International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:4, No:3, 2010

Transmission Lines Loading Enhancement Using ADPSO Approach

M. Mahdavi, H. Monsef, A. Bagheri

***Abstract*—**Discrete particle swarm optimization (DPSO) is a powerful stochastic evolutionary algorithm that is used to solve the large-scale, discrete and nonlinear optimization problems. However, it has been observed that standard DPSO algorithm has premature convergence when solving a complex optimization problem like transmission expansion planning (TEP). To resolve this problem an advanced discrete particle swarm optimization (ADPSO) is proposed in this paper. The simulation result shows that optimization of lines loading in transmission expansion planning with ADPSO is better than DPSO from precision view point.

***Keywords*—**ADPSO, TEP problem, Lines loading optimization.

I. INTRODUCTION

PARTICLE swarm optimization (PSO) [1], is a novel population based metaheuristic which utilize the swarm intelligence generated by the cooperation and competition between the particles in a swarm and has emerged as a useful tool for engineering optimization. Unlike the other heuristic techniques, it has a flexible and well-balanced mechanism to enhance the global and local exploration abilities. By imitating the behaviors of biome, it is highly fit for parallel calculation, and has perfect performance on large-scale optimization problems [2-4].

Transmission expansion planning (TEP) is an essential component of power system planning. Its task is to minimize the network construction and operational cost, while meeting imposed technical, economical and reliability constraints [5, 6]. Generally, the TEP should answer the following questions [5]:

1) Where to build a new transmission line?
2) When to build it?
3) What type of transmission line to build?

TEP is a large-scale, discrete, nonlinear, integral optimization problem with lots of equal and unequal restrictions. To solve such a problem, a lot of methods such as GRASP [6], Bender decomposition [7], HIPER [8], sensitivity analysis [9], genetic algorithm (GA) [10-13], simulated annealing [14, 15], and Tabu search [16] have been proposed. Among them GA has been studied thoroughly in TEP, and many improved versions have got better performance [2]. Since parameters of the TEP problem are discrete time type and the performance of standard PSO is based on real numbers, discrete PSO (DPSO) should be used for solution of this problem. Papers [2, 17] compared the DPSO with GA in TEP problem and concluded that DPSO is more exact, quicker and better in convergence.

Loading rate of lines will assign overloading time and miss network adequacy after the end of planning horizon. 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. Consequently, if expanded network is more reliable and therefore its lines overloaded later, will be more economic and caused to utilize favorably.

The standard DPSO algorithm has also some disadvantages like premature convergence phenomenon similar to the (GA) [18]. Although some improved methods, such as augment the swarm scale and dynamic adjustment inertia weight factors, can improve the optimization performance to some extent but during the running of the algorithm, the swarm premature convergence around the local solution. Thus, in this paper, to overcome these drawbacks and considering lines loading rate, expansion planning has been investigated by including lines loading parameter in the TEP problem and investment cost in fitness function constraints using advanced discrete particle swarm optimization (ADPSO). This technique puts the adaptively changing terms in original constant terms, so that parameters of the original DPSO algorithm changes with the convergence rate which is presented by the fitness function.

The proposed ADPSO method is tested on the Garver's 6-bus system in comparison with DPSO approach to demonstrate its effectiveness and robustness for solution of the desired TEP problem. The results evaluation reveals that the network adequacy is more increased in comparison with standard DPSO. In other words, expanded network will possess a maximum adequacy to support load demand and the transmission lines overloaded later. Finally, by comparing between the convergence curves of proposed ADPSO based method and DPSO, it can be concluded that the precision of proposed algorithm is more than DPSO method. So, ADPSO is indeed more efficient in improving searching capability.

II. THE PROBLEM FORMULATION

Since economic value calculation of lines annual adequacy is very complex and affected by multiple parameters and its addition to network expansion investment cost is acquired with high determination, therefore, theses two parameters separate from each other, and correspondingly, fitness

M. Mahdavi is with the School of Electrical and Computer Engineering, University of Tehran, Tehran, Iran (corresponding author to provide phone: 98-21-61115048; e-mail: me.mahdavi@ece.ut.ac.ir).

H. Monsef is with the School of Electrical and Computer Engineering, University of Tehran, Tehran, Iran.

A. Bagheri is with the Electrical Engineering Department, Zanjan University, Zanjan, Iran.

function will be expanded lines adequacy rate. In a new approach, investment cost is inserted to problem constraints to control lines adequacy growing by entering maximum cost for the network expansion. Therefore, the fitness function could be defined as follows:

$$Fitness = \frac{1}{T_o} \quad (1)$$

Where:

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

It is assumed that if only a line of the network is overloaded in each year, network adequacy is missed.

According to [12, 13] the problem constraints are:

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

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

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

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

$$C \le C_{\max} \quad (6)$$

N-1 Safe Criterion (7)

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 which will have two different rates according to voltage level of candidate line.

$C_{\max}$: Maximum investment for expanding the network.

Ω: Set of all corridors

By defining the foregoing fitness function, a design for transmission network expansion could be acquired to represent a maximum probabilistic adequacy according to a maximum value of specified investment cost ($C_{\max}$). In this paper, the goal is obtaining number of required circuits for appending to the network until it is brought to a maximum adequacy with minimum cost during one specified horizon year. 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. In this study, the advanced discrete particle swarm optimization is used to solve the TEP problem due to flexibility, fast convergence speed and simple implementation.

III. Advanced Discrete PSO

A. Real-Number PSO

The PSO algorithm was introduced by Eberhart and Kennedy in 1995 [1]. Original PSO was inspired by the behavior of a flock of birds or a school of fish during their food-searching activities. The PSO believed to be effective in multi dimensional, linear and nonlinear problems. The form of PSO has the position vector and the velocity vector term, and it is represented as $X_i = (x_{i1}, x_{i2}, \ldots, x_{id})$ and $V_i = (v_{i1}, v_{i2} \ldots v_{id})$ for i-th particle in d-dimensional space. By the function, namely, the fitness function for optimization, the best positions of each particle and whole particle (group) are obtained at best fitness function. Each of them is represented as $Pbest_{id} = (pbest_{i1}, \ldots, pbest_{id})$, $Pbest_g = (pbest_{g1}, \ldots, pbest_{gd})$ [18]. The following equations are used to calculate new velocities and positions of the particles for calculating the next fitness function value [20]:

$$v_{id}(t+1) = \omega \times v_{id}(t) + c_1 r_1 (P_{best_{id}} - x_{id}(t)) + c_2 r_2 (P_{best_{gd}} - x_{id}(t)) \quad (8)$$

$$x_{id}(t+1) = x_{id}(t) + c v_{id}(t+1), \quad i = 1, 2 \ldots, n \quad \text{d} = 1, 2 \ldots, \text{D} \quad (9)$$

Where n is the number of particle in a swarm, and D is the number of swarms, which is the dimension of the search space. t is the iteration number and c_1, c_2 are the acceleration constant. r_1, r_2 are the uniformly distributed random number between 0 and 1, and ω is the inertia weight factor. $v_{id}(t)$ is the current velocity, and $x_{id}(t)$ the current position of i-th particle in d-th swarm. $pbest_{id}$ is the best position of i-th particle, and $pbest_{gd}$ is the best position of the group. The first term of (8), $\omega v_{id}(t)$, provides particles' movements to roam in the search space. The second term, $c_1 r_1 \times (p_{best_{id}} - x_{id}(t))$, represents the individual movement. Third term, $c_2 r_2 \times (pbest_{gd} - x_{id}(t))$, represents the social behavior in finding the global best solution. $v_{id}(t)$ is limited by $-v_d^{\max} \le v_{id}^t \le v_d^{\max}$, and $v_d^{\max}$ is proportional to the velocity of the convergence into the best solution. Usually, $v_d^{\max}$ is fixed in the range of the movement from the past c_1 and c_2, the lower value takes the movement from the past target region, but the higher value takes the movement toward the past target region. 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 [19].

B. Discrete PSO

Regarding the fact that parameters of the TEP 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 TEP problem. There are two methods for solving the transmission expansion planning problem based on the PSO technique [2]:

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 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 that its value is determined by (10).

$$\omega=\frac{1}{\ln t} \tag{10}$$

Finally, position and velocity of each particle is updated by the following equations [17]:

$$v_{id}(t+1)=Fix[\omega\times v_{id}(t)+c_1r_1(P_{id}-x_{id}(t))+c_2r_2(P_{gd}-x_{id}(t))] \tag{11}$$

$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1) \tag{12}$$

Where, P_{id} and P_{gd} are $pbest_{id}$ and $gbest_{gd}$, and *fix* (.) is getting the integer part of *f*. When v_{id} is bigger and smaller than v_d^{max} and $-v_d^{max}$, make $v_{id} = v_d^{max}$ and $v_{id} = -v_d^{max}$, 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 (8) and (9).

C. Advanced Discrete PSO

High searching speed is essential in determining the proper parameters when much iteration is involved. Consequently, the advanced discrete PSO (ADPSO) algorithm was proposed in this study. This technique puts the adaptively changing terms so that the parameters of the original DPSO algorithm can change according to the convergence rate which is presented by the fitness function. The original DPSO is change like this:

$$r_1=1-\frac{fbest_{id}}{f_{id}}+rand \qquad r_2=1-\frac{fbest_{gd}}{f_{id}}+rand \tag{13}$$

Where $fbest_{id}$ and $fbest_{gd}$ are the fitness function values at the best position of each particle and whole particle, respectively. f_{id} is the fitness function value at the present position, and rand is the random value between 0 and 1. r_1 can influence the movement of the second term (individual term) as a weight factor. In early searching stage, the difference of between $fbest_{id}$ and $fbest_{gd}$ are the fitness function values at the best position of between $fbest_{id}$ and f_{id} is relatively bigger than that in the last stage. Accordingly, the value of $\left(1-\frac{f_{best_{id}}}{f_{id}}\right)$,is also bigger than that in the last stage. As an individual particle approaches near the individual best position, the movement of individual particle becomes gradually slow. So we can expect faster convergence than the original. r_2 has an effect on the movement of the third term (group). Likewise, it is interpreted as follows:

$$f_{best_{gd}} \le f_{best_{id}} \le f_{id} \tag{14}$$

$$0 \le 1-\frac{f_{best_{id}}}{f_{id}} \le 1-\frac{f_{best_{gd}}}{f_{id}} \le 1 \tag{15}$$

Because $fbest_{gd}$ is supposed as optimal and lowest value in entire particles' fitness values, (11) can be derived. Equation (12) can be easily derived from (11). If the particles converge to the optimal value, $fbest_{id}$ and f_{id} will have the same value, $fbest_{gd}$. Therefore, the replaced $\left(1-\frac{f_{best_{id}}}{f_{id}}\right)$, $\left(1-\frac{f_{best_{gd}}}{f_{id}}\right)$ will become zero, so that the second and third terms will move slowly. It can derive the fast searching.

$$if \quad \lim_{t\to t_{max}} f_{best_{id}} = \lim_{t\to t_{max}} f_{id} = f_{best_{gdi}}$$

$$\lim_{t\to t_{max}}(1-\frac{f_{best_{id}}}{f_{id}}) = \lim_{t\to t_{max}}(1-\frac{f_{best_{id}}}{f_{id}}) = 0 \tag{16}$$

The flowchart of the proposed ADPSO algorithm is shown in Fig. 2.

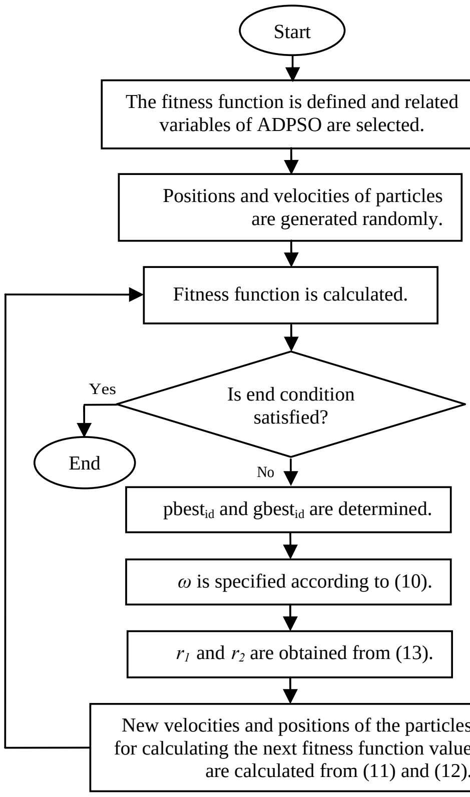

Fig. 2. Flowchart of the advanced DPSO algorithm

In this study, in order to acquire better performance and fast convergence of the proposed algorithm, parameters which are used in advanced DPSO algorithm have been initialized according to Table 1.

TABLE I
VALUE OF PARAMETERS FOR ADPSO

Parameter	Value
Problem dimension	15
Number of particles	20
Number of iterations	100
C_1	1.7
C_2	2.3
v_d^{max}	2

V. NUMERICAL EXAMPLE AND ANALYSIS

To prove the validity of the proposed planning technique, it was applied to the Garver's 6-bus system. The configuration of the test system before expansion is given in Fig. 3. In this network, existed lines are 230 kV with capacity 400 MW. The configuration of network and construction cost of 230 kV lines have been given in [17]. 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 [12]. Finally the planning horizon year is 2014 (5 years ahead).

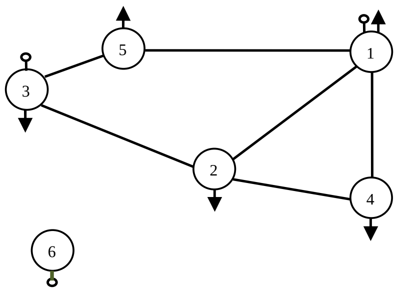

Fig. 3. Garver's 6-bus network

After testing the proposed DPSO method on the network for different values of C_{max} (million dollars), the optimal planning networks are shown in Figs. 4 to 8 (the dash lines into figures are number of required circuits for adding to the network until planning horizon year).

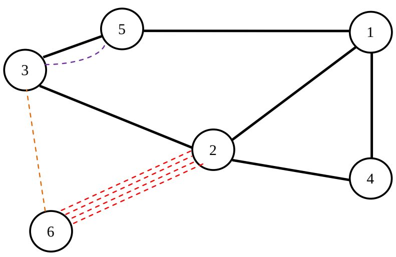

Fig. 4. Proposed configuration by ADPSO for C_{max}=30 M$

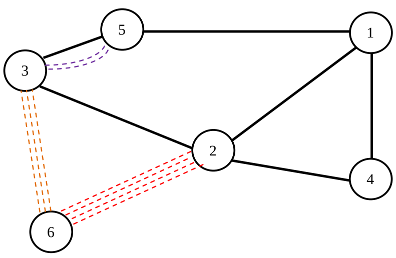

Fig. 5. Proposed configuration by ADPSO for C_{max}=40 M$

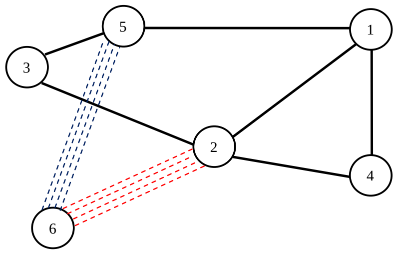

Fig. 6. Proposed configuration by ADPSO for C_{max}=50 M$

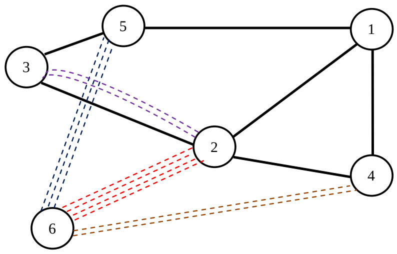

Fig. 7. Proposed configuration by ADPSO for C_{max}=60 M$

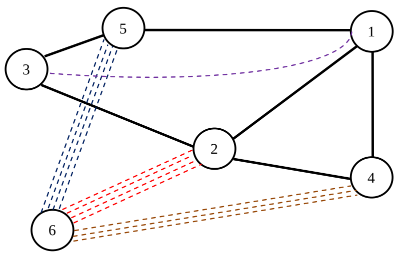

Fig. 8. Proposed configuration by ADPSO for C_{max}=70 M$

Also, expansion cost and T_o for the above mentioned configurations with both methods (ADPSO and DPSO) are given in Tables 2 and 3.

TABLE II
EXPANSION COSTS AND T_O FOR DIFFERENT VALUES OF C_{MAX} BY DPSO

C_{max}	Expansion cost (M$US)	T_o
30	28.69	7 years after planning horizon
40	39.97	9 years after planning horizon
50	46.49	11 years after planning horizon
60	56.04	13 years after planning horizon
70	69.9	15 years after planning horizon

TABLE III
EXPANSION COSTS AND T_O FOR DIFFERENT VALUES OF C_{MAX} BY ADPSO

C_{max}	Expansion cost (M$US)	T_o
30	24.85	9 years after planning horizon
40	39.8	11 years after planning horizon
50	47.52	12 years after planning horizon
60	56.66	14 years after planning horizon
70	65.7	15 years after planning horizon

Moreover, fitness function values of both methods for different iterations are illustrated in Figs. 9-11 to compare precision of the ADPSO with DPSO algorithm. Only three typical cases for C_{max} are selected to exhibit.

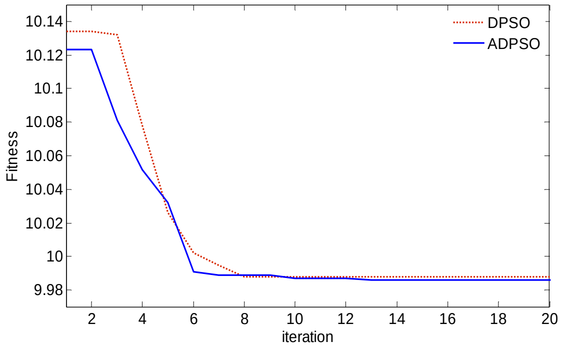

Fig. 9. Convergence curves of ADPSO and DPSO for C_{max}=30

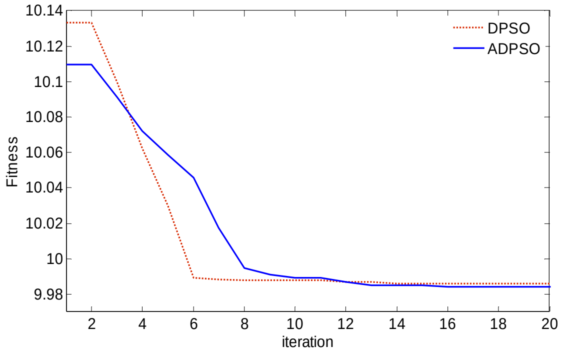

Fig. 10. Convergence curves of ADPSO and DPSO for C_{max}=40

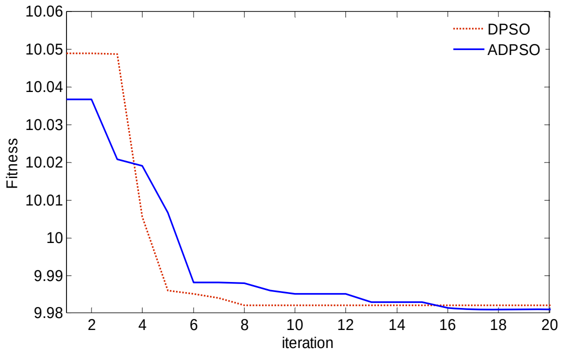

Fig. 11. Convergence curves of ADPSO and DPSO for C_{max}=60

Generally, due to results evaluation of case study systems, it can be said that solution of the lines loading optimization problem by ADPSO is caused that the network adequacy is more increased in comparison with DPSO. Also, it is clear that convergence curves of ADPSO method for different cases show the fitness function is optimized more than DPSO one. Thus, it can be concluded that optimization of lines loading in TEP by advanced discrete PSO is more precise than DPSO method.

V. Conclusion

By including the line adequacy parameter in the fitness function of TEP problem, an optimized arrangement is acquired for the network expansion that is proportional to a specified investment cost value. This arrangement possesses a maximum adequacy for feeding the load. By comparing the results of the proposed method with DPSO one, it can be concluded that precision of proposed ADPSO based method is more than DPSO. Moreover, it can be seen that optimization of lines loading in transmission expansion planning using advanced DPSO is caused that the network adequacy is more increased in comparison with discrete PSO. Therefore, it can be said that although the DPSO is more conventional for solving the TEP problem but improved intelligence method such as ADPSO is caused the amount of fitness function is calculated more precisely and therefore more optimal solutions could be obtained.

References

[1] J. Kennedy and R. Eberhart, Particle swarm optimization, *IEEE International Conference on Neural Networks*, Vol. 4, 1995, pp. 1942–1948.

[2] Y. X. Jin, H.Z. Cheng, J. Y. Yan, and L. Zhang, New discrete method for particle swarm optimization and its application in transmission network expansion planning, *Electric Power Systems Research*, Vol. 77, No. 3-4, 2007, pp. 227-233.

[3] H. Shayeghi, A. Jalili, and H. A. Shayanfar, Multi-stage fuzzy load frequency control using PSO, *Energy Conversion and Management*, Vol. 49, No. 10, 2008, pp. 2570-2580.

[4] J. Kennedy, R. Eberhart, Y. Shi. Swarm intelligence, Morgan Kaufmann Publishers, San Francisco, 2001.

[5] A. R. Abdelaziz, Genetic algorithm-based power transmission expansion planning, *Proc. the 7th IEEE International Conference on Electronics, Circuits and Systems*, Jounieh, Vol. 2, December 2000, pp. 642-645.

[6] S. Binato, G. C. de Oliveira, J. L. Araujo, A greedy randomized adaptive search procedure for transmission expansion planning, *IEEE Trans. Power Systems*, Vol. 16, No. 2, 2001, pp. 247-253.

[7] S. Binato, M. V. F. Periera, S. Granville, A new Benders decomposition approach to solve power transmission network design problems, *IEEE Trans. Power Systems*, Vol. 16, No. 2, 2001, pp. 235-240.

[8] R. Romero, A. Monticelli, A hierarchical decomposition approach for transmission network expansion planning, *IEEE Trans. Power Systems*, Vol. 9, No. 1, 1994, pp. 373-380.

[9] M. V. F. Periera, L. M. V. G. Pinto, Application of sensitivity analysis of load supplying capacity to interactive transmission expansion planning, *IEEE Trans. Power Apparatus and Systems*, Vol. PAS-104, 1985, pp. 381-389.

[10] R. A. Gallego, A. Monticelli, R. Romero, Transmission system expansion planning by an extended genetic algorithm, *IEE Proc. Generation, Transmission and Distribution*, Vol. 145, No. 3, 1998, pp. 329-335.

[11] E. L. da Silva, H. A. Gil, J. M. Areiza, Transmission network expansion planning under an improved genetic algorithm, *IEEE Trans. Power Systems*, Vol. 15, No. 3, 2000, pp. 1168-1174.

[12] H. Shayeghi, S. Jalilzadeh, M. Mahdavi, H. Haddadian, Studying influence of two effective parameters on network losses in transmission expansion planning using DCGA, *Energy Conversion and Management*, Vol. 49, No. 11, 2008, pp. 3017-3024.

[13] M. Mahdavi, H. Shayeghi, A. Kazemi, DCGA based evaluating role of bundle lines in TNEP considering expansion of substations from voltage level point of view, *Energy Conversion and Management*, Vol. 50, No. 8, 2009, pp. 2067-2073.

[14] R. Romero, R. A. Gallego, A. Monticelli, Transmission system expansion planning by simulated annealing, *IEEE Trans. Power Systems*, Vol. 11, No. 1, 1996, pp. 364-369.

[15] R. A. Gallego, A. B. Alves, A. Monticelli, R. Romero, Parallel simulated annealing applied to long term transmission network expansion planning, *IEEE Trans. Power Systems*, Vol. 12, No. 1, 1997, pp. 181-188.

[16] R. A. Gallego, R. Romero, A. J. Monticelli, Tabu search algorithm for network synthesis, *IEEE Trans. Power Systems*, Vol. 15, No. 2, 2000, pp. 490-495.

[17] H. Shayeghi, M. Mahdavi, A. Kazemi, Discrete particle swarm optimization algorithm used for TNEP considering network adequacy restriction, *International Journal of Electrical, Computer, and Systems Engineering*, Vol. 3, No. 1, 2009, pp. 8-15.

[18] Z. S. Lu, Z. R. Hou, Particle swarm optimization with adaptivemutation, *Acta Electronica Sinica*, Vol. 32, No.3, 2004, pp. 416-420.

[19] M. Clerc, J. Kennedy, The particle swarm-explosion, stability, and convergence in a multidimensional complex space, *IEEE Trans. Evolutionary Computation*, Vol. 6, No. 1, 2002, pp. 58-73.

[20] A. Jalilvand, A. Kimiyaghalam, A. Ashouri, M. Mahdavi, Advanced particle swarm optimization-based PID controller parameters tuning, *The 12th IEEE International Multitopic Conference*, Pakistan, 2008, pp. 429-435.