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Analysis of Decentral Platoon Planning Possibilities in Road Freight Transportation Using an Agent-based Simulation Model

Analyse dezentraler Möglichkeiten der Platoon-Planung im Straßengüterverkehr mit Hilfe einer agentenbasierten Simulation

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Abstract: In this paper, a modelling approach is proposed in order to simulate platoon planning possibilities for individual trucks. An agent-based simulation model has been developed using a generic transport network with randomly generated transports between supplier and customer nodes. The model is used to analyse the inter-arrival times of trucks at sections in the network under different parameter settings. By that, potential waiting times of trucks for platooning possibilities are calculated. Furthermore, the percentage of route that can be driven as a platoon is calculated under the assumption that trucks are allowed to wait at intersections for a predefined time. Results show that the model can be used to investigate decentralized platooning possibilities and analyse the trade-off between savings generated by platooning and the cost for necessary waiting times.

1 Introduction

Wireless communication technology enables automatic exchange of data between vehicles in real time. Along with the use of distance-measuring sensors and high performance on-board computational power, this technology can be used for automated driving of trucks in so called platoons (Tsugawa et al. 2016). In such a platoon, a group of trucks automatically follows a leading vehicle. The following trucks thus do not need to be controlled by a human driver. Furthermore, the distance between vehicles can be minimized and fuel consumption caused by aerodynamic drag can be reduced (Bonnet and Fritz 2000).

A general overview and summary of platooning literature in between 1994 and 2010 can be found at Kavathekar and Chen (2011). While technological aspects of platooning are under investigation since the 1950s (Tsugawa et al. 2016; for technological research on platooning see for example Santini et al. 2017; Sugimachi et al. 2013 or Yazbeck et al. 2014), research regarding the management and planning challenges connected to platooning in road freight transportation has gained more and more attention in recent years. This is mainly due to the fact that generating platooning possibilities requires for additional effort when planning routes and scheduling trucks (Larson et al. 2013; Larsson et al. 2015).

While the body of literature on technological aspects is rich, most research on platoon forming and planning mainly concentrates on fuel saving potentials: Liang et al. (2016) try to identify fuel-efficient collaboration opportunities between trucks. They then concentrate on efficient platoon forming manoeuvres under different traffic conditions. Algorithms for fuel-efficient platoon forming as well as breakup manoeuvres are presented in van de Hoef et al. (2015). Larsson et al. (2015) develop a theoretical framework for modelling fuel-optimal platoons and present potential solving heuristics.

In the field of platoon planning, many publications (like for example Larson et al. 2013; Liang et al. 2016; Saeednia and Menendez 2017) have in common that they deal with planning from a global perspective having all necessary information available. Larson et al. (2013) for example simulate a simplified German autobahn network with local controllers at each intersection that decide if it is more fuel-efficient for a truck to increase its speed in order to be able to form a platoon. The authors also mention the possibility of trucks driving detours so that they can form platoons. To calculate their decision, the controllers need to know each truck's position, speed and destination in real-time. However, in the context of a practical application of platooning, the question, how platoons can be planned among trucks of different owners is of great interest. From the point of view of one individual company, a scenario in which only limited information on other companies' truck movement is available appears to be more realistic as road freight carriers might be unable or unwilling to share their routing information with external planners (Bronzini and Singuluri 2009).

The relevant research gap thus lies in the investigation of possibilities on how platoons can be formed with only limited or no information available. To integrate limited information availability into platooning research, this work focuses on platooning decisions on the level of individual trucks. Without having any information on other trucks, one individual truck that wants to join a platoon can only decide whether or not it should wait at an intersection until other trucks that are ready for platooning appear. The longer one truck driver is allowed to wait during his tour, the more opportunities for platooning arise over time. The first research goal is therefore to investigate the influence of the number of trucks with platooning technology on the maximum waiting time. The second research goal lies in analysing the relation between the percentage of the entire route that can be driven as a platoon and the necessary overall waiting time of individual trucks. From an economic point of view, investigating this trade-off between savings generated by platooning and the costs for letting trucks wait is of great interest. Yet, to keep the calculation of waiting times simple, only platoons consisting of two trucks have been considered in this work.

The remainder of this work is structured as follows: First, the simulation model is described in detail. Here, especially network generation and the design of the experiments will be presented. In the subsequent chapter, the obtained results of the simulation study will be presented. Finally, this work closes with brief conclusion and an outlook for future research.

2 Simulation Model

2.1 Generic Network Generation

In order to analyse the relation between the percentage of route that can be driven in a platoon and the necessary waiting time, an agent-based simulation model has been developed. The model uses a randomly generated generic graph of cities (nodes) and connecting roads (arcs) in order to simulate inter-city road freight traffic. Network generation is based on the work of Leyton-Brown et al. (2000), who argue that using a generic network instead of a real-world network is more suitable for the investigation of systematic parameter variation.

A total number of 100 cities have been created which are laid-out randomly over an area of 1000x1000 km. This is roughly equivalent to the extent of larger central European countries and thus regarded as a realistic scale for the simulation model. Cities can either be suppliers, customers or simple intersections. Customers and suppliers were assigned randomly to these cities with a probability of 0.25 of a city being a customer and a probability of 0.3 of a city being a supplier. This configuration has led to a final share of 25 suppliers and 43 customers. The remaining 32 cities are configured as simple intersections of arcs. The setting of having between one and two customer cities per supplier has been chosen in order to generate a fairly high number of routes while only having a limited number of destination nodes. Yet, for future research, evaluating the results in networks with different customer-supplier shares might also be of interest. For the selection of parameter values for the creation of arcs we refer to the work of Leyton-Brown et al. (2000). The values chosen in Leyton-Brown et al. (2000) lead to a slightly non-planar graph with 183 arcs, which is regarded by the authors as a reasonable reproduction of real-world networks. Yet, the number of arcs is certainly smaller than the number of links in a real-world road network. That is why the model only accounts for inter-city motorway traffic.

The network has been generated randomly only once. The resulting network is shown in Figure 1 and has been used subsequently for all experiment runs in order to ensure comparability and reproducibility of the obtained results. Yet, to validate and verify the results, experiments have been repeated with other randomly generated networks.

For the simulation, the software AnyLogic 7 has been used. AnyLogic is a well-established simulation tool that is based on Java and therefore offers a high modeling flexibility (Borshchev 2013). An agent-based simulation model is used, because it is most suitable to depict heterogenic behaviour of multiple actors. Furthermore, agent-based simulation allows for modelling complex interdependencies between agent decisions and strategies and outputs their effects on the overall system (Deckert and Klein 2010).

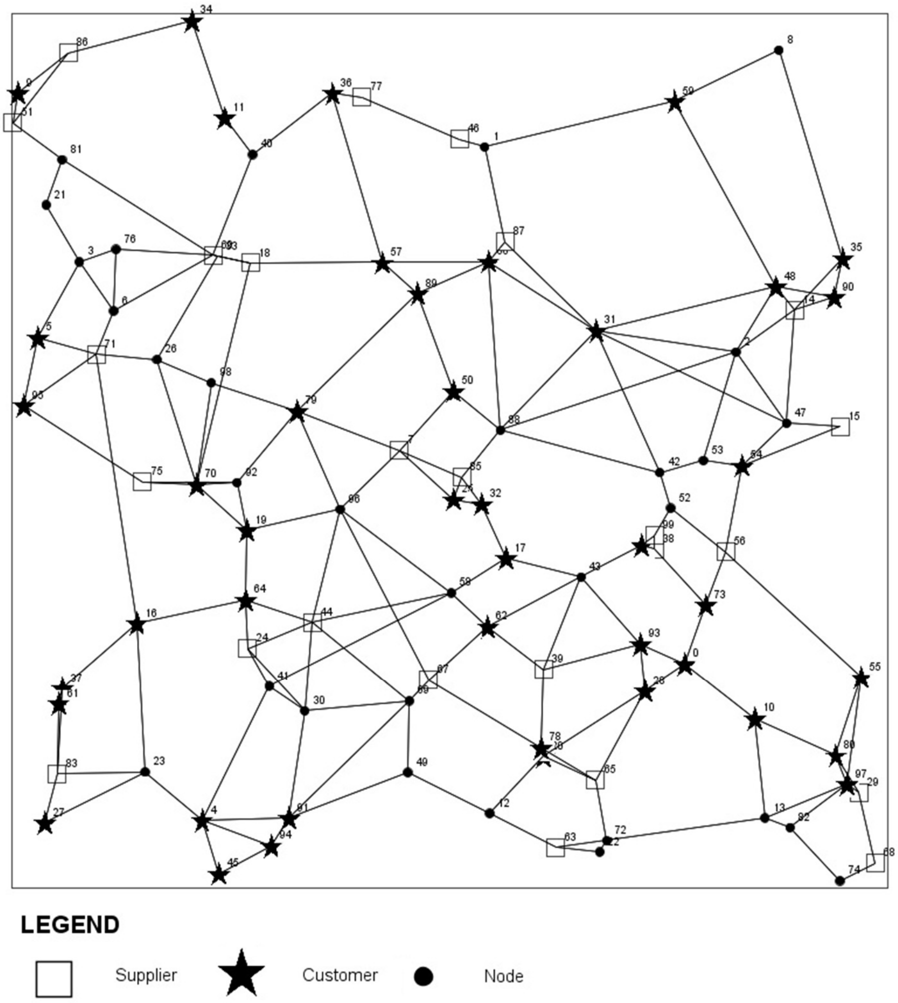

Figure 1: *Generic network created according to Leyton-Brown et al. (2000) that has been used in the simulation model*

2.2 Order Generation and Experimental Design

Each customer in the model is assigned to exactly one supplier. During the runtime of the simulation model, orders for goods are randomly created by customers and send to their suppliers. The creation of new orders happens at a random point uniformly distributed within a predefined 30 min time window. The beginning of the time window is defined by a parameter giving the minimum time between two orders of one customer. By systematically altering this parameter, the frequency and therefore the total number of orders is changed. Ten different configurations for the minimal time between orders have been simulated. The configurations can be found in Table 1. For this research, every configuration has been run 50 times with a model time duration of 4320 minutes (three days) each, leading to a total of 500 simulation runs.

Upon receiving an order, suppliers send a truck on the shortest path to the respective customer in order to fulfil the order. The truck then returns to its home supplier. Therefore, the total number of trucks generated by the simulation model is directly dependent of the number of orders. The average number of orders generated within the three days simulation time of all model runs for one configuration is also given in Table 1.

Table 1: *Different configurations of time between orders used in the simulation model*

Configuration No	Minimal time between orders	Maximal time between orders	Average number of orders created	Average number of trucks per day on busiest section
1	5	35	9514	358
2	10	40	7568	285
3	15	45	6281	236
4	20	50	5364	202
5	25	55	4683	176
6	30	60	4156	156
7	35	65	3733	140
8	40	70	3388	127
9	45	75	3099	116
10	50	80	2857	107

According to traffic census data published by the Bundesamt für Straßenverkehr, the busiest section of German motorways has been used by approximately 21,900 heavy-duty vehicles per day in the year 2015 (Bundesamt für Straßenverkehr 2017). Heavy-duty vehicles include all trucks and busses with a gross weight of more than 3.5 tons. Table 1 gives the average number of trucks per day on the busiest model section during model runtime. Comparing these numbers, it can be seen that the number of trucks on the busiest section of the model is only between 1.6 % and 0.5 % of the number of heavy-duty vehicles on the busiest section of German motorway. Therefore, results of the model are valid under the assumption that just a small share of heavy-duty vehicles is equipped with platooning technology. This is assumed to be a valid assumption, as platooning technology will not be used by every heavy-duty vehicle. Furthermore, the implementation of platooning technology will not happen instantaneously for all vehicles but most likely subsequently over a period of time.

3 Results

3.1 Influence of the Number of Trucks

For each truck in every simulation run of the different configurations, the driven route is saved in a database along with the timestamps of the truck's entry and exit on each section (arc) along its route. By that, the time between two trucks on every section can be obtained and evaluated for every configuration of parameters. This gives the potential time a truck has to wait at an intersection until another truck appears that it can form a two-vehicle platoon with. This time is then analysed in dependence of the number of orders created, i.e. the number of trucks in the system. The number of trucks in the system can be regarded as the number of trucks equipped with platooning technology in a real-world network. Altering the number of trucks in the system is of interest in order to account for the uncertainty when predicting the speed at which platooning technology is integrated into vehicles. The average minimum and maximum waiting time at each section have been calculated over all model runs and are presented in Figure 2. As can be expected, average waiting times decrease with an increasing number of orders in the system. Average maximum waiting times lie between 17 min for configuration 1 (9514 orders on average) and 57 min for configuration 10 (2857 orders on average). Average minimum waiting times range from 6 min for configuration 1 to 18 min for configuration 10. As can be observed in Figure 2, average minimum waiting times are less effected by the number of orders, resulting in a slightly less decreasing curve. Yet, low average waiting times are less probable, leading to the curve for average waiting times being located closer to average maximum waiting times than to average minimum waiting times.

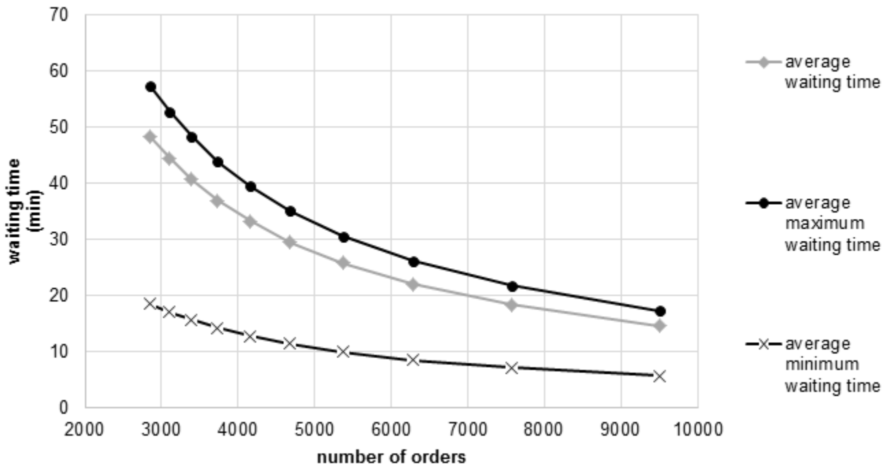

Figure 2: *Average waiting times per section in dependence of the number of generated orders*

Interestingly, results also show that the node degree has only a minor influence on waiting times at the beginning of adjacent sections. On a node that is connected to a higher number of sections, more trucks arrive as the node is potentially part of a higher number of routes. Yet, also the number of possible sections via which a truck can leave the node is higher. Waiting times have to be calculated separately for each section and not for each node as platooning is only possible if two trucks are moving along the same section.

3.2 Influence of the Maximum Waiting Time

Furthermore, a maximum waiting time at each section can be assigned and compared to the calculated inter-arrival times between trucks at intersections. By that, the possibility of trucks waiting at intersections along their route for following trucks to form a platoon with can be analysed. Here, the possible percentage of sections that can be driven in a platoon together with another truck but without exceeding this maximum waiting time at each section is obtained from the model. This percentage is calculated as the percentage of all routes that can be driven as a platoon by all trucks during the simulation's runtime.

The maximum waiting time is varied between 0 and 80 min. Results are presented in Figure 3. It is obvious, that for a maximum waiting time of 0 min, no section can be driven in a platoon, as there are no two trucks arriving at an intersection at the very same moment. Furthermore, it can be observed that for a maximum waiting time of 48 min, even in configuration 10 with an average of only 2857 orders, more than 90 % of routes can be driven in a platoon. For configuration 1 with an average of 9514 orders, more than 90 % of routes can already be driven as a platoon when trucks are allowed to wait 14 min at each intersection.

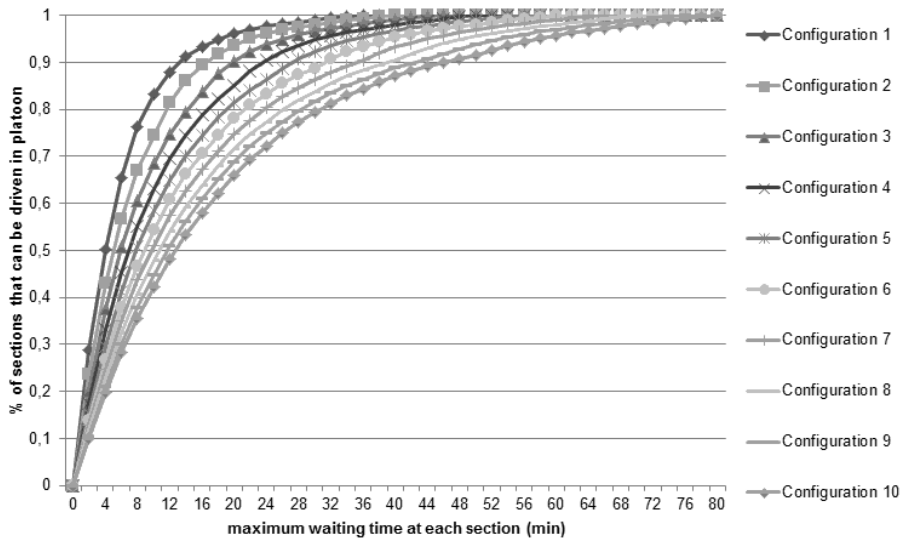

Figure 3: *Percentage of number of sections of all routes that can be driven as a platoon for different maximum waiting times*

As can be seen in Figure 1, sections can differ widely in length. Driving in a platoon on a longer section is advantageous compared to platoon driving on shorter sections as it leads to a higher percentage of the overall length of the route being driven in a platoon. Yet, only the number of sections but not their length is considered in Figure 3. The lengths of each section can be easily calculated as the Euclidean distance between the two adjacent nodes. Therefore, it is of interest to also analyse the total length of all routes that can be driven in a platoon for given maximum waiting times. Results are depicted in Figure 4. Note that the percentage of length that can be driven as a platoon is again calculated as the sum of platooning distance of all tours divided by the total length of all tours. It can be observed that the lines for configurations 4 to 10 in Figure 4 experience a change in their steepness for values around a percentage of route length of approximately 50 %. This change in steepness is caused by the way orders are generated in the model: As can be seen in Figure 4, the change in steepness is always located at a waiting time that is equal to the minimum time between the generation of two orders in the respective configuration. For this waiting time and for waiting times above, even sections that are only part of one route can be driven in a platoon as trucks can now wait for other trucks coming from the same supplier. Because this change in steepness can hardly be seen in Figure 3, it can be assumed that mainly longer routes which have a disproportional high influence on the overall route length are affected by this.

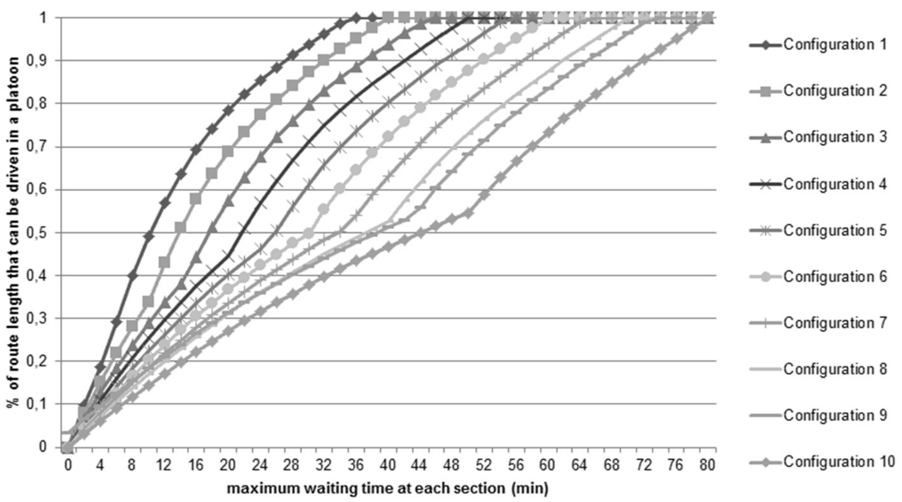

Figure 4: *Percentage of length of all routes that can be driven as a platoon for different maximum waiting times*

4 Conclusion

We have proposed a modelling approach using an agent-based simulation to investigate decentralized platoon planning of trucks in a road freight network. By using a generic network and randomly created transports, the influence of different parameters can be analysed by the model. In a first study, we have analysed the times trucks need to wait at intersections in the network until other potential vehicles to form a platoon with arrive. First of all, the waiting times in dependence of orders have been investigated, showing the expected result that the average waiting times decrease when the number of orders and thus the number of trucks in the system rises. Secondly, the influence of the maximum waiting times at each intersection on the percentage of route that can be driven as a platoon has been investigated. By doing so, the maximum waiting time for a given number of trucks in the system can be calculated, at which all routes in the given simulation model can be driven in a platoon. Waiting leads to later arrival times of trucks at their final destination, resulting in potential costs due to delayed shipments or the requirement for additional planning effort. The model proposed in this work thus helps estimating the trade-off between savings generated by platooning (e. g. because of lower fuel consumption) and the cost for waiting times along a truck's route. Nevertheless, the approach poses some drawbacks:

First of all, it has to be clarified that actual platoons are not simulated in this research. Instead, evaluation of the model output is done retrospectively and only two-vehicle platoons are considered. This means that the possibility of accumulation of waiting times caused by the next truck wanting to wait for a platoon himself as well is not yet part of the model. Still, for a given number of tours inside the network, the research provides an insight into the expected waiting times necessary for platoon forming due to waiting for following trucks.

Secondly, by using a generic network, the applicability of the results to real-world networks is only limited. To better depict real-world networks, simulation experiments should be repeated with higher numbers of orders created during the model's runtime. Instead of creating orders randomly, using real-world traffic data for generating transports in the model might also be an interesting approach. For future research, transferring the model to a real-world network and repeating the experiments is also of interest.

Thirdly, instead of waiting for other trucks at intersections, trucks can decide to deviate from their shortest route in order to take a busier route that offers more platooning possibilities and thus requires less waiting time for platoon forming. The simulation model at hand does offer manifold possibilities to implement route deviation for better platooning options. Nevertheless, this hasn't been in the focus of the research yet but will be targeted in future work.

For future practical application, the model can be used to quantify the trade-off between savings generated by platooning and the costs of the required waiting times. Furthermore, the model may be of help to identify route sections with low necessary waiting times which therefore offer a high potential for platooning.

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