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Development of a robust multi-objective model for green capacitated location-routing under crisis conditions

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A B S T R A C T

Location-Routing Problem (LRP) is a strategic supply chain design problem aimed at meeting customer demands. LRPs involve selecting one or more depot sites from a set of potential locations and determining the best routes to connect them to demand points. With the rising awareness about the environmental impacts of transportation over the past years, the use of green logistics to mitigate these impacts has become increasingly important. To compensate for a gap in the literature, this paper presents a robust bi-objective mixed-integer linear programming (MILP) model for the green capacitated location-routing problem (G-CLRP) with demand uncertainty and the possibility of failure in depots and routes. The final result of this Robust Multi-Objective Model is to set up the depots and select the routes that offer the highest reliability (Maximizing network service) while imposing the lowest cost and environmental pollution. A Nondominated Sorting Genetic Algorithm (NSGA-II) is used to solve the large-sized instances of the modeled problem. The paper also provides a numerical analysis and a sensitivity analysis of the solutions of the model.

1. Introduction

With the intensification of global business competition in a constantly-changing environment, it is now necessary more than ever for manufacturing and industrial enterprises to establish and maintain highly responsive supply chains. In order to gain and maintain a sustainable position in this competitive environment, today's enterprises need to choose and adopt a supply chain management model in alignment with their competitive advantages and customer expectations. Supply chain design and management have always been among the main determinants of how long a business can survive, how well it can adapt and change, and how quickly and effectively it can respond to market changes. Some argue that supply chain design is the main and most important part of any effort to improve the revenue of a supply chain (Simchi-Levi, 2004). To design a supply chain, one has to carefully consider numerous factors and make many decisions, including what facilities in which locations to use and how to distribute the products or serve the customers. These decisions are the subject of the Location-Routing Problem (LRP). LRPs can be viewed as a combination of the Facility Location Problem (FLP) and the Vehicle Routing Problem (VRP). In LRPs, the goal is to minimize the cost of facilities and transportation in a way that customer demand is satisfied by making choices from a set of potential facility and routing options. While the facility location aspect and the vehicle routing aspect of supply chain design can be studied independently, these decisions are effectively interdependent, and not addressing them together is likely to impose extra costs on the chain and lead to suboptimal solutions (Rand, 1976). Being a combination of facility location and vehicle routing problems, LRPs fall into the category of NP-Hard problems (Contardo et al., 2013). The capacitated location routing problem (CLRP) is a special type of LRP in which facilities and vehicles can have a limited capacity. The goal in CLRP is to set up facilities and routes to meet customer demand in a way that costs are minimized without violating the capacity constraints defined for facilities and vehicles

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(Prodhon, 2014). Due to the computational limitations of such problems, exact solutions are used only for small dimensions (Rabbani et al., 2019). Meta-Heuristic and Heuristic algorithms for solving NP-Hard problems in real size are well known (Lopez-Garcia et al., 2016). One of the proposed algorithms to solve these problems is NSGA-II. Recently, Meta-Heuristic and Heuristic algorithms to CLRP issues have been considered (Rabbani et al., 2019). Some of these studies are listed in Table 2 in the literature section. One of the features of our problem is the discontinuous nature of solution space. The application of genetic algorithms in the management of discrete variables is relatively clear because they can directly control the discrete nature of the problem. Another thing that determines the nature of the problem; There are two conflicting objectives in this study. Due to the above reasons, NSGA-II is used in this study, because this algorithm has the ability to solve these problems (Deb et al., 2002; Rabbani et al., 2019). In the real world, there is a degree of uncertainty in almost everything and it can manifest in many ways. In other words, uncertainty is inseparable from real-world problems and solutions. Therefore, to ensure that a supply chain can achieve its goals with as much flexibility as possible against real-world problems, it is necessary to consider a degree of uncertainty in all of its affairs. Since ignoring uncertainty in supply chain design decisions can have serious consequences, including even the failure of the business, enterprises have to find a way to incorporate uncertainty in their decision-making process. Over the years, researchers have proposed several classifications of uncertainty in general and in supply chains from a variety of perspectives. According to Klibi et al. (2010) and Kleindorfer and Saad (2005) uncertainty in supply chains can be divided into two categories: 1- operational uncertainty, which involves events with low to moderate impact and moderate to high probability, such as fluctuations that typically occur in demand and inventory; 2- crisis uncertainty, which involves events with high impact but low probability, such as natural disasters (floods and earthquakes). Here, the term “crisis” can be replaced with other words like “threat” and “failure”. Such uncertainties generally have natural origins, such as earthquakes, floods, tsunamis, or human origins such as war, terrorist attacks, strikes, quarantine, etc. By managing these threats and all the factors that divert organizations from their business goals, the crisis is contained. In order to manage the crisis, one of the effective steps is to prepare for work, which includes any "activities and actions taken" to ensure an effective response to hazards (Goldschmidt & Kumar, 2016). In the present study, uncertainties in the supply chain are assumed to be related to the breakdown of facilities and routes for any reason (e.g. natural or unnatural disasters and other events that constitute a crisis for the enterprise) and also the inaccurate estimations of customer demand (Due to the unpredictability of customer behavior, demand is considered uncertain).There are several methods to deal with uncertainty, including Stochastic programming, Fuzzy scheduling, and Robust optimization (Zahedi-Seresht et al., 2017).This paper presents a robust scenario-based bi-objective model for the green capacitated location-routing problem (G-CLRP) with demand uncertainty. The demand uncertainty is examined by a scenario approach in which each scenario of a set of scenarios P represents different demands for the customers and has probability of occurrence, such that (De Queiroz et al., 2016). In this way, we can construct solutions that are robust in face of the market’s volatility, and simultaneously effective when planning the supply chain. Therefore, according to Goldschmidt and Kumar, (2016) article, in order to manage the crisis, for the depots that are decided to reopen, a backup depot is considered and routes are opened in order to respond to the customers who have the least chance of failure.

Transportation is one of the main pillars of supply chains, but also plays a key role in their environmental impacts. Considering the current trends of population growth and industrialization, there are growing concerns about the rising global consumption of fossil fuels, and particularly their impacts in terms of air pollution and climate change. Therefore, any effort to reduce the use of fossil fuels or mitigate their environmental impacts can attract a lot of attention. Given the significant impact of transportation on environmental pollution, the notion of green transportation has emerged as a popular topic in supply chain management (Toro et al., 2017). This new approach requires businesses to reconsider their logistics operations in order to minimize their externalities in line with their social, economic, and environmental stances; stances that have been influenced by the rising attention of consumers, manufacturers, and governments to the subject of the environment in recent decades. In the model presented in this research, each facility (depot) and each route has a predetermined chance of failure (becoming in operational). Upon failure, a depot will lose its entire capacity and its customers will be reallocated to a backup depot. The first objective function of the model attempts to reduce the cost of routing, the cost of setting up depots, the cost of setting up backups, and also the cost of fuel consumption, which represents the emission reduction aspect of the model. Also, since the solutions of the optimization problems that consider the chance of failure need to ensure reliability (Maximizing network service), the second objective of the model is dedicated to maximizing a reliability measure. In the rest of this paper, Section 2 reviews the LRP literature, Section 3 introduces the variables and parameters of the problem and the proposed model, Section 4 describes how the model is solved, Section 5 the solution method is presented, Section 6 presents evaluation, Section 7 Sensitivity analysis is expressed, and the end in Section 8, conclusion and some suggestions for future studies are offered.

2. Literature review

The location-routing problem (LRP) is a prominent topic in the field of supply chain and business management. In recent years, many articles have been published on this topic. Notable works in this area include the studies carried out by Nagy and Salhi, (2007), Lopes and Ferreira, (2013), and Prodhon and Qureshi, (2015), and also the review study published by Drexl & Schneider, (2015), where they have categorized different types of LRP. These studies have demonstrated the potential complexity of LRPs as well as their importance. In this section, recent studies on supply chain problems, including LRPs, are listed and compared in Table1, and then the existing gaps in the literature are discussed.

Table 1
Research literature

Author(s)	Parameter (Demand)		Decision variables		Number of objective functions		Type of objective functions				Type of fleet		Possibility of failure			Approach taken to address uncertainty (in demand)				Echelon	
	Deterministic	Non-deterministic	Location	Routing	Single	Multiple	Cost minimization	Green	Failure minimization	Other	Homogenous	Heterogeneous	Facilities	Routes	Vehicles	Stochastic programming	Fuzzy programming	Robust Optimization	Hybrid approach	Single-echelon	Multi-echelon
Bent & Van, (2004)		*		*			*				*							*			
Prins & Prodhon, (2006)	*		*	*	*		*				*									*	
Barreto & Ferreira, (2007)	*		*	*	*		*				*									*	
Balcik & Beamon, (2008)	*		*	*	*					*	*			*							*
Vincent et al., (2010)	*		*	*	*		*				*									*	
Christophe et al., (2010)	*		*	*	*		*				*									*	
Li & Ouyang, (2010)	*		*		*						*		*							*	
Peng et al., (2011)	*		*	*	*		*				*									*	
Bozorgi & Jabalameli, (2011)		*	*	*		*	*			*	*							*			*
Cardona & Álvarez, (2011)		*	*	*		*	*			*	*							*			*
Jokar & Sahraeian, (2012)	*		*	*	*		*				*									*	
Contardo et al., (2012)	*		*	*	*		*				*									*	
Cui& Ouyang, (2012)			*		*		*				*									*	
Escobar et al., (2013)	*		*	*	*		*				*									*	
Ghaffari-Nasab et al., (2013)	*		*	*		*	*			*	*									*	
Golozari et al., (2013)		*	*	*	*		*			*	*						*			*	

Table 1
Research literature (continued)

Author(s)	Parameter (Demand)		Decision variables		Number of objective functions		Type of objective functions				Type of fleet		Possibility of failure			Approach taken to address uncertainty (in demand)				Echelon	
	Deterministic	Non-deterministic	Location	Routing	Single	Multiple	Cost minimization	Green	Failure minimization	Other	Homogenous	Heterogeneous	Facilities	Routes	Vehicles	Stochastic programming	Fuzzy programming	Robust Optimization	Hybrid approach	Single-echelon	Multi-echelon
Zarandi, (2013)		*	*	*		*	*			*	*			*			*			*	
Mehrjerdi & Nadizadeh, (2013)		*	*	*	*		*				*			*			*			*	
Ahmadi Javid & Seddighi, (2013)	*		*	*	*		*				*		*		*					*	
Gounaris et al., (2013)		*		*	*		*				*							*		*	
Nadizadeh & Nasab, (2014)		*	*	*		*	*			*		*					*			*	
Azad et al., (2014)	*		*	*	*		*				*		*		*					*	
Rennemo et al., (2014)	*		*	*	*					*	*			*							*
An et al., (2014)	*		*		*		*				*			*							
Karaoglan & Altiparmak, (2015)	*		*	*	*		*				*									*	
Marinakis, (2015)		*	*	*	*		*				*					*				*	
Huang, (2015)		*	*	*	*		*				*					*				*	
Zhang et al., (2015)	*		*	*	*		*				*		*			*				*	
Li & Ouyang, (2015)	*		*	*	*		*						*							*	
Ponboon et al., (2016)	*		*	*	*		*				*									*	

Table 1
Research literature (continued)

Author(s)	Parameter (Demand)		Decision variables		Number of objective functions		Type of objective functions				Type of fleet		Possibility of failure			Approach taken to address uncertainty (in demand)				Echelon	
	Deterministic	Non-deterministic	Location	Routing	Single	Multiple	Cost minimization	Green	Failure minimization	Other	Homogenous	Heterogeneous	Facilities	Routes	Vehicles	Stochastic programming	Fuzzy programming	Robust Optimization	Hybrid approach	Single-echelon	Multi-echelon
Lopes et al., (2016)	*		*	*	*		*				*									*	
Tang et al., (2016)	*		*		*		*				*		*							*	
De Queiroz et al., (2016)		*	*	*	*		*				*							*		*	
Peng et al., (2017)	*		*	*	*		*				*									*	
Quintero& Araujo, (2017)	*		*	*	*		*				*									*	
Toro et al., (2017)	*		*	*		*	*	*			*									*	
Sadegheih, (2017)		*	*	*		*	*			*	*								*	*	
Chang et al., (2017)		*	*	*		*	*			*	*							*		*	
Farham & Hekmatfar, (2018)	*		*	*	*		*				*									*	
Madani et al., (2018)	*		*			*				*	*		*	*						*	
Zhang et al., (2018)		*	*	*		*	*	*		*	*							*	*	*	
Ghaderi, (2018)		*	*	*	*		*				*								*	*	
Zhao et al., (2018)		*	*	*	*		*					*							*		*

Table 1

Research literature (continued)

Author(s)	Parameter (Demand)		Decision variables		Number of objective functions		Type of objective functions				Type of fleet		Possibility of failure			Approach taken to address uncertainty (in demand)				Echelon	
	Deterministic	Non-deterministic	Location	Routing	Single	Multiple	Cost minimization	Green	Failure minimization	Other	Homogenous	Heterogeneous	Facilities	Routes	Vehicles	Stochastic programming	Fuzzy programming	Robust Optimization	Hybrid approach	Single-echelon	Multi-echelon
Hosseini et al., (2019)		*	*	*	*					*	*					*				*	
Pekel & Kara, (2019)		*	*	*	*		*					*					*			*	
Tirkolaee et al., (2019)		*	*	*	*		*				*							*			*
Oudouar et al., (2020)	*		*	*	*		*				*									*	
Zhang et al., (2020)		*	*	*		*	*			*	*								*	*	
Wang et al., (2020)	*		*	*	*		*				*										*
Mohamed et al., (2020)	*		*	*	*		*				*										*
Akpunar & Akpinar, (2021).	*		*	*	*		*				*								*	*	
Negrotto & Loiseau, (2021)	*		*	*	*		*				*								*	*	
Vincent et al., (2021)	*		*	*	*		*				*								*	*	
Ziaei & Jabbarzadeh, (2021)			*	*		*	*	*		*								*		*	
Current research		*	*	*		*	*	*	*		*		*	*				*	*	*	

Table 2
Some of Meta-Heuristic and Heuristic algorithm used in LRP research

Paper	Solution method
Prins et al. (2006)	Greedy Randomized Adaptive Search Procedure (GRASP)& Clarke and Wright
Barreto et al. (2007)	Hierarchical and non-hierarchical clustering techniques
Vincent et al. (2010)	Simulated Annealing (SA) based heuristic for solving the LRP(SALRP)
Duhamel et al. (2010)	Greedy Randomized Adaptive Search Procedure
Jokar and Sahraeian, (2012)	Branch-and-Cut, Adaptive Large-Neighbourhood Search (ALNS)
Contardo et al. (2012)	Contardo et al. (2012)
Ghaffari-Nasab et al. (2013)	Variable Neighborhood Descent-Based Heuristic
Zarandi et al. (2013)	Simulation-Embedded Simulated Annealing (SA) Algorithm
Golozari et al. (2013)	A Greedy Algorithm & Simulated Annealing and Mutation Operator
Escobar et al. (2013)	Memetic Algorithm & Branch and Cut Algorithm
Nadizadeh and Nasab, (2014)	A hybrid algorithm involves random simulation and a local search method
Marinakis, (2015)	Particle Swarm Optimization (PSO)
Huang, (2015)	Tabu Search (TS)
Karaoglan and Altiparmak, (2015)	Branch and Price Algorithm
Ponboon et al. (2016)	Hybrid Genetic Algorithm (GA) Particle Optimization Algorithm
Lopes et al. (2016)	Two-step meta-heuristic algorithm
Sadegheih, (2017)	Hybrid Heuristic Algorithm (HHA)
Hiassat et al. (2017)	Genetic Algorithm
Fazayeli et al. (2018)	Presenting a two-part Genetic Algorithm
Saif-Eddine et al. (2019)	An improved Genetic Algorithm
Yu et al. (2019)	A novel hybrid Genetic Algorithm
Rabbani et al. (2019)	Nondominated Sorting Genetic Algorithm (NSGA-II)
Zhou et al. (2019)	Genetic Algorithm
Wu et al. (2020)	Genetic Algorithm
Oudouar et al. (2020)	A novel approach based on heuristics and a neural network(using Clarke and Wright)
Vincent et al. (2021)	Simulated Annealing

Considering the importance of ensuring that green supply chains can not only handle demand uncertainty but also properly function under crisis conditions, it appears that the literature can benefit from a robust multi-objective model capable of taking into account the possibility of failure in facilities and routes as well as demand uncertainty. In summary, the present study tries to fill this gap in the literature through the development of Toro et al., (2017) article and also provides a reliable service network to be reliable in all conditions. And since the proposed model is a NP-Hard problem, so to achieve the optimal solution, the NSGA-II algorithm has been used.

3. Problem description and proposed solution

3.1. Notation and nomenclature

Presented in the following is a concise description of the parameters and variables used in the problem description and proposed model.

Sets

I	Set of facilities (depots)
J	Set of customers
V	Set of nodes $V = I \cup J$

Parameters

O_i	Cost associated with the use of facility
w_i	Capacity of facility *i*
F	Cost of the vehicle
Q	Maximal weight that the vehicle can carry
D_j	Product demand of the customer $j \epsilon J$
c_{ij}	Cost of traveling between nodes *i* and *j*
d_{ij}	Distance traveled between nodes *i* and *j*
α_{ij}	Parameter that represents the amount of energy per distance (J/km) required by an unloaded vehicle between nodes *i* and *j*
γ_{ij}	Parameter that represents the additional energy per unit of distance and ton of load (J/km-ton) required by a vehicle between nodes *i* and *j*
$E(\$/J)$	Emission cost per unit of energy
q_i	Probability of depot failure *i*
P_{ij}	Probability of road failure between nodes *i* and *j*

$fcost_k$	Fixed cost of additional storage capacity *k*
$v\ cost_k$	Variable cost of additional storage capacity *k*
h_i	Maintenance cost per unit of goods in depot *i*
φ_{ij}	Transportation cost from node *i* to node *j*

Variables

x_{ij} $j, i \in V$	Binary variable indicating the use of the path between nodes i, j
y_i $i \in I$	Binary variable for the use of a facility *i*
f_{ij}	Binary variable that defines if the customer at node $j\epsilon J$ is served by a route that starts at the facility $i\epsilon I$
z_j	Binary variable that determines if the customer at node $j\epsilon J$ is the last one served in a route
a_{ij}	Binary variable that indicates if a vehicle uses path *j* to return from the end of its route (at node j) to a facility (at node *i*)
t_{ij}	Continuous variable indicating the amount of cargo transported between nodes *i* and *j*
u_{ki}	Binary variable for the backup depot (if the depot *k* backs up the depot *i*, the value will be one, otherwise it will be zero)
ec_{ki}	Continuous variable of capacity transferred from depot *i* to backup depot *k*
m_K	Extra capacity required for depot *k* for backup
mm_k	Extra capacity required for depot *k* for backup on the objective
z'_k	Binary variable (If warehouse *k* needs to increase its capacity, the value will be one, otherwise it will be zero)

3.2. Estimation of CO2 emissions due to fuel consumption

This section presents the mathematical formulations used for the estimation of emissions (CO2) produced by vehicles. These formulations are based on the physics of forces acting on a vehicle on the road and are derived from Toro et al., (2017).

Parameters and variables for calculating fuel consumption:

β_{ij}: The display shows the average path gradient between the nodes *i* and *j*.
$\vec{F}_R$: Represents the opposing forces of the vehicle movement
$\vec{F}_M$: Indicates the engine generated power and transmissions to the vehicle's tires.
$m\vec{g}$: Indicates the weight of the vehicle.
$\vec{N}$: Indicates the normal force of the inclined plane acting on the vehicle.
v_{ij}: Indicates the speed of the vehicle between nodes *i* and *j*.

Fig. 1 shows a vehicle moving on a road.

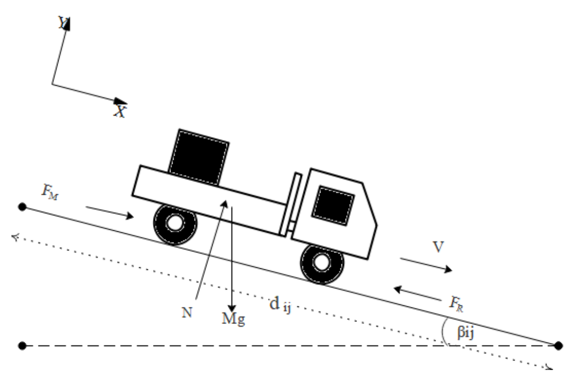

Fig. 1. Forces acting on a vehicle on the road

Using Newton's second law, it is established that $\sum F_x = ma_x$ and $\sum F_y = ma_y$. Assuming that the vehicle is moving at a constant speed, according to Fig. 1, we have:

$$\sum F_x = ma_x \quad, a_x = 0 \implies \quad F_M - F_R - mg \sin \beta_{ij} = 0 \tag{1}$$

$$\sum \mathrm{F_y} = \mathrm{ma_y} \quad , \mathrm{a_y} = 0 \implies \mathrm{N} - \mathrm{mg}\cos\beta_{\mathrm{ij}} = 0 \tag{2}$$

The opposing force consists of the following forces:

$$\mathrm{F_R} = \mathrm{F_{R,tires}} + \mathrm{F_{R,wind}} + \mathrm{F_{R,internal}} + \frac{\mathrm{m{v_{ij}}^2}}{2\mathrm{d_{ij}}} \tag{3}$$

In these equations, $\mathrm{F_{R,tires}}$ is the force exerted by tires against the motion of the vehicle (without considering traction and terrain), $\mathrm{F_{R,wind}}$ is the force exerted by the wind against the motion of the vehicle, $\mathrm{F_{R,internal}}$ represents the sum of internal forces that resist the motion of the vehicle, and $\frac{\mathrm{m{v_{ij}}^2}}{2\mathrm{d_{ij}}}$ is the force that the vehicle needs to achieve kinetic energy. The amount of energy required to move the vehicle is equal to the amount of work that must be done to transfer the kinetic energy to the vehicle.

$$\mathrm{K} = \frac{1}{2}mv^2, \mathrm{W} = \mathrm{F.dcos\theta} \quad \rightarrow \mathrm{F.d.cos}\,0 = {}^1\!/_2\,\mathrm{mV^2} \quad \rightarrow \mathrm{F} = \frac{\mathrm{mv^2}}{2\mathrm{d}} \quad , \mathrm{F} = \frac{\mathrm{m{v_{ij}}^2}}{2\mathrm{d_{ij}}} \tag{4}$$

If the vehicle speed between the nodes and the distance between the nodes are different, then so will be the force required to move between them.

Vehicle weight is the sum of the weight of the unloaded vehicle plus the load carried between nodes i and j:

$\mathrm{m} = \mathrm{m_0} + \mathrm{t_{ij}}$

By definition $\mathrm{F_{R,tires}} = \mathrm{Nb}$ where b depends on the terrain, therefore:

$$\mathrm{F_M} = (\mathrm{mg}\cos\beta_{\mathrm{ij}})\mathrm{b} + \mathrm{F_{R,wind}} + \mathrm{F_{R,internal}} + \frac{\mathrm{m{v_{ij}}^2}}{2\mathrm{d_{ij}}} + \mathrm{mg}\sin\beta_{\mathrm{ij}} \tag{5}$$

When a force acting on an object moves it by distance d in a direction that makes the angle θ with the force, then it is said that the force has done work:

$$\mathrm{U_{ij}} = \mathrm{F_M d_{ij}}\cos\theta$$

For the force $\mathrm{F_M}$, the angle between the force and the displacement is zero, therefore $\cos 0 = 1$ and we have:

$$\mathrm{U_{ij}} = \left[(\mathrm{m_0} + \mathrm{t_{ij}})\mathrm{gb}\cos\beta_{\mathrm{ij}} + \mathrm{F_{M,wind}} + \mathrm{F_{R,internal}} + \frac{(\mathrm{m_0} + \mathrm{t_{ij}}){\mathrm{v_{ij}}}^2}{2\mathrm{d_{ij}}} + (\mathrm{m_0} + \mathrm{t_{ij}})\mathrm{g}\sin\beta_{\mathrm{ij}}\right]\mathrm{d_{ij}} \downarrow \tag{6}$$

$$\mathrm{U_{ij}} = \left[\mathrm{m_0 g}\left(\mathrm{b}\cos\beta_{\mathrm{ij}} + \sin\beta_{\mathrm{ij}} + \frac{{\mathrm{v_{ij}}}^2}{2\mathrm{gd_{ij}}}\right) + \mathrm{F_{R,wind}} + \mathrm{F_{R,internal}}\right]\mathrm{d_{ij}} + \left[\mathrm{g}\left(\mathrm{b}\cos\beta_{\mathrm{ij}} + \sin\beta_{\mathrm{ij}} + \frac{{\mathrm{v_{ij}}}^2}{2\mathrm{gd_{ij}}}\right)\right]\mathrm{t_{ij}d_{ij}}$$

Here, g and b are constant. The above equation can be modified and simplified as follows.

$$\mathrm{U_{ij}} = \alpha_{\mathrm{ij}}\mathrm{d_{ij}} + \frac{{v_{ij}}^2}{2g} + \gamma_{\mathrm{ij}}\mathrm{t_{ij}d_{ij}} + \frac{{v_{ij}}^2}{2g}t_{ij} \tag{7}$$

The coefficient α_{ij} depends on the grade (slope) of the road between nodes i and j, the weight of the empty vehicle, the energy needed to reach a constant speed, the resistance on the tires, the wind resistance, and the internal losses of the vehicle. Some of these parameters depend on the speed of the vehicle. The coefficient γ_{ij} depends on the grade of the road between nodes i and j and the resistance on the tires (Toro et al., 2017). According to the above equation, the work done from node i to j has two components, one related to the empty vehicle, i.e.:

$$\alpha_{\mathrm{ij}}\mathrm{d_{ij}} + \frac{{v_{ij}}^2}{2g}$$

and the other related to the load carried by the vehicles, i.e.:

$$\gamma_{\mathrm{ij}}\mathrm{t_{ij}d_{ij}} + \frac{{v_{ij}}^2}{2g}t_{ij}$$

The work required to traverse a route is equal to the sum of the work required to traverse all edges in that path. To obtain the required work, it is necessary to define the binary variables $\mathrm{x_{ij}}$ and $\mathrm{a_{ij}}$ for each edge (i, j). If you ignore β_{ij} (or assume it to be the same for all edge) and also assume that the speed will be the same on all edges, then:

$$\sum_{\mathrm{i,i\in V}} \mathrm{U_{ij}} = \sum_{\mathrm{i,j\in V}} \left(\alpha \times \mathrm{d_{ij}} + \frac{v^2}{2g}\right)x_{ij} + \sum_{\mathrm{i,j\in V}} \left(\alpha \times \mathrm{d_{ij}} + \frac{v^2}{2g}\right)\mathrm{a_{ij}} + \sum_{\mathrm{i,j\in V}} \left(\gamma \times \mathrm{d_{ij}t_{ij}} + \frac{v^2}{2g}t_{ij}\right) \rightarrow \tag{8}$$

$$\sum_{i,i\in V} U_{ij} = \sum_{i\in V}\sum_{j\in V}\left(d_{ij}\left(\alpha_{ij}x_{ij} + \gamma_{ij}t_{ij}\right) + \frac{v^2}{2g}\left(x_{ij} + t_{ij}\right)\right) + \sum_{i\in I}\sum_{j\in J}\left(d_{ij}\alpha_{ij} + \frac{v^2}{2g}t_{ij}\right)a_{ij} \rightarrow$$

$$\sum_{i,i\in V} U_{ij} = \alpha\left(\sum_{i,j\in V} d_{ij}x_{ij} + \sum_{i,j\in V} d_{ij}a_{ij}\right) + \gamma\left(\sum_{i,j\in V} d_{ij}t_{ij}\right)$$

The conversion factors $E_1(\text{gallons/J})$ and $E_2(\text{kg of co}_2/\text{gallons})$ are used to obtain the amount of fuel needed to carry out the total work ($\sum_{i,i\in V} U_{ij}$) and the equivalent amount of CO2 emission. Accordingly, the equation the total emission is:

$$E_1 \times E_2 \times \sum_{i,j\in V} U_{ij} = E \times \sum_{i,j\in V} U_{ij} \tag{9}$$

The above model is linear and general. Therefore, in case of having roads of different grades in different routes, we will have:

$$\sum_{i,j\in V} U_{ij} = \sum_{i,j\in V} \alpha_{ij}d_{ij}x_{ij} + \sum_{i,j\in V} \alpha_{ij}d_{ij}a_{ij} + \sum_{i,j\in V} \gamma_{ij}d_{ij}t_{ij} \tag{10}$$

Note that this is still a linear function. Thus:

$$\text{Emission} = E \times \Big(\sum_{i\in V}\sum_{j\in V} d_{ij}\alpha_{ij}x_{ij} + \sum_{i\in I}\sum_{j\in J} d_{ij}\alpha_{ij}a_{ij} + \sum_{i\in V}\sum_{j\in V} \gamma_{ij}d_{ij}t_{ij}\Big) \tag{11}$$

$$\text{Emission} = E \times \Big(\sum_{i\in V}\sum_{j\in V} d_{ij}\left(\alpha_{ij}x_{ij} + \gamma_{ij}t_{ij}\right) + \sum_{i\in I}\sum_{j\in J} d_{ij}\alpha_{ij}a_{ij}\Big)$$

The following equation is used to estimate the cost of CO2 emissions.

$$E_1 \times E_2 \times \frac{1}{E_2} \times U_{ij} \times E_3 = \frac{\text{gallon}}{\text{j}} \times \frac{CO_2}{\text{gallon}} \times \frac{1}{\frac{CO_2}{\text{gallon}}} \times \text{j} \times \frac{\$}{\text{gallon}} \tag{12}$$

Hence, the emission cost equation turns into:

$$E_1 \times E_2 \times \frac{1}{E_2} \times E_3 = E \tag{13}$$

$$\textit{Equivalent cost of CO2 emission} = E \times \Big(\sum_{i\in V}\sum_{j\in V} d_{ij}\left(\alpha_{ij}x_{ij} + \gamma_{ij}t_{ij}\right) + \sum_{i\in I}\sum_{j\in J} d_{ij}\alpha_{ij}a_{ij}\Big)$$

Minimizing the above term is equivalent to minimizing CO2 emissions.

Fuel consumption is estimated based on the reports published by the University of Michigan Transportation Research Institute (2014), which has stated that the average fuel consumption of a vehicle with these characteristics is 1 gallon per 15.81 km (Toro et al., 2017).

4. Modeling

In G-CLRP, the goal is to choose the location of depots (facilities) and the routes that connect them to customers in such a way that environmental damage is minimized.

4.1. Model assumptions

In order to make the model more realistic, it is developed with a series of assumptions, including the possibility of failure in depots and routes (an event making them unusable and in operational) and the uncertainty in demand. It is assumed that upon failure, a depot will lose its entire capacity and its customers will be reallocated to a backup depot. Therefore, each depot to be established will be immediately assigned with a backup depot. Since the model considers a chance of failure in routes (the routes becoming unusable), an objective function is dedicated to selecting the routes with the least chance of failure so as to maximize the reliability of the resulting routing plan. Due to the nature of robust optimization, first modeling is done assuming demand is definite and then robust optimization is performed to deal with demand uncertainty.

4.2. Modeling with demand certainty assumption

The problem is modeled as follows.

$$h_1 = \min (\sum_{i\in I} o_i y_i + \sum_{i\in I}\sum_{j\in J} F a_{ij} + \sum_{i\in V}\sum_{j\in V} c_{ij}x_{ij} + \sum_{i\in I}\sum_{j\in J} c_{ij}a_{ij} + \sum_{k\in I}\sum_{l\in I} \mathrm{o_k}(1-\mathrm{y_k})\,\mathrm{u_{kl}}\mathrm{q_l}(1-q_k) \tag{14}$$
$$+ \sum_{k\in I}\sum_{l\in I} \frac{h}{2}\mathrm{ec_{kl}}(1-q_k)\mathrm{q_l} +$$
$$+ \sum_{l\in I}\sum_{k\in I}\sum_{j\in J} x_{ij}c_{ij}f_{li}f_{lj}q_l + \sum_{l\in I}\sum_{k\in I}\sum_{j\in J} x_{lj}c_{kj}u_{kl}q_l + \sum_{l\in I}\sum_{k\in I}\sum_{j\in J} a_{lj}c_{kj}u_{kl}q_l u_{ki}$$
$$+ \sum_{k\in I}\sum_{i\in I} ((\mathrm{fcost_k} \times (z'_k) + mm_k \times \mathrm{vcost_k}) \times (1-q_k)q_i\ ) +$$
$$\mathrm{E} \times \left(\left(\sum_{i\epsilon V}\sum_{j\epsilon V}\left(d_{ij}\left(\alpha_{ij}x_{ij} + \gamma_{ij}t_{ij}\right) + \frac{v^2}{2g}\left(x_{ij}+t_{ij}\right)\right) + \sum_{i\epsilon I}\sum_{j\epsilon J}\left(d_{ij}\alpha_{ij} + \frac{v^2}{2g}\right)a_{ij}\right)\right))$$

$$\mathrm{h_2} = \min (\sum_{\mathrm{i\in I}} \mathrm{q_i y_i} + \sum_{\mathrm{i\in V}}\sum_{\mathrm{j\in V}} \mathrm{P_{ij}x_{ij}} + \sum_{\mathrm{k\epsilon I}}\sum_{\mathrm{i\epsilon I}} \mathrm{q_k} \times \mathrm{U_{ki}} \times \mathrm{q_i}\ ) \tag{15}$$

$$\sum_{i\in V} x_{ij} = 1 \quad \forall j \in J \tag{16}$$

$$\sum_{k\in J} x_{jk} + \sum_{i\in I} a_{ij} = \sum_{i\in V} x_{ij} \quad j \in J \tag{17}$$

$$\sum_{j\in J} x_{ij} = \sum_{j\in J} a_{ij} \quad \forall i \in I \tag{18}$$

$$x_{ij} + x_{ji} \le 1 \quad \forall i,j \in V \tag{19}$$

$$\sum_{i\in V, i\neq j} t_{ij} = \sum_{k\in V, K\neq j} t_{jk} + D_j \quad \forall j \in J \tag{20}$$

$$\sum_{i\in V}\sum\nolimits_{j\in V} x_{ij} = |J| \tag{21}$$

$$\sum_{j\in J} f_{ij} = 1 \quad \forall j \in J \tag{22}$$

$$t_{ij} \le Q x_{ij} \quad \forall i,j \in V \tag{23}$$

$$\sum_{j\in J} t_{ij} \le w_i y_i \quad \forall i \in I \tag{24}$$

$$\sum_{k\in V} x_{jk} = 1 - z_j \quad \forall j \in J \tag{25}$$

$$1 + a_{ij} \ge f_{ij} + z_j \quad \forall i \in I, j \in J \tag{26}$$

$$-\left(1 - x_{ju} - x_{uj}\right) \le f_{ij} - f_{iu} \quad \forall i \in I, j, u \in V \tag{27}$$

$$f_{ij} - f_{iu} \le \left(1 - x_{ju} - x_{uj}\right) \quad \forall i \in I, u \in V \tag{28}$$

$$f_{ij} \ge x_{ij} \quad \forall i \in I, j \in J \tag{29}$$

$$\sum_{i\in I} y_i \ge \frac{\sum_{j\in J} D_j}{\sum_{i\in I} w_i} \quad \forall i \in I \tag{30}$$

$$\sum_{j\in J} x_{ij} \leq {w_i}/{q} \quad i \in I \tag{31}$$

$$\sum_{i\in I}\sum_{j\in J} x_{ij} \geq \sum_{j\in J} {D_j}/{Q} \tag{32}$$

$$u_{ki} \leq y_i \quad k, i \in I \tag{33}$$

$$x_{ij} \leq y_i \quad \forall i \in I, j \in J \tag{34}$$

$$\sum_{k\in I} u_{ki} = y_i \quad \forall i \in I \tag{35}$$

$$\sum_{k\in I} ec_{ki} = \sum_{j\in J} D_j f_{ij} \;\; i \in I \tag{36}$$

$$ec_{kl} \leq u_{kl} \times M \;\; k, l \in I \tag{37}$$

$$m_K = \sum_{\mathrm{j\in J}} \mathrm{t_{kj}} + \sum_{\mathrm{l=1}}^{\mathrm{l}} \mathrm{ec_{kl}} - \mathrm{w_k} \tag{38}$$

$$mm_K \geq m_K \quad \forall K \in K \tag{39}$$

$$mm_K \leq m_K + M * (1 - z_k{}') \quad \forall k \in K \tag{40}$$

$$mm_K \leq M * (z_k{}') \tag{41}$$

$$x_{ij} \in \{0,1\} \;\; \forall i, j \in V \tag{42}$$

$$y_i \in \{0,1\} \quad \forall i \in I \tag{43}$$

$$f_{ij} \in \{0,1\} \; \forall i \in I, j \in V \tag{44}$$

$$z_j \in \{0,1\} \; \forall j \in J \tag{45}$$

$$a_{ij} \in \{0,1\} \;\; \forall i \in I, j \in J \tag{46}$$

$$z'_k \;\; \in \{0,1\} \;\; \forall \mathrm{k} \in \mathrm{I} \tag{47}$$

$$t_{ij} \geq 0, \in \mathbb{R} \tag{48}$$

$$m_k \in \mathbb{R} \quad \forall \mathrm{K} \in \mathrm{I} \tag{49}$$

$$mm_k \;\; \geq 0 \quad \forall \mathrm{k} \in \mathrm{I} \tag{50}$$

In the above model, Equation (14), is the first objective function that minimizes the cost of the entire system, including routing cost, location cost, backup cost, and fuel consumption cost (which also leads to emission reduction). Eq. (15) is the second objective function that guarantees that the selected routes will have the least chance of failure, or in other words, maximizes the reliability of these routes (In other words, with the second objective function network service is maximized). Constraint (16) ensures that each node can have exactly one incoming edge. Constraint (17) states that if a node has an incoming edge, it will also have an outgoing edge. Constraint (18) states that the sum of the incoming edges of each depot will be equal to the sum of the outgoing edges of that depot. Constraint (19) guarantees that there could be only one edge between two consecutive nodes in a route (in other words, the vehicle cannot backtrack an edge). The flow balance of the nodes is formulated in Constraint (20). The number of active edges that will be used to connect all customers to the depots is formulated in Constraint (21). This equation ensures that the routes are radial and are not looped. Constraint (22) ensures that each demand is connected to one depot. Constraint (23) limits the flow of each route to the capacity of the vehicles. Constraint (24) limits the outgoing flow of each facility to its storage capacity. Constraint (25) determines the last node of each route. Constraint (26) guarantees that if a node is the last node of a route, it will have an edge going to the depot. Constraint (27) and (28) connect the active edges to the same depot. Constraint (29) ensures that if the edge between nodes i and j is active, then they will be connected to the same depot. Constraint (30) specifies the lower bound of the number of facilities needed to meet customer demand. Constraint (31) specifies the number of routes that can be going out of a depot. Constraint (32) ensures that the number of routes is sufficient to meet the demand of all customers. Constraint (33) ensures only the opened depots get a backup. Constraint (34) states that if a depot is open, it must have an outgoing edge. Constraint (35) states there should only be one backup depot for each opened depot. Constraints (36) and (37) determine the amount of demand reallocated from failed depots to their backups. Constraints (38-41) determine whether the backup depot will need additional capacity. Constraints (42-47) limit the values of binary variables to zero and one. Constraint (48) shows that the load is carried continuously. Constraints (49) and (50) specify the sign of variables used in the model to implement the backup scheme.

The model presented above is a mixed-integer nonlinear programming model. To linearize the model using the variable change method, the first objective function is changed as shown below and the following constraints (51-66) are added to the model (Chen et al., 2011).

$$h'_1 = \min (\sum_{i\in I} o_i y_i + \sum_{i\in I}\sum_{j\in J} Fa_{ij} + \sum_{i\in V}\sum_{j\in V} c_{ij}x_{ij} + \sum_{i\in I}\sum_{j\in J} c_{ij}a_{ij} + \sum_{k\in I}\sum_{i\in I}(o_k u_{ki} - o_k y_{ki}')(1-q_k)q_i + \sum_{k\in I}\sum_{i\in I}\frac{h}{2} ec_{ki}(1-q_k)q_i$$

$$+ \sum_{l\in I}\sum_{i\in J}\sum_{j\in J} x_{ijl}''' c_{ij}\, q_l + \sum_{l\in I}\sum_{K\in I}\sum_{j\in J} xx_{ljk}c_{kj}\,(1-q_k)q_l + \sum_{l\in I}\sum_{K\in I}\sum_{j\in J} a'''_{ljk}c_{kj}\,(1-q_k)q_l + \sum_{k\in I}(mm''_{ki}\times vcost_k + fcost_k \times u''_{ki})(1-q_k)q_i +$$

$$\mathrm{E}\times\left(\left(\sum_{i\epsilon V}\sum_{j\epsilon V}\left(d_{ij}(\alpha_{ij}x_{ij}+\gamma_{ij}t_{ij})+\frac{v^2}{2g}(x_{ij}+t_{ij})\right)+\sum_{i\epsilon I}\sum_{j\epsilon J}\left(d_{ij}\alpha_{ij}+\frac{v^2}{2g}\right)a_{ij}\right)\right))$$

$$3x'''_{ijl} \le f_{li} + f_{lj} + x_{ij} \quad \forall i,j\in J \quad l\in I \tag{51}$$

$$3x'''_{ijl} + 2 \ge f_{li} + f_{lj} + x_{ij} \quad \forall i,j\in J \quad l\in I \tag{52}$$

$$2xx_{ljk} \le x_{lj} + u_{kl} \quad k,l\in I,\, j\in J \tag{53}$$

$$2xx_{ljk} + 1 \ge x_{lj} + u_{kl} \quad k,l\in I,\, j\in J \tag{54}$$

$$2a'''_{ljk} \le a_{lj} + u_{kl} \quad k,l\in I,\, j\in J \tag{55}$$

$$2a'''_{ljk} + 1 \ge a_{lj} + u_{kl} \quad k,l\in I,\, j\in J \tag{56}$$

$$y_{kl}' \le y_k \tag{57}$$

$$y_{kl}' \le u_{kl} \tag{58}$$

$$y_k' \ge u_{kl} - 1 + y_k \quad \forall k,l\in I \tag{59}$$

$$2u''_{ki} \le z'_k + u_{ki} \tag{60}$$

$$2u''_{ki} + 1 \ge z'_k + u_{ki} \tag{61}$$

$$mm''_{ki} \le mm_k \quad k,i\epsilon I \tag{62}$$

$$mm''_{ki} \le M \times u_{ki} \quad k,i\epsilon I \tag{63}$$

$$mm''_{ki} \ge mm_k - M\times(1-u_{ki}) \quad k,i\epsilon I \tag{64}$$

$$u''_{ki}, y_{kl}', a'''_{ljk}, xx_{ljk}, x'''_{ujl} \in \{0,1\}\ \forall k,l,i\in I, j,u\in J \tag{65}$$

$$mm''_{ki} \ge 0\ k,i\epsilon I \tag{66}$$

4.3. Robust optimization

In mathematical programming, problems are usually solved with the assumption that data are known in advance (deterministic). In the real world, however, most data have a degree of uncertainty. In other words, the main premise of mathematical programming, i.e. that a model can be developed based on certain data, ignores the potential effects of data uncertainty on the quality and feasibility of solutions. Hence, in real-world problems, a change in one piece of data may lead to the violation of a large number of constraints, making the solution suboptimal or even infeasible. Thus, a great challenge in this field is how to ensure the resistance of the solutions against uncertainty in data. The solutions that have this resistance are called robust and this type of optimization is called robust optimization.

In this study, it is assumed that there is a degree of uncertainty in demand. To deal with uncertainty, we use a scenario-based robust programming approach (Mulvey et al., 1995; Pan, 2010). For this purpose, we define a set of scenarios, which represent a range of demand states and the occurrence probabilities. The probability of each scenario is denoted by and is defined as such that. In order to provide a robust model (the model presented in this study), it is necessary to perform the following steps:

4.3.1. Decision variables

hh_s Object function for each scenario
t_{ijs} a continuous variable representing the amount of load carried between nodes *i* and *j* in scenario *s*
D_{js} Demand of customer *j* in scenario *s*
ε_{is} A penalty variable that is added to the constraints to ensure robustness
$\varepsilon 1_{is}$ A penalty variable that is added to the constraints to ensure robustness

The rest of the decision indices, parameters, costs, and variables are similar to the deterministic model.

4.3.2. Formulation of objective functions for robust optimization

Following the approach of Mulvey and Ruszczyński, (1995) and Yu and Li (2000), objective functions of the robust model are defined as follows (Eqs. (67-68)):

$$min \sum_s p_s(hh_s) + \lambda \sum_s p_s \left[hh_s - \sum_s (p_s \times hh_s) + 2\theta_s \right] + w \sum_s p_s(\sum_{i \in I} (\varepsilon_{is} + \varepsilon 1_{is})) \tag{67}$$

$$min \sum_{i \in I} q_i y_i + \sum_{i \in V} \sum_{j \in V} Pr_{ij} x_{ij} + \sum_{k \in I} \sum_{i \in I} q_k \times U_{ki} \times q_i \tag{68}$$

4.3.3. Formulation of robustness constraints

To develop a robust model, constraints (69-70) are added to the formulations.

$$(hh_s) - \sum_s (p_s hh_s) + \theta_s \geq 0 \tag{69}$$

$$\begin{aligned} hh_s = &\sum_{i \in I} O_i y_i + \sum_{i \in I} \sum_{j \in J} F\, a_{ij} + \sum_{i \in V} \sum_{j \in v} c_{ij} x_{ij} + \sum_{i \in I} \sum_{,j \in J} c_{ij} a_{ij} + \sum_{k \in I} \sum_{i \in I} (o_k u_{ki} - o_k y_{ki}{}')(1 - q_k) q_i \\ &+ \sum_{k \in I} \sum_{i \in I} \frac{h}{2} ec_{ki} (1 - q_k) q_i + \sum_{l \in I} \sum_{i \in J} \sum_{j \in J} x_{ijl}{}''' c_{ij}\, q_l \\ &+ \sum_{l \in I} \sum_{K \in I} \sum_{j \in J} xx_{ljk} c_{kj}\, (1 - q_k) q_l \\ &+ \sum_{l \in I} \sum_{K \in I} \sum_{j \in J} a'''_{ljk} c_{kj}\, (1 - q_k) q_l + \sum_{k \in I} (mm''_{ki} \times vcost_k + fcost_k \times u''_{ki})(1 - q_k) q_i \\ &+ E \times \left(\sum_{i \in V} \sum_{j \in V} \left(d_{ij}(\alpha x_{ij} + \gamma t_{ijs}) + \frac{v^2}{2g}(x_{ij} + t_{ijs}) \right) + \sum_{i \in I} \sum_{j \in J} \left(d_{ij}\alpha + \frac{v^2}{2g} \right) a_{ij} \right) \end{aligned} \tag{70}$$

To ensure robustness with strict risk-aversion for decision-makers, a penalty term is added to some of the constraints. These changes are shown below (constraints (71-73)).

$$\sum_{k \in I} ec_{ki} - \varepsilon_{is} = \sum_{j \in J} D_{js} f_{ij} \quad \forall\, i \in I, s \in S \tag{71}$$

$$m_K - \varepsilon 1_{ks} = \sum_{j \in J} t_{kjs} + \sum_{l=1}^{1} ec_{kl} - w_k \quad \forall k \in I, s \in S \tag{72}$$

$$t_{ijs} \geq 0\,, \in \mathbb{R}\;, \varepsilon_{is} \geq 0, \varepsilon 1_{ks} \geq 0\; \forall s \in S \tag{73}$$

5. Solution method

5.1. Exact method

The Epsilon-constraint method ($\varepsilon - \text{constraint}$) for solving multi-objective problems is well known (Haimes, 1971). This method generates all Pareto optimal solutions. Mavrotas and Florio (2013) have explained this method in detail. While the developed model in this paper is multi-objective and NP-Hard, this problem is coded in GAMS and solved by Cplex solver by the Epsilon-constraint method.

5.2. Metaheuristic method

As mentioned, CLRPs belong to the category of NP-Hard problems. Therefore, it takes a very long time for exact methods to produce solutions for larger instances of these problems. A more practical approach to solving these problems is to use heuristic and metaheuristic methods. Heuristic and metaheuristic methods can find near-optimal solutions of such problems in a reasonably short time. Since the research literature has shown the general effectiveness of the nondominated sorting genetic algorithm in this field of optimization, we have used this algorithm to solve the problem. In this method (NSGA-II), first, a number of solutions, which are called chromosomes, are generated at random, forming a set of initial solutions called the initial population. Then, the best (fittest) chromosomes in the population are identified and subjected to two operators called crossover and mutation, which are meant to generate better chromosomes while also ensuring that the population remains diverse. The newly generated population is then merged with the previous population and the same process is repeated until reaching optimal or near-optimal solutions (Lopes et al., 2016).

The steps of the nondominated sorting genetic algorithm for solving the developed model are described below.

5.2.1. Forming and evaluating the initial population

In this step, an initial solution is generated at random (the only condition is that the main problem constraints are met). This initial solution (chromosome) is defined as a matrix with binary entries. Once a predetermined number of initial solutions are generated, each initial solution should be evaluated in terms of its objective function value. An example of the solution is shown below (Fig. 2 and Table 3). In this solution, all problem constraints except those about the capacity of vehicles and depots are considered.

$$pop1 = \begin{bmatrix}
0&0&1&0&0&0&1&0&1&1&1&0&1&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0&1&1&0\\
0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0
\end{bmatrix}$$

Fig. 2. An example of the initial solution of the Nondominated Sorting Genetic Algorithm.

This solution is interpreted as follows.

Table 3
Interpretation of the solution of the NSGA-II

Depot	Condition	Path(s)	Backup depot
1	On	1-7-17 1-9 1-10-6-8-12-14-20 1-11 1-13	**3**
2	Of	-	
3	Of	-	
4	Of	-	
5	On	2-18 2-19-15-16	**4**

5.2.2. Bounding constraints

In this algorithm, the initial solutions are generated randomly but such that all model constraints are met. It should be noted that the two constraints about the capacity of vehicles and depots are met through the penalty term in the evaluation function.

5.2.3. Operators used in the offspring generation

The operators used in offspring generation (generating a population of new solutions from the previous population) are crossover and mutation.

5.2.3.1. Crossover operator

For the initial population, this operator will be applied to two parents selected at random. There are multiple ways to produce an offspring by the crossover operator (single point, two-point, k-point, uniform). In this study, the single point crossover is used for this purpose. It should be noted that sometimes the offspring generated by the single-point crossover (the newly generated matrix) does not meet the requirement of a proper solution matrix. Therefore, the process must be repeated until generating an acceptable solution (a solution that meets the basic requirements).

5.2.3.2. Mutation Operator

This operator will also be applied to two randomly selected parents, generating a new offspring using the swap method. (Lopes et al., 2016).

5.2.4. Stopping condition

For the algorithm of this study, the stopping condition is to reach a certain number of iterations.

5.2.5. Parameter setting

Careful adjustment of the parameters of metaheuristic algorithms plays a key role in the quality of their solution. The Taguchi method is one of the best methods for adjusting the input parameters of metaheuristic algorithms. (Karaoglan et al., 2015) In this study, the Taguchi method with L27 array is used to adjust the following parameters: the size of the population (npop), the percentage of offspring generated by crossover (pc), the percentage of offspring generated by mutation (pm), and the maximum number of iterations (maxiter). The optimal values of these parameters are given in Table 4. The diagrams of the Taguchi method are also shown in Figs.3 and 4.

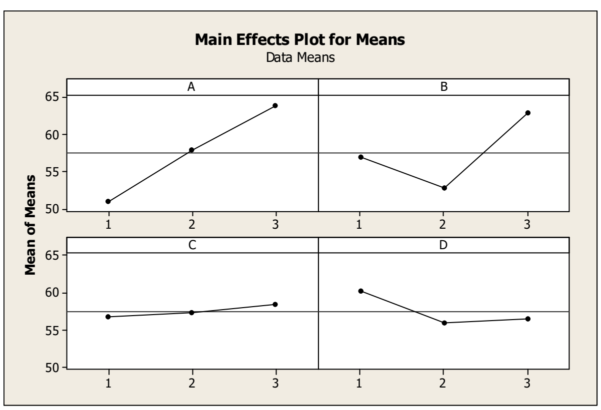

Fig. 3. Parameter adjustment with Taguchi method (Mean of Means)

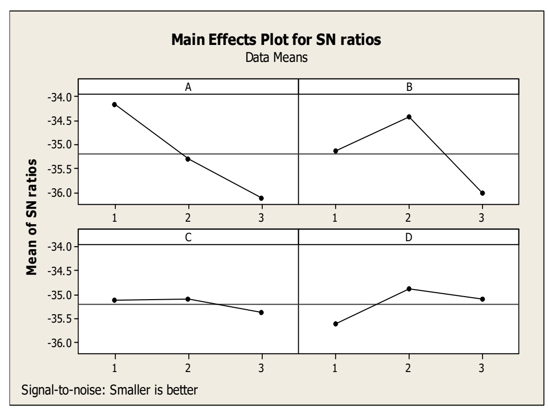

Fig. 4. Parameter adjustment with Taguchi method (Mean of SN ratios)

Table 4
Parameter adjustment with Taguchi method

Parameters	Abbreviation	Factor levels			Optimal Value
Population size (npop)	A	100	200	250	100
Crossover rate (Pc)	B	0.8	0.85	0.9	0.85
Mutation rate (Pm)	C	0.2	0.25	0.3	0.2
Maximum number of iterations	D	150	250	300	250

5.3. Comparison measures

The proposed algorithm is evaluated using 3 quality measures and 2 variability measures. These measures are explained below (Rayat et al., 2017).

5.3.1. Quality metric (QM)

In this metric, the non-dominated solutions for all of the algorithms are determined together and the Pareto solution percentage is calculated for each algorithm, as given below:

$$QA = \frac{number\ of\ non - dominated\ solution\ of\ algorithem}{total\ number\ of\ non - dominated\ solution} \tag{74}$$

This metric is used to compare the quality of the solutions with each other. The solution with higher QM is more desirable.

5.3.2. Spacing metric (SM)

This metric measures the uniformity of the set of non-dominated points in the solution space. The formula of this index is presented below. In this formula, n is the number of Pareto solutions and d_i is the Euclidean distance between two consecutive Pareto solutions in the solution space.

$$SM = \frac{\sum_{i=1}^{n-1} \left| \bar{d} - d_i \right|}{(n-1)d} \tag{75}$$

The algorithms with lower SM values are preferable.

5.3.3. Diversification metric (DM)

This index represents the diversity of Pareto solutions of an algorithm. Larger DM values are indicative of the better distribution of solutions. The formula of this index is given below. In this formula, x_i and y_i are Pareto optimal solutions for objective i. This formula measures the distance between the best Pareto solutions of algorithms.

$$DM = \sqrt{\sum_i max|x_i - y_i|} \tag{76}$$

5.3.4. Mean ideal distance (MID)

Measuring the distance between the best solutions and other Pareto solutions of an algorithm, MID is obtained by the following formula.

$$MID = \frac{\sum_{i=1}^{n} \sqrt{\left(\frac{f_{1i} - f_1^{best}}{f_{1,total}^{max} - f_{1,total}^{min}}\right)^2 + \left(\frac{f_{2i} - f_2^{best}}{f_{2,total}^{max} - f_{2,total}^{min}}\right)^2}}{n} \tag{77}$$

5.3.5. Number of solutions (NOS)

This index is the total number of Pareto optimal solutions generated by each algorithm. The algorithm with higher NOS is preferable.

6. Evaluation

Perhaps the most important and sensitive part of a study is the analysis and summarization of the contents, and framing of the results. To test the model of this study, after reviewing the data related to the studied subject, a series of hypothetical numerical instances of the considered location-routing problem were generated and solved. In the following, this process is described and then the results are analyzed. To solve and analyze the model, a series of input data, which include model parameters and scalars, must be determined. The parameters needed to solve the problem are described below (Tables 5-7).

Table 5
Description of the probability functions of the parameters

Parameter	Probability function	Reference
Probability of failure in depots	Uniform (0.2,0.8)	Azad et al., (2014)
Variable overcapacity cost of depots	Uniform (1,3)	Fan et al., (2018)
Fixed overcapacity cost of depots	Uniform (300,600)	Fan et al., (2018)
Inventory holding cost of depots	Uniform (1,5)	Fan et al., (2018)

Also, the probability of failure in routes and cost of opening depots are considered as possibilities of uniform (0.2,0.5) and uniform (500,1500) respectively.

Table 6 shows the parameters related to the primary vehicles and their corresponding CO2 emissions. It should be noted that the values of these parameters are completely dependent on the type and capacity of vehicles. These particular values are derived from the latest report of the United Kingdom's Department for Business, Energy & Industrial Strategy based on methods, tables, and emission standards of 2016. Here, vehicles are assumed to be homogeneous and available in unlimited numbers.

Table 6
Parameters related to vehicles

Extra energy required for the vehicle (load energy) γ	Energy required for the empty vehicle α	Speed of the vehicles V
0.001004	0.0635	**80**

Other parameters required (related to the physical characteristics of customers and depots) in this part of the study have been extracted from http://prodhonc.free.fr/Instances/instances_us.htm. It should be noted that the instances on this website are standard LRPs and have been used by numerous researchers to evaluate the performance of the models. Also, parameters related to fuel consumption are from http://es.globalpetrolprices.com/gasoline_prices/ and

https://www.eia.gov/energyexplained/units-and-calculators/energy-conversion-calculators.php .

6.1. Defining demand scenarios

For this evaluation, demand scenarios were defined based on those used by De Queiroz (2017) in three levels: optimistic, probable, and pessimistic.

Following the approach of Cao, (2014), demand scenarios were defined with a strategy that involved assuming demands to remain lower than the capacity of each vehicle. The parameters required for robust optimization show in Table 7.

Table 7
Parameters related to robust optimization

Scenario	probability of occurrence
The first scenario (optimistic) **No change in the demand**	0.25
The second scenario (probable) **20% increase in the demand**	0.5
The third scenario (pessimistic) **Doubling of the demand**	0.25
Robustness parameters	
λ	1.75
ω	0.25

In this part of the study, several small and medium-sized instances of the problem were solved. These results are presented in Table 8. Also, the diagrams below (Figs.5-11) illustrate the Pareto front obtained by the methods used in this study. Considering the NP-Hard complexity of the problem and the 7200-second limit set for solving problems in GAMS, the optimal solution of some large-sized instances could not be obtained on a personal computer. (Cardoso et al., 2013; Fazayeli et al., 2018; Shiripour et al., 2017; Ruiz et al., 2019) In Table 8, these instances are marked with ***. This shows that GAMS needed more time to reach the optimal solution of these problems and therefore they were solved with NSGA-II, which was coded and executed in MATLAB. In other words, the exact solution of the small-sized instances of the problem was obtained by GAMS 24.1.2 and the large-sized instances were solved with NSGA-II, which is coded in MATLAB 2015. Computational tests were performed on a PC with the following specifications: Intel Core i5, CPU 2.5 CHz, RAM 4GB, GEFORCE 2GB and 64 bit Windows 10 operating system.

Table 8
Results of solving the instances of G-CLRP

	Solution Method										
	Lower Bound			NSGA-II			Exact			**Gap**	
Problem	h_1	h_2	Run Time	h_1	h_2	Run Time	h_1	h_2	Run Time	h_1	$\mathbf{h_2}$
15-5	164387.78	2.61	115	243349.46	3.30		243404.85	3.83	165	0.000228	**0.14**
20-5	187391.15	2.40	808	355668.94	5.47		343992.48	4.94		0.03394	**0.10826**
35-5	399593.13	4.69	1427	935074.63	9.51		***	***	***	***	***
50-5	1081484.58	3.28	2760	2550944.09	15.07		***	***	***	***	***
85-5	1035200.66	1.81		5121825.80	24.62		***	***	***	***	***
100-5	815963.07	1.92		3567897.80	38.69		***	***	***	***	***
100-10	***	***	***	3838183.75	38.00		***	***	***	***	***

**The unit of time is in seconds.

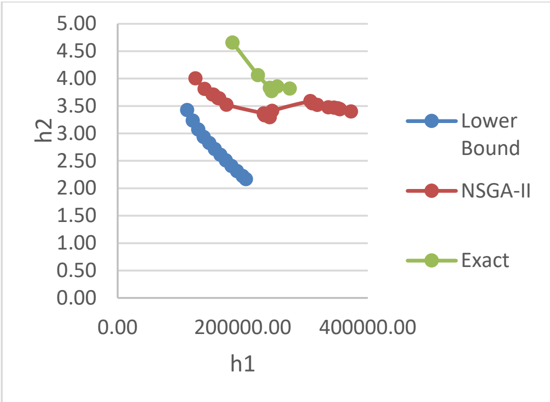

Fig. 5. Pareto front obtained for the G-CLRP instance of size 15-5

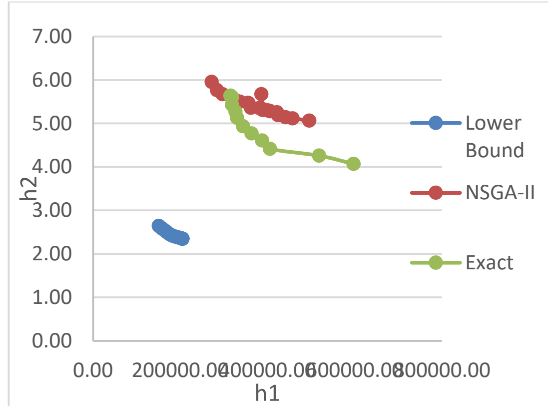

Fig. 6. Pareto front obtained for the G-CLRP instance of size 20-5

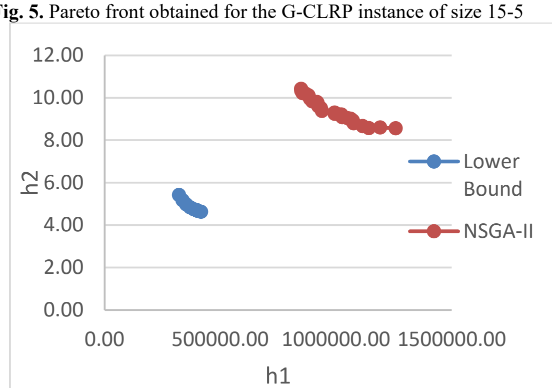

Fig. 7. Pareto front obtained for the G-CLRP instance of size 35-5

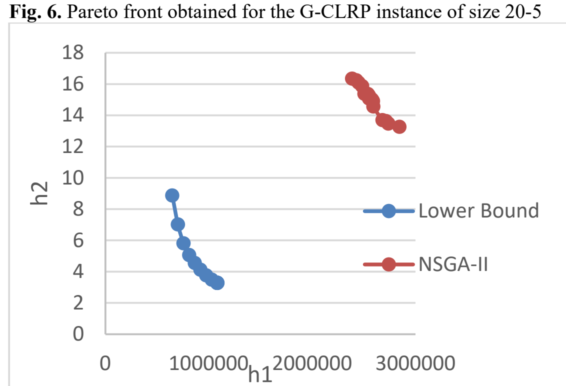

Fig. 8. Pareto front obtained for the G-CLRP instance of size 50-5

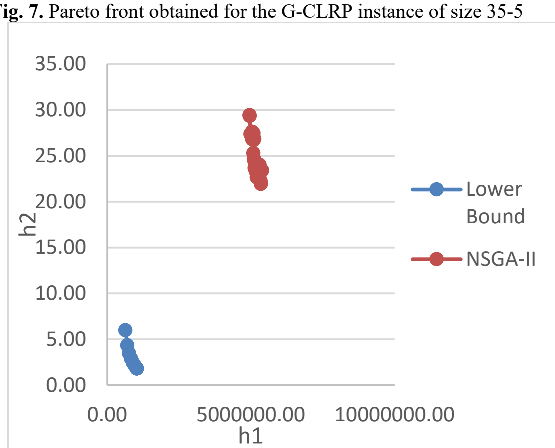

Fig. 9. Pareto front obtained for the G-CLRP instance of size 85-5

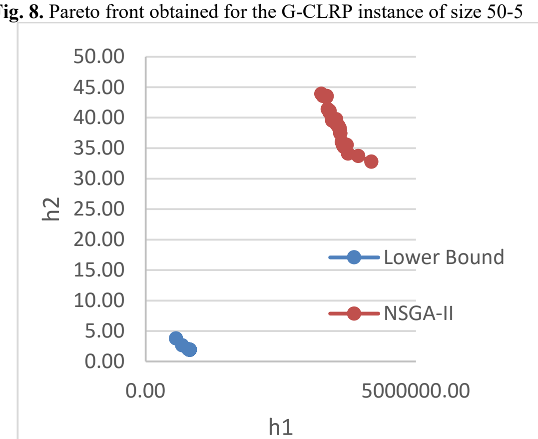

Fig. 10. Pareto front obtained for the G-CLRP instance of size 100-5

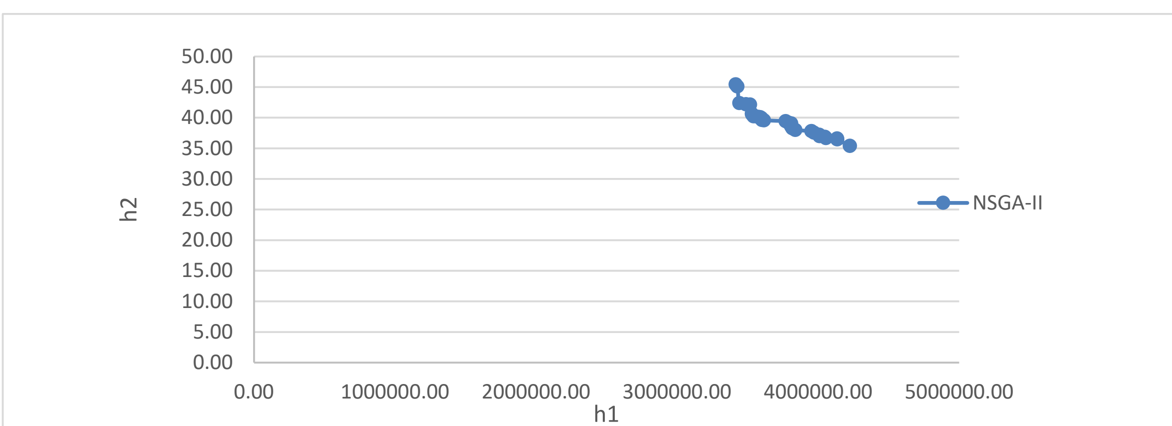

Fig. 11. Pareto front obtained for the G-CLRP instance of size 100-10

The values obtained for the five chosen evaluation measures are compared in Table 9. In this table, the bold entries show the preferred feature in the solution methods in terms of producing better solutions.

Table 9

Evaluation of solution methods

Problem	Lower Bound					NSGA-II					Exact				
	QM	SM	DM	MID	NOS	QM	SM	DM	MID	NOS	QM	SM	DM	MID	NOS
15-5	0.29	**0.07**	306	0.79	12	**0.56**	0.93	**499**	**0.66**	**23**	0.15	0.54	303	0.78	6
20-5	0.35	**0.59**	233	0.83	18	**0.43**	0.67	473	**0.68**	**22**	0.22	0.95	**531**	0.72	11
35-5	0.28	1	308	0.79	13	**0.72**	**0.95**	**640**	**0.68**	**33**	**	**	**	**	**
50-5	**0.51**	1.1	661	0.87	**19**	0.49	**0.77**	**675**	**0.78**	18	**	**	**	**	**
85-5	0.37	1.11	632	0.88	15	**0.63**	**0.78**	**659**	**0.71**	**26**	**	**	**	**	**
100-5	0.38	1.6	502	0.97	16	**0.62**	**0.92**	**961**	**0.69**	**26**	**	**	**	**	**
100-10	**	**	**	**	**	**1.00**	**0.87**	**900**	**0.68**	**28**	**	**	**	**	**

7. Sensitivity analysis

One of the methods to address uncertainty is sensitivity analysis. This section presents the results of sensitivity analysis performed on vehicle capacity, depot capacity, customer demand, and robust optimization parameters. A summary of sensitivity analysis information is provided in Table 10. Also, the analysis process is shown in Figs 12 - 16.

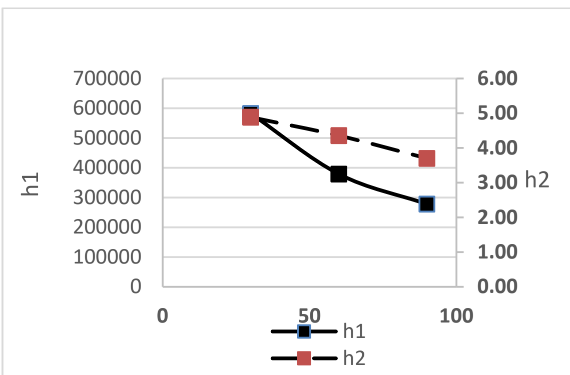

Fig. 12. Sensitivity analysis on vehicle capacity

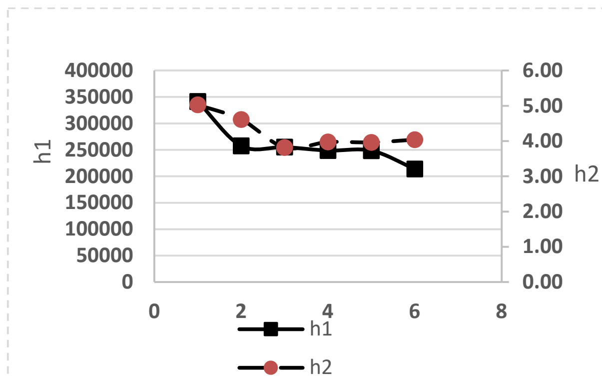

Fig. 13. Sensitivity analysis on depots capacity

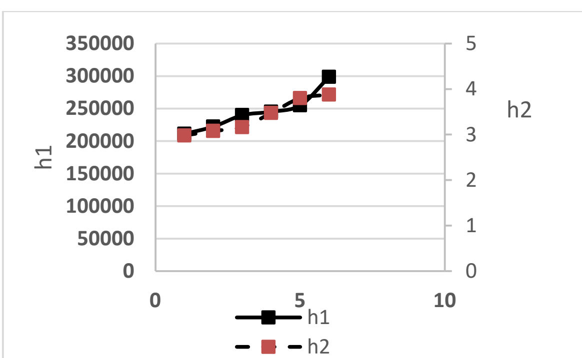

Fig. 14. Sensitivity analysis on customer demand

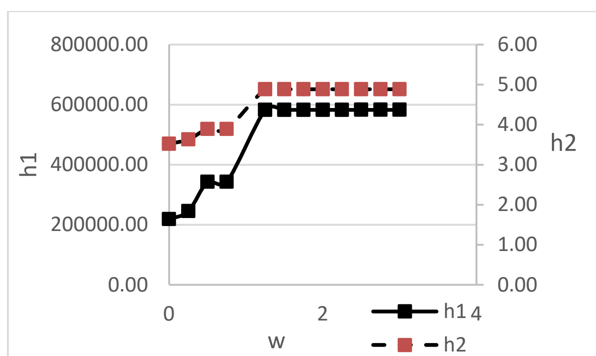

Fig. 15. Sensitivity analysis on Robust optimization parameters(ω)

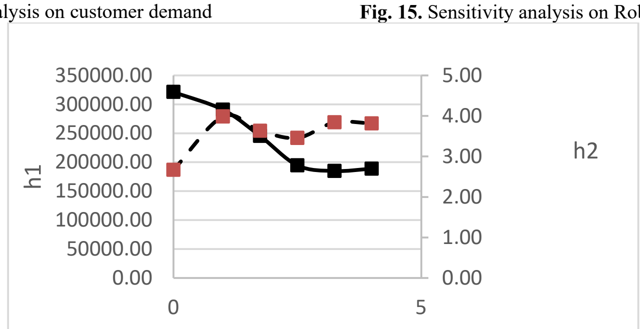

Fig. 16. Sensitivity analysis on Robust optimization parameters(λ)

Table 10
Summary of sensitivity analysis result

Type of change	The rate of change	Description
Vehicle capacity	(+30, +90)	Increasing the capacity of vehicle s will reduce costs.
Customer demand	(-25%, +50%)	Increasing customer demand will lead to increased costs
Depot capacity	(-30%, +50%)	Increasing the capacity of depots will reduce costs.
Robust optimization parameters (ω)	(0,3)	By increasing the(ω), the model moves towards being more Feasibility Robustness solution and moves away from Optimality Robustness solution, thus increasing costs.
Robust optimization parameters(λ)	(0,4)	By reducing the(λ), the model moves away from Optimality Robustness solution, thus increasing costs.

** Positive values mean an increase in the parameter value and negative values will mean a decrease in the parameter value.
** The contrast of the two objective functions is apparent in the sensitivity analysis diagrams.

8. Discussion and conclusion

This paper presented a robust green single-echelon capacitated location-routing problem that is reliable in crisis conditions. The feature that distinguishes this model from other previous works is the incorporation of the possibility of failure in facilities and routes, allocation of backup depots to every depot, and maximization of service such that reliability is ensured as much as possible. In this research, a balance has been created between providing money and financial resources for crisis preparedness (depot backup cost) and other research objectives. Since the robust optimization approach used in this model is a strict approach, it is reliable for the answers obtained from this model in all conditions, but the costs imposed on the system will be higher than normal conditions. Therefore, for factories or organizations where there is a high probability of breakdown in depots and routes to reach their customers or for risk avoider (conservative) organizations and factories, this model is an efficient model that is as reliable as possible

In order to maximize service while minimizing system costs, the problem was modeled with two objectives. The first objective function was focused on minimizing the routing costs and the fuel costs to reduce CO2 emissions, and the second objective function was focused on maximizing network service. Since the problem is NP-Hard, a metaheuristic NSGA-II was proposed for solving the problem. Since the parameter setting of metaheuristic algorithms plays a key role in the quality of their solutions, the Taguchi method was used to calibrate the parameters of the NSGA-II. The proposed models were solved for standard instances. The results obtained by solving the models and specifically the differences in the optimal solutions obtained for each objective function, signify a conflict in the objectives considered in the model. Therefore, it is impossible to optimize both objectives simultaneously in the form of one objective and one has to weigh the tradeoff between them based on decision-making preferences or expert opinions. For the problems with such conflicting objectives and tradeoffs, it is best to use a multi-objective decision-making method to form the Pareto front as a decision support instrument. In this study, the exact solution of the problem (small instances) was obtained using the epsilon-constraint method. However, because of the NP-Hard nature of the problem and the inability of the exact method to produce solutions for larger instances in reasonably short times, these instances are solved with NSGA-II. The low gap between the exact method and the low-dimensional NSGA-II indicates the ability of the proposed NSGA-II to achieve the Pareto front in high dimensions. The presented model can set up facilities and routes with the least chance of failure, the lowest cost, and the lowest emission. It also considers backup depots for every opened depot in order to ensure the continuation of service and prevent confusion in the event of a crisis. In order to ensure robustness with strict risk-aversion for decision-makers, the solutions obtained in all possible scenarios are feasible and therefore slightly suboptimal. In future studies, it is recommended to focus more on three-stage supply chains, the implications of having distinct customers, the use of fuzzy data, the allocation of several backup depots to each depot, and the use of interval-type robust optimization methods or use an optimization approach with a lower degree of difficulty.

References

Ahmadi-Javid, A., & Seddighi, A. H. (2013). A location-routing problem with disruption risk. *Transportation Research Part E: Logistics and Transportation Review*, *53*, 63-82.

Akpunar, Ö. Ş., & Akpinar, Ş. (2021). A hybrid adaptive large neighbourhood search algorithm for the capacitated location routing problem. *Expert Systems with Applications*, *168*, 114304.

An, Y., Zeng, B., Zhang, Y., & Zhao, L. (2014). Reliable p-median facility location problem: two-stage robust models and algorithms. *Transportation Research Part B: Methodological*, *64*, 54-72.

Azad, N., Davoudpour, H., Saharidis, G. K., & Shiripour, M. (2014). A new model to mitigating random disruption risks of facility and transportation in supply chain network design. *The International Journal of Advanced Manufacturing Technology*, *70*(9), 1757-1774.

Balcik, B., & Beamon, B. M. (2008). Facility location in humanitarian relief. *International Journal of logistics, 11*(2), 101-121.

Barreto, S., Ferreira, C., Paixao, J., & Santos, B. S. (2007). Using clustering analysis in a capacitated location-routing problem. *European Journal of Operational Research*, *179*(3), 968-977.

Bent, R. W., & Van Hentenryck, P. (2004). Scenario-based planning for partially dynamic vehicle routing with stochastic customers. *Operations Research*, *52*(6), 977-987.

Bozorgi-Amiri, A., Jabalameli, M. S., & Mirzapour Al-e-Hashem, S. M. J. (2013). A multi-objective robust stochastic programming model for disaster relief logistics under uncertainty. *OR spectrum*, *35*(4), 905-933.

Cao, E., Lai, M., & Yang, H. (2014). Open vehicle routing problem with demand uncertainty and its robust strategies. *Expert Systems with Applications*, *41*(7), 3569-3575.

Cardona-Valdés, Y., Álvarez, A., & Ozdemir, D. (2011). A bi-objective supply chain design problem with uncertainty. *Transportation Research Part C: Emerging Technologies*, *19*(5), 821-832.

Cardoso, S. R., Barbosa-Póvoa, A. P. F., & Relvas, S. (2013). Design and planning of supply chains with integration of reverse logistics activities under demand uncertainty. *European journal of operational research*, *226*(3), 436-451.

Chang, K., Zhou, H., Chen, G., & Chen, H. (2017). Multiobjective location routing problem considering uncertain data after disasters. *Discrete Dynamics in Nature and Society*, *2017*.

Chen, D. S., Batson, R. G., & Dang, Y. (2011). Applied integer programming: modeling and solution. John Wiley & Sons.

Duhamel, C., Lacomme, P., Prins, C., & Prodhon, C. (2010). A GRASP× ELS approach for the capacitated location-routing problem. *Computers & Operations Research*, *37*(11), 1912-1923.

Contardo, C., Hemmelmayr, V., & Crainic, T. G. (2012). Lower and upper bounds for the two-echelon capacitated location-routing problem. *Computers & operations research*, *39*(12), 3185-3199.

Cui, T., Ouyang, Y., & Shen, Z. J. M. (2010). Reliable facility location design under the risk of disruptions. *Operations research*, *58*(4-part-1), 998-1011.

Queiroz, T. A. D., Oliveira, J. F., Carravilla, M. A., & Miyazawa, F. K. (2016). Demand uncertainty for the location-routing problem with two-dimensional loading constraints. In *Computational Management Science* (pp. 47-53). Springer, Cham.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE transactions on evolutionary computation, 6*(2), 182-197.

Drexl, M., & Schneider, M. (2015). A survey of variants and extensions of the location-routing problem. *European Journal of Operational Research*, *241*(2), 283-308.

Escobar, J. W., Linfati, R., & Toth, P. (2013). A two-phase hybrid heuristic algorithm for the capacitated location-routing problem. *Computers & Operations Research*, *40*(1), 70-79.

Fan, J., & Wang, G. (2018). Joint optimization of dynamic lot and warehouse sizing problems. *European Journal of Operational Research*, *267*(3), 849-854.

Farham, M. S., Süral, H., & Iyigun, C. (2018). A column generation approach for the location-routing problem with time windows. *Computers & Operations Research*, *90*, 249-263.

Fazayeli, S., Eydi, A., & Kamalabadi, I. N. (2018). Location-routing problem in multimodal transportation network with time windows and fuzzy demands: Presenting a two-part genetic algorithm. *Computers & Industrial Engineering*, *119*, 233-246.

Ghaderi, A. (2018). A Robust Optimization Model for the Single-Depot Capacitated Location-Routing Problem. *International Journal of Computer and Information Engineering*, *12*(7), 504-508.

Ghaffari-Nasab, N., Jabalameli, M. S., Aryanezhad, M. B., & Makui, A. (2013). Modeling and solving the bi-objective capacitated location-routing problem with probabilistic travel times. *The International Journal of Advanced Manufacturing Technology*, *67*(9), 2007-2019.

Goldschmidt, K. H., & Kumar, S. (2016). Humanitarian operations and crisis/disaster management: A retrospective review of the literature and framework for development. *International Journal of Disaster Risk Reduction*, *20*, 1-13.

Golozari, F., Jafari, A., & Amiri, M. (2013). Application of a hybrid simulated annealing-mutation operator to solve fuzzy capacitated location-routing problem. *The International Journal of Advanced Manufacturing Technology*, *67*(5), 1791-1807.

Gounaris, C. E., Wiesemann, W., & Floudas, C. A. (2013). The robust capacitated vehicle routing problem under demand uncertainty. *Operations Research*, *61*(3), 677-693.

Haimes, Y. (1971). On a bicriterion formulation of the problems of integrated system identification and system optimization. *IEEE transactions on systems, man, and cybernetics*, *1*(3), 296-297.

Hiassat, A., Diabat, A., & Rahwan, I. (2017). A genetic algorithm approach for location-inventory-routing problem with perishable products. *Journal of manufacturing systems*, *42*, 93-103.

Hosseini, M. B., Dehghanian, F., & Salari, M. (2019). Selective capacitated location-routing problem with incentive-dependent returns in designing used products collection network. *European Journal of Operational Research*, *272*(2), 655-673.

Huang, S. H. (2015). Solving the multi-compartment capacitated location routing problem with pickup–delivery routes and stochastic demands. *Computers & Industrial Engineering*, *87*, 104-113.

Jokar, A., & Sahraeian, R. (2012). A heuristic based approach to solve a capacitated location-routing problem. *J. Mgmt. & Sustainability*, *2*, 219.

Karaoglan, I., & Altiparmak, F. (2015). A memetic algorithm for the capacitated location-routing problem with mixed backhauls. *Computers & Operations Research*, *55*, 200-216.

Kleindorfer, P. R., & Saad, G. H. (2005). Managing disruption risks in supply chains. *Production and operations management*, *14*(1), 53-68.

Klibi, W., Martel, A., & Guitouni, A. (2010). The design of robust value-creating supply chain networks: a critical review. *European Journal of Operational Research*, *203*(2), 283-293.

Li, X., & Ouyang, Y. (2010). A continuum approximation approach to reliable facility location design under correlated probabilistic disruptions. *Transportation research part B: methodological*, *44*(4), 535-548.

Lopes, R. B., Ferreira, C., Santos, B. S., & Barreto, S. (2013). A taxonomical analysis, current methods and objectives on location-routing problems. *International Transactions in Operational Research*, *20*(6), 795-822.

Lopes, R. B., Ferreira, C., & Santos, B. S. (2016). A simple and effective evolutionary algorithm for the capacitated location–routing problem. *Computers & Operations Research*, *70*, 155-162.

Lopez-Garcia, P., Onieva, E., Osaba, E., Masegosa, A. D., & Perallos, A. (2016). GACE: A meta-heuristic based in the hybridization of Genetic Algorithms and Cross Entropy methods for continuous optimization. *Expert Systems with Applications*, *55*, 508-519.

Lopez-Garcia, P., Onieva, E., Osaba, E., Masegosa, A. D., & Perallos, A. (2016). GACE: A meta-heuristic based in the hybridization of Genetic Algorithms and Cross Entropy methods for continuous optimization. *Expert Systems with Applications*, *55*, 508-519.

Madani, S. R., Nookabadi, A. S., & Hejazi, S. R. (2018). A bi-objective, reliable single allocation p-hub maximal covering location problem: Mathematical formulation and solution approach. *Journal of Air Transport Management*, *68*, 118-136.

Marinakis, Y. (2015). An improved particle swarm optimization algorithm for the capacitated location routing problem and for the location routing problem with stochastic demands. *Applied Soft Computing*, *37*, 680-701.

Mavrotas, G., & Florios, K. (2013). AUGMECON2: A novel version of the ε-constraint method for finding the exact Pareto set in Multi-Objective Integer Programming problems. *Applied Mathematics and Computation*, *219*(18), 9652-9669.

Mehrjerdi, Y. Z., & Nadizadeh, A. (2013). Using greedy clustering method to solve capacitated location-routing problem with fuzzy demands. *European Journal of Operational Research*, *229*(1), 75-84.

Mohamed, I. B., Klibi, W., Sadykov, R., Şen, H., & Vanderbeck, F. (2022). The two-echelon stochastic multi-period capacitated location-routing problem. *European Journal of Operational Research*.

Mulvey, J. M., & Ruszczyński, A. (1995). A new scenario decomposition method for large-scale stochastic optimization. *Operations research*, *43*(3), 477-490.

Nadizadeh, A., & Nasab, H. H. (2014). Solving the dynamic capacitated location-routing problem with fuzzy demands by hybrid heuristic algorithm. *European Journal of Operational Research*, *238*(2), 458-470.

Nagy, G., & Salhi, S. (2007). Location-routing: Issues, models and methods. *European journal of operational research*, *177*(2), 649-672.

Negrotto, D., & Loiseau, I. (2021). A Branch & Cut algorithm for the prize-collecting capacitated location routing problem. *Top*, *29*(1), 34-57.

Oudouar, F., Lazaar, M., & El Miloud, Z. (2020). A novel approach based on heuristics and a neural network to solve a capacitated location routing problem. *Simulation Modelling Practice and Theory*, *100*, 102064.

Pan, F., & Nagi, R. (2010). Robust supply chain design under uncertain demand in agile manufacturing. *Computers & operations research*, *37*(4), 668-683.

Pekel, E., & Kara, S. S. (2019). Solving fuzzy capacitated location routing problem using hybrid variable neighborhood search and evolutionary local search. *Applied Soft Computing*, *83*, 105665.

Peng, P., Snyder, L. V., Lim, A., & Liu, Z. (2011). Reliable logistics networks design with facility disruptions. *Transportation Research Part B: Methodological*, *45*(8), 1190-1211.

Peng, Z., Manier, H., & Manier, M. A. (2017). Particle swarm optimization for capacitated location-routing problem. *IFAC-PapersOnLine*, *50*(1), 14668-14673.

Ponboon, S., Qureshi, A. G., & Taniguchi, E. (2016). Branch-and-price algorithm for the location-routing problem with time windows. *Transportation Research Part E: Logistics and Transportation Review*, *86*, 1-19.

Prins, C., Prodhon, C., & Calvo, R. W. (2006). Solving the capacitated location-routing problem by a GRASP complemented by a learning process and a path relinking. *4OR*, *4*(3), 221-238.

Prodhon, C., & Prins, C. (2014). A survey of recent research on location-routing problems. *European Journal of Operational Research*, *238*(1), 1-17.

Quintero-Araujo, C. L., Caballero-Villalobos, J. P., Juan, A. A., & Montoya-Torres, J. R. (2017). A biased-randomized metaheuristic for the capacitated location routing problem. *International Transactions in Operational Research*, *24*(5), 1079-1098.

Rabbani, M., Heidari, R., & Yazdanparast, R. (2019). A stochastic multi-period industrial hazardous waste location-routing problem: Integrating NSGA-II and Monte Carlo simulation. *European Journal of Operational Research*, *272*(3), 945-961.

Rand, G. K. (1976). Methodological choices in depot location studies. *Journal of the Operational Research Society*, *27*(1), 241-249.

Rayat, F., Musavi, M., & Bozorgi-Amiri, A. (2017). Bi-objective reliable location-inventory-routing problem with partial backordering under disruption risks: A modified AMOSA approach. *Applied Soft Computing*, *59*, 622-643.

Rennemo, S. J., Rø, K. F., Hvattum, L. M., & Tirado, G. (2014). A three-stage stochastic facility routing model for disaster response planning. *Transportation research part E: logistics and transportation review*, *62*, 116-135.

Ruiz, E., Soto-Mendoza, V., Barbosa, A. E. R., & Reyes, R. (2019). Solving the open vehicle routing problem with capacity and distance constraints with a biased random key genetic algorithm. *Computers & Industrial Engineering*, *133*, 207-219.

Sadegheih, A. (2017). A Hybrid Heuristic Algorithm to Solve Capacitated Location-routing Problem With Fuzzy Demands. *International Journal of Industrial Mathematics*, *9*(1), 1-20.

Saif-Eddine, A. S., El-Beheiry, M. M., & El-Kharbotly, A. K. (2019). An improved genetic algorithm for optimizing total supply chain cost in inventory location routing problem. *Ain Shams Engineering Journal*, *10*(1), 63-76.

Shiripour, S., Mahdavi-Amiri, N., & Mahdavi, I. (2017). A transportation network model with intelligent probabilistic travel times and two hybrid algorithms. *Transportation Letters*, *9*(2), 90-122.

Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (2004). *Managing the supply chain: definitive guide*. Tata McGraw-Hill Education.

Tang, L., Zhu, C., Lin, Z., Shi, J., & Zhang, W. (2016). Reliable facility location problem with facility protection. *PloS one*, *11*(9), e0161532.

Tirkolaee, E. B., Mahmoodkhani, J., Bourani, M. R., & Tavakkoli-Moghaddam, R. (2019). A self-learning particle swarm optimization for robust multi-echelon capacitated location–allocation–inventory problem. *Journal of Advanced Manufacturing Systems*, *18*(04), 677-694.

Toro, E. M., Franco, J. F., Echeverri, M. G., & Guimarães, F. G. (2017). A multi-objective model for the green capacitated location-routing problem considering environmental impact. *Computers & Industrial Engineering*, *110*, 114-125.

Vincent, F. Y., Lin, S. W., Lee, W., & Ting, C. J. (2010). A simulated annealing heuristic for the capacitated location routing problem. *Computers & Industrial Engineering*, *58*(2), 288-299.

Vincent, F. Y., Normasari, N. M. E., & Chen, W. H. (2021). Location-routing problem with time-dependent demands. *Computers & Industrial Engineering*, *151*, 106936.

Wang, M., Bell, M. G., & Miao, L. (2020). A Branch-and-Price Algorithm for a Green Two-Echelon Capacitated Location Routing Problem.

Wu, W., Zhou, W., Lin, Y., Xie, Y., & Jin, W. (2021). A hybrid metaheuristic algorithm for location inventory routing problem with time windows and fuel consumption. *Expert systems with applications*, *166*, 114034.

Yu, C. S., & Li, H. L. (2000). A robust optimization model for stochastic logistic problems. *International journal of production economics*, *64*(1-3), 385-397.

Yu, X., Zhou, Y., & Liu, X. F. (2019). A novel hybrid genetic algorithm for the location routing problem with tight capacity constraints. *Applied Soft Computing*, *85*, 105760.

Zahedi-Seresht, M., Jahanshahloo, G. R., & Jablonsky, J. (2017). A robust data envelopment analysis model with different scenarios. *Applied mathematical modelling*, *52*, 306-319.

Zarandi, M. H. F., Hemmati, A., Davari, S., & Turksen, I. B. (2013). Capacitated location-routing problem with time windows under uncertainty. *Knowledge-Based Systems*, *37*, 480-489.

Zhang, Y., Qi, M., Lin, W. H., & Miao, L. (2015). A metaheuristic approach to the reliable location routing problem under disruptions. *Transportation Research Part E: Logistics and Transportation Review*, *83*, 90-110.

Zhang, B., Li, H., Li, S., & Peng, J. (2018). Sustainable multi-depot emergency facilities location-routing problem with uncertain information. *Applied Mathematics and Computation*, *333*, 506-520.

Zhang, H., Liu, F., Ma, L., & Zhang, Z. (2020). A hybrid heuristic based on a particle swarm algorithm to solve the capacitated location-routing problem with fuzzy demands. *IEEE Access*, *8*, 153671-153691.

Zhao, Q., Wang, W., & De Souza, R. (2018). A heterogeneous fleet two-echelon capacitated location-routing model for joint delivery arising in city logistics. *International Journal of Production Research*, *56*(15), 5062-5080.

Zhou, L., Lin, Y., Wang, X., & Zhou, F. (2019). Model and algorithm for bilevel multisized terminal location-routing problem for the last mile delivery. *International Transactions in Operational Research*, *26*(1), 131-156.

Ziaei, Z., & Jabbarzadeh, A. (2021). A multi-objective robust optimization approach for green location-routing planning of multi-modal transportation systems under uncertainty. *Journal of Cleaner Production*, *291*, 125293.