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Potentials and profitability

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Hub-based Truck Platooning: Potentials and profitability

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Abstract

This paper presents a model for optimising truck platoons formed at a platooning hub. Different planning and dispatching strategies, from static to dynamic, are investigated with respect to profitability and fuel savings across a range of input variables. The problem is solved using a dynamic programming based local search heuristic. As a case study, a virtual platooning hub close to the German Elb Tunnel is examined using data from a large European transport network model. It is concluded that profitability crucially depends on; i) dynamic outlook and ii) if chauffeurs are allowed to rest while driving in platoons.

Keywords: Truck platooning, Logistic planning, Discrete event simulation, Logistic optimisation

1. Introduction

Truck platooning involves the grouping of trucks into connected sequences of vehicles in order to save fuel (Lu & Schladover, 2011; Tsugawa et al., 2016) and emissions (Scora & Barth, 2006), and at later stages, to possibly relax rest hour restrictions (Goel & Rousseau, 2012; Goel, 2014). Truck platooning is not a new technology. It has been researched and debated since the 1940s (Geddes, 1940), and in the last three decades it has resulted in numerous proof of concept projects and demonstration projects (Stevens, 2015; Benz et al., 1996; Fritz et al., 2004; Alkim et al., 2016). The main focus so far has been on the technological aspects of platooning and how vehicle-to-vehicle communication and sensor technology can be applied to facilitate platooning. Today it is clear that platooning technology exists and is close to being fully operational for real-world applications. The development of the

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planning stage that naturally follows the technology stage, however, is much scarcer addressed in the literature. Little is known today about how platooning may be implemented in practice (from a planning perspective) and about its implications and impact from an operator and system perspective.

The aim of this paper is thus to analyse the planning stage of truck platooning in more detail, and in particular investigate the potential with respect to profitability and fuel efficiency. We do so by considering a collaborative platooning system where the pairing of trucks in platoons is orchestrated by a platooning service provider (PSP) (Berger, 2016). The forming of platoons is assumed to take place at strategically placed platooning hubs alongside the motorway network. Two main contributions are offered in the paper. First, we present a new computationally efficient heuristic for hub-based platooning, enabling locally optimal pairing of trucks that passes through a hub. The performance is compared to an exact MIP based solver, and we demonstrate the feasibility of solving instances multiple orders of magnitude larger than possible with the MIP models. The second contribution follows from applying the model. In particular, by considering truck routes obtained from a transport network model which has been calibrated to observed flows of trucks for an European road network, we provide conclusions with respect to the profitability of hub based platooning across a variety of different inputs. The inputs include the flow of trucks that passes through the hub, their destinations and routes, their arrival and departure times, the maximum allowed size of platoons and the cost of driving and the cost of being idle. It is demonstrated that, even under optimistic conditions, the prospects of platooning in the case where chauffeurs cannot rest while driving, are relatively limited from a profitability and impact perspective. However, in the case where chauffeurs can rest while participating as followers in platoons, the potential profitability increases significantly suggesting that viable business models may exist. Consequently, the main conclusion of the paper from an impact perspective is that, although platooning is conceptually appealing, it is unlikely to disrupt the trucking industry on a large scale in the next decades if based on an orchestrated platooning hub design and if it is not possible for chauffeurs to rest while driving in platoons.

The paper is organised in six sections. In Section 2 a literature review is presented. In section 3 we present a problem definition where a framing of the problem is offered and where limitations and inputs are discussed. Section 4 includes a description of the solution methodology. Section 5 presents the case study and results. Finally, in Section 6 we offer conclusions and provides an outlook for further research.

2. Literature review

In the literature, the main focus has been on the technological aspects of platooning and how vehicle-to-vehicle communication and sensor technology can be applied to facilitate platooning (Bergenhem et al., 2012). Along these lines, mathematical models for platooning control and optimal stability as well as adaptive cruise control manoeuvres have been developed (e.g, (Sabau et al., 2017; Nowakowski et al., 2015)). Numerous technological challenges still remain related to platooning, including enabling multi-brand platooning (Fornells & Arrue, 2014; Brizzolara & Toth, 2016; Berger, 2016), restrictions on platoons in mixed

traffic conditions (Alkim et al., 2016) and incompatible braking and acceleration profiles (Nowakowski et al., 2015). However, in general the fundamental technological challenges are no longer the main issue (Stevens, 2015), and at the present time it is clear that the platooning technology is close to market-ready (TNO, 2016).

The main challenge in the coming years is related to the practical implementation of platooning systems, their interaction with the physical infrastructure and the possible impact with respect to traffic safety, security and profitability seen from the operator perspective (Anderson et al., 2014; Janssen et al., 2015). The European Truck Platooning Challenge 2016, which was an initiative of the Dutch Ministry of Infrastructure and the Environment, has in a recent report considered the important challenges of platooning (Alkim et al., 2016), and acknowledges that the formation of platoons (e.g., how to form, maintain and reform platoons during operations) is a significant challenge. Similarly, a recent technology road-map concerning design challenges of different platooning systems support this view (Misener & Zhang, 2015). This is further emphasised in Mallozzi et al. (2016) and Bergenhem et al. (2010), who argue that the formation and joining stages are recognised as critical elements in future platooning systems. Mainly three platooning formation concepts have been considered (Janssen et al., 2015): i) scheduled platooning, ii) 'on-the-fly' or self-organised platooning, and iii) orchestrated platooning facilitated by Platooning Service Providers (PSPs). Scheduled platooning and orchestrated platooning share similarities in that they consider a forward-looking planning stage prior to entering the motorway. The 'on-the-fly' platooning scheme, on the other hand, implicitly assumes that trucks entering the motorway will engage in platoons with the first truck available and without any pre-planning. There is an ongoing debate concerning the potential of on-the-fly platooning. Janssen et al. (2015) suggest that the potential on dedicated corridors is high, but acknowledge that it is likely to be relevant mainly at later platooning technology stages. This point of view is shared in a recent report by SIA Partners (2016). Hall & Chin (2005) argued that it is optimal to form platoons before trucks enter the motorway, and this view is supported in a more recent simulation study by Liang et al. (2014) that showed substantial benefits associated with careful planning of platoons.

An overview of previous optimisation studies of platooning schemes is provided in Bhoopalam et al. (2018). A relevant distinction when considering a coordinated platooning setup is the issue of trucking routes and whether these are fixed or flexible. It might be the case that by making small changes to the planned routes, it would be possible to extend the shared platooning mileage considerably and thereby improve the efficiency. This is shown in Larson et al. (2013) where trucks are monitored and managed through a set of local controllers. By altering routes and adjusting speeds to facilitate pairings in specific junctions (see also Liang et al. (2016)), they attain benefits in the magnitude of 1-9 percent. However, as shown in Zhang et al. (2017) and Liang et al. (2014), the detouring threshold is rather small due to the relatively limited benefits of driving in platoons when chauffeurs are not allowed to rest while driving. Moreover, the platooning matching problem with flexible routes is extremely hard to solve (de Hoef, 2016; Larson et al., 2016; Larsson et al., 2015), as it involves a leader-follower decision in addition to the route and pickup planning. In addition, to be operational it requires wide-spread data sharing among trucks and will also suffer from con-

gestion and travel time uncertainty in the network. These complications will most probably make it hard to obtain efficient pairings at the different junctions.

In the literature, Meisen et al. (2008) is one of few to consider platooning profitability under the assumption of fixed routes. They use data mining techniques to organise and plan platoons and present experimental results which compare different assumptions regarding platooning size and waiting time. The paper offers no formal guarantees with respect to optimal or even locally optimal solutions and is essentially a matching heuristic which is tested on simulated data. Also, no estimate of the expected profit and how this differs across inputs were provided and we therefore believe that our paper extend this work in several ways as will be detailed in Section 3 below. Adler et al. (2016) considers the problem of forming platoons for trucks travelling between two hubs and also the trade-off between idle time when forming platoons and obtained energy savings from driving in platoons. Conceptually, their approach shares similarities with the approach put forward in this paper. However, their assumption of a single destination simplifies the problem significantly. Moreover, they only consider an "all-or-nothing" dispatching policy, where each dispatch of platoons involves all trucks at the hub. From a PSP perspective these assumptions are very restrictive, and are relaxed in this paper.

Hub based platooning can be seen as a special case of more general formulation of the platooning problem which could involve the integration of dynamic routes and theoretically be solved using a corresponding MIP model approach. In this case trucks would be matched according to their entire routes. This approach, however, is unable to scale to the number of trucks considered in this paper, and would furthermore require knowledge of the exact driving and departure times for all trucks for the entire time horizon.

3. Problem definition

In the present paper we focus on optimising a continuous flow of trucks that passes through a fixed hub location and which have fixed routes (see Figure 1). In doing so, we explore how decision variables related to the size of the platoons and the arrival and departure schedules combined with costs for operating trucks (idle time and driving time) affect the platooning benefits. Compared to the literature, in addition to the similarities to the work by Adler et al. (2016) discussed above, the most comparable reference is that of Meisen et al. (2008). However, the current paper extends Meisen et al. (2008) in a few important ways. One extension is that, by using a labelling algorithm, it is possible to solve the problem of creating platoons such that these are 'locally optimal', in that no better platoons can be formed by modifying less than four platoons. Although we cannot guarantee that the solution is globally optimal, tests suggest that this is typically the case, at least on small instances that can be solved to optimality using Mixed Integer Programming models. Another difference is that we consider a semi-realistic case where the full path of trucks that pass through a virtual platooning hub is based on a path-based assignment model which has been calibrated to real-life traffic counts. Finally, in the paper we offer a range of experiments for an extended number of input parameters. It is a deliberate ambition of the paper to suggest an indicative upper bound of the platooning potential when applying an

orchestrated hub design. It is an overestimate of profitability because all trucks are assumed to collaborate irrespective of make, type of transport etc. Hence, we discard all possible restrictions that may be the result of technological limitations and legislation. However, it should be noted that the modelled benefits are likely to increase if on-the-fly platooning and prearranged platooning were allowed on top of the orchestrated system. However, from an analytic perspective the modelling of joint accumulated benefits of these different platooning systems/approaches are outside the scope of this paper.
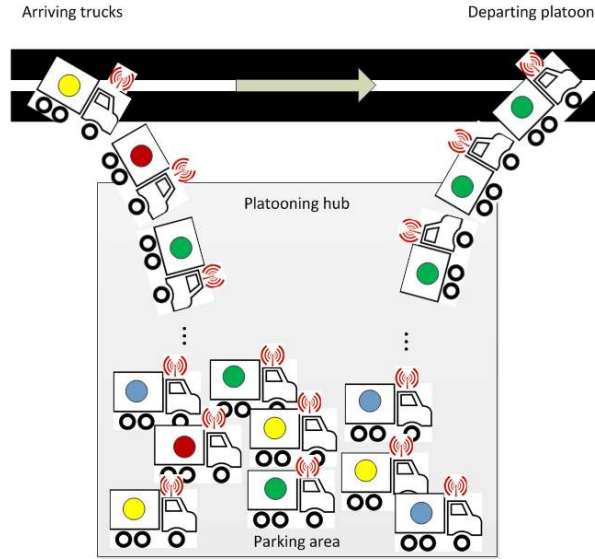

Figure 1: Platooning hub

Below we consider a framing of the problem in more detail by discussing the different assumptions and limitations further.

3.1. Flow of trucks

Clearly, the more trucks passing through the hub, the higher the likelihood of good platoon pairings and the higher the potential profitability. In this respect, the flow can be seen as an important parameter when considering the potential of platooning. It is trivial to investigate scenarios with different flow formations and this has been tested in different simulations in the paper.

3.2. Truck routes

In the paper routes are assumed to be known and fixed. Truck routes are generated from a path-based assignment algorithm (Rasmussen et al., 2015, 2017) which has been applied in a large-scale European transport network model. The assignment model has been calibrated on the basis of European-wide origin destination matrices and traffic counts. The freight demand model is described in further details in Jong et al. (2016).

3.3. Arrival time of trucks

It is assumed that the arrival of trucks follow a uniform random distribution in the time interval $[0, \tau_{max}]$. Clearly, any deviation from the assumption of uniformity is likely to cluster the trucks and thereby possibly increase the potential for platooning during those hours.

3.4. Time of platoon dispatch

The time of dispatch of platoons is important as it is closely linked to waiting time inside the hub. In the paper we consider two dispatching strategies: i) a scheduled dispatch and ii) a dynamic dispatch. In the schedule-based dispatch, trucks are launched at fixed times, whereas the dynamic dispatching pre-calculates the platoon allocations and launch them as soon as they are formed. The latter case implies a forward-looking planning stage where communication between trucks and the PSP is required. For the first dispatching strategy, the launch frequency is an important variable, which we test across a range of values.

3.5. Platooning size

The maximum platooning size is considered as endogenous. More specifically, we investigate systems allowing platoon sizes in the range of $[2, 8]$ vehicles.

3.6. Rest hour restrictions

When trucks arrive at the platooning station we assume that all chauffeurs are rested and that one chauffeur is available as 'platoon leader'. The possibility of resting while driving is explored by analysing the obtained solutions to include the need for resting time, with and without allowing the 45 minutes rest (as prescribed by European Union regulations, (Parliament, 2006)). This enables us to analyse the impact of these 'small rests' inside the truck as, by legislative intent, longer resting periods are not allowed inside the truck.

A driving speed of 80 km/h is assumed, and thus the total estimated driving time dt_n is given by $dt_n = s_{n,n}/80$ where $s_{n,n}$ is the distance driven by truck n. If we further consider a 'normal day of operation' with respect to driving and resting hours, a rest of 45 minutes is required after 4.5 hours of driving. In addition, a long rest is required after 9 hours of driving. In order to measure the difference between operating in platoons and driving alone, a truck that operates alone is subjected to 45 minutes of waiting time per day (out of a maximum of 9 hours of driving) when driving more than 4.5 hours as described in Equation (1) below.

$$rest(n) = 0.75 \left\lceil \frac{dt_n - 4.5}{9} \right\rceil \tag{1}$$

The same equation can be modified and applied to trucks in platoons. First, it is noted that 45 minute rests can be ignored while driving in the platoons as drivers can swap roles while platooning. Secondly, each truck leaves the platoon with 4.5 hours or 3.75 hours remaining until its next short rest, depending on whether the truck led the platoon before it split from the platoon. Refer to Figure 2 for an illustration of the rest-hour profile for a single truck and a platoon of three trucks. As can be seen, trucks in platoons arrives earlier at the terminus of trip leg 2.

Start t=0   Stop t=4:30 Start t=5:15   Last stop t=9:45

0% rested ●————— Trip leg 1 —————● Rest ●————— Trip leg 2 —————● ···· Long rest ····

100% rested ○

Start t=0   t=4:30   t=5:15   t=8:15   t=9:00

0% rested ●————— Trip leg 1 —————● ————— Trip leg 2 —————●···· Long rest ····

83% rested ●

100% rested ●

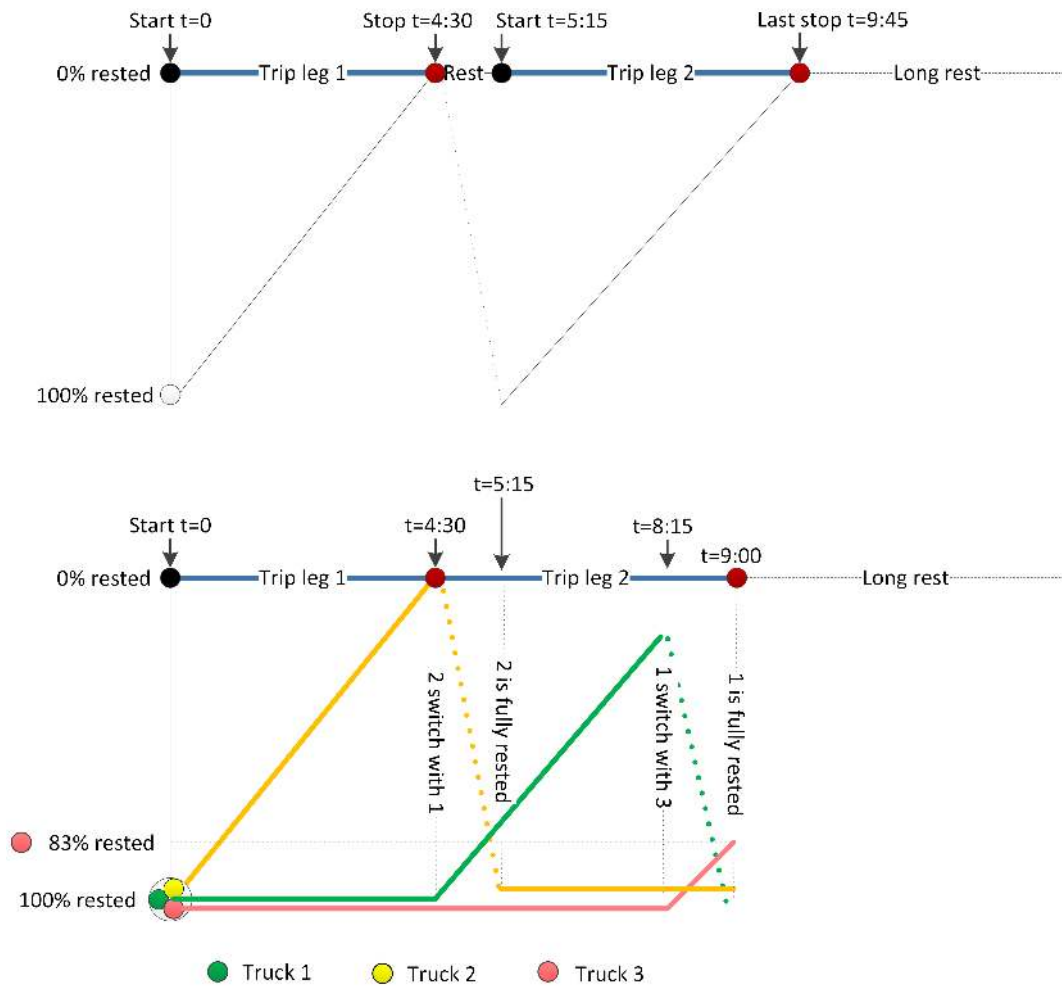● Truck 1   ● Truck 2   ● Truck 3

Figure 2: Illustration of rest hour profiles. Top: Single truck, Bottom: Platoon of three trucks

It is assumed that the choice of platoon leaders is optimal in the sense that the resulting resting time is minimised. The saved resting time has been calculated by comparing with the case where chauffeurs are not in platoons. It would be possible to integrate the consideration of rest hour restrictions in the joint optimisation problem. Hence, when composing platoons and optimising their dispatching scheme, the rest hour profile of each driver could also be considered. This would be relevant as a means to relax the assumption of fully rested drivers arriving at the hub. Unfortunately, it would require prediction of the exact travel time in advance. However, as illustrated in Figure 2, under an assumption of arriving drivers being fully rested and a maximum driving time of 9 hours before a long rest, there is little need to optimise resting hours. This is because the platoon will always be able to operate within the boundaries of the 9 hour period without stops, and it is only the driver of one of the last two remaining trucks in a platoon that cannot by fully rested when the platoon is dissolved. This driver would however still have a minimum of 3:45 driving time before needing the next rest. From the example, it should be clear that any effect of further rest-hour optimisation under the current EU regulation and under the premise of highly uncertain driving times (on which the number of rests depend) will provide minimal added value. For that reason, the effect of rest-hour stops can be investigated after the optimal platoons have been formed.

3.7. Cost and profit assumptions

In general, we consider two types of cost/profit components: i) the cost of a truck being idle (which includes wage and depreciation) and ii) the profit of driving in a platoon, defined by the cost of fuel saved and time saved by potentially avoiding short rests.

Fuel consumption varies by truck fill rate and the distance. For long-haul transports, Delgado et al. (2017) estimates a consumption of 33.1 L/100km for a truck loaded with 19.3 tonnes, and 36.2 L/100 km for a fully loaded truck. In Sharpe & Muncrief (2015) it is estimated that the fuel consumption is in the range of 30.9-38.1 L/100 km. Based on these estimates, the paper will assume a fuel consumption of 35 L/100 km and a fuel price of 1.2 €/L will be used. This amounts to a monetary fuel cost of 42 €/100 km or 0.42 €/km. Fuel savings by platooning have been investigated in numerous projects. Values vary from 5% of the total fuel consumption, to 8% for the front truck and 16% for following trucks. In this study, the savings from platooning are assumed to be 10% for all following trucks and zero for the leading truck.

We assume the hourly cost of waiting time to be 35 €/hour, which corresponds to the salary of the most expensive drivers, or the salary of less expensive drivers plus depreciation of the truck, lost revenue etc. Note that the assumptions regarding fuel consumption and fuel savings are potentially contestable and may vary depending on the specific driver, the urgency of the transport, aerodynamics of the truck etc. We tested various parameter values within a reasonable range, and found that the overall conclusions of the paper are not sensitive to these assumptions.

4. Solution methodology

In the following, two different models and their corresponding solution method are proposed. The first model describes the schedule-based problem where trucks arrive at random

and are dispatched at fixed times. The second model describes the dynamic version of the problem where trucks are dispatched dynamically and where the planner can look ahead in time. The general notation is introduced in Table 1.

Parameter	Description
$h \in H$	A time interval h in the set of time intervals H
N	Set of trucks arriving during the entire time horizon
N_h	Set of trucks arriving during the h'th time interval
M	Maximum number of trucks in each platoon
P	The set of platoons
$w \in \mathbb{R}$	The size of the time window, i.e. the length of the time intervals
$\tau_{max} \in \mathbb{R}$	End of the time horizon
$T = \lceil \frac{\tau_{max}}{w} \rceil$	Number of time intervals optimised
$t_n \in \mathbb{R}$	The arrival time of truck $n \in N$ sampled from the uniform dist. $[0, \tau_{max}]$
$s_{n,m} \in \mathbb{R}$	The number of kilometres the paths of the two trucks $n, m \in N$ overlap
$\alpha \in [0; 1]$	The proportion of fuel saved driving behind another truck
$c_d \in \mathbb{R}$	The cost of fuel expended driving one kilometre
$c_t \in \mathbb{R}$	The cost of a truck waiting one hour

Variable	Description
$x_{n,p} \in \mathbb{B}$	1 if and only if truck $n \in N$ is assigned to platoon $p \in P$
$y_{n,m,p} \in \mathbb{B}$	1 if and only if truck $m \in N$ follows truck $n \in N$ in platoon $p \in P$
$d_p \in \mathbb{R}$	The departure time of platoon $p \in P$
$b_{n,p} \in \mathbb{R}$	The waiting time of truck n in platoon $p \in P$

Table 1: Mathematical notation

4.1. Scheduled dispatch (Arriving trucks unknown until arrival)

The simplest strategy is the schedule-based dispatching where trucks arrive unannounced at a predetermined location and are dispatched at predefined time intervals.

This gives rise to a subproblem, with objective Z_h, for each time horizon $h \in 0, \ldots, T$, where the set of trucks $N_h \subseteq N | h \cdot w < t_n < (h + 1) \cdot w \Leftrightarrow n \in N_h$ must be assigned to platoons.

In general there are $P = 0, \ldots, \lceil \frac{|N_h|}{M} \rceil$ platoons to be formed in this interval, and we indicate by $x_{n,p}$ if truck n is assigned to platoon p. This leads to a mixed integer linear problem as presented in equations (2)-(8) below.

9

$$Z_h = \textbf{maximise}$$

$$\sum_{p \in P} \sum_{n \in N_h} \sum_{m \in N_h | m > n} s_{n,m} \cdot y_{n,m,p} \tag{2}$$

subject to

$$1 = \sum_{p \in P} x_{n,p} \quad \forall n \in N_h \tag{3}$$

$$y_{n,m,p} \leq \frac{1}{2} \cdot (x_{n,p} + x_{m,p}) \quad \forall n, m \in N_h | m > n, p \in P \tag{4}$$

$$1 \geq \sum_{m \in N_h | m > n} y_{n,m,p} \quad \forall n \in N_h, p \in P \tag{5}$$

$$M \geq \sum_{n \in N_h} x_{n,p} \quad \forall p \in P \tag{6}$$

$$x_{n,p} \in \{0, 1\} \quad \forall n \in N_h, p \in P \tag{7}$$

$$y_{n,m,p} \in \{0, 1\} \quad \forall n, m \in N_h | m > n, p \in P \tag{8}$$

The objective function (2) enumerates the number of kilometres a given truck m performs as a platoon follower. Equation (3) ensures a truck is allocated to exactly one platoon. Equation (4) introduces an indicator variable $y_{n,m,p}$ to indicate if trucks n and m are in the same platoon. Combined with the domain definition in Equation (8) this allows us to specify if truck n precedes m in a platoon. Equation (6) restricts the size of platoons to be less or equal to M. Finally, Equations (7) and (8) restrict the domain of the decision variables.

The formulation relies on the fact that the number of kilometres a truck is driving behind another truck in a platoon is independent of the ordering of the trucks in the platoon. Thus, it is not necessary to assign the driven kilometres to a specific truck, and Equation (8) ensures that any kilometres shared in a platoon are only counted once for each pair of trucks.

The accumulated objective function can be computed as a sum over the time intervals, i.e.

$$Z = \sum_{h \in 0, \dots, T} Z_h \tag{9}$$

The problem is solved in a discrete event simulator, where the set of arriving trucks N_h is enumerated and solved using a greedy insertion heuristic. This assigns the truck to the first platoon within the time interval such that the number of kilometres shared with the rest of the trucks in the platoon is maximised. As a final stage, a local search heuristic is introduced. This heuristic enables swapping of trucks between platoons if better solutions exist. This continues until no further improvements can be made and the obtained solution is locally optimal under the swap operator.

It is possible to extend the objective function to account for waiting time as shown in Equation (10).

$$\sum_{p \in P} \sum_{n \in N_h} \sum_{m \in N_h | m > n} \alpha \cdot c_d \cdot s_{n,m} \cdot y_{n,m,p} - \sum_{p \in P} \sum_{n \in N_h} c_t \cdot (d_p - t_n) \cdot x_{n,p} \qquad (10)$$

The waiting time of trucks is a simple function of the size of time intervals. In Equation (10) the d_p is the dispatch time of the platoon, which will always be the smallest multiple of w yielding a non negative $(d_p - t_n)$ due to the dispatching strategy.

When evaluating the dispatching scheme resulting from Equation (10) it was found that a substantial amount of unnecessary waiting time was related to the fixed dispatching. Due to this, an extension of the problem is considered in Equation (11). The idea is to launch platoons as soon as they are formed to save unnecessary waiting time. This strategy assumes no knowledge of the exact arrival times of the trucks, but assumes that the set of arriving trucks during the time interval is known. This will be sub-optimal when compared with a fully dynamic optimisation with known future arrival times as considered in the dynamic dispatching strategy described in Section 4.2.

$$\sum_{p \in P} \sum_{n \in N_h} \sum_{m \in N_h | m > n} \alpha \cdot c_d \cdot s_{n,m} \cdot y_{n,m,p} - \sum_{p \in P} \sum_{n \in N_h} c_t \cdot (d_p - t_n) \cdot x_{n,p} \qquad (11)$$

In (11) d_p is the dispatching time of the platoon such that $d_p \geq t_n x_{n,p}$. Although the evaluation allows platoons to depart as soon as they are formed, results indicated that this extension was insufficient to alleviate the importance of smaller time windows. This led to the conclusion that knowledge of future truck arrivals are important for the solution, and that a fully dynamic dispatching strategy is relevant. This substantially complicates the model as the entire problem needs to be solved jointly and with foresight, using e.g. the dynamic dispatch outlined below.

4.2. Dynamic dispatch (Arriving trucks known in advance)

The mixed integer program for the dynamic dispatching problem is formulated in (12)-(20) below. As discussed, solving the entire problem requires that we relax the assumption of fixed time intervals. Thereby, the waiting time becomes an integral part of the problem.

$$Z = \textbf{maximise}$$

$$\sum_{p \in P} \sum_{n \in N} \sum_{m \in N | m > n} \alpha \cdot c_d \cdot s_{n,m} \cdot y_{n,m,p} - \sum_{p \in P} \sum_{n \in N} c_t \cdot b_{n,p} \tag{12}$$

subject to

$$1 = \sum_{p \in P} x_{n,p} \quad \forall n \in N_h \tag{13}$$

$$y_{n,m,p} \leq \frac{1}{2} \cdot (x_{n,p} + x_{m,p}) \quad \forall n, m \in N | m > n, p \in P \tag{14}$$

$$M \geq \sum_{n \in N_h} x_{n,p} \quad \forall p \in P \tag{15}$$

$$1 \geq \sum_{m \in N_h | m > n} y_{n,m,p} \quad \forall n \in N, p \in P \tag{16}$$

$$d_p \geq t_n \cdot x_{n,p} \quad \forall n \in N, p \in P \tag{17}$$

$$b_{n,p} \geq d_p - t_n - 100 \cdot (1 - x_{n,p}) \quad \forall n \in N, p \in P \tag{18}$$

$$x_{n,p} \in \{0, 1\} \quad \forall n \in N, p \in P \tag{19}$$

$$y_{n,m,p} \in \{0, 1\} \quad \forall n, m \in N | m > n, p \in P \tag{20}$$

Equation (12) differs from the objective function in Equation (11) by first converting the shared kilometres into monetary units (EUR), and secondly by subtracting the waiting costs directly. Equations (13), (14), (15), (16), (19) and (20) are defined as in the previous model, whereas (17) ensures that the platoon cannot depart earlier than the arrival of any truck in the platoon. Finally, Equation (18) defines that the waiting time of each truck, as a minimum, is equal to the waiting time required to join the platoon. By construction, for the last truck, the waiting time $b_{n,p}$ will always equal the lower bound 0.

In practice, the dynamic dispatch model is intractable for all but the smallest instances. Thus, to solve the dynamic dispatch problem we use a 'destroy-repair' heuristic as presented in Algorithm 1 below. The heuristic is build on a labelling algorithm (see Algorithm 2 in Appendix A), which calculates optimal assignments of trucks to 1 to 3 platoons.

The initial solution is constructed by sorting trucks in order of arrival and by adding them to the latest platoon until it is full. Hereafter, a new platoon is created and the process continues. This generates a solution with minimal waiting time, if all platoons are required to be full. In turn, each platoon is investigated by enumerating all possible ways of selecting partnering platoons, such that the total number of trucks does not exceed what fits into three platoons (i.e., 3M trucks where M is the maximum size of a platoon). These sets of platoons are dissolved, and the optimal allocation into 1-3 new platoons is investigated using the labelling algorithm as described in Appendix A.

The overall heuristic is described in Algorithm 1, and by keeping track of when platoons are changed and investigated, most evaluations of the labelling algorithm (solveByLabelling) can be elided. This is because improvements to a set of platoons R is only possible if a

Data: A set of platoons P

Result: An optimised set of platoons

1 improved $\leftarrow true$;

2 while improved **do**

3   improved $\leftarrow false$;

4   **for** $p \in P$ **do**

        /* Iterate through subsets of platoons containing p but not exceeding $3M$ trucks.   */

5   **for** $R \subseteq P | p \in R \wedge nTrucks(R) < 3M$ **do**

6 $R' \leftarrow solveByLabelling(R, profit(R))$;

7   **if** $profit(R') > profit(R)$ **then**

8 $P \leftarrow R' \cup (P \setminus R)$;

9   improved $\leftarrow true$;

Algorithm 1: The destroy-repair heuristic for the dynamic dispatch case. Profit is calculated using Equation 12 evaluated on the given subset of platoons.

platoon $p' \in R$ has been updated at an iteration after p (and thus R) was last investigated.

In order to test how well the presented algorithm performs compared to solving the corresponding mathematical integer program, a CPlex implementation was carried out. This allows computing the 'optimality gap' for a set of dynamic dispatch problems over a period of 30 minutes and by allowing for between 10 and 24 trucks and a maximum platoon size of 4. The models were solved using IBM Cplex version 12.8, and only in a single case did the heuristic fail to find the exact optimal solution. In this case, however, the optimality gap was as low as 0.13% when measured in terms of 'cost savings'. Solving bigger problems is prohibitively expensive as the complexity of the problem increases exponentially as a function of number of trucks involved. Specifically, the calculation time for solving problems representing 25 trucks is measured in days.

5. Case study

The case study is based on data from the TransTools3 transport network model which was recently developed for the European Commission (Jong et al., 2016). The model covers the entire Europe, and in the development and calibration of the model a wide array of data sets collected from various sources was used. The model includes all modes of freight transportation (road, air, sea, inland waterways) as well as private transport modes (Rich & Mabit, 2012). The freight demand model is described in further details in Jensen et al. (2019) and Jong et al. (2017). Detailed network traffic assignment is performed for all modes. For the assignment of road transport (private cars, vans, trucks), a path-based assignment model is applied. The model considers congestion effects and is based on well-established Random Utility Theory to represent the route choice of chauffeurs in a behaviourally realistic manner (Watling et al., 2015; Rasmussen et al., 2015, 2017). The assignment model has been calibrated on the basis of European-wide origin destination matrices and traffic counts (Jong et al., 2016). The path-based approach enables in-memory storage of all routes between all

Origins and Destinations (at zone level) for all trip purposes and vehicle types. This means that, at any potential platooning location, for all trucks passing this location, their origin, destination and route can be enumerated.

The case study considers trucks in and out of a virtual platooning hub located close to the Elb Tunnel. More specifically, we consider modelled routes of south-bound trucks passing the Elb Tunnel on the German motorway A7 near Hamburg. On a daily basis, approximately 6,000 south-bound trucks pass this point that constitutes one of the busiest truck corridors in Europe. The assignment model distributes these trucks across 139,000 paths using a probabilistic route choice model. In the case study only a restricted sample is used in that only trucks with destinations further than 200 km away from the Elb Tunnel are considered. Hereby, we seek to eliminate unrealistic platooning candidates and turn the focus to long-haul truck platooning. This results in a total of 3,051 daily trucks from which individual modelled routes are sampled randomly.

Figures 3a and 3b illustrate the distribution of the destinations and the links of the sampled routes, respectively. As can be seen, destinations are widely distributed across the network and the routes are scattered across most European transport corridors. Clearly, the probability of trucks sharing similar links is highest close to the Elb Tunnel. The sample of trucks passing the Elb Tunnel in south-bound direction represents a total mileage of 2,777,599 truck kilometres from the hub to the final destinations and with distances that vary between 214 km and 2,755 km (see the distance distribution in Figure 3c).

The overlap is measured as the number of shared kilometres, and is calculated for each route pair and used as input to the platooning model. The shared kilometres is calculated from the Elb Tunnel to the first location where the routes diverge. Some route pairs are almost non-overlapping, e.g. they split at the first possible diverge south of the Elb Tunnel, while others are highly overlapping. The 3,051 routes correspond to the daily traffic. In order to represent a denser flow in the busiest hours, $N = 1500$ trucks are sampled randomly, and are assumed to arrive during the 8 busiest hours of the day ($\tau_{max} = 8$). This is to avoid the impact of nighttime where the potential for platooning is likely to be lower. The trucks are assumed to arrive randomly within the time interval $[0, \tau_{max} = 8]$.

6. Results

The analysis is structured around the two dispatching strategies discussed in Section 4. First, we consider variations of schedule-based dispatching where trucks are launched at predefined intervals. Hereafter we continue to consider dynamic dispatching strategies and further investigate the potential of allowing short rest periods of 45 minutes, while driving behind other trucks in a platoon.
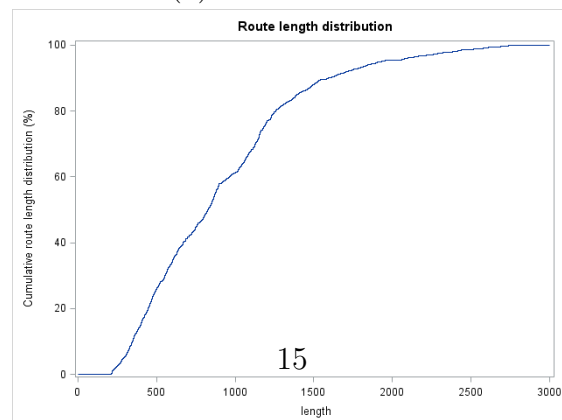
6.1. Scheduled dispatch

First, we consider the profitability in the case where the cost of waiting time is assumed to be zero in a scheduled dispatch environment as illustrated in Figure 4a. This provides an upper bound for the profitability of platooning when using a scheduled dispatch.
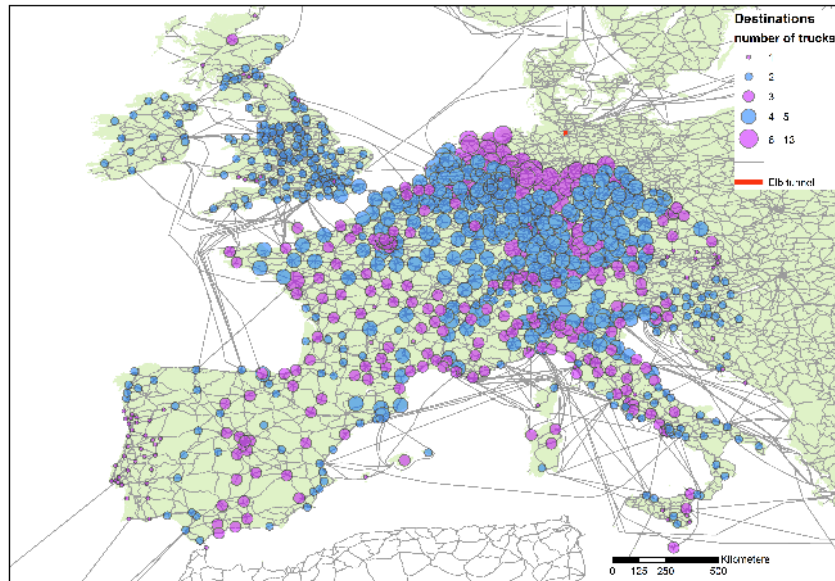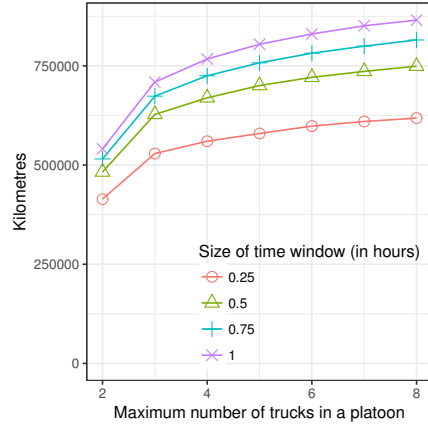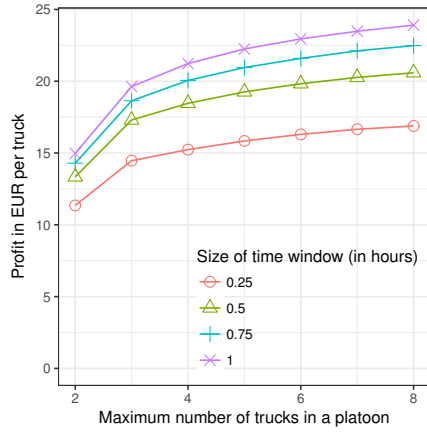
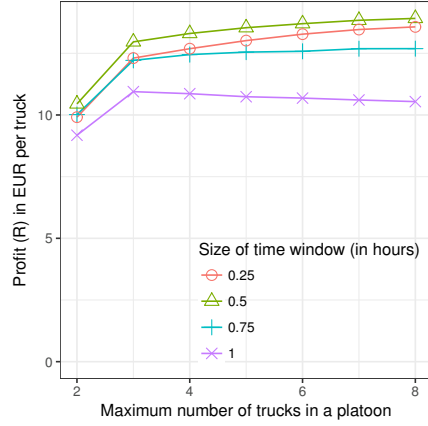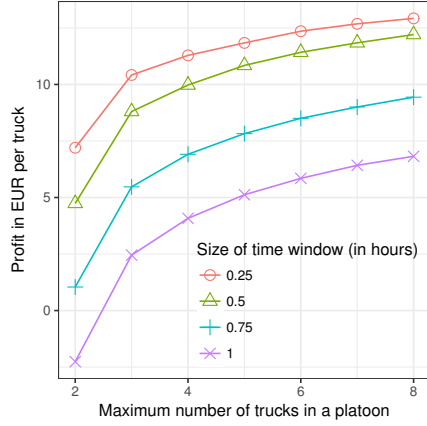(a) Destination distribution
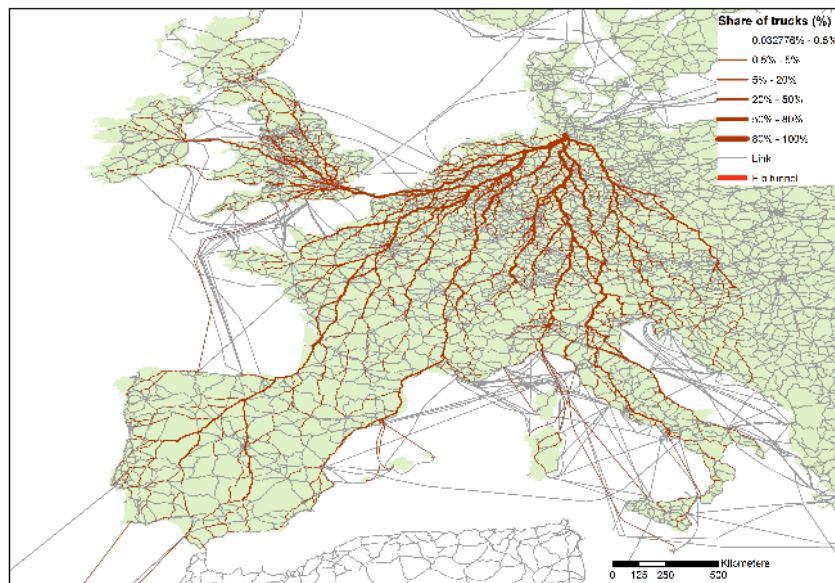
(b) Link flow share
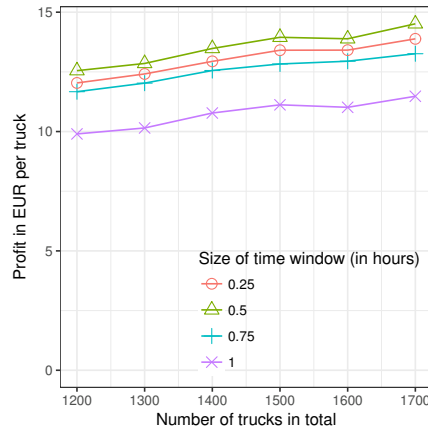

(c) Trip length distribution
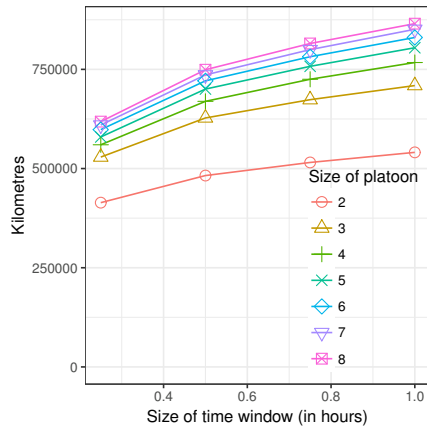
Figure 3: The data visualised.

15

(a) Profit per truck with no cost of waiting.

(b) The number of kilometres driven behind a truck.

(c) Profit after waiting time is paid for.

(d) Profit if platoons are dispatched when formed.

(e) The number of kilometres driven behind a truck.

(f) Sensitivity to the number of trucks.

Figure 4: Results for platooning using static dispatch

16

Figure 4b illustrates the same solution but is evaluated with respect to the mileage driven as 'followers' in platoons. It can be noted that for both measures, the increase in return diminishes as the platoon size increases. The same is true for the size of the time window, although the marginally diminishing return is less pronounced. In contrast, if waiting time is assumed to be costly (using Equation (10)), the solution degrades from the upper bound. This is illustrated in Figure 4c.

As discussed in Section 4 and formulated in Equation (11), some of the waiting time costs can be offset by facilitating dispatching as soon as the platoon is ready. This is illustrated in Figures 4c and 4d. Figure 4c shows that there is an inverse relationship between the size of the time window and the profitability. This indicates that the increased shared mileage in Figure 4b does not compensate for the increased waiting time. A way of addressing the issue is to introduce 'limited foresight' in the dispatching in that dispatching is allowed as soon as platoons are complete. However, this fails to compensate for the increased waiting time as shown in Figure 4d.

As a final test, the effect of flow is investigated. As can be seen in Figure 4f there is an approximately linear and positive relationship between profitability and the flow if the flow is above a certain level. This seems reasonable and indicates that results can be extrapolated to estimate impacts and profitability for different flow volumes.

6.2. Dynamic dispatch

It should be recalled that any solution to the dynamic dispatch version of the problem is locally optimal in the sense that no better solution can be obtained by 'destroying' and subsequently reforming platoons. As opposed to the schedule-based dispatch where platoons were always at their maximum size, this is therefore not the case for a dynamic dispatching strategy. This is particularly true when the maximum size of platoons is large. In that case, it is often beneficial to form smaller platoons in the dynamic dispatch environment. In general, this decreases the number of kilometres driven behind other trucks as evidenced by Figure 5a when compared with Figure 4e. The savings from reduced wait times will, however, make up for this and the profit per truck will increase as shown in Figure 5b.

If further allowing truck drivers to have short rests while driving as followers, the resulting profit per truck increases to around 29 EUR when allowing platoons of up to 4 vehicles (Figure 5c). This is directly proportional to the corresponding amount of saved resting hours as shown in Figure 5d.

The actual size of the platoons is slightly smaller than the maximum platoon size as seen in Figure 5e. This becomes increasingly pronounced as the allowed maximum number of trucks per platoon increases.

The sensitivity with respect to the flow of trucks during the time span of 8 hours is illustrated in Figure 5f. While an almost linear relationship between profit and the number of trucks can be observed for flows above 1,000 trucks, it degenerates more rapidly as the flow decreases below 1,000 trucks per 8 hours. Further analysis shows that when the flow is sufficiently large, removing trucks will decrease the number of platoons dispatched to each geographic area, but not substantially decrease the average number of shared kilometres per truck. Additionally, if trucks with trip length below 1,000 km are removed, the platoons
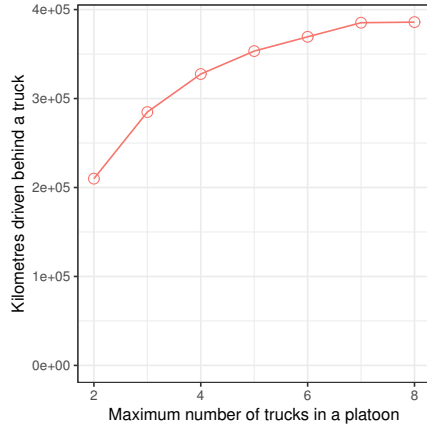
(a) Kilometres driven behind another truck
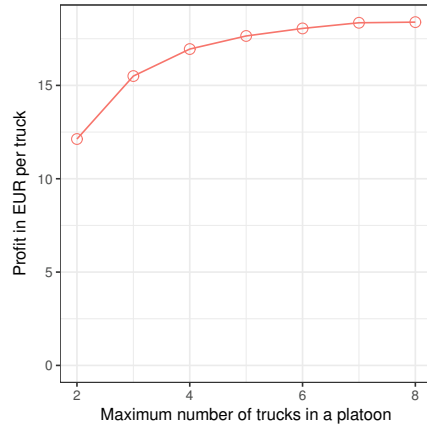
(b) Profit per truck
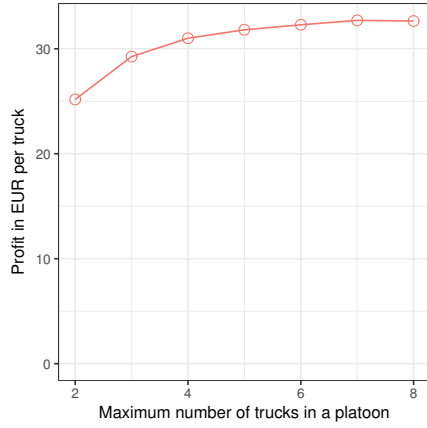
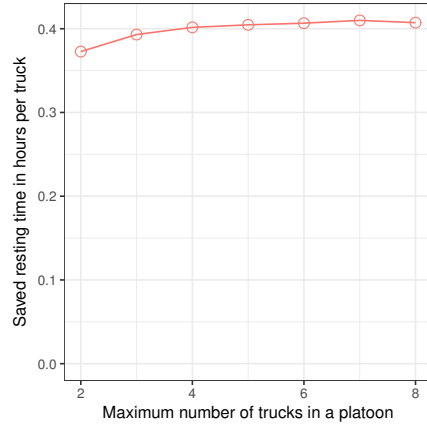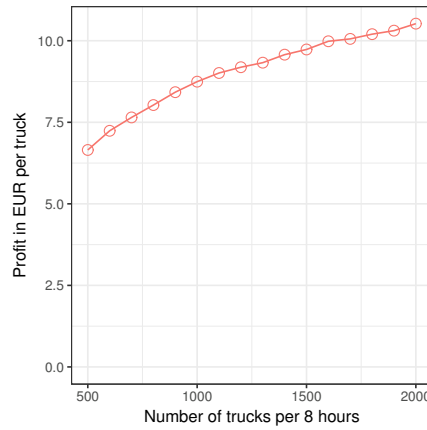(c) Profit when short rests are omitted during platooning

(d) Resting time saved when crediting short rests

(e) The realised average platoon size

(f) Profits vs the total number of trucks. (Platoon size 4)

Figure 5: Results when dispatching dynamically.

are dispatched when only partially filled, or when filled with trucks that have substantial differences in the destination pattern.

Figure 6a and 6b shows that trucks in the dynamic dispatching environment have only short waiting times and carry out most of their trips in platoons. It is also notable that, even platoons that are active only on short distances, can be profitable. This is due to the shorter waiting times when joining platoons.

(a) Waiting time of trucks

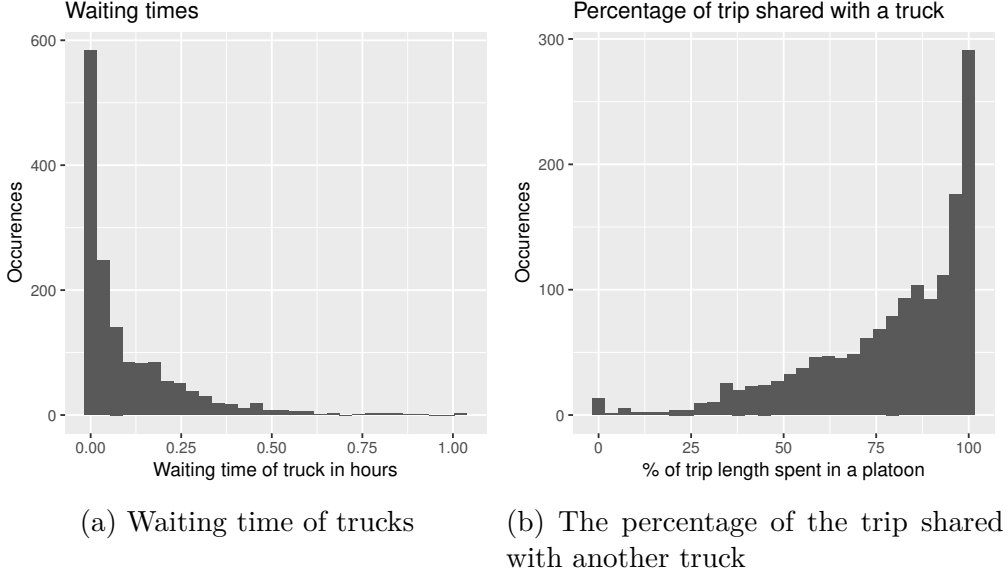(b) The percentage of the trip shared with another truck

Figure 6: Observed waiting times and trip overlap for a maximum platoon size of 4.

We analysed the platoon composition in a final solution where the dynamic dispatch solver were run with a maximum platoon size (M) of 4. The results are shown in Table 2. The column 'obs' indicates the number of trucks within a given distance segment from the hub. The following three columns detail the percentage of the total distance a truck on average will travel while being in platoons of a certain size. Finally, we present a breakdown of the profitability at the truck level by assigning fuel savings equally among the trucks and ignoring any saved resting hours.

Distance	obs	≥ 2	≥ 3	$= 4$	saved	wait	profit	% profit
200–500 km	392	75.9 %	58.7 %	38.6 %	8.1 €	0.05 h	6.41 €	4 %
500–1000 km	524	80.7 %	64.1 %	43.4 %	16.6 €	0.09 h	13.61 €	4.45 %
1000–1500 km	403	79.1 %	61.1 %	43.1 %	26.8 €	0.13 h	22.19 €	4.41 %
1500–2000 km	113	79.7 %	62.4 %	41.3 %	38.3 €	0.17 h	32.39 €	4.53 %
2000+ km	68	80.5 %	60.3 %	45.2 %	52.3 €	0.21 h	44.87 €	4.63 %

Table 2: Breakdown of a solution with $M = 4$, each row representing a grouping of trucks by distance to destination. The columns are: 1) the distance grouping, 2) the number of trucks in the grouping, 3,4,5) the percentage of trips shared with the given number of other trucks, 6) the cost of the saved fuel, 7) the average waiting time, 8) the resulting profit per truck, and 9) the profit as a percentage of the total fuel cost.

We observe from Table 2 that the average waiting time of the trucks increases with the distance travelled. Also, the saved fuel costs more than makes up for the waiting time and thereby results in higher profits as the travel distance increases.

The increased waiting times cause the shared mileage percentages to go up with the travel distance. Recall that if two platoon members driving 500 and 2000 km, respectively, share 400 km, the first truck will platoon for at least 80% of its trip and the second for at least 20%. The increased waiting time is enough to counteract this effect.

7. Conclusions

In the paper we analyse the planning stage of truck platooning by considering profitability and fuel efficiency impact of different planning strategies. The analysis is carried out by considering a collaborative platooning system where the pairing of trucks is orchestrated by a platooning service provider. The forming of platoons is assumed to take place at strategically placed platooning hubs alongside the motorway network.

We introduce a heuristic for the hub based platooning problem, guaranteeing local optimality in that no improvement is possible by modifying less than 4 platoons. Additionally, it is demonstrated that the heuristics can find optimal and near optimal solutions on the small instances solvable by MIP models, and that it is capable of scaling to problems multiple orders of magnitude larger.

By using truck routes (modelled by a European-wide transport network model) that pass through a truck corridor, we are able to identify route overlaps and thereby quantify the collaborative benefits of platooning for long-haul trucks. The investigation of how different planning strategies are likely to affect profit is based on different variations of a dynamic programming framework. A first version considers a simple schedule-based dispatching strategy, whereas later and more advanced versions include dynamic dispatching and possibly the relaxation of short rest hour stops. The methodological framework allows the simulation of a range of different policies across a range of input variables.

The paper provides specific findings as well as a more general conclusion as regard the potential of platooning. At the general level, it is strongly suggested that, even under relative optimistic conditions, the prospects of platooning in the case where chauffeurs cannot rest while driving are relative limited from a profitability and impact perspective. In the case where chauffeurs can rest while driving as followers in platoons, however, the potential profitability increases considerably and suggests that viable business models may exist. Therefore, it is unlikely that truck platooning will disrupt the trucking industry on a large scale in a short to medium time perspective if solely based on an orchestrated platooning hub design and no relaxation of rest hour restrictions are enforced. At the more specific level, the results indicate that idle time is a critical factor when designing a platooning system. Hence, although fuel savings can be attained, the cost of waiting time is more important from an system perspective.

After deducting costs of waiting times, the expected profit is estimated to be in the range of 4-5% of the total fuel cost. For truck trips between 1,500–2,000 km this amounts to approximately 38 EUR per trip. In a very competitive business environment with low profit

margins, this may sound alluring. However, it should be noted that this profit estimate is expected to resemble an upper bound. Firstly, it relies on the assumption that truck arrivals to the hub can be predicted. Secondly, all trucks are assumed capable and electable for platooning. Thirdly, for trucks to engage in platooning activities, investments are required. These costs, which include costs of equipment as well as cost of receiving and transmitting data, should be subtracted from the estimated profit.

The research carried out in this paper can be extended in different ways. Firstly, it will be interesting to consider the joint effect of different platooning systems and in particular on-the-fly platooning combined with orchestrated platooning. It is clear that the joined effect will exceed effects derived from separate systems; however, it is also clear that the two systems will compete. Secondly, the model assumes that routes are fixed and non-negotiable. It could be interesting to investigate the effects on profitability and fuel savings of allowing route choices to be modified. Thirdly, it is relevant to consider a system of hubs compared to a single hub as in this paper. A likely impact is that the average flows will be reduced. This is because a share of the trucks that pass a given hub will be driving in platoons. On the other hand, more hubs will mean more platooning opportunities and the combined effect of more platooning hubs should be positive. Finally, it may be relevant to investigate the validity of some of the simplifications in more detail. For example, the true share of trucks that are able to platoon when accounting for technological barriers, braking constraints and possible legislation issues.

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Appendix A. The labelling algorithm (solveByLabelling)

The labelling algorithm (2) finds optimal solutions to the problem of forming platoons. It does so under the constraint that a maximum of L platoons can be created. It should be noted that algorithm scales poorly for $L > 3$ and is mainly aimed at solving sub-problems to optimality for $L = 2$ and $L = 3$ inside a heuristic. The decision of which truck is assigned to which platoon is taken in increasing order of arrival time of the truck (t_n) and the partial solutions are represented by labels.

A label consists of the following components:

- The accumulated profit obtained so far.

- The current number of trucks in each platoon (*count*).

23

- The earliest possible departure time of each platoon (*depart*).

- A list of platoons trucks are assigned to (*assign*).

The algorithm utilises a lower bound of the profitability. This is provided as an argument and is typically based on the previous assignment of the trucks to platoons. To avoid generating a label for each possible platoon assignment, the labels are pruned based on the provided lower bound of the profitability. To achieve this, the profitability of partial solutions will need to be augmented with an upper bound of the profitability of assigning the remaining trucks to platoons. This bound is computed in line $1 - 10$, by assuming that (i) a truck can be paired with any already assigned truck regardless of platoon size limits, and (ii) only a single truck will incur waiting time if a platoons departure is delayed.

First, an initial label is created in line $11 - 14$ with no truck assigned to platoons.

Next, the set of *currentLabels* is modified in $|N|$ rounds in line $17 - 40$, one round for each truck i. During the ith round, each *label* is extended to a maximum of L new labels, by assigning the ith truck to each possible platoon in the partial solution represented by the label. The *bestMatch* array keeps track of the label resulting from assigning the truck to each of the potential platoons. Each update in line $27 - 31$ corresponds to finding a better matching truck j to the i'th truck ($j < i$) in terms of the number of shared kilometres ($s_{Trucks_i, Trucks_j}$). Only the best such match for each platoon will be used to calculate the profit of the new partial solution. The case of assigning to an empty platoon causes no such update to occur, and is handled in lines $20 - 23$. Note here that assigning to an empty platoon causes neither waiting time nor shared kilometres, and the profit thus remains unchanged.

Line 33 is a 'symmetry breaking mechanism'. We assume without loss of generality that the first truck is assigned to the first platoon. Likewise, if the second truck is not assigned to the first platoon, we assume without loss of generality that it is assigned to the second.

If the truck can be assigned to the platoon, all *bestMatch* labels are checked against the *profitBound* provided for the algorithm, to see if the label (theoretically) can lead to an improved solution. This is accomplished by first adding an upper bound for the increase in profitability by utilising the remaining trucks ($bound[i + 1]$) (refer to line 34). If the label can still result in a better set of platoons, it is assigned to the set of partial solutions (named *nextLabels*). The *currentLabels* and *nextLabels* are swapped and the next truck is processed.

In practice, the algorithm is capable of handling up to three platoons in an effective manner. It is less sensitive to the size of the platoons, and can easily handle the eight trucks as applied as an upper bound in this paper. As the provided bound is important for the algorithms efficiency, it is recommended doing an initial optimisation of all platoons using $L = 2$ platoons.

Data: A set of platoons R, a maximum number of platoons to be formed L, a maximum size of the platoons M and a achievable profit $profitBound$

Result: An optimised set of platoons R'

```
 1  trucks ← sortTrucksByIncreasingArrivalTime(R);
    /* Calculate a bound for profit obtainable using remaining trucks.          */
 2  bound ← newdouble[|trucks| + 1];
 3  bound[|trucks|] ← 0;
 4  for i = |trucks| − 1; i >= 0; i − − do
 5      bestCombo ← −∞;
 6      for j = i − 1; j >= 0; j − − do
 7          candBound ← α · c_d · s_{trucks_j,trucks_i} − c_t · (t_{trucks_i} − t_{trucks_j})/M;
 8          if candBound > bestCombo then
 9              bestCombo ← candBound;
10      bound[i] ← bound[i + 1] + bestCombo;
11  initLabel.profit ← 0;
12  for i = 0; i < M; i + + do
13      initLabel.count[i] ← 0;
14      initLabel.depart[i] ← 0;
    /* Generate labels and extend.                                              */
15  nextLabels ← ∅;
16  currentLabels ← ∅ ∪ initLabel;
17  for i = 0; i < |trucks|; i + + do
18      for label ∈ currentLabels do
19          for p = 0; p < L; p + + do
20              if label.count[j] ≠ 0 then
21                  bestMatch[j].profit = −∞;
22              else
23                  bestMatch[j] = label;
24          for j = 0; j < i; j + + do
25              if label.count[j] ≥ M then
26                  continue;
27              platoon ← label.assign[j];
28              score ← α · c_d · s_{trucks_i,trucks_j} − c_t · label.count[platoon] · |label.depart[platoon] − t_{trucks_i}|;
29              if label.profit + score ≥ bestMatch[platoon].profit then
30                  bestMatch[platoon] ← label;
31                  bestMatch[platoon].profit ← bestMatch[platoon].profit + score;
32          for p = 0; p < L; p + + do
33              if i < p then continue;
34              if label.profit + bound[i + 1] > profitBound then
35                  bestMatch[p].count[p] + +;
36                  bestMatch[p].assign[i] ← p;
37                  bestMatch[p].depart[p] ← t_{trucks_i};
38                  nextLabels ← nextLabels ∪ bestMatch[p];
39      currentLabels ← nextLabels;
40      nextLabels ← ∅;
    /* The best scored label in currentLabels now contains instructions (assign[i]
       indicates the platoon of truck trucks_i) for forming the optimal platoon.  */
```

Algorithm 2: A labelling algorithm for reforming platoons.