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An Efficient Hybrid Approach for Optimal Integration of Capacitors in Radial Distribution Networks with Realistic Load Models Using Giant Trevally Optimizer and Voltage Stability Index

K Bhavana[1]* **V Rajeswari[2]** **Rajan V[3]** **Velmurugan VR[4]** **P Muthukumar[1]**

[1]*Prasad V. Potluri Siddhartha Institute of Technology, Vijayawada, Andhra Pradesh 520007, India*
[2]*Amet University, Kanathur, Tamil Nadu 603112, India*
[3]*MVJ college of engineering White field Bangalore 560067,Karnataka,India*
[4]*P.A.C. Ramasamy Raja Polytechnic College, Rajapalayam, Tamil Nadu 626108, India*
* Corresponding author's Email: bhavana.kadiyala1@gmail.com

Abstract: Radiality and high R/X ratio branches cause EDNs to have low voltage profiles and insufficient security margins. This paper describes the application of a new meta-heuristic called the giant trevally optimizer (GTO) to find the best positions and sizes for capacitor banks (CBs) in low-voltage electrical distribution networks (EDNs) while taking into account various consumer types, including residential, commercial, industrial, and electric vehicles. By simultaneously lowering distribution losses, boosting the voltage profile, and improving the voltage stability margin, the major goal is thought to be to minimise the operational cost of annual energy loss. Different case studies on IEEE 33-bus and 69-bus EDNs are carried out in order to assess the computational effectiveness of the proposed GTO and are compared to the literature. Additionally, 50 independent runs are used to statistically quantify the convergence features of GTO and compare them to those of other meta-heuristics, particle swarm optimization (PSO), teaching-learning-based optimization (TLBO), cuckoo search algorithm (CSA), and flower pollination algorithm (FPA). Both comparative analyses demonstrated how GTO is more effective at finding global optima when tackling non-linear, non-convex optimisation problems with several types of variables and constraints. These technological and economic advantages demonstrate the methodology's capacity for real-time adaptation while taking emerging load trends and their loading patterns in low-voltage EDNs into account.

Keywords: Capacitor banks, Reactive power compensation, Electrical distribution networks, Loss reduction, Voltage stability index, Giant trevally optimizer, Multi-objective optimization.

1. Introduction

Electrical distribution networks (EDNs) connect residential, commercial, industrial, and other consumers. Radiality and high R/X ratio branches reduce EDN voltage profiles and security margins [1]. However, global warming and transportation-related pollutants have increased EV adoption worldwide. Industrialization has increased demand for electrical grid energy. These scenarios worsen low-voltage EDN operations. To alleviate the strain on conventional power plants and address the depletion of fossil-fuel-based energy supplies, renewable energy (RE) and other active and reactive power compensating measures are essential [2]. Capacitor banks (CBs) and other custom power devices (CPDs) can reduce distribution losses and save energy when running and regulating EDNs for reactive power compensation [3]. With CB integration, EDNs can increase voltage profile management, stability margins, power factor, and utility financial benefits [4].

Thus, EDNs' optimum CB allocation problem (OACBP) becomes a continuous optimisation problem. Numerous studies have addressed this issue, possibly using meta-heuristic methods while considering the drawbacks of analytical methods [5]. In [6], grey wolf optimisation (GWO) determines the ideal location and size for several CBs to avoid active power losses. The whale optimisation algorithm (WOA) solves the multi-objective OACBP by focusing on loss, voltage profile, and net savings [7]. In [8], particle swarm optimisation (PSO), harmony search algorithm (HAS), bat algorithm (BA), cuckoo search algorithm (CSA), and grey-wolf optimizer (GWO) are compared for loss reduction and net savings enhancement. After using loss sensitivity factors (LSFs) to identify likely CB integration locations, these methods are used to determine the best locations and sizes. The global optimum makes GWO better than other algorithms. In [9], time-varying acceleration coefficients (TVAC) are embedded in PSO to increase exploration and exploitation while solving the OACBP for loss reduction and net-savings maximisation. EDN's techno-economic benefits were analysed using LSFs and voltage-dependent load models. A genetic algorithm (GA) analyses the techno-economic effects of OACBP under varying seasonal loading conditions [10]. The diffusion and updating techniques-based algorithm (DUTA) reduces loss in the OACBP [11]. The power loss index (PLI) and chicken swarm optimisation (CSO) are used to allocate CBs to reduce loss and total operating costs [12]. Modified loss sensitivity factors (MLSFs) and multiverse optimizers (MVOs) are hybridised for CB integration to reduce loss. [13] The slime mould optimisation algorithm (SMOA) minimises CB integration, operation, and distribution losses in the OACBP [14]. In [15], LSFs reduce CB search space, and the polar bear optimisation (PBO) method is used to determine ideal CB locations and sizes to reduce the cost of loss and CBs. In [16], multi-objective GAs and LSFs optimise the voltage stability index (VSI), distribution losses, and yearly operating cost while setting CB sites and sizes. CSA [17, 18, 25–26] compares GA, PSO, BA, the whale optimisation algorithm (WOA), and the sperm-whale algorithm (SWA) [19]. The sine-cosine optimisation method (SCA) optimises EDN CB allocation and scheduling for energy loss reduction, reliability enhancement, and daily energy savings [20]. In [21], the grasshopper optimisation algorithm (GOA) solves the OACBP with changeable EDN loading circumstances. Rough set theory and LSFs optimise loss reduction and yearly energy loss costs to reduce uncertainty and speed up GOA computation. In [22], GWO, the dragonfly algorithm (DFA), and moth-flame optimisation (MFO) solve the OACB issue and compare their computational efficiency. In [23], the epsilon multi-objective genetic algorithm (e-MOGA) solves fixed and switching CBs in EDNs to minimise installation and network operational expenses. The mine blast algorithm (MBA), improved flower pollination algorithm (IFPA), crow search algorithm (CSA), and shark smell optimisation (SSO) are current meta-heuristic methods for the OACB issue [24].

The above literature shows that OACBP in EDN can achieve multiple purposes. Meta-heuristics solve this multi-objective, challenging optimisation problem. Many meta-heuristics still fall into local traps due to insufficient exploration and exploitation features and a poor switching mechanism. Meta-heuristics may converge poorly when network size expands the search space. In the first stage, most studies select CB candidates using LSFs, VSIs, PLSs, and MPLSs. Meta-heuristics discover the best sites from these sensitivity indices utilising a narrower search area and different CB sizes. Due to approximation loss, these static loading sensitivity indices may not work under varied loading conditions.

In light of this, this study offers a recently developed giant trevally optimizer (GTO) [30] for tackling the OACB issue while taking into account realistic load models, which are not specifically addressed in the literature. The goal of the target function is to reduce the running costs, active power loss, voltage profile, and VSI of CBs.

The paper continues as follows: Section 2 presents a realistic load model and problem formulation with equal and unequal constraints. Section 3 discusses GTO mathematical models and the OACB problem. Section 4 presents GTO simulation findings for solving the OACB problem in typical IEEE 33-bus and 69-bus test systems with constant power demands. Section 5 describes integrated realistic load model GTO results. GTO's computational properties are statistically compared to PSO, TLBO, CSA, and FPA. Section 6 concludes this paper's research.

2. Modelling of relevant concepts

This section introduces the proposed realistic load mode by combining residential, industrial, commercial and electric vehicle loads.

2.1 Proposed realistic load model

EDNs serve residential, commercial, industrial, and EV loads in real time. All loads have sensitive voltage profiles. Since Volt/VAr control using CBs can improve network voltage profiles, a common and accurate load model must take voltage magnitudes into account. Mathematically,

$$\bar{P}_{d(p)} = P_{d(p)} \sum_{k=1}^{nlt} \left\{ \rho_{nlt} \left(\frac{|V_{(p)}|}{|V_{(s)}|} \right)^{\alpha_{nlt}} \right\} \quad (1)$$

$$\bar{Q}_{d(p)} = Q_{d(p)} \sum_{k=1}^{nlt} \left\{ \rho_{nlt} \left(\frac{|V_{(p)}|}{|V_{(s)}|} \right)^{\beta_{nlt}} \right\} \quad (2)$$

2.2 Problem formulation

This section explains the multi-objective optimization problem.

2.2.1. Active power distribution losses

The power losses are mainly due to resistance of the branches, which is dependent on power flows through it. Mathematically,

$$P_{loss} = \sum_{k=1}^{nbr} I_{(k)}^2 r_{(k)} = \sum_{k=1}^{nbr} \left(\frac{P_{(k)}^2 + Q_{(k)}^2}{|V_{(q)}|^2} \right) r_{(k)} \quad (3)$$

2.2.2. Average voltage deviation index

Each form of network load requires a proper voltage profile. Since network length decreases voltage, AVDI can show how network voltage profile compares to sub-station bus voltage. Mathematically,

$$AVDI = \frac{1}{nbus} \sqrt{\sum_{k=1}^{nbus} \left(|V_{(s)}| - |V_{(p)}| \right)^2} \quad (4)$$

The higher value of $AVDI$ indicates poor voltage and unequal voltage profile in the network, and vice-versa.

2.2.3. Voltage stability index

Radial EDNs need $VSI_{(q)} \geq 0$. The lowest VSI bus collapses or the weakest node will initiate voltage collapse. To avoid voltage collapse, it is required to maximise all nodes' VSI [16]. Thus, maximization of weakest node VSI can ensure adequate voltage security margin. Mathematically,

$$VSI_{(q)} = |V_{(p)}|^4 - 4\left(P_{(k)} x_{(k)} - Q_{(k)} r_{(k)}\right) - 4\left(P_{(k)} r_{(k)} + Q_{(k)} x_{(k)}\right) |V_{(p)}|^2 \quad (5)$$

$$VSI = min\left(VSI_{(q)},, \forall q = 2{:}\, nbus \right) \quad (6)$$

2.2.4. Annual energy loss cost savings

The cost of savings can be determined by offsetting the CBs installation and operation cost from the loss cost. Mathematically,

$$C_{svg} = c_{loss} \times (P_{loss} - \bar{P}_{loss}) - \left\{ c_{cb,i} \times ncb \times \left(c_{cb,p} \times \sum_{k=1}^{ncb} Q_{cb(k)} \right) \right\} \quad (7)$$

2.2.5. Multi-objective function

The overall multi-objective function is given by:

$$OF = min\left(P_{loss} + AVDI + \frac{1}{VSI} + \frac{1}{C_{svg}} \right) \quad (8)$$

While solving the objective function, the following equal and unequal restrictions are taken into account. Here, Eqs. (9) - (12) provide descriptions of the real power balance, the reactive power balance, the voltage magnitude constants, and the reactive power compensation limit, respectively.

$$P_{d(s/s)} = \sum_{p=1}^{nbus} \bar{P}_{d(p)} + P_{loss} \quad (9)$$

$$Q_{d(s/s)} = \sum_{p=1}^{nbus} \bar{Q}_{d(p)} + Q_{loss} \quad (10)$$

$$|V_{(p),min}| \leq |V_{(p)}| \leq |V_{(p),max}| \quad (11)$$

$$\sum_{k=1}^{ncb} Q_{cb(k)} \leq \sum_{p=1}^{nbus} \bar{Q}_{d(p)} \quad (12)$$

3. Solution methodology

The problem is aimed to solve using a recent meta-heuristic algorithm called giant trevally optimizer (GTO). Giant trevallies (Caranx ignobilis) are jack family predators. They also knew as the huge kingfish. Around Australia, New Zealand and Indian and Pacific oceans, they are commonly available. The availability of prey attracts roughly fifty huge trevallies from neighbouring reefs, where immature terns learn to fly. After choosing the hunting spot, the gigantic trevally stalks its victim, then dives out of the water and assaults the seabird. This section explains the concept of GTO mathematically and its application to solve OACBP.

3.1 Giant trevally optimizer

The GTO was inspired by these innovative hunting techniques of searching movement patterns, picking the right food source, and springing out of water to assault and grab prey.

3.1.1. Initialization phase

The initial population in GTO can be randomly generated by,

$$X_g = [X_1, X_2, \dots, X_i, \dots, X_N]_{(n \times d)}^T \quad (13)$$

$$X_i = [x_{i,1}, X_{i,2}, \dots, X_{i,j}, \dots, X_{i,d}] \quad (14)$$

$$X_{i,j} = X_{j,min} + (X_{j,max} - X_{j,min}) \times r_1 \quad (15)$$

where X_g is the solution vector of GTO, X_i is the solution of *i*th candidate, *n* is the number of GTO candidates, and d is the number of decision variables of the problem, $i = 1,2,..,n$ & $j = 1,2,\dots,d$, r_1 is random number in the range of (0,1), $X_{j,min}$ and $X_{j,max}$ are the minimum and maximum boundaries of *j*th member.

The objective function OF for each candidate solution by GTO is determined in the initial stage, and the vector for all GTO members F_g is given by,

$$F_g = [F_1, F_2, \dots, F_i, \dots, F_N]_{(n\times 1)}{}^T \quad (16)$$

where $F_i = OF(X_i)$ is the *i*th candidate objective function. The minimum objective function value at this stage is treated as the pre-iterative global optima $F_{g(0)} = min(F_i, \forall i = 1{:}n)$.

3.1.2. Extensive search/ exploration phase

Giant trevallies may travel large distances for food. This hunting behaviour can be treated as exploration phase and thus, Eqs. (17) – (18) simulate their foraging patterns:

$$X_i(k+1) = X_i(best) \times r_2 + [(X_{j,max} - X_{j,min}) \times r_3 + X_{j,min}] \times Levy(d) \quad (17)$$

$$Levy(d) = 0.01 \times \frac{(u\times\sigma)}{v^{1/\beta}} \quad (18)$$

$$\sigma = \left(\frac{\Gamma(1+\beta)\times sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right)\times\beta\times 2^{\left(\frac{\beta-1}{2}\right)}} \right) \quad (19)$$

where $X_i(k+1)$ is the next iterative position of *i*th candidate, $X_i(best)$ is the best position of *i*th GTO member in the current iteration, r_2 and r_3 are random numbers, β is the index of the Levy flight distribution function, which can vary from 0 to 2 and is 1.5 in this study. u and v are random integers normally distributed in the range (0, 1).

3.1.3. Choosing area/ exploration phase

Giant trevallies choose the location with the most food (seabirds) in the designated search zone to pursue prey. This can be treated as exploration phase and it is given by,

$$X_i(k+1) = X_i(best) \times A \times r_4 + X_i(mean) - X_i(k) \times r_5 \quad (20)$$

$$X_i(mean) = \frac{1}{n}\sum_{i=1}^{n} X_i(k) \quad (21)$$

where A is position update control factor in the range (0.3, 0.4), $X_i(k)$ is the position of *i*th GTO member at current iteration, $X_i(mean)$ represents the mean, implies that these giant trevallies have exhausted all preceding data.

3.1.4. Attacking the prey/ exploitation phase

After choosing the best hunting spot, the GTO's exploitation phase begins when the trevally chases the bird. Finally, the trevally leaps out of the water and catches the bird. Mathematically,

$$X_i(k+1) = V_d + L_s + J_s \quad (22)$$

$$V_d = sin(\theta_1^0) \times |X_i(best) - X_i(k)| \quad (23)$$

$$L_s = X_i(k) \times sin(\theta_2^0) \times OF(X_i(k)) \quad (24)$$

$$J_s = r_6 \times (2 - k \times (2/k_{max})) \quad (25)$$

$$sin(\theta_1^0) = (1.33/1.00029) \times sin(\theta_2^0) \quad (26)$$

where V_d, L_s and J_s are visual distortion, launch speed, and jumping slope function, respectively; θ_1^0 and θ_2^0 are the incidence and refraction angles respectively, which are related k_{max} is the maximum iteration number, r_6 refers to gaint trevally motion sensation during exploitation.

3.2 Hybrid approach of GTO and VSI for solving OACB problem

The following steps describe the procedure to solve OACB problem using GTO and VSI.

St 1: Read test system data (i.e., IEEE 33-bus or 69-bus)

St 2: Select type of the load model (i.e., constant power or proposed realistic load model).

St 3: Run the load flow and determined VSI for all the buses. Sort the locations based their VSI and select top 10 locations (having least VSI values) as pre-defined search space for CB integration.

St 4: Define GTO parameters, A, n, d, and k_{max}.

St 5: Using Eqs. (13) to (15), generate initial population for CB locations and sizes.

St 6: Calculate target function value defined in Eq. (8), for each search agent as defined in Eq. (16), $F_i = OF(X_i)$ and determine $F_{g(0)}$.

St 7: For =1: k_{max},

a) *for* =1: n, Update the search agents using Eqs. (17) to (19) and evaluate new solutions, *end*, Go to Step 7.

b) *for* =1: n, Update the search agents using Eqs. (20) to (21) and evaluate new solutions, *end*, Go to Step 7.

c) *for* =1: n, Update the search agents using Eqs. (22) to (26) and evaluate new solutions, *end*, Go to Step 7.

St 8: Start evaluation by checking the lower and upper limits of search agents and update global best for each iteration.

St 9: *end*, Print results.

4. Results for constant power load model

In this section, the competitiveness of proposed GTO is tested on IEEE 33-bus and 69-bus test systems considering constant power load models and compared with literature works in Tables 1 and 2, respectively. In each test system, three CBs are considered to optimally integrate in the network. The minimum and maximum bus voltage limits are considered as 0.9 and 1.1 p.u. The test system data, practically available CB sizes and their cost details are taken from [13]. Also, the cost of P_{loss} is taken as 168 \$/(kW-year) [13]. The simulations are performed in a PC of 64-bit, Intel i3, 2.4 GHz and 8 GB RAM in MATLAB environment.

4.1 IEEE 33-bus EDN

The test system has real and reactive power loads of 3715 kW and 2300 kVAr, respectively. Its operating voltage is 12.66 kV. The base case network has total loss of 202.6771 kW and 135.1409 kVAr, respectively. The network has poor voltage profile with lowest voltage magnitude at bus-18 as 0.9131 p.u. The overall AVDI and VSI values are 0.0104 and 0.6582, respectively. In addition, the cost of operation is estimated as 34050 \$/year.

By solving the proposed multi-objective function, the optimal locations and sizes of three CBs are determined using GTO.

The optimized locations are buses 14, 24 and 30 and corresponding optimal sizes are 300, 600 and 1050 kVAr, respectively. These CBs in the network resulted for improvement in performance is as follows:

The total real and reactive power losses are reduced to 132.4256 kW and 88.5522 kVAr, respectively. The network voltage profile is improved with lowest voltage magnitude at bus-18 as 0.9368 p.u. The AVDI and VSI values are raised to 0.0072 and 0.7345, respectively. In addition, the total operating cost is reduced to 12345 \$/year from 34050 \$/year. In other words, the loss and cost are reduced by 34.6618 % and 34.6608 %, respectively.

4.2 IEEE 69-bus EDN

The test system has real and reactive power loads of 3801.39 kW and 2693.6 kVAr, respectively. Its operating voltage is 12.66 kV. The base case network has total loss of 225 kW and 102.1652 kVAr, respectively. The network has poor voltage profile with lowest voltage magnitude at bus-65 as 0.9093 p.u. The overall AVDI and VSI values are 0.0046 and 0.6835, respectively.

The GTO results are as follows: The optimized locations are buses 52, 61, and 21 and corresponding optimal sizes are 300, 1200, and 300 kVAr, respectively. These CBs in the network resulted for improvement in performance is as follows:

The total real and reactive power losses are reduced to 145.9872 kW and 67.9926 kVAr, respectively. The network voltage profile is improved with lowest voltage magnitude at bus-65 as 0.9307 p.u. The AVDI and VSI values are raised to 0.0035 and 0.7152, respectively. In addition, the total operating cost is reduced to 24940 \$/year from 37800 \$/year. In other words, the loss and cost are reduced by 35.12 % and 34.02 %, respectively.

The results of GTO and literature are given in Tables 1 and 2 for IEEE 33-bus and 69-bus, respectively. In both the systems, it can be seen that the GTO results are better than MVO [13], GWO, DFO, MFO, and PSO [22], and very competitive with IFPA [27], with least objective functions and high loss reduction and cost savings.

5. Results for proposed realistic load model

In this scenario, the realistic load model is considered that the load at each bus is composed of 30% residential, 30% industrial, 20% commercial and 20% electric vehicles. According to the modelling explained in section 2.1, the exponents for real and reactive power loads are taken from [31]. Also, in this section, the OACBP is solved for only loss reduction. Simulations are also performed using GTO and PSO, TLBO, CSA and FPA. The performance of these algorithms is quantified using 50 independent runs in terms best, worst, median, average and standard deviation (std). In addition, the total average computational time is also considered for comparison.

5.1 IEEE 33-bus EDN

By the proposed realistic load model, the real and reactive power loads of test system are determined as 3515.872 kW and 1874.746 kVAr, respectively. The base case network has total loss of 154.411 kW and 102.533 kVAr, respectively. The network has lowest voltage magnitude at bus-18 as 0.9246 p.u. The overall AVDI and VSI values are 0.0089 and 0.7309, respectively. In addition, the cost of operation is estimated as 25941 $/year.

As given in Table 3, the optimized locations are buses 12, 24 and 30 and corresponding optimal sizes are 450, 450 and 900 kVAr, respectively. These CBs in the network resulted for improvement in performance is as follows:

The total real power losses are reduced to 118.031 kW from 154.4114 kW, The total operating cost is reduced to 20221.61 $/year from 25941.12 $/year. In other words, the loss and cost are reduced by 23.561 % and 22.561 %, respectively. Also, the statistical parameters i.e., best (118.031), worst (120.409), mean (118.186), median (118.031), STD (0.519) are less than PSO, TLBO, CSA, and FPA. The computational time (13.125) is also less than other compared algorithms. These figures are highlighting the superiority of GTO than other algorithms.

5.2 IEEE 69-bus EDN

As given in Table 4, the real and reactive power loads of test system by the proposed realistic load model are determined as 3640.917 kW and 872.469 kVAr, respectively. The base case network has total loss of 160.123 kW and 112.545 kVAr, respectively. The network has lowest voltage magnitude at bus-65 as 0.9363 p.u. The overall AVDI and VSI values are 0.0032 and 0.7687, respectively. In addition, The cost of operation is estimated as 26900.66 $/year.

Table 1. Results of GTO in IEEE 33-bus and comparison with literature

Parameter	**Base**	**MVO [13]**	**GWO, DFO, MFO [22]**	**IFPA [27]**	**GTO**
CB buses	–	12, 24, 30	8, 13, 30	14, 24, 30	14, 24, 30
CB sizes (kW)	–	450, 600, 900	450, 300, 900	300, 600, 1050	300, 600, 1050
CB cost ($/year)	–	410.55	383.55	454.2	454.2
P_{loss} (kW)	202.6771	132.6808	134.0725	132.4256	132.4256
P_{loss} cost ($/year)	34050	22290	22524	22248	22248
$AVDI$	0.0104	–	–	0.0072	0.0072
VSI	0.6582	–	–	0.7345	0.7345
C_{total} ($/year)	34050	22701	22908	22248	22248
Q_{loss} (kVAr)	135.1409	–	-	88.5522	88.5522
$\lvert V_{(p),min}\rvert$ (p.u)/ p	0.9131/ 18	0.9355/ –	0.9400/ 18	0.9368/ 18	0.9368/ 18
P_{loss} reduction (%)	–	34.54	33.84	34.6618	34.6618
C_{svg} reduction (%)	–	33.33	32.72	34.6608	34.6608

Table 2. Results of GTO in IEEE 69-bus and comparison with literature

Parameter	**Base**	**MVO [13]**	**GWO, DFO, MFO [22]**	**IFPA [27]**	**GTO**
CB buses	–	12, 61	17, 61	52, 61, 21	52, 61, 21
CB sizes (kW)	–	600, 1200	300, 1350	300, 1200, 300	300, 1200, 300
CB cost ($/year)	–	336	384.45	414	414
P_{loss} (kW)	225	146.6294	146.0194	145.9872	145.9872
P_{loss} cost ($/year)	37800	24634	24531	24526	24526
$AVDI$	0.0046	–	–	–	0.0035
VSI	0.6835	–	–	0.7152	0.7152
C_{total} ($/year)	37800	24970	24915	24940	24940
Q_{loss} (kVAr)	102.1652	–	–	67.9926	67.9926
$\lvert V_{(p),min}\rvert$ (p.u)/ p	0.9093/ 65	0.9308	0.9329/ –	0.9307/ 65	0.9307/ 65
P_{loss} reduction (%)	–	34.83	35.07	35.12	35.12
C_{svg} reduction (%)	–	33.94	34.03	34.02	34.02

Table 3. Results of GTO in IEEE 33-bus with proposed realistic load model

Parameter	**Base**	**PSO**	**TLBO**	**CSA**	**FPA**	**GTO**
CB buses	–	15, 6, 30	30, 25, 8	3, 30, 15	8, 30, 25	12, 30, 24
CB sizes (kW)	–	150, 750, 750	900, 150, 600	900, 1050, 150	600, 900, 150	450, 900, 450
CB cost ($/year)	–	489	371.7	479.1	371.7	392.4
P_{loss} (kW)	154.4114	119.691	119.246	119.704	119.246	118.031
P_{loss} cost ($/year)	25941.12	20108.09	20033.33	20110.27	20033.33	19829.21
C_{total} ($/year)	25941.12	20597.09	20405.03	20589.37	20405.03	20221.61
P_{loss} reduction (%)	–	22.486	22.773	22.477	22.774	23.561
C_{svg} reduction (%)	–	20.601	21.341	20.63	21.341	22.561
Best	–	119.691	119.246	119.704	119.246	118.031
Worst	–	123.45	125.631	136.503	134.521	120.409
Mean	–	119.878	120.426	120.066	120.574	118.186
Median	–	119.691	120.445	119.704	119.246	118.031
Std.	–	0.727	1.286	2.374	2.446	0.519
Avg. Time (sec)	–	14.101	14.002	13.673	13.456	13.125

Table 4. Results of GTO in IEEE 69-bus with proposed realistic load model

Parameter	**Base**	**PSO**	**TLBO**	**CSA**	**FPA**	**GTO**
CB buses	–	61, 2	61, 13	13, 61, 21	61, 2, 68	21, 12, 61
CB sizes (kW)	–	1350, 1200	1200, 450	150, 1200, 150	1200, 900, 450	150, 450, 1200
CB cost ($/year)	–	483.45	317.85	279	368.7	279
P_{loss} (kW)	160.123	129.955	126.312	126.094	126.976	125.384
P_{loss} cost ($/year)	26900.664	21832.44	21220.42	21183.79	21331.97	21064.51
C_{total} ($/year)	26900.664	22315.89	21538.27	21462.79	21700.67	21343.51
P_{loss} reduction (%)	–	18.84052	21.11564	21.25179	20.70096	21.6952
C_{svg} reduction (%)	–	11.51626	14.59959	14.89885	13.95565	15.3718
Best	–	129.955	126.312	126.094	126.976	125.384
Worst	–	149.563	141.853	132.228	137.185	138.431
Mean	–	130.407	126.789	126.417	127.434	125.957
Median	–	129.995	126.312	126.094	126.976	125.657
Std.	–	2.793	2.306	1.995	1.977	1.177
Avg. Time (sec)	–	14.976	14.786	14.784	14.673	14.345

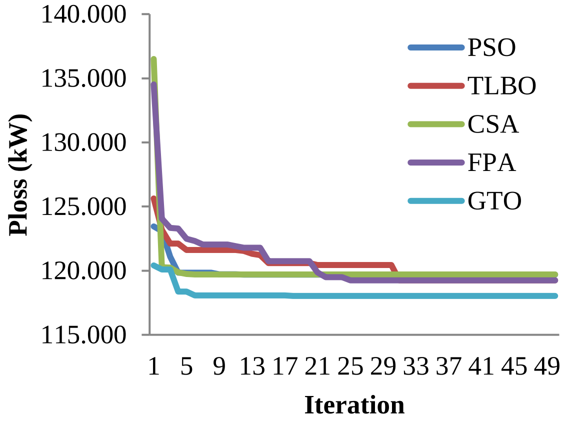

Figure. 1 Convergence characteristics in IEEE 33-bus with realistic load model

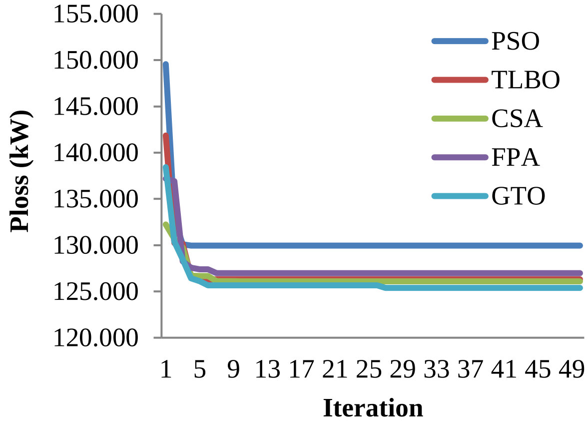

Figure. 2 Convergence characteristics in IEEE 69-bus with realistic load model

The optimized locations are buses 12, 21 and 61 and corresponding optimal sizes are 450, 150 and 1200 kVAr, respectively. These CBs in the network resulted for improvement in performance is as follows:

The total real power losses are reduced to 125.384 kW from 160.123 kW. The total operating cost is reduced to 21343.51 $/year from 26900.664 $/year. In other words, the loss and cost are reduced by 21.6952 % and 15.3718 %, respectively. Also, the statistical parameters i.e., best (125.384), worst (138.431), mean (125.957), median (125.657), STD (1.177) are less than PSO, TLBO, CSA, and FPA. The computational time (14.345) is also less than other compared algorithms. These figures are highlighting the superiority of GTO than other algorithms. The convergence of GTO and other compared algorithms for their best results are given in Figs. 1 and 2 for IEEE 33-bus and 69-bus, respectively.

However, many recent metaheuristics, namely the fixed step average and subtraction-based optimizer (FS-ASBO) [32], puzzle optimisation algorithm (POA) [33], three influential members-based optimizer (TIMBO) [34], guided pelican algorithm (GPOA) [35], stochastic komodo algorithm (SKA) [36], extended stochastic coati optimizer (ESCO) [37], attack-leave optimizer (ALO) [38], quad tournament optimizer (QTO) [39], and multiple interaction optimizer (MIO) [40] are emerging for solving multi-type optimisation problems. In this connection, it is still essential to analyse the effectiveness of the proposed GTO with such new algorithms. This can be treated as the future scope of this research.

6. Conclusion

The OACB problem is solved by hybridising VSI using the effective meta-heuristic GTO technique introduced in this work. By doing simulations for continuous power and realistic load modelling (i.e., made up of residential, industrial, commercial, and electric cars), the efficacy of GTO is evaluated. On IEEE 33-bus and 69-bus test systems, simulations are run to achieve many goals, such as loss reduction, voltage profile improvement, VSI maximisation, and overall operational cost reduction. VSIs are used to predetermine the positions of CBs, and GTO is then used to infer the best locations and sizes from those sites. Based on statistical analysis, 50 independent runs are used to evaluate the computational effectiveness of GTO with PSO, TLBO, CSA, and FPA. The mean, median, standard deviation, and best and worst values outperform other methods. Additionally, the suggested strategy incorporates a search space reduction technique that aids in reducing computation time. Additionally, the efficient CB placement in the IEEE 33-bus reduces energy loss costs by 34.6618 % and 34.6608 % for constant power loads and realistic load models, respectively. On the other side, it is noted as 35.12 % and 34.02 %, reduction in the 69-bus, respectively.

Notations

$P_{d(p)}$	Nominal active power load at bus-*p*
$Q_{d(p)}$	Nominal reactive power load at bus-*p*
$\bar{P}_{d(p)}$	Proposed realistic active power load
$\bar{Q}_{d(p)}$	Proposed realistic reactive power load
ρ_{nlt}	Proportional factor for a load type
α_{nlt}	Active power exponent
β_{nlt}	Reactive power exponent
$\lvert V_{(p)} \rvert$	Voltage magnitude of bus-*p*
$\lvert V_{(s)} \rvert$	Voltage magnitude of bus-*s* (substation)
nlt	Number of type of loads
nbr	Number of branches
$r_{(k)}$	Resistance of branch-*k*,
$x_{(k)}$	Reactance of branch-*k*
$I_{(k)}$	Current flow through the branch-*k*,
$P_{(k)}$	Net-effective active load at bus-*k*
$Q_{(k)}$	Net-effective reactive load at bus-*k*
$nbus$	Number of buses
VSI	Overall voltage stability index
$VSI_{(q)}$	VSI of bus-*q*

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, methodology, writing-original draft preparation, K Bhavana; software, writing—review and editing, Rajan V; validation, V Rajeswari and Velmurugan VR; investigation and formal analysis, Muthukumar.

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