# Micro-simulation Modeling of Coordination of Automated Guided Vehicles at Intersection

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# ABSTRACT

One of the challenging problems with autonomous vehicles is their performance at intersections. This paper shows an alternative control method for the coordination of autonomous vehicles at intersections. The proposed approach is grounded in multi-robot coordination and it also takes into account vehicle dynamics as well as realistic communication constraints. The existing concept of decentralized navigation functions is combined with a sensing model and a crossing strategy is developed. It is shown that, thanks to the proposed approach, vehicles have smoother trajectories when crossing at a four-way intersection. The proposed method is compared to adaptive traffic lights and roundabouts in terms of throughput. Results show that using a decentralized navigation function for the coordination of autonomous vehicles improves the performance by reducing energy consumption and pollution emission.

# INTRODUCTION

Navigation of autonomous vehicles has been an attractive research area both in control and in transportation during the last decade. It is expected that in a very near future autonomous or semi-autonomous driver assistance systems will be available to handle traffic in highways and urban areas. Autonomous navigation deals with the coordination of vehicles that carry out individual or collaborative tasks. Its success relies on the sharing of information between vehicles and with their environment.

Realistic behaviors of autonomous vehicles have been modeled and simulated [1]. The impact of autonomous vehicles has been studied in urban traffic and models have been validated by simulations [2]. Autonomous vehicles are one of the interesting alternative solutions to cope with congested traffic in urban areas [3], as well as on highways. Automated merging maneuvers [4] and platooning [5] are the scenarios that have been addressed successfully.

In this paper, intersections are considered, as they correspond to traffic conditions having potentially a high impact on energy consumption and motion smoothness. Autonomous vehicles could bring better performance in terms of energy consumption and delay reduction. Until now, the first come first go strategy has been proposed for coordination of autonomous vehicles at intersection [6].

When passing an intersection, the main goal of each vehicle is to reach its destination while avoiding collision with other vehicles and fixed obstacles. This problem is very well known in the field of multi-robots coordination. Different control approaches for autonomous navigation have been proposed in the literature. Crossing intersection therefore could be viewed as a multi objective problem for which various solutions have been suggested; such as stochastic optimization [7], cooperative methods of control [8], and decentralized control [9].

Among all these methods, decentralized control has so far received more attention, as it does not rely on long-range communication. This method also shows more robustness to communication failures. The use of navigation functions in decentralized schemes seems promising as they can be implemented in real-time. They are also scalable with respect to the number of vehicles and in dynamic environments [10].

In this paper, a previously proposed decentralized algorithm for coordinating vehicles at intersections [11] is simulated using a microscopic model. An intersection is modeled at which vehicles could travel the straight pass or turn to two directions. It is also compared to existing methods. The proposed navigation function is based on the distance between a vehicle and its destination (which can be a moving point) and with other vehicles. Sensing conditions are defined for each vehicle in order to emulate a real detection and communication range.

In section 2, a dynamical model of the vehicles is introduced. It is simple enough to enable the handling of complex traffic situations, and complex enough to enable vehicle control. The chosen intersection scenario is also detailed. In section 3, a decentralized navigation function that takes dynamical constraints into account is proposed. The microscopic simulator and methods of evaluation of the proposed approach is presented in section 4. The results are discussed in section 5, and concluding remarks and outlook are given in section 6.

# PROBLEM FORMULATION

The considered network consists of a four-road intersection. Each road has one lane in each direction. The whole system involves $N$ vehicles whose goals are passing the intersection. The position of vehicle $i$ is known as $q_i = (x_i, y_i)$ in a global frame attached to the intersection. In practice, position data could be provided using localization methods for autonomous vehicles. The path of each vehicle is predefined and could be described by the path parameter $s_i$.

Hence, the location of the vehicle along its path could be calculated from its position in the global frame using the parametric function $q_i = f_k(s_i)$ corresponding to the path $k$ the vehicle has chosen for its travel.

The motion of each vehicle along its path is modeled using second order dynamics:

$$\ddot{s}_i = \frac{1}{m_i} u_i \tag{1}$$

Where $u_i$ is the control input and $m_i$ is the mass of vehicle $i$. The dynamics proposed for the vehicles is quite realistic. In some previous works [12], first order dynamics has been used to describe the behaviors of the vehicles. Second order dynamics enables to deal with inertia, as well as with acceleration constraints in addition to speed. Therefore, real world limitations like acceleration limit $a_{max}$ as well as braking limit $b_{max}$ are introduced. The speed limit corresponds to road regulations in straight paths. In curves, the speed limit is computed to keep the centripetal acceleration below the acceleration limit.

Each vehicle is controlled using its own navigation function, which is built and updated at each time step. The main challenge is to find an appropriate navigation function. This navigation function could be combined with a proper control input such that each vehicle can reach its destination while avoiding collision with other vehicles located in its sensing zone. In addition, the motion of the vehicles should follow the dynamics given in equation 1.

A circular sensing zone is introduced. Its radius corresponds to a predefined detecting length, unless there is an obstacle blocking the communication. This zone emulates detection capabilities of the autonomous vehicles. It is also considered that vehicles can communicate with each other when they are located in their respective sensing zone.

It should be pointed out that the main concern of this work is the behavior of the vehicles at the intersections. So, it has been assumed that the desired destinations of the vehicles are located at the end of one of the other sections of the intersection. Hence, the convergence to a final configuration is not a critical issue.

# DECENTRALIZED CONTROL METHOD

The control of each vehicle is based on a navigation function. A navigation function is a smooth mapping which should be analytic in the workspace of every vehicle and its gradient would be attractive to its destination and repulsive from other vehicles.

So, an appropriate navigation function could be combined with a proper control law in order to obtain a trajectory for every vehicle leading to the destination and avoiding collisions. The navigation function detailed in this work was firstly introduced by the authors [11]. This decentralized navigation function provides a stable solution and exhibit analytical properties. It is well conditioned to handle local traffic conditions in which many vehicles are involved.

$$\phi_i = \lambda_1(s_{igoal} - s_i)^2 + \lambda_2 \textstyle\sum_{i \neq j} \frac{1}{\beta(q_{i,}q_j)} \tag{2}$$

The navigation function proposed in equation 2 is composed of two terms. The first term is the squared distance of vehicle $i$ from its destination along its path and attains small values as the vehicle approaches the goal. The second term aims at avoiding collision between vehicle $i$ and all other vehicles located in its sensing zone. This function should be large when vehicle $j$ is in the sensing zone of vehicle $i$ in order to create a strong repulsive force and avoid collision risks. This function should be equal to 1 when the vehicle $j$ is out of sensing zone of vehicle $i$. In this work the function $\beta(.)$ given in equation 3 has been chosen. Its value is close to infinity for very short distances between two vehicles in order to provide a strong repulsive force. It is equal to 1 when no vehicles are in its vicinity. No static obstacles or pedestrians are taken into account at this stage.

$$\beta_\sigma(q_i,q_j) = \begin{cases} 3\left(\frac{\| q_i - q_j \|}{\sigma}\right)^2 - 2\left(\frac{\| q_i - q_j \|}{\sigma}\right)^3 & \text{if } \| q_i - q_j \| < \sigma \\ 1 & \text{else} \end{cases} \tag{3}$$

According to the navigation function presented in equation 2 and the vehicles dynamics defined in equation 1, the following control law is proposed. At each step, the vehicle will move according to gradient descent method. This method ensures convergence towards the minimum value of the navigation function, which is the goal point in the working space.

$$u_i = -\nabla_{q_i}\phi_i \tag{4}$$

**Sensing conditions**

Sensing conditions for the vehicles are defined in order to consider the communication constraint and sensor limitations. Moreover, the sensing conditions represent a model, which nearly replicates recent technologies for communication of vehicles. So, the comparisons between the autonomous vehicles with current methods of passing an intersection mainly depict the difference in managing intersection and vehicle control rather than difference in information and sensory data. Figure 1 shows the sensing zone of every vehicle. The other vehicles are taken into account in the navigation function if they are in the sensing zone. Vehicles can also communicate in this range and if they are in the sensing zone of each other. Vehicles are taken into account in the navigation function if they are potentially dangerous. For instance, the red vehicle in figure 1 is not a potential danger for the blue vehicle, as they are travelling in two separate directions and lanes.

Three conditions are required to emulate the detection and communication of vehicles in real world. First, the field of vision of a vehicle is 1.4 radian both to its left and right. Any nearby vehicle outside of this zone is invisible. Second, there is no danger of collision if the heading vector of a nearby vehicle is inside the light green zone (directional visible zone). Third, if the nearby vehicle is in front of the vehicle (in forced visible zone) it should be seen in any rate. These three conditions could be expressed, using the distance vector and heading rotation shown in figure 1.

$$cnd_1 = 0 \leq \delta \leq 1.4 \ \ and \ \ \pi + \delta < \varphi < 2\pi \tag{5}$$

$$cnd_2 = 2\pi - 1.4 \leq \delta \leq 2\pi \ \ and \ \ 0 < \varphi < \delta - \pi \tag{6}$$

$$cnd_3 = 1.4 \leq \delta \leq 2\pi - 1.4 \ \ and \ \ |d.sin\delta| \leq d_{desired} \tag{7}$$

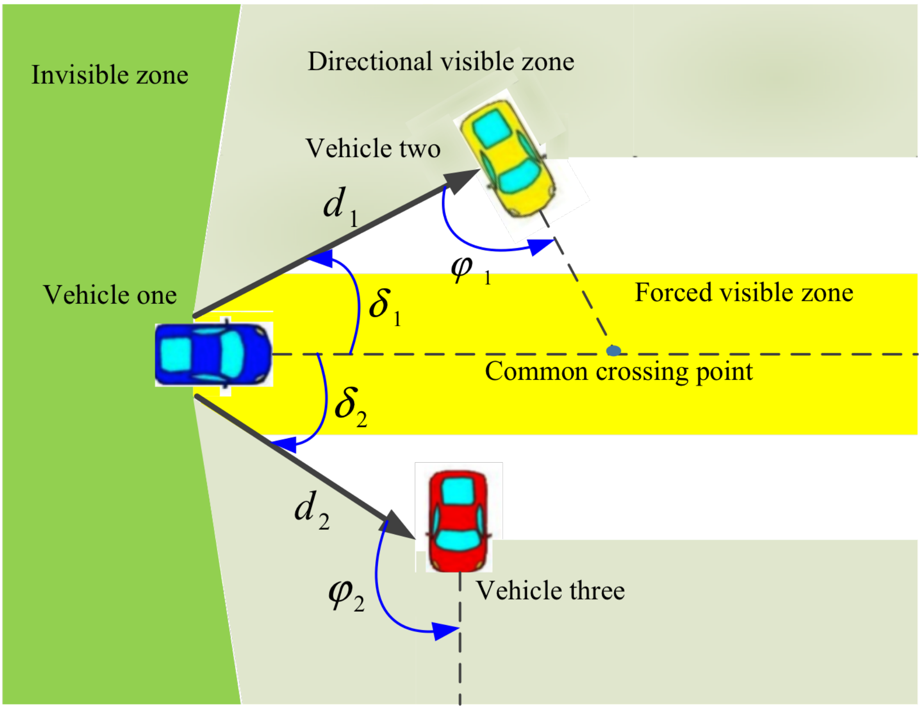

**FIGURE 1 Other vehicles are considered in the navigation function if they are in the sensing zone in which they can communicate and if there is the probability of collision according to distance and direction of the vehicles.**

**Priority Assignment**

So far, all vehicles have been treated equally. However, there are good reasons to give higher priority to some of them. Giving priorities can help avoid blockades of two crossing vehicles. Relying on the previously presented method, all vehicles will avoid collision by braking. But considering the fact that for passing the intersection the deceleration of one vehicle could be sufficient, one vehicle is encouraged to brake earlier and give priority to the other, thus avoiding the blockade.

The decision regarding which vehicle is going to brake and which one pass intuitively depends on the distance to the crossing point. The vehicle that is closer to the crossing point gets priority.

Instead of using the true distances as an indication, which is laborious to establish with curved paths, we use the angle between heading of the vehicles and common distance vector. This distance is calculated between two vehicles. The bigger the angle, the closer the vehicle is to the common crossing point.

In fact, in the case of an interaction of more than two vehicles, it can still happen that two vehicles block each other. Making a nearby vehicle invisible to the vehicle as soon as the latter is in the former's path solves this. The vehicle will thus accelerate, while the nearby vehicle will stay blocked.

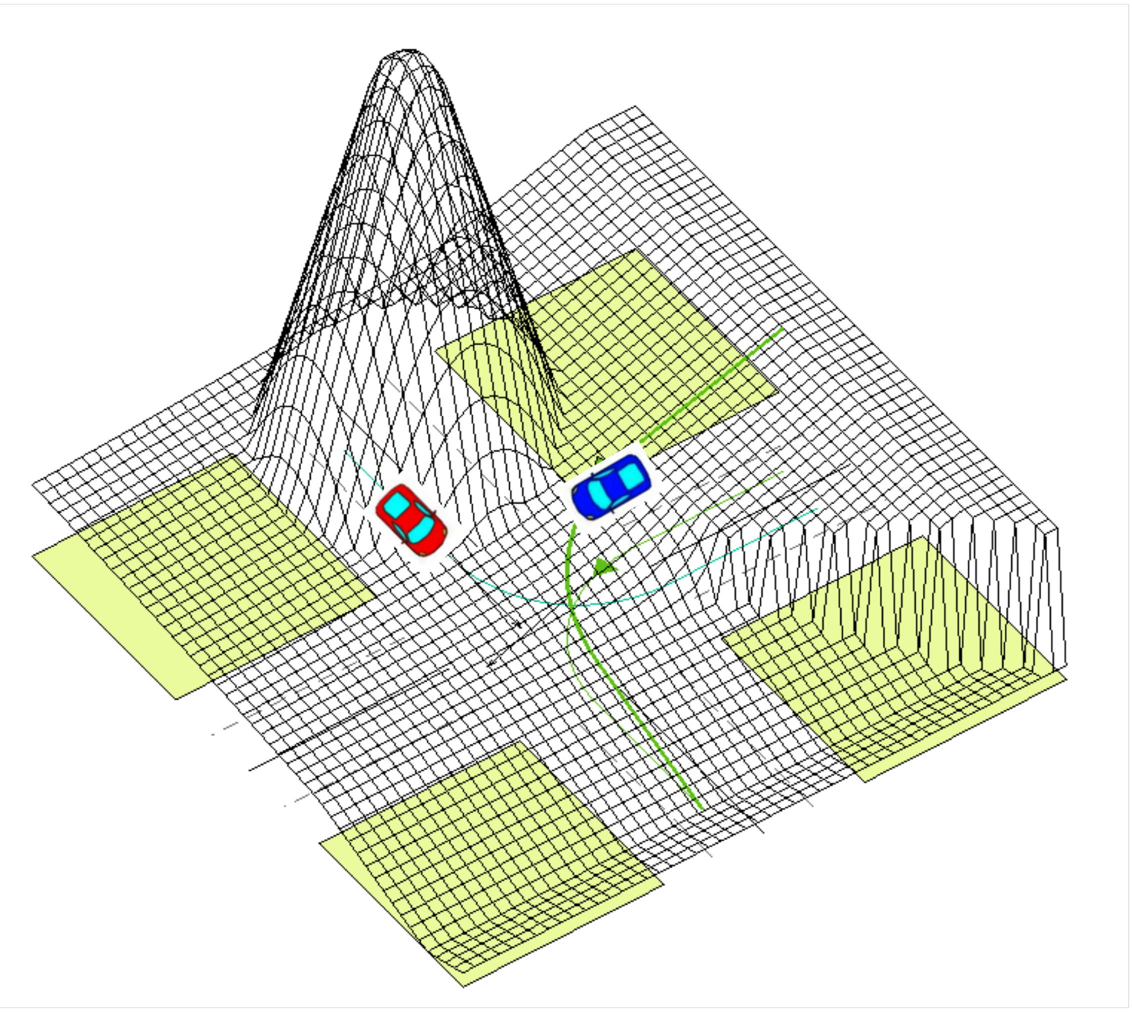

**FIGURE 2 Potential function of blue vehicle. The blue vehicle has to decelerate because of the repulsive force it gets from red vehicle.**

## SIMULATION

In this section, the simulation scenario for the crossing of autonomous vehicles is explained. As the proposed method is a decentralized control of autonomous vehicles, there should be individual controller for each vehicle. In addition, an environment is needed to simulate the whole intersection and animate all vehicles. This helps verifying the performance of the proposed method and also comparing it with other classical methods of crossing of intersection. Classical methods are those that are currently selected to manage intersection for vehicles controlled by human drivers, such as traffic light, give way and roundabout. The AIMSUN micro-simulator is chosen to simulate and animate an intersection. In order to implement decentralized controllers for autonomous vehicles, the controllers and the model of communication has been implemented in MATLAB. MATLAB and AIMSUN communicate through APIs.

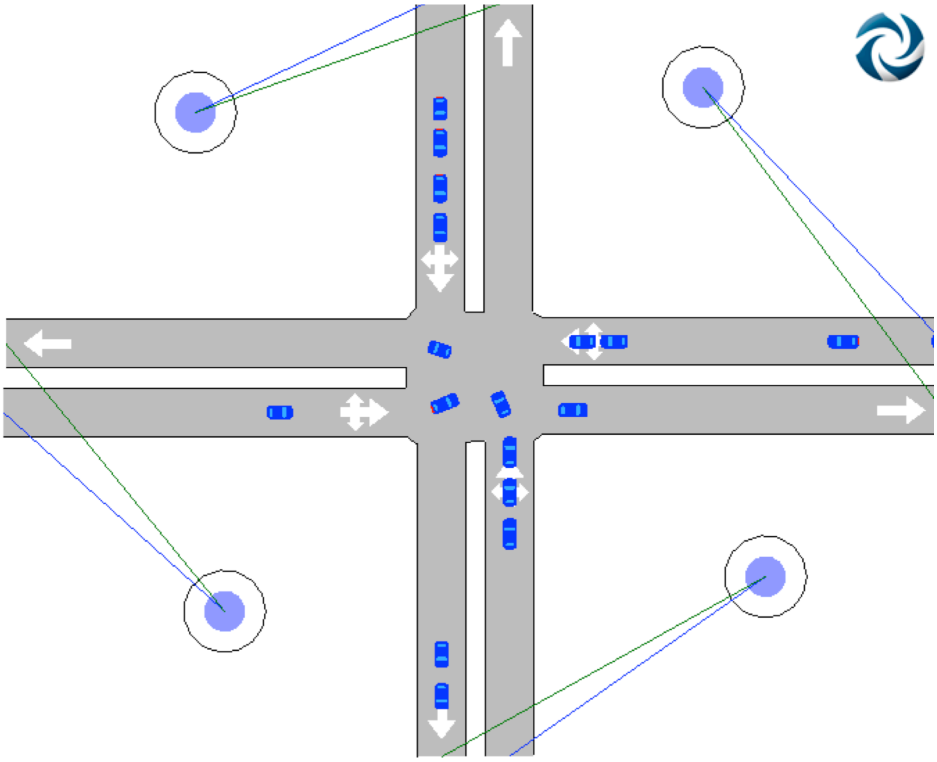

**FIGURE 3 The simulated intersection consists of 8 sections and one junction. Each section is a one-lane road.**

The intersection consists of one junction, eight sections which correspond to 4 two-way streets (Figure 2). The length of each street is 200 meters, which makes an isolated intersection at the junction point. The maximum speed is 50 km/h, like the standard speed limit in urban areas. This speed limit is considered in the Decentralized Navigation Function (DNF) method as well as for traffic lights and roundabout.

In this work, decentralized navigation of autonomous vehicles is compared to actuated traffic lights and roundabout. Traffic lights are a classical way of managing intersection and the most efficient way of controlling normal vehicles in terms of liability and controllability. In this work, the traffic lights are a fully actuated, thanks to detectors integrated in all sections. To obtain useful information, the detectors are set at a long distance from the stop line (100 meters). No pedestrian pass time is considered to enable comparison with the autonomous approach. Detectors are working in a locking mode in which they count the number of vehicles passing in red and yellow intervals. The controller is designed as a single ring with minimum green light of 20s and maximum green light of 50s.

Vehicles entering the intersection have all the same inertia and velocity, acceleration and braking limits. Different levels of traffic have been directed in order to compare the three intersection control methods. In a low-level traffic situation, vehicles will not make spill backs, which mean there would not be any vehicle waiting to enter the intersection outside of the network.

The chosen simulation step is 100 ms. The parameters chosen for the navigation function are $\lambda_1 = 0.02$, $\lambda_2 = 0.8$ and $\sigma = 20$ meters.

Sets of simulations have been carried out with vehicles having three choices at intersection. Vehicles could go straight, turn left or turn right, with the same probability. Simulations have been carried out for 5 sets, each set for one hour.

## RESULTS AND ANALYSIS

In this section, the efficiency of traffic lights and roundabout is compared with the decentralized navigation of autonomous vehicles. These three methods are compared using performance indexes, which are defined in the next subsections. These indexes are chosen to show the total performance of the proposed method for the whole intersection, not just for one vehicle.

### Vehicle average speed

This index of performance is the average speed for all vehicles that have left the network. This is calculated using the mean journey speed for each vehicle and then averaged it over the total number of vehicles that have exited the network.

### Number of stops

The number of stops is the average number of stops of every vehicle averaged over all the vehicles that have left the network from its exit section.

### Vehicle throughput

Vehicle throughput or flow is the average number of vehicles per hour that have passed through the network during the simulation time. It is worth mentioning that the vehicles are counted when leaving the network via an exit section. This means that if a blockade occurs the flow of the vehicles would decrease significantly. The average number of cars that should enter the network could be defined using the O/D matrix of the network.

### Fuel consumption

According to the fuel consumption model presented in AIMSUN, every vehicle is either idling, or cruising at a constant speed, or accelerating or decelerating. The state of each vehicle is determined and the model then uses the appropriate relation to compute the fuel consumed for that state. For idling and decelerating vehicles, the rate is assumed to be constant. Fuel consumption during these four phases is shown in table 1.

**TABLE 1 The fuel consumption for different phases of a vehicle's journey**

| Vehicle phase | Fuel consumption rate |
|---|---|
| Idling | $F_i$ |
| Decelerating | $F_d$ |
| Accelerating with acceleration $a(\frac{m}{s^2})$ and speed $v(\frac{m}{s})$ | $c_1 + c_2 a v$ |
| Cruising at speed $v(\frac{m}{s})$ | $k_1(1 + (\frac{v}{2v_m})^3) + k_2 v$ |

According to the UK department of transportation [13], the constants $c_1, c_2, F_i$ and $F_d$ are considered as 0.42, 0.26, 0.333 and 0.537 respectively. $v_m$ is also the speed at which the fuel consumption rate is at its minimum value for a vehicle cruising at constant speed. This speed is 50km/h for cars simulated in this work. Comparison results for the three methods are shown in figure 3.

The main goal in intersection management using decentralized navigation function is to get smoother trajectories for vehicles. As it could be seen in the comparison of the three methods, there is no significant differences between the proposed method and roundabout in terms of vehicle through put and average speed. On the other hand, number of stops in the proposed method is significantly less than for the two other methods. This shows that the vehicles have smoother trajectories, which leads to less fuel consumption (verified in simulation and shown in figure 3). Limiting decelerations and accelerations decreases fuel consumption. As vehicles are mainly cruising in decentralized navigation method, they consume significantly less energy.

In this set of simulations, the performances with traffic lights are poor compared to the two other methods. However, the simulated method is an actuated scenario. In fact, traffic lights are not the best choice for this intersection as every section has only one lane. Adding lanes might increase the traffic lights performance.

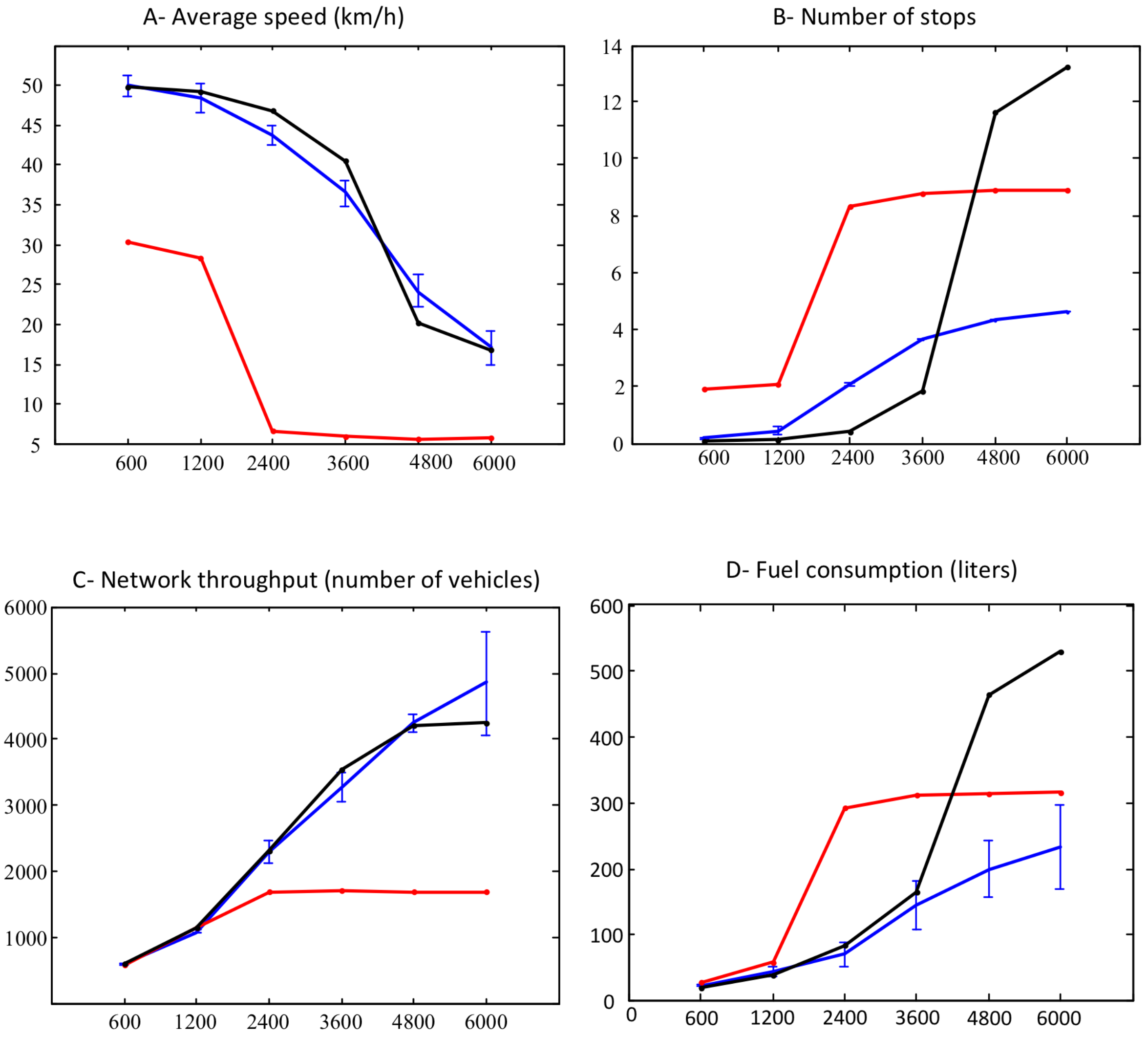

**FIGURE 4 Simulation results for the three methods of control of intersection. Decentralized navigation function is shown in blue, adaptive traffic lights in red and roundabout in black. For decentralized navigation function, the error bars are showing the standard deviation. The horizontal axis shows the total vehicle input to the network.**

### Pollution emission

Pollution emission is also defined in the simulation in four states like that of fuel consumption. This is done by referring to a look-up table for each pollutant, which gives emissions (g/s) for every relevant combination of vehicle behavior [13]. The look up table used in this work is shown in table 2.

**TABLE 2 Pollution emission rates for different phases of a vehicle's journey**

| Vehicle phase | CO emission rate (g/s) | NOx emission rate (g/s) |
|---|---|---|
| Idling | 0.060 | 0.0008 |
| Decelerating | 0.377 | 0.0100 |
| Accelerating | 0.072 | 0.0005 |
| Cruising at speed | | |
| $10\,{}^{km}/_{h}$ | 0.060 | 0.0006 |
| $20\,{}^{km}/_{h}$ | 0.091 | 0.0006 |
| $30\,{}^{km}/_{h}$ | 0.130 | 0.0017 |
| $40\,{}^{km}/_{h}$ | 0.129 | 0.0022 |
| $50\,{}^{km}/_{h}$ | 0.090 | 0.0042 |
| $60\,{}^{km}/_{h}$ | 0.110 | 0.0050 |
| $70\,{}^{km}/_{h}$ | 0.117 | 0.0058 |

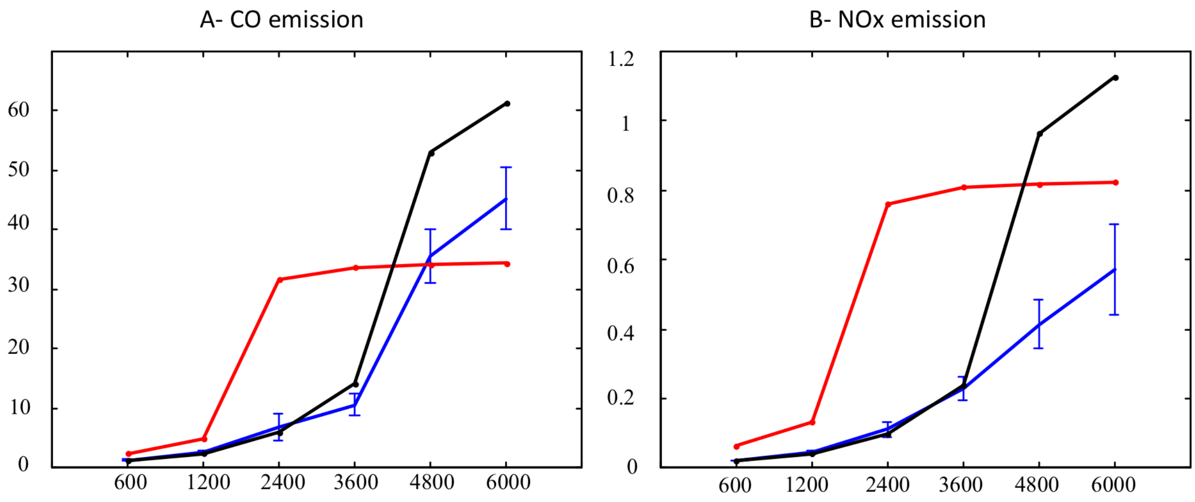

**FIGURE 5 The pollution emission (CO and NOx) for the three methods of control of intersection. Decentralized navigation function is shown in blue with error bars showing the standard deviation from mean. Pollution emission with of adaptive traffic lights and roundabout is shown in red and black respectively. The horizontal axis shows the total vehicle input to the network.**

Results are shown in figure 4. As we can see the CO emission with the DNF method is less than that of in roundabout. However it does not show better results in comparison with traffic lights. These results are not unexpected despite the fact that, in traffic light method the flow of the vehicles is expressively less than the other methods in high level of traffic. This means most of the vehicles are idling in the network in this case and emission of NOx is notably less than cruising. On the other hand, it is not the case with CO emission. Vehicles idling in front of traffic light are producing the same amount of CO as the vehicles cruising with speed of $10 \, {}^{km}/_{h}$. Considering the low flow of vehicles in traffic lights method, DNF can improve the energy consumption and pollution emission for every journey.

The proposed decentralized method for controlling the intersection has been tested in micro-simulation and compared to two current methods of crossing control. The comparison between DNF method and traffic lights shows a 300% of improvement of the network throughput using decentralized control. Although traffic lights could show better performance with more lanes at the intersection, the structure of the intersection has to be kept the same for the sake of fairness in comparing the methods.

Regarding the number of stops, the DNF method induces fewer stops, even in a very highly congested situation, which directly influence the amount of fuel consumption and pollution emission. Even in low and medium traffic levels, the numbers of stops are less than the two other methods. This shows the basic idea behind the decentralized method, which propose smoother trajectories. Smooth passing of intersection may result in a lower average speed (as seen in FIGURE 3) but by reducing number of stops, decelerations and accelerations it reduces the fuel consumption and $CO_2$ emission.

## CONCLUSION AND FUTURE WORKS:

In this work, the decentralized navigation function has been simulated using micro-simulator (AIMSUN with connection to MATLAB). This paves the way towards an on-board energy optimization by investigation on decentralized control of autonomous vehicles at intersections. The proposed method has been compared with current methods of managing intersection, which are adaptive traffic lights and roundabout. The proposed method shows a significant improvement in comparison with classic traffic lights from a travel time and stop times point of view. The flow of the vehicles crossing is also improved simultaneously. The major improvement is related to the number of stops, which directly means less energy consumption and less pollution emission. It could also bring more comfort to passengers as the journey is held in a smoother way.

Our future research will include more realistic features like more complex dynamics of the vehicles. We will also study the behavior of the vehicles under communication constraints and lack of energy as it could happen when using electrical vehicles. Different profiles of acceleration and deceleration will be taken into account in order to have a comfortable driving experience. One future step would be simulation of more than one intersection to investigate the potentials of the proposed method on improving spillbacks and queue length. This will allow us to adapt our work to autonomous vehicles and semi-autonomous driver assistance systems. Priorities could be extended in order to optimize energy consumption. In this way, higher priorities could be given to public transport systems as well as heavier vehicles.

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