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Sizing and Sitting of Static VAR Compensator (SVC) Using Hybrid Optimization of Combined Cuckoo Search (CS) and Antlion Optimization (ALO) Algorithms

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Abstract: Worldwide, due to the abrupt growth of population, the load demand has been rising dramatically in the last few years. This led to an increase in branch overloads, voltage deviations, and power losses. These problems may result in line outages or the occurrence of blackouts. Flexible AC transmission system (FACTS) devices can be installed in the power system to ensure increased power flow capability and flexible voltage control to address these issues. In this paper, one of the most used FACTS is utilised. It is called Static VAR Compensator (SVC). This controller is one of the most commonly used shunt FACTS controllers due to its low cost in comparison to others, ease of operation, and integration into the power grid. Two Optimization algorithms are combined to form a hybrid optimization approach: Cuckoo Search (CS) and Antlion Optimization (ALO). This hybrid approach employs the exploration of ALO to adjust the optimum allocation and size for SVCs in the power system. This study proposes the IEEE 57 bus scheme as a fairly large structure, with the 50 and 41 branch outages considered the worst-case scenarios for line outages in this system. The simulation results show that the proposed methodology balances exploring the research space and exploiting the best existing solutions compared to some of the other introduced approaches in the literature.

Keywords: static var compensator (SVC); cuckoo search (CS); antlion optimization (ALO); hybrid optimization

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1. Introduction

Voltage sags are one of the main significant issues in the electrical power system, as well as excessive power flow in some branches. These problems are mainly caused by the imbalance between power generation and load demand, the lack of reactive power supply, or unexpected interruptions in transmission lines. All these factors may eventually lead to a complete blackout [1,2]. Using flexible AC transmission system (FACTS) devices is quite popular technology to tackle the issues mentioned above [2]. Since the lack of reactive power provided to the loads is a major concern in power system operation, these FACTS devices can supply the system with the necessary reactive power. However, the problem of integrating these into the power system is quite complicated where achieving maximum effectiveness is through proper sizing and siting of SVCs. For this reason, many authors have tried to resolve this problem by using various optimization techniques, such as differential evolution (DE) [3], whale optimization algorithm (WOA) [4], simulated annealing (SA), and particle swarm optimization (PSO) [5], multi-objective genetic algorithm (MOGA) [6], multi-objective cuckoo search (MOCS) [7], imperialistic competitive algorithm (ICA) [3], harmony search (HS) [8].

However, SVC is among the most exquisite FACTS devices owing to its ability to manage reactive power for absorption or generation [9,10]. The problem of sizing and sitting SVC devices is used in many works of literature by various optimization methods to enhance the performance and security of the power system. Multi-objective cuckoo search algorithm (MOCS) [9], improved harmony search (IHS) [11], and Cuckoo Search (CS) [12] have been introduced for the optimum positioning of SVC devices to enhance investment costs, real and reactive power losses. To enhance security and voltage stability, the optimal location of SVC is reported in [13–16]. In recent years, hybrid algorithms have proven to be effective in dealing with real-world engineering problems, for example, antlion algorithm (ALO), moth flame optimization (MFO), salp swarm optimization (SSO) [17], JAYA algorithm and moth flame optimization (MFO) [18], kinetic gas molecular optimization (KGMO), and grey wolf optimization (GWO) [19], cuckoo search algorithm (CSA), and chemical reaction optimization (CRO) [20], particle swarm optimization (PSO), and differential evolution algorithm (DE) [21]. This work proposes a novel hybrid approach of combined cuckoo search (CS) and the antlion algorithm (ALO). The cuckoo search algorithm (CS) is characterized by the use of Lévy flight, which produces a part of the solutions near the local optimal and a part that is far from the optimal local level [22]. This will prevent the CS algorithm from becoming stuck at local optimal. Then, the ALO algorithm is used for fine-tuning to reach a more accurate solution. More precisely, this hybrid approach of CS-ALO ensures collaboration between algorithms to further explore the research space and provide high-quality solutions, as the cuckoo search algorithm provides the best solutions sites and is exploited by applying the exploration mechanism of ALO as adaptive shrinking boundaries during the search process.

The work aims to use the hybrid approach CS-ALO to adopt the advantages of both algorithms thus ensuring a better balance between exploitation ability and exploration ability in the research space, more accurately and reliably, and to provide high-quality solutions. On the application aspect, using the hybrid CS-ALO is to resolve the problem of sizing and sitting of the SVC devices in the power system under the worst contingencies. This targeted application is considered to be a multi-objective optimization with a discrete and continuous mixed variable. The proposed hybrid CS-ALO has been applied to solve the sizing and sitting of static var compensator SVC devices in the IEEE 57 bus test system under the worst-case line outage scenarios (outage of branches 50 and 41) where total power loss, overload, and voltage deviation are considered in the fitness function. The simulation findings show that the introduced hybrid CS-ALO provides better convergences and solutions compared to the cuckoo search algorithm (CS), antlion algorithm (ALO), and some other approaches recorded in the literature as particle swarm optimization (PSO) and gravitational search algorithm (GSA).

2. System under Study

The IEEE 57 bus system was selected as an analyzed case because it is a fairly large system. It is composed of generators distributed across buses 1, 2, 3, 6, 8, 9, and 12, which are connected by 63 transmission lines, 42 loads, and 17 tap setting transformers, with Bus 1 acting as the slack bus. As indicated by the power flows, the total real and reactive power is 1250.8 MW and 336.4 MVar, respectively, and voltage deviation and power loss are 0.0157 and 0.278638, respectively. During the line outage contingencies, it was discovered that the system is primarily affected by voltage deviation. The 50 and 41 branch outages are the most severe line outages in this system based on voltage deviation values, as shown in Figure 1. Outages on branches 50 and 41 have voltage deviations of 3.5657 and 2.6699, respectively. Table 1 displays the generation data for the IEEE 57 bus system, and the other system data is given in [23].

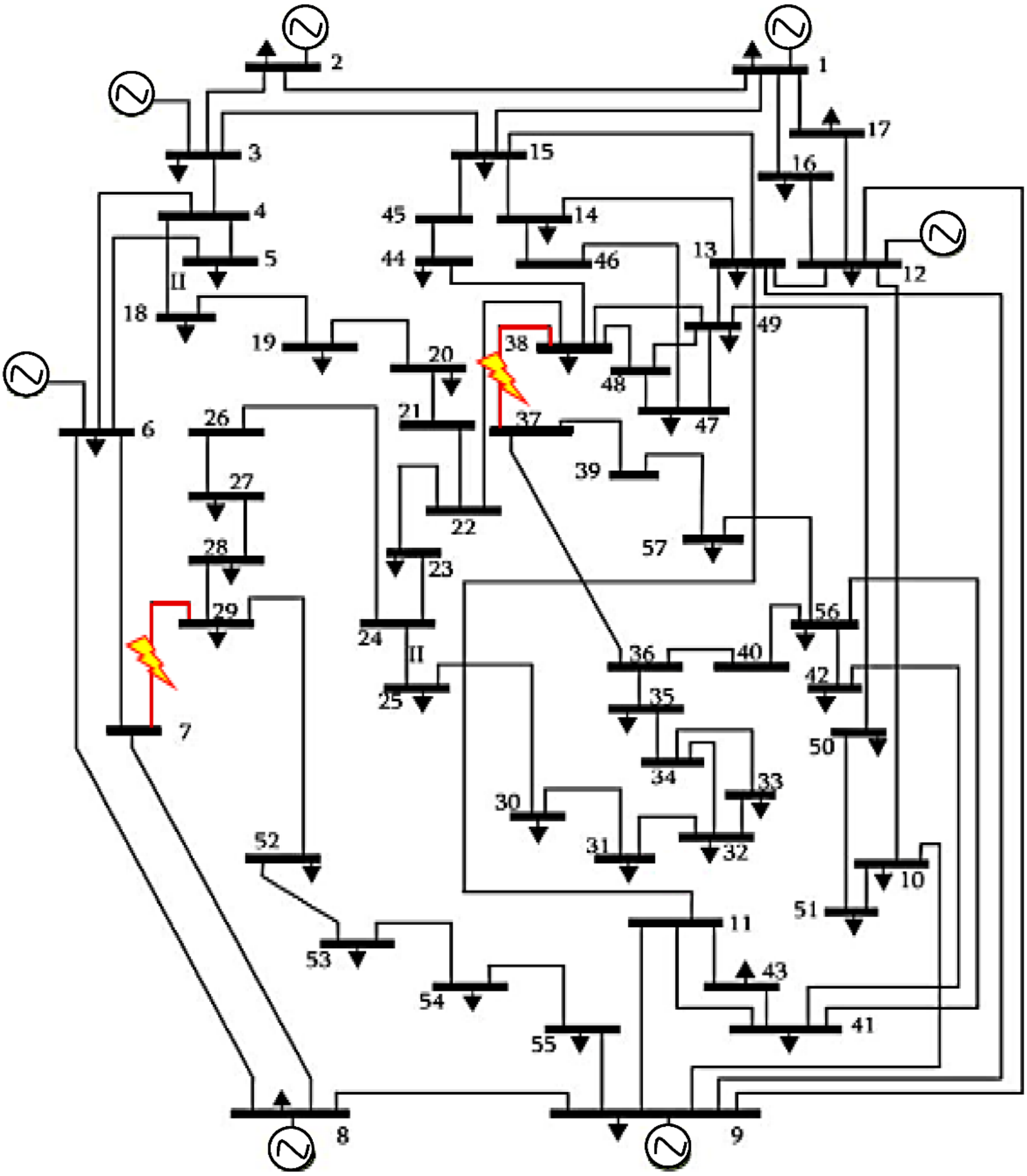

Figure 1. Single line diagram of IEEE 57 bus system two severe line outage contingencies.

Table 1. Generation data of the IEEE 57 bus test system.

Generator Number	P_{gmin}(MW)	P_{gmax}(MW)	Q_{gmin}(MVAR)	Q_{gmax}(MVAR)
1	0	575.88	−140	200
2	0	100	−17	50
3	0	140	−10	60
6	0	100	−8	25
8	0	550	−140	200
9	0	100	−3	9
12	0	410	−150	155

3. Formulation of the Multi-Objective Function

Finding the optimum sizing and sitting of SVC units in the power system can be represented as a multi-objective problem [8]. In this study, the multi-objective function must be minimized as follows.

3.1. Voltage Deviations

Decreasing or increasing the voltage influences the electrical system performance, Moreover, the voltage provided to the customer must be within a standard range. As a result, the first objective function to consider is to reduce the voltage deviations described below [24]:

$$DEV = \sum_{i=1\ i\notin PV\ buses}^{i=NB} DEV_i \tag{1}$$

$$DEV_i = \begin{cases} 0 & if\ 0.95 < V_i < 1.05 \\ (1-V_i)^2 & if\ 0.9 \le V_i \le 0.95\ or\ 1.05 \le V_i \le 1.1 \\ 5(1-V_i)^2 & if\ V_i > 1.1\ or\ V_i < 0.9 \end{cases} \tag{2}$$

where DEV_i represents the voltage deviation at bus i and NB is the total number of buses in the electrical network, and V_i is the voltage of i bus.

The standardized metric of voltage deviations is given as follows:

$$J_1 = \frac{DEV}{DEV_0} \tag{3}$$

where DEV_0 reflects the total voltage deviations prior to optimization.

3.2. Overloads

The second objective function of this study is to enhance overloads in power transmission lines defined as:

$$OL = \sqrt{\sum_{i=1(for\ P_i > P_{i\ max})}^{i=NL} (P_i - P_{i\ max})^2} \tag{4}$$

P_i and $P_{i\ max}$ indicate the active power and boundary of the active power of the transmission line, respectively, where $P_{i\ max}$ equal to 9900 and is uniform across all branches. NL denotes the total number of branches in the system.

If OL is zero before FACTS devices are installed, J_2 is assigned as the system's OL after FACTS devices are installed. The standardized metric of overloads function is given as follows:

$$J_2 = \frac{OL}{OL_0} \tag{5}$$

where OL_0 reflect the overloads prior to optimization.

3.3. Power Loss

The third function considered is to improve the total losses of the active power in the electrical power system as [25]:

$$P_{loss} = \sum_{i=1}^{NL}\sum_{j=1}^{NL} \left(V_i^2 + V_j^2 - 2V_iV_j\cos\left(\delta_i - \delta_j\right)\right)\cdot Y_{ij}\cos\theta_{ij} \tag{6}$$

where V_i and δ_i are the absolute voltage and the angle at node (i), Y_{ij} and θ_{ij} are the absolute value and the line admittance angle.

The standardized metric of the power loss function is given as follows:

$$J_3 = \frac{P_{loss}}{P_{loss\ 0}} \tag{7}$$

where $P_{loss\ 0}$ defines the total power system loss before optimization.

3.4. Overall Function

In this paper, all of the above-mentioned different objective functions are combined into one overall objective function. The voltage deviations, overloads in transmission, and loss of power are denoted by J_1, J_2, and J_3 respectively. In Equation (8), the adjusted multi-objective function is written as follows.

$$J = C_1 \cdot J_1 + C_2 \cdot J_2 + C_3 \cdot J_3 \tag{8}$$

where C_1, C_2 and C_3 are the weighting factors for adapting the different objective functions, which must satisfy the following conditions:

$$C_1 + C_2 + C_3 = 1 \tag{9}$$

$$0 < C_1, C_2, C_3 < 1 \tag{10}$$

After studying the various possible probabilities of these coefficients and plotting the Pareto front (in Appendix A), we chose $C_1 = 0.6$, $C_2 = 0.2$, and $C_3 = 0.2$ as the weight coefficients in this study, as this choice guarantees us to reduce the value of power loss and voltage deviation at the same time.

The reason to apply SVC devices is to take control of the system variables, such as active and reactive power and absolute voltages for which the constraints equations are regarded.

3.5. Constraints

3.5.1. Inequality Constraints

The inequality constraints of switchable susceptance size, bus voltages, and the apparent power of the transmission line are described as follows:

$$\begin{cases} B_{min} \leq B_{SVC} \leq B_{max} \\ V_{min} \leq V_i \leq V_{max} \\ S_{li} \leq S_{lmax} \end{cases} \tag{11}$$

where B_{SVC}, V_i and S_{li} represent the susceptance of the SVC, the bus voltages, and the apparent power respectively. In practical application, the deviations can be up to 10 % of the nominal values [11].

3.5.2. Equality Constraints

The equations of equality constraints are given as the following [26].

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \left(G_{ij} \cos\theta_{ij} + jB_{ij} \sin\theta_{ij} \right) = 0 \tag{12}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \left(G_{ij} \cos\theta_{ij} + jB_{ij} \sin\theta_{ij} \right) = 0 \tag{13}$$

P_{Gi} and Q_{Gi} define the real and reactive power of the generators, P_{Di} and Q_{Di} define the active and reactive load, and G_{ij} and B_{ij} describe the conductance and susceptance between node i and j.

3.6. Modelling of SVC

The SVC is a shunt connected to passive elements that include power electronics converters. This SVC is capable of dynamically exchanging reactive power (absorbing by the reactor or generating by the capacitor) with the network to keep the bus voltage within defined limits. Hence, the static protection of the system can be enhanced [27].

The SVC equivalent circuit was modeled as an adjustable reactance as presented in Figure 2 [28].

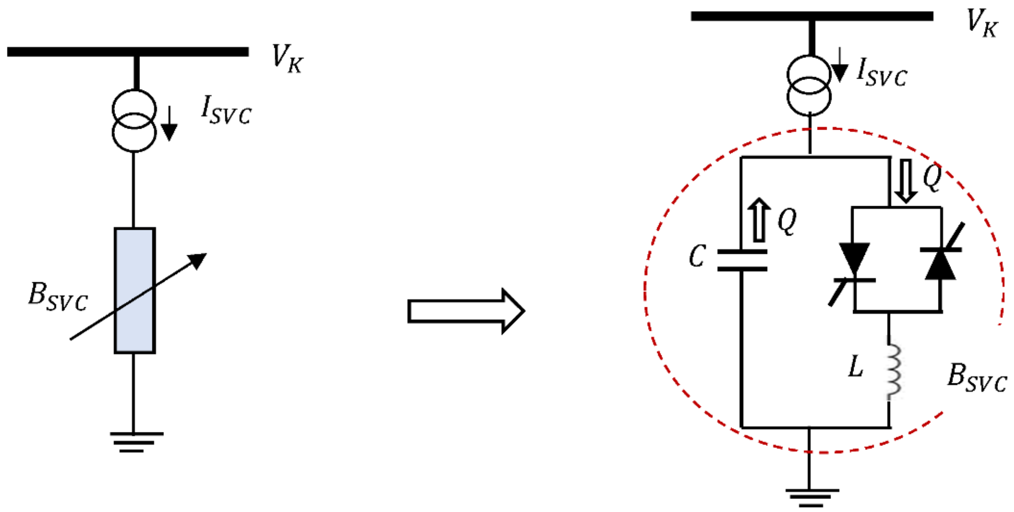

Figure 2. Simplified model of SVC.

The current I_{SVC} and reactive power Q_{SVC} of static var compensator SVC exchanged with the bus (k) can be expressed in Equations (14) and (15):

$$I_{SVC} = jB_{SVC} \cdot V_K \tag{14}$$

$$Q_{SVC} = B_{SVC} \cdot V_K^2 \tag{15}$$

where, B_{SVC} is the shunt susceptance of the SVC and V_K is the bus voltage magnitude to which the SVC is attached.

4. Proposed Methods

4.1. Cuckoo Search Algorithm (CS)

Yang and Deb created the CS algorithm by combining the parasitic breeding behavior of certain cuckoo species with the Lévy flight behavior of some birds and fruit flies [29]. In nature, most cuckoo species rest their eggs in the nests of other birds (host birds) and extract native bird eggs to increase their chances of hatching their eggs. If the host bird finds out about the replacement of its eggs, it either throws the eggs or leaves its nest and builds a new one. Each egg in the nest is essentially a potential solution in CS, and every cuckoo egg corresponds to a new solution. The candidate solutions (eggs in the nests) are replaced by possible solutions (cuckoos' eggs) that may be better than them, and the aim of repeating this process is to improve the quality of the solutions produced by the CS algorithm [30].

A CS technique performs a search using the population of eggs. During the search process, the Lévy flight operator is used to calculate a new solution X_i^{t+1} (cuckoo's egg) as follows:

$$X_i^{t+1} = X_i^t + \alpha \oplus lvy(s, \lambda) \tag{16}$$

where,

$$Lvy(s, \lambda) = \frac{\lambda \Gamma(\lambda) \sin(\pi\lambda/2)}{\pi} \frac{1}{s^{1+\lambda}} \text{ s } >> s_0 > 0 \tag{17}$$

In Equations (16) and (17), $\alpha > 0$ represents a scaling factor of the step size s and the symbol $\oplus$ is the input-wise product, and Γ is the gamma function.

4.2. Antlion Optimization (ALO)

Antlion optimizer ALO is a new metaheuristic algorithm developed by Mirjalili depending on the principle of the hunting mechanism of antlion in nature [31]. The

ALO approach simulates the interaction of antlions and ants in the pit, where ants travel stochastically to forage in the search space, and antlions chase the ants using the pits [31].

The mathematical model of the antlion optimization (ALO) algorithm can be described here:

$$X(t) = [0, cumsum(2r(t_1) - 1), cumsum(2r(t_2) - 1), \ldots, cumsum(2r(t_n) - 1)] \quad (18)$$

Here the cumulative sum determined by $cumsum$, t indicates the random step, n is the maximum number of iterations, and $r(t)$ is a stochastic function specified as in the following:

$$r(t) = \begin{cases} 1 & if\ rand > 0.5 \\ 0 & if\ rand \leq 0.5 \end{cases} \quad (19)$$

$rand$ is a number generated at random between 0 and 1.

In order to maintain the random walks of ants within the search space according to lower and upper boundary changes during the search process, they are normalized using the following expression:

$$X_i = \frac{(X_i - a_i) \times (d_i - c_i)}{(b_i - a_i)} + c_i \quad (20)$$

where a_i and b_i represent the lower and upper boundary of X_i, c_i and d_i indicate the lower and upper boundary around the selected antlion in the i^{th} dimension, respectively.

The lower and upper boundary around the selected antlion to build traps can be calculated using:

$$\begin{cases} c = c' + Antlion \\ d = d' + Antlion \end{cases} \quad (21)$$

where c' and d' denote the lower and upper of changing limit at the current iteration in the process.

Updating each ant's position is done by a random walk around the antlion. The latter is pre-selected by the roulette wheel and the elite. It can be defined as follows:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \quad (22)$$

where Ant_i^t represents the position of i^{th} ant at t^{th} iteration, R_A^t is the random walk around the antlion chosen by the Roulette wheel at t^{th} iteration, R_E^t is the random walk around the elite at t^{th} iteration.

In the ALO algorithm, ants catch prey when ants are fitter (dives inside soft sand) than their attached antlion. To increase its chances of capturing a new victim, an antlion is required to update its position to the latest location of the hunted ant. The process is modeled as follows [31]:

$$Antlion_j^t = Ant_i^t\ if\ f\left(Ant_i^t\right) < f\left(Antlion_i^t\right) \quad (23)$$

where $Antlion_j^t$ indicates the position of the selected j^{th} antlion at t^{th} iteration while Ant_i^t presents the position of i^{th} ant at t^{th} iteration.

4.3. Proposed Hybrid Cuckoo Search and Antlion Optimization (CS-ALO)

The previous studies in the literature indicated that both ALO and CS algorithms have a good performance in achieving the global optimal solution compared to many optimization algorithms. However, some difficulties may appear when suitable solutions for some complex and multimodal optimization issues could not be found. Based on the cuckoo search algorithm (CS) and the antlion optimizer (ALO), a novel CS-ALO hybrid algorithm is proposed based on the opposite advantages and disadvantages of both algorithms by adding a loop to the CS algorithm where new super-elite solutions are generated based on the mechanisms of the ALO algorithm. The main idea of this hybrid method is to increase the exploitation capacity by applying an adaptive limit shrinking mechanism of the antlion algorithm, thus ensuring a good balance between exploring the research space and exploiting the best existing solutions. Figure 3 shows the flowchart of the proposed hybrid algorithm CS-ALO.

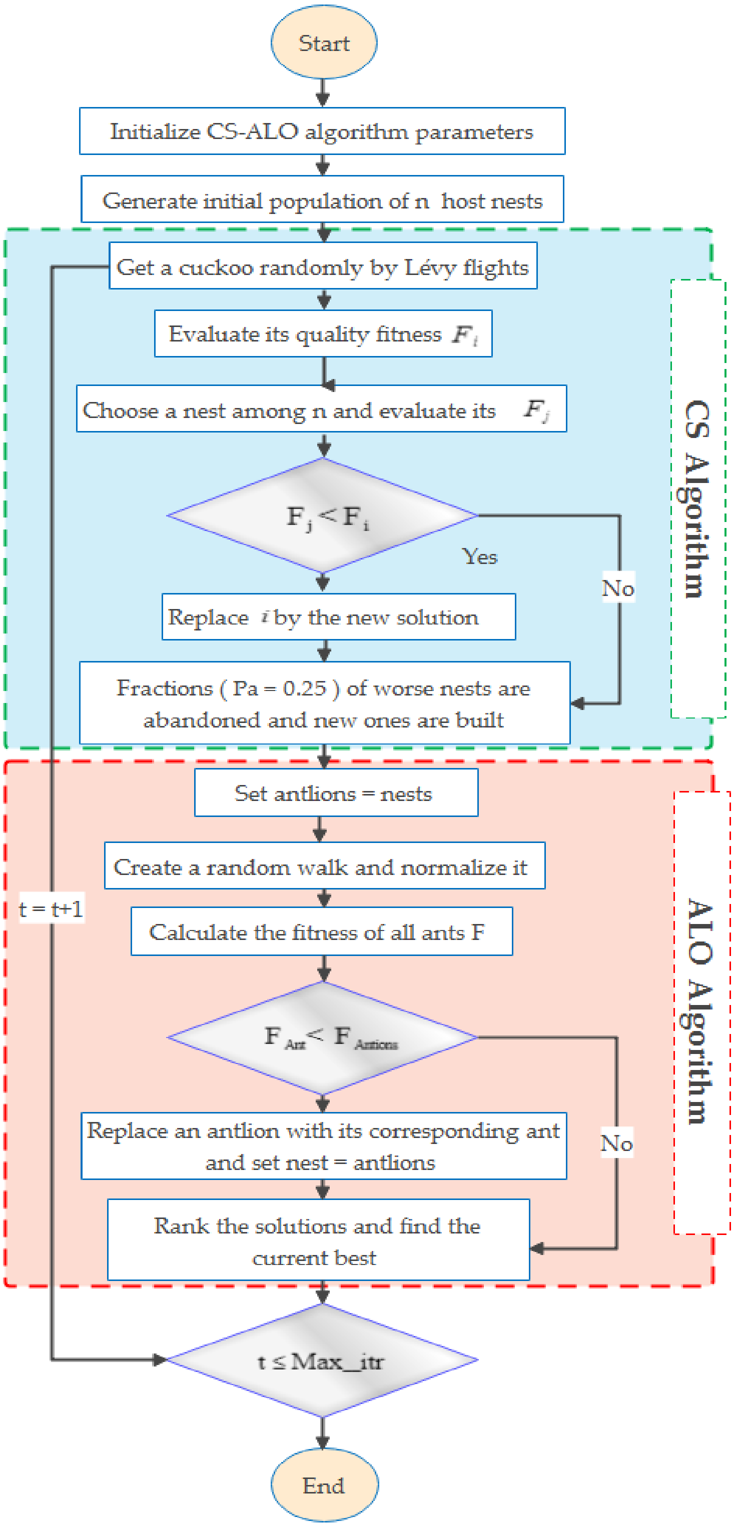

Figure 3. The flow chart of proposed hybrid CS-ALO.

5. Simulation and Results

5.1. Validation of the CS-ALO Algorithm to Benchmark Function

In this part, the robustness of the CS-ALO algorithm is validated using 23 well-known benchmark functions. These functions are classified into three groups [32]: unimodal functions (F1–F7), multimodal functions (F8-F13), and Fixed-dimension multimodal functions (F14–F23). More details on these functions are discussed in [32]. The parameter setup of the proposed CS-ALO, cuckoo search (CS), antlion (ALO), gravitational search (GSA), and particle swarm (PSO) algorithms is reported in Table 2. To ensure fairness in comparative experiments, all methods were conducted under the same conditions. Among them, the population was set to 30, the dimension to 30, and the iteration time to 1000. All of the compared methods were run individually 30 times in each function and averaged as the final running result to minimize the impact of random factors on the findings of the method. The standard deviation (STD), average findings (AVG), and minimum value (MIN) were used to assess performance when measuring experiment findings.

Table 2. Specific setting of the parameters of compared algorithms.

Algorithm	Specific Parameters	Value
PSO	Inertia weight w, Inertia Weight Damping Ratio, c1, and c2	1, 0.99, 1.5, 2
GSA	Alpha, G0, Rnorm, Rpower	20, 100, 2, 1
CS	Discovery rate	0.25
ALO	popsize, *Max_iteration*	30, 1000
CS-ALO	Discovery rate, popsize, *Max_iteration*	0.25, 30, 1000

Table 3 presents the finding of the comparison of the unimodal benchmark functions of the proposed approach with the following optimization algorithms: PSO, GSA, CS, and ALO, in terms of the average value (AVG) and the standard deviation (STD), the minimum value (MIN). It is evident from the finding of this table that the proposed algorithm ranked first on average when solving functions from F1 to F6. However, the average and standard deviation values of the PSO algorithm for the F7 function were slightly better than the results of the proposed algorithm.

Table 3. Results of unimodal benchmark functions.

Function	Stats	PSO	GSA	CS	ALO	CS-ALO
F_1	Ave	4.6653×10^{-6}	2.0950×10^{-17}	0.0036	$9.6514 \times 10-6$	7.0132×10^{-18}
	Std	1.1056×10^{-6}	7.2306×10^{-18}	0.0026	8.1485×10^{-6}	1.1014×10^{-17}
	Min	3.1615×10^{-7}	1.0235×10^{-17}	8.8569×10^{-4}	8.5855×10^{-7}	3.7131×10^{-19}
F_2	Ave	0.0296	5.3973×10^{-8}	0.2982	98.0542	2.5484×10^{-11}
	Std	0.0202	1.3423×10^{-9}	0.1847	1.4454×10^{-14}	1.2883×10^{-11}
	Min	7.1882×10^{-4}	2.7989×10^{-8}	0.1215	98.0542	8.7168×10^{-12}
F_3	Ave	7.2588	461.3663	303.7764	1.1582×10^{3}	0.448
	Std	15.4066	182.0644	71.7279	522.6452	0.2563
	Min	0.2636	181.0675	156.4354	374.8212	0.0597
F_4	Ave	0.6348	1.4477	5.6706	12.6565	0.11
	Std	0.2771	1.2543	2.1251	4.7648	0.064
	Min	0.2252	9.6847×10^{-9}	1.2383	3.917	0.0374
F_5	Ave	51.2677	35.3128	51.5287	29.1538	22.033
	Std	43.8051	23.4802	40.1303	7.2269×10^{-15}	19.1713
	Min	3.6562	25.7798	21.5784	29.1538	1.4643
F_6	Ave	3.0054×10^{-10}	1.0634×10^{-16}	0.0036	7.6753×10^{-6}	6.5789×10^{-18}
	Std	1.3491×10^{-9}	3.4396×10^{-17}	0.0025	4.9301×10^{-6}	9.0468×10^{-18}
	Min	6.3484×10^{-17}	4.9508×10^{-17}	8.7930×10^{-4}	8.2654×10^{-7}	1.6541×10^{-19}

Table 3. *Cont.*

Function	Stats	PSO	GSA	CS	ALO	CS-ALO
F_7	Ave	0.0163	0.0583	0.0421	0.0983	0.0179
	Std	0.0052	0.0185	0.0159	0.0245	0.0092
	Min	0.0080	0.0300	0.0209	0.0403	0.0055

Table 4 presents the findings of the comparison of the proposed method with the other algorithms in the case of the multimodal benchmark functions, in terms of the average value (AVG) and the standard deviation (STD), the minimum value (MIN). This table shows that the CS-ALO method outperformed the other methods in F8 and F11. It is worth noting here that the F8 function is considered to be one of the most challenging functions of this type. However, the suggested approach has provided good results in this case. While in the F9 and F10 functions, GSA showed better performance than the results of the proposed CS-ALO method. The CS algorithm was also ranked first in the F12, and F13 test functions compared to the other algorithms, but the proposed algorithm produced better results at a minimum value.

Table 4. Results of multimodal benchmark functions.

Function	Stats	PSO	GSA	CS	ALO	CS-ALO
F_8	Ave	-6.2103×10^3	-2.5413×10^3	-8.5857×10^3	-5.6850×10^3	-6.7474×10^3
	Std	923.4325	377.5468	294.6083	617.4115	568.8082
	Min	-8.8187×10^3	-3.2992×10^3	-9.2405×10^3	-8.3628×10^3	-1.0711×10^4
F_9	Ave	30.8471	26.5986	75.3270	79.6629	38.5049
	Std	10.7542	7.5364	10.4607	20.1800	10.8053
	Min	15.9193	13.9294	51.7229	45.7681	18.9042
F_{10}	Ave	0.0683	8.0603×10^{-9}	1.1229×10^{-4}	2.1124	6.2630×10^{-9}
	Std	0.3480	1.6945×10^{-9}	1.4341×10^{-4}	0.6619	2.0012×10^{-8}
	Min	3.9460×10^{-9}	5.3680×10^{-9}	1.2382×10^{-5}	1.1551	4.9253×10^{-10}
F_{11}	Ave	0.0421	0.0738	0.0695	0.0140	0.0107
	Std	0.0492	0.0854	0.0503	0.0126	0.0111
	Min	4.7629×10^{-14}	5.2457×10^{-10}	0.0055	3.5451×10^{-4}	0.000
F_{12}	Ave	4.9720×10^{-4}	1.6556×10^{-9}	9.6072×10^{-5}	6.2029	0.1694
	Std	0.0013	$4.9501 \times 10^{-1}0$	2.5802×10^{-4}	3.9109	0.2336
	Min	1.7475×10^{-7}	8.6483×10^{-10}	5.4287×10^{-7}	1.8516	3.8621×10^{-18}
F_{13}	Ave	9.8245×10^{-4}	3.6627×10^{-4}	4.9824×10^{-6}	0.1569	0.0044
	Std	0.0028	0.0020	3.7307×10^{-6}	0.3956	0.0055
	Min	2.0979×10^{-7}	1.3857×10^{-8}	8.7312×10^{-7}	6.3967×10^{-6}	5.5347×10^{-20}

Table 5 summarizes the findings of 10 Fixed-dimension multimodal benchmark test functions for the proposed method, compared with the rest of the other optimization algorithms. This table indicated that the proposed approach outperformed other methods. However, there was no difference between the findings of the CS method seen in the results of the CS method and those of the proposed CS-ALO method for the F16 and F19 test functions. Additionally, the standard deviation value obtained with the PSO for the F18 and the standard deviation value of the GSA for the F20 function were higher than the findings of the proposed method and other methods.

Figure 4 shows the convergence curves for the two functions F1 and F3 for unimodal functions, where the proposed algorithm is compared to the CS algorithm and ALO algorithm, it appears that the convergence of the CS-ALO algorithm tends to be faster than other algorithms. This is confirmed by the fact that the proposed algorithm can exploit partial regions effectively.

Table 5. Results of fixed-dimension multimodal benchmark functions.

Function	Stats	PSO	GSA	CS	ALO	CS-ALO
F_{14}	Ave	3.3274	4.2276	0.9980	1.5605	0.9980
	Std	2.9242	3.3261	0	0.8104	0
	Min	0.9980	0.9980	0.9980	0.9980	0.9980
F_{15}	Ave	0.0018	0.0030	3.0781×10^{-4}	0.0015	4.9062×10^{-4}
	Std	0.0051	0.0018	1.7909×10^{-6}	0.0036	3.7254×10^{-4}
	Min	3.0749×10^{-4}	0.0016	3.0749×10^{-4}	6.5332×10^{-4}	3.0749×10^{-4}
F_{16}	Ave	−1.0316	−1.0316	−1.0316	−1.0316	−1.0316
	Std	6.7752×10^{-16}	5.6835×10^{-16}	6.7752×10^{-16}	8.0540×10^{-14}	6.7752×10^{-16}
	Min	−1.0316	−1.0316	−1.0316	−1.0316	−1.0316
F_{17}	Ave	0.3979	0.3979	0.3979	0.3979	0.3979
	Std	0	0	0	0	0
	Min	0.3979	0.3979	0.3979	0.3979	0.3979
F_{18}	Ave	3.0000	3.0000	3.0000	3.0000	3.0000
	Std	6.0599×10^{-16}	3.3831×10^{-15}	1.9305×10^{-15}	3.2372×10^{-13}	2.1138×10^{-15}
	Min	3.0000	3.0000	3.0000	3.0000	3.0000
F_{19}	Ave	−3.8370	−3.8628	−3.8628	−3.8628	−3.8628
	Std	0.1411	2.3397×10^{-15}	2.7101×10^{-15}	1.6256×10^{-14}	2.7101×10^{-15}
	Min	−3.8628	−3.8628	−3.8628	−3.8628	−3.8628
F_{20}	Ave	−3.2982	−3.3220	−3.3220	−3.2784	−3.3220
	Std	0.0484	1.4402×10^{-15}	1.4189×10^{-13}	0.0583	1.3550×10^{-15}
	Min	−3.3220	−3.3220	−3.3220	−3.3220	−3.3220
F_{21}	Ave	−7.3140	−5.8832	−10.1532	−7.5399	−10.1532
	Std	3.3952	3.4533	7.1740×10^{-15}	2.9214	7.2269×10^{-15}
	Min	−10.1532	−10.1532	−10.1532	−10.1532	−10.1532
F_{22}	Ave	−6.6128	−10.4029	−10.4029	−7.0935	−10.4029
	Std	3.6550	1.1893×10^{-15}	2.1733×10^{-14}	3.2464	8.0799×10^{-16}
	Min	−10.4029	−10.4029	−10.4029	−10.4029	−10.4029
F_{23}	Ave	−6.5285	−10.1069	−10.5364	−6.8672	−10.5364
	Std	3.8524	1.6822	2.2734×10^{-12}	3.3537	1.8949×10^{-15}
	Min	−10.5364	−10.5364	−10.5364	−10.5364	−10.5364

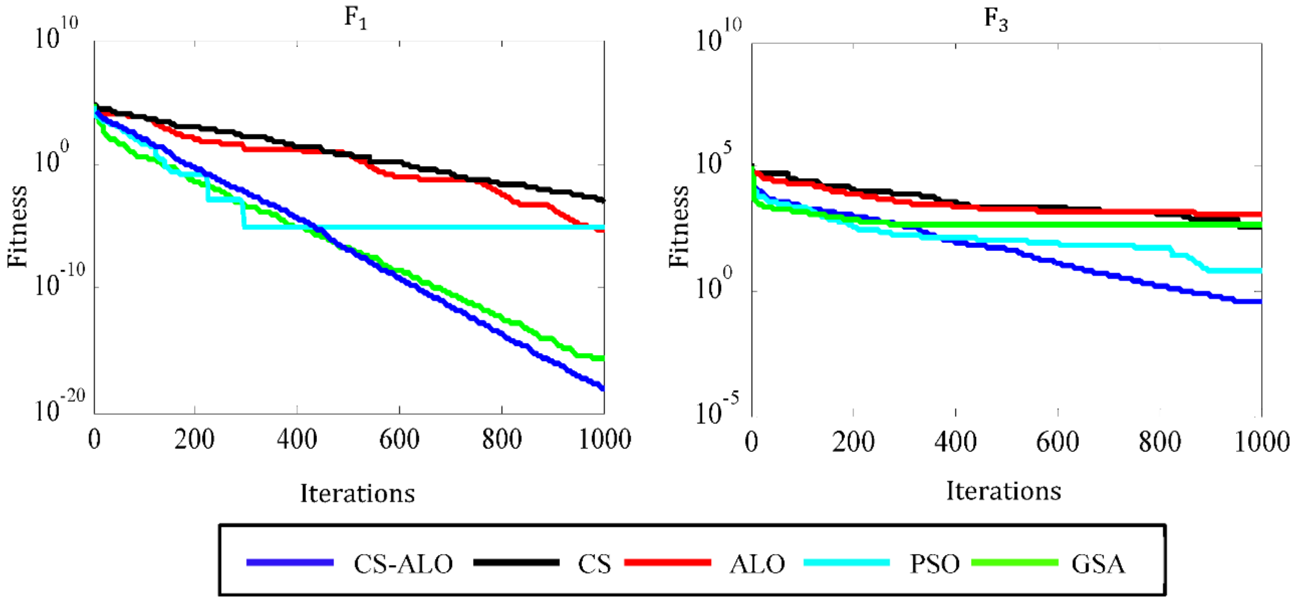

Figure 4. Convergence of algorithms on two of the unimodal test functions.

Figure 5 depicts the convergence graphs of the CS, ALO, and CS-ALO methods for two of the multimodal functions F10, and F11, showing that again the CS-ALO algorithm offers the best solution for the toughest functions.

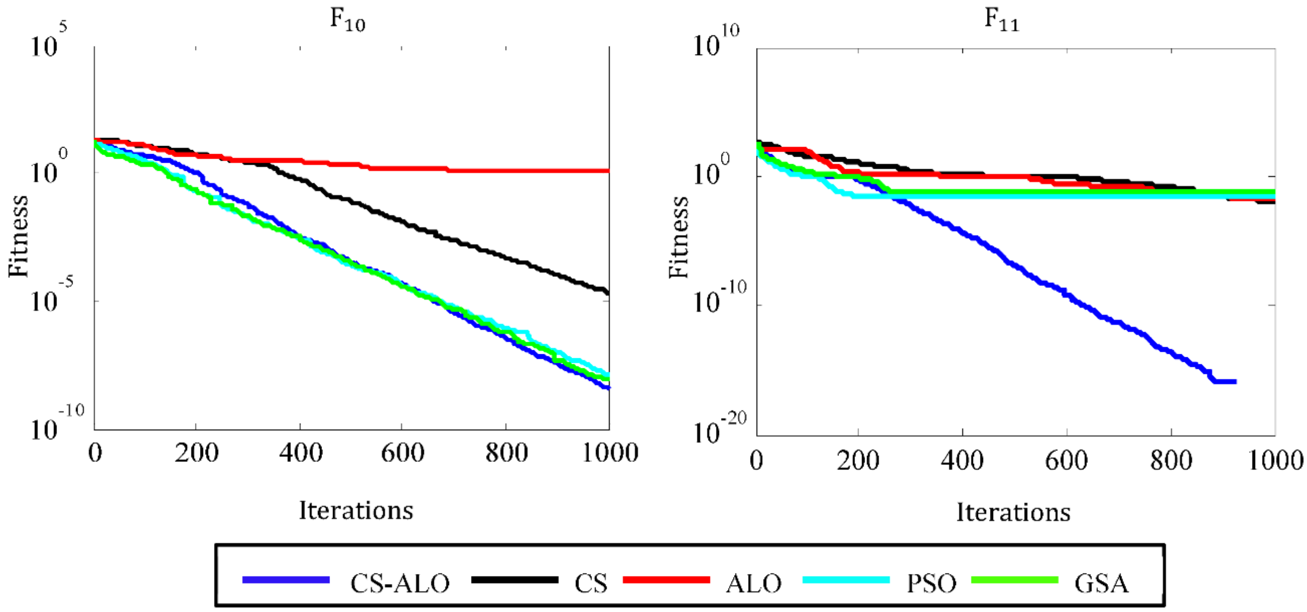

Figure 5. Convergence of algorithms on two of the multimodal test functions.

The convergence curves of the approaches for two of the fixed-dimension multimodal test functions are shown in Figure 6. This figure illustrates that the CS-ALO has better convergence than the cuckoo search and antlion algorithm and other optimization methods listed in the literature.

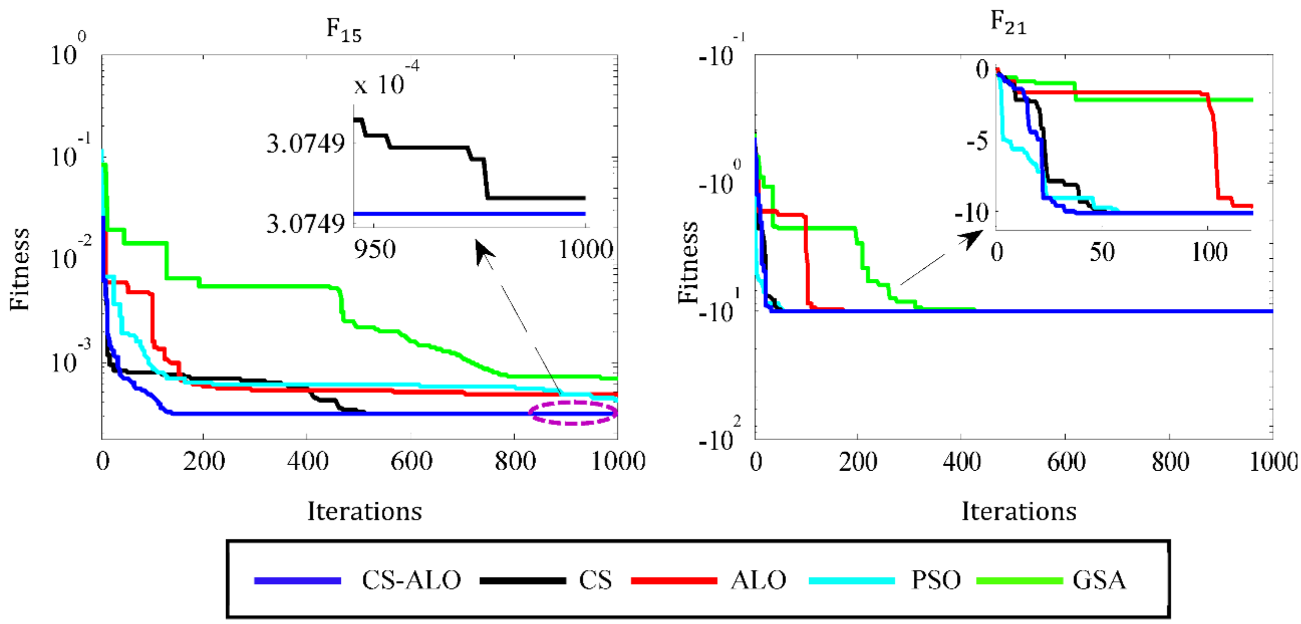

Figure 6. Convergence of algorithms on two of the fixed-dimension multimodal test functions.

Figure 7 depicts the change in the two-dimensional parameters (X_1 and X_2) of the proposed algorithm with the number of iterations, where various types of benchmark functions were evaluated.

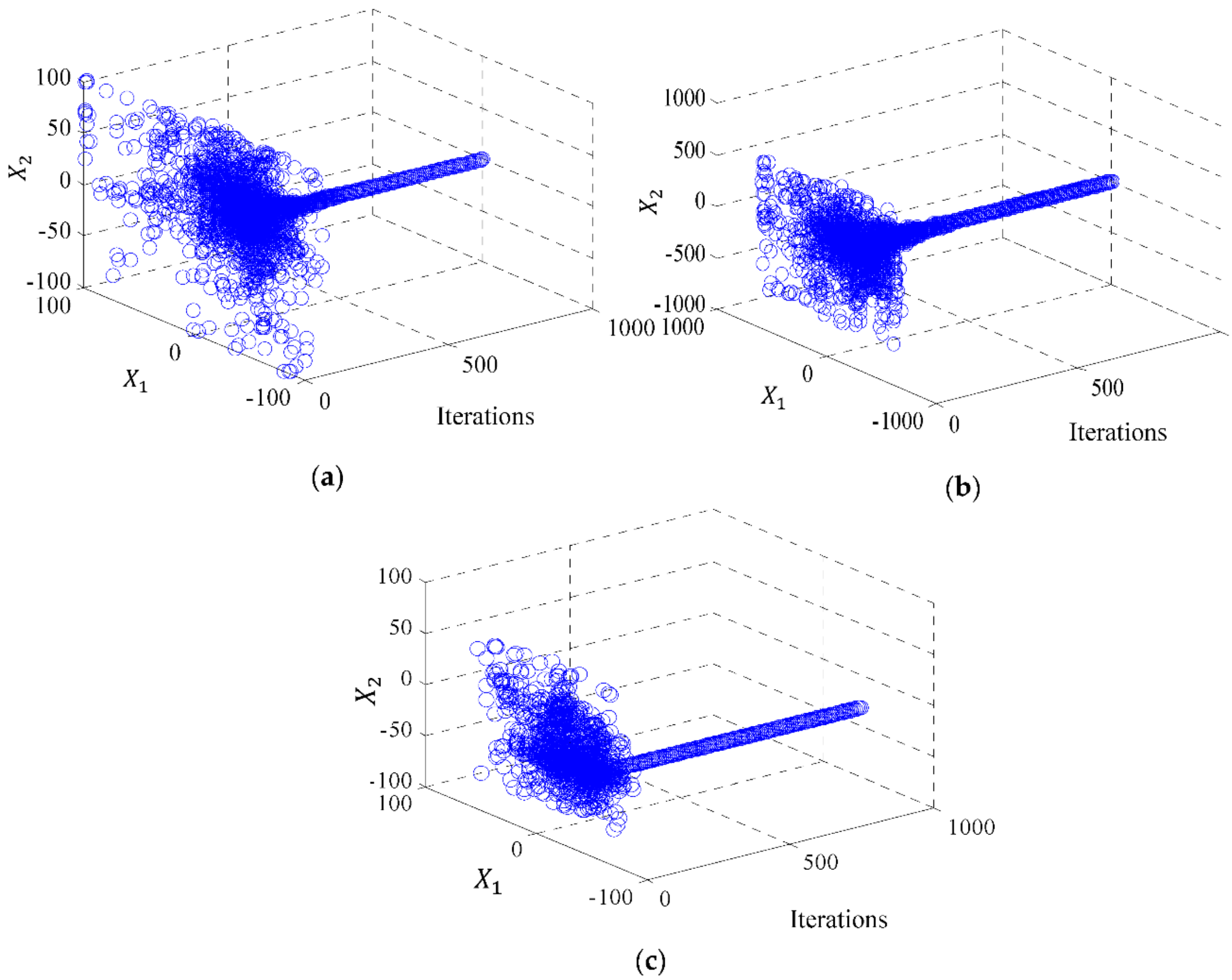

Figure 7. Evaluation of different types of benchmark functions; (**a**): F_1, (**b**): F_{11}, (**c**): F_{14}.

5.2. Application of the CS-ALO Algorithm to the Optimal Sizing and Sitting of SVC Devices

This study aims to determine the best solutions for sizing and sitting of SVC units in the power system during line outage situations using suggested hybrid CS-ALO to reduce overloads, voltage deviations, and power loss in transmission. The simulation was implemented in MATLAB 2011a on an Intel(R) Core (TM) i3-4005U CPU@ 1.70 GHZ Computer with 4 GB RAM under Windows XP, in addition to the following parameters: the number of generations is 2000 iterations, the size of the population is 100 nests (candidates), and the discovery rate of alien eggs is $p_a = 0.75$.

The suggested hybrid CS-ALO has been validated on IEEE 57 bus test systems, and the results are presented for two different cases, namely the outage of branches 50 and 41, which are the worst possible line outage contingencies of this system, after studying various branch outages in different regions as shown in Figure A2 and Table A1 in Appendix A. The proposed algorithm runs 10 independent trials for two different outages, considering 12 SVC units where their susceptances range from -1 to 10. Buses 1, 2, 3, 6, 8, 9, and 12 are excluded from the SVC allocation process because they are connected to generation units.

5.2.1. Outage in Branch 50

Table 6 shows the minimum, maximum, and average of multi-objective functions achieved by different algorithms. Note that the minimum multi-objective function of the suggested method is lower than the rest of the methods mentioned in [23] as shown by the convergence curve for the overall objective function is shown in Figure 8. The minimal number of various objective functions is compared with other methods in Table 7. There is no overload in branches because their values are very small in comparison to $P_{i\ max}$, allowing them to be ignored. The findings show that the suggested method exceeds all other methods in terms of voltage deviation minimization and power loss minimization, and this confirms the ability of the proposed hybrid algorithm to better explore solutions in the search space.

Table 6. Comparison of CS-ALO to the various algorithms in case of an outage in branch 50.

	PSO [23]	GSA [23]	CS	ALO	CS-ALO
Mean	0.1809	0.1826	0.1801	0.1804	0.1799
Std	0.0002	0.0003	0.0000	0.0002	0.0000
Min	0.1806	0.1822	0.1800	0.1801	0.1798
Max	0.1811	0.1831	0.1801	0.1808	0.1801

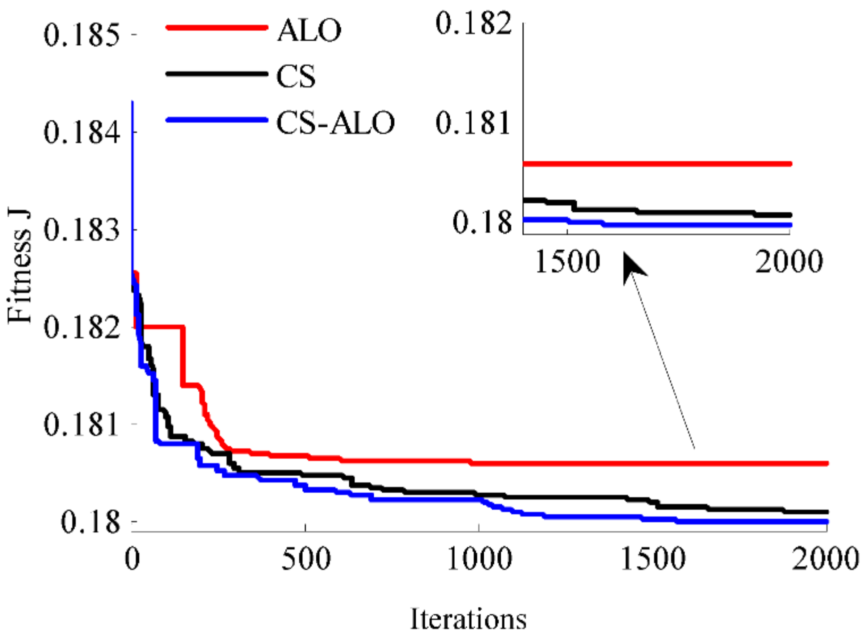

Figure 8. Convergence graph for fitness J in case of branch 50 outages by CS and ALO, CS-ALO.

Table 7. Performance of the minimum multi-objective function in case of an outage in branch 50.

	Without SVC	With SVC				
		PSO [23]	GSA [23]	CS	ALO	CS-ALO
DEV	3.5657	0.0144	0.0192	0.0081	0.0080	0.0081
J_1	1	0.0040	0.0054	0.0023	0.0022	0.0023
P_{loss}	0.3183	0.2840	0.2855	0.2844	0.2845	0.2841
J_3	1	0.8922	0.8970	0.8935	0.8938	0.8926
J	0.8	0.1809	0.1826	0.1801	0.18043	0.1799

Table 8 shows the optimal sizing and sitting of SVC used in this outage case, as the effect of setting these devices in the right places allows for improving the voltage magnitudes in all buses and reducing the power loss in transmission lines as displayed in Figure 9. It is worth noting that the SVC should not be installed in generator buses, and there will be no buses with more than one SVC.

Table 8. Optimal placement and susceptances of SVC units in case of an outage in branch 50.

SVC Number	Optimal Bus Number	Optimal Susceptance
1	17	10.000000
2	30	3.374653
3	41	9.999994
4	40	6.385686
5	42	6.747763
6	39	2.641199
7	49	−0.999999
8	34	4.574809
9	31	2.886868
10	28	2.721426
11	53	6.609649
12	29	9.890116

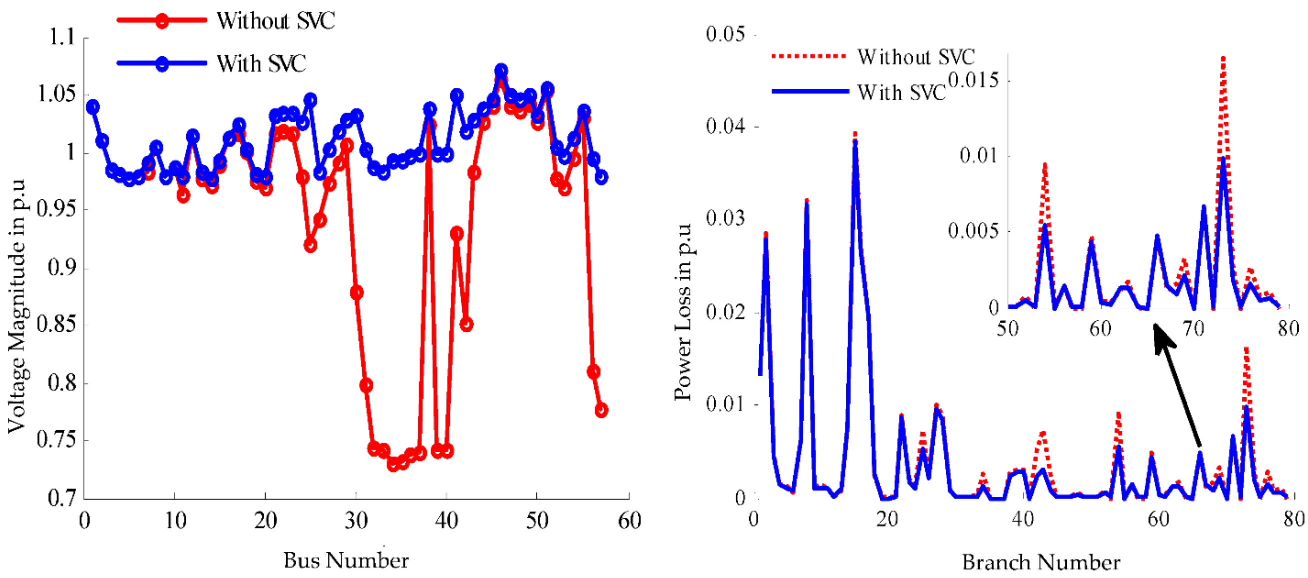

Figure 9. Voltage and power loss before and after SVC installation in case outage of branch 50.

5.2.2. Outage of Branch 41

Table 9 shows the minimum, maximum, and average of multi-objective functions achieved by different algorithms. Note that the minimum multi-objective function of the proposed approach is lower than the other algorithms mentioned in [23]. The minimal number of various objective functions is compared with other methods in Table 10. There is no overload in branches because their values are very small in comparison to $P_{i\ max}$, allowing them to be ignored. The convergence curve for the overall objective function is shown in Figure 10. The findings show that the suggested hybrid CS-ALO is the most efficient in terms of solution quality and convergence. Table 11 shows the optimal sizing and sitting of SVC used in this outage case, as the effect of setting these devices in the right places allows us to improve voltage magnitudes in all buses and reduce the power loss in transmission lines as displayed in Figure 11. The simulation findings confirm that the suggested CS-ALO algorithm can reach an optimal solution with high precision and quality.

Table 9. Comparison of the CS-ALO to the various algorithms in case of an outage in branch 41.

	PSO [23]	GSA [23]	CS	ALO	CS-ALO
Mean	0.1754	0.2048	0.1709	0.1713	0.1705
Std	0.0016	0.0360	0.0001	0.0004	0.0001
Min	0.1730	0.1777	0.1707	0.1706	0.1704
Max	0.1767	0.2564	0.1710	0.1722	0.1709

Table 10. Performance of the minimum multi-objective function in case of an outage in branch 41.

	Without SVC	With SVC				
		PSO [23]	GSA [23]	CS	ALO	CS-ALO
DEV	2.6699	0.0178	0.1563	0.0118	0.0123	0.0124
J_1	1	0.0067	0.0585	0.0044	0.0046	0.0046
P_{loss}	0.4666	0.3999	0.3958	0.3921	0.3917	0.3912
J_3	1	0.8571	0.8483	0.8403	0.8395	0.8384
J	0.8	0.1754	0.2048	0.1709	0.1713	0.1705

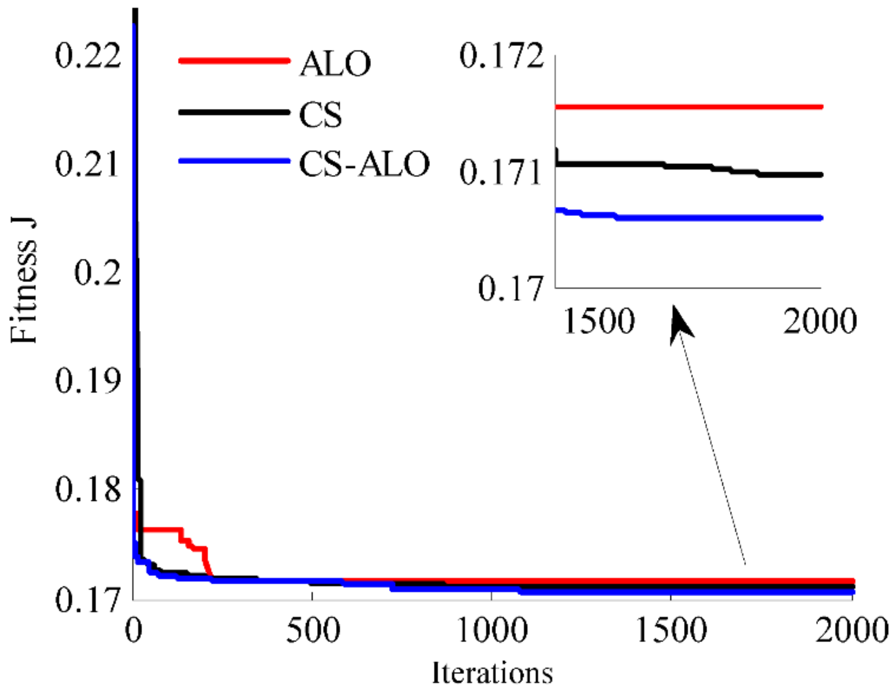

Figure 10. Convergence graph for fitness J in case outage of branch 41 by CS and ALO, CS-ALO.

Table 11. Optimal placement and susceptances of SVC units in case of an outage in branch 41.

SVC Number	Optimal Bus Number	Optimal Susceptance
1	54	9.832125
2	55	9.999988
3	53	9.390575
4	31	3.960381
5	29	9.633920
6	44	4.091333
7	26	6.876093
8	32	5.164825
9	52	5.260811
10	28	8.862748
11	41	8.578958
12	40	9.412178

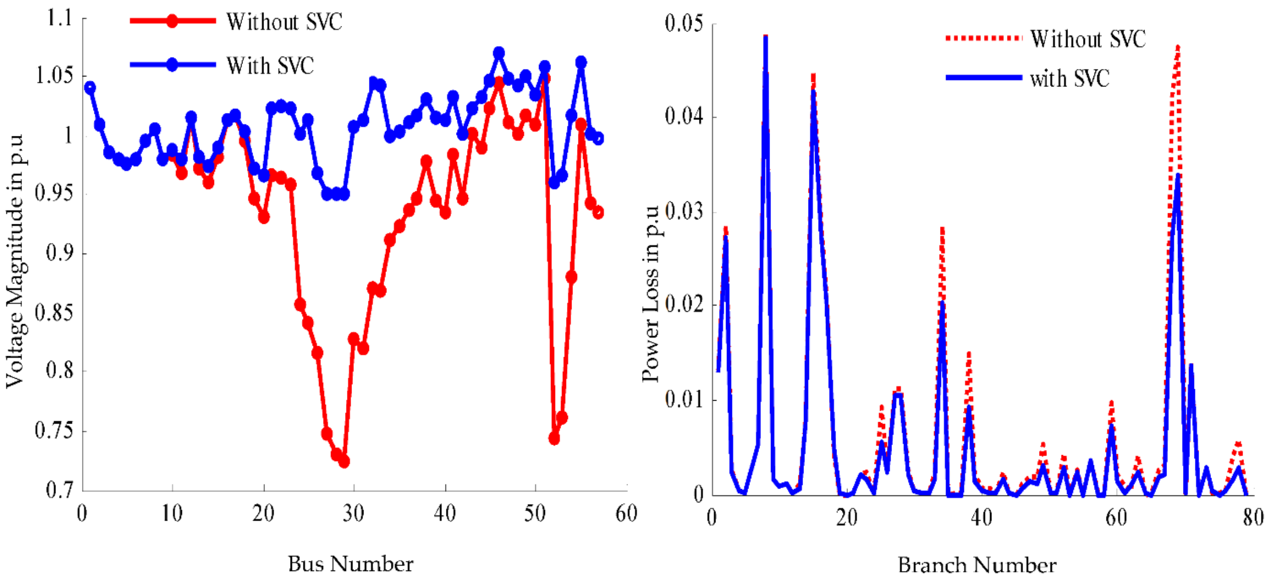

Figure 11. Voltage and power loss before and after SVC installation in case of an outage in branch 41.

6. Conclusions

In this paper, the optimal sizing and placement of Static VAR Compensator (SVC) in a relatively large network, such as the IEEE 57 bus system, was studied using a novel effective hybrid optimization of combined Cuckoo search (CS) and Antlion Optimization (ALO). These two algorithms are regarded as among the most effective algorithms demonstrated in previous studies and combining the advantages of each algorithm into a single algorithm (CS-ALO) allowed us to obtain more accurate and reliable solutions than using an algorithm alone. Furthermore, by selecting the appropriate SVC value and locating it in the proper location, the network remains stable even during the most severe outages. Buses 28, 29, 31, 40, 41, and 53 are critical, and integrating SVC systems into them improves power system performance. The proposed algorithm outperforms the cuckoo search algorithm (CS), the antlion algorithm (ALO), and the other algorithms listed in the literature in terms of finding the lowest losses and voltage deviations. In the future, modern optimization algorithms may play a pivotal role in solving decision-making problems related to sizing, seating, and integrating such as FACTS systems and renewable energies into the power systems to ensure the security of energy supply through optimal management of production and consumption, particularly in a decentralized electricity grid.

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Appendix A

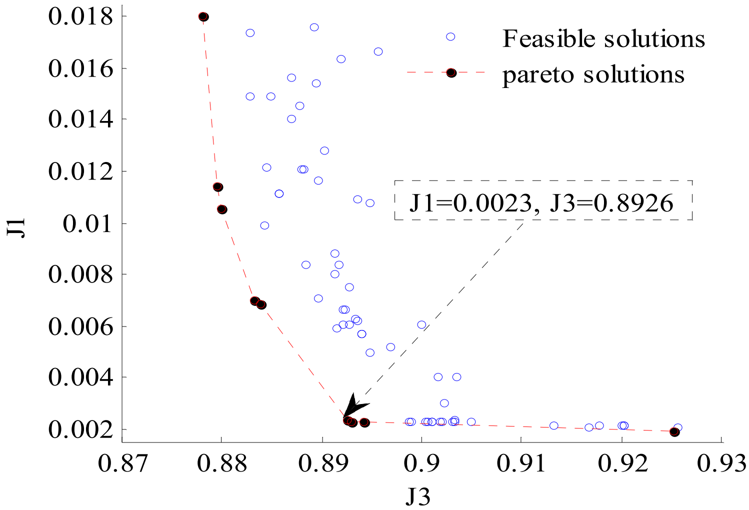

Figure A1. Pareto front for various objective functions with different probabilities of weighting factors.

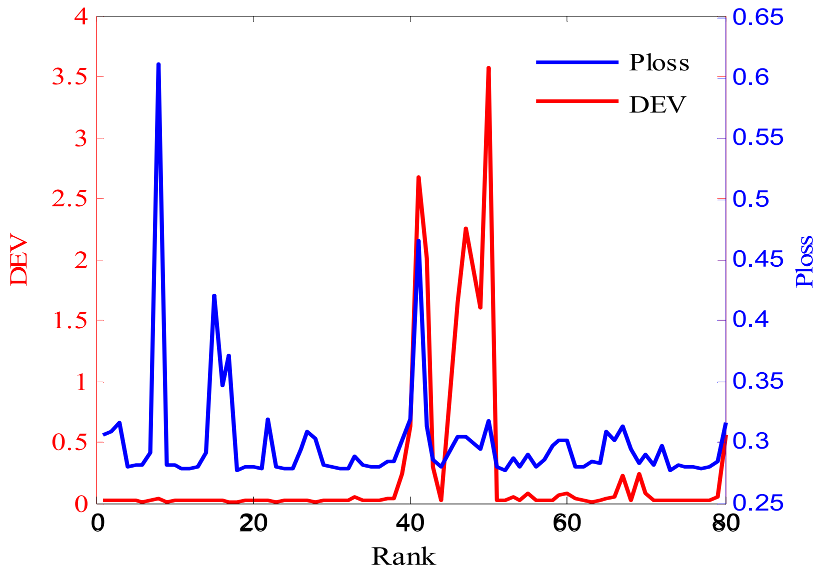

Figure A2. Results of branch outages and their ranking in the IEEE57 bus system with their objective functions.

Table A1. Results of the branch outage and their ranking in various regions.

Rank	Branch Outage	DEV	OL	P_{loss}	Rank	Branch Outage	DEV	OL	P_{loss}
3	(3–4)	0.0164	0	0.3160	33	(22–23)	0.0469	0	0.2885
38	(26–27)	0.0351	0	0.2839	17	(1–17)	0.0133	0	0.3717
41	(7–29)	2.6699	0	0.4666	26	(12–16)	0.0157	0	0.2943
14	(13–15)	0.0159	0	0.2920	52	(36–40)	0.0276	0	0.2775
57	(38–44)	0.0174	0	0.2860	46	(34–32)	1.6464	0	0.3040
50	(38–37)	3.5657	0	0.3182	56	(41–43)	0.0205	0	0.2805
65	(10–51)	0.0314	0	0.3089	22	(7–8)	0.0268	0	0.3196
28	(14–15)	0.0144	0	0.3032	79	(38–48)	0.0518	0	0.2839
8	(8–9)	0.0345	0	0.6111	23	(10–12)	0.0139	0	0.2802
80	(9–55)	0.5577	0	0.3166	37	(24–26)	0.0300	0	0.2840

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