Reducing Empty Truck Trips in Long Distance Network by Combining Trips

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Abstract: Brazilian import and export activities on ports are subject to considerable slow queues and congestion, revealing a lack of medium and/or short-term logistic planning. One of the causes is the number of trucks traveling with empty containers, performing one-way trips, from inland cities to the port or from the port to the cities. This issue may be reduced by combining trips, i.e., after bringing goods to the port (export trip), a truck should, when possible, carry goods from the port to the origin or a nearby city (import trip). In this paper we investigate a combinatorial optimization problem where a set of import/export/inland trips should be combined in order to reduce total traveling time, which in turn reduces the number of empty trucks traveling to/from the port. Individual trips and combined trips must obey national law regulation of resting time, as typical road trips in Brazil covers hundreds, even thousands of kilometers. We also consider opening operation hours on each location (time windows), which may force a driver to wait upon arriving. We test exact and heuristic approaches, and present the total travel time and number of trucks needed for each solution, considering instances based on real freight data.

1 INTRODUCTION

Due to the lack of infrastructure for grain storage, most of the Brazilian production is destined to exportation, leading to a high demand of freightage to the ports, as well as import of fertilizers and other agricultural inputs to the grain exporting regions (Caixeta Filho, 2010). Most of the freight transport is done by road modal, which may bring practicality, agility and flexibility in cases of route exchanges. Nevertheless, a number of disadvantages may be listed, for example, high cost of fuel and tolls, poor condition of roads in some regions, among others. Those disadvantages, allied to lack of good logistic planning, cause an extra cost to the final price of the transported goods, congestion in the port area, delivery delays and also empty trucks, traveling without any freight.

Empty truck trips may be found specially on import/export trips, when the carrier take care only of incoming or outgoing trips. The result is a somehow needless increasing in the number of trucks using the roads and ports, consequently increasing congestion and polluting gas emission generated by fuel combustion (Schulte et al., 2015).

In the context of this work we have import trips, as shown in Figure 1. The truck collects a freight (container, bagged or bulk goods) at the port. Then travels to a customer or depot that demands that freight. After unloading, the truck travels back to the port unladen.
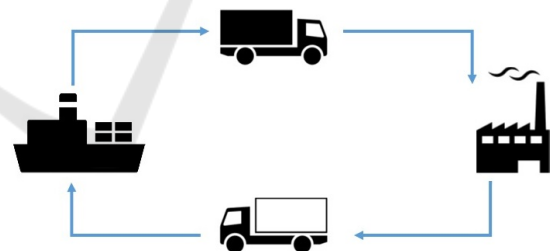

Figure 1: Import scenario.

An empty truck travel also occurs in export trips, as shown in Figure 2. The truck collects goods at a customer or a depot and travels to the port, where sometimes faces a queue of trucks waiting for unloading, due to congestion or ships that are not ready to receive the load. After unloading the truck comes back to the customer empty.

A third situation of empty trucks traveling occurs in inland trips, between cities. The truck travels from one city to another to transport goods from customer to customer and returns empty to the origin point, due to lack of return demand or vice versa (Figure 3).

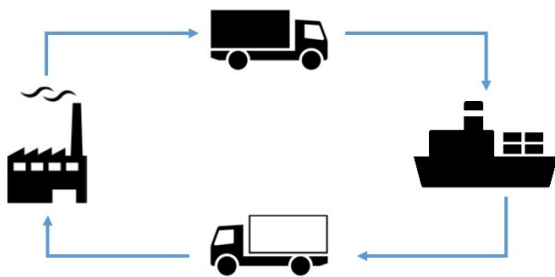Those are, of course, inefficient ways to use the
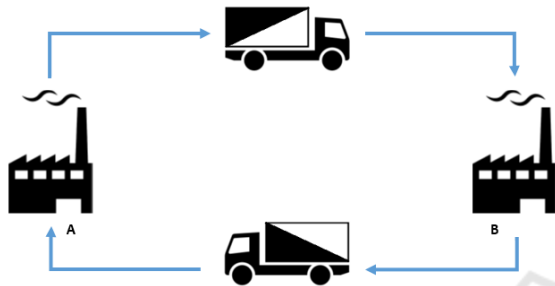
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Figure 2: Export scenario.

Figure 3: Inland trips.

trucks and the road network. It may be the case that a customer that exports goods does not import any goods, at least not from the same port. But generally the customer demands goods as well, and the truck may return loaded if it visits a company that sells the goods the customer needs. Even more, from the port to that company the truck may bring goods imported by the company that are on the port waiting to be transported. Thus, an export trip may be combined to an import trip, or an import trip followed by an inland trip, as shown in Figure 4. A perfect combination would include a sequence of trips in which the destination of a trip is the origin of the next one. A good combination allows a repositioning trip between the end of a trip and the start of the next one, as long as those locations are not far away, i.e., when the repositioning may be done by a small trip.
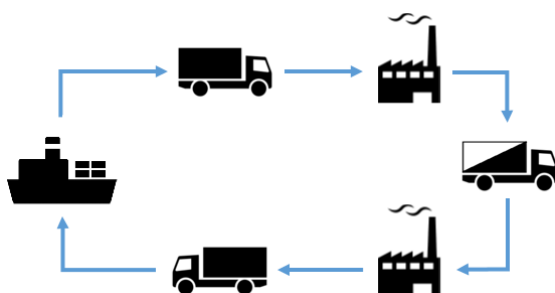

Figure 4: Combination of export, import and inland trips.

The combination of trips becomes an alternative to avoid such problem. Import and export trips that would be performed by different trucks may be per-

formed sequentially by the same truck, thus decreasing the number of empty trucks traveling in the road system, which contributes to the transportation network as a whole (reduction of truck traffic and road congestion) besides to the environment (reduction of emission of polluting gases) (Islam, 2017a). Furthermore, Schulte et al. (Schulte et al., 2015) mention that such combination contributes also to decrease operational costs and additional gains to drivers.

The objective of this work is to propose a mathematical model to find a good (possible the best) combination of trips (export, import and inland trips) to reduce empty trucks travelling through the roads, which besides the contributions aforementioned, may reduce the waiting time in ports and congestion in ports area. The model includes constraints to assure drivers welfare by enforcing current laws regulation.

This paper is organized as follows: in Section 2 we present related works from the literature; a formal definition of the problem is presented in Section 3; in the following, in Section 4, the proposed method is described, which consists of a mixed integer linear programming, a heuristic for evaluating each possible combination of trips, and an integer linear programming for choosing a set of those combinations; experimental results are presented in Section 5 and conclusions and future works in Section 6.

2 LITERATURE REVIEW

The combination of trips to decrease empty trucks traveling along the roads have already been addressed in the literature. Gavish and Schweitzer (Gavish and Schweitzer, 1974) are among the first to propose such approach. Özener and Ergun (Özener and Ergun, 2008) study a logistic network in which shippers collaborate to share a common carrier. Their study has identified routes in which a collaborative scheme may reduce the shared costs among shippers. Audy et al. (Audy et al., 2011) shows that in their context both the cost and the delivery time may be reduced using collaborative transportation.

Caballini et al. (Caballini et al., 2015) studied a problem similar to the one we study here, with export, import and inland trips in a port context, where all trucks may transport two 20 ft containers. They proposed a Mixed Integer Linear Programming formulation (MILP) to minimize the overall costs of trips subject to time windows and time limit in the routes. They study the impact of trips combination on real data in the port of Genoa, Italy, showing that trip combination may reduce the costs and the number of empty tricks traveling to/from the port.

Schulte et al. (Schulte et al., 2015) developed simulation models for coordinated truck appointments and used the proposed approach to solve the problem as a TSP with time windows allowing collaboration. They used instances based on real data of the port of Santo Antonio, Chile, and integrated their approach to a Truck Apointment System (TAS), a tool to schedule and follow cargo arriving, allowing collaboration among ports and transportation companies. As a result, ports could reduce port-related polluting gas emission using the model in real-time.

Islam (Islam, 2017b) also simulated the sharing of trucks in a port environment. He compared two scenario, the first considering sharing/collaboration and the second without it. Using data of a local port, he showed that the collaboration between trucks increases the use of the port capacity as well reduces polluting gas emission and congestion around the port.

A more recent work of Caballini et al. (Caballini et al., 2017) proposes a model to reduce costs and the number of trips that trucks travel empty, take advantage of the capacity of the trucks. They show the efficacy of the proposed approach by computational experiments.

The present work differs from the ones cited above by including local transport regulation laws and time windows, thus adapting previous ideas towards the Brazilian exportation context. Caballini et al. (Caballini et al., 2015) is the one more similar, but here we include a heuristic phase, due the complexity of the resuling model, when all considered characteristis are included.

3 PROBLEM DEFINITION

We are given as input a set $\mathcal{T}$ of trips. For each trip $i \in \mathcal{T}$ we have its origin and destination location, respectively O_i and D_i, and the distance d_i between those locations, in Km. We also have the distance e_{il} between the destination of a trip $i \in \mathcal{T}$ and the origin of a trip $l \in \mathcal{T} \setminus i$, also in Km. This distance is traveled by a truck covering two trips i, l sequentially when $D_i \neq O_l$ (considered 0 when they coincide) and is called repositioning trip. The duration of each trip i is defined by $t_i = d_i/speed$, and the duration of repositioning trip is $e_{il}/speed$. In all cases we consider a constant speed of 80 km/h. This is in fact the maximum speed for heavy trucks in Brazilian roads, but as most of the trips are long distance trips, trucks will using this speed most of the time, and then may be used as average speed. Moreover, there is a service time S that is including in all trips, covering the loading and unloading service at cities and ports.

Trips are under transport regulation laws that impose 30 min of rest after each 5,5 hours of travel, and 8 hours after each 12 hours. The first one imposes a small rest during a trip, and the second one a long rest (night/sleep resting, for example). Besides mandatory resting times, drivers are subject to waiting times due to opening and closing time of locations (deposit in cities and ports). For each location there is a time window, and operations may be done only inside the time window. This is represented in Figure 5; in this case, the truck arrived within the time window. For each trip i we know the time window of the origin location, $[P_i^O, P_i^{\hat{O}}]$, and of the destination location, $[P_i^D, P_i^{\hat{D}}]$. If the truck arrives before the opening time, it must wait until the window opens (see Figure 6). If the truck arrives after the closing time, it must wait until the next day, for the following time window, as represented in Figure 7. This may happen also when starting a trip and in repositioning trips. Those waiting times are added to the total duration of the combination of trips. For some trips there is a good combination to avoid those wasted time, but for some the total duration time may include many hours due to waiting times. The choice of combinations must be carefully done to avoid or minimize that.

Figure 5: Trip arriving inside the time window.

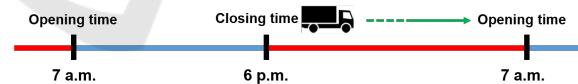Figure 6: Trip arriving before the time window.

Figure 7: Trip arriving after the time window.

We consider combinations of at most 3 trips. A good example of combination of 3 trips is the one depicted in Figure 4 where an import trip is followed by an inland trip and then an export trip. This case happens when the destination of the first trip does not have any goods to send to the port. Instead of coming back to the port empty, the driver travels to a nearby city and carries the truck with goods prepared for exportation. Another case is the combination of export/inland/inland trips: a rural producer exports goods and imports agricultural inputs; after unloading the goods at the port, the driver travels to a nearby city to load the agricultural inputs to bring to the producer. A combination of more than 3 trips would include a

double trip to the port or from the port, which can be modeled as two combinations.

The objective is then to find the best combinations of trips in order to minimize the total duration time, considering the duration of all combinations chosen and trips performed as single trip, if a trip is chosen not to be combined. The formal definition of the objective and the aforementioned constraints is detailed in the MILP formulations proposed in the following section.

4 SOLUTION METHOD

Our first attempt was to propose a MILP formulation that includes all characteristics of the problem, as the one proposed by Caballini et al. (Caballini et al., 2015). The formulation had variables to control which trips belongs to each combination and their sequence in the combination. Moreover there were a considerable number of variables to control resting/waiting time within trips (following law regulations) and between trips (due to time windows). However, we are working with a more complex problem, mainly because we have to deal with some very long distance trips, that may spam more than one day, even when performed as a single trip. The control of the starting and ending of each trip becomes more complex due to different restring times that are mandatory along the way. Although we could indeed include all characteristics in a MILP formulation, it turns out to solve only instances with very small number of trips, and using a long CPU time. Nevertheless we can still solve the problem using exact MILP formulation by decomposing the problem: firstly we do a pre-processing to determine the best way to combine each sequence of 2 or 3 trips, and then we search the best set of combinations that covers all trips at a minimum cost.

For the first phase, we propose a MILP formulation to determine the best duration of a given sequence of trips. This includes determining the best starting and ending time of each trip in order to reduce the total duration time. The proposed formulation is presented in Section 4.1. Although the formulation can handle at a reasonable time all the subsets of 2 or 3 trips, it may be impracticable to use it for large instances because of the exponential number of possible combinations to be solved. We then propose, at Section 4.2, a constructive heuristic to be used when needed as an alternative in this phase. After the pre-processing phase, independently of the method used, a set-covering based formulation (Section 4.3) is used to determine the best set to cover all trips.

4.1 Pre-processing Combinations

In order to choose the best combinations for a given set of trips, we first do a pre-processing to define the optimal cost (in terms of total duration) for each possible combination of 2 or 3 trips, i.e., we generate all sequence of 2 and 3 trips, and for each one of them, we evaluate its total duration time by deciding the start and finish time of each trip, besides the resting and waiting times. In this section we describe a MILP formulation for this task, and in the following section we describe a greedy constructive heuristic.

We propose the following MILP formulation to define the minimal cost for the combination of trips $i, l, k \in \mathcal{T}$ sequentially.

We use indexes i, il, ilk when describing variables or data respectively for trip i, trip l (performed after i) and trip k (performed after i and l). For example, if q denotes the starting time of a trip, q_i, q_{il} and q_{ilk} denote the starting time of trips i, l, k in the combination. Moreover, we use $'$ to indicate a given time in a day, i.e., remaining hours discounting full days. For example, if $q_{ilk} = 83$, the starting time of trip k is 83 hours after time 0 of the planning horizon, i.e., 3 days and 11 hours, then $q'_{ilk} = 11$.

We use the following decision variables:

q: starting time of a trip;

q': starting hour of a trip;

f: ending time of a trip;

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r^j: resting time of a daily journey (8h every 12h);

r^t: resting time during a trip (30' every 5:30h);

w^q: waiting time to start a trip;

w^f: waiting time after finishing a trip;

b^f: binary, if a trip ends before time window;

a^f: binary, if a trip ends after time window;

b^q: binary, if a trip is ready to start before time window;

a^q: binary, if a trip is ready to start after time window;

z: number of full days of a given duration time;

m^j, m^t: number of required resting periods;

The constraints below show how f'_i is defined from f_i (1)-(2), how binaries b_i and a_i are set when trip i did not finish within the operation time $[P_i^O, P_i^{\hat{O}}]$ of the destination of trip i (3)-(6) and how the waiting time is set in these cases (7): the remaining hours until the opening time if arrived early, or the hours until the

opening time of the next day if arrive tardy. Similar constraints are defined for $f_{il}, f_{ilk}, q_{il}, q_{ilk}$.

$$z_i = f_i/24 \tag{1}$$

$$f_i' = f_i - 24\lfloor z_i \rfloor \tag{2}$$

$$f_i'b_i \leq P_i^O \tag{3}$$

$$f_i' \geq P_i^O(1-b_i) \tag{4}$$

$$(24 - f_i')a_i \geq (24 - P_i^{\hat{O}}) \tag{5}$$

$$24 - f_i' \geq (24 - P_i^{\hat{O}})(1-a_i) \tag{6}$$

$$w_i = (P_i^O - f_i')b_i + (24 - f_i' + P_i^O)a_i \tag{7}$$

$$b_i \in \{0,1\} \tag{8}$$

$$a_i \in \{0,1\} \tag{9}$$

$$w_i \geq 0 \tag{10}$$

The integer value $\underline{z_i} = \lfloor z_i \rfloor$ may be defined for a continuous value z_i by the constraint $z_i - 1 \leq \underline{z_i} \leq z_i$.

The following expressions define the total resting time of different types while performing trip i. Similar expressions are used for trips l and k (variables $r_{il}^j, r_{il}^t, r_{ilk}^j, r_{ilk}^t$).

$$m_i^j = t_i/12 \tag{11}$$

$$m_i^t = t_i/5.5 \tag{12}$$

$$r_i^j = 8\lfloor m_i^j \rfloor \tag{13}$$

$$r_i^t = 0.5\lfloor m_i^t \rfloor \tag{14}$$

The complete MILP formulation is then:

$$min\ B_{ilk} = (f_{ilk} + w_{ilk} - q_i) \tag{15}$$

subject to:

$$P_i^O \leq q_i \leq P_i^{\hat{O}} \tag{16}$$

$$f_i = q_i + t_i + r_i^j + r_i^t \tag{17}$$

$$q_{il} = f_i + w_i + e_{il} + r_{il}^q + r_{il}^{\prime q} + s \tag{18}$$

$$f_{il} = q_{il} + w_{il} + t_l + r_{il}^j + r_{il}^t \tag{19}$$

$$q_{ilk} = f_{il} + w_{il} + e_{lk} + r_{ilk}^q + r_{ilk}^{\prime q} + s \tag{20}$$

$$f_{ilk} = q_{ilk} + w_{ilk} + t_k + r_{ilk}^j + r_{ilk}^t \tag{21}$$

$$\tag{22}$$

$$(1)\text{-}(9) \text{ for } f_i, f_{il}, f_{ilk}, q_{il}, q_{ilk}$$

$$(11)\text{-}(14) \text{ for } r_i^j, r_i^t, r_{il}^j, r_{il}^t, r_{ilk}^j, r_{ilk}^t$$

$$f_i, f_{il}, f_{ilk}, f_i', f_{il}', f_{ilk}' \geq 0 \tag{23}$$

$$q_i, q_{il}, q_{ilk}, q_{il}', q_{ilk}' \geq 0 \tag{24}$$

Objective function (15) minimizes the cost (total duration time) of the combination. The starting time of the first trip, i, must be within the operation hour of

the origin location of the trip (16). The finishing time of this trip is the starting time plus the time needed to go from its origin to its destination plus the mandatory resting times (17). As for the next trip, l, it may start after finishing the previous one, plus the repositioning time from the destination of i to the origin of l plus the resting times, if any, during this repositioning (18). Constraints (19)-(21) do the same for other trips.

We run the above formulation for all triplets $i, l, k \in \mathcal{T}$. If the solution is feasible, we have the minimal cost B_{ilk} of the combination. Otherwise we have that trips $i.l.k$ cannot be combined sequentially.

The MILP formulation to define the minimal cost for the combination of two trips $i, l \in \mathcal{T}$ is similar:

$$min\ C_{il} = f_{il} + w_{il} - q_i \tag{25}$$

subject to all constraints except the ones including variables with index ilk.

4.2 Pre-processing Heuristically

Here we propose a greedy constructive heuristic to quickly define an upper bound on the cost and total duration of a sequence of trips i, l, k, considering that each trip departs and a arrives as early as possible. For example, the starting time of the first trip is the opening time of its origin point: $q_i = P_i^O$. The ending time f_i includes the service time, the distance to the destination point, mandatory resting time, and waiting time due to time windows. The starting time of the following trips include also the repositioning from the destination point of the previous trip and the possible incurring resting and waiting time.

It is easy to see that this heuristic gives an upper bound on the cost/total duration because the sequence thereby constructed is feasible: all constraints are considered. One may also notice that it may not be optimal, because starting a trip as early as possible may force waiting times in the future that may increase the total duration time. It is, however, very fast.

Therefore we have an exact ILP formulation that, given a set of trips i, l, k determine the best starting/end time of each trip in order to minimize the cost (albeit costly in terms of computational time), and a heuristic that quickly determines a possible good value. Regardless the method used for this preprocessing time, or even a mixed of both, we still have to decide which trips to combine. This task is done by the set-covering based ILP formulation given in the next section.

4.3 Set-covering ILP Formulation

After pre-processing all combinations up to 3 trips, let $\mathcal{T}^2$ and $\mathcal{T}^3$ be the sets of all feasible combinations of

2 and 3 trips respectively, and let B_{ilk} be the total cost of combining trips i, l, k sequentially, C_{il} the total cost of combining trips i, l sequentially, and D_i the cost of a single travel i (in our case twice the distance because it would be a round trip). We then define the following compact ILP formulation, using variables v_{il} and y_{ilk} as binary decision variables equals to 1 if trips i, l and i, l, k respectively are to be combined and 0 otherwise, and x_i a binary decision variable equals to 1 if the trip i is to be performed as a single trip (i.e., not part of any combination) and 0 otherwise.

$$min\ Z = \sum_{ilk \in \mathcal{T}^3} B_{ilk} y_{ilk} + \sum_{il \in \mathcal{T}^2} C_{il} v_{il} + \sum_{i \in \mathcal{T}} D_i x_i \quad (26)$$

subject to:

$$\sum_{\substack{ilk \in \mathcal{T}^3 \\ i=j \vee l=j \vee k=j}} y_{ilk} + \sum_{\substack{il \in \mathcal{T}^2 \\ i=j \vee l=j}} v_{il} + x_j = 1 \quad \forall j \in \mathcal{T} \quad (27)$$

$$y_{ilk}, v_{il}, x_i \in \{0, 1\} \quad (28)$$

Objective function (26) minimizes the overall cost. Constraints (27) state that each trip may be at most in one chosen combination or performed as a single trip. The last constraints state that all variables are binary.

5 EXPERIMENTAL RESULTS

The MILP formulations were implemented in C/C++ using the Concert Technology Library, and solved by CPLEX 12.5 academic license. The heuristic was implemented in C/C++. The experiments were run on an IntelR Core TM i7-4790K CPU @ 4.00GHz x 8 with 32GB RAM, running Ubuntu 14.04 LTS 64 bits.

5.1 Instances

We generate a set of instances based on real data from the Brazilian transportation network. Data were collected from Fretebras[1], a website containing thousands of freightage offers, filled by drivers and companies in real-time, covering all Brazilian states and some nearby countries. One may freely consults information such as origin and destination of freightage, distance between those sites, vehicle type, freight type, and others.

We selected 10 cities, including Santos - SP, Cubatão - SP, Manhuaçu - MG, Passos - MG, Arcos - MG, Rondonópolis - MT, Sorriso - MT, Dourados - MS and Itumbiara - GO, which are among the main

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[1]http://www.fretebras.com.br

origin or destination points for export of grains (coffee and soy), and import of agricultural inputs (fertilizers and agricultural plaster), thus generating most of the import and export trips on the roads network of the southeast region of Brazil. Santos is a port city that receive plenty of trucks everyday, both for import and export freights. We created seven instances, ranging from 7 to 124 trips, using data from selected trips of the Fretebras website.

The distances of the trips range from 20 to 2246 km, while the estimated duration ranges from 15 min to almost 30 hours (including the repositioning trips, which can be very short). Table 1 shows a summary of the data for each instance, considering the import, export and inland trips.

Table 1: Summary of the instances.

ID	# Trips	Duration (h)		
		min	max	avg
1	15			14.0
2	31			15.8
3	47			14.5
4	62	3.7	26.7	13.1
5	76			15.0
6	94			13.5
7	124			13.9

We consider the same operation time for all cities: 7 am as the opening time and 6 pm as the closing time.

5.2 Results

The instances were solved by the two approaches proposed: pre-processing the combinations by the exact ILP model or the constructive heuristic and then select a subset of combinations by the set-covering model. The results are presented in Table 2, for 4 types of tests: trips allowed to combine in sequence of 2 and/or 3 trips; trips allowed to combine only in sequence of 3 trips; only in sequence of 2 trips; and no combination allowed (last rows, combined type = 1). Notice that for this last type, none of the formulations or approaches are used, one truck is used for each trip, and the total cost may be evaluated at practically zero time.

For each type of test, we report the objective function value (accumulated duration time of all trips), the number of trucks used, and the total time for each approach for pre-processing: MILP of Section 4.1 and Heuristic (Heur) of Section 4.2. We do not report gaps of the formulations because all formulations were solved until a proved optimal is found. For the case of no combination (type 1), each trip is considered as a round trip, then the duration of a trip is twice the travel time and mandatory resting and waiting times.

From the results we can see that for all instances, the proposed approaches could combine the trips, decreasing the overall duration time and the number of trucks, compared to the case of no combinations. This can be seen on the table, and on Figures 8 and 9, which show respectively the objective value and number of trucks for all instances and combination types. In Figure 8, the objective values were scaled to the cost of the 1-type, which was always the highest. In order to have a clearer visualization of the results for the number of trucks, Figure 10 shows the results only for types that allow combinations.

The combination type that reached the minimum objective value was, as expected, the 2&3 combination type, when pre-processing is done exactly. This can be seen on the table and on the graphic of Figure 8. However, the combination that minimizes the most the number of trucks was the 3-combination type, which can be seen on the table and on the graphic of Figure 10.

We may conclude that, using only combinations of 3 trips, we may minimize the number of trucks, but this may not be the best option in terms of total time. In some cases a third trip may force a long waiting time, and the best option is to combine only two trips. Therefore, we have to allow combinations of 2 and of 3 trips, if we want to reduce the overall time.

In general, results obtained by pre-processing using heuristics have higher objective values, regardless the combination type (see Figure 8). This happens because not all trips are combined. In the other hand, pre-processing the combinations by the exact ILP formulation yields lower costs for each combination, and the result is that in the second phase almost all trips are combined, reducing the overall costs.

The exact pre-processing, however, is computational costly. For the larger instances, the exponential number of combinations and the high cost to solve all of them, lead the algorithm to run for more than one day, reaching almost one week for the largest instance allowing 3 or 2&3 combinations. The running time of the heuristic was at most 2 minutes.

The approach here proposed reached all the expected objectives, while satisfying the imposed constraints:

- Minimization of costs

  The combination of trips allows a given driver to perform two or three trips. Doing this, we avoid to use a new driver to cover some trips, reducing the operational costs. Another reason is the smaller distances traveled for repositioning trips, which reduces empty truck trips.

- Minimization of empty truck trips and maximization of the use of trucks capacity

When choosing the best combined route, the model prefers low cost combinations. A low cost combination has generally a small distance for repositioning or no repositioning at all. As those travel times are considered in the objective function, a preference is given for smaller distance for repositioning (which is also empty truck trips), using the capacity of trucks as long as possible.

- Minimization of polluting gas emission

  This is a direct consequence of the combination of trips. As well as the reduction of the number of drivers, lesser vehicles on the road reduces the emission of polluting gases. Another cause is the reduction on the number and distance travelled on repositioning trips.

- Minimization of waiting on port area

  The proposed approach takes in account the arriving and departure time on ports and cities. When a trip arrives outside the time window, the waiting time is added to the objective function. Therefore, the waiting time is reduced in order to minimize the overall time. Moreover, the formulation decides also the best departure time of the first trip, aiming to minimize the required waiting time.

- Solutions conforme to Brazilian transport regulation laws

  The formulation include regulations of the Brazilian transport law 13103/2015, adding the mandatory resting periods. This includes daily rests, of 30 minutes for each 5:30h of driving, and long rest of 8h after 12h driving.
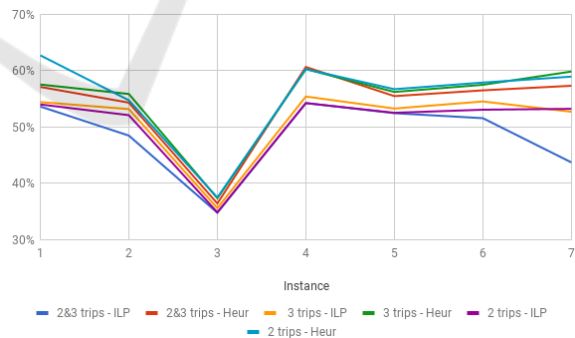

Figure 8: Objective value.

6 CONCLUSIONS

This paper proposes a mathematical programming formulation to meet the needs of a transportation network including export, import and inland trips. The main objective is to reduce empty truck trips, i.e., the number and distance traveled by empty trucks. This

Table 2: Experimental results for all instances, approaches and combinations type.

Comb. type	Instance		Total duration		CPU time (s)		#Trucks	
	ID	Size	ILP	Heur	ILP	Heur	ILP	Heur
	1	15	318.5	339.2	28	<1	7	6
	2	31	720.1	807.1	394	<1	15	14
	3	47	1033.7	1082.6	2789	4	23	19
2&3	4	62	1241.6	1388.3	10792	12	31	25
	5	76	1740.5	1841.0	44535	20	37	32
	6	94	1832.3	1998.2	110329	49	44	38
	7	124	2122.3	2783.5	591482	170	57	53
	1	15	323.2	341.7	33	<1	7	7
	2	31	790.0	829.9	402	<1	10	13
	3	47	1058.0	1110.2	2840	2	17	21
3	4	62	1268.2	1379.7	10829	8	22	30
	5	76	1767.8	1865.5	33358	13	26	34
	6	94	1928.4	2033.1	112263	35	32	40
	7	124	2642.4	2906.2	544535	104	42	62
	1	15	320.7	372.5	<1	<1	7	10
	2	31	774.3	813.3	4	<1	15	18
	3	47	1035.9	1113.8	19	2	23	27
2	4	62	1241.6	1379.4	56	5	31	37
	5	76	1742.7	1881.9	134	8	39	1/46
	6	94	1876.6	2047.0	356	21	47	57
	7	124	2584.6	2862.4	1329	76	62	72
	1	15	594.3		-	-	15	
	2	31	486.7		-	-	31	
	3	47	2975.6		-	-	47	
1	4	62	2290.6		-	-	62	
	5	76	3320.7		-	-	76	
	6	94	3538.8		-	-	94	
	7	124	4859.6		-	-	124	

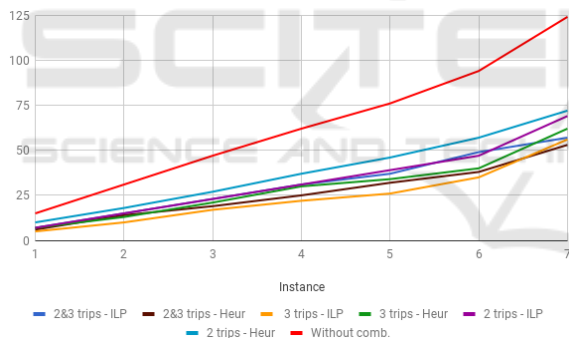Figure 9: Number of trucks for all combination types, including no combinations.

Figure 10: Number of trucks for all combination types.

task was accomplished by minimizing the total duration of trips, which forces the combination of 2 or 3 trips in order to avoid needless trips. The combination was done respecting regulation laws imposed to drivers traveling long distances and also the operation times of ports. Using real-based data of Brazilian scenery, we show that the number of empty trucks was reduced, which directly contributes to reduce the congestion on port areas and polluting gases emission.

For a small number of trips, the MILP formulation showed to be a useful tool for route planning. But as the number of trips increase, the computational time becomes impracticable. In such case, a fast heuristic may find a reasonable solution, not far from the optimal, in short computational time.
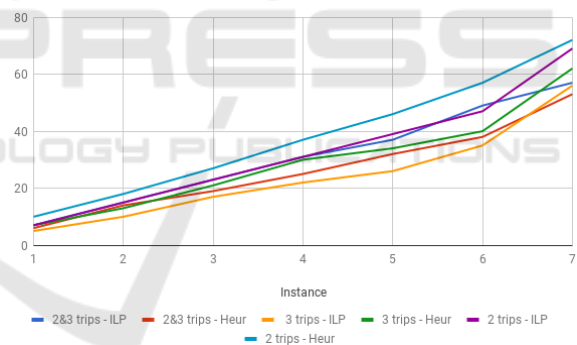
As future works we plan to improve the model in order to reduce the computational time, and use other strategies to reach the optimal solution, for example dynamic programming. Other work would be to improve the quality of the heuristic, maintaining the short computational time. This would allow the set-cover formulation to be used in almost real-time for replanning the combination in case of eventualities. A further step would be to assign the combinations or sequence of combinations of trips to a set of drivers. In this last case, we may have to use metaheuristics, as the problem may become more complex and a simple greedy heuristic, despite the good results achieved in this paper, may not give a good result in this more complex scenery.

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