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A tabu search algorithm to solve a green logistics bi-objective bi-level problem

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Abstract
This paper addresses a supply chain situation, in which a company distributes commodities over a selected subset of customers while a manufacturer produces the commodities demanded by the customers. The distributor company has two objectives: the maximization of the profit gained by the distribution process and the minimization of CO_2 emissions. The latter is important due to the regulations imposed by the government. A compromise between both objectives exists, since profit maximization only will attempt to include as many customers as possible. But, longer routes will be needed, causing more CO_2 emissions. The manufacturer aims to minimize its manufacturing and shipping costs. Since a predefined hierarchy between both companies exists in the supply chain, a bi-level programming approach is employed. This problem is modelled as a bi-level programming problem with two objectives in the upper level and a single objective in the lower level. The upper level is associated with the distributor, while the lower level is associated with the manufacturer. Due to the inherent complexity to optimally solve this problem, a heuristic scheme is proposed. A nested bi-objective tabu search algorithm is designed to obtain non-dominated bi-level feasible solutions regarding the upper level. Considering simultaneously both objectives of the distributor allow us to focus on the minimization of CO_2 emissions caused by the supply chain, but bearing in mind the distributor's profit. Numerical experimentation shows that the Pareto frontiers obtained by the proposed algorithm provide good alternatives for the decision-making process and also, some managerial insights are given.

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1 Introduction

The CO_2 emissions in the atmosphere has increased at an alarming rate over the recent decades. This is caused in part by the boom of factories and vehicles impulsed by fossil fuels (Forster et al. 2007). Presently, the carbon in the atmosphere needs hundreds of years to be absorbed by the biosphere and the oceans. Due to the concerns generated by climate change government regulations and methodologies for calculating emission factors have surged. Significant effort has been done to control greenhouse gases emissions all over the world. For example, in 42 Asian countries (see Liu et al. 2018), in 27 European countries (see Zaman and Shamsuddin 2017), in Brazil, Russia, India, and China (see Aldakhil et al. 2018), among others. In particular, in Mexico many regulations have been decreed over the last 40 years. In 1971, the first federal law was promulgated in Diario Oficial de la Federación (1971), where some articles emphasize the control of emissions. It is worth mentioning that one of the most important laws dealing with emissions reduction was published in Diario Oficial de la Federación (1988a). This law establishes the control and prevention of pollution in the atmosphere. Besides that, regulation that defines technical procedures which the pollutant sources must obey is published in Diario Oficial de la Federación (1988b). Furthermore, licenses and certificates were created to manage and control industrial activities.

Currently, there are rules that establish the maximum emissions allowed for industry and vehicles. For example, Diario Oficial de la Federación (1993) states maximum permitted level of pollutions accordingly to their location in the country. The rule Diario Oficial de la Federación (1999a) establishes maximum emissions level allowed for motor vehicles that use gasoline as a fuel. Maximum emissions are set depending on the year and model of the vehicle. Also, Diario Oficial de la Federación (1999b) settles the maximum emissions level of unburned hydrocarbons, carbon monoxide, nitrogen oxides produced by vehicles, where the maximum emissions depend on the type and weight of the vehicle.

Moreover, environmental programs have been implemented in order to reduce CO_2. One of the most popular is named *Hoy No Circula* in Mexico in which the circulation of vehicles is restricted once a week depending on the last number of the license plate. These laws, regulations and programs have controlled the emissions and the pollution in Mexico. Furthermore, the number of laws have increased over the years to improve the environment and the quality of life. This motivates the study of a problem that considers CO_2 emissions produced by vehicles and by manufacturing facilities. Besides the minimization of emissions, the profit associated with the distribution process is maximized leading to a bi-objective problem. Since the manufacturing process is also considered in the problem, related emissions and costs are taken into account.

The problem herein studied is as follows: consider a situation in which two types of companies interact with each other in a hierarchical way within a supply chain. One company acquires and distributes different types of commodities over a selected subset of customers; while the other company manufactures the commodities demanded by selected customers. In this problem, it is assumed that the company that distributes the commodities designs routes in order to satisfy the selected subset of customers, aiming to maximize the profit. Moreover, due to the regulations imposed by the industry or the government, the minimal polluting should be taken into consideration. Heterogeneous fleet of vehicles is available to deliver commodities to the customers. Accordingly to the previous assumption, each type of

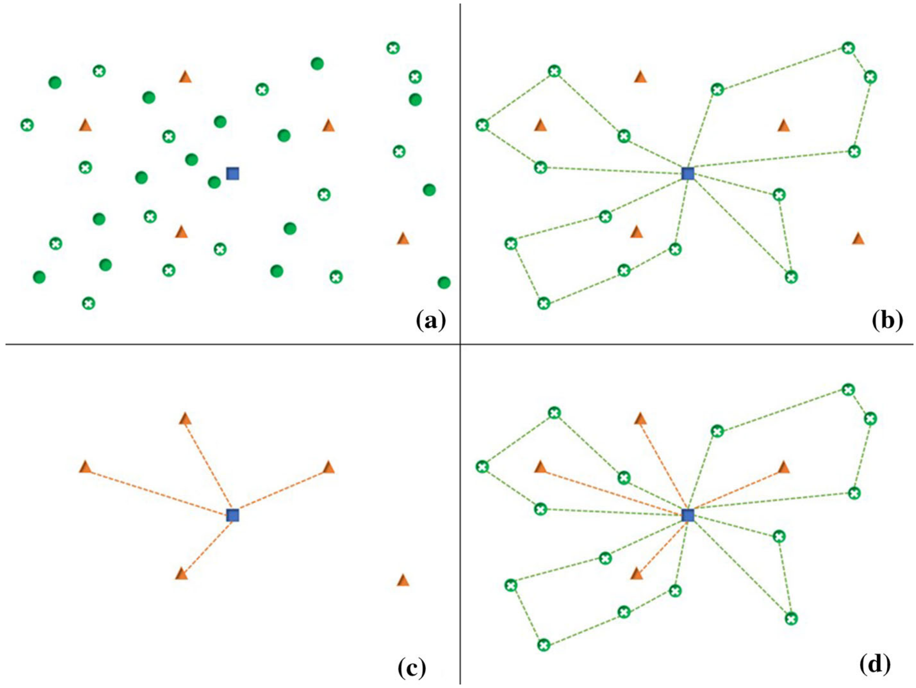

Fig. 1 Illustration of the problem

vehicle has different rates of CO_2 emissions. Hence, the minimization of CO_2 emissions is considered as another objective.

Once the subset of customers has been selected, the distributing company acquires commodities needed to satisfy the accumulated demand of those specific customers. The manufacturer has different capacitated facilities to produce the requested demand. This company must choose the amount of commodities that will be manufactured at each facility. Then, the commodities will be shipped from the facilities to a single depot. To achieve the latter, a homogeneous fleet of vehicles is available. The objective of the manufacturer is to minimize production and shipping costs. Furthermore, in each facility, a pollution rate associated with each manufactured commodity and a maximum pollution rate is imposed.

The problem herein considered is illustrated in Fig. 1. The selection of a subset of customers by the distributing company is depicted in Fig. 1a. Then, the routes are designed (see Fig. 1b) and the demand is accumulated at the depot. After these decisions have been taken, the production plan at the facilities and shipping decisions are established by the manufacturing company (see Fig. 1c). Finally, the complete decision process is shown in Fig. 1d.

Due to the existing hierarchy between companies, and the manner that they are interrelated, the problem is modeled as a bi-objective bi-level programming model, in which the upper level has two objectives and a single objective appears in the lower level. The distributing company will be the leader and the manufacturing company will be the follower. The leader is concerned about the maximization of the profit gained by the distribution process and the minimization of CO_2 emissions, simultaneously. The follower aims to minimize its manufacturing and shipping costs. Due to the characteristics of the follower's problem, the bi-level model cannot be reduced into a single-level one. Hence, classical reformulations using optimality conditions could not be achieved. Therefore, a tabu search algorithm is proposed to solve the bi-objective bi-level problem, that is, to approximate the Pareto front. The proposed algorithm considers leader's solutions with a nested approach, that is, optimally solves the follower's problem for each leader's decision. The obtained results show very well-shaped Pareto frontiers covering a wide range of the objective functions space.

The main contributions of this research are the following: (i) a realistic and relevant green logistics bi-objective bi-level programming model, (ii) the consideration of an eco-friendly hierarchized production-distribution problem, (iii) a nested bi-objective tabu search algorithm to approximate the Pareto fronts of this problem, and (iv) the analysis of results which yield interesting managerial insights. It is important to emphasize that problem studied herein is introduced for the first time and the assumptions made throughout the research are standard and quite reasonable.

The remainder of the paper is organized as follows. Section 2 presents a literature review on green logistics problems that involve routing and multiple objectives. The mathematical bi-objective bi-level model is defined in Sect. 3. Then, Sect. 4 describes the proposed nested bi-objective tabu search algorithm. Section 5 shows the results obtained from the computational experimentation according to a set of adapted instances. Conclusions and recommendations for future research are given in Sect. 6.

2 Literature review

Different papers have appeared to address environmental and sustainable problems. In Dekker et al. (2012), Lin et al. (2014), and Faulin et al. (2019), many decisions in a supply chain where environmental aspects could be considered, such as transportation, routing, production, inventory, facilities (warehouses, ports, and terminals), supply chain design, product recovery (closed loop supply chains), and operational control of supply chains are mentioned.

In Sbihi and Eglese (2010), the authors involve wider environmental and social considerations in dynamic lot-sizing, joint and separate set-up cost model, waste management, household waste collection, and vehicle routing. Furthermore, in Lai and Wong (2012), important contributions in the management of logistic chains are made, where they consider the environment by examining the effects of environmental regulatory pressure. A case study related to food distribution in Spain is proposed in Ubeda et al. (2011). The authors show the manner in which environmental impact could be reduced in practice. In Linton et al. (2007), the authors focus on the interaction between sustainability and supply chains. To better understand environmental supply chains, Beamon (1999) discusses the impact of solid and hazardous waste, natural resource use, water and air pollution, public pressure, environmental legislation, and environmental management standards.

One of the main features of a green logistics problem is that CO_2 emissions must be taken into consideration. For example, the pollution-routing problem (PRP) introduced by Bektaş and Laporte (2011), which consists in an extension of the vehicle routing problem where green house emissions are considered. Extensions of the PRP are the presented in Demir et al. (2012), Franceschetti et al. (2013), and Demir et al. (2014). Also, in Li et al. (2008), the relationship between CO_2 emissions and the operation cost-income ratio in the location of distribution centers is analyzed. Also, the authors presented a case study regarding crude oil, from which is concluded that if the price of crude oil increases, then carbon emissions will decrease. Another interesting finding is that if more distribution centers are opened, then carbon emissions could decrease. In Diabat and Simchi-Levi (2009) the environmental impact of CO_2 emissions is considered as the novelty of a green supply chain management model, which integrates management and environmental impact of the supply chain. A green vehicle routing problem with environmental effects by using alternative fuel vehicles is studied in Erdoğan and Miller-Hooks (2012). Related researches that consider scheduling decisions appear in Xiao and Konak (2015) and Qian and Eglese (2016). Also, in Zhang et al. (2018) alternative fuel stations are included in the green logistics model to reduce greenhouse emissions. Practical and good-quality solutions for green logistics problems can be found in Leggieri and Haouari (2017), Montoya et al. (2016), Çağrı and Karaoglan (2016), and Franceschetti et al. (2017). Additionally, an important study that shows the advantage of using heterogeneous fleets within this green context is presented in Çağrı et al. (2014), and an interesting analysis of emissions caused by different vehicles is presented in Figliozzi et al. (2020).

If other objectives, such as economic or social aspects are considered at the same time, a multi-objective problem appears. Several papers deal with this kind of green logistics problems. For example, an uncapacitated facility location problem is studied in Harris et al. (2009). The authors optimize cost, environmental impact, and uncovered demand, simultaneously. To solve that problem, an evolutionary multi-objective algorithm is implemented. In Harris et al. (2014), a capacitated facility location-allocation problem is presented, where the objectives are related to cost and environmental impact. A simple evolutionary algorithm for multi-objective optimization is applied to obtain a set of non-dominated solutions. Also, delivery costs and gas emissions are minimized in Pérez-Bernabeu et al. (2015) showing the importance of horizontal cooperation in a road transportation network. The latter concept is well-explained in Serrano-Hernández et al. (2017), in which the wide possibilities to improve a green supply chain are pointed out. Other studies that consider multiple objectives can be found in Sawik et al. (2017b) and, Sawik et al. (2017a), in which a real Spanish case-study is solved and some managerial insights regarding the fleet size, the importance of having an heterogeneous fleet, and the usage of different truck types are concluded from the obtained results.

A supplier selection and order allocation problem is studied in Kannan et al. (2013), in which the environmental performance of suppliers is considered. To solve the problem, a fuzzy analytic hierarchy process, fuzzy techniques to order the preferences by similarity to an ideal solution, and a fuzzy multi-objective linear programming model are integrated. The study focuses on an Iranian automobile manufacturing company that aims to establish a systematic approach to meet green supplier selection. A partner selection problem is introduced in Yeh and Chuang (2011), where four objectives are considered, (i) the minimization of the total cost considering production and transportation costs, (ii) the minimization of the time of production and transportation, (iii) the maximization of the average product quality, and (iv) the maximization of a green appraisal score. Two multi-objective genetic algorithms are proposed. Moreover, to analyze the correlations among the objectives, four schemes are tested: three bi-objective problems (different combinations of objectives) and the consideration of all objectives.

On the other hand, there is scarce research in which environment aspects are considered and modeled as bi-level programs. Under this scheme, a hierarchy among decision makers is needed. After an intensive search, only few papers were found. For example, Mathew and Sharma (2006) deals with a green supply chain, in which a network design problem is studied. The leader determines the link capacity expansion subject to user's travel behavior to minimize the system travel costs; and the follower determines the link flows subject to user equilibrium conditions. In a similar manner, Wen and Eglese (2016) handles with a toll-pricing problem to minimize CO_2 emissions. The leader imposes toll in the roads of the network, while the users find an equilibrium that minimizes travel costs. Previous research regarding to reduction of emissions can be found in Wang et al. (2011), where the government (leader) chooses the optimal price for emissions considering the response of the firms (follower) to that price; naturally, the follower aims to maximize its profit. A urban traffic congestion pricing policy is studied in Wang et al. (2014), where the carbon emission cost is considered as part of the travel cost. The traffic management decision-making behavior is represented by the leader, maximizing the customer surplus; while the follower describes the user's choice behavior minimizing travel costs. Also, a model that measures gas emissions throughout a traffic network for urban transportation is considered in Hızır (2006). There, the leader represents transportation managers aiming to make the transport systems sustainable; while the follower represents the decisions of the network users minimizing their travel costs.

In summary, green logistic problems have been modeled as bi-objective programs; but few of them have been studied as bi-level ones. Nevertheless, existing bi-level green logistic problems have not deal with a production-distribution scheme, where customer selection, transportation, and manufacturing decisions are involved. Hence the research herein presented fills an interesting gap in the green logistics area.

3 Mathematical formulation

In this section the mathematical formulation is described. The sets, parameters, decision variables, and the assumptions considered are presented next. Let I, L, M , and N denote the set of customers, types of vehicles, facilities, and commodities, respectively. Also, let $V(l)$ be the set of available vehicles from each type $l \in L$, and $k(l)$ denotes the $k-$th type of vehicle $l \in L$ where $k(l) \in V(l)$.

In a similar manner as in Anderluh et al. (2019), Eskandarpour et al. (2019) and Li et al. (2019), the CO_2 emissions per unit distance from the type of vehicle $l \in L$ are considered as e_l. Let ϵ_{mn} be the CO_2 emissions generated by manufacturing each commodity $n \in N$ at facility $m \in M$. Also, consider ε as the CO_2 emissions per unit distance caused by shipping commodities from a facility to the depot. Let g_n represent the profit associated with each commodity $n \in N$. The distance between a pair of customers $i, j \in I$ is denoted by d_{ij}, and δ_{in} represents the demand of commodity $n \in N$ ordered by customer $i \in I$. Also, let w^{min} represent the minimum profit imposed by the distributing company.

Regarding the costs involved in the leader's objective function, let r_l be the rental cost of vehicle type $l \in L$; c_l is a correction factor that converts the distance travelled into a cost for each vehicle type $l \in L$; α_{mn} is the acquisition cost for each commodity $n \in N$ from facility $m \in M$ (includes the shipping costs from each facility to the depot).

Furthermore, u_l^{max} is the available capacity associated with the type of vehicle $l \in L$, and v^{max} represents the maximum duration of the route. Let t_{ij} denote the required time to arrive from customer $i \in I$ to customer $j \in I$, and it is defined as the sum of the corrected distance and the service time at customer $j \in I$; it is computed as $t_{ij} = d_{ij}\varphi + h_j$, where φ is a factor that converts the distance to time. Also, consider that the service time at the depot can be neglected, that is $h_0 = 0$, where the depot is denoted by sub-index 0. Let γ^1 be a sufficient large positive constant that bounds the number of arcs in a route.

In the follower's problem, f_n represents the raw material required to produce the commodity $n \in N$, β_{mn} represents the manufacturing costs for commodity $n \in N$ at facility $m \in M$, and ρ_m indicates the shipping costs from facility $m \in M$ to the depot. Also, s_m^{max} is the

Table 1 List of sets and parameters

Notation	Description
Sets	
I	Customers
L	Type of vehicle
M	Facilities
N	Commodities
$V(l)$	Available vehicles from each type $l \in L$
Parameters	
e_l	CO_2 emissions from the type of vehicle $l \in L$ (per unit distance, $kg\ CO_2/km$)
ϵ_{mn}	CO_2 emissions for manufacturing each commodity $n \in N$ in facility $m \in M$
ε	CO_2 emissions caused by shipping commodities from a facility to the depot (per unit distance)
g_n	Profit associated with each commodity $n \in N$
d_{ij}	Distance between the pair of customers $i, j \in I$ (km)
δ_{in}	Demand of commodity $n \in N$ by customer $i \in I$
w^{min}	Minimum profit imposed by the distributing company
u_l^{max}	Maximum available capacity associated with the type of vehicle $l \in L$
v^{max}	Maximum duration of the route
r_l	Rental cost of vehicle type $l \in L$
c_l	Correction factor that converts the distance traveled into a cost for each vehicle type $l \in L$
α_{mn}	Acquisition cost for each commodity $n \in N$ from facility $m \in M$
	(includes the shipping costs from each facility to the depot)
t_{ij}	Required time to arrive from customer $i \in I$ to customer $j \in I$
φ	Factor that converts the distance in time
γ^1	Sufficient large positive constant
γ^2	Sufficient large positive constant
f_n	Raw material required to produce the commodity $n \in N$
β_{mn}	Manufacturing costs for commodity $n \in N$ at facility $m \in M$
ρ_m	Shipping costs from facility $m \in M$ to the depot
s_m^{max}	Maximum CO_2 emission rate allowed at facility $m \in M$ ($kg\ CO_2$)
π_m^{max}	Maximum availability that can be manufactured at facility $m \in M$

maximum CO_2 emission rate allowed at facility $m \in M$, and π_m^{max} represents the maximum availability that can be manufactured at facility $m \in M$. Finally, let γ^2 be a sufficient large positive constant that bounds the total manufactured commodities at the facilities. All the sets and parameters are summarized Table 1.

The binary leader's decision variables are detailed next:

$$x_i = \begin{cases} 1, & \text{if the customer } i \in I \text{ is selected} \\ 0, & \text{otherwise} \end{cases}$$

$$y_{ij}^{k(l)} = \begin{cases} 1, & \text{if arc } (i, j) \text{ is in the route of vehicle } k \text{ of type} l \in L \\ 0, & \text{otherwise} \end{cases}$$

Table 2 List of decision variables

Notation	Description
Leader's variables	
x_i	Binary selection of i-th customer
$y_{ij}^{k(l)}$	Binary inclusion of the arc (i, j) in the route of vehicle k of type $l \in L$
$z^{k(l)}$	Binary selection for the k-th vehicle of type l
Follower's variables	
p_{mn}	Amount of commodity $n \in N$ manufactured at facility $m \in M$
q_m	Binary selection of facility $m \in M$

$$z^{k(l)} = \begin{cases} 1, & \text{if the } k\text{-th vehicle of type } l \text{is used} \\ 0, & \text{otherwise} \end{cases}$$

The follower's decision variables are denoted by p_{mn}, indicating the amount of commodity $n \in N$ manufactured at facility $m \in M$, and by q_m, denoting if facility $m \in M$ is used to manufacture commodities or not. All the decision variables herein considered are enlisted in Table 2.

To simplify notation in the mathematical model, let us define the depot as the 0 node, and the set that contains the depot and customers as $I^* = I \cup \{0\}$. Therefore, the proposed bi-objective bi-level programming mathematical model is as follows:

$$\min_{y,x,z} \sum_{i \in I^*} \sum_{j \in I^*} \sum_{l \in L} \sum_{k(l) \in V(l)} (e_l d_{ij}) y_{ij}^{k(l)} + \sum_{m \in M} \sum_{n \in N} \epsilon_{mn} p_{mn} + \sum_{m \in M} \varepsilon d_{m0} q_m \tag{1}$$

$$\max_{y,x,z} \sum_{i \in I} \left(\sum_{n \in N} g_n \delta_{in} \right) x_i - \sum_{l \in L} r_l \left(\sum_{k(l) \in V(l)} z^{k(l)} \right) - \sum_{i \in I^*} \sum_{j \in I^*} \sum_{l \in L} \sum_{k(l) \in V(l)} (c_l d_{ij}) y_{ij}^{k(l)} \\ - \sum_{m \in M} \sum_{n \in N} \alpha_{mn} p_{mn} \tag{2}$$

subject to:

$$\sum_{j \in I} y_{0j}^{k(l)} = z^{k(l)} \qquad \forall l \in L, k(l) \in V(l) \tag{3}$$

$$\sum_{i \in I} y_{i0}^{k(l)} = z^{k(l)} \qquad \forall l \in L, k(l) \in V(l) \tag{4}$$

$$\sum_{j \in I} \sum_{l \in L} \sum_{k(l) \in V(l)} y_{ij}^{k(l)} = x_i \qquad \forall i \in I \tag{5}$$

$$\sum_{j \in I} y_{ij}^{k(l)} = \sum_{j \in I} y_{ji}^{k(l)} \qquad \forall i \in I, l \in L, k(l) \in V(l) \tag{6}$$

$$\sum_{i \in W} \sum_{j \in W} y_{ij}^{k(l)} \leq |W| - 1 \qquad \substack{W \subseteq I^*, 2 \leq |W| \leq |I|+1 \\ \forall l \in L, k(l) \in V(l)} \tag{7}$$

$$\sum_{i \in I^*} \sum_{\substack{j \in I \\ i \neq j}} t_{ij} y_{ij}^{k(l)} \leq v^{max} \qquad \forall l \in L, k(l) \in V(l) \tag{8}$$

$$\sum_{i \in I} \sum_{\substack{j \in I^* \\ i \neq j}} \left(\sum_{n \in N} \delta_{in} \right) y_{ij}^{k(l)} \leq u_l^{max} \qquad \forall l \in L, k(l) \in V(l) \tag{9}$$

$$\sum_{k(l) \in V(l)} z^{k(l)} \leq |V(l)| \qquad \forall l \in L \tag{10}$$

$$\sum_{i \in I} \sum_{j \in I} y_{ij}^{k(l)} \leq z^{k(l)} \gamma^1 \qquad \forall l \in L, k(l) \in V(l) \tag{11}$$

$$\sum_{i \in I} \left(\sum_{n \in N} g_n \delta_{in} \right) x_i - \sum_{l \in L} r_l \left(\sum_{k(l) \in V(l)} z^{k(l)} \right) - \sum_{i \in I^*} \sum_{j \in I^*} \sum_{l \in L} \sum_{k(l) \in V(l)} (c_l d_{ij}) y_{ij}^{k(l)} - \sum_{m \in M} \sum_{n \in N} \alpha_{mn} p_{mn} \geq w^{min} \tag{12}$$

$$y_{ij}^{k(l)}, x_i, z_l \in \{0, 1\} \quad \forall i, j \in I^*, l \in L, k(l) \in V(l) \tag{13}$$

in which for a fixed leader's decision y, x, z, the follower's variables p and q solve

$$\min_{p,q} \sum_{m \in M} \sum_{n \in N} \beta_{mn} p_{mn} + \sum_{m \in M} \rho_m q_m \tag{14}$$

subject to:

$$\sum_{m \in M} p_{mn} = \sum_{i \in I} \delta_{in} x_i \qquad \forall n \in N \tag{15}$$

$$\sum_{n \in N} \epsilon_{mn} p_{mn} \leq s_m^{max} \qquad \forall m \in M \tag{16}$$

$$\sum_{n \in N} f_n p_{mn} \leq \pi_m^{max} \qquad \forall m \in M \tag{17}$$

$$\sum_{n \in N} p_{mn} \leq q_m \gamma^2 \qquad \forall m \in M \tag{18}$$

$$p_{mn} \in Z^+ \cup \{0\} \qquad \forall m \in M, n \in N \tag{19}$$

$$q_m \in \{0, 1\} \qquad \forall m \in M \tag{20}$$

The model defined by (1)-(20) is a bi-objective bi-level linear programming problem. In Eq. (1) the leader's objective function measures the CO_2 emissions caused by the route of each type of vehicle and the CO_2 generated by the manufacturing and shipping process from the facilities. In Eq. (2), the other leader's objective function corresponds to profit maximization. The first term represents the total income per each commodity demanded by the customers, the remaining terms are the total rental cost associated with the vehicles, the total transportation costs of all vehicles, and the commodities' acquisition costs from the facilities. Regarding the leader's constraints, Eq. (3) requires that each vehicle has a single departure from the depot, Eq. (4) ensures that each vehicle only arrives once to the depot. Constraint (5) indicates that the selected customers must be only visited once, Eq. (6) is the flow conservation constraint, and Eq. (7) corresponds to a classical constraint that avoid subtours. Constraint (8) ensures that the time associated with each route should not exceed the maximum time established, Eq. (9) states that the commodities included in each route do not exceed the capacity of each vehicle type, Eq. (10) indicates that there is a maximum availability of vehicles from each type, Eq. (11) ensures that only vehicles that are being used have an assigned route. Constraint (12) establishes a minimum required profit for the company. Note that this constraint involves leader and followers variables, which is known as a coupling constraint in bi-level programming. Thus, feasibility of a solution is achieved by having a feasible value for the leader's variables, the optimal solution for the follower, and by verifying that constraint (12) is also satisfied. Moreover, Eq. (13) establishes the binary constraints for each leader's decision variables y, x, and z.

The follower's problem is defined by Eqs. (14)–(20). In Eq. (14), the follower's objective function is presented, which aims to minimize the manufacturing and shipping costs. In Eq. (15), the supply of all accumulated demand is assured. Constraint (16) guarantees that the CO_2 emissions for manufacturing the demanded commodities cannot exceed the maximum CO_2 emissions rate allowed at each facility, and Eq. (17) states that the manufactured commodities cannot exceed the maximum production at each facility. Eq. (18) ensures that if facility $m \in M$ manufactures some commodities, then the associated shipping costs are taken into account. Finally, Eqs. (19) and (20) restrict that the follower's variables are non-negative integers and binary, respectively.

In order to have a well-defined bi-level problem, an optimistic approach is assumed. In other words, in the case when the follower's problem has multiple optimal solutions for a given leader's decision, the follower chooses the solution that results to be the most convenient one for the leader. In our problem, this is not straightforward, since the leader simultaneously considers two objectives. We are assuming that the follower's solution that implies more profit for the leader is chosen. The rationale behind this assumption relies on the fact that the coupling constraint is related to the profit. By assuming this optimistic approach, bi-level feasibility is being sought. This can be seen as a cooperative scheme. Moreover, since the follower does not benefit by affecting the leader's objective function, the optimistic approach is commonly assumed, see Kalashnikov et al. (2015) and Sinha et al. (2016).

4 A nested bi-objective tabu search algorithm

As mentioned before, the characteristics of the lower level problem prohibit to apply the optimality conditions and reformulate the bi-level programming model into a single-level one. Nevertheless, if a linear relaxation of the lower level is applied, then the equations to avoid subtours appear in the upper level constraints. The latter clearly complicates the exact optimization of the relaxed bi-level problem. Therefore, the use of exact methods to solve this bi-objective bi-level problem is too complicated and computationally inefficient.

On the other hand, the use of meta-heuristics to solve bi-level problems has been a successful option in the recent years (see Talbi (2013)). Additionally, meta-heuristics to obtain good quality solutions of production-distribution bi-level problems have been efficiently applied in different contexts, as in Calvete et al. (2011), Camacho-Vallejo et al. (2015), and Nourifar et al. (2020). In particular, tabu search meta-heuristic has been used to approximate solutions of bi-level routing problems in Marinakis et al. (2007), Mauttone et al. (2008), and Marinakis and Marinaki (2008).

Tabu search is a meta-heuristic first proposed in Glover (1986). The main idea of this meta-heuristic is to prohibit some movements, that have a tabu status, in order to prevent cycling. By doing the latter, worst movements can be performed to search other path of solutions. The tabu status of a movement is lost after a predefined time, converting it into an allowed one. It is convenient to point out that tabu search has been succesfully applied to solve vehicle routing problems, as in Li et al. (2012), Potvin and Naud (2011), Renaud et al. (1996), and Shen et al. (2009).

Therefore, a nested bi-objective tabu search (NBOTS) algorithm is proposed to approximate the Pareto front of the bi-objective bi-level problem defined by Eq. (1)-(20). Our algorithm uses the ideas described in Kulturel-Konak et al. (2006) to randomly select one of the objectives to guide the search. Additionally, the classical nested approach to solve bi-level programming problems is applied; that is, the follower's problem is optimally solved for each leader's solution. A detailed description of the proposed NBOTS is presented next.

4.1 Solution encoding

The solution is represented as a collection of $\sum_{l \in L} |V(l)| + 1$ strings, where the first string represents the unselected customers and the remaining ones correspond to each vehicle.

It is important to specify that only the leader's decision variables are explicitly or implicitly represented in the solution encoding. In the case when the $i-$th customer appears in a string different than the first one, it means that the $i-$th customer is selected, implying that $x_i = 1$. Therefore, variable x is considered explicitly in the solution. In contrast, variable y is implicitly represented. Since y is associated with the routing decision, the solution encoding gives the information about which customers are associated with the vehicles, and then the routes are created in an arbitrary manner. Regarding variable z, note that if there is a customer assigned in the $j-$th string, then the corresponding vehicle is being used and $z_j = 1$. The follower's decision variable p will be obtained by optimally solving the lower level problem for each leader's solution.

4.2 Initial solution

An initial feasible solution is constructed in order to enter into the tabu search scheme. First, given a predefined range of the minimum and maximum number of desired customers, a random number nc in that range is generated. Then, the nc customers are randomly selected and they are assigned to a vehicle randomly (among all the types of vehicles), if and only if, the vehicle's capacity is not exceeded.

After the nc customers have been selected and assigned to a vehicle, CPLEX optimizer is used to obtain the routing. The model solved by CPLEX neglects the maximum duration time of a route. Preliminary results indicated that a high degree of infeasibility can be obtained by including this constraint. Moreover, the computational effort is significantly increased. Therefore, we remove this constraint and the constructed route may be infeasible in terms of the route's maximum duration time. To address this issue, a procedure that repairs an infeasible solution into a feasible one is included.

4.3 Repairing an infeasible solution

The initial routes are constructed by following the same order in which the customers are being appended to a vehicle. Once all customers associated with a vehicle are known, the route is identified and its duration is computed. In case when the route exceeds the maximum duration time, the customer that contributes the largest total distance in the route is removed and added into the string associated with unselected customers. The duration of the route is recalculated and its feasibility is checked. This procedure is repeated until the maximum duration time of the route is not exceeded.

4.4 Evaluating the leader's objective function

Once a leader's feasible solution is obtained, the required demand of the selected customers for each commodity can be computed. These values are given as parameters to the lower level, which is defined by Eqs. (14)–(20). This problem is optimally solved by using CPLEX. Once the optimal follower's variables with respect to the fixed leader's variables are known, the evaluation of both leader's objective functions can be done. Denote F_1 and F_2 as the CO_2 emissions and profit objective functions, respectively. Then, the tabu search is performed. Algorithm 1 depicts the pseudocode for the construction of a feasible solution.

Algorithm 1: Constructing a feasible solution

Input : nc

$x' \leftarrow$ Randomly select nc customers ;
$(y, z) \leftarrow$ Route_CPLEX(x');
if *infeasible* **then**
  $x \leftarrow$ Repair(x');
  $(y, z) \leftarrow$ Route_CPLEX(x);
else
  $x \leftarrow x'$;
end
$p \leftarrow$ SolveLL_CPLEX(x);
$F_1 \leftarrow$ Evaluate $F_1(y, p)$;
$F_2 \leftarrow$ Evaluate $F_2(x, y, z, p)$;
Output: x, y, z, p, F_1, F_2

Detailed description of the NBOTS algorithm is presented next:

Step 0 **Initialization** Construct a feasible leader solution with the procedure described above and continue to Step 1. Initialize the non-dominated (ND) solution list as empty.

Step 1 **Select the objective** Select one of the two objectives to become active by using a Bernoulli probability mass function. This probability varies in each iteration.

Step 2 **Search in neighborhood** Two neighborhoods (N1 and N2) are considered for each objective function. However, N1 varies depending on the selected objective. N2 remains the same for both objective functions.
For the objective related to emissions (F_1), N1 consists of removing a number of selected customers from each vehicle. The number of customers to be removed is randomly chosen as a percentage of the selected customers (between 0 and 40%). In order to decide which customers will be unselected, the farthest customer (in terms of distance) is chosen. The procedure continues until the number of customers to be removed from each vehicle is reached.
For the objective related to the profit (F_2), N1 consists of ordering unselected customers, in terms of their demand, in decreasing order. Also, vehicles are ordered in terms of their remaining capacity, in decreasing order. Then, each unselected customer with the largest demand is inserted into each vehicle with enough remaining capacity. The insertion is performed in the most convenient possible position of the route. Therefore, the best movement is conducted. The procedure is repeated until

no unselected customers can be inserted into a route, which occurs when capacity of the vehicle or maximum duration of the route is violated.

It is important to mention that after each removal or insertion of a customer in N1, number of selected customers and the accumulated total demand vary. To address the former, the routing must be re-optimized; and, for the latter, the lower level problem must be optimally solved again. If F_1 is being considered, then a movement in N1 leads to a decrease in the CO_2 emissions; on the other hand, the profit increases for F_2.

Subsequently, the improved solution enters into N2, which consists in changing customers among vehicles. Each customer will be inserted in the best position of a different one. The best movement will be performed. In this neighborhood, customers are moved to a different vehicle, maintaining the accumulated demand at the same level. In this case, the routing must be also re-optimized, but it is not necessary to solve the lower level problem.

After both neighborhoods have been explored, a candidate solution is obtained and its corresponding objective function values are updated.

Step 3 **Update the ND solutions list** Compare the candidate solution with the current ND solution list as follows: if the candidate solution dominates at least one solution in ND, then remove these dominated solutions from the ND set and add the candidate solution to ND. Also, a candidate solution that is not dominated by any current solution belonging to ND must be added to ND.

Step 4 **Update the tabu structures** Add the accepted movement at Step 2 to the tabu list and update the remaining iterations in tabu for other prohibited movements. The number of iterations that a movement will remain as tabu is randomly chosen between 8 and 15. In case when the candidate solution is in the tabu list, but it dominates any solution in the ND solutions list, it will be included in the ND set (aspiration criterion).

Step 5 **Diversification** A diversification scheme based on restart is used. If ND has not been updated in the last (MaxIter/4) iterations, one of the ND solutions found during the search is uniformly selected as the new current solution. Both tabu structures are reset to empty and the search restarts from the selected solution, that is, return to Step 1.

Step 6 **Stopping criterion** While a stopping criterion is not satisfied, return to Step 1. In this algorithm, two stopping criteria are considered: a maximum number of iterations (MaxIter) conducted without updating ND or a maximum CPU time limit.

In Algorithm 2 the outline of the NBOTS is depicted. The search in neighborhood for F_1 and F_2 is shown in Algorithms 3 and 4 , respectively.

5 Computational experimentation

To test the proposed algorithm's efficiency and its ability to approximate the Pareto front, computational experimentation is carried out.

To have an appropriate set of benchmark instances, we consider the set of instances for the vehicle routing problem with split deliveries (VRPwSD) considered in Cordeau et al. (2002) and complement them with the data of emissions and the manufacture process. The VRPwSD instances contain the data regarding customers' demand and their location, capacity and number of vehicles, and maximum duration time of a route. The parameters related to

Algorithm 2: General pseudocode of the NBOTS algorithm

```
Input  : x, y, z, p, F1, F2
Initialize tabu structures;
ND ← Ø;
while Stopping criteria is not reached do
    rand ← Generate a random number between 0 and 1;
    if rand <=Be(0.5) then
        // F1 is selected ;
        (x, y, z, p) enters into N1 (remove);
        (x, y, z, p) enters into N2 (change) ;
    else
        // F2 is selected ;
        (x, y, z, p) enters into N1 (insert);
        (x, y, z, p) enters into N2 (change);
    end
    Update ND and tabu structures;
    if Diversification criterion is met then
        Randomly select a solution in ND;
        Reset tabu structures;
    end
end
Output: ND
```

Algorithm 3: Exploring the N1 and N2 neighborhoods for F_1

```
Input  : x, y, z, p, F1
// N1 is explored;
for each vehicle do
    rem ← Generate a random number between 0 and 0.4;
    aux ← 1;
    ncv ← Number of customers in the vehicle ;
    while aux <= ⌊ rem × ncv⌋ do
        x ← x\ {farthest customer} ;
        (y, z) ← Route_CPLEX(x);
        aux ← aux+1 ;
    end
    p ← SolveLL_CPLEX(x);
    F1 ← Evaluate F1(y, p) ;
end
// N2 is explored;
while F1 cannot be improved do
    for each selected customer do
        for each vehicle do
            x ← Insert the customer in the most convenient position (if possible);
            (y, z) ← Recalculate_Route(x);
            F1 ← Evaluate F1(y, p) ;
        end
    end
    x ← Perform the best change ;
    (y, z) ← Route_CPLEX(x);
    p ← SolveLL_CPLEX(x);
    F1 ← Evaluate F1(y, p) ;
end
F2 ← Evaluate F2(x, y, z, p) ;
Output: x, y, z, p, F1, F2
```

Algorithm 4: Exploring the N1 and N2 neighborhoods for F_2

```
Input  : x, y, z, p, F2
// N1 is explored;
Sort unselected customers in decreasing order (in terms of demand);
Sort vehicles with remaining capacity in decreasing order (in terms of capacity);
while an unselected customer can be inserted do
    for each unselected customer do
        for each vehicle with remaining capacity do
            x ← x ∪ {customer} ;
            (y, z) ← Recalculate_Route(x);
            p ← SolveLL_CPLEX(x);
            F2 ← Evaluate F2(x, y, z, p) ;
        end
        x ← Insert customer in the most convenient vehicle ;
    end
    (y, z) ← Route_CPLEX(x);
    F2 ← Evaluate F2(x, y, z, p) ;
end
// N2 is explored;
while F2 cannot be improved do
    for each selected customer do
        for each vehicle do
            x ← Insert the customer in the most convenient position (if possible);
            (y, z) ← Recalculate_Route(x);
            F2 ← Evaluate F2(x, y, z, p) ;
        end
    end
    x ← Perform the best change ;
    (y, z) ← Route_CPLEX(x);
    F2 ← Evaluate F2(x, y, z, p) ;
end
F1 ← Evaluate F1(y, p) ;
Output: x, y, z, p, F1, F2
```

the plants were generated following the procedure described in Calvete et al. (2011). The number of located plants was chosen between 3 and 7. Then, the locations of the plants were randomly fixed from the square of $[-200, 200] \times [-200, 200]$. The products' acquisition costs were selected from the interval $[0.5, 1.5]$. For the shipping costs, a number was randomly generated from $[2, 5]$ and it was added to the following term $0.5\times$ distance (plant, distribution center). Finally, the production capacity was randomly generated from the interval [total demand/number of plants, total demand].

The remaining parameters were generated as follows: based on the existing proportionality in the instances, φ is set to 1. Also, the factor that relates cost and distance traveled per each vehicle (c_l) and the profit per commodity (g_n) are set to 100. Regarding the CO_2 emission parameters, 210 is considered as a basis for the vehicles emissions, which it is multiplied by the corresponding percentages obtained from Hill et al. (2013) to reflect freight land transport emissions factors. An average of the maximum production capacity of the plants is considered as a basis, the maximum CO_2 emissions per plant would be the basis times the production capacity. A similar process for the CO_2 emissions per plant is done. The ratio between the average of the maximum production capacity and the smallest production and shipping cost of the plants is considered as the basis, afterwards this number is multiplied

Table 3 Sizes of the instances

Instance	Customers ($\|I\|$)	Plants ($\|M\|$)	Vehicle types ($\|L\|$)	Amount p/type ($\|V(l)\|$)
1	48	4	4	1
2	96	3	4	2
3	144	4	4	3
4	192	3	4	4
5	240	3	4	5
6	288	4	4	6
7	73	3	6	1
8	145	4	6	2
9	217	7	6	3
10	289	5	6	4
11	1008	4	4	21
12	721	3	6	10

by the production and shipping cost of each plant. The minimum profit acceptable for the distributor company is set to 2000.

The previous explained process was implemented to generate 12 different instances for carrying out our computational experimentation. The main differences among these instances consist in the following: the number of customers vary between 48 and 1008; the type of vehicles between 4 and 6; the number of vehicles of each type between 1 and 21; and the plants between 3 and 7. The tests were conducted on a computer with a 3.10 GHz Intel Core i5-4440U CPU with 8 GB of RAM. The libraries of CPLEX version 12.6 were used for routing and solving the lower level problem through Visual Studio 2012. Table 3 shows the sizes of the instances.

The proposed NBOTS algorithm contains very few parameters that need calibration. Recall that the probability to select one objective in the local search is updated through the iterations. The time that a movement will remain as tabu is randomly chosen between 8 and 15 at each iteration. These values are fixed based on Kulturel-Konak et al. (2006) and preliminary experimentation. Note that the length of the tabu list is dynamic and depends on the number of customers and vehicles considered in the instance. In the local search, particularly in N1 for F_1, the number of customers to remove is chosen. In order to maintain diversity we randomly remove between 0 and 40% of the selected customers. The remaining parameters are related to diversity and to the stopping criteria: a maximum number of iterations without updating the ND list and a CPU running time limit, respectively. The former is related with the size of the instance, and the latter is set to 7200 seconds. The experimentation showed that the criterion always used to stop the program's execution was the maximum time limit. Based on this, the running time is not shown in the results.

Due to the randomness involved in the algorithm, ten runs per instance were performed. The results obtained from the experimentation are shown in Table 4. The first column represents the number of the instance we are referencing. The remaining columns are associated with the non-dominated solutions. The second and third columns show the minimum and maximum number of non-dominated solutions obtained by the algorithm, respectively. Finally, the last column shows the average of the non-dominated solutions among the ten runs of the algorithm.

Table 4 Number of non-dominated solutions obtained by the tabu search

Instance	Min	Max	Average
1	31	50	42
2	49	78	65
3	42	65	52
4	52	62	58
5	45	62	55
6	34	49	46
7	46	60	53
8	34	42	37
9	37	50	46
10	39	67	58
11	32	41	36
12	35	54	50

From Table 4 it can be seen that the tabu search obtained at least 32 non-dominated solutions. The largest number of non-dominated solutions corresponds to instance 4, in which 69 solutions were obtained. In average, there is at least 38 non-dominated solutions for each instance. The latter allow us to properly approximate the Pareto fronts.

In order to validate the aforementioned, the approximated Pareto fronts are plotted in Fig. 2 through 13. The run with largest number of non-dominated solutions is plotted for each instance. The approximated Pareto fronts are representative and cover a wide space. Recall that we are assuming that the distributor company has a minimum acceptable profit of 2000. Also, a greedy algorithm is used to compute a bound on the profit, and consequently on the CO_2 emissions. The key feature of the greedy algorithm consists of including customers into the vehicles, such that the maximum possible profit is achieved. Capacity and maximum duration time of a route constraints are considered during the assignment of customers. In the case when a customer cannot be included in any vehicle, it is maintained as unselected. This procedure is finished when all the customers have been considered. Finally, the profit and the CO_2 emissions associated with the feasible greedy solution are evaluated.

The approximated Pareto fronts obtained by the proposed tabu search algorithm are plotted in blue, while the bound obtained by the greedy algorithm is plotted in red.

Regarding the profit, instances 1, 5, 7, 10, and 12 (see Figs. 2, 6, 8, 11, and 13) found solutions that provide profit greater than the minimum acceptable (2000). This is a good feature of the algorithm and implies that it does not have problems with the coupling constraint, which greatly complicates the problem. Instance 4 has a higher threshold value. Its profit started around 35000 (see Fig. 5), below that value, losses were reported. A similar case occurred in instance 11, as it is shown in Fig. 12, where the profit started at 5500.

The obtained results shown that the proposed tabu search is able to find a sufficient number of non-dominated solutions. In other words, the algorithm is able to find the most convenient movements depending on the considered objective function, that is, including customers to increase the profit or unselect customers that generated the largest CO_2 emissions. As a result, a Pareto front with good shape is approximated. Moreover, the bound obtained by the greedy algorithm is always dominated by the obtained approximation of the Pareto fronts. It is worthy to highlight that all the approximated Pareto fronts seem to be non-convex, which indicates

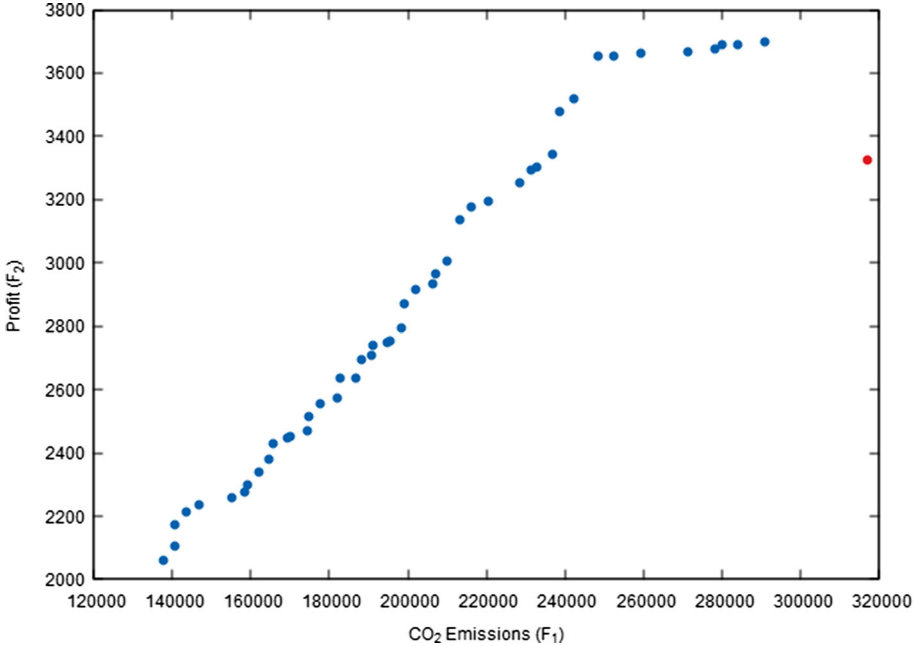

Fig. 2 Approximated Pareto front for instance 1

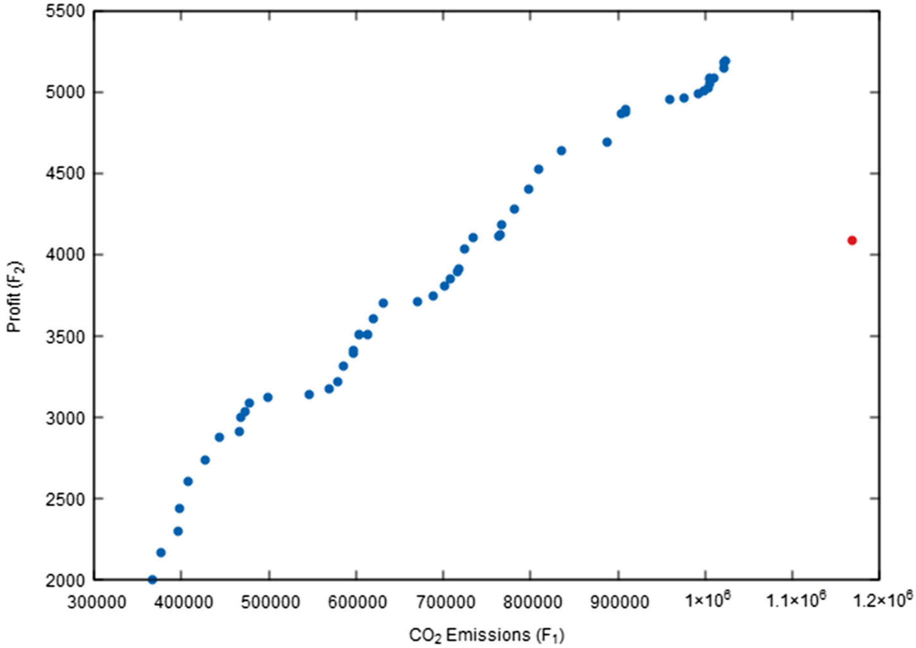

Fig. 3 Approximated Pareto front for instance 2

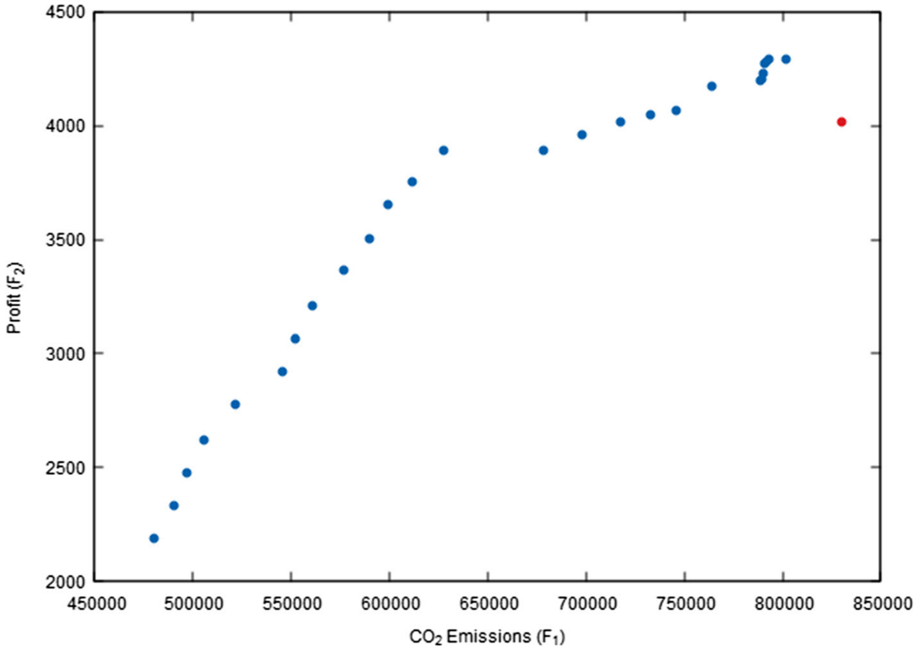

Fig. 4 Approximated Pareto front for instance 3

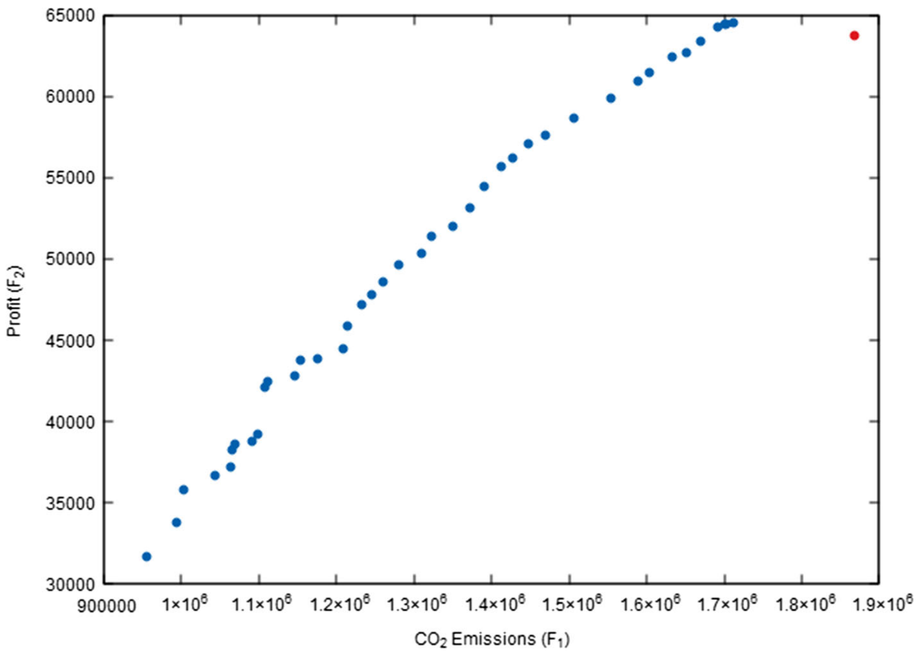

Fig. 5 Approximated Pareto front for instance 4

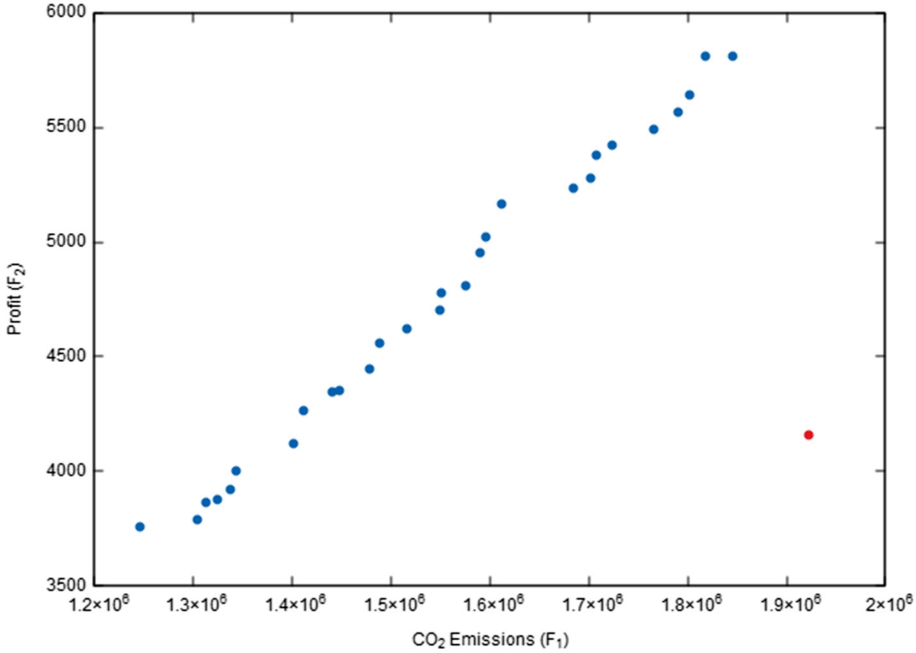

Fig. 6 Approximated Pareto front for instance 5

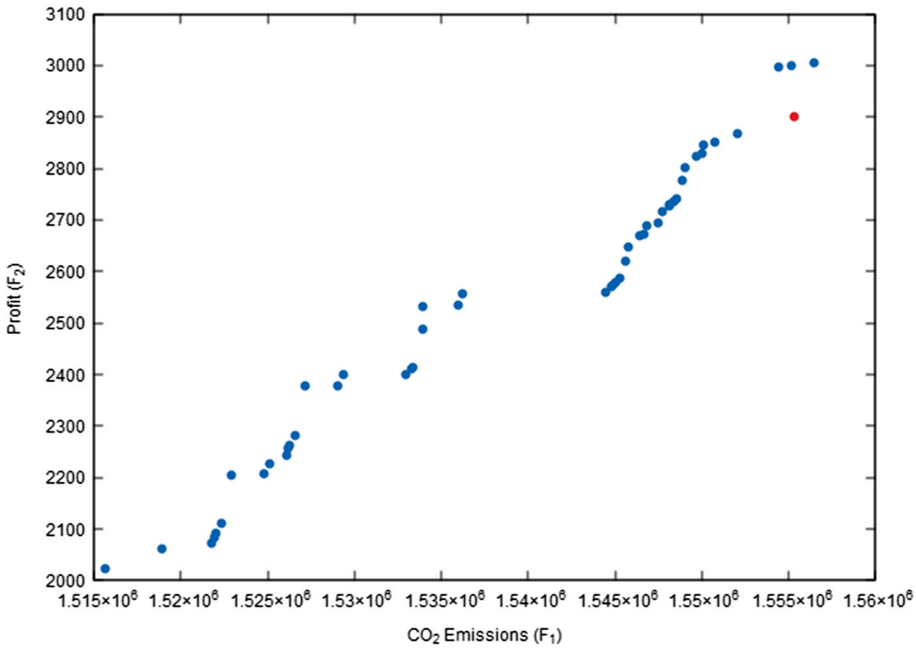

Fig. 7 Approximated Pareto front for instance 6

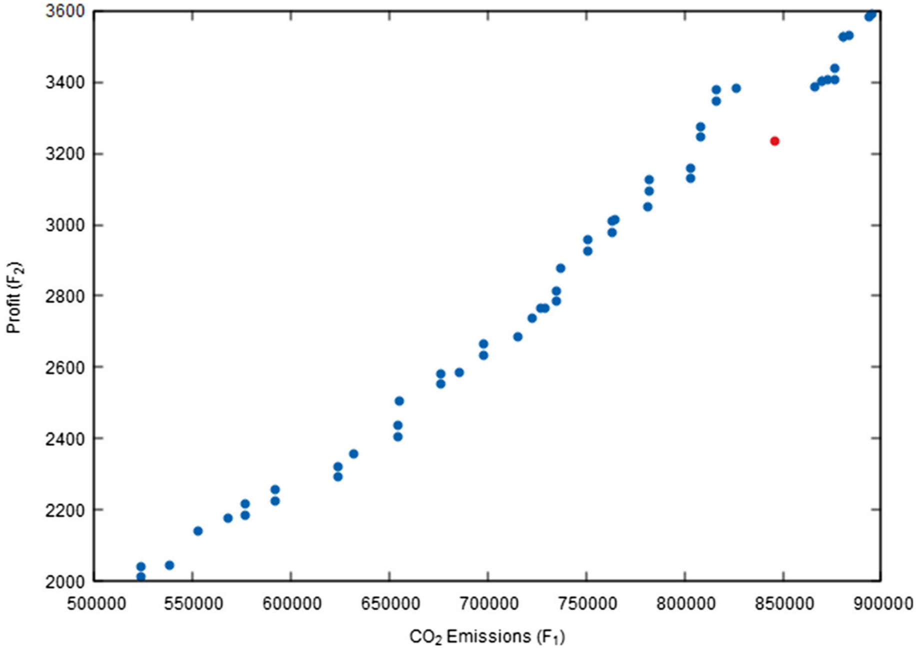

Fig. 8 Approximated Pareto front for instance 7

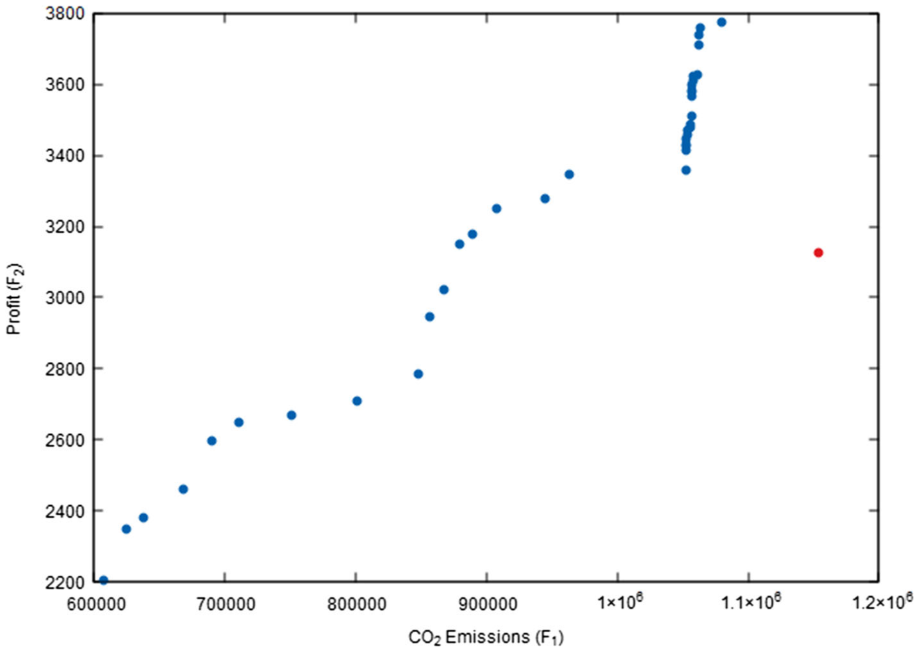

Fig. 9 Approximated Pareto front for instance 8

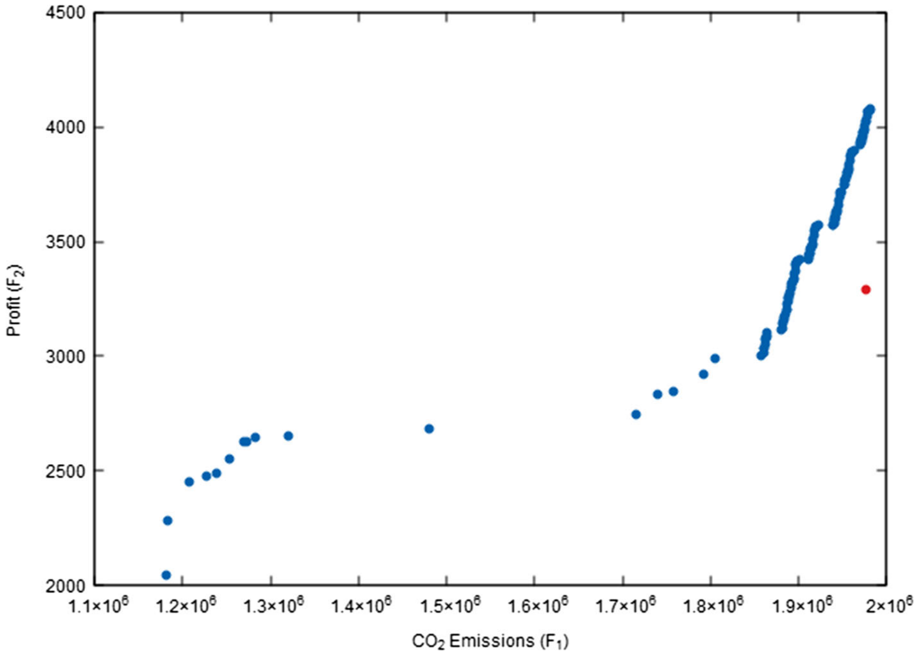

Fig. 10 Approximated Pareto front for instance 9

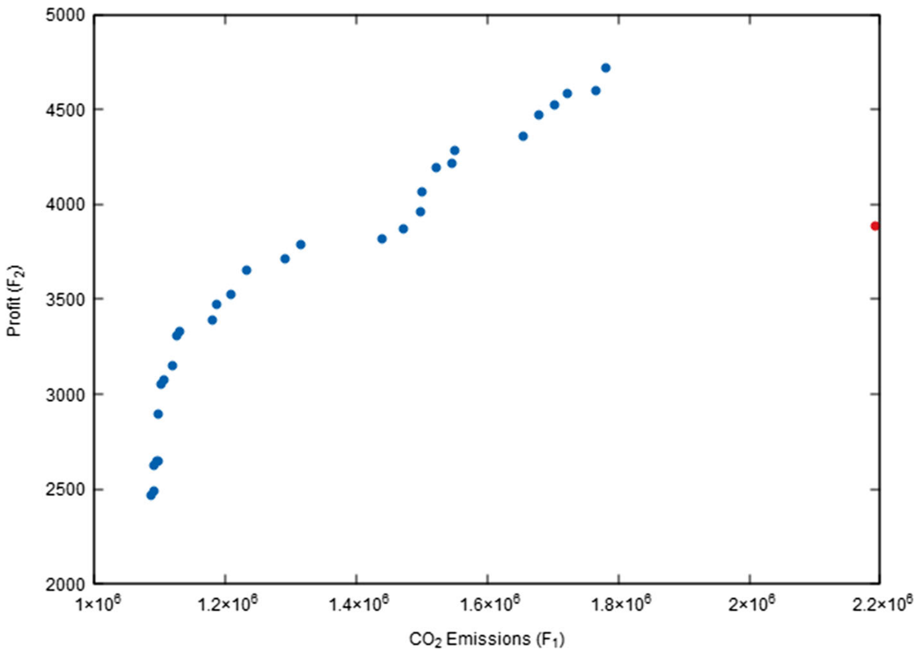

Fig. 11 Approximated Pareto front for instance 10

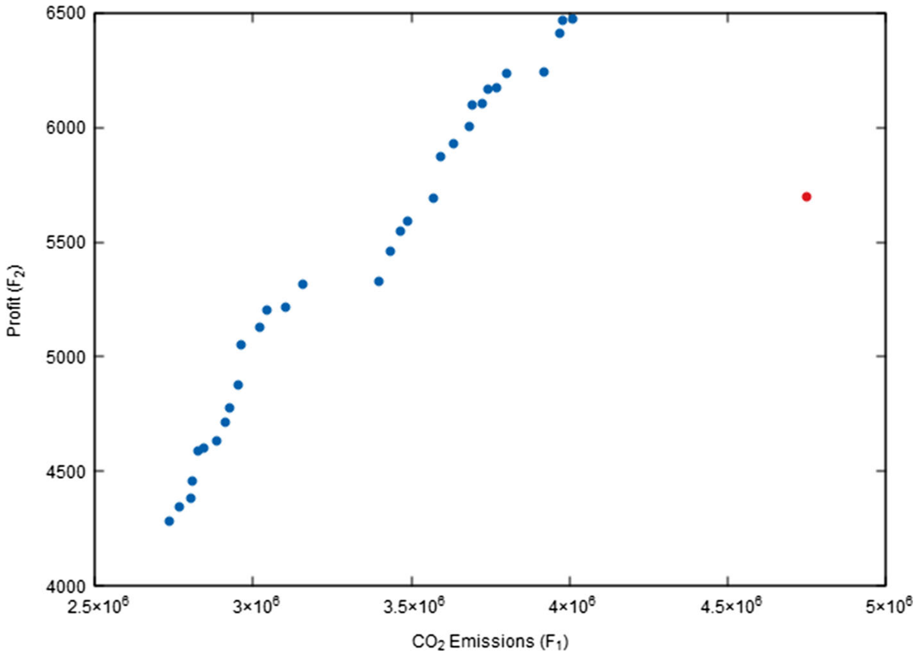

Fig. 12 Approximated Pareto front for instance 11

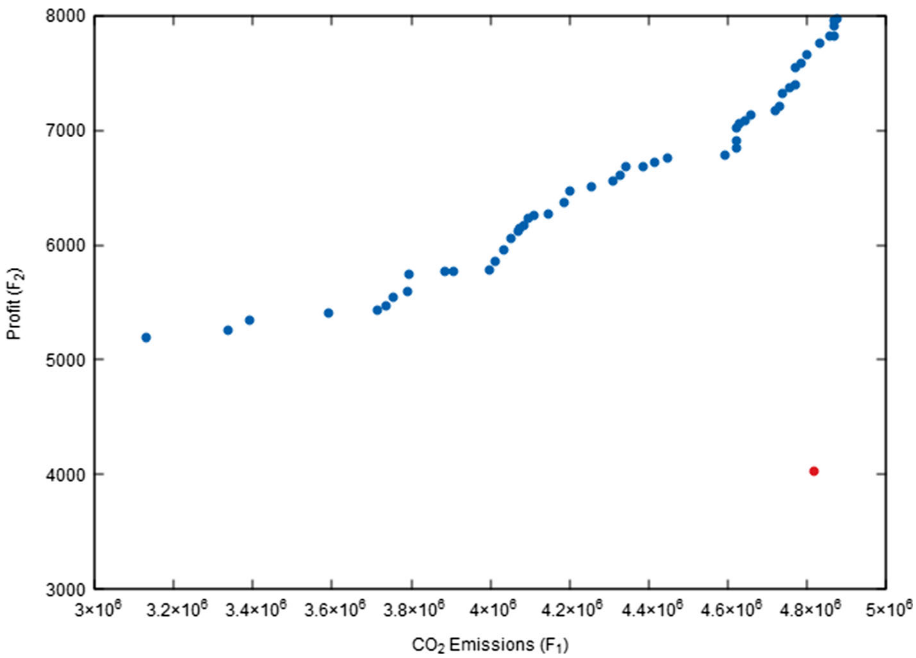

Fig. 13 Approximated Pareto front for instance 12

that the proposed tabu search is able to overcome this issue. Hence, a good exploration of the space is being performed with the proposed search.

The importance of having a set of non-dominated solutions instead of a unique solution is in the support it gives to the decision maker. For example, if the pollution in the environment reaches a high level, the decision maker may consider the maximum CO_2 emissions that could be released but bearing in mind the profit. In this case, the feasible solution that the decision maker may implement to overcome this issue is already known, which is given by the tabu search algorithm. On the other hand, if the air is cleaner, a solution that gives more profit but polluts more could be implemented. A trade-off between profit and CO_2 emissions could be achieved based on the actual conditions of the environment.

6 Conclusions and further research

In this paper, a supply chain situation in which a company distributes commodities over a selected subset of customers while a manufacturer produces the commodities is studied. The distributor company has two objectives: the maximization of the profit gained by the distribution process and the minimization of CO_2 emissions. This situation is modeled as a bi-objective bi-level logistics problem. The main motivation is to help the decision maker (distributor company) to find the trade-off between profit and CO_2 emissions. This is achieved by obtaining an approximation of the Pareto frontier.

Due to the inherent complexity for finding the exact Pareto frontier, a tabu search algorithm is proposed. One of the main characteristics of the proposed algorithm is having two different search neighborhoods. The first one varies depending on the selected objective to improve profit (or CO_2), while both objectives share the second proposed neighborhood. The numerical results from computational experience show that the performance of the proposed tabu search algorithm is very acceptable. The method reduces computational effort by conducting a controlled local search in different neighborhoods, and by performing a diverse exploration of the decision space. The results indicate that the algorithm is able to find a large number of non-dominated solutions. This is the approximation of the Pareto frontier. Consequently, the approximated Pareto frontiers covers large wide region in the decision space.

Recall that in each movement of the local search two different problems are solved by using an optimizer, that is, the routing problem and the lower level problem. Therefore, to make a significant reduction in computational effort, a controlled tabu search hybridized with a path-relinking procedure could be proposed. This further research direction aims to obtain non-dominated solutions in both extremes of the Pareto frontier by using the tabu search, and use the path-relinking procedure to obtain the remaining non-dominated points starting from the extreme ones. This hybridization has achieved a significant CPU time decrease and sometimes a better approximation of the Pareto frontier (see Barbalho et al. 2013).

Another idea to extend this research is to apply a microscopic approach to calculate the CO_2 emissions. For example, the ideas of Bektaş and Laporte (2011) could be considered, in which the cargo in the vehicle and the speed at which a vehicle travels on each arc of the route are taken into account. That approach leads to a more reliable emissions calculation.

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