system. In Section 5, the results are presented and discussed. Comparison of the proposed methodology with existing method is given in Section 6 and finally Section 7 concludes the key findings.

2. Problem Formulation

The paper proposes a multi-objective optimization approach considering DG placement and CS Allocation to minimize system losses, improve voltage profile, and Voltage stability indexing considering LM and traffic congestion (TC).

2.1 Objective Function

To formulate the objective function for DG and EVs placement in a distribution system. That reduces power losses, improving voltage profiles, and maximizing voltage stability. The objective function can be written as follows.

$$Min\, f = \left(w_1 \cdot f_1 + w_2 \cdot f_2 + w_3 \cdot \frac{1}{f_3}\right) \tag{1}$$

where: w_1, w_2 & w_3 are the weighting factors for each objective function f_1,f_2 & f_3 reflecting their relative importance.

2.1.1. Minimization of Power Losses

$$f_1 = \sum_{i=1}^{n}(I_i^2 . R_{ij}) \tag{2}$$

- I_i is the current flows through i^{th} line.
- R_{ij} is the resistance of ij^{th} line.

2.1.2. Voltage Profile Improvement

$$f_2 = VDI = \sum_i^n(|\ 1 - V_i\ |) \tag{3}$$

- V_i respectively represent the voltage of i^{th} bus and the rated voltage in pu.

2.1.3. Voltage stability indexing

The voltage stability index (VSI) can be formulated as

$$f_3 = VSI(t) = \left[|V_i|^4 - 4 * \left(P_i X_{ij} - Q_i R_{ij}\right)^2 - 4 * \left(P_i R_{ij} + Q_i X_{ij}\right) * |V_i|^2\right] \tag{4}$$

Where as X_{ij} *is* the inductance of ij^{th} bus, P_i is the Real Power flowing out of i^{th} bus , Q_i is the reactive power flowing out of i^{th} bus. This objective function captures the essential elements for DG and EVCS placement, and the weighting factors w_1, w_2 & w_3 are changed according to the importance of each objective.

2.1.4. Power Balance Constraints

$$\sum_{i=1}^{n} P_i^{gen} + \sum_{i=1}^{n} P_i^{dg} - \sum_{i=1}^{n} P_i^{load} - \sum_{i=1}^{n} P_i^{evcs} = P_{loss} \quad (5)$$

$$\sum_{i=1}^{n} Q_i^{gen} + \sum_{i=1}^{n} Q_i^{dg} - \sum_{i=1}^{n} Q_i^{load} = Q_{loss} \quad (6)$$

Where as P_i^{gen} and Q_i^{gen} are the active and reactive power generation at node i^{th}, P_i^{load} and Q_i^{load} are the active and reactive power demands at node i^{th}, P_i^{dg} and Q_i^{dg} are the active and reactive power generation of DGs at node i^{th}, P_i^{evcs} is the active power consumed by EVCS at node i^{th}, N_i is the set of neighboring nodes connected to node i^{th}

2.1.5. Voltage Limits

$$V_{nmin} \leq V_i \leq V_{nmax} \quad (7)$$

2.1.6. DG and EVCS Capacity Limits

$$P_{i,min}^{dg} \leq P_i^{dg} \leq P_{i,max}^{dg} \quad (8)$$

$$P_{i,min}^{evcs} \leq P_i^{evcs} \leq P_{i,max}^{evcs} \quad (9)$$

2.1.7. Operational and Reliability Constraints

Include other system operational limits, such as thermal limits of lines and transformers.

Table 1. *Comparison of proposed algorithm with exiting algorithm.*

Feature	Quokka Swarm Optimization (QSO)	Particle Swarm Optimization (PSO)	Genetic Algorithm (GA)	Whale Optimization Algorithm (WOA)	Grey Wolf Optimizer (GWO)
Inspiration	Quokka movement & foraging	Bird flocking/swarm intelligence	Evolution & natural selection	Whale bubble-net hunting	Wolf hunting & leadership
Exploration	High (random movement + Levy flight)	Moderate (velocity updates)	High (mutation & crossover)	Moderate (spiral & encircling)	Moderate (hierarchical hunting)
Exploitation	Strong (attraction to best solutions)	Strong (global & local best)	Moderate (selection & elitism)	Moderate (whale convergence)	Strong (pack leadership)
Convergence Speed	Fast (adaptive learning)	Fast in simple problems	Slower (depends on mutation)	Moderate	Moderate to fast
Avoiding Local Optima	Good (random jumps & adaptive moves)	Moderate (risk of premature convergence)	Poor (can stagnate if diversity is low)	Moderate	Strong
Computational Complexity	Moderate (depends on parameters)	Low(simple velocity update)	High (mutation & crossover steps)	Moderate	Moderate
Scalability	Needs testing for high-dimensions	Good (linear equations)	Moderate (depends on population size)	Good	Moderate
Application Suitability	Optimization problems, robotics, engineering	Engineering, machine learning	Genetic modelling, combinatorial problems	Engineering, medical imaging	Engineering, scheduling

3. Proposed Optimization Algorithm

The Quokka Swarm Optimization (QSO) [23] as a novel metaheuristic inspired by the foraging and movement behaviour of quokkas. The motivation behind the algorithm is to improve the balance between exploration (searching new areas) and exploitation (refining solutions in promising regions), which are critical in optimization tasks. Due to the performance drawbacks of conventional algorithms like PSO, GA, and WOA, including challenges with convergence rate, accuracy, precision solution and susceptibility to local optima as given in table 1., the authors propose the Quokka Swarm Optimization (QSO) algorithm that enhances global exploration, accelerates convergence, and yields reliable and accurate optimization results.

3.1 Mathematical Formulation of Quokka Swarm Optimization (QSO)

The QSO algorithm is inspired by the natural foraging behavior and social interaction of quokkas. It employs mathematical models to update the position of each agent in the search space by simulating exploration and exploitation dynamics. The algorithm incorporates stochastic components to simulate variability in movement, while also guiding agents toward promising regions of the solution space based on fitness evaluation. The position update and convergence mechanisms are governed by the following key equations:

3.1.1. Position Update Equation

The position of each quokka in the search space is updated based on its movement strategy:

$$X_i^{t+1} = X_i^t + r.\left(X_{best}^t - X_i^t\right) + s.\left(X_{rand}^t - X_i^t\right) \tag{10}$$

where:

- X_i^{t+1} = Updated position of the i^{th} quokka at iteration t+1
- X_i^t = Current position of the i^{th} quokka
- X_{best}^t = Best solution identified so far
- X_{rand}^t = Randomly chosen location from the population
- r, s = Random values within the interval [0, 1]

This equation makes sure that exploration (random movements) and exploitation (moving in the direction of the best solution) are balanced.

3.1.2. Exploration Behaviour (Random Movement)

Quokkas use Levy flight-inspired random movement for further diversification.

$$X_i^{t+1} = X_i^t + \alpha.Levy(\lambda) \tag{11}$$

where:

- α = Step size control factor
- $Levy(\lambda)$ = Lévy flight distribution with exponent λ, defined as:
$$Levy(\lambda) = \frac{\mu}{|\vartheta|^{\frac{1}{\lambda}}}$$
- where μ, ϑ are normally distributed random variables.

This allows random jumps to avoid local optima and explore new search areas.

3.1.3. Exploitation Phase (Convergence Towards Optimal Solutions)

In the later stages, movement is refined based on a weighted attraction model:

$$X_i^{t+1} - X_i^t + \beta.\left(X_{best}^t - X_i^t\right) \tag{12}$$

Whereas: β = Learning coefficient, adjusting the intensity of movement towards the best solution. This ensures quokkas converge efficiently to optimal solutions.

3.1.4. Convergence Criteria

The stopping condition for QSO is typically:

$$f\left(X_{best}^{t+1}\right) - f\left(X_{best}^t\right) < \varepsilon \tag{13}$$

Whereas: f(X) is objective function to be minimized/maximized and ϵ is convergence threshold. This ensures the algorithm stops when the solution improvement is negligible. The QSO algorithm effectively balances exploration (random movements, Levy flight) and exploitation (attraction to best solutions) using adaptive mechanisms. The mathematical model ensures robust optimization performance across different problem domains.

3.2. Optimal allocation of DG and EVCS:

An optimization algorithm is used to determine the optimal locations and capacities of Distributed Generation (DG) units and Electric Vehicle Charging Stations (EVCS) in the distribution system to enhance efficiency, reduce power losses, and improve voltage profiles.

The Quokka Swarm Optimization (QSO) algorithm, incorporating heuristic strategies and chaotic opposition-based learning, iteratively identifies optimal DG placements considering grid constraints, load demands, and renewable integration. Similarly, QSO optimizes EVCS placement by accounting for EV demand, traffic flow, and system constraints, ensuring a sustainable, efficient and grid-friendly charging infrastructure as shown in Fig.1

4. Application of Proposed Method

Fig. 2 represents a single-line diagram (SLD) of a power distribution system, shows a radial feeder structure with multiple branching nodes. The diagram begins with a power source. A thick horizontal line extends from the source, representing the main feeder, which distributes electrical power to various locations. Along this feeder, several branch lines extend both upward and downward, indicating connections to different buses or load points. Each node in the diagram is numbered, likely denoting specific distribution points, which could correspond to consumers, transformers, or capacitor banks. The structure suggests a radial distribution network, commonly used in urban and suburban power systems for efficient electricity distribution. Such diagrams are essential in power system studies, including load flow analysis, and optimization of DG and EVCS placement. This layout is often utilized in electrical engineering simulations to analyse power losses, reliability, and energy efficiency in distribution networks. In Table 1, load data specifies the active (P) and reactive (Q) power at each bus and Line data specifies the connection between buses and the impedance (R, X).

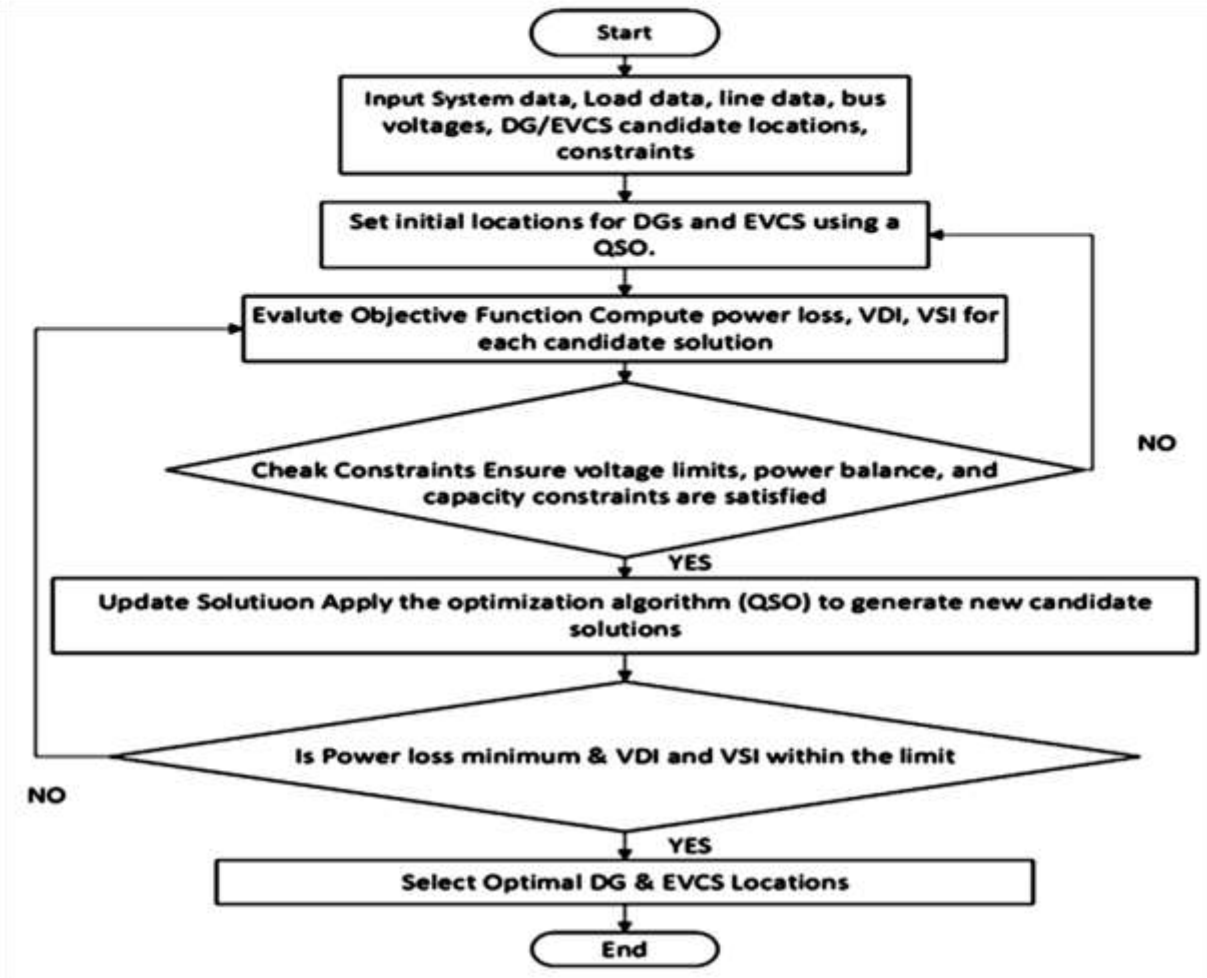

Figure 1. *Flow chart of of simultaneously EV and DG placement*

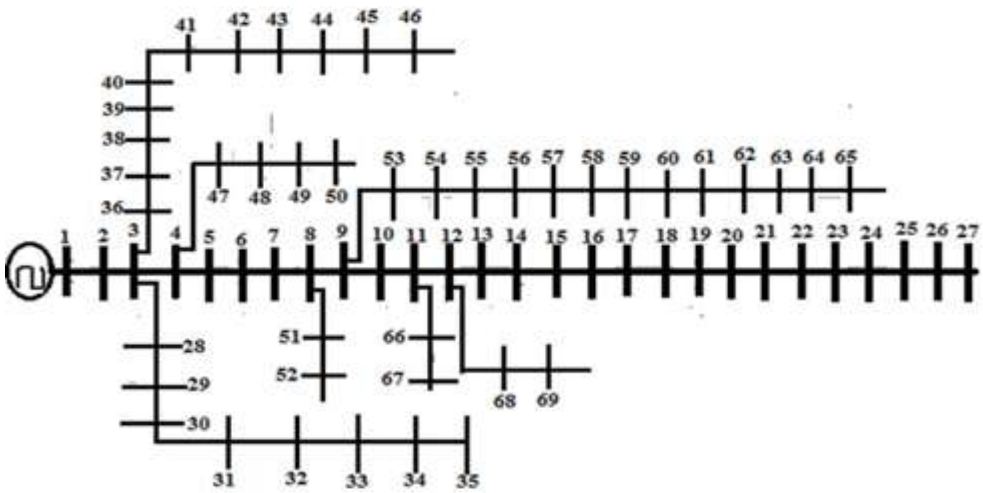

Figure 2. *Modified 69 Bus test system*

Table 1. *Load Data and Line Data of 69 bus test system*

S. No.	From Bus	To Bus	Load (P) (kW)	Load (Q) (kVAR)	R (p.u.)	X (p.u.)
1	1	2	0	0	0.0005	0.0012

2	2	3	0	0	0.0005	0.0012
3	3	4	0	0	0.0015	0.0036
4	4	5	0	0	0.0251	0.0294
5	5	6	2.6	2.2	0.366	0.1864
6	6	7	40.4	30	0.3811	0.1941
7	7	8	75	54	0.0922	0.047
8	8	9	30	22	0.0493	0.0251
9	9	10	28	19	0.819	0.2707
10	10	11	145	104	0.1872	0.0619
11	11	12	145	104	0.7114	0.2351
12	12	13	8	5	1.03	0.34
13	13	14	8	5.5	1.044	0.345
14	14	15	0	0	1.058	0.3496
15	15	16	45.5	30	0.1966	0.065
16	16	17	60	35	0.3744	0.1238
17	17	18	60	35	0.0047	0.0016
18	18	19	0	0	0.3276	0.1083
19	19	20	1	0.6	0.2106	0.069
20	20	21	114	81	0.3416	0.1129
21	21	22	5	3.5	0.014	0.0046
22	22	23	0	0	0.1591	0.0526
23	23	24	28	20	0.3463	0.1145
24	24	25	0	0	0.7488	0.2475
25	25	26	14	10	0.3089	0.1021
26	26	27	14	10	0.1732	0.0572
27	27	28	26	18.6	0.0044	0.0108
28	28	29	26	18.6	0.064	0.1565
29	29	30	0	0	0.3978	0.1315
30	30	31	0	0	0.0702	0.0232
31	31	32	0	0	0.351	0.116
32	32	33	14	10	0.839	0.2816
33	33	34	19.5	14	1.708	0.5646
34	34	35	6	4	1.474	0.4873
35	35	36	26	18.55	0.0044	0.0108
36	36	37	26	18.55	0.064	0.1565
37	37	38	0	0	0.1053	0.123
38	38	39	24	17	0.0304	0.0355
39	39	40	24	17	0.0018	0.0021
40	40	41	1.2	1	0.7283	0.8509
41	41	42	0	0	0.31	0.3623
42	42	43	6	4.3	0.041	0.0478
43	43	44	0	0	0.0092	0.0116
44	44	45	39.22	26.3	0.1089	0.1373
45	45	46	39.22	26.3	0.0009	0.0012
46	46	47	0	0	0.0034	0.0084
47	47	48	79	56.4	0.0851	0.2083
48	48	49	384.7	274.5	0.2898	0.7091
49	49	50	384.7	274.5	0.0822	0.2011
50	50	51	40.5	28.3	0.0928	0.0473
51	51	52	3.6	2.7	0.3319	0.1114
52	52	53	4.35	3.5	0.174	0.0886
53	53	54	26.4	19	0.203	0.1034
54	54	55	24	17.2	0.2842	0.1447
55	55	56	0	0	0.2813	0.1433
56	56	57	0	0	1.59	0.5337
57	57	58	0	0	0.7837	0.263
58	58	59	100	72	0.3042	0.1006
59	59	60	0	0	0.3861	0.1172
60	60	61	1244	888	0.5075	0.2585
61	61	62	32	23	0.0974	0.0496

62	62	63	0	0	0.145	0.0738
63	63	64	227	162	0.7105	0.3619
64	64	65	59	42	1.041	0.5302
65	65	66	18	13	0.2012	0.0611
66	66	67	18	13	0.0047	0.0014
67	67	68	28	20	0.7394	0.2444
68	68	69	28	20	0.0047	0.0016
69	69	70	0	0	0.00	0.0000

5. Results and Discussions

The analysis has been carried out using MATLAB version 9.0 on Windows 10 (Intel® Core TM i3-Processor, 3.30 GHz, RAM: 8 GB). The results are obtained for EVCS allocation and DG placement in modified 69-bus RDS. The voltage profile, power losses, and other aspects of the system's performance are all measured for various load models. The following five scenarios have been used to analyze the results.
Case 1: **BASE CASE**: No DG and no EVCS integration. This represents the original or reference distribution system without any DG and EVCS.
Case 2: **DG_1 EV_4_GWO Algorithm**: One DG unit and four EVCS are integrated into the distribution system using GWO.
Case 3: **DG_1 EV_4_QUOKKA Algorithm**: One DG unit and four EVCS are integrated using the QOA.
Case 4: **DG_2 EV_4_GWO Algorithm**: Two DG units and four EVCS are integrated using GWO.
Case 5: **DG_2 EV_4_QUOKKA Algorithm**: Two DG units and four EVCS are integrated using QOA.Table.2 provides the performance of various DG and EVCS allocation strategies using the Grey Wolf Optimizer (GWO) and Quokka Swarm Optimization (QSO) algorithms has been evaluated based on key power system parameters. The results demonstrate significant improvements in system performance when optimization techniques are applied compared to the base case. In the base case, the system exhibits a total active power loss of 224.96 kW and a reactive power loss of 102.15 kVAR. Significant reductions in power losses are achieved across all optimization scenarios. Among these, the configuration integrating two DG units and four EVCSs, optimized through the QSO algorithm, demonstrates the best performance, reducing active and reactive power losses to 16.34 kW and 11.51 kVAR, respectively. These findings highlight the effectiveness of the proposed approach in establishing a highly efficient power distribution network with substantially minimized energy losses.

The system's improvements are further represented by the voltage stability index and voltage deviation index. A significant reduction in the voltage stability index is observed, decreasing from 0.024699 in the one DG and four EV used by GWO to 0.0041536 in the two DG and four EV used by QSO, representing a significant enhancement in voltage stability. Likewise, the voltage deviation index improves consistently across all scenarios, achieving the highest value of 0.94063 under the two DG and four EV used by QSO configuration, reflecting improved voltage stability throughout the network.The allocation and sizing of DG fluctuate depending on the optimization technique as result shown in table 2, the one DG and four EV used by GWO, strategically placement of one DG with a capacity of 1465 kW is placed at bus 60. On the other hand, the two DG and four EV used by QSO strategically placement of two DG, with capacities of 1726 kW and 1442 kW, at buses 69 and 62, respectively. Similarly, the allocation of EVCSs is modified according to the optimization technique and load profile, with the QSO algorithm choosing key locations such as buses 2, 69, 67, and 3 to efficiently manage EV charging demand and reduce distribution system stress. In the final analysis, the QSO algorithm demonstrates better performance than the GWO method in the two DG and four EV case, offering an optimized arrangement with decreased power losses and improved voltage deviation. This represents the capability of advanced metaheuristic algorithm such as QSO in solving complex multi-objective optimization problem in modern electrical distribution systems. Fig. 3 illustrates the voltage levels at various bus numbers within the power distribution system under multiple optimization scenarios for the simultaneous placement of DG units and EVCSs. The graph compares the base case with four optimization configurations utilizing the GWO and QSO algorithms. In the base case (represented by the red line), the voltage profile exhibits significant drops, particularly at higher bus numbers, indicating poor voltage regulation and potential instability. The implementation of optimization algorithms improves the voltage profile by mitigating these voltage dips. The blue and pink lines represent the results for single DG placement with four EVCSs using GWO and QSO, respectively. Both

Table 2. *Allocation of EVCS and DG Using GWO Algorithm & QUOKKA Algorithm for IEEE 69 bus system*

PARAMETERS	**BASE CASE**	**DG_1 EV_4_GWO Algorithm**	**DG_1 EV_4_QUOKKA Algorithm**	**DG_2 EV_4_GWO Algorithm**	**DG_2 EV_4_QUOKKA Algorithm**
Total Active Power Loss	224.9606	48.7086	67.5158	30.7684	16.3442
Total Reactive Power Loss	102.147	26.7489	34.8542	17.5294	11.5069
VSI	-----	0.024699	0.037411	0.018133	0.0041536
VDI	0.68276	0.86438	0.83224	0.8718	0.94063
DG Active power (kW)	1.4646	1465	1016	1744 1726	753 1442
DG location	0.099577	60	61	2 61	69 62
EV power (kW)	-------	10 30 60 100	10 30 60 100	10 30 60 100	10 30 60 100
EV location	-------	2 23 33 16	23 43 69 65	2 10 11 20	2 69 67 3

optimization methods enhance the voltage profile compared to the base case, with QSO (pink) demonstrating a slightly better performance than GWO (blue).Further improvements are observed when two DGs are incorporated along with four EVCSs. The grey line (GWO with two DGs and four EVCSs) shows better voltage stability than its single DG counterpart. However, the black line (QSO with two DGs and four EVCSs) exhibits the best overall voltage regulation, maintaining higher voltage levels across most buses, particularly at buses experiencing severe voltage drops in the base case. Overall, the Fig.3. highlights the effectiveness of optimization algorithms in enhancing voltage stability within the distribution network. Among the tested approaches, the QSO algorithm with two DG units and four EVCSs (black line) provides the most stable voltage profile, making it the most effective solution for improving grid performance.The provided Fig. 4 illustrates the active power loss distribution across different line numbers in a power distribution system under various optimization scenarios for simultaneous DG and EVCS placement. The x-axis represents the line numbers, while the y-axis shows the active power loss in kilowatts (kW). The graph compares the base case (without optimization) with four optimized configurations using the GWO and QSO algorithms.In the base case (red line with square markers), the system experiences significantly high power losses at multiple line segments, particularly around line numbers 10 and 60, where losses peak at approximately 45 kW. These high losses indicate inefficient power distribution, likely due to optimized DG placement and the additional demand from EV charging stations.

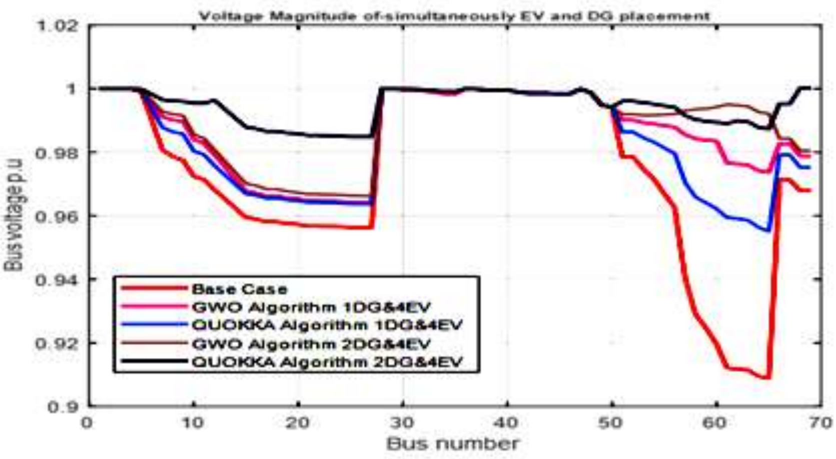

Figure 3. *Voltage magnitude of simultaneously EV and DG placement for 69 buses.*

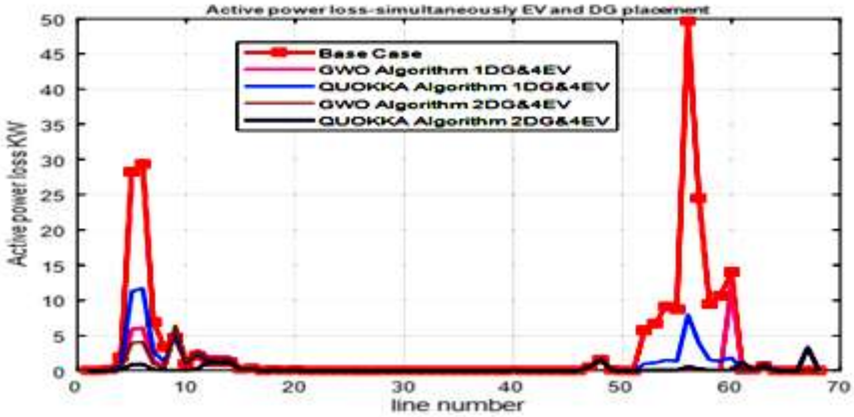

Figure 4. *Active power of simultaneously EV and DG placement for 69 buses.*

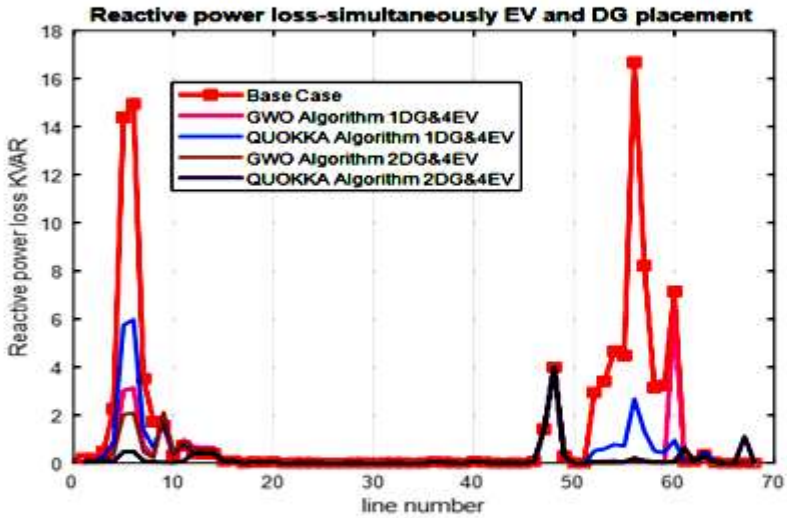

Figure 5. *Reactive power of simultaneously EV and DG placement for 69 buses.*

The implementation of optimization algorithms significantly reduces power losses across the system. The blue and pink lines represent the GWO and QSO results for a single DG with four EVCSs, respectively. Both optimization techniques effectively reduce power loss compared to the base case, with QSO (pink) demonstrating slightly better performance than GWO (blue), particularly in high-loss areas.Further improvements are seen when two DGs are incorporated along with four EVCSs. The gray line (GWO with two DGs and four EVCSs) shows lower power losses than its single DG counterpart, but the most notable reduction is achieved with the black line (QSO with two DGs and four EVCSs). This configuration minimizes power loss across nearly all line segments, with only minor losses remaining in some areas.Overall, the figure highlights the importance of optimization in reducing active power losses in power distribution systems. The QSO algorithm with two DGs and four EVCSs (black line) achieves the most significant reduction in power losses, demonstrating its superior performance in optimizing DG and EVCS placement for efficient energy distribution.The provided Fig.5 illustrates the reactive power loss distribution across different line numbers in a power distribution system under various optimization scenarios for simultaneous DG and EVCS placement. The graph compares the base case (without optimization) with four optimized configurations using the GWO and QSO algorithms.In the base case (red line with square markers), the system exhibits high reactive power losses at multiple line segments, particularly around line numbers 6 and 55, where losses peak at approximately 15 kVAR & 16 kVAR. These peaks indicate inefficient reactive power management, leading to poor voltage regulation and increased system losses. With the application of optimization algorithms, a significant reduction in reactive power loss is observed. The blue and pink lines represent the results for a single DG with four EVCSs using GWO and QSO, respectively. Both methods reduce losses compared to the base case, with QSO (pink) performing slightly better than GWO (blue), particularly in regions with high initial losses.

The integration of two DG units along with four EVCSs further enhances the performance of the distribution system. The grey line (GWO with two DGs and four EVCSs) shows an improvement over the single DG scenario, though the most significant reduction in losses is achieved by the black line (QSO with two DGs and four EVCSs). This configuration effectively reduces reactive power loss across nearly all line segments, ensuring efficient energy distribution and improved voltage stability.
The Fig. 5 illustrates the effectiveness of optimization algorithms in minimizing reactive power losses. The QSO algorithm, incorporating two DGs and four EVCSs (black line), achieves the highest reduction, resulting in superior voltage regulation and enhanced power system performance compared to other configurations.Fig. 6 presents the convergence patterns of various optimization methods employed for the concurrent placement of DG units and EVCSs in a power distribution network. Which is measured in terms of power loss. The graph compares the performance of the GWO and QSO algorithms under different DG and EVCS configurations.The convergence trends reveal a significant reduction in power losses as the optimization algorithms progress through successive iterations. The red and green lines represent the GWO and QSO algorithms with a single DG and four EVCSs, respectively. Both methods exhibit a sharp initial decrease in power loss, but the QSO (green) algorithm results in a lower final loss value compared to the GWO (red). However, both configurations stabilize at fitness values higher than those of the two-DG scenarios. The black and dark green lines represent the GWO and QSO algorithms with two DGs and four EVCSs. These configurations deliver superior performance, with much lower power losses and faster convergence rates. The QSO algorithm with two DGs and four EVCSs (black line) achieves the lowest power loss among all configurations, converging more rapidly and stabilizing at the optimal solution. Broadly, the Fig.6. demonstrates that the integration of two DG units and four EVCSs enhances optimization results, resulting in reduced system losses. Moreover, the QSO algorithm outperforms the GWO algorithm in both the single-DG and two-DG scenarios, achieving lower power losses and faster convergence. Therefore, QSO is identified as a more robust and effective strategy for DG and EVCS integration within distribution grids.Table 3 presents a comparative analysis of the optimal sizing, siting, and average power loss associated with EVCS and DG deployment in the modified 69-bus test system.

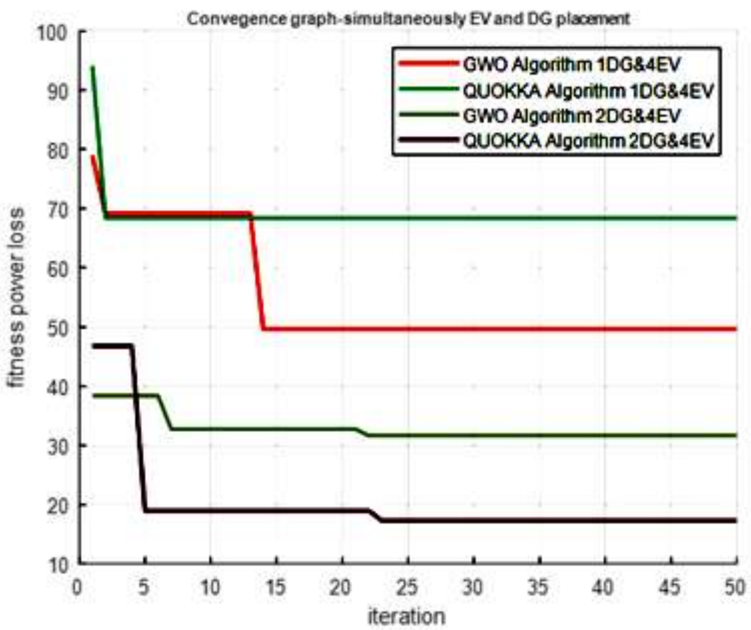

Figure 6. *Convergence performance of simultaneous EVCS and DG placement in a 69-bus system*

Table.3. *Comparison of proposed method with existing method in modified 69-bus test system*

Scenarios	**QSO**				**HGWOPSO[1]**			
	EVCS Location	Optimal DG		APL (kW)	EVCS Location	Optimal DG		APL (kW)
		Location	Size (MW)			Location	Size (MW)	
Base case	-	-	-	224.9	-	-	-	224.9
1 EVCS	46	-	-	225.17	28	-	-	225.31

2 EVCS	5, 43	-	-	226.19	6, 28	-	-	254.45
1 DG	5, 43	65	1.451	76.37	6, 28	61	1.8726	83.2
2 DGs	5, 43	47 22	0.4712 1.2215	70.98	6, 28	17 61	0.5312 1.7815	71.7
3 DGs	5, 43	28 62 63	0.3568 0.5001 1.4390	68.95	6, 28	13 21 67	0.5268 0.3801 1.7190	

6. Comparison of the proposed methodology with existing method of the optimal size, location, and Average Power Loss (APL) for EVCSA and DG:

As shown in table.3 both QSO and HGWOPSO [1] have an equal APL of 224.9 kW in the base case, indicating that without EVCS or DG placement, If one EVCS at locations 46 using HCOPSO and 28 using HGWOPSO, then QSO has an APL of 225.17 kW, slightly lower than HGWOPSO's 225.31 kW. When two EVCSs are placed, QSO shows an APL of 226.19 kW with EVCSs at locations 5 and 43, while HGWOPSO has a significantly higher APL of 254.45 kW with EVCSs at 6 and 28. This suggests that QSO performs better in controlling losses with multiple EVCS placements. Adding one DG with two EVCSs significantly reduces the APL for both methods. QSO achieves a lower APL of 76.37 kW with a DG size of 1.451 MW at location 65, compared to HGWOPSO's 83.2 kW with a DG size of 1.8726 MW at location 61. This again indicates that QSO provides better performance in minimizing power lose, with two DGs, QSO achieves a lower APL of 70.98 kW with DGs at locations 47 and 22, compared to HGWOPSO's APL of 71.7 kW with DGs at locations 17 and 61. Although both methods show reduced losses, QSO has a slight edge. In the configuration with three DGs, QSO achieves the lowest APL of 68.95 kW with DGs at locations 28, 62, and 63. HGWOPSO shows a slightly higher APL of 69.4 kW with DGs at locations 13, 21, and 67. QSO consistently demonstrates slightly better loss reduction capabilities in this configuration as well. QSO performs better than HGWOPSO across all scenarios in terms of APL reduction, especially in configurations with multiple DGs. The difference is more pronounced when more EVCSs and DGs are added, showing QSO's stronger optimization capacity for minimizing power loss.

7. Conclusions

This research paper introduces a novel optimization framework aimed simultaneously allocation of DGs and EVCSs within distribution systems. A significant performance is achieved through the proposed method, which incorporates the impacts of traffic congestion and load variability. The integrated strategy facilitates an optimized balance of energy supply and demand, concurrently mitigating system constraints. The research introduces a resilient and adaptable planning method for the simultaneously allocation of DGs and EVCS, successfully addressing major challenges in existing power distribution system. The findings confirm the effectiveness of the proposed approach in enhancing the reliability, sustainability, and resilience of modern power distribution systems.

Future investigations could have concentrated on integrating real-time data with sophisticated forecasting methods to dynamically optimize the placement of DGs and charging stations in response to transforming system conditions. Integrating energy storage solutions and renewable power sources into the optimization model could further improve the sustainability and operational efficiency of the distribution system.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
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