TRANSMISSION NETWORK EXPANSION PLANNING USING GENETIC ALGORITHMS

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This paper presents a Genetic Algorithm (GA) approach to the transmission network planning problem in electric power systems (TNEP).

The TNEP problem seeks to determine when and where new circuits are needed and should be installed to serve, in an optimal way, the growing electric energy market, subject to a set of electrical, economic, financial, social and environmental constraints. This problem has a dynamic nature, since the requirements of transmission facilities (lines or power transformers) should be defined over time within a given horizon.

On the other hand, the transmission expansion planning can also be done in a "static" way, where the planning is performed for the horizon year, with the goal of determining the reinforcement needed for this specific year only (STNEP). This paper deals with the static approach, the dynamic one being a more complex topic, beyond the scope of this research.

In spite of being simpler than the dynamic planning, the static planning is still very complex, and research has been stimulated worldwide to develop computational tools to facilitate the solving of this task. This is a very large – scaled, mixed integer mathematical programming problem that frequently presents many local, sub – optimal solutions, and for which the number of possible solutions grows exponentially with the network size. The objective of this problem is to determine the most economical planning scheme(s) to meet the load demand in the horizon year subject to the security or reliability constraints.

The STNEP problem and its mathematical modelling are briefly described. The proposed Genetic Algorithm is applied to a reference electric system for which the solution is known and its performance is compared against classical solution methods.

Keywords: transmission network planning, genetic algorithms, static planning.

1. Introduction

The transmission expansion planning of electrical power systems is a complex task, involving the determination of where, when and which facilities must be built to guarantee an economic and reliable supply of the predicted load up to the horizon year.

The planner performs his studies, trying to fulfill the aims mentioned above, considering the following initial data: the topology of the existing

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electrical network, a set of new feasible generating plants, the predicted load for each bus of the system, the operating limits of all equipment which forms the electrical system and the costs of both investment and operation. Afterwards, the planner has to determine the minimum cost plan, taking into account the available initial data and some reliability criteria.

In addition to this, the planner uses his own knowledge, represented by planning heuristics, which he developed as a result of many years of expertise and are associated with his ‘feeling’ of the system under study.

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As the computational burden of obtaining the minimum cost plan is very high, modem techniques have been proposed to decrease the CPU time, or even for searching sub-optimum solutions.

The expansion of transmission systems is generally modelled mathematically using the DC model, which involves mixed integer nonlinear programming. However, its application is problematic for large systems. Various modifications have thus been developed, including relaxed versions of the DC power flow model, such as the transportation model, the hybrid model and the disjunctive model.

This paper presents a development of a genetic algorithm and its application to the static transmission network expansion planning (STEP) problem. A relevant model of fitness function has been constructed and an encoding method is suggested in order to obtain the optimal results. An IEEE 6-bus system is used to validate the proposed method.

2. Problem Formulation

The general trend in TNEP research is the using of several standardized models of the problem. [1]. This paper uses a simplified DC model, presented in the following, taking into consideration the three assumptions:

- Branch resistances R and charging capacitances B_c are negligible (i.e. the branches are lossless);
- All bus voltage magnitudes are close to 1 p.u.;
- Voltage angle differences are small enough that $\sin\theta_{i,j} = \theta_{i,j}$.

The Objective Function for the STEP problem is defined as the sum of the investment costs of new circuits and the penalty for load shedding. The GA implemented in this study uses a simplified version of this objective function, computed only as the investment cost for the new lines. Therefore, the objective function for this study can be put as:

$$\min[z] = \sum_{i,j \in A} c_{i,j} \cdot n_{i,j} \,, \tag{1}$$

where *A* is the set of right-of-ways (undirected arcs in the associated graph), $c_{i,j}$ is the cost of the candidate circuit i-j and $n_{i,j}$ is the number of circuits to be added to the right-of-way i-j.

The proposed approach is to compute a differentiated cost for an existing line and a non-existing one, as building a new line from scratch is much more expensive than adding a new circuit to an existing line.

Moreover, it is hard to asses from the beginning the cost of each line or circuit. This approach uses a cost per kilometre ($cpk_{i,j}$) and the distances between the network nodes ($l_{i,j}$), which are more easily obtained in practice.

Under these considerations, the objective function for the STEP is defined as:

$$\min[z] = \sum_{i,j \in A} n_{i,j} \cdot l_{i,j} \cdot cpk_{i,j} \,, \tag{2}$$

The above objective function represents the investment cost for the new lines, but some *constraints* must be satisfied by the solutions, in order to ensure the feasibility and stability of the reinforced network. Each planner uses his own set of constraints, and the ones used in this study are as follows:

$$S \cdot f + g = d \,, \tag{3}$$

$$\left| f_{i,j} \right| \le (n_{i,j} + n_{i,j}^{0}) \cdot f_{i,j}^{\max} \,, \tag{4}$$

$$0 \le g_i \le g_i^{\max} \,, \tag{5}$$

$$0 \le n_{i,j} \le n_{i,j}^{\max} \,, \tag{6}$$

where

S - the node-branch incidence matrix of the system;

f - a vector with elements f_{ij};

$f_{i,j}$ - the power flow;

$n_{i,j}$ - the number of circuits added to the right-of-way *i-j*;

$n_{i,j}{}^{0}$ - the number of circuits in the original base system;

g - a vector with elements g_k (generation in bus k) with a maximum value of $g_i^{\max}$;

d – the demand vector;

$f_{i,j}^{\max}$ - the corresponding maximum power flow in the right-of-way *i-j;*

$n_{i,j}^{\max}$ - the maximum number of circuits that can be added in the right-of-way *i-j*.

3. Problem Modelling With Genetic Algorithm

Genetic Algorithms are a way of solving problems by mimicking the mechanism of evolution as found in natural processes. They use the same principles of selection, recombination and mutation to evolve a set of solutions towards a "best" one and follow the general algorithm [2]:

```
t := 0;
Compute initial population B0 = (b1,0 . . ., bm,0);
WHILE stopping condition not fulfilled DO
BEGIN
FOR i := 1 TO m DO
select an individual bi,t+1 from Bt;
FOR i := 1 TO m − 1 STEP 2 DO
IF Random[0, 1] ≤ pC THEN
cross bi,t+1 with bi+1,t+1;
FOR i := 1 TO m DO
eventually mutate bi,t+1;
t := t + 1
END
```

Before using any of the GA models, the problem must be represented in a suitable format that allows the application of genetic operators. The GAs work by maximizing a single variable, the fitness function. Hence, the objective function and some of the constraints of the TNEP problem must be transformed into some measure of fitness.

Encodings. The first feature that should be defined is the type of representation to be used, so that an individual represents one and only one of the candidate solutions. The proposed encoding method for this problem is assigning one gene for each right-of-way of the power system, that is, for each branch in the associated graph. A chromosome is, therefore, a vector containing all the additions. The alleles (numerical values of the genes) correspond to each branch and are equal to zero if no additions are necessary, or a number from 1 to $n_{i,j}^{\max}$ if new circuits should be installed. The size of an individual (number of genes) is therefore equal to the number of branches in the network (already existing or not).

This representation gives the chromosome a specific meaning for each gene, as shown in Figure 1, for a 4-bus network.

1-2	1-3	1-4	2-3	2-4	3-4
0	**0**	**2**	**0**	**1**	**0**

Figure 1. Chromosome representation for a 4-bus network.

This solution expresses the fact that two new circuits are to be added to line 1-4 and one to the line 2-4.

Fitness Function. This function is responsible for measuring the quality of chromosomes and it is closely related to the objective function. The objective function for TNEP in this paper is computed as the investment costs for the new lines/circuits under the system constraints. The constraints of this particular problem do not explicitly contain the variables (the genes in this case) and therefore the effect of the constraints must be included in the value of the fitness function. The constraints are checked separately and the violations are handled using a penalty function approach. The assessed violations represent the unfeasibility of the current solution and penalty terms are incorporated into the fitness function in order to increase its value for unfeasible individuals (because this is a minimization problem), accordingly to the magnitude of the violations.

The overall fitness function designed during this study is:

$$f(x) = \sum_{i,j \in A} n_{i,j} \cdot l_{i,j} \cdot cpk_{i,j} + \xi \cdot \sum_{i=1}^{nr} bal_i + \zeta \cdot \sum_{k=1}^{n} rate_k \ , \tag{7}$$

where the first term is the objective function and the following are the penalty functions. bal_i is a factor equal to 0 if the power balance constraint at bus i is not violated and 1 otherwise. The sum of these violations represents the total number of buses in the network that do not follow constraint (3) and it is multiplied by a penalty factor meant to increase the fitness function and therefore to discard the unfeasible solution. The last sum in the fitness function represents the total number of violations of constraints (4) and it is also multiplied by a cost factor. The last two sums in this fitness function are a measure of unfeasibility for each candidate solution x.

Selection Methods. The selection methods specify how the genetic algorithm chooses parents for the next generation. In this study, two selection methods were tested. The first method was Roulette Wheel Selection, which chooses parents by simulating a roulette wheel with different sized slots, proportional to the individuals' fitness. The second method tested was Tournament Selection and it proved to work better for the STEP problem. Each parent is chosen as the best individual from a random selection of *k* individuals, where *k* is a preset number.

Crossover Mechanism. The one – point crossover mechanism was tested for the STEP problem in this study, which exchanges the genetic information found after a random position in the two selected parents. The crossover is applied in each successive generation with a certain probability, known as the crossover fraction or rate. A large crossover rate decreases the population diversity, but in the STEP problem a higher exchange of genetic material is needed. The planner has to compromise between these issues and select an optimal crossover rate for each problem at hand.

Mutation Mechanisms. This mechanism is very important from the genetic diversity point of view, and it prevents landing a local, sub-optimum solution. The mutation rate is highly connected with the crossover fraction. Two mutation mechanisms were tested: uniform and adaptive feasible. The adaptive feasible mutation mechanism showed better results for this particular problem.

Initial Population. Genetic Algorithms are theoretically able to find global optimum solutions, but the initial population must contain individuals with good genetic material for the problem at hand. The most common construction method for the initial population is to randomly generate suitable individuals. Several efficient methods for creating the initial population have been reported [3, 4]. This paper uses an initial population randomly generated. The unfeasible solutions are discarded by penalizing the fitness function.

4. Case Study and Results

The applicability of GAs for STEP was tested on Garver's 6-bus system, having 15 candidate branches, a total demand of 760 MW and a maximum number of circuits on a branch equal to 4. The initial topology and network data can be found in [5].

The optimal expansion plans reported in [6-8] have an associate investment cost *z=200,000* USD and involve adding the following lines: $n_{2,6} = 4$, $n_{3,5} = 1$ and $n_{4,6} = 2$.

The proposed GA generated a solution with this investment cost in 9.2 seconds, in average for 10 runs, with a population of 30 individuals and parents selection by tournament with *k=2,* for a crossover rate of 0,8.

The computer program generates multiple scenarios simultaneously at each run. For a number of scenarios to be generated equal to 3 and the above set parameters, the GA program resulted in one optimal scheme and two suboptimal ones, presented in Table 1 and shown in Figure 2(a) and 2(b-c), respectively. The representation of the optimal solution also contains the power flows.

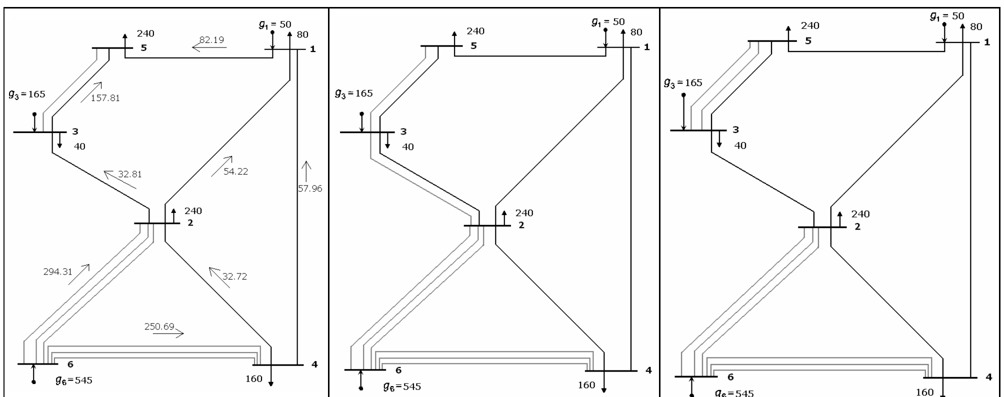
Table 1.

Optimal and suboptimal solutions obtained for Garver's network

No.	Added Circuits															Inv. Cost z	See
	1-2	1-3	1-4	1-5	1-6	2-3	2-4	2-5	2-6	3-4	3-5	3-6	4-5	4-6	5-6	[10^3 USD]	Fig. 2
1	0	0	0	0	0	0	0	0	3	0	1	0	0	3	0	200	a
2	0	0	0	0	0	1	0	0	3	0	1	0	0	3	0	220	b
3	0	0	0	0	0	0	0	0	3	0	2	0	0	3	0	220	c

For space reasons, only a few scenarios are represented, but the number of scenarios generated within this interval of investment costs is much bigger.

The proposed method approaches the environmental issues only from a *Boolean* perspective. The user is asked to input the paths that do not support further expansions, and the program automatically discards of these when encountered within a solution.



a. (z=200)	*b.* (z=220)	*c.* (z=220)

Figure 2. Multiple scenarios for the TNEP, generated by a GA computer program

Figure 3 shows the performance of the GA for one of the runs. The initial population was randomly generated and its fitness is above 2000, which suggests that the fitness has been penalized.

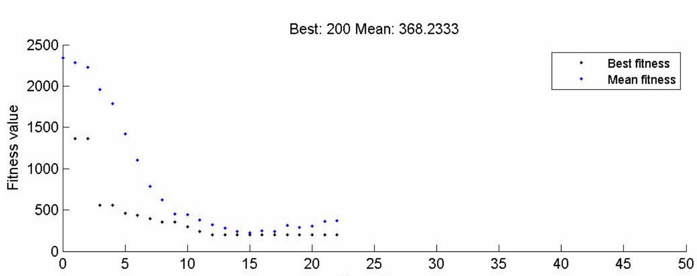


Figure 3. GA run performance

The graph shows a good convergence of the fitness value with the generations. It can be observed that the algorithm could have been stopped even earlier, after about 17-18 generations, as no improvements have been made starting with generation 12. Both the best fitness value and the mean value drop with generations, which shows that GAs are suitable for solving the transmission network expansion planning problem. Even though the maximum number of generations has not been reached, the algorithm stopped because the maximum stall generation number has been encountered.

6. Conclusions

An application of genetic algorithms was presented for finding a transmission network's lowest cost expansion. Results show that the proposed approach is a suitable and promising technique in solving the STEP problem.

The best solution found by GAs and computational time can be improved by tuning the parameters (crossover rate, population size and others).

Because of the flexibility of Genetic Algorithms, further modelling requirements can be included in the fitness function to further improve the transmission design. For example, some of the initial simplifications can be eluded from the design, transforming the problem into a more realistic one.

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