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Article

Bio-Inspired Meta-Heuristics for Emergency Transportation Problems

Min-Xia Zhang [1,2], Bei Zhang [1] and Yu-Jun Zheng [1,*]

[1] College of Information Engineering, Zhejiang University of Technology, 288 Liuhe Road, Hangzhou 310023, China

[2] College of Computer Science & Technology, Zhejiang University of Technology, 288 Liuhe Road, Hangzhou 310023, China

* Author to whom correspondence should be addressed; E-Mail: yujun.zheng@computer.org; Tel.: +86-0571-8529-0085.

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Abstract: Emergency transportation plays a vital role in the success of disaster rescue and relief operations, but its planning and scheduling often involve complex objectives and search spaces. In this paper, we conduct a survey of recent advances in bio-inspired meta-heuristics, including genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization (ACO), *etc.*, for solving emergency transportation problems. We then propose a new hybrid biogeography-based optimization (BBO) algorithm, which outperforms some state-of-the-art heuristics on a typical transportation planning problem.

Keywords: bio-inspired algorithms; transportation problems; planning and scheduling; biogeography-based optimization (BBO)

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1. Introduction

We are now facing increasing threats from natural and man-made disasters, which often cause serious damage to lives and property. During disaster rescue operations, the responders often face significant problems for delivering various kinds and huge amounts of relief supplies to disaster-stricken areas in a timely and accurate manner. Therefore, effective planning and scheduling of emergency transportation plays a key role in rescue operations to mitigate the damage.

Transportation problems are a class of optimization problems in the domain of operations research. Classical transportation problems are modeled as linear programming problems for minimizing the cost of delivering integral quantities of goods from m sources to n targets whilst balancing supply and demand [1]. However, due to the rising complexity of goods and transportation modes, changing customer demands and expanding competition, today's transportation problems involve much more complex sets of objectives and constraints and often have to address variations of uncertainty and randomization. As a consequence, classical mathematical programming methods are often insufficient to effectively handle the problems, and a variety of heuristic and meta-heuristic methods have gained popularity in the research of this topic (e.g., [2–7]).

In comparison with ordinary commercial transportation, transportation of relief supplies in a stressful disaster environment is often characterized by the following additional features [8]:

- There can be various kinds and a huge number of supplies (such as food, water, medicine, clothes, first-aid kits, lifesaving appliance, *etc.*) to be delivered in a timely and efficient manner.
- The operations often involve more than one transportation mode, such as air, rail and road.
- The transportation is heavily constrained by bottlenecks, such as the availability of vehicles/drivers, the capacity of transportation network and strict time windows.
- The available information is often ambiguous, uncertain, incomplete and sometimes even inconsistent and erroneous.
- The transportation solutions should be evaluated based on multiple criteria, which may include cost, time responsiveness and utilization efficiency, as well as damage/loss of relief supplies and rescue forces.
- Quick response and fast delivery are of vital importance to the success of disaster rescue operations, and thus, the transportation solutions should be generated in a very limited time period.
- The environment of the disaster areas is always subject to frequent changes, and the transportation should be flexible enough to cope with the changes.

In recent years, bio-inspired meta-heuristic methods, including evolutionary algorithms (EAs) and swarm intelligence (SI)-based algorithms, have received much research interest and have been applied to emergency transportation planning and scheduling in many real-world problems. Inspired by the process of biological evolution, EAs are a class of stochastic search and optimization methods, including the most widely-used genetic algorithms (GAs) and their variants [9]. SI can be viewed as an extended study of evolutionary intelligence inspired by the collective behavior of social insects [10]. A typical SI-based meta-heuristic includes particle swarm optimization (PSO [11]), ant colony optimization (ACO [12]) and the artificial bee colony (ABC) algorithm [13]. Due to their efficiency and robustness in searching in extra-large solution spaces, bio-inspired meta-heuristics have recently received increased interest in the study of transportation planning and scheduling.

In this paper, we conduct a survey of bio-inspired algorithms for a variety of transportation problems, discussing related work in four focused classes: general transportation problems, location and routing problems, roadway repair problems and integrated problems. We then consider a typical transportation planning problem, propose a new hybrid biogeography-based optimization (BBO) algorithm for the problem and compare the BBO algorithm with some other popular heuristics.

The rest of the paper is structured as follows: Section 2 presents the survey of bio-inspired algorithms according to the problem domains. Section 3 proposes the hybrid BBO algorithm for the typical problem and presents the computational experiment, and Section 4 concludes with a discussion.

2. A Survey of Bio-Inspired Algorithms for Transportation Problems

2.1. Algorithms for General Transportation Planning

The basic transportation problem is to ship at minimum cost a homogeneous good from a set of m sources (warehouses) to a set of n targets (markets). Suppose the supply of source i is a_i, the demand of target j is b_j and the cost for transporting one unit of goods from source i to target j is c_{ij} ($1 \leq i \leq m$, $1 \leq j \leq n$); then, the problem can be modeled as a special case of the linear program (LP) as follows:

$$\min \quad f = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij} \tag{1}$$

$$\text{s.t.} \quad \sum_{i=1}^{m} x_{ij} \geq b_j, \quad j = 1 \ldots n \tag{2}$$

$$\sum_{j=1}^{n} x_{ij} \leq a_i, \quad i = 1 \ldots m \tag{3}$$

$$x_{ij} \geq 0, \quad i = 1 \ldots m, j = 1 \ldots n \tag{4}$$

An early work of Vignaux and Michalewicx [14] proposed some alternative GAs for solving the linear transportation problem, using different representation structures and genetic operators. However, the work was mainly a feasibility study, and in comparison to linear programming and some specialized algorithms, the GAs perform poorly on such a unimodular problem [15].

Real-world transportation problems typically involve heterogeneous goods, multi-modal transportation and strict time windows, especially in emergency logistics [16]. Thus, they should be modeled as integer programming (IP) or mixed integer programming (MIP) problems, which are much more difficult to solve. Chern *et al.* [17] developed a heuristic emergency relief transportation planning algorithm for an MIP transportation problem. The algorithm groups and sorts demands based on multiple criteria and then plans the demands individually using a shortest traveling-time tree and a minimum cost production tree.

Based on the analysis of the practice of emergency management in China, Pang *et al.* [18] presented a distribution model of emergency materials in a three-layer relief transportation network, the aim of which is to minimize the system losses while meeting the constraints of emergency response time and fairness. For the formulated nonlinear IP, they proposed a modified PSO algorithm, where different learning objects are used for different dimensions of the particles.

Considering multiple transportation modes in an emergency relief problem, Na and Zhi [19] designed a GA that uses natural number coding, tournament selection and single-point crossover. The problem model uses the ratio of transport quantity to total demand quantity as the weights of transport time, and the algorithm utilizes a penalty function to handle the constraints.

In [20], Berkoune *et al.* formulated a practical transportation problem with multiple vehicle types and many other constraints, which is often encountered by crisis managers in emergency situations. To handle the problem, which is shown to be NP-hard, they developed a GA in which an individual is represented with genes composed of delivery points and products. The GA initializes a population based on the set enumeration heuristic and uses three fast improvement procedures to evolve each individual in the population, whilst some worst solutions in a new population are replaced by new ones for diversification. Computational experiments show that the method can produce near optimal solutions in relatively short computation times and is fast enough to be used interactively in a decision-support system.

Transportation under a disaster environment and emergency situation often involves a variety of uncertainty and randomization. Bozorgi-Amiri *et al.* [21] studied a disaster relief logistics problem in which demands, supplies, cost of procurement and transportation are considered as uncertain parameters. Therefore, the problem is modeled as an uncertain, nonlinear MIP. They used the robust optimization technique [22] to handle the uncertainty, *i.e.*, describing uncertain parameters by the discrete scenarios or a continuous range. Additionally, they designed for the problem an improved PSO algorithm that combines discrete and continuous components in particles. Experimental results show that the proposed algorithm performs much better than the traditional branch-and-bound (B&B) algorithm.

Complex transportation planning may also involve multiple criteria or objectives, such as time and cost. Transportation under a disaster environment may include additional objectives, such as minimizing the operational risk. A simple approach to handle multiple objectives is to transform them into a single objective. For example, in the study of an urgent relief distribution problem, Liu and Zhao [23] combined the objective functions of transshipment time and cost into a single one based on weight aggregation. The relief-distribution model by Tzeng *et al.* [24] considers three objectives, including minimizing total cost, minimizing total travel time and maximizing satisfaction of fairness, and the model is resolved by maintaining the third objective while transforming the first and second objectives into constraints.

An artificial immune system (AIS) is a model stimulating the adaptive immune system of a living creature to unravel the various complexities in optimization problems [25]. Hu [26] proposed an immune multi-affinity network model of an emergency logistics network and defined affinity measures to represent complex collaborative relationship among emergency logistics components. In [27], the author further presented a container multimodal transport emergency relief problem based on the affinity network and adopted a strategy of aggregating the two objectives by weights into a single one, so as to find the optimal path for emergency relief.

However, in most multi-objective transportation problems, the objectives can conflict with one another, and it is preferable to simultaneously optimize all the objectives by evolving a set of solutions to the so-called Pareto front [28], which can provide more effective support for decision-making. Multi-objective EAs (MOEAs) are preferable for this purpose, because they concurrently evolve a population of possible solutions and, thus, enable one to find several members of the Pareto optimal set in a single run of the algorithm, instead of having to perform a series of separate runs, as in the case of the traditional mathematical programming techniques.

Nolz *et al*. [29] modeled a disaster relief operation planning problem with two objectives, including the maximal covering location and minimum tour length, and they developed a hybrid method based on NSGA-II [30], one of the most well-known MOEAs, together with variable neighborhood search and path relinking. Tests on real world data from Ecuador demonstrated the effectiveness of the proposed approach.

To tackle complicated multi-objective transportation problems much more efficiently, Zheng and Chen [31] proposed a hierarchical cooperative optimization approach that decomposes a problem into low-dimensional subcomponents and applies a Pareto-based particle swarm optimization (PSO) method to the main problem and the subproblems alternately. In [8], Zheng and Ling further extended the approach to a multi-objective fuzzy optimization problem of emergency transportation planning, defined the β-dominance relation and employed three correlated fuzzy ranking criteria for evaluating the solutions. Experiments show that the cooperative algorithm is robust and scalable and outperforms other state-of-the-art MOEAs.

2.2. Algorithms for Location and Routing

Facility location and vehicle routing are important problems in supply chain management [32]. From a mathematical point of view, they are usually modeled as combinatorial optimization problems, which are both NP-hard. Caccetta and Dzator [33] concentrated on the p-median problem in emergency facility location and developed three heuristics, including two reduction heuristics and a repeated reduction heuristic. Experiments show that the latter has the best performance.

More generally, the emergency facility location problem can be formulated based on a location set covering model [34]. Using this formulation, Chai *et al*. [35] studied a highway traffic emergency facility location problem and proposed a heuristic GA, which uses an n-dimensional 0–1 integer vector to present chromosomes and employs a heuristic operator for improving unreliable chromosomes by: (1) remedying the chromosomes that do not cover all demands; and (2) eliminating the redundancy of chromosomes that cover the location set with redundancy. The method has been successfully applied to problems from the highway network of Nanjing, China.

Han [36] studied an extended emergency facility location problem, which is modeled as an IP problem, and proposed a GA in which each chromosome is constituted by the serial number of each target's emergency facility and population diversity is maintained by using a changeable mutation probability. Experiments show that the GA solves the problem much more efficiently than other simple heuristics.

Focusing on the strategic level of emergency medical service system design, Beraldi and Bruni [37] proposed a stochastic model for the location of emergency service facilities under uncertainty, where probabilistic constraints are embedded within a two-stage framework. They developed three different tailored heuristics, namely Mincard, Approx and a combined Pareto optimization heuristic, for the problem. Computational experience is reported with the application to various networks.

Vehicle routing problems (VRP) are also a class of fundamental problems in transportation for which a wide range of heuristics have been studied [38,39]. In their case-oriented paper, Weintraub *et al*. [40] presented a problem of assigning and routing repair vehicles for the Emergency Services Division of Chilectra S.A., the electricity utility for the city of Santiago, the capital of Chile.

A computerized system based on heuristic algorithms was developed for vehicle routing with random demand, which represent breakdowns that require a repair crew. An exponential smoothing method was implemented for the prognosis of breakdowns. The evaluation of the system's performance showed a 16% improvement in service quality as measured by the time required for servicing breakdowns under regular conditions and a 53% improvement under adverse climate conditions.

Paying attention to the reliable route choice of humanitarian response planning for disaster response, Hamedi *et al*. [41] formulated the routing and scheduling of supply transportation as a linear integer programming (LIP) model. They proposed a hybrid algorithm composed of the HRBProuting algorithm and GA, where the value of gene is represented as the priority weight of corresponding truck, to search the shortest paths of multiple objectives and, thus, to optimize the transport arrangement.

Peng *et al*. [42] presented another hybrid heuristic algorithm for large-scale multi-depots VRP in relief work. The algorithm combines GA with ant systems, while simulated annealing is incorporated into the genetic operation. The main flow of the algorithm is controlled by a feedback loop, *i.e.*, the best result of GA is used to improve ant systems and *vice versa*.

Lim *et al*. [43] considered the routing of unmanned reconnaissance aerial vehicles on sparse graphs that mimic inaccessible zones, such as those hit by forest fires, earthquakes or other disasters, and developed a hybrid ACO algorithm, which incorporates local search heuristics for uncovering feasible routes within tractable times. Empirical results demonstrate the excellent convergence property and robustness of the algorithm in uncovering low risk and Hamiltonian visitation paths.

Yuan and Wang [44] also used ACO to solve two path selection problems in emergency logistics management. The first is a single-objective model to minimize total travel time along a path. The second is a multi-objective model to minimize the total travel time, as well as the path complexity, and it further considers the chaos, panic and congestion in times of disaster. However, the multi-objective model is converted into a single-objective model using weighted aggregation.

Zhang *et al*. [45] developed an algorithm combing AIS and ACO, namely the immune ant colony optimization (IACO), for a transportation route choice problem in emergency logistics. The main idea is to obtain pheromone distributions from AIS and optimize the solutions by basic ACO. Computer simulation indicates that IACO has more effective timeliness to the model than basic ACO.

Zhang *et al* . [46] proposed a novel bio-inspired algorithm, which is based on the mathematical model of amoeboid organism, to solve the optimal route selection problem in disaster extension. The problem considers both the travel time and the path length. The algorithm uses the k-th shortest path program to find out the first to k-th shortest path, uses the amoeboid algorithm to find the longest path to construct the dimensionless indexes and, finally, obtains the optimal routes.

Considering vehicle route choosing in urban emergency management, Zhang and Feng [47] proposed an interesting approach that employs ACO for searching optimal solutions to the problem, meanwhile using PSO to optimize the main parameters of the ACO. Simulation results show that the approach has a good convergence performance, meanwhile effectively avoiding being trapped by local optima.

Location and routing are often interrelated. Song *et al*. [48] studied transit bus operations for emergency evacuation, which are similar to the location-routing problem (LRP) with uncertain demands. They designed a new multi-graph street network considering prohibited turns and intersection delays and proposed a hybrid intelligent algorithm, including a GA, an artificial neural network (ANN) and hill climbing to solve the proposed stochastic programming model. The algorithm employs partially matched crossover, route mutation and depot mutation operations. The application of the method in transit evacuation planning is illustrated by a practical example of part of Gulfport, USA.

Xie and Hu [49] modeled an inventory routing problem in emergency logistics with fuzzy demands, which are converted to deterministic demands by Yager's fuzzy number ranking method. They solve the problem using a heuristic algorithm that coordinates inventory control and route optimization for minimizing total cost. Computational result shows that the benefits can be obtained from the integration of inventory and routing.

Rath and Gutjahr [50] studied a warehouse LRP with a medium-term economic, a short-term economic and a humanitarian objective function. They developed a "math-heuristic" method based on an MIP formulation with a heuristically generated constraint pool. As a subproblem, the multiple-depot, multiple-trip capacitated team orienteering problem is solved. Experimental results show that their approach can evolve the solutions towards the Pareto-optimal front and has performance advantage over the NSGA-II.

2.3. Algorithms for Roadway Repair

Destructive disasters often disrupt traffic and lifeline systems. In most cases, the roadway transportation system is still the key channel for relief distribution, and thus, the effectiveness of roadway repair has a great impact on the success of rescue operations. Sato and Ichii [51] conducted a study on the optimization of restoration process of damaged lifelines by earthquakes and developed a simple GA and a hybrid GA to decide the priority of components to restore, where the latter shows better performance than the former. They also applied a single populated GA to distribute restoration teams at damaged sites for optimizing the restoration process of lifeline networks.

Considering the objective of minimizing the length of time needed for emergency repair of a highway network, Yan and Shih [52] proposed a time-space network model, which is a problem with side constraints, and developed a heuristic algorithm that iteratively improves the solution of the problem. However, the heuristic often consumes much computational time on relatively large problems and, thus, is unaffordable in real emergency response situations. Thereby, Yan and Shih [53] developed a hybrid algorithm based on ACO coupled with a threshold accepting technique. An acceptance rule from tabu search is employed to change the work time limit for each work team, which allows each ant to find a better solution. The bio-inspired algorithm exhibits much better performance on different roadway network patterns.

Feng and Wang [54] developed a multi-objective scheduling model for highway emergency rehabilitation right after earthquake attacks. The considered objectives include maximizing the performance of emergency rehabilitation, minimizing the risk of rescuers and maximizing the saving of life. They developed a standard multi-objective program to solve the problem, but its scalability for large-size problems is limited.

Zhang and Lu [55] also proposed a multi-objective model of emergency roadway repair, the aim of which is to minimize the length of time, as well as the risk of repair. They developed a GA that shows satisfying performance on the test problems. Nevertheless, how to appropriately and quantitatively assess the risk remains a difficult challenge.

In [56], Yan *et al.* considered logistical support planning for an emergency repair work. This model is formulated as an integer multiple-commodity network flow problem, the objective of which is to minimize the short-term operating cost subject to time constraints and other related operating constraints. They proposed a heuristic algorithm based on the problem decomposition and variable fixing techniques for the problem. Computational tests using data from Taiwan's 1999 Chi-Chi earthquake demonstrate the effectiveness of the solution algorithm.

Considering emergency equipment maintenance scheduling in disaster rescue operations, Zheng *et al.* [57] presented a multi-objective programming model that aims to achieve a good balance between operational capability, reserved maintenance capability, as well as cost-effectiveness. They designed a compact solution encoding to facilitate the search and developed a multi-objective tabu search-based heuristic for finding the near Pareto optimal frontier using a weighted function based on the decision-maker's preference. The algorithm has been successfully applied to several real-world operations and demonstrated its efficiency and effectiveness.

2.4. Algorithms for Integrated Problems

Usually, transportation in disaster relief operations involves complex interactions between different actors and tasks and, thus, can be modeled as an integrated problem that consists of a set of interdependent subproblems. This implies that we need integrated solution approaches to effectively tackle transportation problems within the response time limits.

One of the most common models in emergency transportation is one that integrates supplies distribution and vehicle routing. Tian *et al.* [58] constructed such a multi-objective optimization model and designed a PSO algorithm in which every particle is encoded as a discrete-continuous vector, and the discrete variables and continuous variables are respectively changed using their own velocity/location update formulas. The fitness function for evaluating particles is defined by combining multiple objectives. However, for large-sized instances, the algorithm is sometimes easily trapped by local optima.

Yi and Kumar [59] considered an emergency logistics planning model, which involves dispatching commodities to distribution centers and evacuating wounded people to medical centers. They proposed an improved ACO algorithm that decomposes the problem into two phases, *i.e.*, the vehicle route construction and the multi-commodity dispatch. The sub-problems are solved in an iterative manner: the first phase builds stochastic paths under the guidance of pheromone trails, while a network flow-based solver is developed in the second phase for the assignment between different types of vehicle flows and commodities. Results show that the ACO solution quality achieved within a minute of runtime is acceptable for the planner in a real emergency situation in which there is continuous uncertainty and information dynamism.

In order to aid the reconstruction planning for the post-quake road-network, Chen and Tzeng [60] established a fuzzy multi-objective model of reconstruction scheduling. The considered problem is formulated as a bi-level network design problem: The upper level is for the work scheduling of many work troops, and the lower level is for asymmetric traffic assignment. They developed a modified

GA for obtaining a heuristic solution that approximately optimizes the objectives on the two levels. Yan and Shih [61] also integrated roadway repair and relief distribution into a network flow model, which is a multi-objective, mixed-integer and multiple-commodity problem. They transformed it to a single-objective problem using the weighting method and developed a heuristic algorithm that first solves a subproblem and, then, repeatedly incorporates the remaining tasks, until a complete solution is obtained.

3. Test of Bio-Inspired Algorithms on a Transportation Planning Problem

In this section, we consider a typical problem of emergency transportation planning, develop a new bio-inspired algorithm for the problem and test the algorithm with several other meta-heuristics.

3.1. Problem Description

Suppose there are m distribution centers (sources) and n demand targets; the quantity of relief supplies that source i can provide is a_i, and the quantity of demanded by target j is b_j $(1 \leq i \leq m, 1 \leq j \leq n)$. According to our experience, in most disaster relief operations, the total quantity of supplies is much larger than the total demand, and the bottlenecks of relief distribution mainly lie in the availability of vehicles/drivers and the capacity of the traffic network. Thus, for simplicity, here, we assume that a target does not need to be supplied by more than one source, and a source can have only one route, due to the limit of traffic flow. The problem is to assign the demands of the targets to the sources and for each source schedule, a sequence (route) in which the targets are supplied, in order to distribute the supplies to targets as efficiently as possible. Under the assumption, the transportation planning problem can be considered as a multi-depot version of the cumulative VRP [63], while one depot has only one route.

Let π_i be the sequence of targets of source i and $C(\pi_i)$ be the set of targets of π_i; a solution should satisfy the following constraints:

$$\sum_{j \in C(\pi_i)} b_j \leq a_i \tag{5}$$

$$t_j \leq \widehat{t}_j \tag{6}$$

where t_j is the arrival time and $\widehat{t}_j$ is the last allowable arrival time of supplies at target j. Let $\widetilde{t}_{i,j}$ be the travel time from source i to target j (including the preparation time of source i), $t_{j,j'}$ be the travel time from target j to j' and $k_j(\pi_i)$ be the index of target j in π_i; t_j can be calculated based on the paths in the roadway network and the schedule π_i to which j belongs:

$$t_j = \widetilde{t}_{i,j} + \sum_{k=1}^{k_j(\pi_i)-1} t_{\pi_i(k),\pi_i(k+1)} \tag{7}$$

In emergency conditions, the cost of transportation is not considered as a major factor, and the objective is defined to minimize the total weighted waiting time of the targets:

$$\min f = \sum_{j=1}^{n} w_j t_j \tag{8}$$

where w_j is a predefined importance weight of target j.

3.2. A Biogeography-Based Optimization (BBO) Algorithm for the Problem

We develop a new algorithm based on biogeography-based optimization (BBO) [62] for the problem. BBO is a relatively new evolutionary algorithm inspired by the science of biogeography. In the meta-heuristic, an individual solution is analogous to a habitat, the solution components are analogous to a set of suitability index variables (SIVs) and solution fitness is analogous to the habitat's suitable index (HSI). Central to the algorithm is the equilibrium theory, which indicates that high HSI habitats have a high species emigration rate and low HSI habitats have a high species immigration rate. To our best knowledge, there is no report in the literature that applies the BBO heuristic to transportation problems in disaster management.

In our algorithm, each solution of the problem is encoded as a set of m sequences (permutations) $\{\pi_1, ..., \pi_i, ..., \pi_m\}$, such that $\bigcup_{i=1}^{m} C(\pi_i) = \{1, ..., n\}$ and $C(\pi_i) \cap C(\pi_{i'}) = \emptyset$ for any two different i and i'.

The algorithm starts by initializing a population, P, of random solutions. At each iteration, the solutions are sorted in increasing order of the objective value, and the immigration rate and emigration rate of the k-th solution is respectively calculated as:

$$\lambda_k = I\frac{k}{|P|} \tag{9}$$

$$\mu_k = E(1 - \frac{k}{|P|}) \tag{10}$$

where I and E are the maximum possible immigration and emigration rates, which are typically set to one.

Then, the population evolved by migration from probably high fitness solutions to low fitness solutions and the random mutation on a part of solutions. The procedure continues, until the termination condition is satisfied. Algorithm 1 presents the framework of our BBO algorithm for the problem, where p is a predefined mutation rate and $rand()$ returns a uniformly distributed random number in [0,1].

Let two solutions $\mathbf{h} = \{\pi_1, ..., \pi_i, ..., \pi_m\}$ and $\mathbf{h}' = \{\pi'_1, ..., \pi'_i, ..., \pi'_m\}$; the migration from $\mathbf{h}$ to $\mathbf{h}'$ at the i-th dimension is performed as follows:

1. Let R_i be the set of tasks in π'_i, but not in π_i.
2. Set $\pi'_i = \pi_i$ in $\mathbf{h}'$.
3. For each $j \in R_i$, find the position, k, such that j belongs to π_k of $\mathbf{h}$, and then, insert j into π'_k of $\mathbf{h}'$, such that the new π'_k has the minimum length of completion time among all permutations of the tasks in π'_k.

For example, suppose there are three sources and eight targets, $\mathbf{h} = \{[5, 3], [7, 4], [2, 6, 8, 1]\}$, $\mathbf{h}' = \{[5, 4, 1], [8, 2], [7, 3, 6]\}$; when migrating the first dimension of $\mathbf{h}$ to $\mathbf{h}'$, we have $R_1 = \{4, 1\}$, and after migration $\pi'_1 = [5, 3]$; Task 4 is in π_2 of $\mathbf{h}$ and, thus, will be inserted into $\pi'_2 = [8, 2]$, such that π'_2 has the minimum length of completion time among all permutations of the set $\{2, 4, 8\}$; similarly, Task 1 will be inserted into π'_3, such that it has the minimum length of completion time among all permutations of $\{1, 3, 6, 7\}$.

The mutation operation of a solution $\mathbf{h} = \{\pi_1, ..., \pi_i, ..., \pi_m\}$ at the i-th dimension is performed as follows: randomly select an i' other than i; drop a task, j, from π_i and reinsert it into $\pi_{i'}$, such that the new $\pi_{i'}$ has the minimum length of the completion time.

If a migration or mutation results in an infeasible solution, the operation is skipped on the current dimension and moves to the next dimension.

Algorithm 1 The new BBO algorithm for the proposed transportation planning problem.

Randomly initialize a population, P, of solutions to the problem;
while the stop criterion is not satisfied **do**
    Sort the solutions and calculate their immigration and emigration rates;
    for each solution $\mathbf{h} \in P$ **do**
        for $i = 1$ **to** m **do**
            if $rand() < \lambda(\mathbf{h})$ **then**
                Select another solution $\mathbf{h}' \in P$ with probability $\propto \mu(\mathbf{h}')$;
                Perform migration from $\mathbf{h}'$ to $\mathbf{h}$ at the i-th dimension;
    Sort the solutions;
    for each solution $\mathbf{h}$ in the second half part of P **do**
        for $i = 1$ **to** m **do**
            if $rand() < p$ **then**
                Perform mutation on $\mathbf{h}$ at the i-th dimension;
return the best solution found so far.

3.3. Comparative Experiments

To test the performance of our BBO algorithm and other typical meta-heuristics on the proposed transportation planning problem, we have implemented the following three bio-inspired algorithms:

- A GA method from [64], which uses a two-part chromosome representation: the first part is a permutation of targets, and the second part gives the number of cities assigned to each source. Accordingly, a two-part chromosome crossover operator is employed in the GA.
- A combinatorial PSO method inspired by [65], where a particle is a $(m \times n)$-dimensional vector, and each component $x_{ij} \in \{0, 1\}$ denotes whether target j is assigned to source i.
- An improved ACO method from [66], which adds to the problem a virtual central depot as the "nest", takes the actual sources as the "entries" of the nest, and takes targets as the "food".

We generate a set of 10 test problems, which are generated based on data from disaster relief operations of the 2010 Yushu earthquake, the 2011 Yingjiang earthquake and the 2012 Ninglang earthquake. For a fair comparison, on every problem, a maximum running time limit, $T^{\max}$ (in seconds), is set for all the algorithms.

The experiments are conducted on a computer with an Intel Core i5-2520M processor and 8 GB memory. Empirically, for our BBO algorithm, we set $I = E = 1$, $p = 0.02$ and $|P| = 50$. The control parameters of other algorithms are set as suggested in the literature. We respectively run each algorithm 30 times with different random seeds on each test problem. Table 1 presents the experimental results, where the problem size is given in terms of $m \times n$, *best* denotes the best objective value obtained by the algorithm among the 30 runs, *mean* denotes the average best objective value over the 30 runs and *std* denotes the corresponding standard deviation. All the objective values are scaled to the range of [0,100] for the convenience of comparison. We also perform the paired t-test between the average bests of BBO and each comparative algorithm on the test problems and mark † in Columns 5, 8 and 11 of the table if BBO has statistically significant improvement over the algorithm (at the 95% confidence level).

Table 1. The summary of experimental results. GA, genetic algorithms; PSO, particle swarm optimization; ACO, ant colony optimization; BBO, biogeography-based optimization; std, standard deviation. † denotes that BBO has statistically significant improvement over the algorithm.

			GA			PSO			ACO			BBO		
Problem	**Size**	$T^{\max}$	*best*	*mean*	*std*	*best*	*mean*	*std*	*best*	*mean*	*std*	*best*	*mean*	*std*
#1	3×10	30	18.65	18.65	(0.00)	18.65	18.65	(0.00)	18.65	18.65	(0.00)	18.65	18.65	(0.00)
#2	5×20	30	38.93	†39.31	(1.17)	38.93	38.93	(0.00)	38.93	38.93	(0.00)	38.93	38.93	(0.00)
#3	6×30	60	21.90	†26.03	(2.00)	20.93	†21.11	(0.71)	20.93	20.93	(0.00)	20.93	20.93	(0.00)
#4	8×40	90	76.27	†83.89	(8.38)	69.33	†76.40	(4.61)	68.98	69.52	(0.83)	68.98	69.28	(0.35)
#5	10×50	120	30.20	†34.90	(4.21)	27.56	†30.90	(4.12)	25.56	26.96	(1.67)	25.56	26.76	(1.37)
#6	12×60	150	84.81	†91.03	(8.42)	80.27	†86.41	(7.60)	72.35	78.96	(5.02)	71.89	76.81	(5.22)
#7	12×75	160	68.26	†73.72	(8.06)	60.30	†66.67	(7.15)	51.75	†57.97	(4.83)	51.75	55.06	(3.86)
#8	15×80	180	52.15	†57.10	(6.66)	48.91	†53.38	(5.75)	40.27	†46.49	(6.42)	38.66	42.28	(4.96)
#9	16×100	240	83.25	†90.03	(9.73)	77.88	†85.16	(8.06)	72.60	†76.33	(5.85)	70.58	72.27	(5.02)
#10	18×118	300	72.63	†81.01	(10.24)	63.97	†74.16	(8.08)	60.37	†65.05	(6.68)	56.03	58.32	(5.92)

As we can see from the results, on the simplest Problem 1, all the algorithms achieve the same optimal value; on Problem 2, PSO, ACO and BBO always achieve the same optimal value, but GA fails to do so. On the remaining problems, the mean bests obtained by ACO and BBO are always better than GA and PSO. In general, the performance of GA is the worst among the four bio-inspired algorithms. PSO exhibits a relatively fast convergency speed, but it is more easily trapped by local optima than ACO and BBO. The statistical tests also show that BBO has significant performance advantage over GA and PSO on nine and eight test problems, respectively. In comparison, the search mechanisms of ACO and BBO make them have more ability to jump out of local optima without sacrificing their performance. Therefore, we can conclude that ACO and BBO are more suitable for solving the proposed transportation planning problem.

By comparing ACO and BBO, we find that the performance of the two algorithms are similar or have no significant differences on small-sized or moderate-sized problems (1–6). However, on large-sized problems (7–10), BBO has more performance advantage over ACO, and the advantage becomes more obvious with the increase of the problem size. In summary, our BBO algorithm exhibits the best performance among the competitive algorithms on the test problems. This also indicates that the new meta-heuristic has potential in solving a wide range of transportation problems and other related disaster relief operational problems.

4. Conclusions

In this paper, we conduct a survey of recent advances in bio-inspired meta-heuristics, including genetic algorithms (GA), particle swarm optimization (PSO) and ant colony optimization (ACO), for solving transportation problems in disaster relief operations. We then propose a typical transportation planning problem and develop a new algorithm based on the BBO meta-heuristic for the problem. Comparison with three other meta-heuristics demonstrates the competitive performance of the BBO algorithm in solving the problem.

The BBO meta-heuristic, to our best knowledge, is for the first time being applied to emergency transportation problems. Furthermore, recent years have seen the emergence of many new bio-inspired meta-heuristics, such as the artificial fish algorithm [67], bacterial foraging optimization [68], the firefly algorithm [69], cuckoo search [70], the bat algorithm [71], *etc*., the reports of which for disaster relief operations in the literature are very few. Hence, there is a need for more efforts from researchers in bio-inspired computation and researchers in operations research to cooperate together to develop more efficient algorithms for a wide range of real-world problems.

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Conflicts of Interest

The authors declare no conflict of interest.

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