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Application of vehicular communications for improving the efficiency of traffic in urban areas

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ABSTRACT

This paper studies the impacts of vehicular communications on efficiency of traffic in urban areas. We consider a Green Light Optimized Speed Advisory application implementation in a typical reference area and present the results of its performance analysis using an integrated cooperative intelligent transportation systems simulation platform. In addition, we study route alternation using vehicle-to-infrastructure and vehicle-to-vehicle communications. Our interest was to monitor the impacts of these applications on fuel and traffic efficiency by introducing metrics for average fuel consumption, average stop time behind a traffic light and average trip time, respectively. For gathering the results, we implemented two traffic scenarios defining routes through an urban area including traffic lights. The simulations are varied for different penetration rates of application-equipped vehicles, driver’s compliance to the advised speed and traffic density. Our results indicate that Green Light Optimized Speed Advisory systems could improve fuel consumption, reduce traffic congestion in junctions and the total trip time. Copyright © 2011 John Wiley & Sons, Ltd.

KEYWORDS
vehicular communications; traffic light advisory; route advisory; fuel consumption; traffic congestion

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1. INTRODUCTION

Advances in wireless communications and in particular vehicular communications have led to the advent of cooperative intelligent transportation systems [1,2]. These systems employ vehicular communication technologies such as IEEE 802.11p [3] to enable deployment of applications that could potentially improve road safety and traffic efficiency and introduce new entertainment and business applications [4]. Exploitation of intelligent transportation systems for traffic congestion control in urban areas as well as fuel consumption reduction are among the most promising applications according to transportation authorities [5,6]. This can be achieved by vehicle-to-vehicle (V2V) or infrastructure-to-vehicle communications, intelligently advising individual drivers about traffic events, such as the traffic light phases and congestion.

In this paper, we study the impacts of application of vehicular communications on improving the efficiency of traffic in urban areas. In particular, we focus on two specific applications: Green Light Optimal Speed Advisory (GLOSA) and Adaptive Route Change (ARC), respectively.

First, we design and implement a GLOSA system to reduce traffic congestion by decreasing the average stop time behind traffic lights and total trip time while reducing fuel consumption and CO₂ emissions. The potential of V2V communication for improving fuel efficiency has been demonstrated in [7], showing that vehicular communications can assist to reduce average fuel consumption especially under high traffic density and long traffic light cycles. Other projects have investigated the impacts on fuel efficiency when using wireless communications between vehicles (V2V) or vehicle to infrastructure employing different algorithms to smoothly slow down at a red traffic light or to reach it at the next green phase. Depending on the used consumption models, different results can be observed. One important aspect, as introduced in [8], is the dependency of the results on different penetration rates of
the communication enabled vehicles. In the same work as well as in [9], the effect of traffic density is studied. In [8], it is also suggested to either cut the fuel delivery or stop the engine when the vehicle stops at the traffic light for long time to achieve less fuel consumption. In [10], the intelligent driver car-following model [11] is used to control a platoon of 10 vehicles, where only the leading one is equipped with communication capabilities, achieving 30% fuel savings. In [12], when the algorithm is used only with one vehicle and one traffic light, fuel savings reached 20%. Although these results seem trustworthy, the simulations are conducted with a small number of vehicles that do not consider the dynamics of the vehicular environment. When the model in [12] is scaled up including 15 traffic light junctions, the results are reduced to 6% reduction in fuel consumption. The optimal activation distance for the algorithm is also investigated in this work and is found that a distance of 500 m achieves the best results in their simulations. Furthermore, in [10] and [9], traffic efficiency is examined using different performance metrics. In [10], the increase of average speed is taken as indicator of traffic efficiency where in [9], the flow and the ratio of motionless vehicles are considered. In our implementation, the GLOSA application provides the advantage of timely and accurate information about traffic lights cycles and traffic lights position information through infrastructure-to-vehicle communication. It provides drivers with speed advice guiding them with a more constant speed and with less stopping time through traffic lights. Our results show up to 7% reduction in average fuel consumption and up to 89% in average stop time and 9.85% in trip time when GLOSA is used in a reference scenario. While conducting the simulations, we found that the optimal GLOSA activation distance is around 300 m.

Second, we implement an ARC application, which uses both vehicle-to-infrastructure and vehicle-to-vehicle (V2X) communications to divert traffic away of congested roads. The avoidance of congested areas by re-routing traffic away of these areas was proposed as a use case in [13]. Vehicles disseminate messages with information regarding the traffic conditions around them, for other vehicles to analyze and make a decision whether a change of route is needed or not. An advantage that this algorithm possesses is that vehicles also know about the congestion on roads nearby. This aims to prevent vehicles reverting to a route that is also congested. The main metric that the algorithm uses to implement this feature is the speed of the vehicles in the area. The average speed of each vehicle passing a road segment is sent to the other vehicles. On the receiving edge, vehicles calculate the “edge weights” for these road segments; on the basis of these weights, they calculate the optimal route. Two simulation scenarios were studied: an urban scenario and a highway scenario. For the purposes of this paper, we discuss solely about the former scenario. Vehicles travel on a predefined route, which becomes congested near traffic lights. Their simulation results suggest that depending on application penetration rate, the algorithm benefits all vehicles, even those with no communication support. This happens because V2V equipped vehicles take alternative routes, unloading the roads that were in their past route. Therefore, all vehicles display lower travel times. As for the CO₂ emissions and fuel consumption, they are also proportionally affected by the number of equipped vehicles. Additional factors like longer alternative routes reduce the positive effects. But emissions and fuel consumption are lower compared with 100% conventional vehicle scenarios. Finally, the information exchange that takes place eventually balances the traffic flow within greater part of the road network. Another study of such an application is presented in [14]. Results showed that high V2X penetration rate leads to more vehicles using alternative routes. About 50% of the total travel time was reduced for all vehicles at a V2X penetration rate of 80% or higher, whereas V2X-equipped vehicles benefit from much lower penetration rates. Another noteworthy observation is that on penetration rate equal to 80%, all vehicles benefitted equally. In our implementation, vehicles inform traffic lights about their position and status. Traffic lights assess the traffic congestion in terms of the number of stopped vehicles using information gathered from vehicles. When a certain threshold of congestion is passed, they geo-broadcast this congestion information using V2V communication towards previous junctions so the vehicles can adaptively change their route. Regarding ARC effects on traffic and fuel efficiency, we observed reduction of 26.7% in stop time and 18% in total trip time. The consumption is also reduced up to 15.86%.

In the aforementioned works, different communication technologies are adopted. The authors in [7,9,12,15] do not discuss in depth the communication mechanisms of their simulations. They assume successful dissemination of the messages. Others, such as [10] and [16], use general purpose wireless communication technologies, such as wireless sensor networks and IEEE 802.11 [17]. Lately, the IEEE 802.11 standard is preferred because of operational cost. The highly dynamic network topology of vehicular communications has led to the introduction of IEEE 802.11p [3] that is more suitable for such applications and is the one we used in our simulations.

The main challenges in the implementation of the previous applications include the modeling of the vehicle traffic, the communications between traffic lights and vehicles and finally the driver’s behavior. Individual research has been performed for each one of these areas, but complete simulations by taking into account the dynamics of all parameters are scarce. Thus, for our implementation of GLOSA and ARC, we used an integrated simulation tool based on the Fraunhofer VSimRTI [18], which enables online two-way coupling of different simulators for monitoring the influence of GLOSA and ARC application on the traffic and fuel consumption.

The contributions of this paper are as follows:

- Design and implementation of two V2X applications (GLOSA and ARC), which aim at increasing
fuel and traffic efficiency, using the Fraunhofer VSI RTI platform.

- Extensive simulation experiments using different scenarios to find the optimal point of GLOSA activation, the influence of application penetration rate on fuel and traffic efficiency and the effect of traffic density on GLOSA performance.
- Design and implementation of a stochastic driver model to investigate the influence of the driver’s compliance to the advisory speed.
- Extensive simulation experiments using different scenarios to find the influence of ARC application penetration rate on fuel and traffic efficiency and the effect of traffic density on ARC performance.

The rest of this paper is organized as follows. In Section 2, we present our integrated simulation approach, and in Section 3, we give an overview of the integrated simulation platform. The design of the GLOSA algorithm is thoroughly discussed in Section 4. In Section 5, the ARC algorithm is described. In Section 6, the simulation set-up is presented followed by our evaluation results. Finally, in Section 7, we conclude and provide ideas for future work.

2. SYSTEM MODEL

We designed and tested GLOSA and ARC in an integrated simulation platform. The first step was to define a reference scenario that is depicted in Figure 1. In this reference area, we placed a traffic light. Vehicles will enter following a common arrival process such as Poisson distribution. In the scenario, the equipped vehicles rate is varied because we want to investigate the influence of the penetration rate and which is the minimum percentage of equipped vehicles for GLOSA and ARC to have a positive impact on the traffic efficiency and fuel consumption. Road traffic is modeled using the microscopic Stefan Krauss (SK) model [19], a car-following model with two basic rules. First, vehicles in free motion have a target speed and try to cruise at it. Second, when a vehicle senses the distance to the vehicle ahead to be less than a certain threshold, it slows down keeping a safe distance. The speed of the vehicles is within a certain range \([V_{\text{min}}, V_{\text{max}}]\) where \(V_{\text{min}}\) is the minimum speed that vehicles can cruise without causing further traffic congestion and \(V_{\text{max}}\) is the maximum speed that is forced by the speed limit of the area. Acceleration is also bounded and asymmetric – higher deceleration than acceleration – for more realistic simulations. The SK model is integrated in Simulation of Urban Mobility (SUMO) [20] traffic simulator that we used in our work.

We have set up two simulation scenarios for each application to compare the results. In the first scenario \((S_0)\), there is no driver’s assistance information (advisory speed or alternative route), and the traffic is governed by the SK model. In the second scenario \((S_1)\), we provide information through the GLOSA or ARC messages, and the driver receives speed advisory messages or an alternative route. We assume that all drivers who get an advise will follow it. We control the percentage of GLOSA and ARC equipped vehicles to monitor the impact of penetration rate. Therefore, we have defined three performance metrics that we check in all scenarios to derive our conclusions. The first metric \((P_1)\) is the average stop time of vehicles waiting at the intersection behind red lights measuring the traffic efficiency.
efficiency of GLOSA and ARC application. We assume that there is no other reason for the vehicles to halt apart from stopping at a traffic light or a queue caused by the traffic light (we do not simulate brake downs or accidents in our scenarios). The second metric ($P_2$) is the average trip time of vehicles from the moment they enter the reference area until the moment they exit. The third metric ($P_3$) is the fuel consumption derived from the fuel consumption and emission model in [21] measuring the fuel efficiency of the applications. The emissions of $CO_2$ are estimated from the same model to be proportional to fuel consumption.

3. INTEGRATED SIMULATION PLATFORM

Simulating the GLOSA and ARC use cases poses a challenge in terms of combining different simulation aspects, for example, vehicular traffic, network communication and application handling. For these challenges to be addressed, the integrated simulation platform VSimRTI [18] was used to simulate the use cases.

VSimRTI borrows some concepts of the High Level Architecture [22] to enable the coupling of the most appropriate simulators for a scenario. It is not only a lightweight framework interaction between them and life-cycle management of simulators but also its applications. Using VSimRTI enables access to all relevant traffic objects such as road-side units (RSUs), application-equipped vehicles or traffic lights through common interfaces regardless of the specific simulator instance, for example Vissim or SUMO.

For the applications to be simulated, the integrated application simulator VSimRTI_app was used. It provides a couple of simple JAVA interfaces to create V2X applications, while offering access to all relevant simulation data such as vehicle status or communication modules. V2X messages sent to specific vehicles are forwarded to the associated application, and application output can be directed to a specific vehicle (e.g., giving speed advisory to a simulated vehicle). Specialized for V2X simulations, VSimRTI and its simulators have been built with current V2X technologies in mind; that is, all simulations have been performed using standardized V2X protocols such as IEEE 802.11p.

Figure 2 shows the general concept of VSimRTI. Each simulator is coupled to the runtime infrastructure (RTI) by implementing generic interfaces to communicate to the RTI (VSimRTI Ambassador) or to receive messages from the RTI (Federate Ambassador).

4. GREEN LIGHT OPTIMAL SPEED ADVISORY ALGORITHM

The GLOSA algorithm has been implemented to support the aforementioned simulation approach and is presented in Algorithm 1. First, vehicles enter the communication stage of the traffic light, then calculate the distance and time to reach the traffic light $T_{TL}$, find the phase at the traffic light $T_{TL}$, and calculate the remaining red time $T_{red}$. Then, calculate the target speed for $T_{red} + T_{TL}$ and $T_{yellow}$. If the remaining yellow time is greater than the remaining red time, calculate the target speed for $T_{yellow} + T_{red} + T_{TL}$ and $U_t$. If the remaining yellow time is less than the remaining red time, calculate the target speed for $T_{yellow}$ and $T_{red} + T_{TL}$. The advisory speed is determined by the MAX of $U_t, U_{min}$ and the MIN of $U_t, U_{max}$.

Algorithm 1 GLOSA Algorithm

1: Find the most relative traffic light
2: Calculate Distance and Time to traffic light $T_{TL}$
3: Check phase at $T_{TL}$
4: if GREEN then
5: Continue Trip
6: Target Speed ($U_t$) = $U_{max}$
7: else if RED then
8: Calculate remaining Red Time ($T_{red}$)
9: Calculate target speed for $T_{red} + T_{TL}$ : $U_t$
10: else if YELLOW then
11: Calculate remaining Yellow Time ($T_{yellow}$)
12: Check for possible acceleration
13: Calculate target speed for $T_{yellow} + T_{red} + T_{TL}$ : $U_t$
14: end if
15: Advisory speed = MAX ($U_t$, $U_{min}$) & MIN ($U_t$, $U_{max}$)

Figure 2. VSimRTI system.
range of a traffic light according to the Poisson distribution as mentioned before. The RSU attached to a traffic light broadcasts periodically cooperative awareness messages including the position, timing information and additional data for the traffic light. When the on-board unit receives a cooperative awareness message, the algorithm checks if its source is a traffic light or not. From the position information within the message and the vehicle’s own position and heading, it calculates whether this traffic light is relevant (on its route) or not (line 1). The application can then calculate the distance from the traffic light and with the current speed and acceleration, the time that it would take to reach it (time-to-traffic-light $T_{TL}$) (line 2). Next, it checks the traffic light phase at that time ($T_{TL}$) (line 3). If the traffic light is green when the vehicle reaches it, then the vehicle continues its trip trying to reach the maximum speed limit of the road (lines 4–6). If it is red, it calculates the speed that it should have to reach it in the next green phase (lines 7–9). If it is yellow, depending on the remaining yellow time and the acceleration capabilities of the vehicle, it could advice to accelerate or decelerate again within the permitted range (lines 10–13). Finally, the driver gets an advise with the speed limited within the permitted range $[V_{min}, V_{max}]$ (line 15). This algorithm runs every second, which makes it more robust against external interference, such as other vehicles, that do not follow the same advisory speed or are non-equipped.

The algorithm has as input the current speed $U_0$, acceleration $a$ of the vehicle and the distance to the traffic light $D_{TL}$. With the utilization of basic rules of motion, given by (1),

$$d = ut + \frac{1}{2}at^2$$

(1)

where $d$ is the distance, $u$ is the initial speed, $t$ is the time and $a$ is the acceleration; the time to reach the traffic light ($T_{TL}$) can be calculated as shown in (2).

$$T_{TL} = \begin{cases} \frac{d}{u} & \text{when } a = 0 \\ \frac{u}{a} + \sqrt{\frac{u^2}{a} + \frac{2d}{a}} & \text{when } a \neq 0 \end{cases}$$

(2)

The target speed ($U_t$) for the red and yellow light phases is calculated using (3) after rearranging (1) and setting $a = (U_t - U_0)/t$

$$U_t = \frac{2d}{t} - U_0$$

(3)

where $d$ is the distance to traffic light ($D_{TL}$), $t$ is the time to reach the traffic $T_{TL}$ light plus the remaining time for the next green phase ($T_{red}$ or $T_{yellow} + T_{red}$, respectively) and $U_0$ is the current speed. The algorithm can be visualized with the help of Figure 3. A vehicle without GLOSA accelerates until it reaches the maximum allowed speed and then suddenly has to break because of the upcoming red light. The worst-case scenario is that it has to stop for the complete duration of traffic light’s red phase (25 s in our example). On the other hand, using GLOSA, a vehicle obtains information about the phases and adjusts accordingly its speed so that it reaches the traffic light at the moment it turns green again. Thus, it does not have to come into a complete halt. Even though the advised speed is lower than the road limit, the vehicle’s average speed and thus trip time is not increased. On the contrary, it is decreased because of the fact that when the vehicle passes the traffic light, it has an initial speed greater than zero.

5. ADAPTIVE ROUTE CHANGE ALGORITHM

In this section, we describe the ARC algorithm. Vehicles enter the reference area following the Poisson distribution as before. When they stop at a traffic light, they broadcast a message with information about their position, the road they are on and their ID. Upon receipt of such a message, a traffic light updates its local database with the stopped vehicle on that road. When a vehicle departs from a traffic light, it sends a second message so that the traffic light can keep track of the number of stopped vehicles; thus, the congestion level on each road. When the congestion level passes a certain threshold, the traffic light geo-broadcasts a message towards the previous junction where the decision about an alternative route may be made. The protocol that is used for geo-broadcasting is Cached Greedy Geocast (CGGC) [23]. This message includes information related to the road that the congestion has occurred. However, when the traffic is again lowered, it sends a second message so that vehicles can switch back their initial route.

6. SIMULATION SET-UP AND EVALUATION RESULTS

For the evaluation of the GLOSA and ARC application, a series of simulations were conducted. The configuration of
the environment for the project consists of the SUMO [20] traffic simulator used to produce and cope with the vehicle traffic, the JiST/SWANS [24] used for the communications and finally the application simulator described in Section 3 that runs the GLOSA and ARC application written in Java. We simulated two road networks. The first underlying simulation scenario is a road network section of Guildford town center in the UK as depicted in Figure 4. It consists of one route where vehicles start from point A on York Road according to a Poisson distribution and travel until point B on Waterden Road on one lane and without overtaking. The number of vehicles is defined to 100 to gather sufficient data in terms of time and number of independent vehicles to obtain statistically accurate results. The travel distance is approximately 0.6 miles (0.965 km). Within this route, there are two traffic lights (TL\(_1\) and TL\(_2\)). For these two traffic lights, the timing regarding the previous route is 20–4–6 (green–yellow–red) and 20–4–36 s, respectively. The difference in red time for TL\(_2\) is because of the London Road’s green phase duration. The second road network is a 2 × 2 grid with four traffic lights as depicted in Figure 5. There are multiple routes for this scenario. The basic route follows intersections A, B and D. The alternative one travels through intersections A, C and D, respectively to avoid congestion at B and D. A third route follows intersections C and D only and works as a control for the congestion. The speed limit on the road is set to 15 m/s (54 km/h), which is near the usual limit in an urban area. The minimum advisory speed is set to 6 m/s (21.6 km/h) in order not to travel too slow and cause more congestion. The simulation runs until every vehicle has left the simulation area. The communication range of the vehicles and traffic lights is set near 500 m and use IEEE 802.11p communication as access mechanism to broadcast their messages.

6.1. Green Light Optimal Speed Advisory evaluation

The simulations can be divided into four categories. First, we tested the influence of the activation distance for GLOSA on the overall performance. In these simulations, all vehicles are equipped with the GLOSA application. Also, to check the integrity of the algorithm, we excluded the first traffic light and run only with one (TL\(_2\)). The timing for this was also altered to have equal red and green phases. The results of the two performance metrics can be seen in Figure 6. An optimal point of activation is found at a distance near 350 m. At shorter activation distances, the reaction time (time required for the driver to slow down to the advised velocity) is not enough to have benefits. The fuel consumption is also slightly increased because of the fact that the average trip time is increased (vehicles are advised to travel at lower speeds). At longer activation distances, the benefits regarding fuel consumption are slightly decreased but remain near the optimal levels. The results for two traffic lights with a distance near 400 m between them (Figure 4) shift this optimal point to a shorter distance of 250 m, which will be the value used to produce the next set of results. This is due to the fact that vehicles do not have enough time to accelerate and reach a higher velocity after the effect the first traffic light has on their velocity before they run the GLOSA algorithm once again for the second traffic light. Hence, further simulations have to be made for larger scale scenario and more traffic lights to conclude which activation distance to use. Having a shorter activation distance means that we can reduce the transmission power of the RSU and thus having

![Figure 4. Simulation scenario map number 1.](image1)

![Figure 5. Simulation scenario map number 2.](image2)

![Figure 6. Influence of activation distance on GLOSA.](image3)
better resource allocation and less collisions in the communications. Compared with the work in [12], where the minimum activation distance is found near 500 m, our work shows better characteristics in this aspect.

Second, we measured the influence that GLOSA penetration rate has on the three performance metrics and how the non-equipped vehicles are affected. The simulations were conducted in a high traffic density environment (Poisson expected value $\lambda = 0.2$). From [8], we learn that an increase in penetration rates of equipped vehicles allows for a better reduction of fuel consumption in the overall traffic scenarios. As it can be seen from Figures 7–9, this is verified not only for fuel efficiency but also for traffic efficiency. The most interesting outcome from these figures is that even the non-equipped vehicles are getting affected in a beneficial way from the GLOSA equipped vehicles and this is due to the SK model. They follow the leading vehicle that, if equipped with GLOSA, forces them to adjust their speeds accordingly because we assume that there are no overtaking in our simulations. The second notice is that the average stop time is reduced even when the penetration rate is small; but to see positive results in fuel efficiency, we need at least 50% equipped vehicles. The observed average maximum reduction in fuel consumption is 7%, which is slightly higher than the average maximum fuel savings in [12] for their scaled up scenario. Finally, the trip time is reduced by 9.85%. The sharp decline after 70% is due to the reduction in stop time; vehicles stop for maximum one traffic light cycle.

Third, we evaluated the impact of the driver’s compliance to the advisory speed on the performance of the GLOSA algorithm. Driver’s behavior is simulated using a random value uniformly distributed, which indicates the compliance of the driver to the advised speed. This is described by (4). It has to be noted that the driver’s speed is again constrained by the road’s limit and minimum advised speed as described previously. We simulated a scenario where all vehicles are equipped with the GLOSA application, and we vary the maximum deviation from the advisory speed. The results presented in Figure 10 indicate that if the driver does not follow the exact advisory speed, then the fuel consumption is potentially increased. According to our simulations, similar results are observed for average

Figure 7. Influence of Green Light Optimal Speed Advisory penetration rate on average stop time.

Figure 8. Influence of Green Light Optimal Speed Advisory penetration rate on average fuel consumption.

Figure 9. Influence of Green Light Optimal Speed Advisory penetration rate on average trip time.

Figure 10. Influence of driver’s compliance to the advised speed on fuel consumption.
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Figure 11. Influence of vehicle traffic density on the GLOSA performance

Figure 12. Influence of Adaptive Route Change penetration rate on average trip time.

Figure 13. Influence of Adaptive Route Change penetration rate on average stop time.

Figure 14. Influence of Adaptive Route Change penetration rate on average fuel consumption.

where $U_{\text{driver}}$ is the speed that the driver will follow, $U_T$ is the advised speed calculated from the GLOSA algorithm and $a$ is a uniformly random number that takes values from the range of [0, 0.4], namely an average increase of 20% from the optimal advisory.

Finally, we simulated different traffic densities (high, medium and low) to capture the influence they have on the overall performance of the GLOSA application. The results shown in Figure 11 suggest that the higher the traffic density (moving from left to right in the plot), the more benefits we have regarding fuel efficiency reaching a maximum of 7% fuel reduction. On the other hand, the benefits we get regarding traffic efficiency are decreased, which was also reported in [9]. This is because the vehicles are more scarcely distributed; therefore, they do not influence each other, they all follow precisely the advisory speed and there are smaller queues at the traffic lights making the GLOSA algorithm work better.

6.2. Adaptive Route Change evaluation

For the evaluation of ARC, we varied the penetration rate of ARC-equipped vehicles. However, those vehicles that are not ARC equipped have wireless module and act as relays for the geo-broadcast messages. As presented in Figures 12 and 13, the average trip time is reduced by as much as 26.5% and the average stop time up to 32.5% for 150 vehicles in the simulation, respectively. In addition, fuel consumption is also reduced by 17.3% as depicted in Figure 14. The minimum values are observed not at 100% penetration but at 70–80%. The reason behind this is the fact that for 100% penetration, all vehicles receive the change route message; thus, all of them change their route and cause congestion on the other route. However, when less vehicles are equipped, the non-equipped ones will continue their initial route, which has less vehicles now.
One possible amendment to the algorithm would be a proportional selection of the new route, so as not all vehicles to change their route.

Moreover, the vehicles make an instant estimation of the local queue size, calculating the number of stopped cars in front of them, without using further communication with the traffic light using (5). They measure the distance from the closest traffic light \(D_{tl}\); by subtracting the distance of the first stopped car from the traffic light \(D_0 \approx 2\ m\), approximated using simulations), they divide it by the length of vehicles \(L = 5\ m\), constant for our simulations) to find the local queue size \(Q\). We simulated two scenarios with different number of vehicles running, and the results presented in Figures 15 and 16 suggest that the maximum and average queue sizes are decreased as ARC penetration is increased. Again the maximum is not observed at 100% as explained before.

\[
Q = \frac{D_{tl} - D_0}{L}
\]  

(5)

**Figure 15.** Influence of Adaptive Route Change penetration rate on maximum queue size.

**Figure 16.** Influence of Adaptive Route Change penetration rate on average queue size.

### 7. CONCLUSIONS AND FUTURE WORK

The results suggest that both GLOSA and ARC applications have a positive effect on all performance metrics. The higher the GLOSA penetration rate is, the more benefits we have with a maximum of 80% reduction in stop time, 9.85% in trip time and up to 7% reduction in fuel consumption in a high traffic density scenario. There is a critical point of 50% of equipped vehicles where the effect of GLOSA starts to be more visible on fuel consumption and of 70% where the trip time is sharply decreased. As the density decreases, the benefits for fuel efficiency are reduced, but there is still improvement compared with non-equipped vehicles. The traffic efficiency on the other hand is increased with the decrease in traffic density reaching 89%. There is also an optimal activation distance where the GLOSA application should advise the driver; this is near 300 m from the traffic lights, but it depends slightly on the road network. Closer to this distance, the time to react is limited; further away, there are no more benefits. If the complexity of the algorithm is to be increased, the distance could be also increased. Our simulation results for the ARC application suggest increase in both traffic and fuel efficiencies. We observe an 18% reduction in average trip time and 26.7% reduction in average stop time. Fuel consumption is reduced by 15.86%. The work presented by this paper is an example of what can be achieved in terms of fuel and traffic efficiencies when vehicles are enabled to communicate with traffic lights and how we can exploit an integrated simulation platform to achieve this.

There are various ways in which these applications could be extended to achieve more accurate results. First of all, for GLOSA we assumed that there are no vehicles waiting at the traffic light, which is not always the case. Therefore, the distance to traffic light could be replaced by the distance to the end of the queue instead to achieve more reasonable results. The simulation network should also be extended to a larger scale scenario using real data for vehicle input. Finally, having results from field tests would provide data to compare field tests and simulations to evaluate the estimations made by the simulations.

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