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Optimal Placement of Electric Vehicle Charging Stations in Active Distribution System Using Combined Genetic Dragonfly Algorithm Based on Active Power Losses

VV Appalanaidu Menda[1]*, D Vijaya Kumar[2]

[1]Department of Electrical Engineering, Andhra University (A), Visakhapatnam, Andhra Pradesh, India, [2]Department of Electrical and Electronics Engineering, Aditya Institute of Technology and Management, Tekkali, Srikakulam, Andhra Pradesh, India. *Corresponding Author's Email: naidueee54@gmail.com

Abstract

In the context of digital transformation within the bureaucratic system, namely in West Kalimantan, the effect of The fast use of electric vehicles (EVs) presents substantial difficulties to active distribution systems (ADS), specifically higher power losses and network performance deterioration. Optimal location of EVCS is therefore critical to ensure the efficient and stable operation of distribution networks. This work offers a combined Genetic-Dragonfly Algorithm (CGDA) for optimally allocating EVCS in ADSs, having the purpose of lowering actual energy losses. The proposed algorithm combines the Genetic Algorithm (GA)'s global exploration capabilities with the Dragonfly Algorithm's efficient exploitation and swarm intelligence properties, resulting in faster convergence and higher solution quality. The proposed GADA's performance is validated using two test systems. A standard IEEE 15-bus considered as Test System – 1 and PG and E 69-bus distribution test system is considered as Test System - 2 in live network settings. In this optimization-based study, line flow limits and voltage limits are considered as inequality constraints. The simulation results show that the proposed GADA consistently outperforms traditional GA, PSO, and DA in terms of power loss reduction and convergence characteristics. The results show that the suggested hybrid optimization framework is a reliable and effective approach for arranging EVCS in current active distribution networks. The proposed GADA method is also validated in stochastic environment.

Keywords: Active Distribution System, Dragonfly Algorithm, Electric Vehicle Charging Stations, Genetic Algorithm, Hybrid Optimization, Power Loss Minimization.

Introduction

The contemporary power distribution systems functioning features are changing due to the increasing use of electric vehicles (EVs). Globally, widespread EV adoption is promoted to reduce carbon dioxide emissions and dependency on fossil fuels. Nevertheless, distribution networks face major technical difficulties when integrating EV charging infrastructure. Especially in active distribution systems with distributed generation (DG) and bidirectional power flow, high and spatially concentrated charging demand can result in excessive real power losses, voltage deviations, feeder congestion, and degradation of power quality (1, 2).

The best positioning of EVCS is one of the many planning challenges that are essential to ensuring the dependable and effective operation of distribution networks. The voltage profile, network losses, and overall system stability are all directly impacted by the locations of charging stations. The advantages of EV deployment can be undermined by poorly designed charging infrastructure, which can dramatically raise system losses and operating expenses. As a result, EVCS optimal planning has become a crucial research issue in contemporary power systems (3). As per the system constraints, different charging locations, and varying load conditions, the EV charging station placement problem is inherently nonlinear, non-convex, and combinatorial. Such complex problems are often beyond the scope of classical deterministic and quantitative optimization techniques, especially in large-scale distribution systems. Because of their adaptability, resilience, and capacity to investigate vast solution spaces without gradient information, meta-heuristic optimization algorithms are frequently employed. The use of fuzzy analytic hierarchy and genetic algorithms for EVCS placement in passive radial distribution systems (RDS) is suggested (4). The authors' objective function in this paper was to minimize active power losses. Using mixed integer

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nonlinear programming, the location of an EV charging station in a passive RDS is suggested (5). The authors of this paper set the goal function to minimize the voltage variation from the nominal rated voltage. Particle swarm optimization is suggested for the best positioning of EVCS in an unbalanced radial passive distribution system (6). The authors' goals in this paper were to reduce energy waste and voltage deviation from the nominal voltage profile. The artificial hummingbird algorithm is used to suggest the best locations and sizes for DG units, capacitors, and EVCS in reconfigured radial and passive distribution infrastructures (7). The study's authors talk about goals like DG depth limit, power factor enhancement, line waste reduction, and voltage error eradication.

Using a combined GA and PSO, suggests the best location for EVCS and capacitors in a passive distribution network based on reducing active electrical losses (8). The best location and dimensions for EVCS are suggested, which uses PSO based on cost, voltage deviation, and loss mitigation (9). A novel approach based on reducing expenses by optimizing EVCS quantity using BWM and game theory in a passive distribution network (10). An inventive approach to determining the location of EVCS in Romania is proposed (11). This technique reduces the longest distance between a location without a charging station and the closest location with one by using mixed integer linear programming. ADSs are rarely taken into account in most of these studies, which are primarily concerned with figuring out the optimal location and size of EVCS in passive distribution networks. The complete summary of the literature is presented in Table 1. The electrical distribution system with DG units is known as ADS. The ability of Active Distribution Systems (ADS) to incorporate dispersed energy resources like renewable generation and EV charging stations sets them apart from conventional passive distribution systems. ADS operates with bidirectional power flow and necessitates sophisticated monitoring and control, in contrast to passive systems with unidirectional power flow. Additional issues like voltage fluctuations, higher power losses, and network congestion are brought about by the integration of EV charging stations. In order to guarantee the effective and dependable operation of the active distribution network, EV charging stations must be placed optimally.

Table 1: Literature Summary

Objective Function	Methodology	Limitation	References
Active power loss minimization	Fuzzy analytic hierarchy and genetic algorithms	Active Distribution System in not considered	(4)
Minimization of voltage deviation	Mixed integer nonlinear programming	Considered only passive distribution system	(5)
Reduction in losses and voltage deviation	Particle swarm optimization	Considered only passive distribution system	(6)
Power factor enhancement, active power loss and voltage deviation minimization	Artificial hummingbird algorithm	Distribution system with DGs is not considered	(7)
Reducing active electrical losses	Combined GA and PSO	Only passive distribution network considered	(8)
Reduction cost, losses and voltage deviation	Particle swarm optimization	Active Distribution System in not considered	(9)
Cost minimization	Genetic Algorithm	Only passive distribution network considered	(10)
Reduces the longest distance between a location without a charging station	Mixed integer nonlinear programming	Only passive distribution network considered	(11)

This research proposes an innovative hybrid algorithm that combines the GA and the DA for optimum positioning of EVCS in ADS based on real power loss mitigation. The suggested approach for the aforementioned problem has been evaluated in a probabilistic setting in terms of Wilcoxon rank sum test against the GA, DA, and PSO optimization methodologies. The null hypothesis, significance level is considered as 0.05. This study is carried out on two test systems, namely the IEEE 15-bus RDS as Test System - 1 and the PG and E 69-bus RDS as Test System - 2.

The primary contributions of this paper are as follows:

a) For the first time, the combined genetic dragonfly algorithm (GADA) is put forth for EVCS positioning optimization.
b) In uncertain circumstances, the GADA is verified through comparison with alternative meta-heuristic approaches.
c) Based on active electrical losses in various ADS sizes, the GADA determines the best location for EVCS.

Methodology

This section provides the details about the GA, the DA, and the proposed GADA method.

Optimization Problem Formulation

In this study, minimization of active power losses in ADS is considered as objective function, given by Equation [1]. Voltage and line limits are considered as inequality constraints and EVCS size and location are considered as variables (Equations [2-5].

Objective Function:

$$\text{Minimize Loss} = \sum_{i=1}^{nline} I(i)^2 R_i \qquad [1]$$

Inequality constraints:

$$\mathrm{V_{min}} \leq \mathrm{V} \leq \mathrm{V_{max}} \qquad [2]$$

$$\mathrm{S_l} \leq \mathrm{S_l^{max}} \qquad [3]$$

$$2 \leq \mathrm{EVCS_{loc}} \leq \mathrm{nbus} \qquad [4]$$

$$0 \leq \mathrm{EVCS_{size}} \leq 0.35\mathrm{MW} \qquad [5]$$

Genetic Algorithm (GA)

John Goldberg proposed the Genetic Algorithm (GA), which extended on Holland's theories (12). In Georgia, chromosomes represent a collection of all control factors. The size of the population determines how many chromosomes are created. New generations have been assessed since older generations utilize genetic operators like recombination, Crossovers and mutations. The elitism operator was utilized to retain the best individuals from the preceding generation. This study employs an authentically coded GA. Table 2 displays the values of the GA parameters utilized in this work.

Table 2: GA **-** Hyper Parameters and values

Parameter	Value
Pop (Population Size)	80
Pc (Crossover Probability)	0.9
Pm (Mutation Probability)	0.01
Pe (Elitism Probability))	0.05
Epochs	100

Dragonfly Algorithm (DA)

Conventional approaches have shortcomings, including a tendency to settle on local optimum solutions and a highly sensitive starting point. Techniques inspired by biology have been developed to address particular challenges (13-15). The DA developed suitably and was inspired by the swarming movement of dragonflies. Swarming can be classified as either static or dynamic. In order to find other flying prey, dragonflies travel short distances in small groups. When a sizable number of dragonflies travel a considerable distance in the same direction, dynamic swarms are created. Static swarming with low alignment and strong cohesion is linked to exploitation in optimization problems, whereas dynamic swarming with high alignment and minimal cohesion is linked to exploration. There are five reasons why dragonflies swarm: separation, alignment, cohesiveness, food attraction, and predator avoidance. A model was created for these variables (16). Table 3 displays the DA parameter values used in this work.

Table 3: DA **-** Hyper Parameters and Values

Parameter	Value
Pop (Population Size)	80
W (Weight)	0.9-0.4
s (Separation factor)	0.2-0
a (Alignment factor)	0.2-0
c (Cohesion factor)	0.2-0
f (Food factor)	0-2
e (Enemy factor)	0.1-0
Epochs	100

Combined Genetic Dragonfly Algorithm (GADA)

To find a global minimum with population-centered techniques, it's crucial to find a compromise among exploring and exploiting the search vicinity. The present optimal solution is used to explore the global and local solution spaces. Too much variation and increasing complexity make the convergence period longer and make it more likely that a solution will get stuck at the local equilibrium (17, 18).

While GAs might be challenging to locate correct solutions, they can be effective for global exploration and progressive convergence. GA functions along the notion of adaption. DA avoids examining individuals from the same group from generation to generation. Simple GA has no memory; therefore, earlier familiarity with the problem is lost if the population changes (19). To respond to this question, we need to talk about elitism. This means that the GA idea of elitism has a history of keeping people safe from the neighbourhood that came before them. DA is faster at converging and makes algorithms better when the best people are available, but it doesn't have internal memory like GA does. DA often misses possible solutions that could lead to the global optimum because it doesn't have enough internal memory. This could mean that the solution stays stuck at the local optimum (20). Particularly in intricate, multimodal optimization problems, particle swarm optimization (PSO) frequently experiences premature convergence and is prone to becoming stuck in local minima. As particles rapidly converge, its exploration capacity diminishes. By using dynamic swarm behaviours, the Dragonfly Algorithm, on the other hand, improves global search capabilities while maintaining a better balance between exploration and exploitation.

This research presents a hybrid algorithm that integrates Genetic Algorithm (GA) and Differential Algorithm (DA) to enhance their respective strengths, thereby mitigating the previously mentioned deficiencies. Hybridization includes two new features of DA: intrinsic memory and the ability to search on its own. The GADA method incorporates local and global searching capacities to avoid restricting the outcome to a confident optimal level. Figure 1 shows how GADA works step by step. And the complete pseudo code is shown below.

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Combined Genetic Dragonfly Algorithm (GADA) – Pseudo Code

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Step 1: Read input data like population size (pop), Iterations, Pc, Pm, number variables and limits. Initialize ΔYi, Dragonfly algorithm parameters like s, a, c, f and e, inertia weight w.

Step 2: Generate initial population (X)

Step 3: Evaluate the objective function with "X" i.e., active power loss and identify food source Y+ and enemy source Y−

Step 4: Calculate separation (s) using Equation [6], alignment (a) using Equation [7], cohesion (c) using Equation [8], food attraction (F) using Equation [9], enemy distraction (E) using Equation [10].

$$Si = - \Sigma (Yi-Yj) \qquad [6]$$

$$Ai = \frac{1}{N}\Sigma Vj \qquad [7]$$

$$Ci = \frac{1}{N} \Sigma (Yi-Yj) \qquad [8]$$

$$Fi = (Y+ \;\; - Yi) \qquad [9]$$

$$Fi = (Y- + Yi) \qquad [10]$$

Step 5: Update step vector using Equation [11] and update population using Equation [12].

$$\Delta Yt+1 = (sSi + aAi + cCi + fFi + eEi) + w\Delta Yt \qquad [11]$$

$$Yt+1=Yt+\Delta Yt+1 \qquad [12]$$

Step 6: Apply genetic algorithm operators like selection, crossover, mutation and elitism on population X and get new population X'.

Step 7: Merge both updated DA population (Y) and GA based population (X') and the select best "pop" populations as new "X" then goto step 3.

Step 8: Repeat step 3 to 7 till maximum number of iterations reached.

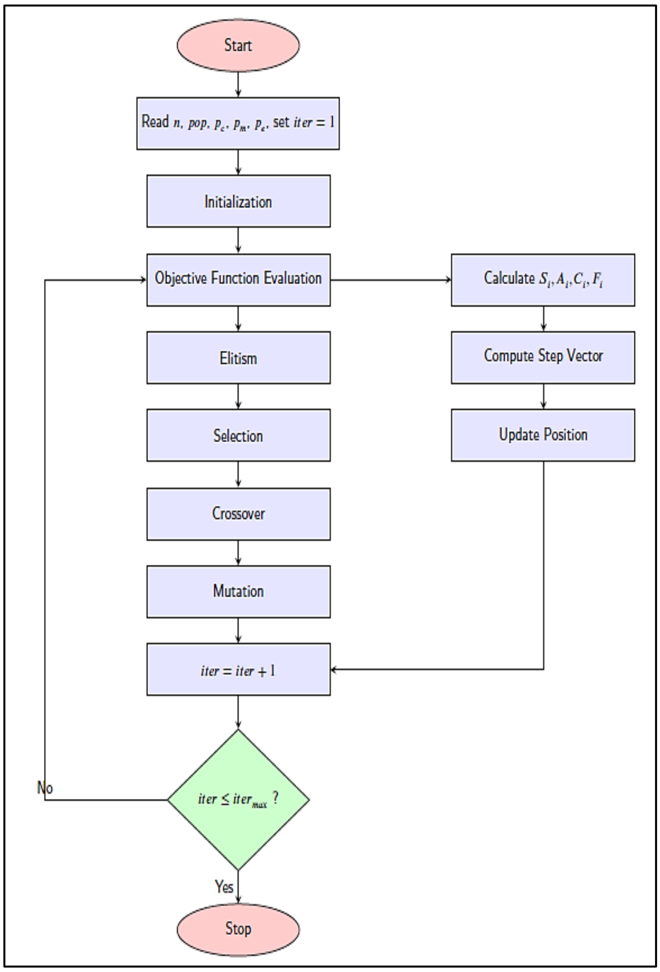

Figure 1: Combined Genetic Dragonfly Algorithm

Results and Discussion

The location of two EV charging units with a lagging power factor of 0.95 was optimized in the MATLAB environment by applying the proposed GADA to the Test System – 1 and Test System - 2 (Figures 2 and 3, respectively). The data for the IEEE 15 bus test system is taken from (21).For this study, two test systems considered they are IEEE 15 bus as test System – 1 and PG & E 69 bus test system as test System - 2. Total active and reactive power load on IEEE 15 bus test system are 1.2264MW and 1.2510MVar respectively. The active IEEE 15 bus test system was considered with two DG units with capacity of 476kW and 1MW, and their respective positions are bus 9 and bus 4. Similarly, total active and reactive power load on PG & E 69 bus test system are 3802.3kW and 2694.1kVar respectively. The active PG & E 69 bus test system was considered with two DG units with each capacity of 1000kW, and their respective positions are bus 61.

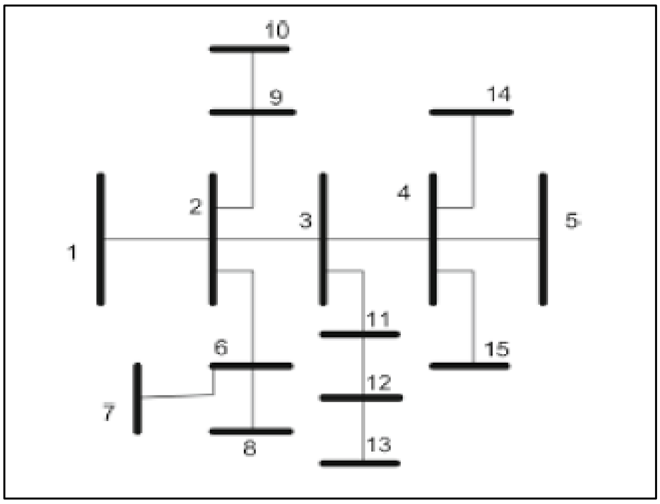

Figure 2: Test System – 1

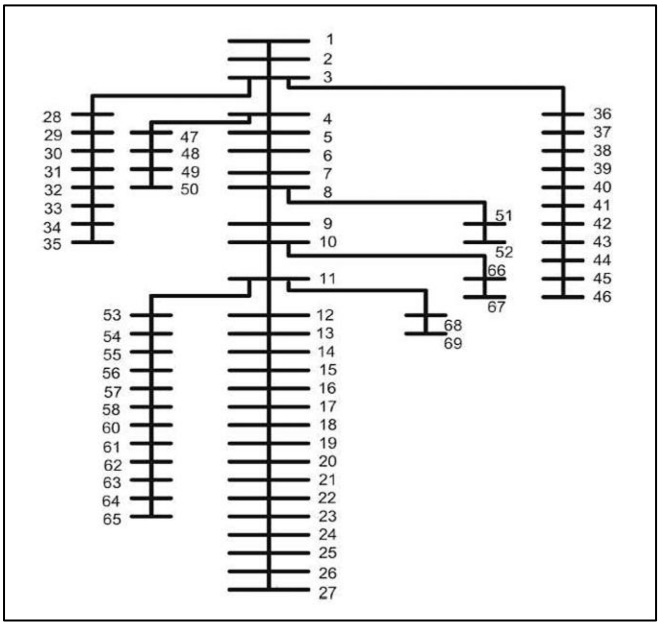

Figure 3: PG and E 69 Bus Test System

Case Study - 1: IEEE 15 Bus Test System

To find the best place for EV charging stations, the GADA was run ten times. Out of ten simulations, the one with the lowest active power losses is selected to decide where to put EV charging devices. The performance of the recommended approach in a stochastic environment is displayed in Table 4. The recommended method produces minimal standard deviation by providing consistent losses across runs. With a low standard deviation of 222W, the proposed GADA provides an unambiguous solution. The performance curves of the suggested GADA for the best location of EV charging stations throughout ten simulations are displayed in Figure 4. Figure 4 shows that the suggested approach achieves active power losses of 4300 Watts with a per-unit value of 0.0215 most of the time among all 10 simulations.

Table 4: Statistical Information of GADA on Test System – 1

Simulation	Active Power Loss (W)	Simulation	Active Power Loss (W)
I	4300	VI	4760
II	4720	VII	4300
III	4720	VIII	4300
IV	4300	IX	4720
V	4300	X	4300
Min.	4300	Max.	4750
Mean	4472	Std.	222

Table 5 shows the optimal placement of two EVCS with a capacity of 0.35 MW each. As per Table 5, the best location for both EVCS of capacity 0.35 MW is bus number 5. At this location the Test System – 1 operated with active power loss of 4.3 kW. Whereas base case active power losses are 12 kW. Active power losses on base case i.e., distribution system without DGs is 12KW. The active power losses in active distribution system in presence of EV charging stations are 4.3kW. The reduction in loss in comparison with base case even increase in load due to EV charging stations integration, is due to presence of DG units in active distribution system.

Table 5: Optimal Placement of EVCS for Test System - 1

EV-1		EV-2		Loss	Base
Location	Size (MW)	Location	Size (MW)	(kW)	(kW)
5	0.35	5	0.35	4.3	12

The proposed combined GA - DA for optimal placement of EVCS in Test System – 1 is verified by comparison with DA (22), GA (23) and Particle Swarm Optimization (24). To compare metaheuristic algorithms for EVCS optimum placement in stochastic environments, it is necessary to consider their stochastic character. Table 6 shows that the performance of each method was evaluated using statistical metrics such as mean and standard deviation after ten simulations on a Test System - 1. From Table 6 shows that the planned GADA has standard deviation of 222W. However, other meta-heuristic algorithms have more except GA but GA produces more losses which is not acceptable. When comparing standard deviation values, GADA outperforms other meta-heuristic methods in determining optimal placement of EVCS. The Wilcoxon rank sum test was used to probabilistically validate the performance of the proposed GADA for the best EVCS placement (25). Table 5 displays the p-values. With p-values less than 0.05, the proposed GADA is more significant than DA (22), GA (23), and PSO (24).

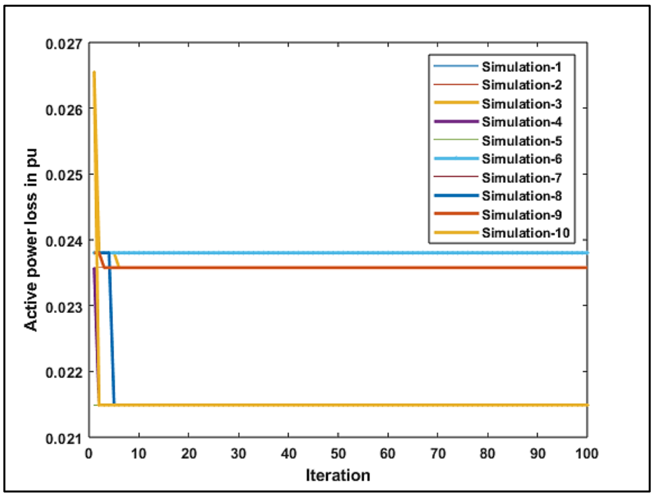

Figure 4: GADA Performance Curves - Test System - 1

Table 6: Test System - 1: loss assessment (in Watts) in a random setting

Parameter	GADA	GA (23)	DA (22)	PSO (24)
	4300	4960	12860	4960
	4720	4960	13500	4960
	4720	4960	9380	4960
	4300	4960	10280	4960
Simulations	4300	4960	9380	4960
	4760	4960	12860	4960
	4300	4960	13500	4960
	4300	4960	9380	4960
	4720	4960	10280	4960
	4300	4960	10280	4960
Average	4472	4960	11170	4960
Standard Deviation	222	0	1781	0
Minimum	4300	4960	9380	4960
Maximum	4760	4960	13500	4960
P-Value	NA	1.74E-6	6.6E-10	0.0018

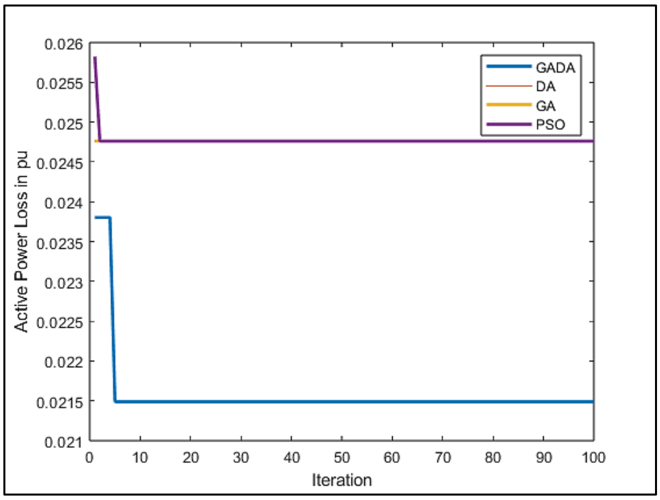

Figure 5: Validation of GADA— Test System - 1

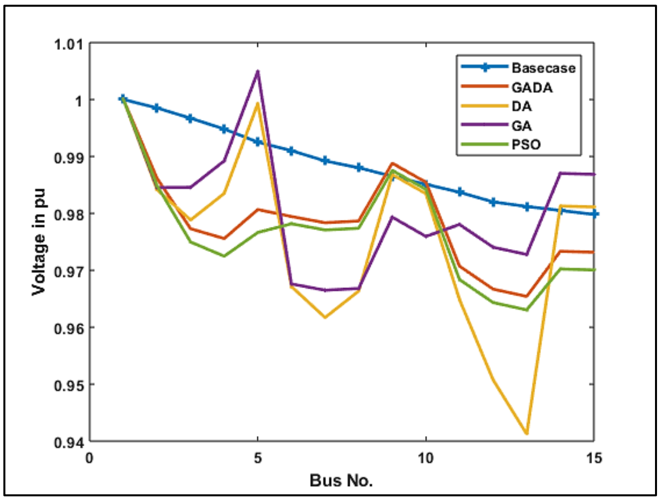

Figure 6: Validation of GADA in Terms of Bus Voltages — Test System – 1

Figure 5 compares the proposed GADA to existing metaheuristic algorithms based on convergence characteristics. The proposed GADA exhibits smooth convergence when compared to DA, PSO, and GA. GADA achieves optimum point (less losses) than DA, GA, and PSO.

Figure 6 shows the comparison between GADA, GA, DA, and PSO in terms of bus voltages. GADA provides voltages below the base case voltages even though EVCS are connected in ADS due to increase in load with EVCS integration.

GADA provides superiors voltage profile over GA, DA, PSO as it had less voltage deviation from flat voltage profile. GADA has average voltage deviation of 0.000531 which is less in comparison with GA which 0.000862 voltage deviation, DA which has 0.000576 and PSO which has 0.000634 voltage deviation as shown in Figure 7.

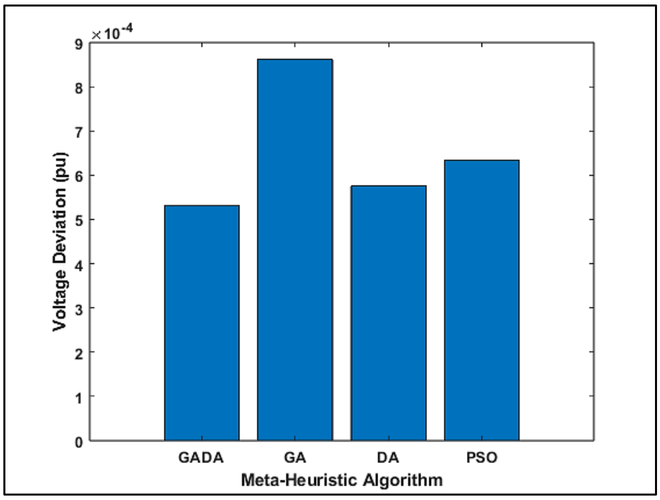

Figure 7: Validation of GADA in Terms of Bus Voltages Deviation from Flat Voltage Profile -Test System–1

Case Study - 2: PG and E 69 Bus Test System

To find the best location for EV charging units in PG and E 69 bus RDS, the combined GA-DA was conducted ten times. Out of ten simulations, the one with the lowest active power losses is selected to decide where to put EV charging devices. The performance of the recommended approach in a stochastic environment is displayed in Table 7. The recommended method produces minimal standard deviation by providing consistent losses across runs. With a low standard deviation of 516W, the proposed GADA provides an unambiguous solution. The performance curves of the suggested GADA for the best location of EV charging stations throughout ten simulations are displayed in Figure 8. Figure 8 shows that the suggested approach achieves active power losses of 279000 Watts with a per-unit value of 0.0279 most of the time among all ten runs.

Table 7: Statistical Information of GADA on Test System – 2

Simulation	Active Power Loss(W)	Simulation	Active Power Loss (W)
I	279000	VI	279000
II	280000	VII	279000
III	279000	VIII	279000
IV	280000	IX	279000
V	280000	X	280000
Minimum	279000	Maximum	280000
Average	279400	Standard Deviation	516

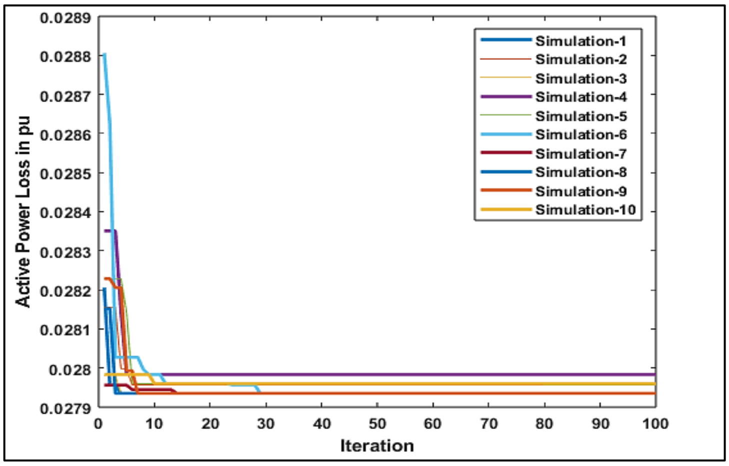

Figure 8: GADA Performance Curves - Test System – 2

Table 8: Optimal Placement of EVCS for Test System – 2

EV-1		EV-2		Loss	Base
Location	Size (MW)	Location	Size (MW)	(kW)	(kW)
2	0.5	2	0.5	279	221.8

Table 8 shows the optimal placement of two EVCS with a capacity of 0.5 MW each. As per Table 7, the best location for both EVCS of capacity 0.5 MW is bus number 2. At this location the Test System – 1 operated with active power loss of 279000W. Whereas base case active power losses are 221800W.

The proposed combined GA - DA for optimal placement of EVCS in an PG and E 69 bus distribution system is verified by comparison with DA (22), GA (23), and Particle Swarm Optimization (24). To compare metaheuristic algorithms for EVCS optimum placement in stochastic environments, it is necessary to consider their stochastic character. Table 9 shows that the performance of each method was evaluated using statistical metrics such as mean and standard deviation after ten simulations on an PG and E 69 bus test system. From Table 9 shows that the planned GADA has standard deviation of 516W. However, meta-heuristic algorithms like GA and particle swarm optimization (PSO) have zero standard deviation, but these algorithms produce more losses and PSO struct at local which is not acceptable. When comparing standard deviation values, GADA outperforms DA in determining optimal placement of EVCS. The Wilcoxon rank sum test was used to probabilistically validate the performance of the proposed GADA for the best EVCS placement (25). Table 9 displays the p-values. With p-values less than 0.05, the proposed GADA is more significant than DA (22), GA (23), and PSO (24).

Table 9: Test System - 2: Loss Assessment (in Watts) in a Random Setting

Parameter	GADA	GA (23)	DA (22)	PSO (24)
Simulations	279000	280000	279000	279000
	280000	280000	279000	279000
	279000	280000	279000	279000
	280000	280000	279000	279000
	280000	280000	367000	279000
	279000	280000	279000	279000
	279000	280000	279000	279000
	279000	280000	279000	279000
	279000	280000	279000	279000
	280000	280000	279000	279000
Average	279400	280000	287800	279000
Standard Deviation	516	0	27828	0
Minimum	279400	280000	279000	279000
Maximum	280000	280000	367000	279000
P-Value	NA	0.0017	0.3525	0.0247

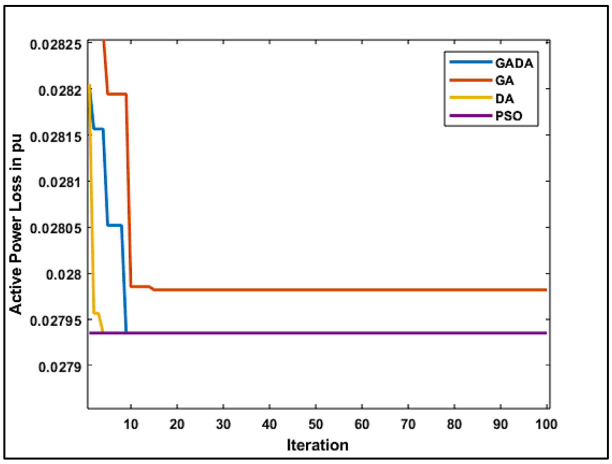

Figure 9: Validation of GADA— Test System - 2

Figure 9 compares the proposed GADA to existing metaheuristic algorithms based on convergence characteristics. The proposed GADA exhibits smooth convergence when compared to DA, PSO, and GA. GADA achieves optimum point (less losses) than GA. In comparison with DA and PSO, GADA has better convergence characteristics; the remaining two look struck earlier.

Conclusion

Active distribution system optimal operation is measured in terms of active power losses which is highly affected by increasing load growth due installation of EVCS, hence this paper proposed a novel hybrid optimization approach to integrate EVCS at optimal location and with optimal size so that total active power losses not increased more. In this paper, new hybrid optimization method i.e., combined genetic dragonfly algorithm is proposed for optimal placement of EVCS in ADS. Combination of both genetic and dragonfly algorithms provides good balance between exploration and exploitation in searching optimal solution. This study optimizes EVCS deployment with coupled GA-DA using two test systems: the IEEE 15 bus and the PG and E 69 bus. The suggested combined GA-DA has been validated by comparing it to different meta-heuristic algorithms, including DA, GA, and PSO, in a stochastic environment using wilcoxon rank sum test with respect to voltage deviation and losses. The outcomes demonstrate that coupled GA-DA performs better than alternative meta-heuristic techniques. Voltage limits and line loading limits are regarded as inequality constraints. In this paper, for the first time EVCS placement in active distribution system is discussed as most of the literature is based on passive distribution system. By taking voltage stability into account as an objective function in an ADS, this work can be further expanded.

Abbreviations

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Author Contributions

VV Applanaidu Menda: methodology, software, validation, formal analysis, research, resources, data curation, writing—original draft preparation, writing—review & editing, project administration, D Vijay Kumar: supervision. The authors have reviewed and approved the manuscript's published version.

Conflict of Interest

The author declares no conflict of interest.

Data availability

The data are available from the corresponding author upon a reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

All content was created solely by the authors. Authors declared that no AI tools used while preparing manuscript.

Ethics approval

Not Applicable.

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