A Real-Time Collaborative System For Container Trucks In The Port Of Antwerp: A Large Scale Simulation

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Abstract— **In this work, a primary proof of concept of a real-time shared planning system (SPS) for container trucks for the port of Antwerp is presented. The aim of such an SPS is to provide a flexible system which allows horizontal collaboration between road carriers with the aim on improving the overall efficiency of the logistic chain. Its impact on the drayage in the port is studied in the context of a large-scale simulation which models the relevant operations in the logistic chain that handles container transport over roads. In this simulation, the traffic network will explicitly be taken into account along with the interaction between trucks on this network, which will be modelled by a mesoscopic traffic model. A first version of a globally optimising SPS will be implemented within this simulation, and a comparison will be made to the situation where each carrier optimises its own individual planning.**

I. INTRODUCTION

The port of Antwerp is continuously facing new challenges in meeting transport growth rates while the capacity of infrastructure stagnates. Roads become more and more saturated in and near the port of Antwerp [1], leading to extra costs for transport companies and other stakeholders during their daily operations. A main problem is the lack of transparency and predictability of the traffic situation around the port (especially for trucks). This lack of transparency also makes it difficult to take the different traffic situations into account during the planning phase. Secondly, there is a need for cross-process communication and collaboration through the logistic chain. Many stakeholders are involved in the containers transport, but there is little coordination between them.

With the aim on tackling these problems, the authors in [2] conducted a technical-functional analysis for a "truck guidance system" in the port of Antwerp. The approach taken by this report consisted of both desk research and interviews with logistics stakeholders having their activity linked with the port of Antwerp. This qualitative study gave a global overview of a solution in which digital data is provided to the end-users on a centralised platform. In our work presented here, the focus will lie on an explicit horizontal collaboration scheme for road carriers and its evaluation in a large scale simulation.

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A. Literature Review

Collaboration within the logistic chain and the setting of a port has been the subject of much research. Often a distinction is made between horizontal collaboration and vertical collaboration [3]. Horizontal collaboration encompasses all cooperative schemes between two or more independent parties belonging to the same level of the logistic chain, such as joint distribution centres. On the other hand, a form of collaboration that is established among stakeholders acting at different levels of the logistic chain (for instance shippers, carriers, and/or customers) is called a vertical collaboration. Vertical collaboration schemes in hinterland chains of seaports have been studied in i.a. [4] and [5]. The authors in [6] proposed new concepts of collaborative transportation management and carriers' flexibility. They used a simulation approach, based on a simplified supply chain including one retailer and one carrier, to evaluate and optimise the proposed collaborative management.

Horizontal collaboration has been studied before as well, for example in [7] the authors provide an extensive qualitative overview of possible obstacles for truck-sharing and successful ways to deal with them, based on a number of semi-structured interviews with road carriers. In [8] the cooperation between carriers is studied in a quantitative way. An objective function is adopted which considers the total carriers' profit which is maximised by suitably combining the import and export trips shared by the carriers involved in the collaboration. Within their cooperative scheme, a compensation mechanism is designed to take into account the competitive nature of the trucking industry and to encourage carriers to share some of their trips. The problem in their work was formulated as a binary linear program and a few cases were evaluated using real data sets from the Italian port of Genoa. The scale of the case studied was however small; the primary case only contained 30 daily trips in total and only 3 road carriers were considered. The authors in [9] present a collaborative framework for trucks to be operated within a TAS, with an emphasis on reducing port-related empty truck emissions. The framework was mathematically described as a mixed linear program with an objective function containing transit costs as well as explicit terms for the emissions, based on the multiple travelling salesman problems with time windows. The scale of the instances tested on was again small; the number of trucks considered range from 4 to 50. Side payments were not studied in their experiments.

Collaboration in transportation and logistics have also been studied from a game theoretic point of view. For example, [10] considers the optimal allocation of the cost of an optimal route configuration among the customers in the context of a vehicle routing problem. Regarding a collaboration between road carriers, in order for it to be effective, it is required that the costs and/or profits are divided in a fair way between the participants of the coalition, such that each participant has an incentive to stay in the coalition [11]. In [12] the distribution of costs and saving in a horizontal collaboration between carriers is studied using cooperative game theory; a simple allocation method was used, namely the Shapely value. However, efficient algorithms or heuristics for computation of allocations in large collaborations in logistic planning remain to be investigated.

With regard to the adopted methodology in studying the optimisation of drayage operations through collaboration among carriers, and optimisation in logistics in general, two types of experimental approach can be taken. One is formulating the problem as a mixed linear program and optimising it as such [8], [9]. Another, less common, approach is the utilisation of simulations for measuring and testing proposed schemes [6], [13]. Simulations are in general able to mimic complex emergent behaviour, such as traffic jams, which are difficult to capture in a linear program. As it already might have become clear, the instances typically considered in literature have a rather small scale. Here, the problem will be studied on a very large scale, i.e. approximately 5 000 trucks and 600 road carriers. Since we will be considering collaboration on a very large scale, the simulation approach will be the one taken here for the evaluation of the collaboration.

B. Statement of Contribution

The basic idea behind the proposed shared planning system (SPS) is that as opposed to constructing a full planning for the whole day beforehand, the planning will be dynamically constructed on-the-go, enabling great flexibility and allowing to take real-time information into account. The fact that the planning is shared allows for participating trucking companies to exchange orders, providing a bigger pool for the algorithm to pick optimal orders from. To summarise, our main contributions are:

- A flexible, yet simple shared planning scheme for the horizontal collaboration between road carriers is presented.
- The collaborative framework is studied in a large-scale simulation, explicitly taking into account traffic and congestion.
- The proposed SPS works in real-time, its on-the-go character allows for great flexibility with regards to carriers or single trucks entering or leaving the collaboration.

C. Organisation

The remainder of this article is organised as follows: Section II will cover the different aspects of the simulation; in Section III the planning strategies which are studied in the simulation framework are described, including the shared planning system; in Section IV the results are presented; finally, Section V contains the final discussion and conclusion of this work.

Fig. 1. The road network (for trucks) around Antwerp and its port and the 5 container terminals.

II. SIMULATION

A. Traffic Simulation

At the base of every traffic model, being it micro-, macro- or mesoscopic, lies a network structure that represents the traffic network. The network considered in this simulation is the complete road network in a rectangle of about 30 km $\times$ 25 km around Antwerp and its port, see Fig. 1. The networks consists of $|V| = 20\,489$ nodes or intersections and $|A| = 46\,685$ arcs or roads connecting them (only roads where trucks are allowed are included). The traffic network data was obtained from OpenStreetMap [14].

The framework that is used in this study is the one of mesoscopic traffic modelling, allowing for realistic simulations while being computationally efficient. More specifically a model based on (state-dependent) queueing theory will be used. In terms of queueing theory, each link of a street network is regarded as a queue (obeying the FIFO principle), i.e. a service device operating at a certain service rate which corresponds to the flow capacity of the link, being the maximum throughput in [vehicles/h] which can be maintained. Queues of vehicles (congestion) occur in the system, whenever the current demand exceeds the flow capacity of a service. In consequence, vehicles queue up in front of the service device, and experience additional waiting times before being served. Moreover, the service times will depend on the state (i.e. the density) of the considered link. This allows to replicate the phase transition that occurs in real vehicular traffic systems, namely from the free flow phase to the jamming phase, where a jam or *shock wave* propagates backwards through the system. The model presented here is based on the work in [15], the μ-Queue model, although some additions and adaptations are made. The resulting simulator allows us to put vehicles in the traffic network with a certain predetermined route and let them drive through the network and interact with one another. The efficiency of the mesoscopic model allows to simulate ten thousands of vehicles in a large network with hundreds of thousands of arcs/roads, while being able to reproduce traffic jams and track individual vehicles. Routing trucks from their origin to their destination is done by shortest paths based on arc weight given by the exponential moving average (with $\tau = 10$ min) of the current travel time at each point in time for each arc.

B. Simulation of Container Transportation in the Port

1) Terminals: The port of Antwerp has five large container terminals [16], see Fig. 1. In Table I their annual capacity is given in TEU (twenty-foot equivalent unit). The total amount of containers handled in the port of Antwerp in 2019 is 11 860 204 TEU, 58 % of which is handled by trucks, 34 % by barge and 8 % by rail, [16]. This means that 3 439 459 40-foot (FEU) containers were handled by trucks in the year 2019. We thus assume that all orders consist of a 40-foot container, which is by far the most common type. If there are any 20-foot container orders, it is assumed that they are combined on one trailer. All of the terminals are opened (landside) 24/5, except for Antwerp Container Terminal which opened 5 days from 6:00 to 21:15. So there is a total of about 250 operating days in a year, meaning that on average $N_o = 13\,758$ (40-foot) containers are handled each day. Assuming that the number of containers processed in each terminal is proportional to the respective capacity, this can be converted to the average daily processed number of containers by trucks for each terminal, see the last column in Table I.

The terminals operate in similar ways although there is a difference in how much of the truckflow inside each terminal is automated. Some terminals have an online time slot booking system (or TAS), however, these time slots are not binding and trucks can arrive at any time in the day. The internal operations of the terminals are abstracted away and the processing time is modelled by a queueing model, with a certain average service rate μ. The service rate is a measure of how many trucks are processed per unit of time and thus of the capacity of that terminal; it is assumed that $\mu \propto$ capacity (see Table I). The time at which a truck ν exits the terminal t^{ν}_{exit} is given by

$$t^{\nu}_{\text{exit}} = \max(t, t^{\nu-1}_{\text{serv}}) + T^{\nu}_s + T_h \qquad (1)$$

where $t^{\nu-1}_{\text{serv}} = \max(t, t^{\nu-2}_{\text{serv}}) + T^{\nu-1}_s$ is the service time of the previous truck that entered the terminal and $T^{\nu}_s \sim \text{Exp}(\mu)$ is the service time (time between services), which follows an exponential distribution with average service time $1/\mu$. This first part of (1) is a direct consequence of a G/M/1 queue. The last term $T_h \sim \mathcal{N}(\mu_h, \sigma_h)$ represents the extra handling time due to different kinds of operations inside the terminal (multiple checks, waiting in the parking area for the container to be loaded etc), which we assumed to follow a normal distribution. Note that due to this last term, trucks will not necessarily exit the terminal in the same order in which they arrived. The parameters are set to $1/\mu = 2.0 \cdot (9\,000\,000/C)$ s, with C the annual capacity of said terminal, $\mu_h = 1\,800$ s and $\sigma_h = 200$ s.

2) Orders: In the context of this study, an order is a 40-foot container which has to be picked up somewhere and has to be dropped off in another location. One of these locations, either the pick-up or drop-off, will be a terminal, the other locations will be somewhere in an industrial area in the hinterland. There are thus 2 types of orders, *drop-off*, meaning a container is picked up somewhere and dropped off at a terminal, and *pick-up*,the reverse. It is assumed that roughly equal amounts of the orders are pick-up or drop-off, [16], and that the handling times in the terminals are similar for both.

Detailed data on the origin-destination pairs of containers in the port of Antwerp is not available. In order to roughly approximate potential drop-off or pick-up locations, map data from [14] was used. On these maps, different areas are classified according to the main activities or characteristics of these areas (building, forest, waterway, etc.). All patches that are classified as “industrial” are filtered out and all road segments that fall inside one of those industrial patches are used as potential locations for container pick-ups or drop-offs, see Fig. 2 for the resulting distribution. Finally, orders are generated as follows: a random terminal is chosen (weighted by the capacities), a random industrial road segment is chosen (with a probability proportional to its length), and finally with 50 % probability, the order is set to either drop-off or pick-up. During the simulation, when an order is loaded or unloaded on a non-terminal location, a delay is added to simulate the time needed to carry out this operation, drawn from a normal distribution $\mathcal{N}(\mu_l = 1\,800 \text{ s}, \sigma_l = 200 \text{ s})$.

3) Trucking companies: The players that handle the orders and are responsible for the majority of the container transport over land are the trucking companies, each having their own fleet of trucks. Fig. 3 presents a snapshot of the road transport market in Belgium. Note that of a total of approximately 8 700 road transport companies, around 3 200 (37%) are companies with one vehicle. A similar distribution of trucking companies and fleet sizes that operate in and around the port of Antwerp will be assumed. The total number of (container) trucks operating in the port will be set to $1/3$ of the total number of orders handled daily (such that every truck handles 3 orders each day, on average), i.e. $N_t = 4\,586$. The resulting distribution of the number of companies N_i with fleet size i can be modelled by a power law: $N_i = N_1 i^{-1.3}$. The constant N_1 is determined by the condition that the total number of trucks should be equal to N_t, so $N_t = \sum_i^k i N_i = N_1 \sum_i^k i^{-0.3}$ with $k = 50$ a cut-off.

TABLE I
THE 5 CONTAINER TERMINALS IN THE PORT OF ANTWERP.

Terminal	Capacity (TEU)	Daily throughput (FEU)
MSC PSA European Terminal (MPET)	9 000 000	7327 (53 %)
DP World Antwerp Gateway Terminal	2 500 000	2035 (15 %)
PSA Antwerp Europa Terminal	1 800 000	1465 (11 %)
PSA Antwerp Noordzee Terminal	2 600 000	2117 (15 %)
Antwerp Container Terminal	1 000 000	814 (6%)

Fig. 2. A heatmap showing the resulting distribution of drop-off or pick-up locations that are not located at one of the five terminals.

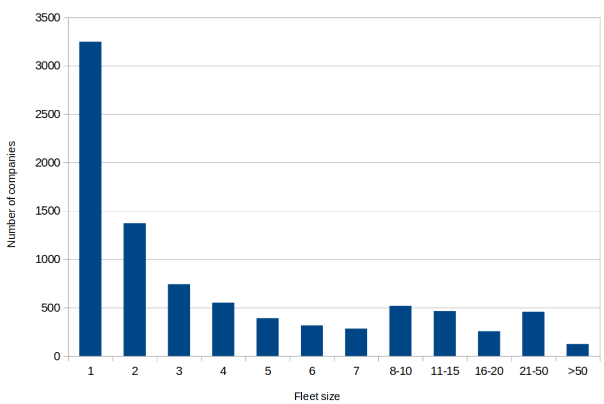

Fig. 3. Overview of Belgium trucking companies' fleet size, [17].

III. COLLABORATIVE PLANNING

With the framework described in the previous section, a simulation can be set up: orders are allocated to trucks by a certain planning strategy and trucks carry out the orders by visiting the necessary location and terminal. The simulation ends once all orders are processed. By planning strategy of a trucking company, we mean the way in which pending orders in the order book are allocated to trucks which will handle them. It is by adopting different strategies that profit can be made in terms of lost time. In describing and discussing planning strategies, for reasons of simplicity, it will always be assumed that all the orders for that day are known from the start and that no new orders will be added during the day, the contrary would however not pose a problem for the techniques that will be used here (real-time planning).

It is possible to make a complete planning before the start of the day, if all orders are known. Trucks could be assigned all the orders they have to handle that day in the order in which they have to be carried out such that e.g. the total driven distance is minimised. A main problem with this is that it is very difficult to make accurate predictions of traffic situations and situations at the terminals and to take them into account in optimising the planning. Another main problem in the same line is that such a method is not very flexible, which is a necessity when serving this many independent road carriers. For example, new urgent orders being placed during the day or trucks/drivers that cannot drive that day for unforeseen reasons are difficult to take into account. Which are things that are bound to happen when such a large amount of trucks and orders are involved. These are the main reasons why on-the-go real-time planning strategies will be considered here. They are very flexible and allow one to anticipate on real-time information on traffic situations, terminal waiting times, etc. This flexibility will be especially important when considering global planning in the proposed SPS, see Section III-B below.

A. *Local planning: individual planning*

The first strategy that will be discussed is *local planning*, denoting planning strategies where each competitive trucking company plans for its own orders and trucks, without any collaboration.

A first method of "planning", to which others can be compared, is *random planning*. This represents the case where trucking companies do not really take any objectives or information into account and just carry out orders on the go. As will be the case with other real-time planning strategies discussed here, trucks that are inactive (i.e. have no order assigned to them) request an order and receive one. Once they finished this order, they can again request an order, if there are any left in the order book of that trucking company, until all orders are processed.

An important factor that can be taken into account in assigning orders to trucks is the expected driving times from the current location of the trucks to the pick-up location of the order. Given a set of pending orders and pending trucks, one can assign (timewise) shortest order-truck pairs to one another. One can see this as $|O_p|$ orders and $|T_p|$ trucks with $|O_p||T_p|$ links between them with a weight representing the shortest timewise distance between the location of the truck and the pick-up location of the order. Trucks have to be assigned to orders such that the total sum of the expected travelling times is minimised. This is a well known combinatorial optimisation problem for which good algorithms exist [18], [19]. The complexity of the *Hungarian algorithm* which solves this problem exactly, amounts to $O(|O_p||T_p|\min(|O_p|,|T_p|))$ for our application. This is, however, too slow for our application and here an approximate technique will be used (this algorithm could in practice be carried out on a powerful server, in which case the exact solution might be feasible). Instead of looking for the optimal combination of assignments, assignments with the shortest travel times are picked in a greedy fashion, the pseudocode is given in Algorithm 1. The time-complexity of this approximate algorithm is $O(|O_p| + |T_p|)$. It works by taking the set T_p and going over trucks one by one, and assigning the closest order to it. This is done by doing a Dijkstra search from one location to a set of possible locations (*ClosestLeaf* in the pseudocode), which can be done efficiently, resulting in $|T_p|$ calls to the Dijkstra algorithm.

Note that a lot of orders/trucks can have the same location, namely one of the 5 container terminals. That is why the map L_o is used, for each location they contain a linked list (LL) with the orders with the same pick-up locations. These linked lists are randomised for reasons of fairness. The order in which the trucks are iterated through is randomised. This will ensure no truck will be favoured over another and more importantly, in the case of global planning that will be discussed below, no trucking company gets an advantage over another one when using this system.

Algorithm 1 Assign-Orders-Local()

$O_p = \{...\}$ ▷ Set of pending orders
$T_p = \{...\}$ ▷ Set of pending (inactive) trucks
$A = \{(.,.),...\}$ ▷ Empty map of (order, truck) pairs
if O_p **not** empty **and** T_p **not** empty **then**
    $L_o = \{(., LL[\,]),...\}$
    for each truck t in T_p **do**
        $a \leftarrow$ ClosestLeaf(t.location(), L_o.keys())
        $o \leftarrow L_o$.get(a).pop() ▷ Closest order to truck t
        A.put(o, t)
        O_p.remove(o)
    T_p.clear()
return A

B. Global planning: a shared planning system (SPS)

By *global planning* we mean a planning strategy that aims at optimising the container transport for trucking companies and terminals by collaborating and sharing orders. An important property/constraint to keep in mind is that the strategy should be beneficial for all participating parties in order for it to be successful, i.e. it should be individually rational in a game theoretic sense. Keeping this in mind, the following scheme is proposed: create a *master set* of pending orders in which all pending orders of participating trucking companies are put, all trucks of the participating companies are treated equally. Upon requesting an order, trucks are assigned an order in a similar fashion as in the local Algorithm 1. The basic idea behind this is that the system now has a bigger pool of orders from which optimal ones are picked and allocated to trucks, compared to individual trucking companies. This results in companies sharing orders while being profitable for each company using this joint sharing system. An important constraint that is introduced in this global planning strategy is that each trucking company can only get as many orders from the master set as it has put in at the start of the day/simulation; assuming all orders are of equal value; if they are not, it is straightforward to generalise this to variable values. This will ensure no trucking company can obtain more orders than they put into the shared system. The pseudocode is given in Algorithms 2 (initialisation) and 3 (actual planning).

Algorithm 2 Initialize-Master-Set()

$MO_p = \{...\}$ ▷ Master set of pending orders
$Cr = \{(.,.),...\}$ ▷ Empty map of (trucking company, credit)
for each trucking company tc **do**
    $O_p \leftarrow tc$.pendingOrders() ▷ Set of pending orders of tc
    MO_p.addAll(O_p)
    Cr.put(tc, $|O_p|$)

Algorithm 3 Assign-Orders-Global()

$MO_p = \{...\}$ ▷ Master set of pending orders
$Cr = \{(.,.),...\}$ ▷ Map containing credit for each trucking company
$A = \{(.,.),...\}$ ▷ Empty map of (order, truck) pairs
$MT_p = \{...\}$ ▷ Set of pending (inactive) trucks
for each trucking company tc **do**
    if Cr.get(tc) > 0 **then**
        MT_p.addAll(tc.pendingTrucks())
if MO_p **not** empty **and** MT_p **not** empty **then**
    $L_o = \{(., LL[\,]),...\}$
    for each truck t in MT_p **do**
        $tc \leftarrow t$.truckingCompany()
        $C \leftarrow Cr$.get(tc)
        if $C = 0$ **then**
            continue
        $a \leftarrow$ ClosestLeaf(t.location(), L_o.keys())
        $o \leftarrow L_o$.get(a).pop() ▷ Closest order to truck t
        A.put(o, t)
        MO_p.remove(o)
        Cr.put($tc, C - 1$)
return A

We thus propose a real-time planning system that is used by multiple participating parties, being different road carriers. In this dynamic on-the-go planning, pending orders are shared between transport companies as a common good which allows for a more profitable planning and allocation of orders to trucks compared to individual planning. Every time a truck is free, it can request a new order from the system, which will return an optimal one taking into account current traffic situations and the current position of the truck. The real-time nature of this planning system inherently allows the use of real-time information, such as current traffic situations, which is done through the shortest-path allocation of orders to trucks which uses the current load on the road network. Moreover, this real-time booking allows for great flexibility, orders, trucks and even trucking companies can join and leave the system without the need of redoing the planning.

IV. RESULTS

In this section the results of the simulation and the different planning strategies will be discussed. The simulation was implemented in Java 11.0.7 and the experiments were performed on a computer with an Intel Core i7-8650U CPU @ 1.90GHz×8 processor and 16 GB of RAM, under Ubuntu 18.04 x64. The time needed to complete a full simulation depends on the parameters used, planning strategy, frequency of updating the routing weights and trees, etc.; for the parameters mentioned in the previous sections this amounts to approximately 220 s.

A. Comparing planning strategies

To compare the different planning strategies described in the previous section, 10 simulations were done for each strategy, with otherwise the same parameters and initial conditions. In Fig. 4 the distribution of the times spent in traffic by each truck is shown for 4 different cases: random planning, local planning, global planning, and a transitional case with 50 % of the trucks in the shared planning scheme and 50 % with an individual local planning (randomly picked). As can be expected, by doing no planning or optimisation, i.e. random planning, the traffic times are much greater. When comparing random planning with local planning, the traffic times are on average reduced by 27.4 ± 3.9 % (errors denote the standard deviation across the different simulations). On average the reduction in traffic times amounts to 13.2 ± 1.3 % when going from local to global planning. When 50 % of the trucks and their corresponding companies have joined the SPS, the average time spent in traffic per truck is already reduced by 9.2 ± 1.3 % when compared to the case where all trucking companies apply an individual real-time planning. The average traffic times per truck for the different cases are given in the first column of Table II.

B. Influence of fleet size

Let us now look in more detail at the impact of the fleet size of a trucking company on its improvements when joining the SPS. In Fig. 5, the average traffic time per truck for companies with different fleet sizes is depicted. The results are summarised in Table III. From this, it can be seen that joining a coalition in the shared planning is relatively more beneficial for trucking companies with smaller fleets. This is a result which one intuitively expects, as the pool of potential orders to choose from is increased more for smaller companies joining the SPS than for larger companies. In order to make the coalition more stable and the division of profit more equal, side payments could be introduced, this is however outside the scope of our work.

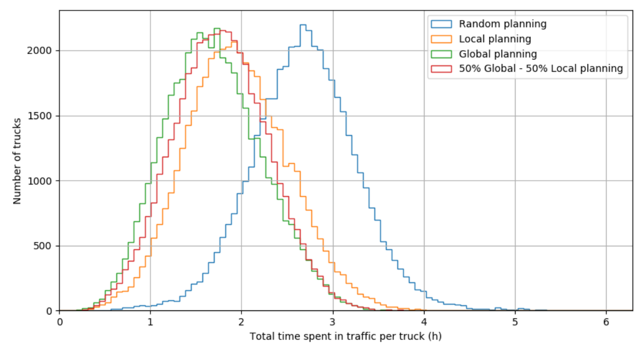

Fig. 4. Distribution of time spent in traffic per truck for the three different planning strategies: random, local and global.

TABLE II
AVERAGE TIME SPENT IN TRAFFIC (IN SECONDS) AND AVERAGE TOTAL DISTANCE DRIVEN (IN KM) PER TRUCK FOR THE THREE PLANNING STRATEGIES.

Strategy	Traffic time	Distance
Random planning	9 671	124.1
Local planning	7 022	92.0
Global planning	6 094	82.5
50 % Global - 50 % Local	6 373	87.2

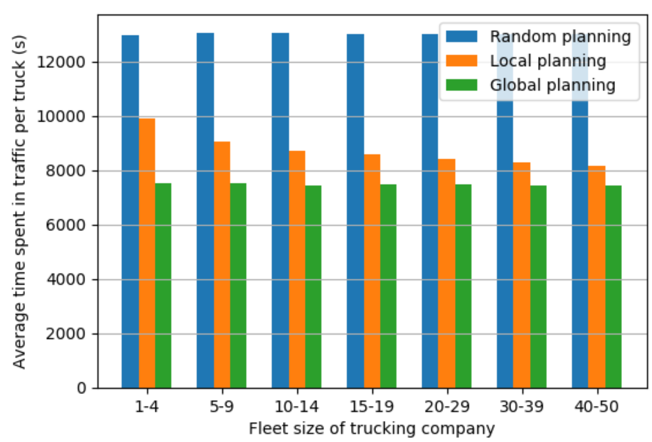

Fig. 5. The average time spent in traffic per truck for different fleet sizes of the trucking companies under different planning strategies.

V. CONCLUSIONS

In this work, the possibility of a shared on-the-go planning system for container trucks in the port of Antwerp is studied

TABLE III

RESULTS FOR AVERAGE TRAFFIC TIMES PER TRUCK FOR COMPANIES WITH DIFFERENT FLEET SIZES.

Fleet size:	1-4	5-9	10-14	15-19	20-29	30-39	40-50
Random planning (s)	9 734	9 742	9 782	9 807	9 777	9 760	9 780
Local planning (s)	8 157	7 473	7 149	6 976	6 903	6 810	6 760
Global planning (s)	6 288	6 127	6 086	6 043	6 113	6 074	6 088
Improvement: Random $\rightarrow$ Local (%)	16.2	23.3	26.9	28.8	29.4	30.2	30.9
Improvement: Local $\rightarrow$ Global (%)	22.9	18.0	14.9	13.4	11.4	10.8	9.9

by means of a large-scale simulation. It was demonstrated that a real-time SPS showed great improvements when compared to an individual real-time planning. This increase in efficiency is not only positive for the participating road carriers, but may benefit the whole supply chain by decreasing road congestion around the port, reducing carbon emissions, and transportation costs, and increasing the system-wide truck capacity.

Container terminals could also benefit from this system. Firstly, greater efficiency in container transport on the side of trucks and trucking companies means that more orders can be processed each day. Secondly, this SPS would allow for great transparency towards the terminals. For all trucks using this booking/planning system, they can get precise information on when to expect which truck and for which order; this information could be used to further optimise their internal operations. A possible extension of this system when assigning orders to trucks would be to actively take into account the current load on the terminals and the expected future loads on the terminals. To accurately model this, more detailed and accurate information on the internal operations of each individual container terminal has to be available.

It was demonstrated that when only 50 % of the trucks and their corresponding companies (picked at random) join the shared system, the improvement in efficiency is already close to the case where all trucks are in the SPS. This illustrates that it is not necessary for all companies to join the system before benefits are noticeable, which creates an incentive for trucking companies to join the SPS in the early phase and will facilitate the introduction of such a shared system in practice. Note that in the description and experiments in this work, the constraint was set such that each trucking company gets the same number of orders allocated by the SPS as they had at the start of the day. The sharing of orders is thus kept in balance on the scale of one day. In principle, it is also possible to extend this to longer time scales (i.e. building up credit over a longer period of time). The issue of the correct assignment of side payments between trucking companies in order to make the coalition stable has not been covered in this work. As mentioned in the literature review, efficient methods for determining profit allocations in large coalitions in the context of collaboration in transport remains an open problem and a possible subject for future research.

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