A CO_2 emissions minimization model for Location-Routing

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Abstract

In this thesis, the location-routing problem (LRP) is studied considering a minimum CO_2 emissions objective function with load dependency. We propose a mathematical model and an adaptation of the traditional LRP model. A computational comparison between these two models is carried out using adapted benchmark instances from the literature. Experiments evaluate the performance of both models in terms of the minimization of total cost (traditional objective function) and level of CO_2 emissions ("green" objective function). These objective functions are evaluated independently (i.e., mono-objective version), as well as a bi-objective version. When evaluating both, costs and level of CO_2 emissions, in a separate way, results show that the proposed model can reduce CO_2 emissions by 37% but with a high increase in cost. However, by constructing the Pareto frontier, solutions with a better trade-off between objectives are computed, showing that it is possible to reduce CO_2 emissions by 20% with a small penalty in the optimal cost compared to classical location-routing results. Valid inequalities are also proposed in order to enhance the performance of the proposed model in terms of computational time. The impact of these inequalities is also evaluated and reported herein.

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1 Introduction

1.1 Justification

Green logistics has been receiving important attention from different stakeholders in the search of sustainable supply chains (Lin et al., 2014). The need to design green and efficient logistics has grown since they become differentiating factors in terms of productivity and customer service (Mallidis et al., 2010; Memari et al., 2015). Lin et al. (2014) also acknowledge the risks of not taking into account green objectives when making strategic, tactical, and operational decisions on the supply chain design, which potentially imply that production operations and logistics are not sustainable in the long-term given their environmental and social consequences.

When designing an environmentally sustainable supply chain, two key decisions are to be made. These are the location of depots, and transportation (routing) decisions. In this paper, the design of a two-echelon supply chain is studied integrating location and routing decisions while minimizing the environmental impact.

These decisions have been widely studied independently. Facility location and vehicle routing optimization models and methods are not scarce among the operations research/operations management literature. An integrated approach, denoted as the location-routing problem (LRP), has also been considered, yielding to better results (Salhi & Rand, 1989), despite the increased resolution complexity of this integrated problem from the computational standpoint. The LRP considers a set of candidate depots and a set of geographically dispersed customers with deterministic demands. Each customer must be assigned to an open depot which will supply its demand. The shipments of customer demands are performed by a fleet of capacitated vehicles which are dispatched from the open depots, and the vehicle routes might include visits to multiple customers. There is a fixed cost associated with opening a depot, a distribution cost associated with the cost of using the vehicles, and the cost associated to the sequence in which customers are visited by the vehicles. The LRP consists on determining the location of the depots, the allocation of customers to depots, and the sequence in which customers are visited by each vehicle in order to minimize the total cost of the design, computed as the sum of the location and distribution costs (Tuzun & Burke, 1999). The LRP has been an important research field; a recent survey is presented by Prodhon & Prins (2014).

Moreover, large types of variants have been studied (Drexl & Schneider, 2015; Prodhon & Prins, 2014) where different features such as considering a heterogeneous fleet, time windows at the customers, pick-up and delivery routes, split deliveries, among others variants have been considered. However, despite the importance of evaluating the environmental impact of distribution decisions, the integrated location-routing problem in which the performance measures consider the level of CO_2 emissions generated by both, the transportation decisions and the number and locations of the depots to be opened, has not yet been deeply studied in the academic literature (see for example McKinnon et al. (2015)).

Further, integrating routing decisions with other decision problems in logistics is relevant from the academic and the industrial point of views. For example, combining inventory management decisions and routing is studied by Archetti et al., (2012); Pérez & Guerrero, (2015). These two decisions are proven to be mutually dependent, with or without the existence of time windows, since the size of the orders shipped to customers is limited by the vehicle capacity and thus, the routing decisions might be changed if the inventory policies at the customers are modified. The integration of these two decisions is often applied when implementing a vendor-managed inventory (VMI) system (Cordeau et al., 2015). On a similar context, inventory management, routing and location decisions are also proven to be mutually dependent. A matheuristic is presented by Guerrero et al. (2015) integrating a Lagrangian relaxation on a column generation framework. These articles show the impact of combining different levels of decisions within the same model, in order to obtain benefits in the long term.

This thesis presents an analysis of mathematical models to solve the LRP with environmental impact considerations. Two mixed-integer programming models are presented. The models aim to decide the number and location of depots to be opened, to allocate customers to those depots and to design the routes that must be performed by a homogeneous fleet of vehicles to distribute a single product while satisfying customer demands. Likewise, the measure of the environmental impact is computed by quantifying the level of CO_2 emissions from vehicles and the selected depots. In this sense, it is assumed that CO_2 emissions depend proportionally on both the distance traveled and the load carried by each vehicle on the arcs of the route. This problem is NP-hard, since it reduces to the Vehicle Routing Problem, which is known to be NP-hard (Montoya-Torres et al., 2015), if the decision is to open one depot with very large capacity, while the capacity of vehicles is also large.

The main contribution of this thesis is twofold. Firstly, the thesis proposes a mathematical model based on mixed-integer programming, which presents a way to make supply chain design decisions based on the global trend associated with green initiatives. Secondly, a study on the implications of choosing this optimization criterion is presented.

The thesis is organized as follows. Chapter 2 presents a review of related literature. The problem statement and the proposed mathematical model are both detailed in Chapter 3. Chapter 4 is dedicated to the computational results and comparisons between the proposed model and the classical mathematical model for the LRP adapted to minimize environmental impact. Conclusions and directions for future research are presented in Chapter 5.

1.2 Objectives and Research Question

1.2.1 Research Question

- How CO_2 emissions could be taken into account in a linear programing model for the location routing problem with homogeneous fleet and deterministic demand?

- Using those considerations, Is it possible to generate less environmental impacts? (in terms of CO_2 emissions)

1.2.2 General objective

Formulate a mixed integer programming model for Location Routing Problem with environmental considerations to evaluate how it could affect the strategical and operational decisions involved in this problem.

1.2.3 Specific objectives

- Design a mixed integer programing model for the “Green” LRP with homogeneous fleet that allows minimizing the environmental impact in terms of CO_2 emissions.

- Compare the performance of the proposed model versus an adapted version of the traditional formulation of LRP.

- Analyze the consequences of make decisions with the green LRP instead of make them with the LRP.

2 Literature Review

The optimization problems embedded in supply chain design have been studied from different perspectives, due to the importance of optimizing these decisions to increase the efficiency in logistics. The first jobs dedicated to study simultaneously the location of depots and vehicle routing date from the 1960s (Boventer, 1961; Maranzana, 1963; Webb, 1968). Authors like Martínez-Salazar et al. (2014) and Prodhon & Prins (2014) agree that one of the first researchers to analyze the LRP, as it is known nowadays, are Watson-Gandy & Dohrn (1973). Following that publication, the LRP has been deeply studied under different considerations, as evidenced in the review papers proposed by Balakrishnan et al. (1987), (Berman et al. (1995), Drexl & Schneider (2015), Min et al. (1998), Laporte (1989), Nagy & Salhi (2006) and Prodhon & Prins (2014) where it is possible to identify advances in the different variants of the original problem.

Moreover, according to Lin et al. (2014), green logistics has been receiving more attention from governments and companies worldwide. Therefore, it is interesting to review how in the literature has been treating the environmental considerations of logistics. First, Yang & Sun (2015) propose a location-routing model aiming to minimize the total routing costs for electric vehicles plus the location costs of battery stations where the vehicles can swap batteries in order to increase their driving ranges. The problem is solved using hybrid metaheuristics. Then, two more works are be associated to the LRP with environmental issues. Koç et al. (2016) develop a model describing a situation where the customers are located in zones with different speed limits affecting fuel consumption, and hence the total CO_2 emissions; while the work of Dukkanci & Kara (2015) is, to the best of our knowledge, the first paper to establish a Green Location-Routing Problem (GLRP) presenting a comprehensive model to quantify the impact of the CO_2 emissions. It is important to note that these works compute the cost of the CO_2 emissions and add it to the total cost function. None of them consider the level of emissions due to the location and number of the open facilities.

Regarding the environmental issues in facility location models (FLP), Li et al. (2008) and Wang et al. (2011) proposed multi-objective methods to minimize carbon emissions and logistic costs under different situations such as transportation operations outsourcing. Diabat & Simchi-Levi (2009) analyze how total operational cost is impacted by having a limit in CO_2 emissions. However, overall CO_2 emissions associated with opening depots are dependent on the number of customers to be attended. Nevertheless, there are other considerations that could be taken into account when choosing the location of depots. Ansbro & Wang (2013) presents a mixed integer linear programming formulation for the FLP. It considers not only external cost, but also the impact of waste disposal. So landfills and recycling facilities locations are included in the model and it is applied on a commercial case of study. A review on sustainability aspects considered within manufacturing facility location literature is presented by Chen et al. (2014), exposing the need and the relevance of developing research on the topic. Also, Diabat et al. (2013) propose a closed-loop supply chain design model including location decisions on a carbon emissions trading context to analyze how to make sustainable supplier selection decisions considering carbon emissions costs. A review on optimization models and methods for sustainable supply chain design is presented by Eskandarpour et al. (2015). They discuss how sustainable transportation and industrial facility activities, which account for about 40% of global CO_2 emissions, are optimized by including greenhouse gas indicators and social measures.

On the other hand, the green VRP has received more attention from the academic community. State of the art surveys are presented by Eguia et al. (2013), Lin et al. (2014), Demir et al. (2014), Zhang et al. (2015) and Bektaş et al. (2016). Accordingly, there are several authors that have oriented their research to measure and minimize total fuel consumption, while others focused their research to reduce CO_2 emissions taking into account travel times, vehicles speeds, traffic conditions in cities, among others. For example, Alinaghian & Naderipour (2016) present a study a time-dependent vehicle routing problem to minimize fuel comsumption considering, among other factors, the road gradient, the vehicle load, and the urban congestion. Ehmke et al. (2015) also study the problem of minimizing the expected emissions for vehicle routing in urban areas, modeling the problem as a time-dependent vehicle routing problem and proposing a method to precompute the customer-to-customer expected time-dependent emissions paths. Qian & Eglese (2016) study this problem by implementing a column generation based tabu search algorithm. On the other hand, Koç & Karaoglan (2016) study the green VRP (G-VRP) which consists of optimizing routing decisions for a fleet of vehicles by minimizing the total travelled distance, respecting the fuel tank capacity of the vehicle and allowing the vehicle to replenish its fuel tank if required. A new formulation and some valid inequalities are presented by Koç & Karaoglan (2016), together with a heuristic solution based on simulated annealing. Montoya et al. (2014) also present a heuristic based on multi-space sampling for the problem, obtaining eight new best known solutions for benchmark instances of the literature. Madankumar & Rajendran (2016) generalize the study by including pick-up and delivery constraints and propose three mixed-integer programing models.

Intermodal transportation to minimize total gas emissions has also been considered. The special case of the pollution vehicle routing problem is proposed by Bektaş & Laporte (2011) where the objective function integrates cost of carbon emissions with operational costs of drivers and fuel consumption. While Xiao et al. (2012) presents a model where a Fuel Consumption Rate is considered. In their paper the fuel costs are dependent on the load carried and the distance traveled which are linearly associated.

In conclusion, to the best of our knowledge, there is not a LRP work in which the main objective function is to minimize the CO_2 emissions generated by both, the location of facilities and the routing of vehicles. From the practical and the academic points of view, it is interesting to analyze and identify the features, the viability and the consequences of making location and routing decisions based on the total CO_2 emissions generated by these operations.

3 Problem definition and proposed mathematical model

The GLRP studied in this paper is defined on a weighted and directed graph $G = (V, A)$, with V being a set of nodes composed by a subset I of m candidate depot locations and a subset $J = V \setminus I$ of n customers. A fixed capacity H_i and a fixed amount of CO_2 emissions O_i are associated to each candidate depot $i \in I$. The distance matrix between nodes i and j is defined as D_{ij}. Each customer $j \in J$ has a demand L_j. Let A be the set of arcs connecting depots and customers, and customers between them. An unlimited fleet of identical vehicles of capacity Q is available.

The following constraints must hold:

- the demand of each client Lj must be served by a single vehicle;
- each route must begin and end at the same depot, and its total load must not exceed the vehicle capacity;
- the total load of the routes assigned to a depot must fit the capacity of that depot;

The objective is to find which depots to open and the sequence of customers to visit per vehicle in order to minimize the total CO_2 emission computed as the sum of the fixed CO_2 emissions per opened depot plus the total variable CO_2 emissions resulting from routing decisions as explained next in section 3.1.

3.1 Environmental impact measures

Based on the fuel consumption model proposed by Xiao et al. (2012), it is assumed that CO_2 emissions depend proportionally on both the distance traveled and the load carried by each vehicle on the arcs of the route. In order to exhibit the model, let E be equal to the amount of CO_2 produced per kilometer traveled by a vehicle, in kilograms, while carrying a load of q kilograms. As defined earlier, let Q be the vehicle capacity. Thus, let E be computed as follows:

$$E = P_0 + \left(\frac{P_f - P_0}{Q}\right) * q \qquad (1)$$

Where P_0 is the level of CO_2 emissions when the vehicle travels without any load, and P_f is the level of CO_2 emissions when the vehicle is fully loaded. For an easier writing and in order to generalize and parametrize the model, the equation is simplified to:

$$E = P_0 + \alpha * q \qquad (2)$$

Where α is a rate of CO_2 emissions per Kg carried per Km.

3.2 Proposed model

The following binary decision variables are used: Let y_k =1 if depot $k \in I$ is opened, f_{ik} =1 if and only if customer $i \in J$ is assigned to depot $k \in I$, and let x_{ijk} =1 if and only if arc $(i,j) \in A$ is traversed from i to j in the route performed by a vehicle that departures from depot $k \in I$; and a positive variable q_{ij} equals to the load carried from node $i \in V$ to node $j \in V$. Thus, the proposed model formulation is:

$$\min Z = \sum_{i \in V} \sum_{j \in V} D_{ij} \left(\sum_{k \in I} \left(P_o x_{ijk} \right) + \alpha q_{ij} \right) + \sum_{k \in I} y_k * O_k \qquad (3)$$

Subject to:

$$\sum_{j \in V} \sum_{k \in I} x_{ijk} = 1 \qquad \forall\, i \in J \qquad (4)$$

$$\sum_{i \in V} \sum_{k \in I} x_{ijk} = 1 \qquad \forall\, j \in J \qquad (5)$$

$$\sum_{i \in J} f_{ik} L_i \leq H_k y_k \qquad \forall\, k \in I \qquad (6)$$

$$\sum_{j \in V} x_{ijk} = f_{ik} \qquad \forall\, i \in J, \forall\, k \in I \qquad (7)$$

$$x_{ijk} = 0 \qquad \forall\, j \in J, \forall\, k \in I\,, \forall\, i \in I \mid\, i \neq k \qquad (8)$$

$$\sum_{i\, \in V\, \mid\, i \neq j} q_{ij} - \sum_{i\, \in J \mid\, i \neq j} q_{ji} = L_j \qquad \forall\, j \in J \qquad (9)$$

$$\sum_{k\, \in\, I} Q x_{ijk} \geq q_{ij} \qquad \forall\, i \in V, \forall\, j \in V \qquad (10)$$

$$\sum_{j\, \in V} x_{ijk} - \sum_{j \in V} x_{jik} = 0 \qquad \forall\, i \in V, \forall\, k \in I \qquad (11)$$

$$x_{ijk} \in \{0\,, 1\} \qquad \forall\, i \in V, \forall\, j \in V, \forall\, k \in I \qquad (12)$$

$$y_k \in \{0\,, 1\} \qquad \forall\, k \in I \qquad (13)$$

$$f_{ik} \in \{0\,, 1\} \qquad \forall\, i \in J, \forall\, k \in I \qquad (14)$$

$$q_{ij} \geq 0 \tag{15}$$

The objective function (3) sums all the CO_2 emissions resulting from routing operations plus those resulting from location decisions. Constraints (4) and (5) guarantee that every customer must be visited once, and that each customer has only one predecessor and one successor in the route. Storage capacity constraints associated to depots, are satisfied by inequalities (6). Constraints (7) and (8) state the relation between the customer and depot allocation and routing decisions. Constraints (9) guarantee the flow of product at each route as it ensures load balance conservation and customer's demand satisfaction. These also work as sub-tour elimination constraints. Constraints (10) limit the load per vehicle to be less than the vehicle capacity. Constraints (11) guarantee the flow conservation of vehicles in every node in the graph. Finally, Constraints (12), (13) and (14) state the binary nature of the decision variables, while (15) state the positive nature of the q variable.

In this paper, a set of valid inequalities is proposed. These aim to reduce the computational time to solve the problem to optimality when using a commercial solver since they reinforce the mathematical formulation. These valid inequalities are presented next.

3.3 Valid inequalities

In this section, we introduce some new families of constraints that have been proven to be useful in order to strengthen the presented formulation. Also, we assume that distance matrix satisfies the triangular inequality. Their effectiveness will be discussed in Section 4.

Theorem 1 *The inequalities*

$$q_{ij} \geq \sum_{k \in I} x_{ijk} * L_j \qquad \forall i \in V; \forall j \in J; i \neq j \tag{16}$$

are valid for the GLRP.

Proof Since each customer must be assigned to only one depot, the right side of constraints (16) sums up to L_j if and only if the arc *(i,j)* is traversed. Thus, the constraint ensures that the vehicle carries at least the demand of the destination node *j* through the arc *(i,j)*. If the corresponding arc is not traversed, Constraints (10) force the quantity to be 0. In other words, the inequalities (16) guarantee that if an arc, arriving to a customer, is traversed, then the associated vehicle must be non-empty.♦

Theorem 2 *The inequalities*

$$\sum_{k \in I} y_k \geq \left\lceil \frac{\sum_{i \in J} L_i}{\max\{H_k\}} \right\rceil \tag{17}$$

are valid for the GLRP.

Proof The minimum number of depots to be opened can be estimated by computing the ceiling function of the ratio between the total customer demand and the capacity of the largest depot. The right-hand side of constraints (17) establish the rounded number of depots to be opened whose total storage capacity is able to satisfy the total customer demand in the case when the optimal solution implies to use of the largest depots. ♦

These last inequalities are inspired by the strengthened capacity inequalities often used for vehicle routing problems (see Baldacci et al. (2012)).

Theorem 3 *The inequalities*

$$\sum_{i \in S} \sum_{j \in S} x_{ij} \leq |S| - 1 \qquad \forall\, S \subset J \mid |S| = \gamma\ ;\ D_{ij} \leq \rho\ \forall\, i,j \in S \qquad (18)$$

are valid for the GLRP.

Proof For every subset *S* of customers, composed by exactly *γ* customers, the number of arcs used in the optimal solution has to be less or equal than *γ – 1*. This inequality reinforces the sub-tour elimination constraint (9) and it is often used in vehicle routing formulations (Baldacci et al., 2012). In our version, it is intended to separate every subset of customers *S* with exactly *γ* customers that are in a radio of *ρ* distance each from another, in order to strengthen the sub-tour elimination constraints for these subsets. That is, a subset of customers that are relatively close, making a geographical cluster, are likely to compose a sub-tour in the linear relaxation of the model. Then, we add some (but not all) sub-tour elimination valid inequalities to reinforce the linear relaxation of the model for the routing variables. ♦

In the last inequalities, note that when ρ tends to infinity, the number of constraints is exponential and it could be inefficient based on the computational times. On the other hand, when *ρ* is small, the equation only considers subsets of customers which form a very compact cluster. In this paper *γ* is equal to 3 and *ρ* is 40% of the largest distance in the distance matrix D_{ij}.

4 Computational experiments

4.1 Test instances and workstation

The mathematical formulation described in Section 3 is solved using GAMS 23.5.1 and using CPLEX 12.2. The following experiments are executed on an Intel® Xeon® X5560 @ 2.80 GHz 2.79 GHz and 12 GB RAM with a maximum running time of twelve hours. Prodhon and Barreto's classical instances for LRP (publicly available at http://prodhonc.free.fr/) are adapted with additional parameters as P_o equal to 30 and α equal to 2, these values are based on the fuel economy standards for medium and heavy-duty vehicles proposed by The National Highway Transportation Safety Administration (NHTSA) and the Environmental Protection Agency (EPA) (EESI, 2015)

Further, the impact of the valid inequalities is tested by comparing the performance of the commercial solver with and without the valid inequalities. This analysis is presented in section 4.2. Section 4.3 presents our experiments on large instances composed by up to 100 customers, the largest instances we could solve. In section 4.4, the performance of our proposed model is compared against the traditional formulation presented by Prins et al. (2007) with a straightforward adaptation of the objective function. In Section 4.5, we provide a comparative analysis of the results between the LRP and the GLRP.

4.2 Impact of the valid inequalities

Table 4-1 and Table 4-2 show the results of the mathematical formulation presented in section 3.2 with and without the valid inequalities. The comparison is made in terms of computational time and number of iterations to reach the optimal solutions, for several Prodhon and Barreto's instances, respectively. Column 1 presents the name of the studied instance. Column 2 presents the size of the instance in terms of number of customers (n) and candidate depots (m). The column $KgCO_2$ shows the optimal value for each instance. Also, the computational time (CPU(s)) in seconds and number of iterations required to compute the optimal solution (Iter) are presented. The column variation establishes a comparison represented as a percentage assuming the data of proposed model without valid inequalities as 100%.

Table 4-1 *Comparison between model with and without VI on Prodhon's Instances*

Instance	n-m	Kg CO_2	Proposed Model Without VI		Proposed Model		Variation	
			CPU (s)	Iter	CPU (s)	Iter	CPU (s)	Iter
coord20-5-1	20-5	1.462,7	11,0	56.884	3,4	23.611	-68,56%	-58,49%
coord20-5-1b	20-5	2.067,5	17,2	103.622	18,3	123.679	6,54%	19,36%
coord20-5-2	20-5	1.247,0	2,2	13.822	1,9	12.948	-13,87%	-6,32%
coord20-5-2b	20-5	1.466,7	2,6	15.384	0,5	1.840	-82,34%	-88,04%
coord50-5-1	50-5	4.109,7	12892,9	25.119.555	4.537,6	9.964.695	-64,81%	-60,33%
coord50-5-1b	50-5	3.964,7	28893,6	42.945.623	3.821,4	3.915.452	-86,77%	-90,88%
coord50-5-2	50-5	3.148,8	17283,7	42.494.903	9.805,8	12.727.241	-43,27%	-70,05%
coord50-5-2b	50-5	NOF*	NOF*	NOF*	NOF*	NOF*	-	-
coord50-5-2bBIS	50-5	NOF*	NOF*	NOF*	NOF*	NOF*	-	-

coord50-5-2BIS	50-5	NOF*	NOF*	NOF*	NOF*	NOF*	-	-
coord50-5-3	50-5	3.331,1	8.146,2	16.985.399	923,2	1.931.276	-88,67%	-88,63%
coord50-5-3b	50-5	3.267,5	1.927,3	2.860.244	910,4	1.454.520	-52,77%	-49,15%
		Average	7.686,3	14.510.604	2.224,7	3.350.585	**-54,94%**	**-54,73%**

*No optimal solution founded

Table 4-2 *Comparison between model with and without VI on Barreto's Instances*

Instance	n-m	g CO_2	Proposed Model Without VI		Proposed Model		Variation	
			CPU (s)	Iter	CPU (s)	Iter	CPU (s)	Iter
coordGaspelle	21-5	765.703,1	0,5	529	0,4	1.363	-12,55%	157,66%
coordGaspelle2	22-5	506.639,8	1,4	779	0,7	1.625	-45,43%	108,60%
coordGaspelle3	29-5	590.099,5	1,2	1.079	0,6	2.901	-49,66%	168,86%
coordGaspelle4	32-5	1.312.571,3	1,8	1.287	1,3	4.163	-28,80%	223,47%
coordGaspelle5	32-5	1.312.571,3	2,0	1.505	0,9	3.739	-56,27%	148,44%
coordGaspelle6	36-5	50.899,7	25,2	65.015	1,3	4.694	-94,81%	-92,78%
coordMin27	27-5	2.158.788,8	1,1	998	1,0	1.935	-13,63%	93,89%
coordChrist50	50-5	39.077,6	103,9	185.425	68,1	109.280	-34,45%	-41,07%
coordChrist75	75-10	NOF*	NOF*	NOF*	NOF*	NOF*	-	-
		Average	17,1	32.077	9,3	16.213	**-41,95%**	**95,88%**

*No optimal solution founded

Results show significant differences in the performance of the mathematical models when solving the problem to optimality applying the presented valid inequalities. For the Prodhon's instances, the proposed model solved them, on average 54,94 % faster and requiring 95,48% less iterations than the model without valid inequalities. The instances coord50-5-2b, coord50-5-2bBIS, and coord50-5-2BIS could not be solved by any of the versions of the model within the imposed time limit. For Barreto's instances, the proposed model solved them, on average, 41,95 % faster but required to perform 95,88% more iterations to reach the optimal solution. This results show the valid inequalities reduce significantly the computational time, on average, in 48,83%. In this set of instances, problems with up to 50 customers could be solved.

We also estimate the impact of the presented valid inequalities in the proposed model at the early iterations of the execution of the model. To identify this, the proposed model without valid inequalities is executed with a time limit based on the total execution time of the proposed model with valid inequalities. For example, the instance coord20-5-1 is solved with a time limit of 3.4 seconds, corresponding to the total computation time of the model with valid inequalities. The results of this experiment are shown in Table 4-3 and Table 4-4.

Table 4-3 *Proposed model without VI and time limit on Prodhon's instances.*

Instance	n-m	Kg CO_2	Proposed Model with VI	Proposed Model without VI and Time Limit**	
			CPU (s)	Kg CO_2	%GAP
coord20-5-1	20-5	1.467,3	3,4	1.545,9	5,69%
coord20-5-1b	20-5	2.067,5	18,3	2.067,5	0,00%
coord20-5-2	20-5	1.247,0	1,9	1.265,1	1,45%
coord20-5-2b	20-5	1.466,7	0,5	NISF*	-
coord50-5-1	50-5	4.109,7	4.537,6	4.109,7	0,00%
coord50-5-1b	50-5	3.964,7	3.821,4	3.994,7	0,76%

coord50-5-2	50-5	3.148,8	9.805,8	3.148,8	0,00%
coord50-5-3	50-5	3.079,4	923,2	3.333,2	0,06%
coord50-5-3b	50-5	3.331,1	910,4	3.267,5	0,00%
		Average	2.224,7	2.841,5	1,00%

*No integer solution founded

**The time limit for each instance corresponds to the total computational time of the proposed model with VI.

Table 4-4 *Proposed model without VI and time limit on Barreto's instances.*

Instance	n-m	g CO_2	Proposed Model with VI	Proposed Model without VI and Time Limit**	
			CPU (s)	Kg CO_2	%GAP
coordGaspelle	21-5	765.703,1	0,4	NISF*	-
coordGaspelle2	22-5	506.639,8	0,7	NISF*	-
coordGaspelle3	29-5	590.099,5	0,6	NISF*	-
coordGaspelle4	32-5	1.312.571,3	1,3	NISF*	-
coordGaspelle5	32-5	1.312.571,3	0,9	NISF*	-
coordGaspelle6	36-5	50.899,7	1,3	NISF*	-
coordMin27	27-5	2.158.788,8	1,0	NISF*	-
coordChrist50	50-5	39.077,6	68,1	39.323,5	0,63%
		Average	9,3	39.323,5	0,63%

*No integer solution founded

**The time limit for each instance corresponds to the total computational time of the proposed model with VI.

Based on these results, two benefits can be identified when using the valid inequalities. First, using valid inequalities accelerates the search within the solver in order to demonstrate the optimality of the solution faster, as is exposed in Table 4-3. In fact, the mathematical formulation without valid inequalities could find the optimal solution for the instances coord20-5-1b, coord50-5-1, coord50-5-2, and coord50-5-3b by the same time the version with valid inequalities did. Nevertheless, the optimality of the solution could not be proved as fast. Second, the valid inequalities help the solver to find an integer solution faster. This is the case for Barreto’s instances in Table 4-4, where the version without valid inequalities could not find any integer solution by the same computational time that the version with the Valid Inequalities could find the optimal solution.

4.3 Proposed formulation versus the traditional formulation

The formulation of the LRP presented by Prodhon & Prins (2014), denoted hereby as the traditional formulation in this paper, is adapted to match the proposed objective function according to equation (2). The routing decision variables x_{ijk} are redefined to be equal to 1 if the arc (i,j) is traversed by the vehicle $k \in K$, where K is the set of vehicles, in our case homogeneous and with unlimited number. Also, we include into the traditional formulation the q_{ij} variables representing the quantity of product transported by a vehicle in the arc $(i,j) \in A$. The rest of sets and variables remain the same as presented in chapter 3. The adapted objective function is as follows:

$$min\ Z = \sum_{i \in V} \sum_{j \in V} D_{ij} \left(\sum_{k \in K} (P_o x_{ijk}) + \alpha q_{ij} \right) + \sum_{w \in I} y_w * O_w \qquad (19)$$

Additionally, the set of constraints (9) and the adapted version of constraints (10) are included into the traditional formulation to make it valid. The adapted version of constraints (10) is as follows:

$$\sum_{k \in K} Q x_{ijk} \geq q_{ij} \qquad \forall\ i \in V, \forall\ j \in V \qquad (20)$$

The adapted traditional model is compared to our proposed formulation. Tables 4-5 and 4-6 present the obtained results. The proposed model reaches optimal solutions, on average, 91,69% faster than the adapted traditional model. Also, the traditional model could reach 11 optimal solutions (out of 21 instances tested), while the proposed model did for 17 instances under the same computational conditions. These results can be explained by noticing that the routing decision variables in the proposed mathematical model eliminate the symmetries that the traditional model has by indexing them on the set of identical vehicles. This leads to an average reduction of 81,19% on the number of iterations required to reach to the optimal solution when running a commercial solver with the proposed model.

Table 4-5 *Proposed model versus traditional model (adapted) on Prodhon's instances*

Instance	n-m	Kg CO_2	Traditional Model Adapted		Proposed Model		% Variance	
			CPU (s)	Iter	CPU (s)	Iter	CPU	Iter
coord20-5-1	20-5	1.462,7	130,1	495.781	3,4	23.611	-97,35%	-95,24%
coord20-5-1b	20-5	2.067,5	346,7	995.319	18,3	123.679	-94,72%	-87,57%
coord20-5-2	20-5	1.247,0	243,7	1.063.420	1,9	12.948	-99,23%	-98,78%
coord20-5-2b	20-5	1.466,7	116,3	460.739	0,5	1.840	-99,60%	-99,60%
coord50-5-1	50-5	4.109,7	NOF*	NOF*	4.537,6	9.964.695	-	-
coord50-5-1b	50-5	3.964,7	NOF*	NOF*	3.821,4	3.915.452	.	-
coord50-5-2	50-5	3.148,8	NOF*	NOF*	9.805,8	12.727.241	.	-
coord50-5-2b	50-5	NOF*	NOF*	NOF*	NOF*	NOF*	.	-
coord50-5-2bBIS	50-5	NOF*	NOF*	NOF*	NOF*	NOF*	.	-
coord50-5-2BIS	50-5	NOF*	NOF*	NOF*	NOF*	NOF*	.	-
coord50-5-3	50-5	3.331,1	NOF*	NOF*	923,2	1.931.276	.	-
coord50-5-3b	50-5	3.267,5	NOF*	NOF*	910,4	1.454.520	.	-
Average					2.224,7	3.350.585	-97,73%	-95,30%

*No optimal solution founded

Table 4-6 *Proposed model versus the traditional model (adapted) on Barreto's instances*

Instance	n-m	g CO_2	Traditional Model Adapted		Proposed Model		% Variance	
			CPU (s)	Iter	CPU (s)	Iter	CPU	Iter
coordGaspelle	21-5	765.703,1	1,7	2.093	0,4	1.363	-75,03%	-34,88%
coordGaspelle2	22-5	506.639,8	5,3	12.238	0,7	1.625	-86,03%	-86,72%
coordGaspelle3	29-5	590.099,5	6,0	6.093	0,6	2.901	-90,30%	-52,39%
coordGaspelle4	32-5	1.312.571,3	6,3	9.124	1,3	4.163	-79,38%	-54,37%
coordGaspelle5	32-5	1.312.571,3	16,3	38.628	0,9	3.739	-94,66%	-90,32%
coordGaspelle6	36-5	50.899,7	1350,2	2.379.752	1,3	4.694	-99,90%	-99,80%
coordMin27	27-5	2.158.788,8	12,9	29.399	1,0	1.935	-92,41%	-93,42%
coordChrist50	50-5	39.077,6	NOF*	NOF*	68,1	109.280	-	-

coordChrist75	75-10	NOF*	NOF*	NOF*	NOF*	NOF*	-	-
Average					9,3	16.213	-88,24%	-73,13%

*No optimal solution founded

Also, in Tables 4-7 and 4-8, the results of the linear relaxation of the models are exposed. It is shown that the proposed model computes a better lower bound on the root node for the solver. In fact, the average gap to optimality of linear relaxation of proposed model is 3,68% while for the traditional model is 14,19%. Although for large instances the optimal solution could not be found, results show that the linear relaxation of proposed model is a better lower bound that the bound computed when using the traditional model.

***Table 4-7** Linear relaxation proposed model versus linear relaxation of the adapted traditional model on Prodhon's instances*

Instance	n-m	Kg CO_2	LR Traditional Model Adapted		LR Proposed Model	
			Kg CO_2	%GAP	Kg CO_2	%GAP
coord20-5-1	20-5	1.462,7	11.705,9	20,0%	13.980,2	4,42%
coord20-5-1b	20-5	2.067,5	15.881,3	23,2%	18.952,4	8,33%
coord20-5-2	20-5	1.247,0	9.728,1	22,0%	11.429,8	8,34%
coord20-5-2b	20-5	1.466,7	11.355,3	22,6%	13.978,1	4,70%
coord50-5-1	50-5	4.109,7	34.648,0	15,7%	38.901,1	5,34%
coord50-5-1b	50-5	3.964,7	31.013,8	21,8%	36.889,6	6,95%
coord50-5-2	50-5	3.148,8	26.045,8	17,3%	29.413,4	6,59%
coord50-5-2b	50-5	NOF	-	-	-	-
coord50-5-2bBIS	50-5	NOF	-	-	-	-
coord50-5-2BIS	50-5	NOF	-	-	-	-
coord50-5-3	50-5	3.331,1	27.497,9	17,5%	31.607,3	5,11%
coord50-5-3b	50-5	3.267,5	24.954,8	23,6%	30.626,0	6,27%
coord100-5-1	100-5	NOF*	85.498,8	-	90.191,1	-
coord100-5-1b	100-5	NOF*	73.966,9	-	81.596,1	-
coord100-5-2	100-5	NOF*	42.284,4	-	47.361,7	-
coord100-5-2b	100-5	NOF*	37.863,4	-	44.837,3	-
coord100-5-3	100-5	NOF*	44.330,8	-	49.627,8	-
coord100-5-3b	100-5	NOF*	39.678,1	-	46.514,1	-
coord100-10-1	100-10	NOF*	42.947,4	-	49.168,0	-
coord100-10-1b	100-10	NOF*	38.860,1	-	46.754,0	-
coord100-10-2	100-10	NOF*	42.542,8	-	47.537,8	-
coord100-10-2b	100-10	NOF*	37.965,3	-	44.585,5	-
coord100-10-3	100-10	NOF*	40.690,9	-	45.556,1	-
coord100-10-3b	100-10	NOF*	36.257,4	-	42.535,7	-
Average			35.986,5	20,4%	41.049,7	6,23%

*No optimal solution founded

***Table 4-8** Linear relaxation proposed model versus the linear relaxation of the adapted traditional model on Barreto's instances*

Instance	n-m	g CO_2	LR Traditional Model Adapted		LR Proposed Model	
			g CO_2	%GAP	g CO_2	%GAP
coordGaspelle	21-5	765.703,1	754.401,2	1,48%	765.673,1	0,00%
coordGaspelle2	22-5	506.639,8	490.492,5	3,19%	505.881,3	0,15%
coordGaspelle3	29-5	590.099,5	571.860,1	3,09%	589.989,5	0,02%
coordGaspelle4	32-5	1.312.571,3	1.290.297,2	1,70%	1.312.448,6	0,01%
coordGaspelle5	32-5	1.312.571,3	1.289.418,3	1,76%	1.312.443,3	0,01%
coordGaspelle6	36-5	50.899,7	40.980,4	19,49%	50.139,2	1,49%
coordMin27	27-5	2.158.788,8	2.078.558,2	3,72%	2.155.143,7	0,17%
coordChrist50	50-5	39.077,6	29.986,8	23,26%	37.253,3	4,67%

coordChrist75	75-10	NOF*	-			
Average			818.249,3	7,21%	841.121,5	0,82%

*No optimal solution founded

These tests are also performed on larger instances to check if conclusions remained the same. Using Prodhon's instances with up to 100 customers, 5 and 10 candidate depots the proposed model is tested, but after 12 hours of computation, no optimal solution is found. In some cases, the solver stopped because of lack of memory. Nevertheless, after 4 hours of computation, the proposed model had an average GAP to the best lower bound of 3,7%, while the adapted traditional model could not find any integer solution. It shows that still on large instances the proposed model seems to perform better than the adapted traditional model.

4.4 Minimizing costs versus minimizing CO_2 emissions

Implementing a decision-making tool that aims to minimize CO_2 emissions of a supply chain instead of the logistic costs is good for the environment but an analysis of the trade-off between costs and environmental impact is required in order to make a sustainable supply chain. In fact, Prodhon's Instances with up to 50 customers are analyzed by comparing the near-optimal solutions for the LRP reported by Prins et al.(2007) in terms of costs ($) and its estimated CO_2 (Kg CO_2) emissions, against the optimal solution found by solving the GRLP. Proven optimal solutions are marked in bold font.

Table 4-9 *Comparison LRP versus GLRP in terms of cost and CO_2 emissions on Prodhon's instances*

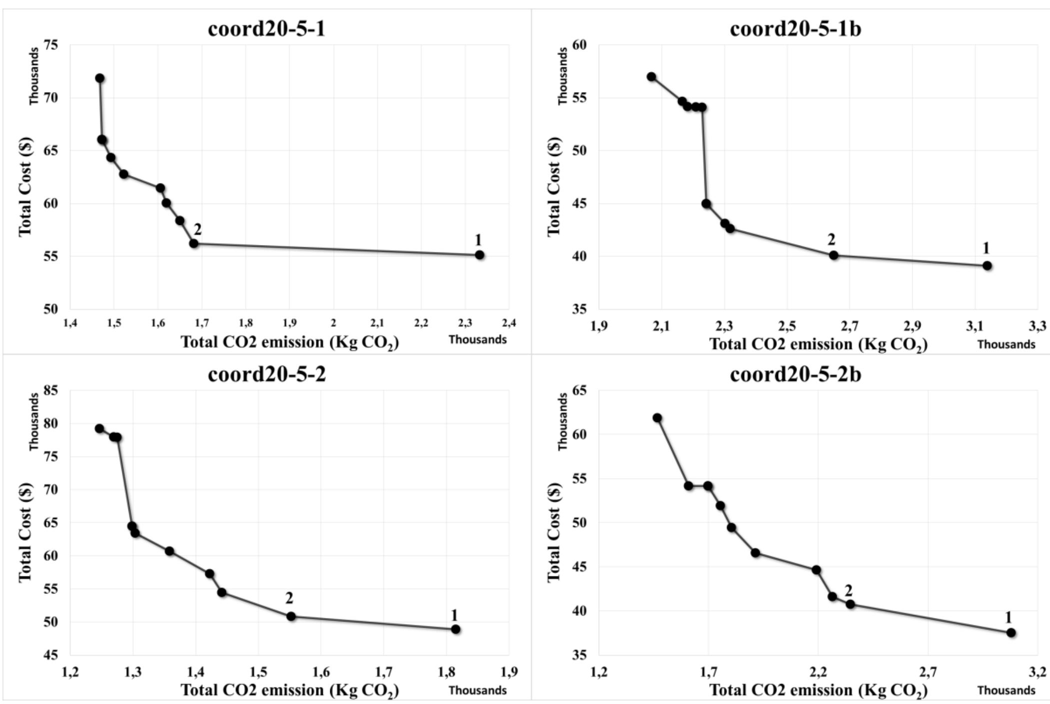
Instance	LRP		GLRP		% Variance	
	Kg CO_2	$	Kg CO_2	$	Kg CO_2	$
coord20-5-1	2.333,3	55.131,0	**1.467,3**	71.840,0	-37,31%	30,31%
coord20-5-1b	3.138,7	**39.104,0**	**2.067,5**	56.966,0	-34,13%	45,68%
coord20-5-2	1.815,2	**48.908,0**	**1.247,0**	79.191,0	-31,30%	61,92%
coord20-5-2b	3.078,5	**37.542,0**	**1.466,7**	61.887,0	-52,36%	64,85%
coord50-5-1	5.045,9	90.160,0	**4.109,7**	120.870,0	-18,55%	34,06%
coord50-5-1b	6.654,9	63.256,0	**3.964,7**	111.795,0	-40,42%	76,73%
coord50-5-2	4.583,9	88.715,0	**3.148,8**	103.343,0	-31,31%	16,49%
coord50-5-2b	5.915,1	67.698,0	**3.079,4**	99.919,0	-47,94%	47,60%
coord50-5-3	5.305,6	86.203,0	**3.331,1**	109.378,0	-37,22%	26,88%
coord50-5-3b	5.553,6	61.830,0	**3.267,5**	105.373,0	-41,17%	70,42%
Average	2.591,4	45.171,3	1.562,1	67.471,0	-37,17%	47,49%

Table 4-9 shows the comparative results. While CO_2 emissions could be reduced, on average, on 37,17%, the total cost of the operation increases on average in 47,49%. Therefore, it represents a significant increase in costs for the evaluated instances. However, it should be noted that the LRP completely ignores the costs associated to CO_2 emissions that depend on the load of the vehicles, then, in real situations, solutions with a better trade-off between these economic and environmental costs could exist. Despite this, it seems that the two objectives, cost and CO_2 emissions, oppose to each other. For this reason, a bi-objective optimization analysis is developed. Results are shown in the next section.

4.4.1 Bi-objective optimization

A bi-objective model is formulated and solved applying the ε-constraint method, based on imposing a limit on the total cost of the solution and minimizing the level of CO_2 emissions. Pareto frontiers are built and are shown in Figure 4-1 for instances with up to 20 customers and 5 candidate depots. Results show a large tail to the right side which means that, in these situations, it is possible to have a significant reduction on CO_2 emissions with a very small sacrifice of the total cost. As shown by these results, moving from the optimal solution of cost-based LRP (points marked as 1) to the next point in the left of the Pareto frontier (points marked as 2), on average for these instances, means a reduction in CO_2 of 20,4% and increase of 4,2% of the cost. It is therefore a more competitive strategy than just using the GLRP criteria, and provides a more sustainable solution than using the LRP optimal solution.

Figure 4-1 *Pareto frontiers for four Prodhon's instances*



5 Conclusions and perspectives

A mathematical model for the decision making process of strategic and operational decisions associated to a two-echelon supply chain design is presented, aiming to generate a lower environmental impact of distribution operations. As shown by the literature review, this is interesting to industries worldwide, to dangerously polluted cities, and governments. A new mathematical formulation and a set of valid inequalities for the green location-routing problem are presented and compared to straight-forward adaptations of the formulations in the literature. The presented formulation is stronger than the adapted traditional formulations, as shown by the computational results performed on a set of benchmark instances.

Further, the implications on logistic costs are analyzed when solving a minimum CO_2 emissions problem and a bi-objective version of the model. By using the ε-constraint method, a near-optimal Pareto frontier is built for a set of test instances. The shapes of these frontiers show that important savings in CO_2 emissions can be achieved by a making small increase in logistic costs. Therefore, a decision-aid tool using the presented model could help practitioners and companies to find more competitive and sustainable strategies for supply chain design by evaluating the decisions with a trade-off between economic costs and the corresponding CO_2 emissions.

Finally, a novel way of approaching the LRP is presented, and its benefit is twofold: on the one hand, to be used by companies who want to have greener operations; and on the other hand, to promote the fulfillment of national and international regulations concerning carbon footprint. Future research should be dedicated to evaluate the impact of the sensitivity factor of the CO_2 emissions as a function of the vehicle's load in the solutions, denoted as α, and to analyze how the features of the roads and the vehicles could affect the location and routing decisions. Also, well-known variants of the LRP could be evaluated under the same considerations.

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