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Sub-transmission sub-station expansion planning based on bacterial foraging optimization algorithm

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Abstract
In the recent years, significant research efforts have been devoted to the optimal planning of power systems. sub-station expansion panning (SEP), as a sub-system of power system planning, consists of finding the most economical solution with the optimal location and size of future sub-stations and/or feeders to meet the future load demand. The large number of design variables and combination of discrete and continuous variables make the sub-station expansion planning a very challenging problem. So far, various methods have been presented to solve such a complicated problem. Since the bacterial foraging optimization algorithm (BFOA) yield to proper results in power system studies, and it has not been applied to SEP in sub-transmission voltage level problems yet, this paper develops a new BFO-based method to solve the sub-transmission sub-station expansion planning (STSEP) problem. The technique discussed in this paper uses BFOA to simultaneously optimize the sizes and locations of both the existing and new installed sub-stations and feeders by considering reliability constraints. To clarify the capabilities of the proposed method, two test systems (a typical network and a real one) are considered, and the results of applying GA and BFOA to these networks are compared. The simulation results demonstrate that BFOA has the potential to find more optimal results than the other algorithms under the same conditions. Also the fast convergence and consideration of the real-world network limitations, as the problem constraints, and the simplicity in applying it to real networks are the main features of the proposed method.

Keywords: *Bacterial Foraging Optimization Algorithm, Genetic Algorithm, Sub-station Expansion Planning.*

1. Introduction

Along with the electric power consumption growth, new power system equipment are needed to overcome the possible lack of adequacy problems, so that with the least costs, various operational constraints are met. In the so-called sub-station expansion planning (SEP), the problem is to determine the required expansion capacities of the existing sub-stations as well as the locations and sizes of new sub-stations together with the required availability times, so that the loads can be adequately supplied [1].

Usually, according to the geographic distribution of actual consumers, the service areas of an electric power distribution system are divided into many small irregular areas, which are called "electrical domains". Each domain has a load-point showing the power consumption of customers in this domain. Moreover, there are some candidate places for installing new sub-stations as well as the possibility of expanding some of the existing ones.

Various constraints should also be observed during the optimization process such as the maximum permissible voltage drop, maximum allowable capacity of feeders, maximum permitted capacity of sub-station equipment, accessibility to upward and downward networks, and considering enough space for possible future developments [2].

The expansion cost components include new sub-station installation cost, no-load and loading loss cost in sub-stations' transformers, and also, the installation and loss cost of feeders. The solution that leads to the minimum total expansion and

operational costs and satisfies the constraints is considered as the optimal solution to the SEP problem. So far, different algorithms have been developed by researchers for this purpose. Most of the existing methods can be categorized into two groups, numerical methods and heuristic ones.
Mixed integer linear programming (MILP) [3,4], non-linear programming (NLP) [5], dynamic programming (DP) [6], ordinal optimization (OO) [7], and direct solution [8] are from numerical methods.
The other group consists of heuristic methods which are listed as follow.

Genetic algorithm (GA): GA is applied for the solution of the SEP problem [9-12]. SEP is solved by GA in combination with quasi-Newton [13], optimal power flow (OPF) [14], and branch exchange [15].

Tabu search (TS): The SEP problem, considering DG and uncertainties, is solved by TS with an embedded Monte Carlo simulation-based probabilistic power flow model [16]. Multi-objective TS solves a dynamic SEP [17]. TS and simulated annealing (SA) have been applied to solve SEP, and it has been concluded that TS is more efficient than SA [18].

Particle swarm optimization (PSO): The medium-voltage (MV) and low-voltage (LV) networks are simultaneously designed by a discrete PSO (DPSO) [19]. A modified DPSO solves SEP considering DG and cross-connections [20]. SEP, considering DGs and storage units, is solved by a modified PSO with local search [21]. An evolutionary PSO solves the SEP under uncertainty considering the DG units [22].

Ant colony system (ACS): A dynamic ACS algorithm solves SEP, considering the installation of DG together with the reinforcement of feeders and sub-stations [23].

Simulated annealing (SA): SEP has been solved by SA in conjunction with MILP in [24].

Artificial bee colony (ABC): ABC algorithm computes the network reinforcements and the commitment schedule for the installed generating units [25].

Shuffled frog leaping algorithm (SFLA): SFLA considers placement and sizing of DGs optimally with respect to the reliability indices improvement [26].

Practical heuristic algorithms: A minimum spanning tree method solves the feeder routing problem in distribution networks including DG [27]. A heuristic method solves SEP in order to increase the penetration of DG units [28]. SEP is solved by a branch-exchange technique in combination with minimum spanning tree [29] and DP [30]. A heuristic method for dynamic SEP has been proposed based on back-propagation of the planning procedure starting from the final year [31].

Bacterial foraging optimization (BFO): A BFO technique solves the optimal feeder routing problem [32]. The multi-stage radial distribution system expansion planning problem in the presence of the distributed generator in a multi-objective optimization framework has been addressed in [33]. The complex multi-objective optimization problem has been solved using BFO. Reference [34] analyzes the impacts of the characteristics of electricity generation and consumption of micro-grid on the distribution network losses and the reliability of electric power supply to consumers. Considering these impacts, a distribution network flexible planning model containing micro-grid has been established and solved by the bacteria colony chemotaxis (BCC). Also [35] applies the BCC algorithm to distribution network planning, and makes some improvements about the algorithm.
In [36], a new mathematical model for unified sub-station planning of two voltage levels has been presented that makes the total cost of two voltage levels as the objective function and the geographical information as the restrictive condition, while the BCC algorithm optimizes the problem.
In most of the methods proposed for SEP, the effect of uncertainty on the input parameters is ignored. However, the study of the provided papers presents such items that include uncertainty studies. Information gap decision theory, robust optimization, stochastic modeling, and fuzzy logic theory are the main methods used for applying uncertainty to input parameters [37-42].
By reviewing the previous studies, it can be concluded that the heuristic methods have many applications that can be used to solve the SEP problem. GA and PSO are the most popular heuristic algorithms, and usually, they lead to more optimal results.
According to references [33-35], it is evident that bacterial foraging optimization algorithm (BFOA) has been applied mainly to the distribution networks, and has not been applied to the sub-transmission voltage level networks. The only paper that has applied BFOA to the planning

studies for high-voltage levels is Ref. [36]. The presented study is in the transmission voltage level, and it has some drawbacks like ignoring network configuration for low-voltage level and ignoring the downstream network expansion.
Since BFOA obtains proper results for power system studies [32-36, 43-46], and it has not been applied to the STSEP problem yet, this paper develops a new BFO-based method to solve the STSEP problem. The results of applying the presented method to the SEP problem are compared with those of GA and PSO as the most famous heuristic methods.

Solution of STSEP is obtained by investigating the pre-determined candidates. In this method, the candidates are obtained by dividing the area under study into certain squares, and then considering the center of each square as the candidate for a new sub-station installation. Clearly, by using smaller squares, the results become more accurate. However, this leads to more computational effort and solution time. After finding the candidates, BFOA is applied to find the best solution among the available solutions. Some important features of the proposed approach are its applicability to transmission and sub-transmission networks, its fast convergence, and having the capability of applying to large-scale networks.
This paper is organized as follows. Section 2 provides the sub-station expansion planning problem. Section 3 introduces the BFO algorithm. The results of applying the proposed method to a typical and a real network are presented in section 4. Finally, section 5 concludes the paper.

2. Sub-station expansion planning

The power system planning studies consist of studies for the next 1–10 years or higher. This planning aims to decide on installation of new equipment as well as upgrading the existing ones to adequately meet the load growth in a foreseen future [1].
This equipment may include the followings:
- Generation facilities
- Sub-stations
- Transmission lines and/or cables
- Capacitors/Reactors

This paper focuses on the case of sub-stations. The aim of sub-station expansion planning is to determine a set of decision variables including sub-stations' locations, sizes, and associated service areas with minimum expansion cost respecting technical constraints [47].
Mathematically, the problem can be defined as (1)-(6):

$$\begin{aligned} Fitness &= \sum_{i=1}^{n_s} C_i^S + \sum_{i=1}^{n_s}\sum_{j=1}^{n_l} C_{ij}^F .d_{ij}.\beta_{ij} \\ &+ \sum_{h=1}^{n_y} PW^h . \sum_{i=1}^{n_s}\sum_{j=1}^{n_l} \alpha.\gamma.\beta_{ij}.C^l.P_{ij}^{loss} \\ &+ \sum_{h=1}^{n_y} PW^h . \sum_{i=1}^{n_s} \alpha.C^l.P_i^{iron} \\ &+ \sum_{h=1}^{n_y} PW^h . \sum_{i=1}^{n_s} \alpha.\gamma.C^l.P_i^{cu}.\left(\frac{S_i^s}{CS_i}\right)^2 \end{aligned} \tag{1}$$

$$PW = \frac{1+\inf\_r}{1+\mathrm{int}\_r} \tag{2}$$

$$P_{ij}^{loss} = \frac{\left(S_j^l\right)^2.d_{ij}.r_{ij}}{\left|V_n\right|^2}, \quad \forall i \in \Omega^s, \quad \forall j \in \Omega^l \tag{3}$$

$$S_i^s = \sum_{j=1}^{n_l} \beta_{ij}.\left(S_j^l + P_{ij}^{loss}\right), \quad \forall i \in \Omega^s \tag{4}$$

$$\psi^{\min}.CS_i \le S_i^s \le \psi^{\max}.CS_i, \quad \forall i \in \Omega^s \tag{5}$$

$$\left|\frac{S_j^l.\sum_{k=1}^{n_s}\left[\beta_{kj}.d_{kj}.z_{kj}\right]}{V_n}\right| \le \Delta V_{\max}, \quad \forall j \in \Omega^l \tag{6}$$

where n_s is total number of selected sub-stations, n_l is number of load points, n_y is the number of years at the planning period, d_{ij} is the distance between nodes *i-j* (km), β_{ij} is the binary decision variable that is equal to 1 if sub-station *i* supplies load point *j* and is 0 otherwise, α is the number of hours in a year (8760), γ is the loss factor, C_i^S is the total expansion and maintenance cost of sub-station *i* within the planning period ($), C_{ij}^F is the construction cost of feeder located between nodes *i-j* ($/km), C^l is the per unit cost of energy loss ($/kWh), *PW* is the present worth factor, P_{ij}^{loss} is the copper losses of feeder located between nodes *i-j* (kW), P_i^{iron} is the iron loss in sub-station *i* (kW), P_i^{cu} is the copper loss in sub-station *i* at the rated loading (kW), S_i^s is the total power provided by sub-station *i* (MVA), CS_i is the specified capacity of sub-station *i* (MVA), $\inf - r$ is the inflation rate, $\mathrm{int} - r$ is the interest rate, S_j^l is the expected load demand at node *i* (MVA), r_{ij} is the resistance per length of feeder constructed between nodes *i-j* (Ω/km), V_n is the nominal voltage magnitude (V), Ω^s is the set of selected sub-stations (existing and proposed), Ω^l is the set of load points (electrical domains), $\psi^{\min}$ is the minimum permissible loading percentage of sub-stations, $\psi^{\max}$ is the maximum permissible loading percentage of sub-stations, Z_{ij} is the impedance per length of feeder constructed between nodes *i-j* (Ω/km), and $\Delta V_{\max}$ is the maximum allowed voltage drop.

The objective function of the SEP problem is presented in (1), where the terms show expansion costs of the selected sub-stations, total required cost for expanding the medium voltage feeders, total cost associated with the medium voltage feeder losses, sub-stations' no-load loss cost, and sub-stations' loading loss cost, respectively.
Equations (5) and (6) exhibit the SEP constraints. Each feeder, regarding its conductor type, is able to transfer a certain amount of power. Also due to the reliability considerations, the sub-stations should have less loading than the nominal capacity. These requirements are guaranteed by (5). Finally, constraint (6) ensures the proper supply of electric consumers with permissible voltage drop at the load points [47].
BFOA, as a powerful tool for solving the above complicated optimization problem, will be discussed in the following section.

3. Bacterial foraging optimization algorithm

BFO method was first invented by Passino [48]. This algorithm is inspired from the natural selection that tends to eliminate the animals with poor foraging strategies, and favor those having successful foraging strategies. The foraging strategy is governed basically by four processes namely chemotaxis, swarming, reproduction, elimination and dispersal [49]. According to [50], the four processes of the algorithm are as follows:

3.1. Chemotaxis

The chemotaxis process includes the characteristics of movement of bacteria in search for food, and it consists of two processes namely swimming and tumbling. A bacterium is said to be "swimming" if it moves in a pre-defined direction and "tumbling" if it moves in an altogether different direction. Let j be the index of the chemotactic step, k be the reproduction step, and l be the elimination dispersal event. Let $\theta^i(j,k,1)$ be the position of the ith bacteria at the jth chemotactic step, kth reproduction step and lth elimination dispersal event, C be the size of the step taken in the random direction specified by the tumble, and ϕ be the angle of the direction that is randomly generated in the range of (0, 2π). The position of the bacteria in the next chemotactic step after a tumble is given by (7):

$$\theta^i(j+1,k,l)=\theta^i(j,k,l)+C\times\angle\phi \tag{7}$$

If the health of the bacteria improves after the tumble, they will continue to swim to the same direction for the specified steps or until the health degrades.

3.2. Swarming

Bacteria exhibit a swarm behavior, i.e. a healthy bacterium tries to attract another one, so that together they reach the desired location (solution point) more rapidly. The effect of swarming is to make the bacteria congregate into groups and move as concentric patterns with a high bacterial density. In mathematical terms, the swarming behavior can be modeled as (8):

$$\begin{aligned} J_{cc}\left(\theta^i(j,k,l),\theta(j,k,l)\right) &= \sum_{i=1}^{s} J^{t}{}_{cc}\left(\theta^i,\theta\theta\right) \\ &= \sum_{t=1}^{s}\left[-d_{attract}\exp\left(-\omega_{attract}\sum_{m=1}^{p}\left(\theta^{i}{}_{m}-\theta^{t}_{m}\right)^2\right)\right] \\ &+ \sum_{t=1}^{s}\left[-d_{repellant}\exp\left(-\omega_{repellant}\sum_{m=1}^{p}\left(\theta^{i}{}_{m}-\theta^{t}_{m}\right)^2\right)\right] \end{aligned} \tag{8}$$

where, $J_{cc}(\theta^i,\theta)$ is the cost function value to be added to the actual cost function to be minimized to present a time-varying cost function, s is the total number of bacteria, p is the number of parameters to be optimized, and $d_{attract}$, $\omega_{attract}$, $d_{repellant}$, and $\omega_{repellant}$ are different coefficients that must be chosen properly.

3.3. Reproduction

In this step, the population members having sufficient nutrients will reproduce, and the least healthy bacteria will die. The healthier half of the population is substituted with the other half of bacteria being eliminated, owing to their poorer foraging abilities. This keeps the population of bacteria constant in the evolution process.

3.4. Elimination-Dispersal

In the evolution process, a sudden unforeseen event may drastically alter the evolution, and may cause the elimination and/or dispersion to a new environment. Elimination and dispersal help in reducing the behavior of stagnation, i.e. being trapped in a premature solution point or local optima.

4. Numerical results

4.1. Results of applying BFOA to a typical network

In this section, a typical network is assumed, and the results of sub-station expansion planning using BFOA are obtained. In the horizon year (2020), the typical network consists of 31 load centers and 5 existing sub-stations [51]. The network parameters, feeder parameters, investment cost of the existing sub-stations, and new sub-station installation cost are presented in [51].
In this paper, the candidates are acquired by dividing the area under study into a number of

small squares, and the center of each square is considered as the candidate point.

In order to compare the performance of the proposed algorithm with other methods, at first, the SEP results for the proposed network are obtained by GA and PSO as the well-known methods in SEP.

In order to make sure that GA, PSO, and BFOA have really found the best solution, the simulations are executed many times, and the best results are considered as the optimum solution.

Figure 1 depicts the results of applying GA on a typical network. After running the program, all the loads are fed by sub-stations in the horizon year. As it can be seen, six new sub-stations have been installed, and two of the existing sub-stations have been expanded. Table 1 provides more details.

After running the program, the genetic algorithm is converged after about 560 iterations in 327 seconds.

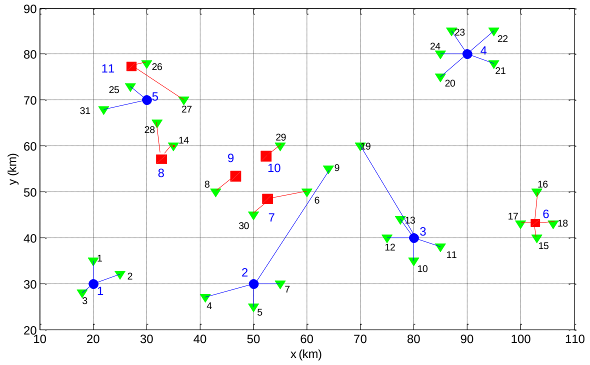

Figure 1. Results of applying GA to solve SEP problem on a typical network.

▼: Load Centers, ●: Existing Sub-stations, ■: New Sub-stations

Table 1. Detailed results of applying GA to solve SEP problem on a typical network.

Number of new installed sub-stations	6
Sum of loads	152 (MW)
Sum of the new sub-stations capacity	105 (MVA)
Installation cost of the new sub-stations	10,500,000($)
Expanded sub-stations	2,4
Sum of the old sub-stations expansion capacity	30 (MVA)
Expansion cost of the old sub-stations	860,000($)
Low-voltage expansion cost	1,125,000 ($)
Total cost of expansion	12,485,000($)

Figure 2 depicts the results of applying PSO to a typical network. After running the program, all of the loads are fed by sub-stations in the horizon year. Six new sub-stations have been installed in the positions shown and one sub-station has been expanded. Table 2 provides more details.

After running the program, PSO is converged after about 530 iterations in 312 seconds.

In the following, the results of applying BFOA to a typical network are presented.

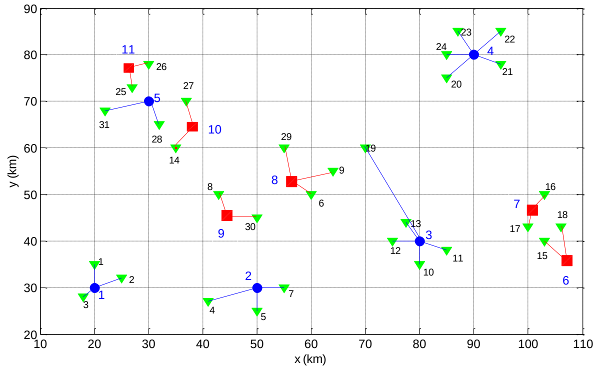

Figure 2. Results of applying PSO to solve SEP problem on a typical network.

▼: Load Centers, ●: Existing Sub-stations, ■: New Sub-stations

Table 2. Detailed results of applying PSO to solve SEP problem on a typical network.

Number of new installed sub-stations	6
Sum of loads	152 (MW)
Sum of new sub-stations capacity	120 (MVA)
Installation cost of new sub-stations	12,000,000($)
Expanded sub-stations	4
Sum of old sub-stations expansion capacity	15 (MVA)
Expansion cost of old sub-stations	430,000($)
Low-voltage expansion cost	502,000 ($)
Total expansion cost	12,932,000($)

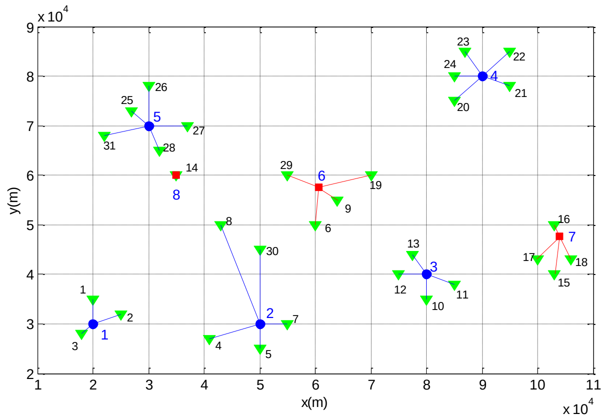

Figure 3. Results of applying BFOA to solve SEP problem on a typical network.

▼: Load Centers, ●: Existing Sub-stations, ■: New Sub-stations

figure 3 and table 3 show the results. It is clear that by installing three new sub-stations in the positions shown and by expanding two existing sub-stations, the loads will be adequately supplied in the horizon year. For more details, see table 3. After running the program, the BFO algorithm is converged after about 480 iterations in 263 seconds.

Table 3. Detailed results of applying BFOA to solve SEP problem on a typical network.

No. of new installed sub-stations	3
Sum of loads	152 (MW)
Sum of capacity of new sub-stations	90 (MVA)
Installation cost of new sub-stations	9,000,000($)
Expanded sub-stations	2,4
Sum of expansion capacity of the old sub-stations	30 (MVA)
Expansion cost of old sub-stations	860,000($)
Low-voltage expansion cost	1,575,000($)
Total expansion cost	11,435,000($)

By comparing tables 1, 2, and 3, it is clear that the expansion cost of the network by BFOA is lower. Thus, the solution presented by BFOA is preferable.

By considering the results of GA, PSO, and BFOA, it is clear that GA and PSO fall in local minima and are not as able as BFOA at solving the SEP problem. In other words, BFOA is more able than GA and PSO to find an optimal solution to SEP. Also by considering the results of GA and PSO in tables 1 and 2, it is clear that GA is better than PSO in finding an optimal solution to SEP. Therefore, in section 4.2, the BFOA results are compared with the GA results in applying to a real presented network.

4.2. Results of applying BFOA to a real network

In order to illustrate the capabilities of the proposed method, the algorithm is carried out on a real network, and the results obtained are compared with those for GA. The considered network is a part of Iran's electric grid, and consists of 92 load centers in the horizon year (2020), while the existing sub-stations are 19 [51].

Table 4. Results of applying GA to a Real network.

No. of new installed sub-stations	7
Sum of loads	328 (MW)
Sum of capacity of new sub-stations	120 (MVA)
Installation cost of new sub-stations	12 (M$)
Expanded sub-stations	6, 10
Sum of expansion capacity of old sub-stations	30 (MVA)
Expansion cost of old sub-stations	860,000($)
Low-voltage expansion cost	7,020,000($)
Low-Voltage Loss	8.8 MW
Sum expansion cost	19,880,000($)

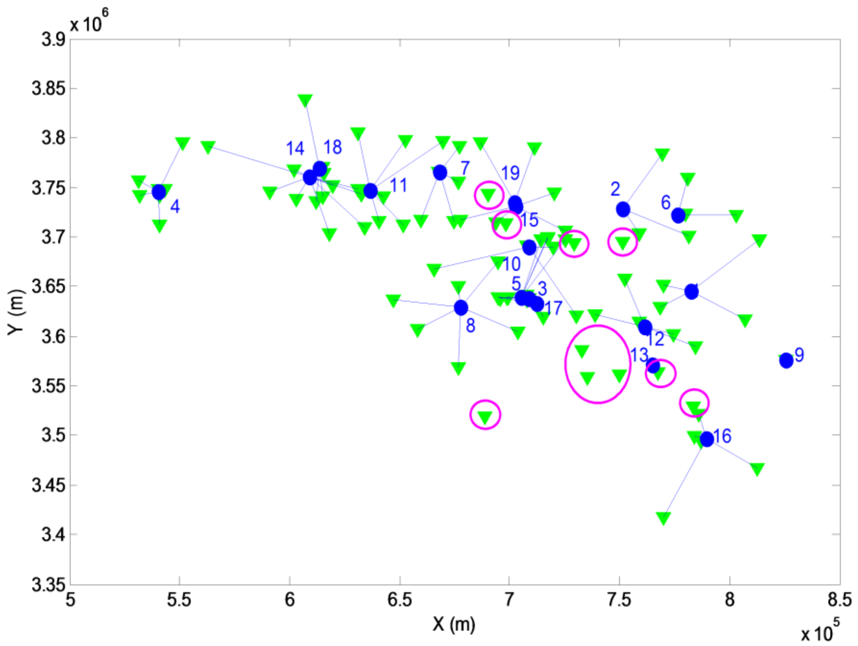

Figure 4. Real network in horizon year without solving SEP.

▼: Load Centers, ●: Existing Sub-stations, ■: New Sub-stations

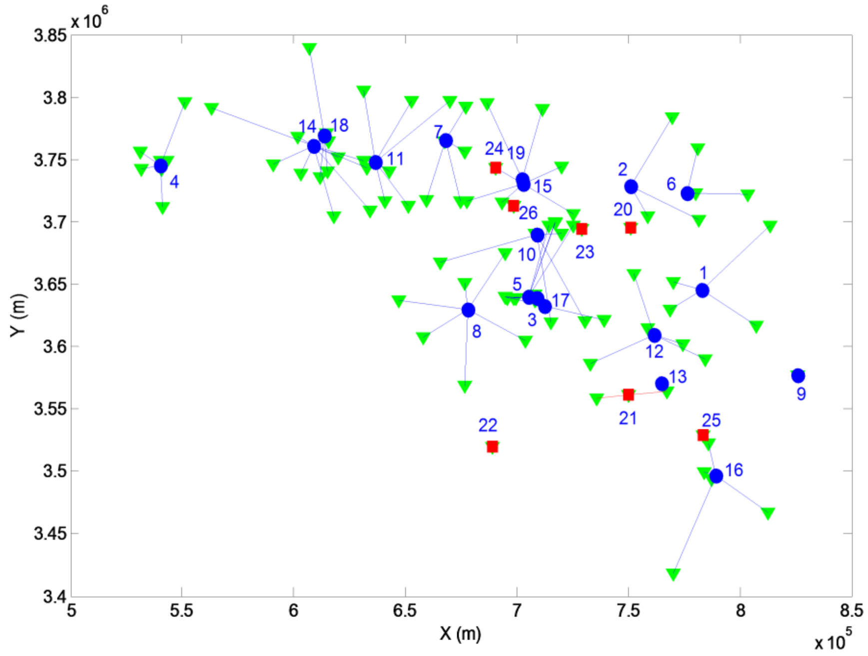

Figure 5. Results of applying GA to solve SEP problem on a real network.

▼: Load Centers, ●: Existing Sub-stations, ■: New Sub-stations

As the loads are increased in the horizon year, some of the loads are not supplied without expanding the existing network (those shown in figure 4 with a circle around them). Thus there is a need to expand the network by installing new sub-station(s) and/or by expanding some existing sub-stations.

To find the best solution to the SEP problem on the real presented network, GA and BFOA are executed on the network, and the results are illustrated in figures 5 and 6, and tables 4 and 5.

As shown in figure 5, GA solves the SEP problem by installing seven new sub-stations and by expanding two existing sub-stations. Also the total cost of the network expansion is 19,880,000 dollars. On the other hand, figure 6 shows that BFOA finds the SEP solution by installing six

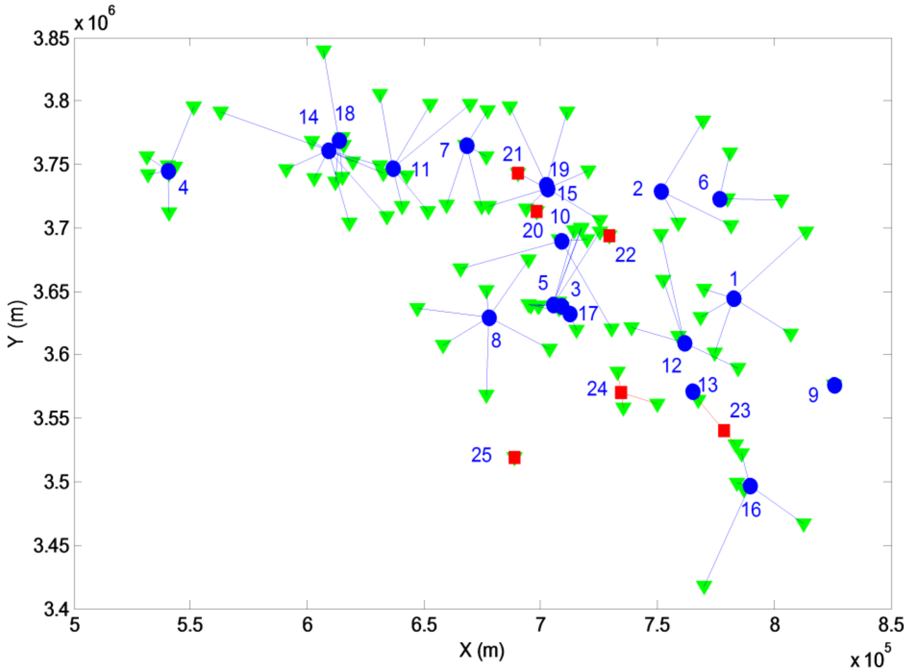

Figure 6. Results of applying BFOA to solve SEP problem on a real network.

▼: Load Centers, ●: Existing Sub-stations, ■: New Sub-stations

new sub-stations and by expanding one existing sub-station. Table 5 declares that the total cost of the network expansion by this method is 18,321,820 dollars.

Table 5. Results of applying BFOA to a real network.

No. of new installed sub-stations	6
Sum of loads	328 (MW)
Sum of capacity of new sub-stations	105 (MVA)
Installation cost of new sub-stations	10,500,000($)
Expanded sub-stations	1
Sum of expansion capacity of old sub-stations	15 (MVA)
Expansion cost of old sub-stations	430,000($)
Low-voltage expansion cost	7,391,820($)
Low-Voltage Loss	9.3 MW
Sum cost of expansion	18,321,820($)

With deeper looks at figures 5 and 6, it is obvious that sub-station No. 22 in figure 5 and sub-station No. 25 in figure 6 feed a load that the voltage droop constraint does not permit other sub-stations to feed it. Thus a new sub-station has been installed just to supply this load. Also in the horizon year, due to exhaustion, the lifetime of sub-station no. 13 is over, and no load is allocated to the sub-station. Thus, to feed the nearby loads, sub-station No. 13 has been replaced by sub-station No. 21 in figure 5, and by sub-station No. 23 in figure 6.

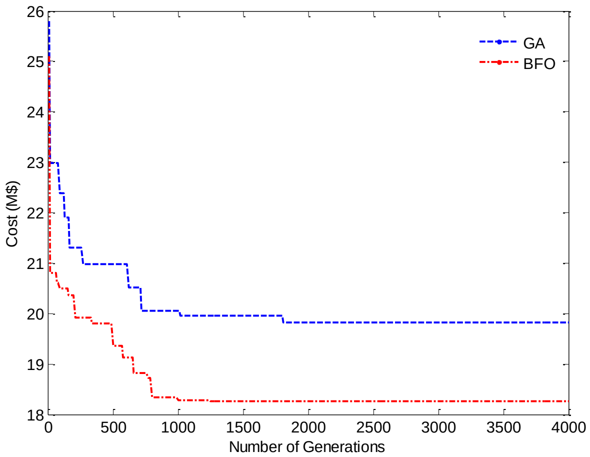

Figure 7. Convergence curve for BFOA and GA.

By comparing the results of GA and BFOA, it is clear that both methods have the ability to find proper solutions to SEP but BFOA is more able than GA to find an optimal solution to SEP. Also BFOA is faster than GA in finding the SEP results. This fact is obvious from figure 7. According to this figure, GA is converged after about 1800 iterations and 1257 seconds, whereas BFOA is converged after about 1000 iterations and 543 seconds.

5. Conclusion

Sub-station expansion planning is one of the important parts of the power system expansion planning studies. The diversity of decision variables in the SEP problem has made the solution process more difficult. This paper introduced a new method for solving SEP as an optimization problem. The optimization method was based on BFOA. To demonstrate the capabilities of BFOA, GA and PSO were used as the benchmark methods for assessing validity. A typical and real network was assumed, and the results of SEP by the use of GA, PSO, and BFOA were obtained. The results obtained showed that GA was more capable than PSO, and BFOA was more efficient than GA in finding the solutions. The results of applying BFOA to a real network showed the functional capabilities of the presented method. Other features of this method are the capability to be applied to the sub-transmission and transmission networks, high speed of convergence, high quality of solutions, consideration of real-world network limitations as SEP constraints, and its simplicity in applying to real networks.

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