A Green Transportation Problem for e-Commerce Deliveries

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Abstract: To get involved in the fight against climate change, e-commerce actors should reduce the environmental impact of their activities. For retailers, a key challenge to is identify the stock sources for fulfilling online orders. In this paper, our goal is to orchestrate orders while minimizing the associated environmental impact. We propose a model of Green Transportation Problem for E-commerce Deliveries (`GTP-ED`) which can be seen as a general case of Fixed Charge Transportation Problem. We detail how we obtain the environmental objective function and how we generate instances based on real world and realistic data and that good quality solutions can be obtained quickly. Then, we show the relevance of our environmental objective function by comparing the results with an orchestration based on minimizing the distance traveled by the parcels, which leads to a 30% increase of environmental cost. Finally, we compare the `GTP-ED` with an economic approach and outline a significant tension between our environmental and economic objectives in that context.

1 INTRODUCTION

The development of e-commerce has raised new technical and operational challenges for retailers. Everyday, retailers have to prepare, to pack and to ship orders to satisfy their customers, leading to billions of deliveries all around the world. The dedicated logistics generate environmental impacts that should be mitigated to take part in the fight against the environmental crisis. In 2022, the logistics to ship the billion of parcels delivered in France was responsible for approximately 1 MteqCO_2 (CPV Associés et al., 2023). In few years, the e-commerce sector has become omnichannel, meaning that orders come from various sales channels (websites, marketplaces, call centers...) and can be fulfilled using any stock, including stores' stocks. Thus, the retailers take into account a unified stock, but this additional flexibility, very efficient to increase sales and reduce unsold stock, raises operational issues. Among them are the stock management and the determination of the stock location to be used to fulfill orders. To handle these challenges, most retailers use an Order Management System (OMS). Based on unified stocks, the OMS informs whether products are available to be sold online or not. Once orders are placed through a retailer's channel, the OMS orchestrates and monitors the orders. Order orchestration aims at deciding which stock location will be chosen to ship each item for each order. Usually, retailers use dispatching rules to optimise a given monetary cost based criteria. This paper presents an optimization model designed to minimise the environmental impact of order orchestration. The studied problem is related to the Transportation Problem, in which the goal is to minimise the distribution cost of products from a set of sources to a set of destinations. The remainder of this paper is organised as follows: Section 2 proposes a literature review on order orchestration, transportation problems and environmental costs over Operational Research field. Section 3 introduces the proposed environmental objective function and formalises the problem.. In Section 4, we expose how we obtained realistic datasets to test our model and detail some results. We analyse the computational performances and the relevance of our environmental objective function. Finally, conclusion and future works are drawn in Section 5.

2 LITERATURE REVIEW

Order Orchestration for e-Commerce Retailers: on order orchestration mainly focused on monetary objective functions. The first optimisation model for e-commerce retailers was proposed in (Xu et al., 2009), whose aim is to orchestrate orders over a time

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horizon while minimizing split orders, i.e. multi-items orders shipped from multiple stock locations. They propose to periodically re-evaluate the orchestration of orders which have not been fulfilled yet. A MILP formulation is provided, identified as a network design problem where minimizing the number of splits is equivalent to minimizing the number of activated arcs in the network. They perform a decomposition and a heuristic approach to solve large scale instances. In (Acimovic and Graves, 2015) or in (Jasin and Sinha, 2015), the goal is to determine the optimal order fulfillment policy which minimises the shipping costs of e-commerce retailers including an estimate of shipping cost for future orders. They use a MILP formulation to elaborate demand forecasts and then propose heuristic methods to determine the optimal order fulfillment policy. In (Lei et al., 2018), the authors address a problem in which retailers must take about items pricing and orders fulfillment. The objective is to maximize the total profits equal to the sales profits minus the expected shipping costs. The resulting problem is NP-hard. They propose two heuristics which separate item pricing decisions and order fulfillment decisions. (Cheref et al., 2018) study an orchestration problem including fixed and variable costs, respectively related to shipping costs and products costs. They use a matheuristic and provide some performance guarantees.

Transportation Problem: The order orchestration we consider in this paper can be related to a variant of Transportation Problem with multiple items. We perform below a short literature review on this problem, for a more detailed survey, we refer to (Kacher and Singh, 2021) or (Malacký and Madleňák, 2023).
In the Transportation Problem (`TP`), the goal was to match the supplies of factories in a given product with the demand of several cities while minimizing the transportation cost and it was assumed that the total supply and the total demand were equal (Hitchcock, 1941). The `TP` could be modeled with the following linear program: $\min \sum_{i,j} c_{ij} x_{ij}$, s.t. $\sum_i x_{ij} = d_j$, $\sum_j x_{ij} = q_i$ where $x_{ij} \geq 0$ represent the decision variables (amount of products from factory i to city j), d_j the demands, q_i the stocks and c_{ij} the costs. As shown in (Matsui and Scheifele, 2016), lots of efficient algorithms exist to solve the `TP`.
Since then, many variants appeared. (Haley, 1962) introduces a three-dimensional `TP`, called Solid Transportation Problem. For this problem, a third index is used to model several types of products which have to be delivered and three capacity constraints are considered. The Fixed Charge Transportation Problem (`FCTP`) has also received a lot of attention. (Balinski, 1961) introduced the `FCTP` as a variant where fixed costs are added to classical variable costs. Binary decision variables are introduced to take into account those fixed costs. The `FCTP` was shown to be NP-hard (Klose, 2008). To solve large instances in a reasonable amount of time, (Roberti et al., 2015) and later (Mingozzi and Roberti, 2018) proposed a column generation scheme, which allowed them to significantly improve the size of solved instances. The Transportation Problem with Packing Constraints, is a variant of `FCTP`, introduced by (Flamand et al., 2023). It takes into account variable costs proportional to the amount of products bought at a given supplier and fixed costs depending on the usage of the vehicles for each path. In addition to that, they add packing constraints, ensuring that vehicles used between a supplier and a customer have a sufficient capacity to carry all the goods shipped on this way.

Environmental Cost: Over the path of a parcel, several sources of environmental impacts can be found: transportation, handling, storage and packaging (CPV Associés et al., 2023). Transportation is the most often considered impact and may include transportation from factories to warehouses, between warehouses or from warehouses to customers.
In (Colissimo, 2023), the French carrier Colissimo, describes how to compute the environmental cost of a parcel traveling through its network. In their work, the environmental cost corresponds to the amount of CO_2 emitted. It includes transportation and building impacts and depends on origin and destination zip codes, parcel volume and parcel mass. The path of a parcel is decomposed into several legs, and for each one a formula is given for evaluating the environmental impact. Data are based on average data from the previous year and include vehicle types, motorisation, load factor etc... Regarding the building impacts, a unit environmental cost is affected to each parcel depending on previous year data.
In the literature, `TP` with environmental objective function are often multi-objective with a second objective being economic. In (Shojaie and Raoofpanah, 2018), the authors add a fixed environmental cost for each vehicle having to deliver a certain customer from a certain supply. This cost corresponds to the vehicle pollution and depends on the type of vehicle and the pair origin-destination. In their variant of Green Transportation Problem with Multi Objective, (Midya et al., 2021) also consider the vehicle emissions as the environmental cost but adopted a different measuring strategy as they consider the cost proportional to the amount of goods to be shipped on the given path.

3 PROBLEM FORMULATION

In this paper, our goal is to solve the order orchestration faced by retailers, with a special care about environmental impacts. Thus, we aim at providing every item of every order, while respecting the stocks and minimising a given environmental cost function. More precisely, we have two specific locations, the stock locations associated to sources and, for each order, the customer delivery locations associated to destinations. Our goal is to determine which stock locations can be associated with each delivery location as in classical TP. We underline that in the problem we consider, the routing decisions are not part of the retailers' scope. Indeed, in our problem, the transportation from a source to a destination is ensured by an external carrier and, is associated to a unique link. Moreover, the orders we consider are placed by individuals, meaning that the amounts demanded are quite low and enforce the use of integer decision variables. Before presenting the Mixed Integer Linear model of our problem, we focus on the considered environmental cost function.

The Environmental Cost Function: Along the shipping of an item, types of environmental impacts are numerous. The environmental impacts considered in this paper are evaluated by the amount of greenhouse gases emissions, measured in g CO_2 equivalent, whereas deliveries are also causes of pollution, waste or resource depletion. Items leaving the Stock Location are packed into parcels and may be gathered with other items having the same origin and destination. Thus, costs upstream the Stock Location are item related, while costs downstream the Stock Location, including packaging, are parcel related. The environmental impact of a shipped item can be seen as the sum of the following elements:

- Manufacturing costs ($\mathbf{MC_k}$) caused by the manufacturing of item k.
- Supply costs ($\mathbf{SuC_{ks}}$) including all the environmental impacts to store, handle and carry the item k to the stock location s.
- Storage costs ($\mathbf{StC_{ks}}$) due to the functioning of buildings used for the storage. They are related to the item k and the stock location s.
- Packaging costs ($\mathbf{PC_b}$) due to the packaging used to ship the item. They are proportional to the amount of packaging required and depends on the material used. $\mathbf{PC_b}$ are related to the characteristics of the chosen box b.
- Transportation costs ($\mathbf{TC_{bso}}$) caused by the transportation of the parcel b from the stock location s to the customer destination o through one or several hubs. We consider $\mathcal{K}_{bso}$ the set of items sent from the stock location s to the customer location for order o in a box b, m_k the mass of an item k and M_b and V_b the mass and volume of a box b. Then, we use the formula provided by Colissimo (Colissimo, 2023) to compute the transportation costs. $TC_{bso} = EV_{so} \times V_b + EM_{so} \times (M_b + \sum_{k \in \mathcal{K}_{bso}} m_k)$, where EV_{so} and EM_{so} are two emission factors proportional to the volume and to the mass respectively. EV_{so} and EM_{so} are specific to each path (from stock location to customer) and depend on the distance covered, the vehicle type and the fuel used by the carrier.
- Handling costs ($\mathbf{HC_{bso}}$) due to sorting and handling along the transportation leg. They are related to the origin s and destination o and to the parcels b to be handled.
- Consumer Travel costs ($\mathbf{CTC_o}$) due to the travel of customers to pick up their parcel (equals 0 in case of Home Delivery). They are fixed costs depending on the customer's distance and mean of transportation.

Order orchestration is only about assigning items to stock location. Thus, for the remaining of the paper, Manufacturing and Consumer Travel costs are not taken into account in the objective function. Indeed, they can be considered as non-decisionary fixed costs as the same amount has to be added no matter the decisions taken. Moreover, the measure of the environmental cost requires information about parcels to be shipped. In particular, the Transportation costs formula to compute TC_{bso} requires the volume and the mass of the parcel. We chose this formula as it is used by a major carrier. Among the drawbacks we identified, the requirement for the parcel volume was the most detrimental. Indeed, it implies to determine the volume of the parcel depending on the items to be shipped. This problem is close to the well-know NP-hard 3D-Bin Packing Problem (Martello et al., 2000). We chose to simplify the computation of the parcels volume by simply requiring the total volume of parcels shipped to be higher than the total volume of items to be shipped. This method can be used for a retailer sending clothes for example. However, to avoid products jamming, a small margin on the volume of the parcel is considered.

Resulting MILP - Green Transportation Problem for e-Commerce Deliveries (GTP-ED): Our Green Transportation Problem for E-commerce Deliveries, denoted by GTP-ED, can be seen as a variant of a Fixed-Charge Transportation Problem (FCTP) that includes an environmental cost function. The stock locations of items correspond to sources of the TP. Also, a unique delivery location is associated to each customer order. Thus the orders correspond to their respective delivery point, that are the destinations of the TP. Let us consider $\mathcal{O}$ the set of orders, $\mathcal{K}$ the set of items, $\mathcal{S}$ the set of stock locations and $\mathcal{B}$ the set of boxes. We denote by d_{ko} the demand in item k for order o and by q_{ks} the stock for item k in stock location s. Let v_k be the volume of an item k and V_b the volume of a box b. The model of the GTP-ED is:

$$\textbf{(GTP-ED)} \quad \min F_G = \sum_{s\in\mathcal{S}} \sum_{o\in\mathcal{O}} \Big(\sum_{k\in\mathcal{K}} I_{kso} x_{kso} + \sum_{b\in\mathcal{B}} P_{bso} y_{bso} \Big) \quad (1)$$

$$\sum_{s\in\mathcal{S}} x_{kso} = d_{ko} \qquad \forall k \in \mathcal{K}, \forall o \in \mathcal{O} \quad (2)$$

$$\sum_{o\in\mathcal{O}} x_{kso} \leq q_{ks} \qquad \forall k \in \mathcal{K}, \forall s \in \mathcal{S} \quad (3)$$

$$\sum_{b\in\mathcal{B}} y_{bso} V_b - \alpha \sum_{k\in\mathcal{K}} x_{kso} v_k \geq 0 \qquad \forall s \in \mathcal{S}, \forall o \in \mathcal{O} \quad (4)$$

$$x_{kso} \in \mathbb{N} \qquad \forall k \in \mathcal{K}, \forall s \in \mathcal{S}, \forall o \in \mathcal{O} \quad (5)$$

$$y_{bso} \in \mathbb{N} \qquad \forall b \in \mathcal{B}, \forall s \in \mathcal{S}, \forall o \in \mathcal{O} \quad (6)$$

where x_{kso} is an integer variable (Constraints (5)) accounting for the number of items k used from the stock location s to fulfill the order o and y_{bso} is an integer variable (Constraints (6)) representing the number of boxes b sent from the stock location s to the destination of order o. Let us notice that decision variables are chosen as integers and unbounded but simple upper bounds can be found. Indeed, the number of items k to be sent from a stock location s can neither be higher than the stocks q_{ks} of item k in location s nor than the demand d_{ko} of order o for item k, i.e., $\forall k \in \mathcal{K}, s \in \mathcal{S}, o \in \mathcal{O}, x_{kso} \leq \min(d_{ko}, q_{ks})$. Then, for each order o, the maximum number of boxes of type b is lower than the number of boxes b required to get more space than the total volume required for the order o, i.e., $\forall b \in \mathcal{B}, s \in \mathcal{S}, o \in \mathcal{O}, y_{bso} \leq \lceil \frac{\alpha \sum_{k\in\mathcal{K}} d_{ko} v_k}{V_b} \rceil$. Constraints (2) ensure that demands are fulfilled, Constraints (3) ensure that stocks are not exceeded and Constraints (4) ensure that the total volume of parcels shipped from a stock location s to the destination of order o is higher than the total volume of items to be shipped on this path with a margin coefficient $\alpha \geq 1$.
The Objective (1) of the GTP-ED is to minimise the environmental cost, denoted F_G and expressed in $geqCO_2$, which can be decomposed into item related costs and parcel related costs. Item related costs I_{kso} correspond to the cost of sending one item k from the stock location s to the destination of order o and are equal to $I_{kso} = SuC_{ks} + StC_{ks} + EM_{so} m_k$ with SuC_{ks} the cost caused by the supply of an item k to the stock location s, StC_{ks} the cost of storing one item k in the stock location s, EM_{so} the mass transportation cost over the path (so) and m_k the mass of an item k. Parcel related costs P_{bso} correspond to the cost of sending one box of size b from the stock location s to the destination of order o and are equal to $P_{bso} = PC_b + HC_{bso} + EV_{so} V_b + EM_{so} M_b$ with PC_b the cost due to packaging of a box of size b, HC_{bso} the cost for handling a box of size b over the path (so), EV_{so} the volumetric transportation cost over the path (so), EM_{so} the mass transportation cost over the path (so) and M_b the mass of a box b.
This resulting model can be proven to be NP-hard. Indeed, under the hypothesis $\mathcal{H}_1 : |\mathcal{B}| = 1, \mathcal{H}_2 : |\mathcal{K}| = 1$ and $\mathcal{H}_3 : \frac{V_b}{\alpha v_k} \geq \max_{o\in\mathcal{O}} d_{ko}$, the GTP-ED becomes an integer version of the FCTP, known as NP-hard.
To scale-up when solving the GTP-ED, the initial set of orders can be decomposed into subsets of orders which can be solved independently. Let us consider a multi-graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$. The set of nodes corresponds to the set of orders i.e. $\mathcal{V} = \mathcal{O}$. For each pair of node (o, o'), an edge is drawn between o and o' for each item k demanded in both orders, i.e. $d_{ko} \geq 1$ and $d_{ko'} \geq 1$. Each connected component of graph $\mathcal{G}$ corresponds to a subset of independent orders on which GTP-ED can be solved independently without loss of optimality. Such decomposition was also considered in (Xu et al., 2009) through a graph based on items instead of graph based on orders.

4 EXPERIMENTS

In this section, we start by describing the datasets used and the experimental setup. Then we detail the results obtained and provide an analysis to identify trends and future work.

4.1 Datasets

Based on the literature review, we did not find public datasets related to our problem. So, we create our own datasets to evaluate our contribution. The first dataset is based on a real retailer anonymised operating in France, while the second dataset [1] was randomly generated using realistic hypothesis.

[1] data2 is publicly available on https://gitlab.laas.fr/chaire-retail-responsable/gtped

Dataset Based on Real Data. This dataset (`data1`) is based on average characteristics of a fashion omnichanel retailer operating in France. We consider 100 orders that were randomly selected from past anonymised orders (we fixed $|\mathcal{O}| = 100$ based on preliminary experiments on the limit of the MILP solver). With the selected orders, we then have a number of associated items ($|\mathcal{K}| = 244$) and a number of stock locations ($|\mathcal{S}| = 135$) where these items are available. The demand in items for each order and the stock level for each item in every stock location is based on average real data.

Dataset Based on Realistic Randomized Generation. This generated dataset (`data2`) is similar to `data1` based on real data. First, we consider the same value for the set of orders, items and stock locations: $|\mathcal{O}| = 100$, $|\mathcal{K}| = 244$ and $|\mathcal{S}| = 135$. The geographical coordinates of stock locations and destinations of orders are randomly generated following a uniform law $\mathcal{U}(-4,8)$ for the longitude and a $\mathcal{U}(42,51)$ for the latitude. To generate demands and stocks, we respected the orders of magnitude observed in the real data. For each order o, we first generate a number n_o of items such that $n_o = \max(1, \lfloor \mathcal{N}(2,4) \rfloor)$ (where $\mathcal{N}$ stands for the normal law). Then, we perform n_o draws with replacement to determine the items which have been ordered. For each item and stock location, the stock level is generated using a uniform law: $\forall k, s\ q_{ks} \sim \mathcal{U}(\{0,1,2,3,4,5\})$. Whereas it is theoretically possible to get an unfeasible problem due to lack of stocks, it never occurred in our experiments.

Additional Data. For each dataset, we have to generate some additional data for parcels and for cost parameters. Based on French carrier data (available on public web site), we fixed the number of boxes ($\mathcal{B} = 6$) and obtained their characteristics (size, mass and volume). All the cost values were obtained from different sources. Items volume and mass were randomly generated but in a way to obtain realistic values for the fashion industry. Storage Costs, Supply Costs and Handling Costs, relies on a report about environmental impacts of e-commerce (CPV Associés et al., 2023). The values are randomly generated so as to respect the orders of magnitude provided in the report. All details about the generation of these parameters are publicly available (see footnote 1).

4.2 Experimental Setup

For each dataset, made of 100 orders, we build several subsets from 10 to 100 orders with their respective numbers of items and stock locations. To do that, we successively consider the orders of the initial dataset (the 10-order instance corresponds to the first 10 orders in the initial dataset, and so on). For each subset of data (from 10 to 100 orders), we first generate values for stocks, demands and boxes. Then, we randomly generate 10 instances by changing the values for items masses, items volumes and costs. We used Julia 1.10 and CPLEX 20.1 (in single thread mode) for the implementation of the mathematical model of all MILP models. The experiments ran on a server with a Intel E5-2695 v4 2.1G processor. Finally, 16GB of RAM and 1h of solving time were allocated to each instance.

4.3 Computational Results and Analysis

We present the results of the experiments which have been performed to test and analyse the `GTP-ED`. We first detail the computational performances of the model and then analyse the relevance of the environmental objective comparatively to other objective functions. In this paper, we only present the results for `data1`, however more complete results are publicly available (see footnote 1).

Performances Analysis. Firstly, we looked at the performances of our MILP model for the `GTP-ED`. Table 1 presents the computation time (CPU), the gap at root node (RG), the final gap (FG) and the number of instances optimally solved for `data1`. For each size of instance, we provide the mean, denoted as μ, and the standard deviation, denoted as σ, observed over the 10 instances of the set for CPU, RG and FG.

Table 1: Performance computational results - `data1`.

	`data1`						
	CPU(s)		RG(%)		FG(%)		#Opt / 10
$\lvert\mathcal{O}\rvert$	μ	σ	μ	σ	μ	σ	
10	2.5	0.8	4.9	1.5	0.0	0.0	10
20	6.3	1.2	4.8	1.8	0.0	0.0	10
30	10.3	1.4	3.0	1.7	0.0	0.0	10
40	25.0	6.9	3.1	2.3	0.0	0.0	10
50	406.6	1069.6	2.8	0.6	0.1	0.1	9
60	413.2	1068.2	2.3	0.5	0.0	0.1	9
70	2784.5	1383.3	2.6	0.5	0.1	0.2	4
80	2695.1	1467.7	2.7	0.4	0.3	0.3	3
90	2116.7	1579.5	2.4	0.3	0.3	0.3	5
100	3395.8	738.9	2.5	0.4	0.3	0.2	1

In terms of computing time, solving small size instances is quite fast as the mean solving time is less than 30 seconds for instances up to 40 orders for `data1` and up to 20 for `data2`. Larger instances require much more computing time and lots of them reach the one hour time limit. Indeed, for both datasets, solving to optimality large instances is difficult. Less than half instances above 70 orders are optimally solved for `data1` and no instance above 50 orders are optimally solved for `data2`. Those results tend to confirm that the `GTP-ED` is hard to solve. However, we still notice that good quality solutions are obtained as the mean FG is always lower than 2% with low standard deviation. The RG confirms the ability to quickly get good quality solutions as for large instances the mean is most often lower than 5% with a low standard deviation. We notice two exceptions for instances of size 30 and 70 for `data2`, where one instance is observed to have a huge RG. Besides, we observe significant differences in terms of performance between `data1` and `data2`. The generation of stocks data may be part of the explanation. Indeed, we chose a uniform law to generate stocks for `data2`, while in `data1`, averaged on real data, empty stocks seem to appear more often. From an operational point of view, retailers could prefer good quality solutions quickly obtained to orchestrate orders during working days to prevent from stock changes due to physical store sales. Nevertheless, retailers may appreciate optimal solutions to orchestrate orders placed during nights and week-ends when time is less constraining.

To improve the scalability of our problem, we used the decomposition presented at the end of the section 3. It actually helps to improve the resolution as about 10% more instances are solved to optimality after one hour. Besides, for instances solved to optimality, the savings in terms of CPU are significant, about two times faster in average for both datasets.

Objectives Analysis. In the `GTP-ED`, we consider a new objective function which requires lots of parameters and data. Such complexity was justified to measure an overall environmental cost. However, we still need to justify the relevance of this objective function in the optimisation process. To do so, we compare the results obtained on `GTP-ED` with two other optimisation problems.

The first problem is the Distance Transportation Problem for E-commerce Deliveries (`DTP-ED`). In this problem, we want to minimise the total distance traveled by the parcels subject to the same constraints as for the `GTP-ED`. This problem can be seen as a simple way to reduce the overall environmental cost by reducing the number of kilometers traveled. The model is given hereafter with D_{so} representing the Haversine distance (in km) between the stock location s and the destination of the order o :

$$\textbf{(DTP-ED)} \ \min F_D = \sum_{s \in \mathcal{S}} \sum_{o \in O} D_{so} \sum_{b \in \mathcal{B}} y_{bso} \qquad (7)$$
$$s.t. \ (2) - (6)$$

To compare the solutions of `GTP-ED` and `DTP-ED`, we solve both problems and collect the results for the instances solved to optimality after one hour, respectively $F_G^*, (x_G^*, y_G^*)$ and $F_D^*, (x_D^*, y_D^*)$. After solving `DTP-ED` we perform a post processing on y_D^* variables. Indeed, the solver tends to select the largest boxes even if smaller ones are sufficient. Thus, for each pair (so) we keep the number of boxes assigned by the solvers but perform an optimisation to select the best ones.

Then, we compute:

- $\Delta G(\texttt{DTP-ED}) = F_G(x_D^*, y_D^*) - F_G^*$, the surplus of environmental cost obtained with the optimal solutions of `DTP-ED`
- $\Delta D(\texttt{GTP-ED}) = F_D(x_G^*, y_G^*) - F_D^*$, the additional distance obtained with the optimal solutions of `GTP-ED`

Table 2 compares the results obtained on the problems `GTP-ED` and `DTP-ED` for optimally solved instances of `data1`. The first column ($|O|$) indicates the size of the instance and the second column (#) the number of instances optimally solved for both problems. The third column F_G^* shows the optimal environmental cost when solving `GTP-ED`. The fourth column $\Delta G(\texttt{DTP-ED})$ shows the surplus of environmental cost for solutions of `DTP-ED`. Similarly, the fifth column, F_D^*, shows the optimal distance obtained while solving `DTP-ED` and the sixth column, $\Delta D(\texttt{GTP-ED})$, indicates the surplus of distance induced by `GTP-ED`.

Table 2: Objective comparison between `GTP-ED` and `DTP-ED` - `data1`.

		F_G (kg eqCO2)		F_D (1000km)	
$\|O\|$	#	F_G^*	$\Delta G(\texttt{DTP-ED})$	F_D^*	$\Delta D(\texttt{GTP-ED})$
10	10	27.3	+8.9	8.7	+9.7
20	10	46.9	+14.9	18.0	+25.1
30	10	67.9	+21.4	27.6	+36.0
40	10	99.5	+31.9	41.4	+39.1
50	9	110.2	+36.0	47.6	+50.1
60	10	136.6	+44.4	67.0	+69.6
70	8	122.9	+41.0	63.0	+61.6
80	6	101.6	+33.1	50.5	+49.4
90	6	108.1	+35.6	58.2	+53.7
100	4	80.9	+25.4	42.9	+42.7
Total	83	902.0	+292.6	436.9	+424.8

From this table, we can observe that using `DTP-ED` to solve the 83 instances of `data1` increases the environmental cost by 32% compared to using the

GTP-ED. In the same way, this rise is about 28% for data2. Consequently, the savings offered by GTP-ED compared to a more basic model are significant and highlight its relevance from an environmental point of view. However, the environmental gains of the GTP-ED are accompanied by a significant increase in terms of logistics flows and kilometers traveled. Indeed, the solutions of GTP-ED almost double the total distance compared to the solutions of DTP-ED. This can be explained by the measurement of the environmental cost that does not only rely on transportation costs, which themselves do not only depend on distance traveled but are driven by the volume of parcels carried. Thus, our objective function proposed in the GTP-ED seems to be relevant from an environmental point of view.

Furthermore, the objective functions used operationally are most of the time monetary related. Thus, our objective function should be evaluated from an economic point of view. For this purpose, we introduce a third optimisation problem called Economic Transportation Problem for E-commerce Deliveries (ETP-ED) whose aim is to minimise the economic costs. As many carriers charge a fixed price per parcel collected, the economic cost we consider is proportional to the number of parcels shipped. In our case, we assume that the collection price of each parcel is set at 1€. The model of the ETP-ED is given hereafter, with $M_{so} = 0$ if o is a Click and Collect order whose pick-up location is s (no parcel collected from the carrier), $M_{so} = 1€$ otherwise:

$$\textbf{(ETP-ED)} \ \min F_E = \sum_{s \in \mathcal{S}} \sum_{o \in O} M_{so} \sum_{b \in \mathcal{B}} y_{bso} \quad (8)$$

$$s.t. \ (2) - (6)$$

As done previously, we solve GTP-ED and ETP-ED to collect $F_G^*, (x_G^*, y_G^*)$ and $F_E^*, (x_E^*, y_E^*)$ Then, we perform the same post-processing on y_E^* as the one exposed for y_D^* and then compute :

- $\Delta G(\text{ETP-ED}) = F_G(x_E^*, y_E^*) - F_G^*$, the surplus of environmental cost obtained with the optimal solutions of ETP-ED
- $\Delta E(\text{GTP-ED}) = F_E(x_G^*, y_G^*) - F_E^*$, the surplus of economic cost obtained with the optimal solutions of DTP-ED

The objective comparison between GTP-ED and ETP-ED are given in Table 3 for data1. The first, second and third columns are same as the ones of Table 2. The fourth column shows, $\Delta G(\text{ETP-ED})$, the surplus of environmental cost obtained while solving the ETP-ED. The fifth column shows F_E^* the optimal economic cost and the sixth column, $\Delta E(\text{GTP-ED})$ indicates the surplus of economic cost induced by GTP-ED.

Table 3: Objective comparison between GTP-ED and ETP-ED - data1.

		F_G (*kgeqCO2*)		F_E (€)	
$\lvert O \rvert$	#	F_G^*	$\Delta G(\text{ETP-ED})$	F_E^*	$\Delta E(\text{GTP-ED})$
10	10	27.3	+18.7	90.0	+126.0
20	10	46.9	+32.9	182.0	+213.0
30	10	67.9	+47.1	270.0	+315.0
40	10	99.5	+64.6	343.0	+428.0
50	9	110.2	+75.3	391.0	+487.0
60	10	136.6	+91.4	491.0	+619.0
70	8	122.9	+79.0	468.0	+544.0
80	6	101.6	+64.5	383.0	+444.0
90	6	108.1	+68.5	429.0	+438.0
100	4	80.9	+48.2	313.0	+353.0
Total	83	902.0	+590.3	3360.0	+3967.0

From the table, we can see that ETP-ED induces a 65% surplus of environmental cost over the 83 instances of data1. This surplus rises to 70% over the 43 instances of data2. Once again, the GTP-ED proves its relevance from an environmental point of view. In parallel, GTP-ED causes a significant economic cost rise. We observe a 118% increase for data1 and a 68% increase for data2. As it could have been expected, our environmental and economic objectives seem to be in opposition. If retailers want to operate an eco-friendly order orchestration with the GTP-ED, they would have to pay additional fees. Besides, by favouring economic costs in a context where the pricing depends only on the number of parcels shipped, they renounce to reduce their environmental footprint. However, the considered economic function F_E is only based on the number of collected parcels. By integrating other parameters, such as fuel expenses or volume to be carried, it may lead to different trade-offs.

5 CONCLUSION

In this paper, we introduce the Green Transportation Problem for E-commerce Deliveries which aims at minimizing the environmental footprint of order orchestration. The resulting model is a general case of the well-known Fixed Charge Transportation Problem with an environmental objective function. We perform a few experiments to test the performances of the GTP-ED and the relevance of its objective function. We see that the solver struggles to solve to optimality instances above 60 orders in a reasonable amount of time, whereas good quality solutions are provided quickly. We highlight that the performances are improved by decomposing the model into subsets of independent orders. Then, we show that our GTP-ED is relevant from an environmental point of view compared to a simpler orchestration strategy based on distance minimisation. However, in a context where the pricing depends only on the number of parcels shipped, the `GTP-ED` causes an increase of economic costs that enforces retailers to favour either environmental matters or economic ones.

Future works include additional experiments to deeper analyse parameters influence. First, we expect the stocks level and the number and types of boxes to impact the performances and results. Secondly, the `GTP-ED` uses a complex objective function with different terms and we will explore their interactions. Lastly, it would be interesting to compare the results of the `GTP-ED` with real world orchestration rules used by retailers. It can highlight the environmental relevance of our model but also reveal its deficiencies from an operational point of view.

Finally, our model can be improved to gain in relevance and scalability. To solve larger instances to optimality, we aim to develop decomposition methods such as column generation. Moreover, as retailers would probably prefer quick good solutions rather than slow but optimal ones, using heuristics or Lagrangian decomposition may be relevant. Lastly, rather than opposing environment and economy, a multi-objective optimisation should be performed to provide a tool to retailers to make the best trade-off between environmental and economic issues.

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