79 International Journal of Smart Electrical Engineering, Vol.12, No.2, Spring 2023 ISSN: 2251-9246
EISSN: 2345-6221
pp. 79:87

Optimal Placement and Scheduling of Switched Capacitor Banks Using Multi-Objective Hybrid Optimization Algorithm under Load Uncertainty Conditions

Ehsan Akbari

Department of Electrical Engineering, Mazandaran University of Science and Technology, Babol, Iran, e.akbari@ustmb.ac.ir

Abstract

A straightforward and affordable way to improve the power factor and account for reactive power (RP) in the distribution network (DN) is to employ switched capacitor banks (SCBs). The optimal placement of these capacitors helps to reduce costs and power losses in the network. This essay offers a hybrid algorithm by combining the Harris Hawks Optimization algorithm (HHO) and the Non-dominated Sorting Genetic Algorithm Type 2 (NSGA-II) to arrange the switched capacitors (SCs) in the DN in the best possible location and scheduling. Power plant active and reactive power (ARP) generation, capacitor bank (CB) capital expenditure (CapEx) and maintenance costs, ARP losses in DN, and switching costs of SC are all factored into the proposed objective function.

Furthermore, the load uncertainty in this study is modeled using the normal distribution function. Finally, the proposed optimization problem is implemented on IEEE standard 33-bus networks, and the performance of the suggested hybrid approach is compared with other commonly used multi-objective optimization algorithms. The simulation results show the higher performance of the proposed algorithm in terms of convergence speed and the objective function value.

Keywords: Optimal placement and scheduling of switched capacitors, Harris Hawks Optimization Algorithm, Non-Dominant Sorting Genetic Algorithm Type 2, Load uncertainty
Article history: Submitted 2022-09-27; Revised 2022-10-29; Accepted 2022-12-16. Article Type: Research paper

https://doi.org/10.30495/ijsee.2022.1968418.1229

1. Introduction

In a DNs, loss reduction is one of the main goals since it is both economically and technically profitable and can be achieved using power compensation methods. [1] RP consumption by non-linear loads in the system reduces the active power (AP) transmission capacity in distribution and transmission networks and directly affects AP losses in the network [2]. In addition, RP consumption on the demand side leads to voltage drop in distribution feeders. In order to compensate for the RP consumed by the demand side and reduce the power losses in the distribution and transmission systems, various compensation models have been presented in the literature. One of the simplest and most economical methods is utilizing CBs which are still used in many DNs [3]. SCs applications are voltage profile improvement, power factor correction and compensating RP in the distribution system. If these capacitors are optimally placed and scheduled, power losses and maintenance costs could be minimized [4], [5].

In recent studies, the optimal placement of SCBs in the DN is of great interest. In [6], a hybrid method for optimal placement and determining the optimal size of switching capacitors in the DN is presented, which is determined based on a dual objective function, and a hybrid optimization algorithm is used to solve this problem. In this paper, the proposed objective function consisting of ARP factors, CapEx and maintenance costs, and ARP losses in the DN and transformers is minimized. The effect of the load model on the placement and sizing of switching capacitors has also been investigated.

The allocation of switching capacitors in unbalanced systems has been examined using the three-level optimization model in [7]. The primary objective of the optimization problem is to minimize energy losses. In the first step, the interior point method is used to solve the problem of optimal power distribution. This problem is solved with two scenarios of heavy load and light load. By solving the problem, the amount of RP and the number of fixed and SCBs are obtained. In the second step, the location of CBs is determined using the genetic algorithm. Finally, in the third step, the switching state of the SCs is specified with a binary optimization method.

In [8], an integer-mixed linear programming model is used to optimally place CBs in DNs. The problem of rearranging the DN and optimal placement of CBs in this system is defined in order to minimize losses, increase reliability and improve the voltage profile in electricity DNs. The main goal is to determine the optimal size and location of switching capacitors in order to control the RP in the system. A review of RP compensation methods based on optimal placement and sizing of compensation devices in the DN has been done in [9]. In this paper, reduction of power losses, improvement of voltage stability, increase of voltage profile and improvement of load capacity in the network is considered. Various RP compensation devices have been investigated, including FACTS devices, CBs, etc. Compensation methods have been categorized based on analytical, traditional, and innovative methods.

In [10], various shunt compensation technologies are inspected in order to compensate and schedule the RP in the DN. Mechanically SCBs, static VAR compensation (SVC), and static synchronous compensation (STATCOM) are examples of shunt compensation devices. This paper utilized the genetic algorithm to solve the mixed-integer non-linear programming problem. Finally, according to the IEEE standard in England, the proposed method was implemented on a real distribution system. The optimal placement of multi-mode switching capacitors in radial DNs has been investigated in [11]. This research developed a strategy for the optimal allocation of multi-mode SCs in the radial DN, with the objective of minimizing energy losses and enhancing the voltage profile. In the proposed method, each planning period was divided into several sections, and the number of sections (NOS) was defined. Finally, the optimization problem is solved to optimize increasing or decreasing capacity steps.

In [12], the problem of integrating solar system, energy storage system and SCBs in a weak DN is investigated. In order to optimally allocate these three parts in the DN, Slime Mold Algorithm (SMOA) is used. The purpose of the optimization model is to simultaneously minimize two objective functions: the first objective is the AP loss in the DN, and the second objective is the annual investment costs related to the network equipment. Finally, the proposed model was implemented on IEEE 33 bus network.

Switching SCBs in the DN causes transient fluctuations in low and medium-pressure distribution systems. These fluctuations vary based on different characteristics, which can cause severe damage to electronic network equipment. In [13], a method is presented to identify the transient state fluctuations caused by the switching of SCs in the distribution system.

To identify these fluctuations, methods such as Notch filter, wavelet transform and methods based on mathematical processing were used. [14] explored the optimal arrangement of capacitors in a DN using Remora's mathematical optimization algorithm, considering operating cost and load conditions. The main goal of the optimization problem is to determine the optimal size and location of capacitors in the DN. The optimal performance of the SCs under varying loads was defined as the objective function, coupled with minimizing losses, purchasing, and installation costs in the distribution system.

To find the best location for distributed energy resources (D.E.Rs) and CBs in DNs, the authors of [15] propose a two-stage approach. The main aim is to determine the optimal size and location of DERs and SCs in the distribution system in the form of a two-objective problem. The Bat algorithm is used to solve the optimization problem. The main goal is to minimize voltage deviation, maximize voltage stability index (VSI) and reduce AP losses. The optimal placement of voltage regulators and SCs to increase the efficiency of DNs based on fuzzy logic is presented in [16]. An optimization method based on fuzzy logic is investigated to determine the optimal location of voltage regulators and SCs in the distribution system. The paper investigated a real DN in Ethiopia. Power losses indices and voltage profile indices are modeled using fuzzy membership functions and optimized by the proposed method.

In [17], the optimal placement of fixed and SCBs in distribution systems is presented based on the Monkey search algorithm. The main goals of this article are to minimize power losses, improve voltage levels and reduce greenhouse gas emissions. Monkey Search Algorithm is a metaheuristic method inspired by behavior of monkeys in searching for food. In the proposed optimization problem, different load levels, voltage constraints and generation costs of each generation unit are considered along with the greenhouse gas emission coefficients of each unit. The optimal placement strategy of SCs in smart distribution networks is investigated in [18]. First, an analysis step of the network parameters is performed to determine whether the switching of the SCs causes fluctuations in the system or not. Then, the indices of ARP increase in the network are calculated in order to determine the candidate buses for connecting SCs. In this case, the exact location and the exact capacity of the SCBs in the system were determined.

[19] investigated the optimal location of SCs in the distribution system. The main objective of the CBs in the system was to increase the reliability of the network, improve the power factor, and increase the transmission capacity in the system. These capacitors were switched at the end of the network path according to the amount of connected load. This paper compares the measured data in the DN in the case where the SCBs are installed downstream with the case where they are installed upstream and, in this way, determines the optimal location for installing these capacitors. In [20], the authors proposed a method to control and coordinate SCs and voltage regulating transformers in the DN. The main objective is to maintain voltage levels within the standard range, minimize system losses and limit the number of SCs in the network. Determining the optimal location of SCBs in distribution systems using ANFIS is presented in [21].

In this study, a new index based on network transient flows is used for ANFIS training, which is obtained offline based on system data and online based on real-time simulations. The proposed method only used the transient current waveform before and after capacitor switching. For this reason, this method was simple and implemented online. Wavelet transform is also used to determine the switching times of capacitors. In this study, in order to optimally place and plan SCs in a DN, a multi-objective hybrid optimization algorithm is proposed by combining Shahin-Harris optimization (HHO) and non-dominated sorting genetics type 2 (NSGA-II) algorithms. The optimization problem consists of several objectives, including ARP of generation units, investment and maintenance costs of CBs, ARP losses, and switching cost of SCs, that should be optimized simultaneously. Also, in order to investigate the effect of load on the result of the optimization problem, load uncertainty is modeled using the normal distribution function. Finally, the proposed optimization problem is tested on the IEEE 33-bus system.

The novelties of the article can be expressed as follows:

- Modeling load uncertainty in the multi-objective optimization problem and investigating the effect of different loads on the optimal placement of SCs
- Proposing a hybrid optimization algorithm with higher performance that can be used for single-objective and multi-objective objective functions
- Optimal scheduling of CB switching based on the system load pattern

Considering the comprehensive, objective function, including CapEx and maintenance costs, power losses, power generation and switching costs, the rest of this paper is structured as follows: In the second section, the optimization problem, including the proposed objective functions, is defined. In the third section, the proposed optimization algorithm is described. Software simulations and implementation of the optimization problem on the IEEE standard 33 bus system are done in the fourth section, and finally, the fifth section explains the conclusion of the study.

2. Formulation of the optimization problem

In this section, the proposed objective function in the optimization problem is described. The objective function is defined as the minimization of ARP generation costs of generation units, CapEx and maintenance costs of CBs, ARP losses costs, and switching costs of SCs. The objective function is in the form of Eq. (1).

$$Min\left(C_{gen}^{p}+C_{gen}^{q}+COST_{cap}+C_{sw}\right) \tag{1}$$

In (1) C_{gen}^{p} and C_{gen}^{q} are the annual generation costs of ARP, respectively, and $COST_{cap}$ is the CapEx and maintenance cost of CBs. Also, C_{sw} is the switching cost of the total SCs. Each of these factors is defined below.

$$Min\left(C_{gen}^{p}+C_{gen}^{q}+COST_{cap}+C_{sw}\right) \tag{2}$$

In Eq. (2), a, b and c are the coefficients of the AP generation cost function. $P_{g,h,s}$ is the total AP produced at hour h of season s, which is defined as follows:

$$P_{g,h,s}=\sum_{i=1}^{n}\left(P_{d,h,s,i}\right)+Ploss_{h,s}^{line}+Ploss_{h,s}^{trans}, \quad h=1,2,\dots,24 \quad , \quad s=1,2,3,4 \tag{3}$$

In (3), $P_{d,h,s}$ is the AP demand in the i-th bus at hour h and in season s. In Eq. (3), the amount of power demand is an uncertain parameter, which is modeled using the normal distribution function. Also, $Ploss_{h,s}^{line}$ and $Ploss_{h,s}^{trans}$ are AP losses in lines and transformers of the studied DN at hour h and in season s, respectively. The annual generation cost of RP, C_{gen}^{q}, is also calculated from Eq. (4):

$$C_{gen}^{q}=\sum_{s=1}^{4}\left(90\times\sum_{h=1}^{24}\left(a'Q_{g,h,s}^{2}+b'Q_{g,h,s}+c'\right)\right) \tag{4}$$

In (4), a', b' and $c'$are coefficients of RP generation cost function, which are respectively equal to: $a'=a\times sin^{2}\left(\theta_{h,s}\right)$, $b'=b\times sin^{2}\left(\theta_{h,s}\right)$ and$c'=c$. Also, $sin\left(\theta_{h,s}\right)$ is calculated based on the ratio of active and RPs according to Eq. (5):

$$sin(\theta_{h,s}) = \frac{Q_{g,h,s}}{\sqrt{Q_{g,h,s} + P_{g,h,s}}} \quad (5)$$

In the following $Q_{g,h,s}$ the total RP generated in the network at hour h and in season s is defined as Eq. (6):

$$Q_{g,h,s} = \sum_{i=1}^{n}(Q_{d,h,s,i}) + Qloss_{h,s}^{line} + Qloss_{h,s}^{trans} - \sum_{k=1}^{m} Q_{h,s,k}^{comp}, \quad h = 1,2,\dots,24, \quad s = 1,2,3,4 \quad (6)$$

where, $Q_{d,h,s,i}$ is the RP demanded by the i-th bus at hour h and in season s. $Qloss_{h,s}^{line}$ and $Qloss_{h,s}^{trans}$ are the total RP losses in lines and transformers of the DN at hour h and in season s, respectively .$Q_{h,s,k}^{comp}$ is the value of RP compensated in bus k at hour h and season s. In fact, this RP is generated by the SCB connected to bus k. In addition, in all the above equations, n is the number of buses of the entire network, and m is the number of buses compensated by CBs .The third parameter in the proposed objective function (1) is $COST_{cap}$, which is defined as follows:

$$COST_{cap} = \sum_{k=1}^{m}(C_{cap,k} \times inv_{cap} \times crf) \quad (7)$$

$$crf = \frac{i(i+1)^y}{i(i+1)^y - 1} \quad (8)$$

In (7) and (8), $C_{cap,k}$ is the capacity of the capacitor connected to bus k, inv_{cap} is the investment cost of the capacitor connected to bus k, and crf also represents the conversion factor of the initial cost to annual cost. i is the interest rate, and y is the number of years .And finally, the fourth parameter of the proposed objective function, namely C_{sw}, is defined as follows:

$$C_{sw} = \sum_{s=1}^{4}\left(90 \times \sum_{h=1}^{24}\left(\sum_{k=1}^{m} C_{sw}^{fix} \times x_{h,s,k}\right)\right) \quad (9)$$

In (9), C_{sw}^{fix} is the fixed switching cost of the SC and is a constant value. $x_{h,s,k} \in \{0,1\}$ is also a binary variable that indicates the switching of the CB connected to the compensation bus k at hour h in season s. This variable is determined according to the following conditions:

$$x_{h,s,k} = \begin{cases} 1 & if\ Q_{g,h,s} - (Qloss_{h,s}^{line} + Qloss_{h,s}^{trans}) < Q_{d,h,s} \\ 0 & if\ Q_{g,h,s} - (Qloss_{h,s}^{line} + Qloss_{h,s}^{trans}) \geq Q_{d,h,s} \end{cases} \quad (10)$$

Eq. (10) shows that if the RP generated minus the losses of the RP of the lines and network transformers provides the required RP on the demand side, then the switching of the SC does not happen otherwise for every bus, If the first condition is met, switching occur, and the cost of this switching should be calculated based on (9).

The constraints of the proposed optimization problem (1) are defined below.

$$Q_{g,h,s} + \sum_{k=1}^{m} Q_{h,s,k}^{comp} = \sum_{i=1}^{n}(Q_{d,h,s,i}) + Qloss_{h,s}^{line} + Qloss_{h,s}^{trans}, \quad h = 1,2,\dots,24, \quad s = 1,2,3,4 \quad (11)$$

$$P_{g,h,s} = \sum_{i=1}^{n}(P_{d,h,s,i}) + Ploss_{h,s}^{line} + Ploss_{h,s}^{trans}, \quad h = 1,2,\dots,24, \quad s = 1,2,3,4 \quad (12)$$

$$C_{cap,k} \leq C_{max}, \quad k = 1,2,\dots,m \quad (13)$$

$$\sqrt{(P_{h,s,j}^{line})^2 + (Q_{h,s,j}^{line})^2} < S_{max,j}, \quad j = 1,2,\dots,n-1 \quad (14)$$

$$\sqrt{(S_{h,s,i}^{trans})^2} < S_{mas,i}^{trans}, \quad i = 1,2,\dots,n \quad (15)$$

Eqs. (11) and (12) are associated with the balance of ARP in the DN. Constraint (13) is the maximum allowed capacity of the CB, and (14) and (15) are related to the power capacity of lines and network transformers, respectively. In the above equations, C_{max} is the maximum allowed capacity of the SC, $P_{h,s,j}^{line}$ and $Q_{h,s,j}^{line}$ are the ARP transmission from line j at hour h and in season s, respectively. , $S_{max,j}$ is the maximum apparent power that can be transmitted from line j, $S_{h,s,i}^{trans}$ is the apparent power of the transformer connected to bus i at hour h and in season s, and finally $S_{mas,i}^{trans}$ shows the maximum apparent power capacity of the transformer connected to bus i.

3. The proposed optimization algorithm

In this paper, in order to optimize the proposed objective function (1), a combination of the Harris Hawk Optimization algorithm (HHO) and the NSGA-II is used. Shahin-Harris algorithm is reputable for its fast convergence and excellent ability to avoid local optimum points [22]. Also, the NSGA-II algorithm is prominent for solving multi-objective optimization problems [23]. Due to the fact that this algorithm produces a set of solutions in each execution of the algorithm, each objective function is calculated independently for each individual from the initial population, and finally, the set of optimal solutions is obtained .

A) Harris Hawks Optimization (HHO) Algorithm

In this algorithm, several hawks simultaneously attack a prey, usually a rabbit, to tire and confuse it. This phase of the algorithm is called the exploration phase. Based on the behavior of the prey, the hawks change the type of attack in order to overcome it finally. This phase is also called the exploitation phase. According to the prey energy defined in Eq. (16), this transferring of the algorithm is between the exploration and exploitation phases.

$$E = 2E_0\left(1 - \frac{iter}{Iter_{max}}\right) \tag{16}$$

In Eq. (16), E_0 is the initial energy of the prey in each iteration, iter is the iteration number of the algorithm, and $\mathrm{Iter_{max}}$ is the termination condition of the algorithm based on the maximum number of iterations. If |E|≥1, the algorithm enters the exploration phase, and the hawks' position will be updated according to (17), and if |E|<1, the algorithm enters the exploitation phase.

$$X(t+1) = \begin{cases} X_{rand}(t) - r_1|X_{rand}(t) - 2r_2X(t)| & q \geq 0.5 \\ \left[X_{prey}(t) - X_m(t)\right] - r_3\left(LB + r_4(UB - LB)\right) & q < 0.5 \end{cases} \tag{17}$$

In (17), $X(t+1)$ is the position of the hawk at the next moment, $X_{rand}(t)$ is a randomly selected hawk from the population of hawks, $X(t)$ is the current position of the hawk, $X_{prey}(t)$ is the current position of the prey and $X_m(t)$ represents the average positions of the current population of hawks. Also, LB and UB are the minimum and maximum distance of the hawk to the prey, respectively [24]. Similar to the HHO algorithm pseudo-code is presented in "Algorithm 1". In the first step, the initial population of hawks is determined, then the values of E and E0 are calculated for each hawk, and based on the value of E, exploration or extraction steps are implemented. This process continues until the termination condition of the algorithm is met.

B) *Non-Dominated Sorting Genetic Algorithm Type 2 (NSGA-II)*

NSGA-II is one of the multi-objective forms of the traditional GA algorithm which has unique features in terms of convergence and optimization speed. The steps of this algorithm can be summarised as follows [23]

- Initializing the population
- Calculating the criterion or fitness function
- Sorting the population based on the conditions of dominance
- Calculating crowding distance (CD) operator
- Compositing initial population and new population generated during the process of mutation and mating
- Replacing the parents with the best individuals of the new composite population. In the first step, the members whose fitness criterion is lower during ranking are replaced by the previous parent and then sorted by the crowding distance (CD) operator. The initial population and the population resulting from the application of mutation and mating operators are ranked in the first stage, and then those with a lower fitness criterion are eliminated. In the next step, the remaining population will be re-ranked according to the population distance.
- Iterating this process until the algorithm termination condition is met. The termination condition is determined either based on the limitation of the iteration number of the algorithm or based on the fitness criterion.

It should be noted that the population distance factor is a parameter that is used to select solutions from the set of feasible solutions. The following assumptions apply to CD. The CD between the beginning and end points of the set of feasible solutions is assumed to be infinite. For each assumed point in the set of feasible solutions, the CD is determined based on (18)

$$CD_i = \frac{f_m^{i+1} - f_m^{i-1}}{f_m^{max} - f_m^{min}} \tag{18}$$

In (18), CD_i is the crowding distance corresponding to the i-th individual on the solution set of F. f_m^{i+1} and f_m^{i-1} are respectively the values of the mth objective function corresponding to the (i+1)th and (i-1)th individual on the solution set Ff_m^{max} and f_m^{min} show the maximum and minimum values of the mth objective function, respectively. Among the set of possible solutions in its iteration, the set with the largest CD is determined as the global solution of the multi-objective optimization problem.

4. Simulation Results

In this section, in order to properly evaluate the proposed optimization model, including the objective function, optimization constraints and the multi-objective hybrid algorithm HHO-NSGA-II, it is implemented for the IEEE standard 33-bus system. This system is shown in Fig. 1, where the maximum allowed capacity of the SCB per unit, namely, C_max, is assumed equal to 1 MVAr. Also, the base values for voltage and power are assumed to be 100 kW and 12660 V, respectively. The maximum and minimum system bus voltages are 1.02 p.u and 0.95 p.u. In order to model the load uncertainty, the normal distribution function is used, which is defined as follows:

$$Y = F(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{19}$$

In Eq. (19), x, μ and σ are the average value and the standard deviation of the ARP profile, respectively. In this study, the actual data of the ARP consumption profile in the network is obtained based on load distribution, and its uncertainty is calculated with a 10% error probability according to Eq. (19). Finally, the ARP seasonal consumption profile of the studied system is obtained by considering the uncertainty in Figs. 2. and 3. Also, the stepwise price of AP consumption is also presented in Table 1 [25]. The value of resistance and reactance of the studied distribution system transformers is considered to be 0.01 p.u and 0.005 p.u, respectively. Seven CBs are considered in the system, where investment and maintenance costs of them are 12 \$/kVAr and 8 \$/kVAr, respectively [26]. Each CB consists of 30 SCs, and the capacity of each unit is assumed to be 100 kVAr. The optimal capacity of each CB is determined based on the switching scheduling of the SCs, which is one of the objectives of the optimization problem. Also, the optimal location of the switching capacitors is determined based on the RP profile of the demand side, which is presented in Fig. 4. The coefficients a, b, and c in Eq. (2) are determined as 0.00482, 7.97, and 78, respectively, according to [26], and the interest rate is assumed to be 0.1.

A) Optimization results

By implementing the optimization problem on the 33-bus system, the simulation results are presented in this section. In Fig. 5, the optimal switching process of the SCs related to the first CB in winter is shown. In this CB, which consists of 30 SCs with a capacity of 100 kVAr, each SC is switched according to the optimal pattern obtained from the implementation of the optimization algorithm. Likewise, similar patterns are obtained for 6 other CBs in each season. By determining the number of switched SCs at each hour, the optimal RP generation schedule of each CB is determined at each scheduling hour. Fig. 6 shows this optimal schedule for winter. Similarly, for each season, an optimal daily program corresponding to each CB is calculated, and the optimal capacity of each CB is obtained based on the highest amount of RP among the four seasons of the year. In Table 2, the optimal location and optimal capacity of each CB are obtained. To evaluate the performance of the optimization algorithm, two traditional genetic and particle swarm algorithms in multi-objective form (MOGA and MOPSO, respectively) are applied to the optimization problem, and the results are presented in Table 2.

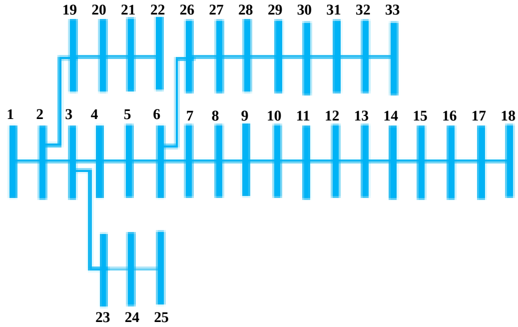

Fig. 1. IEEE standard 33 bus system

Fig. 7 shows the hourly winter's profile of network bus voltage in a state where compensation by SCBs is not done. By solving the optimization problem and adding CBs with optimal capacity (based on the values obtained by the proposed HHO-NSGA-II algorithm) to the studied distribution system, the hourly profiles of network bus voltage in winter are obtained as shown in Fig. 8.

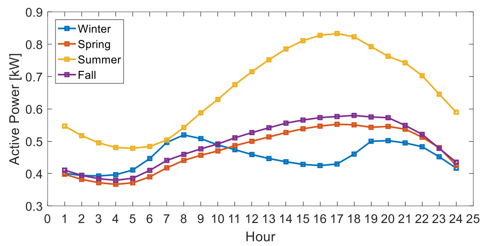

Fig. 2. AP consumption profiles in the studied system for four sea

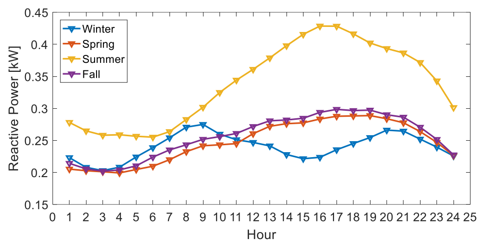

Fig. 3. RP consumption profiles in the studied system for four seasons

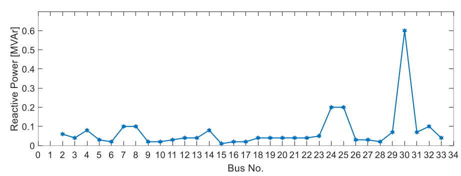

Fig. 4. Load side RP profile in IEEE 33-bus system

Table.1.
The stepwise cost of AP generation

AP generation (kW)	*Price (\$/kWh)*
Power <50	0.1
50 <Power ≤100	0.105
100 <Power ≤150	0.11
150 <Power ≤200	0.115
Power ≤250	0.12

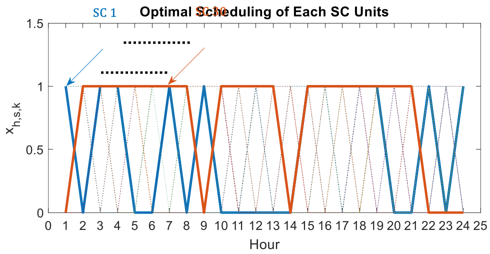

Fig. 5. SCs optimal scheduling of the first CB in winter

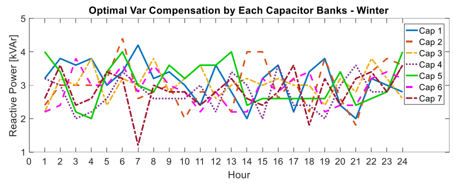

Fig. 6. RP generation optimal scheduling of each CB in winter

Table.2.
Optimal placement and capacity of CBs(kVAt) by applying MOGA, MOPSO and HHO-NSGA-II

CB	*HHO-NSGA-II*		*MOPSO*		*MOGA*	
	Capacity	*location (bus)*	*Capacity*	*location (bus)*	*Capacity*	*location (bus)*
CB 1	2.1	24	3.1	18	3.2	33
CB 2	2.2	30	2.0	17	2.2	32
CB3	1.9	8	2.2	12	2.3	18
CB4	1.8	4	2.0	15	2.0	17
CB5	2.0	25	1.9	14	2.1	24
CB6	1.9	7	1.8	23	1.9	25
CB7	1.8	32	2.5	24	2.7	19
Total capacity	13.7	–	15.5	–	16.4	–

As can be seen in Table 2, the total capacity of the CBs using the proposed HHO-NSGA-II algorithm is equal to 13.7 kVAr, which is significantly reduced compared to the MOGA and MOPSO algorithms. The capability of the proposed algorithm in complete search of initial solutions and avoiding the trap of local solutions make the final optimization solution, which is the set of four cost factors in (1), to be less, and as a result, less compensation capacity is needed for the CBs.

Fig. 9 shows the optimization results over 100 iterations by applying the proposed HHO-NSGA-II algorithm and the conventional MOGA and MOPSO algorithms. As can be seen, the proposed HHO-NSGA-II optimization algorithm performs better in minimizing the objective function with fewer iterations. This is due to its high capability to avoid the trap in locally optimal solutions in the first phase of the algorithm, i.e., HHO, and the ability to comprehensively search for possible solutions in the second phase, i.e., NSGA-II. By combining these two algorithms as a hybrid algorithm to solve multi-objective optimization problems, the advantages of these two algorithms can be used simultaneously. Also, for a better comparison, the final value of the objective function, the total system losses, the minimum value of the hourly bus voltage profile, the total cost of power generation and the total cost of switching in the studied period (one year) using different algorithms in Table 3 are presented.

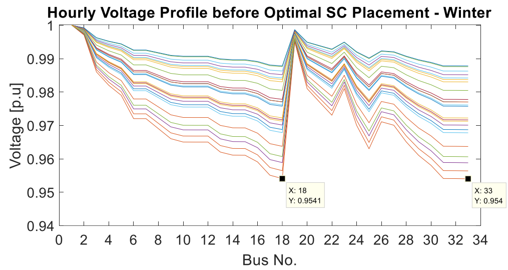

Fig. 7. Hourly voltage profile of network buses in winter before optimal placement of SCBs

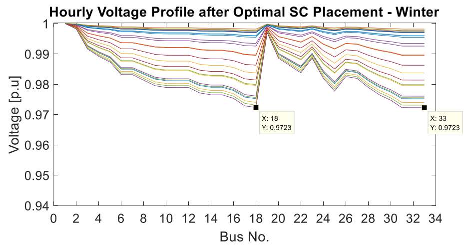

Fig. 8. Hourly voltage profile of network buses in winter after optimal placement of SCBs

As can be seen in Fig. 8. and Fig. 9., with the optimal placement of SCs in the studied system using the HHO-NSGA-II algorithm, the voltage profile of the network buses are significantly improved. This is due to the compensation of the RP on the load side by using SCs and the modification of the power factor in the studied network.

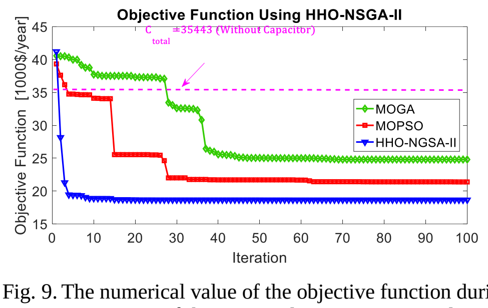

Fig. 9. The numerical value of the objective function during 100 iterations of the proposed HHO-NSGA-II algorithm and the traditional MOGA and MOPSO algorithms

As Fig. 9. shows, the proposed HHO-NSGA-II algorithm is able to give a more optimal solution in a smaller number of iterations. Table 3 shows the comparison between the final value of the objective function and other optimization parameters using three optimization algorithms. As Table 3 shows, the proposed HHO-NSGA-II algorithm is able to reduce the final value of the objective function to a greater extent. By reducing the objective function that consists of cost factors, the cost of system losses and the required compensation capacity will be significantly reduced. With the optimal placement of SCBs in the studied distribution system and the implementation of load spreading, the hourly bus voltage profile is obtained according to Fig. 9. The comparison of the minimum value of the resulting voltage profile using three optimization algorithms in Table 3 shows the better performance of the HHO-NSGA-II algorithm in improving the network voltage profile and correcting its power factor.

Table.3.
Comparison of optimization results

With SCs			*Without SC*	*Optimization method*
HHO-NSGA-II	***MOPSO***	***MOGA***		
131.44	135.12	138.48	210.97	Total losses (kW)
13.7	15.5	16.4	-	Total compensation capacity (kVAr)
0.9723	0.9635	0.9589	0.9540	Min of voltage profile (p.u)
18935	22564	25879	35443	Total annual expenses ($/year)

5. Conclusion

In this paper, a hybrid algorithm is presented by combining HHO and non-dominant sorting NSGA-II for optimal placement and scheduling of SCs in the DN. The proposed objective function includes four cost parameters, namely: generation costs of ARP of generation units, investment and maintenance costs of CBs, cost of ARP losses, and switching cost of SCs. Also, load uncertainty is modelled as an ARP profile using a normal distribution function.

By implementing the proposed optimization problem on the IEEE 33-bus system, the performance of the hybrid HHO-NSGA-II algorithm in solving the optimization problem is evaluated. The simulation results show that the optimization algorithm is able to reach a better optimal solution compared with other multi-objective algorithms with a limited number of iterations. Also, due to the comprehensiveness of the proposed objective function, the location, capacity and optimal switching process of SCs are obtained by solving the optimization problem. Total losses, total annual cost and total compensation capacity using the proposed algorithm are obtained as 131.44 kW, 18953$/year and 13.7 kVAr, respectively, which are significantly reduced compared to the results of MOGA and MOPSO algorithms.

Also, with the optimal placement of SCs in the studied distribution system, the minimum value of the system bus voltage profile increases from 0.9540 p.u in the case without capacitive compensation to 0.9723 p.u, which is a significant value. Therefore, the proposed hybrid optimization algorithm performs better than other multi-objective algorithms in solving the optimization problem.

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