

Model Predictive Control for the Coordination of Autonomous Vehicles at Intersections [★]

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Abstract: The paper describes a method for defining the crossing order of autonomous vehicles at a non-signalized intersection. The safe passage of vehicles through the intersection is achieved by a centralized Model Predictive Control (MPC) method. The minimization of traveling time or energy consumption and the condition of collision-avoidance are incorporated in the control design. The goal of the research is to guarantee safe passage of the autonomous vehicles by taking uncertainties of position measurements into consideration. The operation of the proposed control method is demonstrated by simulation examples made in a high-accuracy simulation environment to present its efficiency.

Keywords: intersection control, optimization, model predictive control, autonomous vehicle control.

1. INTRODUCTION

The interaction between autonomous vehicles appeared on the roads and the need for the control design of highly automated vehicles to secure collision avoidance in particular uncleared traffic situations have become important research fields of automation in transport systems. Various types of traffic scenarios have been revealed and several control strategies have been designed to give solution for them. Significant part of the scientific research focuses on the challenges of control design of vehicles at non-signalized intersections, i.e. the ordering of autonomous vehicles at intersections in which time and energy optimality criteria and the condition of collision-free passage are taken into consideration.

Multi-agent systems are developed for the control of non-signalized intersections and approached in several papers, see Dresner and Stone (2008), Zohdy and Rakha (October 2012). The proposed optimization algorithms are used to secure collision-free passage of vehicles through the intersection. The optimization problem for the control of autonomous vehicles crossing an intersection is reformulated as a convex program, see inMurgovski et al. (2015), while an optimal scheduling is proposed for the ordering problem as a Mixed-Integer Linear Program by Fayazi et al. (2017).

For the determination of the crossing order of vehicles through the intersection Model Predictive Control (MPC) is used frequently to get an optimal solution by both centralized or decentralized controllers. An algorithm taking the expected entering time of vehicles into consideration is proposed, see Kneissl et al. (2018). A decentralized

MPC is used for the determination of crossing time, while the negotiation between vehicles and the detection of the safety critical situations are guaranteed by V2I communication units. Two different decentralized MPC methods are presented to consider efficient fuel consumption, the requirement of comfort and to handle unexpected vehicle maneuvers during the passage through the intersection, see Qian et al. (2015). A MPC method is used for the assignment of priorities of automated vehicles to guarantee the optimal scheduling at the intersection by solving its control problem as a Mixed Integer Programming problem, Yao and Zhang (2018). In the control strategy optimal traveling speed is designed for each vehicle to secure safety constraints. A centralized intersection control is presented by Riegger et al. (2016) formulating the control problem as a convex quadratic program, while a decentralized solution is given in de Campos et al. (2013). A centralized Optimal Control Problem (OPC) has been solved in a distributed fashion in Katriniok et al. (2017) using a decomposition technique to create local OCPs with coupled constraints.

The contribution of the paper is an MPC-based coordination method for autonomous vehicles crossing a non-signalized intersection. For safety reasons, constraints as speed limits, predefined minimum and maximum accelerations are built in the control strategy. As the purpose of the research is to determine the ordering of vehicles, the requirements of minimum traveling time and energy consumption are incorporated in the control design, see also Gáspár and Németh (2018); Liu et al. (2019). All features (e.g. velocity, driving intentions, position at the intersection) of autonomous vehicles are collected by a centralized controller transmitting measured data and control input for all participants of the traffic situation. As the measurement and transmission can include faults of

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data, the novelty of the proposed control method is the consideration and handling of these uncertainties.

The paper is organized as follows. The challenges of autonomous vehicle control at non-signalized intersections are presented in Section 2. Section 3 deals with the multi-objective fault tolerant control procedure, as well as introducing the constraints in the design. The proposed method is validated with multiple simulation examples presented in Section 4, while conclusions are drawn in Section 5.

2. PROBLEM STATEMENT

The fundamental of the research is to define the design difficulties of autonomous vehicle control at non-signalized intersections. Conventionally the exact ordering at an intersection with traffic lights and signs is given by traffic rules followed by the driver of the vehicles. By the increasing automation in traffic systems, the coordination of autonomous vehicles at non-signalized intersection scenarios have become significant challenge in traffic control design. The strategy of autonomous vehicles at an intersection can be more complex by

- the number of vehicles having different characteristics (e.g. related to danger or priority),
- different types of intersection,
- the predefined traffic rules considered in control design,
- the defined purpose of the control design of the vehicles like the minimization of time, energy losses and fuel consumption,
- the consideration of disturbances and uncertainties.

A non-signalized intersection scenario with several autonomous vehicles is proved to signify more complex situation in designing control for the crossing of the vehicles, see Figure 1. The safety condition of collision avoidance, the achievement of minimizing traveling time or energy consumption and the consideration of uncertainties of the measured data (e.g. distance of the vehicles from the origin of the intersection) affect the control strategy. The proposed multiple step method considers most of the above-mentioned conditions, increasing the complexity of the control design.

The motion prediction of intelligent vehicles is also an important subject in the research, which has been studied already by several authors, see Lefevre et al. (2014), Törő et al. (2019), Goodall (2013). Also, in relation with the driving intention of the controlled vehicles, several research focuses on considering different indicator signals, see Casares et al. (2012), Almagambetov et al. (2015). Another important aspect is the communication methods used between intelligent vehicles and traffic infrastructures Shi et al. (2018), Kokuti et al. (2017).

3. MODEL PREDICTIVE INTERSECTION CONTROL DESIGN

3.1 Intersection scenario

In the examined intersection scenario autonomous vehicles can turn in all possible directions, thus the probability

of collision may arise, see Shen et al. (2019). The aim of the of the research is to design a centralized controller guaranteeing safe travel for all vehicles, while minimizing total time spent in the intersection or total energy consumption of the vehicles. Hence, the proposed controller must define vehicle ordering and accelerations of each controlled vehicles, in order to avoid collision and to fulfill the above stated performances.

The MPC intersection controller algorithm is founded on some presumptions, i.e. a double lane intersection is considered divided into zones as shown in Figure 1.

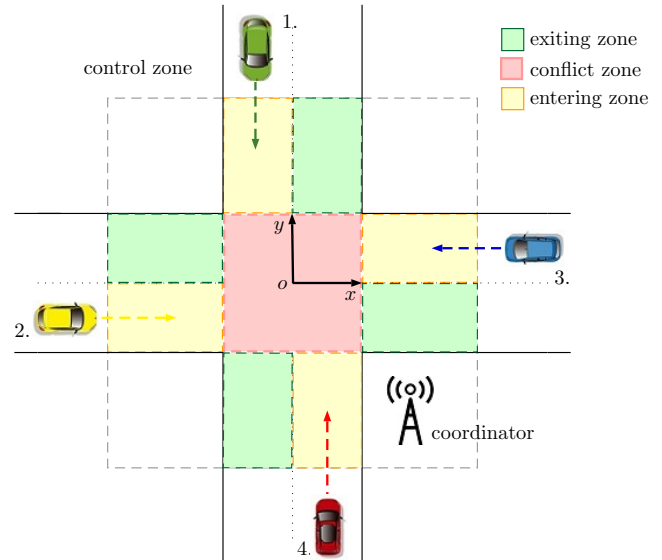


Fig. 1. Illustration of intersection scenario with the relevant zones for the control design

Before entering the control zone, autonomous vehicles are driven independently. In case they enter the control zone, based on their actual velocity and turning goal, the proposed MPC controller designs an optimal velocity trajectory for each autonomous vehicle and transmits the needed acceleration commands via V2I communication. Note, that the proposed calculation is reconfigured in case a new vehicle arrives at the intersection.

3.2 Design constraints

An important aspect in the intersection control design is to secure the motion of the autonomous vehicles by introducing speed constraints $v_{i,max}$ $i \in [1..n]$. Thus, $v_l = \sqrt{R_l g \mu}$ is calculated for left and $v_r = \sqrt{R_r g \mu}$ for right turnings, where R_l and R_r are the corresponding radius given by the intersection geometry, g is the gravitational constant, μ is the road adhesion given by estimation methods, see e.g. Gustafsson (1997); Li et al. (2007); Alvarez et al. (2005). In case of straight heading of the autonomous vehicle $v_s = v_{lim}$ is the only constraint, where v_{lim} is the speed limit on the road. Choosing a common urban intersection with four directions and $\mu = 0.8$ adhesion coefficient, these velocity constraints are $v_r \approx 16$ km/h and $v_l \approx 28$ km/h, while $v_s = 50$ km/h. Note, that maximal and minimal acceleration constraints must also be introduced to preserve passenger comfort, thus $a_{max} = 5$ m/s² and $a_{min} = -5$ m/s² are introduced as

suggested by Bichiou and Rakha (2019). In order to avoid collision between the controlled vehicles, in the centralized design another safety constraint is considered, i.e. only one vehicle can be in the intersection conflict zone at the same time. Note, that oncoming vehicles in the same lane must wait for the previous vehicle to exit the intersection before entering.

3.3 Time-optimal intersection management

In order to reduce the probability of a congestion, one of the performance measure in the control design is the minimization of total traveling time T_{total} . Thus, vehicle ordering and prescribed acceleration is calculated to ensure the biggest velocities achievable at the intersection.

Hence, a constant acceleration a_i $i \in [1..n]$ is calculated for each vehicle in the entering zone by which the maximal velocities $v_{i,max}$ $i \in [1..n]$ can be attained at the exit of the entering zone. The initial step of the iterative optimization is to calculate an initial acceleration for each vehicle as follows:

$$a_i = \frac{v_{i,max}^2 - v_{i,0}^2}{2s_{i,ent}} \quad (1)$$

where $v_{i,0}$, $s_{i,ent}$ $i \in [1..n]$ are the initial velocities and distances from the intersection origin.

In case the calculated acceleration for a vehicle overcomes the threshold value given as a constraint, $a_i = \{a_{max}; a_{min}\}$ are substituted and the maximal entering velocity is modified:

$$v_{i,max} = \sqrt{v_{i,0}^2 + 2a_i s_{i,ent}} \quad (2)$$

The basis of the proposed algorithm is to compare traveling times of the autonomous vehicles, and use a first in, first out (FIFO) method for the decision making in the ordering. In case a conflict situation occurs, vehicle with the smallest traveling time gets priority and does not modify the acceleration value calculated in the first step given in (1). Other autonomous vehicle reduce their calculated accelerations iteratively until their conflict with the first vehicle disappears, and recalculate their traveling time and conflicts among each other in the same manner. In some cases of multiple conflict situations, the stopping of vehicles before the conflict zone is needed and a waiting time is calculated.

In order to define time windows the autonomous vehicles occupy the conflict zone, entering time is calculated first by solving the following equation:

$$\frac{1}{2}a_{i,0}t_{i,ent}^2 + v_{i,0}t_{i,ent} - s_{i,ent} = 0 \quad (3)$$

where $t_{i,ent} \geq 0$ $i \in [1..n]$ is the entering time of the autonomous vehicles. Assuming constant accelerations, the second order equation is simplified as:

$$t_{i,ent} = \frac{s_{i,ent}}{(v_{i,max} + v_{i,0})/2} \quad (4)$$

In the intersection conflict zone it is presumed that vehicles do not accelerate or brake, hence time spent in the conflict

zone is given as $t_{i,con} = s_{i,int}/v_{i,max}$ $i \in [1..n]$, where $s_{i,int}$ depends on the chosen vehicle trajectory.

In case an autonomous vehicle must stop for giving priority, a waiting time is defined before it starts off again. Hence, $v_{i,max} = 0$ is applied in the calculation, and the difference between the final time of the priority vehicle and the entry time of the subject vehicle is given as the waiting time $t_{i,wait}$. After the waiting time is over, i.e. $t > t_{i,ent} + t_{i,wait}$, the vehicle enters the conflict zone with the predefined maximal acceleration a_{max} , thus the time in the intersection conflict zone is given as follows:

$$t_{i,con} = \sqrt{2s_{i,int}/a_{max}} \quad (5)$$

Hence, the final time when the vehicle leaves the intersection is $t_{i,fin} = t_{i,ent} + t_{i,wait} + t_{i,con}$, with the total traveling time for all vehicles is $T_{total} = \max(t_{i,fin}) \quad \forall i \in [1..n]$.

The iterative calculation is evaluated as follows:

- Maximal velocities $v_{i,max}$ $i \in [1..n]$ for all vehicles based on their turning intentions are calculated. Based on their initial positions and velocities, a constant acceleration a_i $i \in [1..n]$ is then given using (1), which is overwritten with $a_i = (a_{max}; a_{min})$ in case the constraints are violated.
- Entry and exit times $t_{i,ent}$ and $t_{i,fin} \in [1..n]$ are then calculated, and conflicts are defined based on the overlapping time windows in the conflict zone.
- When a conflict is detected, autonomous vehicle with the minimal exit time gets priority, while other vehicles reduce their acceleration until their entry time is bigger than the final time of the priority vehicle. The above mentioned process is evaluated for all the following vehicles.
- In case of a new vehicle entering the intersection, an adaptive cruise control mode is set until the preceding vehicle leaves the intersection, in which case the new vehicle joins the algorithm.

3.4 Energy-optimal intersection management

The other performance measure in the intersection control design is the minimization of total energy consumption of the autonomous vehicles, while preserving safety constraints detailed in Section 3.2. Thus, in this case energy optimality is considered in the vehicle ordering and velocity design process, focusing on the minimization of kinetic energy $E_{i,kin} = 0.5m_i v_i^2$ $i \in [1..n]$ loss. For this purpose, autonomous vehicles must send data about their mass m_i $i \in [1..n]$ beside their position and velocity to the coordinator of the intersection.

The calculation of the optimal control inputs is evaluated in a similar iterative manner as in the time optimal case as follows:

- Based on the turning intentions and speed limits, maximal velocities $v_{i,max}$ $i \in [1..n]$ are given for all vehicles entering the intersection. In case the initial velocity $v_{i,0}$ $i \in [1..n]$ is smaller than the calculated constraint, $a_i = 0$ is used for further computation. Else, a_i $i \in [1..n]$ is given by which the maximal velocity can be reached before the conflict zone.

- Entry and exit times based on vehicle positions, velocities and the previously calculated accelerations are given for all autonomous vehicles. If no conflict is detected based on the time windows, the previously given accelerations are used.
- If a conflict situation arise among autonomous vehicles, the vehicle with the biggest kinetic energy $\max(E_{i,kin})$ $i \in [1...n]$ at the entry of the conflict zone gets priority. The iterative reduction of other vehicles acceleration happens similarly to that detailed for the time-optimal case, as well as the handling of newly arrived vehicles at the intersection.

3.5 Operation of the MPC controller

The operation of the intersection MPC control is shown in Figure 2. The coordinator of the intersection collects the position and velocity data $s_{i,ent}(k)$, $v_{i,ent}(k)$ $i \in [1...n]$ of each autonomous vehicle entering the intersection at a discrete time step k using a sampling time T_s , along with their turning intention d_i . For the newly entered vehicle, a decision is made based on the position of the preceding vehicle, whether to add the vehicle to the MPC optimization process, or switch to adaptive cruise control mode. At each discrete time step k , the solution of the time-optimal or energy-optimal vehicle ordering is calculated based on the analytical method detailed in Section 3.4 and Section 3.3 for a time horizon $T = \max(t_{i,fin})$ $i \in [1...n]$, which time horizon depends on the vehicle states and the intersection geometry. The solution of the optimization gives the control variable $a_i(k+1)$ $i \in [1...n]$, which the autonomous vehicles in the intersection follow until the subsequent time step, where the optimization is repeated with the forward shifted horizon. Since the vehicle ordering and prescribed accelerations are recalculated at every time step for vehicles in the entering zone, a sampling time $T_s = 0.1s$ is selected to avoid chattering of the control signals. A method to handle unreliable communication links (noises, packet drops, delays) in the autonomous vehicle trajectory planning has been presented in Chohan (2019). In Khayatian et al. (2018) a robust intersection management method has been presented based on position tracking, compensating the effects of model mismatch and disturbances. Note that present MPC method is inherently robust against bounded initial errors in the measurement signals, since as the accuracy of the signals improve as the vehicles get closer to the intersection origin, the online recalculation of the MPC controller adjusts the vehicle order and control inputs to the punctual data.

3.6 Vehicle control model

The calculated acceleration for the autonomous vehicles a_i $i \in [1...n]$ is accomplished by applying the necessary longitudinal force given as:

$$F_{i,l} = m_i a_i + F_{i,d} \quad (6)$$

where m_i $i \in [1...n]$ is the vehicle mass, $F_{i,l}$ is the control input force, $F_{i,d} = F_{i,a} + F_{i,r} + F_{i,s}$ is the disturbance affecting the vehicle Rajamani (2005). The latter consists the aerodynamic drag $F_{i,a} = 0.5C_{i,d}\rho_i A_i v_i^2$, where $C_{i,d}$ is the drag coefficient, ρ_i is the air density and A_i is the surface of the vehicle. Rolling resistance is given as $F_{i,r} = m_i g f_i \cos(\alpha_i)$, where f_i is the road coefficient and

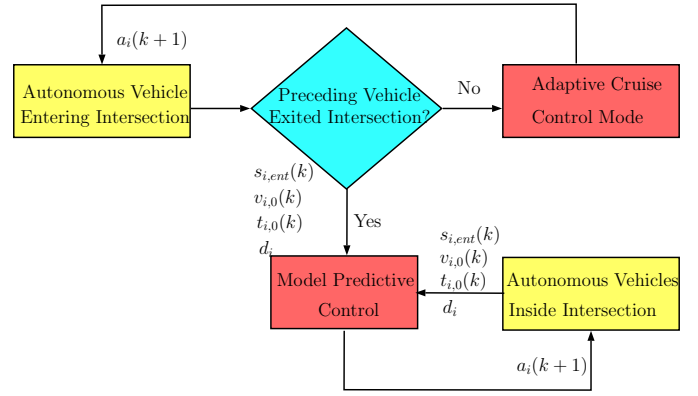


Fig. 2. Intersection control process

α_i is the slope angle. Lastly, the road slope disturbance is given as: $F_{i,s} = m_i g \sin \alpha_i$.

4. SIMULATION RESULTS

The operation of the proposed MPC intersection controller is demonstrated through a complex simulation example performed in CarSim environment. In this scenario five autonomous vehicle arrive to the intersection with turning intentions and initial conditions depicted in Figure 3. For safety purposes a maximal velocity of 50 km/h is allowed for vehicles heading straight, while 30 km/h for vehicles turning left. Note that an initial position measurement error of 2 meters has been added to each vehicle, which errors are assumed to disappear as the vehicles reach the conflict zone, see Figure 4.

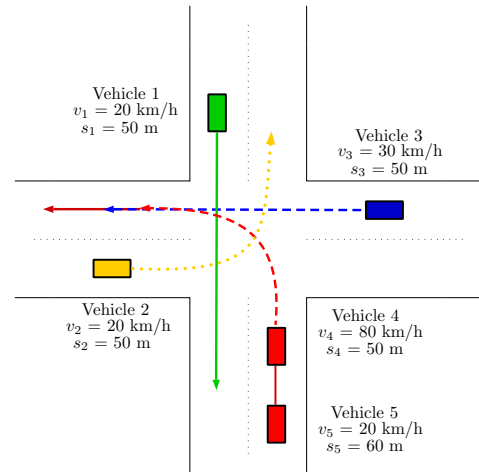


Fig. 3. Intersection scenario with five vehicles

Here, the passing order and velocity trajectory of the autonomous vehicles is determined with the aim to minimize total traveling time of the vehicles. This scenario shows that the arriving fifth vehicle can change the original ordering of the vehicles to achieve the smallest traveling time.

Several conflict arises among autonomous vehicles, due to their turning intentions and initial conditions. All traveling times in the conflict zone and the crossing order are shown in Figure 5 for two distinct time instances with and without the position measurement errors. The first situation in Figure 5 (a) and Figure 5 (b) shows the

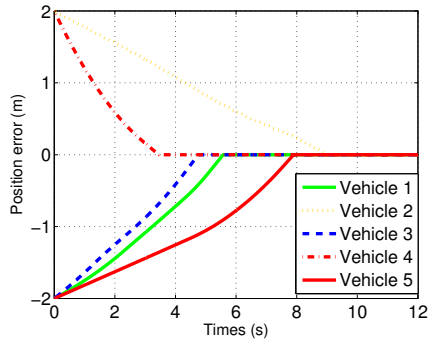
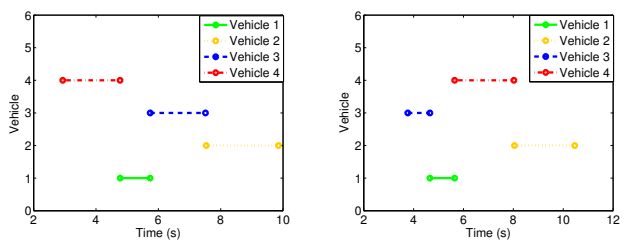


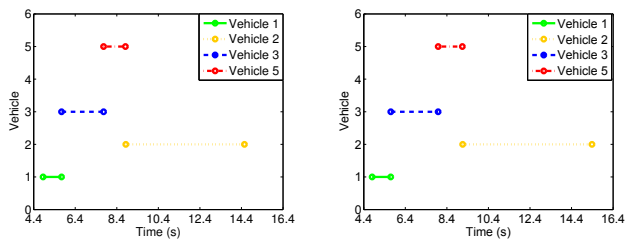
Fig. 4. Position measurement errors

result of the time-optimal solution of the proposed MPC method for the initial state of the vehicles. It is well demonstrated, that calculated initial vehicle orders and the corresponding accelerations differ in the presence of position measurement errors. Since *Vehicle 3* is measured closer and *Vehicle 4* further from the intersection origin, their initial ordering is switched, meaning a suboptimal solution is given for the vehicles.

However, as the vehicles get closer to the center of the intersection and the measurement errors decrease, the vehicle ordering changes to be similar to that without measurement errors. The second situation depicted in Figure 5 (c) and Figure 5 (d) shows the results of the optimization at the point where *Vehicle 4* leaves the intersection conflict zone and the cruise control mode of *Vehicle 5* switches to the centralized MPC control mode. Hence, the original crossing order is modified after *Vehicle 4* exits, thus *Vehicle 5* gets wedged between *Vehicle 3* and *Vehicle 2* during the optimization process in both cases. It is well demonstrated, that the proposed centralized MPC algorithm is suitable for reallocating the vehicle order and prescribed acceleration in case of a new vehicle entering the intersection, and is also able to handle initial position measurement errors effectively.



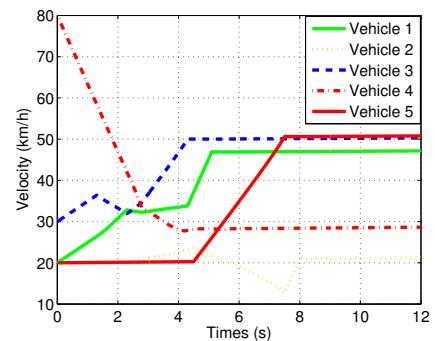
(a) First situation without fault (b) First situation with fault



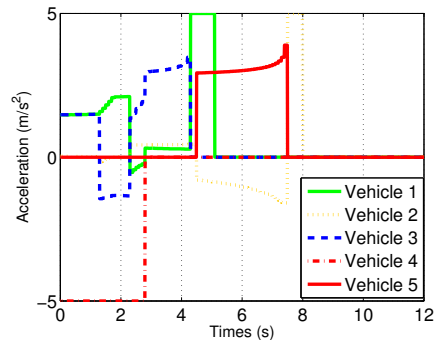
(c) Second situation without fault (d) Second situation with fault

Fig. 5. Traveling time of vehicles in the conflict zone

The speed and acceleration of the vehicles are illustrated in Figure 6(a) and Figure 6(b). It can be seen, that the velocity of *Vehicle 4* is decreasing with the maximal possible acceleration to achieve the speed limitation for turning left at the intersection, and then keeps a constant velocity with zero acceleration. On the other hand, *Vehicle 5* keeps a constant velocity until *Vehicle 4* leaves the intersection, then accelerates with around 3 m/s until reaching the conflict zone. The other vehicles both accelerate and decelerate during their travel in the entering zone due to the reallocation of the crossing order. Note that due to the robust MPC centralized method, the initially unpunctual position error is handled and the prescribed acceleration and corresponding longitudinal force (see Figure 7) is constantly modified slightly as the measurement signals get more and more punctual.



(a) Velocity



(b) Acceleration

Fig. 6. Velocities and accelerations of vehicles in the conflict zone

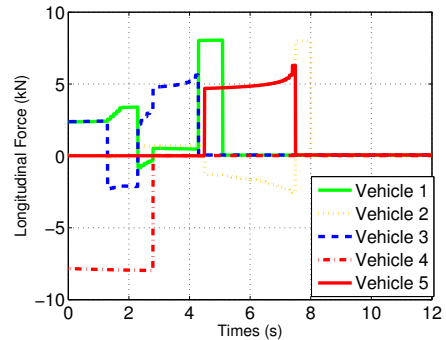


Fig. 7. Actuated control force

5. CONCLUSION

The crossing order of autonomous vehicles at non-signalized intersections is affected by multiple factors. In the control design the main purposes are reduction of traveling time or energy consumption of the vehicles while guaranteeing safety and robustness against measurement noises. The paper proposed a centralized MPC algorithm fulfilling these performance specifications with guaranteeing collision avoidance. The operation of the presented method has been validated with a complex simulation performed in CarSim environment.

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