Genetic algorithm-based power transmission expansion planning

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Large-scale combinatorial problems such as the network expansion problem present an amazing high number of alternative configurations with practically the same investment, but with substantially different structures (configurations obtained with different sets of circuit/transformer additions). This paper presents a development of a genetic algorithm (GA) and its application to a least-cost and reliable transmission expansion-planning (TEP) problem. TEP problem concerns with a highly constrained nonlinear dynamic optimization problem that can only be fully solved by complete enumeration, a process that is computationally impossible in a real-world TEP problem. In this paper, a GA incorporating stochastic reproduction technique and an artificial initial population scheme are developed to provide a faster search mechanism. The objective is to optimize the system adequacy (cost, and reliability). The proposed genetic string represents the number of reinforcement ways, which is limited to a certain ways for each line of the system, subjected in total to a pre-specified maximum number of reinforcements as well as the project budget. Excellent performance is reported in the test results.

إن التخطيط التوسعي لخطوط نقل القدرة الكهربية تعتبر من المشكلات المعقدة جدا وكثيرا ماتعطي مثل هذه المشـــكلات حلـــولا كثيرة لها نفس تكلفة التنفيذ.في هذا البحث نقدم تطويرا في الخوارزم الجيني حتى يمكننا من ايجاد تخطيـــط توســـعي للشـــبكات الكهربية بأقل التكاليف وأكثر اعتمادية بدلا من استخدام طرق لاخطية مقيدة تحتاج الى استعراض جميع الحلول الممكنة لاختيـــار الأمثل منها.ومن التطويرات التي تمت في هذا البحث على الخوارزم الجيني هو استخدام الجيـــل الأول الاصطنـــاعي وأيضـــا استحداث طرق في تطوير الأجيال الأخرى حتى تعطينا أسرع طريق للوصول للحل الأمثل.وفي الخوارزم الجيني المقترح تمثـــل الجينات بأرقام صحيحة موجبة تعبر عن عدد مرات تقوية خط من خطوط الشبكة آخذين في الاعتبار أن لا يتجاوز هذا الرقم عدد مرات معينة وأيضا تكلفة العمليات المقترحة لتقوية الشبكة لايتجاوز التكلفة المقترحة للخطة المقترحة.هذا وقد تم اختبار الطريقة المقترحة بأمثلة أثبتت صحتها وقدرتها في الحصول على خطط توسعية لشبكات نقل القوى الكهربية مهما بلغت حجمها وتحت أية قيود يراها المخطط.

Keywords: Genetic algorithm, Network synthesis, Combinatorial optimization, Transmission expansion planning.

1. Introduction

TEP is an important part of power system planning. Its task is to determine an optimal network configuration according to load growth.

The basic principle of TEP is to minimize the network construction and operational cost satisfying the requirement of delivering electric power safely and reliably to load centers. Generally speaking, the TEP should answer the following questions:

i. Where to build a new transmission line?
ii. When to build it?
iii. What type of transmission line to build?

It is recognized that the allocation of transmission costs in a competitive environment will require more careful evaluation of alternative transmission expansion plans. As a result, the need for methods that are able to synthesize optimal transmission expansion plans has become more important than ever.

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GA generates a sequence of populations (generations) by using three basic operators: selection, crossover and mutation [4-10]. Crossover is a mechanism of exchange of information among members f eneration. A uses mutation as an important search mechanism. The paper is organized as follows. An overview of the genetic algorithm applied to the TEP problem is presented, some practical aspects of the genetic algorithm are described, the proposed algorithm is summarized, and tests performed with both 5-bus and 14-bus systems.

2. Overview of the approach

In this paper, the problem is to distribute optimally a given total number of K expansions among lines in a network considering that:

i. Each line of the network has a finite set of improvement m, where.

ii The cost of each line is known.

iii Similar ones had reinforced each line.

Notation

e is the number of lines,

k_j is the number of improvements for line j, where $j \in \{1,..,e\}$, and $k_j \in \{0,..,m\}$, and

$C_{j;k_j}$ is the cost of line j, which has k_j improvements.

3. Optimization by genetic algorithm

Genetic algorithms (GAs) are derivative-free stochastic optimization methods based loosely on the concepts of natural selection and evolutionary processes. The characteristics of GA are as the following:

Chromosome: All living organisms consist of cells. In each cell there is the same set of chromosomes. A chromosome consists of genes; each gene encodes a particular protein.

Basically it can be said that each gene encodes a trait, for example color of eyes. Possible settings for a trait (e.g. blue ,brown) are called alleles. Each gene has its own position in the chromosome. This position is called locus.

Reproduction: During reproduction, first occurs recombination (or crossover). Genes from parents form in some way the whole new chromosome.

The new created offspring can then be mutated. Mutation means, that the elements of chromosome are a bit changed. These changes are mainly caused by errors in copying genes from parents.

Despite the algorithm's success, some open issues remain:

i. the choice of control parameters,
ii. the exact roles of crossover and mutation,
iii. convergence pproperties, i.e. achieving optimal result however initial population, and
iv. ability to solve large-scale practical problems.

All these issues will be discussed when solving the TEP problem.

3.1. Size of population

Choosing the size of population is the first thing the programmer has to do. To increase the probability of finding an optimum solution, a large size of population has to be used, but this also affects the speed of computation, besides large population means large number of computation, which means decreasing the power of GA. It was found that a population size of 20 is adequate for our problem.

3.2. Codification of chromosomes

Binary representation, traditionally, are used in GA. However it has some drawbacks when applied in certain types of problems of optimization. Integer vectors representation was used successfully in optimization problems in which the solution is a permutation, such as in optimal TEP. This is the reason to choose, precisely, a vector of integers as representation method. Each gene of the chromosome is an integer representing the line affected and the type of modification that will be made on this line.

In this case the representation by means of strings of bits was chosen. Each gene j of the chromosome can store a 0, which indicates absence of improvements in the corresponding line or an integer different from 0 ($\leq m$) that indicates the improvement type or number of added lines that is made in the line j. Another restriction is imposed on the sum of all improvements performed on a certain vector population, i.e. the sum of all vector components does not exceed K. Therefore a chromosome (Chrom) can be represented as:

k_1	k_2	k_3	..	..	k_e

Subjected to the following:

i. $k_j \leq m$, for $\forall j$,

ii. $\sum_{j=1}^{e} k_j = K$

iii. $\sum_{j=1}^{e} C_{j;k_j} \approx \text{budget}$ (1)

3.3. Artificial initial population

GA starts with an initial population of the individuals according the following steps:

Step1: Choose randomly an individual, in which each gene j of the chromosome can store an integer ($\leq m$) that indicates the number of added lines. The chromosome will represent another restriction that the sum of all alleles does not exceed K and the cost of corresponding expansion plan is close to a pre-specified budget.

Step 2: Determine the fitness (value of the objective function) of a network configuration for the current chromosome.

Step 3: *Store* a new individual in case of its fitness is best than the fitness obtained in step 1.

Step 4: Repeat steps 1-3, until the number of stored individuals reaches the specified population size.

Excellent performance of GA based on such initial population is reported in the test result section.

3.4. Selection method

The selection rule is used to determine the individuals that will have a representation in the next generation of the GA. Two major selection mechanisms are commonly adopted in a GA search:

i. Roulette-wheel selection, the probability of being selected is proportional o n individual's fitness value.

ii. Tournament selection, a fraction of the individuals in the population are randomly selected into a sub-population and competition carried out to select the fittest individuals in each sub-population.

In this paper, a modified tournament selection mechanism has been used to produce the best new population from old one. In the modified selection method, a fraction of the individuals (called generation parents) in the old population are statistically selected (individuals that have fitness best than the average fitness of old one) into new-population. If the number of stored individuals does not reach the specified population size, random selection from generation parents is carried out, until the number of stored individuals reaches the specified population size.

The aforementioned selection mechanism gives excellent convergence properties. These properties are reported in the test result section.

3.5. Genetic operators (crossing, mutation)

In this paper, genetic operators are used to create new individuals called children. The most commonly used genetic operators are crossover and mutation, which are used here. The combination ules act on individuals that have been previously elected as generation parents to produce children that become individuals in the rest of the current generation.

Crossover is a combination rule that produces offspring in the aiming interpolation of the parents. In this paper the uniform crossover is adopted.

A crossover robability s ot eeded or production of children but the generation is running until population size is reached.

At this time, we don't believe that all children will satisfy our problem constrains, so mutation operator is needed to correct unsuitable children again. Moreover, mutation probability is not needed.

3.6. Objective function

The objective function used here is to minimize a function F given by:

$$F = \sum_{j=1}^{e} \sum_{i=1}^{e} I_{j;k_i} \qquad (2)$$

Where,

$I_{j;k_i}$ j^{th} link importance associated with k_i improvements. It is worth mentioning here that any improvement added to the network will change the importance of a given link and the other links associated with that link forming different network cut sets, i.e.,

$$I_{j;k_i} = \sum_{i=1}^{h} b^{(h-i)} d_i \quad , \qquad (3)$$

d_i represents how many times that the j^{th} link performs an i^{th} order cut set

h represents the highest order of the network cut sets,

$b^{(h-i)}$ to amplify the weight of i^{th} order than $(i-1)^{th}$ order,

$\sum_{i=1}^{e} I_{j;ki}$ Summation giving link importance

$\sum_{j=1}^{e} \sum_{i=1}^{e} I_{j;ki}$ Summation giving link importance

Subject to:

i. the cost of expansion improvements is very close to a certain given budget;

i.e. $\sum_{j=1}^{e} C_{j;k_j} \approx \text{budget}$,

ii. the total number of network improvements is limited to a total of K improvements; i.e. $\sum_{j=1}^{e} k_j = K$, and

iii. each link has a maximum of m improvements; i.e. $k_j \le m$, for $\forall j$.

4. Test results

The 5-bus power network shown in fig. 1 is considered. The network contains 5 nodes and 7 links. Considering that each link has one improvement (m=1) while the network has a maximum of 3 improvements (K=3). All nodes are perfect. Applying the cut set technique mentioned in [11], the cut sets of the network given in Fig. 1 are {1,5}, {1,2,6}, {2,5,6}, {2,3,7}, {1,4,6,7}, {3,5,6,7}, {4,5,6,7}, {1,3,6,7}, {2,4,7}, and {3,4}. Table 1 gives the cost of each link. Table 2 gives the results of GA for different budgets and b equal to 2.

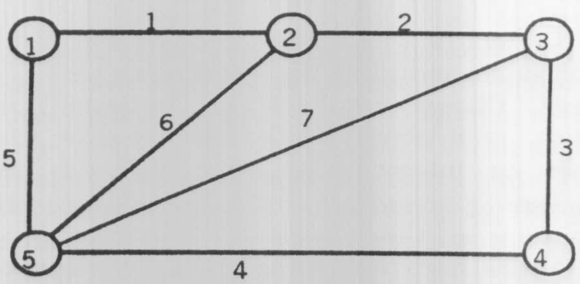

Fig. 1. A 5-bus/ 7-links network.

Table 1
List of link-cost.

Link #	$C_{j;0}$ *
1	1.6
2	1.4
3	1.5
4	1.7
5	1.2
6	1.5
7	1.3

*Per-unit values

Table 2
Optimal solutions and corresponding fitness for various budgets.

Budget	Optimal solution	F
4.0	0100101	8340.00
5.0	0111000	1560.00
6.0	0111000	1560.00

5. Applications to large power systems

The 14-bus power network shown in fig. 2. is considered. The network contains 14 nodes and 20 links. Considering that each link has two improvements (m=2) while the network has a maximum of 7 improvements (K=7). There are 111 cut sets of the network. Table 3 gives the cost of each link.

Table 4 gives the results of GA for different budgets and b equal to 2.

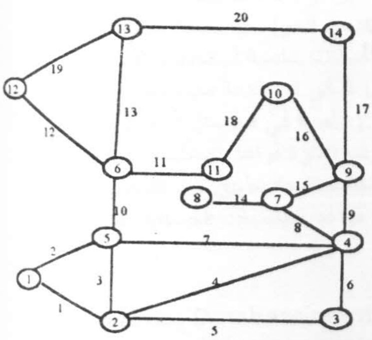

Fig. 2. IEEE-14 bus syste.

The optimum locations of added lines were obtained for the networks shown in Figs. 1 ,2. using the solution methodology described in the previous section.

Table 3
List of link-cost

Link #	$C_{j;0}^*$	Link #	$C_{j;0}^*$	Link #	$C_{j;0}^*$
1	1.0	8	1.0	15	1.7
2	1.1	9	1.1	16	1.8
3	1.2	10	1.2	17	1.9
4	1.3	11	1.3	18	0.8
5	1.4	12	1.4	19	0.9
6	1.5	13	1.5	20	0.7
7	1.6	14	1.6		

*Per-unit values

Table 4
Optimal solutions and corresponding fitness for various budgets.

Budget	Optimal solution	F
10.0	01001100010000001101	5796.00
15.0	01010001010000001101	5352.00
20.0	01010001010000001101	5352.00

The variation in the budget is taken into account and the results are presented in tables 2, 4 It can be seen from each table that the optimal solution is not changed while the corresponding budget is increased.

So, the usage of the above genetic algorithm and the new objective function give the planner the global optimal planning of power networks. Also, the size of network is not becoming a great problem in power system planning as in case of conventional optimization techniques. Moreover, the planner can add more objectives to convert the problem from static expansion planning to dynamic expansion planning in which the problem is to optimize the total loss cost under various load steps, voltages violations, and the system stability during different outages.

5. Conclusions

GAs are optimization techniques based on a well-known process found in nature and which has been successfully applied to a number of electrical engineering problems. We have successfully extended and applied the approach to large-scale transmission network expansion planning problems. Test results have shown that the new methodology has proved to be more efficient than other traditional methods tried before. Also, using system importance as a reliability index has given good results.

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