Comparing Efficiency of PSO with GA in Transmission Expansion Planning Considering Network Adequacy

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Abstract: - The lines adequacy of the network is necessary to provide load demands when the network is expanding, because its lack caused by load interruption. In this paper, in order to take the transmission lines condition after expansion into account from the line loading view points, the adequacy of the transmission network is considered for the solution of the STNEP problem. To obtain the optimal network arrangement, a discrete particle swarm optimization (DPSO) algorithm is being used for minimizing the network construction and operational cost and compared with genetic algorithm (GA). The particle swarm optimization is a recently developed evolutionary algorithm based on the swarm behavior in the nature and has a strong ability to find the most optimistic results. The motivation for using the DPSO technique is to reduce design effort and find an optimum planning network. The effectiveness of the proposed idea is tested on the Garver's six-bus network and an actual transmission network of the Azerbaijan regional electric company in Iran. The evaluation results evaluation reveals that the annual worth of the network adequacy has a considerable effect on the network arrangement. In addition, the obtained network, based on the DPSO algorithm, has lower investment cost and higher adequacy rate. To verify the results, expansion cost index on adequacy rate for IEEE Garvers network has been compared with GA results.

Key-Words: - DPSO, GA, STNEP, Network adequacy, Optimization problem, Transmission lines.

1 Introduction

The main task of the transmission network expansion planning (TNEP) is the minimization of the network expansion and operational costs and providing required adequacy of lines during the planning horizon, while meeting the technical, economic and security constraints [1, 2]. The long-term TNEP is a hard, large-scale and highly non-linear combinatorial optimization problem that generally, can be classified as static or dynamic. Static expansion determines where and how many new transmission lines should be added to the network up to the planning horizon. If in the static expansion the planning horizon is categorized in several stages, we will have dynamic planning [3-4]. The static TNEP (STNEP) problem acquires a principal role in the power system planning and

should be evaluated carefully. Because, any effort to reduce the transmission system expansion cost significantly improves the cost saving. The electricity companies had capable engineering planning groups that planned the lines and the earlier lines (in the 1970s) were well designed to meet the loads. But, there was typically little or no external consultation or discussion about building the lines [5].

After Garver's paper that was published in 1970 [6], much research has been done on the field of the TNEP problem. Some of them such as [7-16] are related to the problem solution method. Some others, have been proposed different approaches for the solution of this problem considering various parameters such as uncertainty [3, 17], reliability criteria [18-20] and economic factors [21]. Also,

some of them investigated this problem and generation expansion planning together [22, 23].

Recently, global optimization techniques like genetic algorithm [9, 13-14], simulated annealing [11, 15], Tabu search [10] and decimal coded genetic algorithm (DCGA) [24, 25] have been proposed for the solution of the STNEP problem. These evolutionary algorithms are heuristic population-based search procedures that incorporate random variation and selection operators. Although, these methods seem to be good methods for the solution of the TNEP problem, however, when the system has a highly epistatic objective function (i.e. where parameters being optimized are highly correlated), and number of parameters to be optimized is large, then they have degraded efficiency to obtain global optimum solution and also simulation process takes a lot of computing time. Moreover, in all of them, the network adequacy in the transmission expansion planning has not been studied. The network adequacy is necessary to provide load demands when the network is expanding because of its lack (i.e. lines overloading) caused by load interrupting. In Ref. [16], STNEP problem by considering both the network losses and construction cost of the lines has been solved by discrete particle swarm optimization, but the network adequacy has not been studied. In Ref. [26], the voltage level of transmission lines has been considered as a subsidiary factor, but its objective function only includes expansion and generation costs and one of the reliability criteria i.e.: power not supplied energy. Moreover, expansion planning has been studied as a dynamic type and the lines adequacy has not been considered. In Ref. [7], authors proposed a neural network based method for the solution of the TNEP problem by considering both the network losses and construction cost of the lines. But the adequacy rate of transmission lines has not been investigated in this study. Also, in Ref. [27], the effect of losses coefficient on static transmission network expansion planning has been studied using the decimal codification based genetic algorithm. It was showed that this coefficient has not any role in determining of network configuration and arrangement. However, considering its effect in expansion planning of transmission networks with various voltage levels is caused the total cost of the network (expansion and losses costs) is reduced considerably and therefore the STNEP problem is solved more exactly and correctly. But, the network adequacy in the transmission expansion planning has not been studied in this research. Finally, in Ref. [28] the bundle lines effect on network losses has been

investigated in STNEP problem and indicated that these lines have important role in reduction of network losses and subsequent operational costs. However, the network adequacy effect has not been studied. It should be noted that the lines adequacy of the transmission network is proportional to the investment cost. In fact, the lines adequacy is increased by increasing the investment cost and using the exact planning and the proper solution method. On the other hand, with a low costing, the network operates weakly to support load demand and becomes overloaded early. Thus, by compromising between two parameters, i.e. investment cost and network adequacy rate and finally defining a total index, static transmission network expansion planning can be implemented in order to have a network with maximum efficiency technically and economically. In order to overcome these drawbacks and considering the network adequacy, expansion planning has been investigated by including adequacy parameter in the fitness function of the STNEP problem using discrete particle swarm optimization (PSO) algorithm in this paper. PSO is a novel population based metaheuristic, which utilizes the swarm intelligence generated by the cooperation and competition between the particles in a swarm and has emerged as a useful tool for the engineering optimization [28-29]. Unlike the other heuristic techniques, it has a flexible and well-balanced mechanism to enhance the global and local exploration abilities. Also, it suffices to specify the fitness function and to place finite bounds on the optimized parameters.

The proposed DPSO method is tested on the Garver's 6-bus system and a real transmission network of the Azerbaijan regional electric company in order to demonstrate its effectiveness for the solution of the desired STNEP problem. The best solution obtained from the DPSO is the configuration for network expansion which has a lower cost and higher adequacy that will be lately overloaded. Meanwhile the annual worth of network adequacy has a considerable effect on the obtained result. For this purpose, in the case studies, various values of this parameter is investigated. Also, performance of DPSO for solution of desired STNEP problem is compared with GA.

2 Fitness Function and the Solution Method for the Problem

The STNEP problem is a mixed-integer nonlinear optimization problem. Due to consideration of the transmission lines condition after expansion from

the loading viewpoint, the adequacy of the transmission network is included in the STNEP fitness function. Thus, the proposed fitness function could be defined as follows:

$$Fitness = K + \sum_{i,j \in \Omega} (C_{1ij} + C_{2ij}) \times n_{ij} - C_A T_A \quad (1)$$

Where:

C_{1ij}: Construction cost of each 230 kV line in branch i-j.

C_{2ij}: Construction cost of each 400 kV line in branch i-j.

n_{ij}: Number of new circuits in corridor i-j.

T_A: Required time for missing the expanded network adequacy (year).

C_A: Annual worth of the transmission network adequacy ($/year). Determination of this parameter is based on the importance of network adequacy for network owners. Naturally, its high quantities lead to have a network with high adequacy and of course expensive configuration for the expansion.

K: A constant parameter that is large enough to prevent obtaining negative values of the objective function.

Ω: Set of all corridors.

It should be mentioned that by performing DC load flow to load growth for years after expansion, in each year that only one line of the network is overloaded, network adequacy is missed.

Several restrictions have to be modeled in a mathematical representation to ensure that the mathematical solutions are in line with the planning requirements. These constraints are as follows (see Refs. [25, 26] for more details):

$$Sf + g - d = 0 \quad (2)$$

$$f_{ij} - \gamma_{ij}(n_{ij}^0 + n_{ij})(\theta_i - \theta_j) = 0 \quad (3)$$

$$|f_{ij}| \leq (n_{ij}^0 + n_{ij})\overline{f_{ij}} \quad (4)$$

$$0 \leq n_{ij} \leq \overline{n_{ij}} \quad (5)$$

N-1 Safe Criterion $\quad (6)$

Where, $(i, j) \in \Omega$ and:

S: Branch-node incidence matrix.

f: Active power matrix in each corridor.

g: Generation vector.

d: Demand vector.

θ: Phase angle of each bus.

γ_{ij}: Total susceptance of circuits in corridor i-j.

n_{ij}^0: Number of initial circuits in corridor i-j.

$\overline{n_{ij}}$: Maximum number of constructible circuits in corridor i-j.

$\overline{f_{ij}}$: Maximum of transmissible active power

through corridor i-j.

In this study, the objective function is different from those which are mentioned in [1-4, 6-14, 15-21, 23-25] and in part of the problem constraints, $\overline{f_{ij}}$ has been considered as a new condition. The goal is obtaining the number of required circuits for adding to the existed network so that it will have maximum adequacy and minimum investment cost during the specified horizon year. Thus, the problem parameters are discrete time type and consequently the optimization problem is an integer programming problem. For the solution of this problem, there are various methods such as classic, non-classic and heuristic methods [1-3, 5-7, 9-18]. In this study, the discrete particle swarm optimization algorithm is used for the solution of the STNEP problem due to the flexibility and simple implementation.

3 DPSO Algorithm

Particle swarm optimization algorithm, which is tailored for optimizing difficult numerical functions and is based on the metaphor of human social interaction, is capable of mimicking the ability of human societies to process knowledge [28]. It has roots in two main component methodologies: artificial life (such as bird flocking, fish schooling and swarming); and, evolutionary computation. Its key concept is that the potential solutions are flown through hyperspace and are accelerated towards better or more optimum solutions. Its paradigm can be implemented in simple form of the computer codes and is computationally inexpensive in terms of both memory requirements and speed. It lies somewhere in between evolutionary programming and the genetic algorithms. As in evolutionary computation paradigms, the concept of fitness is employed and candidate solutions to the problem are termed particles or sometimes individuals, each of which adjusts its flying based on the flying experiences of itself and its companion. It keeps track of its coordinates in hyperspace which are associated with its previous best fitness solution, and also of its counterpart corresponding to the overall best value acquired thus far by any other particle in the population. Vectors are taken as presentation of the particles since most optimization problems are convenient for such variable presentations. In fact, the fundamental principles of the swarm intelligence are adaptability, diverse response, proximity, quality, and stability [30]. It is adaptive corresponding to the change of the best group value. The allocation of responses between the individual and group values ensures a diversity

of the response. The higher dimensional space calculations of the PSO concept are performed over a series of time steps. The population is responding to the quality factors of the previous best individual values and the previous best group values. The principle of the stability is adhered, since the population changes its state if and only if the best group value changes. As it is reported in [28], this optimization technique can be used to solve many of the same kinds of problems as GA and does not suffer from some of GAs difficulties.

It has also been found to be robust in solving problems featuring non-linearity, non-differentiability and high-dimensionality. It is the search method to improve the speed of convergence and find the global optimum value of the fitness function.

PSO starts with a population of random solutions ''particles'' in a D-dimension space. The ith particle is represented by $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$. Each particle keeps track of its coordinates in hyperspace, which are associated with the fittest solution it has achieved so far. The value of the fitness for particle i is stored as $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$ that its best value is represented by (pbest). The global version of the PSO keeps track of the overall best value (gbest), and its location, obtained thus far by any particle in the population. PSO consists of, at each step, changing the velocity of each particle toward its pbest and gbest according to Eq. (7). The velocity of particle i is represented as $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and gbest. The position of the ith particle is then updated according to Eq. (8) [28, 30]:

$$v_{id}(t+1) = \omega \times v_{id}(t) + c_1 r_1 (P_{id} - x_{id}(t)) + c_2 r_2 (P_{gd} - x_{id}(t)) \quad (7)$$

$$x_{id}(t+1) = x_{id}(t) + c v_{id}(t+1) \quad (8)$$

Where, P_{id} and P_{gd} are $pbest$ and $gbest$. It is concluded that the $gbest$ version performs best in terms of median number of iterations to converge. However, $pbest$ version with neighborhoods of two is most resistant to the local minima. The results of past experiments about PSO show that ω was not considered at an early stage of the PSO algorithm. However, ω affects the iteration number to find an optimal solution. If the value of ω is low, the convergence will be fast, but the solution will fall into the local minimum. On the other hand, if the value will increase, the iteration number will also increase and therefore the convergence will be slow. Usually, for running the PSO algorithm, value of inertia weight is adjusted by training process. It was

shown that the PSO algorithm is further improved by using a time decreasing inertia weight, which leads to a reduction in the number of iterations [30]. In Eq. (7), term $c_1 r_1 (P_{id} - x_{id}(t))$ represents the individual movement and term of $c_2 r_2 (P_{gd} - x_{id}(t))$ represents the social behavior in finding the global best solution.

Regarding the fact that parameters of the TNEP problem are discrete time type and the performance of the standard PSO is based on the real numbers, this algorithm can not be used directly for the solution of the STNEP problem. There are two methods for solving the transmission expansion planning problem based on the PSO technique [16]:

1) Binary particle swarm optimization (BPSO).

2) Discrete particle swarm optimization (DPSO).

Here, the second method has been used to avoid difficulties which are happened at coding and decoding problems, increasing convergence speed and simplification. In this method, each particle is represented by three arrays: start bus ID, end bus ID and number of transmission circuits (the both of constructed and new circuits) at each corridor. In the DPSO iteration procedure, only number of transmission circuits needs to be changed, while start bus ID and end bus ID are unchanged in the calculation, so the particle can omit the start and end bus ID. Thus, particle can be represented by one array. A typical particle with 12 corridors is shown in Fig. 1.

$$X_{typical} = (1, 2, 3, 1, 0, 2, 1, 0, 0, 1, 1, 2)$$

Fig. 1 A typical particle

In Fig. 1, in the first, second, third corridor and finally 12th corridor, one, two, three and two transmission circuits have been predicted, respectively. Also, the particle's velocity is represented by circuit's change of each corridor. ω is considered as a time decreasing inertia weight which its value is determined by Eq. (9).

$$\omega = \frac{1}{\ln t} \quad (9)$$

Finally, position and velocity of each particle is updated by the following equations:

$$v_{id}(t+1) = Fix[\omega \times v_{id}(t) + c_1 r_1 (P_{id} - x_{id}(t)) + c_2 r_2 (P_{gd} - x_{id}(t))] \quad (10)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (11)$$

Where, t is the number of algorithm iterations, $v_{min} \leq v_{id} \leq v_{max}$, and fix (.) is getting the integer part of f. When v_{id} is bigger and smaller than v_{max} and v_{min}, make $v_{id} = v_{max}$ and $v_{id} = v_{min}$, respectively. While, x_{id} is bigger than upper bound of circuit number allowed to be added to a candidate corridor

for the expansion, then make x_{id} equal the upper bound. While $x_{id} < 0$, make $x_{id} = 0$. The other variables are the same Eqs. (7) and (8). The flowchart of the proposed algorithm is shown in Fig. 2. In this study, in order to acquire better performance and fast convergence of the proposed algorithm, parameters which are used in DPSO algorithm have been initialized according to the Table 1.

Table 1-Value of Parameters for the DPSO Algorithm

Parameter	Value	
	Garver's network	Azerbaijan network
Problem dimension	15	153
Number of particles	30	100
Number of iterations	500	500
C_1	1.7	1.7
C_2	2.3	2.3
v_{max}	3	3
v_{min}	-3	-3
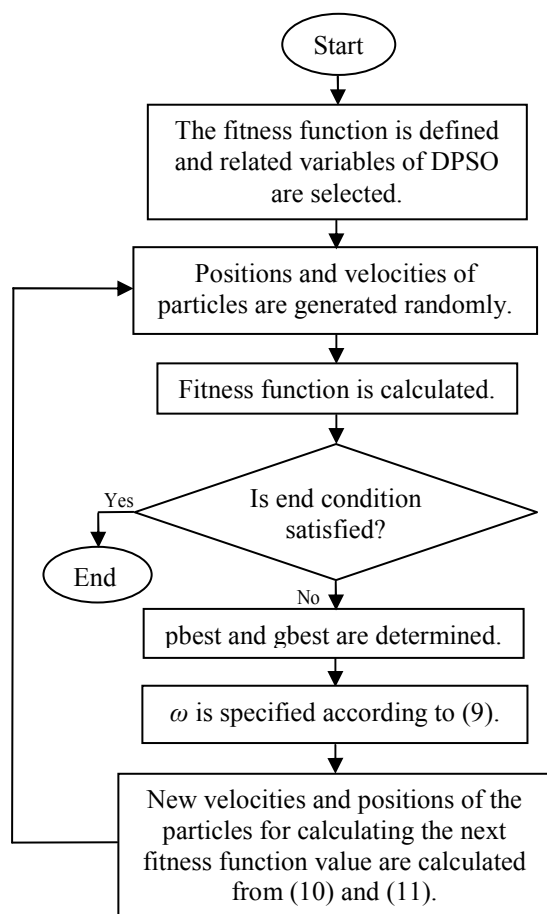
Fig. 2 Flowchart of the DPSO algorithm

It should be noted that PSO algorithm is run several times and then optimal results is selected.

4 Genetic Algorithm

Genetic algorithm is a random search method that can be used to solve non-linear system of equations and optimize complex problems. The base of this algorithm is the selection of individuals. It doesn't need a good initial estimation for sake of problem solution, In other words, the solution of a complex problem can be started with weak initial estimations and then be corrected in evolutionary process of fitness. The genetic algorithm manipulates the binary strings which may be the solutions of the problem. This algorithm can be used to solve many practical problems such as transmission network expansion planning. The genetic algorithm generally includes the three fundamental genetic operators of reproduction, crossover and mutation. These operators conduct the chromosomes toward better fitness. A new idea has been applied in the solution whose parameters are integer number for creating the chromosomes and operators performance that caused to increasing convergence speed and simplification. According to this idea, each chromosome is a set of non-minus integer numbers.

Selection operator selects the chromosome in the population for reproduction. The more fit the chromosome, the higher its probability of being selected for reproduction. Thus, selection is based on the survival-of-the-fittest strategy, but the key idea is to select the better individuals of the population, as in tournament selection, where the participants compete with each other to remain in the population. The most commonly used strategy to select pairs of individuals that has applied in this paper is the method of roulette-wheel selection. After selection of the pairs of parent strings, the crossover operator is applied to each of these pairs.

The crossover operator involves the swapping of genetic material (bit-values) between the two parent strings. Based on predefined probability, known as crossover probability, an even number of chromosomes are chosen randomly. A random position is then chosen for each pair of the chosen chromosomes. The two chromosomes of each pair swap their genes after that random position. Crossover may be applied at a single position or at multiple positions. In this work, because of choosing smaller population multiple position crossover is used with probability of 0.9.

Each individuals (children) resulting from each crossover operation will now be subjected to the mutation operator in the final step to forming the

new generation. The mutation operator enhances the ability of the GA to find a near optimal solution to a given problem by maintaining a sufficient level of genetic variety in the population, which is needed to make sure that the entire solution space is used in the search for the best solution. In a sense, it serves as an insurance policy; it helps prevent the loss of genetic material. This operator randomly flips or alters one or more bit values usually with very small probability known as a mutation probability (typically between 0.001 and 0.01). In a binary coded GA, it is simply done by changing the gene from 1 to 0 or vice versa. In DCGA, as in this study, the gene value is randomly increased or decreased by 1 providing not to cross its limits. Practical experience has shown that in the transmission expansion planning application the rate of mutation has to be larger than ones reported in the literature for other application of the GA. In this work mutation is used with probability of 0.1 per bit.

After mutation, the production of new generation is completed and it is ready to start the process all over again with fitness evaluation of each chromosome. The process continues and it is terminated by either setting a target value for the fitness function to be achieved, or by setting a definite number of generations to be produced. In this study, a more suitable criteria termination has accomplished that is production of predefined generations after obtaining the best fitness and finding no better solution. In this work a maximum number of 2000 generations has chosen.

5   Results and Discussion

To confirm the validity of the proposed planning technique, it was applied to the two test networks. First case is the IEEE Garver's 6-bus system and second case is transmission network of the Azerbaijan regional electric company, Iran. The planning horizon year and load growth rate for both case study systems is considered 2016 (5 years ahead) and 10%, respectively. In following, results of the proposed algorithm on these networks will be described.

5.1 Garver's network

First studied network is Garver's 6-bus system which its configuration before expansion is shown in Fig. 3. In this network, existed lines are 230 kV with capacity 400 MW. The construction cost of 230 kV lines has been given in [1]. Resistance and leakage reactance per kilometer of each line are 0.00012 and 0.0004, respectively. The generation and loads data have also given in [25].
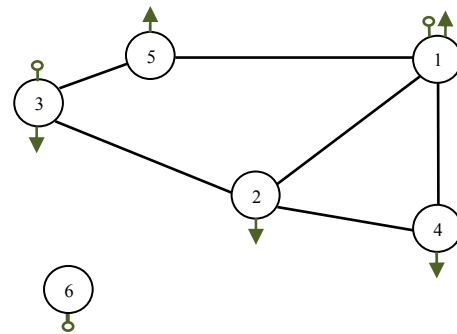

Fig. 3 Garver's 6-bus network

As mentioned, because of the importance of the network adequacy worth (CA), the DPSO based proposed method is carried out for different values of this parameter. The optimal planning networks for different values of CA (million \$/year) are shown in Figs 4-7 (the dash lines into figures are number of required circuits for adding to the network until planning horizon year). Also, expansion cost and year of missing the network adequacy for the above obtained configurations are given in Table 2. It can be seen that network expansion cost has a nonlinear relationship with the network adequacy. Thus, a parameter, named expansion cost index on adequacy rate, is defined for obtaining best design according to the expansion cost and the network adequacy. This parameter is the expansion cost per the network adequacy rate (year). It is worth mentioning that the lower the value of this index is, the better the system configuration.
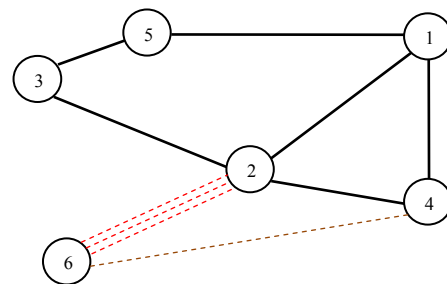

Fig. 4 The Proposed configuration using DPSO for $C_A=1$
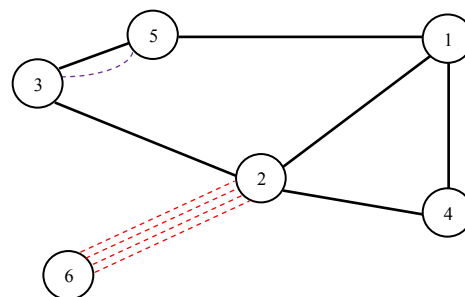

Fig. 5 The Proposed configuration using DPSO for $C_A=2$
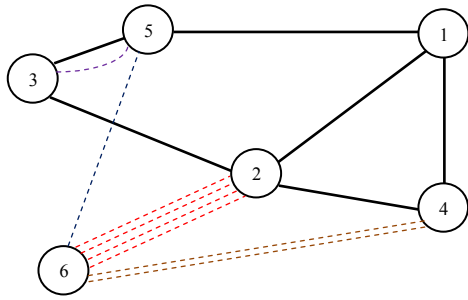
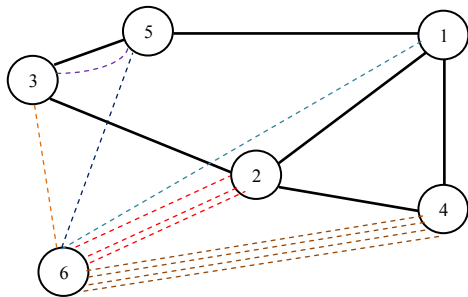Fig. 6 The Proposed configuration using DPSO for $C_A=4$

Fig. 7 The Proposed configuration using DPSO for $C_A=5$

Table 2-Expansion costs and year of missing the network adequacy for $C_A=1$-5 (M\$/year)

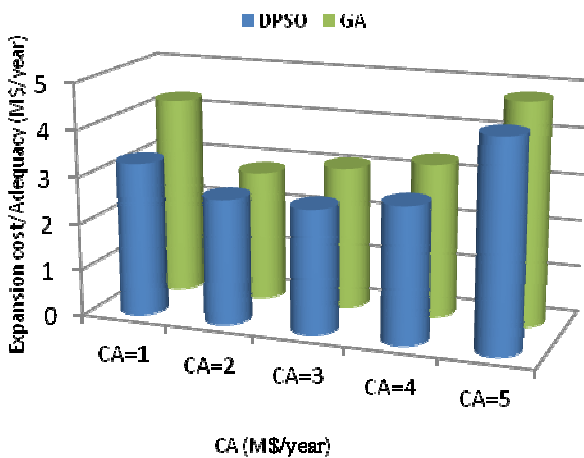| C_A	Expansion Cost (M\$US)	T_A
1	16.42	5 years after horizon (2021)
2	18.79	7 years after horizon (2023)
3	23.93	9 years after horizon (2025)
4	35.58	12 years after horizon (2028)
5	66.78	15 years after horizon (2031)

Fig. 8 The curve of the expansion cost index on adequacy rate versus C_A for Garver's network

As shown in Fig. 8, this index has been acquired according to the various expansion costs listed in Table 2. It can be seen that the index obtained by DPSO is lower than GA for CAs. The fact shows that expansion costs and network adequacy proposed by DPSO are lower and higher than ones proposed by GA. In simple words, it can be concluded that the performance of PSO for finding the best solution is better than GA in solution of STNEP problem considering network adequacy. Also, from this figure, it can be seen that $C_A=3$ relatively give a better solution from the technical (network adequacy) and economical (expansion cost) viewpoints. Regarding the efficiency and robustness of PSO in comparison with GA, DPSO method is used for implementation of the proposed model on the real case study. In following, the details of this actual system and its results are described.

5.2 Transmission network of the Azerbaijan regional electric company

Second studied network is transmission network of the Azerbaijan regional electric company. This actual network has been located in northwest of Iran and is shown in Fig. 9. All details of the network are given in [31]. In this network, 400 kV lines are with capacity 750 MW. Resistance and leakage reactance per kilometer of each 400 kV line are 0.000035 and 0.000124, respectively. It should be noted that characteristics of 230 kV lines are similar to Garver's network.
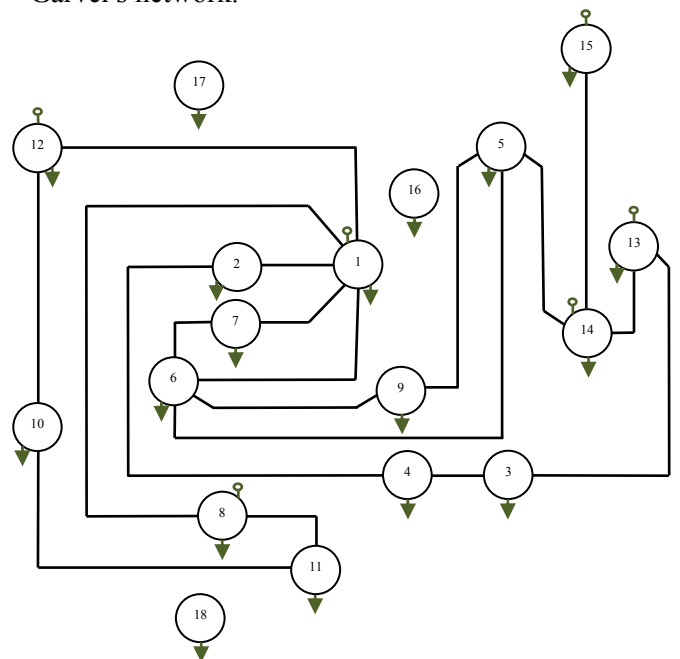

Fig. 9 Transmission network of the Azerbaijan regional electric company

The proposed DPSO method is applied to this case study system for finding the optimal planning networks under different values of C_A (million $/year) and the results are shown in Figs. 10 and 11 and Table 3.
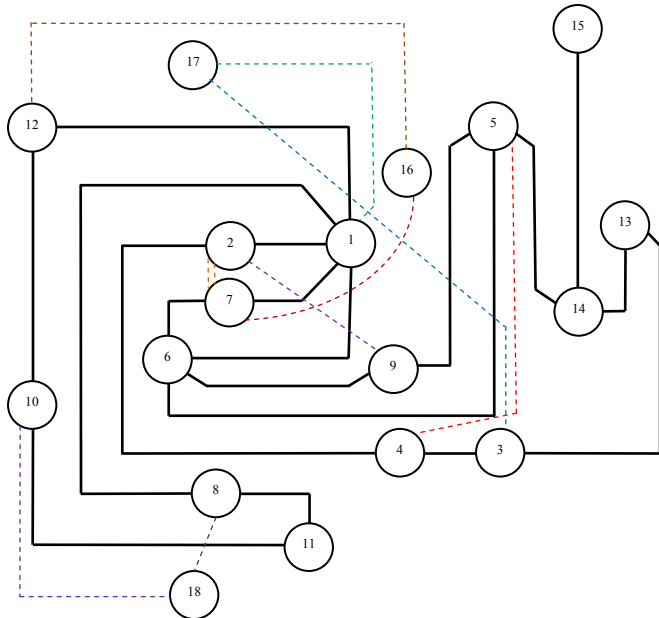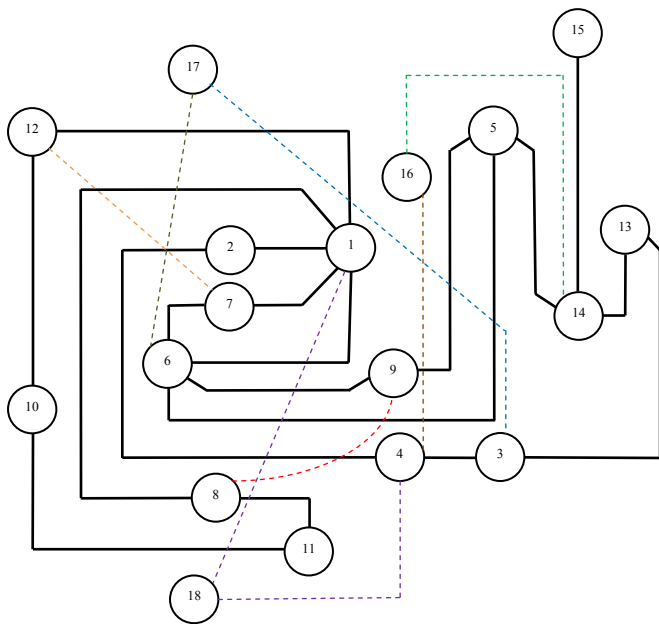

Fig. 10 Proposed arrangement for C_A=1

Fig. 11 Proposed arrangement for C_A=2

Also, the expansion costs and year of missing the network adequacy (T_A) is given in Table 4. According to expansion cost index on adequacy, as shown in Fig. 12, C_A=2 relatively give a better solution from the technical and economical viewpoints. Due to the evaluation results of both case study systems, it can be seen that increasing the

annual worth of network adequacy is caused more lines added to the network for expansion and subsequent the network satisfies the requirement of delivering electric power more safely and reliably to the load centers.

Table 3. Proposed arrangements with respect to C_A=3 and 4 (M$/year)

C_A=3		C_A=4	
Corridor	Number of Circuits	Corridor	Number of Circuits
1-2	2	1-2	2
1-9	1	1-11	1
2-5	1	1-18	1
2-9	2	2-6	1
2-17	1	5-10	1
3-8	1	6-13	1
4-6	1	6-17	1
4-13	1	6-18	1
4-14	1	7-10	1
4-16	1	7-12	1
4-18	1	7-16	1
5-13	1	7-17	1
7-16	1	8-12	2
7-17	1	9-16	1

Table 4. Expansion costs and T_A with respect to C_A=1-4 (M $/year)

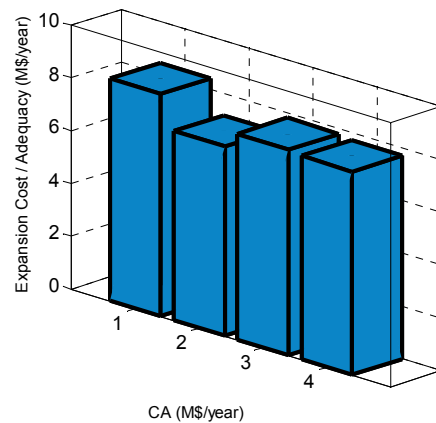| CA	Expansion Cost (M$US)	T_A
1	50.48	6 years after horizon (2022)
2	57.34	8 years after horizon (2024)
3	85.71	11 years after horizon (2027)
4	107.65	14 years after horizon (2030)

Fig. 12 The curve of the expansion cost index on adequacy rate versus C_A for Azerbaijan network

Generally, it can be concluded that there should be a trade-off between the desired level of adequacy and capital investment of network owners. But it seems that relatively lower investment cost can be given a reasonable adequacy for transmission network.

6 Conclusion

By including the transmission network adequacy in the fitness function of the STNEP problem, an optimized network arrangement is acquired for the network expansion using discrete particle swarm optimization algorithm. The proposed arrangement satisfies a maximum adequacy for the feeding of loads in the network with minimum expansion cost. The solution of the STNEP problem using the DPSO method for various quantities of network adequacy worth shows that the annual worth of network adequacy has a nonlinear relationship with network expansion cost and therefore, a trade-off between the desired level of network adequacy and capital investment of network owners is required. Also, the system performance characteristics in terms of 'the expansion cost per the network adequacy rate' index reveals that the solution of TNEP problem by relatively lower investment cost can lead to an expansion design with a reasonable network adequacy.

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