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A Gradient-Based Optimizer with a Crossover Operator for Distribution Static VAR Compensator (D-SVC) Sizing and Placement in Electrical Systems

Ghareeb Moustafa [1,2], Mostafa Elshahed [3,4], Ahmed R. Ginidi [5], Abdullah M. Shaheen [5,*] and Hany S. E. Mansour [2]

1 Electrical Engineering Department, Jazan University, Jazan 45142, Saudi Arabia
2 Electrical Engineering Department, Suez Canal University, Ismailia 41522, Egypt
3 Electrical Engineering Department, Engineering and Information Technology College, Buraydah Private Colleges, Buraydah 51418, Saudi Arabia
4 Electrical Power Engineering Department, Faculty of Engineering, Cairo University, Giza 12613, Egypt
5 Department of Electrical Power Engineering, Faculty of Engineering, Suez University, Suez 43533, Egypt
* Correspondence: abdullahshaheen2015@gmail.com

Abstract: A gradient-based optimizer (GBO) is a recently inspired meta-heuristic technique centered on Newton's gradient-based approach. In this paper, an advanced developed version of the GBO is merged with a crossover operator (GBOC) to enhance the diversity of the created solutions. The merged crossover operator causes the solutions in the next generation to be more random. The proposed GBOC maintains the original Gradient Search Rule (GSR) and Local Escaping Operator (LEO). The GSR directs the search to potential areas and aids in its convergence to the optimal answer, while the LEO aids the searching process in avoiding local optima. The proposed GBOC technique is employed to optimally place and size the distribution static VAR compensator (D-SVC), one of the distribution flexible AC transmission devices (D-FACTS). It is developed to maximize the yearly energy savings via power losses concerning simultaneously different levels of the peak, average, and light loadings. Its relevance is tested on three distribution systems of IEEE 33, 69, and 118 nodes. Based on the proposed GBOC, the outputs of the D-SVCs are optimally varying with the loading level. Furthermore, their installed ratings are handled as an additional constraint relating to two compensation levels of 50% and 75% of the total reactive power load to reflect a financial installation limit. The simulation applications of the proposed GBOC declare great economic savings in yearly energy losses for the three distribution systems with increasing compensation levels and iterations compared to the initial case. In addition, the effectiveness of the proposed GBOC is demonstrated compared to several techniques, such as the original GBO, the salp swarm algorithm, the dwarf mongoose algorithm, differential evolution, and honey badger optimization.

Keywords: gradient-based optimizer; reactive power optimization; distribution systems; distribution static VAR compensator

MSC: 68T20

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Citation: Moustafa, G.; Elshahed, M.; Ginidi, A.R.; Shaheen, A.M.; Mansour, H.S.E. A Gradient-Based Optimizer with a Crossover Operator for Distribution Static VAR Compensator (D-SVC) Sizing and Placement in Electrical Systems. *Mathematics* **2023**, *11*, 1077. https://doi.org/10.3390/math11051077

Academic Editor: Mario Versaci

Received: 4 January 2023
Revised: 10 February 2023
Accepted: 20 February 2023
Published: 21 February 2023

1. Introduction

Electric systems typically have three sectors: production, transmission, and distribution. The distribution sector is the last connection between the transmission sector and the customers. The primary goal of this sector is to provide electrical energy to end consumers while maintaining the necessary levels of efficiency, reliability, and quality, which in turn reduces power loss. Due to the low voltage and high current, distribution system power losses are substantial and account for roughly 70 percent of all losses [1]. Additional expenditures are incurred because of these losses, which cannot be eliminated and so mitigation is the aim. Several strategies are employed to achieve minimal losses, including distributed generators (DGs) allocation [2–4], reactive power compensation [5–7], automatic voltage regulators [8], and network reconfiguration [9].

Reactive power compensation is an approach that has gained recognition for its potential to reduce energy losses. It also provides additional advantages, such as enhancing system stability, improving the voltage of the distribution nodes, and power factor correction, which are all subject to different operational constraints [10]. The distribution static VAR compensator (D-SVC) is one of the most used devices for this purpose in distribution systems. The reactive power exchange, injecting, and absorbing can effectively control the bus voltage that affects the distribution grid [11]. The allocation of D-SVC in the distribution system should be performed optimally. Finding the optimal positions and sizes of the connected D-SVCs is required [12]. As a result of the distribution system's specificity and characteristics, the proper allocation of D-SVC has become a highly critical issue requiring a complicated solution. Several approaches have been suggested to solve the allocation problem of the incorporated D-SVC. An improved grey wolf algorithm (IGWA) was developed [13] to address the corresponding allocation problem for several types of compensators in distribution systems, including capacitors, DGs, and D-SVCs. The suggested approach was executed on two practical-Egyptian distribution systems at three loading levels. The objective function was formulated to maximize the net savings resulting from the power loss reduction after the compensators were installed at minimum cost.

The voltage stability index was suggested to find the optimal locations of embedded D-SVCs [14]. The genetic algorithm (GA) optimization technique was suggested to select the optimal sites and capacities of installed D-SVCs [15,16]. The problem was formulated to achieve the minimum standard voltage deviation in distribution systems integrated with renewable resources. The power sensitivity index was applied to determine the optimum locations for D-SVCs' installation [17]. The coordination problem between the on-load tap changer and D-SVC was investigated for voltage control in imbalanced distribution networks integrated with renewable resources [18].

The particle swarm optimization (PSO) technique was presented first to find the optimal allocation of the D-SVC and then to determine its dispatch approach. The problem was designed to achieve maximum savings while considering the voltage and total harmonic distortion constraints [12]. X. Xu et al. [19] formulated two objectives. The first was to boost the photovoltaic (PV) hosting capacity, and the second was to minimize the investment and operation costs of D-SVC. The optimal allocation of DGs, capacitors, and D-SVCs was addressed to reduce power loss [20]. Furthermore, the D-SVCs were optimally allocated in light of plug-in hybrid electric vehicle charging stations [21]. First, the PSO method addressed the optimal placement and charging schedule. After that, the optimal allocation of the D-SVC problem was solved using the cuckoo search optimizer (CSO). The objective function in the first stage was formulated to minimize the system losses and daily load profile variations. It was intended to improve voltage deviation and lower D-SVC allocation costs in addition to lowering system losses. The CSO was also suggested to address the optimal D-SVC allocation problem in distribution networks integrated with wind turbines [22].

A gradient-Based Optimizer (GBO) [23] is a recently developed population-based meta-heuristic technique that utilizes Newton's gradient-based approach as an example to direct it toward the optimal answer. The Local Escaping Operator (LEO) and the Gradient Search Rule (GSR) are its two key parts. A GBO has been efficiently applied to several engineering issues, such as economic load dispatch problems [24], structural optimization problems [25], human activity recognition using smartphones [26], proton exchange membrane fuel cell parameter identification problems [27], parameter estimation of photovoltaic models [28], and feature selection (FS) problems [29,30]. In [31], a modified GBO was presented for the optimal allocation of PV sources in the medium-voltage distribution system of the IEEE 34-bus system. In this modified GBO version, the general rule of the GBO evolution strategy was both improved by combining it with its counterpart linked to the vortex searching optimization [32] by using non-concentric hyper-ellipses formed utilizing a Gaussian distribution and also developed surrounding the solution space at the present iteration. In [33], a hybrid technique between GBO and a moth–flame optimizer (MFO) was designed and applied for the optimal allocation of some FACTS devices, including SVC and thyristor-controlled series compensators. Despite the hybrid performed GBO-MFO in [33] which demonstrated significant advantages over the original GBO and MFO in obtaining the best solution, the utilized model handled only the peak loading condition of the power system.

In this paper, an advanced developed version of the GBO merged with a crossover operator (GBOC) to enhance the diversity of the created solutions. The merged crossover operator causes the solutions in the next generation to be more random. The proposed GBOC also maintains the original GSR and LEO. The proposed GBOC is employed to optimally place and size the D-SVC which is one of the distribution flexible AC transmission (D-FACTs) devices. The outputs of the D-SVCs are varied with the loading level in an optimal way based on the proposed GBOC. It was created to maximize the yearly energy savings in power losses while considering peak, average, and light loading levels concurrently. Its applicability is examined on three distribution systems with IEEE 33, 69, and 118 nodes. Additionally, to represent financial installation limitations, the installed D-SVCs ratings are handled as a second restriction linked to two compensation levels of 50% and 75% of the total reactive power demand. Additionally, the effectiveness of the suggested GBOC is shown in comparison to several methods, including the original GBO, the salp swarm algorithm (SSA) [34,35], the dwarf mongoose optimization algorithm (DMOA) [36], differential evolution (DE) [37], the honey badger algorithm (HBA) [38], and Bernstein-Levy Search DE (BSDE).

The key contributions of the paper can be summarized as follows:

- A novel GBOC version with a merged crossover operator was developed for D-SVC sizing and placement in electrical distribution systems;
- A financial installation limitation is introduced and represented in terms of the implemented D-SVC rating threshold;
- Substantial economic reductions in yearly energy losses are accomplished using the proposed GBOC for the IEEE 33- and 69-node distribution systems with increasing compensation levels and iterations;
- The suggested GBOC is more effective than the original GBO, SSA, DMOA, DE, and HBA in decreasing yearly energy losses for a large-scale 118-node distribution system when all operational restrictions are met.

2. Proposed GBOC: Mathematical Model

A GBO combines gradient-based approaches and population-based approaches to address challenging optimization issues. Using the GBO technique, the search agent's direction is managed using Newton's approach while it explores the issue space [23]. To further enhance the diversity of the created solutions, an advanced developed GBOC technique is presented by merging the crossover operator with the original GBO. While maintaining the original GSR and LEO in the proposed GBOC, the merged crossover operator causes the solutions in the next generation to be more random.

2.1. Stage 1: Initialization

The GBO method starts with a randomized group of starting solutions and upgrades every agent location to a gradient-determined direction. There are Nv vector agents in the population. Each agent is referred to as a "vector," and there are D dimensions to the searching space. After that, the initialization procedure is carried out as follows:

$$Gb_k = LB + (UB - LB) \times rand(1, D) \quad k = 1 : N_v \tag{1}$$

where Gb_k refers to each search agent in the GBO population. *LB* and *UB* are the lower and upper limits of the control variables.

2.2. Stage 2: GSR

The GSR uses a gradient-based process to enhance the space exploring search and hasten the convergence of the optimum option. The GBO technique employs the following formula to modify the results after every iteration:

$$Gb_{k,It+1} = z_a \times \left(z_b \times Gb1_{k,It} + (1 - z_b)Gb2_{k,It}\right) + (1 - z_a)Gb3_{k,It} \quad k = 1 : N_v; It = 1 : It_{Max} \tag{2}$$

where z_a and z_b are random values within range [0, 1]; *It* and It_{Max} refer to the existing and maximum iteration numbers; $Gb_{k,It+1}$ and $Gb_{k,It}$ are new and old vectors related to the GBO method of the kth searching individual; and $Gb1_{k,It}$, $Gb2_{k,It}$ and $Gb3_{k,It}$ are three artificial vectors that can be evaluated as follows:

$$Gb1_{k,It} = Gb_{k,It} - GSR + rand \times \sigma_1(Gb_{Best} + Gb_{k,It}) \quad k = 1 : N_v; It = 1 : It_{Max} \tag{3}$$

$$Gb2_{k,It} = Gb_{Best} - GSR + rand \times \sigma_1(Gb_{R1} + Gb_{R2}) \quad k = 1 : N_v; It = 1 : It_{Max} \tag{4}$$

$$Gb3_{k,It} = Gb1_{k,It} - \sigma_2(-Gb1_{k,It} + Gb2_{k,It}) \quad k = 1 : N_v; It = 1 : It_{Max} \tag{5}$$

$$GSR = \sigma_1 \times randn\left(\frac{2 \times Gb_k \times \Delta Gb}{yp_k - yq_k + \varepsilon}\right) \quad k = 1 : N_v \tag{6}$$

where σ_1 is a significant parameter that changes depending on the sine function while σ_2 is a randomized coefficient; ***rand*** and ***randn*** are, respectively, a number generator function using uniformly distributed within the range [0, 1] and integer number production; Gb_{Best} is the best search individual that provides the best fitness value; and Gb_{R1} and Gb_{R2} are two unequal search agents that are picked randomly.

2.3. Stage 3: LEO

The LEO aids in preventing local optima in the algorithm. The GBO technique employs the following formula to modify the results after every iteration:

$$Gb_{k,It+1} = \begin{cases} \begin{cases} Gb_{k,It+1} + \phi_1(m_a Gb_{Best} - m_b X_{k,It}) + \phi_2\sigma_1(m_c Gb2_{k,It} - Gb1_{k,It}) + \\ m_b(Gb_{R1} - Gb_{R2}) & if\ z_c < 0.5 \\ Gb_{k,It+1} + \phi_1(m_a Gb_{Best} - m_b X_{k,It}) + \phi_2\sigma_1(m_c Gb2_{k,It} - Gb1_{k,It}) + \\ \frac{m_b(Gb_{R1} - Gb_{R2})}{2} & Otherwise \end{cases} & if\ z_d < \mathrm{Pr} \end{cases} \tag{7}$$

where *Pr* is the probability value to activate LEO stage; z_c and z_d are random values within range [0, 1]; m_a, m_b, and m_c refer to three random values generated via Equations (8)–(10); and ϕ_1 and ϕ_2 indicate two random numbers generated via uniform distribution inside the range [−1, 1].

$$m_a = 2 \times z_d \times C_1 + (1 - C_1) \tag{8}$$

$$m_b = z_d \times C_1 + (1 - C_1) \tag{9}$$

$$m_c = z_d \times C_1 + (1 - C_1) \tag{10}$$

$$C_1 = \begin{cases} 1 & \mu \le 0.5 \\ 0 & Else \end{cases} \tag{11}$$

where μ is a number that is randomly generated in the range [0; 1];

$$Gb_{k,It} = \begin{cases} Gb_{Randp} & if\ \mu_* < 0.5 \\ LB_k + rand(UB_k - LB_k) & Otherwise \end{cases} \tag{12}$$

where Gb_{RandP} is a randomly picked solution from the GBO population and μ_* is a random number inside the range [0, 1].

2.4. Crossover operator

In this paper, an enhanced evolved GBOC approach is provided by combining the crossover operator with the original GBO to increase the diversity of the generated solutions. The crossover operator is activated for each solution in each iteration based on a crossover probability. The crossover operation creates a new solution vector ($Gb_{k,It}$) by exchanging the components of the current solution vector and a random solution vector as:

$$Gb_{k,It+1} = \begin{cases} Gb_{SR} & if\ IR < 0.25 \\ Gb_{k,It} & Otherwise \end{cases} \quad k = 1 : N_v \tag{13}$$

where $Gb_{k,It}$ indicates the current solution vector and Gb_{SR} refers to a solution vector to be picked randomly from the population. IR is a random value generally chosen from the range [0, 1]. This includes a binomial crossover approach that is used on every one of the control variables. Figure 1 displays the main stages of the proposed GBOC.

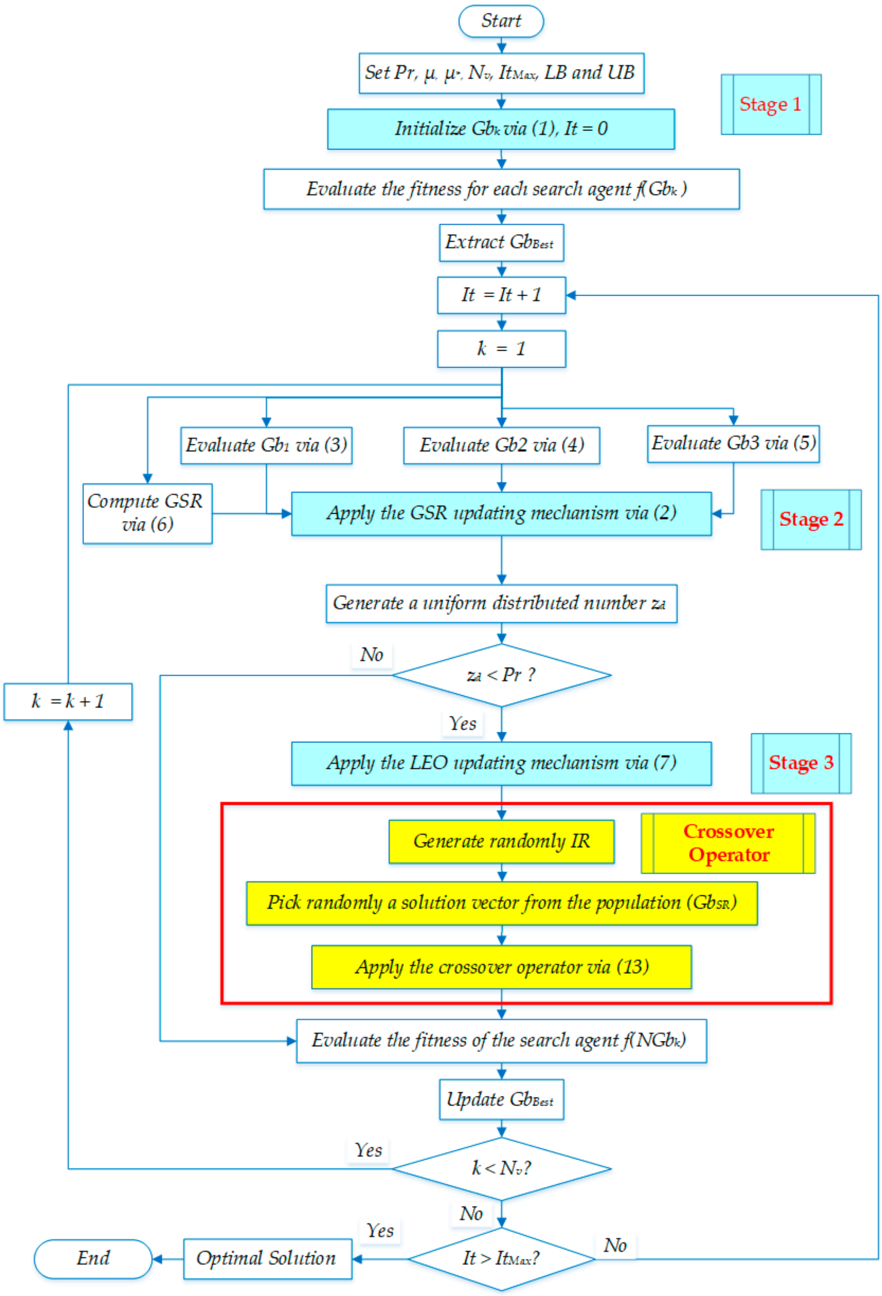
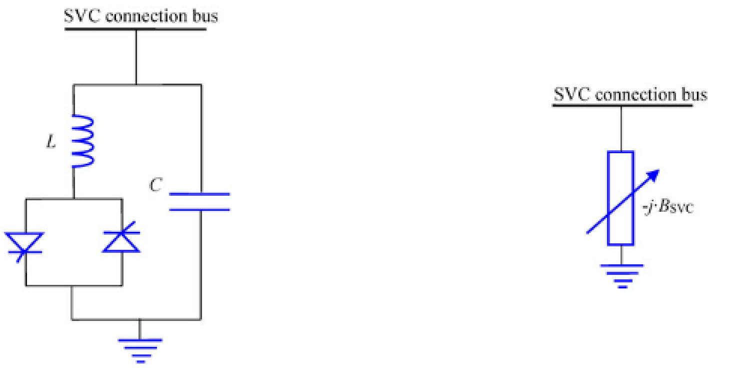


Figure 1. Main stages of the employed GBOC.

3. D-SVC Sizing and Placement in Electrical Systems

The D-SVC is a member of the FACTS shunt-linked instrument group. It can actively handle network voltage via generating and absorbing (capacitive and inductive, respectively) reactive power based on network voltage level characteristics. As a consequence of the SVC's high dynamic performance and short-term reaction, operators can regulate voltages at the Point of Common Coupling (PCC) [39] to the specific level by adjusting the amplitude and angle of the internal voltage [15–17]. Figure 2 depicts the overall circuit design of a D-SVC [40]. As can be observed, D-SVC is made up of a fixed capacitor and a thyristor-controlled reactor.



(**a**) circuit structure (**b**) equivalent model

Figure 2. A Distribution-Static Var Compensator (D-SVC).

The firing angle of the thyristor determines the equivalent susceptance BSVC of the D-SVC device. In the ith node, the equivalent susceptance and reactive power given by D-SVC may be written as follows:

$$B_{SVC} = B_L(\alpha) + B_C \tag{14}$$

$$B_L(\alpha) = \frac{1}{\omega L}\left(1 - \frac{2\alpha}{\pi}\right) \tag{15}$$

$$B_C = \omega C \tag{16}$$

where L and C are the reactor's inductance and capacitor's capacitance and V_i represents the voltage magnitude at the D-SVC installed distribution node i. If the network demand is capacitive, the D-SVC employs thyristor-controlled coils to absorb reactive power from the system. If the network demand is largely inductive, the D-SVC uses parallel-coupled capacitors to create reactive energy, thus improving voltage conditions. A D-SVC's primary function is to provide quick and continuous control. Therefore, it can be modeled as an injected source of reactive power that may take a positive or negative sign as follows:

$$Qsvc = -B_{SVC}(V_i)^2 \tag{17}$$

Thus, the injected current from the D-SVC can be modeled as follows:

$$Isvc_i = \frac{Qsvc_i}{V_i} \tag{18}$$

Therefore, for each distribution node, the equality constraints in terms of the load flow balance equations should be maintained, whichcould be formulated as follows:

$$\left(QG_i - Qd_i + Qsvc_i - V_i \sum_{j=1}^{N_b} V_j (G_{ij} \sin\theta_{ij} - \mathrm{B_{ij}} \cos\theta_{ij})\right)_{Level} = 0,\ i = 1, 2, \ldots N_{PQ},\ Level = 1 : N_{Level} \tag{19}$$

$$\left(PG_i - Pd_i - V_i\sum_{j=1}^{N_b} V_j(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij})\right)_{Level} = 0,\ i = 1,2,\ldots\ldots N_{buses} - slack,\ Level = 1 : N_{Level} \tag{20}$$

where B_{ij} and G_{ij} indicate mutual susceptance and conductance between bus i and j, respectively; N_{PQ} is the load buses; Pd_i represents the active demand power at bus i; PG_i and QG_i are, respectively, the generated active and reactive power at bus i; and Qd_i is the demand reactive power at bus i. Thus, the balance restrictions are adjusted at the three loading levels to incorporate the SVC model into the power distribution grid. As a result, the reactive and active power balance constraints are mathematically evaluated using the following equations:

$$P_{S/S,Level} = \sum_{k=1}^{N_{buses}} Pd_{k,Level} + P_{Loss,Level},\ Level = 1 : N_{Level} \tag{21}$$

$$Q_{S/S,Level} + \sum_{i=1}^{N_{svc}} Qsvc_{i,Level} = \sum_{k=1}^{N_{buses}} Qd_{k,Level} + Q_{Loss,Level},\ Level = 1 : N_{Level} \tag{22}$$

where $P_{S/S}$ and $Q_{S/S}$ manifest the total active and reactive power supplied via the substation; $Nsvc$ illustrates the number of mounted SVC; P_{loss} characterizes the active power losses of the entire system; Pd_k elaborates the actual power demand at node (k); N_{Level} refers to every loading level; $Qsvc_i$ is the reactive power absorption/injection from SVC installed at node (i); and Q_{loss} represents the reactive power losses over the distribution system.

The savings maximization due to the energy losses (OF) in \$/year must be considered while allocating SVC for auxiliary services provided in distribution systems, as depicted in Equation (15).

$$OF = K_e \sum_{L=1}^{N_{Level}} \left(P_{Loss_0} - P_{Loss_A}\right)_L \times Period_L \tag{23}$$

where P_{Loss_0} represents the initial power losses, while P_{Loss_A} indicates the power losses after optimally pacing, sizing, and operating the D-SVCs by the GBO. K_e is the cost in \$/kWh. $Period_L$ refers to the period in which each loading level (L) is supplied, which is 2920 h per year. The system's real power losses can be modeled as follows:

$$P_{Loss,Level} = \sum_{i,jN_b} G_{ij}\left(V_i^2 + V_j^2 - V_i V_j \cos\theta_{ij}\right), Level = 1 : N_{Level} \tag{24}$$

The potential of the D-SVC capacity ($Qsvc_i^{Rate}$) at each installed bus (i) is taken into consideration to be less than the maximum rate to be considered ($Qsvc^{Max\_Rate}$), as handled in Equation (16). At the same time, its capability to alter its outputs to concurrently inject and absorb reactive power throughout the day and night is taken into consideration as handled in Equation (17).

$$Qsvc_i^{Rate} \le Qsvc^{Max\_Rate},\ i = 1 : N_{svc} \tag{25}$$

$$-Qsvc_i^{Rate} \le Qsvc_{i,Level} \le +Qsvc_i^{Rate},\ i = 1 : N_{svc},\ Level = 1 : N_{Level} \tag{26}$$

Furthermore, the current flow across all distribution branches and the voltage at all distribution terminals should be kept within the allowed limits at all times as follows [8]:

$$-I_{br}^{Max} \le I_{br,Level} \le +I_{br}^{Max},\ br = 1 : N_{branches},\ Level = 1 : N_{Level} \tag{27}$$

$$V_j^{Max} \le V_{j,Level} \le V_j^{Min},\ j = 1 : N_{buses},\ Level = 1 : N_{Level} \tag{28}$$

where I_{br}^{Max} signifies the maximum thermal capacity of the distribution branch while V_j^{Max} and V_j^{Min} represent the higher and lower voltage boundaries at the nodes with a permitted range of 10% [8].

4. Simulation Results

The suggested GBOC's relevance is tested on three IEEE distribution networks of 33, 69, and 118 nodes. Light, medium, and peak loading levels are considered, with each loading level receiving supply for eight hours daily. They are handled with 60, 80, and 100% of the nominal loading [41]. Three D-SVCs are the most that may be placed. The maximum rate of the D-SVC device to be installed is ±3000 kVAr. The suggested GBOC, original GBO, SSA, DMOA, DE, and HBA are applied with settings of 100 iterations and 20 search agents. The detailed parameter settings of each algorithm are illustrated in Table A1 in the Appendix A. Two scenarios are considered based on the maximum value of the sum of installed SVCs ratings as follows:

In Scenario 1, a compensation limit of 50% of the total reactive power load is handled.

Whereas, Scenario 2 considers a compensation limit of 75% of the total reactive power load.

4.1. The IEEE 33-Node Distribution Network

There are 33 nodes and 32 distribution sections in this network. Figure 3 depicts the system's one-line topology with a standard voltage of 12.66 kV. The total active (MW), reactive (MVAr), and apparent (MVA) loads are 3.715, 2.3, and 4.369 considering the nominal condition, respectively [42].

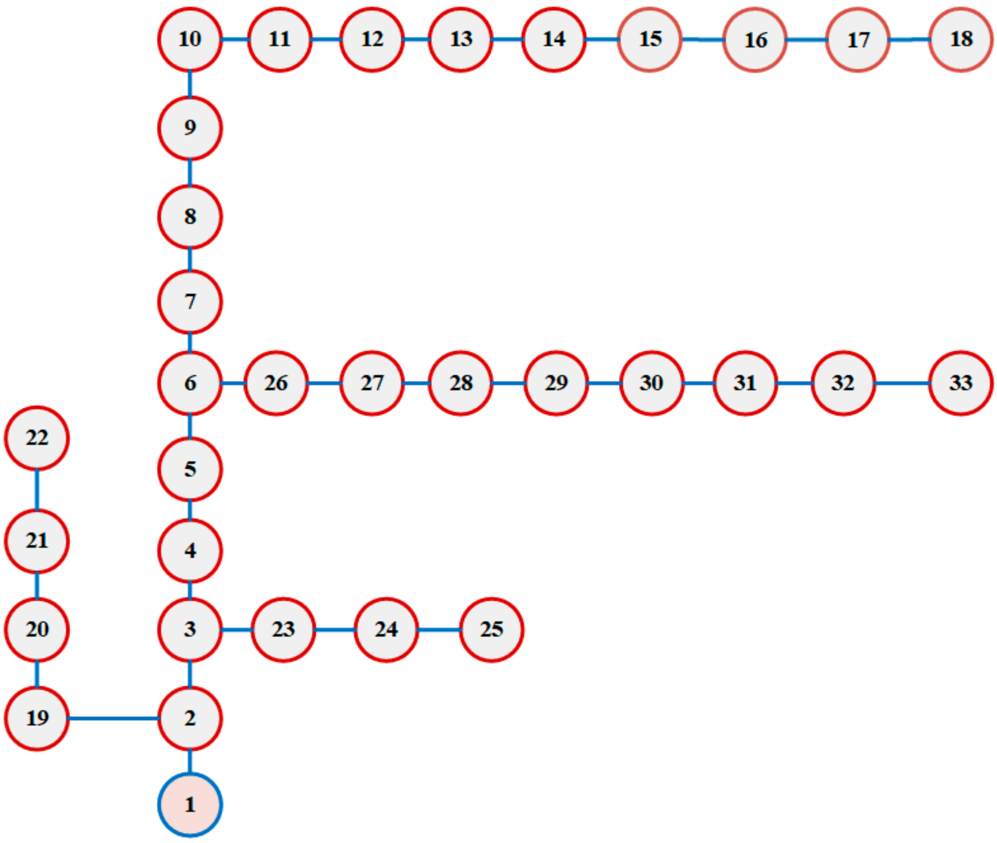


Figure 3. The IEEE 33-distribution system.

4.1.1. First Scenario

In this scenario, a compensation limit of 50% of the total reactive power load is handled as a financial limit. For that purpose, the proposed GBOC is compared to the original

GBO, SSA, DMOA, DE, and HBA to identify the suitable placement and sizing of the D-SVC device in the IEEE 33-distribution system, to maximize the dollar savings due to the power losses. Table 1 tabulates the placement and sizing of D-SVC devices for the IEEE 33-distribution system for scenario one and the corresponding economic savings per year. In addition, Figure 4 depicts the convergence characteristics of the proposed GBOC, GBO, SSA, DMOA, DE, and HBA for the IEEE 33-distribution system for Scenario 1. The proposed GBOC finds the maximum yearly savings of USD 21,883.8 displaying the best performance. Secondly, GBO achieves yearly savings of USD 21,474.1, DE achieves yearly savings of USD 21,466.9 in the third rank, and HBA achieves yearly savings of USD 21,078.8 in the fourth rank. Fifthly, DMOA achieves yearly savings of USD 21,015.6 while BSDE achieves yearly savings of USD 15,223.6 in the sixth rank. Overall, across all of the techniques, the worst performance is related to the SSA which finds yearly savings of USD 15,131.6.

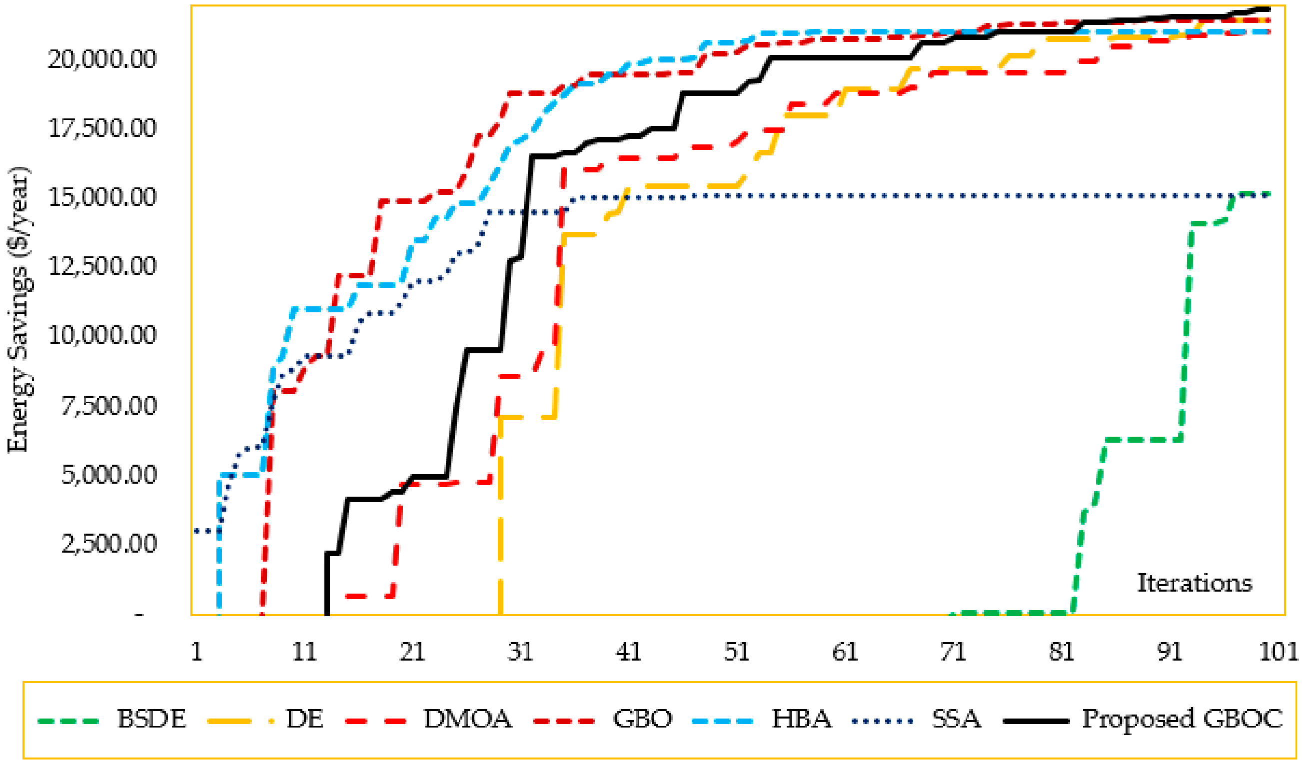


Figure 4. Convergence characteristics of GBOC, GBO, SSA, DMOA, DE, and HBA for the IEEE 33-distribution system for Scenario 1.

Nevertheless, Figure 5 describes the minimum voltage at each loading level for the proposed GBOC, GBO, SSA, DMOA, DE, and HBA compared to the initial case. All the applied algorithms maintain voltage limitations where the minimum voltage at each loading level exceeds the considered limit. In addition, all the applied algorithms enhance the minimum voltage compared to the initial case. The proposed GBOC enhances the minimum voltage from 0.944, 0.9244, and 0.9037 at the initial case to 0.9563, 0.94, and 0.92 for light, medium, and peak loading levels, respectively.

To illustrate the range of voltage improvement, Figure 6 displays the voltage profile based on the proposed GBOC compared to the initial case for light, medium, and peak loading levels. As shown, great improvements are achieved for all of the distribution nodes and all of the loading levels. The greatest improvement in the voltage profile is derived at the 33rd distribution node with 1.74, 1.97, and 2.11% for light, medium, and peak loading levels, respectively.

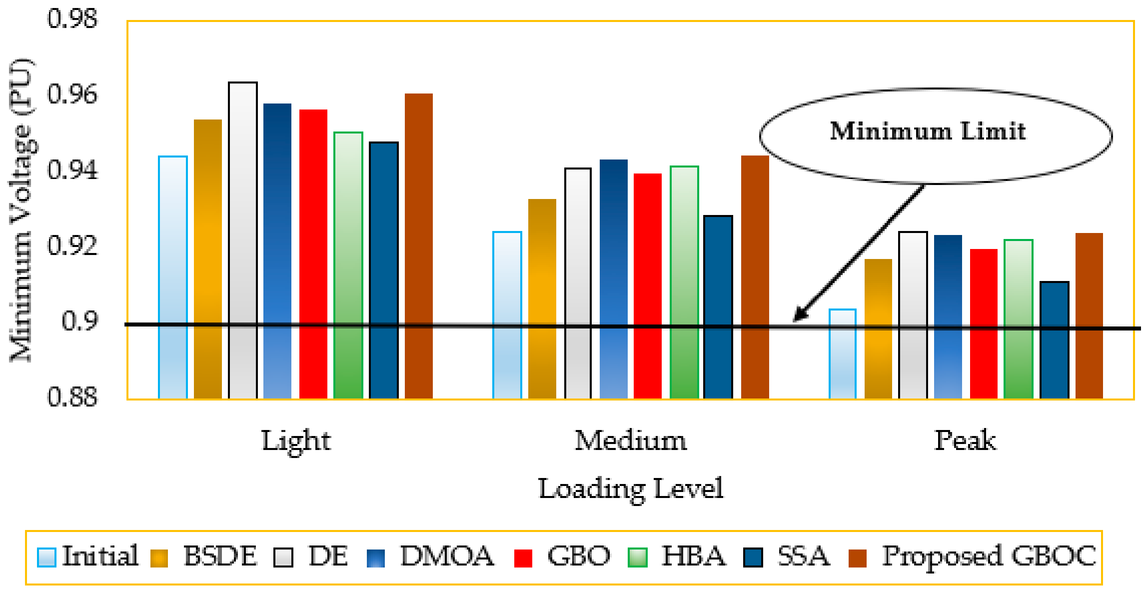
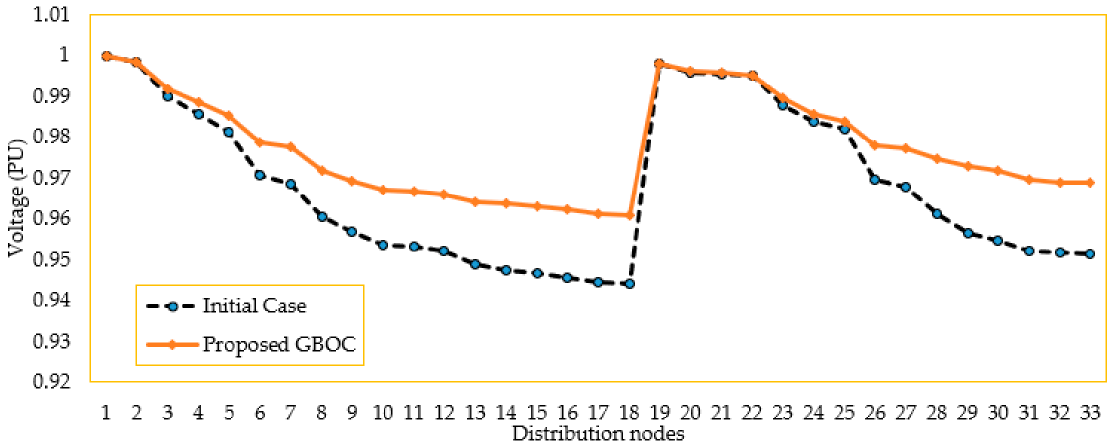


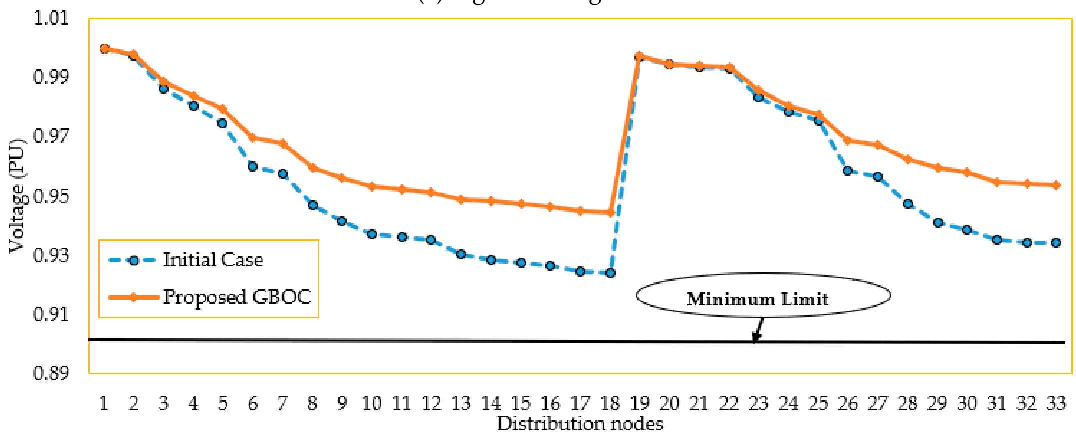
Figure 5. Minimum voltages for the IEEE 33-distribution system of the GBOC versus GBO, SSA, DMOA, DE, and HBA for Scenario 1.

Table 1. Placement and sizing of D-SVC devices for the IEEE 33-distribution system for Scenario 1.

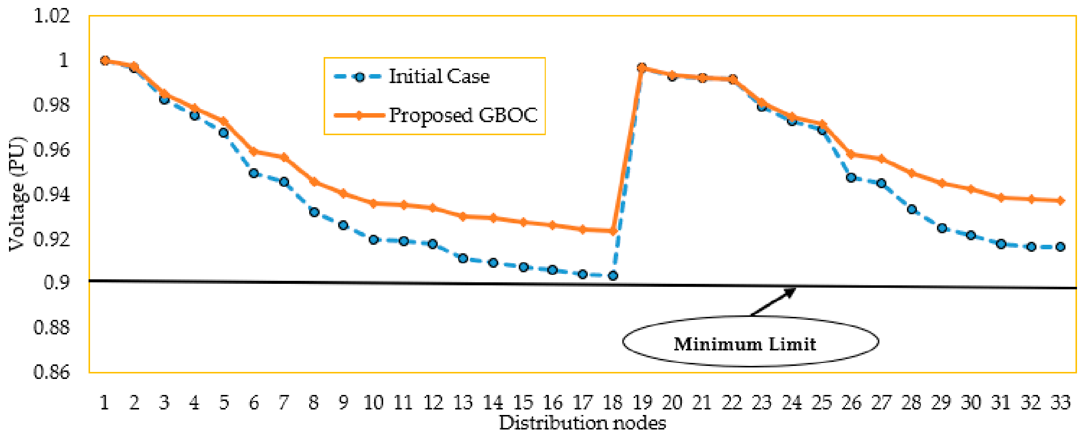
Algorithm	Dollars Savings Per Year	Installed Buses	Rate (kVAr)	Operational Value (kVAr)		
				Light	Medium	Peak
BSDE	15,223.6	14	±212	126	135	212
		21	±334	84	303	334
		33	±505	505	313	483
DE	21,466.9	16	±279	279	206	264
		30	±588	467	471	588
		31	±271	228	271	271
DMOA	21,015.6	9	±328	165	285	328
		14	±147	121	147	145
		30	±651	511	651	583
GBO	21,474.1	7	±116	−33	116	113
		16	±136	124	134	136
		30	±898	739	855	898
Proposed GBOC	21,883.8	14	±316	249	316	302
		30	±833	693	767	833
HBA	21,078.8	13	±289	−29	269	289
		30	±831	811	771	831
SSA	15,131.6	30	±258	107	198	258
		32	±239	239	194	199



(**a**) Light Loading Level



(**b**) Medium Loading Level



(**c**) Peak Loading Level

Figure 6. Voltage profile for the IEEE 33-distribution system based on the proposed GBOC versus the initial case.

4.1.2. Second Scenario

In this scenario, the financial limit to be considered is increased with a compensation limit of 75% of the total reactive power load. Therefore, the proposed GBOC is applied compared to the original GBO, SSA, DMOA, DE, and HBA. Table 2 illustrates the placement and sizing of D-SVC devices and the corresponding economic savings per year. For this scenario, Figure 7 depicts the convergence characteristics of the proposed GBOC, original GBO, SSA, DMOA, DE, and HBA.

Table 2. Placement and sizing of D-SVC devices for the IEEE 33-distribution system for Scenario 2.

Algorithm	Dollars Savings Per Year	Installed Buses	Rate (kVAr)	Operational Value (kVAr)		
				Light	Medium	Peak
BSDE	20,424.7	26	±431	431	298	339
		29	±818	646	818	732
		30	±313	276	86	313
DE	23,612.1	13	±294	164	289	294
		26	±574	441	574	558
		30	±821	449	623	821
DMOA	23,382.7	11	±640	277	335	640
		25	±200	25	163	200
		30	±859	536	772	859
GBO	23,784.24	12	±497	274	440	497
		25	±261	228	230	261
		30	±967	489	855	967
Proposed GBOC	23,988.449	7	±421	384	417	421
		14	±346	171	263	346
		30	±958	575	806	958
HBA	23,197	13	±358	289	358	351
		30	±1171	652	950	1171
SSA	14,249.2	14	±362	91	104	362
		30	±132	−11	132	81
		31	±336	178	198	336

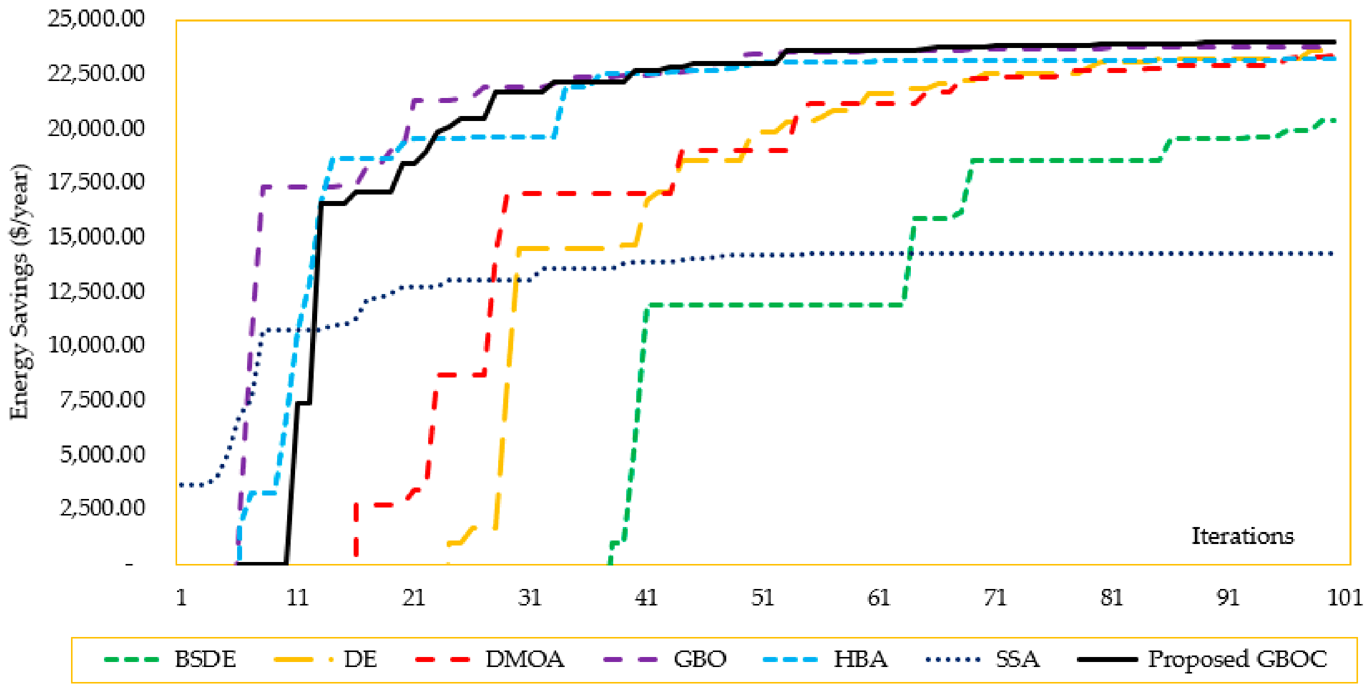


Figure 7. Convergence characteristics of GBOC, GBO, SSA, DMOA, DE, and HBA for the IEEE 33-distribution system for Scenario 2.

From Table 2 and Figure 7, the proposed GBOC finds the maximum yearly savings of USD 23,988.45 displaying the best performance. Secondly, GBO achieves yearly savings of USD 23,784.24, DE achieves yearly savings of USD 23,612.1, while DMOA achieves yearly savings of USD 23,382.7 in the fourth rank. Fifthly, HBA achieves yearly savings of USD 23,197 while BSDE achieves yearly savings of USD 20,424.7 in the sixth rank. Overall, out of all of the techniques, the worst performance is related to the SSA which finds yearly savings of USD 14,249.2.

For each loading level, based on the obtained D-SVC devices in Table 2, Table 3 displays the power losses and their percentage relative to their demand. From this table, the proposed GBOC obtains the minimum power losses of 0.0483, 0.08755, and 0.1402 MW, respectively, for light, medium, and peak compared to 0.0713, 0.1307, and 0.2110 MW at the initial case with improvement percentages of 31.69, 33.36, and 33.55%.

Table 3. Power losses (MW) and the percentage of each loading level are based on the obtained D-SVC devices in Table 2.

	Initial	BSDE	DE	DMOA	GBO	Proposed GBOC	HBA	SSA
Light	0.0713 (3.1%)	0.0533 (2.3%)	0.0487 (2.1%)	0.0494 (2.2%)	0.0487 (2.1%)	0.048331 (2.1%)	0.0490 (2.1%)	0.0608 (2.7%)
Medium	0.1307 (4.3%)	0.0933 (3.1%)	0.0881 (2.9%)	0.0883 (2.9%)	0.08761 (2.9%)	0.087557 (2.9%)	0.0889 (2.9%)	0.1073 (3.5%)
Peak	0.2110 (5.6%)	0.1498 (3.9%)	0.1414 (3.7%)	0.1419 (3.7%)	0.1402 (3.7%)	0.1402 (3.7%)	0.1427 (3.8%)	0.1636 (4.3%)

Nevertheless, Figure 8 describes the minimum voltage at each loading level for GBO, SSA, DMOA, DE, and HBA compared to the initial case. All of the applied algorithms enhance the minimum voltage compared to the initial case. The proposed GBOC enhances the minimum voltage from 0.944, 0.9244, and 0.9037 at the initial case to 0.9574, 0.9459, and 0.9282 for light, medium, and peak loading levels, respectively.

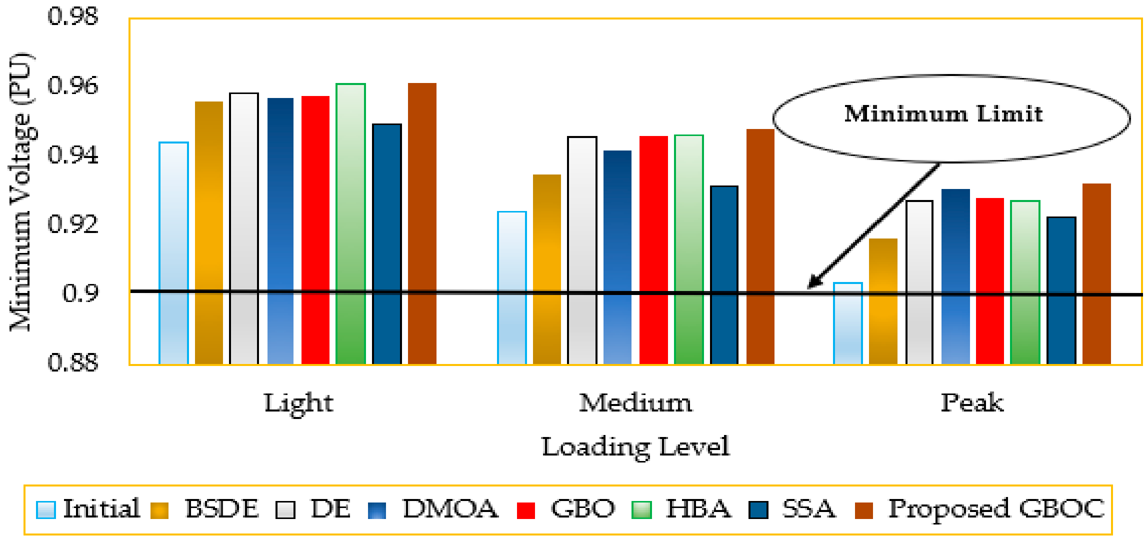


Figure 8. Minimum voltages for the IEEE 33-distribution system of the GBOC versus GBO, SSA, DMOA, DE, and HBA for Scenario 2.

The number of iterations is increased three times compared to 300 to discuss the impacts of increasing the number of iterations on the obtained objectives. All of the algorithms are applied for this scenario to guarantee complete convergence. Figure 9 describes the related convergence. As shown, the high ability of the proposed GBOC is demonstrated in finding the highest savings of 24,156.63 $/year while BSDE, DE, DMOA, GBO, HBA, and SSA obtain 22,911.81, 23,996.83, 23,934.15, 23,935.84, 23,505.26 and 19,413.11 $/year, respectively.

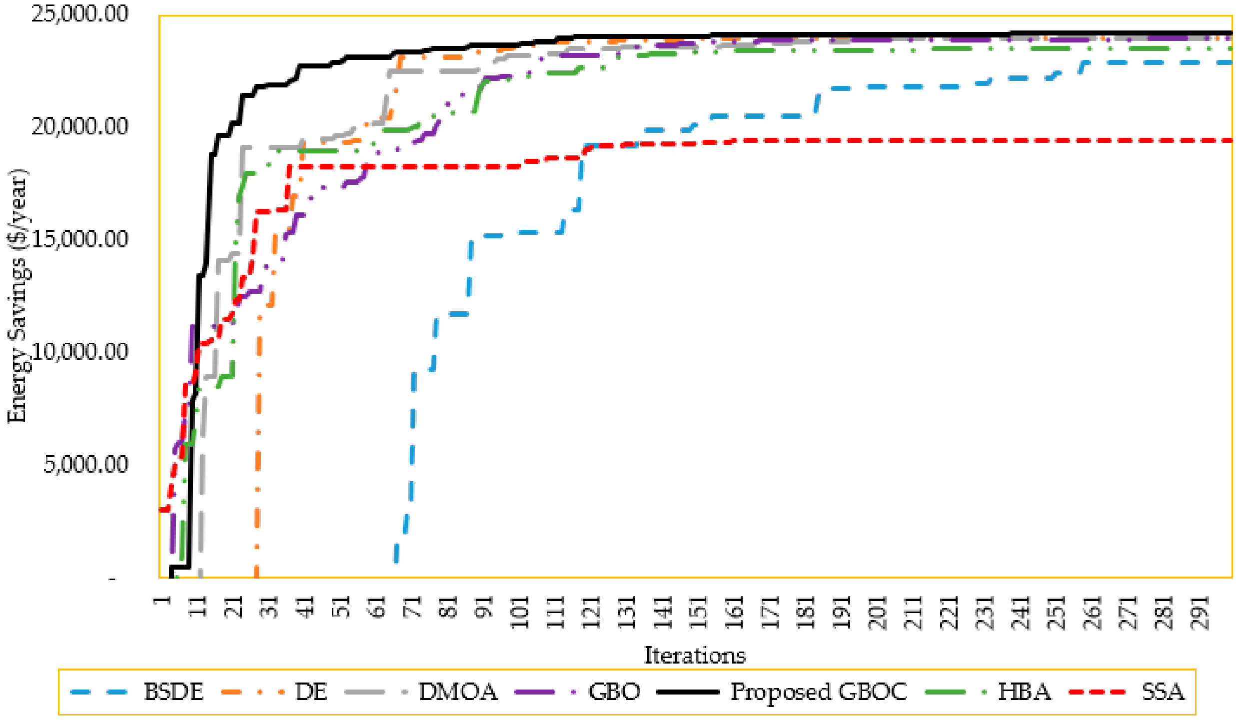


Figure 9. Convergence characteristics of GBOC, GBO, SSA, DMOA, DE, and HBA for the IEEE 33-distribution system for Scenario 2.

4.1.3. Objective Analysis with Further Comparison of Algorithms with Improved Compensation

To further compare the applied algorithms with improved compensation levels, Table 4 describes the objective values obtained by the applied techniques for 50, 62.5, 75, and 87.5% compensation levels. Furthermore, the accuracy of all of the applied techniques is evaluated considering a target level of 25,000 $/year cost saving. As shown, the highest accuracy is always achieved by the proposed GBOC compared to the others. For a 50% compensation level, the proposed GBOC provides an accuracy of 87.54%, while GBO obtains the closest accuracy of 85.9%. For a 62.5% compensation level, the proposed GBOC provides an accuracy of 93.08%, while the GBO obtains the closest accuracy of 92.6%. For a 75% compensation level, the proposed GBOC provides an accuracy of 95.95%, while the GBO obtains the closest accuracy of 95.14%. For an 87.5% compensation level, the proposed GBOC provides an accuracy of 95.83%, while the GBO obtains the closest accuracy of 95.52%.

4.1.4. Discussions for the First Studied Distribution System

For this system, the proposed GBOC derives the best performance compared to the other compared algorithms as it finds the maximum yearly savings with different compensation levels. The proposed GBOC obtains the minimum power losses for light, medium, and peak loadings. In addition, the minimum voltage at each loading level is enhanced compared to the initial case for light, medium, and peak loading levels, respectively. Moreover, the high ability of the proposed GBOC is demonstrated in finding the highest savings compared to the others with a high number of iterations. Furthermore, Figure 10 illustrates the improvement percentages of the proposed GBOC versus the original GBO, SSA, DMOA, DE, and HBA for the IEEE 33-distribution system for different compensation levels.

Table 4. Obtained objectives and related accuracies of all of the applied techniques with improved compensation levels.

	BSDE	E	DMOA	GBO	HBA	SSA	Proposed GBOC
50%	15,223.58	21,466.85	21,015.59	21,474.12	21,078.76	15,131.58	21,883.75
Accuracy	60.89%	85.87%	84.06%	85.90%	84.32%	60.53%	87.54%
62.50%	18,807.15	22,886.68	22,914.02	23,150.15	21,533.93	14,724.84	23,268.94
Accuracy	75.23%	91.55%	91.66%	92.60%	86.14%	58.90%	93.08%
75%	20,424.74	23,612.12	23,382.69	23,784.24	23,197.04	14,249.20	23,988.45
Accuracy	81.70%	94.45%	93.53%	95.14%	92.79%	57.00%	95.95%
87.50%	22,159.16	23,717.17	23,772.13	23,881.17	23,865.75	16,396.81	23,956.64
Accuracy	88.64%	94.87%	95.09%	95.52%	95.46%	65.59%	95.83%

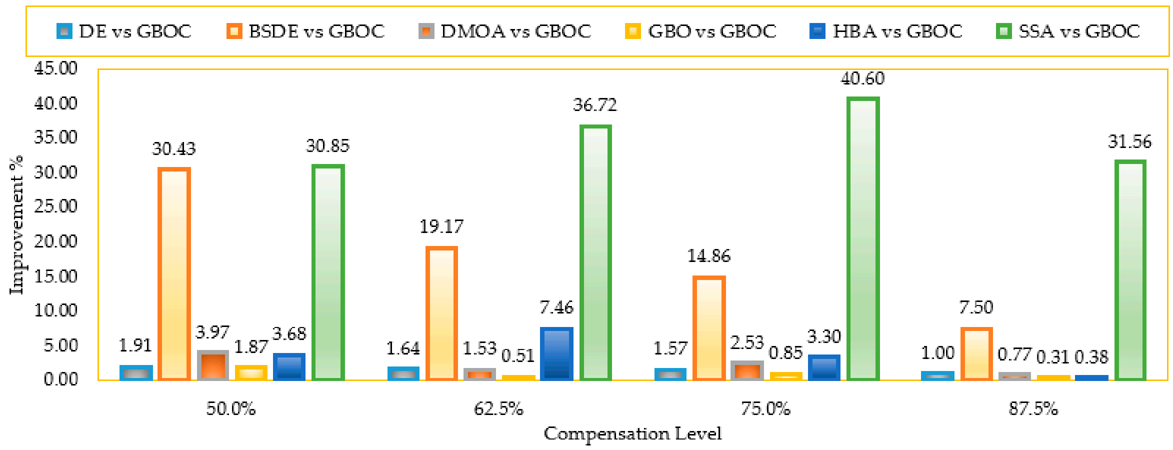


Figure 10. Improvement percentages of the proposed GBOC versus GBO, SSA, DMOA, DE, and HBA for the IEEE 33-distribution system with improved compensation levels.

In addition, the proposed GBOC derives significant improvement compared to the others. As shown, the proposed GBOC greatly improved by 30.85, 36.72, 40.60, and 31.56% compared to SSA, increasing compensation levels of 50, 62.5, 75, and 87.5%, respectively. In addition, the proposed GBOC greatly improved by 30.43, 19.17, 14.86, and 7.50% compared to BSDE, with compensation levels of 50, 62.5, 75, and 87.5%, respectively.

4.2. The IEEE 69-Node Distribution Network

The second system has 69 nodes and 68 distribution sections. Its one-line topology is depicted in Figure 11 and its standard voltage is 12.66 kV.

4.2.1. First Scenario

In this scenario, the proposed GBOC is applied compared to the original GBO, SSA, DMOA, DE, and HBA, with a compensation limit of 50% of the total reactive power load. Table 5 displays the candidate buses for D-SVCs installation and their rates, where the corresponding economic savings per year are also stated. Figure 12 depicts the conforming convergence characteristics of the proposed GBOC, GBO, SSA, DMOA, DE, and HBA for this scenario. The proposed GBOC finds the maximum yearly savings of USD 24,050.615 displaying the best performance. Secondly, GBO achieves yearly savings of USD 23,567.079, DE achieves yearly savings of USD 22,789.45 while DMOA achieves yearly savings of USD 22,451.285 in the fourth rank. Fifthly, HBA achieves yearly savings of USD 21,036.073 while SSA achieves yearly savings of USD 18,007.217 in the sixth rank. Overall, out of all of the techniques, the worst performance is related to the BSDE,which finds yearly savings of USD 13,754.46.

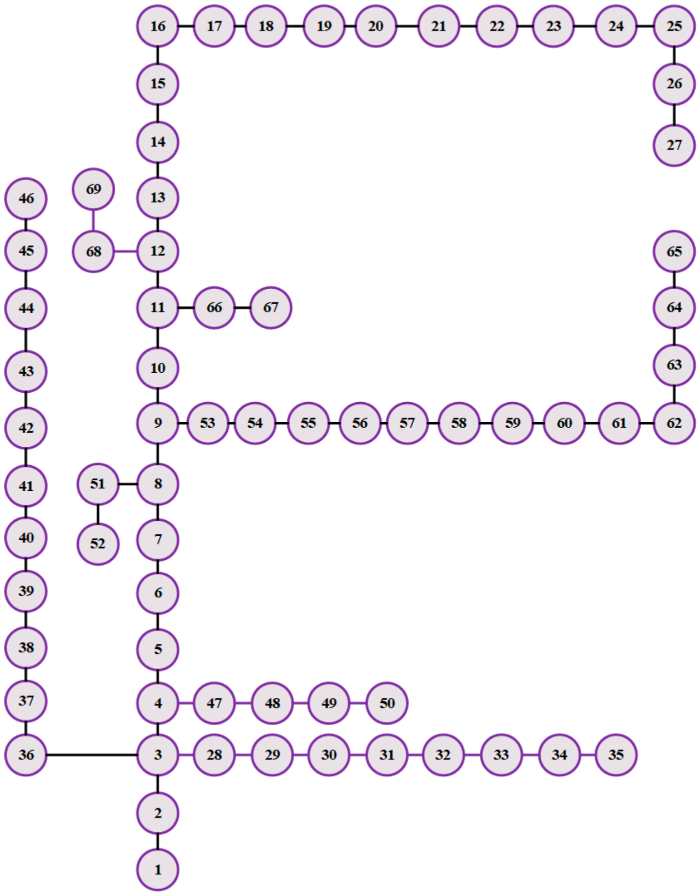


Figure 11. The IEEE 69-distribution system.

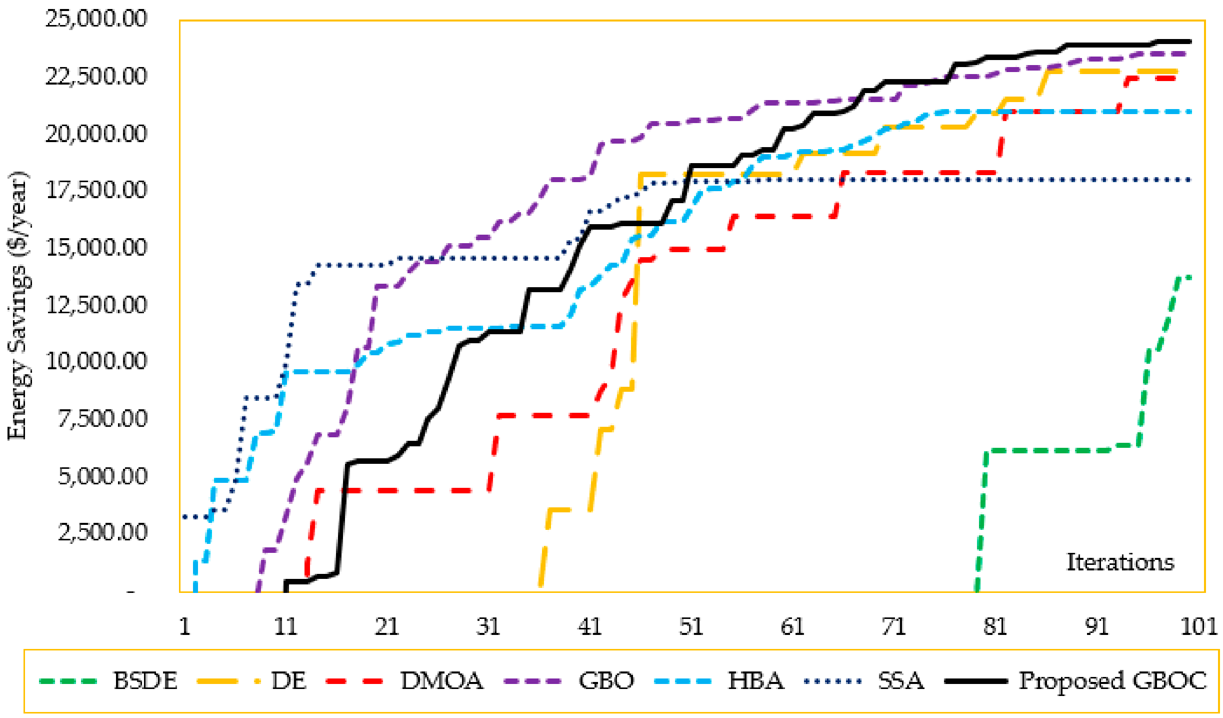


Figure 12. Convergence characteristics of GBOC, GBO, SSA, DMOA, DE, and HBA for the IEEE 69-distribution system for Scenario 1.

Table 5. Placement and sizing of D-SVC devices for the IEEE 69-distribution system for Scenario 1.

Algorithm	Dollars Savings Per Year	Installed Buses	Rate (kVAr)	Operational Value (kVAr)		
				Light	Medium	Peak
BSDE	13,754.46	54	±171	171	6	0
		61	±251	53	251	31
		62	±282	578	282	259
DE	22,789.45	62	±557	332	452	557
		63	±484	383	484	382
		69	±82	59	82	82
DMOA	22,451.285	62	±393	275	358	393
		63	±416	261	416	236
		64	±332	303	332	309
GBO	23,567.079	21	±876	149	165	189
		61	±876	781	876	876
Proposed GBOC	24,050.615	21	±204	173	194	204
		62	±589	539	587	589
		64	±355	227	283	355
HBA	21,036.073	61	±321	96	321	321
		62	±618	277	618	618
SSA	18,007.217	61	±263	257	263	226
		64	±211	211	154	259

In addition, Figure 13 illustrates the power losses (MW) in each loading level based on the obtained D-SVC devices in Table 5 compared to the initial case. As shown, the proposed GBOC obtains the minimum power losses of 0.0505, 0.0943, and 0.1572 MW, respectively, for light, medium, and peak compared to 0.0755, 0.1388, and 0.2249 MW at the initial case with improvement percentages of 33.33, 32.02, and 28.88%. Similarly, all the applied algorithms satisfy the voltage limitations and enhance the minimum voltage compared to the initial case, as described in Figure 14, for light, medium, and peak loading levels.

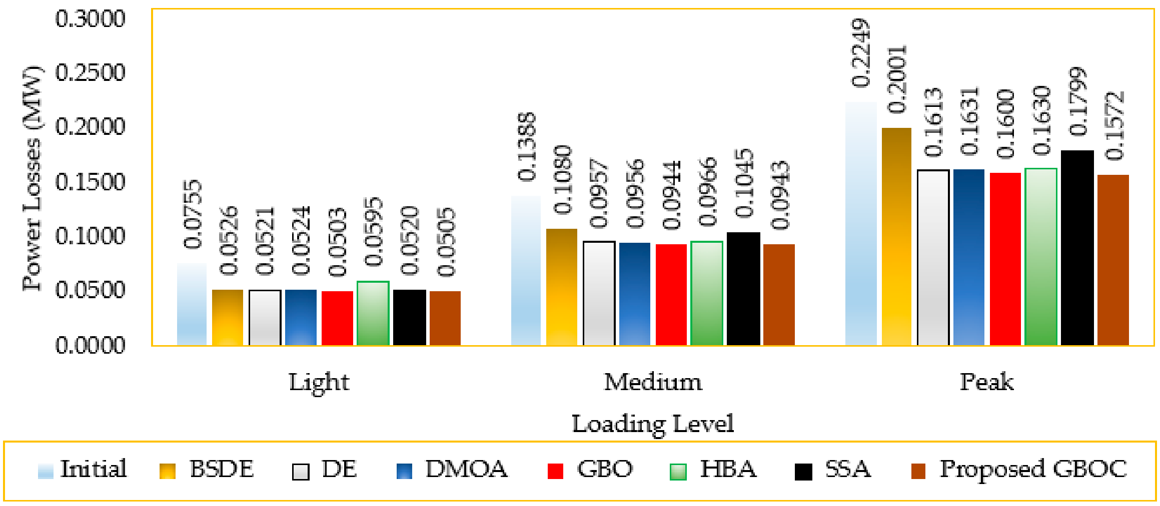


Figure 13. Power losses (MW) in each loading level based on the obtained D-SVC devices in Table 5 compared to the initial case.

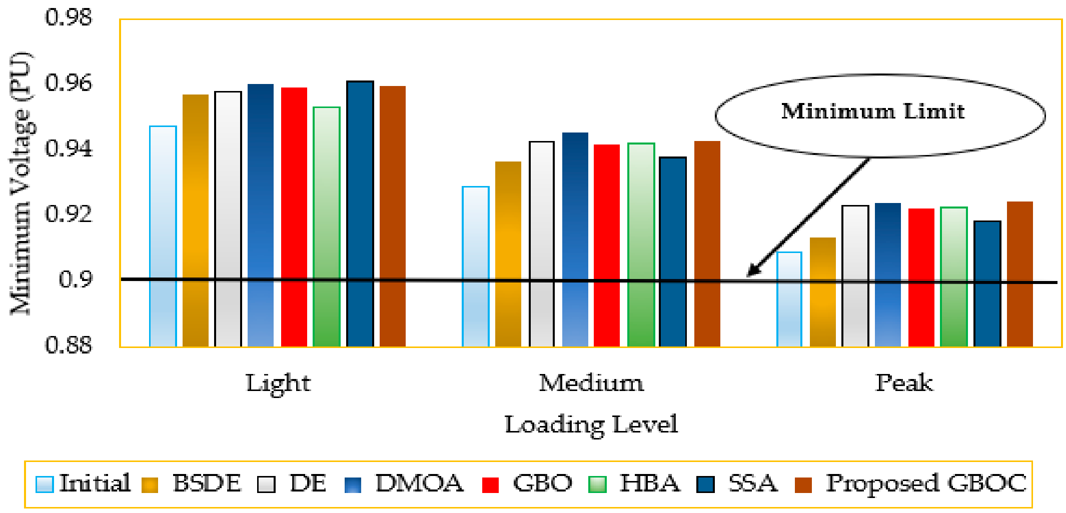


Figure 14. Minimum voltages for the IEEE 69-node system of the GBOC versus GBO, SSA, DMOA, DE, and HBA for Scenario 1.

To illustrate the range of voltage improvement, Figure 15 displays the voltage profile based on the proposed GBOC compared to the initial case for light, medium, and peak loading levels. As shown, great improvements are achieved for all distribution nodes and all loading levels. The greatest improvement in the voltage profile is derived at the 65th distribution node with 1.21, 1.4, and 1.54% for light, medium, and peak loading levels, respectively.

4.2.2. Second Scenario

In this scenario, the financial limit is increased with a compensation limit of 75% of the total reactive power load. The proposed GBOC is applied compared to the original GBO, SSA, DMOA, DE, and HBA. Table 6 and Figure 16 illustrate the outcomes and convergence characteristics, respectively.

Table 6. Placement and sizing of D-SVC devices for the IEEE 69-distribution system for Scenario 2.

Algorithm	Dollars Savings Per Year	Installed Buses	Rate (kVAr)	Operational Value (kVAr)		
				Light	Medium	Peak
BSDE	21,631.82	22	±314	124	125	560
		62	±314	97	314	233
		63	±560	560	533	413
DE	25,975.39	16	±370	370	323	285
		62	±291	574	968	1060
		64	±291	178	15	291
DMOA	26,104.413	22	±289	60	289	240
		61	±801	579	752	801
		64	±603	233	321	603
Proposed GBOC	26,589.292	18	±286	160	203	286
		61	±1288	882	1088	1288
		68	±143	84	150	143
GBO	26,341.923	21	±245	216	245	244
		61	±1102	1085	735	1102

Table 6. *Cont.*

Algorithm	Dollars Savings Per Year	Installed Buses	Rate (kVAr)	Operational Value (kVAr)		
				Light	Medium	Peak
SSA	20,232.116	61	±436	431	436	−11
		64	±311	121	311	297
HBA	25,923.958	12	±366	358	228	366
		24	±266	−110	266	257
		61	±1092	791	1085	1092

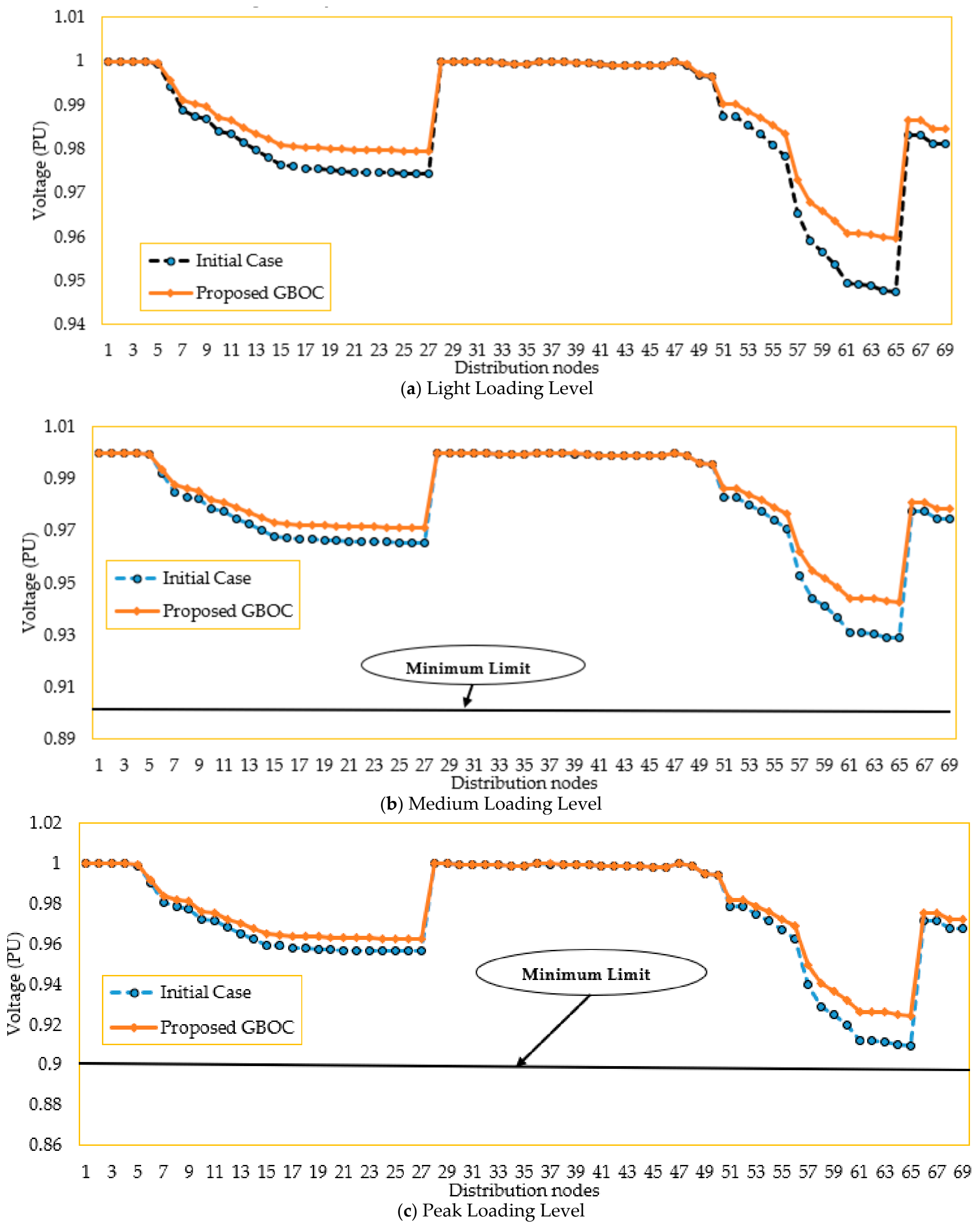


Figure 15. Voltage profile for the IEEE 69-distribution system based on the proposed GBOC versus initial case.

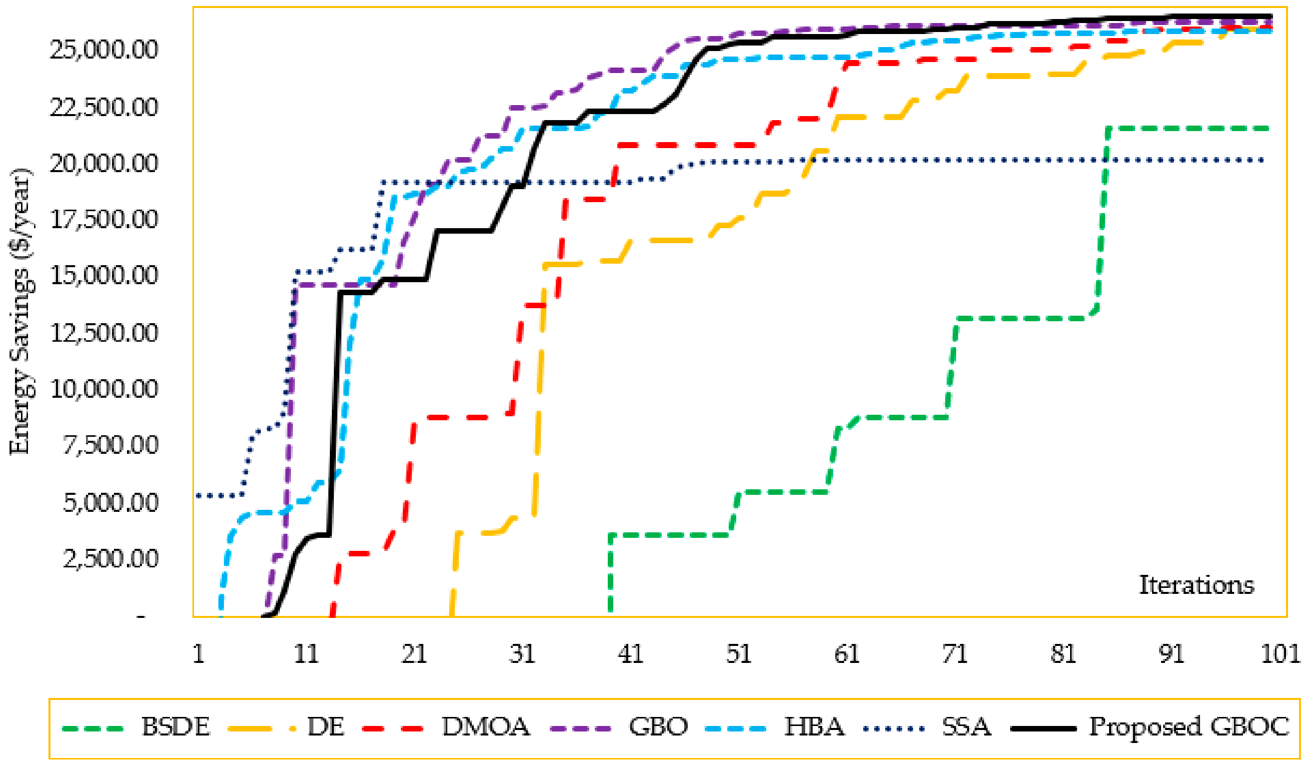


Figure 16. Convergence characteristics of GBOC, GBO, SSA, DMOA, DE, and HBA for the IEEE 69-distribution system for Scenario 2.

The proposed GBOC finds the maximum yearly savings of USD 26,589.29 displaying the best performance. Secondly, the GBO achieves yearly savings of USD 26,341.923, DMOA achieves yearly savings of USD 26,104.413, and DE achieves yearly savings of USD 25,975.39 in the fourth rank. Fifthly, HBA achieves yearly savings of USD 25,923.958 while BSDE achieves yearly savings of USD 21,631.82 in the sixth rank. Overall, out of all of the techniques, the worst performance is related to the SSA that finds yearly savings of USD 20,232.116.

In addition, Figure 17 illustrates the power losses (MW) in each loading level based on the obtained D-SVC devices in Table 6 compared to the initial case. As shown, the proposed GBOC obtains the minimum power losses of 0.05, 0.0908, and 0.1466 MW, respectively, for light, medium, and peak compared to 0.0755, 0.1388, and 0.2249 MW at the initial case with improvement percentages of 33.76, 34.57, and 34.8%. As Figure 18 describes the initial case, all applied algorithms fulfill the voltage restrictions and increase the minimum voltage relative to it. This is true for light, medium, and peak loading levels.

To discuss the impacts of increasing the number of iterations on the obtained objectives, Figure 19 describes the convergence of the applied algorithms with several iterations of 300 to guarantee complete convergence. As shown, the high ability of the proposed GBOC is demonstrated in finding the highest savings of 26,690.04 $/year while BSDE, DE, DMOA, GBO, HBA, and SSA obtain 25,641.73, 26,463.23, 26,405.01, 26,489.72, 24,639.96, and 22,594.49 $/year, respectively.

4.2.3. Objective Analysis with Further Comparison of Algorithms with Improved Compensation

To further compare the applied algorithms with improved compensation levels, Table 7 describes the objective values obtained by the applied techniques for 50, 62.5, 75, and 87.5% compensation levels. Furthermore, the accuracy of all of the applied techniques is evaluated considering a target level of 28,000 $/year cost saving.

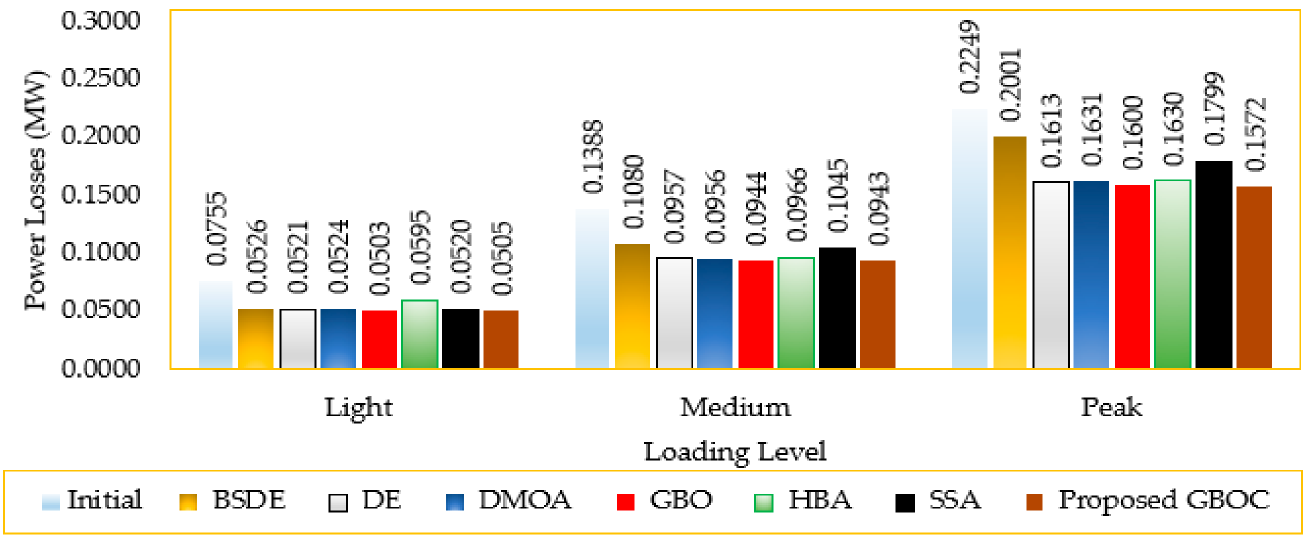


Figure 17. Power losses (MW) in each loading level based on the obtained D-SVC devices in Table 6 compared to the initial case.

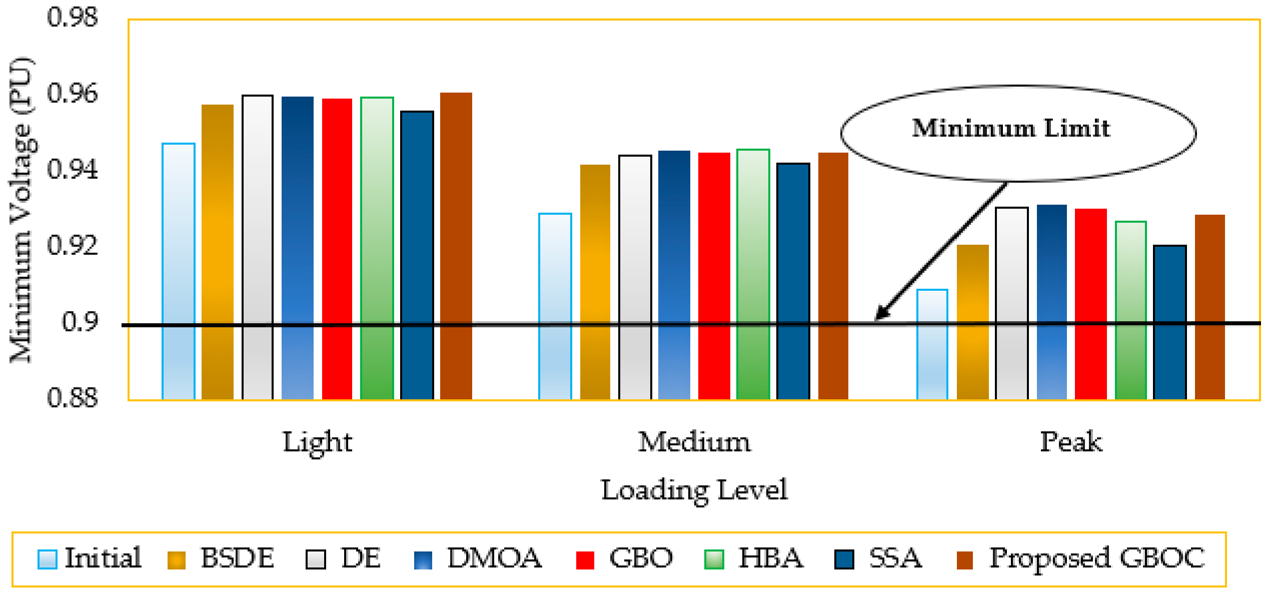


Figure 18. Minimum voltages for the IEEE 69-distribution system of the GBOC versus GBO, SSA, DMOA, DE, and HBA for Scenario 2.

As shown, the highest accuracy is always achieved by the proposed GBOC compared to the others. For a 50% compensation level, the proposed GBOC provides an accuracy of 85.9%, while the GBO obtains the closest accuracy of 84.17%. For a 62.5% compensation level, the proposed GBOC provides an accuracy of 94.59%, while DMOA obtains the closest accuracy of 90.9%. For a 75% compensation level, the proposed GBOC provides an accuracy of 94.96%, while the GBO obtains the closest accuracy of 94.08%. For an 87.5% compensation level, the proposed GBOC provides an accuracy of 95.89%, while the GBO obtains the closest accuracy of 95.7%. Additionally, the cost saving increased to 24050.61, 25644.87, 26589.29, and 26849.08 $/year, with increasing compensation levels of 50, 62.5, 75, and 87.5%, respectively.

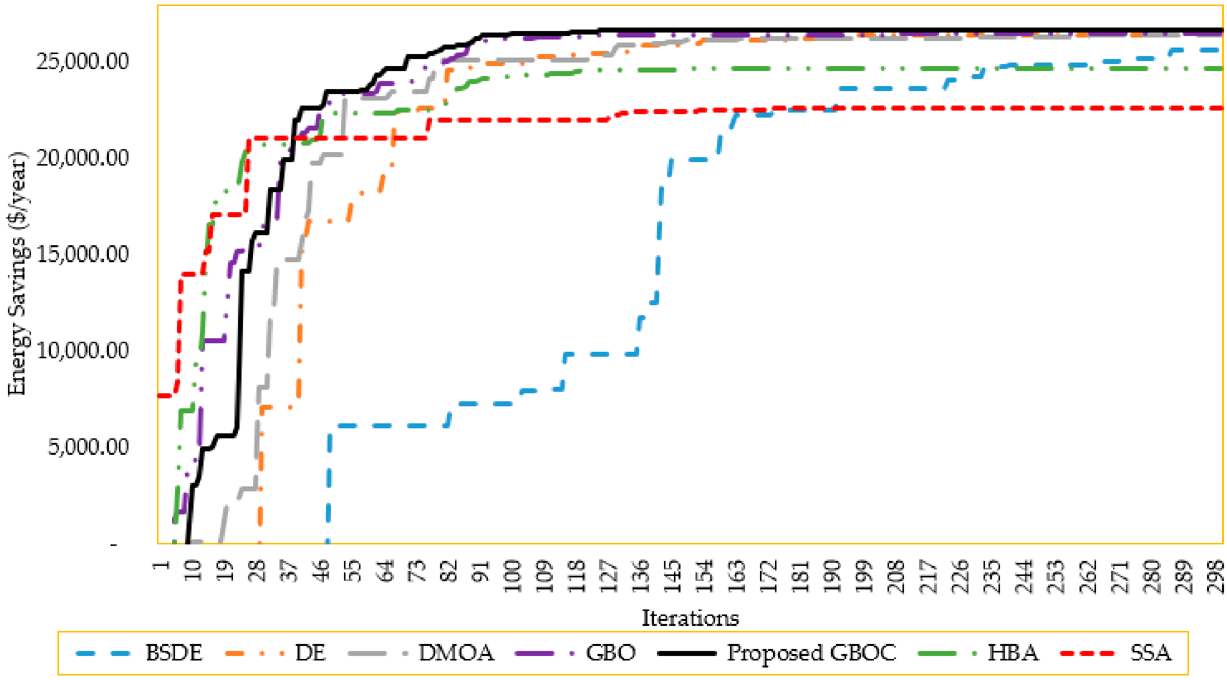


Figure 19. Convergence characteristics of GBOC, GBO, SSA, DMOA, DE, and HBA for the IEEE 69-distribution system for Scenario 2.

Table 7. Obtained objectives and related accuracies of all of the applied techniques with improved compensation levels.

	BSDE	DE	DMOA	GBO	HBA	SSA	Proposed GBOC
50%	13,754.46	22,789.45	22,451.28	23,567.08	21,036.07	18,007.22	24,050.61
Accuracy	49.12	81.39	80.18	84.17	75.13	64.31	85.90
62.50%	18,822.64	25,379.43	25,451.37	25,239.36	22,990.71	18,117.48	25,644.87
Accuracy	67.22	90.64	90.90	90.14	82.11	64.71	91.59
75%	21,631.82	25,975.39	26,104.41	26,341.92	25,923.96	20,232.12	26,589.29
Accuracy	77.26	92.77	93.23	94.08	92.59	72.26	94.96
87.50%	23,007.21	26,325.31	26,266.50	26,795.80	26,361.20	18,423.33	26,849.08
Accuracy	82.17	94.02	93.81	95.70	94.15	65.80	95.89

4.2.4. Discussions for the Second Studied Distribution System

Similar findings are attained for this system. The proposed GBOC derives the best performance compared to the other compared algorithms as it finds the maximum yearly savings with different compensation levels. The proposed GBOC obtains the minimum power losses for light, medium, and peak loadings. In addition, the minimum voltage at each loading level is enhanced compared to the initial case for light, medium, and peak loading levels, respectively. Moreover, the high ability of the proposed GBOC is demonstrated in finding the highest savings compared to the others with a high number of iterations. Furthermore, Figure 20 illustrates the improvement percentages of the proposed GBOC versus the original GBO, SSA, DMOA, DE, and HBA for the IEEE 69-distribution system for different compensation levels.

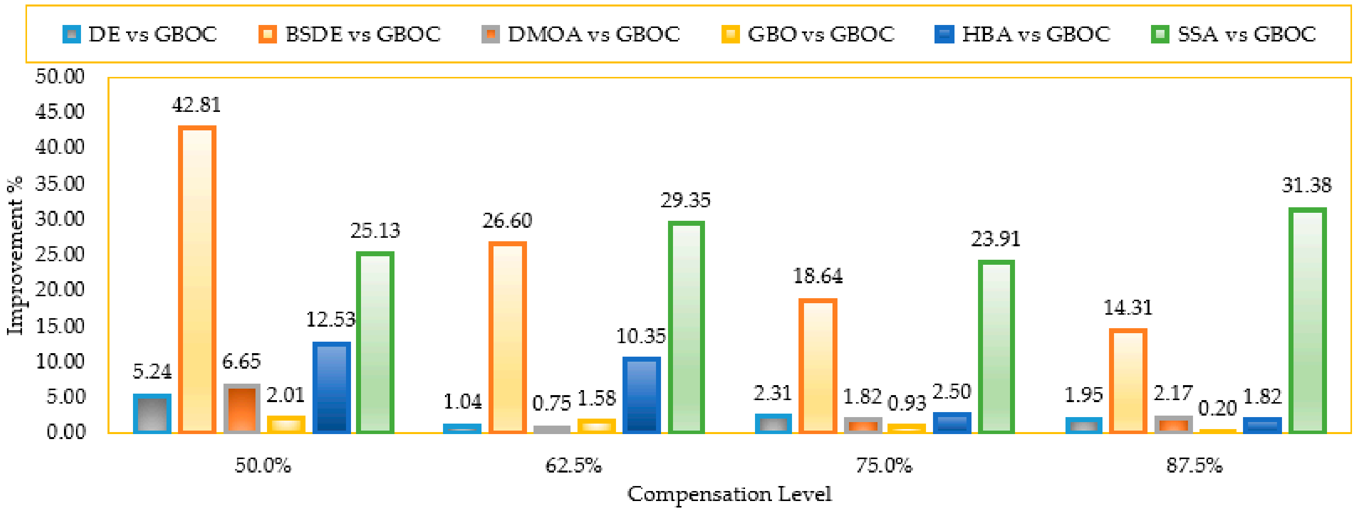


Figure 20. Improvement percentages of the proposed GBOC versus GBO, SSA, DMOA, DE, and HBA for the IEEE 69-distribution system with improved compensation levels.

As shown, at 50% compensation the proposed GBOC greatly improves by 5.24, 42.81, 6.65, 2.01, 12.53 m and 25.13% compared to DE, BSDE, DMOA, original GBO, HBA, and SSA, respectively. For 62.5% compensation, the proposed GBOC provides a great improvement of 1.04, 26.6, 0.75, 1.58, 10.35, and 29.35% compared to DE, BSDE, DMOA, original GBO, HBA, and SSA, respectively. For 75% compensation, the proposed GBOC greatly improves by 2.31, 18.64, 1.82, 0.93, 2.5, and 23.91% compared to DE, BSDE, DMOA, original GBO, HBA, and SSA, respectively. For 87.5% compensation, the proposed GBOC provides a great improvement of 1.95, 14.31, 2.17, 0.2, 1.82, and 31.38% compared to DE, BSDE, DMOA, original GBO, HBA, and SSA, respectively.

4.3. The IEEE 118-Node Distribution Network

The proposed GBOC algorithm is evaluated on a large-scale 118-node RPDN to demonstrate its efficiency. Ref. [43] received the 118-distribution system data. At 100% network loading, the real power loss with the base case architecture is 1298.09 kW with a minimum voltage magnitude of 0.8688 PU at the 77th node. At 80% network loading, the real power loss for the base case architecture is 1298.09 kW, with a minimum voltage magnitude of 0.8979 PU. At 60% network loading, the actual power loss for the base case architecture is 1298.09 kW, with a minimum voltage magnitude of 0.9253 PU.

Considering the 50% compensation limit, the proposed GBOC is applied compared to the original GBO, SSA, DMOA, DE, and HBA with several iterations of 300. Table 8 displays the candidate buses for D-SVC installation and their rates, where the corresponding economic savings per year are also stated. Figure 21 depicts the conforming convergence characteristics of the proposed GBOC, GBO, SSA, DMOA, DE, and HBA for this scenario. The proposed GBOC finds the maximum yearly savings of USD 129,406.09 displaying the best performance. Secondly, GBO achieves yearly savings of USD 129,345.445 while HBA achieves yearly savings of USD 129,344.857 in the third rank. Fourthly, DMOA achieves yearly savings of USD 129,324.227 while BSDE achieves yearly savings of USD 129,025.419 in the fifth rank and DE achieves yearly savings of USD 129,025.42 in the sixth rank.

In addition, Figure 22 illustrates the power losses (MW) in each loading level based on the obtained D-SVC devices in Table 8 compared to the initial case. As shown, the proposed GBOC minimizes the power losses of 0.3125, 0.5694, and 0.9131 MW, respectively, for light, medium, and peak loading levels compared to 0.435, 0.8005, and 1.2981 MW at the initial case with improvement percentages of 28.16, 28.86, and 29.65%. Similarly, all of the applied algorithms satisfy the voltage limitations and enhance the minimum voltage compared to the initial case, as described in Figure 23, for light, medium, and peak loading levels.

Table 8. Placement and sizing of D-SVC devices for the IEEE 119-distribution system.

Algorithm	Dollars Savings Per Year	Installed Buses	Rate (kVAr)	Operational Value (kVAr)		
				Light	Medium	Peak
BSDE	129,025.419	39	±2829	1598	2335	2829
		72	±2200	1128	1694	2200
		110	±2487	1691	2069	2487
DE	128,470.108	39	±2848	1633	2227	2848
		71	±2317	1261	1763	2317
		118	±2531	1426	1961	2531
DMOA	129,324.227	39	±2861	1618	2230	2861
		72	±2193	1176	1638	2193
		110	±2680	1480	2042	2680
GBO	129,345.445	39	±2847	1635	2227	2847
		72	±2212	1208	1682	2212
		110	±2675	1503	2071	2675
HBA	129,344.857	39	±2851	1634	2227	2851
		72	±2212	1203	1682	2212
		110	±2675	1492	2071	2675
Proposed GBOC	129,406.0889	39	±2848	1633	2227	2848
		71	±2317	1261	1762	2317
		110	±2673	1506	2071	2673

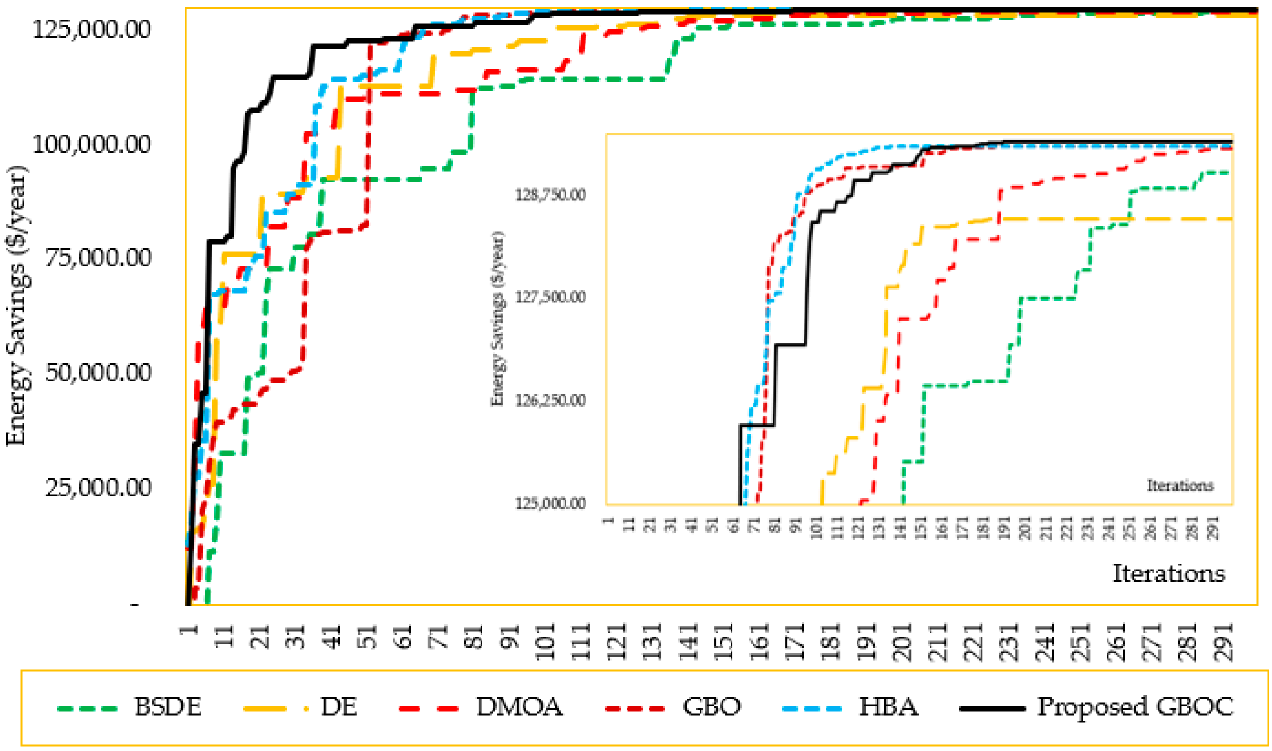


Figure 21. Convergence characteristics of GBOC, GBO, SSA, DMOA, DE, and HBA for the IEEE 119-distribution system.

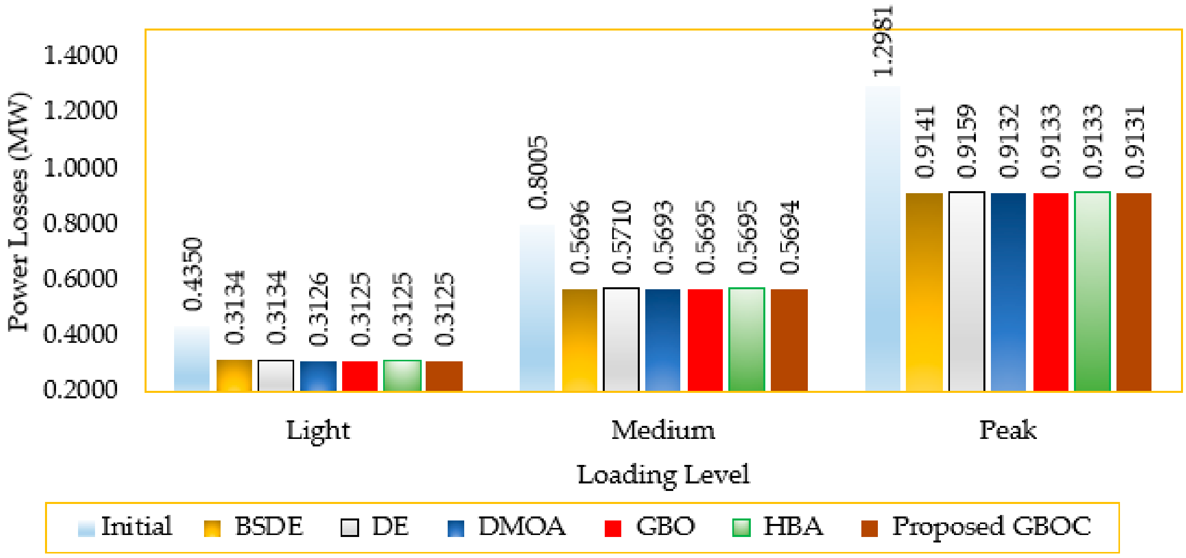


Figure 22. Power losses (MW) in each loading level based on the obtained D-SVC devices in Table 8 compared to the initial case.

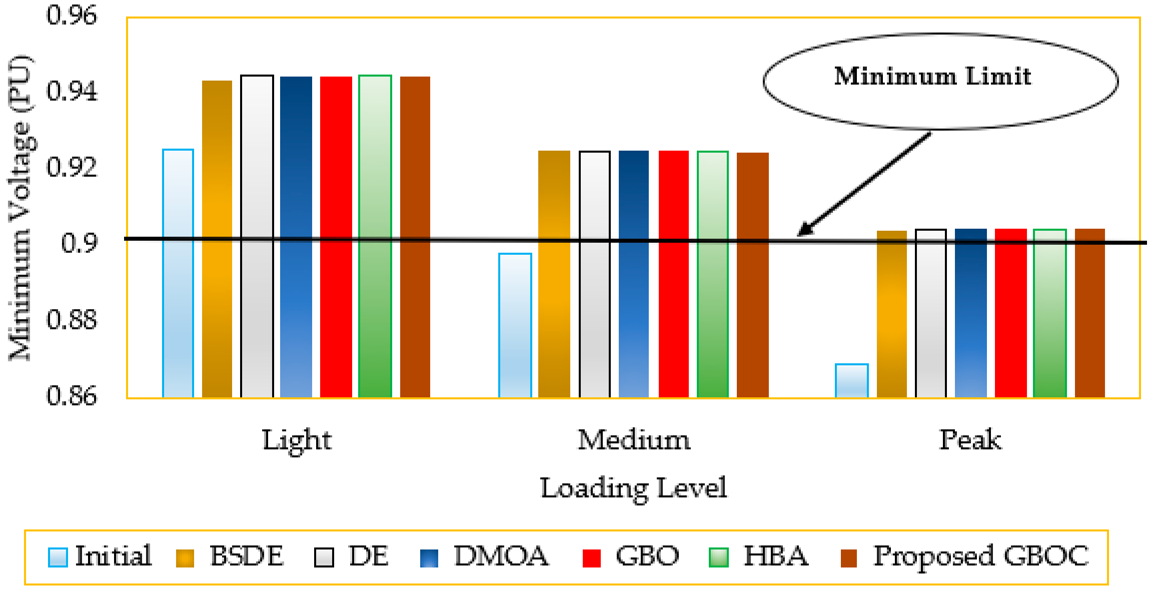


Figure 23. Minimum voltages for the IEEE 119-distribution system via the GBOC versus GBO, SSA, DMOA, DE, and HBA.

To illustrate the range of voltage improvement, Figure 24 displays the voltage profile based on the proposed GBOC compared to the initial case for light, medium, and peak loading levels. As shown, great improvements are achieved for all of the distribution nodes and all of the loading levels. The greatest improvement in the voltage profile is derived at the 43rd distribution node with 2.32, 3.16, and 4.06% for light, medium, and peak loading levels, respectively.

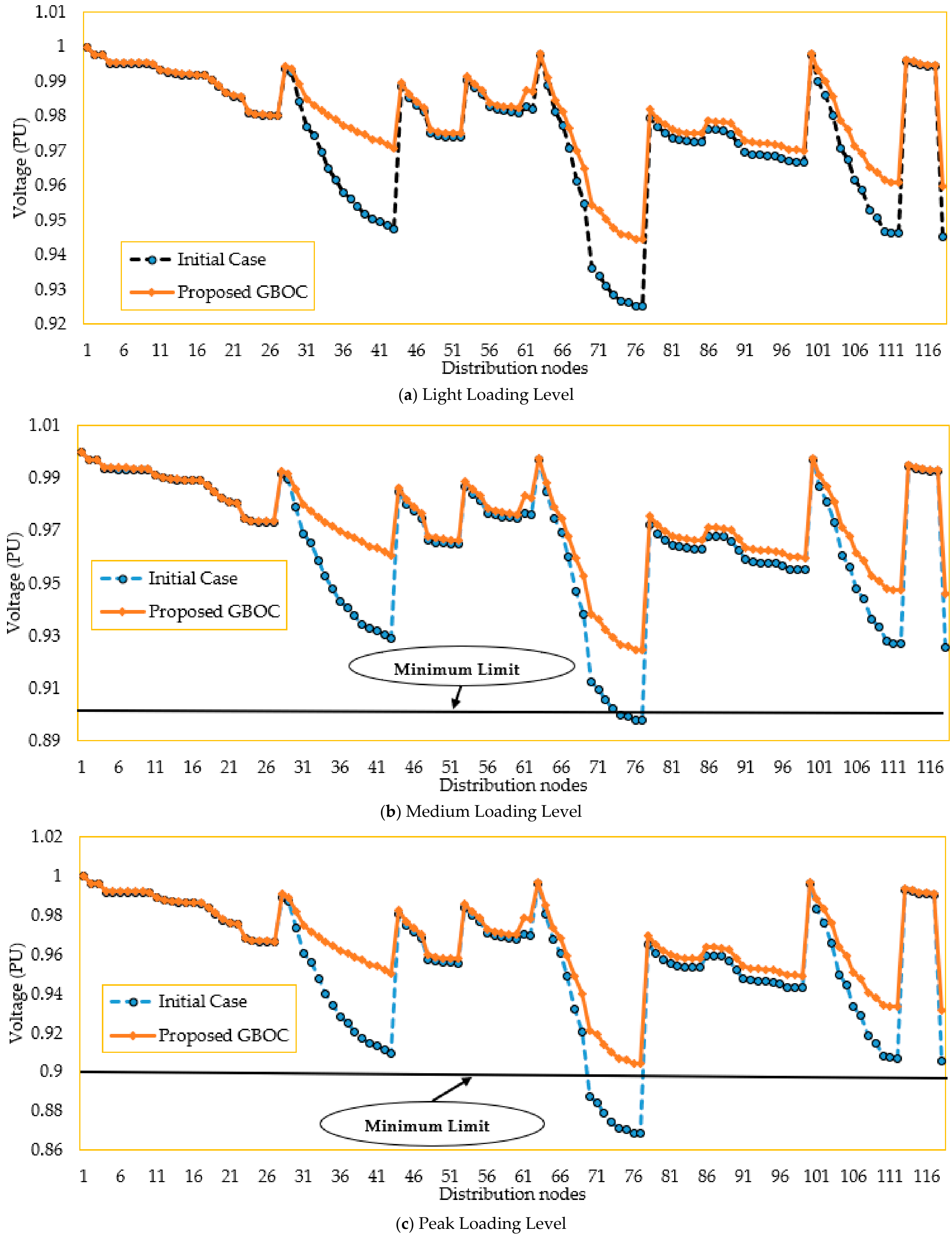


Figure 24. Voltage profile for the IEEE 119-distribution system based on the proposed GBOC versus initial case.

5. Conclusions

This study proposes an enhanced, evolved version of the gradient-based optimizer (GBO) integrated with the crossover operator (GBOC) to increase the variety of the solutions generated. The combined crossover operator makes the following generation's solutions more random. The novel proposed GBOC is employed for optimal placement and sizing of the distribution static VAR compensator (D-SVC) to maximize yearly energy savings in power losses. Furthermore, the proposed methodology via proposed GBOC is created to simultaneously consider various degrees of the peak, average, and light loadings. Additionally, the outputs of the D-SVCs are optimally varied with the loading level. Otherwise, to represent a financial installation limit, the installed SVC ratings are handled as a second restriction linked to two compensation levels of 50% and 75% of the total reactive power demand.

Moreover, the effectiveness of the proposed GBOC is investigated in comparison to several methods, including the original GBO, SSA, DMOA, DE, HBA, and BSDE. The applicability of the compared algorithms is examined on three distribution systems with IEEE 33, 69, and 118 nodes. The simulation applications of the proposed GBOC provide 29.13% and 33.16% improvements, at both compensation levels, for the IEEE 33-nodes system and 31.01% and 34.23% for the IEEE 69-nodes system. In addition, the feasibility of the suggested GBOC is proved for the large-scale 118-node distribution system with the improvement of power losses of 28.16, 28.86, and 29.65%, respectively, for light, medium, and peak loading levels compared to the initial case. The proposed GBOC demonstrates a superior performance by finding the maximum yearly savings in power losses for all scenarios studied compared to the original GBO, SSA, DMOA, DE, HBA, and BSDE algorithms. Nevertheless, the minimum voltages at each loading level are improved.

Author Contributions: Conceptualization, A.M.S. and H.S.E.M.; Data curation, A.R.G.; Formal analysis, H.S.E.M.; Methodology, A.R.G. and A.M.S.; Project administration, G.M.; Resources, A.R.G. and H.S.E.M.; Software, A.M.S.; Supervision, G.M. and M.E.; Validation, A.M.S.; Visualization, M.E.; Writing—original draft, A.R.G.; Writing—review and editing, G.M. and M.E. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1 provides detailed parameter settings of the suggested GBOC, original GBO, SSA, DMOA, DE, and HBA.

Table A1. Parameter settings of the employed algorithms for the optimal placement and sizing of D-SVC devices in distribution systems.

Algorithm	Parameters
BSDE	100 iterations and 20 search agents Adaptive random parameters
DE	100 iterations and 20 search agents F = 0.5; % differentiation (or mutation) constant CR = 0.5; % crossover constant
DMOA	100 iterations and 20 search agents nBabysitter = 3; % Number of babysitters nAlphaGroup = 17; % Number of Alpha group L = 22 % Babysitter Exchange Parameter peep = 2; % Alpha femaleç—vocalization

Table A1. *Cont.*

Algorithm	Parameters
GBO	100 iterations and 20 search agents pr = 0.5; % Probability Parameter
HBA	100 iterations and 20 search agents beta = 6; % the ability of HBA to get the food C = 2; % constant
SSA	100 iterations and 20 search agents Adaptive random parameters
Proposed GBOC	100 iterations and 20 search agents pr = 0.5; % Probability Parameter crossover probability = 0.25;

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