COST EFFECTIVE COMPARISON OF PSO & GA FOR THE ELECTRIC TRANSMISSION NETWORK EXPANSION PLANNING PROBLEM

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ABSTRACT

The problem of choosing an optimal transmission network expansion policy is an extremely complex problem that has not yet been satisfactorily solved. In the last years, several techniques have been proposed to solve transmission expansion problem. In particular, metaheuristic techniques have been successful in tackling power systems related problems, and constitutes a serious option when one has to solve complex optimization. The main objective of the proposed problem is to minimize investment cost by finding the location, installation of new transmission lines required to ensure that the power system meets the forecasted demand in the most economic and reliable way. In this paper, both Particle swarm Optimization (PSO) & Genetic Algorithm (GA) is applied to classical dc model for obtaining optimal plan. The proposed algorithms have been successfully applied to Garver's 6-bus and IEEE 14-bus test system and their performance and results has been compared with each other. The comparison results testify to the feasibility and efficiency of the developed algorithm in solving the transmission expansion planning problem.

Keywords: Genetic Algorithm, Metaheuristic, Optimal, Particle Swarm Optimization, STNEP.

I. INTRODUCTION

Transmission expansion planning (TEP) is one of the important decision-making activities in electric utilities. The TEP problem consists of determining all the changes needed in the transmission system infrastructure, i.e. additions, modifications and/or replacements of obsolete transmission facilities, in order to allow the balance between the projected demand and the power supply, at minimum investment and operational costs. However, cost effective transmission expansion planning becomes one of the major challenges in power system optimization due to the nature of the problem that is complex, large-scale, difficult, and nonlinear and generally, can be classified as static or dynamic [1]. There are several methodologies proposed in the specialized literature to solve the Transmission network expansion planning (TNEP) problem. Initially, Garver[2] proposes a linear power flow estimation method to efficiently determine a preliminary network that can be used to determine the optimal network. In constructive heuristic algorithms [3]–[5] have been used to solve the TNEP problem. Mathematical models based on classical optimization techniques, such the Benders' decomposition [6]–[8] and branch and bound methods [9], [10], have also been used to solve the TNEP problem. Intelligent metaheuristic algorithms such as (1) simulated annealing, (2) tabu search, (3) harmony search algorithm and (4) genetic algorithms, have been proposed in [11]–[15], respectively, to solve TNEP problem.

Classical methods demand large computing time due to the dimension challenge present in the transmission planning problem. The use of metaheuristic techniques has been very attractive since they are able to find good feasible solutions, moderate computational effort depending on the size of the system and the technique used to solve the problem. Nowadays, novel meta-heuristic techniques like PSO and GA have been successful in tackling power systems related problems. The theory of GA can be found in [16]. The strength of GA's is that they are free from limitations about the search space, and they are very flexible in the choice of an objective function and can work on very large and complex spaces. Compared with other techniques, PSO concept is simple, and its superiority has been proven in many different application areas [17]. In this paper, the transmission network planning is first formulated as a mixed integer, non-linear programming problem using DC model and then solved with the application of a genetic algorithm and PSO. The performances of both algorithms are tested on Garver's 6-bus system and IEEE 14-bus test system. This paper focus on the comparison and performance of the two algorithms on basis of optimal network expansion and minimum investment cost. Including introductory part Paper is divided into following sections: Section 2. details the mathematical formulation of the TEP. Section 3. gives the overview of PSO and GA techniques with their implementation to formulated TEP problem. Finally, Section 4 includes two Case Studies based on the Garver's system and on the IEEE 14 bus test system and Section V presents the most relevant conclusions.

II. MATHEMATICAL FORMULATION

Normally, the TEP problem can be formulated by using a mathematical model called the DC power flow model. It is a nonlinear mixed-integer problem with high complexity, especially for large-scale realistic transmission networks. In this paper, the classical DC power flow model is applied for static TEP [18] and the objective function is formulated as follows:

$$\min S = \sum_{ij \in \Omega} c_{ij} \qquad (1)$$

where , and represent, respectively, investment cost of the transmission, circuit cost, which is a candidate for addition to the branch i–j and the number of circuits added to the branch i–j. Here Ω is the set of all candidate branches for expansion. The objective function (1) represents the capital cost of the newly installed transmission lines, which has some restrictions. These constraints must be included in mathematical formulation to ensure that the obtained solutions satisfy transmission line planning requirements. These constraints can be formulated in the following (2) – (7).

2.1 DC Power Flow Node Balance Constraint

The conservation of power at each node is represented by this linear inequality constraint:

$$g = d + i \qquad (2)$$

Where , d and B are respectively, the real power generation vector in the existing power plants, the real load demand vector in all network nodes and the susceptance matrix of the existing and added lines in the network. Here is the bus voltage phase angle vector.

2.2 Power Flow Limit on Transmission Lines Constraint

In order to limit the power flow for each path, the inequality constraint is as follows:

$$f_{ij} \leq \left(n_{ij}^{0} + n_{ij}\right) f_{ij}^{m} \qquad (3)$$

In the DC power flow model, each element of the branch power flow in constraint (3) can be calculated by using (4):

$$f_{ij} = \frac{(n_{ij}^{0}+nij)}{x_{ij}} * (\theta_i - \theta \tag{4}$$

Where , f_{ij}^{m}, r and r represent, respectively, the total branch power flow in the branch i–j, the maximum power flow in the branch i–j, the number of circuits which is to be added to the i-j branch, the number of circuits in the original base system and reactance in the i-j branch. Here and are the voltage phase angle of the terminal at i_{th} and j_{th} bus respectively.

2.3 Power Generation Limit Constraint

In this paper, resizing of the generation is considered in the TEP problem. Therefore the limit of power generation has to be included in the TEP constraints and is represented as follows:

$$g_{imin} \leq g_i \leq g_{im} \tag{5}$$

where g_i, g_{in} and g_{im} are the real power generation at node i.e. the lower and upper real power generation limit at node i respectively.

2.4 Right-of-Way Constraint

It is significant for an accurate TEP that planners need to know the exact location and capacity of the newly required circuits. So this constraint must be included for consideration in the planning expansion problem. In Mathematical form, this constraint defines the new circuit location and the maximum number of circuits that can be installed in a specified location. It can be represented as follows:

$$0 \leq n_{ij} \leq n_{ijm} \tag{6}$$

where and n_{ijm} represent the total integer number of circuits which is to be added to the i–j branch and the maximum number of circuits that can be added to the i–j branch respectively.

2.5 Bus Voltage Phase Angle Limit Constraint

The bus voltage magnitude is not a factor in this analysis since a DC power flow model is used. The voltage phase angle is included as a TEP constraint and the calculated phase angle should be less than the predefined maximum phase angle:

$$\theta_{ijcal} \leq \theta_{ijm} \tag{7}$$

2.6 Fitness Function

Fitness Function for the TEP problem is as follows:

$$F = \frac{1}{S+pf} \tag{8}$$

Where,

$$C = \sum_{i=1}^{k} V_i$$

is number of constraints. is violation of i_{th} constraint in percentage. is the penalty factor.

III. OVERVIEW OF PSO AND GA ALGORITHM

Particle swarm optimization algorithm, which is tailored for optimizing difficult numerical functions and is based on the metaphor of human social interaction, is capable of mimicking the ability of human societies to process knowledge [19]. The main roots of PSO are artificial life and evolutionary computation. In a PSO system, each particle flies through the multidimensional search space, adjusts its position in search space according to its own experience and that of neighbor particles [20]. Its key concept is that the potential solutions are flown through hyperspace and are accelerated towards better or more optimum solutions. In PSO, the position of each agent is represented in X–Y plane with position (,), $_x$ (velocity along X-axis), and $_y$ (velocity along Y-axis). Modification of the agent position is realized by the position and velocity information. Bird blocking optimizes a certain objective function. Each agent knows its best value so far, called 'Pbest', which contains the information on position and velocities. This information is the analogy of personal experience of each agent. Moreover, each agent knows the best value so far, in the group 'Gbest' among Pbest .This information is the analogy of knowledge, how the other neighboring agent shave performed. Each agent tries to modify its position by considering current positions (,), current velocities ($_x$,), the individual intelligence (Pbest), and the group intelligence (Gbest).

The following equations are utilized, in computing the position and velocities, in the X–Y plane:

$$v_{ik+1} = \omega \times v_{ik} + C_1 \times rand_1 \times (P_{besti} - s_{ik}) + C_2 \times rand_2 \times (G_{best} - s \qquad (9)$$

$$s_{ik+1} = s_{ik} + v_{ik} \qquad (10)$$

where v_{ik} is the velocity of $(k+1)_{th}$ iteration of i_{th} individual, $\imath$ is the velocity of k_{th} iteration of i_{th} individual, ω is the inertial weight, $_i$, are the positive constants, having values [0, 2], ran, ran are the random numbers selected between 0 and 1, P_{besti} is the best position of the i_{th} individual, G_{b} is the best position among the individual (group best) and s is the position of i_{th} individual at k_{th} iteration.

The velocity of each agent is modified according to (9) and the position is modified according to (10). The weighting factor is modified using (11) to enable quick convergence:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{iter_{max}} \times it \qquad (11)$$

ω_m is the initial weight, ω_n is the final weight, it is the current iteration number and $iter_m$ is the maximum iteration number.

3.1 Implementation of PSO to TEP Problem

This section provides application of PSO algorithm to solve STNEP (Static Transmission Network expansion Planning) problem as follows:

Step 1: Define input parameters with all constraints for the swarm.

Step 2: Initialize the position (Line to be added) for all particles randomly with satisfying all the constraints.

Step 3: Calculate the fitness value (cost) of each particle in the swarm using equation (8).

Step 4: Compare the fitness value of each particle found in step 4 with Pbest of each particle. Update Pbest of a particle if its fitness is greater than its Pbest.

Step 5: Update Gbest if any particle has greater fitness than fitness of current Gbest.

Step 6: Update the inertia weight 'ω' by using (11).

Step 7: Modify the velocity of each particle by (9).

Step 8: Modify the position of each particle by using (10) with the updated velocity in step 7.

Step 9: Check iteration counter, if it reaches its maximum then go to step 10, else go to step 3.

Step 10: The swarm that generates the latest Gbest in step 5 is the optimal value.

3.2 Genetic Algorithm

The GA is a methodology that solves combinatorial optimization problems with excellent solutions and low computational cost, especially for medium and large problems. It is based on the principle of natural selection that occurs in nature, in which more adapted individuals have more chances to survive and transmit their genetic code to their offspring. The genetic algorithm generally includes the three fundamental genetic operators of reproduction, crossover and mutation. These operators conduct the chromosomes toward better fitness. Crossover is the main genetic operator that allows information to be exchanged between individuals in the population.

Mutation operator is to prevent the permanent loss of any particular bit values (genes), as without mutation there is no possibility of re-introducing a bit value that is missing from the population.

3.3 Implementation of GA to TEP Problem

The application of GA to solve STNEP problem is explained as follows:

Step 1: Specify input parameters with all constraints to generate chromosomes. Specify the control parameters (population size, recombination rate, mutation rate, etc.).

Step 2: Specify genetic characteristics of the algorithm: codification type, initial population assembly, selection type, and so forth.

Step 3: Initialize population (Line to be added) randomly satisfying all constraints and evaluate it to become the current population.

Step 4: Assign fitness value to the entire population corresponding to the objective function.

Step 5: Implement a selection to choose only two generating solutions. Selection operator in this analysis used is tournament selection.

Step 6: Implement the recombination and preserve an offspring.

Step 7: Implement the mutation of the preserved offspring.

Step 8: Evaluate fitness of final population consisting of chromosomes of best solutions.

Step 9: Check generation count, if it reaches its maximum then go to step 10, else go to step 5.

Step 10: Final population consisting of chromosomes with best solutions is the optimal value.

Table 1 and Table 2 gives the details of the value of parameters used in PSO and GA for both test system.

Table 1: Parameter values of PSO

Parameter Value	Garver's 6 bus system	IEEE 14 bus system
Number of particles	50	100
Problem dimension	8	20
Number of iterations	70	70
C_1	2	2
C_2	2	2
ω_{max}	0.9	0.9
ω_{min}	0.4	0.4

Table 2: Parameter values of GA

Parameter Value	Garver's 6 bus system	IEEE 14 bus system
Population size	50	100
Problem dimension	8	20
Number of iterations	70	70
Crossover rate	0.8	0.8
Mutation rate	0.1	0.1
Tournament size	2	2

IV. RESULT AND DISCUSSION

STNEP problem is solved for two test cases by applying proposed algorithms and is implemented in Matlab 7.9. To validate the performance of both algorithms the results obtained are compared with each other. The best results for optimal investment cost, C_{inv} is in US $ obtained by proposed algorithms after 20 trial runs and 100 iterations. Penalty factor in both the test systems is taken as 2.

4.1 Garver's 6 bus system

Garver's system is used as a first test system in this paper which comprises of 6 buses and 8 branches. All the necessary system data can be found in [21]. Fig.1 and Fig. 2 shows cost convergence characteristic of GA and PSO for this system.

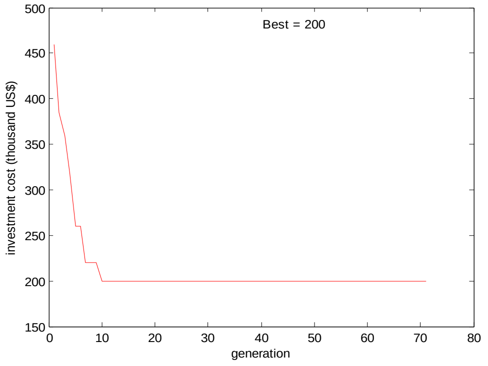

Fig. 1 Cost convergence characteristic of GA.

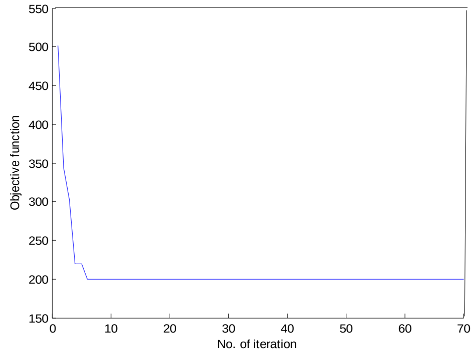

Fig. 2 Cost convergence characteristic of PSO

4.2 IEEE 14 bus system

The second test system is IEEE 14-bus system consisting of 14 buses and 20 existing branches. The system data is available in [21]. Fig 3 and Fig. 4 shows the comparison of cost convergence of GA and PSO for IEEE 14 Bus system. TABLE 3 gives the comparison of both the algorithms in terms of best cost for the optimal plan and Elapsed time for processing of both algorithms. Finally, TABLE 4 emphasis on the optimal expansion plan for both test system using GA and PSO.

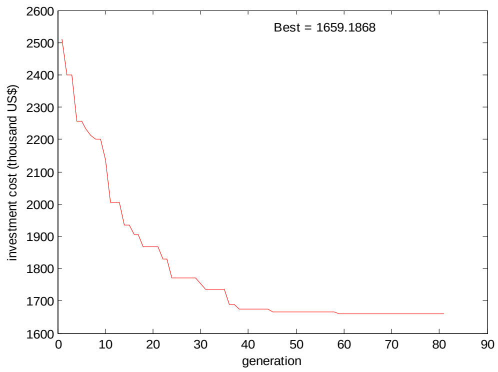

Fig. 3 Cost convergence characteristic of GA

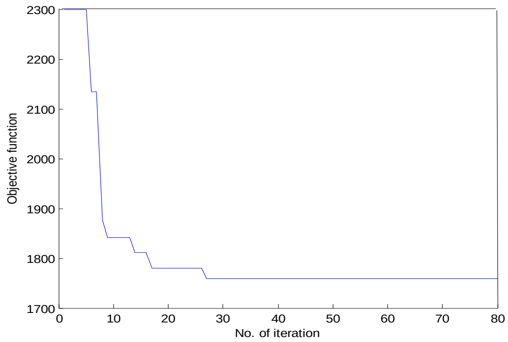

Fig. 4 Cost convergence characteristic of PSO

Table 3

Comparison of PSO and GA

COMPARSION BASIS	**GARVER'S 6 BUS SYSTEM**		**IEEE 14 BUS SYSTEM**	
	PSO	**GA**	**PSO**	**GA**
BEST COST,US $	200	200	1637.3	1659.2
CPU TIME IN SECONDS	1.660	4.667	11.831	13.190

Table 4

Optimal Expansion Plan for Garver's 6 Bus System and IEEE 14 Bus System

Gaver's 6 Bus system	PSO	$n_{2-6} = 4, n_{3-5} = 1, n_{4-6} = 2$
	GA	$n_{2-6} = 4, n_{3-5} = 1, n_{4-6} = 2$
IEEE 14 Bus system	PSO	$n_{3-4} = 1, n_{4-7} = 1, n_{6-11} = 4,\ n_{6-12} = 1, n_{6-13} = 4,\ n_{7-8} = 1, n_{7-9} = 4, n_{9-10} = 1,\ n_{10-11} = 1, n_{13-14} = 4$,
	GA	$n_{2-3} = 4, n_{3-4} = 1, n_{4-7} = 1,\ n_{5-6} = 4, n_{6-11} = 1, n_{6-12} = 1,\ n_{6-13} = 4,, n_{7-9} = 2, n_{9-10} = 1,$ $, n_{10-11} = 1, n_{13-14} = 4$

V. CONCLUSION

An optimized plan is acquired with lower investment cost with equality and inequality constraints with both the algorithms. Also, by comparing the results of the proposed methods, it can be concluded that precision and convergence speed of PSO is more than GA. Computational time required by PSO is very less as compared to GA for both test system. Experimental results show that For GA it is 4.667 for Garver's six bus system and 13.190 for IEEE 14 bus system, whereas for PSO it is very less i.e. 1.660 for 6 bus system and 11.831 for 14 bus system. Similarly best cost in US $ for Garver's 6 bus system for both GA and PSO is same i.e. 200. But for IEEE 14 bus system, best cost in US $, for PSO is comparatively less i.e. 1637.3 US $ than GA i.e. 1.659.2 US $. Additional line requirement is less for PSO than GA. PSO is very simple, flexible, easy to implement and it needs fewer parameters than GA. For Garver's six bus system, optimal expansion plan is same for both algorithms. But for IEEE 14 bus system, expansion plan for PSO is more optimal than GA. Based on experimentation results, it can be concluded that PSO has better results than GA.

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