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Analysis of Model Predictive Intersection Control for Autonomous Vehicles

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Abstract
Autonomous vehicles are in the main focus for automotive companies and urban traffic engineers as well. As their penetration rate in traffic becomes more and more pronounced due to improvement in sensor technologies and the corresponding infrastructure, new methods for autonomous vehicle controls become a necessity. For instance, autonomous vehicles can improve the performance of urban traffic and prevent the formation of congestions with the usage of Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication based control methods. One of the key area for improvement is centralized intersection control for autonomous vehicles, by which traveling times can be reduced and efficiency of traffic flow can be improved, while safety of passengers can be guaranteed through constraints built in the centralized design. The paper presents the analysis of a Model Predictive Control (MPC) method for the coordination of autonomous vehicles at intersections by comparing it with an offline constraint optimization considering time and energy optimal intervention of vehicles. The analysis has been evaluated in high-fidelity simulation environment CarSim, where the speed trajectories, traveling times and energy consumptions have been compared for the different methods. The simulations show that the proposed time-optimal MPC intersection control method results in similar traveling times of that given by the time-optimal offline constraint optimization, while the energy optimal optimization re-quires significantly more time for the autonomous vehicle to achieve. Due to the possibility of a congestion forming in the latter case, the proposed centralized MPC method is more applicable in real traffic scenarios.

Keywords
autonomous road vehicles, Model Predictive Control, constraint optimization, Vehicle-to-Infrastructure (V2I) communication

1 Introduction

An emerging field of scientific research is connected to the development of autonomous vehicle technologies. The aim of these studies is to develop new methods based on state-of-the-art sensor and communication technologies by which the control of autonomous vehicles can provide enhanced safety and better efficiency. One of the key motivation in the development of autonomous vehicle control strategies in urban traffic scenarios is to prevent collision among vehicles at intersections, which is considered the most safety critical areas in urban traffic due to the high number of fatal crashes.

In conventional traffic scenarios with human-driven vehicles, ordering of vehicles and management of traffic is evaluated by traffic lights or traffic rules, which the driver has to follow. As intelligent transportation systems along with autonomous vehicle technology gain more and more attention, several research focus on the coordination and control of vehicles using autonomous functions or advisory systems at non-signalized intersection (Chen and Englund, 2016). These intersection control methods aim to guarantee collision-free passage of the vehicles by developing multi-agent systems (Dresner and Stone, 2008; Zohdy and Rakha, 2012).

Generally, an optimization problem is formed and solved using different methods including convex optimization (Murgovski et al., 2015) or Mixed-Integer Linear Program (Fayazi et al., 2017). For example, a real-time optimal intersection control system has been introduced (Bichiou and

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Rakha, 2019) for autonomous vehicles, where the formulated optimization is subjected to dynamic and static constraints and uses Pontryagin's minimum principle and convex optimization to give a solution minimizing the trip time.

Several methods apply Model Predictive Control (MPC) for centralized and decentralized intersection coordination (Kneissl et al., 2018; Qian et al., 2015; Riegger et al., 2016; Yao and Zhang, 2018). For example, a distributed MPC approach has been introduced (Katriniok et al., 2017), where the non-convex distributed control problem is solved in parallel by applying constraint prioritization.

In recent years, several studies apply artificial intelligence (AI) approaches in the design of intersection controls. Support vector machine, linear regression, and deep learning algorithms has been adapted for the coordination of autonomous vehicles at urban traffic scenarios such as intersection crossings (Chen et al., 2019a; 2019b).

Moreover, several study focus on optimizing network-wide performance of autonomous vehicle based urban traffic by considering microscopic dynamics in junctions and macroscopic model for the whole traffic (Tettamanti et al., 2017).

The motivation of the present paper is to analyze the efficiency of a centralized MPC method introduced earlier (Mihály et al., 2020). The proposed method has the advantage of real-time implementation possibility due to the simplified optimization procedure based on a first-in-first-out (FIFO) strategy. However, as the proposed strategy relies on some simplification in vehicle dynamics and constraints are given based on traffic engineering aspect, the efficiency of the method needs to be validated by comparison with other global optimization solutions. Thus, in the paper three different methods have been compared through a simulation example in CarSim environment: firstly, the operation of the centralized MPC method has been studied, secondly an offline optimization has been evaluated minimizing traveling time, finally the same optimization has been carried out with the aim to minimize control energy requirement from autonomous vehicles.

2 Intersection controller

2.1 MPC intersection control

In the proposed MPC intersection control method, a non-signalized four direction intersection is considered separated into different sections, as illustrated in Fig. 1. A centralized intersection controller is responsible for the coordination of AVs using V2V and V2I communication methods and different on-board sensors (radar, Lidar, GPS, etc.) of the AVs. It is assumed, that the central intersection

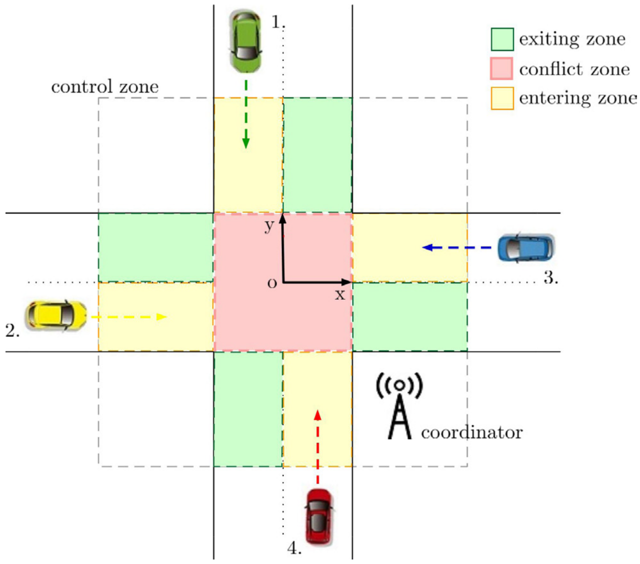

Fig. 1 Intersection scenario for the centralized MPC method

coordinator can receive position and velocity data from AVs and can transmit longitudinal acceleration request signals for the vehicles controlled.

The detailed description of the MPC intersection control algorithm is introduced in earlier paper (Mihály et al., 2020), thus here only a brief summary of the operation is given. The iterative computation of the prescribed acceleration signals, are given as follows: first, each for each vehicle entering the intersection a maximal safe velocity and acceleration is determined based on the turning intention, the geometry of the intersection and the estimated road surface friction. Next, an acceleration value is determined for each AV, buy which the maximal velocity for the given vehicle trajectory can be reached. A safety constraint is set in order to avoid collisions among vehicles, which limits only one AV at a time in the conflict zone. Thus, predicted entry and exit times for each AV are calculated based on their initial positions and speeds along with their planned trajectories in the intersection. The MPC coordination method is based on the analysis of time-overlaps for AVs in the conflict zone, iteratively adjusting prescribed acceleration to eliminate time overlaps. Finally, when a new AV enters the intersection, the algorithm applies the vehicle tracking mode until the previous vehicle exits the conflict zone of the intersection. If this happens, the above the procedure must be repeated with the new initial conditions for all vehicles in the intersection control zone. Hence, the complexity of the calculation does not evolve with the number of vehicles, as only four AVs take part in the detailed MPC procedure at the same time. By using an appropriately small sampling time for the optimization algorithm, the real-time application of the proposed method is possible.

2.2 Simulation based on time and energy optimization

The simulation-based constraint optimization aims to find optimal acceleration values for the AVs by which total traveling time or energy consumption can be minimized, while collisions can be avoided. The constraint optimizations running in MATLAB and CarSim environment is depicted in Fig. 2 and Fig. 3 and is operating as follows:

- Upper and lower bounds for the acceleration values are calculated for all AVs based on their trajectories, which are used as constraints for the optimization.
- The constrained optimization algorithm evaluates the CarSim intersection simulation with the given initial conditions applying different constant acceleration values, which are the variables needed to be found in the minimization procedure.

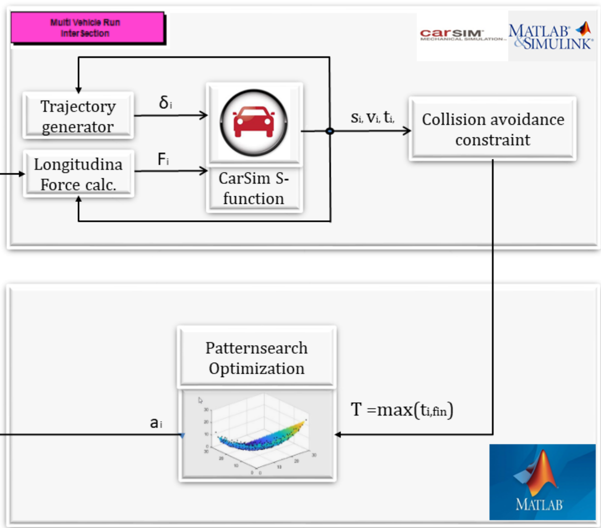

Fig. 2 Time-optimal optimization in CarSim environment

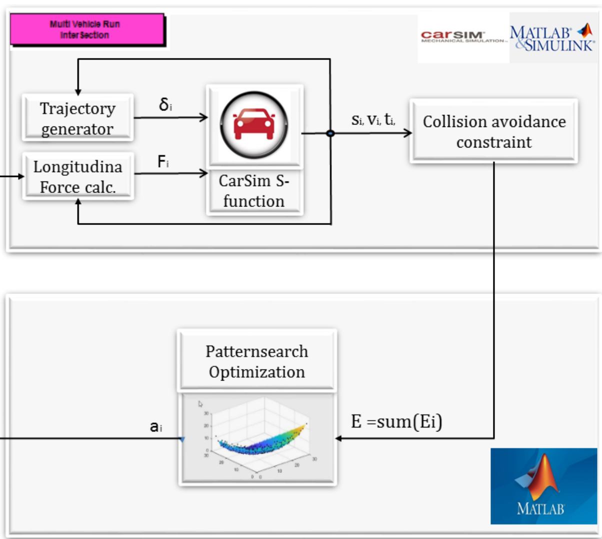

Fig. 3 Energy-optimal optimization in CarSim environment

The objective function of the minimization algorithm for the time-optimal solution is given as the total traveling time of the AVs. Note, that the simulation ends in case the last AV exits the intersection conflict zone. The objective function of the minimization algorithm for the energy-optimal solution is the total actuated energy of the AVs during the simulation. Thus, for the energy optimal solution braking and propulsion forces of AVs are both considered.

Note, that the safety constraint is realized by adding a large number to the objective function in case the inter-vehicular distance of the AVs falls below 3 meters, in which case the algorithm discards the corresponding acceleration values. Note, that the value of this inter-vehicular safety distance can be tuned in order to reach either a more optimal solution with higher risk of collision due to sensor noises and thus unpunctual vehicle data, or vice versa.

The constrained optimization runs the predefined CarSim intersection simulation iteratively until it founds the best acceleration values for the AVs by which a local minimum for the traveling time or energy consumption can be reached.

A more detailed description of the Pattern Search Algorithm has already been introduced (Lewis and Torczon, 2000; Torczon, 1997).

3 Simulation results and discussion

The proposed real-time optimal MPC intersection control method has been compared to the results of the two offline optimization performed in CarSim environment: the time-optimal and energy optimal solution.

For the simulation, a typical four directional intersection has been designed in CarSim, similar to that illustrated in Fig. 1. The four simulation vehicle has been selected with the parameters of a conventional midsize vehicle with 1600 kg of mass and 2.7 m of wheelbase, while their initial position has been set to 50 m from the origin of the intersection, as depicted in Fig. 4. Note, that their initial velocities and their turning intention differ: *Vehicle 1* (green) approaches the intersection entering zone at 30 km/h and heads straight on, *Vehicle 2* (yellow) arrives at 20 km/h and turns left, *Vehicle 3* (blue) enters the intersection at 40 km/h and heads straight on, while *Vehicle 4* (red) is the slowest with an initial velocity of 10 km/h and turning left.

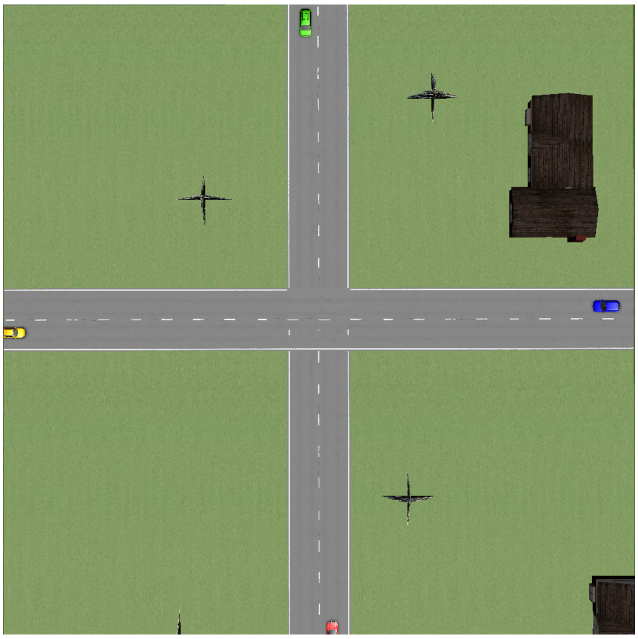

Fig. 4 Initial conditions for the AVs at intersection

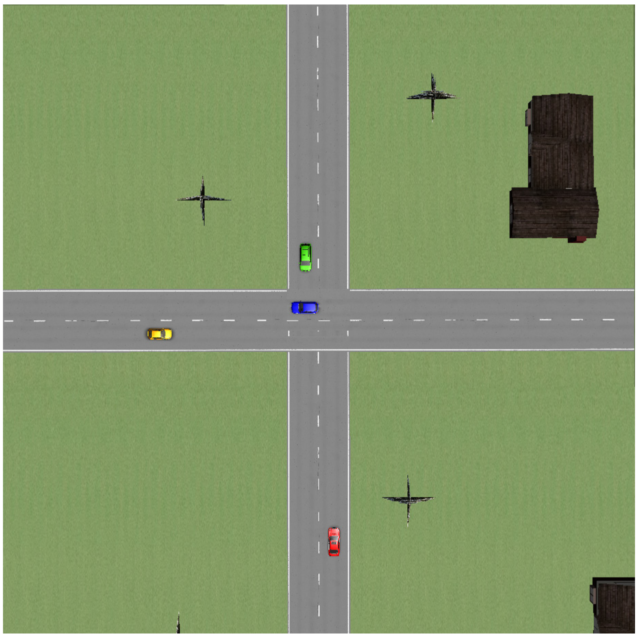

Fig. 5 First (blue) AV crossing intersection with MPC controller

The ordering of the autonomous vehicles along with their velocity trajectories has been coordinated with the MPC control method by the central coordinator in the first case using a sampling time of 0.1 seconds. Here, *Vehicle 3* having the highest initial velocity crosses the intersection first, as depicted in Fig. 5. Next, *Vehicle 1* drives through the intersection shortly after *Vehicle 3* left the conflict zone, as depicted in Fig. 6. Thirdly, *Vehicle 2* crosses the intersection and turns left, see Fig.7. Finally, *Vehicle 4* drives through the intersection by turning left, where the simulation ends as it leaves the conflict zone, see Fig. 8.

The velocity profiles of the autonomous vehicles coordinated by the MPC controller are depicted in Fig. 9. It is well demonstrated, that in order to achieve a small traveling time each AV accelerates to reach the desired velocity profile for their given trajectories. Thus, *Vehicle 1* and *Vehicle 3* heading straight accelerates trying to reach the speed limit without collision, thus their final velocities are the biggest as they leave the conflict zone. *Vehicle 2* and *Vehicle 4* follows them with approximately one seconds of time lag, as they have to limit their velocity to approximately 28 km/h to meet the safety constraint of the left turn, while also avoid collision among each other.

The time interval spent in the conflict zone for the AVs is illustrated in Fig. 10. showing that total traveling time in this intersection scenario with the proposed MPC control is 10.45 seconds.

Next, the offline optimization detailed in Section 2.2 and illustrated in Fig. 2 has been evaluated with the same initial condition for the AVs. Note, that this constraint optimization procedure cannot be applied for real-time applications, as the optimization process has significant computational time. Moreover, even small changes in initial conditions can result in different outcomes for vehicle acceleration, thus in this paper this method is only used for comparison. The result of the constraint optimization has been the following: *Vehicle 1* and *Vehicle 2* both have 0.0156 m/s^2 of longitudinal acceleration, *Vehicle 4* uses 0.583 m/s^2 of acceleration, while *Vehicle 3* applies zero acceleration.

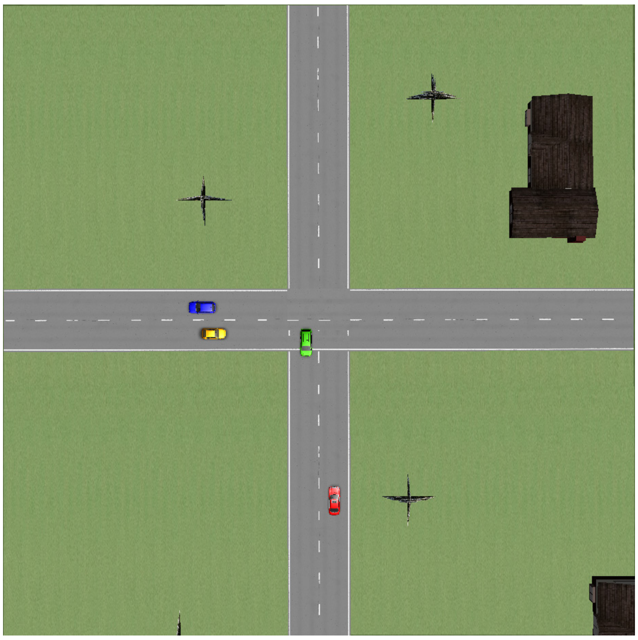

Fig. 6 Second (green) AV crossing intersection with MPC controller

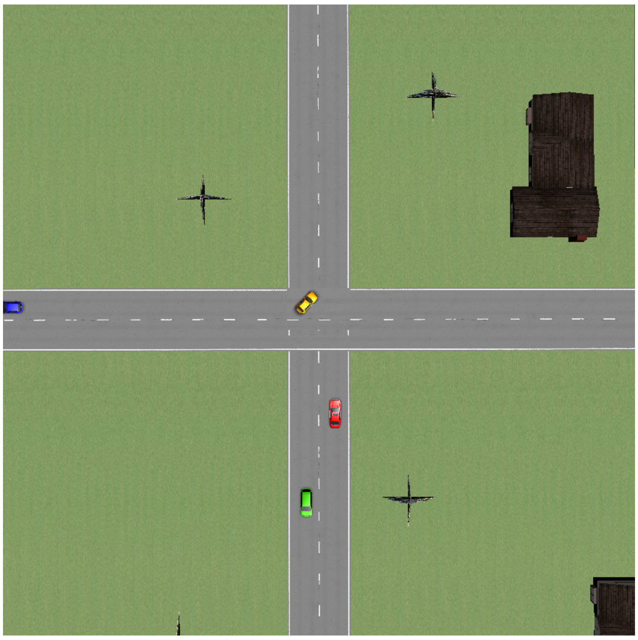

Fig. 7 Third (yellow) AV crossing intersection with MPC controller

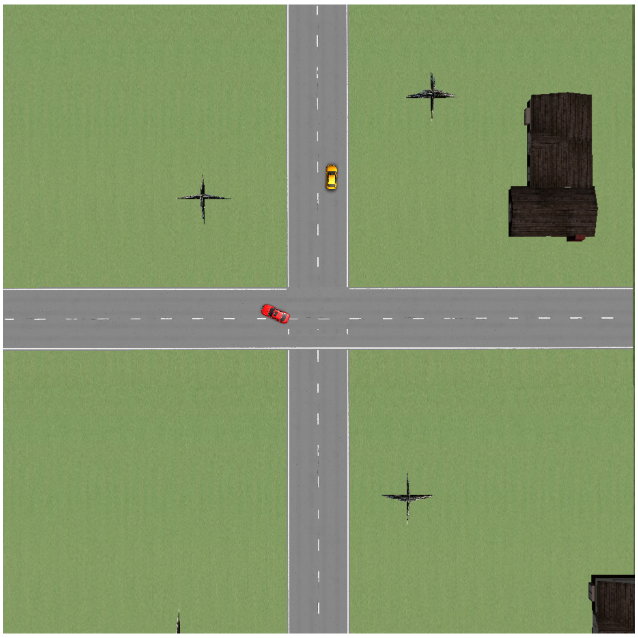

Fig. 8 Fourth (red) AV crossing intersection with MPC controller

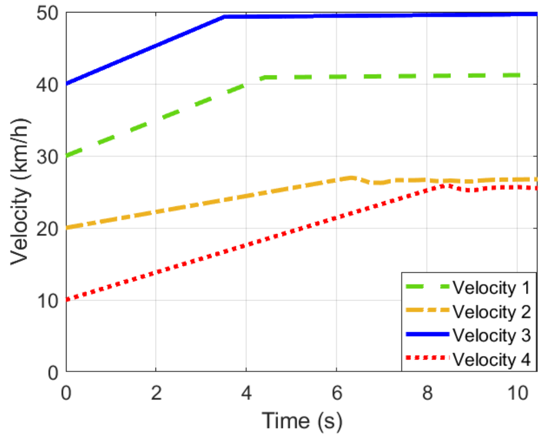

Fig. 9 Speed trajectory of AVs crossing intersection MPC method

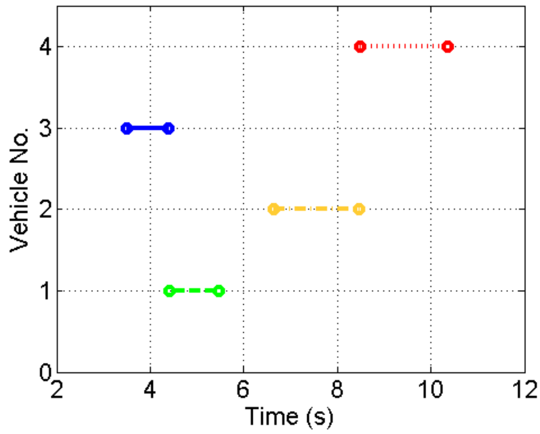

Fig. 10 Time spent in the conflict zone by AVs

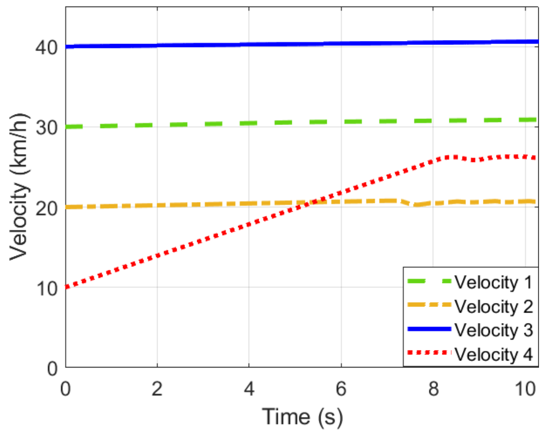

Fig. 11 Speed trajectory of AVs with time-optimal method

The speed profiles of the AVs as a result of the offline time-optimal optimization is illustrated in Fig. 11. Note, that the ordering of the vehicles are similar of that given by the MPC method. For the given scenario, it is well illustrated that the total traveling time used for the cost function of the minimization procedure depends heavily on the AV having the smallest initial velocity. Thus, *Vehicle 4* is the only vehicle accelerating heavily, which results in a total traveling time of 10.35 seconds. Note, that this traveling time given by the offline-optimization is only 0.1 seconds better than that given by the time-optimal real-time MPC method.

The speed profiles of the AVs as a result of the offline energy-optimal optimization is illustrated in Fig. 12. The ordering of the vehicles are the same as in the real-time MPC and time-optimal optimization method, however, accelerations of AVs are closer to zero, in order to reduce control energy. This results in that *Vehicle 4* leaves the

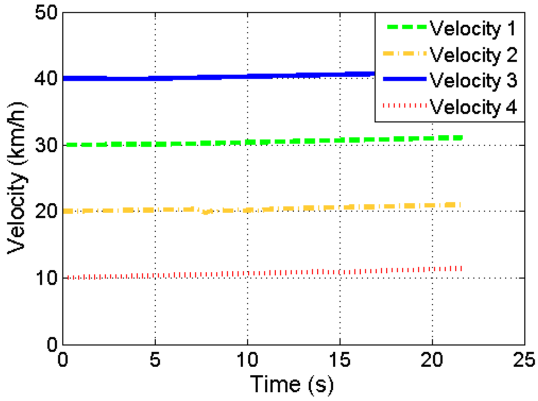

Fig. 12 Speed trajectory of AVs with energy-optimal method

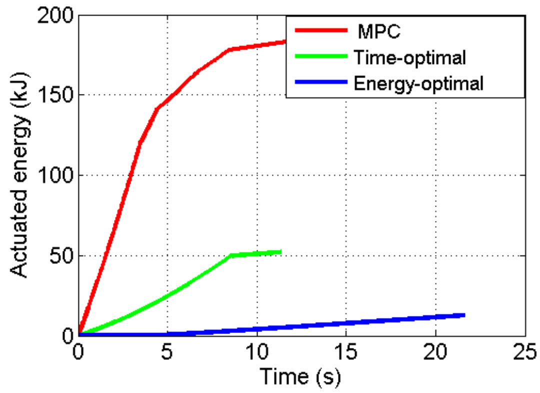

Fig. 13 Actuated control energy for the different methods

intersection conflict zone at 21.62 seconds, thus total traveling time of AVs is more than twice as much as in case of the time-optimal solutions detailed above.

Next, the actuated energy (both braking and propulsion) has been compared for the three different methods, as illustrated in Fig. 13. As expected, the smallest amount of energy is required by the result of the offline energy-optimal optimization, followed by the time-optimal optimization method, with approximately four times more control energy required. Finally, the real-time MPC method required significantly more control energy, as AVs are accelerated to the possible biggest velocities given by the constraints.

Note, that actuated energies are only calculated until AVs leave the conflict zone of the intersection, thus the real total actuated energy of the AVs may vary significantly, as they might speed up after leaving the conflict zone. Hence, depending on the traffic environment, the total actuated energy for AVs might come close to each other considering the consumption of the exiting zone, which is not included in this analysis.

4 Conclusion

In the paper an MPC intersection control method for autonomous vehicles has been analyzed by comparing the operation of the MPC coordination to the results of two different offline optimizations performed in CarSim environment. For the proposed four-directional intersection scenario it has been shown, that the suggested baseline MPC coordination method performs very close to the offline time-optimal constraint optimization. However, as it requires more control energy by the AVs, future work should include the consideration of preceding vehicles in the intersection exiting zone in order to avoid unnecessary accelerations of the vehicles.

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