

TRANSMISSION NETWORK EXPANSION PLANNING BASED ON ARTIFICIAL INTELLIGENCE METHODS

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Abstract - The paper is focusing on transmission network expansion planning (TNEP) problem solved using artificial intelligence techniques. It is divided into two parts. The particle swarm optimization (PSO) and genetic algorithm (GA) concepts and mechanisms are presented. Practical considerations are discussed. IEEE 24 RTS test power system is used as case study. The TNEP problem is solved using both techniques: PSO and GA. The results are compared.

Keywords: modelling, genetic algorithms, particle swarm optimization, power transmission network expansion planning.

1. INTRODUCTION

Garver in [1] has proposed the use of linear programming technique for TNEP solving. The initial data have been represented by: power system configuration, consumed power forecast and real power sources' evolution plan. The power flow is computed and new lines are introduced, having as a goal to avoid power system branches overloading. The optimization problem is solved using linear programming techniques. The drawbacks of such an approach are as follows: a linear mathematical model is used for power flow computing, reactive power flow is not tackled, real power losses are neglected, objective function (OBF) refers to the power system branch overloading cost minimization, etc. [2].

In [3] it is stipulated that the TNEP is a mixed nonlinear optimization problem, with real and integer variables. In [4] the real power losses are approximately considered. Also, the OBF is extended referring to the total cost minimization formed by investment cost (related to the transmission network expansion) and generating units operation cost. These type of problems are solved in [5] applying a meta-heuristic technique for exploring the solution space. In [6] an additional term is added to the OBF expression, taking into consideration aspects related to the power system safety operation. It is computed based on several $N-I$ criterion operating conditions.

TNEP is approached from the linear integer programming point of view in [7]. A "branch and bound" type algorithm is applied. To control the power system expansion candidate set the algorithm is trained based on a knowledge data-base. The inappropriate solutions are avoided imposing inferior and superior OBF limits.

Currently, the (meta)heuristic methods are largely

applied for optimization problems solving. In case of TNEP, these techniques are applied to generate possible solutions, to evaluate them and to select the most appropriate ones. The algorithm continues, until it is not able to improve the solution anymore, based on evaluation criteria. They are referring to the investment and operation costs. Most recent approaches are including within the OBF congestion costs, aspects related to the transmission capacity, safety operation, environment constraints, etc.

Particle Swarm Optimization (PSO) has been developed by Kennedy and Eberhart [8]. In [9] the TNEP is solved based on a discrete PSO problem. The PSO algorithm specific parameter numerical values are discussed for an optimal method tuning (population size, maximum admissible velocity, convergence). The TNEP issue is defined in [10] as a mixed nonlinear optimization problem, implemented within a discrete PSO algorithm. The power flow is solved in d.c., small scale test power systems have been used. In [11] an adaptive PSO algorithm is considered for TNEP solving. It has been applied on IEEE 24 test power system. A discrete PSO evolutionary algorithm is discussed in [12].

The TNEP is solved in [13] based on GA. An improved version of the algorithm is presented in [14], based on differential evolution. An auto-adaptive technique is used for control parameter numerical values modification. The tournament selection type is used, to overpass the difficulties related to the OBF penalty coefficients values establishment. In [15] an improved GA for TNEP is proposed. The genetic mutation operator is adjusted applying a simulated annealing technique. The initial population is obtained using a linear technique (rather than random generation) and algorithm parameters' tuning is discussed.

Following the introduction already presented within the 1st section, the 2nd one refers to PSO based TNEP mathematical model. The same problem is tackled within the 3rd section using the GA approach. The 4th and 5th sections are focusing on the case study. The TNEP problem is solved for the same test power system using both approaches. The conclusions are synthesized within the 6th section.

2. PSO BASED TNEP MATHEMATICAL MODEL

The swarm S has the configuration presented in Fig. 1. It contains np particles. Each particle represents a possible solution for the network expansion problem.

x_1				x_2				...	x_{np}			
1 st particle				2 nd particle				...	np particle			
x_{11}	x_{12}	...	x_{1d}	x_{21}	x_{22}	...	x_{2d}	...	x_{np1}	x_{np2}	...	x_{npd}
components				components				...	components			

Fig. 1. Swarm structure diagram

The particles are formed by d components corresponding to the candidate network elements status. These components are rounded real values ranging between $[0, 1]$ (1 – connected, included within the solution, 0 – disconnected, not included within the solution).

Less than 30 particles should not be used for the swarm dimension. In case of small scale power systems, it is recommended to be used at least equal with d (number of components forming the particle).

Particles' evaluation is performed based on OBF value. A valid solution is obtained once the OBF value is not able to be improved (function value is not decreasing anymore).

The TNEP flowchart is presented in Fig. 2.

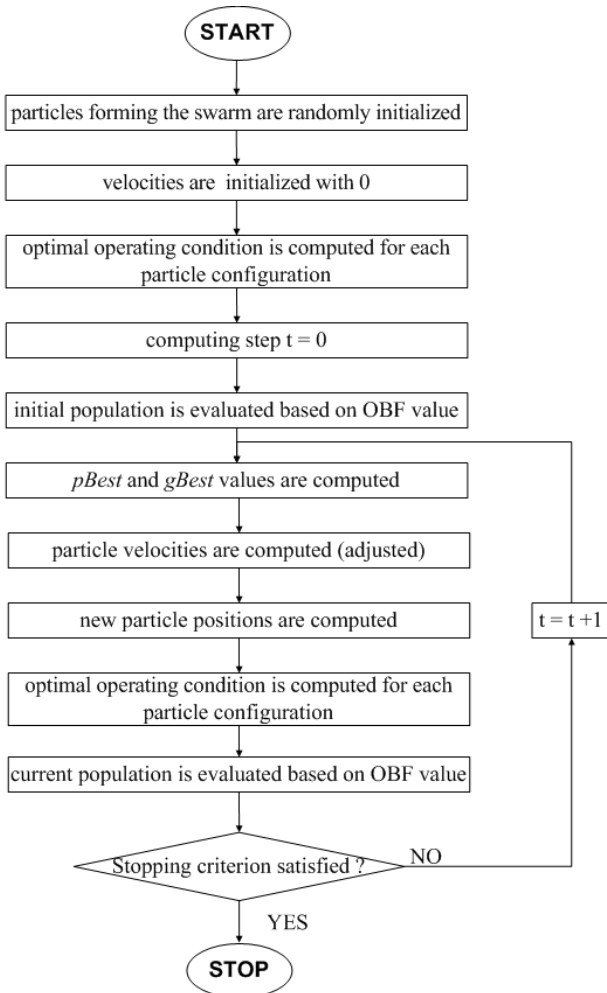


Fig. 2. PSO based TNEP flowchart

The following components are included within the objective function (OBF):

- power system operating costs (OPF OBF value) transposed for one year period;
- investment equivalent yearly cost related to new power transmission capacities installation (overhead lines, autotransformers);

- total available transmission capacity, correlated with other two criteria.

3. GA BASED TNEP MATHEMATICAL MODEL

The same problem is approached using the genetic algorithm technique.

The GAs are also population based algorithms. In this case the *swarm* terminology is replaced with *population*. In PSO case it was formed by particles, in this case the chromosomes are forming the population (Fig. 3). For this case too, each chromosome is going to code a solution for the TNEP problem (meaning a specific configuration for the transmission network).

x_1				x_2				...	x_{nc}			
1 st chromosome				2 nd chromosome				...	nc chromosome			
x_{11}	x_{12}	...	x_{1d}	x_{21}	x_{22}	...	x_{2d}	...	x_{nc1}	x_{nc2}	...	x_{ncd}
genes				genes				...	genes			

Fig. 3. Population structure diagram

The GA based TNEP flowchart is presented in Fig. 4.

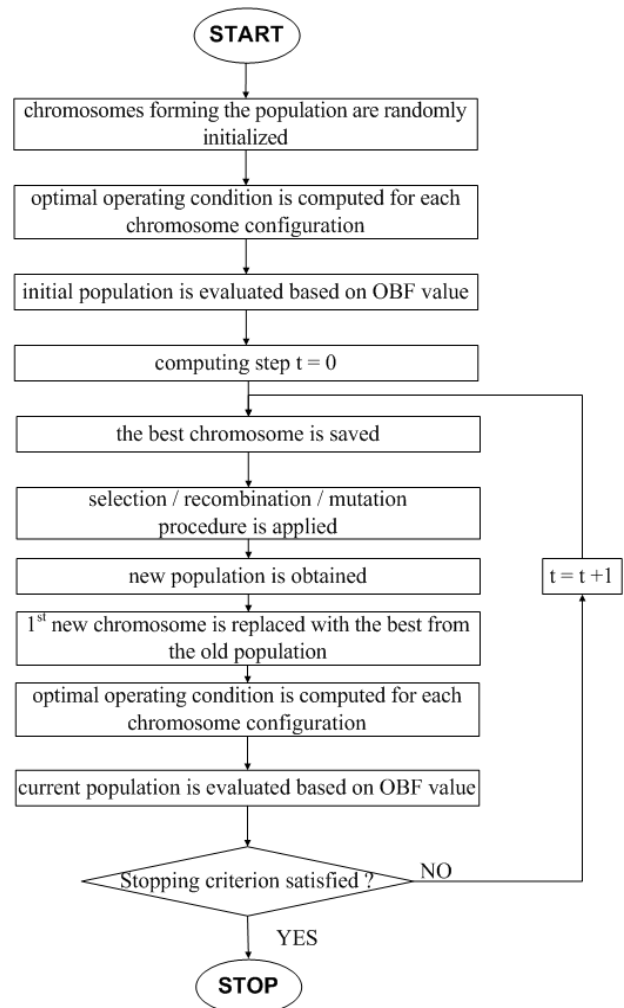


Fig. 4. GA based TNEP flowchart

The OBF includes the same components like the previous approach.

4. CASE STUDY – GA APPROACH

IEEE 24 RTS (Reliability Test System) comprises 24 buses (11 PV buses and 13 PQ buses), 33 overhead lines and 5 autotransformers (Fig. 5).

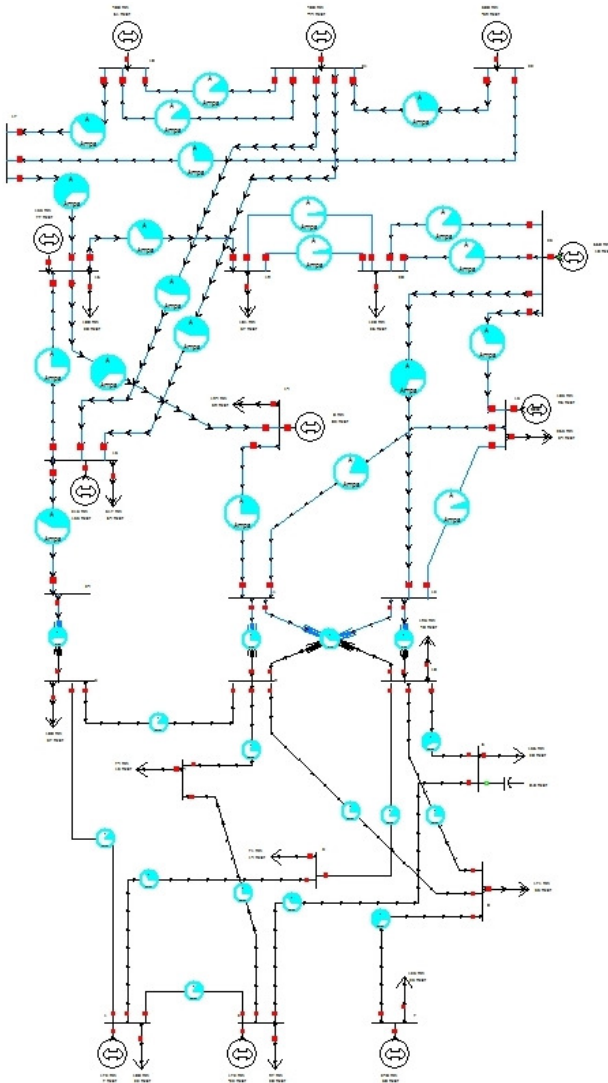


Fig. 5. IEEE 24 RTS one-line diagram

For the base case voltage values the following limits have been considered:

- p.u. voltage values are ranging between (0.95-1.10) in case of 110 kV and 220 kV voltage;
- values are situated between (0.95-1.15), in case of terminal voltage PV buses.

The consumed power is 2850 MW the generated power is 2897.4 MW, leading to 47.4 MW real power losses.

4.1. IEEE 24 RTS Maximum Expansion System

The transmission network expansion is performed for 15 years time period, using the last year power consumption forecasted values. The generated power corresponding to the end of the analyzed time period is known. For the associated power system, 5700 MW total real consumed power has been considered. The power generating units have been extended, including other 11 units. The following

elements are included within the network expansion candidate list:

- 2nd 230 / 138 kV autotransformer between buses 11 and 10, 12 and 9, 24 and 3, 12 and 10, 11 and 9, 16 and 17;
- 2nd circuit in case of 138 kV OHLs between buses: 1-2, 2-6, 3-9, 1-3, 5-10, 6-10, 7-8, 8-9, 8-10, 1-5, 4-9, 2-4;
- 2nd circuit in case of 230 kV OHLs between buses: 21-22, 19-20, 14-11, 13-23, 14-16, 15-16, 15-24, 16-17, 16-19, 17-18, 17-22, 19-20, 13-11;
- 3rd and 4th circuits in case of 230 kV OHLs between buses: 20-23, 12-13, 15-21, 18-21.

The maximum power system expansion one-line diagram is presented in Fig. 6.

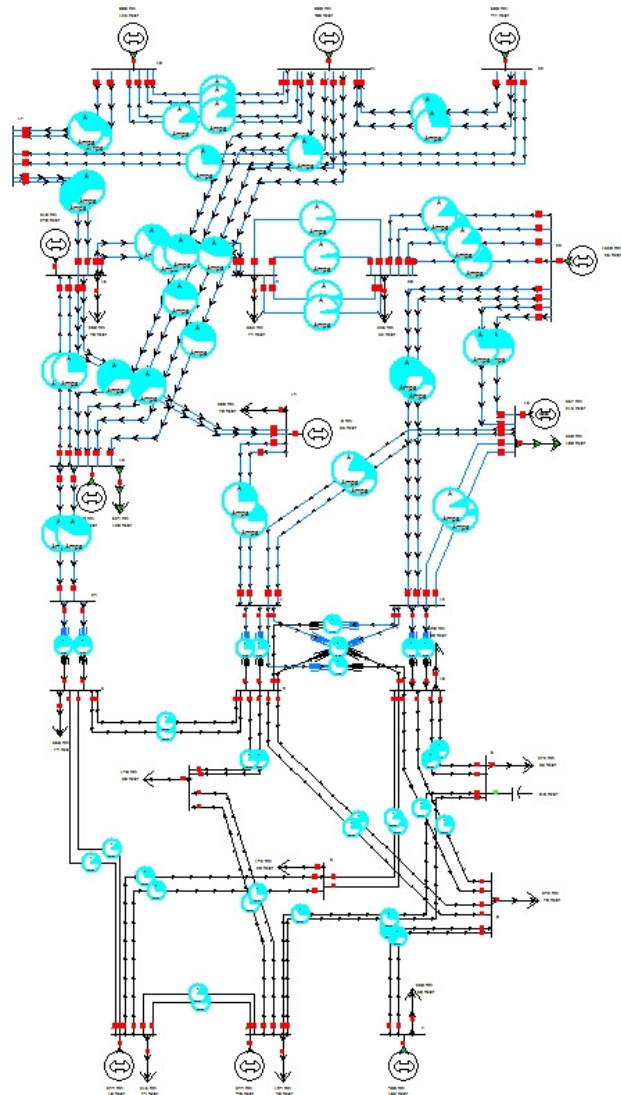


Fig. 6. IEEE 24 RTS maximum expansion one-line diagram

4.2. IEEE 24 RTS optimal power system expansion solution

Optimal IEEE 24 RTS test power system expansion has been performed using the GA OPF & TNEP software tool. The solution has been provided after 20 computing steps.

The expansion optimal solution is characterized by the following elements:

- 24 buses – 11 PV buses and 13 PQ buses;
- 60 network elements – 50 OHL and 10 transformers (autotransformers).

The IEEE 24 RTS test power system optimal expansion solution includes (compared to the base operating condition):

- 2nd 230 / 138 kV autotransformer between buses 11 and 10, 12 and 9, 24 and 3, 12 and 10, 11 and 9;
- 2nd circuit in case of 138 kV OHLs between buses: 1-5, 2-4, 2-6, 7-8, 8-10;
- 2nd circuit in case of 230 kV OHLs between buses: 12-23, 13-11, 14-16, 15-24, 16-17, 16-19, 17-18;
- 3rd circuit in case of 230 kV OHLs between buses: 15-21, 19-20, 20-23;
- 4th circuits in case of 230 kV OHLs between buses: 15-21, 19-20.

The real and reactive generated power and bus voltage values are presented within Figs. 7, 8 and 9. The base operating condition, the optimal maximum expansion system and the optimal expansion solution values are provided within these figures.

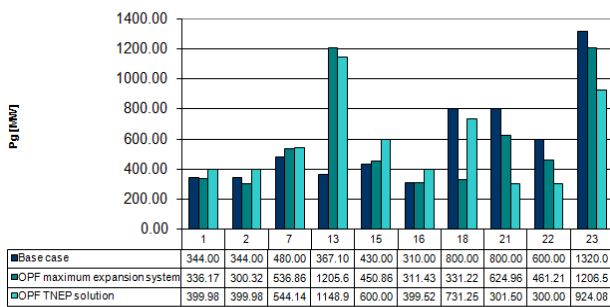


Fig. 7. Real generated power

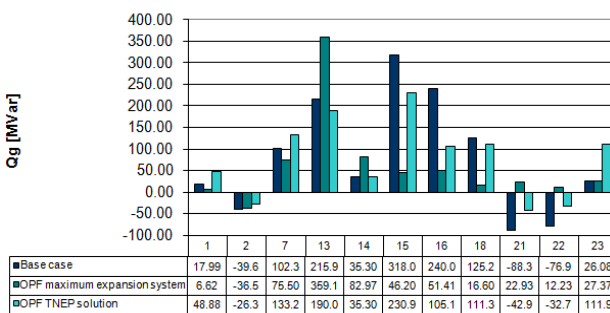


Fig. 8. Reactive generated power

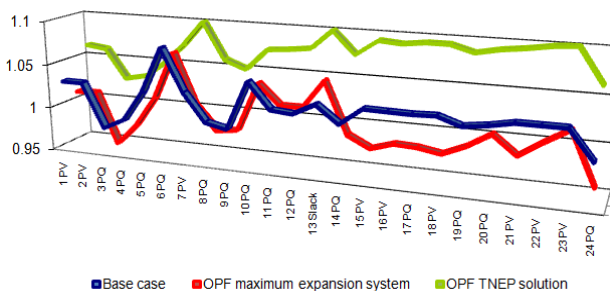


Fig. 9. Power system bus voltage values [p.u.]

The voltage values are greater within the OPF TNEP solution compared to the base case.

5. CASE STUDY – PSO APPROACH

The optimal TNEP problem is solved for the same power system but the PSO approach is used.

5.1. IEEE 24 RTS Maximum Expansion System

It is the same as the one presented in section 4.1.

5.2. IEEE 24 RTS optimal power system expansion solution – PSO approach

The following elements have been selected as part of the solution according to the PSO approach:

- 2nd 230 / 138 kV autotransformer between buses 11 and 10, 12 and 9, 24 and 3, 12 and 10, 11 and 9, 16 and 17;
- 2nd circuit in case of 138 kV OHLs between buses: 1-2, 2-6, 6-10, 7-8, 8-10, 1-5, 4-9, 2-4;
- 2nd circuit in case of 230 kV OHLs between buses: 21-22, 19-20, 13-11, 14-16, 15-16, 15-24, 16-17, 16-19, 17-18;
- 3rd circuit in case of 230 kV OHLs between buses: 20-23, 12-13, 15-21;
- 4th circuits in case of 230 kV OHLs between buses: 15-21, 20-23, 12-23.

Optimal IEEE 24 RTS test power system expansion has been performed using the GA OPF & TNEP software tool. The solution has been provided after 13 computing steps.

The expansion optimal solution is characterized by the following elements:

- 24 buses – 11 PV buses and 13 PQ buses;
- 67 network elements – 56 OHL and 11 transformers (autotransformers).

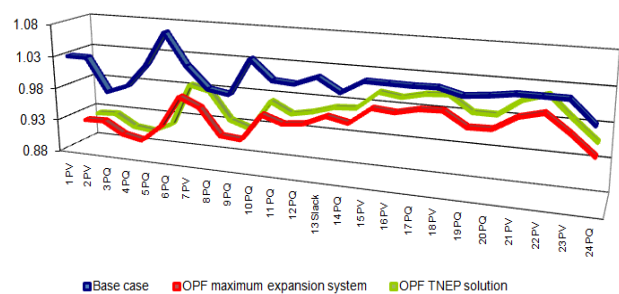


Fig. 10. Power system bus voltage values [p.u.]

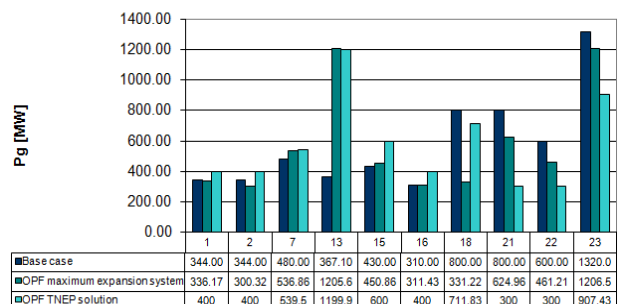


Fig. 11. Real generated power

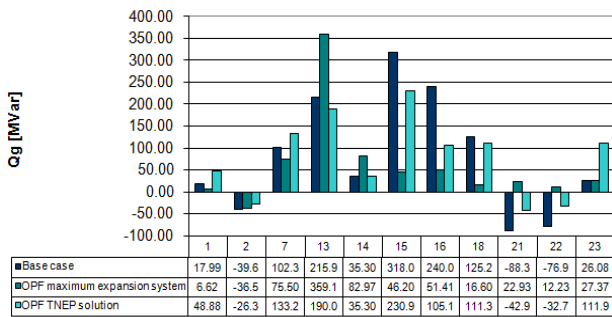


Fig. 12. Reactive generated power

The TNEP evolution algorithm is presented in Fig. 13.

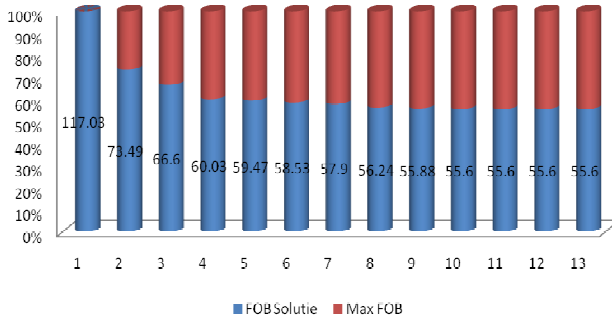


Fig. 13. TNEP OBF value evolution

The ratio (in p.u.) between OBF value corresponding to the TNEP algorithm and the one corresponding to the maximum expansion scenario is represented.

Due to the power systems dimension (buses, number of variables) and large candidate list for power systems expansion, an improvement of the solution is highlighted along the entire OPF process.

According to the results, the computing time increases in case of GA approach. Another difference is represented by the number of settings that are influencing the algorithm evolution. A greater number of parameters are necessary to be set in case of GA (compared to PSO): selection type, crossover, mutation rate. In case of PSO approach the particles' velocity and *gBest* value are influencing the convergence.

The number of power system buses is the same for the optimal TNEP solution identified applying both approaches. But, the transmission network elements selected from the candidate list is different. Additionally, six OHLs and one (auto)transformer have been selected from the candidate list as being part of the TNEP solution in case of PSO approach.

6. CONCLUSION

In case of PSO based algorithms, the potential solutions (particles) are associated with a random velocity, spreading through the problem space by following the best particles (having as a goal to improve them). The particles are able to evolve towards the global optimum having random velocities (based on their memory mechanism).

The PSO and GA based approach in comparison with classic methods avoids the complex mathematical

computations. It is more easily to be implemented within a software tool. It is characterized only by arithmetic relations; not algebraic ones (jacobian, matrix processing, derivatives implementation and computing, etc.). Also, if these algorithms are correctly implemented the computing time decreases.

Comparing both artificial intelligence techniques the GA approach is slower than the PSO approach. The number of parameters that have to be set is greater in case of the GA, than the PSO.

In case of the GA approach a different mutation method with an adaptive step size has been used, having as a goal to accelerate the convergence.

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REFERENCES

- [1] Garver, L.L. –Transmission network estimation using linear programming, IEEE Transactions on Power Apparatus and Systems, vol.89, nr.7, 1970, pp. 1688-1697
- [2] Villasana, R., Garver, L.L., Salon, S.J. – Transmission network planning using linear programming, IEEE Transactions on Power Apparatus and Systems, vol.104, nr. 2, 1985, pp. 349-356
- [3] Hashimoto, S.H.M., Romero, R., Mantovani, J.R.S., Efficient linear programming algorithm for the transmission network expansion planning problem, IEE Proceedings, Generation, Transmission and Distribution, vol.150, nr.5, 2001, pp. 536-542
- [4] Alguacil, N., Motto, A.L., Conejo, A.J. – Transmission expansion planning: A mixed-integer LP approach, IEEE Transactions on Power Systems, vol. 18, nr. 3, 2003, pp. 1070-1077
- [5] Bustamante-Cedeño, E., Arora, S. – Multi-step simultaneous changes constructive heuristic algorithm for transmission network expansion planning, Electric Power Systems Research, vol.79, nr.4, 2009, pp. 586-594
- [6] Hu, Z., Li, F. – Network expansion planning considering N-1 security criterion by iterative mixed-integer programming approach, IEEE Power and Energy Society General Meeting, 2010, pp. 1-6,
- [7] Haffner, S., Monticelli, A., Garcia, A., Mantovani, J., Romero, R. – Branch and bound algorithm for transmission system expansion planning using a transportation model, IEE Proceedings, Generation, Transmission and Distribution, vol.147, nr.3, 2000, pp. 149-156
- [8] Kennedy, J., Eberhart, R.C. – Particle swarm optimization, Proceedings of the IEEE International Conference on Neural Networks, Australia, 1995, pp. 1942-1948
- [9] Jin, Y.X., Cheng, H.Z., Yan, J.Y., Zhang, L. – New discrete method for particle swarm optimization and its application in transmission network expansion planning, Electric Power Systems Research, Elsevier, vol.77, nr.3, 2007, pp. 227-233

- [10] Shayeghi, H., Mahdavi, M., Kazemi, A. – Discrete particle swarm optimization algorithm used for TNEP considering network adequacy restriction, *International Journal of Electrical and Electronics Engineering*, vol.3, nr.1, 2009, pp. 8-15
- [11] Verma, A., Panigrahi, B.K., Bijwe, P.R. – Transmission network expansion planning with adaptive particle swarm optimization, *World Congress on Nature & Biologically Inspired Computing NaBIC*, Coimbatore, India, 2009, pp. 1099-1104
- [12] Rocha, da M.C., Saraiva, J.T. – Discrete evolutionary particle swarm optimization for multiyear transmission expansion planning, *Proceedings of the 17th Power Systems Computation Conference PSCC*, Stockholm, Sweden, 2011, pp. 1-8
- [13] Sum-Im, T., A novel differential evolution algorithmic approach to transmission expansion planning, PhD Thesis, Department of Electronic and Computer Engineering, Brunel University, Uxbridge, UK, 2009
- [14] Qiu, X., Zhang, Z., Wei, Q., An improved differential evolution algorithm for transmission network planning, *Proceedings of the 4th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT)*, 2011, pp. 1246-1249
- [15] Silva, E.L., Gil, H.A., Areiza, J.M., Transmission network expansion planning under an improved genetic algorithm, *IEEE Transactions on Power Systems*, vol.15, nr.3, 2000, pp. 1168-1175