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R3TO: Algorithm for the Routing of Electrical Networks with Pole Allocation and Obstacle Transposition

Danrley Rafael Fernandes, Géssica Michelle Dos Santos Pereira, Maricler Toigo, Roberto Tadeu Raittz

Institute of Technology for Development (LACTEC), Curitiba-PR, Brazil

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Abstract— *The increase in energy consumption and the need to maintain continuity in supply, make it essential to plan for the expansion of electricity networks. Although there is extensive literature regarding the automatic generation of distribution network routing, the costs for pole allocation still deserve attention. This study presents the R3TO proposal, which combines Evolutionary Algorithms, with the deterministic Dijkstra algorithm, to solve network routing problems considering the adequacy of pole allocation. R3TO is able to determine the posting in a network, with minimization in the number of posts and transposition of obstacles, such as rivers or roads. In order to evaluate the method, tests were performed in a theoretical area and in a mapping of a pilot test region in a real area. The results obtained with the R3TO showed a cost reduction when compared to the traditional deterministic algorithm, and was successful in allocating poles across restricted areas, shortening the total path. Thus, it was proven that R3TO generates a minimized path, and with suggested positions for pole placement presenting good perspectives to improve current approaches to the problem.*

I. INTRODUCTION

The book *On the Origin of Species by Means of Natural Selection* [1] inspired scientific revolutions in several areas. In the field of computing this was expressed in the emergence of Evolutionary Algorithms and their various aspects [2]. Among these, one can highlight the Genetic Algorithms (GA) [3], which use evolutionary concepts such as mutation and genetic recombination, to generate appropriate solutions to an environment of evolutionary pressure. This selectivity is modeled by a cost function (*fitness function* - FF), which aims to obtain solutions that tend to be optimal. The optimization seeks to minimize or maximize the value returned by the FF according to the adopted algorithm. Thus an algorithm can be applied - as in this study – to obtain a trace that **minimizes** the function that determines the cost of a given routing of a network. The characteristics of GA have made them a common approach to several recent studies, which seek to solve tracing optimization problems [4][5][6]. Particularly, one of the applications that can benefit from this type of methodology is the routing of power cables.

Non-urban areas often offer several challenges for the distribution of electrical networks. Of these, we can highlight the long distances between roads and houses, rugged terrain and natural obstacles, such as rivers and cliffs [7]. To overcome these problems, engineers presented several projects, techniques and systems for distribution solutions of electrical networks, but it is necessary to consider that most of the electrical wiring routes are still planned manually, through the trial and error method.

One of the main gains from the application of trace optimization algorithms is the economical one. By reducing wire lengths, complexity in the networks and decreasing voltage drops, it is possible to maximize the profitability of an electrical route. In addition, the reduction of voltage drops can ensure greater safety and durability of electrical equipment [8].

In this article we present an algorithm for Routing Rural Networks with pole allocation – R3TO, whose main objective is to optimize electrical wiring routes, in order to reduce the length of the circuits and avoid obstacles through AG, exploring and improving initial solutions. We seek to expand the capacity offered by the Dijkstra algorithm by reducing the costs of tracings and adding new possibilities in constraint modeling.

The solution presented, when possible, overlaps the obstacles, instead of diverting them, innovating the automatic planning of expansion of distribution systems of rural networks with pole allocation, which presents paths capable of overcoming terrestrial obstacles, such as water bodies, irregular terrain.

The R3TO model has the ability to explore latissimus graphs, in addition to the points immediately nearby. This feature allows the R3TO to use lines between mapped points to pass through paths that do not need to be restricted to the limitations of a graph's point-to-point transitions. This makes the route better match the actual relief of an analyzed map. Figure 1 illustrates a situation where the R3TO algorithm outperforms Dijkstra in a simulated situation.

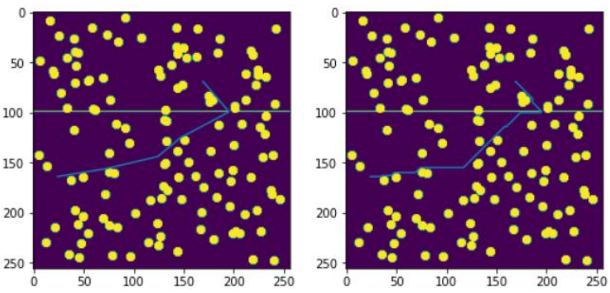

Fig.1 – Comparison between R3TO (left) and the Dijkstra method (right).

II. ALGORITHM R3TO

For R3TO, the initial search space is given by a latisse graph determined on a *raster* with a cost value at each point. By identifying the point of origin and destination, the objective is determined, which is to obtain the lowest possible cost route that unites these points. A set of points, in a specific order, defines a candidate solution. Each possible solution can be represented by a set of bits - chromosome. The genetic algorithm builds evolution through successive substitutions of solution populations. The strategy developed for this work is to feed the initial population by adding chromosomes with high evolutionary potential to the set of randomly generated solutions. For the first chromosomes were modeled containing:

a) Intermediate points on the straight line containing the start and end points;

b) The points that define the direction inversions in the solution obtained by the Dijkstra algorithm.

We have also established a feedback strategy that includes chromosomes tailored to the best solutions in each generation.

Each chromosome consists of a string of bits whose size depends on the dimensions of the raster and the maximum number of intermediate points to be considered, which are determined by the analyst. To the bits that represent the coordinates of the points is added a logical bit that enables (1) or not (0) the use of the coordinate in the represented solution. The number of bits per chromosome is given by:

$$\underline{BS = PM * [bool + DR1 + DR2]}$$

Where:

BS: length of the bit chain (in bits)

PM: maximum number of intermediate points (parameter defined by the user);

Bool: 1 bit that enables the coordinate;

DR1: number of bits required to represent the number of rows of the matrix (raster);

DR2: number of bits required to represent the number of columns of the matrix (raster).

The decoding of each chromosome provides a trace that is evaluated by fitness function. The cost of each solution of the populations is calculated until the maximum number of iterations is reached. The evaluation is given by calculating an average cost to go through the latisse by the points indicated by the trajectory, multiplied by the total Euclidean distance to go through the path by the intermediate points contained in the solution - decoded corresponding chromosome.

In addition to seeking the lowest possible cost value for the network, the fitness function aims to optimize pole allocation. Due to this, the algorithm is able to suggest strategic points in the graph for pole placement, allowing the layout to "jump" obstacles. It is important to note that the algorithm is not intended to define the precise placement for each of the poles, but to obtain a route where there are no insurmountable regions by possible posting. The solution identifies two distinct types of obstacles: insurmountable and transposable. The insurmountable obstacles are marked as a very expensive knot in the raster, which, therefore, forces the layout to divert them. Traversible obstacles are passed in a raster, with specific points of the graph. This is used to penalize only the suggested posts in this area, not the trace itself. In the parameterization, the analyst defines two values:

- Weight 1, (Ω1), which presses for a decrease in the number of poles, avoiding unnecessary suggestions.
- Weight 2 (Ω2) to prevent poles from being suggested within insurmountable obstacle areas.

The value of Ω1, is defined by dividing the cost of the trace by the weight 1. The Ω1 is multiplied by the number of posts in the trace generating the penalty 1. The value of Ω2, defined by multiplying the cost of tracing by weight 2. The Ω2 is multiplied by the number of posts placed in restricted areas (obstacles), generating the penalty 2. In the end, penalties 1 and 2 are added to the cost of the trace, returning the final cost of the trace by:

$$\underline{FO = MIN\ CM + (\Omega 1 \div x1) + (\Omega 2\ y2)}$$

Where:

FO: objective function;

CM: average cost of routing without poles;

Ω1: weight that penalizes the number of poles;

X1: number of poles;

Ω2: weight that penalizes poles allocated in transposition areas;

X2: number of poles allocated in transposition areas.

The model fulfills the following main steps in its process: generation of the initial solution, chromosome decoding and chromosome evaluation. The general flowchart of the method is presented in Figure*2*.

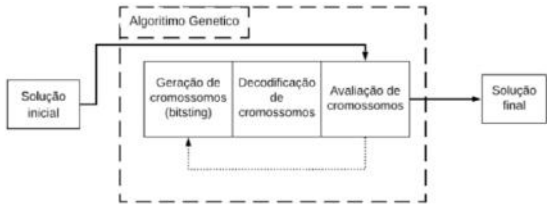

Fig.2 - General flowchart of the method

The development of the algorithm was done in the Python language, from a prototype built in MatLab ®. To solve the initial solution of Dijkstra, the Skimage library was used, with the Graph module and the Route_Through_Array function. For the genetic algorithm, the SciPy library was used, using the Brusque Scanning method considering the parameters:

● Strategy: best1bin

● Mutation: 0.8

● Crossover: 0.35

● Seed: 10

● Maxiter: 1000

III. RESULTS

The following figures demonstrate the application of this method in a pilot area, in the rural region of the city of Piên/PR.

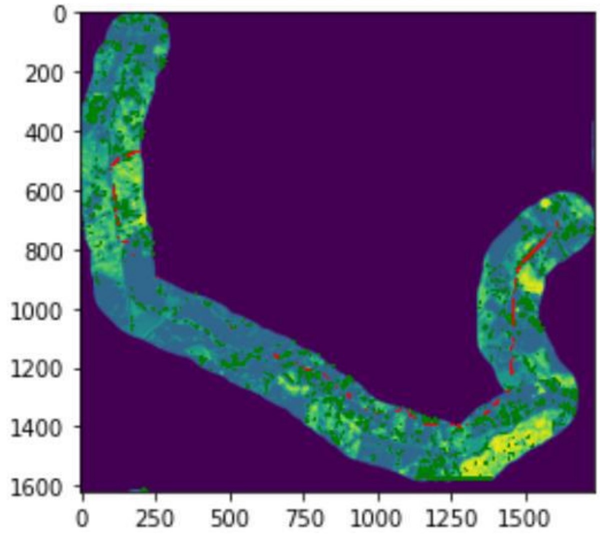

Fig.3 - The red dots represent possible poles, and the pixels in green the restricted area. Lines between the indicated poles do not contain insurmountable regions

Figure 3 is a bitmap generated from the cost matrix of the Piên pilot area. In this image the pixels in green mark the areas that do not allow placement of poles, as determined by an analyst. The red dots, on the other hand, are an amplified marking of the pixels representing the area where it may be interesting to place poles. It is possible to note that the suggestions for renting poles transpose the restricted areas in green. It is also possible to check the quality of the result through the final output of the R3TO, which is an array where each line represents the YX coordinates for each post within the bitmap image. Figure 4 shows an excerpt of a georeferenced image of the mapping of the Piên region where the transposition of an obstacle (road) by the R3TO is notable.

Fig.4 – Highlight showing how the algorithm allows solutions crossing a road

In this test, the algorithm was successful in finding an optimized network path, with transposition of obstacles and minimization of poles in a real region. However, a processing time of 65 hours and 24 minutes was observed to process it. The computational cost is compensating, however, for economic gains.

IV. CONCLUSION

This article sought to highlight the need for studies to solve the problems of network expansion in rural areas. A solution proposal was presented using the Python programming language, including an algorithm that reduces the number of posts allocated and the transposition of obstacles, unlike other previous studies that only diverted them, disregarding that air lines can overcome obstacles instead of just diverting them. This was evidenced by the presentation of tests on a synthetic map and a real test area. We show a promising solution that can contribute in several ways to the automatic generation of network routing. However, other studies aiming at more tests and improvement in processing time to obtain the solutions are necessary.

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