An extended version of adaptive large neighborhood search for a relief commodities distribution network design under uncertainty

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Abstract

Natural and technology-induced disasters have posed significant threats to human life all around the world and caused many damages and losses so far. The current study addresses a location-routing problem to make an efficient and timely distribution plan in response to a possible earthquake. This problem considers uncertainty in such parameters as demand, access to routes, travel time, and the number of available vehicles. To deal with these uncertainties, stochastic programming (SP) is performed while the objective function is to minimize the time of carrying relief commodities (RCs) to affected areas. The problem is coded in the CPLEX solver to obtain optimal solutions to small-scale problems, and an adaptive large neighborhood search (ALNS) is proposed to solve mixed-integer linear formulas for large-scale problems. To validate the formulation and evaluate the performance of the proposed ALNS, several types of tests are devised. To shows the efficiency of the proposed ALNS, two other metaheuristic algorithms, the Genetic algorithm (GA) and simulated annealing algorithm (SA), are used as well. The results of the calculations suggest the satisfactory performance of the suggested algorithm and the effectiveness of the model for the desirable delivery of humanitarian aids to affected areas.

Keywords: Humanitarian logistics, Disaster management, Location-routing problem, Adaptive large neighborhood search, Scenario-based planning.

1. Introduction

The vehicle routing problem (VRP) is one of the most attractive and important planning problems that has been studied widely since its introduction. In recent years, the problem has gained special significance due to the introduction of new meta-heuristic and heuristic [1]. The VRP was first introduced by Dantzig & Ramser in 1959 [2]. The objective of the classical VRP is to minimize the time of product delivery to customers. There are various classifications of VRP, such as maximum length of route, pickup and delivery, service time windows, and backhauls [3-6]. The capacitated VRP (CVRP) and the time window (VRPTW) are two important problems in these categories [7]. In the CVRP, the objective is to meet customer demand with the lowest number of vehicles and the least cost. Location-routing problems (LRPs) address two critical issues in logistics planning [8] including vehicle routing problems (VRPs) and classical location problems (LPs) [9]. An LRP is solved to find responses to the following basic questions [9]:

a) Which locations (facilities) should be in use and which ones should be closed?

b) Which vehicles and from which route should deliver the RCs to the distribution centers (DCs)?

Due to its features, an LRP is categorized of NP-HARD problems [10]. According to it, as the number of applicants and vehicles grows, the problem-solving time grows too through an exact algorithm. In recent years, meta-heuristic algorithms (e.g., GA, SA, PSO) have been widely applied to solve this type of problem. Studies show the usefulness of meta-heuristic algorithms in this regard [11]. In such studies, the problems have usually been investigated in deterministic circumstances, while this is impossible in the real world [12]. For example, in critical situations, the amount of demand in several conditions can be different at any time. As a result, uncertainty can bring the study closer to the real situation.

Natural disasters are an integral part of human life. In recent years, disasters such as floods and earthquakes have imposed great financial and human costs on many countries. In some cases, they have been so severe, making it very difficult to help the injured people. This is where a routing problem and the timely delivery of RCs to the injured applicants gains importance. According to Clark and Culkin, humanitarian efforts should be based on three principles, including impartiality, neutrality, and humanity[13]. In this view, the main objective should be to deliver RCs to the injured people without any discrimination. In other words, fairness should be fully respected in times of crisis. Also, the delivery of RCs to the most affected groups, such as children and injured people, is a priority. Meeting the demands of all the affected areas may require a great deal of facilities, but the distribution of RCs to the regions should be fair and prompt as much as possible. These issues should be taken into consideration by any model of relief. The present study aims at an LRP in critical situations. As mentioned before, a state of uncertainty brings simulations closer to real situations. Scenario-based planning is done to formulate the problem of the current study. There are several LDs in the problem. Each LD has its own number of vehicles and helicopters. In addition, there are a number of DCs that distribute RCs. The problem is modeled in two steps. In the first step, the vehicles transport the RCs to the DCs and finally return to the local LDs. In the second step, the helicopters deliver the remaining RCs of the first step and the RCs of the second step simultaneously. The aim is to reduce the time of delivering the RCs to the affected areas. Based on what explained, the primary contributions of this study are as follows:

- Studying a joint resource allocation, location, and routing problem under disaster conditions;
- Implementing humanitarian logistics operations through minimizing delivery time of RCs;
- Considering uncertainty of demand, capacity, as well as time;
- Employing an extended version of ALNS to solve the suggested formulation and comparing it with some other solution algorithms.

The residue of the paper is as follows: Section 2 is dedicated to the literature review. In Section 3, problem description and mathematical modeling are presented. Section 4 provides solution methods. In Section 5, various numerical examples are studied. Lastly, Section 6 discusses conclusions.

2. Literature review

In this section, related studies are reviewed. Then, the research gap is discussed.

2.1. Related studies

The literature is rather rich in the research conducted on the subjects relevant to the topic of this study. Barbarosoǧlu and Arda offered a model for RCs in two-stage while the demand was considered uncertain in transportation planning. The objective of the first stage was to minimize the total transportation cost. In the second stage, it was to minimize the total in-network costs, maintenance costs, and mode shift costs [14]. Tzeng, Cheng studied how to design relief delivery systems for victims. They used a multi-objective planning method to describe their problem. The study aimed to minimize the total time and the total costs of the delivery of RCs to injured people. It also sought to maximize the satisfaction of the applicants during the course [15]. In another study, Ukkusuri and Yushimito focused on resolving potential network disruptions as well as vehicle routing. Predicting the RCs required in natural disasters was an essential issue in their study. To find the best location of resources, they used an integer programming model and a highly reliable path approach [16]. A location-allocation problem was also studied by Zhan and Liu. The demand and the available paths were considered uncertain. The researchers used goal programming, scenario-based planning and chance constraints to insert uncertainty into the model [17]. Afshar and Haghani designed a response network to control the circulation of several RCs. Their model involved planning for the optimal locations of facilities and routing and provided delivery schedules [18]. Rawls and Turnquist proposed a dynamic plan to examine the allocation of resources to demand points in the short term. The proposed plan was a two-stage SP [19]. Rath and Gutjahr applied a formulation with three-objective to deal with short-term and medium-term economic issues, carry out humanitarian tasks and solve the location and routing problem of intermediate warehouses after natural disasters. The ε-constraint was applied to solve the problem accurately. The NSGA-II meta-heuristic was also used to compare the results [20]. To solve a problem of locating DCs and deal with VRP in emergencies, Wang, Du examined a nonlinear model of integers. Total cost, reliability, and travel time in separate deliveries were the points of focus in the model. The dominated sorting genetic algorithm (DSGA) and the non-dominated sorting differential evolution algorithm (NDSDEA) were used [21]. Similarly, Vahdani, Veysmoradi formulated a three-level relief chain. Their problem was investigated under time window constraints in multi-periods and for multi-commodities. To solve the model, NSGA-II and MOPSO were applied as two efficient meta-heuristic algorithms [22]. Plus, Davoodi and Goli presented an integrated routing, location, and allocation formulation for a disaster relief logistics problem. They considered that their model is under deterministic conditions. Finally, they solved their developed model employing the benders decomposition approach and variable neighborhood search algorithm [23]. Additionally, Molladavoodi, Paydar studied a facility location problem for a RCs distribution network using mathematical modeling. The objective functions of their proposed model were aimed at minimizing the total cost, maximizing the coverage and accessibility of relief centers, and minimizing unfulfilled demand. To solve their multi-objective model, they developed a hybrid algorithm by combining the LP-metric method with the GA [24]. Moreover, Beiki, Seyedhosseini investigated location-routing problems for RCs during a disaster. To that aim, they developed a multi-objective MIP formulation. Their model's objective functions minimized response time, minimized operational costs, and maximized the transportation network's reliability. Eventually, they used ε -constraint approach to deal with the multi-objectivity of their proposed model [25]. With multiple trips taken into account for disaster response operations, Maghfiroh and Hanaoka presented a multi-modal relief distribution model using a three-level chain made up of (1) supply nodes, (2) logistics operational areas, and (3) affected areas[26]. Determining operational regions, modes of transportation, and the volume of commodities allocated to each mode of transportation were the objectives of the model that was given. In order to assist sustainability in the context of humanitarian relief operations, a three-level relief chain problem is developed in the Boostani, Jolai, and Bozorgi-Amiri's study in the before and post-disaster phases [27]. They considered a mixed-integer stochastic programing model in which minimizing total costs of the humanitarian relief supply chain, the environmental impacts, and maximizing social welfare were the objective functions. Similarly, Ali and Reza investigated the topic of sustainability in the problem of natural disasters. They developed a multi-objective mathematical programming model for designing a sustainable distribution network of emergency goods in disaster relief logistics. For validation of the proposed model, they considered a real case study. In order to obtain simultaneous routing and scheduling of trucks to transport people from impacted areas to shelters and supply them with essential relief commodities, Sabouhi, Bozorgi-Amiri,Moshref-Javadi, and Heydari suggest an integrated evacuation and distribution logistic system[28]. The goal of the suggested Mixed-Integer Linear Programming model for the problem was to minimize the total time it takes for vehicles to arrive to distribution points, shelters, and affected areas; Memetic Algorithm (MA) was used by authors to solve the model.

Table 1 presents a summary of the reviewed studies along with their corresponding features.

2.2. Research gap

Disaster relief operations require several resources [29]. By resources, we mean RCs. In fact, the manner of managing RCs is highly critical from different perspectives. Plus, when it comes to disaster, the criticality of such problems is accentuated even more. So, in this paper, resource allocation decisions are studied. Plus, it is clear that routing in the distribution of RCs to demand points is another critical point, which has vast impacts on humanitarian operations. Moreover, location of facilities can be highly influential in such problems. Hence, investigating a joint location-routing problem is thoroughly crucial during a crisis. So, this paper tries to shed light on the importance of the resource allocation problem along with a joint location-routing problem in disaster relief operations. Plus, considering uncertainty in such problems is very necessary. A Recent paper by Davoodi and Goli has neglected uncertainty [23]. So, this paper considers demand uncertainty, capacity uncertainty, as well as time uncertainty to bridge the gap in the literature. Above all, a novel ALNS algorithm is developed to deal with the NP-hardness of the proposed model.

3. Problem description and the mathematical model

Natural disasters such as earthquakes can destroy roads, and, depending on the situation, the demand can change for the damaged areas at any time. Therefore, logistics planning is a basic problem in critical situations. In such situations, logistics planning is different from commercial conditions [30]. In a crisis such as an earthquake, it is important to deliver RCs as soon as possible and meet the needs of all the affected areas. In the literature on the subject, the demand and the routes in which vehicles have to deliver relief supplies to DCs are predetermined, but the issue of delay in the delivery of RCs and the type of vehicle delivering the RCs (e.g., trucks and helicopters) have not been addressed. In this study, a two-stage stochastic programming approach is proposed to design a problem of distributing humanitarian aids by the available vehicles from local depots (LDs) to distribution centers (DCs) in the event of an earthquake. The LDs are considered to be temporary; when there is no crisis, they are non-static and nonfunctional. They are generally located in suitable positions for managing large inflows and outflows. DCs are the centralized locations in which people can collect their immediate needs (e.g., canned food, water bottles and blankets) faster and more easily. They are selected among the existing schools and stadiums in nearly every one of the districts in need. LDs are in charge of the operation and, finally the demobilization of DCs. The type and the quantity of the stuffs to be sent to different DCs are determined at LDs.

There are some factors that restrict the local agents in making decisions and planning influential strategies. The amount and the type of demands, the size of the available vehicles and the state of infrastructures are the highly uncertain factors in this study. Moreover, due to the uncertainty in the road network, transportation time is uncertain too. So, the knowledge of the time is not gained until the damaged routes are determined. As far as uncertainty is concerned, these issues and their consequences are the particular points of focus in this study.

It is to be noted that the demand districts may be in remote areas, and the disaster areas might be in a chaotic state under emergencies, making it impossible to have a comprehensive overview. Hence, demand is often considered as one of the most uncertain parameters in humanitarian logistics.

It can fluctuate unexpectedly because of other factors such as aftershocks. Unpredictable demand patterns affect the distribution plans as well as the management of relief efforts. Therefore, the planning of distribution activities is complicated by uncertain and limited data.

In general, based on the location of the demand districts, several DPs are inaugurated in the area to provide RCs for the affected people. The location of the DPs serves as the basis for the determination of the LDs to open and operate. In this study, it is assumed that RCs are available in the local depots and that they are transported from the local depots to the DCs to be delivered to the victims. An overview of the decisions at each stage is presented in Fig. 1.

The initial data on the demand are received from the DCs, and the number of the available vehicles at each LD, the status of access to the routes in the road network, and the time of travels are confirmed.

Accordingly, the initial distribution plan is designed in the first stage. Assignment of DCs to LDs, selection of appropriate routes for different vehicles, and determination of the number of RCs to deliver to DCs are the essential actions in the first stage. Because there is no access to accurate data on the level and the nature of the demand in the DCs when the vehicles leave the local warehouses, at least some data on the demand (i.e., the main demand) must be gained initially. Therefore, the vehicles sent must deliver the RCs to the extent possible. In some cases, due to demand fluctuations, additional demand, called extra demand, is taken into account at the DCs.

The second stage corresponds to the updated demand information and the required actions for the RCs re-transported toward different DCs. It is assumed that new data on demand are received when the vehicles have arrived at DPs and delivered RCs to them. The challenges involved in the second stage include assigning DCs to LDs, determining the number of RCs to be carried, and finding routes and a sequence for helicopter movements. The faster the relief operations, the more people are saved from serious injuries. For this reason, in the second stage, RCs are sent from LDs to DCs through an air transportation network. The first-stage transportation is carried out by various vehicles in the road network. A set of routes is also defined between every two nodes in the second-stage road network so that alternative routes will be available to use if some of them are destroyed. At this stage, multiple depots are opened, but a vehicle must start its tour from one of the LDs, travel to one or a few DPs and then return to the same depot without a sub-tour. The second-stage transportation is carried out by helicopters in the air network. Choosing routes for the helicopters is based on the same requirements as for the other vehicles; each helicopter must start its tour from a single LD, visit its assigned DCs and come back to that center without sub-tours. In short, the current study presents a multi-depot multi-transportation mode for a locating-routing model with a two-level relief chain in an uncertain environment, which includes LDs and DPs. Fig. 2 presents the scheme of the relief supply chain.

The proposed formulation is according to the following assumptions:

(i) In the first and the second stages, split delivery is allowed.

(ii) Multiple vehicles can serve each DC. That is, one DC can receive RCs with different carriers, and one of them can partly satisfy the demand of one DC.

(iii) Capacity considerations are essential to determine the quantities to deliver.

(iv) The total RCs delivered by a vehicle on one tour cannot exceed its capacity.

(v) The total RCs sent from each LD should not exceed its capacity.

(vi) The maximum number of the available vehicles at LDs is limited.

(vii) Each DC can receive services from only one LD in the first and the second stage.

(viii) Each vehicle is assigned to one LD.

3.1. Sets, parameters and decision variables

This section defines the sets, indices, parameters and decision variables involved in the mathematical formulation.

Sets:

I LDs indexed by $i, i' \in I = \{1, 2, ..., |I|\}$,

J DCs indexed by $j, j' \in J = \{1, 2, ..., |J|\}$,

G DCs and LDs indexed by $i, j \in G = \{1, 2, ..., |I + J|\}$,

R Vehicles in the first stage indexed by $r \in R = \left\{1, 2, ..., \underset{s \in S}{Max}\left\{\sum_{i \in I} F_{is}^{V}\right\}\right\}$,

R' Helicopters in the second stage indexed by $r' \in R' = \left\{1, 2, ..., \underset{s \in S}{Max}\left\{\sum_{i \in I} F_{is}^{H}\right\}\right\}$,

S Disaster scenarios indexed by $s \in S = \{1, 2, ..., |S|\}$.

Deterministic parameters:

Q The occupied volume of each unit of RC $\left(m^3\right)$,

C^V The load capacity of each vehicle in the first stage $\left(m^3\right)$,

C^H The load capacity of each helicopter in the second stage $\left(m^3\right)$,

N_S^V Maximum number of the potential LDs that can be opened in the first stage and in scenario *s*,

N_S^H Maximum number of the potential LDs that can be opened in the second stage and in scenario *s*,

P_S The probability of disaster occurrence in scenario s $\left(0 \le P_s \le 1; \sum_s P_s = 1\right)$,

M A large positive number.

Stochastic parameters:

D_{js}^V Initial demand for DC_j in scenario *s*,

D_{js}^H Additional demand for DC_j in scenario *s*,

F_{is}^V Total number of the available vehicles at LD_i in scenario *s*,

F_{is}^H Total number of the available helicopters at LD_i in scenario *s*,

T_{ijs}^V Travel time between nodes $i \in G$ and $j \in G$ in the road transportation network in scenario s(in minutes),

T_{ijs}^H Travel time between nodes $i \in G$ and $j \in G$ in the air transportation network in scenario s(in minutes).

Variables in the first stage:

L_{is}^V 1 if LD_i is opened in the first stage and in scenario *s*; 0 otherwise,

X_{ijs}^V 1 if DC_j is assigned to LD_i in the first stage and in scenario *s*; 0 otherwise,

Z_{ijrs}^V 1 if vehicle r travels from node $i \in G$ to node $j \in G$ in the road network in scenario *s*; 0 otherwise,

T_{js}^V The arrival time of the vehicle (s) at DC_j in scenario *s*,

U_{js}^V Accumulated demand distributed by vehicles in scenario s when they reach DC_j,

A_s^T The maximum value of vehicle arrival times at different DCs in scenario *s*(at the end of the second stage).

Variables in the second stage:

L_{is}^{H} 1 if LD_i is opened in the second stage and in scenario *s*; 0 otherwise,

X_{ijs}^{H} 1 if DC_j is assigned to LD_i in the second stage and in scenario *s*; 0 otherwise,

$Z_{ijr's}^{H}$ 1 if helicopter r travels from node $i \in G$ to node $j \in G$ in the air network in scenario *s*; 0 otherwise,

T_{js}^{H} The arrival time of the helicopter (s) at DC_j in scenario *s*,

U_{js}^{H} Accumulated demand distributed by helicopters in scenario s when vehicles reach the DC_j.

3.2. Mathematical formulation

Objective function (1), as follows, optimizes the total waiting time for DCs to receive RCs or the total latency, which is equal to the sum of the helicopters' arrival times at DCs at the end of the second stage.

$$\text{Min} \quad Z = \sum_{j \in J} \sum_{s \in S} P_s . T_{js}^{H} \tag{1}$$

Constraints (2) and (3) show the vehicle flow continuity in routes, and constraint (2) emphasizes that each vehicle entering a node must depart from the same node. Constraint (4) ensures that every vehicle visits any given DC at most once. Constraint (5) guarantees that every DC is assigned to only one route and every route begins exactly one LD. Constraint (6) denotes that a DP is assigned to an LD if there is a route connecting them together. Constraint (7) guarantees that each DC is supplied from exactly one LD. Constraints (8) guarantees that each DC is visited by at least one vehicle. Constraint (9) shows that the number of vehicles sent from each LD is restricted to the maximum number of vehicles in that LD. Constraint (10) guaranteed that the number of the potential DCs that are opened is restricted to the maximum number allowed. Constraints (11) and (12) are sub-tour elimination constraints. Constraint (12) also ensures that the total load carried by each vehicle does not exceed the vehicle capacity. Latency at different DCs is calculated using constraints (13) and (14). If vehicles arrive at a DC from an LD, their arrival time is equal to the sum of the travel times between the LD and the DC and the arrival time of vehicles at the LD in the first stage. If they arrive at a DC from another DC, their arrival time is equal to the sum of the travel time between the two DCs and the arrival time of vehicles at the first DC. Moreover, constraint

(15) emphasizes that vehicles can visit DCs only when they are assigned at least to one LD. Constraint (16) calculates the maximum time of visiting all the DCs at the end of the first stage.

First-stage constraints:

$$\sum_{\substack{j\in G\\ j\neq i}} Z^V_{ijrs} - \sum_{j\in G} Z^V_{jirs} = 0, \qquad \forall i\in G, r\in R, s\in S, \qquad (2)$$

$$\sum_{\substack{j'\in J\\ j'\neq j}} Z^V_{jj'rs} \leq 1, \qquad \forall j\in J, r\in R, s\in S, \qquad (3)$$

$$\sum_{\substack{i\in G\\ i\neq j}} Z^V_{ijrs} \leq 1, \qquad \forall j\in J, r\in R, s\in S, \qquad (4)$$

$$\sum_{i\in I}\sum_{j\in J} Z^V_{ijrs} \leq 1, \qquad \forall r\in R, s\in S, \qquad (5)$$

$$\sum_{j\in J} Z^V_{ijrs} + \sum_{\substack{j\in G\\ j\neq j'}} Z^V_{jj'rs} \leq 1 + X^v_{ij's}, \qquad \forall i\in I, j'\in J, r\in R, s\in S, \qquad (6)$$

$$\sum_{i\in I} X^V_{ijs} = 1, \qquad \forall j\in J, s\in S, \qquad (7)$$

$$\sum_{\substack{i\in G\\ i\neq j}}\sum_{r\in R} Z^V_{ijrs} \geq 1, \qquad \forall j\in J, s\in S, \qquad (8)$$

$$\sum_{j\in J}\sum_{r\in F^V_{is}} Z^V_{ijrs} \leq F^V_{is}.\mathrm{L}^V_{is}, \qquad \forall i\in I, s\in S, \qquad (9)$$

$$\sum_{i\in I} L^V_{is} \leq N^V_s, \qquad \forall s\in S, \qquad (10)$$

$$U^V_{js} - U^V_{j's} \leq C^V.(1 - Z^V_{jj'rs}) - D^V_{j's}.Q, \qquad \forall j\in J, j'\in J, j'\neq j, r\in R, s\in S, \qquad (11)$$

$$D^V_{js}.Q \leq U^V_{js} \leq C^V, \qquad \forall j\in J, s\in S, \qquad (12)$$

$$T^V_{ijs} - (1 - Z^V_{ijrs}).M \leq T^V_{js}, \qquad \forall i\in I, j\in J, r\in R, s\in S, \qquad (13)$$

$$T^V_{j's} + T^V_{jj's} - (1 - Z^V_{j'jrs}).M \leq T^V_{js}, \qquad \forall j\in J, j'\in J, j'\neq j, r\in R, s\in S, \qquad (14)$$

$$T^V_{js} \leq M.\sum_{i\in I} X^V_{ijs}, \qquad \forall j\in J, s\in S, \qquad (15)$$

$$T^V_{js} \leq A^T_s, \qquad \forall j\in J, s\in S, \qquad (16)$$

Constraints (17) -(30) correspond to (2) -(15) of the first stage.

Second-stage constraints:

$$\sum_{\substack{j\in G\\ j\neq i}} Z^H_{ijr's} - \sum_{j\in G} Z^H_{jir's} = 0, \qquad \forall i\in G, r'\in R', s\in S, \qquad (17)$$

$$\sum_{\substack{j'\in J\\ j'\neq j}} Z^H_{jj'r's} \leq 1, \qquad \forall j\in J, r'\in R', s\in S, \qquad (18)$$

$$\sum_{\substack{i\in G\\ i\neq j}} Z^H_{ijr's} \leq 1, \qquad \forall j\in J, r'\in R', s\in S, \qquad (19)$$

$$\sum_{i\in I}\sum_{j\in J} Z^{H}_{ijr's} \le 1, \qquad \forall r' \in R', s \in S, \tag{20}$$

$$\sum_{j\in J} Z^{H}_{ijr's} + \sum_{\substack{j\in G\\ j\ne j'}} Z^{H}_{jj'r's} \le 1 + X^{H}_{ij's}, \qquad \forall i \in I, j' \in J, r' \in R', s \in S, \tag{21}$$

$$\sum_{i\in U} X^{H}_{ijs} = 1, \qquad \forall j \in J, s \in S, \tag{22}$$

$$\sum_{\substack{i\in G\\ i\ne j}}\sum_{r'\in R'} Z^{H}_{ijr's} \ge 1, \qquad \forall j \in J, s \in S, \tag{23}$$

$$\sum_{j\in J}\sum_{r'\in F^{H}_{is}} Z^{H}_{ijr's} \le F^{H}_{is}.\mathrm{L}^{H}_{is}, \qquad \forall i \in I, s \in S, \tag{24}$$

$$\sum_{i\in I} L^{H}_{is} \le N^{H}_{s}, \qquad \forall s \in S, \tag{25}$$

$$U^{H}_{js} - U^{H}_{j's} \le C^{H}.(1 - Z^{H}_{jj'r's}) - D^{H}_{j's}.Q, \qquad \forall j \in J, j' \in J, j' \ne j, r' \in R', s \in S, \tag{26}$$

$$D^{H}_{js}.Q \le U^{H}_{js} \le C^{H}, \qquad \forall j \in J, s \in S, \tag{27}$$

$$A^{T}_{s} + T^{H}_{ijs} - (1 - Z^{H}_{ijr's}).M \le T^{H}_{js}, \qquad \forall i \in I, j \in J, r' \in R', s \in S, \tag{28}$$

$$T^{H}_{j's} + T^{H}_{j'js} - (1 - Z^{H}_{j'jr's}).M \le T^{H}_{js}, \qquad \forall j \in J, j' \in J, j' \ne j, r' \in R', s \in S, \tag{29}$$

$$T^{H}_{js} \le M.\sum_{i\in I} X^{H}_{ijs}, \qquad \forall j \in J, s \in S, \tag{30}$$

Non-negativity constraints for all the stages:

$$A^{T}_{s} \ge 0, \quad \text{and Integer} \qquad \forall s \in S, \tag{31}$$

$$T^{V}_{js}, U^{V}_{js}, T^{H}_{js}, U^{H}_{js} \ge 0, \quad \text{and Integer} \qquad \forall j \in J, s \in S, \tag{32}$$

$$X^{V}_{ijs}, X^{H}_{ijs} = \{0,1\}, \qquad \forall i \in I, j \in J, s \in S, \tag{33}$$

$$L^{V}_{is}, L^{H}_{is} = \{0,1\}, \qquad \forall i \in I, s \in S, \tag{34}$$

$$Z^{V}_{ijrs}, Z^{H}_{ijr's} = \{0,1\}, \qquad \forall i \in G, j \in G, i \ne j, r \in R, r' \in R', s \in S. \tag{35}$$

Finally, constraints (31) -(35) define the ranges and the types of decision variables.

4. Solution methods

4.1. CPLEX solver

In order to obtain optimal solutions, the proposed mathematical model is coded in the IBM ILOG CPLEX® solver environment. Due to the capabilities of CPLEX, as reported in several studies, it is used to obtain optimal solutions to models with integer and mixed-integer properties. To solve a model, CPLEX uses the branch-and-cut exact solution algorithm. In this method, the algorithm adds a cut to the model in each iteration to obtain an optimal solution. As the number of the scenarios and distribution points of the problem increases, the number of constraints and, consequently, the time required to solve the problem by the algorithm increase too. Therefore, to deal with this problem, heuristics or meta-heuristic algorithms are preferred. In this study, the CPLEX solver has been employed to solve small test examples optimally in order to find the efficiency of the suggested ALNS and compare ALNS with other well-known metaheuristic algorithms (e.g., GA, and SA).

4.2. Simulated annealing algorithm (SA)

According to the literature, the SA is one of the effective metaheuristic algorithms in the field of transportation issues [31]. It was created and inspired by a physical process, the solid annealing principle. Generally, the SA works like other metaheuristic optimization algorithms [32]. The pseudo-code of the SA is represented in Fig. 3.

Note. For more details, see supplementary file (A).

4.3. Genetic Algorithm (GA)

Previous studies showed that GA is one of the metaheuristic algorithms that can be adapted to lot kind of problems. According to nature of GA there are a lot of ways and operators to evaluate and generate new solutions [33, 34]. In current paper, the GA proposed by Ghoseiri and Ghannadpour is used [35]. The generalized procedure of the GA in this study is represented in Fig. 4.

Note. The value of parameters of the GA algorithm is shown in the supplementary file (B).

4.4. Adaptive large neighborhood search (ALNS)

The local search algorithm improves the initial solution just by applying operations on a small part of that solution. The ALNS algorithm works like a local algorithm, except that it can change a large part of a solution instead of making changes to a limited part of it. This feature is applied by two important types of operators including a) removal operators (destruction) and b) insert operators (repair). Generally, the ALNS is an expanded version of the LNS algorithm, which was first introduced by Shaw [36]. The LNS consists of a series of pick-up and drop-out movements, and the search for a neighbor is done by removing several parts (nodes) from the solution and putting them back on the track. The feature that distinguishes these two algorithms is the number of the operators implemented to apply removal and insert operators. In the removal section of the ALNS algorithm, several different criteria and methods can be applied to remove the nodes from the solution. Also, several criteria and methods can be used to insert the removed nodes in the solution. The algorithm works in a specific manner. First, it starts with a feasible solution, and then it uses the insertion and removal operators to make changes to the initial solution and generate a new solution. If the new solution is better, it will be entered into the algorithm as an input in the next step. The removal and insertion operators are selected using the Roulette Wheel mechanism (RWM). The chances of each operator are updated according to its past performance. The operators that have improved the solutions have higher chances to be selected. A sample of an algorithm implementation process is presented in Fig. 5.

The pseudo-codes of the ALNS algorithm are listed in Fig. 6.

4.4.1. The removal operators (destruction)

After the initial feasible solution is entered into the algorithm as the input, it uses the operators to create a new solution. In the removal operators, a number of customers are removed in each period. As the nodes are removed, two types of lists are created. The first list is a reduced solution, which is obtained as the selected nodes are removed from the previous solution, and the second list includes the deleted nodes. In general, the pseudo-code of the removal operators is as follows (Fig. 7):

The present study draws upon eight types of removal operators including (I) Random removal (RR), (II) Worst-distance removal (WDR), (III) Proximity-based removal (PBR), (IV) Random tour removal (RTR), (V) Worst-time removal (WTR), (VI) Neighborhood removal (NR), (VII) Depots costs, and (VIII) Choice based on the geographical location.

Methods (I) to (VI) are picked from a study by [37], but methods (VII) and (VIII) are presented as two new heuristic ones.

I) Random removal

In this method, a certain number of nodes are randomly selected among the nodes in the solution set and removed from the set. The operator starts with an empty list and puts the deleted nodes inside the list when it is executed.

II) Worst-distance removal

In this operator, for each iteration, the algorithm selects the β nodes among the nodes in the present solution set that enter the model at the highest cost and removes them from the solution set. Here, the cost is considered equal to the distance between the nodes:

$$\mathrm{Cost}(n) = \mathrm{Distance}(n, n-1) + \mathrm{Distance}(n, n+1) \tag{36}$$

III) Proximity-based removal

Of all the nodes, one node is randomly selected (e.g., node i). Using Eq. (37), the Euclidean distance between node i and the other nodes is calculated. Finally, the Θ percentage of the consumers that have a minimum distance from the selected node is chosen and put in the removal list. The selected node is deleted from all the routes.

$$\text{distance}(i, j) = \sqrt{(x_i - x_j)^2} + \sqrt{(y_i - y_j)^2} \tag{37}$$

How this operator works is shown in Fig. 8.

IV) Random tour removal

This operator randomly selects a complete path or tour and removes all the nodes on that tour (Fig. 9).

V) Worst-time removal (WTR)

In this method, for each customer i, the deviation of the service start time from time α_i is calculated. After that, the customer with the largest deviation is removed. This operator prevents long waits and delays in the starting service.

VI) Neighborhood removal (NR)

This method regards the average distance of paths in the network. The path with the longest average distance in the network is selected. Then, among the customers present in the selected route, those that have the greatest difference from the average value are chosen. For each path, the following relation is taken into account:

$$A = \{j_1, ..., j_{|A|}\} : \bar{d}_A = \sum_{(i_1, i_2) \in B} \frac{d_{i_1, i_2}}{|A|} \text{ and } i^* = \text{argmax}_{i \in A} \{\bar{d}_A - d_{A \backslash \{i\}}\}. \tag{38}$$

VII) Depot costs

In this method, from each depot, a vehicle that has provided the service is randomly selected. Among the customers who have been served by the vehicle, the one who has entered the route with the highest cost is selected and removed from the route.

VIII) Choice based on geographical location

In this method, the applicants are divided into four categories in terms of location. The areas with the highest and the lowest densities are selected. If the α percent of the customers is to be removed at each stage, the $1-\alpha$ percent of the customers is selected from the part with the highest density and the rest from the low-density region. The customers are randomly selected.

4.4.2. Insertion operators (repair)

Insertion operators use the list of the deleted nodes at the destruction step and in the reduced solution. They place the removed nodes in the appropriate position using special methods and repair the reduced solution. The pseudo-code of the insertion operators is as follows (Fig. 10):

In this study, greedy insertion (GI), greedy insertion with noise function (GIN), and regret insertion (RI) are the operators applied to repair the solution in the ALNS algorithm.

A) Greedy insertion (GI)

This operator places each node of the list of the removed nodes in the best position in the reduced solution. To find the best position for each node, Eq. (39) is applied, where d is the distance between nodes j and i.

$$\text{Cost}(i) = \text{distance}(j, i) + \text{distance}(i, j+1) - \text{distance}(j, j+1) \tag{39}$$

B) Greedy insertion with noise function (GIN)

GIN acts like GI, but there is a difference; after the greedy insertion of each node, the cost that it puts in the network is multiplied by a random number from 0.8 to 1.2.

C) Regret insertion (RI)

This operation works like GI. First, the operator calculates the cost of the nodes in the list of the eliminated nodes, similar to GI. Then, it chooses the first best position to place node i, φ_{i1}, followed by the second-best position, φ_{i2}. These two values are calculated for all the points by the use of the difference in the objective function value. Finally, according to Eq. (40), the node is replaced in a proper place.

$$Best(i) = \text{argmax}_i \{\varphi_{i2} - \varphi_{i1}\} \tag{40}$$

Note. Additional explanations about the proposed ALNS algorithm and the values of the parameters are given in the supplementary file (C).

5. Numerical examples

To validate the proposed model, 30 different tests are generated. In each test, the mathematical formulation is coded in GAMS 25.1.2 and solved by a CPLEX solver on a PC with the configurations of Intel Core i7, 2.90 GHz, 64-bit and RAM 8.00 GB. To compare the proposed solutions, the problem is coded in the MATLAB R2019b software using the ALNS algorithm. The specifications of the tests and the results of solving the formulation are given in Table 2, and also it presents the running time and the objective value of the algorithms. That also reports the lower bounds of the meta-heuristic algorithm and the CPLEX (LB). LB is the objective value of the LP relaxation. The percentage of the gap between the objective values of the best solution found and the LB, and the ratio of the running time and the value of the objective function between the two methods are calculated with Eqs. (41)- (44)[38].

$$Ratio_{Time}(\%) = \left(\frac{Time_{\text{metaheuristics}}}{Time_{CPLEX}} \right) \times 100 \quad (42) \qquad Gap_{CPLEX}(\%) = \left(\frac{Obj.V_{CPLEX} - LB}{Obj.v_{CPLEX}} \right) \times 100 \quad (41)$$

$$Ratio_{Obj.v}(\%) = \left(\frac{Obj.v_{\text{metaheuristics}}}{Obj.V_{CPLEX}} \right) \times 100 \quad (44) \qquad Gap_{\text{metaheuristics}}(\%) = \left(\frac{Obj.V_{\text{metaheuristics}} - LB}{Obj.V_{\text{metaheuristics}}} \right) \times 100 \quad (43)$$

Fig. 11(a) to 11(c) show changes in the computational time of the proposed meta-heuristic algorithm (ALNS), GA, SA, and the CPLEX method. According to the figures and the results reported in Table 2, on average, the proposed meta-heuristic algorithm works nearly 30% faster than the exact algorithm, and it is much faster than GA and SA algorithms.

According to the figures, as the number of the problem constraints grows, the time to solve the problem increases in the CPLEX method. On average, when the number of constraints is more than 455,000, the problem cannot be solved within an acceptable time or within a specified time frame. Given the maximum problem-solving time in the proposed meta-heuristic algorithm and the nature of the CPLEX method, the upper limit for the problem-solving time is set at 3,500 seconds.

Fig. 12(a) to 12(c) show the percentages of the cost gap for the three scenarios. According to the figures, the percentage of the gap between the ALNS and exact method is very low, especially in problems with more constraints. On the other hand, it is quite clear that SA and GA behave quite similarly. In problems with a small number of constraints (in all three scenarios), all three algorithms have almost the same accuracy, but as the number of constraints grows, the accuracy of SA and GA decreases sharply compared to the proposed ALNS. As a concluding remark, averagely, all of the algorithms are run 30 times for each problem to reach the final feasible solution. Regarding Fig. 11 and 12, the proposed ALNS algorithm and the form of definitional chromosome to representation solution in this problem (supplementary file C.1), has a more desirable performance than SA and GA algorithms, especially in large size problem.

6. Conclusions

In this study, a location-routing problem in critical situations was investigated. First, a mathematical formulation was suggested for the problem. The problem was modeled under uncertainty, and a scenario-based approach was used in the modeling. Then, to validate the proposed model, 30 problems in different aspects and with different parameter values were set and examined. Four methods were also applied to solve the formulation. First, the formulation was coded by the GAMS software and solved with a CPLEX solver. Due to the complexity of solving the studied problem in large-scale sizes, the ALNS, GA, and SA were used as meta-heuristic algorithms to deal with the problem. In addition, two new operators (depot costs, choice based on geographical location) were proposed to improve the ALNS algorithm. As indicated previously, the proposed algorithm is fast and efficient. Given the gap between the four methods, it can be concluded that the solution to the problem is acceptable to a large extent.

In order to expand the approach presented in this study, other concepts related to the field of uncertainty (e.g., fuzzy theory and probability) are recommended to be investigated. Also, the expansion of the proposed algorithm and the comparative use of other meta-heuristic algorithms such as PSO and hybrid of some algorithms can make desirable topics for future research.

Compliance with ethical standards

Conflict of interest: The authors declare that they have no conflict of interest.

Supplementary data is available at:

http://scientiairanica.sharif.edu/jufile?ar_sfile=173256

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Table 1. Specifications of the reviewed papers

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Fig. 6 The pseudo-codes of the ALNS algorithm

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Table 1. Specifications of the reviewed papers

Authors (Year)	Problems				Uncertainty origins			Other characteristics			Solution methods
	RAP	FLP	VRP	LRP	Demand	Capacity	Time	Multi-route	Multi-mode	Two-stage	
Rawls and Turnquist [39]	✓	✓			✓					✓	Lagrangian L-shaped
Salmerón and Apte [40]	✓				✓		✓			✓	CPLEX
Mete and Zabinsky [41]		✓	✓		✓		✓			✓	CPLEX
Zhan and Liu [17]	✓	✓			✓						Goal programming
Tricoire, Graf [42]			✓		✓					✓	Branch-and-cut and ε -constraint
Najafi, Eshghi [43]			✓		✓	✓					CPLEX
Rath and Gutjahr [20]				✓							Math-heuristic and VNS
Abounacer, Rekik [44]		✓									ε -constraint
Rennemo, Rø [45]	✓	✓			✓	✓	✓				Heuristic algorithm
Ahmadi, Seifi [46]				✓						✓	VNS algorithm
Rath, Gendreau [47]	✓	✓					✓	✓			CPLEX
Rezaei-Malek, Tavakkoli-Moghaddam [48]		✓			✓		✓	✓	✓	✓	ε -constraint
Caunhye, Zhang [49]	✓			✓	✓			✓			CPLEX
Moshref-Javadi and Lee [50]	✓			✓							Memetic Algorithm (MA) & Recursive Granular Algorithm (RGA)
Tofighi, Torabi [51]	✓	✓			✓	✓	✓	✓			Differential evolution algorithm (DEA)
Paul, Lunday [52]		✓									ε -constraint
Nedjati, Izbirak [53]				✓							ε -constraint and NSGA-II
Vahdani, Veysmoradi [22]				✓		✓					NSGA-II and MOPSO
Molladavoodi, Paydar [24]		✓			✓	✓					a hybrid LP–GA approach
Beiki, Seyedhosseini [25]				✓							ε -constraint
Current paper	✓			✓	✓	✓	✓	✓	✓	✓	CPLEX and SA, GA, and ALNS algorithms

Notation: Vehicle routing problem (VRP), resource allocation problem (RAP), facility location problem (FLP), location-routing problem (LRP).

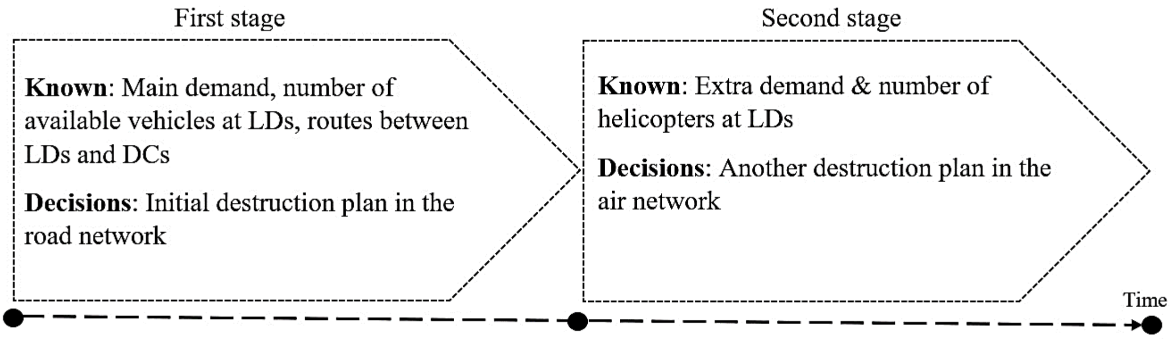


Fig. 1 The decision-making structure of the problem over time

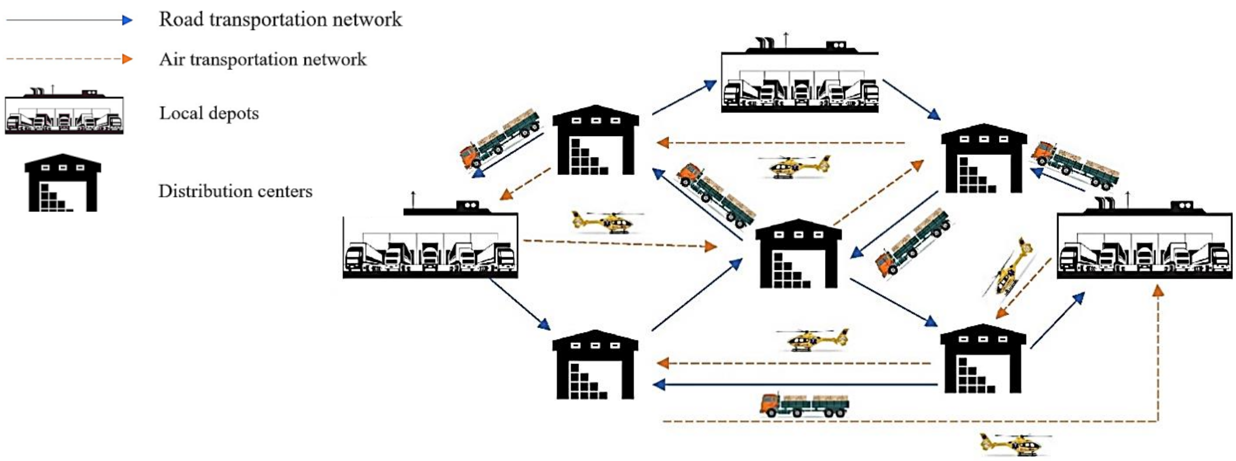


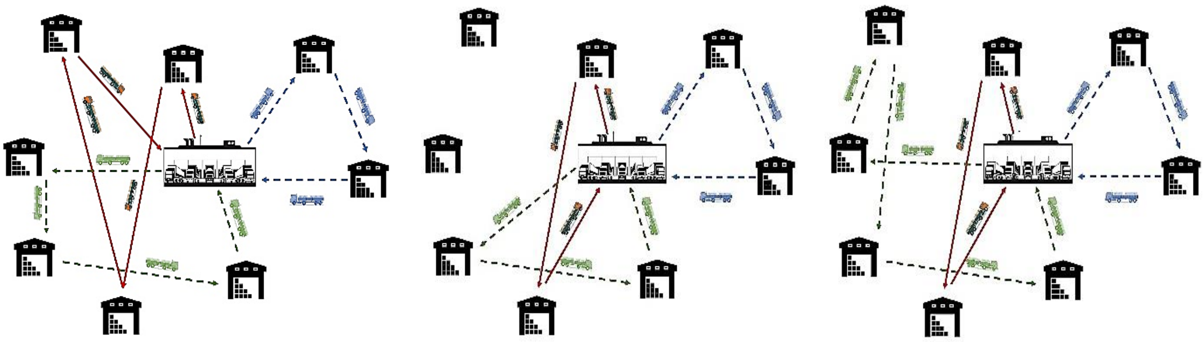
Fig. 2 The general scheme of the distribution system in the proposed relief chain

Select the best solution vector x_0 to be optimized
Initialize the parameters: temperature T, Boltzmann's constant k, reduction factor c
while termination criterion is not satisfied **do**
    For number of new solutions
        Select a new solution: $x_0 + \Delta x$
        if $f(x_0 + \Delta x) < f(x_0)$ **then**
            $f_{new} = f(x_0 + \Delta x); x_0 = x_0 + \Delta x$
        else
            $\Delta f = f(x_0 + \Delta x) - f(x_0)$
            Random $r(0,1)$
            if $r > \exp(-\Delta f / kT)$ **then**
                $f_{new} = f(x_0 + \Delta x); x_0 = x_0 + \Delta x$
            else
                $f_{new} = f(x_0)$
            end if
        end if
        $f = f_{new}$
        Decrease the temperature periodically: $T = c \times T$
    end for
end while

Fig .3 The pseudo-codes of the SA algorithm

Create an initial feasible population of individuals
Evaluate the fitness of each common of population
When *stop criterion is not met*, **do**
    Select the best individuals to be used by the genetic operators
    Generate new individuals using crossover and mutation
    Evaluate the fitness of new individuals
    Replace the worst individuals of the population by the best new individuals

Fig .4 The pseudo-codes of the GA algorithm



(a) Initial solution (a feasible solution) **(b)** Removal step **(c)** Insertion step

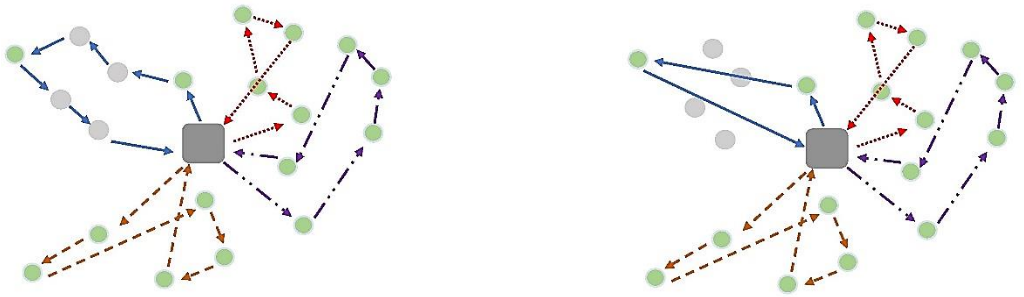
Fig .5 Graphical format of ALNS algorithm steps

Create an initial feasible solution s
$s_{best} \to s$
Initialize weights (scores to operators)
When *stop criterion is not met,* **do**
For *I iterations,* **do**
a. *Depending on the current weights of each operator, select one operator to remove and one operator to insert.*
b. *Apply the removal and insertion operators to s and create a new solution (s′)*
c. **If** *s′ satisfies the acceptance criterion,* **then**
$s \to s'$
If *s′ is better than* s_{best}, **then** $s_{best} \to s'$.
Adjust the weights and probabilities of the operators.
Return s_{best}.

Fig .6 The pseudo-codes of the ALNS algorithm

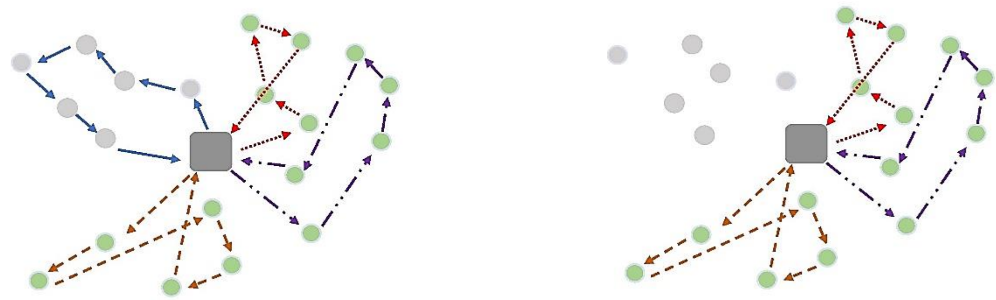
Inputs: A feasible solution and the number of the removed nodes (*N*)
Run the following process to the removed nodes (e.g. *N*)
    For *N iteration,* **do**
    a. *Select a node from the current solution.*
    b. *Add the selected node in the removal list.*
    c. *Delete the selected node from the current solution.*
Output: *the removal list and the reduced solution*

Fig .7 Destruction algorithm



(a) Feasible solution **(b)** Destroyed solution

Fig .8 Proximity-based removal



(a) Feasible solution **(b)** Destroyed solution

Fig .9 Random tour removal

Inputs: The reduced solution and the list of removed nodes in the previous step

Run the following process to the number of the removed nodes (e.g. *M*).

  For *M iteration,* **do**

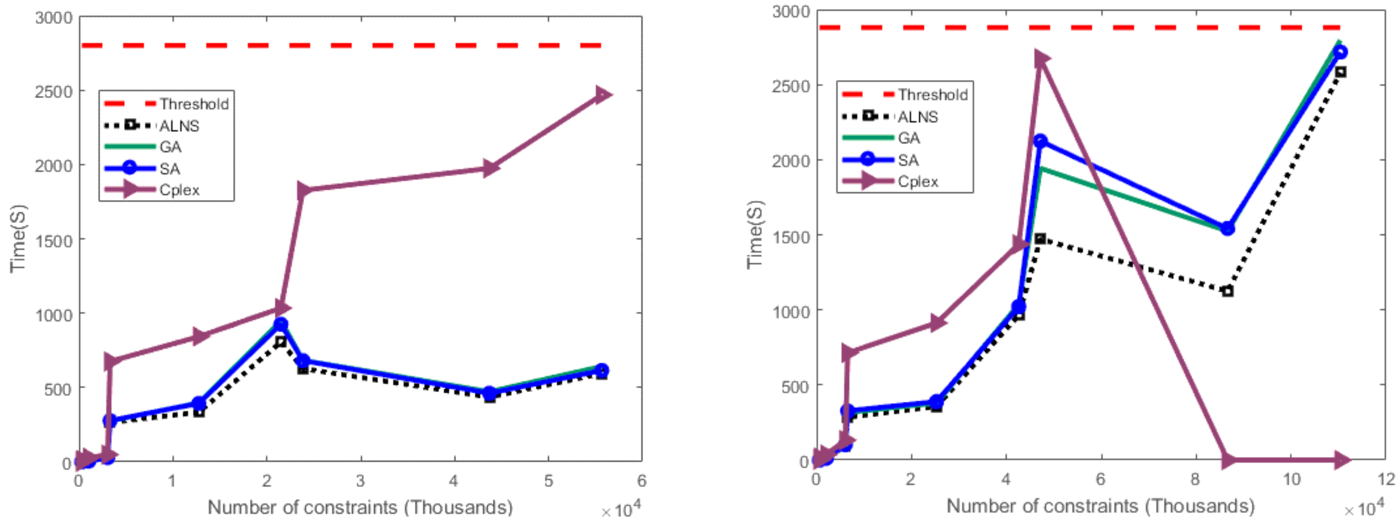
   a. *Select a node from the removal list to insert.*

   b. *Add the selected node in the appropriate position of the reduced solution.*

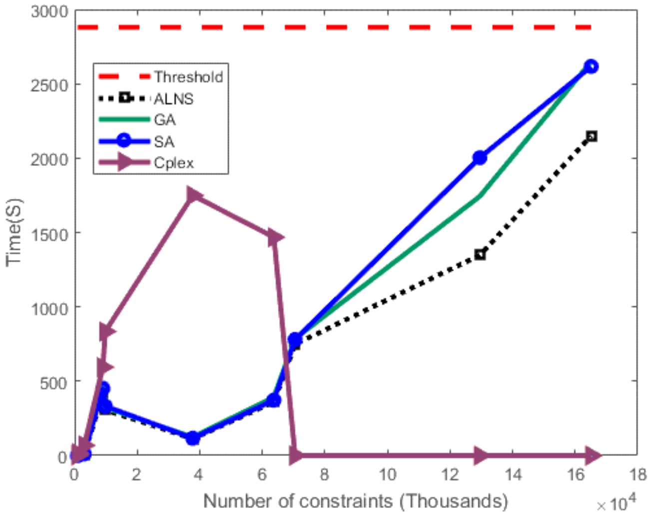
   c. *Delete the selected node from the list of the removed nodes.*

Output: The created solution is returned to the algorithm as a new solution.

Fig .10 Repairing algorithm

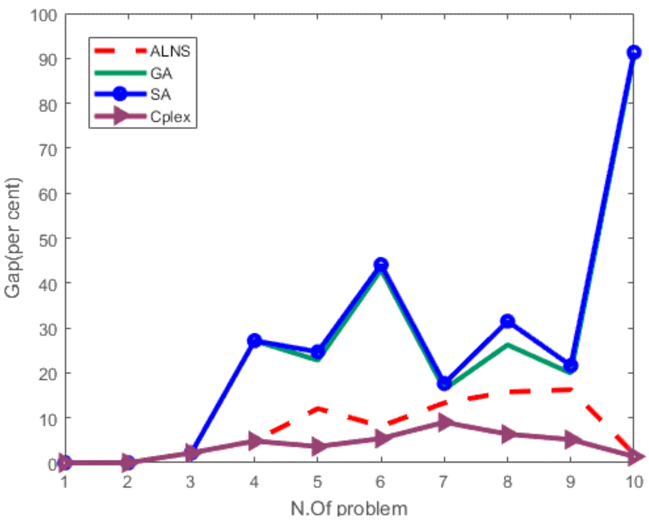


(a) The first scenario **(b)** The second scenario

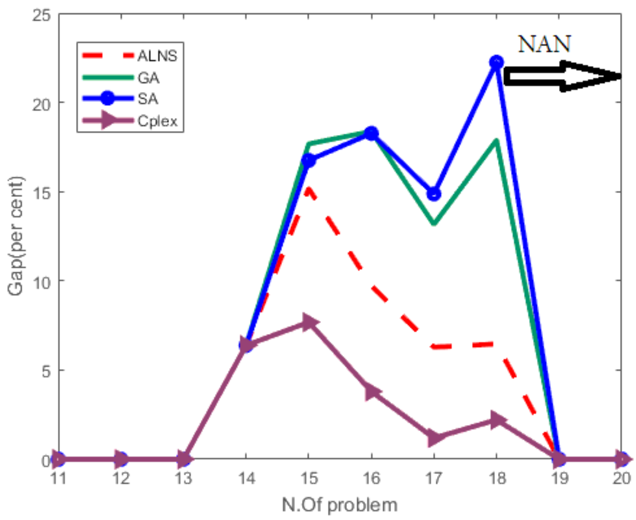


(c) The third scenario

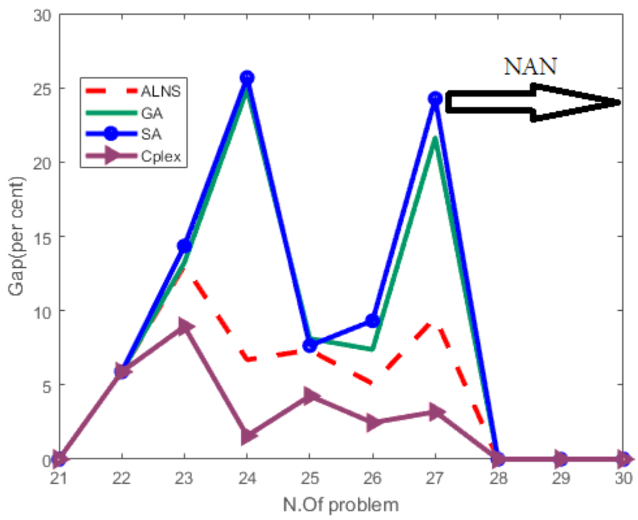
Fig .11 The run times of ALNS and CPLEX



(a) The first scenario



(b) The second scenario



(c) The third scenario

Fig .12 Comparison of the performances of the suggested ALNS and the CPLEX with different gaps in the objective values

Table 2. The values obtained from the four methods for the tests

No. test	(I/J/S/N_s^v /N_s^H)	Proposed ALNS			GA			SA			CPLEX solver			Ratio (%)		LB	No. constraints
		Ob. value	Running time	Gap (%)	Ob. value	Running time	Gap (%)	Ob. value	Running time	Gap (%)	Ob. value	Running time	Gap (%)	Ratio Time (%) (ALNS, GA, SA)	Ratio Value (%) (ALNS, GA, SA)		
1	(1,5,1,1,1)	5149	0.035	0	5149	0.069	0	5149	0.043	0	5149	1.024	0	(3.42,6.74,4.1)	(100,100,100)	5149	297
2	(2,5,1,2,1)	1048	2.14	0	1048	3.74	0	1048	2.43	0	1048	12.6	0	(16.99,29.69,19.28)	(100,100,100)	1048	353
3	(4,7,1,2,2)	2037	3.55	2.19	2037	5.75	2.19	2037	5.31	2.19	2037	27.8	2.19	(12.77,20.68,19.1)	(100,100,100)	1992.46	1041
4	(5,10,1,3,2)	1336	28.05	4.84	1336	29.35	27.15	1336	28.11	27.15	1336	48.9	4.83	(57.37,60.02,57.48)	(100,100,100)	973.23	3052
5	(6,8,1,4,2)	959	265.12	12.06	963	275.64	22.80	987	277.32	24.69	875	675.2	3.61	(39.27,40.82,41.07)	(109.6,110.06,112.8)	743.37	3312
6	(9,18,1,6,6)	3042	333.6	8.14	3091	397.04	42.98	3152	393.12	44.08	2954	842.3	5.40	(39.6,47.14,46.67)	(102.9,104.64,106.7)	1762.51	12760
7	(12,20,1,9,6)	4573	805.35	13.32	4620	949.01	16.36	4691	925.25	17.63	4356	1034.3	9.01	(77.87,91.75,89.45)	(104.9,106.06,107.7)	3863.83	21500
8	(15,25,1,12,9)	2327	627.2	15.75	2387	683.004	26.24	2570	680.7	31.5	2093.76	1825.7	6.37	(34.35,37.41,37.28)	(111.1,114.06,122.7)	1760.45	23840
9	(15,30,1,12,10)	3380	435.41	16.26	3534	471.64	19.92	3611	461.78	21.62	2984.7	1974.1	5.17	(22,23.9,23.39)	(113.24,118.4,120.9)	2830.3	43700
10	(15,35,1,12,10)	5030	594	1.98	5063	641.76	90.84	5347	615	91.33	5000.3	2467.4	1.39	(24.07,26,24.92)	(100.6,101.25,106.9)	463.56	55655
11	(1,5,2,1,1)	3612	0.085	0	3612	0.051	0	3612	0.083	0	3612	2.32	0	(3.7,2.19,3.57)	(100,100,100)	3612	604
12	(2,5,2,2,1)	2916	2.4588	0	2916	2.82	0	2916	2.8249	0	2916	14.6	0	(16.8,19.31,19.34)	(100,100,100)	2916	706
13	(4,7,2,2,2)	1708	10.82	0	1708	14.37	0	1708	12.04	0	1708	36.48	0	(29.66,39.39,33)	(100,100,100)	1708	2054
14	(5,10,2,3,2)	2952	95.68	6.38	2952	98.49	6.38	2952	101.73	6.38	2952	132.66	6.38	(72.12,74.24,76.68)	(100,100,100)	2763.63	6044
15	(6,8,2,4,2)	2358	284.403	15.16	2430	316.691	17.67	2403	327.31	16.75	2167	713.7	7.68	(39.85,44.38,45.86)	(108.8,112.14,110.9)	2000.46	6560
16	(9,18,2,6,6)	2781	356.462	9.72	2831	380.17	18.37	2827	389.075	18.26	2610	912.6	3.80	(39.06,41.66,42.63)	(106.5,108.5,108.3)	2310.79	25268
17	(12,20,2,9,6)	2116.4	964.364	6.28	2284	1035.648	13.16	2330	1021.07	14.87	2007.33	1436.15	1.19	(67.15,72.11,71.09)	(105.4,113.8,116.08)	1983.47	42600
18	(15,25,2,12,9)	1311	1,470.72	6.46	1493.4	19, 43.07	17.88	1577	2,124.0	22.24	1254	2674.68	2.21	(54.99,72.64,79.42)	(104.5,119.09,125.7)	1226.27	47160
19	(15,30,2,12,10)	2401	1,124.33	n/a	2834	1,524.33	n/a	2967	1,541.9	n/a	n/a	n/a	n/a	n/a	n/a	n/a	86620
20	(15,35,2,12,10)	5129.6	2580.33	n/a	5701	2796.33	n/a	6176	2717.18	n/a	n/a	n/a	n/a	n/a	n/a	n/a	110400
21	(1,5,3,1,1)	1836.9	0.11188	0	1836.9	0.37	0	1836.9	0.174	0	1836.9	1.74	0	(6.43,21.26,11.15)	(100,100,100)	1836.9	911
22	(2,5,3,2,1)	2617.5	0.089	5.88	2617.5	0.64	5.88	2617.5	0.141	5.88	2617.5	14.8	5.88	(0.6,4.32,0.95)	(100,100,100)	2463.48	1059
23	(4,7,3,2,2)	1646.1	7.74	13.04	1649.74	18.55	13.24	1671.3	11.24	14.35	1571.8	68.47	8.93	(11.3,27.09,16.42)	(104.72,104.9,106.3)	1431.4	3067
24	(5,10,3,3,2)	1421.3	416.61	6.69	1428	472.19	24.90	1443	451.66	25.68	1347.5	594.3	1.57	(70.1,79.45,75.99)	(105.48,105.9,107.1)	1072.39	9036
25	(6,8,3,4,2)	726.6	306.76	7.35	732.73	324.721	8.12	729.04	332.11	7.65	703.2	834.46	4.26	(36.77,38.91,39.80)	(103.3,104.2,103.7)	673.22	9808
26	(9,18,3,6,6)	4495.6	112.72	5.08	4607	123.03	7.38	4706	117.09	9.32	4374.9	1749.32	2.46	(6.44,7.03,6.69)	(102.76,105.3,107.6)	4267.17	37776
27	(12,20,3,9,6)	4246.5	360.40	9.53	4419.43	393.33	21.64	4573	372.92	24.27	3968.47	1467.85	3.19	(24.55,26.8,25.40)	(107,111.36,115.23)	3463.04	63700
28	(15,25,3,12,9)	2776.2	747.919	n/a	3076.49	786.47	n/a	2913	780.134	n/a	n/a	n/a	n/a	n/a	n/a	n/a	70480
29	(15,30,3,12,10)	4714.2	1347.963	n/a	4802.44	1743.318	n/a	5337.07	2003.041	n/a	n/a	n/a	n/a	n/a	n/a	n/a	129540
30	(15,35,3,12,10)	9451.8	2,149.49	n/a	9833	2,649.49	n/a	10372.3	2,616.7	n/a	n/a	n/a	n/a	n/a	n/a	n/a	165145
Avg.	-	3003.3	514.4637	6.644	3099.75	556.49	16.124	3186.50	610.38	17.03	2539.21	774.538	3.421	(32.29,38.19.36.43)	(103.6,105.58,107.2)	2172.59	32801.6

Biographies

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