

# NETWORK PLANNING USING ITERATIVE IMPROVEMENT METHODS AND HEURISTIC TECHNIQUES

*A. Sadegheih*

*Department of Industrial Engineering, Yazd University  
Yazd, Iran, [sadegheih@myazduni.ac.ir](mailto:sadegheih@myazduni.ac.ir)*

*P. R. Drake*

*Intelligent Systems Laboratory, System Division, School of Engineering, University of Wales Cardiff,  
UK, [drake@cardiff.ac.uk](mailto:drake@cardiff.ac.uk)*

**(Received: May 5, 2000 – Accepted in Revised Form: May 8, 2001)**

**Abstract** The problem of minimum-cost expansion of power transmission network is formulated as a genetic algorithm with the cost of new lines and security constraints and Kirchhoff's Law at each bus bar included. A genetic algorithm (GA) is a search or optimization algorithm based on the mechanics of natural selection and genetics. An applied example is presented. The results from a set of tests carried out on the prototype show that the application of GA techniques is feasible in transmission network planning. An empirical analysis of the effects of the parameters of the algorithm is also presented in the context of this novel application. Existing mathematical programming, heuristic techniques, artificial intelligence (AI) and iterative improvement methods are also reviewed briefly.

**Key Words** Transmission Network Planning, Genetic Algorithm, Mathematical Programming, Artificial Intelligence, Iterative Improvement Methods, Heuristic techniques.

چکیده در این مقاله مساله برنامه ریزی خطوط انتقال به وسیله الگوریتمهای ژنتیکی فرموله شده است که هزینه های خطوط جدید و محدودیتهای دیگر در هر باس در مساله مورد توجه قرار گرفته است. الگوریتم ژنتیکی بر اساس سیستمهای تکاملی و تدریجی و قواعد موروثی استوار بوده و روش حل بدین صورت است که با مجموعه ای از حلهای بالقوه از جمعیت مورد مطالعه حل را شروع کرده و از آن برای تولید نسلهای آینده استفاده می کند که یکی از شناخته شده ترین الگوریتمهای مدرن برای مسائل بهینه سازی است. مثالی از برنامه ریزی خطوط انتقال شرح داده شده است. نتایج نشان می دهد که الگوریتم ژنتیکی متد خوبی برای حل اینگونه شبکه ها می باشد. همچنین آنالیز نشان داده است که حدود پارامترهای الگوریتم ژنتیک برای حل چنین مسائلی چه مقدار می تواند باشد. در ضمن متدهای ریاضی، ابتکاری، هوش مصنوعی و متد جستجو شرح داده شده است.

## INTRODUCTION

The long-range planning of an electrical power transmission network is concerned with finding the most economical expansion plan for the power system over an extended but finite planning period, 20 years for example. It is a complex process in which the application of computing techniques has grown steadily from the well-established areas of load flow and security analysis

for high voltage transmission and distribution system analysis.

The transmission solution method suited to solve power system planning problem uses the linear (DC) load flow model because [1]:

- i. it can be solved by a standard linear programming code;
- ii. it uses only active power - Mega Watt, forecasts;
- iii. the error introduced by using the linear load flow approximation is acceptable in long-range

planning studies.

Transmission network expansion is a complex mathematical optimization problem because it involves, typically, a large number of problem variables. The commonly used methods reported in the literature can be categorized into mathematical programming, heuristic based, artificial intelligence and iterative improvement methods [2-22].

## MATHEMATICAL PROGRAMMING BASED TECHNIQUES

The general form of the above techniques is:

Optimize:  $F(X_1, X_2, \dots, X_n)$  Subject to the constraints:

$$G_i(X_1, X_2, \dots, X_n) \begin{cases} \leq \\ \geq \\ = \end{cases} b_i, \quad i = 1, 2, \dots, m$$

and according to  $F, G$  and  $\tilde{X}$ , the techniques are classified into linear, integer, mixed-integer linear, zero-one, or non-linear programming, etc.

As long ago as 1960, Knight [2] used such a method in which starting from the geographical positions of the substations required to interconnect, a set of equations is obtained and solved by linear programming to obtain a minimum cost power transmission network design. The drawback of this method is that the load flow constraints are not taken into consideration. Garver [3] proposed a method that starts by converting the electrical network expansion problem into a linear programming problem. The mathematical programming technique used in solving the linear network model minimizes a loss function defined as power times a guide number summed over all network links. The overload path with the largest overload is selected for circuit addition. The drawback of this method is that the model has no user interaction and is fixed by program formulation. Villasana et al [1] and Serna et al [4] also proposed methods used a DC linear power flow model and a transportation model respectively. In both methods, the model is intractable.

Berg and Sharaf [5] proposed a method, using

the admittance approach and linear programming, for planning transmission capacity additions. The method consists of two phases. In the first phase admittance addition is made, while in the second phase VAR (Voltage Amper Reactive) allocation is specified. In this method, losses have been excluded. Kaltenbach et al. [6] proposed a model, which uses a combination of linear and dynamic, programming techniques to find the minimum cost capacity addition to accommodate a given change in demand and generation. The drawback of this method is that a very large number of decision variables is required.

Farrag and El-Metwally [7] proposed a method, using mixed-integer programming, in which the objective function contains both capital cost represented in its discrete form and the transmission loss cost in a linear form. Kirchhoff's first and second laws are included in the constraints, in addition to the line security constraints. In this method the loss term is linearized and a large number of decision variables is required. Sharifnia and Ashtiani [8] proposed a method for the synthesis of a minimum-cost secure network. In this method the loss terms are linearized in the constraints and a large number of decision variables is required. Adam et al [9] proposed a method, which is based on an interpretation of, fixed cost transportation type models, and includes both network security (in the transmission network) and cost of loss (in the distribution network). The drawback of this method is that the loss term is in a linearized form and it requires a large number of decision variables, due to the use of the mixed-integer linear programming technique as the solution tool.

Lee et al [10] proposed a method which is based on static expansion of networks using the zero-one integer programming technique and Romero and Monticelli [11] proposed a zero-one implicit enumeration method for optimizing investments in transmission expansion planning. These methods require a large number of decision variables and are computationally very expensive. Padiyar et al [12] made a comparison of the computation times required by four different optimization techniques: the transportation model; linear; zero-one and non-linear programming. The use of zero-one and non-linear programming

requires high CPU times compared to other methods which makes them ineffective for large scale systems [13] and all of the methods reviewed are fixed by program formulation.

Yousef and Hackam [14] proposed a model capable of dealing with both static and dynamic modes of transmission planning, using non-linear programming. The cost function includes the investment and transmission loss cost. Again, this method requires long computation times and a large number of decision variables [15].

### **HEURISTIC TECHNIQUES.**

El-Sobki et al [16] proposed a heuristic method, which is a systematic procedure to cancel the ineffective lines from the network. The process is directed in a good manner such that the minimum cost network will be obtained containing the most effective routes with the best number of circuits. The DC-load flow model is used. The drawback of this method is that power losses are not taken into account.

Albuyeh and Skiles [17] presented a planning method involving three integral parts. The first is a network model using a fast-decoupled load flow relating the changes in active and reactive powers to changes in bus angles and voltages, respectively. In the second part, a selection contingency analysis is employed to determine the maximum overload on each branch and the maximum voltage deviation for each bus. Finally, the line cost, maximum overload and a sensitivity matrix are combined into two formulae to determine the branch to be added and the susceptance of that branch. The procedure is repeated until the contingency analysis shows no overload. In this method losses have been included as a linear term.

Ekwue [18] proposed a method derived on the basis of a DC-load flow approach. The method determines the number of lines of each specification to be added to a network to eliminate system overloads at minimum cost. A static optimization procedure, based on the steepest-descent algorithm, is then used to determine the new admittances to be implemented along these rights of way. In this method, the

model is only applicable to already connected systems and not expansion as considered here.

In general, a characteristic of heuristic techniques is that strictly speaking an optimal solution is not sought, instead the goal is a "good" solution. Whilst this may be seen as an advantage from the practical point of view, it is a distinct disadvantage if there are good alternative techniques that target the optimal solution.

### **ARTIFICIAL INTELLIGENCE**

With the development of artificial intelligence (AI) theory and techniques, some AI-based approaches to transmission network planning have been proposed in recent years. These include the use of expert systems [19] and artificial neural network (ANN) based [20] methods. The main advantage of the expert system based method lies in its ability to simulate the experience of planning experts in a formal way. However, knowledge acquisition is always a very difficult task in applying this method. Moreover, maintenance of the large knowledge base is very difficult. Research into the application of the ANN to the planning of transmission networks is in the preliminary stages, and much work remains to be done. The potential advantage of the ANN is its inherent parallel processing nature.

### **ITERATIVE IMPROVEMENT METHODS**

In recent years, there has been a lot of interest in the application of simulated annealing (SA) and taboo search (TS) to solving some difficult or poorly characterized optimization problems of a multi-modal or combinatorial nature. SA is powerful in obtaining good solutions to large-scale optimization problems and has been applied to the planning of transmission networks [21]. In this reference, the transmission network planning is first formulated as a mixed integer non-linear programming and then solved using SA. The strength of GA's is that they are free from limitations about the search space, e.g., continuity, differentiability and unimodality and they are very

flexible in the choice of an objective function. Furthermore, GA's can work on very large and complex spaces. These properties give GA the ability to solve many complex real-world problems. Cooling schedule could be important and neighborhood function is crucial to its effectiveness. TS has emerged as a highly efficient, search paradigm for finding quickly high quality solutions to combinatorial problems [22-25]. It is characterized by gathering knowledge during the search, and subsequently profiting from this knowledge. TS has been applied successfully to many complicated combinatorial optimization problems in many areas including power systems [26-27]. The drawback of this method is that its effectiveness depends very much on the strategy for tabu list manipulation. Obviously, how to specify the size of the tabu list in the searching process plays an important role in the search for good solutions. In general, the tabu list size should grow with the size of a given problem.

### WHY GENETIC ALGORITHMS?

From the above review, the following conclusions are drawn regarding previous methods:

- i. most allow no user interaction [1-5];
- ii. most require a large number of decision variables [6-10];
- iii. models fixed by program formulation [11-16];
- iv. long computation times [17-18,21-22];
- v. considerable effort and good mathematical knowledge is usually required for adaptation to specific problems [9-14].

In this paper, the application of a genetic algorithm (GA) is proposed to solve the transmission network-planning problem.

GA's are based in concept natural genetic and evolutionary mechanisms working on populations of solutions in contrast to other search techniques that work on a single solution. Searching not on the real parameter solution space but on a bit string encoding of it, they mimic natural chromosome genetics by applying genetics-like operators in search of the global optimum. An important aspect of GA's is that although they do not require any prior knowledge or any space limitations such as smoothness, convexity or unimodality of the

function to be optimized, they exhibit very good performance in the majority of applications [28]. They only require an evaluation function to assign a quality value (fitness value) to every solution produced. Another interesting feature is that they are inherently parallel (solutions are individuals unrelated with each other); therefore their implementation on parallel machines reduces significantly the CPU time required [28].

Compared with other optimization methods, GA's are suitable for traversing large search spaces since they can do this relatively rapidly and because the use of mutation diverts the method away from local minima, which will tend to become more common as the search space increases in size. GA's give an excellent trade-off between solution quality and computing time and flexibility for taking into account specific constraints in real situations.

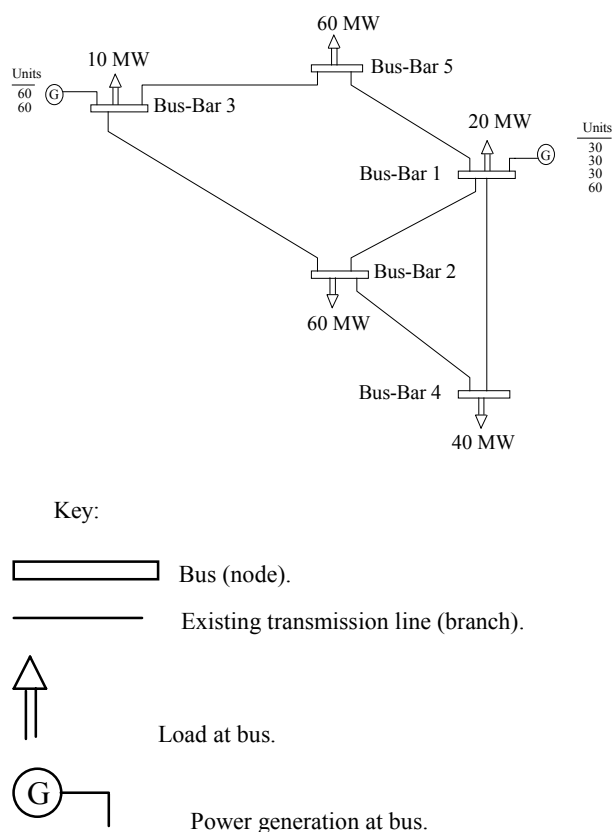
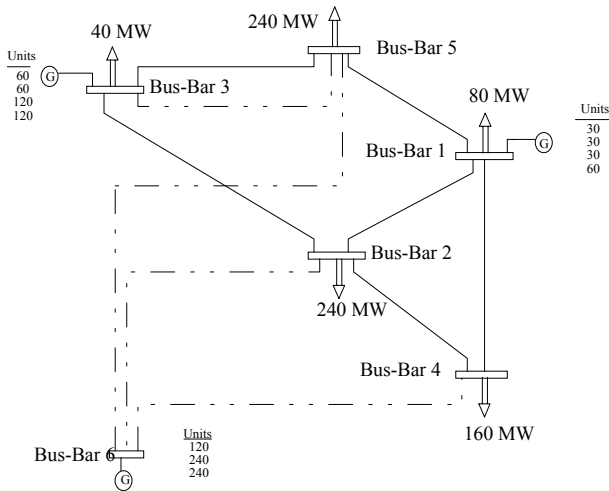


Figure 1. Existing conditions of the 6-bus network.



Key:

- Proposed transmission line
- Existing transmission line

**Figure 2.** Six buses network and proposed new transmission lines.

### EXAMPLE TRANSMISSION NETWORK

The 5-bus network to be expanded to 6-bus, as described in [3], is shown in Figure 1 before expansion (existing conditions). The existing network consists of three load only buses and two generator and load buses. Single 3-phase paths already exist between some of the buses, as indicated.

The conditions for the expanded system are shown in Figure 2, where the loads of the network are increased by a factor of 4. Two additional 120 MW generating units are added at Bus 3. A new generating Bus 6 with a total generation capacity of 600 MW is also added to the network. The data for the existing and new transmission lines is given in Table 1, where the determination of the capacity of each line is based on thermal limitations and stability considerations.

The net generation minus load is computed from the load forecast at each bus and the generation scheduled to exactly match the total load as given in Table 2. This assumes that Bus 1

**TABLE 1.** Transmission Line Data for the 6-Bus Network.

From Bus	To Bus	Length (miles)	Power Capacity (MW)	Line Number
1	2	40	100	1
1	4	60	80	2
1	5	20	100	3
2	3	20	100	4
2	4	40	100	5
2	6	30	400	6
3	5	20	400	7
4	6	30	400	8
5	6	61	312	9

**TABLE 2.** Net Generation.

Bus	Generation /MW	Load /MW	Net Generation/ MW
1	50	80	-30
2	0	240	-240
3	165	40	125
4	0	160	-160
5	0	240	-240
6	545	0	545
Total	760	760	0

dispatches 50 MW, Bus 3 dispatches 165 MW, and a new site (Bus 6) has been selected for a new generating station with a maximum capacity of 600 MW - but dispatching 545 MW.

For the expanded network, the goal is to determine which new line to construct in order to supply the future load pattern.

### FORMULATION FOR LINEAR PROGRAMMING

The transmission network synthesis used here is based on the linearized power-flow model [12]. The mathematical formulation of the minimum-cost circulation problem for solution by linear programming is:

Minimize:

$$Z = \sum_{j \in NP} K_j (P_j^+ + P_j^-) \quad (1)$$

Subject to:

$$\sum_{\substack{j \in A \\ s(j)=i}} (P_j^- - P_j^+) + \sum_{\substack{j \in A \\ e(j)=i}} (P_j^+ - P_j^-) = PL_i - PG_i, \quad \forall i, j \quad (2)$$

$$P_j^+ + P_j^- \leq PM_j, \quad j \in A \quad (3)$$

$$P_j^+, P_j^- \geq 0$$

Where:

$NP$ : The set of proposed paths.

$A$ : The complete of transmission paths.

$K_j$ : Cost per unit flow in line  $j$ .

$s(j) = i$ : Lines that start from Bus  $i$ .

$e(j) = i$ : Lines that end at Bus  $i$ .

$PM_j$ : Maximum power flow of line  $j$ .

$PG_i$ : Power generation at Bus  $i$ .

$PL_i$ : Load at Bus  $i$ .

$Z$ : Total cost of network.

$P_j^+$ : Oriented power in line  $j$  from its "start" to its "end".

$P_j^-$ : Oriented power in line  $j$  from its "end" to its "start".

In the example considered here the existing and proposed transmission lines are considered to be of the same voltage and the cost per unit length ( $K'$ ) is considered to be a constant = 400 [12].

$$K_j = K' \frac{\ell_j}{c_j} \quad (4)$$

Where

$\ell_j$  = Length of right-of-way  $j$ .

$c_j$  = Capacity of line along right-of-way  $j$ .

### GENETIC ALGORITHM

The transmission network planning used GA is illustrated in Figure 3. It starts with an initial

population of possible solutions. Each member of the population comprises a bit string, called a chromosome, to represent a particular set of possible transmission line power capacities:  $P_1, P_2, \dots, P_n$ . Each individual line capacity is encoded by sufficient bits to cover its allowable range of values. For example, if  $P_x$  has a maximum capacity of 400 MW, in either direction, then the range is MW. This range (with a resolution

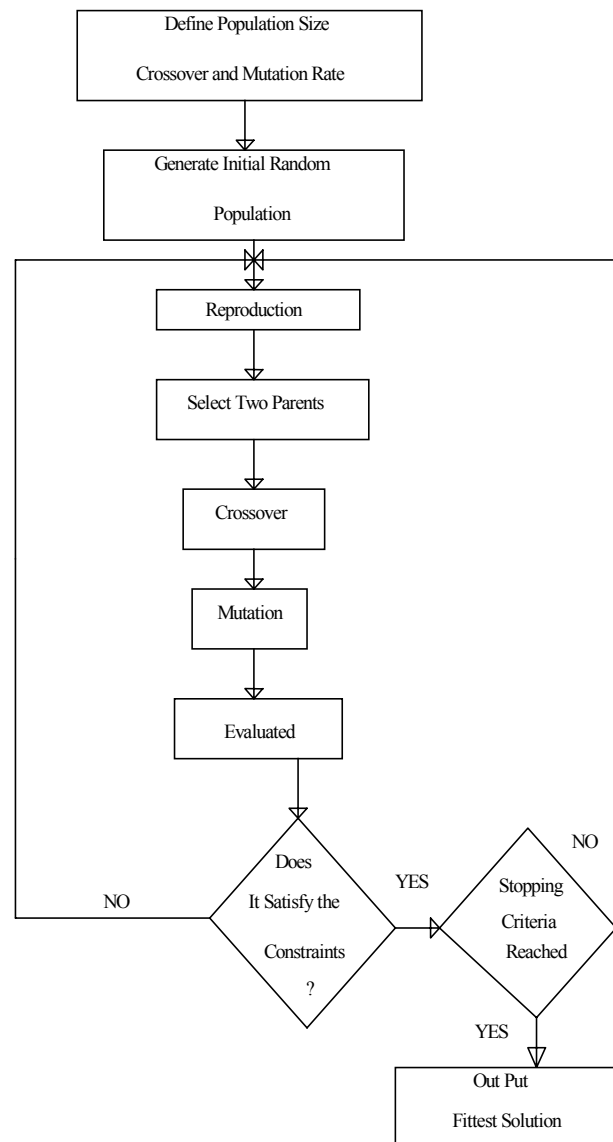


Figure 3. Flowchart the genetic algorithm.

of 1 MW) requires 10 bits with - 400 MW being encoded as all zeros and +400 MW as 1100100000. The bit strings for each  $P_i$  are concatenated to form a chromosome. It is important to note that in the GA formulation there is no need to constrain decision variables to being non-negative. Consequently, the total number of decision variables is greatly reduced. The initial population is generated randomly, that is, each bit in each chromosome is set randomly to either 1 or 0. Whenever a new chromosome is generated it is checked to see that in decoded form it produces valid values for the  $P_i$ 's. In the example, it is possible for  $P_x$  to be given a value greater than +400 MW due to the length of the bit string. When an invalid value is produced the chromosome is discarded and another one is generated. The fitness value of a chromosome is determined according to how well it meets the desired object. In this case the objective is the minimization of the network's cost function, so the fitness value is the reciprocal of this cost. A steady-state GA is used here. This means that at each iteration, two parent chromosomes are selected from the population for reproduction. These parents produce a child who is added into the existing population and the weakest member of the population is then deleted. The alternative generational GA produces a whole new population of children at each iteration. Reproduction is the process that implements natural selection. It is the mechanism by which two parent chromosomes are selected randomly from the population for subsequent crossover and mutation to produce a new child chromosome. According to the principles of natural selection, the more fit members of the population should have a greater chance of reproduction. Whilst there are many different methods to achieve this, a rank based method is used here. This means that the members are ranked in order of their fitness and the probability of selection is inversely related to this ranking. The advantage of a rank based approach is that it helps to avoid too rapid a rate of convergence that may lead to the population being swamped by a local optimum due to the loss of diversity [29,35]. Whilst various methods of crossover have been proposed uniform crossover is used here as demonstrated in Figure 4. Empirically, uniform crossover has been shown to be

more effective on a variety of function optimization problems [30]. In this method a child is formed by taking a mixture of bits from its two parents according to a random bit string. The proportion of bits coming from the first parent is defined by the user-defined crossover rate in the range zero to one. The process is illustrated in Figure 4 where a '1' in the random bit string indicates that in that position the child inherits the corresponding bit from parent-1, whilst a '0' causes inheritance from parent-2.

Parent Chromosome 1: 1001001110

Parent Chromosome 2: 0101110011

To mimic the function of genetic mutation found in nature, each bit in a child chromosome can be randomly mutated. This mutation involves randomly inverting each bit with a probability defined by the mutation rate.

The GA iterates for a specified number of generations or until a measure of convergence is observed in the "best" solution. The GA stops when a convergence criterion is reached. In the experiments performed here, this is when the change in the best fitness in the last 100 trials is less than 0.0001 unit cost.

The work presented here is carried out using proprietary spreadsheet software and an 'add-in' to provide the basic GA. This demonstrates how simple it is to adopt the GA approach.

GA's are different from traditional optimization and search procedure in following ways [31].

- i. they work with a symbolic representation of solution parameters rather than the parameters themselves,
- ii. they treat a set of potential solutions, not a single solution,
- iii. they use only information about the pay off (or the objective function), not any other auxiliary information,
- iv. they use probabilistic transition, not deterministic rules.

There has been a big growth in their application and development since the mid-1980s when the

Random Bit String: 1010111000

Child Chromosome 1: 1101001011

Child Chromosome 2: 0001110110

**Figure 4.** Uniform crossover.

practical application for GA's became apparent. GA has been successfully applied in various areas [31] such as computer science, engineering, operations research and transmission network planning in particular.

### APPLICATION OF GA TO TRANSMISSION NETWORK

The GA formulation of the transmission network-planning problem is:

$$\text{Minimize: } Z = \sum_{NP} K_{ij} |P_{ij}| \quad (5)$$

subject to:

$$\sum_{j \in A_k^+} P_{jk} - \sum_{i \in A_k^-} P_{ki} = PL_i - PG_i, \forall i, j \quad (6)$$

$$-PM_j \leq P_{ij} \leq +PM_j, \forall i, j \quad (7)$$

Equation 6 satisfies Kirchoff's current or first Law (KCL), in which:

NP : Set of proposed lines.

$K_{ij}$  : Cost per unit flow in line (i, j).

$P_{ij}$  : Power in line (i, j).

$A_k^+$  : Set of lines that are directed toward Bus k.

$A_k^-$  : Set of lines that are directed away from Bus k.

$PM_j$  : Maximum power flow of line j.

$PG_i$  : Power generation at Bus i.

$PL_i$  : Load at Bus i.

Z : Total of cost network.

Comparison of this formulaic with the previous mathematical programming formulaic shows a significant simplification due to the "power in line" variable  $P_{ij}$  being allowed to take negative values.

In linear programming the variables must be non-negative so separate variables ( $P_i^+$  and  $P_i^-$ ) are required to provide power flow in each direction.

### EXPERIMENTAL RESULTS

In the approach, several GA parameters such as population size and genetic operator probability are included. In this problem, combination of following GA parameters is tested.

For each combination of the parameters the GA is run for 8 different random initial populations. These 8 populations are different for each combination. Thus, in total, the GA is run 480 times. The values chosen for the population size are representative of the range of values typically seen in the literature, with 0.016 being included to

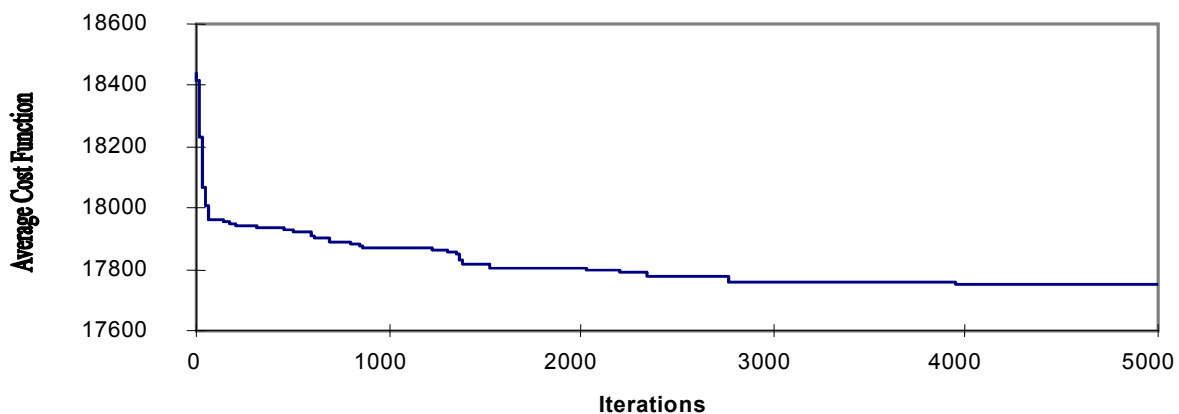


Figure 5. Performance of GA using population size = 50, crossover rate = 0.5, and mutation rate = 0.006 for the 6 bus-bar TNP.



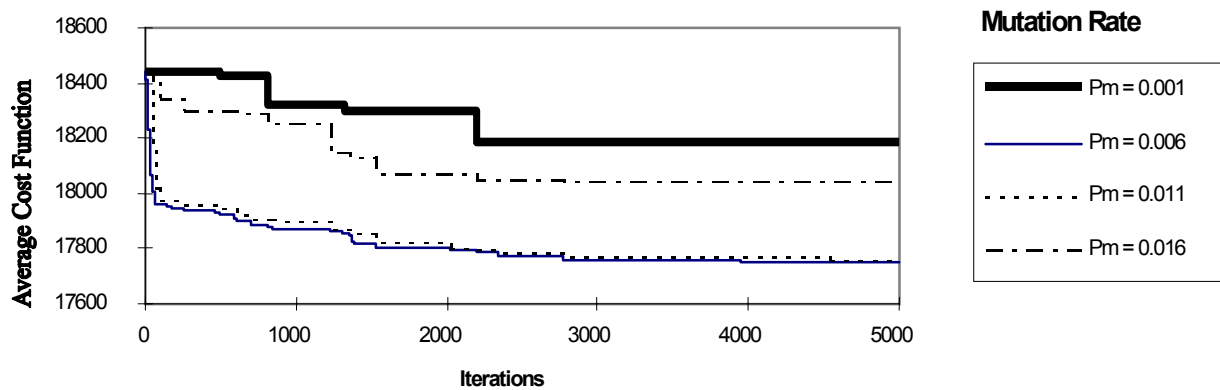


Figure 6. Effect of mutation rate on performance for crossover rate = 0.5 and population size = 50.

highlight the effect of a relatively large mutation range. The crossover rates chosen are representative of the entire range (0.2, 0.4, 0.5, 0.6, 0.8).

Distribution of number of iterations required to

analyze the distribution of the number of trials required reaching the optimal solution. Iterations show that the number of iterations they require is a very good fit to lognormal distribution. This means that statistical analysis techniques that assume

TABLE 4. Natural Logarithm of the Number of Iterations for Different Crossover Rates with Mutation Rate = 0.006 and Population Size = 50.

Run	0.2	0.4	0.5	0.6	0.8
1	7.32	8.67	3.66	7.66	7.09
2	7.20	7.75	5.85	8.10	7.76
3	7.36	4.87	7.52	8.21	7.37
4	9.12	8.56	6.66	6.74	7.50
5	6.24	7.30	8.62	7.24	6.12
6	8.38	7.68	7.46	8.25	8.01
7	3.78	4.06	8.47	7.94	8.68
8	8.39	8.31	7.82	7.49	8.55
Average	7.22	7.15	7.00	7.70	7.63

TABLE 5. One-Way ANOVA for Crossover Rate Using Results in Table 4.

Source of Variation	SS	Df	MS	F	P-value	F crit
Between Groups (treatment)	3.040285	4	0.760071	0.406412	0.802737	2.641464
Within Groups (error)	65.45703	35	1.870201			

normality can be applied to log of the number of iterations required.

Average of objective function result is displayed in Figure 5. This figure is the result of which population size is 50, crossover rate is 0.5 and mutation rate is 0.006.

Meanwhile, combinations are tested by analysis of variance techniques (ANOVA) using the F-test, in order to examine relation between the parameters and the performance. For example, Table 4 shows the natural logarithm of the number of iterations for different crossover rates with the mutation rate fixed at 0.006 and a population size of 50. Table 5 displays the one-way ANOVA table for this data.

If the value of the F falls in the rejection region i.e.  $F > F_{crit}$ , then reject the null hypothesis; otherwise, do not reject the null hypothesis. In Table 5,  $F = 0.406412$ , this does not fall in the rejection region. Thus the null hypothesis is accepted. The data provide sufficient evidence to conclude that the means for the five different crossover rates are not significantly difference and that the crossover rate is therefore an insignificant factor across the range [0.2:0.8] in the performance of GA. This is in line with the findings of Gupta et al. [32] and Haida and Akimoto [33].

Results, which are observed in these experiments, indicate that the crossover rate is an insignificant factor in the performance of GA.

In Figure 6 effect of mutation rate on the GA approach is displayed in case that crossover rate and population size are fixed. There is a degree of insensitivity to mutation rate (in this research, mutation rate of which range from 0.006 to 0.011

are suitable) in so far as “good“ value form a fairly broad range rather than coming at a more precise point. However, outside of the “good“ range performance soon deteriorates greatly that is significant. And also it is observed that there are trade off relation between a mutation rate and a population size. That is, low mutation rate is desirable if population size is large, and high mutation rate is desirable if population size is small.

The sensitivity to population size is greatly reduced when the mutation rate is in the “good“ range and is an insignificant. However, outside of the “good“ range is significant.

Table 6 summarizes the results found by GA in comparison with minimum-cost network. Optimal solution in Minimum-Cost network is spanning tree [34]- a spanning tree is a connected subset of a network including all nodes and containing no loops - that is the fundamental theorem for the network simplex method [34]. But GA solutions show that is both spanning tree and no spanning tree. And also Equations 1, 2 and 3 with 5, 6 and 7 show that decision variables for solving GA in the transmission network planning are less than minimum-cost network. These results demonstrate the validity and effectiveness of the proposed methodology and flexible and straightforward method.

## CONCLUSIONS

In this paper, transmission network planning by using genetic algorithm is proposed. GA is able to

TABLE 6. Optimal Power Line Capacities (MW).

Method	Line								Cost Function
	1-5	2-1	2-3	3-5	4-1	4-2	6-2	6-4	
Linear Programming	100	100	15	140	30	100	255	290	17750
GA 1	100	100	15	140	30	100	255	290	17750
GA 2	100	100	15	140	30	98	257	288	17750
GA 3	100	100	15	140	30	99	256	289	17750
GA 4	100	98	15	140	32	100	253	292	17750
GA 5	100	100	15	140	30	95	260	285	17750

produce optimal solution by simulating the adaptive nature of natural genetics. From the numerical example, it can be seen that the crossover rate is an insignificant factor in the performance of the GA and there is a degree of insensitivity to the mutation rate (range 0.006 to 0.011) in so far as the “good“ values form a fairly broad range rather than coming at a more precise point. However, outside of the “good“ range performance is significant. It is observed that a low mutation rate is desirable when the population size is large and higher mutation rate is desirable when the population size is small and the sensitivity to population size is greatly reduced when the mutation rate is in the “good“ range. However, outside of the “good“ range is significant. GA solutions are showed that is both spanning tree and no spanning tree and the decision variables for solving GA are less than minimum-cost. These results show that GA techniques are feasible in transmission network planning.

## REFERENCES

- Villasana, R., Garver, L. L. and Salon, S. J., “Transmission Network Planning Using Linear Programming”, *IEEE Trans. on PAS*, Vol. PAS-104, No. 2, (February 1985), 349-356.
- Knight, U. G. W., “The Logical Design of Electrical Networks Using Linear Programming Methods”, *Proc. IEE*, Vol. 107A, No. 33, (1960), 306-319.
- Garver, L. L., “Transmission Network Estimation Using Linear Programming”, *IEEE Trans. on PAS*, Vol. PAS-89, No. 7, (September-October 1970), 1688-1697.
- Serna, C., Duran, J. and Camargo, A., “A Model for Expansion Planning of Transmission Systems: A Practical Application Example”, *IEEE Trans.*, Vol. PAS-97, No. 2, (1978), 610-615.
- Berg, G. and Sharaf, T. A. M., “Reliability Constrained Transmission Capacity Assessment”, *Electric Power Systems Research*, Vol. 15, (1988), 7-13.
- Kaltenbach, J. C., Peschon, J. and Gehring, E. H., “A Mathematical Optimization Technique for the Expansion of Electric Power Transmission System”, *IEEE Trans. on PAS*, Vol. PAS-89, No. 1, (1970).
- Farrag, M. A. and El-Metwally, M. M., “New Method for Transmission Planning Using Mixed-Integer Programming”, *IEE Proc. C, Gen. Trans. and Distrib.*, Vol. 135, No. 4, (1988), 319-323.
- Sharifnia, A. and Ashtiani, H. Z., “Transmission Network Planning: A Method for Synthesis of Minimum-Cost Secure Networks”, *IEEE Trans. on PAS*, Vol. PAS-104, No. 8, (1985).
- Adams, R. N. and Laughton, M. A., “Optimal Planning of Power Networks Using Mixed-Integer Programming”, *IEE Proc. C, Gen. Trans. and Distrib.*, Vol. 121, No. 2, (1974), 139-147.
- Lee, T. V. and Hick, K. L., “Transmission Expansion by Branch-Bound Integer Programming with Optimal Cost-Capacity Curves”, *IEEE Trans. on PAS*, Vol. PAS-93, No. 5, (1974).
- Romero, R. and Monticelli, A., “A Zero-One Implicit Enumeration Method for Optimizing Investments in Transmission Expansion Planning”, *IEEE Trans. on PS*, Vol. 9, No. 3, (1994), 1385-1391.
- Padiyar, K. R. and Shanbhag, R. S., “Comparison of Methods for Transmission System Expansion Using Network Flow and D.C. Load Flow Models”, *Electric Power and Energy Systems*, Vol. 10, No. 1, (1989), 17-24.
- El-Metwally, M. M. and Al-Hamouz, Z. M., “Transmission Network Planning Using Quadratic Programming”, *Electric Machines and Power Systems*, Vol. 18, No. 2, pp. 137-148, 1990.
- Youssef, H. K. and Hackam, R., “New Transmission Planning Model”, *IEEE Trans. on PS*, Vol. 4, No. 1, (February 1989), 9-17.
- El-Metwally, M. M. and Harb, A. M., “Transmission Planning Using Admittance Approach and Quadratic Programming”, *Electric Machines and Power Systems*, Vol. 21, (1993), 69-83.
- El-Sobki, S. M., El-Metwally, M. M. and Farrag, M. A., “New Approach for Planning High-Voltage Transmission Networks”, *IEE Proc.*, Vol. 133, No. 5, (1986), 256-262.
- Albuyeh, F. and Skiles, J. J., “A Transmission Network Planning Method for Comparatives Studies”, *IEEE Trans. on PAS*, Vol. PAS-100, No. 4, (1981), 1679-1684.
- Ekwue, A. O., “Investigations of the Transmission System Expansion Problem”, *Electric Power and Energy Systems*, Vol. 6, No. 3, (1984), 139-142.
- Galiana, F. D., McGillis, D. T. and Marin, M. A., “Expert System in Transmission Planning”, *Proc. IEEE*, Vol. 80, No. 5, (1992), 712-726.
- Yoshimoto, K., Yasuda, K. and Yokoyama, R., “Transmission Expansion Planning Using Neuro-Computing Hybridized with Genetic Algorithm”, *Proc. 1995 IEEE Int. Conf. Evolutionary Computation*, Perth, Australia, (1995), 126-131.
- Romero, R., Gallego, R. A. and Monticelli, A., “Transmission System Expansion Planning by Simulated Annealing”, *Proc. 1995 IEEE Power Industry Computer Application Conference (PICA'95)*, USA, 278-283.
- Fushuan, W. and Chang, C. S., “Transmission Network Optimal Planning Using the Tabu Search Method”, *Electr. Power Syst. Res.*, Vol. 42, No. 2, (1997), 153-163.
- Glover, F., Laguna, M., Taillard, E. and DeWerra, D. (Eds.), “Tabu Search”, Science Publishers, Basel, Switzerland, (1993).
- Glover, F., “Tabu Search-Part I”, *ORSA J. Comput.*, Vol. 1, No. 3, (1989), 190-206.
- Glover, F., “Tabu Search-Part II”, *ORSA J. Comput.*, Vol. 2, No. 1, (1990), 4-32.
- Bai, X. and Shahidehpour, S., “Hydro-Thermal Scheduling

- by Tabu Search and Decomposition Method”, *IEEE PWRS*, Vol. 11, No. 2, (1996), 968-974.
27. Fushuan, W. and Chang, C. S., “A Tabu Search Approach to Alarm Processing in Power Systems”, *IEE Proc. Generation, Transmission and Distribution*, Vol. 144, No. 1, (1997), 31-38.
  28. Bakirtzis, A., Petridis, V. and Kazarlis, S., “Genetic Algorithm Solution to the Economic Dispatch Problem”, *IEE Proc.-Gener. Transm. Distrib.*, Vol. 141, No. 4, (July 1994).
  29. Baker, J. E., “Adaptive Selection Methods for Genetic Algorithms”, In J. J. Grefenstette, Ed., *Proceedings of First International Conference on Genetic Algorithms*, Erlbaum, (1985).
  30. Davis, L., “Handbook of Genetic Algorithms”, Van Nostrand Reinhold, New York, (1991).
  31. Goldberg, D. E., “Genetic Algorithms in Search Optimization and Machine Learning”, Addison Wesley, (1989).
  32. Gupta, M. C., Gupta, Y. P. and Kumar, A., “Minimizing the Flow Time Variance in a Single Machine System Using Genetic Algorithms”, *European Journal of Operational Research*, Vol. 70, (1993), 289-303.
  33. Haida, T. and Akimoto, Y., “Genetic Algorithms Approach to Voltage Optimization”, *Proceedings of the IEEE First International Forum on the Applications of Neural Networks to Power Systems*, (1991), 139-143.
  34. Frederick, S. H. and Gerald, J. L., “Introduction to Operations Research”, McGraw-Hill, (1990).
  35. Imran, A., “Manufacturing Shop Scheduling Using Genetic Algorithms”, Ph.D, Intelligent Systems Laboratory Systems Division, School of Engineering, University of Wales, Cardiff, UK, (1997).