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Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation

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July 2017

CIRRELT-2017-41

Document de travail également publié par la Faculté des sciences de l'administration de l'Université Laval, sous le numéro FSA-2017-007.

Minimizing Emissions in Integrated Distribution Problems

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Abstract. The integration of operational decisions of different supply chain functions is an important success factor in minimizing their total costs. Traditionally, supply chain optimization has merely concentrated on costs or the economical aspects of sustainability, neglecting its environmental and social aspects. However, with the growing concern towards green operations, the impact of short term decisions on the reduction of carbon emissions can no longer be overlooked. In this paper, we aim to compare the effect of operational decisions not only on costs but also on emissions, and we reassess some well-known logistic optimization problems under new objectives. We study two integrated systems dealing with production, inventory, and routing decisions, in which a commodity produced at the plant is shipped to the retailers over a finite time horizon. These two problems are known as the production-routing and the inventory-routing problems. We define and measure several metrics under different scenarios, namely by minimizing total costs, routing costs only, or minimizing emissions. Each solution is evaluated under all three objective functions, and their costs and business performance indicators are then compared. We provide elaborated sensitivity analyses allowing us to gain useful managerial insights on the costs and emissions in integrated supply chains, besides important insights on the cost of being environmentally friendly.

Keywords. Sustainability, multi-tier supply chain management, integrated optimization.

Acknowledgements. This project was partly funded by the Natural Sciences and Engineering Research Council of Canada (NSERC) under grant 2014-05764. This support is greatly acknowledged.

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Dépôt légal – Bibliothèque et Archives nationales du Québec
Bibliothèque et Archives Canada, 2017

1. Introduction

Increasing environmental concerns have changed the definition of competitive advantage. To be competitive, companies need to make a proper balance between economical, environmental, and social dimensions of their business. Today the market urges companies not only to be efficient in terms of cost but also to consider the environmental and social impacts of their operations. To be efficient, they have to make decisions that boost their margins, make them fulfill their customers demands in a fast and flexible manner and to be sustainable; they have to evaluate the trade-offs between efficient solutions versus sustainable ones. Recently, the negative impacts of operational decisions on the environment have become more important, especially in terms of greenhouse gases (GHGs) emissions. All production, inventory, and distribution activities contribute to environmental problems, however, transportation and particularly road-based transportation is considered as one of the principal sources of GHG (Jabali et al., 2012), mainly measured by carbon dioxide (CO_2) emissions from burning fossil fuels. Nonetheless, to reduce emissions, one cannot simply avoid using trucks, as the distribution of many products and services relies on their operation (Coelho et al., 2016). To date, much research is devoted to evaluate how truck usage affects the environment, such as estimating the amount of GHG emitted (Demir et al., 2011), or to develop new approaches to tackle the traditional vehicle routing problem (VRP), such as the green VRP (Bektaş and Laporte, 2011). A number of variants of these problems has recently appeared (Dabia et al., 2017; Franceschetti et al., 2017). They reinforce the need of better understanding how business operations can affect the environment, and also what can be done to be environmentally friendly while at the same time be efficient from a business perspective. Despite the significant recent literature on the green VRP, the incorporation of the evaluation of GHG emissions into multi-echelon supply chain models is not extensively studied (Absi et al., 2013). This paper revisits classical inventory-routing and production routing problems (IRP and PRP) taking both economic and environmental objectives into consideration. These problems already combine multiple contradicting objectives, such as minimizing transportation, inventory and production costs. In the following, we briefly describe these two classical problems.

The IRP is a multi-period problem in which a supplier must distribute a commodity from its depot to a set of customers. Both transportation and inventory costs are considered, and all demand must be satisfied without backlogging. The problem was initially proposed by Bell et al. (1983) and many algorithms have been proposed for its resolution, including heuristics methods (e.g., Bertazzi et al. (2002); Archetti et al. (2012); Coelho et al. (2012); Coelho and Laporte (2013a)) and exact algorithms (e.g., Archetti et al. (2007); Desaulniers et al. (2015)). A set of benchmark instances exists and has been vastly used to assess the performance of the solution algorithms. A review of the practical aspects of the IRP is available in Andersson et al. (2010) while methodological aspects are surveyed in Coelho et al. (2014).

Adding production optimization into the IRP and simultaneously determining production, inventory, and distribution decisions creates the PRP (Absi et al., 2014). Introduced by Chandra (1993), in this problem the objective is to minimize total costs, including fixed and variable production costs, inventory holding, and transportation costs. Several heuristics (e.g., Bard and Nananukul (2009); Armentano et al. (2011); Adulyasak et al. (2012); Absi et al. (2014)) and exact algorithms (e.g., Bard and Nananukul (2010); Archetti et al. (2011); Adulyasak et al. (2014)) exist for its resolution, as well as a set of benchmark instances. A recent survey of the PRP can be found in Adulyasak et al. (2015).

In the integrated logistics literature, Benjaafar et al. (2013) highlight the potential impact of operational supply chain decisions on carbon emissions and the need to incorporate them in integrated optimization models. Taking emissions into consideration can be performed in two different ways. The first one is to add carbon capacity constraints but without changing the goal of the optimization (e.g., Benjaafar et al. (2013); Absi et al. (2013); Helmrich et al. (2015); Absi et al. (2016); Qiu et al. (2017)). This method is not preferable as one simply aims to respect the carbon capacity but ignores the hidden potential reductions. The other approach, indeed, aims at minimizing the emissions (e.g., Soysal et al. (2015); Kumar et al. (2016); Soysal et al. (2016)). In this category, the authors consider distance, load or speed factors when minimizing emissions or fuel consumption. Among these factors, distance has been the traditional factor directly influencing emissions, even though the literature provides comprehensive emission models that optimize distribution decisions using very rich and detailed fuel consumption estimation models. These advanced models take into consideration many vehicle related factors (aerodynamics, engine specifications, etc.) and environment related factors (type and quality of the pavement, gradient of the roadway, etc.). See Demir et al. (2014) for a comprehensive list of factors affecting the fuel consumption.

A very important factor affecting the emissions is the payload (Demir et al., 2014) as each load carried by the vehicle increases the fuel consumption and ultimately the emissions (Bektaş and Laporte (2011); Suzuki (2011); Kopfer et al. (2014)). A straightforward and commonly used approach to estimate vehicle emissions is presented by Kara et al. (2007). They compare distance minimization models with energy minimization ones. Here, energy consumption is a function of the load of the vehicle and the distance being traveled. The rationale is that the heavier a truck, the more fuel it consumes. Xiao et al. (2012) consider the same approach to estimate fuel consumption and develop an optimization model for the VRP. Comparing different factors affecting fuel consumption, they argue that all other factors being constant, emissions mainly depend on the distance traveled and the load.

Our goal in this paper is to understand and measure the existing trade-offs between solutions that are economically optimized (i.e., the traditional objective) versus fully environmental friendly solutions, as well as other alternatives in between. We compare how much pollution a minimum cost solution would emit, whereas how much an emission optimized solution would cost financially. We study the trade-offs between three different objectives: reducing the total cost, the total distance, and the emissions. We contribute to the literature by modeling and solving emission minimization integrated distribution problems, conducting extensive computational experiments, and sensitivity analysis in order to better understand the trade-offs between the components of each model. Based on sensitivity analysis of several performance indicators, we provide managerial insights for production and distribution systems.

The remainder of this paper is structured as follows. Section 2 provides a general description of the problems being solved as well as their formal formulations. Extensive computational experiments are presented in Section 3 which is followed by conclusions and managerial insights in Section 4.

2. Problem descriptions and formulations

We now formally describe the mathematical formulation of the IRP and the PRP. The definition of the IRP is based on Coelho and Laporte (2013b) and that of the PRP on Archetti et al. (2011). Both problems are defined on a complete undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V} = \{0, ..., n\}$ is the vertex set and $\mathcal{E} = \{(i, j) : i, j \in \mathcal{V}, i < j\}$ is the edge set. Vertex 0 represents the supplier and the remaining vertices of $\mathcal{V}' = \mathcal{V} \setminus \{0\}$ represent n retailers. The set

$\mathcal{T} = \{1, ..., H\}$ denotes the discrete planning horizon. A single commodity is produced/stored at the supplier and shipped to the retailers through a single vehicle. A vehicle based at the supplier has a capacity Q and can perform one route per period. Let h_i ($i \in \mathcal{V}$) represent the unitary inventory holding cost per period at vertex i, and assume that each retailer has a maximum inventory holding capacity C_i. Initial inventories at the supplier and the retailers ($I_i^0, i \in \mathcal{V}$) and the demand of each retailer i (d_i^t) are known. Backlogging is not allowed. A routing cost c_{ij} satisfying the triangle inequality is associated with each edge $(i, j) \in \mathcal{E}$. Finally, for the PRP, let s and u be the fixed set-up and the variable production costs, respectively.

The following decision variables are used to formulate the problems. Routing variable x_{ij}^t are equal to the number of times edge (i, j) is used in period t. If vertex i is visited in period t, variables y_i^t is set to one. Variables I_i^t represent the inventory level at vertex i at period t. The quantity delivered to retailer i in period t is given by q_i^t. Let r_t represent the quantity produced at the supplier. For the IRP it is a parameter of the problem, while for the PRP, it is a decision variable. For the PRP, variable z_t is equal to one if production occurs in period t.

In Section 2.1, we provide the mathematical models under the traditional cost minimization objectives. Our different proposed objective functions are elaborated in Sections 2.2 and 2.3, where we show how the total cost minimization formulations can be adapted.

2.1. Total cost minimization models

We now present the mathematical models for the IRP in Section 2.1.1 and for the PRP in Section 2.1.2. These models use the traditional total cost minimization objective function.

2.1.1. IRP

The total cost minimization formulation for IRP is shown below (Coelho and Laporte, 2013b):

$$\text{minimize} \sum_{i \in \mathcal{V}} \sum_{t \in \mathcal{T}} h_i I_i^t + \sum_{(i,j) \in \mathcal{E}} \sum_{t \in \mathcal{T}} c_{ij} x_{ij}^t, \tag{1}$$

subject to

$$I_0^t = I_0^{t-1} + r^{t-1} - \sum_{i \in \mathcal{V}'} q_i^{t-1} \quad t \in \mathcal{T} \setminus \{1\} \tag{2}$$

$$I_0^t \geq \sum_{i \in \mathcal{V}'} q_i^t \quad t \in \mathcal{T} \tag{3}$$

$$I_i^t = I_i^{t-1} + q_i^{t-1} - d_i^{t-1} \quad i \in \mathcal{V}' \quad t \in \mathcal{T} \setminus \{1\} \tag{4}$$

$$q_i^t \le C_i - I_i^t \quad i \in \mathcal{V}' \quad t \in \mathcal{T} \tag{5}$$

$$q_i^t \le C_i y_i^t \quad i \in \mathcal{V}' \quad t \in \mathcal{T} \tag{6}$$

$$\sum_{i \in \mathcal{V}'} q_i^t \le Q y_0^t \quad t \in \mathcal{T} \tag{7}$$

$$\sum_{j \in \mathcal{V}, i<j} x_{ij}^t + \sum_{j \in \mathcal{V}, j<i} x_{ji}^t = 2y_i^t \quad i \in \mathcal{V} \quad t \in \mathcal{T} \tag{8}$$

$$\sum_{i \in \mathcal{S}} \sum_{j \in \mathcal{S}, i<j} x_{ij}^t \le \sum_{i \in \mathcal{S}} y_i^t - y_m^t \quad \mathcal{S} \subseteq \mathcal{V}' \quad t \in \mathcal{T} \quad m \in \mathcal{S} \tag{9}$$

$$y_i^t \le 1 \quad i \in \mathcal{V}' \quad t \in \mathcal{T} \tag{10}$$

$$I_i^t, q_j^t \ge 0 \quad i \in \mathcal{V} \quad j \in \mathcal{V}' \quad t \in \mathcal{T} \tag{11}$$

$$x_{0j}^t \in \{0,1,2\} \quad j \in \mathcal{V}' \quad t \in \mathcal{T} \tag{12}$$

$$x_{ij}^t \in \{0,1\} \quad (i,j) \in \mathcal{E} \quad t \in \mathcal{T} \tag{13}$$

$$y_i^t \in \{0,1\} \quad i \in \mathcal{V} \quad t \in \mathcal{T}. \tag{14}$$

The objective function (1) minimizes the total cost including inventory and transportation costs. Constraints (2) and (3) are the inventory conservation constraints at the supplier and constraints (4) have the same function for the retailers. Constraints (5) limit the delivery to each retailer assuring that the inventory capacity is respected. Constraints (6) guarantee that only visited retailers receive deliveries. The total quantity loaded in each vehicle cannot exceed its capacity as imposed by constraints (7). Constraints (8) are degree constraints and constraints (9) eliminate subtours. Constraints (10) prevent split deliveries. Constraints (11)−(14) enforce integrality and non-negativity conditions on the variables.

2.1.2. PRP

The total cost minimization formulation for PRP is shown below (Archetti et al., 2011):

$$\text{minimize} \sum_{i \in \mathcal{V}} \sum_{t \in \mathcal{T}} h_i I_i^t + \sum_{(i,j) \in \mathcal{E}} \sum_{t \in \mathcal{T}} c_{ij} x_{ij}^t + \sum_{t \in \mathcal{T}} (s z_t + u r_t), \tag{15}$$

subject to

$$I_0^t = I_0^{t-1} + r^t - \sum_{i \in \mathcal{V}'} q_i^t \quad t \in \mathcal{T} \setminus \{1\} \tag{16}$$

$$I_i^t = I_i^{t-1} + q_i^t - d_i^t \quad i \in \mathcal{V}' \quad t \in \mathcal{T} \setminus \{1\} \tag{17}$$

$$I_i^t \leq C_i \quad i \in \mathcal{V} \quad t \in \mathcal{T} \tag{18}$$

$$\sum_{i \in \mathcal{V}'} q_i^t \leq Q y_0^t \quad t \in \mathcal{T} \tag{19}$$

$$q_i^t \leq (C_i + d_i^t) y_i^t \quad i \in \mathcal{V}' \quad t \in \mathcal{T} \tag{20}$$

$$p_t \leq z_t \sum_{i \in \mathcal{V}'} \sum_{t \in \mathcal{T}} d_i^t \quad t \in \mathcal{T} \tag{21}$$

$$\sum_{j \in \mathcal{V}, i<j} x_{ij}^t + \sum_{j \in \mathcal{V}, j<i} x_{ji}^t = 2y_i^t \quad i \in \mathcal{V} \quad t \in \mathcal{T} \tag{22}$$

$$\sum_{i \in \mathcal{S}} \sum_{j \in \mathcal{S}, i<j} x_{ij}^t \leq \sum_{i \in \mathcal{S}} y_i^t - y_m^t \quad \mathcal{S} \subseteq \mathcal{V}' \quad t \in \mathcal{T} \quad m \in \mathcal{S} \tag{23}$$

$$y_i^t \leq 1 \quad i \in \mathcal{V}' \quad t \in \mathcal{T} \tag{24}$$

$$I_i^t, q_j^t, r_t \geq 0 \quad i \in \mathcal{V} \quad j \in \mathcal{V}' \quad t \in \mathcal{T} \tag{25}$$

$$x_{0j}^t \in \{0, 1, 2\} \quad j \in \mathcal{V}' \quad t \in \mathcal{T} \tag{26}$$

$$x_{ij}^t \in \{0, 1\} \quad (i, j) \in \mathcal{E} \quad t \in \mathcal{T} \tag{27}$$

$$z_t, y_i^t \in \{0, 1\} \quad i \in \mathcal{V} \quad t \in \mathcal{T}. \tag{28}$$

The objective function (15) minimizes the total cost including production, inventory, and transportation costs. Constraints (16) and (17) define the inventory conservation constraints at the supplier and the retailers, respectively. Constraints (18) impose the maximal inventory level at the retailers, and constraints (19) and (20) limit the delivery to each customer assuring that the vehicle capacity is respected. Constraints (21) force the production setup. Constraints (22) are degree constraints and constraints (23) eliminate subtours. Constraints (24) prevent split deliveries. Constraints (25)−(28) enforce non-negativity and integrality conditions on the variables.

2.2. Distance minimization

We now formulate the problems by considering that the more mileage a truck covers, the more emissions it generates. Hence, from transportation and environmental perspectives, it means to fulfill all demand by driving as few miles as possible. In terms of mathematical formulation, this can be easily done as follows. For each problem (IRP or PRP), one should consider all the constraints presented in Sections 2.1.1 and 2.1.2 with the following objective function:

$$\text{minimize} \sum_{(i,j)\in\mathcal{E}} \sum_{t\in\mathcal{T}} c_{ij} x_{ij}^t. \tag{29}$$

This objective function ignores all costs except the transportation one and aims to satisfy all demand by driving the least distance.

2.3. Emission minimization

As mentioned in the introduction, a measure which is widely used to evaluate the emissions is the one proposed in Kara et al. (2007) and Xiao et al. (2012), i.e., the distance traveled multiplied by the vehicle load. In order to use this objective function, one needs to know the flow of goods traversing each edge and the corresponding direction. Thus, we propose a directed load-based formulation for the IRP and the PRP. For this purpose, we define a directed graph $\mathcal{G}' = (\mathcal{N}, \mathcal{A})$, where $\mathcal{N} = \{0, ..., n\}$ is the node set and $\mathcal{A} = \{(i,j) : i, j \in \mathcal{N}\}$ is the arc set. In addition, we define binary variables ω_{ij}^t representing the directed arcs. Therefore, the objective functions of both problems become:

$$\text{minimize} \sum_{(i,j)\in\mathcal{A}} \sum_{t\in\mathcal{T}} c_{ij} \omega_{ij}^t q_j^t. \tag{30}$$

Objective function (30) is clearly non-linear as it contains the product of two variables. In order to linearize it, we define variables $\sigma_{ij}^t = \omega_{ij}^t q_j^t$. The objective function (30) becomes:

$$\text{minimize} \sum_{(i,j)\in\mathcal{A}} \sum_{t\in\mathcal{T}} c_{ij} \sigma_{ij}^t, \tag{31}$$

and we add the following constraints:

$$\sigma_{ij}^t \leq Q\omega_{ji}^t \quad i, j \in \mathcal{N} \quad t \in \mathcal{T} \tag{32}$$

$$\sum_{j\in\mathcal{N}'} \sigma_{0j}^t \leq \sum_{j\in\mathcal{N}'} q_j^t \quad t \in \mathcal{T} \tag{33}$$

$$\sum_{i\in\mathcal{N}} \sigma_{ij}^t - \sum_{i\in\mathcal{N}} \sigma_{ji}^t = q_j^t \quad j \in \mathcal{N}' \quad t \in \mathcal{T} \tag{34}$$

$$\sigma_{i0}^t, \sigma_{ii}^t = 0 \quad i \in \mathcal{N} \quad t \in \mathcal{T}. \tag{35}$$

Moreover, we replace constraints (8) and (9) of the IRP and constraints (22) and (23) of the PRP with the following:

$$\sum_{j \in \mathcal{N}} \omega_{ij}^t = y_i^t \quad i \in \mathcal{N} \quad t \in \mathcal{T} \tag{36}$$

$$\sum_{j \in \mathcal{N}} \omega_{ij}^t = \sum_{j \in \mathcal{N}} \omega_{ji}^t \quad i \in \mathcal{N} \quad t \in \mathcal{T} \tag{37}$$

$$\omega_{ij}^t + \omega_{ji}^t = x_{ij}^t \quad i, j \in \mathcal{N}, i < j \quad t \in \mathcal{T} \tag{38}$$

$$\omega_{ij}^t \in \{0, 1\} \quad (i, j) \in \mathcal{A} \quad t \in \mathcal{T}. \tag{39}$$

3. Computational Experiments

A branch-and-cut algorithm is used to solve the problems. First, excluding the subtour elimination constraints, the model is solved by a general purpose mixed-integer programming solver. Then violated subtour inequalities are identified and added to the formulation and the model is reoptimized. For details on the branch-and-cut algorithm and on how subtour elimination constraints are separated, the reader is referred to Archetti et al. (2011) and Coelho and Laporte (2013b). The formulations presented in Section 2 have been solved through CPLEX 12.7.0 and IBM Concert Technology. All computations are conducted on Intel Core i7 processor running at 3.4 GHz with 64 GB of RAM installed, with the Ubuntu Linux operating system. The maximum execution time is set to 3,600 seconds.

3.1. Instances

We used the benchmark instance sets created by Archetti et al. (2007) for IRP and Archetti et al. (2011) for PRP.

The attributes of the IRP instances are as follows: the time horizon is either three or six periods; in the instances with three periods, up to 50 retailers exist and in the ones with six periods, up to 30 retailers are considered. Inventory costs are low or high, and, in this paper, we identify the instances by the number of periods and their inventory holding cost category, therefore, 3-High, represents 3 periods and high holding cost. There is a total of 160 instances for the IRP.

The PRP instances are characterized by six time periods, 14 retailers, two levels for inventory cost, two intervals for the distance coordinates, and three values for the capacity of the vehicle.

Four classes of instances are identified: (1) base case, (2) high variable production costs, (3) high transportation cost, and (4) no inventory cost at the retailers. There is a total of 480 instances for the PRP.

3.2. Computational results

The computational results for IRP and PRP are presented in Sections 3.2.1 and 3.2.2, respectively.

3.2.1. Computational results for the IRP

Table 1 presents the performance summary for IRP. We report the average optimality gap at the end of computation and the average solution time. Each row reports the average results over the 5 instances with the same number of customers, horizon and inventory cost.

While all instances with total cost and distance objective functions are solved to optimality within a few seconds, after an hour of execution the case with emission objective function is not solved to optimality.

In order to study the trade-offs between different objectives for IRP, for each instance, we take the solution obtained from one objective function and evaluated it in terms of the other two objectives. Table 2 summarizes the corresponding results. Columns are grouped in three clusters of two columns each. Each cluster refers to one objective function, i.e., total cost, distance, emissions. For each cluster, we evaluate the percentage increase value of the corresponding objective function when considering the solution obtained by minimizing the other two objective functions. For example, considering the first cluster and the first row, in the first column we show that a solution obtained by minimizing the distance incurs 0.35% increase in the total cost, when compared to the solution that minimized the total cost. Likewise, still comparing with a solution obtained by minimizing that total cost, there is a 23.28% increase in the costs by using a solution that minimizes emissions. The percentage increase is calculated as $100 \times \dfrac{z(F) - z(TC)}{z(TC)}$, where $z(F)$ is the value of the total cost related to the solution that minimizes function F (distance in the first column and emissions in the second) and $z(TC)$ is the total cost related to the solution that minimizes the total cost. A similar procedure is followed for clusters 2 and 3. In cluster 2, the distance is evaluated for solutions that minimize the total cost, first, and the emissions, second. For cluster 3, the emissions are evaluated for solutions that minimize the total cost, first, and the distance, second.

Table 1: Performance summary for IRP

Instance	# retailers	Total cost Gap (%)	Total cost Time(s)	Distance Gap (%)	Distance Time(s)	Emissions Gap (%)	Emissions Time(s)
3-High	5	0.00	0	0.00	0	0.00	0
	10	0.00	0	0.00	0	22.99	3600
	15	0.00	0	0.00	0	31.62	3600
	20	0.00	1	0.00	1	39.15	3600
	25	0.00	1	0.00	1	43.61	3600
	30	0.00	3	0.00	3	56.67	3600
	35	0.00	1	0.00	1	57.98	3600
	40	0.00	8	0.00	6	68.57	3600
	45	0.00	10	0.00	8	70.19	3600
	50	0.00	38	0.00	37	69.65	3600
Average		0.00	6.24	0.00	5.62	46.04	3240.16
3-Low	5	0.00	0	0.00	0	0.00	0
	10	0.00	0	0.00	0	22.99	3600
	15	0.00	0	0.00	0	31.47	3600
	20	0.00	1	0.00	1	37.73	3600
	25	0.00	1	0.00	1	43.05	3600
	30	0.00	2	0.00	3	56.15	3600
	35	0.00	1	0.00	1	59.58	3600
	40	0.00	5	0.00	6	69.11	3600
	45	0.00	13	0.00	8	70.95	3600
	50	0.00	43	0.00	38	69.98	3600
Average		0.00	6.58	0.00	5.76	46.10	3240.12
6-High	5	0.00	0	0.00	0	0.74	1849
	10	0.00	0	0.00	1	27.92	3600
	15	0.00	2	0.00	2	34.04	3600
	20	0.00	7	0.00	47	43.67	3600
	25	0.00	12	0.00	43	53.94	3600
	30	0.00	26	0.00	65	64.21	3600
Average		0.00	7.93	0.00	26.43	37.42	3308.37
6-High	5	0.00	0	0.00	0	0.66	1808
	10	0.00	1	0.00	0	28.50	3600
	15	0.00	2	0.00	2	33.94	3600
	20	0.00	13	0.00	15	43.27	3600
	25	0.00	24	0.00	17	55.07	3600
	30	0.00	58	0.00	52	64.18	3600
Average		0.00	16.30	0.00	14.57	37.60	3301.40

As shown in the table, when minimizing the distance we obtain a slight increase in total cost. Instead, when we minimize emissions, the cost increases on average up to 50.42%. Minimizing the total cost would almost always provide solutions coinciding with those obtained when minimizing the distance. However, compared to the total cost minimization, when only distances are minimized the emission level increases. Despite the large optimality gap obtained for the emission objective function problems, they always yield the best solutions in terms of emissions. As shown in Table 2 emission levels increase by at least 22.16% and at most 56.62% under any of the other objective functions.

3.2.2. Computational results for the PRP

Table 3 presents the performance summary for the PRP instances. Class I instances with total cost and distance objective functions are solved to optimality within on average 2.2 and 25.11 seconds, Class II instances within 2.68 and 51.19, Class III within 5.04 and 22.04, and finally Class IV within 4.98 and 42.51. Again, when considering the emission objective function, the problem becomes more difficult to be solved to optimality within one hour of computing time. The maximum gap belongs to Class II instances, for which, after 3404 seconds, the average gap is 11.36%. However, further analysis indicates that even with large optimality gaps, still the emission objective function provides the best solution in terms of emission level compared to the results obtained when minimizing distances or total costs.

For class I instances, presented in Table 4, we see that the increase in total cost when minimizing the distance is 5.33% while, on the contrary, the increase in distance when minimizing the total cost is 8.60%. Thus, we can say that the two objectives obtain almost the same solutions. On the other side, when considering emissions, we get a totally different picture. In fact, when minimizing the emissions, the total cost increases by 11.22% and the distance increases by 38.01%, thus leading to a substantial difference. In addition, when we minimize both total cost and distance, we incur a large increase in emissions, of 41.93% and 39.61%, respectively. A similar behavior is realized for the other classes of instances (Tables 5– 7) with a lower difference between the solutions obtained when minimizing the total cost and the distance.

3.3. Key performance indicators

In order to compare solutions obtained from different objective functions and to better understand the trade-offs, we have defined a set of key performance indicators (KPIs). These

Table 2: Comparison of solution values when considering different objective functions for the IRP

Instance	# retailers	From distance	From emissions	From total cost	From emissions	From total cost	From distance
		To total cost		To distance		To emissions	
3-High	5	0.35	23.28	0.00	35.95	42.13	43.88
	10	0.32	20.94	0.00	40.85	47.60	45.24
	15	0.27	18.72	0.00	39.97	56.49	55.57
	20	0.20	18.30	0.00	42.59	52.64	51.29
	25	0.21	19.10	0.00	47.49	53.12	51.13
	30	0.29	22.13	0.00	55.56	52.22	50.20
	35	0.42	30.15	0.00	65.56	48.03	45.94
	40	0.27	35.18	0.42	71.32	40.65	39.77
	45	0.35	35.60	0.00	73.41	35.00	32.37
	50	0.18	43.88	0.27	79.54	25.49	23.23
Average		0.28	28.73	0.07	55.22	45.34	43.86
3-Low	5	0.07	34.08	0.00	35.95	43.39	43.88
	10	0.08	37.26	0.00	40.85	47.60	45.24
	15	0.06	36.22	0.00	40.35	56.62	55.69
	20	0.05	36.99	0.00	42.01	53.21	52.16
	25	0.07	41.79	0.00	48.00	53.72	51.74
	30	0.09	47.28	0.00	54.70	52.85	50.50
	35	0.14	59.47	0.00	66.33	46.13	44.12
	40	0.08	65.50	0.00	72.08	40.57	39.10
	45	0.13	72.03	0.00	78.31	34.22	31.23
	50	0.05	73.56	0.00	79.56	23.91	22.16
Average		0.08	50.42	0.00	55.81	45.22	43.58
6-High	5	0.61	16.24	0.06	25.95	35.71	32.42
	10	0.37	17.25	0.00	29.58	40.22	40.01
	15	0.28	16.83	0.37	32.58	49.03	47.05
	20	0.39	18.84	0.29	36.66	38.77	39.36
	25	0.57	33.82	0.20	58.02	35.09	35.79
	30	0.59	35.05	0.41	63.37	23.49	24.30
Average		0.47	23.00	0.22	41.03	37.05	36.49
6-Low	5	0.10	24.46	0.00	25.95	36.19	32.42
	10	0.07	29.21	0.00	31.31	39.76	39.61
	15	0.04	27.55	0.00	30.29	47.37	47.12
	20	0.06	33.70	0.00	36.96	41.19	39.85
	25	0.11	53.36	0.00	57.29	35.55	34.14
	30	0.11	58.36	0.01	63.18	23.44	23.40
Average		0.08	37.77	0.00	40.83	37.25	36.09

Table 3: Performance summary for PRP

	Total cost		Distance		Emissions	
Instance	Gap (%)	Time(s)	Gap (%)	Time(s)	Gap (%)	Time(s)
Class I	0.00	2.20	0.00	25.11	10.79	3439.25
Class II	0.00	2.68	0.00	51.19	11.36	3404.27
Class III	0.00	5.04	0.00	22.04	9.49	3129.88
Class IV	0.00	4.98	0.00	42.51	7.97	3058.49

Table 4: Comparison of solution values when considering different objective functions for PRP-Class I

		From distance	From emissions	From total cost	From emissions	From total cost	From distance
Instance		To total cost		To distance		To emissions	
	1	9.69	12.67	14.60	42.32	51.77	50.86
	2	5.83	12.28	27.00	39.96	48.57	40.40
	3	9.35	11.05	17.57	31.39	37.61	26.37
	4	4.86	8.80	3.45	44.80	49.71	50.60
	5	3.37	8.33	1.93	40.16	43.38	40.37
	6	4.57	7.42	4.16	29.81	27.69	28.00
	7	5.18	13.24	1.40	44.80	51.59	50.60
Class I	8	3.39	12.20	1.93	40.16	43.38	40.37
	9	4.19	9.93	4.16	29.81	27.74	28.00
	10	6.21	12.02	11.71	42.71	49.12	50.84
	11	3.95	11.10	8.40	39.13	39.99	40.64
	12	3.54	8.71	4.90	30.34	29.02	27.80
	13	7.73	14.68	9.20	41.89	51.85	50.81
	14	5.61	13.91	8.72	40.69	44.47	41.12
	15	5.47	12.03	9.87	32.24	33.09	27.37
Average		5.53	11.22	8.60	38.01	41.93	39.61

Table 5: Comparison of solution values when considering different objective functions for PRP-Class II

Instance		From distance	From emissions	From total cost	From emissions	From total cost	From distance
		To total cost		To distance		To emissions	
	16	4.43	10.32	0.53	41.30	47.97	50.19
	17	2.20	10.02	0.95	39.80	41.65	40.94
	18	3.30	8.64	1.74	30.45	28.77	27.50
	19	4.31	16.27	0.53	41.30	47.97	50.19
	20	2.11	16.02	0.95	40.74	41.67	40.97
	21	2.72	12.71	1.74	31.05	28.77	27.49
	22	5.50	13.25	7.75	41.30	48.61	50.19
	23	2.58	12.69	2.81	40.32	42.30	41.13
	24	2.98	10.12	3.00	31.08	27.43	27.44
	25	3.45	2.36	14.60	43.53	51.66	50.78
	26	1.48	2.26	25.11	38.68	49.57	40.71
	27	1.75	2.10	17.57	32.96	38.30	27.17
	28	2.50	1.24	0.87	42.50	51.18	50.71
	29	0.47	1.21	1.93	40.55	43.65	40.63
	30	0.65	1.14	4.16	32.91	27.06	27.23
	31	2.56	2.01	0.87	43.53	51.24	50.78
Class II	32	0.48	1.89	1.93	40.46	43.69	40.67
	33	0.62	1.67	4.16	32.91	26.99	27.23
	34	2.63	1.55	11.71	41.68	48.96	50.69
	35	0.49	1.46	8.40	40.46	40.37	40.67
	36	0.45	1.20	4.90	32.05	28.50	27.33
	37	3.18	3.08	6.75	41.30	49.86	50.19
	38	1.07	2.96	7.51	39.91	43.81	40.89
	39	1.08	2.46	9.87	31.65	34.24	28.62
	40	2.48	1.59	0.53	41.56	47.70	49.94
	41	0.31	1.56	0.96	39.63	41.89	41.07
	42	0.48	1.36	1.74	31.65	29.81	28.62
	43	2.49	2.83	0.53	41.39	47.76	50.00
	44	0.33	2.75	0.96	39.63	41.89	41.07
	45	0.43	2.25	1.74	31.65	29.91	28.62
	46	2.58	1.87	7.75	41.59	48.35	49.95
	47	0.33	1.82	2.81	40.15	42.27	41.09
	48	0.39	1.43	3.00	31.65	28.58	28.62
Average		1.90	4.73	4.86	37.92	40.68	39.68

Table 6: Comparison of solution values when considering different objective functions for PRP-Class III

		From distance	From emissions	From total cost	From emissions	From total cost	From distance
Instance		To total cost		To distance		To emissions	
Class III	49	4.58	27.07	0.13	42.35	50.35	50.56
	50	4.01	24.89	0.63	39.23	39.91	39.60
	51	3.58	20.52	1.38	32.00	30.02	27.38
	52	2.61	20.57	0.01	42.35	49.45	50.56
	53	2.53	19.14	0.44	39.23	39.34	39.60
	54	2.78	15.99	1.39	32.00	28.93	27.38
	55	1.89	29.87	0.01	42.35	49.46	50.56
	56	1.63	27.54	0.44	39.23	39.34	39.60
	57	1.30	22.30	13.19	31.86	26.64	27.30
	58	2.52	23.32	0.01	42.35	49.36	50.56
	59	2.42	21.66	0.60	39.23	39.95	39.60
	60	1.55	17.12	0.65	32.00	26.88	27.38
	61	3.01	32.91	0.10	42.55	50.25	49.74
	62	2.09	30.91	0.65	40.14	39.82	41.15
	63	1.94	23.59	0.52	30.75	28.02	28.60
	64	2.61	26.85	0.01	42.55	49.04	49.69
	65	1.32	26.17	0.46	41.26	39.30	41.19
	66	1.78	19.51	1.39	30.75	29.20	28.60
	67	1.64	33.96	0.01	41.49	49.41	49.91
	68	0.61	33.76	0.46	41.26	39.30	41.19
	69	0.65	25.50	0.52	31.34	26.94	28.54
	70	2.94	29.01	0.01	42.55	49.10	49.74
	71	1.27	28.10	0.56	41.26	41.11	41.19
	72	1.21	20.48	0.52	30.31	26.89	28.49
Average		2.19	25.03	1.00	37.93	39.08	39.51

Table 7: Comparison of solution values when considering different objective functions for PRP-Class IV

		From distance	From emissions	From total cost	From emissions	From total cost	From distance
Instance		To total cost		To distance		To emissions	
Class IV	73	5.74	16.56	9.18	44.11	46.01	50.63
	74	3.54	15.36	4.37	40.16	37.24	40.37
	75	2.20	10.90	3.23	30.36	28.81	28.00
	76	7.06	13.97	13.50	44.80	47.37	50.60
	77	4.36	12.63	8.62	38.81	39.95	40.77
	78	2.71	8.74	3.23	29.81	28.93	28.00
	79	4.89	19.42	1.38	41.95	47.76	49.72
	80	2.20	18.94	0.96	40.26	40.12	41.18
	81	1.87	14.33	2.78	31.65	28.63	28.62
	82	6.45	15.15	9.52	41.33	45.01	49.61
	83	2.88	14.28	6.07	39.63	37.72	41.07
	84	2.72	10.81	3.25	31.65	29.89	28.62
	85	2.57	2.32	9.18	44.80	45.88	50.60
	86	0.44	2.08	4.37	38.81	37.63	40.77
	87	0.28	1.49	3.23	29.81	29.93	28.00
	88	2.69	1.75	13.50	44.80	47.20	50.60
	89	0.50	1.60	8.62	40.16	39.20	40.37
	90	0.32	1.10	3.23	30.30	30.28	27.92
	91	2.53	3.07	1.38	41.63	47.36	49.95
	92	0.30	2.98	0.96	39.63	40.41	41.07
	93	0.27	2.29	2.78	31.65	29.39	28.62
	94	2.67	1.97	9.52	41.60	45.75	50.07
	95	0.34	1.90	6.07	39.63	37.92	41.07
	96	0.34	1.45	3.25	31.65	28.63	28.62
Average		2.50	8.13	5.51	37.87	38.21	39.79

KPIs are categorized in three groups: inventory, delivery, and load. Inventory KPIs category includes quantity and cost of inventory at retailers and at the depot. Delivery KPIs measure the total number of deliveries, total quantity delivered to all retailers, and finally the average trip length. The average trip length is obtained by calculating the total distance traveled divided by the number of arcs used. Finally, we define vehicle fill, average load, empty running, logistic ratio, and distribution cost per delivery as the load KPIs. The vehicle fill is the total load on the vehicle divided by its capacity. The average load is the ratio between the total load and number of deliveries. The empty running KPI is the distance the vehicle travels getting back to the depot, after the last delivery, as all vehicles come back empty to the depot. For the emission problem in which the graph is directed, the empty running of each vehicle is the distance the vehicle travels from the last visited customer to the depot. For the total cost and distance minimization problems, as the edges are not directed, we use the average of the distance from the depot to the first and last visited customer as the empty running KPI. Note that, for the emission problem, the direction in which the route is traversed has an impact on the emission value. Thus, we cannot consider the reverse direction. Finally, logistic ratio is the distance traveled per quantity of items delivered, and the distribution cost per delivery, as the name suggests, is the cost per units delivered.

We use the above mentioned KPIs mainly for two reasons. First, they are already established in the literature, as they are well documented by Mckinnon and Hr (2007). Second, they are all based on measures that we are able to evaluate by running our models on benchmark IRP and PRP instances, i.e., distance and vehicle load. In fact, one may argue that traffic and congestion are also important factors that have an impact on emissions. However, they are difficult to measure in general and not suited for the models and instances under study.

3.3.1. Analysis for the IRP

The average of inventory KPIs for the IRP are presented in Table 8. Inventory costs and quantities remain roughly unchanged within the three different objective functions. This leads to the conclusion that the difference in total cost observed when optimizing the different objective functions, especially emissions, is mainly due to transportation cost (Table 2). The inventory at the depot is the lowest under the total cost minimization and the highest under the distance minimization. However, for the amount of inventory kept at the retailers we observe the opposite.

Table 8: Average inventory KPIs for IRP

Instance	Objective	Inventory retailer	Inventory cost retailer	Inventory depot	Inventory cost depot
3-High	Total cost	4530.32	1350.01	18694.32	5608.30
	Distance	4370.66	1330.00	18853.98	5656.19
	Emissions	4381.96	1336.06	18842.68	5652.80
3-Low	Total cost	4511.68	134.88	18712.96	561.39
	Distance	4370.66	133.17	18853.98	565.62
	Emissions	4365.16	133.49	18859.48	565.78
6-High	Total cost	5096.50	1472.65	21390.57	6417.17
	Distance	4750.57	1443.13	21736.50	6520.95
	Emissions	4907.47	1494.70	21579.60	6473.88
6-Low	Total cost	5016.87	147.72	21470.20	644.11
	Distance	4750.57	142.93	21736.50	652.10
	Emissions	4904.67	149.47	21582.40	647.47
Average	**Total cost**	**4788.84**	**776.31**	**20067.01**	**3307.74**
	Distance	**4560.61**	**762.31**	**20295.24**	**3348.71**
	Emissions	**4639.81**	**778.43**	**20216.04**	**3334.99**

Table 9 shows the average delivery KPIs for the IRP. As indicated, the total number of deliveries when minimizing the emissions is almost double the number of deliveries in total cost and distance minimization problems. Total deliveries are similar in all three problems, however, in the total cost minimization, more quantities are delivered to the retailers. The extra delivery is kept as the inventory at the retailers and, as shown before by inventory KPIs, the total cost minimization problem tends to keep more inventory at the retailers. This is due to the structure of inventory costs. While the average length of the trip does not vary in total cost and distance minimization problems, they considerably increase with an emission minimization objective function. This is due to the fact that, when minimizing the emissions, we consider both distance and quantity delivered, so a higher number of deliveries is performed.

Table 9: Average delivery KPIs for IRP

Instance	Objective	# Deliveries	Total delivery	Trip length
3-High	Total cost	29.60	2257.98	91.74
	Distance	29.54	2159.30	91.54
	Emissions	45.42	2155.26	148.11
3-Low	Total cost	29.54	2250.04	91.54
	Distance	29.54	2159.30	91.54
	Emissions	45.84	2155.26	150.34
6-High	Total cost	49.57	4380.37	115.13
	Distance	49.00	4275.90	116.04
	Emissions	62.63	4271.37	162.54
6-Low	Total cost	49.03	4337.33	116.02
	Distance	49.00	4275.90	116.04
	Emissions	61.93	4271.37	163.48
Average	**Total cost**	**39.44**	**3306.43**	**103.61**
	Distance	**39.27**	**3217.60**	**103.79**
	Emissions	**53.96**	**3213.31**	**156.12**

As shown in Table 10, which reports the average load KPIs, the vehicle fill is the same with all three objective functions, and, when minimizing the distance, the average load on the vehicle tends to be the biggest among the three objective functions and significantly lower with respect to the case in which we minimize the emissions. The differences between the empty running KPIs obtained by three objective functions is quite notable. In the emission minimization problem, the empty vehicles travel a much longer distance. This is mainly due to the fact that we define emissions as the product of the load and the distance, therefore, to reduce the emissions, the vehicle has to travel the longer way with no load. Logistic ratio and distribution cost per delivery are also higher while minimizing emissions, as the number of deliveries increase.

Table 10: Average load KPIs for IRP

Instance	Objective	Vehicle fill	Average load	Empty running	Logistic ratio	Distribution cost per delivery
3-High	Total cost	0.35	73.79	141.91	1.34	91.74
	Distance	0.33	91.54	141.03	1.43	91.54
	Emissions	0.33	49.96	841.98	3.15	148.11
3-Low	Total cost	0.35	73.87	140.93	1.34	91.54
	Distance	0.33	91.54	141.03	1.43	91.54
	Emissions	0.33	49.72	887.38	3.23	150.34
6-High	Total cost	0.51	86.55	447.57	1.37	115.13
	Distance	0.50	116.04	442.20	1.39	116.04
	Emissions	0.50	70.57	1706.07	2.35	162.54
6-Low	Total cost	0.51	86.64	444.33	1.38	116.02
	Distance	0.50	85.56	442.20	1.39	116.04
	Emissions	0.50	71.08	1703.17	2.35	163.48
Average	**Total cost**	**0.43**	**80.21**	**293.69**	**1.36**	**103.61**
	Distance	**0.42**	**96.17**	**291.62**	**1.41**	**103.79**
	Emissions	**0.42**	**60.33**	**1284.65**	**2.77**	**156.12**

3.3.2. Analysis for the PRP

The inventory KPIs for the PRP are shown in Table 11. The table shows that to minimize the total cost, one needs to reduce the inventory level at the depot, while to minimize the emissions, the inventory at the depot should almost be doubled. Although almost the same amount of inventory is kept at the retailers in both total cost and emission minimization, it is quite lower when the distance is minimized.

Table 11: Average inventory KPIs for PRP

Instance	Objective	Inventory retailer	Inventory cost retailer	Inventory depot	Inventory cost depot
Class I	Total cost	1,729.23	8,308.91	651.45	2,939.69
	Distance	2,033.77	10,517.09	1,022.44	5,079.85
	Emissions	1,809.12	9,367.11	1,232.88	6,168.37
Class II	Total cost	1819.91	7986.11	678.49	3343.10
	Distance	2014.83	9419.35	1046.70	5756.85
	Emissions	1796.38	8,411.05	1245.63	6849.58
Class III	Total cost	1,870.23	8,471.42	632.87	3344.18
	Distance	2046.60	9571.50	997.40	5,485.70
	Emissions	1796.50	8385.93	1245.50	6856.50
Class IV	Total cost	2045.13	0.00	479.93	2590.55
	Distance	2014.83	0.00	1046.70	5756.85
	Emissions	1802.38	0.00	1239.63	6818.00
Average	**Total cost**	**1866.13**	**6191.61**	**610.69**	**3054.38**
	Distance	**1622.01**	**5901.59**	**822.65**	**4415.85**
	Emissions	**1801.09**	**6541.02**	**1240.91**	**6673.11**

The delivery KPIs are shown in Table 12. It is interesting to note that with the distance minimization objective function, the number of deliveries, the total quantities delivered, and the average length of the trip are also minimized. The number of deliveries slightly increases when minimizing the emissions rather than the total cost, while the total deliveries remain the same. As was the case with IRP, the trip length of each vehicle increases when reducing the emissions with respect to the case of minimizing the total cost or distance.

Table 13 shows the load KPIs for PRP. Just like for the IRP, the vehicle fill does not vary with respect to the objective function. When minimizing the emissions, the average load

Table 12: Average delivery KPIs for PRP

Instance	Objective	# Deliveries	Total Delivery	Trip Length
Class I	Total cost	24.59	543.60	163.54
	Distance	22.72	548.28	161.18
	Emissions	26.03	543.60	227.78
Class II	Total cost	23.78	543.60	205.30
	Distance	22.70	548.30	201.67
	Emissions	26.05	543.60	284.60
Class III	Total cost	22.43	543.60	2044.86
	Distance	22.43	546.53	2037.68
	Emissions	25.82	543.60	2867.04
Class IV	Total cost	22.63	543.60	213.90
	Distance	22.70	548.30	201.67
	Emissions	25.85	543.60	285.53
Average	**Total cost**	**23.36**	**543.60**	**656.90**
	Distance	**18.11**	**438.28**	**520.44**
	Emissions	**25.94**	**543.60**	**916.24**

tends to decrease while the empty running, logistic efficiency, and distribution cost per delivery considerably increase. Concerning the total cost and distance minimization objective functions, while the distribution cost per delivery remains almost the same, the average load and empty running increase when minimizing the distance and the logistic ratio decreases.

Table 13: Average load KPIs for PRP

Instance	Objective	Vehicle fill	Average load	Empty running	Logistic ratio	Distribution cost per delivery
Class I	Total cost	0.41	21.91	608.76	7.44	163.54
	Distance	0.41	24.23	606.54	6.72	161.18
	Emissions	0.41	20.87	1840.34	10.95	227.78
Class II	Total cost	0.41	22.69	740.78	8.95	205.30
	Distance	0.41	24.24	753.15	8.40	201.67
	Emissions	0.41	20.85	2299.36	13.66	284.60
Class III	Total cost	0.41	22.64	7186.53	84.97	2044.86
	Distance	0.41	24.39	7855.75	84.18	2037.68
	Emissions	0.41	21.04	22877.78	136.49	2867.04
Class IV	Total cost	0.41	22.64	797.51	8.91	213.90
	Distance	0.41	24.24	753.15	8.40	201.67
	Emissions	0.41	21.02	2293.50	13.61	285.78
Average	**Total cost**	**0.41**	**22.47**	**2333.39**	**27.57**	**656.90**
	Distance	**0.41**	**24.28**	**2492.15**	**26.93**	**650.55**
	Emissions	**0.41**	**20.94**	**7327.74**	**43.68**	**916.30**

4. Conclusions

In this paper we have studied what is the impact of minimizing emissions on classical integrated logistics optimization problems. We have considered the IRP and the PRP, two classical supply chain problems treated under a cost minimization objective, and we have assessed their solutions under a more encompassing objective in which one aims to decrease emission levels and be more environmentally friendly. To that end, we have focused on both minimizing the total distance traveled to satisfy all the demand, and a more complex and richer function serving as a proxy for true emissions. After solving sets of benchmark instances under these three scenarios, we have evaluated the shape of the solutions in terms of different business KPIs designed to highlight the impact of the objective function chosen on costs, distances, and emissions.

Our findings indicate that an important factor in reducing the emissions is the empty running of the vehicle.In fact, when minimizing emissions, a 'lighter' load is preferable, and, as a consequence, empty running to come back to the depot tends to be longer. In addition, the findings indicate that there needs to be a balance between the load on the vehicle and the distance it travels. In order to reduce fuel consumption, it would be preferable to perform more deliveries to the customers with respect to the number of deliveries obtained when optimizing classical objective functions like total cost or distance. Finally, our computational experiments corroborate the previous studies pointing out that to reduce emissions, it is important to measure not only the distance traveled but also the load of the vehicles. This may lead to counter-intuitive solutions in which the distance traveled increases and the average vehicle load decreases. However, given that vehicles travel with a lower load, this may lead to benefits in terms of emissions. Our evaluation of several KPIs has shed some light on the shape the solutions should have in order to minimize the total costs or emission levels.

In conclusion, our work highlight that solutions may differ a lot when changing the objective function. Hence, managers have to properly evaluate what is best for their company before planning the corresponding operations.

References

Absi, N., Archetti, C., Dauzère-Pérès, S., Feillet, D., 2014. A two-phase iterative heuristic approach for the production routing problem. Transportation Science 49 (4), 784–795.

Absi, N., Dauzère-Pérès, S., Kedad-Sidhoum, S., Penz, B., Rapine, C., 2013. Lot sizing with carbon emission constraints. European Journal of Operational Research 227 (1), 55–61.

Absi, N., Dauzère-Pérès, S., Kedad-Sidhoum, S., Penz, B., Rapine, C., 2016. The single-item green lot-sizing problem with fixed carbon emissions. European Journal of Operational Research 248 (3), 849–855.

Adulyasak, Y., Cordeau, J.-F., Jans, R., 2012. Optimization-based adaptive large neighborhood search for the production routing problem. Transportation Science 48 (1), 20–45.

Adulyasak, Y., Cordeau, J.-F., Jans, R., 2014. Formulations and branch-and-cut algorithms for multi-vehicle production and inventory routing problems. INFORMS Journal on Computing 26 (1), 103–120.

Adulyasak, Y., Cordeau, J.-F., Jans, R., 2015. The production routing problem: A review of formulations and solution algorithms. Computers & Operations Research 55, 141–152.

Andersson, H., Hoff, A., Christiansen, M., Hasle, G., Løkketangen, A., 2010. Industrial aspects and literature survey: Combined inventory management and routing. Computers & Operations Research 37 (9), 1515–1536.

Archetti, C., Bertazzi, L., Hertz, A., Speranza, M. G., 2012. A hybrid heuristic for an inventory routing problem. INFORMS Journal on Computing 24 (1), 101–116.

Archetti, C., Bertazzi, L., Laporte, G., Speranza, M. G., 2007. A branch-and-cut algorithm for a vendor-managed inventory-routing problem. Transportation Science 41 (3), 382–391.

Archetti, C., Bertazzi, L., Paletta, G., Speranza, M. G., 2011. Analysis of the maximum level policy in a production-distribution system. Computers & Operations Research 12 (38), 1731–1746.

Armentano, V. A., Shiguemoto, A. L., Løkketangen, A., 2011. Tabu search with path relinking for an integrated production–distribution problem. Computers & Operations Research 38 (8), 1199–1209.

Bard, J. F., Nananukul, N., 2009. Heuristics for a multiperiod inventory routing problem with production decisions. Computers & Industrial Engineering 57 (3), 713–723.

Bard, J. F., Nananukul, N., 2010. A branch-and-price algorithm for an integrated production and inventory routing problem. Computers & Operations Research 37 (12), 2202–2217.

Bektaş, T., Laporte, G., 2011. The pollution-routing problem. Transportation Research Part B: Methodological 45 (8), 1232–1250.

Bell, W. J., Dalberto, L. M., Fisher, M. L., Greenfield, A. J., Jaikumar, R., Kedia, P., Mack, R. G., Prutzman, P. J., 1983. Improving the distribution of industrial gases with an on-line computerized routing and scheduling optimizer. Interfaces 13 (6), 4–23.

Benjaafar, S., Li, Y., Daskin, M., 2013. Carbon footprint and the management of supply chains: Insights from simple models. IEEE Transactions on Automation Science and Engineering 10 (1), 99–116.

Bertazzi, L., Paletta, G., Speranza, M. G., 2002. Deterministic order-up-to level policies in an inventory routing problem. Transportation Science 36 (1), 119–132.

Chandra, P. J., 1993. A dynamic distribution model with warehouse and customer replenishment requirements. Journal of the Operational Research Society 44 (7), 681–692.

Coelho, L. C., Cordeau, J.-F., Laporte, G., 2012. The inventory-routing problem with transshipment. Computers & Operations Research 39 (11), 2537–2548.

Coelho, L. C., Cordeau, J.-F., Laporte, G., 2014. Thirty years of inventory routing. Transportation Science 48 (1), 1–19.

Coelho, L. C., Laporte, G., 2013a. A branch-and-cut algorithm for the multi-product multi-vehicle inventory-routing problem. International Journal of Production Research 51 (23-24), 7156–7169.

Coelho, L. C., Laporte, G., 2013b. The exact solution of several classes of inventory-routing problems. Computers & Operations Research 40 (2), 558–565.

Coelho, L. C., Renaud, J., Laporte, G., 2016. Road-based goods transportation: a survey of real-world logistics applications from 2000 to 2015. INFOR: Information Systems and Operational Research 54 (2), 79–96.

Dabia, S., Demir, E., Van Woensel, T., 2017. An exact approach for a variant of the pollution-routing problem. Transportation Science 51 (2), 607–628.

Demir, E., Bektaş, T., Laporte, G., 2011. A comparative analysis of several vehicle emission models for road freight transportation. Transportation Research Part D: Transport and Environment 16 (5), 347–357.

Demir, E., Bektaş, T., Laporte, G., 2014. A review of recent research on green road freight transportation. European Journal of Operational Research 237 (3), 775–793.

Desaulniers, G., Rakke, J. G., Coelho, L. C., 2015. A branch-price-and-cut algorithm for the inventory-routing problem. Transportation Science 50 (3), 1060–1076.

Franceschetti, A., Demir, E., Honhon, D., Van Woensel, T., Laporte, G., Stobbe, M., 2017. A metaheuristic for the time-dependent pollution-routing problem. European Journal of Operational Research 259 (3), 972–991.

Helmrich, M. J. R., Jans, R., van den Heuvel, W., Wagelmans, A. P. M., 2015. The economic lot-sizing problem with an emission capacity constraint. European Journal of Operational Research 241 (1), 50–62.

Jabali, O., Van Woensel, T., de Kok, A. G., 2012. Analysis of travel times and CO_2 emissions in time-dependent vehicle routing. Production and Operations Management 21 (6), 1060–1074.

Kara, İ., Kara, B. Y., Yetis, M. K., 2007. Energy minimizing vehicle routing problem. In: International Conference on Combinatorial Optimization and Applications. Springer, pp. 62–71.

Kopfer, H. W., Schönberger, J., Kopfer, H., 2014. Reducing greenhouse gas emissions of a heterogeneous vehicle fleet. Flexible Services and Manufacturing Journal 26 (1-2), 221.

Kumar, R. S., Kondapaneni, K., Dixit, V., Goswami, A., Thakur, L. S., Tiwari, M. K., 2016. Multi-objective modeling of production and pollution routing problem with time window: A self-learning particle swarm optimization approach. Computers & Industrial Engineering 99, 29–40.

Mckinnon, A. C., Hr, E., 2007. Synchronised auditing of truck utilisation and energy efficiency: a review of the British Government's transport KPI programme. In: Proceedings of the 11 th World Conference on Transport Research.

Qiu, Y., Qiao, J., Pardalos, P. M., 2017. A branch-and-price algorithm for production routing problems with carbon cap-and-trade. Omega 68, 49–61.

Soysal, M., Bloemhof-Ruwaard, J. M., Haijema, R., van der Vorst, J. G. A. J., 2015. Modeling an inventory routing problem for perishable products with environmental considerations and demand uncertainty. International Journal of Production Economics 164, 118–133.

Soysal, M., Bloemhof-Ruwaard, J. M., Haijema, R., van der Vorst, J. G. A. J., 2016. Modeling a green inventory routing problem for perishable products with horizontal collaboration. Computers & Operations Research.

Suzuki, Y., 2011. A new truck-routing approach for reducing fuel consumption and pollutants emission. Transportation Research Part D: Transport and Environment 16 (1), 73–77.

Xiao, Y., Zhao, Q., Kaku, I., Xu, Y., 2012. Development of a fuel consumption optimization model for the capacitated vehicle routing problem. Computers & Operations Research 39 (7), 1419–1431.