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### ABSTRACT

Node placement problems, such as the deployment of radio-frequency identification systems or wireless sensor networks, are important problems encountered in various engineering fields. Although evolutionary algorithms have been successfully applied to node placement problems, their fixed-length encoding scheme limits the scope to adjust the number of deployed nodes optimally. To solve this problem, we develop a flexible genetic algorithm in this paper. With variable-length encoding, subarea-swap crossover, and Gaussian mutation, the flexible genetic algorithm is able to adjust the number of nodes and their corresponding properties automatically. Offspring (candidate layouts) are created legibly through a simple crossover that swaps selected subareas of parental layouts and through a simple mutation that tunes the properties of nodes. The flexible genetic algorithm is generic and suitable for various kinds of node placement problems, Two typical real-world node placement problems, i.e., the wind farm layout optimization and radio-frequency identification network planning problems, are used to investigate the performance of the proposed algorithm. Experimental results show that the flexible genetic algorithm offers higher performance than existing tools for solving node placement problems.

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#### 25 **1. Introduction**

The node placement problem (NPP) is an important problem in 26**03** many fields, such as radio frequency identification (RFID) [1], wire-27 less sensor networks (WSNs) [2], wind farm design [3], and oil and 28 gas industry [4]. The task of an NPP solver is to place a number of 29 nodes optimally in a given area to meet certain predefined objec-30 tives. For this, there are mainly three issues to be addressed: (1) the 31 number of nodes being deployed; (2) the positions of the nodes; (3) 32 their property settings. 33

NPPs have been studied separately in the literature. They have different names in different contexts. For example, in the field of WSNs, an NPP is sometimes referred to as a 'relay node placement problem' [2,5–8]. In other fields, specific terms such as RFID

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http://dx.doi.org/10.1016/j.asoc.2016.10.022 1568-4946/© 2016 Elsevier B.V. All rights reserved. network planning (RNP) [1,9–12], wind farm layout optimization (WFLO) [3,13–16], and well placement optimization (WPO) [4,17–19] problems are used. The definitions of the problems are different, but have something in common. Noticing that a solver to one of the problems may be applicable to the others with similar characteristics, this paper considers the problems in a generic prospective. To this end, we provide a general framework for NPPs and develop an approach capable of solving various NPP instances.

During the past decade, a substantial amount of research has been undertaken to address *ad hoc* NPPs. One sort of approach is to use deterministic algorithms such as integer linear programming [20,21], mixed integer programming [22,23], geometric programming [24], and some other approximation algorithms [6,8,25]. These algorithms are designed for particular problems with precise models. The defect is that the strong assumptions made by the models narrow the scope of application of the algorithms. On the other hand, an NPP is usually coupled with a series of constraints and has multiple objectives. These make the problem complex. As an example, the planning of RFID systems has been proven to be NP-Complete [26,27].

Recently, the use of alternative methods such as heuristic [7], evolutionary algorithms (EAs) [28,29] and swarm intelligence (SI)

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Fig. 1. Fixed-length encoding scheme.

[30] has attracted an increasing attention. In the literature, both EAs 60 such as genetic algorithms (GAs) [31-36] and SI techniques such as particle swarm optimization (PSO) [10,11,37] have been utilized 62 to tackle ad hoc NPPs. However, since an EA uses a fixed-length encoding scheme to represent a candidate solution, it is hard to adjust the number of nodes.

To illustrate this, suppose a square area is given to place a 66 number of nodes to meet predefined requirements. Fig. 1 shows 67 the fixed-length encoding scheme used in [11,31,37-40], where 68 *n* stands for the estimated number of nodes, and  $(x_i, y_i)$  and  $p_i$ 69 represent the coordinates and property setting of the *i*th node 70 respectively. However, it is difficult to accurately estimate the num-71 ber of nodes in need, which plays a vital role in the assessment of 72 layouts. Hence, the deployment in [11,31,37-40] still has room to 73 improve. An alternative is a grid-based binary encoding approach 74 as used in [10,13,15,32-36], which divides the target area into mul-75 tiple grids and uses a binary variable to indicate whether to place 76 a node in the center of the corresponding grid, as shown in Fig. 2. 77 In this way, a candidate solution (layout) can be represented by a 78 binary string in a GA or PSO [41] to handle NPPs. 79

Although the grid-based approach is capable of pruning the 80 number of nodes, there are two disadvantages. First, because the 81 positions of the nodes are confined to the centers of the grids, the 82 layout can only be optimized at a coarse-grained level. Second, it is 83 inconvenient to incorporate additional properties of nodes (such as 84 85 the transmitted power of RFID readers [12]) into the optimization 86 process.

To optimize the number of nodes as well as the deployment, 87 a variable length encoding scheme is required. In the literature, 88 research efforts have been devoted to the design of variable length 89 representations. One prominent research is the messy GA (mGA) 90 proposed by Goldberg et al. [42]. Suppose the solution to a prob-91 lem consists of *n*-bits. The algorithm allows the chromosome length 92 to be larger or less than n. When evaluating the fitness of an indi-93 vidual, additional processing is used to interpret the chromosome 94 if its length is not exactly n. A new operator called "cut and splice" 95 is used to replace the traditional crossover operator. In [43], mGA is 96 employed to solve the vehicle routing problem. Kajitani et al. [44] 97 proposed a variable length chromosome GA (VGA) for hardware 98 evolution. The cut and splice operators are adopted in VGA to realize 99 recombination. In [45], Srikanth et al. proposed a variable-length 100 GA for clustering. Each cluster is approximated by an ellipse and 101 is encoded as a fixed length 0-1 bit string. The chromosome of an 102 individual is allowed to grow or shrink through genetic operators, 103 but the length of the chromosome must be a multiple of the length 104 of a basic element (cluster). Hu and Yang [46] proposed a simple 105 path representation for GA to handle the path planning problem of 106 mobile robots. The robot's environment is given by a set of num-107 bered grids and a path is encoded as a sequence of grid numbers. 108

The first and last element of the sequence denotes the starting point and destination of the path. The number of intermediate nodes may vary from individual to individual. In [47], instead of using the grid numbers to represent the path, each element of the path is given by a coordinate. Kim and Weck [48] proposed variable chromosome length GA (VCL-GA) to handle the structural topology optimization problem. The algorithm starts from a short chromosome and progressively lengthens the encoding to refine the individuals. Most of the encoding schemes are designed to handle a specific kind of problem and cannot be generalized to tackle the node placement problem.

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To overcome the shortcomings, this paper develops a flexible GA (fGA). The proposed fGA adopts a variable-length encoding for chromosomes eligibly to accommodate a variable number of nodes, with new crossover and mutation operators designed accordingly. The encoding of fGA is based on the characteristics of nodes being deployed. Each element (gene) of the encoding has its specific meaning (the coordinates and properties of the nodes). The basic unit of the encoding is a single node and the building blocks of fGA are in the form of partial layouts instead of bit strings. The new crossover, termed subarea-swap crossover, generates offspring by swapping selected subareas of one layout with another. The size and location of the crossover area are dynamically determined by the distribution of nodes. This ensures that the algorithm can be suited for node placement problems with different characteristics. Then, Gaussian mutation is performed on the offspring to adjust nodes positions and properties. Compared to the existing methods, fGA has the following advantages:

- 1. Automatically adjusting the number of nodes in a legible and efficient manner.
- 2. Capable of optimizing the nodes' positions and attached properties simultaneously.
- 3. Enable a fine-grained placement of nodes (since the nodes' positions are not restricted to the predetermined positions).

To investigate the performance of fGA, experiments on two realworld problems (RNP and WFLO) are conducted. The experimental results show that fGA is superior to existing population-based optimization algorithms for NPPs.

The rest of this paper is organized as follows. The NPP is introduced in Section 2. Section 3 provides a detailed description of the proposed flexible genetic algorithm. Experiments on RNP and WFLO problems are presented in Section 4, with thorough analysis of the experimental results. The sensitivity of fGA to the parameter setting is also investigate in this section. Finally, Section 5 gives some concluding remarks and future research directions.

#### 2. Problem description

NPP is a common and important problem in many engineering fields. In this section, we give a formal description of the problem and provide a discussion on its components. Then, two typical realworld RNP and WFLO problems are briefly described.



Fig. 2. Grid-based method and its encoding scheme.

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