Automated Negotiation Mechanism and Strategy for Compensational Vehicular Platooning

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Abstract. Our research is developing flexible strategies for forming and routing future platoons of automated urban logistics vehicles. We propose the notion of compensational platooning using automated negotiation between agents representing vehicles. After the vehicles reach the end of a common route, an agent can propose part of its route along with a monetary value to platoon partners for further together-travel. If negotiation is successful, a new platoon is formed and follows the proposed route. If the compensation is too small or the route proposed oversteps the agent's limitations, the offer is rejected and the vehicles continue their travel separately. A contribution of this paper is a negotiation strategy that proposes compensation based on beliefs of what the opponent's payment threshold would be. In doing so, the bid with the highest acceptance likelihood is calculated, keeping negotiations short and effective. Our model is tested on a synthetic network and a real urban example. We show that by using negotiation, vehicles can identify mutually beneficial new routes that a centralised/distributed approach would not find, with utility improvements of up to 8%.

Keywords: Automated negotiation · Opponent modelling · Platoon matching · Decentralised agent coordination.

1 Introduction

With the steady growth of e-commerce, logistic providers are expanding and accelerating the way they conduct their shipments to same-day deliveries. To reduce emissions, road occupancy and the costs of logistics companies, small electric autonomous delivery vehicles could take over deliveries. However, having multiple such vehicles in an already congested network could further impede traffic and ultimately prove to be chaotic and counterproductive.

As a solution we investigate platoons, a formation where vehicles travel with small inter-vehicular distances, behaving as one unit. Platooning has been shown to positively affect traffic through better usage of road-space [1], and decongestion of intersections in urban environments [8]. To increase the probability of platoons forming, we require technology that allows vehicles from different logistic service providers to cooperate. Encouraging such competitive formations will be done by monetarily incentivising vehicles, along the lines of the fuel savings sharing presented in [4]. The authors found that optimal individual utility is reached with an even distribution of profits between competing vehicles.

While optimisation methods can create mutually beneficial routes for all vehicles considered, agent negotiation can be leveraged on top of existing centralised and distributed solutions to further improve utility. Therefore, compensational platooning is offering payment for vehicles to travel together in a platoon after the end of an optimiser-found route. The compensation needs to be high enough to convince the opponent to participate, while also being low enough for the ego-vehicle to prefer cooperation over the status quo solution. To increase the likelihood of an agreement being reached, vehicles should be equipped with an opponent modelling module. Our work presents a general model of turning knowledge collected about the opponent into a bid acceptance probability. By having an approximate insight of the opponent's reservation value, we can calculate agreeable bids, ensuring that at every round, only the best offer is being made. We show that negotiation provides a benefit when added to a distributed solution (presented in [10]), by allowing vehicles to form platoons on routes that may not necessarily be beneficial for all vehicles, but can be made more attractive through payments.

2 Related work

A distributed approach to platoon formation is presented in [10], which uses an optimisation algorithm to find the longest common route between vehicles while respecting their limitations. Road-side units (RSU) equipped with the algorithm are distributed at every node in the network and get triggered when two or more vehicles are at the same place at the same time. The algorithm dynamically groups and routes the vehicles according to traffic density, the vehicles' current position, destinations and restrictions.

In the context of traffic and platooning, negotiation is used mainly as a conflict resolution mechanism; either merging [7], vehicle ordering [6], or intersection crossing [9]. None of these works employ negotiation as a platoon formation method.

Ensuring that the strategy used during negotiation will lead to win-win, as well as non-exploitative solutions, we turned to opponent modelling techniques. Previous works focused on estimating reservation value [13] or strategy [3]. Acceptance probability research [5] considered the case where the two negotiation parties have interacted before and can use previous knowledge to model the bids their opponent is more likely to accept. In this work, however, we tackle the problem of opponent modelling by creating an acceptance probability of bids based on estimations of the opponent's reservation value without prior knowledge.

3 Model

Routes Each vehicle has a route, which is given to it by its logistics provider or the RSU situated in the environment. The latter is responsible for the initial creation and routing of the platoon with an optimiser approach. For our scope we consider a route to be a sequence of edges defined as $R = ((Split, V_i), (V_i, V_{i+1}), ..., (V_n, Destination))$ for all vehicles, where $Split$ is the split point (end of the common route given by the RSU) and V_i intermediary nodes.

Pricing To incentivise platoon travel, traffic management authorities can use congestion pricing, represented by traffic density d_e (the number of vehicles per time unit in a specific space). Alone travel incurs full payment, whereas platoons receive preferential prices due to their proven decongestion abilities [8]. The congestion price of an edge increases with the platoon size, which is then shared among the vehicles comprising it [4].The price function is defined as

$$p_e = \begin{cases} d_e/nvp + d_e/\omega, & \text{if } nvp > 1 \\ d_e, & \text{otherwise} \end{cases} \tag{1}$$

where nvp is the number of vehicles in a platoon and ω the increase coefficient imposed by traffic management (based on the congestion in the immediate area).

Utility function Traditionally, the goal of routing problems is to either minimise cost, travel distance or travel duration [12]. With these three aspects, we can represent the vehicle's preferences using an additive utility function depending on route length(l) and pricing(p). The latter encompasses costs and time spent in traffic due to their dependence on traffic density. Therefore, the utility function is defined as

$$U_{veh} = -\sum_{e \in R} (\pi \cdot l_e + \rho \cdot p_e) \tag{2}$$

with the purpose of maximising, π, ρ representing the vehicle's preferences and $\pi + \rho = 1$; $\pi, \rho \geq 0$.

Agents Vehicles are represented by agents that have a set of preferences and limitations. They seek to improve their utility through platoon formation by communicating with nearby agents and making offers about alternative routes they can travel on together.

Offers An offer consists of a route and a monetary compensation $(R, comp)$. The route will contain a subsequence of the initiating agent's best route and be noted as R'_i. The compensation is an amount of money offered by the initiator to convince a potential accepting agent to agree to travel together on the proposed route. A viable compensation lies at the intersection of both agents' acceptable offer spaces.

Compensation offer space This is defined by the aspiration and reservation values. For the initiating agent i, the compensation offered is financed through the savings generated from platooning. The maximum compensation offered will be denoted as the reservation value $comp_i = [0; RV_i]$. For the accepting agent a, the compensation offered has to be high enough to get it to change its route. The minimum compensation it will accept, also noted as reservation value, is the one that provides the same utility as its original best route $comp_a = [RV_a; \infty)$.

Protocol We consider bilateral negotiations with the protocols used being either a *Take it or Leave it (ToL)* or an *Alternating Offers* protocol. Allowing for feedback from the opponent, an agent can adjust their bids to increase the likelihood of the negotiation ending in an agreement. We included *ToL* as a baseline approach to negotiation for comparison with our more advanced bidding strategy.

Deadline A deadline is the upper limit on negotiation rounds and is set by the traffic management authority based on how congested the immediate area is.

3.1 Problem solution

The initiator selects a subset of edges from its ideal route, computes a compensation based on its reservation value and sends it out to possible accepting agents. The reservation value is calculated as $RV_i = \sum_{e \in R'_i} d_e - p_e$. For an accepting agent to be able to fully assess the viability of an offer, it needs to receive a complete route, from the split point to their destination. This is done by the RSU, supplementing the route offered by the initiator and having it finish at the acceptor's destination. The acceptor knows the compensation *comp* offered and the d_e and l_e for all the edges in the new route R'_a. However, it does not know the price it is expected to pay and by extension the platoon savings; since it could then extrapolate the initiator's ideal route and reservation value. This is covered by the RSU, which supplements the value of the offer with the corresponding platoon savings. The acceptor ensures the proposed route does not exceed its limitations by calculating the utility.

$$U'_a = -\pi \cdot \sum_{e \in R'_a} (l_e) - \rho \cdot [\sum_{e \in R'_a} (d_e) - comp] \tag{3}$$

If any limitations are met, the utility returned is 0. Afterwards, it computes its reservation value for the proposed route.

$$RV_a = (U_a + \sum_{e \in R'_a} \pi \cdot l_e)/\rho \tag{4}$$

If the compensation offered by the initiator is below the previously calculated reservation value, the accepting vehicle can send a counter-offer with higher compensation to increase its utility. The agents engage in making alternative offers within their defined offer space until an agreement is reached or the deadline expires.

4 Negotiation Strategy

To increase the likelihood of bids being accepted, they are chosen based on the knowledge agents can extrapolate about their opponent. Agents keep track of a probability distribution of their opponent's reservation value which they update with every new bid received. Based on this they calculate which of their bids can be accepted. However, the bid that has the highest likelihood of being accepted does not necessarily translate to better utility, since the concession made could be too large. Determining how much to concede at every step, is done by Baarslag et al.[2] with the Greedy Concession Algorithm. Given our setting, we assume that the opponents follow a time-based strategy, making concessions based on the time available until the deadline.

Estimating the reservation value The agent's offer space is bound by their aspiration and reservation values, but during negotiation, the aspiration value will change to reflect the possible payment interval at a specific time. Therefore, we consider a fixed interval when calculating bids, which will be $[X(0)_i, RV_i]$ for an initiator and $[RV_a, X(0)_a]$ for an accepting opponent, where $X(0)$ represents their first offer/counteroffer. The opponent's bids follow a concession curve [3], dependent on time and strategy, encompassed in the α coefficient, which can follow either a polynomial or exponential curve.

$$X(n) = \begin{cases} RV + (1-\alpha(n)) \cdot (X(0) - RV), & \text{if agent is initiator} \\ X(0) + \alpha(n) \cdot (RV - X(0)), & \text{if agent is acceptor} \end{cases} \tag{5}$$

While a correct estimate of the reservation value can be obtained by studying the opponent's strategy, our approach is to transform a probability distribution of the reservation value to an acceptance probability of bids. An agent starts negotiations with an uninformed prior and with every round updates its beliefs about the opponent, thus skewing the reservation value distribution.

RV to Acceptance Probability As mentioned before, bids follow a concession curve as time progresses based on the agent's strategy, which ends at the deadline in their reservation value. By having a distribution of the potential reservation value, we can create multiple such curves, with a higher density at its peak (the black lines in Figure 1). The acceptance probability of any of our bids depends on the values on these curves for the specific time-step considered. Our bid has a higher acceptance probability if it is higher than the projected values for an initiator opponent, and lower for an acceptor opponent. Therefore, the probability of a bid $Y(s)$ being accepted is:

$$P(Y(s))^{accepted} = \begin{cases} P(X(s) \leq Y(s)), & \text{if opponent is acceptor} \\ P(X(s) \geq Y(s)), & \text{if opponent is initiator} \end{cases} \tag{6}$$

where $X(s)$ is defined in Equation 5. With the resulting tuples of bid and acceptance probability, the agents calculate their ideal bids and their sequence using the Greedy Concession Algorithm [2].

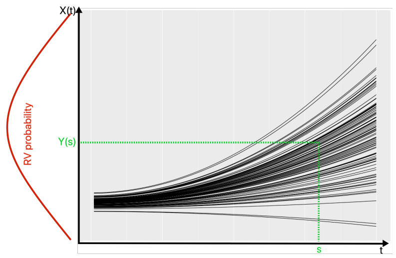

Fig. 1. Bid Y(s) with respect to the concession curves of a normal RV distribution for an initiator opponent.

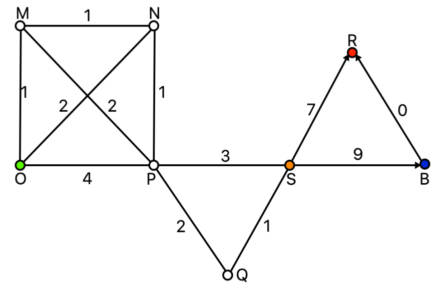

Fig. 2. Example network.

5 Experiments

To validate our approach, we used a simulation framework that incorporated vehicular movement and platooning, as well as a negotiation component containing the bidding module. As a benchmark for comparison, we are using the distributed platooning approach presented in [10]. This current paper studies strictly the effect negotiation has on platoons when they reach the end of the distributed-found route. As an illustration, we present the network in Figure 2 where the notations on the edges represent their respective traffic density. We currently consider just a two-vehicle platoon (Blue and Red) starting at node O, trying to get as "cheaply" as possible to their destinations B and R. For generalisability, an alternative network was modelled, depicting the Tiergarten neighbourhood in Berlin paired with a realistic traffic demand model derived from [11]. For the experiments we considered greedy agents that seek to maximise their profit, hence the coefficients of the utility function were: $\pi = 0.2, \rho = 0.8$.

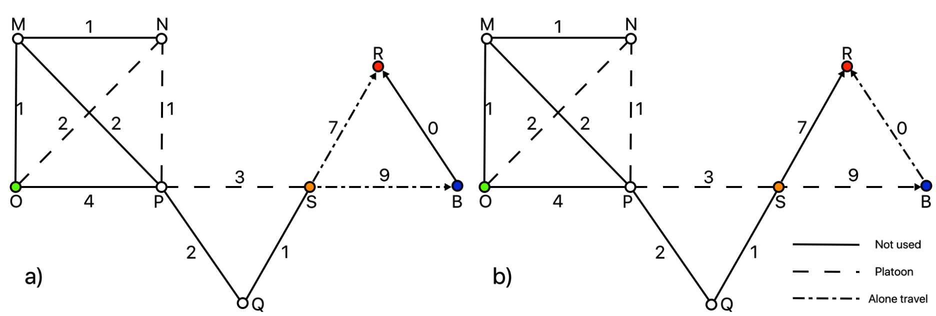

Fig. 3. Vehicle platooning with optimisation(a) and negotiation(b) approach.

Illustration With the optimiser approach presented in Figure 3a, the platooning stops at node S, with each vehicle travelling individually to their destination from there. When we introduced negotiation Blue made an offer for edge S-B, and with the *ToL* protocol the compensation offered lead to rejection and thus, the same results as the optimiser solution. When using the *Alternating Offers* protocol paired with the bidding strategy, Red accepted the offer and the vehicles continued travelling in a platoon until node B (Figure 3b)), where Red continued alone to its destination R. The costs accrued by the vehicles were improved using negotiation and by extension, so did the utility (see Table 1). For the cost, we have a saving of 1.88% for Blue and 12% for Red. As for the utility, we measured a 1.83% and 8.13% improvement for Blue and Red respectively.

Berlin Tiergarten We also investigated the applicability of our approach on a realistic example, namely the Tiergarten neighbourhood of Berlin. For the sake of continuity, we consider Blue to be the initiating agent and Red to be the accepting agent. They split after platooning for two edges, Blue offers one extra edge, which leads to Red travelling an extra three edges alone. Much like the previous example, the compensation of the offer made with the *ToL* protocol is not sufficient and leads to rejection. This is attributed to the length of the detour route, whose influence can be more clearly seen in Table 2. Using the *Alternating Offers* protocol an agreement is reached and the agents continue platooning. The savings that negotiation offers, in this case, are rather small. We do note that the example provided as the illustration is also based on the Berlin network. Therefore, we claim that more notable improvements are realistic, in the case of shorter and less crowded streets.

Table 1. Numerical results for Illustration network.

Vehicle	Cost	Distance	Utility
Optimiser			
Blue	9	1	-7.4
Red	7	1	-5.8
Negotiation			
Blue	8.83	1	-7.264
Red	6.16	2	-5.328

Table 2. Numerical results for Berlin Tiergarten.

Vehicle	Cost	Distance	Utility
Optimiser			
Blue	324	0.466	-259.2932
Red	1191	0.094	-952.8188
Negotiation			
Blue	318.11	0.466	-254.5812
Red	1155.89	3.2	-925.325

6 Conclusion and Outlook

With this paper, we incorporate negotiation between vehicles as a way of decentralised platoon building while addressing the specific requirements related to negotiation in urban traffic (effective bids and quick agreements). To ensure that the offers made will lead to a win-win conclusion, vehicles are equipped with an opponent modelling module. We present a negotiation strategy that models the acceptance probability of an agent's bids based on ever-updating knowledge about the opponent. This allows the vehicle agents to reach an agreement quickly and effectively by offering bids with a high likelihood of being accepted. The experiments show an improvement in both cost and utility. Testing on a real urban network with realistic traffic demand proved that this approach is effective, but would be best suited on short and non-traffic heavy streets, where there is a higher number of alternative routes that the vehicles can follow. This model can support platoon-to-vehicle and platoon-to-platoon negotiation as well, since a platoon would act as a singular agent, aggregating the utility functions of its vehicles and then negotiating on their behalf. Further research can address those scenarios, as well as multilateral negotiations.

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