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SIMULATION OF REAL-TIME AND OPPORTUNISTIC TRUCK PLATOONING AT THE PORT OF ROTTERDAM

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ABSTRACT

Truck platooning is the concept of multiple trucks driving at aerodynamically efficient inter-vehicle distances in a cooperative and semi-autonomous fashion. Advanced sensor technology and wireless communication is used to maintain short and safe following distances between the trucks. This paper proposes an agent-based simulation model to evaluate a matchmaking system for trucks to find a suitable partner to platoon with. We consider two types of platoon matching: real-time (at a truck stop) and opportunistic (while driving on the highway). We evaluate the proposed system using a case study at the Port of Rotterdam and the surrounding area, where we study various factors influencing platoon formation and profitability. Results show that the most influential factors in both platoon formation and the total platoon profitability are wage savings and the possibility of different truck brands to platoon together.

1 INTRODUCTION

Truck platooning is a recent innovation within the logistics sector for (semi)autonomous driving. A platoon consists of two or more digitally connected trucks that drive with short following distances on highways, as illustrated in Figure 1. By using advanced board computers and sensors (e.g., lidars), the trucks communicate with each other to create a safe and efficient autonomous driving solution in a mixed traffic situation. Truck platooning is in fact an advanced version of adaptive cruise control technology in consumer cars, which can autonomously adjust speeds and maintain distance to other cars. We denote this advanced version as Cooperative Adaptive Cruise Control (CACC). The short following distances enabled by CACC decrease the aerodynamic drag of the following trucks and result in fuel and emission savings (Robinson et al. 2010; Alam et al. 2015). Moreover, it increases road utilization (Li and Ioannou 2004) and traffic safety in general (Taleb et al. 2010).

This paper focuses on a specific aspect of platooning: the matchmaking process. In order for trucks to form a platoon, agreements have to be made with other trucks on when and where to drive, at which speed, and in which order. Furthermore, the origin, destination and route of the truck are important criteria for finding a feasible match. Also, an important part of the matchmaking process is how to divide the costs and savings of a platoon. To exemplify, suppose Truck 1 and Truck 2 have decided to platoon with Truck 1 as leading truck. Truck 2 gains from the fuel savings by its position in the platoon. For Truck 1 there are considerably less fuel savings. Therefore, some sort of mechanism needs to be designed to fairly allocate the costs and savings among the members of the platoon. Into this allocation mechanism any waiting or delay time of one of the trucks – due to platoon forming – should be incorporated. The matchmaking process thus consists of (i) finding a truck to platoon with and (ii) allocating costs and savings among the members of the platoon. In this paper, we use an agent-based approach to model the platoon matchmaking process and use simulation to study the factors influencing the matchmaking process. We focus on a case study at the Port of Rotterdam and its surrounding highways.

The remainder of the paper is structured as follows. Section 2 reviews the literature and states our contribution. We describe the problem setting and case study in Section 3. In Section 4, we present our agent-based simulation model and Section 5 discusses our results. We close with conclusions and directions for further research in Section 6.

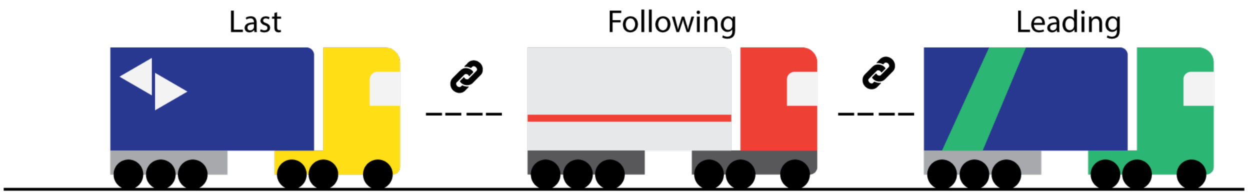

Figure 1: Illustration of a three-truck platoon.

2 RELATED WORK

To classify our work, we first distinguish between different types of platoon matching. A classic approach within Operations Research is to distinguish between offline and online algorithms. The former generates static solutions upfront, based on the data available at that moment in time, whilst the latter is a dynamic approach where solutions may change over time when new information becomes available. Also in platooning, this distinction can be made and similarly to Bhoopalam et al. (2018), we define the following types of platoon matching: scheduled, real-time and opportunistic.

Scheduled platooning is the offline (or static) variant of matchmaking where all matches are generated before the trucks depart. This implies that a matchmaking system needs to have information on the current location, destination and route of the trucks in order to find suitable matches. When this information is only available for a subset of the available trucks (e.g., due to limited information sharing), the potential performance of the matchmaking system decreases. However, in some cases this centralized approach might be relevant. For example, on frequently used routes with similar departure times (e.g., resupplying supermarkets) or for logistics service providers that manage their own fleet. As all information of the own fleet is available, potential matches can be found more easily, especially when there are many recurring trips (e.g., departures in the morning and arrivals in the evening). For smaller countries, such as the Netherlands, this is relevant as national deliveries are done within the timespan of one day, where the trucks depart from the depot in the morning and return to the same depot in the evening.

Real-time platooning is an online variant of matching, where the matches are made close before departure based on the latest information available. In practice, this could occur during breaks at truck stops or when refueling. During these periods, there are small windows of opportunity for a truck to find a match based on other trucks in close proximity and their characteristics (e.g., overlap in routes). This type of matching is thus more dynamic in nature and focuses on local decision making. As truck drivers have strict regulations on driving and resting times, this type of matching might be relevant in situations where many truck drivers take their obligatory rest periods. Real-time platooning does not require to have all information in advance. Information is only required on the opportunities that occur in real-time. This makes this type of matching especially useful for trucks of different logistics service providers as gains can be shared without tedious coordination beforehand, which is the case with scheduled platooning.

Opportunistic platooning is a second online variant where matches are made while driving. That is, trucks continuously seek for potential platoon partners while driving on the highway. The scope of this type of matching is typically limited, as looking for matches far away leads to practical objections (e.g., speed changes may be required to get the trucks together). The matchmaking process thus focuses on the area close to the truck (e.g., at most a few kilometers up). Whilst this scope may be limited, matches are made more easily as there is hardly any waiting time to form a platoon, since trucks are already driving and close to each other. The costs of forming a platoon are thus negligible, hence, the earnings of the platoon quickly become non-negative. This type of matching is relevant in areas with high truck intensity and with enough opportunities to physically form the platoon. This can for example take place at highway entries and exits, or gas stations where one truck waits for the other truck to catch up. From a practical point-of-view, these places are perfect to form a platoon as catching up while driving might cause disruptions in the traffic flow.

For each of the three types of platoon matching, literature is rather scarce. This is mainly due to the novelty of the CACC-technology. Most papers related to truck platooning are devoted to technology and safety aspects. Papers that deploy simulation in platooning, specifically focus on coordination mechanisms (van de Hoef et al. 2015), highway merging (Liang and Jonas 2016; van de Hoef et al. 2017), speed consensus seeking (Saeednia and Menendez 2017), route formation (van de Hoef et al. 2018), travel times (Haas and Friedrich 2018), aerodynamics (Vohra et al. 2018), and vehicle controllers (Turri et al. 2017).

Literature on the operational side of truck platooning – such as planning, scheduling and routing – is far from abundant. This specific literature stream has recently been reviewed by Bhoopalam et al. (2018). The matching of trucks using an agent-based approach and deploying simulation to evaluate this approach, has not been adequately addressed in the literature. A more aggregated approach has been proposed by Liang et al. (2014) to study the fuel saving potential of truck platooning using simulation.

The paper closest to this research is Gerrits (2019). We extend the latter by focusing on the simulation modeling aspects of truck platoon matching and propose a mixed simulation model. We consider both matching at a truck stop (real-time) and while driving on the highways of the hinterland connections of the Port of Rotterdam (opportunistic).

3 CASE DESCRIPTION

The context in which we study truck platoon matching is at (i) the Ring of Rotterdam (RoR) and (ii) the Maasvlakte Plaza. The RoR is located in the Western part of the Netherlands and consists of the highways A20, A4, A15, and the A16. The Maasvlakte Plaza is a truck stop on the Maasvlakte 2 at the Port of Rotterdam. The Plaza is an area where truck drivers can take their obligatory rest periods. Both areas are connected via the N15/A15, which is approximately 30 kilometers long. The two areas are depicted in Figure 2.

Figure 2: Location of the case study in the Western part of the Netherlands.

We deploy an agent-based matchmaking system in the two areas described. We take the schedules of the trucks, as well as other relevant properties (e.g., truck brand, departure times and destinations) as input.

In our approach, the trucks are represented by agents whose goal it is to find a suitable platoon partner in their neighborhood. At the Plaza we use real-time platooning and on the RoR we use opportunistic platooning. As the Plaza is an area with a high intensity of trucks and where obligatory rest periods are held, it serves well for real-time platooning. Recall that in real-time platooning a match is made just before departure, without any prior scheduling. During a relatively small period (typically between 15 and 45 minutes), the agents have an opportunity to find a match. The RoR serves well for opportunistic platooning as there is a high intensity of trucks already on the road.

We assume that in both situations any arriving truck that is not yet part of a platoon tries to find another truck to platoon with. This may result in three outcomes: (i) no match, (ii) match with a single truck or (iii) match with a truck that is part of an existing platoon. We propose two agent-based matching algorithms: (i) First-Viable match (FVM) and (ii) Best-Match (BM) for both real-time and opportunistic platooning. The former accepts the first truck for which the earnings (costs minus savings) are non-negative. To illustrate, the agent first calculates the savings of platooning with the other agent based on the overlap of their routes and the platooning sequence. Second, it calculates the waiting time and assigns costs to it. As soon as the savings of platooning with a certain agent exceed the costs, FVM selects this agent to platoon with. For opportunistic platooning this implies that it platoons with the truck driving closest by. For real-time platooning it depends on the estimated departure time, which is typically the earliest release time (i.e., the arrival time plus the rest period). Due to the simple nature of this algorithm, it is particularly suitable for matching in dynamic and stochastic environments.

The BM algorithms loops over all trucks in the neighborhood and chooses the best match. In our focus, the best match is defined as the match with the highest earnings; however, other objective functions might also be suitable, such as maximizing the overlap in routes or minimizing waiting time. This approach may result in higher earnings than FVM, but it also requires to loop over all agents, which might result in scalability problems. For real-time platooning, the neighborhood is defined by all trucks that are present at the Plaza. For opportunistic platooning, the neighborhood consists of all trucks in the search area of the truck.

For both algorithms, we use an equal-share allocation rule to divide the earnings among the agents in the platoon. In real-time platooning, the platoon is only allowed to leave at the maximum of the earliest release times of all trucks in the platoon due to regulations. As a match is made before the platoon actually departs, an arriving agent might match with an agent already in a platoon (case (iii) above). In this case a platoon consists of three (or more) trucks and this is only allowed when the newly calculated savings (i.e., with an extra truck in the platoon) is economically viable for all agents in the platoon based on the equal-share allocation rule.

Our choice of a distributed planning approach for truck platooning matching results in a scalable, highly-configurable and flexible system. To visualize and test the effectiveness of agent-based matchmaking for our case study, a simulation model is developed that captures the essence of the agent-based matchmaking and the characteristics of the Plaza and the RoR.

4 SIMULATION MODELING

Based on the case study described, we propose a discrete-event agent-based simulation model. As stated by Law (2015), discrete-event simulation is suitable to model agent-based systems as in virtually all agent-based simulation models state changes occur at a countable number of points in time. The simulation model is used to evaluate the performance of the matchmaking process for both real-time and opportunistic platooning. We describe the three main components of our simulation model: (i) the network, (ii) the agents and (iii) the events, as well as the model assumptions and limitations. We illustrate the components based on the case study, but the modeling approach is also applicable to other scenarios.

4.1 Network

The simulation model consists of two parts of the network: (i) the Plaza and (ii) the RoR. The Plaza is modelled using approximately 200 parking spaces and an entry and exit road to the A15 as shown in Figure 3a. The Plaza is connected to the RoR with a highway of approximately 30 kilometers. An abstraction has been made of the RoR for modelling purposes as shown in Figure 3b. The lengths of the segments are such that they approximate the actual network as depicted in Figure 2. The entire network consists of tracks on which the trucks are able to drive. All trucks depart from the Rotterdam area and have a destination that is beyond the network (e.g., Germany or Belgium). We use the Plaza and the RoR as areas to find a match. When a platoon is formed, it starts on the Plaza or RoR and continues to its final destination beyond the network.

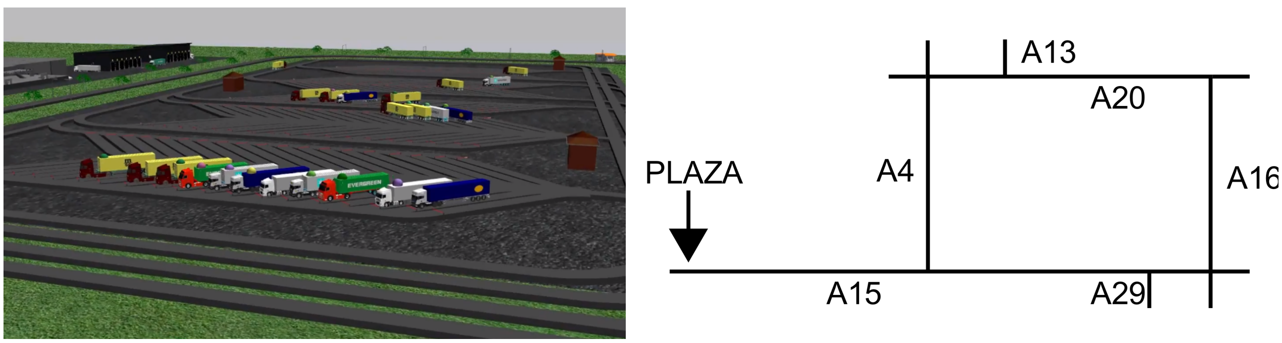

Figure 3: Modelling of the Plaza (a) and abstraction of the RoR, including location of the Plaza (b).

4.2 Agents

We deploy a single-agent type matchmaking system where every truck is represented by an agent. Every agent is capable of communicating with the other agents in the neighborhood to find a match. The agents exchange information on their route, destination and other properties (e.g., the brand). We use the Transport Management Systems (TMS) for input on these properties. The matchmaking system is denoted by a mid-level control layer. The low-level control consists of the CACC system of the truck to physically form a platoon. This architecture is shown in Figure 4. For real-time platooning, the agents have an additional set of properties and attributes, such as the length of the rest period and the earliest release time (i.e., arrival time plus rest period). The trucks are the moving entities in the model and each truck has a set of user-defined attributes and methods to resemble the intelligence of the agent. The reader interested in the characteristics of the agents is referred to Gerrits (2019).

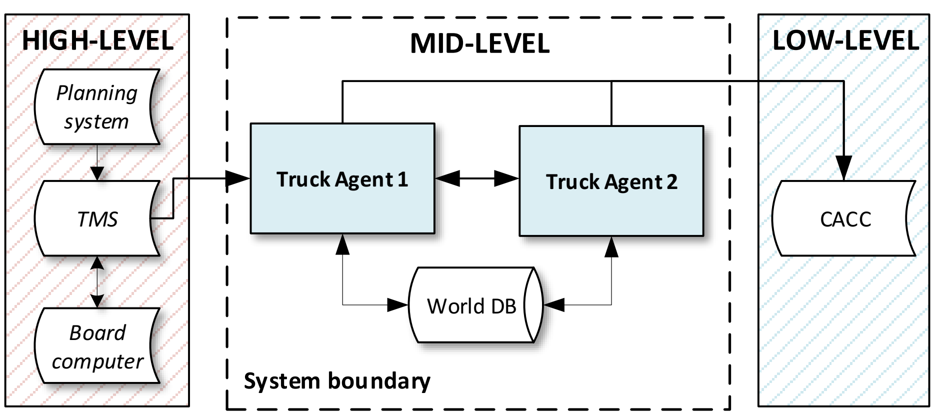

Figure 4: Data coupling diagram of the proposed agent system.

4.3 Events

We consider the following most important events: (i) the initialization of a truck, (ii) a truck entering the Plaza, (iii) a truck leaving the Plaza, (iv) a truck arriving at the RoR from the A15, and (v) a truck leaving the system.

The first event is used to generate the trucks (and agents). At the initialization, the properties (e.g., the brand) are set using various input parameters, which are discussed in Section 4.5.1. The agents are initialized at multiple points in the network, to create flows on the network shown in Figure 3b. At the A15 entrance in the East, the agents either travel to the RoR or are sent to the Plaza, based on relative frequencies and random selection. After initialization, the trucks drive to their destination.

At the second event, the truck arrives at the gate of the Plaza. At this point in time, the real-time platooning matchmaking algorithm (either FVM or BM) starts. Depending on the algorithm, the agent loops over the agents present at the Plaza and tries to find an economically viable match. When a match has been found, the agents agree on a departure time and the truck sequence and store this information as attributes. After the algorithm has finished, the trucks enter the Plaza and select a random free parking slot.

When the rest period of the truck is over, the third event is triggered. When the truck has not found a match during the rest period, it leaves the Plaza alone. When a truck did find a match, the first truck in the platoon sequence drives to the exit of the Plaza and waits there for the other trucks. When the platoon is complete, it continues to the RoR (via the A15) and ultimately to its final destination.

Whenever a truck that is not in a platoon arrives at the RoR, the opportunistic platooning starts. In the neighborhood search area, the trucks follow a similar procedure as with the second event. When a match has been found, the trucks meet at a matching location near the highway. When all trucks are present at this location, they continue as a platoon.

The final event is when the trucks leave the system in the southeast corner of the network, either via de A15 or A16. At this point in time, the trucks are removed from the system and all statistics are gathered (e.g., whether the truck exited in a platoon).

4.4 Model Assumptions and Limitations

To reduce the complexity of the simulation model, we introduce several assumptions. First, we assume that the maximum platoon size consists of three trucks and all trucks in the model have CACC (i.e., are able to platoon). As there are currently no reliable estimates on the costs of implementing CACC in a truck, we omit these investment costs from the analysis. When reliable estimates are available, they can easily be incorporated in the analysis to calculate the profitability for specific use-cases. Regarding real-time platooning we assume that (i) the platoon departs at the latest release time of the members of the platoon due to obligatory rest periods and (ii) when a third truck wants to join a platoon, this is only allowed when the third truck has an overlap strictly within the already established overlap between the other two trucks. Regarding opportunistic platooning (i.e., while driving on the RoR), we limit the complexity of continuously searching for matches by introducing fixed areas where trucks may search for potential partners and fixed areas where they can physically form a platoon. Also, due to waiting time restrictions, we limit ourselves to a maximum of two trucks in a platoon with opportunistic platooning. Furthermore, we assume that when a platoon exits the network (i.e., in the southeast corner of the RoR), they keep platooning to their final destination. Finally, we assume that all trucks have the same fixed search area in which they can find platoon partners (e.g., by searching up to two kilometers ahead of the truck).

4.5 Experimental Design

To perform experiments with the simulation model, inputs, outputs and experimental factors are used. Section 4.5.1 describes the input of the model, Section 4.5.2 the outputs and Section 4.5.3 the experimental factors.

4.5.1 Input

Traffic intensity. To model a realistic scenario, we used the Dutch National Datawarehouse for Traffic Information (NDW) to find traffic intensities in our network. We used data from September 2017 and used the average intensities of the timeslots 07:00-08:00, 11:00-12:00, and 17:00-18:00 as input to a Poisson arrival process. The distribution of trucks among the several entry and exit points of the simulation model was chosen to realistically represent the routes between origin and destination. We calculated this distribution such that the aggregated flows on the segments, match with the intensities of the NDW data. We focus only on trucks that depart from the Plaza or the Rotterdam area. Table 1 shows the intensities of trucks at the entry points of the network and related route in the network.

Table 1: Traffic flows and intensities.

Origin	Route	Intensity (per hour)
A20 – West entry	Via A4/A15	65
A20 – East entry	Via A16/A15	90
A4 – North entry	Via A4/A15	30
A13	Via A20/A16/A15	30
A38	Via A16/A15	30
A29	Via A15	150
Maasvlakte (to Ring)	Via A15	155
Maasvlakte (to Plaza)	Via Plaza to A15	50

Destinations. We consider the top 15 destinations (5 national and 10 foreign) with as origin the Port of Rotterdam. Based on the destination, we calculate the maximum amount of kilometers that can be platooned. Every truck is assigned to a destination based on its frequency and has a fixed exit point in the simulation model, as shown in Table 2. Although in the simulation model the trucks exit the system near the RoR, we assume that the trucks continue to their final destination. Based on this information we calculate the kilometers driven in a platoon.

Table 2: Destinations used in the model, their frequencies and properties.

Destination	Foreign	Frequency	Cumulative frequency	Maximum platoon kilometers	Exit in model
Antwerp	Yes	8.3	0.08	107	A29
Flanders	Yes	5.5	0.14	184	A29
North Rhine-Westphalia Southwest	Yes	4.4	0.18	250	A20
Southern Germany	Yes	3.2	0.21	538	A15
Western France	Yes	3.1	0.24	373	A29
Ruhr	Yes	2.9	0.27	243	A15
Wallonia and Luxembourg	Yes	2.6	0.30	222	A29
Northern Germany	Yes	2.5	0.32	386	A20
North Rhine-Westphalia North	Yes	1.5	0.34	214	A20
Southern France	Yes	0.8	0.35	934	A29
Utrecht	No	19.1	0.54	70	A20
Amsterdam	No	16.2	0.70	83	A4
Zeeland	No	10.3	0.80	86	A29
North Brabant	No	10.0	0.90	79	A15
Gelderland	No	9.9	1.00	84	A15

Truck related. The inputs related to the trucks consist of the (i) hourly wage of the truck driver, (ii) fuel efficiency, (iii) fuel price, and (iv) the rest periods. We fix the hourly wage at 50 euros and assume that every truck consumes 0.28 liter fuel per kilometer with a fuel price of 1.08 euro per liter. Every truck that goes to the Plaza is assigned a resting time drawn from a uniform distribution with a minimum of 15 minutes and a maximum of 45 minutes.

Platoon related. The inputs related to the platoon are (i) the fuel savings and (ii) the search area. The fuel savings depend on the position of the truck in the platoon. We distinguish between three positions: (i) leading (4% savings), (ii) following (16% savings), and (iii) last (10% savings). In case of a three-truck platoon, all types are present, whereas in a two-truck platoon the following truck is automatically the last truck and thus has the fuel savings associated with the last truck. The search area is the area in which the truck is able to find candidates to platoon with. For real-time platooning this area consists of the Plaza and for opportunistic platooning this is expressed in kilometers. For this study we fix the search area at looking two kilometers ahead.

Urgency related. By using an urgency parameter, we model trucks that are only allowed to wait a small amount of time for another truck to form a platoon. For example, on the Plaza trucks may not want to wait beyond their obligatory rest period to depart (e.g., due to strict time-windows or uncertain travel times). For opportunistic platooning, this parameter is less relevant as the waiting time to form a platoon is already short.

Multi-brand platooning related. The model consists of five different truck brands, each with their own frequency. These frequencies are given by (0.14; 0.22; 0.23; 0.06; 0.32) for the five brands, and are based on real-life data of the brands that are typically used in the Port of Rotterdam region. In the model, each truck is assigned a brand based on these frequencies irrespective of its route. With the multi-brand factor, we model whether trucks are able to platoon with trucks from other brands to assess the impact of CACC standardization.

Exact match related. With the exact match option, we only allow platoons with trucks having the same destination (as shown in Table 2), such that each truck platoons the maximum number of kilometers possible. When this option is turned off, we also allow platoons with partially overlapping routes.

4.5.2 Output

The simulation model has the following outputs for both real-time and opportunistic platooning: (i) the number of platoons with two trucks, (ii) the number of platoons with three trucks, (iii) the percentage of trucks in a platoon, (iv) average kilometers driven in a platoon, (v) the average savings per platoon and (vi) the average savings per kilometer.

4.5.3 Experimental Factors

Using the inputs described in Section 4.5.1, we define several scenarios using the following five experimental factors: (i) the hourly wage savings, (ii) multi-brand platooning, (iii) the urgency factor, (iv) exact matching and (v) the number of matching locations on the RoR. The impact of the hourly wage savings is evaluated using three scenarios: (i) all trucks require a driver (0% savings), (ii) platoons are compensated with reduced road taxes (8% savings) and (iii) the following trucks do not require a driver (90% savings). Furthermore, the number of urgent trucks is varied between 20% (low) and 40% (high) and the factors multi-brand platooning and exact matching are either turned on or off. For the RoR, we have two options from where platoons can be formed: (i) at the southwest corner (A15/A20) and (ii) further eastbound on the A15, after the A29. Either the first or both are used. The experimental settings are summarized in Table 3.

Table 3: Experimental factors.

Experimental factor	Low	Middle	High
Hourly wage savings	0%	8%	90%
Urgency level	20%		40%
Multi-brand platooning	Off		On
Exact matching	Off		On
Matching locations (RoR)	1		2

We vary one factor at a time and study all possible combinations (i.e., 48 scenarios). We find the impact of a factor by varying all other factors and keeping the value of the factor under consideration fixed. We base our findings on the average results over all scenarios.

5 RESULTS

In this section, we present the simulation results of the two types of platoon matching under consideration. We focus on the most insightful results of both real-time and opportunistic platooning and address the similarities and differences between the two types. We present the results varying the matching algorithms (Section 5.1), varying wage savings (Section 5.2), varying the urgency level (Section 5.3), whether multi-brand platooning is allowed (Section 5.4), whether an exact match is required (Section 5.5) and the number of matching locations on the RoR (Section 5.6).

Table 4 shows an overview of the results with the percentage of trucks in a platoon (also denoted by the platoon ratio) and the earnings per kilometer in euro (between parenthesis) for the experimental factors.

Table 4: Simulation results.

		Plaza		Ring of Rotterdam	
		FVM	BM	FVM	BM
Hourly wage savings	0	16.8% (-)	17.5% (-)	23.3% (0.01)	23.3% (0.01)
	8	27.8% (0.02)	29.9% (0.02)	22.7% (0.03)	22.7% (0.03)
	90	45.9% (0.18)	54.7% (0.21)	21.9% (0.26)	21.9% (0.26)
Urgency level	20%	30.7% (0.07)	35.3% (0.08)	-	-
	40%	29.0% (0.07)	32.9% (0.08)	-	-
Multi-brand	On	38.9% (0.07)	44.3% (0.08)	31.9% (0.10)	30.7% (0.10)
	Off	21.4% (0.07)	24.7% (0.08)	13.3% (0.10)	14.6% (0.10)
Exact matching	On	30.1% (0.07)	39.9% (0.08)	21.2% (0.10)	21.2% (0.10)
	Off	24.5% (0.07)	31.8% (0.08)	22.6% (0.10)	22.6% (0.10)
Matching locations	1	-	-	11.0% (0.10)	11.0% (0.10)
	2	-	-	28.4% (0.10)	28.4% (0.10)

5.1 Varying Matching Algorithms

On the Plaza, the BM algorithm performs on average across all runs slightly better than the FVM algorithm in terms of platoon ratio (30% versus 34%). The difference on the RoR is neglectable and both algorithms perform equally well. This is due to the fact that for opportunistic platooning there is limited time to find a match, and typically there is only one feasible match in the neighborhood area and thus both algorithms perform equally well. For real-time platooning, the BM algorithm has more potential as it shows higher platoon ratios in some runs. This is caused by more platoons with three trucks, where the fuel savings per truck per kilometer are the highest. The earnings highly depend on the hourly wage savings, which is discussed in the next section.

5.2 Varying Wage Savings

When no wage savings are allowed (i.e., truck drivers are required in all vehicles, with no compensation) the earnings per kilometer are low. However, when drivers in the following vehicles are compensated (i.e., 8% savings) by being able to drive longer in-between rest periods or get a discount on road taxes, the earnings increase almost by a factor three. When no drivers are required for the following vehicles (i.e., 90% savings) the earnings further increase by a factor nine. In the latter case, also more platoons with three trucks are formed as the hourly wages of two truck drivers are saved and thus platooning quickly becomes profitable. Also, for real-time platooning the platoon ratio is highly dependent on the hourly wage savings, whilst the impact on opportunistic platooning is small as the size of the neighborhood is small. Finding a match thus does not depend on the profitability, but whether a truck is present that meets all other requirements (e.g., the same route).

5.3 Varying Urgency Level

For real-time platooning on the Plaza, doubling the urgency factor accounts for 6% less platoons with FVM and 7% less platoons with BM. This relatively small effect is explained by the fact that when one truck is urgent, but the other is not, the non-urgent truck is still willing to wait for the urgent truck. The urgent truck thus dictates the departure time of the platoon, such that it does not have to wait, but can still platoon. The urgency factor is not relevant for opportunistic platooning as the waiting times are always below the threshold value.

5.4 Allowing Multi-brand Platooning

By allowing multi-brand platooning, all five brands in the model can platoon with one another. The results show that on average with real-time platooning, the number of platoons increases around 80% while for opportunistic platooning an increase between 110% (BM) and 140% (FVM) is expected. For opportunistic platooning this parameter has a higher impact as the number of trucks in the search area on the RoR at a given moment in time is considerably lower than the number of trucks arriving during the rest period on the Plaza.

5.5 Requiring Exact Matching

The impact of exact matching is found to be considerable for real-time platooning and small for opportunistic platooning. When exact matching is required, the number of platoons decrease by 23% (FVM) and 25% (BM) at the Plaza and 6% on the RoR (both FVM and BM). Although the number of platoons decreases, the earnings per kilometer stay the same. The lower platoon ratio when exact matching is turned off, can be explained by the fact that most of the overlaps in routes are not large enough to gain positive earnings; especially for real-time platooning, when a truck has to wait and when this is not compensated by high hourly wage savings, given the relative high costs of waiting for other trucks.

5.6 Varying the Number of Matching Locations

Increasing the number of matching locations on the RoR, by including a match location after the A29, accounts for over 150% times more platoons than solely matching at the A4/A15. Opportunistic platooning thus highly depends on the intensity of trucks in the neighborhood. As this factor only influences the matches on the RoR and not on the Plaza, the table omits results for real-time platooning.

6 CONCLUSIONS

In this paper, we presented two matchmaking algorithms, First-Viable Match and Best-Match, and analyzed the potential for both real-time and opportunistic truck platooning. Specifically, we presented the design and implementation of an agent-based simulation model based on the Port of Rotterdam and its surrounding highways to study the potential benefits of truck platooning. For real-time platooning we studied a truck stop at the Port of Rotterdam, whereas for opportunistic platooning we considered the Ring of Rotterdam. The results show that the most influential factors in both platoon formation and the total platoon profitability are wage savings and the possibility of different truck brands to platoon together. More specifically, we showed that without any wage savings, i.e. only considering fuel savings, platooning does not provide significant benefits in our case study. However, with wage savings, potential savings of 0.26 euro per kilometer can be realized.

Further research directions include: (i) testing the robustness of the matchmaking algorithms by performing a more in-depth sensitivity analysis related to our assumptions and input parameters, (ii) designing a control system for drivers when they are no longer required in the following vehicles (to pick up drivers leaving their truck and delivering drivers at trucks that leave the platoon), (iii) considering longer platoons (especially for the opportunistic case) and their impact on traffic flow and (iv) introducing a virtual currency (and/or penalties) to create a more dynamic matchmaking system where agents are allowed to change matches over time when new opportunities arise.

Moreover, our matchmaking algorithms can be extended in many other ways. In the present algorithms, an arriving truck searches for only one other truck in order to make a platoon match. As discussed earlier, the preferred match may be with a truck already in a platoon. Conversely, in real-time truck platooning, we may think of an algorithm where the arriving truck - based upon platform information - searches over all sets of (say no more than five) feasible trucks and selects the most profitable set to platoon with. Furthermore, instead of solely focusing on profits, we might also take past performance into account as an indication of the reliability of platoon partners. When, for instance, a certain truck does not wait when this has been agreed upon, then this truck will end up at the bottom of a priority list.

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