Research Journal of Applied Sciences, Engineering and Technology 7(13): 2605-2611, 2014
DOI:10.19026/rjaset.7.575
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: March 28, 2013 Accepted: May 21, 2013 Published: April 05, 2014

Research Article

Application of Particle Swarm Optimization for Transmission Network Expansion Planning with Security Constraints

Ehsan Sarrafan
Fars Regional Electric Company (FREC), Shiraz, Iran

Abstract: In this study, a new discrete parallel Particle Swarm Optimization (PSO) method is presented for long term Transmission Network Expansion Planning (TNEP) with security constraints. The procedure includes obtaining the expansion planning with the minimum investment cost using a model based on DC load flow formulation. (N-1) contingency is included in this model. The Particle Swarm Optimization algorithm presented in this study is used to solve the planning problem for two different models: without security constraints and with security constraints. Also to solve the problem of transmission expansion planning for a medium network, new improved particle swarm optimization algorithms, the so called, Parallel Particle Swarm Optimization (PPSO) is proposed in this research. The algorithm presents high performances for such networks. The performances with this new algorithm are shown to be better than the ones with the standard PSO. Simulation results show the effectiveness of the parallel particle swarm optimization algorithm.

Keywords: Parallel PSO, particle swarm optimization algorithm, transmission network expansion planning

INTRODUCTION

Power systems, are one of the most important sectors of the economy and energy supply. Development of power systems is affected by a series of factors including increased demand for electricity, supply of primary energy sources, electrical equipments and financial resources. The long-term transmission network expansion planning is a nonlinear, mixed integer optimization problem that its complexity increases exponentially as the network size increases. Transmission network expansion planning has been studied actively in recent years, several methods such as branch and bound; sensitivity analysis and Benders decomposition have been proposed for solving transmission network expansion planning. In Latorre *et al*. (2003) development of network has been divided into three general categories:

- Methods based on mathematical optimization
- Methods based on heuristic models
- Methods based on meta-heuristic

In Garver (1970) used the linear programming approach for Transmission Expansion Planning (Garver, 1970). DC load flow relationships were used to investigate the behavior of the network. Nonlinear and dynamic programming methods also have been used for solving TNEP. The limitations of mathematical optimization models, the implementation of all the details of network expansion planning, heuristic and meta-heuristic models as a good substitution for a mathematical optimization model has been suggested (Bayona and Arriaga, 1994; David and Zhao, 1989). Meta-heuristic methods show better performance in solving optimization problems with better flexibility and speed. Some of the most important meta-heuristic methods which are popular in academia and the industry are: genetic algorithm, tabu search, simulated annealing, game theory and Expert Systems.

There are two types of expansion planning: static and dynamic network expansion planning. Static expansion planning gives the network configuration for a specific year. Dynamic planning is usually, multiyear expansion planning that goes from initial year to horizon year.

In recent years, particle swarm optimization has been widely used in facing optimization problem. Ping Ren and colleagues in Ren *et al*. (2005), are the first group who used particle swarm optimization algorithm for solving Transmission network expansion planning. The main advantage of this method is its ability to find global answer under certain constrains. There are some other works such as Sensarma *et al*. (2002) in which small network expansion planning are considered. It has been shown that the response time to reach optimal PSO method is less in comparison to other heuristic optimization methods. In Kavitha and Swarup (2006) a network planning PSO procedure based on linear programming is used. A network of 18 bus test network is used in this work and selected parameters are similar to other researches. In Jin *et al*. (2007), a new approach for transmission network expansion planning with PSO is presented. Rather than binary PSO method, discrete

PSO method is used for TNEP. Garver (1970) system was the Test network. In Eghbal *et al*. (2011) three different meta-heuristic algorithm including Shuffled Frog Leaping Algorithm (SFLA), GA and PSO is compared and proved SFLA and PSO are more suitable for solving the problem than GA. In Murugan (2012) the application of the PSO method, with a novel initialization, for improving performance of PSO is presented.

The main difference between discrete and the binary optimization method is matrix dimension that indicates the status of the network and the optimization time.

This study aims is to improve the PSO method for static transmission network expansion planning with security constraints. Reason for transmission network expansion planning is to find a network with minimum cost function. With the increase of network busburs, standard PSO method encounter two major problems, scattering and maintaining a minimum distance between the particles are dispersed and causing rapid convergence and local optimum is reached.

To overcome these issues, parallel PSO method is presented and the results demonstrate the effectiveness of this approach for transmission network expansion planning of medium networks.

The study is organized as follows: second, PSO is described; third, Used models for transmission network expansion planning based on DC load flow formulation are explained; fourth discrete PSO method is presented; fifth, PSO parameters are detailed; next, parallel PSO provided; finally, test results are presented and the relevant conclusions are summarized.

PARTICLE SWARM OPTIMIZATION

The PSO algorithm is a partly new population-based heuristic optimization method which is based on a metaphor of social interaction, specifically bird flocking (Khooban *et al*., 2012, 2013a, b). The main benefits of PSO are:

- The cost function's gradient is not needed
- PSO is more compatible and robust compared with other classical optimization techniques (Kennedy and Eberhart, 1995a)
- PSO guarantees the convergence to the optimum solution (Kennedy and Eberhart, 1995b)
- In comparison with GA, PSO lasts fewer times for each function evaluation as it does not apply many of GA operators such as mutation, crossover and selection operator (Kennedy and Eberhart, 1995a)

In PSO, any nominee solution is named "Particle". Each particle in the swarm demonstrates a nominee solution to the optimization problem and if the solution is composed of a series of variables, the particle can be a vector of variables. In PSO, each particle is flown through the multidimensional search space, regulating its position in search space based on their momentum and both personal and global histories. Then the particle uses the best position faced by itself and that of its neighbor to position itself toward an optimal solution. The appropriateness of each particle can be assessed based on the cost function of optimization problem. At each repetition, the speed of every particle will be computed as follows:

$$V_{id}^{k+1} = V_{id}^{k} + \rho_1 r_1 (P_{besti} - X_{id}^{k}) + \rho_2 r_2 (G_{best} - X_{id}^{k}) \quad (1)$$

After computing the speed, the new position of each particle will be computed as follows:

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1},\ i = 1,2,...,n\ ,\ d = 1,2,....,m \quad (2)$$

The PSO algorithm is replicated using Eq. (1) and (2) which are updated at each repetition, up to pre-defined number of generations is achieved:

V_{id}^{k+1} : Velocity of particle i at iteration k+1
X_{id}^{k+1} : Position of particle i at iteration k+1
X_{id}^{k} : Position of particle i at iteration k
ρ_1, ρ_2 : Cognition factor and social-learning factor
r_1 : Random number between 0 and 1
r_2 : Random number between 0 and 1
P_{besti} : P_{best} position of particle i
G_{best} : G_{best} position of swarm
m : Dimension of each particle
n : Population size

Parameter selection is very important for the performance of PSO method (Silva *et al*., 2005; Shi and Eberhart, 1998; Khemka, 2005).

MODELING OF TRANSMISSION NETWORK EXPANSION PLANNING

Transmission network expansion planning problem can be formulated based on DC load flow model with a single event constraints as defined in the following expression. An analysis of the two types of planning is also presented.

Mathematical planning model without security constraints (basic model): Static mathematical model of a transmission network, using the DC model without network security constraints is as follows:

$$\begin{aligned}
&Min\, v = \sum_{i,j\in\Omega} c_{ij} n_{ij} \\
&s.t. sf + g = d \\
&f_{ij} - \gamma_{ij}(n_{ij}^{o} + n_{ij})(\theta_i - \theta_j) = 0 \\
&\left| f_{ij} \right| \le (n_{ij}^{o} + n_{ij}) \bar{f}_{ij} \\
&0 \le g \le \bar{g}\, 0 \le n_{ij} \le \bar{n}_{ij} \\
&n_{ij}\ \text{integer}; \theta_j\ unbounded\,(i,j) \in \Omega
\end{aligned} \quad (3)$$

where,

c_{ij} : The cost of a circuit that candidate for the right-of-way i-j
n_{ij} : The number of candidate circuits in the right-of-way i-j
n^o_{ij} : The number of existing circuits in the right-of-way i-j
$\bar{n}_{ij}$: The maximum number of circuits in the right-of-way i-j
$\bar{g}$: Maximum of real power production
$\gamma_{i,j}$: The Susceptance in the right-of-way i-j
$f_{i,j}$ and $\bar{f}_{i,j}$: The total power flow and the corresponding maximum power flow by circuit in right-of-way i-j
θ_j : Busbar angle j
Ω : Extensible set of all circuits
S : The branch-node incidence transposed matrix of the power system
F : Vector of real power through the branches
g : Vector of real power production
d : Load demand vector prediction
v : The investment cost

The constraint, respectively represents the active power balance in the network nodes, real power through the branches, network lines limit loading, maximum number of devices is available Between branches i and j.

Mathematical planning model with security constraints: In many studies, transmission network expansion planning is used for the normal and maximum load it takes in horizon year. More studies, planning are done based on the N-1 criterion. Also In this study, (N-1) criterion is considered to be satisfied in Garver Network.

Static mathematical model of a TNEP, using the DC model with (N-1) criterion is as follows:

$$
\begin{aligned}
& Min v = \sum_{i,j\in\Omega} c_{ij} n_{ij} \\
& s.t. Sf + g = d \\
& f_{ij} - \gamma_{ij}(n^o_{ij} + n_{ij})(\theta_i - \theta_j) = 0 \\
& \left| f_{ij} \right| \le (n^o_{ij} + n_{ij})\bar{f}_{ij} \\
& \qquad \forall (i,j) \in 1,2,\ldots nl; and (i,j) \ne p \\
& f_{ij} - \gamma_{ij}(n^o_{ij} + n_{ij} - 1)(\theta_i - \theta_j) = 0 \\
& \left| f_{ij} \right| \le (n^o_{ij} + n_{ij} - 1)\bar{f}_{ij} \qquad for (i,j) = p \\
& 0 \le g \le \bar{g}; 0 \le n_{ij} \le \bar{n}_{ij} \\
& n_{ij}\ integer; \theta_j\ unbounded (i,j) \in \Omega
\end{aligned}
\tag{4}
$$

In this equation, *nl* whole set of possible states of the network to select all of the lines considered *P* for (N-1) criterion.

Table 1: Garver network structure for each particle

A1, 2	A1, 3	A1, 4	A1, 5	A1, 6	A2, 3	A2, 4	….
1-2	1-3	1-4	1-5	1-6	2-3	2-4	….

In order to strengthen the network, a common approach is adding a line between two buses which elimination of the line between this two buses cause overload of other lines.

For instance, a line deletion in the branch between bus i and j and the other lines cause overload that an extra line between bus i and j is added to compensate the loss of a line. However, this method does not make an optimal network so here all the network that use for initial state and the network that found in the process of optimization should consider (N-1) criterion and this make it difficult to find an optimal solution and optimization running time increase exponetially.

APPLICATION OF DISCRETE PARTICLE SWARM OPTIMIZATION (DPSO) FOR TNEP

The PSO methods, in each case with a set of particles that act as a symbol of any bird or fish are being described. The relationship between the network and each group has a one to one relationship. Corresponding to a situation where each group is identified, the objective function can be calculated and compared.

In this study instead of the binary PSO procedure discrete PSO method is used to reduce the computing time and dimension of networks matrix to show network status Each particle represents as 1*N matrix, where, N represents the number of paths available. For example, the network Garver, fifteen routes are proposed, each particle is represented by a matrix of 15*1. In this matrix, the matrix elements are lines connecting buses. Table 1 shows how to assign matrix elements to the grid lines. Particle optimization method developed for network planning needs to calculate the cost function. At the start of the optimization, it is necessary that all states are considered as the initial population, are states that have replied once in the load flow.

After selecting all the elements of the random matrix, the following modifications are performed on matrix element. If the random matrix produced elements that eliminate line of major network show that they are equal to zero, the element is converted to 1.

Therefore, there is two constrain for each element of network:

- All element should be between 0-4
- Existent line should not be eliminate

In case of violation of the constraints, the network change is necessary.

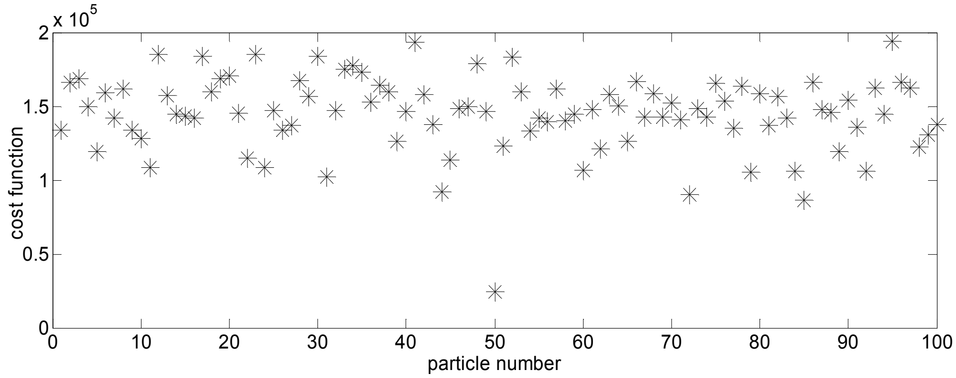

Fig. 1: Distribution of the initial population toward the global optimum

Due to the discrete nature of the transmission network expansion planning variables, Eq. (5) must be modified:

$$V_{id}^{k+1} = Fix\ (\omega \times V_{id}^{k} + \rho_1 r_1 (P_{besti} - X_{id}^{k}) + \rho_2 r_2 (G_{best} - X_{id}^{k})) \tag{5}$$

In order to make the equation variable speed varies from continuous to discrete fix function were used.

Application of standard PSO for TNEP:

The initial population: In mathematical optimization method, it is critical to investigate an initial population in order to converge to a global optimum. If the initial population is high, time to achieve optimal response is increased and if the initial population of a small amount is selected, the network will converge to a local optimum. Figure 1 shows the distribution of the particles and cost function in compare with g_{best} cost function at the end of executing of PSO optimization program. Maximum population that test is 500, but after testing different parameters and initial populations, 100 populations is suitable for test systems. Figure 1, shows the Distribution of 100 initial populations toward the global optimum.

The velocity limit: In order to have a new location, maximum and minimum changes of velocity values in each of iteration, has influence on search area of each particle. In most studies, the maximum and minimum allowable rate of changes in each of iteration is about 10-20% of maximum speed. Therefore, it should be in the range of 0.4-0.8. Because these values are inappropriate according to the experiments, the maximum allowable level of 50% is considered.

Cognition factor and social-learning factor: According to the results of tests done, ρ_1 = 2.5 and ρ_2 = 1.5, are suitable.

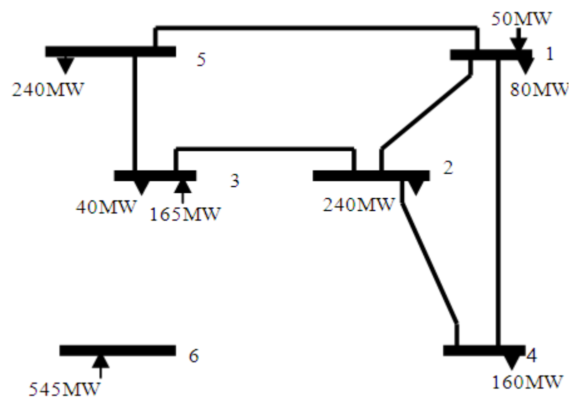

Fig. 2: Basic Garver test system

Inertia weight: According to the experiments conducted in this study for PSO method the coefficient w = 0.9 is considered.

Application of parallel PSO for TNEP: This section presents a Parallel Particle Swarm Optimization algorithm (PPSO) for solving long term transmission expansion planning. It shows that parallel PSO methods reduce computing time and increase the chance of finding global answer. There are two reasons for using parallel PSO: first computing time; second solution quality. In hard multi-dimensional problems like TNEP, the number of alternative and the number of local minimum increase with the dimension of network. The increase in dimensions of networks and alternatives increases computing time and the chance of finding local minimum points. It has been shown that parallel PSO increase the speed of solution finding as well as increasing the chance of global finding.
The parallel PSO has the following structure:

Step 1: Selection of the parameter and initial population (N1)

Step 2: Solving network expansion planning problem by using standard PSO With selected

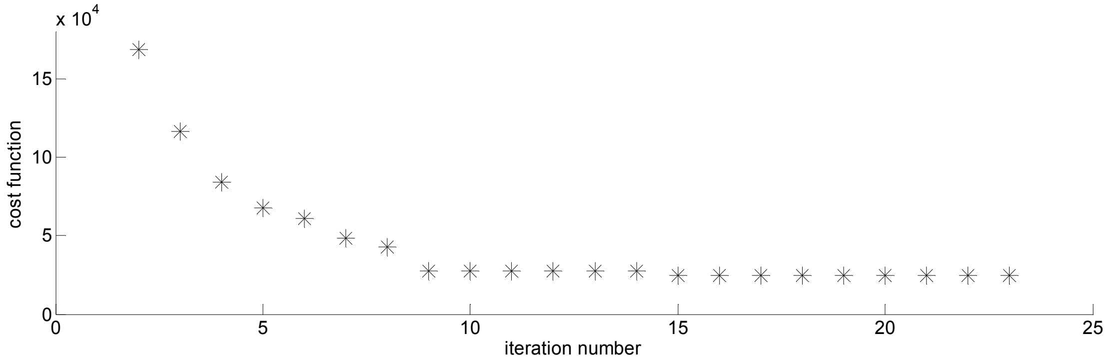

Fig. 3: Convergence of global optimum of the particles for Garver is shown

parameters and the initial population with the number of repetition (N2)

Step 3: Storage of cost function and global optimal for (N2)

Step 4: Repeat step 2 and 3 until all N2 particle have different cost function (Remove particles have the same cost function and repeat step 2

Step 5: Global optimum cost function taking values stored as part of the initial population for the second stage of the optimization problem

Step 6: Select (N1-N2) random initial population so all initial population is N1

Step 7: Solving PSO method with this new initial population

The proposed parallel PSO search algorithm has shown to be effective for solving TNEP.

SIMULATION AND RESULTS

In particle swarm optimization section network have been selected, Garver system and South Brazilian system. These networks have been used in several studies and networks as appropriate for the planned network expansion are discussed. For simulation of TNEP with PSO method MATLAB and MATPOWER functions were used for solving power flow equations.

Garver system: According to the Fig. 2 the network normally has five buses, two power plants with a capacity of 150, 120 and 190 MW of load, respectively.

Load of this network in horizon year is 760 MW. Two previous plant capacities are increased and new power plants with capacity of 600 MW are under construction to meet load in horizon year. The electrical data, generation data and load data have been taken form Seifi *et al*. (2007).

In this study, for selection of PSO parameters, different parameters tested and the best parameters selected. Figure 3, shows the convergence of global optimum of the particles at different iterations for

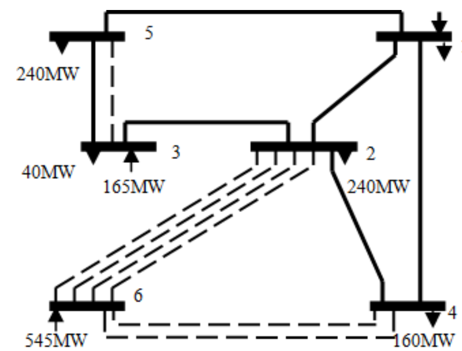

Fig. 4: Development of optimal designs Garver network without network security constraints

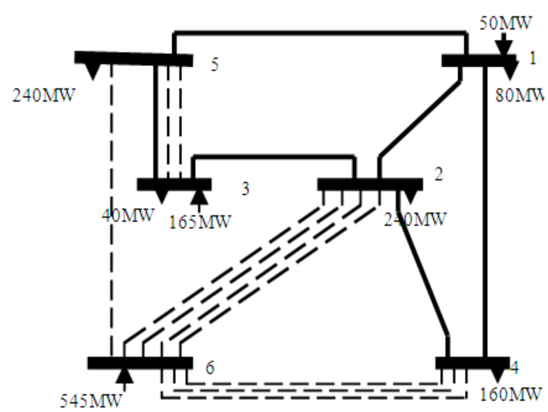

Fig. 5: Development of optimal designs Garver network with network security constraints

Table 2: The various development of Garver networks using standard PSO

	Network regardless of security constraints	Network taking into account network security constraints
New lines	$N_{3-5} = 1$; $N_{2-6} = 4$; $N_{4-6} = 2$	$N_{3-5} = 2$; $N_{2-6} = 4$ $N_{4-6} = 3$; $N_{3-6} = 1$
Investment cost ($)	200000	298000

Table 3: Comparison of TNEP with security constrain for southern Brazil network using standard PSO and PPSO

	Parallel PSO	Standard PSO
Investment cost ($)	337809000	432350000

Table 4: The various development of southern Brazil network using PPSO

	Network regardless of security constraints	Network taking into account security constraints
New lines	$n_{20\text{-}21} = 1$, $n_{42\text{-}43} = 2$	$n_{31-32} = 1$, $n_{28-30} = 1$
	$n_{46\text{-}6} = 1$, $n_{19\text{-}25} = 1$	$n_{26-29} = 3$, $n_{29-30} = 2$
	$n_{31\text{-}32} = 1$, $n_{28\text{-}30} = 1$	$n_{17-19} = 1$, $n_{27-38} = 1$
	$n_{26\text{-}29} = 3$, $n_{5\text{-}6} = 2$	$n_{46-11} = 3$, $n_{11-5} = 6$
		$n_{12-14} = 1$, $n_{42-43} = 3$
		$n_{23-24} = 1$, $n_{20-21} = 1$
		$n_{24-25} = 3$, $n_{25-21} = 1$
		$n_{25-32} = 1$, $n_{26-27} = 1$
		$n_{32-43} = 1$, $n_{2-5} = 1$
		$n_{19-21} = 1$, $n_{20-21} = 1$
Investment cost ($)	154420000	337809000

Garver system. It shown that the network converged to best answer after 10 iteration. Figure 4 and 5 show the optimal designs of Garver network without and with network security constraints.

The investment cost for the networks is shown in Table 2.

South Brazilian system: This network is a simplified model of a real network of southern Brazil and as one medium-scale networks is used for transmission network expansion planning studies. This system has 46 buses, 79 branches, a total demand equal to 6880 MW. The electrical data, generation data and load data can be obtained in Haffner *et al*. (2000).

The results with PSO algorithm, indicate a low success rate and high convergence rate to local optimum. After reviewing the results and P_{besti} values in different iterations, it was found that rapid convergence to a local optimum happened for this system. According to the obtained test results the rate of finding global optimum with standard PSO around (23-28%). Therefore Parallel PSO method was tested. The results indicate the better performance of Parallel PSO procedure.

According to Table 3, it can be observed that the network with PPSO has less investment cost than the network that was found with SPSO. Table 4 shows The various development of southern Brazil network using PPSO.

Executing 100 times of PPSO method shows that successful rate around 83-89% for South Brazilian system. Convergence of global optimum of the particles happened after 300-450 iteration for South Brazilian system. The average executing time was for the network regardless of security constraints around 190S and for Network taking into account network security constraints around 530 S. It is observed that using the proposed PPSO method with a novel initialization of particles improves the performance of PSO method.

CONCLUSION

In order to improve the performance of PSO algorithm for transmission network expansion planning, this study presented a new discrete Particle Swarm Optimization method (PPSO) for static transmission network expansion planning with security constraint. Comparisons of PPSO with standard PSO in solving TNEP show that PPSO is more suitable for medium and large scale networks. Results for Garver system shows the performance and robustness of PSO for TNEP and Results for 46-bus south Brazilian shows the better performance of PPSO for TNEP of medium network when it was compared with PSO. The results show the importance of initial population in the performance of PSO algorithm.

REFERENCES

Bayona, G.L. and I.J.P. Arriaga, 1994. A heuristic model for long term transmission expansion planning. IEEE T. Power Syst., 9(4): 1886-1894.

David, A.K. and R. Zhao, 1989. Integrating expert systems with dynamic programming in generation expansion planning. IEEE T. Power Syst., 4(3): 1095-1101.

Eghbal, M., T.K. Saha and K.N. Hasan, 2011. Transmission expansion planning by meta-heuristic techniques: A comparison of shuffled frog leaping algorithm, PSO and GA. Proceeding of IEEE Power and Energy Society General Meeting, pp: 1-8.

Garver, L.L., 1970. Transmission network estimation using linear programming. IEEE T. Power Ap. Syst., 89(7): 1688-1697.

Haffner, S., A. Monticelli, A. Garcia, J. Mantovani and R. Romero, 2000. Branch and bound algorithm for transmission system expansion planning using a transportation model. IEE Proc-C, 147(3): 149-156.

Jin, Y.X., H.Z. Cheng, J.Y. Yan and L. Zhang, 2007. New discrete method for particle swarm optimization and its application in transmission network expansion planning. Electr. Pow. Syst. Res., 77(3-4): 227-233.

Kavitha, D. and K.S. Swarup, 2006. Transmission expansion planning using Lp-based particle swarm optimization. Proceeding of the IEEE Power India Conference.

Kennedy, J. and R.C. Eberhart, 1995a. Particle swarm optimization. Proceeding of the IEEE International Conference on Neural Network. IEEE Service Center, Piscataway, NJ, pp: 1942-1948.

Kennedy, J. and R.C. Eberhart, 1995b. A new optimizer using particle swarm theory. Proceeding of the 6th International Symposium on Micro Machine and Human Science. IEEE Press, Nagoya, Japan, pp: 39-43.

Khemka, N., 2005. Comparing particle swarm and evolution strategies: Benchmarks and application. M.Sc. Thesis, University of Calgary, Alberta.

Khooban, M.H. and M.R. Soltanpour, 2013b. Swarm optimization tuned fuzzy sliding mode control design for a class of nonlinear systems in presence of uncertainties. J. Intell. Fuzzy Syst., 24: 383-394.

Khooban, M.H., A. Alfi and D.N.M. Abadi, 2013a. Control of a class of non-linear uncertain chaotic systems via an optimal Type-2 fuzzy proportional integral derivative controller. IET Sci. Meas. Technol., 7(1): 50-58.

Khooban, M.H., M.R. Soltanpour, D. Nazari Maryam Abadi and E. Zahra, 2012. Optimal intelligent control for HVAC systems. J. Power Technol., 92(3): 192-200.

Latorre, G., R.D. Criz, G.M. Ateza and A. Villegas, 2003. Classification of publication and models on transmission expansion planning. IEEE T. Power Syst., 18(2).

Murugan, P., 2012. Modified particle swarm optimization with a novel initialization for finding optimal solution to the transmission expansion planning problem. IET Gener. Transm. Dis., 6(11): 1132-1142.

Ren, P., L.Q. Gao, N .Li, Y. Li and Z.L. Lin, 2005. Transmission network optimal planning using the particle swarm optimization method. Proceeding of the International Conference on Machine Learning and Cybernetics, 7: 4006-4011.

Seifi, H., M.S. Sepasian, H. Haghighat, A. Akbari Foroud, G.R. Yousefi and S. Rae, 2007. Multi-voltage approach to long-term network expansion planning. IET Gener. Transm. Dis., 1(5): 826-835.

Sensarma, P.S., M. Rahmani and A. Carvalho, 2002. A comprehensive method for optimal expansion planning using particle swarm optimization. Proceeding of the IEEE Power Engineering Society Winter Meeting, 2: 1317-1322.

Shi, Y. and R.C. Eberhart, 1998. Parameter selection in particle swarm optimization. Proceeding of the Seventh Annual Conference on Evolutionary Programming. New York, USA, pp: 591-600.

Silva, I.D.J., M.J. Rider, R. Romero, A.V. Garcia and C.A. Murari, 2005. Transmission network expansion planning with security constraints. IEE Proc-C, 152(6).