ORIGINAL RESEARCH

A multi-objective optimization model for a multi-period mobile facility location problem with environmental and disruption considerations

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Abstract

The present work addresses a multi-period facility location decision during crisis—Pandemic—situation with highly uncertain demand. Our paper identifies failing distribution centres (DCs) over several periods of time and decides about relocation. Several scenarios arise: DCs can be opened, displaced from one location to another, closed or even reopened during a certain time, using mobile facility. We recommend a multi-objective non-linear mixed-integer mathematical model that identifies, for each period, the best possible location for DCs and their allocation to customers. Our model analyses the trade-off between economic costs and CO_2 emissions generated by facilities operations. We suggest a multi-objective approach based on a Non-dominated Sorting Genetic Algorithm II (NSGA-II). Our simulations demonstrate how mobile facility should be managed to ensure a good balance between economic and environmental criteria.

Keywords Facility planning and design · Multi-objective programming · Disruptions · Environmental sustainability

1 Introduction

Supply chains (SC) are subject to natural and human risks and uncertainties that lead to major financial losses for companies. The World Economic Forum indicates that supply chain disruptions reduce the share price of impacted companies by an average of 7% (see Garcia-Herreros et al., 2014). As a result, disruptions and uncertainties must be taken into account in the supply chain design, and facility location decisions. Snyder et al. (2006)

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classified the reliable supply chain design models into two categories: models intended to create a reliable network when no network exists and models aiming at improving an existing network and make it reliable.

A major example of risks, that appeared in December 2019, addressing disruptions of facilities is the Coronavirus (COVID-19). The virus infected more than 445 millions people and caused almost 6 millions deaths worldwide. In addition to the reported health emergency, many studies discussed the economic consequences of this crisis, particularly on supply chains. Indeed, according to the survey conducted by The Institute for Supply Management, almost 75% of companies report disruptions in their supply chains due to transport and health restrictions caused by the pandemic (https://www.prnewswire.com/news-releases/covid-19-survey-impacts-on-global-supply-chains-301021528.html).

In this context, dynamic facility location seems to be the most adapted solution to respond to disruptions. Dynamic facility decisions aim at deciding on facility opening/closing and allocating in an uncertain environment (Daskin et al., 1992). When dealing with facility location problem (FLP), many researchers consider a single objective function related to an aggregated economic cost. However, optimising the transportation and related SC costs of facility location decisions, can reduce the carbon impact. Therefore, several works investigated multi-objective FLPs by considering the trade-off between logistic costs and the quantity of CO_2 emissions related to transport and/or manufacture/warehouses operations (Manupati et al., 2019; Chaabane et al., 2011).

The present paper investigates dynamic facility location problems under random demand and disruption scenarios as during the COVID-19 pandemic period. In this context, a number of innovative contributions are proposed. The first contribution addresses the risk of DCs' unavailability in multiple separate periods. Second, the proposed decision integrates a simulation/optimization model within a dynamic multi-period supply chain network. Therefore, our model can propose for each DC when it should be shut, reopened or moved at any period. The third contribution is to consider multiple objectives that are solved through a Non-dominated Sorting Genetic Algorithm II (NSGA-II) to minimize the economic costs and absorb the environmental damages evaluated in terms of CO_2 emissions.

The remainder of the paper is organised as follows: a review of related works in reliable, dynamic, mobile and sustainable facility location problems are presented in Sect. 2. Section 3 highlights the assumptions of this work and provides details about the studied problem. Section 4 introduces the mathematical formulation of our problem. Section 5 details the proposed solution approach. A numerical experiment is presented and discussed in Sect. 6. Finally, in Sect. 7 we provide concluding remarks and some future directions of this study.

2 Related works

The facility location problem is widely studied in many areas, as for example, re-manufacturing (Mishra & Singh, 2020), telecommunication and hub location (Contreras & O'Kelly, 2019), robotics location (Moarref & Sayyaadi, 2008), ambulance location (El Itani et al., 2019a; El Itani et al., 2019b), humanitarian relief chain (Balcik & Beamon, 2008), food grain supply network (Sharma et al., 2021),…, using different techniques and tools, like exact methods (Christensen & Klose, 2020), metaheuristics (Chalupa & Nielsen, 2019), heuristics (Silva et al., 2020).

Due to their strategic impact on the supply chain performance, facility location has become a very active research field during last decades. Many variants of this problem have been developed since the first formulation (Weber et al., 1929).

2.1 Reliable facility location problems

Snyder and Daskin (2005) define the "reliability" of a system as the ability to perform well even when parts of the system do fail. The concept of reliability was introduced in network reliability theory by Shooman (2003), and is often considered when designing a telecommunication networks, energy and petroleum products transmissionr locating facilities (plants, warehouses and DCs) or vehicles of emergency services. Klibi and Martel (2012) proposed a supply chain design able to rebound quickly when affected by disruptions. Sheffi (2005) Designed flexible network structures for better resilience policies. Li and Ouyang (2010) observed that in the event of failing facilities, excessive transportation costs apply as customers have no alternative but to travel long distances to obtain the service from another facility. Snyder and Daskin (2005) presented two reliability models by assigning each customer to a primary supplier and to a number of backup suppliers. Li et al. (2013) extended both models by analysing heterogeneous facility failure probabilities and facility fortifications under budget constraints. Lim et al. (2010) considered expensive reliable facilities and solved the problem using a Lagrangian relaxation algorithm. Lim et al. (2013) proposed an extension to capacitated case with correlated disruptions. Vansia and Dhodiya (2021) adapted different evolutionary algorithms (Genetic algorithm (GA), non-dominated sorting genetic algorithm (NSGA-II and NSGA-III), modified Self-Adaptive Multi-Population Elitism Jaya Algorithm (SAMPE JA)) to minimize the transportation time, transportation cost and carbon emission in a multi-objective transportation p-facility location problem. Nayeri et al. (2021) addressed a responsive-resilient inventory-location problem with presence of uncertainties and considering location, allocation and inventory decisions. They proposed a scenario-based on a mixed-integer programming model to minimize the total cost. The authors applied queuing theory and robust fuzzy stochastic optimization to deal with uncertainties. The proposed model was solved by adapting several metaheuristics.

2.2 Dynamic facility location problems

Basic facility location models are, in general, static and deterministic. However, the facility environment, like population dynamics, market trends, distribution costs, demand patterns etc. may change over time and thus compel supply chain designers revise, re-adapt and relocate facilities. In this context, the emergence of dynamic models aims to determine the best location of each facility, over all periods (Arabani & Farahani, 2012).

It seems that the dynamic version of the FLP was initially introduced in Wesolowsky (1973), Wesolowsky and Truscott (1975) and Roodman and Schwarz (1975), where location changes may occur through a planning horizon. Since then, several authors proposed different variants of the dynamic facility location problem (DFLP). Farahani et al. (2015) allowed facility relocation during a continuous horizon. Marufuzzaman et al. (2016) proposed three algorithms to solve a capacitated model with a Benders algorithm. Jena et al. (2016) considered an open capacity that is available for use and a close capacity that is temporarily unavailable for a multi-period multi-commodity (FLP). More recently, Pearce and Forbes (2018) presented a Benders decomposition to solve a Dynamic Uncapacitated Facility Loca-

tion and Network Design problem to minimize operating facilities and routing costs for each period through the considered time horizon.

2.3 Mobile facility location problems

Güden and Süral (2014) was among the first authors to consider mobile and immobile facilities in the same model for a railway construction project. In their paper, the authors introduced the terms location "relocation" and "moving". facility relocation relates to existing facility that can be closed by the transfer of the equipment to another existing or to a new facility; whereas facility mobile term relates to mobile facilities that can be moved entirely from their existing location to a new one.

Introduced originally by Demaine et al. (2009), mobile facility location problem (MFLP) aims to relocate facilities from one location to another, and assign existing customers to new facilities in order to minimize all transfer costs. One of the most important applications of the MFLP is facilities location in response to natural disasters or pandemic situations. One should remember that two facilities can be moved from two different locations to one single location in the MFLP, as considered by Halper et al. (2015).

Bashiri et al. (2018) propose a new p-hub location problem as a multi-period mobile and immobile facilities location model. The authors fixed the number of opened hubs and define mobile and immobile hubs in the first period. Mobile hubs are moved from a location to another in each period according to a designed mobility infrastructure in order to respond to demand variations. If there is no mobility infrastructure, new hubs are established. Raghavan et al. (2019) addressed (MFLP) with a capacity constraint. The problem was solved via two dedicated heuristics. Calogiuri et al. (2021) deal with a p-center problem multi-period extension using mobile facilities that can be reallocated many times during the planning horizon and in which arc traversal times vary over time. A mathematical model was proposed and solved with a decomposition heuristic. This approach was tested on a set of instances based on Paris city road graph. Güden and Süral (2019) considered dynamic p-median problem with mobile facilities dynamic by proposing a mixed integer programming model which allows facilities to be opened, reallocated or closed in each period. They developed a branch and price algorithm and constructive heuristics to minimize the total costs.

2.4 Sustainable facility location problems

Most FLP models minimize fixed and distribution costs. However, other objective functions can be considered as: minimizing average time/distance travelled, maximising service/responsiveness or minimizing the number of located facilities. Recently, environmental and social objectives, like minimizing the noise and/or the pollution, have become of major concern in FLP studies.

According to a recent report of International Energy Agency (2019), transportation, in 2018, is responsible for 24% of direct CO_2 emissions from fuel combustion. Xifeng et al. (2013) considered amount of goods being transported and the distance travelled as factors affecting emissions levels for an extended Uncapacitated Facility Location Problem (UFLP). A p-median based model is proposed by Vélazquez-Martínez et al. (2014) to determine sustainable locations by considering carbon emissions that are related to transportation fuel consumption, the vehicle speed, the load of the engine over travelled the distance and engine size. Martí et al. (2015) proposed a model for sustainable supply chain network (SCND), that takes into account demand uncertainty and aims to show the effect of different carbon

policies, and carbon taxes on logistic costs and network structure. More recently, Banasik et al. (2018) and Colapinto et al. (2019) reviewed the use of multiple-criteria decision-making (MCDM) approaches in the design of green supply chain. The authors determined the trade offs between economic, social and environmental criteria.

The COVID19 pandemic situation and the resulting demand uncertainty induced many facility disruptions. This kind of situation cannot be addressed without considering three aspects: (i) the dynamic aspect: as it seems irrelevant to solve the facility location for the different periods separately; (ii) the mobility aspect, that enables cost minimization and (iii) the sustainability consideration to avoid environmental damages of the proposed solutions.

The three previous aspect were not addressed simultaneously in the literature. Therefore, in this work, we propose a mobile facility location model that deals with facilities' disruptions and not only demand fluctuation. We suppose, in our model, that if a facility is shutdown it can be reopened later on. Moreover, we include in our objective the minimization of the carbon footprint generated from facilities displacement in addition to the emissions generated from the transportation and the facilities' operations.

3 The considered problem

3.1 Assumptions and hypothesis

This study intends to develop a new multi-objective and multi-period model that integrates mobile facilities due to facilities' disruptions. The proposed model aims to find the best location of facilities in each period to satisfy demand fluctuations and to deal with facility disruptions while looking at best trade-offs between total costs and CO_2 emissions quantity. In our paper, it is important to note that potential locations are decided a-priory in a strategic way. Our model generates tactical decisions about where and when to open, close or move a DC. The assumptions of our model are the following:

- The studied distribution network is interconnected where the facilities have an infinite capacity.
- The number of facilities to locate is not predefined and can change from a period to another.
- The facilities have the same probability of disruption in each period.
- Disruption scenarios are generated at the end of each period to determine failed facilities for the next period.
- Each failed facility in a given period can be closed or moved to a next period (see Sect. 4) using an existing mobility infrastructure.
- In a given period, a location can receive only one facility.

Note that the nature of new located DCs depends on the nature of the considered supply chain. For example, vaccination centres are easily moved or installed. For supermarkets, if the potential locations are determined and prepared a priory, the moving, closing or reopening is doable easily.

In addition, in the proposed model the planning horizon is divided in several periods to deal with random disruptions. The number and duration of periods are case sensitive. It can be a year for some heavy industries, and only few days for a rescue and humanitarian supply chain.

3.2 Problem description

We consider a two-stage supply chain network $G = (C, A)$ where C is the set of nodes and A is the set of arcs; C is composed by the set of customers regions or locations. Each customer location represents a candidate distribution centre (DC) location. Each customer is assigned to one located DC to satisfy its demand. We perform the study trough several periods when customers' demands change over periods. We consider dynamic facilities as our supply chain can be disrupted by DCs failures due to various events like Pandemic situations, workers strike, natural or human disasters etc. Consequently, we divide our simulation horizon in several period times to determine the best location allocation decisions in each period. We suppose that failed DCs at the end of a given period can be moved from a location to another in the next period by moving entirely the DC from its location to a new one (mobile facility) or by the transfer of its equipment to a new facility location. The moving of DCs depends on the number of new locations. If the number of opened locations does not allow the moving of all failed DCs, some DCs should be shut down. It is also assumed that opening and closing facilities can occur many times during the planning horizon.

A set of DCs is opened in the first period. During the subsequent periods, two sets of DCs are considered: the opened and the closed facilities. When a DC fails during the period t, the DC is moved to a new location with the associated moving cost conceding that two DCs cannot be moved to the same location. Otherwise, the DC is closed with the associated closing cost. Customers are reallocation to available DCs consequently. Two possibilities can be considered for our case:

- The number of failed facilities N at the end of period t is less than the number of new located facilities M in the next period $t+1$. In this case, all N facilities are moved towards new locations, then $M - N$ new facilities are opened during period $t + 1$.
- The number of failed facilities N at the end of period t is greater than the number of new located facilities M in period $t + 1$. In this case, M facilities are moved towards new locations, $N - M$ facilities are shut down during the period $t + 1$.
- The number of failed facilities at the end of period t is equal to the number of new located facilities period $t + 1$. In this case, all facilities are moved towards new locations.

Figure 5 presents a dynamic location problem with fifteen potential locations nodes. In the first period, four facilities are located in nodes 3, 7, 10 and 12. It is shown that customers 2, 7 and 8 are assigned to DC 7, DC 12 is reserved for customers 4, 5, 12 and 15,…

It is assumed that DC 7 and DC 10 fail at the end of the first period. Indeed, our objective is to reallocate customers 2, 7, 8, 9, 10, 11 and 13 assigned in this period to DC 7 and DC 10 to opened DCs in the next period. Thus, the proposed model considers three scenarios displayed in Fig. 6.

In the first scenario, one new facility is located in node 4 in the period 2; DC 7 is moved from its location to location 4 and DC 10 is closed. Customers 2, 7, 8 and 9 are assigned to DC 4 and customers 10, 11 and 13 are assigned to DC 3. Three DCs are operational in the period 2.

In the second scenario, three new facilities are located in nodes 4, 6 and 15 during the period 2, DC 7 and DC 10 are moved from their locations to locations 4 and 6 respectively and DC 15 is opened. Customers 2, 7 and 8 are assigned to DC 4; customers 10, 11 and 13 are assigned to DC 6 and customer 9 is assigned to DC 15. Five DCs are operational in the period 2. In the third scenario, two new facilities are located in nodes 4 and 6 in the period 2, DC 7 and DC 10 are moved from their locations to locations 4 and 6 respectively. Customers
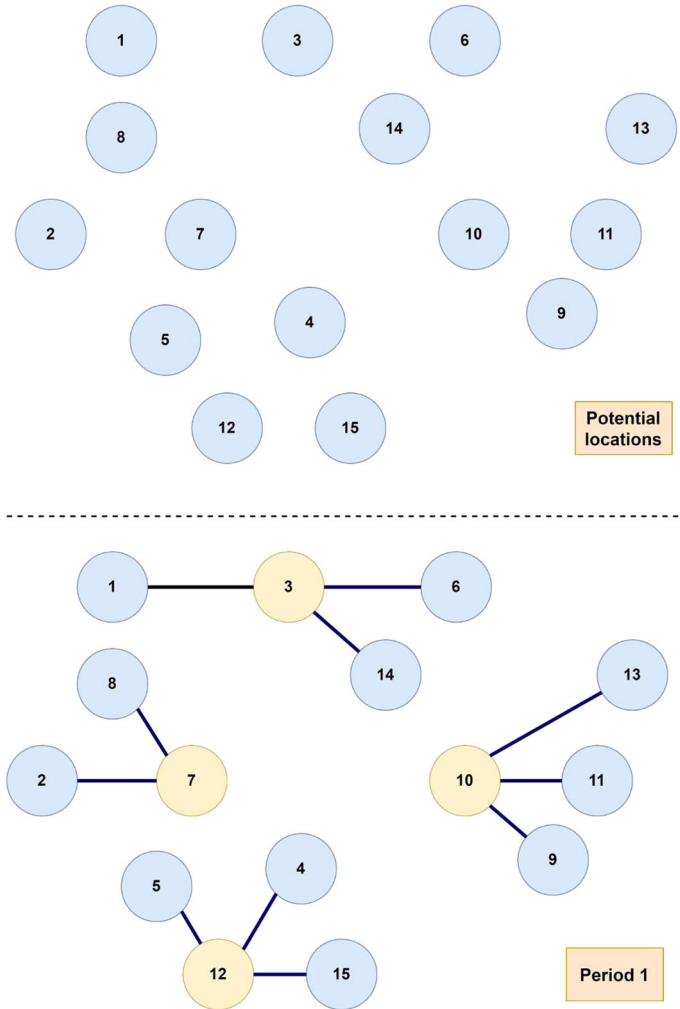
Fig. 1 The initial structure of the studied network

2, 7 and 8 are assigned to DC 4 and customers 9, 10, 11 and 13 are assigned to DC 6. Four DCs are operational in the period 2.

4 Mathematical model

This section presents the proposed multi-objective mixed integer programming (MIP) model. The resolution of this model allows to determine the values of the decision variables X_j^t, Y_{ij}^t and $Z_{jj'}^t$ and therefore the supply chain structure for each period. We use the following parameters and decision variables for the mathematical formulation of our problem:

Fig. 2 The three considered scenarios
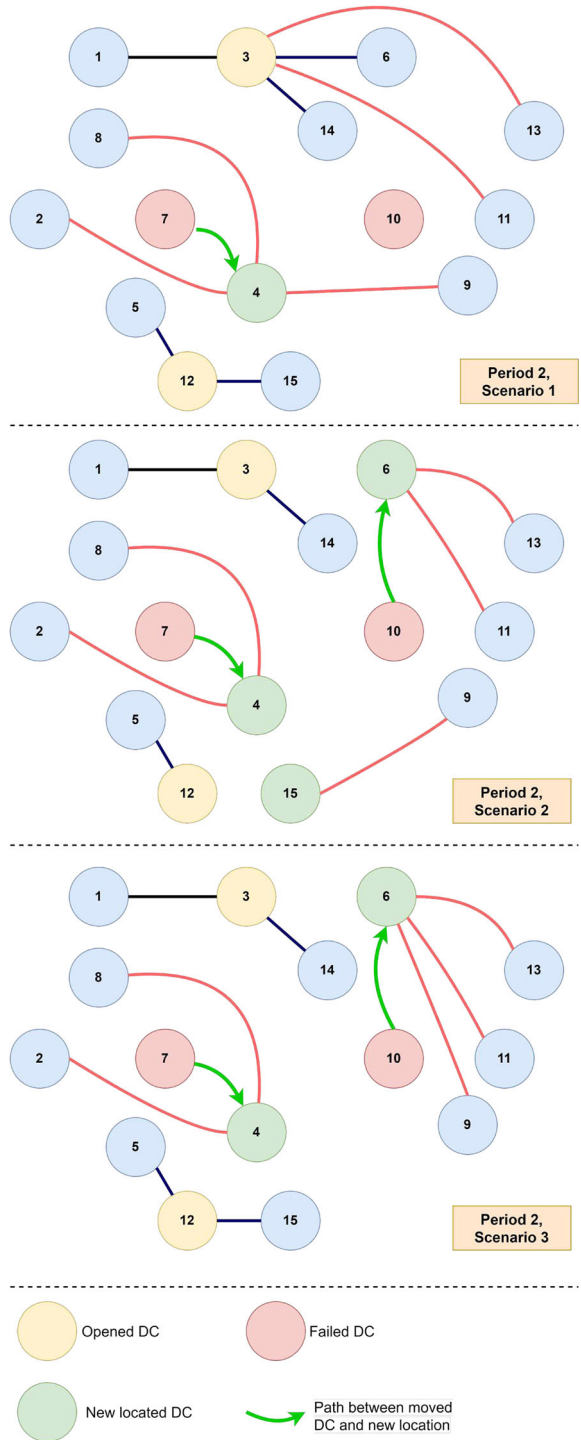
Sets	
T	Set of periods
N	Number of periods
I	Set of customers
L	Set of potential distribution centres (DCs)
S_t^f	Set of opened DCs in period t that can be closed in the next period
S_t^o	Set of DCs closed in period t that represents potential DCs to perform new locations in the next period. $S_t^o \cup S_t^f = L \; \forall \; t$

Indices	
i	Customers indices
j	DCs indices
t	Period times indices

Costs	
CL_j^t	Fixed location cost of DC_j in period t
CF_j^t	Fixed cost associated to closing DC_j at the end of period t
h_j	Inventory holding cost in DC_j
CC_j	Fixed order cost (including transport fixed cost) placed by DC_j at the supplier
CT_{ij}	Per-unit shipment cost from DC_j to customer i
$CD_{jj'}^t$	Cost of moving the DC from its location j at period $t-1$ to location j' in period t

Parameters	
D_i^t	Daily demand of customer i in period t
V_i^t	Global demand variance of customer i in period t
L_j	Mean lead time in days from supplier to DC_j
Λ_j	Variance of lead time from supplier to DC_j
θ	Number of days per period
α	Desired service level at DCs
W_α	Standard normal variant such that $P(W \leq W)$
$dist_{jj'}$	Distance between location j and location j'
CEL_j	Fixed CO_2 emissions from DC_j
$CEM_{jj'}$	CO_2 emissions factor due to moving DC from location j to location j' by km
CET_{ij}	CO_2 emissions factor due to transportation of products from DC_j to customer i by km

Decisions variables	
X_j^t	1 if a DC is open in location j at period t; 0 otherwise
U_j^t	1 if the DC_j change state by passing from period t-1 to period t; 0 otherwise
Y_{ij}^t	Allocation variable equal 1 if customer i is served by DC_j at period t, 0 otherwise
$Z_{jj'}^t$	1 if DC is moving from its location j at period $t-1$ to location j' at period t; 0 otherwise

4.1 Objective functions

Our model aims to determine, in each period, the best location of DCs that minimizes two objective functions. The first objective represents the economic cost of opening, moving, closing DCs and transportation and is composed of four terms. The first term represents the cost of opening DCs during the first period. The second and the third terms represent the cost of closing and opening DCs from the second period. The fourth term indicates the cost of moving DCs from a location to another location. The fifth term represents the transportation costs from DCs to customers. The last two terms represent the total holding, inventory and safety stock costs at the DCs (assuming that each DC uses an EOQ policy):

$$
J(X, Y, U, Z) = min \sum_{j \in L} CL_j^1 X_j^1 + \sum_{t=2}^{N} \sum_{j \in S_{t-1}^f} CF_j^t \left(U_j^t - \sum_{j' \in S_{t-1}^o} Z_{jj'}^t \right)
$$
$$
+ \sum_{t=2}^{N} \sum_{j' \in S_{t-1}^o} CL_{j'}^t \left(U_{j'}^t - \sum_{j \in S_{t-1}^f} Z_{jj'}^t \right)
$$
$$
+ \sum_{t=2}^{N} \sum_{j \in S_{t-1}^f} \sum_{j' \in S_{t-1}^o} CD_{jj'}^t Z_{jj'}^t + \sum_{t=1}^{N} \sum_{j \in L} \sum_{i \in I} \theta D_i^t CT_{ij} Y_{ij}^t \qquad (1)
$$
$$
+ \sum_{t=1}^{N} \sum_{j \in L} \sqrt{2 h_j CC_j \theta \sum_{i \in I} D_i^t Y_{ij}^t}
$$
$$
+ \sum_{t=1}^{N} \sum_{j \in L} W_\alpha h_j \sqrt{L_j \sum_{i \in I} V_i^{t2} Y_{ij}^t + \Lambda_j^2 \left(\sum_{i \in I} D_i^t Y_{ij}^t \right)^2}
$$

The second objective is composed of three terms aiming to minimize the total environmental impact by considering CO_2 emissions generated by located facilities in the first term, products transportation in the second term and facilities displacement operations for all considered periods in the last term.

$$
K(Y, Z) = min \sum_{t=1}^{N} \sum_{j \in L} CEL_j X_j^t + \sum_{t=1}^{N} \sum_{j \in L} \sum_{i \in I} CET_{ij} \theta dist_{ij} Y_{ij}^t
$$
$$
+ \sum_{t=2}^{N} \sum_{j \in S_{t-1}^f} \sum_{j' \in S_{t-1}^o} CEM_{jj'} dist_{jj'} Z_{jj'}^t \qquad (2)
$$

4.2 Constraints

The presented model is subject to the following constraints:

$$
\sum_{j \in L} X_j^t \geq 1 \qquad\qquad \forall \, j \in L, t \in T \qquad (3)
$$

$$
\sum_{j \in L} Y_{ij}^t = 1 \qquad\qquad \forall \, i \in I, j \in L, t \in T \qquad (4)
$$

$$Y_{ij}^t \leq X_j^t \qquad\qquad \forall\, i \in I,\, j \in L,\, t \in T \tag{5}$$

$$Z_{jj'}^t = 0 \qquad\qquad \forall\, j \in L,\, \forall\, j' \in S_{t-1}^f,\, \forall\, t \geq 2 \tag{6}$$

$$U_j^t = \max(X_j^t - X_j^{t-1},\, X_j^{t-1} - X_j^t) \qquad \forall\, j \in L,\, \forall\, t \geq 2 \tag{7}$$

$$\sum_{j' \in S_{t-1}^o} Z_{jj'}^t \leq U_j^t \qquad\qquad \forall\, j \in S_{t-1}^f,\, \forall\, t \geq 2 \tag{8}$$

$$\sum_{j \in S_{t-1}^f} Z_{jj'}^t \leq U_{j'}^t \qquad\qquad \forall\, j' \in S_{t-1}^o,\, \forall\, t \in T \tag{9}$$

$$\sum_{j \in S_{t-1}^f} \sum_{j' \in S_{t-1}^o} Z_{jj'}^t = \min\left(\sum_{j \in S_{t-1}^f} U_j^t,\, \sum_{j' \in S_{t-1}^o} U_{j'}^t \right) \qquad \forall\, t \geq 2 \tag{10}$$

$$X_j^t,\, Y_{ij}^t,\, U_j^t,\, Z_{jj'}^t \in \{0, 1\} \qquad \forall\, i,\, j,\, j' \in L,\, t \in T \tag{11}$$

Constraints (3) ensure that at least one DC is located in each period; constraints (4) require that each customer is assigned to only one opened DC in each period. Constraints (5) ensure that customers are exclusively served by opened DCs. Constraints (6) forbid the move of DCs from their locations to DCs locations that can be closed in the next period. Constraints (7) determine the value of the variable U_j^t in each period. Constraints (8) ensure that an opened facility in a period $t - 1$ can be moved to another location in the next period only if its state changes. Constraints (9) ensure that a closed facility in a period $t - 1$ cannot receive a facility in its location in the next period only if its state changes. constraints (8) and (9) guarantee that each DC is moved from its location to only one other location and each new location can receive only one DC. Constraints (10) show that the number of moved DCs in each period t is the minimum between the number of opened DCs and closed DCs in the period $t - 1$.

5 Solution approach

Solving the previous model is equivalent to find the set of non dominated solutions or the Pareto optimal set. As the considered problem is an NP-hard problem, see (Cornuéjols et al., 1983), we will use multi-objective evolutionary algorithm (MOEA) metaheuristic to generate solutions. A solution representation is defined using a binary encoding. A solution of our model is encoded into two parts, DC location and DC allocation respectively. We use a matrix $(N \times M = C + squared(C))$ where N represents the number of periods and C represents the number of customers.

For example, suppose that $N = 5$ and $C = 6$, the first part in Fig. 7 indicates the location of the DCs in each period; DC 1, DC 4 and DC 6 are opened in the first period and the second part indicates to assignment of customers to DCs. In this example, S_1^f = DC 1, DC 4, DC 6 and S_1^o = DC 2, DC 3, DC 5. We suppose that DC 1 and DC 6 are shut in the next period and DC 3 is opened, DC 1 is closed in period 2 and DC 6 is moved to location 3.

The new contents of S_2^f and S_2^o are S_2^f = DC 3, DC 4 and S_2^o = DC 1, DC 2, DC 5, DC 6. All customers assigned to DC 1 and DC 6 in the first period are reallocated to opened DCs in the second period. We calculate values of variables U and Z, in this period we have $U_1^2 = 1$, $U_2^2 = 0$, $U_3^2 = 1$, $U_4^2 = 0$, $U_5^2 = 0$, $U_6^2 = 1$ and $Z_{63}^2 = 1$. The same operation is repeated through the planning horizon of four periods, a schematic view of a feasible solution evolution of our

X_j	Y_{1j}	Y_{2j}	Y_{3j}	Y_{4j}	Y_{5j}	Y_{6j}	
100101	100000	000100	100000	000100	100000	000001	$t = 1$
001100	001000	000100	001000	000100	000100	001000	$t = 2$
100110	100000	000100	100000	000100	000100	000010	$t = 3$
110010	100000	010000	100000	010000	000010	000010	$t = 4$

Fig. 3 A feasible solution proposed representation
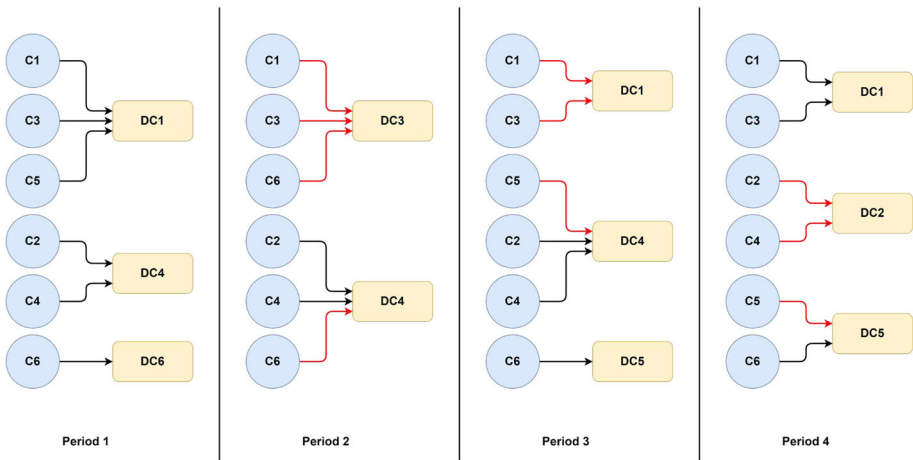
Fig. 4 The evolution of a feasible solution through periods

problem is explained by Fig. 8. The presented example shows that DC 1 is opened in period 1, closed in period 2 and reopened in period 3.

5.1 The non-dominated sorting genetic algorithm II (NSGA-II)

We propose to use the non-dominated sorting genetic algorithm II (NSGA-II), proposed by Deb et al. (2002) and Coello et al. (2007) to solve the considered problem. The NSGA-II uses a modified ranking procedure to reduce computational complexity. It improves a population of candidate solutions using an evolutionary process based on Pareto dominance ordering to obtain a diverse front of non-dominated solutions (Krishnapriya & Rahiman, 2016). The most important advantage of the NSGA-II is its ability to create a Pareto front based on a non-dominated sorting approach for each individual and implement the density estimation using the crowding distance assignment (Souier et al., 2019).

The proposed NSGA-II algorithm starts with a random initial population P of size N. Infeasible solutions are modified, the two objectives are calculated for each chromosome and a rank is assigned to each chromosome to obtain a non-dominated sort. The rank of each chromosome is equal to its non-dominant level. The next step generates a child population G of size N using binary tournament and uses crossover and mutation operations. Infeasible solutions are modified, and each child solution is evaluated. The new population is generated based on the elitism concept, the populations P and G are combined forming a population R of size $2 \times N$, the crowding distance between individuals is then calculated and a non-dominated sorting is applied to R. A new parent population P is then formed from R beginning by adding solutions having rank 1, then rank 2 and so on to make up a population of size N.

If all solutions of a same rank cannot be inserted into population P (the size of P exceeds N), solutions are added to P according to descending order of their crowding distances until reaching size N. This procedure is repeated until reaching a termination condition. The pseudo code of the used NSGA-II is presented in the Algorithm 1.

Algorithm 1: NSGA-II pseudo code algorithm

    Step 1 (Generate initial population):
    Generate parent population **P** of size N randomly
    Evaluate solutions of **P** by calculating the objectives functions J and K
    Fast non-dominated sort
    Step 2 (Generate new population):
    while $t \leq number\_of\_iterations$ **do**
        Generate child population **G** of size N from **P** by applying binary tournament selection
        (**select solution having the smallest rank value**), crossover and mutation
        Correct infeasible solutions
        Evaluate solutions of **G** by calculating the objectives functions J and K
        R = P ∪ G
        F = fast non-dominated sort(**R**)
        F = Crowding distance assignment(**F**)
        Sort **F** (**A solution i is better than a solution j: if $rank_i < rank_j$ or $rank_i = rank_j$ but solution i has a better crowding distance then solution j**)
        Select N solutions from sorted **R** and obtain new parent population **P**
        Fast non-dominated sort
    end while

The use of crossover and mutation in NSGA-II can generate infeasible solutions. Therefore, we use a correction procedure able to:

- For each period, keep open (resp. close) the opened (resp. closed) DCs in the previous period.
- Close DCs that are not assigned to any customer.
- Keep the allocation of customers not affected by the disruptions in each period.
- Make sure that each customer is assigned to only one opened DC in each period.

5.2 Order preference by similarity to ideal solution (TOPSIS)

The proposed NSGA-II approach generates a set of non-dominated solutions. These solutions are classified using TOPSIS technique (Technique for Order Preference by Similarity to Ideal Solution). Developed by Hwang and Yoon (1981), TOPSIS is a multi-criteria decision making technique that allows to classify the set of non-dominated solutions to help selecting the most suitable solution for the decision maker. In our case, we propose one solution at the end of each period that proposes the opened DCs and customers allocations decisions. A scenario is generated to define failed DCs and consider relocation facilities decisions for the next period. This is repeated through the planning horizon. We use then, the TOPSIS method and assign compromise weights ω_1 and ω_2 to the two considered objectives based on the distance to ideal and nadir solutions.

Table 1 The model parameters values

Parameters	Value	Parameters	Value
N	5	D_i^t	$U \sim [100, 1600]$
CL_j^t	$U \sim [2000, 6000]$	V_i^t	$U \sim [50, 100]$
CF_j^t	$U \sim [1000, 3000]$	L_j	$U \sim [10, 30]$
$CD_{jj'}^t$	$U \sim [300, 700]$	Λ_j	$U \sim [5, 10]$
CT_{ij}	$U \sim [10, 20]$	α	97.5 %
h_j	25	W_α	1.96
CC_j	$U \sim [50, 100]$	CEL_j	$U \sim [10, 30]$
$dist_{jj'}$	$U \sim [10, 20]$	$CEM_{jj'}$	$U \sim [0.1, 1]$
θ	250	CET_{ij}	$U \sim [0.1, 1]$

6 Numerical experiments

6.1 Illustrative example

In this section we present a numerical experiment inspired from the retailers supply chain networks during the last Covid'19 Pandemic. In this sector, the importance of DCs locations is very often overlooked. Actually, according to Chaturvedi et al. (2013), most retailers networks do not have many DCs in order to efficiently fulfil customers' orders over a large geographic area, especially in terms of the shipping duration.

The numerical experiments are performed using a Pentium core 2 Duo 2.20 GHZ and 2 GB of RAM. The proposed NSGA-II approach and TOPSIS technique are implemented in "VBA" programming language.

To evaluate the performances of the proposed NSGA-II based approach, we study the performance of 30 instances, with the parameters described in Table 1. Table 2 details the parameters of the NSGA-II algorithm. This section details the obtained results and the evolution of the structure of a supply chain network with 20 potential DCs.

The Fig. 5 shows the supply chain evolution per periods: the number of opened, closed and moving DCs. The results show that 2 DCs are opened in the first period (DC17 and DC9), DC9 is disrupted at the end of the period. One DC is operational in the second period, the operational DC from the first period (DC17). However, the remaining DC is closed (DC9) and this period generates DCs closing costs. DC17 is disrupted at the end of the period. In period 3, one DC is operational (DC9 is reopened), the disrupted DC in the previous period (DC17) is moved from its location in the second period to new location in the third. This period generates DCs moving costs and DC9 is disrupted at the end of the period. 7 DCs are operational in the period 4 (DC1, DC4, DC5, DC6, DC7, DC11 and DC17). The disrupted DC in the previous period (DC9) is moved from its location in the third period to new location in the fourth period. This period generates DCs opening and moving costs and 2 DCs are disrupted at the end of the period (DC7 and DC11). 5 DCs are operational in the period 5 where the 5 operational DCs are from the previous period (DC1, DC4, DC5, DC6, and DC17) and the two disrupted DCs are closed. Period 5 generates DCs closing costs. The same idea is applied for following periods. So, each period generates either opening or closing costs with possible moving costs. Generated costs in each period are illustrated in Fig. 6.

Table 2 NSGA-II parameters values

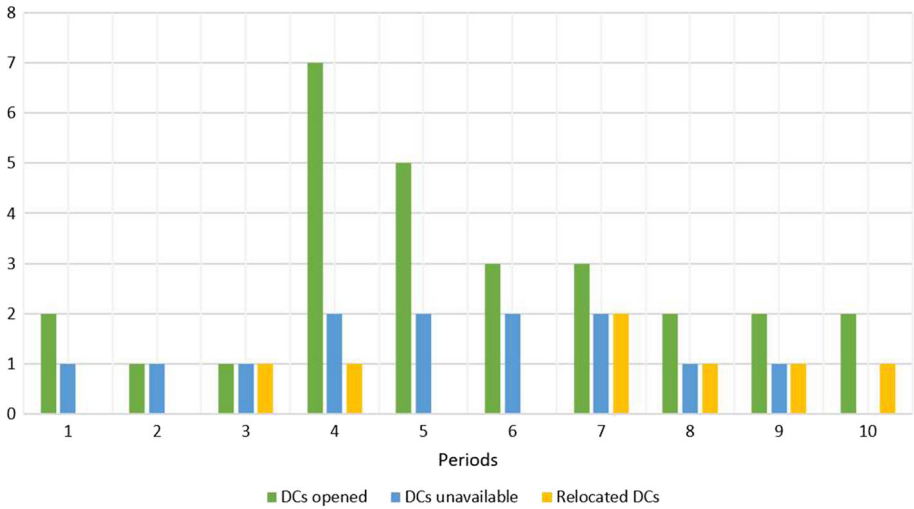| Parameters	Value
Number of iterations	70
Size of population	80
Percent of crossover	0.7
Percent of mutation	0.1

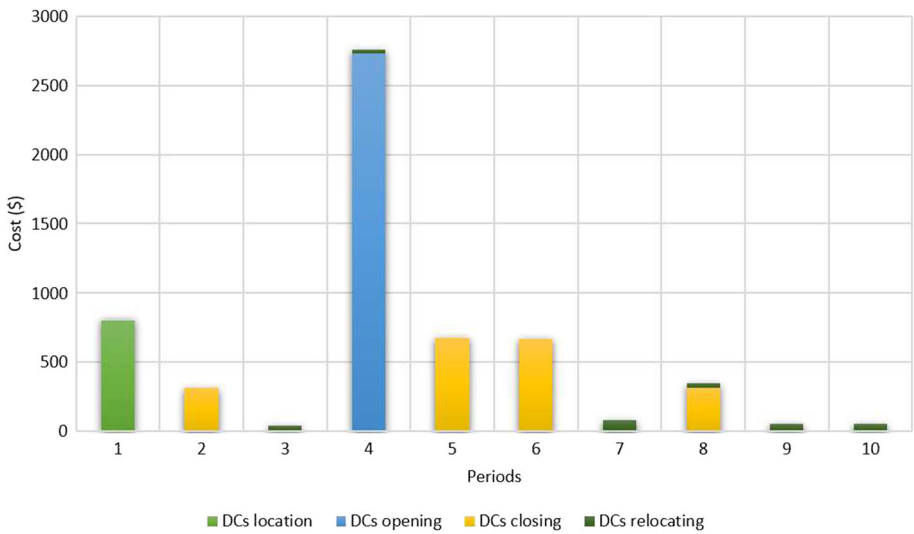**Fig. 5** Supply chain evolution per period

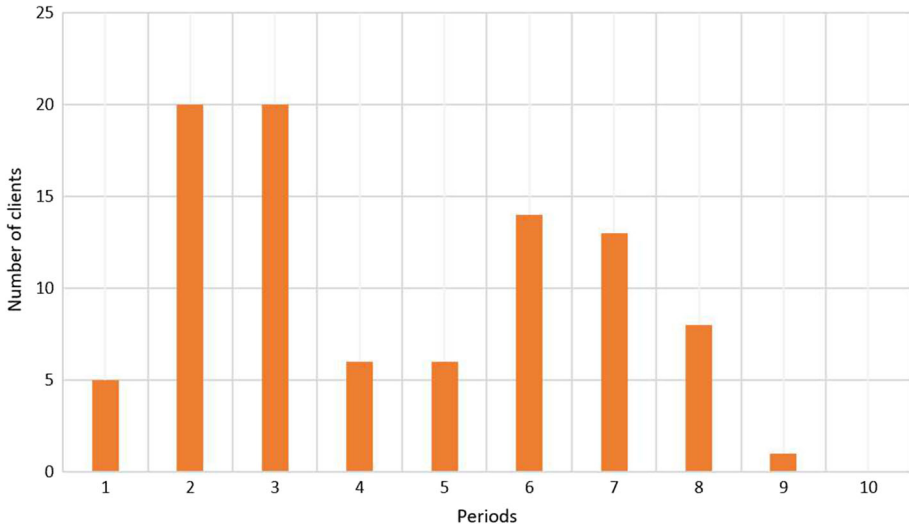**Fig. 6** Costs generated by the supply chain evolution

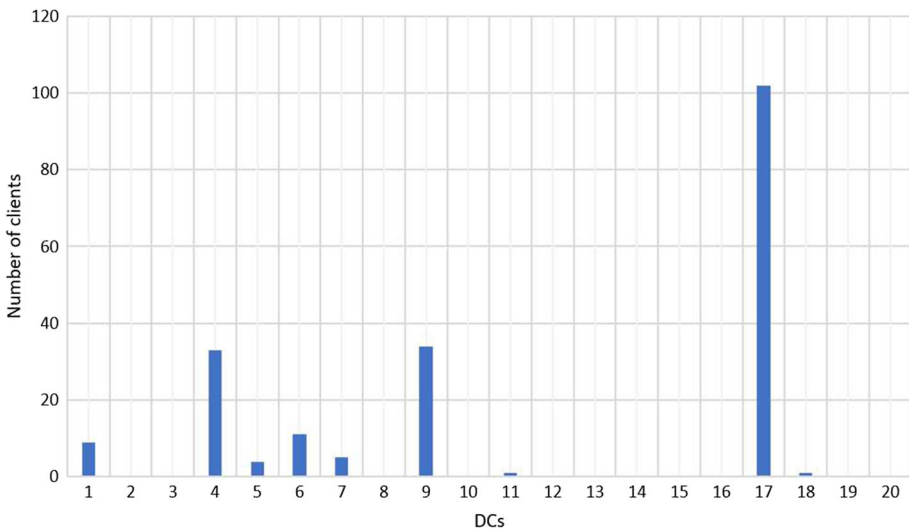**Fig. 7** Number of clients affected by the DCs unavailability per period

Fig. 8 Number of clients assigned for each DC

As described in the Fig. 5, at the end of each period the disrupted DCs are either moved or closed in the next period depends on the number of opened DCs. This affect the clients allocated to the disrupted DCs that must change allocation in the next period. The Fig. 7 shows the number of reallocated clients in each period.

Figures 8 and 9 represents the total number of assigned clients for each DC and the number of assigned clients for each DC per period respectively. We remark that DC 17 is the most used DC, this can be justified by its low transportation cost. Also, only nine DCs are used trough the ten periods to satisfy all clients demands.
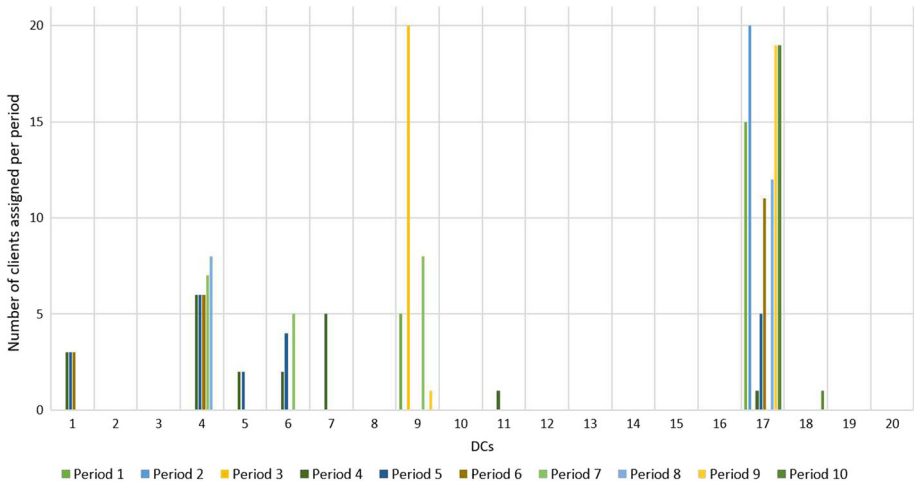
Fig. 9 Number of clients assigned for each DC per period

The obtained optimal Pareto curve for this case is presented by Fig. 16. The TOPSIS thechnique is used to choose one solution from this front. More results are presented in the next section using the TOPSIS NSGAII approach.

6.2 TOPSIS results for a representative set of instances

We present several experiments with different number of nodes, in relation with the extent of the geographical area to cover the supply chain. The conducted numerical experiences aim to show the performance of the proposed solution approach by :

- Varying the supply chain size: The instances are obtained by varying the number of customers that represents the number of candidate DCs. We apply the proposed approach on six different sizes of 10, 20, 30, 50, 60 and 80 nodes.
- Varying the importance of cost and carbon emissions in the multiobjective problem: The instances are also obtained by varying the TOPSIS weights related to the total cost and the total CO_2 importance, respectively ω_1 and ω_2. We apply the TOPSIS technique with five different variants representing the couple (ω_1, ω_2): (0.2, 0.8), (0.4, 0.6), (0.5, 0.5), (0.6, 0.4), (0.8, 0.2).

Table 3 shows the results obtained for different instances of the studied problem with the consideration of five time periods. Each period represents one year of 250 days.

For each instance, table 3 provides the performance of the best solution in terms of opened, failed and moved DCs, reallocated customers, and total cost and CO_2 emission. For each instance, the NSGA-II metaheuristic provides a set of non-dominated solutions. This set is then ranked with the TOPSIS technique.

Table 3 Computational results for $N = 5$ using NSGA-II approach

Instance	TOPSIS parameters (ω_1, ω_2)	Number of nodes	Number of opened DCs	Number of failed DCs	Number of moved DCs	Number of reallocated customers	Total Cost (millions of \$)	Total CO_2 amount (kg)
1	0.2, 0.8	10	19	11	8	25	139.46	42,720.94
2		20	25	12	10	46	251.34	103,939.77
3		30	40	16	9	68	471.35	151,206.17
4		50	47	18	15	95	791.46	292,938.7
5		60	66	35	30	164	906.96	408,568.05
6		80	74	23	14	98	1280.19	474,570.08
7	0.4, 0.6	10	18	9	8	21	145.23	43,910.95
8		20	28	8	6	34	238.38	93,165.71
9		30	33	13	6	65	406.2	130,412.34
10		50	52	23	20	111	774.56	267,759.52
11		60	69	8	4	31	907.88	312,671.8
12		80	85	43	38	201	1296.35	518,535.53
13	0.5, 0.5	10	22	6	4	11	145.09	20,302.64
14		20	28	9	8	34	258.32	77,957.24
15		30	35	18	11	64	410.95	131,707.51
16		50	47	21	14	102	775.56	272,467.53
17		60	63	29	21	132	924.09	379,374.6

Table 3 continued

Instance	TOPSIS parameters (ω_1, ω_2)	Number of nodes	Number of opened DCs	Number of failed DCs	Number of moved DCs	Number of reallocated customers	Total Cost (millions of \$)	Total CO_2 amount (kg)
18		80	93	30	27	125	1290.1	461,180.19
19	0.6, 0.4	10	16	8	7	14	154.48	46,839.21
20		20	27	16	10	49	257.33	89,693.83
21		30	33	20	15	75	397.91	143,999.33
22		50	67	17	9	53	810.56	229,519.83
23		60	80	48	38	175	926.64	384,522.89
24		80	95	43	34	182	1306.75	463,371.87
25	0.8, 0.2	10	17	7	5	17	159.37	31,045.08
26		20	31	13	9	43	270.66	81,209.83
27		30	32	12	7	58	404.52	151,137.71
28		50	57	21	17	88	806.4	296,708.98
29		60	76	41	33	156	933.44	327,390.03
30		80	106	64	53	262	1358.95	429,099.13
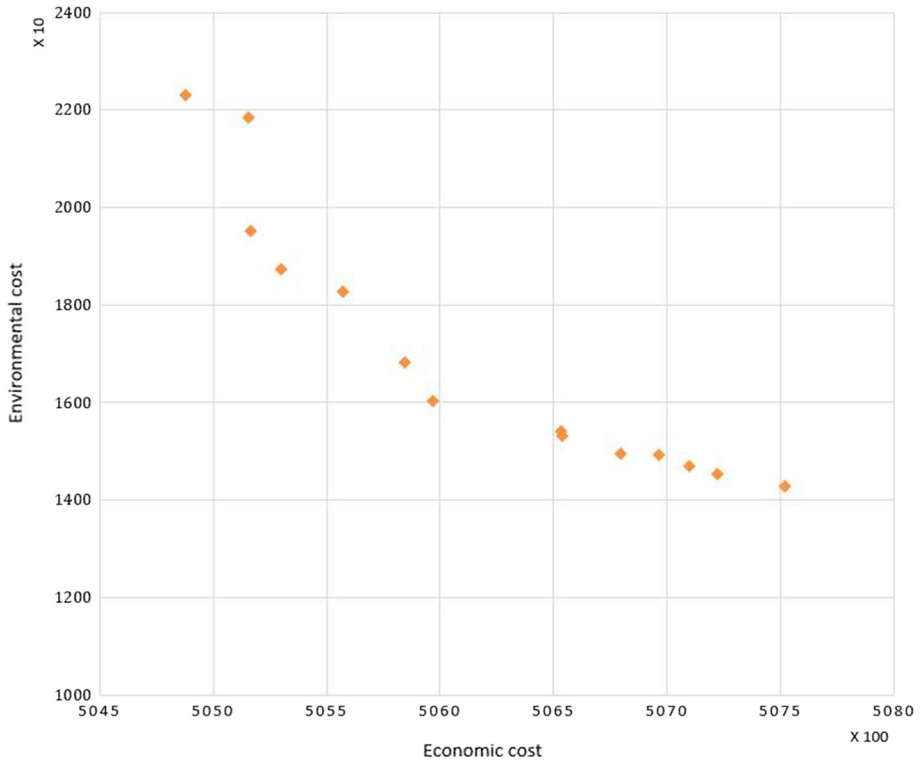
Fig. 10 The optimal Pareto front
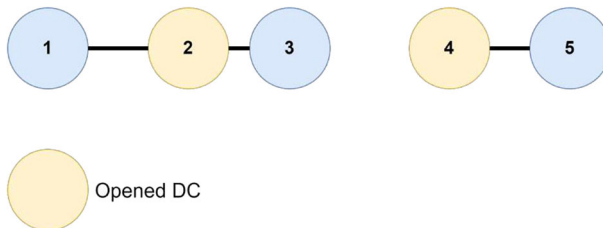
Fig. 11 Supply chain example

6.3 Simulation results for the integration of mobile facilities

In this section we aim to show the impact of the integration of the mobile facilities on the performance of a retailers supply chain subject to DC unavailability. Thus, we compare two approaches based on the integration or not of the mobile facilities concept:

- The proposed approach based on the integration of mobile facilities: As detailed above, this approach gives the opportunity to move a failed DC to another location, in order to avoid the opening of a new DC.
  Thus, after each period, if a DC is failed (e.g. DC 2 in Fig. 11), the optimization of the supply chain of the next period tries to determine the best supply chain structure with the possibility of moving the failed DC. In Fig. 12, the failed DC is moved, without changing
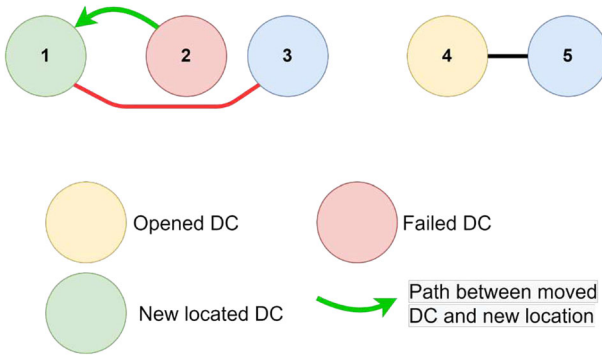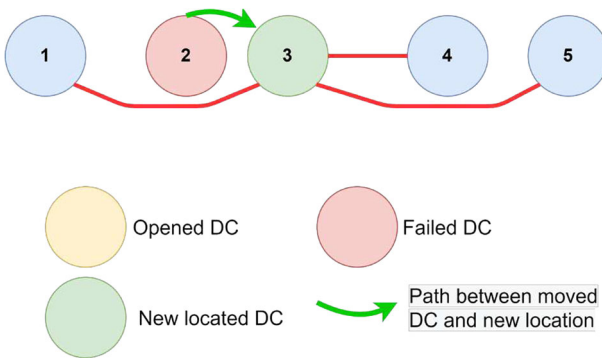
Fig. 12 Moved DC

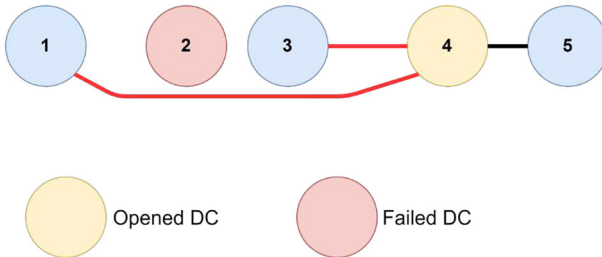**Fig. 13** Moved and closed DCs
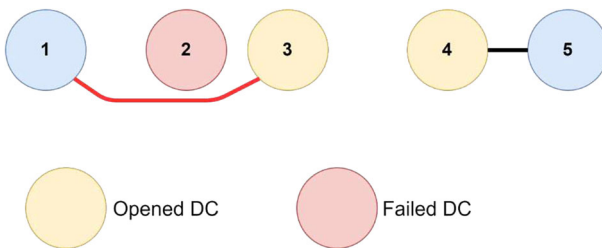

Fig. 14 Customers reallocation

Fig. 15 Opening of new DC

Fig. 16 Performance of mobile facilities integration

the state of the other opened DC. In Fig. 13 the failed DC is moved and the other DC is closed, with reallocation of its customers.

- In the second approach the facilities are not mobile. In this case when a DC is failed, in the next period the optimization of the supply chain will try to reallocate customers (Fig. 14) , or to open new DCs (Fig. 15).

Note that in both approaches the objective is to ensure the best management of the supply chain subject to uncertainties, in terms of total cost and CO_2 emissions. We use the same instances (10, 20, 30, 50, 60 and 80 nodes) with $\omega_1 = 0.5$ and $\omega_2 = 0.5$ as TOPSIS parameters.

In order to show the performance of mobile facilities integration we determine the economical and the environmental gain of the proposed approach compared to the second approach. The comparison is performed over different time horizon: 2, 3, 5, 6 and 10 periods.

Results show that the use of mobile facilities generates an economical profit by saving extra opening and closing costs using facilities displacements. However, it generates an increase in CO_2 emissions due to moving facilities.

6.4 Solution sensitivity vis-a-vis of CO_2 emissions

We investigate in this section the number of opened DCs through the planning horizon for both objectives with $\omega_1 = 0.5$ and $\omega_2 = 0.5$ in order to show how the consideration of CO2 emissions affect the number of opened DCs.

Figure 17 depicts the number of opened DCs and shows that the consideration of CO_2 emissions objective increases the number of opened DCs, this can be explained by the assumption that **the higher is the facility location cost, the lower is the CO_2 emissions quantity generated by the facility**. For this reason, our multi-objective model locates more DCs in order to find a trade-off between logistic costs and CO_2 emissions quantity which increases costs. The evolution of cost values is depicted for both models in Fig. 18.
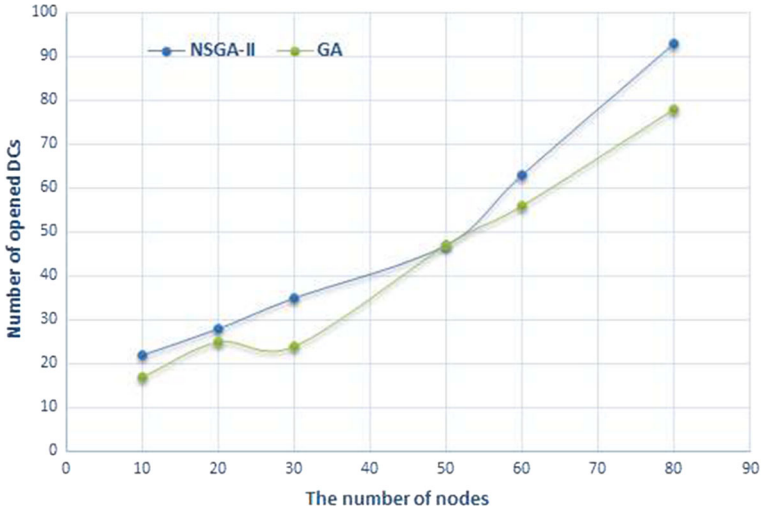
Fig. 17 The number of opened DCs for multi-objective and mono-objective approaches
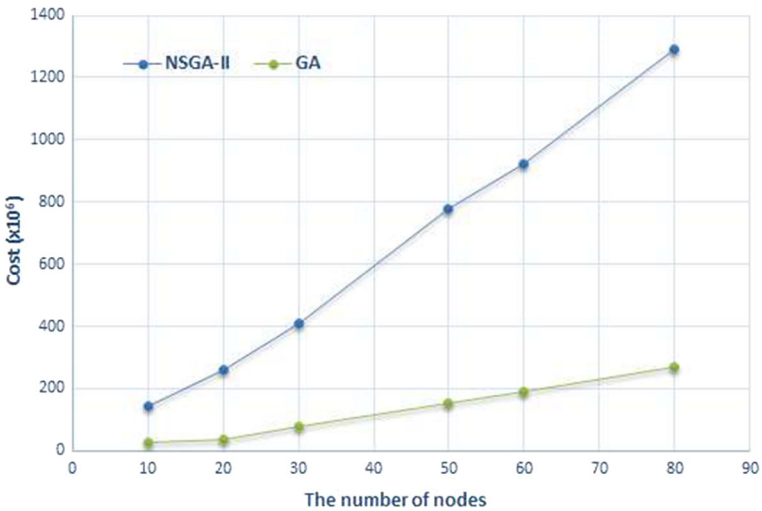

Fig. 18 Total cost evolution for multi-objective and mono-objective approaches

7 Conclusions and perspectives

A dynamic mobile facility location/relocation problem was considered in this study to address facilities disruptions. The paper aims to minimize the logistic costs and CO_2 emissions. This problem is solved using a non-dominated sorting genetic algorithm II (NSGA-II), and the obtained results show that the consideration of mobile facilities saves extra opening and closing costs and more DCs are needed when we consider CO_2 emissions in order to find a trade-off between logistic costs and environmental constraints.

Our sensitivity analysis shows that the use of mobile facilities allows earning in costs by saving extra opening and closing costs using facilities displacements. Otherwise, the

displacement of mobile facilities increases the CO_2 emission quantity compared to a classical model due to emissions generated by moved facilities.

The proposed model can be applied to large number of real situations, such as mobile post office, bloodmobiles and mobile emergency care centres. We can also use this model to locate vaccination centres for COVID 19, the idea is to locate a set of centres in the first period and closing the centres located in regions where there are no more people to be vaccinated in each period.

For future works, the first direction is to consider capacity of facilities with capacity transfer from failed facilities to operational facilities. Our model can suppose that facilities can be opened and closed for a limited number of times. Other objectives can be also added like maximising customer satisfaction and minimizing penalty costs due to unsatisfied demands.

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