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Evolutionary optimization for disaster relief operations: A survey

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ABSTRACT

Effective planning and scheduling of relief operations play a key role in saving lives and reducing damage in disasters. These emergency operations involve a variety of challenging optimization problems, for which evolutionary computation methods are well suited. In this paper we survey the research advances in evolutionary algorithms (EAs) applied to disaster relief operations. The operational problems are classified into five typical categories, and representative works on EAs for solving the problems are summarized, in order to give readers a general overview of the state-of-the-arts and facilitate them to find suitable methods in practical applications. Several state-of-art methods are compared on a set of real-world emergency transportation problem instances, and some lessons are drawn from the experimental analysis. Finally, the strengths, limitations and future directions in the area are discussed.

1. Introduction

Our world is full of threats from natural and man-made disasters. Particularly, there are an increasing number of heavy disasters occurred in recent years, such as the 2008 Wenchuan earthquake, the 2010 Zhouqu mudslides, the 2011 Japan tsunami, and the recent Haiyan typhoon in Philippines, which have caused serious damage to lives and property. In a disaster situation, relief operations have to be planned and implemented effectively in order to be able to mitigate the damage as much as possible.

From a mathematical viewpoint, disaster relief operations involve a wide variety of complex optimization problems. The area of optimization has a vast and fertile overlap between operations research (OR) and computer science (CS). In general an optimization problem can be defined as to find a feasible solution $x^* \in X$ that maximizes (minimizes) a objective function f, while X is a finite or infinite solution space.

Being confronted with an optimization problem, the first concern of computer scientists is whether the problem can be solved by some efficient algorithms (and in particular in polynomial time). However, most problems arising in OR are proved to be *NP*-hard, i.e., polynomial-time intractable unless $P = NP$ [1]. Moreover, under emergency conditions the solutions to operational problems need to be developed within a very limited time. Hence, traditional exact methods are often computationally unaffordable and of too limited applicability.

Evolutionary computation is a class of optimization methods drawing inspiration from natural evolution and adaptation [2]. Due to their simplicity, sufficient flexibility and general applicability, evolutionary algorithms (EAs) are well suited to tackle a wide range of computationally intractable problems. They do not always guarantee reaching the exact optimal solution in a single simulation run, but in most cases they can obtain satisfying solutions within an acceptable computational time. Particularly, intrinsic probabilistic behaviors render them capable of effectively handling real world problems involving nonlinearity, complexity, noisy environment, imprecision, uncertainty and vagueness [3,4]. Consequently, evolutionary optimization has attracted wide attention and has been extensively explored in OR in recent decades.

The research on evolutionary optimization methods for disaster relief operations, in comparison with other sub-areas of OR, is limited. But it has started to evolve a lot in the last years. A variety of EAs, including genetic algorithm (GA) [5], particle swarm optimization (PSO) [6], ant colony optimization (ACO) [7], etc., have found a growing number of applications in relief operations (as shown in Fig. 1), and demonstrated their effectiveness on many challenging emergency problems.

In this paper we present a survey of research works on this topic, the main purpose of which is threefold:

1. Provide readers a general overview of the major developments emerged throughout the years.

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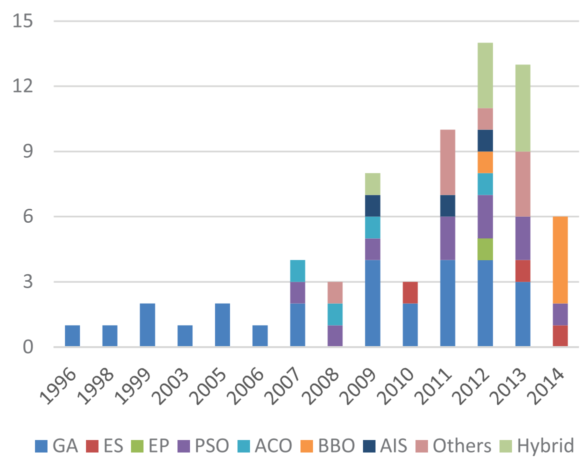

Fig. 1. The numbers of research articles on EAs for disaster relief operations in recent ten years (the data of 2014 is up to May).

2. Show major strengths and shortcomings of the state-of-the-arts, and help practitioners to find valuable approaches that can be referred in the practice of disaster relief.
3. Discuss potential directions for future research, and stimulate more interest in this cross-disciplinary field.

In the remainder of the paper, we first classify optimization problems in disaster relief operations into five typical categories in Section 2, and describe recent advances in EAs for solving the problems in Section 3. Section 4 presents the experiment of six typical EAs on a set of real-world emergency transportation problem instances. Section 5 discusses the strengths, limitations and future directions in the area, and finally Section 6 concludes.

2. Problem classification

Disaster relief operations involve activities including establishing emergency facilities, searching and rescuing survivors, providing health and medical assistance, distributing relief supplies, transferring injuries, scheduling rescue forces, etc., and the coordination of these activities across organizations [8,9]. Thus they are associated with a variety of operational problems that often lie outside the scope of the conventional optimization methods. In this paper, we classify the problem into the following five categories:

- General transportation planning problems, which are to make up programs for delivering relief supplies from distribution centers (sources) to demand points (targets). But we do not place detailed path planning and vehicle routing in this category.
- Facility location problems, which are to arrange emergency facilities on appropriate locations to serve the demand points.
- Routing problems, which include planning routes for vehicles, rescuers, and evacuees.
- Roadway repair problems, which are to repair damaged roadways and rehabilitate the lifelines to demand areas.
- Integrated problems, which need to solve a set of above individual problems under one or more common objectives.

2.1. General transportation planning problems

As a classic problem in OR, the basic transportation problem considers delivering a homogeneous commodity from a set of m sources to a set of n targets. Suppose the supply of source i is a_i, the demand of target j is b_j, the cost for transporting one unit of commodity from source i to target j is c_{ij}, then the problem is to determine the commodity amount x_{ij} from each source i to each target j ($1 \le i \le m$, $1 \le j \le n$), such that the total transportation cost is minimized. It can be modeled as a special case of the linear program (LP) as follows:

$$\begin{aligned} \min \quad & f = \sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij}x_{ij} \\ \text{s.t.} \quad & \sum_{i=1}^{m} x_{ij} \ge b_j, \quad j = 1, \ldots, n \\ & \sum_{j=1}^{n} x_{ij} \le a_i, \quad i = 1, \ldots, m \\ & x_{ij} \ge 0, \quad i = 1, \ldots, m, \; j = 1, \ldots, n \end{aligned} \tag{1}$$

Although this problem can be solved by specialized methods that are more efficient than standard linear programs [10], EAs can provide much better performance on very large problem instances [11]. Moreover, real-world problems typically have to deal with heterogenous commodities and transportation modes, involving additional (and often nonlinear) objectives and constraints [12]. Such problems should be characterized by more complex integer programming (IP) or mixed integer programming (MIP) models, which are much better suited for evolutionary optimization than standard optimization method.

Furthermore, transportation in emergency logistics [13] is often subject to uncertainty and randomization, has very limited time constraints, focuses more concern on timeliness and/or risk rather than transportation cost. Taking these extra properties into consideration, much more efforts should be put into the design of efficient algorithms.

2.2. Location problems

The problems of locating emergency facilities, such as fire stations, medical services, shelters, etc., based on the topography of potential facilities, can be divided into two sub-classes: continuous facility location problems, where facilities are allowed to be sited on every point in a planning area, and discrete facility location problems, where there is a discrete set of candidate locations. Generally speaking, the first class often uses formulation of LP and nonlinear programming (NLP) problems, while the second class is often modeled by classical covering problems and their variants, such as set covering, vertex/egde covering, covering location, and partial covering [14,15].

The simplest form of the facility location problem, which considers providing a single facility to cover a maximum number of demand points, has efficient exact solution methods [16,17]. However, involving multiple facilities leads to *NP*-hard problems, such as the *p*-median problem (2) and the maximum covering problem (3):

$$\begin{aligned} \min \quad & f = \sum_{i \in D}\sum_{j \in F} c_{ij}y_{ij} \\ \text{s.t.} \quad & \sum_{j \in F} x_j = p \\ & \sum_{j \in F} y_{ij} = 1, \quad \forall i \in D \\ & x_j \in \{0, 1\}, \quad \forall j \in F \\ & y_{ij} \in \{0, 1\}, \quad \forall i \in D, \; \forall j \in F \end{aligned} \tag{2}$$

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