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ANALYSIS AND OPTIMIZATION OF POWER TRANSMISSION GRIDS BY GENETIC ALGORITHMS

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ABSTRACT

Two applications of multi-objective genetic algorithms (MOGAs) are reported with regards to the analysis and optimization of electrical transmission networks. In a first case study, an analysis of the topological structure of a network system is carried out to identify the most important groups of elements of different sizes in the network. In the second case study, an optimization method is devised to improve the reliability of power transmission by adding lines to an existing electrical network.

1 INTRODUCTION

In this paper, two applications of multi-objective genetic algorithms (MOGAs) are reported with regards to the analysis and optimization of electrical transmission networks.

In the first case study, Genetic Algorithms (GAs) are used within a multiobjective formulation of the search problem, in which the decision variables identify groups of components and the objectives are to maximize the importance of the groups while minimizing their dimension.

In the second case study, a GA method is developed for identifying strategies of expansion of an electrical network in terms of new lines of connection to add for improving the reliability of its transmission service, while maintaining limited the investment cost. To realistically restrict the search space to small numbers of new connections, the so-called guided multi-objective genetic algorithm (G-MOGA) has been applied. In this approach, the search is based on the guided domination principle which allows to change the shape of the dominance region specifying maximal and minimal trade-offs between the different objectives so as to efficiently guide the MOGA towards Pareto-optimal solutions within these boundaries (Zio et al. 2009).

The paper is organized as follows. Section 2 presents the group closeness centrality measure which can be used to quantify the importance of groups of nodes. The concept of network global reliability efficiency is also presented. In Section 3 and Section 4, the case studies regarding the IEEE 14 BUS network system (Christie 1993) and IEEE RTS 96 (Billinton & Li 1994) are presented and solved by MOGA. Conclusions on the outcomes of the analysis are eventually drawn in Section 5.

2 TOPOLOGICAL GROUP CLOSENESS CENTRALITY AND GLOBAL RELIABILITY EFFICIENCY

Mathematically, the topological structure of a network can be represented as a graph $G(N,K)$ with N nodes connected by K edges. The connections are defined in an $N \times N$ adjacency matrix $\{a_{ij}\}$ whose entries are 1 if there is an edge joining node i to node j and 0 otherwise.
The group closeness centrality (Everett & Borgatti 1999), $C^C(g)$, is based on the idea that a node

can quickly interact with all other nodes if it is easy accessible (close to) all others. If d_{ij} is the topological shortest path length between nodes i and j (i.e., the minimum number of arcs on a path connecting them), the closeness of a group g of N_g nodes is the sum of the distances from the members of the group to all vertices outside the group:

$$C^C(g) = \frac{N - N_g}{\sum_{i \in g, j \in G} d_{ij}} \tag{1}$$

This measure is normalized by dividing the distance score into the number of non-group members, with the result that larger numbers indicate greater centrality.

When the group consists of a single node, the group closeness centrality is the same as the individual node closeness centrality (Freeman 1979, Sabidussi 1966, Wasserman & Faust 1994).

To capture the failure behavior of the network, the reliability of its connecting edges is included in the framework of analysis by means of the formalism of weighted networks, the weight w_{ij} associated to the edge between the pair of nodes i and j being its reliability:

$$p_{ij} = e^{-\lambda_{ij} \cdot T} \tag{2}$$

where λ_{ij} is the failure rate of edge ij linking nodes i and j and T is a reference time ($T = 1$ year, in this work).

On the basis of the adjacency and reliability matrices $\{a_{ij}\}$ and $\{p_{ij}\}$, the matrix of the most reliable path lengths $\{rd_{ij}\}$ can be computed (Zio 2007). The group reliability closeness centrality can then be computed as in equation 1, with rd_{ij} replacing d_{ij}.

The global reliability efficiency $RE[G]$ of the graph G can also be defined as (Zio 2007):

$$RE[G] = \frac{1}{N(N-1)} \sum_{i, j \in G, i \neq j} \left(1 / rd_{ij}\right) \tag{3}$$

3 CASE STUDY 1: IEEE 14 BUS ELECTRICAL TRANSMISSION NETWORK

The topological structure of the electrical transmission network system of the IEEE (Institute of Electrical and Electronic Engineers) 14 BUS) is considered for the analysis of the importance of groups of components, measured in terms of reliability closeness centrality. The system considered represents a portion of the American Electric Power System and consists of 14 bus locations connected by 20 lines and transformers. The topology of the system can be represented by the graph G(14,20) of Figure 1.

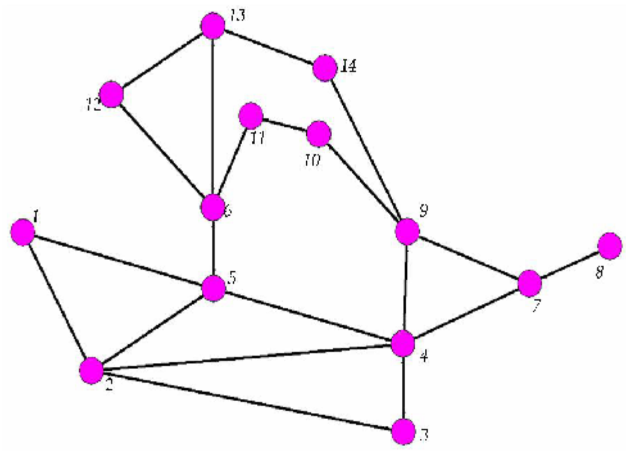

Figure 1. Graph representation of the IEEE 14 BUS transmission network

A MOGA has been implemented to identify the most reliability-central groups of nodes of different sizes in the network of Figure 1, considering as objective functions the group reliability closeness centrality measure and the dimension of the group.

Figure 2 shows the results obtained on the importance of the group in terms of reliability closeness centrality. In the Figure, the values of the objective functions in correspondence of all the nondominated groups of nodes contained in the MOGA archive at convergence are shown to identify the two-dimensional Pareto-optimal surface (circles). The results are compared for validation with those obtained by exhaustive computation of all groups of nodes (i.e., the computation of the group reliability closeness centrality measure for all the possible combinations of n out of N nodes; due to the fact that the number of groups obtained is 2^N, its implementation is feasible here thanks to the small size of the network but would require impractical computational resources for large networks).

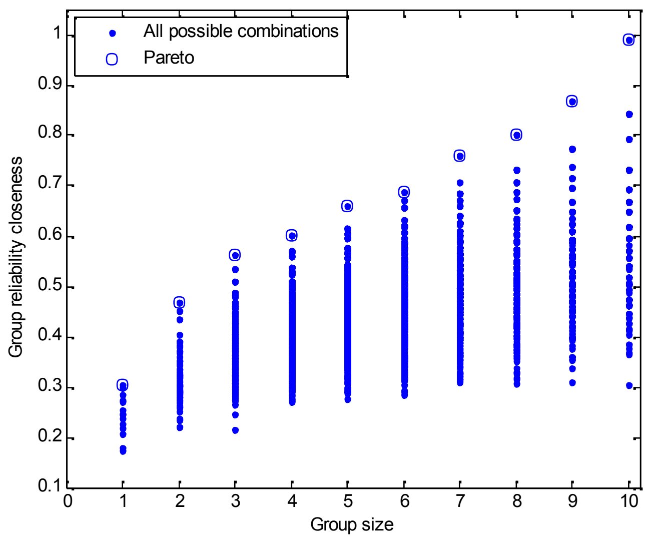

Figure 2. Results of the multi-objective search of the most central groups of nodes in terms of reliability closeness centrality

Actually, different groups of equal size can have the same centrality measure value: Table 1 reports all the nondominated solutions contained in the archive, identified by the MOGA.

In the present case, the smallest group with maximal reliability closeness is of size 10 and there are 2 of these. The group {1, 2, 3, 5, 7, 10, 11, 12, 13, 14} is particularly interesting because it does not contain the highly central node {4} and contains the node {1} that have the smallest individual reliability closeness centrality measure, as it can be seen in Table 2.

Table 1. Pareto optimal results of the multi-objective search for reliability closeness centrality groups

Group reliability closeness centrality	Group Size	Components
0.303	1	4
0.47	2	(4, 6), (6, 9)
0.562	3	(2, 6, 9)
0.602	4	(1, 2, 6, 9), (1, 3, 6, 9), (2, 3, 6, 9)
0.659	5	(1, 2, 3, 6, 9)
0.688	6	(1, 2, 3, 6, 7, 9), (1, 2, 3, 6, 8, 9)
0.761	7	(1, 2, 3, 5, 7, 10, 13), (1, 2, 3, 5, 7, 11, 13), (1, 2, 3, 6, 7, 10, 13), (1, 2, 3, 6, 7, 10, 14), (1, 2, 3, 6, 7, 11, 13), (1, 2, 3, 6, 7, 11, 14)
0.802	8	(1, 2, 3, 5, 7, 10, 11, 13), (1, 2, 3, 5, 7, 10, 12, 13), (1, 2, 3, 5, 7, 11, 12, 14), (1, 2, 3, 6, 7, 10, 11, 13), (1, 2, 3, 6, 7, 10, 12, 13), (1, 2, 3, 6, 7, 11, 12, 14) …
0.868	9	(1, 2, 3, 5, 7, 10, 11, 12, 13), (1, 2, 3, 5, 7, 10, 11, 13, 14), (1, 2, 3, 6, 7, 11, 12, 13, 14) …
0.99	10	(1, 2, 3, 5, 7, 10, 11, 12, 13, 14), (1, 2, 3, 6, 7, 10, 11, 12, 13, 14)

Table 2. Individual reliability closeness centrality

Node	Reliability closeness centrality
4	0.3031
9	0.2998
5	0.2835
7	0.2742
6	0.2716
14	0.253
10	0.2448
13	0.2448
11	0.2371
2	0.2272
8	0.2184
12	0.2081
3	0.1793
1	0.1723

4 CASE STUDY 2: IEEE RTS 96 ELECTRICAL TRANSMISSION NETWORK

The transmission network system IEEE RTS 96 (Figure 3a) (Billinton 1994) consists of 24 bus locations (numbered in bold in the Figure) connected by 34 lines and transformers. The transmission lines operate at two different voltage levels, 138 kV and 230 kV. The 230 kV system is the top part of Figure 3a, with 230/138 kV tie stations at Buses 11, 12 and 24.

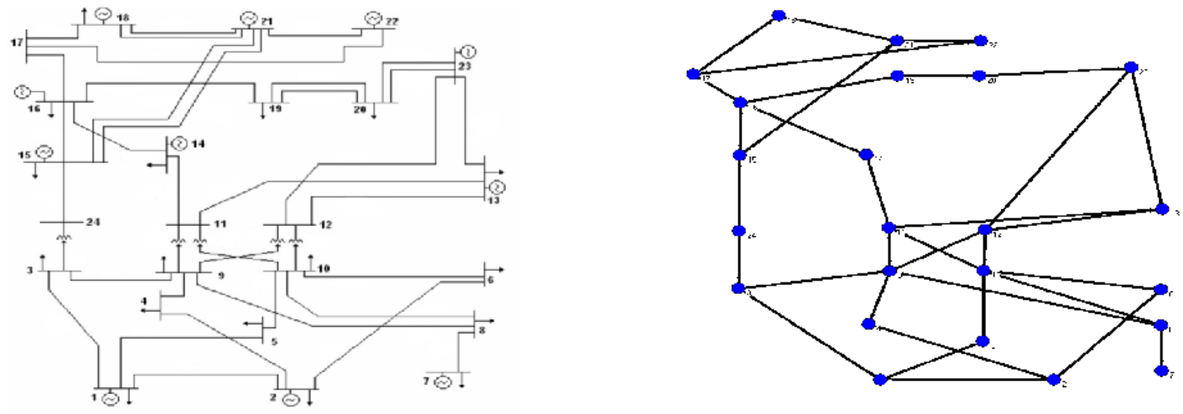

Figure 3. a) IEEE RTS 96 transmission network; b) IEEE RTS 96 graph representation

Figure 3b gives the representation of the graph $G(24,34)$ of the transmission network; the corresponding 24×24 adjacency matrix $\{a_{ij}\}$ has entry equal to 1 if there is a line or transformer between bus locations i and j and 0 otherwise.

A MOGA has been constructed for identifying the best improvements in the connection of the network, aimed at increasing its global reliability efficiency in transmission at acceptable costs. The improvements are obtained by addition of new lines between nodes with no direct connection in the original network. Given the lack of geographical information on the nodes locations, for simplicity and with no loss of generality, three typologies of lines have been arbitrarily chosen as the minimum, the mean and the maximum values of the failure rates of the transmission lines taken from (Billinton 1994):

$$\lambda_1 = 0.2267 \text{ outages/yr}$$
$$\lambda_2 = 0.3740 \text{ outages/yr}$$
$$\lambda_3 = 0.5400 \text{ outages/yr}$$

The addition of a new line requires an investment cost assumed inversely proportional to the failure rate. The network cost can be then defined as:

$$C[G] = \sum_{i,j\in N, i\neq j} \left(1/\lambda_{ij}\right) \qquad (4)$$

The reliability cost of the original IEEE RTS 96 is $C\left[G\right] = 332.0120$ in arbitrary monetary units and the reliability efficiency is $RE\left[G\right] = 0.2992$, which is a relatively high value representative of a globally reliable network.

From the algorithmic point of view, a proposal of improvement amounts to changing from 0 to 1 the values of the elements in the adjacency matrix corresponding to the added connections. The only physical restriction for adding direct new connections is that the connected nodes must be at the same voltage level (138 or 230 kV), otherwise the addition of a transformer would also be needed. From the genetic algorithm point of view, the generation of proposals of network improvements can be achieved by manipulating a population of chromosomes, each one with a number of bits equal to 214 which is double the number of zeros (i.e., the number of missing direct connections *ij*) in the upper triangular half of the symmetric adjacency matrix $\{a_{ij}\}$. The bits are dedicated to each missing direct connection *ij* so as to code the three different available types of lines with failure rates λ_1, λ_2 and λ_3: in other words, the bit-string (00) is used to code the absence of connection, (01) connection line with a λ_1-type line, (10) connection with a λ_2-type line and (11) connection with a λ_3-type line. The initial population of 200 individuals is created by uniformly sampling the binary bit values.

During the genetic search, each time a new chromosome is created, the corresponding matrices $\{a_{ij}\}$ and $\{p_{ij}\}$ are constructed to compute the values of the two objective functions, network global reliability efficiency and cost of the associated improved network.

Figure 4 shows the Pareto dominance front (squares) obtained by the MOGA at convergence after 10^3 generations; the circle represents the original network with $RE[G] = 0.2992$ and $C[G] = 332.0120$, while the star represents the network fully connected by the most reliable transmission lines $\lambda_1 = 0.2267$ occ/yr, for which $RE[G] = 0.57$ and $C[G] = 804.1072$.

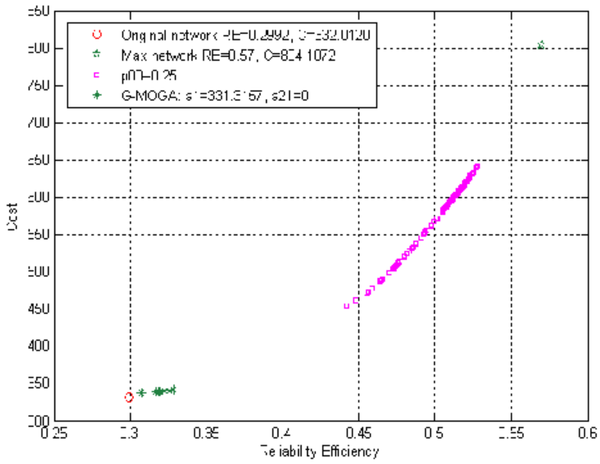

Figure 4. Pareto front reached by the MOGA

The optimality search is biased from the beginning (from the initial population) towards highly connected network solutions, because the string (00) has a probability of 0.25 whereas the probability of adding a connection of any one of the three available types (i.e., the probability of the strings 01, 10, 11) is 0.75; this drives the population evolution to highly connected networks in the Pareto front (squares in Figure 4), all with values $RE\left[G\right] \geq 0.4417$, $C\left[G\right] \geq 454.4738$ and numbers of added connections exceeding 60.

In practical applications only a limited number of lines can be added, due to the large investment costs and other physical constraints. To drive the genetic search towards low cost solutions (i.e., low number of added lines) maximal and minimal trade-offs to the two objectives of the optimization (network global reliability efficiency and cost) can be defined within a Guided Multi-Objective Genetic Algorithm (G-MOGA) scheme, (Zio 2007). The preferential optimization has been performed by using G-MOGA, with the same population size, evolution procedures and parameters of the previous search. In this approach, the search is guided by defining the maximal and minimal trade-offs that allow to identify a precise section of the Pareto front. The values of the trade-off parameters have been set by trial-and-error to $a_{12} = 331.3157$ and $a_{21} = 0$; the search converges to a small number of solutions in a Pareto front which is more concentrated on low cost networks, characterized by a limited number of added connections (asterisks in Figure 4).

Table 3 lists the five solutions of lowest cost identified by the G-MOGA search: the added connections improve the network global reliability efficiency and they do so with relatively small costs.

Table 3. The five solutions on the Pareto front obtained by the G-MOGA

G-MOGA	
Reliability Efficiency	Cost
0.3072	337.6
0.3168	339.4
0.3186	339.4
0.3187	339.4
0.3193	339.4

5 CONCLUSIONS

In this paper, the electrical transmission network system of the IEEE 14 BUS has been taken as case study for the MOGA analysis of the importance of groups of components, measured in terms of their centrality in the structure of interconnection paths. The results obtained using the group reliability closeness centrality measure as importance indicator have shown that the groups classified as most central indeed contain the nodes of individual highest centrality but may also include nodes with a relatively low centrality.

Also, a MOGA for improving an electrical transmission network (IEEE RTS 96) has been implemented with the objective of identifying the lines to be added for maximizing the network transmission reliability efficiency, while maintaining the investment costs limited. A preferential procedure of optimization has been implemented for individuating realistic network expansion solutions made of few new transmission lines.

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