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Multi-objective Adaptive Fuzzy Campus Placement based Optimization Algorithm for optimal integration of DERs and DSTATCOMs

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A R T I C L E I N F O

Keywords:
Distributed Energy Resources (DERs)
Distribution STAtic COMpensator (DSTATCOM)
Battery Energy Storage System (BESS)
Adaptive Fuzzy Campus Placement based Optimization Algorithm (AFCPOA)

A B S T R A C T

The novel Adaptive Fuzzy Campus Placement based Optimization Algorithm (AFCPOA) presented in this paper is expected to solve the issue of single objective and multi objective optimal optimization problems. AFCPOA's performance was evaluated on 25 benchmark optimization test functions and compared to other existing methods. Optimal location and sizing of Distributed Generation (DG), Distribution STATtic COMpensator (DSTATCOM), DGs and DSTATCOMs, Battery Energy Storage Systems (BESS) in the presence of PVDGs, and BESS in the presence of PVDGs and DSTATCOMs were integrated into Radial Distribution System (RDS) to fulfil the objectives. Technical advantages of DG include active power losses reduction and control of voltage dips. DSTATCOM functions as a capacitor, injecting reactive power to improve the consistency and quality of power flow and sustain voltage against any imbalance and distortion on load side or supply side. The appropriate location and capacity for BESS present a significant barrier for the integration of BESS and renewable DGs with distribution networks. The objective functions in this problem are to minimize total real power losses, reactive power losses, and voltage deviation. Additionally, the improvement of voltage profile was taken into consideration as a constraint while choosing the best location. Finally, the suggested algorithm is evaluated on IEEE 33 bus RDS and PG & E 69 bus RDS. Simulation results show the proposed method's excellent performance and applicability.

1. Introduction

Because of growing concerns with air pollution, global warming, and the depletion of fossil fuels, RES are now seen as the future of supply systems. The use of renewable energy in DG and its penetration into the distribution network has presented many challenges to network distribution operators in terms of planning and management. Power losses in distribution network are greater than those in transmission systems. Because of recent increase in load demand, DG can be used as active power support, which can also provide significant benefits. There is a lot of research on optimal distribution system planning using various optimization methods while taking into account multiple objectives. Using the concept of IWD algorithm, which takes nature as its inspiration and always finds an easier path to flow from source to destination when all feasible paths are open, the optimal DG placement was determined using a sensitivity factor, and the optimal DG size was determined using IWD for loss minimization [1]. A new combined algorithm [2] for solution quality was proposed to evaluate the DG location and size in the Distribution network, in which GA searches for DG location and PSO optimizes its size. The HSA was proposed [3] to solve the problem of distribution system network reconfiguration in the presence of distributed generation for loss reduction. To assign DGs along radial distribution networks, backtracking search optimization algorithm (BSOA), and swarm optimization technique [4] were used to decrease real network loss and improve voltage profile. In a stochastic programming environment, a hybrid ACO-ABC algorithm [5] was designed to locate DERs as efficiently as possible while taking wind and load uncertainty into account. This approach makes use of both global and local search capabilities of ACO and ABC algorithms. In order to reduce power loss, hybridization of analytical method (the sizes of DGs are assessed) and heuristic search (locations are chosen using PSO-based technology) [6] for the best placement of multiple DGs in power distribution networks has been proposed. LSF was utilized to discover the optimal placement for minimizing losses and operational cost while enhancing voltage stability IWO, an ecologically inspired method [7], was used to find the appropriate sizing of several DGs. To evaluate the best placement of solar-based distributed generators in the distribution system and reduce distribution network power losses, an effective method based on bat algorithm was proposed in [8]. To address the DG optimization problem with active power loss minimization as the

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Nomenclature

DG_{loc}	DG location
DG_{Size}	DG Size
Opt_{loc}^{bus}	Optimal bus location
P_{BESS}^{max}	Maximum limit of BESS active power
P_{BESS}^{min}	Minimum limit of BESS active power
P_{DG}^{max}	Maximum limit of DG active power
P_{DG}^{min}	Minimum limit of DG active power
$P_{DSTATCOM}^{max}$	Maximum limit of DSTATCOM
P_d	Active power demand
P_g	Active power generation
P_{loss}^{wdg}	Active power loss with DG
P_{loss}^{wodg}	Active power loss without DG
$Q_{DSTATCOM}^{min}$	Minimum limit of DSTATCOM
Q_d	Active power demand
Q_g	Reactive power generation
Q_{loss}^{wdg}	Reactive power loss with DG
Q_{loss}^{wodg}	Reactive power loss without DG
VDI_{wdg}	Voltage Deviation Index with DG
VDI_{wodg}	Voltage Deviation Index without DG
ABC	Artificial Bee Colony Optimization
ACO	Ant Colony Optimization
BA	Bat Algorithm
BFOA	Bacterial Foraging Optimization Algorithm
CBs	Capacitor Banks
CGPA	Cumulative Grade Point Average
CLS	Chaotic Local Search
CSCA	Chaotic Sine Cosine Algorithm
DE	Differential Evolution
E(i)	ith bus voltage
EMA	Exchange Market Algorithm
ESS	Energy Storage System
FWA	Fire Works Algorithm
GA	Genetic Algorithm
GAMS	General Algebraic Modeling System
GSA	Gravitational Search Algorithm
HGWO	Hybrid Grey Wolf Optimizer
HSA	Harmony Search Algorithm
I_{line}	line current
IWD	Intelligent Water Drop Algorithm
IWO	Invasive Weed Optimization
JA	Jaya Algorithm
LSF	Loss Sensitivity Factor
MOTA	Multi-Objective Taguchi Approach
NSGA	Non-dominated Sorting Genetic Algorithm
Obj1	Objective function 1
Obj2	Objective function 2
Obj3	Objective function 3
PSO	Particle Swarm Optimization
PVDG	Photo Voltaic Distributed Generation
QOBL	Quasi-Opposition-Based Learning
R	Resistance of distribution line
RES	Renewable Energy Sources
SCA	Sine Cosine Algorithm
SFLA	Shuffled Frogs Leaping Algorithm
SKHA	Stud Krill Herd Algorithm
SKHA	Stud Krill Herd algorithm
SOS	Symbolic Organism Search
SPEA2	Strength Pareto Evolutionary Algorithm 2
SSA	Salp Swarm Algorithm
TLBO	Teaching Learning based Optimization
TM	Taguchi Method
VSI	Voltage Stability Index
w1	Weightage for objective function value 1
w2	Weightage for objective function value 2
w3	Weightage for objective function value 3
WCA	Water Cycle Algorithm
X	Reactance of distribution line

objective function, one of the new bio-inspired, heuristic techniques, Krill herd algorithm with stud operators, called SKHA, was implemented in [9]. Utilizing the HGWO, a hybrid meta heuristic approach [10] was proposed, to determine non-convex, discrete DG allocation problem's globally optimal solution. The technique for order of preference by similarity to ideal solution is used in a new method that Taguchi proposed [11] to solve a multi-objective DG integration problem in order to select the nearly optimal position and size of DGs in a given distribution system out of a range of solutions. A new heuristic EMA was used to tackle the problem of where to locate the DGs, with least amount of power loss and best voltage profile [12]. The placement and sizing of combined DGs and CBs in distribution networks were optimized using WCA [13] as single and multi-objective frameworks to maximize technical, economic, and environmental benefits. SPEA2 was recommended to solve the multi-objective optimization problem to minimize active power loss, reduce annual operation costs, and also reduce gas emissions produced by the power plant feeding the substation of the distribution network [14]. Optimal DG and CBs allocation problem in the distribution system was proposed to be solved using SSA [15] for maximizing technical, economic, and environmental benefits. A better version of SOS algorithm called Quasi-Oppositional Chaotic Symbiotic Organisms Search (QOCSOS) combines SOS with QOBL and CLS strategies for faster convergence and higher-quality solution to optimal location and sizing of DG problems discussed in [16]. The distribution network reconfiguration problem combined with DG placement problem was solved using a new Adaptive SFLA [17], with the objective functions as power loss reduction and VSI improvement. A multi-objective hybrid approach [18] using GSA and GAMS has been presented for the best integration of DGs based on renewable energy sources and network reconfiguration to reduce power loss and increase annual cost savings. SCA and chaotic map theory [19] were used to solve the problem of siting and sizing distributed generation, taking into account the typical profiles of PV generation and the load profiles of distribution network users. In the radial distribution system with various types of loads, BFOA, a quick and innovative computation method [20], was used to determine the ideal size and location of multiple DGs for loss minimization, operational cost minimization, and to increase voltage stability. In order to simultaneously optimize power loss, reduce voltage deviation, and provide voltage stability index of the radial distribution network and overcome TLBO's shortcomings, an updated quasi-oppositional teaching learning based optimization (QOTLBO) methodology [21] was developed. To determine the best location and size for multiple DG problems with different objectives, the Quasi-Oppositional Swine Influenza Model based Optimization with Quarantine (QOSIMBO-Q) was developed [22] to improve the quality of solutions and accelerate convergence. A two-stage fuzzy multi-objective approach based on Grasshopper optimization algorithm [23] and an improved NSGA-II [24] have been discussed as multi-objective models with optimized placement and capacity of the DGs, shunt capacitors and BESS to improve the substation power factor, reduce power loss, and improve voltage profile. In [25], the important characteristics, strengths, and limitations of the research done on coordinated DG and ESS allocation, ESS allocation, and DG allocation with uncertainty modelling with different objectives, have been thoroughly examined. With the capacity to quickly and continuously compensate for capacitive and inductive modes, DSTATCOM is a shunt-connected device that has been utilized in distribution networks to handle the bus voltage and improve power factor and reactive power control as discussed in [26].

DSTATCOMs were used to correct for reactive power needs in the distribution network. Extensive investigation of optimal location and sizing of DSTATCOM inside the distribution system was carried out in [27]. The DSTATCOM allocation has several goals, including reducing overall power losses, minimizing voltage shifts, enhancing voltage stability, and improving reliability metrics. However, integrating DGs and DSTATCOMs into distribution networks simultaneously produces the best results [28]. Power distribution networks with optimal ESS planning enhance overall performance and reliability while lowering investment and operating costs [29]. According to studies in [30], in order to reduce voltage fluctuations, BESS should be situated adjacent to PVDG. On the other hand, the best location and BESS size were chosen using an optimization technique to reduce overall system losses. It was determined that BESS should be located adjacent to a heavy load for effective total loss reduction based on case studies with a number of PV and BESS in the distribution system. As an extension to new algorithm AFCPOA [31] was developed by the authors; the optimal integration of DERs and DSTATCOMs was carried out using AFCPOA for multi-objective problem for the first time. Further, AFCPOA demonstrates a reduction in the number of solutions with each iteration, effectively eliminating unsuitable solutions from the process. This unique feature has not been documented in the existing literature on evolutionary algorithms.

The following is a summary of the paper's primary contribution: (a) Using a novel adaptive fuzzy campus placement based optimization algorithm (AFCPOA), a single and multi-objective analysis of optimal location and sizing problem of a DG in a radial distribution system was conducted. (b) Studies on DGs and DSTATCOMs alone, BESS alone, a combination of DGs and DSTATCOMs, and BESS in the presence of PVDGs and DSTATCOMs have all been considered in order to reduce active and reactive power loss and improve voltage profiles. (c) To show the effectiveness and superiority of the proposed algorithm AFCPOA, the simulated results were compared with those reported in the literature.

This work is divided into five sections. Section 2 illustrates problem formulation. Section 3 formulates the proposed algorithm and how to apply it to the problem of optimal location and size. Section 4 covers the simulation results from various case studies, and Section 5 presents the study's overall conclusion.

2. Problem formulation

The purpose of this study is to reduce active power losses, reactive power losses, and voltage variations in order to determine the best location and size for single to multiple DG, DSTATCOM, and BESS in RDS. The expression for the objective function is showed in Eq. (1).

$$minimization(F) = w_1 Obj_1 + w_2 Obj_2 + w_3 Obj_3 \tag{1}$$

The following describes the problem's objective function:

Before installing and sizing DG, DSTATCOM, and BESS into the system, the distribution system's power flow was computed initially to determine the active and reactive power losses for arriving at base case values. For base case study, run the backward forward distribution power flow for test systems and compute the total active, reactive power losses and maximum voltage deviation in the distribution network using Eqs. (2), (3) and (4) respectively.

$$P_{loss} = \sum_{i=1}^{n_l} I_i^2 R \tag{2}$$

$$Q_{loss} = \sum_{i=1}^{n_l} I_i^2 X \tag{3}$$

$$VDI = max \sum_{i=2}^{N} abs(\frac{E(i) - E(1)}{E(1)}) \tag{4}$$

After DG, DSTATCOM, and BESS placement and sizing of DGs, the losses are computed. Eq. (5) defines active power loss index (Obj_1) as the comparison of active power losses with and without DG/ DSTATCOM/ BESS. Eq. (6) defines reactive power loss index (Obj_2) as the comparison of reactive power losses with and without DG/ DSTATCOM/ BESS. All three objectives are minimization problems, with the weighted sum multi objective study used in this problem determined by giving equal weight to all three objectives. The total weights sum is 1 (w1+w2+w3 =1). Weighted sum methods are easier to understand and implement. Weighted sum methods are generally computationally less demanding compared to Pareto-based methods. All three separate objectives are formulated as a single objective function given in Eq. (1). Here the fitness function considered as 1/(1+Objective function (1)) and the transformation inverts the objective function. This inversion is useful because many optimization algorithms are designed for minimization problems.

$$Obj_1 = \frac{P_{loss}^{wdg/wdstatcom/wbess}}{P_{loss}^{wodg/wodstatcom/wobess}} \tag{5}$$

$$Obj_2 = \frac{Q_{loss}^{wdg/wdstatcom/wbess}}{Q_{loss}^{wodg/wodstatcom/wobess}} \tag{6}$$

Eq. (7) defines the Voltage Deviation Index (VDI) (Obj_3) as the difference between voltage deviation with and without DG/ DSTATCOM/ BESS.

$$Obj_3 = \frac{VDI_{wdg/wdstatcom/wbess}}{VDI_{wodg/wodstatcom/wobess}} \tag{7}$$

The objective function is subjected to the following equality and inequality constraints as shown in Eqs. (8) to (14).

$$P_g - P_d - \sum_{q=1}^{N_b} |E_p||E_q|Y_{pq}| \cos(\delta_p - \delta_q - \theta_{pq}) = 0 \tag{8}$$

$$Q_g - Q_d - \sum_{q=1}^{N_b} |E_p||E_q|Y_{pq}| \sin(\delta_p - \delta_q - \theta_{pq}) = 0 \tag{9}$$

$$V_g^{min} \le V_g \le V_g^{max} \tag{10}$$

$$I_{line}^{min} \le I_{line} \le I_{line}^{max} \tag{11}$$

$$P_{DG}^{min} \le P_{DG} \le P_{DG}^{max} \tag{12}$$

$$Q_{DSTATCOM}^{min} \le Q_{DSTATCOM} \le Q_{DSTATCOM}^{max} \tag{13}$$

$$P_{BESS}^{min} \le P_{BESS} \le P_{BESS}^{max} \tag{14}$$

3. Adaptive Fuzzy campus placement based optimization algorithm (AFCPOA)

Multinational companies and startups visit campuses to hire undergraduate and graduate students who are in their final year of study and they account for a significant percentage of employment in a nation like India. This algorithm was developed after taking into account the entire hiring process, including the filtering of resumes, calculation of CGPA, results of written test and interview, and the training time. Based on the method described in [31], authors developed a novel adaptive fuzzy campus placement based optimization algorithm (AFCPOA) that achieves the best global solution quickly without compromising accuracy. The flow chart of proposed AFCPOA method is given in Fig. 2.

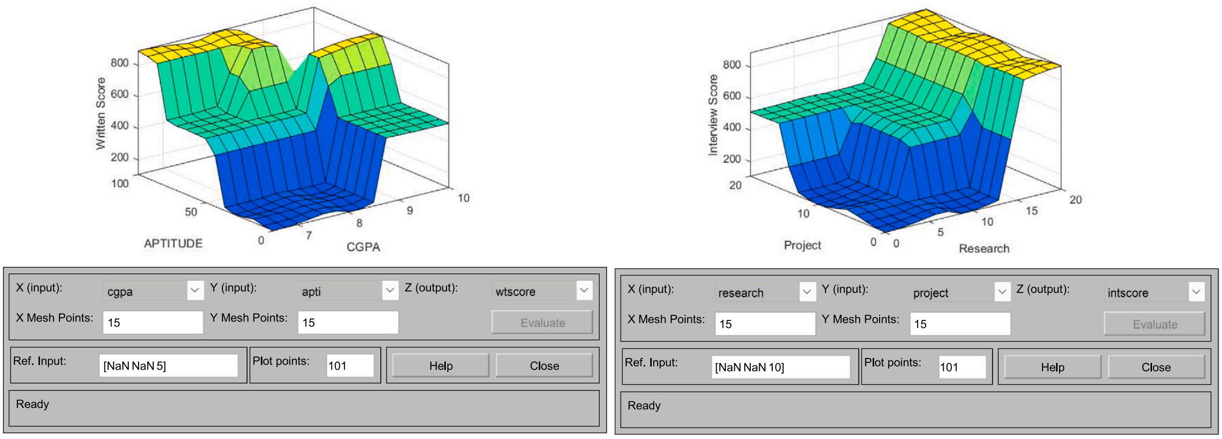

Fig. 1. Surface view plot of written test and interview models.

3.1. Application of optimal placement and sizing problem by AFCPOA

Step 1: Initialize the test system data (i.e. line data, bus data), DG data, DG limits, Dstatcom data, Dstatcom limits, BESS data, BESS limits and initialize the number of candidates (N_c) within the search space with a number of variables (N_v).

Step 2: Run the distribution power flow and find the active, reactive power losses and voltage deviations in the system.

Step 3: Compute the Objective function and fitness of each candidate using Eq. (15) and (16). Sort the fitness of all the candidates as follows.

$$min(F) = w1 * Obj_1 + w2 * Obj_2 + w3 * Obj_3 \tag{15}$$

$$fitness = 1/(1 + min(F)) \tag{16}$$

Step 4: Randomly discard r_f % (resume filtering) of candidates from the list. Generally r_f considered 5%.

Step 5: Now compute Written test score which has three parameters to be considered i.e. CGPA, Aptitude score and Programming skills.
(a) CGPA score of each candidate is computed using Eq. (17). The CGPA score should be between 6.5 and 10.

$$CGPA_{Score} = \left(\frac{Fitness - min(Fitness)}{max(Fitness) - min(Fitness)}\right) * (10 - 6.5) + 6.5 \tag{17}$$

(b) Aptitude score of each candidate can be computed using CGPA score of candidate using Eq. (18). Range of aptitude score can be considered between 0 to 100.

$$Aptitude_{Score} = 100 * \frac{CGPA_{Score}}{max(CGPA_{Score})} \tag{18}$$

(c) The programming skill score of candidate can be computed using Eq. (19).

$$Programming_{score} = rand * 10 * \frac{candidate(CGPA_{Score})}{max(CGPA_{Score})} \tag{19}$$

Step 6: A Fuzzy rule base is designed to obtain the final score of the Written test based on three parameters i.e. CGPA, Aptitude, and Programming scores. The fuzzy surface viewer plot of Written test is shown in Fig. 1. The fuzzy rules are tabulated in Table 1. The sample fuzzy logic diagram of written test and interview models are shown in Fig. 3.

Step 7: Now Compute the Interview score which has three parameters to be considered i.e. Research output, Projects and Communication skills of each candidate.
(a) The research score can be computed using Eq. (20):

$$Research_{Score} = 0.95 * 20 * \frac{CGPA_{Score}}{max(CGPA_{Score})} \tag{20}$$

(b) The project score can be computed using equation (21):

$$Project_{Score} = 0.8 * 20 * \frac{CGPA_{Score}}{max(CGPA_{Score})} \tag{21}$$

(c) The score in communication skills can be computed using Eq. (22):

$$Communication_{Score} = rand * 20 * \frac{CGPA_{Score}}{max(CGPA_{Score})} \tag{22}$$

Step 8: A Fuzzy rule base is designed to obtain the final score of the Interview based on three parameters i.e. Research output, Projects, and Communication skill scores. The fuzzy surface viewer plot of Interview is shown in Fig. 1. The fuzzy rules are tabulated in Table 1.

Step 9: The Final score of the candidate can be computed by adding both written test and interview scores which is defined as the calibre of candidate in Eq. (23). The weightage for written test is considered to be 60% and while 40% is allocated for interview.

$$Calibre_{finalscore} = 0.6 * WrittenTest_{Score} + 0.4 * Interview_{Score} \tag{23}$$

Step 10: Now, based on calibre scores, candidates are divided into trainable and untrainable candidates. u_t% of untrainable candidates are eliminated from the process and the remaining candidates are trained based on elite candidate in the list. The computation of elite new and train candidates equations is given in (24) and (25) respectively.

$$Elite_{new} = Elite + sigmoid(Attempts) * (-ulim + 2 * ulim * rand)/100 \tag{24}$$

$$Train = Candidate + (-1 + 2 * rand) * (Elite_{new} - abs(Candidate)) \tag{25}$$

Step 11: The Written test part and interview test part are repeated until the algorithm converges. At convergence phase, the knowledge level of candidates is equal and optimum.

Step 12: Now, with optimal candidate solution, run the power flow and compute the total active power losses, reactive power losses, and voltage deviations in the system

4. Simulation results

The designed AFCPOA has been applied to IEEE 33 bus test system and PG & E 69 bus test system for determining the optimal sizing and location of DG units, DSTATCOM and BESS. For the purpose of implementing the proposed methods, MATLAB-R 2022a was uploaded to a personal computer with an Intel (R) Core I5 processor and 8 GB of RAM. The proposed algorithm's performance was evaluated by considering the 25 benchmark test functions listed in Table 2 and compared with the other methods. The results of test functions (see

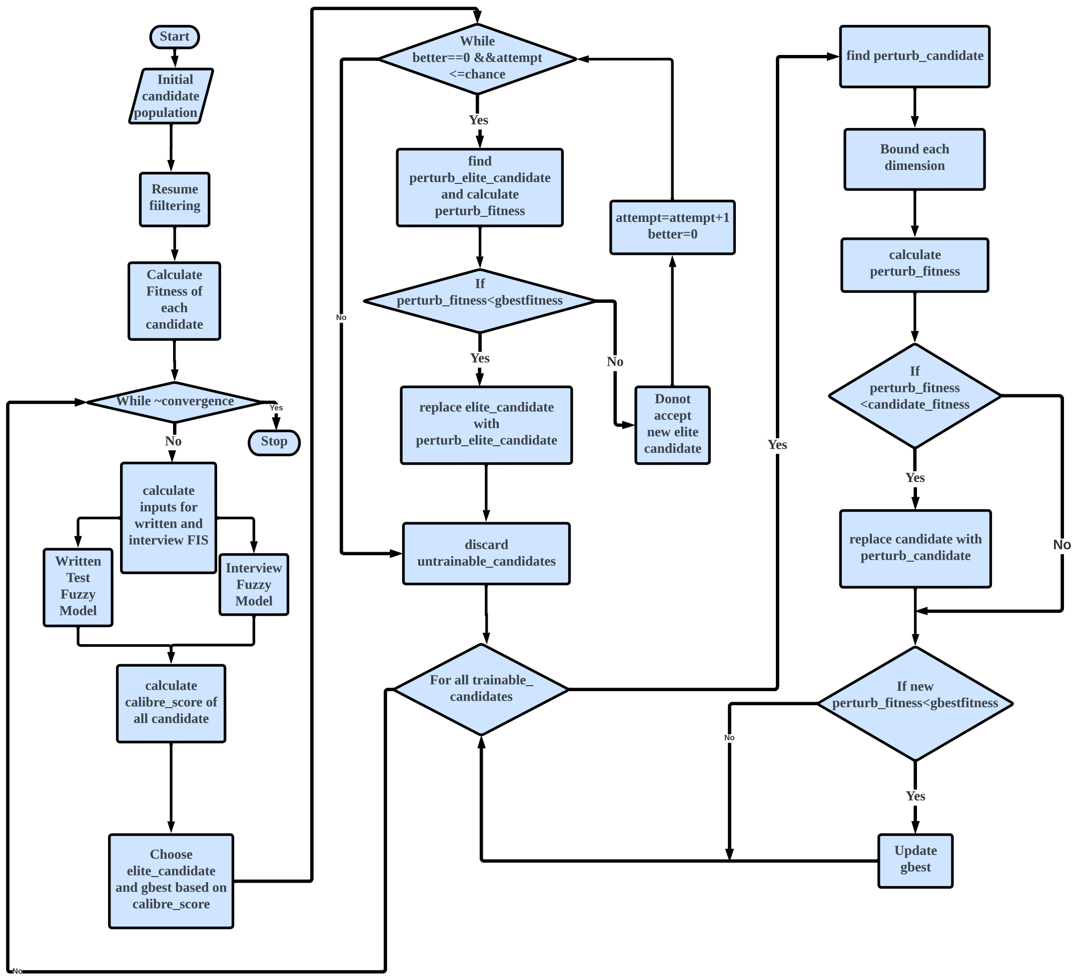

Fig. 2. Flow chart of proposed AFCPOA.

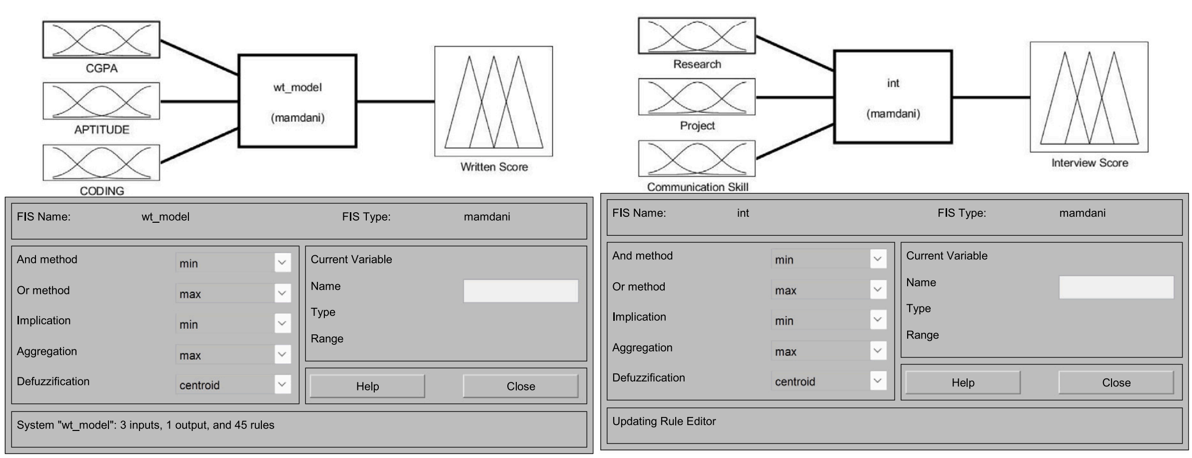

Fig. 3. A sample fuzzy logic diagram of written test and interview model.

Figs. 4–6) such as optimal best, worst, mean, and standard deviation are listed in Table 3. The statistical parameter comparison results of benchmark test functions are listed in Table 4. By integrating single to numerous DSTATCOM, BESS, and DG units, active power losses, reactive power losses, and voltage variations can be reduced. The single objective active power loss reduction and multi objectives for active power loss reduction, reactive power loss reduction and, voltage deviation minimization for optimal placement and sizing problem were considered for both test systems using AFCPOA. The results obtained by AFCPOA outperformed other existing methods in the literature for both single objective and multi objective problems. For each test system, five case studies were taken into consideration: the first was the best allocation and sizing of DGs alone, the second was the best allocation and sizing DSTATCOMs alone, the third was the best allocation and sizing with a combination of DGs and DSTATCOMs, the fourth was the best allocation and sizing with a combination of BESS and PVDGs, and the fifth best allocation and sizing with a combination of BESS, PVDGs and DSTATCOMs.

Table 1
Fuzzy rules of written test and interview models.

Written part input				Output	Interview part input				Output
Rules	CGPA	Aptitude	Coding	Written score	Rules	Research	Project	Communication skills	Interview score
Rule1	Low	Poor	Poor	Poor	Rule1	Low	Low	Poor	Poor
Rule2	Low	Poor	Good	Poor	Rule2	Low	Low	Good	Poor
…	…	…	…	…	…	…	…	…	…
Rule9	Low	Good	Excellent	Excellent					
…	…	…	…	…	Rule13	Medium	Medium	Poor	Good
Rule25	Medium	Very Good	Poor	Good	…	…	…	…	…
…	…	…	…	…	Rule20	High	Low	Good	Excellent
Rule35	High	Average	Good	Good	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…
Rule45	High	Excellent	Excellent	Excellent	Rule27	High	High	Excellent	Excellent

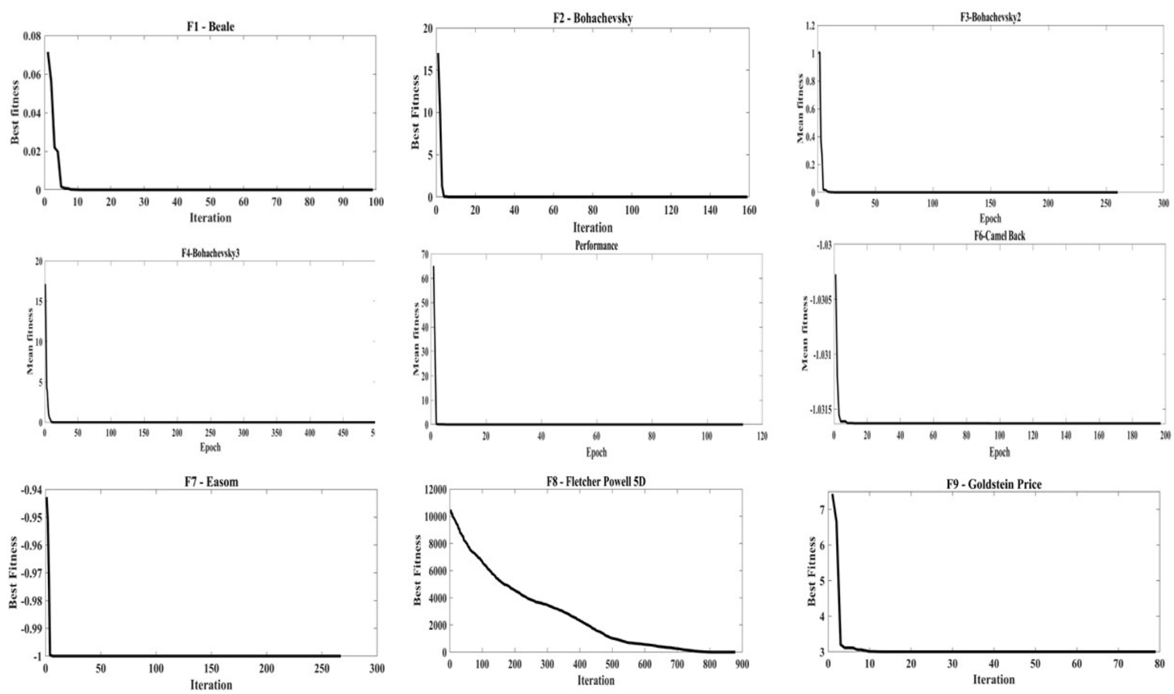

Fig. 4. Convergence plots of Test Functions F1 to F9.

4.1. Case study I: IEEE 33 bus RDS

The base case was IEEE 33 bus RDS without considering any DGs, DSTATCOMs, or BESS in the system. With the distribution power flow applied on IEEE 33 bus RDS, the total active power losses were 210.99 kW, reactive power losses 143.03 kVAR, maximum voltage deviation value is 0.0808 p.u and the minimum bus voltage was 0.9192 p.u at 18th bus, and these are considered base case values. In order to validate the performance of AFCOPA algorithm with other existing algorithms, a single and multi objective function is considered for optimal location and sizing of 3 DGs integration into IEEE 33 bus RDS. From Table 1 the optimal locations 24, 14, 30 and sizes will be 1102 kW, 757 kW, and 1075 kW respectively, with a reduction percentage of 72.8%. In case of multi objective problem, the optimal locations are at 7, 15, 31 and the sizes 1000 kW, 680.9 kW, and 1000 kW respectively with a minimum real power loss of 80.8 kW, reactive power loss of 57 kVAR and maximum voltage deviation of 0.00202 p.u. The comparison results of single and multi objective problems are tabulated in Table 5 and Table 6 respectively.

4.1.1. By DGs integration

The total active power losses, total reactive power losses, and voltage deviations are reduced as a result of DG integration into IEEE 33 bus RDS using AFCPOA. The best position, size, active power loss with DG, reactive power loss with DG, percentage of active power reduction, percentage of reactive power reduction, maximum voltage deviation value, minimum bus voltage, and bus number are all shown in Table 7. When integrating single to multiple DGS into IEEE 33 bus RDS, all three objectives were given the same weight. Fig. 7 shows the voltage profile plot of IEEE 33 bus RDS for all experiments with a combination of single DG to multiple DGs integration. The best result was 61.70% of active power reduction, 60.91% of reactive power loss reduction, maximum voltage deviation of 0.01 p.u with a minimum bus voltage of 0.99 p.u at 18th bus.

4.1.2. By DSTATCOMs integration

The total active power losses, total reactive power losses, and voltage deviations were reduced as a result of DSTATCOM integration into IEEE 33 bus RDS using AFCPOA. The best position, size, active power loss with DG, reactive power loss with DG, percentage of active power reduction, percentage of reactive power reduction, maximum voltage deviation value, minimum bus voltage, and bus number are all shown in Table 7. When integrating single to multiple DSTATCOMs into IEEE 33 bus RDS, all three objectives were given the same weight. Fig. 8 shows the voltage profile plot of IEEE 33 bus RDS for all experiments with a combination of single DSTATCOM to multiple DSTATCOMs integration. The best result is 30.7% of active power reduction, 29.1% of reactive power loss reduction, maximum voltage deviation of 0.0412

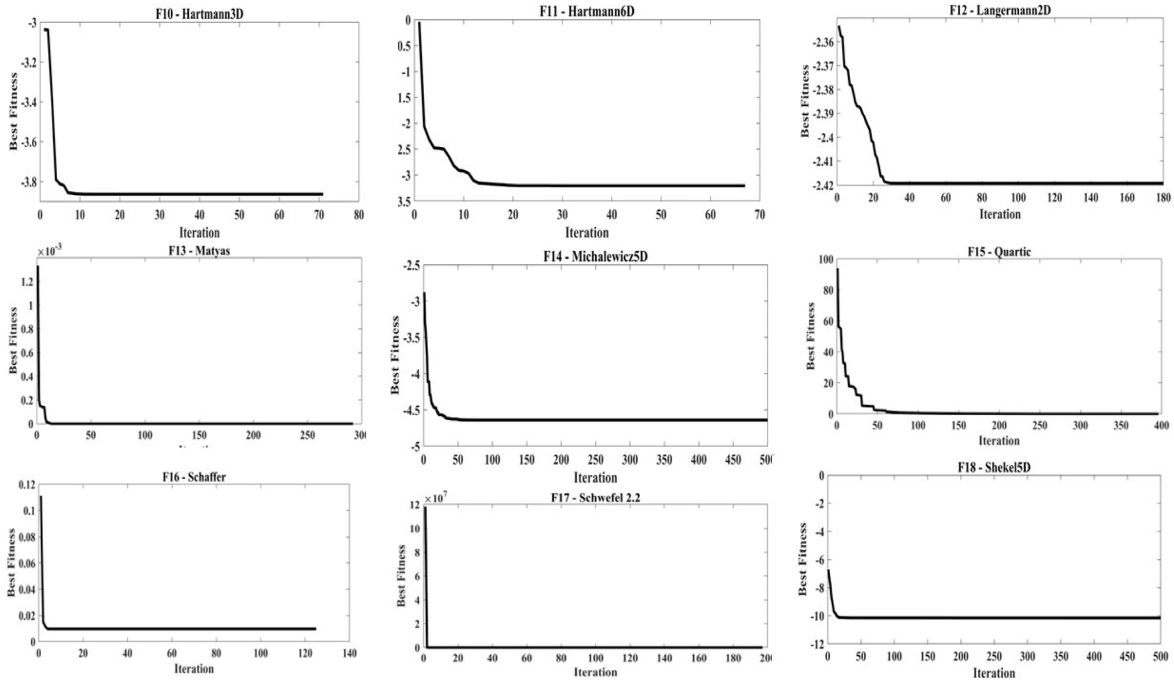

Fig. 5. Convergence plots of Test Functions F10 to F18.

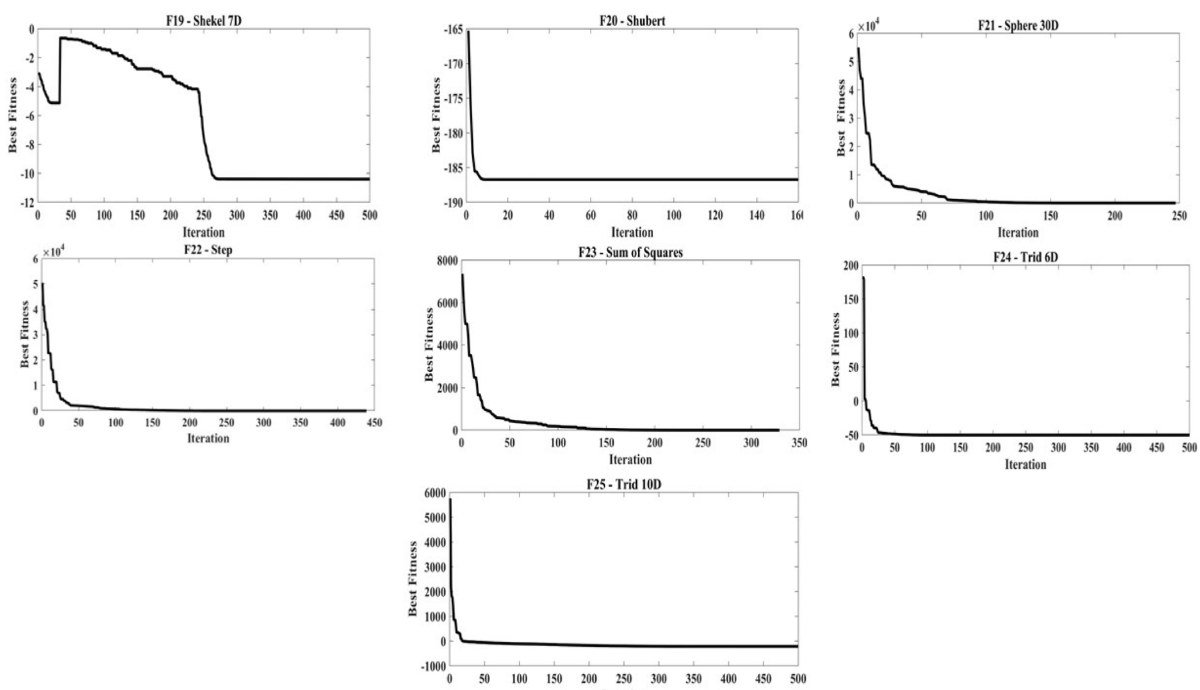

Fig. 6. Convergence plots of Test Functions F19 to F25.

p.u with minimum bus voltage of 0.9588 p.u at 30th bus. But integration of DSTATCOM alone did not yield efficient results in terms of losses or voltage improvement when compared to integration of DGs. If we integrate both DGs and DSTATCOM into the system, the best results of system performance are obtained.

4.1.3. By integrating DGs and DSTATCOM

The total active power losses, total reactive power losses, and voltage deviations were reduced as a result of DG+DSTATCOM integration into IEEE 33 bus test system. The best position, size, active power loss with DG+DSTATCOM, reactive power loss with DG+DSTATCOM, percentage of active power reduction, percentage of reactive power reduction, maximum voltage deviation value, minimum bus voltage, and bus number are all shown in Table 7. When integrating single to multiple DG+DSTATCOMs into IEEE 33 bus RDS, all three objectives were given the same weight. Fig. 9 shows the voltage profile plot of IEEE 33 bus RDS for all experiments, from single DG+DSTATCOM to multiple DG+DSTATCOMs, which yields voltage values with the integration of DG+DSTATCOMs. In this study, DGs help to reduce active power losses and DSTATCOMs help to reduce reactive power

Table 2
List of unconstrained benchmark test functions and its properties.

S. No	Name	Dim	Range	Type	Global minima	Function
1	Beale	5	[−4.5, 4.5]	UN	0	$\left(1.5-x_1+x_1x_2\right)^2+\left(2.25-x_1+x_1x_2^2\right)^2+\left(2.625-x_1+x_1x_2^3\right)^2$
2	Bohachevsky1	2	[−100, 100]	MS	0	$x_1^2+2x_2^2-0.3\cos\left(3x_1\right)\ -0.4\cos\left(4x_2\right)\ +0.7$
3	Bohachevsky2	2	[−100, 100]	MN	0	$x_1^2+2x_2^2-0.3\cos\left(3x_1*4x_2\right)\ +0.3$
4	Bohachevsky3	2	[−100, 100]	MN	0	$x_1^2+2x_2^2-0.3\cos\left(3x_1+4x_2\right)\ +0.3$
5	Booth	2	[−10, 10]	MS	0	$\left(x_1+2x_2-7\right)^2+\left(2x_1+x_2-5\ \right)^2$
6	Camel Back	2	[−5, 5]	MN	−1.03163	$4x_1^2-2.1x_1^2+\frac{1}{3}x_1^6+x_1x_2-4x_2^2+4x_2^4$
7	Eason	2	[−100, 100]	UN	−1	$-\cos\left(x_1\right)\ \cos\left(x_2\right)\ \exp(-\left(x_1-\right)^2-\left(x_2-\right)^2)$
8	Fletcher Powell5	5	[-π, π]	MN	0	$\sum_{i=1}^{n}\left(A_i-B_i\right)^2$ $A_i=\sum_{j=1}^{n}a_{ij}sin_j+b_{ij}cos_j$ $B_i=\sum_{j=1}^{n}a_{ij}sinx_j+b_{ij}cosx_j$
9	Goldstein Price	2	[−2, 2]	MN	3	$\left[1+\left(x_1+x_2+1\right)^2\left(19-14x_1+3x_1^2-14x_2+6x_1x_2+3x_2^2\right)\right]$ $\left[30+\left(2x_1-3x_2\right)^2(18-32x_1+12x_1^2+48x_2-36x_1x_2+27x_2^2)\right]$
10	Hartmann3	3	[0, 1]	MN	−3.86	$-\sum_{i=1}^{4}c_i\exp[\sum_{j=1}^{3}a_{ij}\left(x_j-p_{ij}\right)^2]$
11	Hartmann6	6	[0, 1]	MN	−3.32	$-\sum_{i=1}^{4}c_i\exp[\sum_{j=1}^{6}a_{ij}\left(x_j-p_{ij}\right)^2]$
12	Langermann2	2	[0, 10]	MN	−1.08	$-\sum_{i=1}^{m}c_i(\exp(-\frac{1}{}\sum_{j=1}^{n}\left(x_j-a_{ij}\right)^2)\cos(\sum_{j=1}^{n}\left(x_j-a_{ij}\right)^2))$;m=5
13	Matyas	2	[−10, 10]	UN	0	$0.26\left(x_1^2+x_2^2\right)-0.48x_1x_2$
14	Michalewicz5	5	[0, π]	MS	−4.6877	$-\sum_{i=1}^{n}\sin\left(x_i\right)\ \left(\sin\left(\frac{ix_i^2}{}\right)\ \right)^{2m};m=10$
15	Quartic	30	[−1.28, 1.28]	US	0	$\sum_{i=1}^{n}i(x_i)^4+random(0,1)$
16	Schaffer	2	[−100, 100]	MN	0	$0.5+\frac{\left(\sin\sqrt{x_1^2+x_2^2}\right)^2-0.5}{\left(1+0.001\left(x_1^2+x_2^2\right)\right)^2}$
17	Schwefel2.2	30	[−10, 10]	UN	0	$\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert$
18	Shekel5	4	[0, 10]	MN	−10.15	$-\sum_{i=1}^{5}\left[\left(x-a_i\right)\left(x-a_i\right)^T+c_i\right]^{-1}$
19	Shekel7	4	[0, 10]	MN	−10.4	$-\sum_{i=1}^{7}\left[\left(x-a_i\right)\left(x-a_i\right)^T+c_i\right]^{-1}$
20	Shubert	2	[−10, 10]	MN	−186.73	$\left(\sum_{i=1}^{5}icos\left(\left(i+1\right)x_1+i\right)\right)\left(\sum_{i=1}^{5}icos\left(\left(i+1\right)x_2+i\right)\right)$
21	Sphere	30	[−100, 100]	US	0	$\sum_{i=1}^{n}(x_i)^2$
22	Step	30	[−100, 100]	US	0	$\sum_{i=1}^{n}(x_i+0.5)^2$
23	Sum of Squares	30	[−10, 10]	US	0	$\sum_{i=1}^{n}i(x_i)^2$
24	Trid6	6	[-D^2, D^2]	UN	−50	$\sum_{i=1}^{n}\left(x_i-1\right)^2-\sum_{i=2}^{n}x_ix_{i-1}$
25	Trid10	10	[-D^2, D^2]	UN	−210	$\sum_{i=1}^{n}\left(x_i-1\right)^2-\sum_{i=2}^{n}x_ix_{i-1}$

Table 3
Statistical parameters obtained by novel AFCPOA on 25 unconstraint benchmark test functions.

S.No	Function name	Optimum	Best	Worst	Mean	SD
1	Beale	0	0	0	0	00E+00
2	Bohachevsky1	0	0	0	0	00E+00
3	Bohachevsky2	0	0	0	0	00E+00
4	Bohachevsky3	0	0	0	0	00E+00
5	Booth	0	0	0	0	00E+00
6	Camel Back	−1.03163	−1.03163	−1.02075	−1.03026	0.002273
7	Eason	−1	−1	−1	−1	00E+00
8	Fletcher Powell5	0	0	0	0	00E+00
9	Goldstein Price	3	3.000029	3.027537	3.003569	0.00578
10	Hartmann3	−3.86	−3.86278	−3.85573	−3.86254	0.001287
11	Hartmann6	−3.32	−3.32237	−2.84796	−3.16408	0.102589
12	Langermann2	−1.08	−1.08	−1.08	−1.08	0.000
13	Matyas	0	0	0	0	00E+00
14	Michalewicz5	−4.6877	−4.68766	−4.33313	−4.56657	0.104172
15	Quartic	0	0	0	0	00E+00
16	Schaffer	0	0	0	0	00E+00
17	Schwefel2.2	0	0	0	0	00E+00
18	Shekel5	−10.15	−10.1532	−10.1506	−10.1528	0.000747
19	Shekel7	−10.4	−10.4029	−10.4016	−10.4028	0.000352
20	Shubert	−186.73	−186.651	−184.044	−185.669	0.8803207
21	Sphere	0	0	0	0	00E+00
22	Step	0	0	0	0	00E+00
23	Sum of Squares	0	0	0	0	00E+00
24	Trid6	−50	−50	−50	−50	0
25	Trid10	−210	−210	−210	−210	0

SD: standard deviation.

Table 4
Comparison of the statistical parameters of AFCPOA with other algorithms on benchmark test functions.

F. No	Statistic	GA	PSO	DE	ABC	TLBO	JA	AFCPOA (Proposed)
F1	M	0	0	0	0	0	0	0
	SD	0	0	0	0	0	0	0
	Best	–	–	–	–	–	0	0
F2	M	0	0	0	0	0	0	0
	SD	0	0	0	0	0	0	0
	Best	–	–	–	–	–	0	0
F3	M	0.06829	0	0	0	0	0	0
	SD	0.078216	0	0	0	0	0	0
	Best	–	–	–	–	–	0	0
F4	M	0	0	0	0	0	0	0
	SD	0	0	0	0	0	0	0
	Best	–	–	–	–	–	0	0
F5	M	0	0	0	0	0	0	0
	SD	0	0	0	0	0	0	0
	Best	–	–	–	–	–	0	0
F6	M	−1.03163	−1.031629	−1.031628	−1.031629	–	–	−1.03026
	SD	0	0	0	0	–	–	0.002273
	Best	–	–	–	–	–	–	−1.03163
F7	M	−1	−1	−1	−1	−1	−1	−1
	SD	0	0	0	0	0	0	0
	Best	–	–	–	–	–	−1	−1
F8	M	0.004303	1457.8834	5.98878	0.173550	2.203813	0.00016	0
	SD	0.009469	1269.3624	7.334731	0.068175	4.386320	5.2E−4	0
	Best	–	–	–	–	–	0	0
F9	M	5.870093	3	3	3	3	3	3.003569
	SD	1.07173	0	0	0	0	0	0.00578
	Best	–	–	–	–	–	3	3.000029
F10	M	−3.86278	−3.63335	−3.86278	−3.86278	−3.86278	−3.86278	−3.86254
	SD	0	0.116937	0	0	0	0	0.001287
	Best	–	–	–	–	–	−3.86	−3.86278
F11	M	−3.29822	−1.85913	−3.226881	−3.321995	–	–	−3.16408
	SD	0	0.116937	0	0	–	–	0.102589
	Best	–	–	–	–	–	–	−3.32237
F12	M	−1.08094	−0.67927	−1.08094	−1.08094	−1.08094	−1.08094	−1.08094
	SD	0	0.274621	0	0	0	0	0
	Best	–	–	–	–	–	−1.08094	−1.08094
F13	M	−0.96842	−0.5048579	−1.49999	−0.93815	–	–	0
	SD	0.004532	0	0	0.000183	0	0	0
	Best	–	–	–	–	–	−1.5	–
F14	M	−4.64483	−2.490873	−4.683482	−4.6876582	−4.6726578	−4.680138	−4.56657
	SD	0.09785	0.256952	0.012529	0	4.74E−02	1.58E−02	0.104172
	Best	–	–	–	–	–	−4.6877	−4.6877
F15	M	0.1807	0.001157	0.001363	0.0300166	–	–	0
	SD	0.02712	0.00028	0.00042	0.00487	–	–	0
	Best	–	–	–	–	–	–	0
F16	M	0.004239	0	0	0	–	–	0
	SD	0.004763	0	0	0	–	–	0
	Best	–	–	–	–	–	–	0
F17	M	11.0214	0	0	0	–	–	0
	SD	1.386856	0	0	0	–	–	0
	Best	–	–	–	–	–	–	0
F18	M	−5.66052	−2.08701	−10.1532	−10.1532	–	–	−1.01528
	SD	3.86674	1.17846	0	0	–	–	0.000747
	Best	–	–	–	–	–	–	0
F19	M	−5.34409	−1.989871	−10.40294	−10.402941	–	–	−10.4028
	SD	3.517134	1.420602	0	0	–	–	0.000352
	Best	–	–	–	–	–	–	−10.1532
F20	M	−186.731	−186.73091	−186.7309	−186.73091	–	–	−185.669
	SD	0	0	0	0	–	–	0.8803207
	Best	–	–	–	–	–	–	−186.651
F21	M	1.11E+03	0	0	0	0	0	0
	SD	74.214474	0	0	0	0	0	0
	Best	–	–	–	–	–	0	0
F22	M	1.17E+03	0	0	0	–	–	0
	SD	76.5615	0	0	0	–	–	0

(continued on next page)

Table 4 (*continued*).

F. No	Statistic	GA	PSO	DE	ABC	TLBO	JA	AFCPOA (Proposed)
	Best	–	–	–	–	–	–	0
F23	M	1.48E+02	0	0	0	0	0	0
	SD	74.214474	0	0	0	0	0	0
	Best	–	–	–	–	–	0	0
F24	M	−49.9999	−50	−50	−50	−50	−50	−50
	SD	2.25E−05	0	0	0	0	0	0
	Best	–	–	–	–	–	−50	−50
F25	M	0.193417	0	0	0	0	−210	−210
	SD	0.035313	0	0	0	0	0	0
	Best	–	–	–	–	–	−210	−210

'M': Mean and 'SD': Standard Deviation and '-': means Not Reported.

Table 5
Optimal location and size values considering single objective as active power reduction using various optimization methods on IEEE 33 bus RDS.

Optimization method	Year	DG_{Size} (MW)	DG_{Loc}	P^{wdg}_{Loss} (%)	V_{min} (p.u)
AFCPOA [Proposed]	**2023**	**1.102, 0.757, 1.075**	**24, 14, 30**	**72.8**	**0.9686**
CSCA [19]	2020	0.871, 1.09147, 0.95408	13, 24, 30	64.5	0.969
GSA-GAMS [18]	2019	0.80122, 1.0913, 1.05359	13, 24, 30	65.64	0.9686
ASFLA [17]	2019	0.5457, 0.9936, 1.2094	24, 29, 12	67	0.9781
SFLA [17]	2019	0.5639, 0.3182, 0.5144	28, 30, 14	58.86	0.977
FWA [17]	2019	0.5897, 0.1895, 1.0146	14, 18, 32	56.24	0.968
QOCSOS [16]	2019	0.8017, 1.0913, 1.0536	13, 24, 30	65.5	NA
SSA [15]	2019	0.7536, 1.1004, 1.0706	13, 23, 29	64.8	0.9686
SPEA2 [14]	2018	0.691, 0.7334, 0.7429	18, 29, 8	71.1	0.9616
WCA [13]	2018	0.8546, 1.1017, 1.181	14, 24, 29	65	0.973
EMA [12]	2018	0.9766, 1.16909, 0.94354	30, 24, 12	64.32	0.9684
TM [11]	2017	0.7199, 0.7199, 1.4397	15, 26, 33	49.52	0.996
MOTA [11]	2017	0.980, 0.960, 1.340	7, 14, 30	52.4	0.9986
HGWO [10]	2017	0.802, 1.090, 1.054	13, 24, 30	64.4	NA
SKHA [9]	2017	0.80181, 1.091, 1.0536	13, 24, 30	64.4	0.9687
BA [8]	2016	0.8163, 0.95235, 0.95235	15, 25, 30	63	0.98
IWO [7]	2016	0.6247, 0.1049, 1.056	14, 18, 32	57.7	0.9716
PSO & Analytical [6]	2016	0.790, 1.070, 1.010	13, 24, 30	64.1	NA
ACO-ABC [5]	2016	0.7547, 1.0999, 1.0714	14, 24, 30	62.8	0.9735
BSOA [4]	2015	0.632, 0.487, 0.550	13, 28, 31	56.1	0.9554
BFOA [20]	2014	0.633, 0.090, 0.947	17, 18, 33	51.5	0.964
HSA [3]	2013	0.5724, 0.107, 1.0462	17, 18, 33	52.3	0.967
GA-PSO [2]	2012	0.925, 0.863, 1.200	11, 16, 32	49.2	0.967
IWD [1]	2011	0.6003, 0.300, 1.0112	9, 16, 30	57.7	0.9696

Table 6
Optimal location and size values considering multi objective as active power reduction and maximum voltage deviation minimization using various optimization methods on IEEE 33 bus RDS.

Optimization method	DG_{Loc}	DG_{Size} (MW)	P^{wdg}_{Loss} (kW)	Q^{wdg}_{Loss} (kVAR)	VD^{wdg} (p.u)
Base Case	–	–	210.99	143.03	0.9223
GA [11]	11, 29, 30	1.5000, 0.4228, 1.0714	106.3	NA	0.0407
PSO [11]	8, 13, 32	1.1768, 0.9816, 0.8297	105.3	NA	0.0335
GA-PSO [11]	11, 16, 32	0.9250, 0.8630, 1.2000	103.4	NA	0.0124
TLBO [21]	12, 28, 30	1.1826, 1.1913, 1.1863	124.7	NA	0.0011
QOTLBO [21]	13, 26, 30	1.0834, 1.1876, 1.1992	103.4	NA	0.0011
TM [11]	15, 26, 33	0.7199, 0.7199, 1.4397	102.30	NA	0.0040
MOTA [11]	7, 14, 30	0.9800, 0.9600, 1.3400	96.30	NA	0.0014
MOSCA [19]	13, 25, 32	1.247, 1.061, 1.223	89.92	NA	0.0023
MOCSCA [19]	13, 4, 30	1.098, 0.986, 1.584	88.43	NA	0.0016
AFCPOA [Proposed]	**7, 15, 31**	**1.000, 0.6809, 1.000**	**80.8**	**57**	**0.00202**

losses. The best result is 93.33% active power reduction, 92.1% reactive power loss reduction, maximum voltage deviation of 0.0059 p.u with a minimum bus voltage of 0.9941 p.u at 22th bus.

4.1.4. By integrating BESS and PVDGs

In this case, the PVDGs were fixed at optimal locations with a capacity of 500 kW and the power generation from PVDG is available only around 7 h in a day (say 10 am–5 pm). The BESS for each unit capacity was considered 500 kW. Now it was optimally placed and sized to minimize energy loss in addition to providing energy supply to the system, as shown in Table 7. AFCPOA was applied for optimal placement and sizing of BESS units in the presence of PVDGs. The best result is 64.54% active power reduction, 63.92% reactive power loss reduction, a maximum voltage deviation of 0.0106 p.u with a minimum bus voltage of 0.9894 p.u at 33th bus. Fig. 10 shows the voltage profile plot of IEEE 33 bus RDS in this case.

4.1.5. By integrating BESS, PVDG and DSTATCOM

In this case, PVDGs and DSTATCOMs were fixed at optimal locations with a capacity of 500 kW and 500 kVAR. The BESS at each unit capacity was considered as 500 kW and it was optimally placed and sized to minimizes the energy loss in addition to providing energy supply to the system as shown in Table 7. AFCPOA was applied for optimal placement and sizing of BESS units in the presence of PVDGs,

Table 7
Optimal results of various case studies on IEEE 33 bus RDS using proposed AFCPOA.

Type of device	Number	Opt_{loc}^{bus}	Opt_{size} (MW)	P_{loss} (kW)	Q_{loss} (kVAR)	$\%P_{loss}$	$\%Q_{loss}$	VD_{max} (p.u)	V_{min}^{bus} (p.u)
By integrating DGs	1	12	1	129.4	86	38.67	39.87	0.0684	0.9316, 33
	2	31	1	88.7	60.4	57.96	57.77	0.0297	0.9703, 30
		13	1						
	3	7	1						
		15	0.6809	80.8	57	61.70	60.14	0.0202	0.981, 33
		31	1						
	4	27	1						
		31	1	81.8	55.9	61.23	60.91	0.01	0.99, 18
		24	1						
		13	0.9322						
	5	13	0.9402	85	58.3	59.71	59.23	0.006	0.994, 29
		26	0.9738						
		31	0.8894						
		24	1.0000						
		28	0.4140						
By integrating DSTATCOM	1	30	1	146.9	98.1	30.37	31.41	0.077	0.9230, 18
	2	31	1	149	101.8	29.38	28.82	0.047	0.9530, 18
		14	0.7952						
	3	16	0.5320	149.8	104.7	29.01	26.7	0.0413	0.9587, 18
		31	0.9982						
		7	0.8979						
	4	33	0.4443	148.7	103.6	29.5	27.5	0.0409	0.9591, 31
		29	0.6938						
		7	0.8969						
		17	0.4684						
	5	7	0.7792	146.2	101.3	30.7	29.1	0.0412	0.9588, 30
		17	0.2842						
		31	0.9940						
		24	0.4487						
		13	0.2771						
By integrating DGs& DSTATCOM combination	1	30	1	75.6	52.4	64.16	63.36	0.0617	0.9383, 18
	2	10	0.8637	34.6	24.4	83.60	82.94	0.0166	0.9884, 18
		30	1						
	3	25	0.6737	19.3	14.8	90.85	89.65	0.0062	0.9938, 22
		13	1						
		30	0.6990						
	4	25	0.5973	14.5	11.5	93.12	91.95	0.0047	0.9953, 20
		30	0.8269						
		6	0.6697						
		14	0.4580						
	5	15	0.3928	14.1	11.2	93.33	92.1	0.0059	0.9941, 22
		7	0.6122						
		4	0.4663						
		31	0.7136						
		25	0.5499						
By integrating BESS & PVDG combination	1	15	0.5	113.5	75.1	46.20	47.49	0.0583	0.9417, 33
	2	15	0.5	81.9	54.8	61.18	61.68	0.0304	0.9696, 33
		32	0.5						
	3	32	0.5	74.4	50.7	64.73	64.55	0.0179	0.9821, 33
		16	0.4158						
		28	0.5						
	4	17	0.1943	74.8	51.6	64.54	63.92	0.0106	0.9894, 33
		32	0.5						
		8	0.4970						
		30	0.2830						
	5	24	0.4398	79.2	46.2	62.46	61.89	0.0062	0.9942, 29
		32	0.4075						
		29	0.5000						
		17	0.1374						
		10	0.2578						
By integrating	1	14	0.5	63.1	41	70.09	71.33	0.0414	0.9586, 33
	2	7	0.5	28.4	20.3	86.53	85.80	0.0189	0.9811, 18
		31	0.4608						

(continued on next page)

Table 7 (*continued*).

Type of device	Number	Opt^{bus}_{loc}	Opt_{size} (MW)	P_{loss} (kW)	Q_{loss} (kVAR)	$\%P_{loss}$	$\%Q_{loss}$	VD_{max} (p.u)	V^{bus}_{min} (p.u)
BESS, PVDG and	3	3	0.5	12.4	9.6	94.12	93.28	0.0058	0.9941, 22
		7	0.4742						
		31	0.3391						
DSATCOM	4	3	0.5	11.2	8.5	94.69	94.05	0.0028	0.9972, 24
		21	0.1937						
		32	0.2911						
		8	0.0731						
combination	5	30	0.2174	12.9	9.9	93.88	93.07	0.002	0.9949, 29
		21	0.1054						
		2	0						
		3	0						
		22	0.0735						

$P^{basecase}_{loss}$ = 210.99 kW, $Q^{basecase}_{loss}$ = 143.03 kVAR, max ($VD^{basecase}$)= 0.0808.

Table 8
Optimal location and size values considering single objective as active power reduction using various optimization methods on PG & E 69 bus RDS.

Optimization method	Year	DG_{Size} (kW)	DG_{Loc}	P^{wdg}_{Loss} (%)	V_{min} (p.u)
AFCPOA [Proposed]	2023	0.8157, 0.5253, 0.9248	61, 17, 61	70.2	0.9979
CSCA [19]	2020	0.3659, 1.67585, 0.06552	17, 61, 67	68.8	0.98
QOCSOS [16]	2019	0.5268, 0.3804, 1.719	11, 18, 61	69.14	NA
ASFLA [17]	2019	1.9626, 0.6274, 0.9939	62, 16, 40	69.13	0.9913
SFLA [17]s	2019	1.0887, 0.1673, 0.9809	57, 63, 26	65.43	0.9752
FWA [17]	2019	0.4805, 1.1986, 0.2258	65, 61, 27	65.39	0.974
SSA [15]	2019	0.380, 0.527, 1.718	17, 10, 60	69.1	0.9789
WCA [13]	2018	0.775, 1.105, 0.438	61, 62, 23	68.2	0.987
EMA [12]	2018	0.91072, 1.2639, 0.68906	69, 69, 50	69.3	0.9817
HGWO [10]	2017	0.527, 0.380, 1.718	11, 17, 61	69.14	0.98
BFOA [20]	2014	0.2954, 0.4476, 1.3451	27, 65, 61	66.56	0.9808
HSA [3]	2013	1.3024, 0.369, 0.1018	63, 64, 65	61.4	0.967
GA [2]	2012	0.9297, 1.0752, 0.9848	21, 62, 64	60.4	NA
PSO [2]	2012	1.1998, 0.7956, 0.9925	61, 63, 17	63.02	NA
GA-PSO [2]	2012	0.9105, 1.1926, 0.8849	21, 61, 63	63.9	NA

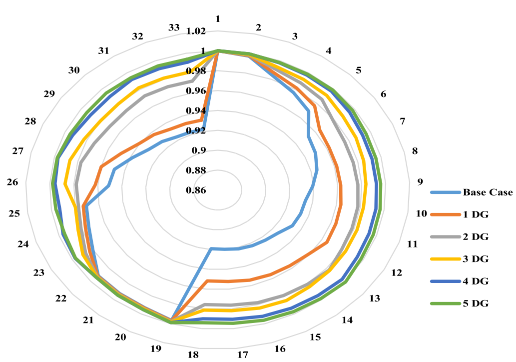

Fig. 7. Voltage profile radar chart of IEEE 33 bus RDS with integration of DGs.

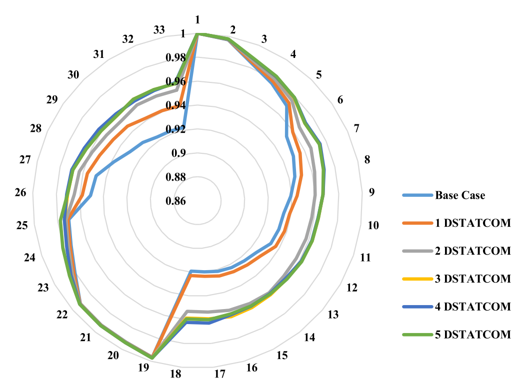

Fig. 8. Voltage profile radar chart of IEEE 33 bus RDS with integration of DSTATCOMs.

and DSTATCOMs. The best result was 94.69% active power reduction, 94.05% reactive power loss reduction, maximum voltage deviation of 0.002 p.u with a minimum bus voltage of 0.9972 p.u at 24th bus. Fig. 11 shows the voltage profile plot of IEEE 33 bus RDS.

4.2. Case study II: PG & E 69 bus RDS

The base case was considered as PG & E 69 bus RDS without considering DGs, DSTATCOMs, or BESS in the system. With the distribution power flow on PG & E 69 bus RDS, the total active power losses were 224.96 kW, reactive power losses were 102.15 kVAR, the maximum voltage deviation value was 0.0083 p.u and the minimum bus voltage was 0.9092 p.u at 65th bus and these were base case values. In order to validate the performance of AFCPOA algorithm with other existing algorithms, a single and multi objective optimization problem

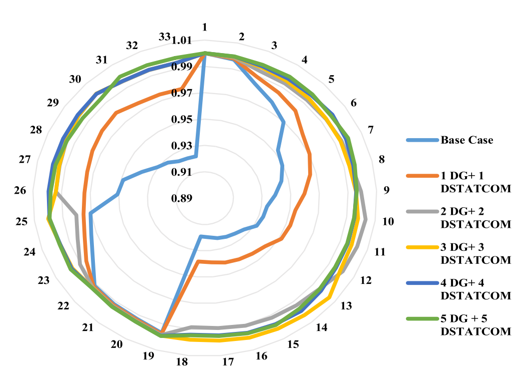

Fig. 9. Voltage profile radar chart of IEEE 33 bus RDS with integration of DGs and DSTATCOMs.

Table 9
Optimal location and size values considering multi objectives as active power reduction and maximum voltage deviation minimization using various optimization methods on PG& E 69 bus RDS.

Optimization method	DG_{Loc}	DG_{Size} (MW)	P_{Loss}^{wdg} (kW)	VD^{wdg} (p.u)	Q_{Loss}^{wdg} (kVAR)
AFCPOA [Proposed]	15, 61, 61	0.7366, 0.5468, 1.000	69	0.0021	35
Base Case	–	–	225	100	0.9092
GA [2]	21, 62, 64	0.9297, 1.0752, 0.9848	89	0.0012	NA
PSO [2]	17, 61, 63	0.9925, 1.199, 0.7956	83.2	0.0049	NA
GA-PSO [2]	21, 61, 63	0.9105, 1.1926, 0.8849	81.1	0.0031	NA
TLBO [21]	13, 61, 62	1.0134, 0.9901, 1.1601	82.2	0.0008	NA
QOTLBO [21]	15, 61, 63	0.8114, 1.147, 1.0022	80.6	0.0007	NA
SIMBO-Q [22]	15, 61, 62	0.7722, 1.3526, 0.8232	80	0.0007	NA
QOSIMBO-Q [22]	15, 61, 63	0.7754, 1.4385, 0.7235	79.7	0.0007	NA
MOSCA [19]	21, 61, 61	0.785, 1.1265, 1.0721	83.2	0.0010	NA
MOCSCA [19]	21, 61, 67	0.453, 2.190, 0.763	79.69	0.0002	NA

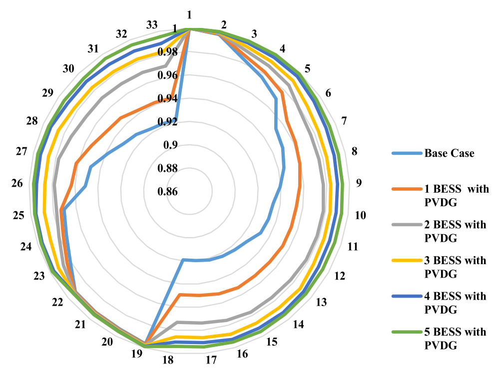

Fig. 10. Voltage profile radar chart of IEEE 33 bus RDS with integration of BESS in the presence of PVDG.

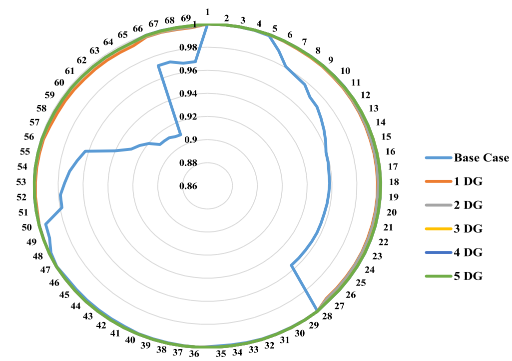

Fig. 12. Voltage profile radar chart of PG & E 69 bus RDS with integration of DGs.

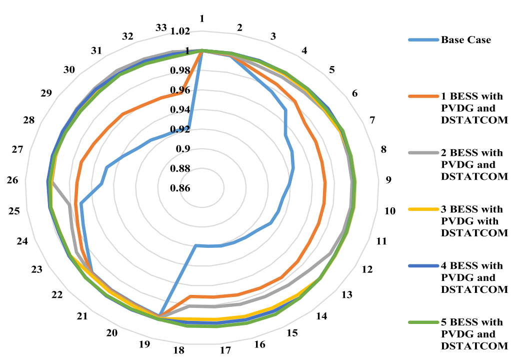

Fig. 11. Voltage profile radar chart of IEEE 33 bus RDS with integration of BESS in the presence of PVDG and DSTATCOM.

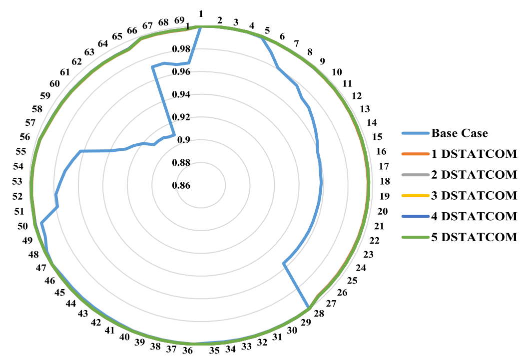

Fig. 13. Voltage profile radar chart of PG & E 69 bus RDS with integration of DSTATCOMs.

was considered for optimal location and sizing of 3 DGs into PG & E 69 bus RDS. From Table 8, the optimal locations were at 61, 17, 61 and sizes were 815.7 kW, 525.3 kW, and 924.8 kW respectively with reduction percentage of 70.2%. In case of multi objective problem, the optimal locations were at 15, 61, 61 and the sizes were 736.6 kW, 546.8 kW, and 1000 kW respectively with a minimum real power loss of 69 kW, reactive power loss of 35 kVAR and maximum voltage deviation of 0.0021 p.u. The comparison results of single and multi objective problem results are tabulated in Table 8 and Table 9 respectively.

4.2.1. By integrating DGs

The total active power losses, total reactive power losses, and voltage deviations were reduced as a result of DG integration into the PG&E 69 bus test system using AFCPOA. The best position, size, active power loss with DG, reactive power loss with DG, percentage of active power reduction, percentage of reactive power reduction, maximum voltage deviation value, minimum bus voltage, and bus number are shown in Table 10. When integrating the single to multiple DGS into PG& E 69 bus RDS, all three objectives were given the same weight. Fig. 12 shows the voltage profile plot of PG& E 69 bus RDS for all experiments, from single DG to multiple DGs, which yields voltage values with integration of DGs. The best result is 70.6% of active power loss reduction, 70% of reactive power loss reduction, maximum voltage deviation of 0.0022 p.u with a minimum bus voltage of 0.9978 p.u at 65th bus.

4.2.2. By integrating DSTATCOMs

The total active power losses, total reactive power losses, and voltage deviations were reduced as a result of DSTATCOM integration into PG & E 69 bus test system using AFCPOA. The best position, size, active power loss with DG, reactive power loss with DG, percentage of active power loss reduction, percentage of reactive powerloss reduction, maximum voltage deviation value, minimum bus voltage, and bus number are shown in Table 10. When integrating single to multiple DSTATCOMs into PG & E 69 bus RDS, all three objectives were given the same weight. Fig. 13 shows the voltage profile plot of PG & E 69 bus RDS

Table 10
Optimal results of various case studies on PG & E 69 bus RDS using proposed AFCPOA.

Type of device	Number	Opt_{loc}^{bus}	Opt_{size} (MW)	P_{loss} (kW)	Q_{loss} (kVAR)	$\%P_{loss}$	$\%Q_{loss}$	VD_{max} (p.u)	V_{min}^{bus} (p.u)
By integrating DGs	1	61	1.000	103	50	54.22	50	0.0050	0.9951, 64
	2	61 61	0.8055 0.7888	80	39	64.44	61	0.0031	0.997, 20
	3	61 15 61	0.7366 0.5468 1.000	69	35	69.33	65	0.0021	0.9979, 65
	4	61 11 21 61	0.7457 0.5372 0.3442 0.9321	67	34	70.2	66	0.0021	0.9979, 65
	5	61 49 61 12 21	0.8055 0.7888 0.8843 0.4814 0.3082	66	30	70.6	70	0.0022	0.9978, 65
By integrating DSTATCOM	1	61	1	139	65	38.2	35	0.0070	0.993, 65
	2	61 12	1 0.6229	133	62	40.8	38	0.0068	0.9932, 65
	3	9 61 18	0.5954 1.000 0.3019	131	62	41.77	38	0.0067	0.9933, 65
	4	20 11 61 64	0.2369 0.3735 0.9948 0.2040	130	61	42.22	39	0.0064	0.9936, 65
	5	51 18 62 49 12	0.3664 0.2273 1.000 0.5664 0.2702	131	61	41.77	39	0.0067	0.9933 65
By integrating DG & DSTATCOM combination	1	63	1	50	27	77.77	73.56	0.0033	0.9092, 65
	2	54 61	1 1	31	17	86.2	83.35	0.0024	0.9967, 64
	3	16 62 61	0.4875 0.5222 0.9978	13	10	94.22	90.2	0.0006	0.9977, 65
	4	61 61 49 15	0.9336 0.6355 0.7110 0.5644	12	5.3	94.66	94.81	0.0003	0.9997, 11
	5	69 13 61 62 22	0.2122 0.1775 0.9770 0.5178 0.2366	10	9.2	95.55	90.99	0.0006	0.997, 11
By integrating BESS & PVDG combination	1	61	0.5	140	66	37.76	35.38	0.0052	0.9936, 65
	2	61 65	0.5 0.5	103	50	54.21	51.05	0.0047	0.9953, 65
	3	17 57 64	0.5 0.5 0.5	98	47	56.43	53.98	0.0050	0.995, 65
	4	64 61 15 61	0.5 0.5 0.5 0.5	71	36	68.43	64.75	0.0027	0.9973, 65
	5	61 54 60 62 18	0.5 0.5 0.5 0.5 0.4841	70	35	68.88	65.73	0.0027	0.9973, 65
By integrating	1	61	0.5	78	38	65.32	62.79	0.0054	0.9946, 65
	2	61 62	0.5 0.5	48	26	78.66	74.54	0.0035	0.9965, 65

(*continued on next page*)

Table 10 (*continued*).

Type of device	Number	Opt_{loc}^{bus}	Opt_{size} (MW)	P_{loss} (kW)	Q_{loss} (kVAR)	$\%P_{loss}$	$\%Q_{loss}$	VD_{max} (p.u)	V_{min}^{bus} (p.u)
BESS, PVDG and	3	16 62 59	0.5 0.5 0.5	34	20	84.88	80.4	0.0034	0.9966, 65
DSTATCOM	4	61 17 61 62	0.5 0.4426 0.5 0.4850	12	10	94.66	90.21	0.0008	0.9992, 65
combination	5	18 61 61 49 63	0.4403 0.5 0.5 0.5 0.4769	10	5.19	95.55	94.91	0.0007	0.9993, 65

$P_{loss}^{basecase}$ = 224.96 kW, $Q_{loss}^{basecase}$ = 102.15 kVAR, max ($VD^{basecase}$)= 0.0083 p.u.

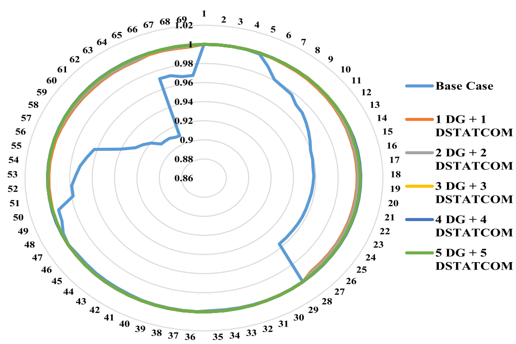

Fig. 14. Voltage profile radar chart of PG & E 69 bus RDS with integration of DGs and DSTATCOMs.

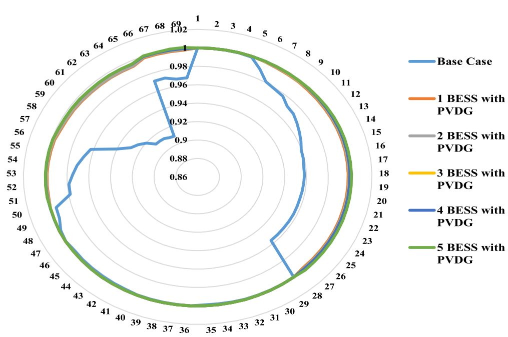

Fig. 15. Voltage profile radar chart of PG & E 69 bus RDS with integration of BESS in the presence of PVDGs.

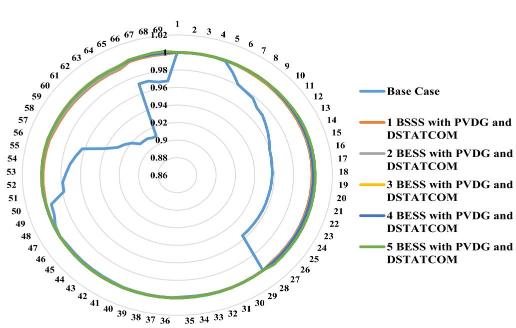

Fig. 16. Voltage profile radar chart of PG & E 69 bus RDS with integration of BESS in the presence of PVDG and DSTATCOMs.

for all experiments, from single DSTATCOM to multiple DSTATCOMs, which yields a range of voltage values. The best result is 42.22% active power reduction, 39% reactive power loss reduction, maximum voltage deviation of 0.0064 p.u with a minimum bus voltage of 0.9936 p.u at 65th bus. Integration of DSTATCOM alone does not give efficient results in terms of losses or voltage improvements compared to integration of DGs. If we integrate both DGs and DSTATCOM into the system, it gives the best results of system performance.

4.2.3. By integrating DGs and DSTATCOMs

The total active power losses, total reactive power losses, and voltage deviations were all reduced as a result of DG and DSTATCOM integration into PG & E 69 bus test system. The best position, size, active power loss with DG and DSTATCOM, reactive power loss with DG and DSTATCOM, percentage of active power loss reduction, percentage of reactive power loss reduction, maximum voltage deviation value, minimum bus voltage, and bus number are all shown in Table 10. When integrating single to multiple DG and DSTATCOMs into PG & E 69 bus RDS, all three objectives were given the same weight. Fig. 14 shows the voltage profile plot of PG & E 69 bus RDS for all experiments, from single DG and DSTATCOM to multiple DG and DSTATCOMs, which yields voltage values on integration of DG and DSTATCOMs. In this study, DGs help to reduce active power losses and DSTATCOM helps to reduce reactive power losses. The best result is 95.55% of active power loss reduction, 94.81% of reactive power loss reduction, maximum voltage deviation of 0.0006 p.u with a minimum bus voltage of 0.9997 p.u at 11th bus.

4.2.4. By integrating BESS and PVDGs

In this case, PVDGs were fixed at optimal locations with a capacity of 500 kW and the power generation from PVDG was available only around 7 h in a day (10 am–5 pm). Each BESS unit's capacity was considered to be as 500 kW. Now it was optimally placed and sized to minimize energy loss in addition to energy supply to the system as shown in Table 10. AFCPOA was applied for optimal placement and the sizing of BESS units was in the presence of PVDGs with the best result of 68.88% of active power reduction, 65.73% of reactive power loss reduction, maximum voltage deviation of 0.0027 p.u with a minimum bus voltage of 0.9973 p.u at 65th bus. The voltage profile radar chart of PG & E 69 bus RDS for the case study given in Fig. 15.

4.2.5. By integrating BESS, PVDG and DSTATCOM

In this case, the PVDGs and DSTATCOMs were fixed at optimal locations with a capacity of 500 kW and 500 kVAR. BESS unit's capacity was 500 kW and it was optimally placed and sized to minimizes energy loss to the system as shown in Table 10. AFCPOA was applied for optimal placement and the sizing of BESS units was done in the presence of PVDGs, DSTATCOMs, and the best result is 95.55% of active power loss reduction, 94.91% of reactive power loss reduction, maximum voltage deviation of 0.0007 p.u with a minimum bus voltage of 0.9993 p.u at 65th bus. Among all the case studies this one gives best results with a huge amount of power loss reduction and best voltage profiles. The voltage profile radar chart of PG & E 69 bus RDS for this case study is given in Fig. 16.

Each case study represents a different set of results in the distribution network. This helps researchers understand how various components (like DGs, DSTATCOMs, BESS, PVDGs) interact and influence the overall system performance in terms of objectives such as total system losses and voltage variations. From the study, researchers can evaluate and compare the performance of the system under various conditions. Different case studies may have different optimal (locations and size) values of DGs/DSTATCOMs/BESS in the presence of PVDGs. By studying various cases, researchers can identify the most effective combination of components for specific performance objectives. The AFCPOA algorithm converges very fast with smaller iterations to settle at optimal values. This is because the size of population decreases from iteration to iteration as we discarded untrainable candidates from the population so that at the end, very few optimal solutions remain in the list. This makes the AFCPOA algorithm computationally efficient.

5. Conclusions

A single objective and multi objective optimization problem of optimal placement and sizing using AFCPOA is presented in this article. The main objectives are minimization of active power loss, minimization of reactive power loss, minimization of voltage deviations, and improving the voltage profiles by optimally placing and sizing DGs, DSTATCOMs, DGs and DSTATCOMs, BESS in the presence of PVDGs, and BESS in the presence of PVDGs and DSTATCOMs, respectively. DSTATCOMs, which assess cost-benefit, total power losses, and voltage profiles, are among the most affordable contemporary devices used in distribution networks for reactive compensation. DSTATCOMs are strategically positioned to reduce overall distribution system losses while maximizing financial savings. Due to the increasing use of renewables in distribution networks, BESS has grown to be a crucial part of modern electrical distribution network. The reduction in energy loss in electrical network is significantly influenced by the optimal sizing and location of BESS. Simulation tests were carried out on IEEE 33 bus RDS and PG & E 69 bus RDS. The results illustrate that the proposed AFCPOA is highly efficient to determine global optimal solution and is able to produce better quality results when compared with other methods.

Declaration of competing 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.

Data availability

Data will be made available on request.

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