

## Transmission expansion planning based on a hybrid genetic algorithm approach under uncertainty

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**Abstract:** Transmission expansion planning (TEP) is one of the key decisions in power systems. Its impact on the system's operation is excessive and long-lived. The aim of TEP is to determine new transmission lines effectively for a current transmission grid to fulfill the model objectives. However, to obtain a solution, especially under uncertainty, is extremely difficult due to the nonlinear mixed-integer structure of the TEP problem. In this paper, first genetic algorithm (GA) approaches for TEP are reviewed in the literature and then a new hybrid GA with linear modeling is proposed. The proposed GA method has a flexible structure and the effectiveness of the method is assessed on Garver 6-bus, IEEE 24-bus, and South Brazilian test problems in the literature. It is observed that newly proposed hybrid GA shows a rapid convergence on the test problems. Scenarios are then generated for uncertainties such as change in demand, oil prices, environmental issues, precipitation amounts, renewable generation, and production failures. Numerical results demonstrate that test problems are resolved successively under uncertainty conditions with the proposed hybrid algorithm.

**Key words:** Transmission expansion planning, genetic algorithm, linear model, uncertainty

### 1. Introduction

Electricity is a crucial resource due to its social, economic, and strategic aspects. In particular, governments, businesses, and societies cannot operate at full capacity without adequate sources of power, and this is an obstacle to economic growth. Socially, the absence of electricity is a negative factor that directly affects the public welfare [1]. Therefore, electric energy is the result of many systems working together and an indispensable part of our daily life. Electric networks are usually interconnected regional systems. As an activity at one location affects other locations, the system must always be in balance to ensure reliable operation. Electrical energy systems become available with the implementation of four basic operations. These operations are electricity generation, electricity transmission, electricity distribution, and electricity consumption.

Many uncertainties exist in electricity operations. Demand for electricity consumption varies both on the basis of daylight hours and year-on-year. Uncertainties are especially dominant in the production part. Variables such as weather conditions and precipitation rate change the amount of production. In addition, smart grid technologies and increasingly distributed energy sources (wind and solar) can be added to uncertainties. There may also be fires and leaks in the transmission section. Increasing the use of electric vehicles and integration

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with distribution systems are the other issues that include uncertainty [2–4]. As a consequence, uncertainties should be carefully considered when identifying the problem. Given that large-scale electricity storage is not yet economically and technologically feasible, design and configuration of the transmission network should ensure real-time balancing of the electricity demand and supply. From an economic point of view, this balancing should be done with minimum cost from existing power sources. However, from a social point of view, it should be done without disruption [5]. The balance is only possible with very good planning of production, transmission, and consumption. Transmission plans are usually evaluated via ten-year plans and revised as conditions change. Preparing a transmission expansion plan by taking into account load growths and predicted demand has worked over many years. Transmission expansion planning (TEP) generally decides when, where, and how many new lines will be made [6]. When making decisions, the main goal is to balance total supply and demand considering technical, economic, and political constraints. TEP has been investigated by many researchers considering its important role in power systems. TEP problems have been studied from many different perspectives, such as model structure, solutions methods, consideration of reliability, reactive power planning, handling of uncertainty, structure of time period, consideration of environmental issues, and considering distributed generation [7–10].

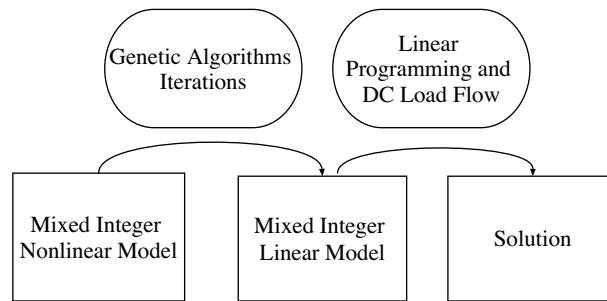
There are two different types of models according to the structure of the electric current model. These are alternating current (AC) models and direct current (DC) models. The AC model is realistic and complete, but complex. It can be formulated using four variables per node (voltage angle, voltage magnitude, and active and reactive power injections). Unlike the DC model, AC models take into account reactive power. Power losses can be included in the AC model. Because the AC model has more variables and parameters than the DC model, it becomes a larger nonlinear mixed-integer structure. The DC model differs from the AC model in three basic assumptions: i) line resistances (active power losses) are negligible, ii) the voltage angle differences are small, and iii) the magnitude of the voltages in the stations is set to 1.0 (flat voltage profile) per unit [11]. It is a common practice that the solution obtained from the DC model should be redefined by taking into account the AC operations. This problem was addressed by considering the AC operations in [12, 13].

Conejo et al. [1] addressed the TEP problem with eight different objectives. These objectives are: i) minimization of cost, ii) minimization of risks, iii) improving reliability and security, iv) considering distributed generation, v) minimization of environmental damages, vi) ensuring a competitive environment for all players, vii) allocating competition among market shareholders, and viii) considering transmission congestion. In particular, economic, reliability, and environmental issues conflict with each other, so it is not possible to improve all objectives at the same time. Use of different objectives together transforms the TEP problem into a multiobjective optimization problem [14].

TEP can be also classified into the following two categories based on planning horizon: static (single stage) and dynamic (multistage). In static planning [15], the decision maker seeks the optimal plan for a single year. In dynamic planning, multiple years have to be considered and planners seek the optimal strategy for the whole planning period. The multistage planning problem is very complex as it considers the planning horizon.

The nonlinear mixed integer structure of TEP makes it very difficult to reach the solution, especially for large types of problems. Studies first started with the linear transformation of the nonlinear problem with some assumptions [15]. Solution methods for TEP can be classified as mathematical optimization model and metaheuristic methods. The mathematical modeling methods are linear programming (LP), nonlinear programming, mixed integer programming, the Benders decomposition algorithm [16, 17], the branch and bound algorithm [18, 19], game theory [20, 21], and dynamic programming [22]. When the complexity and

the size of the problem are increased, many researchers have used heuristic or metaheuristic methods because of the nonlinear nature of the problem. The metaheuristic methods used for TEP problem are ant colony [23], particle swarm optimization [24], fuzzy systems [25], genetic algorithm (GA), simulated annealing [26], tabu search [27], and harmony search [28]. Studies that deal with uncertainty generally involve uncertainty of demand and production possibilities [29–31]. Also, the robust optimization method is generally used for uncertain environments [32–35]. Ruiz and Conejo [35] took into account different sources of uncertainty in their original work. The resulting mixed integer problem was solved efficiently by decomposition using a two-level model and a cutting plane algorithm. According to the stochastic programming models, robust models have two advantages in representing uncertainty [36]. First, there is no need to produce scenarios. Second, robust models typically have less computation time.



**Figure 1.** Hybrid method structure.

This paper deals with the problem of a single-stage TEP problem under uncertainty. For the solution of this challenging problem, a new hybrid GA that includes linear modeling is proposed. With the proposed approach, the nonlinear mixed integer TEP problem is converted to a linear mixed integer problem after the solutions are obtained from the GA, as shown in Figure 1. This hybrid GA and LP structure has been tested for its efficiency. With the help of the flexible structure of the proposed GA model, solutions have been produced by taking into account uncertainty in the system. Even in cases where the demand is unclear in a certain range, solutions have been produced with the help of the GA. The main contributions are listed as follows:

1. An up-to-date literature review focusing specifically on GA approaches in TEP is given.
2. A new hybrid GA approach based on GA and LP is proposed.
3. The efficiency of the proposed approach is analyzed on Garver 6-bus, IEEE 24-bus, and South Brazilian test problems.
4. New cases are created for DC, static, and uncertain models of TEP at the same time.

The remainder of this paper is as follows. Section 2 presents a review of the related TEP works based on GAs. The mathematical model of TEP is given in Section 3. Section 4 describes the structure and properties of the GA approach. The efficiency of the proposed method is tested on test data and the numerical results are given in Section 5 for uncertainty conditions. Section 6 provides the conclusions and the future works.

## 2. Related works

TEP studies based on GAs are listed in Table 1.

Leou [30] produced a solution with GA and LP for TEP. A 5-year expansion plan was considered in an environment where demand increased by three percent each year and generation levels increased five percent.

**Table 1.** Review of genetic algorithms applied for TEP.

Reference no.	Representation	Initial population	Mutation	Crossover	Selection
[30]	0, 1 code	Random	One point	Two point	Roulette wheel
[37]	No information	Random	No information	No information	Roulette wheel
[38]	Decimal code	Random and suboptimal algorithm	Variable mutation rate controlled by simulated annealing	No information	No information
[39]	Decimal code	Local improvement algorithm	One point	One point	Tournament
[40]	0, 1 code	No information	No information	No information	Roulette wheel
[41]	Decimal code	Heuristic	One point	One point	Tournament
[42]	Decimal code, two part	No information	One point	Two point	Roulette wheel
[43]	Decimal code, three part	No information	One point	Two point	Roulette wheel
[44]	0, 1 code	No information	No information	No information	No information
[45]	No information	Heuristic	No information	No information	No information
[46]	Decimal code	No information	No information	No information	No information
[47]	Decimal code	Heuristic	One point	One point	Tournament
[48]	Decimal code	Heuristic	One point	One point	Tournament

In the objective function part, unlike the traditional problem, the operation cost, the unmet demand cost, and the investment cost were considered. Yang et al. [37] examined the uncertainty for TEP and used the Monte Carlo simulation technique, chance constrained programming, and GA to solve the problem. In their example, the possibility of adding a new line was treated as discretely uniform and future demands were assumed to be normally distributed. Gallego et al. [38] investigated the basic operators of the GA, such as selection, crossover, and mutation. The advantages and disadvantages of the encoding method to be selected were also mentioned. In addition, a variable mutation rate controlled by annealing simulation was applied. Chu and Beasley's genetic algorithm (CBGA) was used in many studies for the TEP problem [39, 41–43, 46–48]. The CBGA was initially designed to solve the generalized assignment problem; however, it was used to solve the transmission network expansion planning problem. The CBGA has some special features: it uses both fitness function and unfitness function, it substitutes only one individual in the population in each iteration, and it performs an efficient strategy of local improvement for each individual tested [49].

When Table 1 is examined, it is seen that decimal coding is dominant. Chromosome width is equal to the width of the existing and candidate lines. The single-point or two-point crossover operators are used as a requirement for digit encoding. As selection methods, roulette wheel and the tournament method were used.

All of the models used the DC model but uncertainty was considered in only two studies. Eight models are single-stage and four are multistage. Garver 6-bus, IEEE 18-bus, IEEE 24-bus, South Brazilian, and Colombian test systems were generally used for tests.

The algorithm proposed in this paper differs from the literature in terms of coding logic and selection strategy. It is a hybrid method that controls the uncertainty process with the GA and reaches a solution using LP.

### 3. Mathematical modeling of TEP

TEP aims to improve the current system to find the most appropriate expansion solution [21]. The expansion plan determines where, when, and how many new lines should be added to system by taking into account future demand and generation values [8].

TEP is a long-term strategic decision. It is not possible to correct wrong or incomplete planning in the short and medium term. Considering the structure of electric power systems, transmission planning is extremely important as it forms the backbone between production and consumption. A bottleneck occurring in the transmission field causes the required demand to be insufficiently met. The transmission expansion plan should be implemented as cost-effectively and reliably as possible.

The mathematical model of the TEP problem is defined as follows [50]:

$$Min \sum_{i,j \in \gamma} c_{ij} n_{ij} + \sum_i \alpha_i * r_i, \tag{1}$$

s.t.

$$Sf + g + r = d, \tag{2}$$

$$f_{ij} - s_{ij} * (n_{ij}^0 + n_{ij}) * (\theta_i - \theta_j) = 0, \tag{3}$$

$$|f_{ij}| \leq (n_{ij}^0 + n_{ij}) * f_{ij}^{max}, \tag{4}$$

$$0 \leq g \leq g^{max}, \tag{5}$$

$$0 \leq n_{ij} \leq n_{ij}^{max}, \tag{6}$$

$$n_{ij} integer; \theta_j unbounded, \tag{7}$$

$$\forall i, j \in \gamma, \tag{8}$$

where  $n_{ij}$  and  $\theta_j$  are the integer variable and unbounded variables coexisting, respectively. Multiplication of integer variable  $n_{ij}$  and infinite variable  $\theta_j$  makes the model nonlinear. Eq. (1) is the objective function. The objective is to minimize total investment cost and total penalty cost of unmet demand. Demand is considered fixed. Eq. (2) relates to energy balance in the stations and is derived from Kirchhoff's current rule for conservation of the limiting load. Eq. (3) is the ohm linear current law. Constraints 4, 5, and 6 are the capacity constraint for flow, the capacity constraint for production, and the capacity constraint for line number, respectively.

The model given in Eqs. (1)–(8) is a mixed integer nonlinear model. This mixed integer nonlinear model is transformed into a linear model by changing constraints 3, 4, and 6 with the new constraints below. First, Eq. (3) is treated as two separate parts for candidate lines and existing lines.  $n_{ijk}$  denotes a 0,1 binary variable. In this view, the model is linearized by constraints 12 and 14. If  $n_{ijk}$  is 0 (no line junction is made), constraint 12 is abundant and does not narrow the solution space in any way. It is guaranteed that there is no flow with the fourteen restrictions. When  $n_{ijk}$  is 1,  $f_{ijk} - s_{ij} * (\theta_i - \theta_j) = 0$  with constraint 12 and the related line capacity is limited by constraint 14

$$Min \sum_{i,j \in \gamma} c_{ij} * n_{ij} + \sum_i \alpha_i * r_i, \tag{9}$$

s.t.

$$Sf + g + r = d, \tag{10}$$

$$f_{ij}^0 - s_{ij} * n_{ij}^0 * (\theta_i - \theta_j) = 0, \tag{11}$$

$$-M * (1 - n_{ijk}) \leq f_{ijk} - s_{ij} * (\theta_i - \theta_j) \leq M * (1 - n_{ijk}), \tag{12}$$

$$-n_{ij}^0 * f_{ij}^{max} \leq f_{ij}^0 \leq n_{ij}^0 * f_{ij}^{max}, \tag{13}$$

$$-n_{ijk} * f_{ij}^{max} \leq f_{ijk} \leq n_{ijk} * f_{ij}^{max}, \tag{14}$$

$$f_{ij} = f_{ij}^0 + \sum_{k=1}^n f_{ijk}, \tag{15}$$

$$0 \leq g \leq g^{max}, \tag{16}$$

$$\sum_{k=1}^n n_{ijk} \leq n_{ij}^{max}, \tag{17}$$

$$n_{ij2} \leq n_{ij1},$$

$$n_{ij3} \leq n_{ij2},$$

...

$$n_{ijn} \leq n_{ijn-1},$$

$$n_{ijk} \in (0, 1); \theta_j \text{unbounded}, \tag{18}$$

$$n = n_{ij}^{max}, \tag{19}$$

$$k \in (0, 1, 2, \dots, n_{ij}^{max}), \tag{20}$$

$$\forall i, j \in \gamma. \quad (22)$$

Constraint 17 represents the number of lines to be added and is limited to  $n_{ij}^{max}$ . Constraint 18 is for the sequential addition of binary decision variables. It is not allowed to add the second line without adding the first line with Eq. (18).

## 4. Materials and methods

### 4.1. Genetic algorithm

Genetic algorithms have selection, crossover, and mutation operators in a population of sequences. A new population (offspring) occurs after the implementation of these operators. Some parents are replaced with offspring. Each chromosome has a fitness value and selection is based on the fitness value. The evolutionary process gradually increases adaptation in the population and provides better adaptation values in the advancing population. The GA produces fast and excellent solutions for medium and large problems. Although many different methods have been used in the TEP field, the GA has been preferred for the speed and quality of the solution [37, 38].

### 4.2. Proposed hybrid genetic approach

The proposed hybrid genetic approach produces a solution by using the GA and LP together, as shown in Figure 2. After candidate corridors to be added are determined by the GA, the problem is solved by linear modeling over the determined line scheme. Unlike other GAs in the literature, our proposed algorithm has completely different characteristics in terms of coding logic. The first advantage of this new coding structure is that the chromosome width is reduced only to candidate line levels. In addition, since the coding structure of 0 and 1 is developed, it does not impair the feasibility of any operation problem to be done by genetic algorithm operators. Another difference from GAs in the literature is the use of the  $\mu + \lambda$  selection method [51] as the probing selection mechanism. This method involves selecting the best individual from a given number of parents and offspring. Uncertainty could be included in the model with the help of the hybrid structure. While the uncertainty process and line structure are controlled by genetic algorithm iterations, lower level operation decisions are decided by the linear model. The nonlinear structure of the problem and the solution space are broken by this method. The shape of the transmission network is obtained by using the GA and then the problem is solved by using the DC linear model assumptions over the obtained shape. After line corridors and system shape are determined with the GA, load flow is estimated by making the DC model linear with the current demand and production data.

**Table 2.** An example of the chromosome structure.

Lines	1-3	1-6	2-5	2-6	3-4	3-6	4-5	4-6	5-6
Solutions	1	0	0	1	0	1	0	0	0

In our study, it is decided whether to invest between stations using 0 and 1 coding instead of line number. The value 0 in the cell represents the case where it is not allowed to invest between the two related stations, while the value in cell 1 means that it can be invested between two related stations. Figure 3a shows the structure of existing lines for the Garver-6 station. For the Garver-6 station example, there are nine alternative new line corridors available and 6 existing line corridors. The chromosome width is equal to the number of

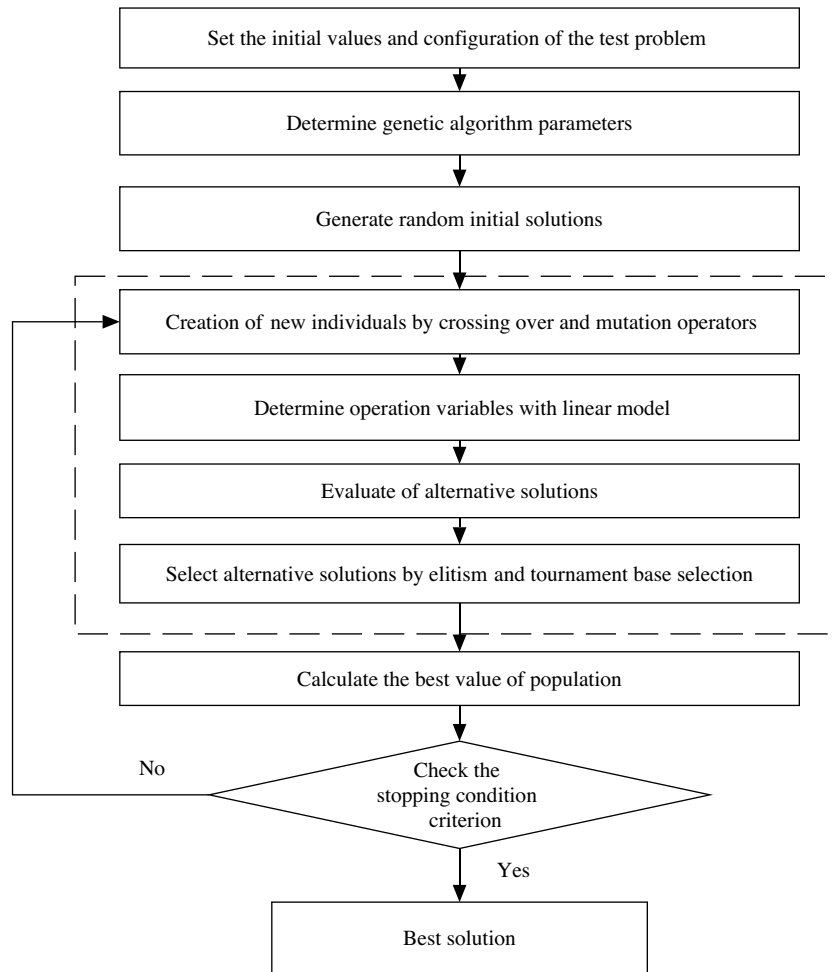


Figure 2. Flowchart of proposed hybrid GA algorithm.

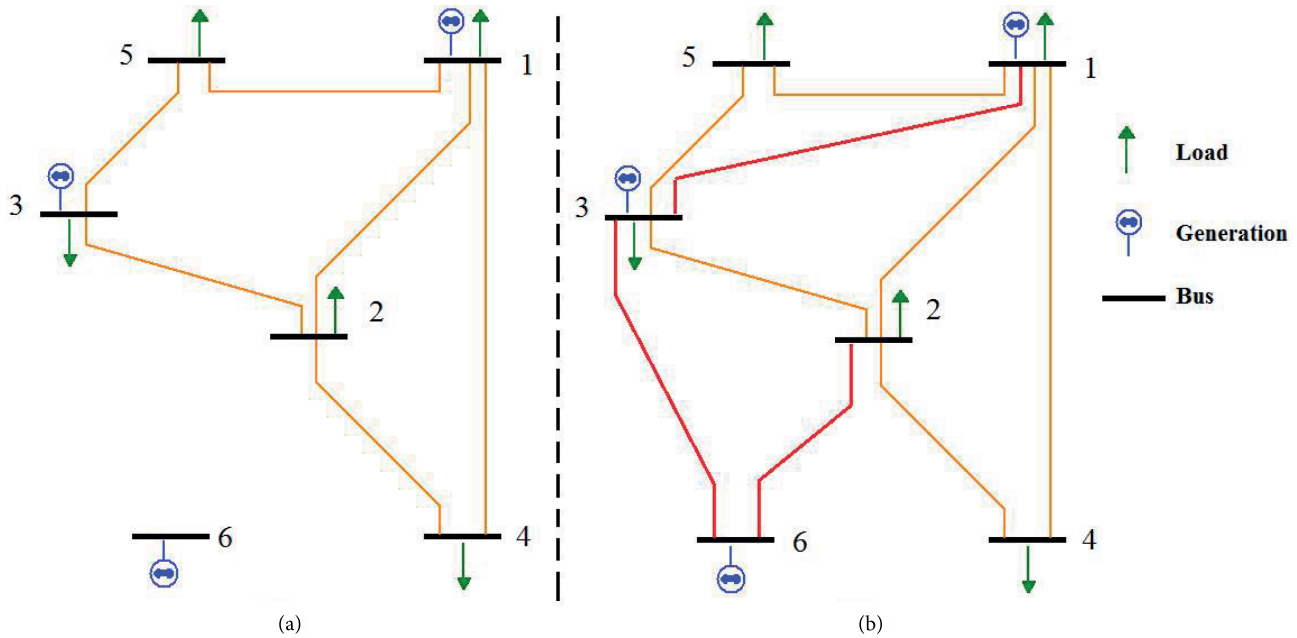
candidate line alternatives and set as 9. An example solution is the following. The chromosome structure of the sample solution is listed in Table 2.

According to this solution, line investments are allowed between stations 1 and 3, between stations 2 and 6, and between stations 3 and 6. Other investment decisions are restricted and 0 values are given. The number of lines to be added or improved is determined by using LP over these 6 old networks and 3 new networks. The system representation of the chromosome structure of Table 2 is illustrated in Figure 3b.

### 5. Results

The proposed hybrid method is tested for the Garver 6-bus [15], IEEE 24-bus [52], and South Brazilian [53] data. The best solutions of these deterministic test systems are known and listed in Table 3. The results obtained for the hybrid GA and GA are also given in Table 3. Since no precise comparison can be made under uncertainty, the effectiveness of the proposed hybrid method is tested for deterministic models. Once the effectiveness of the proposed hybrid GA method is examined, a solution can be obtained under uncertainty conditions with the proposed hybrid GA. The proposed algorithm finds the optimum solution for the Garver 6-bus station without a generation resizing example in less than 1 s in 3 iterations.





**Figure 3.** (a) Initial Garver 6-bus example; (b) a solution of the GA for Garver 6-bus example.

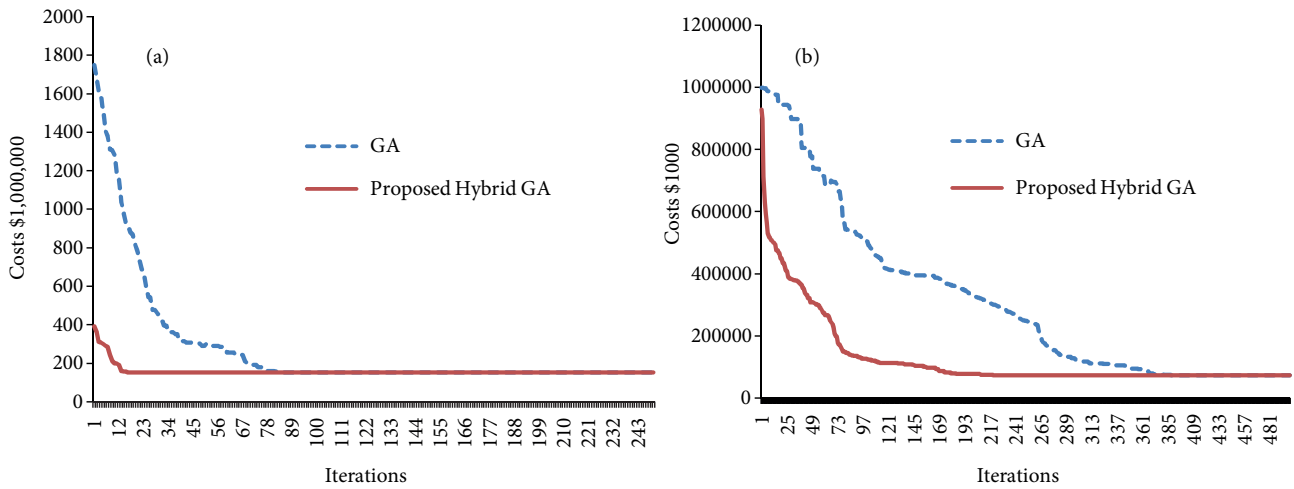
**Table 3.** Comparison of proposed hybrid GA and GA for the test systems.

Test systems	Costs (\$)	GA	Proposed hybrid GA
Garver 6-bus [15]	200,000	25 iterations [38]	3 iterations
IEEE 24-bus [52]	152,000,000	80 iterations [54]	15 iterations
South Brazilian [53]	72,870,000	400 iterations [46]	220 iterations

The IEEE 24-bus problem [55] has 8550 MW load and 10,215 MW generation capacities. There are 34 existing line corridors, 38 existing lines, and 7 new line alternatives. The optimal solution for the IEEE 24-bus problem with generation resizing is 152 million dollars [56]. The IEEE 24-bus problem without generation scheduling has different solutions due to generation decisions. The proposed GA for the IEEE 24-bus system shows a very rapid convergence compared to the GA [57] and finds the best solution of the IEEE 24-bus after 15 iterations on average, as shown in Figure 4a. The algorithm’s chromosome structure has only been created for candidate lines and this increases solution speed. In addition, 0-1 coding has been advantageous by reducing the solution alternatives according to the decimal coding mostly used in GA representation.

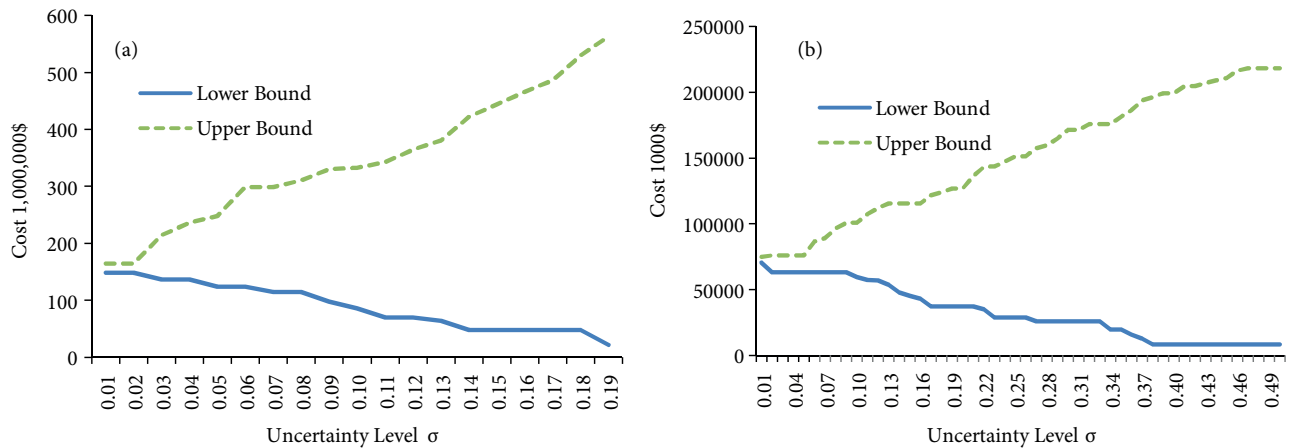
The South Brazilian problem has 6880 MW load, 10,545 MW generation capacity, and 79 line corridors [53]. The optimal solution for the South Brazilian problem with generation resizing is \$72,870,000. The developed algorithm finds the best solution of the South Brazilian problem after approximately 220 iterations, as shown in Figure 4b. The fastest convergence known in the literature is about 400 iterations [46]. It is clear from Figure 4a and Figure 4b that the proposed hybrid method quickly converges to the best solutions for deterministic test systems.

After testing the efficiency of the developed hybrid GA, the IEEE 24-bus and South Brazilian problems are re-solved by the developed method considering cases where the demand is uncertain. Demand uncertainty is represented by  $\sigma$ .  $\sigma$  shows the uncertainty range in demand.  $\sigma = 0.05$  denotes positive and negative 5 percent



**Figure 4.** Convergence graph for (a) IEEE 24-bus data and (b) South Brazilian data.

uncertainty in demand  $[\mu - \sigma, \mu + \sigma]$ . The uncertainty range in demand is shown Figure 5a and Figure 5b. The South Brazilian bus problem has 10,545 MW generation capacity and 6880 MW expected demand. Demand increase does not influence the South Brazilian system dramatically due to relatively high generation capacity, as shown in Figure 5b. Investment decisions for the South Brazilian system are higher in effect because marginal cost varies dramatically, as shown in Figure 6. Planners should make decisions carefully under uncertainty.



**Figure 5.** Costs for (a) IEEE 24-bus data and (b) South Brazilian data.

It is observed that uncertainty is mainly addressed due to the increase in demand and increase in production when the literature on uncertainty is examined. Uncertainty is defined in 10 different scenarios for the IEEE 24-bus problem. In the objective function of the problem, in addition to the cost of line addition and the cost of unmet electricity, a new cost element has been added considering carbon dioxide emission. Production costs of production facilities in MW/dollar production are also included in the model. Considering social and economic costs of power outages, the min-max regret method is used in order to minimize risk. This method finds the solution that minimizes maximum regret in all possible scenarios.

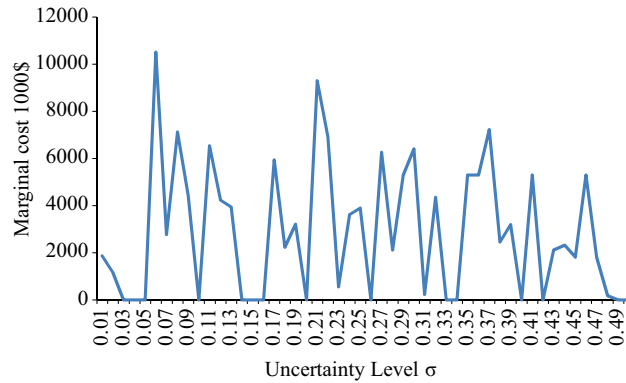


Figure 6. Marginal cost graph for South Brazilian data.

The IEEE 24-bus problem is solved by min-max regret. Ten different scenarios are as follows:

Scenario 1 (S1): Demand in all stations increased by 3 percent. {Low demand increase}

Scenario 2 (S2): Demand in all stations increased by 5 percent. {Medium demand increase}

Scenario 3 (S3): Demand in all stations increased by 10 percent. {High demand increase}

Scenario 4 (S4): The case where production plant number 7 works with a capacity of 50 percent for renovation and maintenance work. {Generation maintenance}

Scenario 5 (S5): The situation where production plant 13 works with 40 percent capacity for renovation and maintenance work. {Generation renovation}

Scenario 6 (S6): The situation where production facility 18 becomes inoperable for renovation and maintenance work. {Generation failure}

Scenario 7 (S7): The situation in which the capacity of the hydropower and river power plants is reduced by 75 percent, which serves as a result of drought and precipitation rate. {Renewable uncertainty}

Scenario 8 (S8): The situation in which oil and natural gas prices double due to the sharp increase in oil prices. {Price uncertainty}

Table 4. Best solutions for 10 different scenarios.

Scenarios	Best solutions, dollars	Added lines
Scenario 1	2,991,354	6-10: one line, 7-8: two lines, 10-12: one line, 11-13: one line
Scenario 2	3,679,407	6-10: one line, 7-8: two lines, 10-11: one line, 11-13: one line, 14-16: one line, 20-23: one line
Scenario 3	4,558,335	1-5: one line, 3-24: one line, 6-10: one line, 7-8: two lines, 10-12: one line, 14-16: one line, 15-24: one line, 16-17: one line
Scenario 4	6,811,957	6-10: one line, 9-12: one line, 10-12: one line, 12-13: one line, 14-16: one line, 16-17: one line, 1-8: one line
Scenario 5	7,123,712	1-5: one line, 3-24: one line, 6-10: one line, 7-8: two lines, 14-16: one line, 15-24: one line, 16-17: one line
Scenario 6	2,764,146	6-10: one line, 7-8: two lines, 10-12: one line, 13-14: one line
Scenario 7	3,679,290	1-5: one line, 3-24: one line, 6-10: one line, 7-8: two lines, 11-13: one line
Scenario 8	2,864,600	6-10: one line, 7-8: two lines, 10-12: one line, 14-16: one line
Scenario 9	3,679,290	6-10: one line, 7-8: two lines, 10-12: one line, 14-16: one line, 16-17: one line
Scenario 10	3,723,666	6-10: one line, 7-8: two lines, 10-12: one line, 13-14: one line

Scenario 9 (S9): The situation where CO oscillation cost is increased 10 times considering green energy and environmental pollution. {Environmental issues}

Scenario 10 (S10): Considering the radioactive risks, the additional cost per MW unit produced by the nuclear power plants. {Radioactive risks}

The best solutions of these 10 different scenarios are given in Table 4.

The best value of each scenario is considered as an alternative solution and the value of 10 alternative solutions in all scenarios is calculated and given in Table 5.

Maximum regret for solution 1 is  $5353275 = \text{Max}(2991354 - 2991354 = 0; 3884223 - 3678407 = 204813; 6392954 - 4558335 = 1834619; 5511698 - 4336146 = 1175552; 9437660 - 4084385 = 5353275^*; 2803215 - 2764146 = 39069; 4044094 - 3679290 = 364804; 2989021 - 2864600 = 124421; 6509446 - 643423 = 75214; 3822099 - 3723666 = 98433)$ .

Regret values for other solutions are 2701015, 2660957, 5578922, 3475081, 5382363, 4442962, 2667862, 1838710\*, and 5382360, respectively.

The ninth solution, which has the smallest value among these solutions, is the most robust solution for all possible scenarios with a minimum cost of \$1,838,710.

**Table 5.** Solutions for 10 different alternatives for scenarios (\$).

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Sol. 1	2,991,354	3,884,220	6,392,954	5,511,698	9,437,660	2,803,215	4,044,094	2,989,021	6,509,446	3,822,099
Sol. 2	3,650,763	3,679,407	5,054,827	5,248,644	6,785,400	3,641,177	4,307,158	3,810,626	7,347,797	4,435,427
Sol. 3	4,457,589	4,485,774	4,558,335	5,244,627	5,261,079	5,425,103	4,521,736	4,590,779	7,842,555	5,791,733
Sol. 4	4,637,062	5,254,725	6,832,203	4,336,145	9,663,307	4,843,783	6,935,678	4,364,077	7,648,451	5,533,741
Sol. 5	4,616,316	5,208,835	6,724,967	6,782,298	4,084,385	6,239,227	4,786,026	4,090,196	7,374,327	5,843,445
Sol. 6	3,495,166	4,233,911	6,430,774	5,786,732	9,466,748	2,764,146	4,116,088	2,958,531	6,470,720	3,723,666
Sol. 7	4,153,342	4,782,043	6,994,790	6,379,805	8,527,347	3,460,725	3,679,290	3,443,235	6,951,103	4,601,275
Sol. 8	3,313,949	3,838,872	6,146,218	5,566,249	6,752,247	3,154,923	4,146,465	2,864,600	6,444,917	3,942,941
Sol. 9	3,230,660	3,785,129	5,505,315	5,658,057	5,923,095	3,494,313	3,857,271	3,185,092	6,434,232	4,296,870
Sol. 10	3,495,166	4,233,911	6,430,774	5,786,732	9,466,748	2,764,146	4,116,088	2,958,531	6,470,720	3,723,666

## 6. Conclusion and future works

In this paper, first a review of genetic algorithm works regarding TEP was presented. Then a new approach based on GA and LP was proposed for TEP problems, which has a nonlinear mixed-integer structure. The performance of the proposed methodology has been tested on the Garver 6-bus, IEEE 24-bus, and South Brazilian test systems. The proposed method has a linear model-based hybrid GA that guarantees model convergence. Finally, scenarios have been generated for uncertainty conditions and the solutions have been obtained for discrete min-max regret criteria. The proposed solution can be a support system for decision makers when the speed and flexibility of access are taken into consideration.

Future works will be resolving the TEP problem for N-1 security constraints for extraordinary conditions and testing of the solutions' stability. Besides, since the perfect voltage profile assumption is critical for DC models, the solutions are also tested for AC models. Final future work will be to develop a continuous min-max model for uncertain situations and solve the model using the Monte Carlo simulation technique with hybrid GA.

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## Notations

$c_{ij}$	: Cost of the line to be made to $i$ - $j$ line
$s_{ij}$	: Susceptance of line $i$ - $j$
$n_{ij}$	: Number of lines to be added to line $i$ - $j$
$n_{ij}^0$	: Number of lines existing on $i$ - $j$ line
$f_{ij}$	: Flow between $i$ and $j$
$f_{ij}^{max}$	: Maximum capacity of $i$ - $j$ line
S	: Incidence matrices
f	: Vector including $f_{ij}$ and $\theta_j$ for node $j$
g	: Production vector for all nodes
d	: Demand vector for all nodes
$g^{max}$	: Maximum generation capacity
$n_{ij}^{max}$	: Maximum line capacity
$\gamma$	: A cluster of all possible lines
$r_i$	: Unmet demand at each station
$\alpha$	: Penalty cost for unmet demand

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