

Article

Optimal Capacitor Bank Allocation in Electricity Distribution Networks Using Metaheuristic Algorithms

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Abstract: Energy losses and bus voltage levels are key parameters in the operation of electricity distribution networks (EDN), in traditional operating conditions or in modern microgrids with renewable and distributed generation sources. Smart grids are set to bring hardware and software tools to improve the operation of electrical networks, using state-of the art demand management at home or system level and advanced network reconfiguration tools. However, for economic reasons, many network operators will still have to resort to low-cost management solutions, such as bus reactive power compensation using optimally placed capacitor banks. This paper approaches the problem of power and energy loss minimization by optimal allocation of capacitor banks (CB) in medium voltage (MV) EDN buses. A comparison is made between five metaheuristic algorithms used for this purpose: the well-established Genetic Algorithm (GA); Particle Swarm Optimization (PSO); and three newer metaheuristics, the Bat Optimization Algorithm (BOA), the Whale Optimization Algorithm (WOA) and the Sperm-Whale Algorithm (SWA). The algorithms are tested on the IEEE 33-bus system and on a real 215-bus EDN from Romania. The newest SWA algorithm gives the best results, for both test systems.

Keywords: electricity distribution networks; optimal capacitor allocation; Genetic Algorithm; Particle Swarm Optimization; Bat Algorithm; Whale Algorithm; Sperm-Whale Algorithm

1. Introduction

Distribution Network Operators take into account the implementation of smart solutions to improve both the voltage level in the subordinate networks and the power factor, with the aim to maintain the balance between power generation and consumption while meeting the quality of supply standards and regulations.

In this context, the use of capacitor banks is an easy solution to be implemented with technical and economic benefits to the smart grid, maximizing the long-term return on investment as the network develops. An intelligent control of capacitor banks leads to improved energy efficiency and voltage level in the buses of distribution networks, resulting in an increase in the percentage of energy delivered to consumers [1].

The advantages of integrating capacitor banks in the flexible smart grid communication and control infrastructure are the increase of network energy efficiency and power quality improvement [2]. Thus, the technologies and modern techniques enable today the large-scale integration of capacitor banks managed with smart control algorithms.

In the literature, many methods have been proposed to solve the Optimal Capacitor Banks Allocation (OCBA) in distribution networks as a combinatorial optimization problem. These techniques

can be grouped in four main categories: numerical [3]; analytical [4]; heuristic [5–7]; and artificial intelligence, population based (Artificial Neural Networks, metaheuristics) [8,9]. An overview about the metaheuristics used for the problem of capacitor banks allocation is made in the following, highlighting their specific purpose. The OCBA solution for power losses or cost minimization is obtained using a genetic algorithm in [10,11], a fuzzy technique in [12] and an artificial neural network in [9]. Regarding the metaheuristics, a significant number of papers consider the joule loss minimization, voltage bus improvement, and total cost minimization. Thus, in [13–15] a Multi-Objective Particle Swarm Optimization (MOPSO) algorithm is proposed. For active power loss reduction using load flow computation, the branch and bound method is generally preferred, for its reduced computation time. For example, for the minimization of the total annual costs, the Crow Search Algorithm (CSA) is used in [16,17], the Particle Swarm Optimization (PSO) and hybrid PSO algorithm are adapted in [18–21], the Flower Pollination Algorithm (FPA) is preferred in [22,23], and an Improved Harmony Algorithm is chosen in [24]. On the other hand, the OCBA problem based on active power minimization was approached in [25,26] using the Bacterial Foraging Optimization Algorithm, the Intersect Mutation Differential Evolution (IMDE) Algorithm in [27], the Artificial Bee Colony (ABC) in [5,28] and the Ant Lion Optimization Algorithm in [29]. The improvement of the voltage profile carried out using the Symbiotic Organisms Search Algorithm (SOSA) in [30]. Another paper proposes the JAYA optimization algorithm [31] for power factor correction. For voltage profile improvement, the Oppositional Cuckoo Optimization Algorithm (OCOA) was used in [32]. It must be mentioned that the authors' previous approaches regarding the OCBA problem used several metaheuristic algorithms, such as PSO, BOA, Fireworks Algorithm (FWA), and WOA [33].

A brief description of the papers that use metaheuristics in the CBA problem considering both objective functions (OF) and constraints (C) is presented in Table 1. The considered objective functions are: OF1, active power losses minimization; OF2, voltage profile improvement; OF3, voltage deviation minimization; OF4, cost minimization; OF5—net savings maximization; OF6, voltage stability improvement. The main constraints for the OCBA problem are a combination of the following: C1, bus voltage allowable limits; C2, current flow limits on the branches; C3, bus reactive allowable limits; C4, maximum stock of capacitors; C5, bus apparent power balance; C6, maximum number of transformer tap changer steps; C7, the total reactive power injected should not exceed the total reactive power demand; C8, power flow limits on the branches; and C9, bus power factor limits.

This paper is focused on a comparative study of several metaheuristic algorithms adapted for solving the OCBA problem with the objective of energy loss minimization in MV distribution networks. During the analysis, the well-known GA and PSO are tested against two newer metaheuristics that have seen previous uses in power engineering applications, the BOA and WOA, and another recent but much less used method, the SWA. The latter is shown to outperform all its predecessors, when tested on two MV distribution networks with different characteristics: the smaller IEEE 33—bus test network [5,13,25] and a larger 215—bus 20/0.4 kV distribution network from Romania. During the case study, the algorithms use the same initial population and fitness function. Results are shown regarding active power and energy losses and bus voltage levels, for which the best results are obtained with the SWA.

Table 1. Literature review regarding the capacitor allocation problem based on artificial intelligence.

Objective Function	Constraints									Test Network	References
	C1	C2	C3	C4	C5	C6	C7	C8	C9		
OF1	X	X	-	-	-	-	-	-	-	38 bus—Roy–Billinton Test System	[8]
	X	-	X	-	X	X	-	-	-	IEEE 30, 57, 118 and 300 bus	[10,27,29]
	X	-	X	-	X	-	-	-	-	IEEE 33 bus	[13]
	X	X	X	X	-	-	-	-	-	IEEE 33 and 94 bus	[14,15]
	X	X	X	-	X	X	-	-	-	IEEE 30 bus	[21]
	X	X	X	-	X	-	-	-	-	IEEE 33 and 85 bus	[25,28]
OF2	X	X	X	X	X	-	-	-	-	IEEE 33 and 119 bus	[5]
	X	-	-	-	-	-	-	-	-	IEEE 10, 23 and 34 bus	[12]
OF3	X	-	X	-	X	-	-	-	-	IEEE 22, 69, 85 and 141 bus	[32]
	X	-	X	-	X	X	-	-	-	IEEE 30, 57, 118 and 300 bus	[10,27]
OF4	X	X	X	-	X	X	-	-	-	IEEE 30 bus	[21]
	X	-	X	-	-	-	X	-	X	IEEE 10, 33 and 69 bus	[16,17,22,26]
	X	-	X	-	-	-	-	X	-	IEEE 10, 15 and 34 bus	[19]
	X	-	X	-	-	-	-	-	-	IEEE 30 and 85 bus	[20]
	X	-	X	-	-	-	-	-	-	IEEE 33, 34, 69 and 85 bus	[23,27]
	X	-	X	-	X	-	X	-	X	IEEE 85 and 118 bus	[24]
OF5	X	-	-	-	X	-	-	-	-	IEEE 28-bus	[11]
	X	-	-	-	-	-	-	-	-	IEEE 9-bus	[30]
OF6	X	-	X	-	-	X	X	-	-	IEEE 30 bus	[18]
	X	-	X	-	X	X	X	-	-	IEEE 30, 57 and 118 bus	[27]
	X	-	X	-	X	-	-	-	-	IEEE 30, 118 and 300 bus	[29]

2. Metaheuristic Algorithms

Metaheuristics are a special class of algorithms that can be used to solve search and optimization problems. As described in [34], they are approximate, usually non-deterministic methods that aim to search for solutions near the global optimum, exploring this space through a partly guided and partly random search. While the main disadvantage of metaheuristics is the uncertainty of reaching the global optimal solution, their advantages lie in not being problem-specific (allowing the flexibility of applying the same solving principle to several types of problems) and having intuitive mathematical models, borrowing concepts and approaches from the natural world, rather than from theoretical mathematical models. This contributes to their accessibility for a wider range of users. Most modern metaheuristics are population-based, starting from an initial group of solutions, called ‘population’, generated randomly, and refining it in an iterative process, according to a set of specific steps, until a stopping criterion is met. The performance of each individual from the population is assessed by computing its fitness function. The basic block diagram of a population-based metaheuristic algorithm (PMA) is depicted in Figure 1, where the steps common to all algorithms are represented with white boxes, and the part specific to each algorithm, delimited by symbols (A) and (B) is presented in gray.

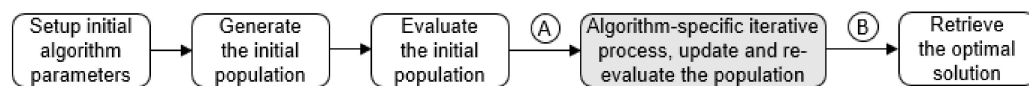


Figure 1. The basic flowchart of a population-based metaheuristic algorithm.

The initial parameters are partially common to all algorithms, such as population size N or maximum number of iterations $maxit$, and partially specific to each algorithm, such as the mutation rate $rmut$ for the Genetic Algorithm (GA) or inertia value w for the Particle Swarm Optimization (PSO). An individual from a population with N members, denoted in the following as

$$X_i = [x_1, x_2, \dots, x_m], \quad i = 1 \dots N \quad (1)$$

is encoded as a vector with length m , and element types and values dictated by the problem that needs to be solved. It usually represents an input parameter combination or a possible solution for the problem, which must satisfy all the constraints of the optimization model. The fitness evaluation of each population member requires the decoding of the information contained in the solution that it represents, solving the problem and evaluating the results. The optimality degree of the solution is assessed with the fitness function value associated to the respective population member. For a population with N members, $X_i, i = 1, \dots, N$, N fitness functions will be computed and ranked.

The (A) to (B) section from Figure 1 consists of several steps, which describe each specific metaheuristic algorithm. While in the figures accompanying Sections 2.1–2.5 are presented all the details specific to each algorithm, delimited by (A) to (B), Table 2 summarizes their main steps, emphasizing their particularities.

Table 2. The metaheuristic algorithms used in the paper for solving the OCBA problem.

Algorithm	Main Steps
Genetic Algorithm (GA)	Selection, crossover, mutation, using the entire population
Particle Swarm Optimization (PSO)	Speed and position update, using the entire population, and exploration followed by exploitation of the search space
The Bat Optimization Algorithm (BOA)	Speed and position update, frequency adaptation, and local search in each iteration, using the entire population, exploration followed by exploitation
The Whale Optimization Algorithm (WOA)	Continuous choice between three search methods: exploration, encircling, and spiral attack, using the entire population
The Sperm Whale Algorithm (SWA)	Population divided in subgroups that perform the search independently, using dominant crossover in each subgroup

Among the various metaheuristic algorithms available in the literature, those from Table 2 were chosen taking into account the following reasoning: the genetic algorithm and the particle swarm optimization are the best known and widely used metaheuristics, with numerous applications in power systems, which makes them a valid basis for comparison. The bat algorithm and the whale optimization algorithm are newer algorithms, previously used by the authors in solving similar optimization problems and shown to improve the quality of the results, compared with GA and PSO [35,36]. On the other hand, the sperm whale algorithm is a novelty in solving optimization problems in the power systems field. The results from the case study will show that the SWA outperforms the previous algorithms, making it a viable new alternative for solving optimization problems related to power systems applications.

The best-known PMAs are the genetic algorithm and the particle swarm optimization, which also describe two fundamental search principles used by metaheuristic algorithms: the evolutionary and performance-based patterns.

2.1. Genetic Algorithms

The Genetic Algorithm (GA), proposed in [37], is probably the best-known metaheuristic algorithm. In the GA, population members are named ‘chromosomes’, and their elements are ‘genes’. The search and optimization mechanisms use Darwinist natural evolution, based on perpetuation through genetic material exchange and mutation inside a population of same-species individuals, across a significant number of generations (iterations).

For finding new and improved solutions for an optimization problem, the GA relies on changing the population by using in each iteration the three main genetic operators (Figure 2):

- Selection: From the existing population, whole individuals are selected based on their performance, expressed by the fitness function. The better-adapted individuals are favored for surviving. In the standard GA, the population size is constant. Thus, the lesser adapted individuals, which are discarded, are replaced by clones of the survivors.
- Crossover: Pairs of parent chromosomes exchange a number of genes, the resulting offspring having new characteristics, possibly resulting in better solutions for the problem.
- Mutation: Randomly generated variations on gene values, resulting in chromosomes with minor structural changes, simulating genetic mutations of real living organisms.

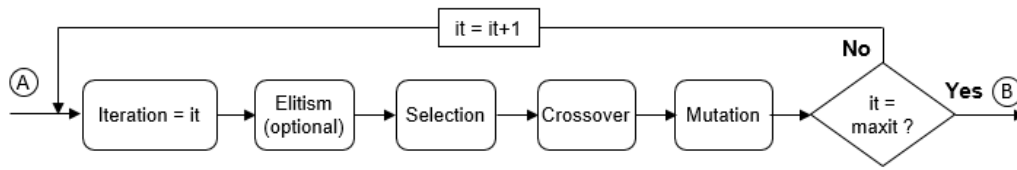


Figure 2. The flowchart of a GA iteration.

Optionally, an elitist procedure can also be incorporated in the GA, which ensures the preservation of the best-found optimal solution and its fitness function across generations.

The literature offers a high variety of selection [38] and crossover [39] types, which together with the user-chosen crossover and mutation rates provide significant customization possibilities, making the GA a flexible problem-solving tool.

In this paper, the tournament selection method was used, which draws randomly p members from the existing population, out of which retains the best q , according to their fitness function. The procedure is repeated until a new population of size N is created.

The method of choice for the crossover operator was the uniform crossover, illustrated in Figure 3. Two parents are randomly chosen from the population and, for each gene, a random number is generated. The parents swap the genes only if the generated random number exceeds a customizable threshold tr .

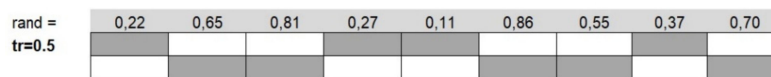


Figure 3. The uniform crossover.

2.2. Particle Swarm Optimization

On the other hand, the PSO algorithm [40] uses a different search method, based on variable travel speeds and position shifting in the search space. Each individual ('particle') from the population ('swarm') changes its speed in each iteration based on its current distance from two reference points: The best solution found so far by the swarm leader and the best position ever achieved by the particle itself. Compared with the GA, the PSO mechanism, presented in Figure 4, is very simple, requiring for each particle j , $j = 1, \dots, N$, only the computation of its new speed and position:

$$sp_j^{(it)} = w \cdot sp_j^{(it-1)} + 2 \cdot rnd_1 \cdot (x_{j,best}^{(it)} - x_{j,crt}^{(it)}) + 2 \cdot rnd_2 \cdot (leader^{(it)} - x_{j,crt}^{(it)}) \quad (2)$$

$$x_j^{(it+1)} = x_j^{(it)} + sp_j^{(it)} \quad (3)$$

followed by the update of each particle's best position and the change of the leader position, if better solutions are found. The particle speeds are initialized with low random values, which would not influence the search direction.

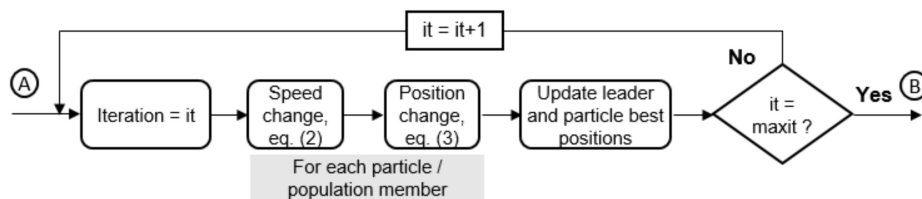


Figure 4. The flowchart of a PSO iteration.

In Equations (2) and (3), $sp_j^{(it)}$ and $sp_j^{(it-1)}$ are the speed of particle x_j ($j = 1 \dots N$) in the previous ($it - 1$) and current (it) iteration, rnd_1 and rnd_2 are random vectors, $x_{j,best}^{(it)}$ and $x_{j,crt}^{(it)}$ are the best personal

and the current position of particle x_j , $leader^{(it)}$ is the position of the leader in iteration it , and $x_j^{(it)}$ is the position of particle x in the current iteration. The factor w from Equation (2) is an inertia term, which decreases over the iteration count, larger initial values encouraging exploration, and smaller final values enabling the exploitation or local search around the best-known optimal solution.

It should be noted that while the GA explores the search space using crossover to make random changes of the information that is already present in the population, the mutation probability being much smaller, PSO changes randomly the speed of each particle element, moving it in the direction of the leader and personal best position.

The newer metaheuristic methods used in this paper, while sharing the natural inspiration of GA and PSO, combine elements found in the two algorithms and increase the number of input parameters and the complexity of their mathematical model in order to improve their optimization performance. They are the Bat Optimization Algorithm (BOA), Whale Optimization Algorithm (WOA) and Sperm-Whale Algorithm (SWA).

2.3. The Bat Optimization Algorithm

Bats hunt for prey using echolocation. In the initial search stage, they emit high amplitude/low frequency ultrasound impulses, with low emission rate (10–20 imp/sec), decoding in real time the reflected waves in order to identify the approximate position of the prey. When a potential target is identified, the bat increases the pulse rate up to 200 imp/sec, and the pulse frequency, which enables it to search accurately the space separating it from the prey, identifying the obstacles in its path and precisely locating the victim and its movement pattern.

The bat optimization algorithm [41] uses the PSO principle of changing the speed and position of the population members (here called ‘bats’), but the speed update formula is more elaborated, considering the principle of raising the signal frequency and pulse rate as the bats are getting close to the prey, i.e., to the optimal solution. The basic flowchart of a BOA iteration is depicted in Figure 5.

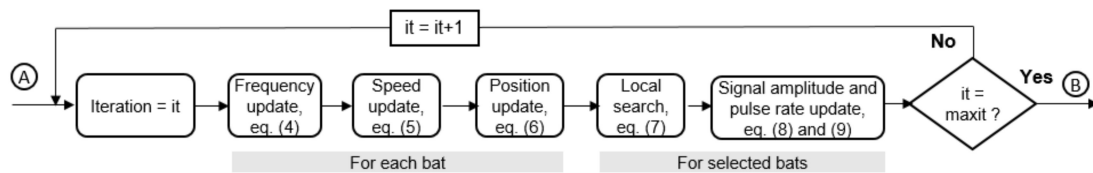


Figure 5. The flowchart of a BOA iteration.

The bats’ speeds are initialized in the same manner as in the PSO algorithm but are accompanied by the initial signal amplitude, A_j , maximum pulse rate, $r_{j,max}$ and random pulse frequency $f_j \in [f_{min}, f_{max}]$, $j = 1, \dots, N$.

In each iteration it , every bat from the population performs three operations:

- Frequency update:

$$f_j = f_{\min} + rnd \cdot (f_{\max} - f_{\min}) \quad (4)$$

- Speed update, with an equation inspired from (2):

$$sp_j^{(it)} = w \cdot sp_j^{(it-1)} + f_j \cdot rnd_1 \cdot (x_{j,crt}^{(it)} - x_{j,best}^{(it)}) \quad (5)$$

- Position update, identical to the formulation from (3):

$$x_j^{(it+1)} = x_j^{(it)} + sp_j^{(it)} \quad (6)$$

The BOA also includes a local search. The best individuals from the population are randomly moved in the search space, with

$$x_j^{(it+1)} = x_j^{(it+1)} + pp \cdot \bar{A}, \quad j = 1 \dots M, \quad M < N \quad (7)$$

where $\bar{A}$ is the average bat amplitude for iteration it and $pp \in [-1, 1]$.

The new bat positions computed with Equations (4) to (7) are accepted in the population with random probability and only if the newly obtained position is better than the previous.

At the end of each iteration, if a bat improves its position, its signal amplitude is decreased:

$$A_j^{(it+1)} = \alpha \cdot A_j^{(it)} \quad (8)$$

and its pulse emission rate increases:

$$r_j^{(it+1)} = r_j^{(it)} \cdot (1 - e^{-\gamma \cdot it}) \quad (9)$$

where $\alpha \in (0, 1)$ and $\gamma > 0$.

This behavior, much like the inertia term for PSO, increases the probability of performing local searches when the iteration count is nearing $itmax$.

2.4. The Whale Optimization Algorithm

The hunting behavior of humpback whales is the source of inspiration for the Whale Optimization Algorithm (WOA). The whales hunt in groups, and when they find their prey, consisting of schools of krill or small fish near the water surface, they attack it from below using two maneuvers: encircling and spiraling.

The WOA uses a population of vector solutions ('whales'), which are hunting for prey independently, guiding their search by following a reference individual, usually their leader, i.e., the whale closest to the problem solution ('food'), according to its fitness function.

During the algorithm, whales use initially encircling, then spiral attack, in the same way PSO and BOA use the broad exploration and the exploitation of the search space near the optimal solution.

In each iteration it , the encircling performed by each whale j from the population is described by [42]:

$$x_j^{(it+1)} = reference^{(it)} - A \cdot D_1 \quad (10)$$

where

$$A = 2 \cdot a \cdot rnd_1 - a \quad (11)$$

$$D_1 = |C \cdot reference^{(it)} - x_j^{(it)}|, \quad C = 2 \cdot rnd_2 \quad (12)$$

The coefficient a from equation (11) is a scalar value decreasing during the iterative from a positive value to 0. The $(\cdot)$ sign denotes the element-by-element multiplying of vectors, and $||$, an absolute value.

For the extreme values of $a = 0$ and $a = 1$, equations (10) to (12) show that position $x_j^{(it+1)}$ will always lie between $x_j^{(it)}$ and $reference^{(it)}$, thus moving any whale towards the reference solution used to guide the population. If values larger than 1 are given to a , factor A from (11) will also increase, moving the whales beyond the target and exploring a possibly uncharted portion of the search space.

If the reference position is $reference^{(it)} = leader^{(it)}$, the leader from the current iteration, when A decreases, whales get closer to the leader, encircling the prey or the optimal solution. If another whale is used as reference, $reference^{(it)} = random(x^{(it)})$, the search will shift towards its path, simulating the exploration of the sea in search for food performed by real whales.

The spiral attack phase is described by an equation that combines oscillatory and exponentially varying components:

$$x_j^{(it+1)} = D_2 \cdot e^{b \cdot l} \cdot \cos(2 \cdot \pi \cdot l) + leader^{(it)} \quad (13)$$

with

$$D_2 = |leader^{(it)} - x_j^{(it)}| \quad (14)$$

In equation (13), b is a constant, and l is a random value from the $[-1, 1]$ interval [42].

The initially large, then gradually decreasing values of a , so that first $|A| > 1$, then $|A| < 1$, $|A| \rightarrow 0$, first move the whales away from the leader in exploration, then encourage encircling, followed by spiral attack. If p denotes a random number, the general equation for changing the position of a whale follows as:

$$x_j^{(it+1)} = \begin{cases} reference^{(it)} - A \cdot D_1, & \text{if } p \geq 0.5 \\ D_2 \cdot e^{bl} \cdot \cos(2 \cdot \pi \cdot l) + leader^{(it)} & \text{if } p < 0.5 \end{cases} \quad (15)$$

The flowchart of a WOA iteration is presented in Figure 6.

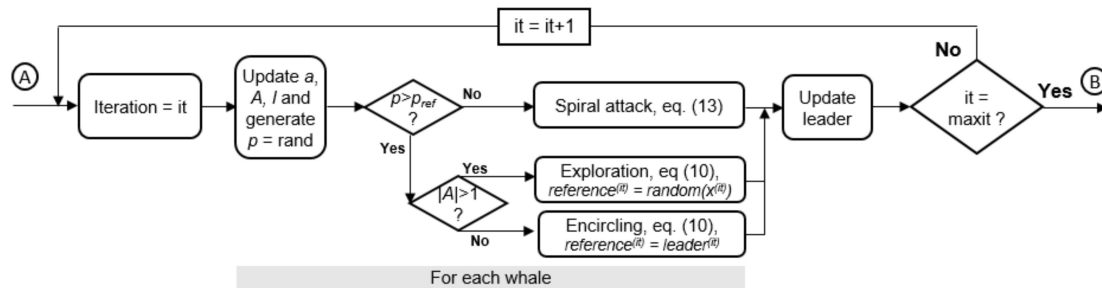


Figure 6. The flowchart of a WOA iteration.

WOA has two specific parameters that can be tuned for better performance: coefficient a from Equation (11) and constant b from (13).

2.5. The Sperm-Whale Algorithm

The search used by the SWA mimics the hunting behavior of sperm whales, which live alone or in small groups at the bottom of the sea and must come to the surface to hunt and breathe [43]. In each iteration, the population of the SWA is split into smaller search groups consisting in uniformly distributed better and worse adapted members ('sperm whales'). Consequently, the search for the optimal solution occurs independently in each group. First, the sperm whales change their position from the bottom of the sea to the surface. This step is simulated only for the worst adapted member of the group, for which the opposite position is computed. The positions of the leader and of the worst individual in a group g , $leader^{(g,it)}$ and $worst^{(g,it)}$, are used to compute an in-between distance $dist^{(g,it)}$:

$$dist^{(g,it)} = worst^{(g,it)} + w \cdot leader^{(g,it)} \quad (16)$$

The reflex position of $worst^{(g,it)}$ is then computed with Equation (17).

$$reflex^{(g,it)} = worst^{(g,it)} + 2 \cdot (dist^{(g,it)} - worst^{(g,it)}) = 2 \cdot dist^{(g,it)} - worst^{(g,it)} \quad (17)$$

The newly computed individual $reflex^{(g,it)}$ will replace $worst^{(g,it)}$ only if its fitness function is better. At the beginning of the iterative process, when the inertia w from Equation (16) is large, the individual will search beyond $leader^{(g,it)}$ (exploration phase, Figure 7a). As w decreases, the search will focus between $worst^{(g,it)}$ and $leader^{(g,it)}$, exploiting the search space around the known optimal solution (Figure 7b).

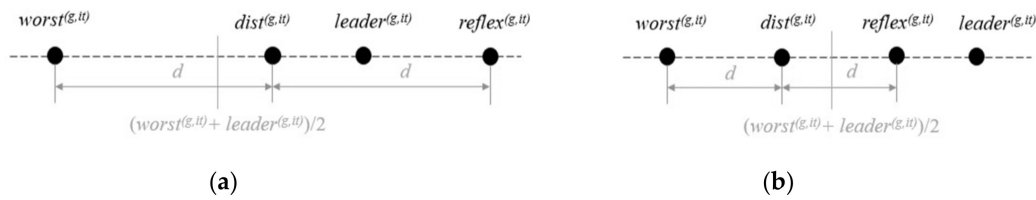


Figure 7. Reflex search in the SWA algorithm: (a) exploration, (b) exploitation.

In the second stage, a Good Gang is formed within the group, gathering the best *gg* individuals ranked according to their fitness function. Every Good Gang member performs several local searches in which its elements *k* are displaced randomly, within a small radius *r*:

$$x_{j,k} = \pm r \cdot x_{j,k}, \quad j = 1 \dots gg \quad (18)$$

The original Good Gang members are replaced only if better sperm-whale positions are found during the local search.

Finally, the best Good Gang member from the group (the dominant sperm-whale) performs genetic crossover with all other group individuals. One of the two resulting children is chosen randomly to replace the worst of the two parents.

At the end of the iteration, the groups are reunited in the final population, which will repeat the search process until the stopping criterion of the algorithm is met. The basic flowchart of a SWA iteration is presented in Figure 8.

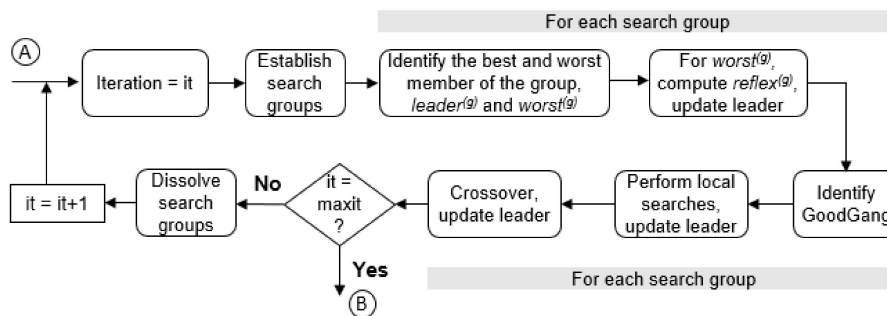


Figure 8. The flowchart of a SWA iteration.

The SWA offers several tuning options for the user. The population size, number of search groups within the population, the inertia *w* and its decrement, the Good Gang size and number of local searches for its members, the local search radius *r*, and the crossover method can be adjusted for better performance.

3. The Implementation of the Optimal Reactive Compensation for Loss Minimization Problem

The five metaheuristic algorithms presented in the previous chapter were run in an implementation of the Optimal Capacitor Banks Allocation (OCBA) problem for active energy loss minimization. The approach used in this paper is stated as follows: Find the optimal buses in an EDN where capacitor banks (CB) should be installed and the amount of reactive load compensation in each bus, with the objective of operating the EDN with minimal active power and energy losses for the interval of a typical day. For an EDN with *NN* buses (nodes) and *NB* branches, the mathematical expression of the objective function of the OCBA problem was defined as:

$$\Delta P[\%] = \sum_{h=1}^{24} \Delta P_h / \left(\sum_{h=1}^{24} \sum_{bus=1}^{NN} P_{b,h} + \sum_{h=1}^{24} \Delta P_h \right) * 100 = \min \quad (19)$$

The mathematical model of the fitness function considered the following constraints:

Cr1. The available CB stock cannot be exceeded:

$$\sum_{bus=1}^{NN} NCB_{bus} \leq stock_{CB} \quad (20)$$

Cr2. The compensation level in each bus cannot exceed the reactive bus load (avoid reversed reactive power flows):

$$NCB_{bus} \cdot q_{CB} \leq Q_{bus}, \quad bus = 1 \dots NN \quad (21)$$

Cr3. Branch current flows after compensation cannot exceed the branch rated current:

$$I_{br} \leq I_{max,br}, \quad br = 1 \dots NB \quad (22)$$

Cr4. Bus voltages after compensation cannot exceed the maximum allowed value:

$$U_{bus} \leq U_{max,bus}, \quad bus = 1 \dots NN \quad (23)$$

In Equations (19) to (22), $\Delta P[\%]$ is the percent active power loss in the EDN over 24 h, ΔP_h is the active power loss in the EDN at hour h , NCB_{bus} is the number of CBs installed in a generic bus; q_{CB} is the reactive power rating of a CB, Q_{bus} is the reactive load of a generic bus, $stock_{CB}$ is the CB stock; I_{br} is the current flow on a generic branch br , $I_{max,br}$ is the rated current of branch br , U_{bus} is the voltage of a generic bus after compensation, and $U_{max,bus}$ is the maximum bus voltage allowed in a generic bus.

All the algorithms tested in the case study used the same solution encoding for their population members. They were generated as vectors of the type described by Equation (1), with integer numbers and length equal to the number of buses in which compensation was possible in the network. The significance of the value of a generic element represented the number of CBs placed in the bus to which it was designated. All the algorithms started in the first iteration with the same population, generated randomly but considering constraint Cr2 of maximum allowed number of CBs in each bus and Cr1, the maximum CB stock (Figure 9).

	bus 1	bus 2	bus 3	...	bus M-1	bus M
max. allowed in bus	5	0	3		2	4
actual compensation	3	0	1		2	2

Figure 9. The encoding of the solutions used by the OCBA problem.

The fitness of the optimal solutions was assessed in all the algorithms using the objective function (19), which also considered the constraints from Equations (20) to (23). The methodology employed for calculating the fitness of each solution is described in Figure 10.

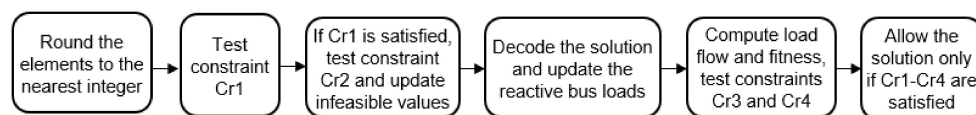


Figure 10. Fitness computation and solution validation for the OCBA problem.

By applying any of the equations (2) to (18) or by genetic crossover and mutation, the changes undergone by population members can result in their invalidation because of

- Non-integer values, leading to invalid number of CBs installed in a bus;
- Values exceeding the interval $[0, NCB_{bus}]$ allowed by the constraint Cr2;
- Violation of constraint Cr1, by exceeding the available CB stock;
- Solutions otherwise valid but which lead to the violation of the constraints Cr3 or Cr4.

Thus, every newly generated population member, for each algorithm, must pass through a validation procedure before being allowed in the population created for the next iteration.

If constraint Cr1 is not satisfied, the solution is always discarded as unfeasible. If the constraint Cr2 is not fulfilled, the solution is modified by setting the unfeasible values to the nearest allowed value, using for each element x_j from Figures 1 and 9 the following correction:

$$x_j = \begin{cases} 0, & \text{if } x_j = 0 \\ NCB_j, & \text{otherwise} \end{cases} \quad (24)$$

For each population member, the active power losses used in equation (19) are computed with the Newton–Raphson load flow (LF) algorithm, which is slower, but generally considered more accurate than the branch-and-bound methods preferred in the analysis of distribution networks. The LF algorithm also provides the results required for checking the constraints Cr3 and Cr4, bus voltage and branch current flow limits. Prior to computing the LF, the compensation solution is simulated subtracting from the bus reactive loads the CB injection for each compensated bus, according to the population member/solution being tested.

4. Results

The OCBA problem was solved using the metaheuristics presented in Section 2, with the aim of comparing the performance of the newer algorithm designs, BOA, WOA, and SWA against the two well established methods, GA and PSO. For comparison purposes, all the algorithms had a common representation for the members of the population, illustrated in Figure 9, and the same fitness function, active power and energy loss minimization, computed with Equation (19) and subjected to the constraints given by Equations (20) to (23), Section 3. The initial parameters used for the algorithms are presented in Table 3.

Since for all algorithms there was no improvement for the optimal solution beyond generation 350, the graphical representations of the results will be limited to the first 360 generations.

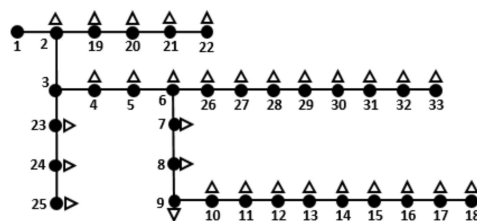
Two test networks were used to validate the comparison: the smaller sized IEEE 33-bus MV radial voltage distribution system (Figure 11) and a larger 215-bus MV EDN from a residential area of a major city from Romania (Figure 12).

Synthetic data regarding the physical characteristics for the IEEE 33-bus system is given in Table 4. The system does not include MV/LV transformer data; thus, the active power losses computed by the algorithms do not include transformer losses. The extended data regarding branch characteristics (connecting buses, type line or transformer, electrical parameters resistance and reactance, maximum branch current) is provided in Appendix A, Table A1. For the active and reactive bus loads, the study uses a custom representation consisting of daily 24-h profiles, described below.

For this particular test system, the literature provides only a set of instantaneous active and reactive bus loads. In this paper, these values were used as reference, in conjunction with a set of typical load profiles (TLP) provided in the Supplementary Materials attached to the paper, to create 24-h profiles. The TLPs considered several types of loads, residential, industrial, and their distribution in the network is summarized in Table 5.

Table 3. The initial parameters used for the metaheuristic algorithms.

Common Parameters for All the Algorithms:	
Population size: 40, Number of generations: 500	
GA	
Selection method: tournament—keep best 2 from a random draw of 4	
Crossover method: uniform at threshold 0.5	
Mutation: random	
Crossover and mutation rates: 0.9/0.1	
PSO	
Inertia: 0.9 decreasing to 0.4, linear descent	
BOA	
Initial amplitude: 1	
Initial pulse emission rate: 0.3	
Amplitude attenuation rate: 0.7	
Pulse emission increase rate: 0.3	
Pulse frequency domain: $[-0.9, 1.2]$	
Number of bats used for local search: dynamic. If a randomly generated number is greater than the bat's pulse emission rate, the bat is selected for local search in the current iteration.	
WOA	
Coefficient a : decreasing from 3 to 0, linear descent	
Coefficient l : random	
Coefficient b : 1	
SWA	
Number of search groups: 4	
Good Gang size: half of the search group size, rounded to the nearest integer	
Number of searches performed by each Good Gang member: 10	
Local search radius: 1	
Crossover type: uniform	

**Figure 11.** The IEEE 33-bus test system.

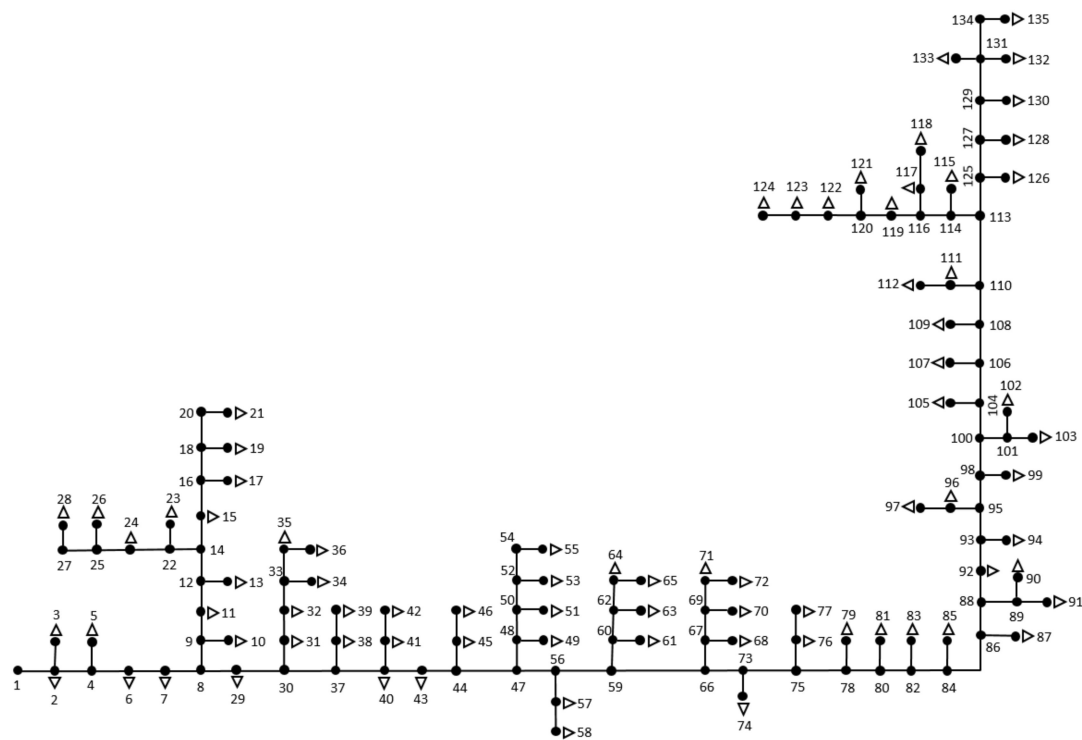


Figure 12. The residential 215-bus EDN.

Table 4. The physical characteristics of the IEEE 33-bus system.

Number of Buses	Transformer Rated Power/Number	Feeder Type	Feeder Cross-Section (mm ²)	Total Length(km)
12.66 kV: 33	None	Unknown ⁽¹⁾	Unknown ⁽¹⁾	Unknown ⁽¹⁾

⁽¹⁾ Only the total resistance and reactance is known for each branch

Table 5. The TLP categories used for the IEEE 33 -bus system and their bus distribution.

TLP Category	Bus
Residential	4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18
Industry	2, 3, 19, 20, 21, 22, 23, 24, 25
Commercial	26, 27, 28, 29, 30, 31, 32, 33

The second test system used in the case study is a much larger EDN, consisting of 135 MV buses to which 80 loads are connected through MV/LV transformers. For simplicity, the transformers are omitted in Figure 12, together with the corresponding 80 bus numbers for the transformer LV busbars (from 136 to 215). A summary of the transformer rated power, together with the feeder and bus general information, is given in Table 6. The electrical parameters of the branches are given in Appendix A, Table A2. For this network, the bus loads were also modelled as 24-h daily profiles, being measured by the smart metering infrastructure installed by the local distribution utility for a typical working day.

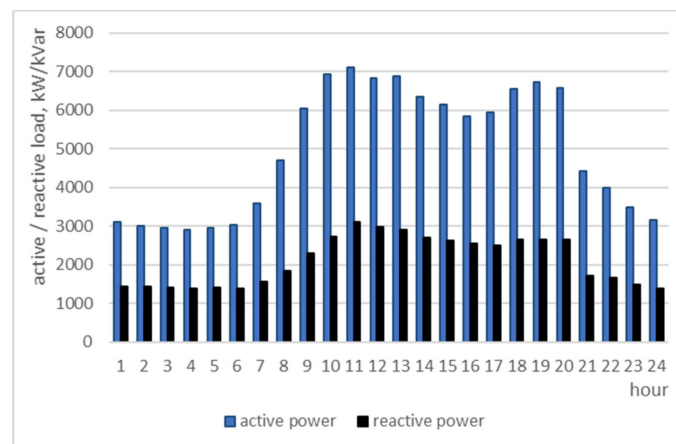
Table 6. The physical characteristics of the 215-bus EDN.

Number of Buses	Transformer Rated Power/Number	Feeder Type	Feeder Cross-Section (mm ²)	Total Length (km)
20 kV: 135 (1–135) 0.4 kV: 80 (136–215)	63 kVA: 33; 100	Cable	3 × 95	2.5
	kVA: 14		3 × 120	84.45
	160 kVA: 15, 250		3 × 150	3.2
	kVA: 15			
	400 kVA: 3			

Because a 24-h voltage profile was not available for the 215-bus network, the voltage reference for the slack bus was recommended by the distribution utility at the value of 1.06 pu. For the IEEE 33-bus system, the setpoint was 1 pu (nominal voltage). The slack bus for both networks is bus 1, and all the other buses are modeled as PQ (consumer) buses.

4.1. Results for the IEEE 33-Bus System

The first step of the study was the choice of the maximum CB stock used for optimization. For this purpose, the load profile of the network for 24 h, given in Figure 13, was analyzed. Since the purpose was to test the performance of each algorithm, the CB stock was set at 70×7.5 kVar units, which would ensure a maximum of 525 kVar of VAR compensation, about half of the minimal value of the reactive load, occurring at night hours. In this way, the number of possible CB allocation variants is maximized, while reducing the investment cost.

**Figure 13.** The active and reactive load profiles of the IEEE 33-bus test system—hourly values.

The GA, PSO, BOA, WOA, and SWA were run using this CB stock, the initial parameters from Table 3, and the same initial population. The solution identified by each algorithm, compared with the reference case (no reactive power compensation), and their corresponding fitness functions (percent losses) are presented in Table 7. The first line of Table 7 also presents the maximum number of CBs that can be allocated in each bus, computed according to the minimal reactive power load, so that constraint Cr2 would be always fulfilled. The same results are displayed graphically in Figure 14. In Figure 15, the parallel evolution of the fitness function of each algorithm over the first 350 generations is presented, on a typical run, emphasizing the fact that the SWA and BOA obtain the solutions corresponding to the lowest loss values, followed by the PSO, GA, and BAT.

Table 7. The OCBA solutions found by the metaheuristic algorithms for the IEEE 33-bus system.

Bus	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
CB																	
limit	3	2	4	0	0	6	3	1	4	0	6	4	4	0	0	0	14
Reference	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GA	1	1	1	0	0	1	1	1	2	0	5	1	2	0	0	0	13
PSO	0	0	0	0	0	4	0	1	0	0	0	4	4	0	0	0	14
BAT	0	2	4	0	0	3	1	1	1	0	6	4	3	0	0	0	2
WOA	0	0	0	0	0	0	0	1	0	0	1	4	4	0	0	0	14
SWA	0	0	0	0	0	0	0	0	0	0	4	4	4	0	0	0	14
Bus	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	CB Used	Fitness
CB																	
limit	6	1	17	2	3	7	5	0	0	0	3	39	4	5	0	143	N/A
Reference	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5.482
GA	1	1	1	1	1	1	1	0	0	0	1	27	4	2	0	70	4.982
PSO	0	1	0	0	0	0	0	0	0	0	3	39	0	0	0	70	4.947
BAT	0	1	0	1	3	7	2	0	0	0	2	24	2	1	0	70	5.038
WOA	0	1	0	0	0	0	0	0	0	0	0	39	1	5	0	70	4.939
SWA	0	0	0	0	0	0	0	0	0	0	0	35	4	5	0	70	4.934

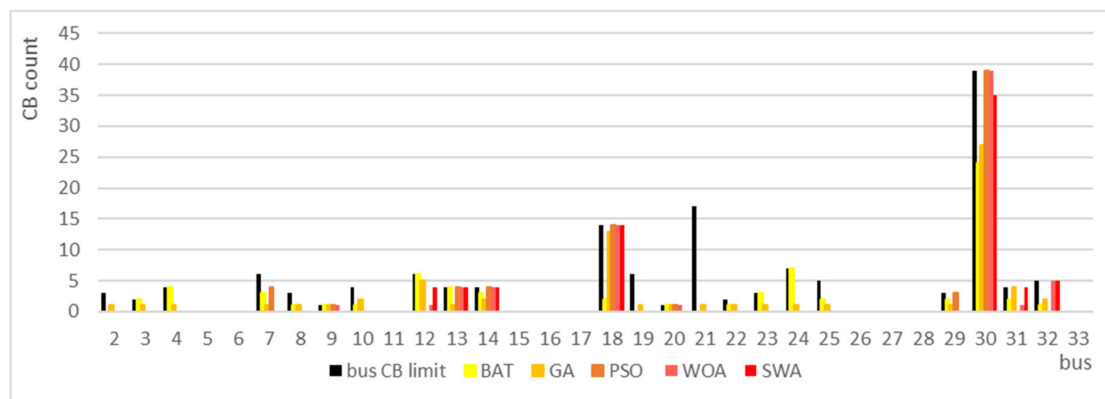


Figure 14. The number of CBs allocated in the buses of the IEEE 33-bus system by each algorithm.

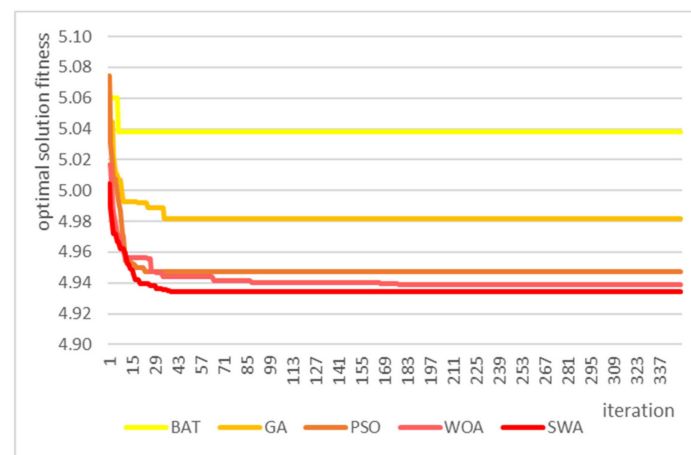


Figure 15. The fitness of the optimal solution found by the metaheuristic algorithms after 360 iterations, for the IEEE 33-bus system.

The results from Table 7 and Figure 14 show that the best fitness function values are obtained when maximum compensation is applied at buses 18 (feeder end), 29–32 (feeder end), and 12–14, while for other buses with compensation potential, such as 21–25, where the reactive load is high, no capacitor banks are allocated. All the algorithms use the entire CB stock available, with differences in the buses chosen for compensation and number of CBs allocated to each bus.

The results regarding the active power losses, for each hour and algorithm, compared with the reference case are plotted in Figure 16 and presented in Table 8. Table 9 gives the loss reduction in percent, against the reference case, for which the total values are represented in Figure 17. The loss reduction ranges between 6.55% and 16.78%, depending on the algorithm and network load. The improvement is higher in off-peak hours, and the best results are obtained with SWA (8.17% to 16.78%), with a global value of 10.51% over 24 h. PSO, WOA, and SWA are the closest to the optimal solution.



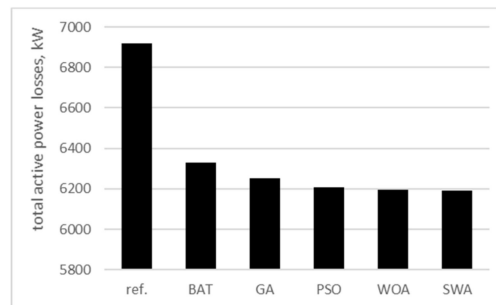
Figure 16. Hourly active power losses in the IEEE 33-bus system, for each algorithm.

Table 8. Hourly and total active power losses in the IEEE 33-bus system, in kW, for each algorithm.

Hour	Ref.	BAT	GA	PSO	WOA	SWA
h01	140.04	122.53	120.22	118.98	118.74	118.51
h02	128.61	111.53	109.32	108.14	107.93	107.70
h03	122.58	105.89	103.74	102.65	102.45	102.22
h04	119.17	102.76	100.65	99.59	99.39	99.17
h05	118.50	102.35	100.31	99.31	99.13	98.90
h06	128.54	112.25	110.25	109.23	109.04	108.82
h07	205.62	184.05	181.30	179.43	178.99	178.75
h08	314.56	287.82	284.37	281.89	281.25	280.98
h09	374.57	345.89	342.50	340.05	339.35	339.12
h10	448.92	416.40	412.92	410.21	409.41	409.15
h11	462.22	427.75	424.10	421.26	420.40	420.17
h12	404.06	373.11	370.05	367.81	367.11	366.87
h13	408.02	377.17	373.94	371.64	370.97	370.72
h14	364.61	335.05	331.31	328.94	328.27	328.03
h15	324.39	296.90	293.33	291.25	290.70	290.45
h16	277.75	254.32	251.42	250.06	249.70	249.46
h17	298.98	275.44	272.52	271.10	270.71	270.50
h18	421.48	391.95	388.02	385.68	385.03	384.78
h19	466.73	436.14	431.94	429.53	428.93	428.60
h20	458.26	427.14	422.83	420.32	419.70	419.36
h21	329.63	302.53	298.48	295.98	295.44	295.03
h22	273.68	248.43	244.68	242.37	241.88	241.51
h23	187.07	167.53	164.73	163.25	162.98	162.67
h24	139.61	123.09	120.90	119.80	119.60	119.37
total	6917.59	6328.03	6253.83	6208.47	6197.11	6190.86

Table 9. Hourly and total power loss reduction in the IEEE 33-bus system, in %, for each algorithm.

Hour	BAT	GA	PSO	WOA	SWA
h01	12.50	14.15	15.03	15.21	15.37
h02	13.28	15.00	15.91	16.08	16.26
h03	13.62	15.37	16.26	16.42	16.61
h04	13.77	15.54	16.43	16.60	16.78
h05	13.62	15.35	16.19	16.35	16.54
h06	12.67	14.22	15.02	15.17	15.34
h07	10.49	11.83	12.74	12.95	13.06
h08	8.50	9.60	10.39	10.59	10.67
h09	7.66	8.56	9.22	9.40	9.47
h10	7.24	8.02	8.62	8.80	8.86
h11	7.46	8.25	8.86	9.05	9.10
h12	7.66	8.42	8.97	9.15	9.20
h13	7.56	8.35	8.92	9.08	9.14
h14	8.11	9.13	9.78	9.97	10.03
h15	8.47	9.57	10.21	10.38	10.46
h16	8.44	9.48	9.97	10.10	10.18
h17	7.87	8.85	9.32	9.46	9.53
h18	7.00	7.94	8.49	8.65	8.71
h19	6.55	7.46	7.97	8.10	8.17
h20	6.79	7.73	8.28	8.41	8.49
h21	8.22	9.45	10.21	10.37	10.50
h22	9.23	10.60	11.44	11.62	11.76
h23	10.45	11.94	12.73	12.88	13.04
h24	11.83	13.40	14.19	14.33	14.49
total	8.52	9.60	10.25	10.42	10.51

**Figure 17.** The total active power loss reduction in the IEEE 33-bus system, in kW, for each algorithm.

Compared with the reference case, the best compensation solution found by the SWA leads to a loss reduction of 726.73 kW for the analyzed day, which, if it is extrapolated for a year, amounts to 265.26 MW loss saving. The difference between SWA and the second best result, given by WOA, is of 6.25 kW per day or 2.28 MW for an entire year. As Figure 16 shows, SWA achieves these savings mainly during two hours, at 19.00 and 24.00.

Reactive power compensation with capacitor banks is mainly used in EDN for voltage profile improvement, where specific networks configurations and load patterns lead to high voltage drops along the feeders. In the case of the IEEE 33-bus system, the nominal voltage setting for the slack bus and the load profiles from Appendix A lead, in the reference case without compensation, to the voltage profile described by Figure 18.

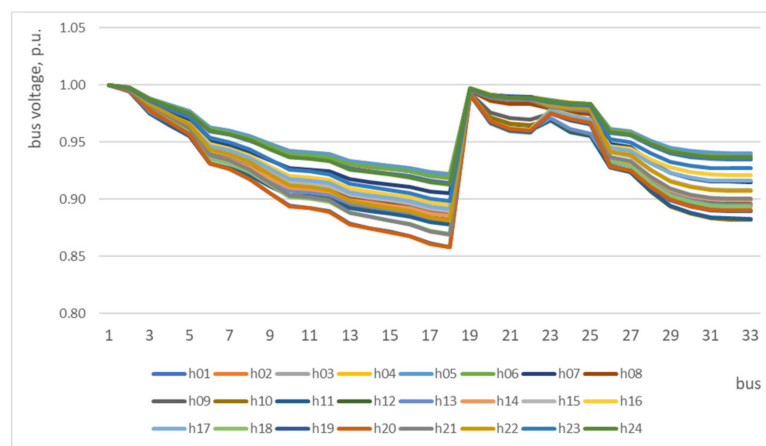


Figure 18. The bus voltages in the IEEE 33-bus system without compensation, for each hour from the analyzed day.

The values show voltage drops that exceed the lower limit of -10% prescribed by the Romanian standards, in several buses located near the end of the main two supply paths, ending in buses 18 and 33. For bus 18, the voltage has the minimum value of 0.858 pu, at hours 19.00 and 20.00, while for bus 33, the minimum voltage is 0.882 pu, at hour 10.00.

The improvement of the voltages obtained hourly with each algorithm is depicted in Figure 19 for bus 18 and in Figure 20 for bus 33. The percent improvements over the reference values (no compensation) are given in Tables 10 and 11, respectively. Again, the SWA gives the best results, with the maximum voltage improvement. The minimum reference voltage value of 0.858 pu in bus 18 (hour 10.00) is raised by 1.65%, to 0.872 pu. However, the voltages remain below the 0.9 pu minimum allowed limit, for 10 h from the 24-h analysis interval. Better voltage regulation can be possible using a larger CB stock or raising the voltage in the reference bus, by changing the HV/MV transformer tap position from the substation at bus 1.

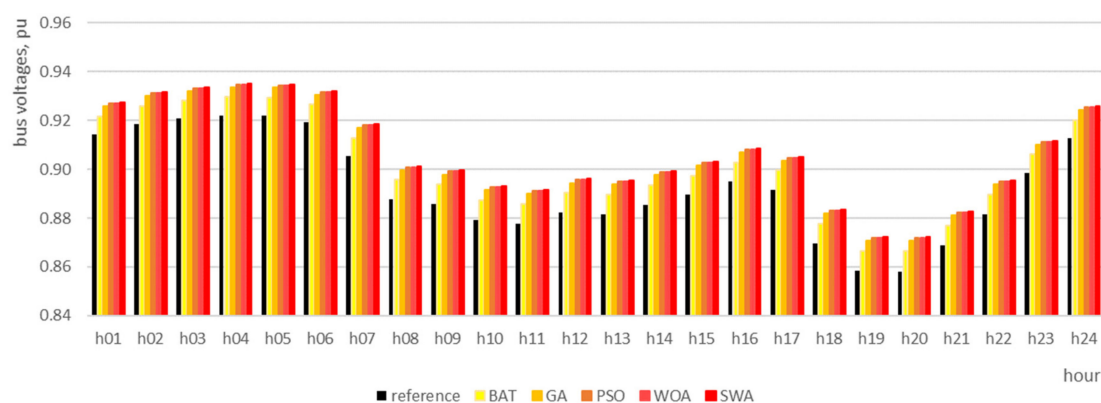


Figure 19. Voltage improvement after compensation for bus 18, the IEEE 33-bus system.

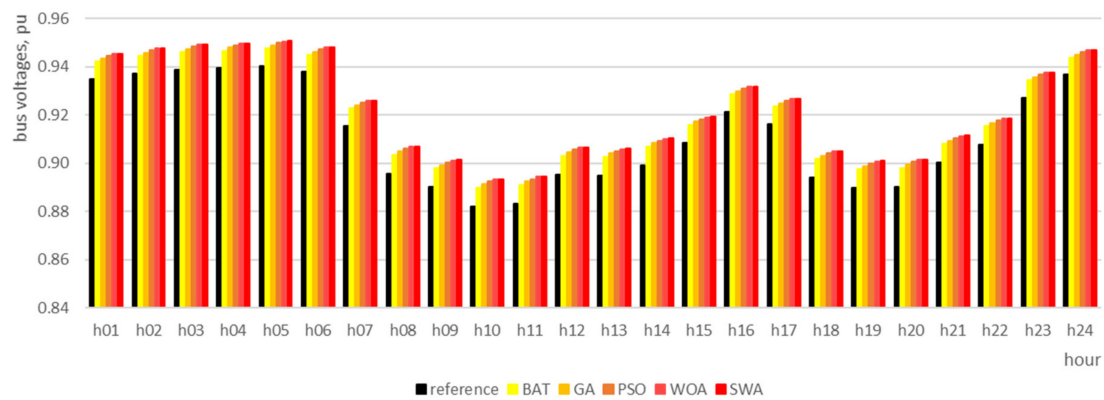


Figure 20. Voltage improvement after compensation for bus 33, the IEEE 33-bus system.

Table 10. Hourly reference voltage values for bus 18 and percent improvements after compensation, the IEEE 33-bus test system.

Hour	Voltage, pu	Improvement, %				
	Ref.	BAT	GA	PSO	WOA	SWA
h01	0.914	0.82	1.26	1.38	1.38	1.42
h02	0.919	0.81	1.25	1.37	1.37	1.41
h03	0.921	0.80	1.24	1.36	1.36	1.40
h04	0.922	0.80	1.23	1.36	1.36	1.40
h05	0.922	0.80	1.23	1.36	1.36	1.40
h06	0.919	0.80	1.24	1.36	1.36	1.40
h07	0.905	0.84	1.29	1.42	1.42	1.46
h08	0.888	0.88	1.35	1.48	1.48	1.53
h09	0.886	0.88	1.36	1.49	1.49	1.54
h10	0.879	0.90	1.38	1.52	1.52	1.56
h11	0.878	0.91	1.39	1.53	1.53	1.57
h12	0.882	0.89	1.37	1.50	1.50	1.55
h13	0.882	0.89	1.37	1.51	1.51	1.55
h14	0.885	0.89	1.36	1.50	1.50	1.54
h15	0.890	0.88	1.35	1.48	1.48	1.52
h16	0.895	0.86	1.32	1.45	1.45	1.50
h17	0.892	0.86	1.33	1.46	1.46	1.51
h18	0.870	0.92	1.41	1.55	1.55	1.60
h19	0.858	0.95	1.45	1.60	1.60	1.65
h20	0.858	0.95	1.45	1.60	1.60	1.65
h21	0.869	0.92	1.42	1.55	1.56	1.60
h22	0.882	0.89	1.37	1.51	1.51	1.55
h23	0.898	0.85	1.31	1.44	1.44	1.48
h24	0.913	0.82	1.26	1.38	1.39	1.43
minimum value, pu	0.858					
max. improvement, %		0.95	1.45	1.60	1.60	1.65

Table 11. Hourly reference voltage values for bus 33 and percent improvements after compensation, the IEEE 33-bus test system.

Hour	Voltage, pu	Improvement, %				
	Reference	BAT	GA	PSO	WOA	SWA
h01	0.935	0.78	0.91	1.02	1.10	1.11
h02	0.937	0.77	0.90	1.01	1.09	1.10
h03	0.939	0.77	0.90	1.01	1.09	1.10
h04	0.939	0.77	0.90	1.01	1.09	1.10
h05	0.940	0.77	0.90	1.01	1.08	1.10
h06	0.938	0.77	0.90	1.01	1.09	1.10
h07	0.915	0.82	0.96	1.08	1.16	1.17
h08	0.896	0.86	1.01	1.14	1.22	1.24
h09	0.890	0.88	1.02	1.15	1.24	1.25
h10	0.882	0.90	1.05	1.18	1.27	1.28
h11	0.883	0.90	1.05	1.18	1.27	1.28
h12	0.895	0.87	1.01	1.14	1.23	1.24
h13	0.895	0.87	1.01	1.14	1.23	1.24
h14	0.899	0.86	1.00	1.13	1.22	1.23
h15	0.908	0.84	0.98	1.10	1.19	1.20
h16	0.921	0.81	0.94	1.06	1.14	1.15
h17	0.916	0.82	0.96	1.07	1.16	1.17
h18	0.894	0.87	1.02	1.14	1.23	1.24
h19	0.890	0.88	1.03	1.15	1.24	1.26
h20	0.890	0.88	1.03	1.15	1.24	1.26
h21	0.900	0.85	1.00	1.12	1.21	1.22
h22	0.908	0.84	0.98	1.10	1.19	1.20
h23	0.927	0.79	0.93	1.04	1.12	1.14
h24	0.937	0.77	0.90	1.01	1.09	1.11
minimum value, p.u.	0.882					
max. improvement, %		0.90	1.05	1.18	1.27	1.28

The voltage improvements are smaller for bus 33, with a maximum of 1.28% with the SWA, but with three algorithms (SWA, PSO and WOA), the voltage levels are raised after compensation above the maximum -10% deviation allowed by the regulations during 7 h (8.00, 9.00, 12.00, 13.00, 18.00, 19.00, and 20.00), only two hours remaining below this threshold (10.00 and 11.00), as it can be seen in Figure 20.

4.2. Results for the 215-Bus Distribution Network

In this case, the CB stock used for compensation was chosen using the 24-h load profile of the network from Figure 21. In comparison with the IEEE 33-bus system, the minimum off-peak reactive load is reduced, while the number of buses available for compensation increases significantly, allowing a higher number of possible solutions. Thus, the CB stock was set at 90 units of 7.5 kVar each, providing a maximum of 675 kVar of reactive power. As the solutions from Figure 22 and Table 12 show, all the algorithms use the entire stock, with different bus allocation. The SWA provides the best solution (6.19% active power losses), followed by the PSO (6.21%). In Table 12, since the VAR compensation is performed at the LV side of the substation transformers, the bus numbers are given for both the MV buses denoted in Figure 12, and for their corresponding LV transformer busbars. In Figure 22, only the LV bus numbers are used, for better readability. Figure 23 presents the evolution of the fitness function of each metaheuristic algorithm over the first 360 generations, on a typical run.

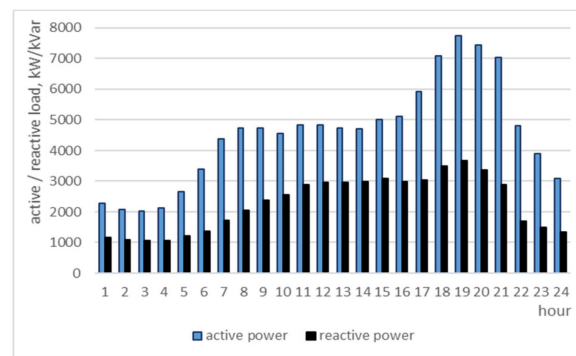


Figure 21. The active and reactive load profiles of the 215-bus network—hourly values.

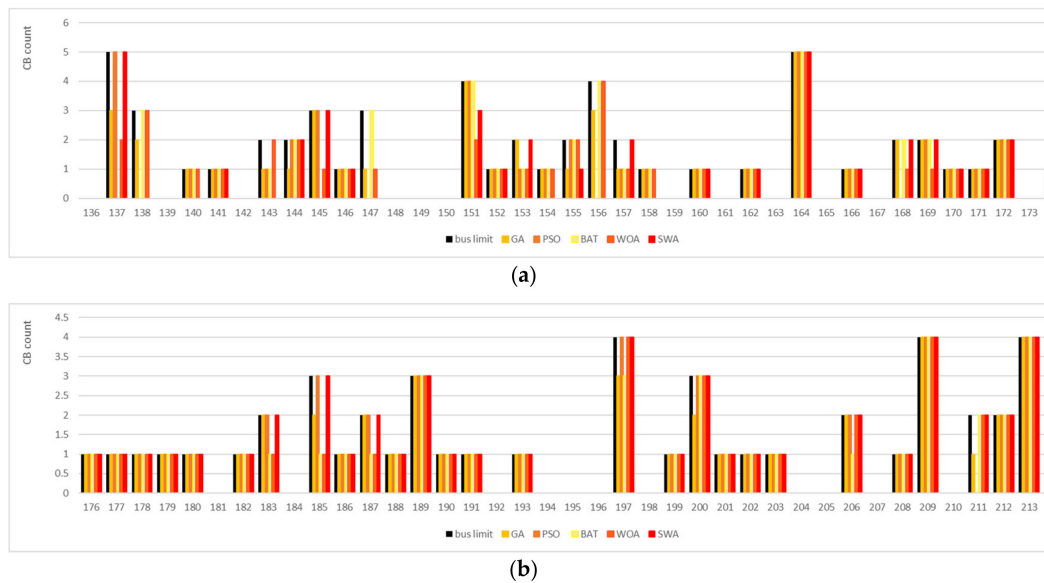


Figure 22. The number of CBs allocated in the buses of the 215-bus network by each algorithm: (a)—buses 136–175, (b)—buses 176–215.

For this network, as Figure 22 shows, the best two solutions (SWA, PSO) are mainly differentiated by the CB allocation at buses 151, LV side (28, MV side); 153 (31); 155 (34); 156 (35); and 157 (36), located at the beginning of the network, and having significant reactive power loads. This behavior is triggered by the use of the 90 CB stock, which is close to the maximum possible number of CBs that can be allocated for compensation, 107, and because of the sufficient stock, most of the buses can use the maximum possible CB allocation.

The comparison between the hourly active power losses computed by the Newton–Raphson algorithm for the reference case (no compensation) and the losses determined for each best compensation solution found by the metaheuristic algorithms is presented in Table 13 and Figure 24. Furthermore, Table 14 gives the percent reduction in losses obtained using the compensation solutions, while Figure 25 allows for an overview of the total losses obtained in each case, based on the values computed in Table 13.

Table 12. The OCBA solutions found by the metaheuristic algorithms for the 215-bus network.

MV Bus	2	3	5	6	7	10	11	13	15	17	19	21	23	24	26	28	29	31	32	34	35
LV Bus	136	137	138	139	140	141	142	143	144	145	146	147	148	149	150	151	152	153	154	155	156
bus limit	0	5	3	0	1	1	0	2	2	3	1	3	0	0	0	4	1	2	1	2	4
reference	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GA	0	3	2	0	1	1	0	1	1	3	1	1	0	0	0	4	1	2	1	1	3
PSO	0	5	0	0	1	1	0	1	2	3	1	0	0	0	0	4	1	1	1	2	0
BAT	0	0	3	0	1	1	0	1	2	0	1	3	0	0	0	4	1	1	1	2	4
WOA	0	2	3	0	1	1	0	2	2	1	1	1	0	0	0	2	1	1	1	2	4
SWA	0	5	0	0	0	1	0	0	2	3	1	0	0	0	0	3	1	2	0	1	0
MV Bus	36	38	39	40	41	42	43	45	46	49	51	53	55	57	58	61	63	64	65	68	70
LV Bus	157	158	159	160	161	162	163	164	165	166	167	168	169	170	171	172	173	174	175	176	177
bus limit	2	1	0	1	0	1	0	5	0	1	0	2	2	1	1	2	0	1	1	1	1
reference	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GA	1	1	0	1	0	1	0	5	0	1	0	2	2	1	1	2	0	1	1	1	1
PSO	1	1	0	1	0	1	0	5	0	1	0	0	2	1	1	2	0	1	1	1	1
BAT	1	1	0	1	0	1	0	5	0	1	0	2	2	1	1	2	0	1	1	1	1
WOA	1	1	0	1	0	1	0	5	0	1	0	1	1	1	1	2	0	1	1	1	1
SWA	2	0	0	1	0	1	0	5	0	1	0	2	2	1	1	2	0	1	1	1	1
MV Bus	71	72	74	76	77	79	81	83	85	87	90	91	92	94	96	97	99	102	103	105	107
LV Bus	178	179	180	181	182	183	184	185	186	187	188	189	190	191	192	193	194	195	196	197	198
bus limit	1	1	1	0	1	2	0	3	1	2	1	3	1	1	0	1	0	0	0	4	0
reference	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GA	1	1	1	0	1	2	0	2	1	2	1	3	1	1	0	1	0	0	0	3	0
PSO	1	1	1	0	1	2	0	3	1	2	1	3	1	1	0	1	0	0	0	4	0
BAT	1	1	1	0	1	1	0	1	1	1	1	3	1	1	0	1	0	0	0	3	0
WOA	1	1	1	0	1	1	0	1	1	1	1	3	1	1	0	1	0	0	0	4	0
SWA	1	1	1	0	1	2	0	3	1	2	1	3	1	1	0	1	0	0	0	4	0
MV Bus	109	111	112	115	117	118	119	121	122	123	124	126	128	130	132	133	135				
LV Bus	199	200	201	202	203	204	205	206	207	208	209	210	211	212	213	214	215	CB Used	Fitness		
bus limit	1	3	1	1	1	0	0	2	0	1	4	0	2	2	4	1	3	107			
reference	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		6.8578		
GA	1	2	1	1	1	0	0	2	0	1	4	0	1	2	4	1	0	90	6.2385		
PSO	1	3	1	1	1	0	0	2	0	1	4	0	0	2	4	1	3	90	6.2050		
BAT	1	3	1	1	1	0	0	1	0	1	4	0	2	2	4	1	3	90	6.2278		
WOA	1	3	1	1	1	0	0	2	0	1	4	0	2	2	4	1	3	90	6.2175		
SWA	1	3	1	1	1	0	0	2	0	1	4	0	2	2	4	1	3	90	6.1910		

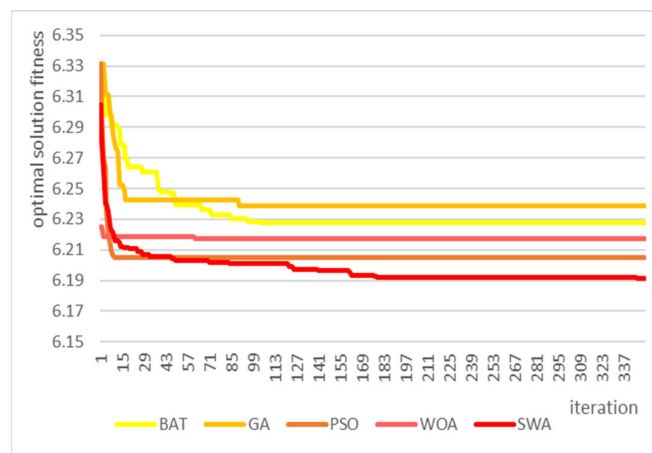


Figure 23. The fitness of the optimal solution found by the metaheuristic algorithms after 360 iterations, for the 215-bus network.

Table 13. Hourly and total active power losses in the 215-bus network, in kW, for each algorithm.

Hour	Ref.	BAT	GA	PSO	WOA	SWA
h01	67.331	55.673	55.609	55.539	55.583	55.305
h02	56.182	45.636	45.575	45.517	45.541	45.319
h03	53.214	43.113	43.053	43.000	43.016	42.817
h04	58.190	47.878	47.818	47.762	47.782	47.572
h05	90.377	77.534	77.467	77.382	77.446	77.109
h06	147.228	131.143	131.068	130.941	131.065	130.562
h07	245.758	223.025	223.059	222.583	222.867	222.029
h08	290.292	262.257	262.479	261.527	261.962	260.864
h09	303.227	270.552	271.077	269.405	270.026	268.696
h10	296.025	261.012	261.713	259.595	260.336	258.874
h11	354.181	312.943	313.922	311.078	312.050	310.247
h12	363.306	320.607	321.658	318.606	319.647	317.753
h13	352.690	310.099	311.147	308.090	309.134	307.242
h14	350.992	308.310	309.373	306.281	307.332	305.437
h15	394.674	349.439	350.570	347.313	348.428	346.400
h16	393.582	349.764	350.799	347.811	348.843	346.908
h17	505.757	458.845	459.845	456.827	457.938	455.824
h18	741.209	680.993	682.464	678.467	679.882	677.100
h19	892.805	825.937	827.555	823.210	824.773	821.637
h20	795.742	736.564	737.748	734.379	735.670	732.945
h21	672.197	623.613	624.385	621.999	622.971	620.808
h22	304.238	280.233	280.128	279.887	280.171	279.245
h23	194.076	175.399	175.315	175.153	175.327	174.688
h24	122.607	107.163	107.100	106.949	107.055	106.594
total	8045.88	7257.73	7270.93	7229.30	7244.84	7211.97



Figure 24. Hourly active power losses in the IEEE 33-bus system, for each algorithm.

Table 14. Hourly and total power loss reduction in the 215-bus network, in %, for each algorithm.

Hour	BAT	GA	PSO	WOA	SWA
h01	17.31	17.41	17.51	17.45	17.86
h02	18.77	18.88	18.98	18.94	19.33
h03	18.98	19.09	19.19	19.16	19.54
h04	17.72	17.82	17.92	17.89	18.25
h05	14.21	14.28	14.38	14.31	14.68
h06	10.92	10.98	11.06	10.98	11.32
h07	9.25	9.24	9.43	9.31	9.66
h08	9.66	9.58	9.91	9.76	10.14
h09	10.78	10.60	11.15	10.95	11.39
h10	11.83	11.59	12.31	12.06	12.55
h11	11.64	11.37	12.17	11.90	12.40
h12	11.75	11.46	12.30	12.02	12.54
h13	12.08	11.78	12.65	12.35	12.89
h14	12.16	11.86	12.74	12.44	12.98
h15	11.46	11.17	12.00	11.72	12.23
h16	11.13	10.87	11.63	11.37	11.86
h17	9.28	9.08	9.67	9.45	9.87
h18	8.12	7.93	8.46	8.27	8.65
h19	7.49	7.31	7.80	7.62	7.97
h20	7.44	7.29	7.71	7.55	7.89
h21	7.23	7.11	7.47	7.32	7.64
h22	7.89	7.92	8.00	7.91	8.22
h23	9.62	9.67	9.75	9.66	9.99
h24	12.60	12.65	12.77	12.68	13.06
total	9.80	9.63	10.15	9.96	10.36

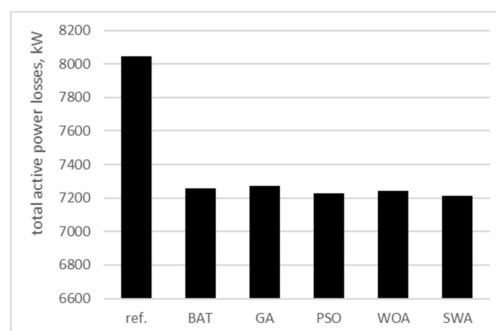


Figure 25. The total active power loss reduction in the 215-bus network, in kW, for each algorithm.

The best CB allocation solution, obtained with the SWA, achieves a loss reduction of 833.91 kW or 10.36% for the entire network, in 24 h, which amounts to 304.38 MW in an entire year. The next best

solution, found with the PSO algorithm, achieves only 816.58 kW (10.15%). The difference between the two solutions is of 17.33 kW in the analyzed day, or 6.32 MW in a year. The improvement over the IEEE 33-bus system regarding the loss reduction can be attributed to the presence of the MV/LV transformers.

The bus voltage levels for all 24 h and buses from the 215-bus network are presented in Figure 26. The length of the main feeder and the bus loadings lead to low voltage levels at the last buses on the main supply path, with values below the 0.9 pu limit at the LV side. At the MV side, the voltages are inside the allowed range, varying from 1.060 pu in the slack bus to 0.940 pu.

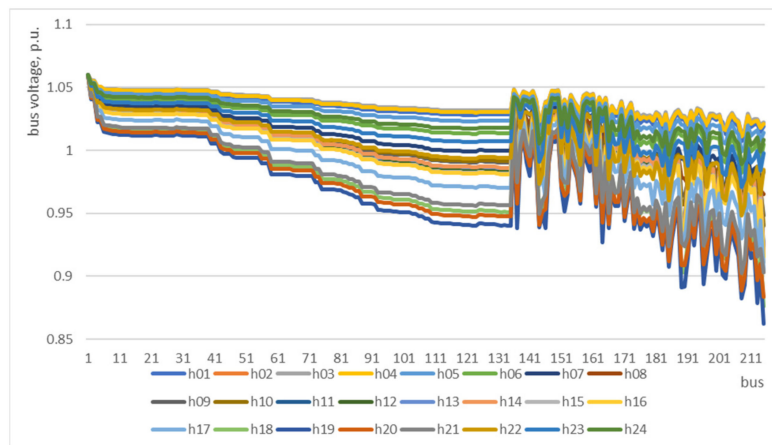


Figure 26. The bus voltages in the 215-bus network without compensation, for each hour from the analyzed day.

Figures 27 and 28 depict the effect of VAR compensation on the voltages at bus 135 (MV) and 215 (LV). By allocating the available CB stock according to the solutions found by the five metaheuristic algorithms, the bus voltages increase with maximum 1.36%, as shown in Table 15 for bus 215 (LV). This increase is not sufficient for raising the lowest voltage values above the desired limit of 0.9 pu. Since the CB stock is near the maximum allowed reactive load compensation which fulfills constraint Cr2 specified by the optimization model, an alternative solution is to change the MV/LV transformer tap settings in the affected buses.



Figure 27. Voltage improvement after compensation for bus 135, medium voltage, the 215-bus network.

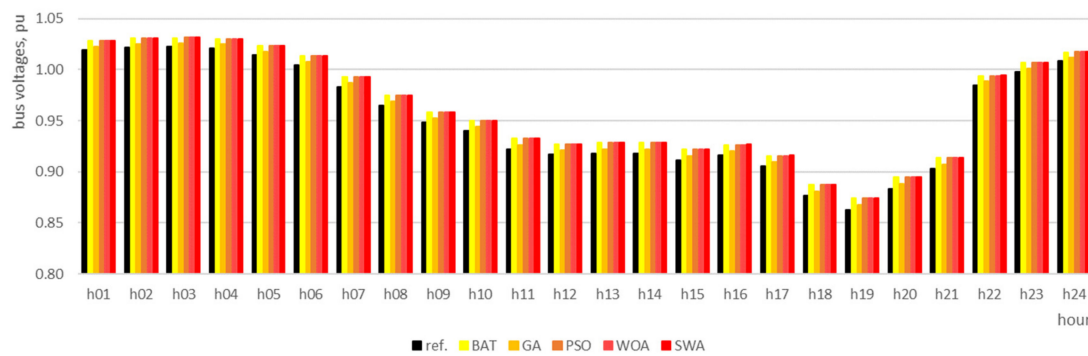


Figure 28. Voltage improvement after compensation for bus 215, low voltage, the 215-bus network.

Table 15. Hourly reference voltage values for bus 215 and percent improvements after compensation, the 215-bus network.

Hour	Voltage, pu		Improvement, %				
	Ref.	BAT	GA	PSO	WOA	SWA	
h01	1.019	0.86	0.36	0.86	0.87	0.88	
h02	1.022	0.85	0.35	0.86	0.86	0.87	
h03	1.022	0.85	0.35	0.86	0.86	0.87	
h04	1.021	0.86	0.35	0.86	0.86	0.87	
h05	1.014	0.87	0.36	0.87	0.88	0.89	
h06	1.004	0.89	0.37	0.89	0.90	0.91	
h07	0.983	0.94	0.39	0.94	0.95	0.96	
h08	0.965	0.99	0.41	0.99	0.99	1.01	
h09	0.948	1.04	0.43	1.04	1.04	1.06	
h10	0.940	1.06	0.45	1.07	1.07	1.09	
h11	0.922	1.12	0.47	1.13	1.13	1.15	
h12	0.917	1.14	0.48	1.15	1.15	1.16	
h13	0.918	1.14	0.48	1.14	1.15	1.16	
h14	0.918	1.14	0.48	1.14	1.15	1.16	
h15	0.911	1.16	0.49	1.17	1.17	1.18	
h16	0.916	1.14	0.48	1.15	1.15	1.17	
h17	0.905	1.17	0.49	1.18	1.18	1.20	
h18	0.876	1.28	0.54	1.28	1.29	1.30	
h19	0.863	1.33	0.57	1.33	1.34	1.36	
h20	0.884	1.24	0.53	1.25	1.25	1.27	
h21	0.903	1.17	0.50	1.17	1.18	1.19	
h22	0.985	0.93	0.39	0.94	0.94	0.95	
h23	0.998	0.90	0.38	0.91	0.91	0.92	
h24	1.008	0.88	0.37	0.89	0.89	0.90	
minimum value, pu	0.863						
max. improvement, %		1.33	0.57	1.33	1.34	1.36	

5. Discussions and Conclusions

The reactive power flow in the active electricity distribution networks has an important influence on the bus voltage level and the active power losses. Therefore, in order to control the reactive power absorbed by consumers, their consumption must be characterized by a power factor approximately equal to the neutral value (0.9 in Romania). Optimal allocation of reactive sources in the electricity distribution networks is made for power losses reduction, power factor correction and/or voltage profile improvement.

The optimization model considered in the paper has as main objective the optimal allocation of capacitor banks (CBs) in the medium voltage networks to minimize the power/energy losses, taking into account the technical restrictions imposed by the available CB stock, the compensation

level in each bus, branch current flows, and bus voltages. This is very useful for distribution network operators that install now large amounts of capacitor banks (CB) in the distribution networks. In order to optimize the location of these CBs, the used test networks (the IEEE 33-bus system and a real 215-bus EDN from Romania) were modelled considering the MV lines, the MV/LV transformers from the electric distribution substations, where available, and the MV and LV buses. The different algorithms (Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Bat Optimization Algorithm (BOA), Whale Optimization Algorithm (WOA) and Sperm-Whale Algorithm (SWA)) were tested to see which would be the best to solve the problem of capacitor bank allocation. The study, made using the IEEE 33-bus system, highlighted the fact that the SWA leads to the best results compared to the other algorithms. Compared with the reference case, the best compensation solution found by the SWA leads to a loss reduction of 726.73 kW for the analyzed day, which, if it is extrapolated for a year, amounts to 265.26 MW loss saving. The difference between SWA and the second best result, given by WOA, is of 6.25 kW per day or 2.28 MW for an entire year. In the case of the voltage level, an improvement was observed on the entire electricity distribution network, in all nodes, also obtained with the help of SWA. The minimum reference voltage value in bus 18 (the farthest node), at hour 10.00, was increased by 1.65%.

Moreover, the algorithms were tested in a real electricity distribution network (215-bus EDN) from Romania. The best CB allocation solution, obtained again with the SWA, achieves a loss reduction of 833.91 kW or 10.36% for the entire network, in 24 h, which amounts to 304.38 MW in an entire year. The next best solution, found with the PSO algorithm, achieves only 816.58 kW (10.15%). The difference between the two solutions is of 17.33 kW in the analyzed day, or 6.32 MW in a year. The solutions found led to an increase of the voltage in the farthest node (215) with maximum 1.36%.

Based on the obtained results, it can be affirmed that the use of capacitor banks is an easy solution to be implemented with technical and economic benefits to the electricity distribution networks that maximizes long-term return on investment as the network develops. An intelligent control of capacitor banks leads to improved energy efficiency and voltage level in the buses of electricity distribution networks, resulting in an increase in the percentage of energy delivered to consumers. Amongst the tested algorithms, the SWA finds the best compensation solutions, which can lead to significant additional loss savings and shorter investment recovery times.

Supplementary Materials: The following are available online at <http://www.mdpi.com/1996-1073/12/22/4239/s1>, file IEEE33_load_data.xls, active and reactive load profiles for the IEEE-33bus test system, and file EDN215_load_data.xls, active and reactive load profiles for the 215-bus distribution network.

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Appendix A

Table A1. Branch parameters for the IEEE 33-bus system.

Bus 1	Bus 2	I _{max} , A	Type ¹	Resistance, Ω	Reactance, Ω
1	2	420	1	0.092	0.047
2	3	420	1	0.493	0.251
3	4	420	1	0.366	0.186
4	5	420	1	0.381	0.194
5	6	420	1	0.819	0.707
6	7	420	1	0.187	0.619
7	8	420	1	0.711	0.235
8	9	420	1	1.03	0.74

Table A1. Cont.

Bus 1	Bus 2	I _{max} , A	Type ¹	Resistance, Ω	Reactance, Ω
9	10	420	1	1.044	0.74
10	11	420	1	0.197	0.065
11	12	420	1	0.374	0.124
12	13	420	1	1.468	1.155
13	14	420	1	0.542	0.713
14	15	420	1	0.591	0.526
15	16	420	1	0.746	0.545
16	17	420	1	1.289	1.721
17	18	420	1	0.732	0.574
19	20	420	1	1.504	1.356
2	19	420	1	0.164	0.157
20	21	420	1	0.41	0.478
21	22	420	1	0.709	0.937
23	24	420	1	0.898	0.709
24	25	420	1	0.896	0.701
26	27	420	1	0.284	0.145
27	28	420	1	1.059	0.934
28	29	420	1	0.804	0.701
29	30	420	1	0.508	0.259
3	23	420	1	0.451	0.308
30	31	420	1	0.975	0.963
31	32	420	1	0.311	0.362
32	33	420	1	0.341	0.53
6	26	420	1	0.203	0.103

¹ Branch type can be 1—line; 2—transformer.

Table A2. Branch parameters for the 215-bus distribution network.

Bus 1	Bus 2	I _{max} , A	Type	Resistance, Ω	Reactance, Ω
1	2	235	1	0.80625	0.314159
2	3	315	1	0.1051	0.061104
2	4	295	1	0.7701	0.358142
4	5	295	1	0.00154	0.000716
4	6	295	1	0.30804	0.143257
6	7	295	1	0.021306	0.009909
7	8	295	1	0.021306	0.009909
8	9	295	1	0.272102	0.126543
8	29	295	1	0.056474	0.026264
9	10	295	1	0.02567	0.011938
9	11	295	1	0.213061	0.099086
11	12	295	1	0.115515	0.053721
101	102	295	1	0.141185	0.065659
101	103	295	1	0.02567	0.011938
104	105	295	1	0.02567	0.011938
104	106	295	1	0.361947	0.168327
106	107	295	1	0.02567	0.011938
106	108	295	1	0.2567	0.119381
108	109	295	1	0.05134	0.023876
108	110	295	1	0.467194	0.217273

Table A2. Cont.

Bus 1	Bus 2	I _{max} , A	Type	Resistance, Ω	Reactance, Ω
110	111	295	1	0.115515	0.053721
110	113	295	1	0.12835	0.05969
12	13	295	1	0.07701	0.035814
12	14	295	1	0.019253	0.008954
111	112	295	1	0.041072	0.019101
113	114	295	1	0.2567	0.119381
113	125	295	1	0.07701	0.035814
114	115	295	1	0.173273	0.080582
114	116	295	1	0.035938	0.016713
116	117	295	1	0.369648	0.171908
116	119	295	1	0.07701	0.035814
117	118	295	1	0.202793	0.094311
119	120	295	1	0.562173	0.261443
120	121	295	1	0.15402	0.071628
120	122	295	1	0.110381	0.051334
122	123	295	1	0.187391	0.087148
123	124	295	1	0.187391	0.087148
125	126	295	1	0.038505	0.017907
125	127	295	1	0.169422	0.078791
127	128	295	1	0.02567	0.011938
127	129	295	1	0.064175	0.029845
129	130	295	1	0.20536	0.095504
129	131	295	1	0.361947	0.168327
14	15	295	1	0.097546	0.045365
14	22	295	1	0.035938	0.016713
131	132	295	1	0.120649	0.056109
131	133	295	1	0.17969	0.083566
131	134	295	1	0.2567	0.119381
134	135	295	1	0.033371	0.015519
15	16	295	1	0.15402	0.071628
16	17	295	1	0.15402	0.071628
16	18	295	1	0.019253	0.008954
18	19	295	1	0.17969	0.083566
18	20	295	1	0.019253	0.008954
20	21	295	1	0.02567	0.011938
22	23	295	1	0.351679	0.163551
22	24	295	1	0.248999	0.115799
24	25	295	1	0.23103	0.107442
25	26	295	1	0.071876	0.033427
25	27	295	1	0.392751	0.182652
27	28	295	1	0.10268	0.047752
29	30	295	1	0.038505	0.017907
30	31	295	1	0.071876	0.033427
30	37	295	1	0.056474	0.026264
31	32	295	1	0.123216	0.057303
32	33	295	1	0.087278	0.040589
33	34	295	1	0.192525	0.089535
33	35	295	1	0.071876	0.033427
35	36	295	1	0.351679	0.163551
37	38	295	1	0.10268	0.047752
37	40	295	1	0.318308	0.148032
39	38	309	1	0.46244	0.268858
40	41	295	1	0.41072	0.191009
40	43	295	1	0.403019	0.187427
42	41	295	1	0.12835	0.05969

Table A2. Cont.

Bus 1	Bus 2	I _{max} , A	Type	Resistance, Ω	Reactance, Ω
43	44	295	1	0.084711	0.039396
44	45	295	1	0.33371	0.155195
44	47	295	1	0.189958	0.088342
45	46	295	1	0.02567	0.011938
47	48	295	1	0.238731	0.111024
47	56	295	1	0.338844	0.157582
48	49	295	1	0.17969	0.083566
48	50	295	1	0.238731	0.111024
50	51	295	1	0.288788	0.134303
50	52	295	1	0.040045	0.018623
52	53	295	1	0.07701	0.035814
52	54	295	1	0.10268	0.047752
54	55	295	1	0.23103	0.107442
56	57	295	1	0.05134	0.023876
56	59	295	1	0.659719	0.306808
57	58	295	1	0.10268	0.047752
59	60	295	1	0.043639	0.020295
59	66	295	1	0.084711	0.039396
60	61	295	1	0.02567	0.011938
60	62	295	1	0.074443	0.03462
62	63	295	1	0.441524	0.205335
62	64	295	1	0.028237	0.013132
64	65	295	1	0.17969	0.083566
66	67	295	1	0.17969	0.083566
66	73	295	1	0.467194	0.217273
67	68	295	1	0.10268	0.047752
67	69	295	1	0.120649	0.056109
69	70	295	1	0.02567	0.011938
69	71	295	1	0.210494	0.097892
71	72	295	1	0.02567	0.011938
73	74	295	1	0.02567	0.011938
73	75	295	1	0.467194	0.217273
75	76	295	1	0.64175	0.298451
75	78	295	1	0.021306	0.009909
76	77	295	1	0.30804	0.143257
78	79	295	1	0.15402	0.071628
78	80	295	1	0.084711	0.039396
80	81	295	1	0.02567	0.011938
80	82	295	1	0.12835	0.05969
82	83	295	1	0.10268	0.047752
82	84	295	1	0.189958	0.088342
84	85	295	1	0.23103	0.107442
84	86	295	1	0.2567	0.119381
86	87	295	1	0.05134	0.023876
86	88	295	1	0.5134	0.238761
88	89	295	1	0.07701	0.035814
88	92	295	1	0.084711	0.039396
89	90	295	1	0.02567	0.011938
89	91	295	1	0.02567	0.011938
92	93	295	1	0.5134	0.238761
93	94	295	1	0.02567	0.011938
93	95	295	1	0.084711	0.039396
95	96	295	1	0.07701	0.035814
95	98	295	1	0.12835	0.05969
96	97	295	1	0.053907	0.02507

Table A2. Cont.

Bus 1	Bus 2	I _{max} , A	Type	Resistance, Ω	Reactance, Ω
98	99	295	1	0.084711	0.039396
98	100	295	1	0.064175	0.029845
100	101	295	1	0.07701	0.035814
100	104	295	1	0.12835	0.05969
2	136	1000	2	0.06	0.082
3	137	1000	2	0.011	0.037
5	138	1000	2	0.011	0.037
6	139	1000	2	0.011	0.037
7	140	1000	2	0.011	0.037
10	141	1000	2	0.019	0.036
11	142	1000	2	0.06	0.082
102	195	1000	2	0.04	0.05
103	196	1000	2	0.06	0.082
105	197	1000	2	0.011	0.037
107	198	1000	2	0.06	0.082
109	199	1000	2	0.011	0.037
111	200	1000	2	0.006	0.023
112	201	1000	2	0.011	0.037
115	202	1000	2	0.06	0.082
117	203	1000	2	0.06	0.082
118	204	1000	2	0.06	0.082
119	205	1000	2	0.06	0.082
13	143	1000	2	0.019	0.036
121	206	1000	2	0.011	0.037
122	207	1000	2	0.06	0.082
123	208	1000	2	0.06	0.082
124	209	1000	2	0.019	0.036
126	210	1000	2	0.06	0.082
128	211	1000	2	0.019	0.036
130	212	1000	2	0.019	0.036
132	213	1000	2	0.006	0.023
133	214	1000	2	0.06	0.082
135	215	1000	2	0.019	0.036
15	144	1000	2	0.06	0.082
17	145	1000	2	0.04	0.05
19	146	1000	2	0.06	0.082
21	147	1000	2	0.011	0.037
23	148	1000	2	0.06	0.082
24	149	1000	2	0.06	0.082
26	150	1000	2	0.06	0.082
28	151	1000	2	0.019	0.036
29	152	1000	2	0.06	0.082
31	153	1000	2	0.04	0.05
32	154	1000	2	0.019	0.036
34	155	1000	2	0.019	0.036
35	156	1000	2	0.011	0.037
36	157	1000	2	0.04	0.05
38	158	1000	2	0.011	0.037
39	159	1000	2	0.019	0.036
40	160	1000	2	0.019	0.036
41	161	1000	2	0.04	0.05
42	162	1000	2	0.06	0.082
43	163	1000	2	0.019	0.036
45	164	1000	2	0.006	0.023
46	165	1000	2	0.06	0.082
49	166	1000	2	0.06	0.082
51	167	1000	2	0.06	0.082

Table A2. Cont.

Bus 1	Bus 2	I _{max} , A	Type	Resistance, Ω	Reactance, Ω
53	168	1000	2	0.04	0.05
55	169	1000	2	0.04	0.05
57	170	1000	2	0.019	0.036
58	171	1000	2	0.06	0.082
61	172	1000	2	0.011	0.037
63	173	1000	2	0.06	0.082
64	174	1000	2	0.06	0.082
65	175	1000	2	0.06	0.082
68	176	1000	2	0.06	0.082
70	177	1000	2	0.04	0.05
71	178	1000	2	0.06	0.082
72	179	1000	2	0.06	0.082
74	180	1000	2	0.06	0.082
76	181	1000	2	0.06	0.082
77	182	1000	2	0.04	0.05
79	183	1000	2	0.04	0.05
81	184	1000	2	0.06	0.082
83	185	1000	2	0.04	0.05
85	186	1000	2	0.04	0.05
87	187	1000	2	0.011	0.037
90	188	1000	2	0.011	0.037
91	189	1000	2	0.011	0.037
92	190	1000	2	0.06	0.082
94	191	1000	2	0.04	0.05
96	192	1000	2	0.019	0.036
97	193	1000	2	0.04	0.05
99	194	1000	2	0.019	0.036

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