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# Evaluation of Decentralized Algorithms for Coordination of Autonomous Vehicles at Intersections

SeyedeZahra Chamideh[1], William Tärneberg [2] and Maria Kihl [3]

*Abstract*— **Connected Autonomous Vehicles (AVs) with Vehicle-to-Vehicle (V2V) communication are becoming an essential component of the transportation system. Self-driving cars have the potential to optimize the roads' traffic flow, fuel consumption and remove the possibility of human error and distractions. In these systems, all involved vehicles must be fully autonomous for maximum gain. However, a fully automated system requires major updates in the transportation and network infrastructure. In this paper, we investigate intelligent traffic control mechanisms for autonomous vehicles at intersections as a replacement of traditional intersection control (i.e traffic lights). Two well-cited decentralized optimization algorithms for cooperative vehicles are compared with realistic simulations in SUMO. We investigate the safety and feasibility of deploying the proposed algorithms in the real world. Further, we study the scalability and performance of the algorithms in the presence of communication impairments associated with wireless channels. This side-by-side comparison helps to gain insight into the strengths and limitations of these types of algorithms.**

## I. INTRODUCTION

Intelligent Transportation Systems and in particular Autonomous Vehicles (AVs) combined with cooperative strategies will likely have a significant effect on future traffic management systems. Currently, road intersections are controlled by traffic lights. However, these systems are burdened with several fundamental problems. For example, human recognition errors or vehicles unnecessarily braking can result in many accidents and significantly increase travel times [1], [2]. Therefore, there is a rising concern on the efficiency and safety of traditional intersection management methods. Recent advances in embedded sensors, on-board computing combining with communication technologies [3], [4], have enabled the emergence of Autonomous Intersection Management (AIM) strategies that can remove the need for traffic lights.

Papers proposing traffic control strategies and coordination algorithms in the context of AVs, usually formulates the problem as an optimization problem. The main objective is to find the best trajectories and vehicles' passing sequences through negotiation and cooperation between road users and infrastructure, by considering system dynamics and collision avoidance constraints. However, imperfect system models for vehicles' dynamic and non-ideal wireless communication channel lead to uncertainties that make the design of a perfect control algorithm challenging.

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[1] Department of Electrical and Information Technology Lund University, Sweden Seyedezahra.chamideh@eit.lth.se
[2] Researcher with the Department of Electrical Information Technology Lund University, Sweden william.tarneberg@eit.lth.se
[3] Professor in the Department of Electrical and Information Technology Lund University, Sweden Maria.kihl@eit.lth.se

Cooperative intersection management can be classified into three main categories: centralized, distributed and hybrid [5]. Centralized methods rely on a central intersection manager that gives instructions to vehicles based on the collected information from wireless communications. In distributed methods, decisions are made locally by each vehicle based on the information achieved by negotiation between vehicles and observation of the environment through local sensors. In hybrid methods, vehicles are allowed to communicate with each other and with a centralized intersection manager in order to have a more efficient intersection management.

In [6] and [7], centralized optimal intersection controllers for autonomous vehicles were proposed. Centralized approaches have been shown to work well in numerical simulations and theoretical analysis. However, our investigation in [8] shows that centralized methods are poorly scalable when the vehicle density increases and finding an exact solution becomes intractable for realistic vehicles densities. Therefore, these algorithms are practically limited to intersections with low vehicle densities, for example rural areas or city intersections during night.

In order to solve the complexity and scalability problems of the centralized approaches, distributed methods can be introduced. Here, each vehicle inside the intersection area solves a problem that is much smaller and easier to solve than in centralized approaches. In [9], [10], a distributed algorithm is proposed where vehicles sequentially solve a local optimization problem to avoid collisions. The solution is based on a receding horizon formulation with a predefined decision order. Authors complement their previous work [9], and combined the proposed optimal controller with a sequential decision making in [11]. Each vehicle's decision depends on already decided and available solutions from the preceding vehicles.

A non-linear Model Predictive Control (MPC) approach was proposed in [12]. At each optimization step, each vehicle has to find an optimal control input based on the predicted trajectories of vehicles in the intersection with the objective to minimize travel times. In [13], a linear non-convex distributed MPC approach was proposed, where all coordinated vehicles can solve the problem simultaneously.

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The overall aim of our research is to develop robust and safe AIM systems for cooperative vehicles. Obviously, an fully autonomous intersection control system must guarantee total safety for passengers, that is, no collisions can occur, which means that the collision probability must be zero for all possible scenarios. Further, the computational requirement of an algorithm must be limited, in order to be feasible to run in real-time. Also, the control system must be robust to communication uncertainties, since the wireless communication will never be 100% perfect in a vehicular scenario.

In this paper, we compare the previously mentioned decentralized intersection control algorithms [11], [13] by implementing them in the realistic simulation environment SUMO [14]. We have chosen these two algorithms, since they have different optimization approaches for the same type of intersection control, and they are well-cited in the literature. Our investigation shows that both algorithms have the potential to improve traditional signalized methods for commonly used performance metrics such as *average traveling speed*, *fuel consumption* and *intersection throughput*.

However, in order for an AIM algorithm to be deployed in the real world, where vehicles cannot be allowed to collide, performance metrics as *collision probability*, *scalability*, and *robustness* will be much more important performance metrics. For these performance metrics, both algorithms perform well only for low traffic densities. When the traffic density increase, none of the algorithms will be able to keep a collision probability of zero. Also, none of the algorithms are robust to packet losses, since they both assume that all information needed for the optimization is delivered with 100% reliability. Our main conclusion is that these algorithms only work very well for low traffic densities and in order to use them in high traffic intensity they need to be modified and combined with centralized methods.

## II. TARGETED SYSTEM

Intersections are the most common cause of traffic congestion in urban transportation networks [15]. Congestion wastes time, fuel and creates more uncertainty for travelers [16].

In this papers, we consider the problem of Autonomous Vehicles coordination at a crossroad intersection without traffic lights. Coordinated intersection traffic management enables a vehicle to communicate with roadside equipment or other vehicles, and thereby improves the road traffic safety and efficiency. The system is composed of vehicles equipped with On Board Unit (OBU), which may employ a wide range of sensors. The OBUs are connected to computing nodes and receive messages from other entities via wireless communication links.

The fully automated vehicles cooperate by exchanging information through 5G enabled Cellular Vehicle-to-Everything (C-V2X) technology where vehicle to everything (V2X) communication is enabled with both cellular network based links through the infrastructure and direct communication links between vehicles and other entities over sidelink (PC5) interfaces [17]. For 5G, 3GPP Release 16/17 has specified a reliability of 90-99.999% with a maximum end-to-end latency of 3-100 ms, when considering a data rate of 10-50 Mbps broadcast messages between vehicles within a communication range of about 360-700 meters for advance driving scenarios [18].

In our scenario, each vehicle can transmit a message informing about its characteristics, position and movement to all its neighbors within a defined range through direct inter-vehicle V2V communication links. In order to have a desired trajectory for vehicles, the longitudinal velocity of each vehicle is defined as the system output, which should be controlled by the acceleration at each time step. We consider a limited speed and acceleration, and, since the vehicles are not allowed to make U-turns at the intersection area, the minimum speed is always positive along their path. The maximum allowed speed on the road is defined by $v_{max}$. In addition, the maximum acceleration and deceleration are described by $u_{min}$ and $u_{max}$, respectively. However, maximum and minimum acceleration of each vehicle depends on its current velocity and speed limitation.

## III. INVESTIGATED ALGORITHMS

In this paper, we investigate the performance of two decentralized AIM algorithms. The first algorithm is the *Model Predictive Control* algorithm [13], which be called the *MPC algorithm* in the rest of the paper. In this algorithm, all coordinated vehicles solve a local optimization problem in parallel by predicting the system model in a given finite prediction horizon. The second algorithm is the *Pure Sequential* algorithm [11]. This algorithm defines a linear fast converging optimization problem for each vehicle to solve sequentially. In the MPC algorithm, the objective for each vehicle is to maintain a minimum distance to the vehicle ahead. In the Pure Sequential algorithm, the goal for each vehicle is to reserve a safe time slot to cross the intersection.

We surveyed the advantages and disadvantages of the algorithms by implementing them in the realistic Simulation of Urban MObility (SUMO) [14]. In this section, we first describe our general system model and then present high level descriptions of the two algorithms.

### A. System Model

In this section we present the system model that is used by the Autonomous Intersection Management algorithms. $\mathcal{N}_t = \{1, 2, \ldots, N_t\}$ AVs exist in a coordination area of an intersection at time $t$. Each vehicle $i \in \mathcal{N}_t$, has a predetermined path $\gamma_i$ that is perfectly followed. $p_i(t)$ is the position (the distance from the center of the intersection) of vehicle $i$ along its paths at time $t$. Similarly, $v_i(t) = \dot{p}_i(t)$ and $u_i(t) = \ddot{p}_i(t)$ denote the velocity and acceleration of vehicle $i$.

The longitudinal motion of each vehicle, $x_i = [p_i, v_i]^\intercal \in \mathcal{X}_i$, is defined as the system state and can be controlled by its acceleration. We assume that the control input is updated in discrete time $\tau$. The discrete time state model of vehicle $i$ is given in equation (1).

$$x_{i,t+1} = \begin{bmatrix} 1 & -\tau \\ 0 & 1 \end{bmatrix} x_{i,t} + \begin{bmatrix} -\frac{1}{2}\tau^2 \\ \tau \end{bmatrix} u_{i,t} \tag{1}$$

The state space model (1) represents the relation between the acceleration as the input of the system and the longitudinal motion of vehicle $i$. As described in II, a limited speed and acceleration is considered for the system states, These above-mentioned limitation result in the following inequality constraints on the input and the states of the system:

$$\begin{aligned} & u_{min} \leq u_{i,t} \leq u_{max} \qquad \forall t \geq 0 \\ & 0 \leq v_{min} \leq v_{i,t} \leq v_{max} \qquad \forall t \geq 0 \end{aligned} \tag{2}$$

### *B. Data Dissemination*

Information exchange between the involved vehicles is crucial to solve the optimization problems, regardless of how the control problem is modeled. Communication between vehicles will be affected by the impairments associated with the wireless channels, which will lead to packet drops and/or random latency in packet arrivals. In this section we will describe how information is disseminated between vehicles.

In the MPC approach every vehicle $i \in \mathcal{N}_t$ solves its local optimization problem at time $t$. The optimization problem results, that is, the vehicle characteristics, position and movement, are immediately broadcast to all its neighbors within its radio range at time $t+1$. Therefore, in each time instance the total number of $N_t$ messages are required to be exchanged between involved vehicles.

In the Pure Sequential approach, vehicles need to sequentially solve the local optimization problems. Initially, vehicles cooperatively agree on a decision order, which enables a sequential decision-making procedure. Each vehicle solves a local problem and then the expected occupancy times are broadcast over wireless communication links to the remaining vehicles. Therefore, the total number of $(N\tau + 1)N_t$ messages are required to be exchanged between the vehicles, where $N$ is the rate of vehicle arrivals per second.

### *C. Model Predictive Control algorithm*

In this section, we give a high-level description of the *Model Predictive Control (MPC)* algorithm proposed in [13].

The MPCs methods are generally used to represent the behavior of complex dynamic systems. An MPC algorithm uses the current measurements, dynamic system model and the system limitations to predict future changes and allows the current time slot to be optimized. The MPC is an iterative optimization model that in each time slot, compute a cost minimizing control strategy for a time horizon in the future. Only the first step of the calculated control strategy is implemented and the calculation will be repeated for the next time slots [19].

In order to use the MPC for our dynamic system represented in (1) and then calculate the optimal control strategy, $u_{i,t}$, we need to define the system cost, which is a function of system's states $x_i = [p_{i,t}, v_{i,t}]$, and the control input $u_{i,t}$ based on the algorithm objectives. The paper [13] defines three main objectives for the intersection control algorithm along with safety constraints. To avoid any rear-end collisions and that every vehicle $i \in \mathcal{N}_t$ passes the intersection in a safe way, a minimum separation distance between two vehicles on the same lane, $d_{min}$, is defined. The following constraint in equation (3) is defined to prevent rear-ends collisions between vehicle $i$ and its leading vehicle $j \in \mathcal{L}_{i,t}$ where $\mathcal{L}_{i,t}$ is the set of vehicle's $i$ leading vehicles.

$$p_{i,t} - p_{j,t} \geq d_{min} \qquad j \in \mathcal{L}_{i,t}, \forall t \geq 0 \tag{3}$$

To ensure that no collisions occur between vehicle $i$ and vehicle $j$ from different approaching lanes inside the critical zone, i.e a side collision, a linear inequality constraint is defined as in equation (4) below.

$$|p_{i,t} - p_{j,t}| \geq R_{min} \quad p_{i,t} \wedge p_{j,t} \geq 0, \gamma_j \in \Gamma_i, \forall t \geq 0 \tag{4}$$

Where $\Gamma_i$ is a set of all paths that have the potential to collide with vehicle $i$ from path $\gamma_i$. $R_{min}$ is a constant that denotes the minimum separation distance between the centers of two vehicles. (4) is a non-convex inequality, which results in a non-convex optimization problem.

Further,a problem cost function needs to be defined. The first objective is that the vehicles should cross the intersection with almost constant and high speed, which is called the desired speed ($v_d$). The second objective is to achieve a minimum fuel consumption, which translates into minimizing the absolute accelerations and acceleration rate. In addition, a smooth flow of vehicles, and thereby, a smooth change of acceleration is desired. Therefore, the system cost for vehicle $i \in \mathcal{N}_t$, $J_i$ is defined as in (5) where $v_{i,t}$ and $v_d^i$ are the MPC algorithm control and reference variables, respectively, and $u_{i,t}$ is the manipulated variable.

$$\begin{aligned} J_i = & \sum_{t=0}^{T} (w_{v_i}(v_{i,t+1} - v_d^i)^2 + w_{u_i}(u_{i,t})^2) + \\ & \sum_{t=0}^{T-1} w_u(u_{i,t+1} - u_{i,t})^2 \end{aligned} \tag{5}$$

Here, $w_{v_i}$ ,$w_{u_i}$ and $w_u$ are weight coefficients and $J_i$ is the problem cost for vehicle $i$ to be minimized, subject to the given current states of the vehicles as defined in (1) and constraints as defined in (2), (3) and (4). Solving the optimization problem with these safety constraints is a challenging task due to its non-convex nature. To cope with non-convex limitation a semi-definite programming relaxation is applied in the paper, which is achieved by introducing a priority scheme on vehicles, such that a vehicle with lower priority must give right of way in case of a potential conflict.

### *D. Pure Sequential Algorithm*

In this section, we give a high-level description of the Pure Sequential algorithm proposed in [11]. This collision avoidance solution relies on the design of a controller that prevents the system of reaching a given configuration. The paper [11] defines, for each vehicle $i$, the critical set $C_i$ as the set of all displacements along its path leading to a potential collision. Thus, $C_i$ can be defined as:

$$C_i \triangleq \{x_{i,t} \in \mathcal{X}_i | p_{i,t} \in [L, H]\} \tag{6}$$

Where $[L, H]$ describes the junction boundary. Therefore, the set of all conflicting configurations that result in collision at intersection can be represented as in equation (7).

$$\mathcal{S} = \{x \in R^n : \exists(i,j) \in \mathcal{N}_t, (x_{i,t} \in C_i \wedge x_{j,t} \in C_j)\} \quad (7)$$

Safety is ensured if only one vehicle, $i$, is allowed to cross the critical area at time $t$. To avoid collision, vehicle $i \in \mathcal{N}_t$ needs to reserve a time slot to cross the critical zone. Therefore, the safe state set for vehicle $i$ can be defined as follow:

$$C_i^{safe} = \{x_{i,t} \in \mathcal{X}_i | p_{i,t} \in [L, H], t \in \mathcal{K}_i\} \quad (8)$$

Where $\mathcal{K}_i$ is a unique time slot, $\mathcal{K}_i \neq \mathcal{K}_j$, when only vehicle $i$ is allowed to cross the intersection. The objective of each vehicle $i$ is to find the $\mathcal{K}_i$. For this aim, the already reserved time slots need to be known as a constraint, in order to solve the local control problem. Therefore, it is necessary to define a decision order set for the vehicles in $\mathcal{N}_t$. The decision order $\mathcal{O}$ is a permutation of the indices in $\mathcal{N}_t$, where vehicles will solve the optimization problem sequentially based on this decision order set. Let $\mathcal{O}_i^b$ and $\mathcal{O}_i^a$ be the sets having the indices of all vehicles $j \neq i$ appearing before and after $i$ in $\mathcal{O}$ respectively. For simplicity, in this paper, a first-come-first-served protocol is used for the decision order policy. This means that if vehicle $j$ arrives earlier than vehicle$i$, then $j \in \mathcal{O}_b^i$.

Vehicle $i$ in the decision order will solve the two sub-problem explained as follows.

**Problem A:** Finding the optimal control policy such that vehicle $i$ enters the intersection only after all preceding vehicle(s) $j \in \mathcal{O}_i^b$ have crossed the intersection.

**Problem B:** Finding the optimal control policy such that vehicle $i$ exits the intersection only before any preceding vehicle(s) $j \in \mathcal{O}_i^b$ enters the intersection.

For each vehicle $i \in \mathcal{N}_t$, the expected occupancy time of the intersection at time $t$ can be expressed as (9), and the sum of the occupancy times of all preceding vehicles of vehicle $i$ is shown in equation (9a)

$$\mathcal{I}_i = \{k \in R : x_{i,t+k} \in C_i\} \quad (9)$$

$$\mathcal{T}_i = \sum_{j \in \mathcal{O}_b^i} \mathcal{I}_j \quad (9a)$$

Therefore, for vehicle $i$ in *Problem A*, the earliest intersection entry time is $T_{max} = \max\{\mathcal{T}_i\}$ and the latest intersection exit time in *Problem B* is $T_{min} = \min\{\mathcal{T}_i\}$. The Problems A and B can then be formulated as the following constrained linear quadratic regulator (LQR) programs in equation (10).

$$\min_{u_{i,t}} \quad J(x_{i,t}, u_{i,t}) \quad (10)$$

$$s.t \quad (1), (2) \quad (10a)$$

$$p_{i,T_{max}} < L \quad \text{If Problem A} \quad (10b)$$

$$p_{i,T_{min}} < H \quad \text{If Problem B} \quad (10c)$$

The constraints (10b) and (10c) are sufficient to ensure that vehicle $i$ is outside the critical area during $\mathcal{T}_i$. Both problems A and B are the combination of two optimization sub-problems. First, a finite time solution optimization problem defines a collision free trajectory up to time $T_{max}$ ($T_{min}$ for problem B). Second, an infinite optimization problem defines the trajectory for all times after $T_{max}$ ($T_{min}$ for problem B).

The algorithm considers the same cost function for all vehicles and given as (11) for finite sum-problem A:

$$J_i = \sum_{t=0}^{T_{max}} w_{v_i}(v_{i,t+1} - v_d^i)^2 + w_{u_i}(u_{i,t})^2 \quad (11)$$

The same holds for the cost function of the finite sub-problem for $B$, if $T_{max}$ is replaced by $T_{min}$ in (11). For the second sub-problem, it is assumed that the only objective is to minimize the deviation of the vehicle's speed from the desired value. Therefore, the infinite optimization problem can be defined as $\sum_{t=0}^{T}(v_{i,t+1} - v_d^i)^2$ subject to (1) ,(2) where $T$ is an arbitrary time step.

## IV. EVALUATION

In this section, we describe our simulation environment and experiments with the objective to evaluate the performance of the proposed decentralized algorithms, and investigate the safety, scalability and feasibility of implementing them in the real world.

### A. Evaluation Environment

To evaluate and compare the control methods, a realistic simulation program based on Simulation of Urban MObility (SUMO) [14] has been developed. SUMO is an open source, highly portable, microscopic traffic simulator that gives the user control over all aspects of the network. In our work, we have modified SUMO by allowing each vehicle's movement to be controlled by proposed algorithm control strategy instead of using the default microscopic flow algorithms.

In our simulation all vehicles have the same physical properties and they arrive to the intersection according to a pre-generated traffic demand stored in a route XML-file. In route file the vehicles' arrivals are randomized based on a Poisson distribution and the probability that trips will start/end at the different entrance/exit lanes are the same.

### B. Experiments

In this work, we consider a four-way intersection with two lanes in each way. Each lane is 3.5m wide with a maximum speed limit of 20m/s, i.e., about 70 km/h. We assume that the vehicles enter the intersection with an arbitrary initial speed close to desired speed. In addition, the intersection area is modelled as a circle with radius 150m. Table I summarizes the simulation parameters and specifications that we used in our simulation program.

The scalability and the feasibility of the control algorithms were evaluated for different traffic flow rates, i.e. the rate at which vehicles pass a given point on the roadway.

### C. Evaluation Metrics

In this paper, we use the following performance metrics when we evaluate the algorithms:

- **Average speed** of vehicles. An algorithm is well performed in term of speed when all vehicles travel at similar velocity and the relative movement is smooth.

TABLE I: Simulation Parameters

| General Parameters | | |
|---|---|---|
| $v_d^i$ | 16 $m/s$ | Targeted Speed |
| $u_{max}$ | 5 $m/s^2$ | Maximum acceleration |
| $u_{min}$ | -6 $m/s^2$ | Maximum deceleration |
| $v_{max}$ | 20 $m/s$ | Maximum speed |
| $v_{min}$ | 0 $m/s$ | Minimum speed |
| **MPC** | | |
| $T$ | 10 $s$ | Prediction horizon |
| $R_{min}$ | 7 $m$ | Minimum separation distance between vehicles from different approaching lane |
| $d_{min}$ | 7 $m$ | Minimum separation distance between vehicles in the same lane |
| **Pure Sequential** | | |
| $L$ | 7 $m$ | Junction lower bound |
| $H$ | -7 $m$ | Junction upper bound |

- **Fuel consumption** is a form of thermal efficiency, and an algorithm with lower fuel consumption is desired.
- **Throughput** An intersection can be modeled as a queuing system where the maximum throughput of an intersection can be calculated as either the maximum number of vehicles that can coexist in an intersection, or the minimum time a vehicle spends in the intersection.
- **Safety**: AIM methods usually perform well for low traffic density. However, for high flow rates, a feasible solution with safety constraints, may be harder to find. An infeasible solution may lead to car crashes. Therefore, the expected collision probability increases when the algorithm can not find a solution for the optimisation problem within a sampling period.
- **Scalability**: AIM methods must be able to handle a large number of vehicle movements. Therefore, it is important to evaluate the algorithms' complexity, and problem size, when the traffic flow rate increases. In this paper the maximum scalability of an AIM algorithm translates to a minimum increase in the required iterations to solve the optimization problem when the flow rate increases.
- **Robustness**: An AIM method is robust to the limitations set by the wireless channel such as packet loss and latency, when these limitations have a minimum impact on the algorithm's performance. The maximum robustness is calculated as the maximum probability of a reliable solution in the presence of wireless channel impairments.

The first three performance metrics are the most used metrics in the literature when evaluating the performance of intersection control algorithms. However, the objective of our work is to find intersection control algorithms that can be implemented in the real world. Therefore, we have added three more performance metrics in our investigation, that is collision probability, scalability and robustness. These performance metrics will be crucial when deploying an algorithm in an operational systems.

In addition, all results will be compared with a standard signalized, controlled by traffic light, intersection with 90 second green phase and 90 second red phase.

## V. RESULTS AND DISCUSSION

We performed simulations to compare the two algorithms and evaluate them according to the performance metrics described above. All results are compared with the results that would be achieved in an intersection controlled by traffic lights, assuming perfect driving behavior for all vehicles.

### *A. Average Speed and Fuel Consumption*

Figure 1.a illustrates the average speed of each vehicle during one time slot for different flow rates. It is apparent that both the MPC and the Pure Sequential perform better compared to an intersection controlled by traffic lights.

Since in the MPC algorithm, one objective of the optimization problem is to drive in a smooth and comfortable acceleration, the vehicles controlled by this algorithm avoid high acceleration changes. Therefore, in comparison with the Pure Sequential algorithm, where a given vehicle can reach the maximum speed faster, the MPC has a lower average speed.

Several factors can have an effect on the fuel consumption, and it varies with the vehicle type, weather condition, driving behaviors such as rapid acceleration, speed. The Environmental Protection Agency (EPA) study [20] shows that the acceleration rates have a significant effect on a vehicle's fuel consumption. In our experiments, we assumed that all vehicles are of the same type. Therefore, the main factor in fuel efficiency will be the driving behavior.

Figure 1.b shows an estimation of the average fuel consumption for each vehicle during one time slot. 1.b shows that the MPC algorithm results in the lowest fuel consumption, and this is due to that the minimum acceleration and the acceleration rate are defined as costs of the optimization problem. As expected, intersections controlled by traffic lights, where many vehicles unnecessarily brake, will have the maximum average fuel consumption for each vehicle.

### *B. Throughput*

Figures 1.c and 1.d illustrate the average number of vehicles that coexist in the intersection, and the average time a vehicle spends in the system, respectively. Both algorithms improve the intersection throughput compared with an intersection controlled by traffic lights. As can be seen in Figure 1.d, the average traveling time for vehicles controlled by the Pure Sequential algorithm at flow rate 500 vehicles/hour is about 50% (21 sec) of the traveling time in an intersection controlled by traffic lights. The same holds for the average number of vehicles inside the intersection. It is clear that, for both the MPC algorithm and Pure Sequential algorithm, there are much less vehicles inside the intersection, and the vehicles have lower traveling time compared to the signalized intersection. This result shows that the algorithms have the potential to increase the capacity of the intersection.

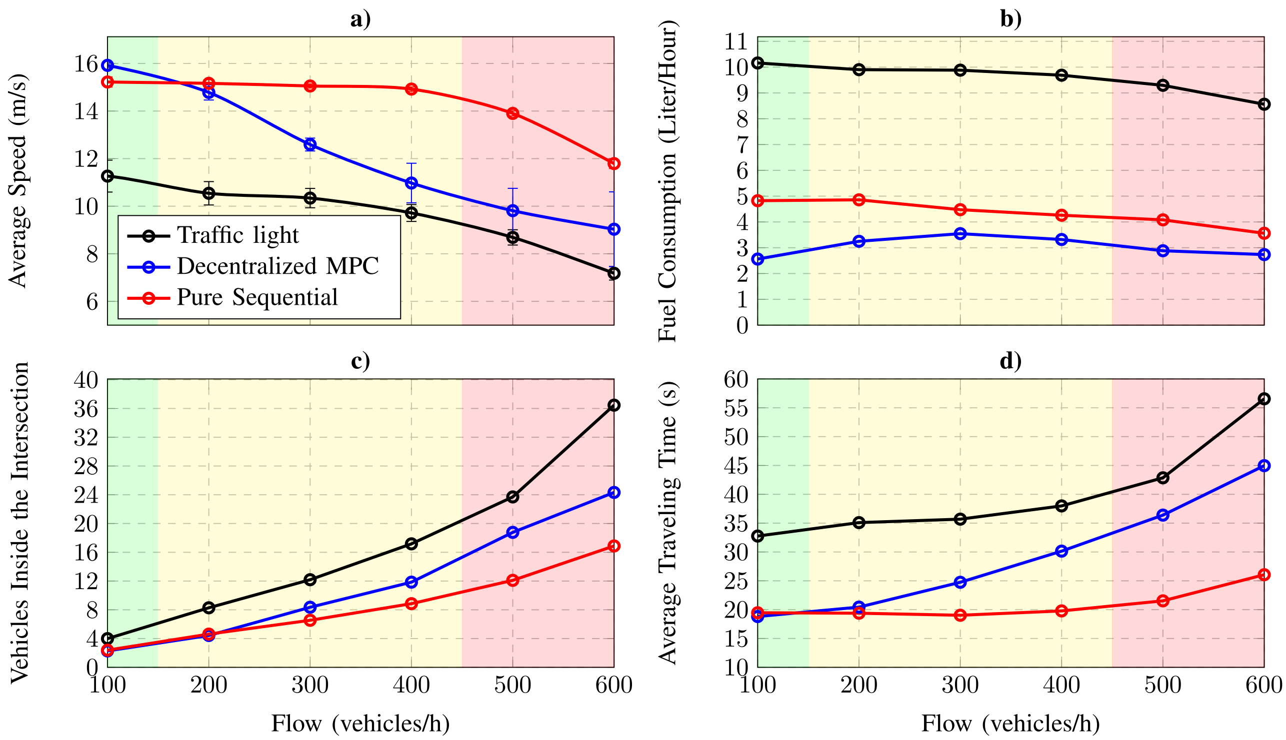


Fig. 1: a) The average speed of each vehicle inside the intersection. b) The average fuel consumption for each vehicle. c) The average number of vehicles that coexist inside the intersection. d) The average traveling time for each vehicle when crossing the intersection. The intersection is defined as a circle with radius 150m.

### C. Safety

In order to evaluate the traffic safety, we have also estimated the collision probabilities for each algorithm and traffic flow rate, as shown in Figure 2. The collision probability is calculated as the expected number of collisions/hour/vehicle. For example, a collision probability of $0.2\%$ for a flow rate of 500 vehicles/hour correspond to, in average, that about one collision per hour can be expected in the intersection. An intersection controlled by traffic light is assumed to have zero probability of collisions for all flows, since this is the main reason for deploying traffic lights in intersections. The Pure Sequential algorithm performs safe for flow rates less than 200 vehicles/hour. However, for arrival rate higher than 300 vehicles/hour the collision probability increases exponentially. In the Pure Sequential only one vehicle is allowed to exist in the critical area at each time instance. For traffic intensity higher than 400 vehicles/hour/lane the arrival rate to critical area is higher than 1600 vehicles/hour (2 sec/vehicle). Therefore, the probability of a feasible solution for optimization problem decreases with increasing flow rate.

In the MPC algorithm, several vehicles are allowed to coexist in the critical area at the same time. The algorithm prevents collisions in the whole intersection area over the given time horizon (10 sec) by keeping vehicles at a safe distance to each other. However, a problem occurs when the arriving flow rate increases to more than 400 vehicles/hour. At this flow rate, the vehicles' initial speed may stop the optimizer from finding a feasible solution that keeps a safe distance to all other vehicles and thereby avoids collisions in a specific time slot. The decentralized MPC performs almost the same as the centralized MPC algorithm [8]. However, by increasing flow rate and consequently increasing the problem size finding the exact solutions for centralized algorithm become intractable.

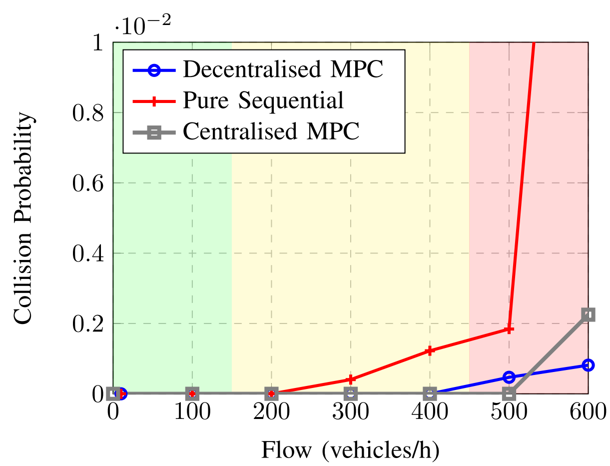


Fig. 2: Collision probability in different traffic intensity

### D. Scalability

Scalability is another crucial requirement for operational systems to fulfill the extreme real-time properties of these

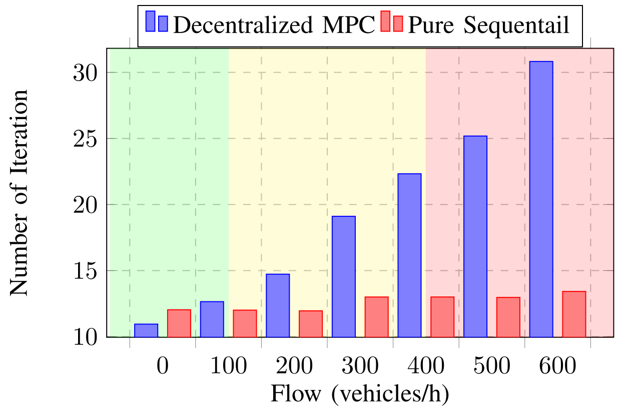


Fig. 3: Average required iteration for feasible solution

types of systems. An intersection control algorithm must be scalable in order to handle a large number of vehicles inside an intersection in a real-world scenario.

To evaluate and compare the algorithms' scalability, the average number of iterations that each optimization solver needs to have in order to find a feasible solution for increasing flow rates, are shown in Figure 3. The MPC algorithm needs to predict the system states of all vehicles involved in the intersection for the prediction horizon. Therefore, by increasing the flow rate, thereby the problem size, the number of required iterations increases exponentially. On the other hand, the Pure Sequential is a linear convex optimization problem and the other vehicles' occupancy time is the only constraint imposed from other entities. Therefore, the problem size and the number of required iterations is almost constant when increasing the number of vehicles involved in the control problem.

As it is shown in Figure 3, when the flow rate is 600 vehicles/hour/lane (that is an average number of 24 vehicles witin the intersection, see Figure 1.c), the MPC algorithm needs on average 32 iterations, while the Pure Sequential algorithm needs only 13 iterations to find a feasible solution.

### *E. Robustness*

Figure 4.a illustrates the maximum required number of messages that needs to be transmitted at each time instance for each control algorithm. These messages include the occupancy time for Pure Sequential and initial states for MPC. In most evaluations of AIM algorithms, it is assumed that the limitations set by the wireless communication, that is the packet losses and delay, are negligible. However, this is not a correct assumption for real world scenarios with current technologies. The measurements in [21] for C-V2X show that the average end-to-end latency in PC5-based communication is 30ms with almost 2.5% packet loss (i.e. 97.5% reliability).

For the Pure Sequential algorithm, each vehicle will start its local optimization problem when it has collected all message(s) from all preceding vehicle(s) Therefore, if only one message is dropped, the optimization problem cannot be formulated and the algorithm fails.

For the MPC algorithm, the vehicles work in parallel, and each vehicle can solve its local problem regardless of the other vehicles' problem formulation. Therefore, packet loss for one vehicle has no effect on the other vehicle(s) local optimization problems. However, an unreliable solution for one vehicle can increase the collision probability of the entire system. Therefore, it is crucial to evaluate how robust the algorithms are to channel impairment.

Figure 4.b shows the probability that each vehicle receives all messages it needs to solve its local optimization problem for a specific time slot. We provide the results when the wireless channel has the reliability of 99.999%, which is the standard for C-V2X 5G, Ultra Reliable Low Latency Communication (URLLC), in Release 16, and the reliability of 97.5% that was measured in [21] for existing technologies. The simulation results confirm that both algorithms perform well in an URLLC wireless channel. However, a packet loss rate of 2.5% can reduce the reliability if the algorithms significantly. For instance, in Figure 4.b for a flow rate of 600 vehicles/hour, when deploying the MPC algorithms, vehicles are not aware of 30% of the other vehicles. For the Pure Sequential algorithm, there is, for the same flow rate, a probability of 40% that a vehicle will not receive all messages from preceding vehicle(s) and, therefore, the optimization problem will fail in this time step.

In order to have a safe intersection *all* vehicles inside the intersection need to find a reliable solution during each time step. Therefore, Figure 4.c shows the average probability that all vehicle(s) involved in the intersection receive their messages in each time step. From Figure 4.c it is apparent that MPC algorithm performs better than the Pure Sequential algorithm for low flow rates. For example, with a flow rate of 300 vehicles/hour, the MPC algorithm will have a probability of 62% that all vehicle(s) receive the messages from other vehicles. For the Pure Sequential, this probability is only 41%. However, for high flow rates both algorithms perform poor with regards to packet loss, and the probability of a completely safe intersection is almost zero. This means that the algorithms' performance highly depends on the reliability of the wireless communication channel and the algorithms are, therefore, not robust to packet loss.

## VI. CONCLUSIONS

The objective of this paper is to evaluate two previously proposed and well-cited algorithms for autonomous intersection management [13] [11] in a realistic simulation environment.

It is seen that using these schemes improve the performance for low vehicle flow rates compared with intersections controlled with traffic lights. However, our results clearly show that the safety conditions are guaranteed for high traffic densities, and therefore, the algorithms would only be usable for low traffic rate. When increasing the flow rate, he collision probability rather quickly becomes larger than zero. Also, the algorithms are not robust to wireless channel impairments that results in packet loss. So to summarize, new types of Autonomous Intersection Management algorithms

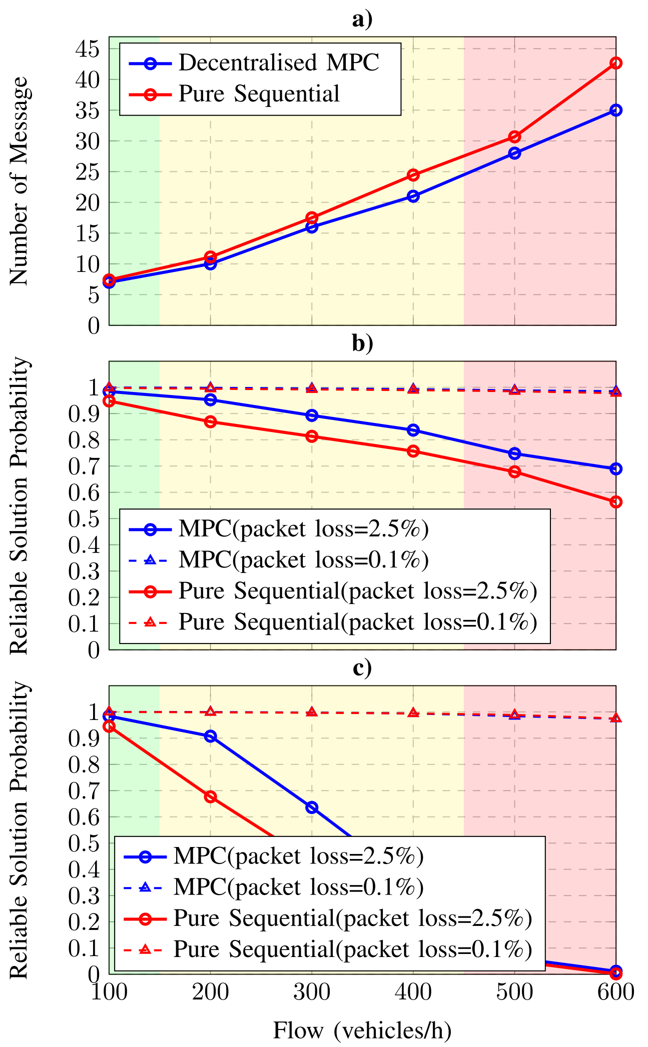


Fig. 4: a) Maximum number of required messages in each time step b) The average probability that a vehicle receives the required information from all other vehicle(s) inside the intersection. c) The average probability that all vehicles receive the required information during each time step. All results are shown with packet dropping rates of 0.1% and 2.5%

are required in order to fulfil the visions of completely autonomous and cooperated vehicles.

## VII. Future Work

The design of real time intersection management systems is a complex task that involves many different steps. Full understanding of all distinct parts of the design procedure requires deep knowledge of theory. In this paper and our previous work [8], we briefly describe the principles of different centralized and decentralized traffic management methods. In the future, the goal is to design an efficient, scalable and robust control method for managing vehicles at intersections.

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