Discrete Particle Swarm Optimization Algorithm Used for TNEP Considering Network Adequacy Restriction

H. Shayeghi, M. Mahdavi, A. Kazemi

Abstract**—**Transmission network expansion planning (TNEP) is a basic part of power system planning that determines where, when and how many new transmission lines should be added to the network. Up till now, various methods have been presented to solve the static transmission network expansion planning (STNEP) problem. But in all of these methods, transmission expansion planning considering network adequacy restriction has not been investigated. Thus, in this paper, STNEP problem is being studied considering network adequacy restriction using discrete particle swarm optimization (DPSO) algorithm. The goal of this paper is obtaining a configuration for network expansion with lowest expansion cost and a specific adequacy. The proposed idea has been tested on the Garvers network and compared with the decimal codification genetic algorithm (DCGA). The results show that the network will possess maximum efficiency economically. Also, it is shown that precision and convergence speed of the proposed DPSO based method for the solution of the STNEP problem is more than DCGA approach.

Keywords—DPSO algorithm, Adequacy restriction, STNEP.

I. INTRODUCTION

TRANSMISSION network expansion planning (TNEP) is an important component of power system planning. It determines the characteristic and performance of the future electric power network and influences the operation of power system directly. Its task is to minimize the network construction and operational cost, while meeting imposed technical, economic and reliability constraints. TNEP should be satisfied required adequacy of the lines for delivering safe and reliable electric power to load centers during the planning horizon [1-3]. Calculation of investment cost for network expansion is difficult because it is dependent on the various reliability criteria [4]. Thus, 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 [5], [6].

In the majority of power systems, generating plants are located far from the load centers. In addition, the planned new projects are still far from completion. Due to these factors, investment cost for transmission network is huge. Thus, the STNEP problem acquires a principal role in power system planning and should be evaluated carefully. Because any effort to reduce transmission system expansion cost significantly improves cost saving. After Garver's paper that was published in 1970 [7], much research has been done on the field of TNEP problem. Some of them such as [1]-[3], [6], [8]-[25], [33] is related to problem solution method. Some others, proposed different approaches for solution of this problem considering various parameters such as uncertainty in demand [5], reliability criteria [4], [26]-[27], and economic factors [28]. Also, some of them investigated this problem and generation expansion planning together [29]-[30]. Recently, different methods such as GRASP [3], Bender decomposition [6], HIPER [17], branch and bound algorithm [31], sensitivity analysis [15], have been proposed for the solution of STNEP problem. In all of them, transmission planning considering network adequacy restriction has not been studied. Loading rate of lines will assign overloading time and miss network adequacy after the end of planning horizon. In Ref. [8], authors proposed a neural network based method for solution of the TNEP problem with considering both the network losses and construction cost of the lines. But TNEP considering adequacy restriction has not been investigated in this study. In Ref. [10], the network expansion costs and transmitted power through the lines have been included in objective function and the goal is optimization of both expansion costs and lines transmitted power. In addition, the objective function is different from those which are represented in [6], [11]-[12], [15]-[17], [20], [31]. However, transmission expansion planning problem considering network adequacy constraint has not been studied. In Ref. [32], 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 dynamic type and the network adequacy restriction has not been considered. In Ref. [33], STNEP problem with considering both the network losses and construction cost of the lines has been solved by discrete

H. Shayeghi is with the Department of Technical Eng., University of Mohaghegh Ardabili, Ardabil, Iran.

M. Mahdavi is with the Electrical Engineering Department, Zanjan University, Zanjan, Iran (corresponding author to provide phone: 98-511-8916522; fax: 98-511-8916522; e-mail: meysam@znu.ac.ir).

A. Kazemi is with the Electrical Engineering Department, Iran University of Science and Technology, Tehran, Iran.

particle swarm optimization. But the adequacy constraint of transmission lines has not been studied.

The lines adequacy of network is necessary to provide load demands when the network is expanding because its lack (i.e. lines overloading) caused to load interrupting. It should be noted that the network expansion cost is proportional to the lines adequacy of transmission network. In fact, the expansion cost is increased by increasing the lines adequacy and using the exact planning and the proper solution method. On the other hand, with a low network adequacy, the network operates weakly to support load demand and becomes overloaded early. Thus, with compromising between two parameters, i.e. network adequacy rate and expansion cost 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.

Recently, global optimization techniques like genetic algorithm [1], [11], [20], simulated annealing [16], [25], Tabu search [12] and in our pervious papers [34], [35] decimal coded genetic algorithm (DCGA) have been proposed for the solution of 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 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 use a lot of computing time. Moreover, in all of them, transmission expansion planning considering the network adequacy restriction has not been studied. In order to overcome these drawbacks and considering network adequacy restriction, expansion planning has been investigated by including adequacy parameter in the fitness function of STNEP problem using discrete particle swarm optimization (PSO) algorithm in this paper. PSO is a novel population based metaheuristic, which utilize the swarm intelligence generated by the cooperation and competition between the particle in a swarm and has emerged as a useful tool for engineering optimization [36], [37]. 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 in comparison with DCGA approach [34], [35] (see Appendix for more details) in order to demonstrate its effectiveness and robustness for solution of the desired STNEP problem (see Appendix for more details). The results evaluation reveals that expansion costs is more decreased in comparison with decimal codification genetic algorithm (DCGA). Also, expanded network will possess a proper adequacy to support load demand. Finally, by comparing between the convergence curves of proposed PSO based method and DCGA, it can be concluded that both the precision and convergence speed of proposed algorithm are more than DCGA method.

II. Mathematical Model of the Proposed STNEP Problem

The STNEP problem is a mixed-integer nonlinear The STNEP problem is a mixed-integer nonlinear optimization problem. Due to consider the network adequacy restriction in STNEP problem, the proposed objective function is defined as follows:

$$Fitness = \sum_{i,j\in\Omega} CL_{ij} n_{ij} - C_{Aw} \times (T - T_o)^2 \quad (1)$$

Where,

CL_{ij}: Construction cost of each line in branch i-j.

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

Ω: Set of all corridors.

C_{Aw}: Annual worth of transmission network adequacy ($/(year)^2). Determination of this parameter is based on importance of network adequacy for network owners.

T_o: Required time for missing the expanded network adequacy which is determined by network owners (in year).

T: Required time for missing the expanded network adequacy which is calculated by DPSO and DCGA approaches (in year). It should be noted that value of this parameter must be equal to T_o.

It should be mentioned that with performing DC load flow to load growth for years after expansion, in each year that only a 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. [5], [34] for more details):

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

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

$$\left|f_{ij}\right| \le \beta \cdot (n_{ij}^0 + n_{ij})\overline{f_{ij}} \quad (4)$$

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

N-1 Safe Criterion (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.

N: Number of network buses.

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]-[20], [23]-[28], [30], [31], [33]-[35] and the goal is obtaining the number of required circuits for adding to the existed network in order to ensure desirable required adequacy of the network along the specific planning horizon. Thus, 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 mathematical and heuristic methods [5]-[21]. In this study, the discrete particle swarm optimization algorithm is used to solve the STNEP problem due to flexibility and simple implementation.

III. DPSO Algorithm and Particle Structure of the Problem

Particle swarm optimization algorithm, which is tailored for optimizing difficult numerical functions and based on metaphor of human social interaction, is capable of mimicking the ability of human societies to process knowledge [36]. 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 potential solutions are flown through hyperspace and are accelerated towards better or more optimum solutions. Its paradigm can be implemented in simple form of 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 both 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 particles since most optimization problems are convenient for such variable presentations. In fact, the fundamental principles of swarm intelligence are adaptability, diverse response, proximity, quality, and stability [38]. 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 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 stability is adhered to since the population changes its state if and only if the best group value changes. As it is reported in [36], 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 problem featuring non-linearing, non-differentiability and high-dimensionality. It is the search method to improve the speed of convergence and find the global optimum value of fitness function.

PSO starts with a population of random solutions ‘‘particles’’ in a D-dimension space. The *i*th 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 *i*th particle is then updated according to Eq. (8) [36], [37]:

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

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

Where, P_{id} and P_{gd} are *pbest* and *gbest*. It is concluded that *gbest* version performs best in terms of median number of iterations to converge. However, *pbest* version with neighborhoods of two is most resistant to local minima. The results of past experiments about PSO show that ω was not considered at an early stage of 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 in training process. It was shown that PSO algorithm is further improved via using a time decreasing inertia weight, which leads to a reduction in the number of iterations [38]. In Eq. (7), term of $c_1 r_1 (P_{id} - x_{id}(t))$ 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 standard PSO is based on real numbers, this algorithm can not be used directly for solution of the STNEP problem. There are two methods for solving the transmission expansion planning problem based on the PSO technique [33]:

1) Binary particle swarm optimization (BPSO).
2) Discrete particle swarm optimization (DPSO).

Here, the second method has been used due to avoid difficulties which are happened at coding and decoding problem, increasing convergence speed and simplification. In this approach, the 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 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 twelfth 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 that 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 expansion, then make x_{id} equal the upper bound. While $x_{id} < 0$, make $x_{id} = 0$. The other variables are the same to Eqs. (7) and (8). The flowchart of the proposed algorithm is shown in Fig. 2.

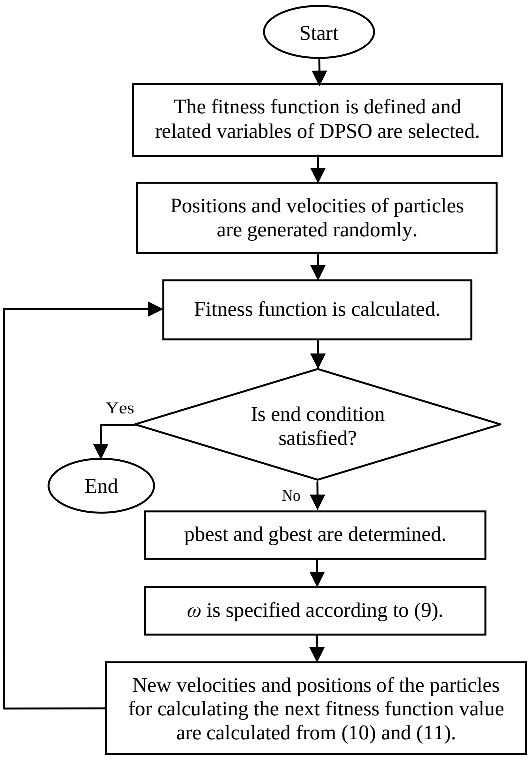

Fig. 2 Flowchart of the DPSO algorithm

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

TABLE I
VALUE OF PARAMETERS FOR DPSO ALGORITHM

Parameter	Value
Problem dimension	15
Number of particles	30
Number of iterations	1000
C_1	1.7
C_2	2.3
v_{max}	3
v_{min}	-3

IV. RESULTS AND DISCUSSION

To prove the validity of the proposed planning technique, it was applied to the IEEE Garver's 6-bus system. The configuration of the test system before expansion is given in Fig. 3. The length of possible corridors and construction cost of 230 kV lines has been given in Tables II and III respectively. In this network, existed lines are 230 kV with capacity 400 MW. Resistance and leakage reactance per kilometer of each line are 0.00012 and 0.0004, respectively. Substations 1, 3 and 6 are generator busses that their generation limit are 100 MW, 250 MW and 450 MW, respectively. The load data has also given in Table IV. Finally the planning horizon year is 2014 (5 years ahead).

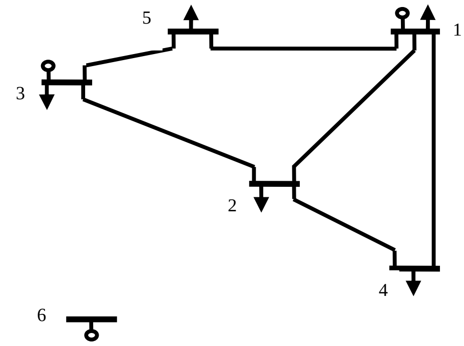

Fig. 3 Garver's 6-bus network

TABLE II
CONFIGURATION OF THE NETWORK

From bus	To bus	Length (Km)
1	2	100
1	3	95
1	4	150
1	5	60
1	6	170
2	3	55
2	4	110
2	5	65
2	6	75
3	4	155
3	5	50
3	6	120
4	5	157
4	6	85
5	6	160

TABLE III
CONSTRUCTION COST OF 230 KV LINES

Number of Line Circuits	Fix Cost of Line Construction ($\times 10^3$ dollars)	Variable Cost of Line Construction ($\times 10^3$ dollars)
1	546.5	45.9
2	546.5	63.4

TABLE IV
ARRANGEMENT OF THE LOAD

Bus	Load (MW)	Bus	Load (MW)
1	80	4	160
2	240	5	240
3	40	6	0

In order to solve the transmission expansion planning problem considering the network adequacy restriction, the proposed method (DPSO) is implemented on the case study system for various times of missing the expanded network adequacy (T_o changes between 6 to 14 years by 2 year steps) and the results are obtained as follows (numbers into the tables are required lines for adding to the network until planning horizon year).

TABLE V
PROPOSED CONFIGURATION AND COST FOR NETWORK EXPANSION WITH RESPECT TO T_o= 6 YEARS

Corridor	Number of required circuits	Expansion cost
2-6	3	19.86 M$US
5-6	1	

TABLE VI
PROPOSED CONFIGURATION AND COST FOR NETWORK EXPANSION WITH RESPECT TO T_o= 8 YEARS

Corridor	Number of required circuits	Expansion cost
2-6	4	23.75 M$US
5-6	1	

TABLE VII
PROPOSED CONFIGURATION AND COST FOR NETWORK EXPANSION WITH RESPECT TO T_o= 10 YEARS

Corridor	Number of required circuits	Expansion cost
2-6	4	27.69 M$US
3-5	1	
4-6	2	

TABLE VIII
PROPOSED CONFIGURATION AND COST FOR NETWORK EXPANSION WITH RESPECT TO T_o= 12 YEARS

Corridor	Number of required circuits	Expansion cost
2-6	4	36.59 M$US
3-5	2	
3-6	1	
4-6	2	

TABLE IX
PROPOSED CONFIGURATION AND COST FOR NETWORK EXPANSION WITH RESPECT TO T_o= 14 YEARS

Corridor	Number of required circuits	Expansion cost
2-6	4	48.52 M$US
4-6	2	
5-6	3	

It is noted that, by network adequacy (T_o) increasing, required lines which could be appended to the network is expanded and therefore expansion cost of the network is increased. However, it seems that the network adequacy may be acquired with lower relative expansion cost. Network adequacy versus network expansion cost has been depicted in Fig. 4.

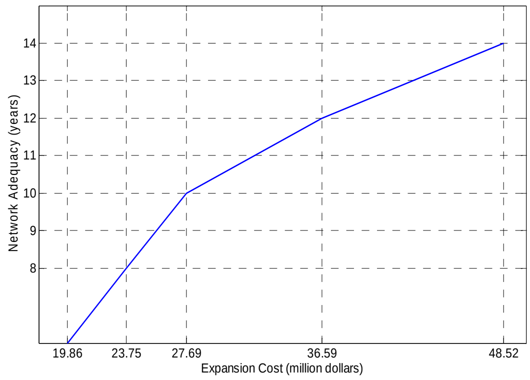

Fig. 4 Adequacy curve with respect to network expansion cost

As shown in Fig. 4, increasing in higher expansion cost (36.59 to 48.52 million dollars), changes the network adequacy more slightly than other expansion costs. Thus, a parameter, named adequacy index on expansion cost rate, is defined for obtaining best design according to the network adequacy and the expansion cost. This parameter is the network adequacy rate (year) per the expansion cost. Thus, a high value is desirable for this index. This index has been acquired according to various expansion costs listed in Tables 5 to 9, as shown in Fig. 5. According to Fig. 5, the optimized point is T_o=10 years.

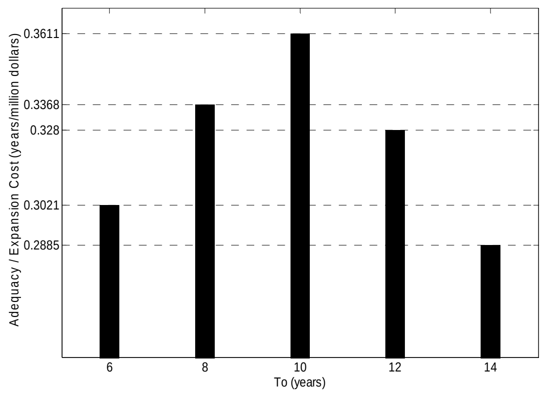

Fig. 5 The curve of adequacy index on the expansion cost versus T_o

Also, in order to illustrate the accuracy and validity of the proposed method, DCGA method is applied to the desired STNEP problem and results (expansion costs) versus T_o for both methods are shown in Figs. 6. Moreover, fitness function values of both methods for different iterations are illustrated in Figs. 7-9 to compare the convergence speed and precision of the DPSO algorithm. It should be mentioned that only three cases of T_o= 6, 8 and 12 years, as instant, have been selected to display.

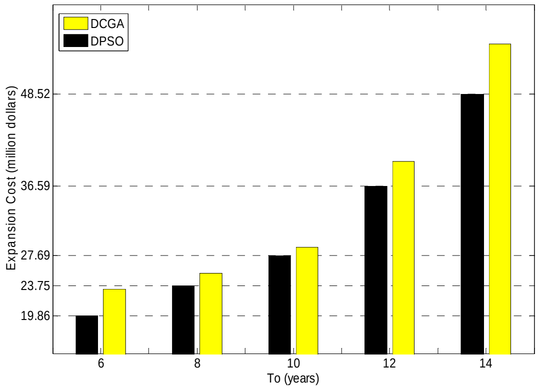

Fig. 6 Diagram of expansion cost versus T_o

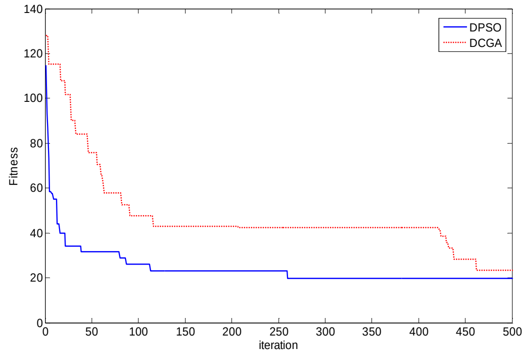

Fig. 7 Convergence curves of DPSO and DCGA for T_o=6

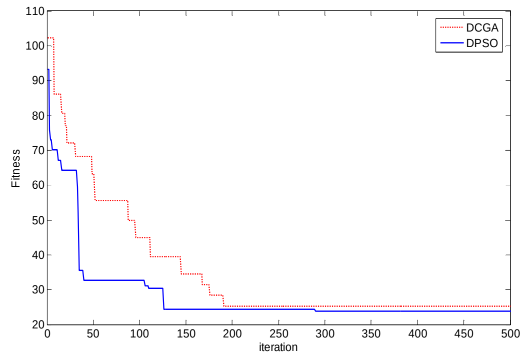

Fig. 8 Convergence curves of DPSO and DCGA for T_o=8

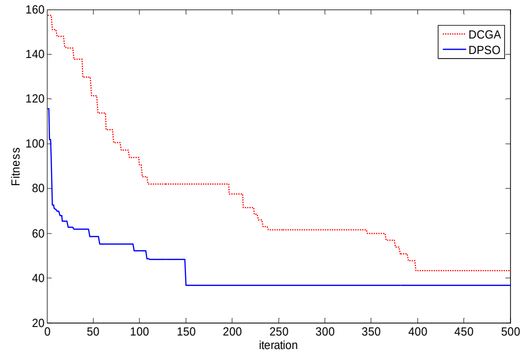

Fig. 9 Convergence curves of DPSO and DCGA for T_o=12

Generally, it can be seen that solution of STNEP problem considering network adequacy restriction by DPSO is caused that the expansion cost is more decreased in comparison with DCGA. Also, it is clear that convergence curves of DPSO method for different cases show the fitness function is optimized more and faster than DCGA one. Thus, it can be concluded that solution of transmission expansion planning problem considering the adequacy constraint by discrete PSO algorithm is more precise, faster and finally better than DCGA method.

V. Conclusion

By including the network adequacy restriction in the fitness function of STNEP problem, an optimized arrangement is acquired for the network expansion using discrete particle swarm optimization algorithm that is proportional to a specified adequacy rate. This arrangement possesses a proper adequacy for feeding the load with a respectively lower cost. The obtained conclusions from adequacy-cost curve show that a more robust network with respect to lines overloading has not been obtained for more expansion cost (indeed, adding more new lines to the network). Finally, using the adequacy index on the expansion cost, an optimized plan is acquired with respectively lower expansion cost, according to a specified adequacy. Also, by comparing the results of the proposed method with DCGA one, it can be concluded that precision and convergence speed of proposed DPSO based method is more than DCGA. Moreover, it can be seen that solution of STNEP problem considering the network adequacy restriction using discrete PSO is caused that the expansion cost is more decreased in comparison with decimal codification GA.

Appendix

A. DCGA and Chromosome Structure of the Problem

Decimal codification genetic algorithm (DCGA) is a random search method that can be used to solve non-linear system of equations and optimize complex problems. It generally includes the three fundamental genetic operators of reproduction, crossover and mutation. These operators conduct the chromosomes toward better fitness. In this method crossover can take place only at the boundary of two integer numbers. Mutation operator selects one of existed integer numbers in chromosome and then changes its value randomly. Reproduction operator, similar to standard form, reproduces each chromosome proportional to value of its fitness function. Therefore, the chromosomes which have better fitness functions will be selected more probable than other chromosomes for the next population (i.e., Elitism strategy) [33, 34]. In this study, each gene in the chromosome includes number of transmission circuits (the both of constructed and new circuits) at each corridor. Fig. 10 illustrates a typical chromosome with 12 corridors. Also, the flowchart of the DCGA approach has been represented in Fig. 11.

1	2	3	1	1	2	1	0	0	1	1	0

Fig. 10 A typical chromosome

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. In this work, 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. 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 [34]. In this work mutation is used with probability of 0.1 per bit. The process continues and it is terminated after production of 1000 generations (iterations). It should be mentioned that number of initial population is considered 30 in DCGA method.

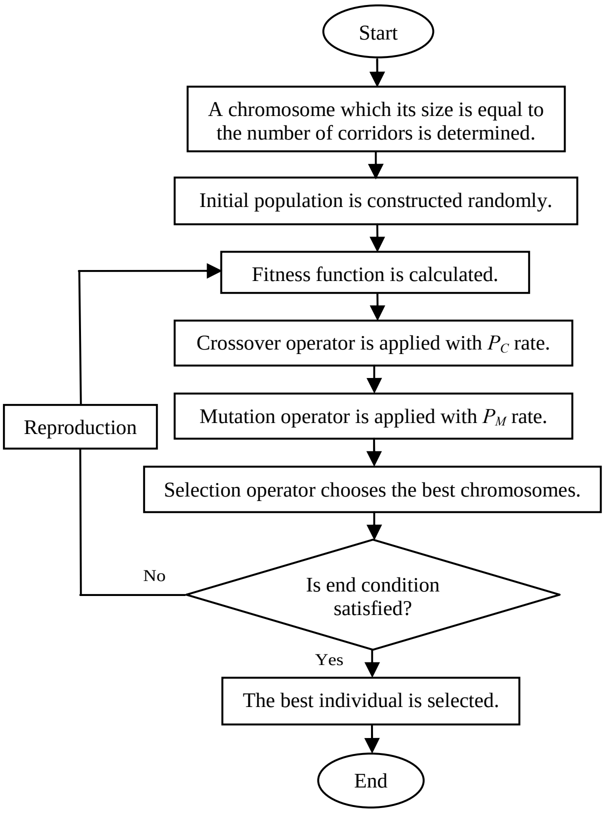

Fig. 11 Flowchart of the DCGA method

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