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Research Article

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 (*GLOSA*) application implementation in a typical reference area, and present the results of its performance analysis using an integrated cooperative ITS simulation platform. In addition, we study route alternation using Vehicle to Infrastructure (V2I) and Vehicle to Vehicle (V2V) 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, drivers compliance to the advised speed and traffic density. Our results indicate that *GLOSA* systems could improve fuel consumption, reduce traffic congestion in junctions and the total trip time. Copyright © 0000 John Wiley & Sons, Ltd.

KEYWORDS

vehicular communications; traffic light 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 (ITS) [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, traffic efficiency, and introduce new entertainment and business applications [4]. Exploitation of ITS 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 (I2V) 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 CO_2 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 (V2I) 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 in order to achieve less fuel consumption. In [10], the IDM 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 small number of vehicles which does 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 500m 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 (I2V) 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 300m.

Second, we implement an *ARC* application which uses both V2I and V2V 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 and based on 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 CO_2 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 which 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, while V2X-equipped vehicles benefit from much lower penetration rates. Another noteworthy

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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, like [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 due to 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 modelling of the vehicle traffic, the communications between traffic lights and vehicles and finally the driver's behaviour. 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 :

- Design and implementation of two V2X applications (*GLOSA* and *ARC*), which aim at increasing fuel and traffic efficiency, using the Fraunhofer VSimRTI platform.
- Extensive simulation experiments using different scenarios in order 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 in order 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 organised 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 which is depicted in Fig. 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, since 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 modelled 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 $[V_{min}, V_{max}]$ where V_{min} is the minimum speed that vehicles can cruise without causing further traffic congestion and V_{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 SUMO [20] traffic simulator that we used in our work.

We have set up two simulation scenarios for each application in order to compare the results. In the first

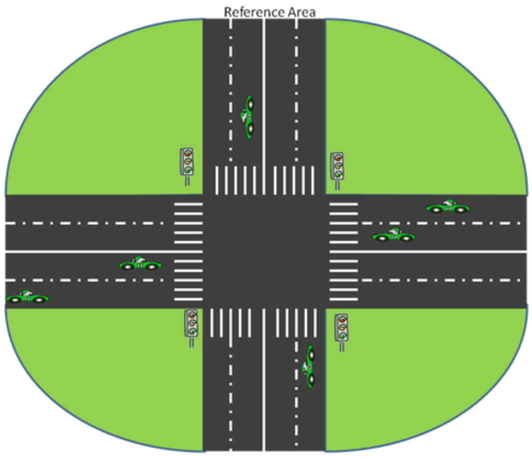

Figure 1. Reference Scenario for GLOSA

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 in order 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 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 and synchronizing different simulation aspects, e.g. vehicular traffic, network communication and application handling. To address these challenges, the integrated simulation platform VSimRTI [18] was used to simulate the use cases.

VSimRTI borrows some concepts of the High Level Architecture (HLA) [22] to enable the coupling of the most appropriate simulators for a scenario. It is a lightweight framework, which is responsible for tasks such as synchronization of simulators, interaction between them and lifecycle management of simulators but also applications. Using VSimRTI enables access to all relevant traffic objects such as road-side units, application-equipped vehicles or traffic lights through common interfaces regardless of the specific simulator instance, e.g. Vissim or SUMO.

To simulate the applications, 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, i.e. all simulations have been performed using standardized V2X protocols such as IEEE 802.11p.

Fig.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. *GLOSA* ALGORITHM

The *GLOSA* algorithm has been implemented to support the aforementioned simulation approach and is presented in the Algorithm 1. First, vehicles enter the communication range of a traffic light according to the Poisson distribution

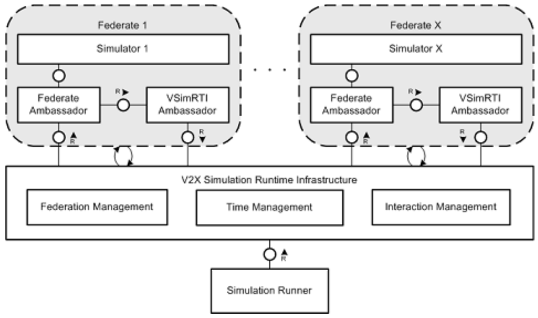

Figure 2. VSimRTI System

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})

as mentioned before. The RSU (Road Side Unit) attached to a traffic light broadcasts periodically CAM's (Co-operative Awareness Messages) including the position, timing information and additional data for the traffic light. When the OBU (On-board Unit) receives a CAM, 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 in order 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 gets as input the current speed U_0, acceleration a of the vehicle and the distance to the traffic light D_{tl}. Using basic rules of motion, given by (1)

$$d = u * t + 1/2 * a * t^2, \tag{1}$$

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).

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

The target speed (U_t) for the red and yellow light phase is calculated using (3)

$$U_t = \frac{2 * d}{t} - U_0 \tag{3}$$

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 Fig.3. A vehicle without *GLOSA* accelerates until it reaches the maximum allowed speed and then suddently 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 (25sec in our example). On the other hand, using *GLOSA*, a vehicle gets 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. Eventhough 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

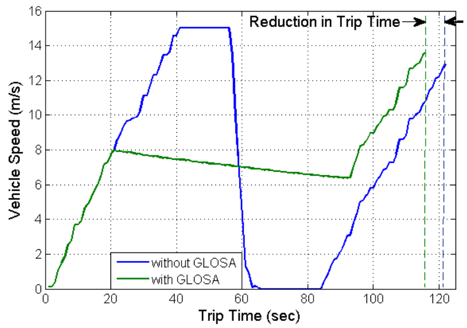

Figure 3. Vehicle's speed over time with and without GLOSA

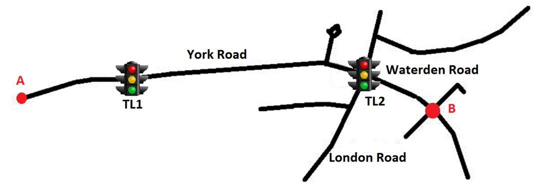

Figure 4. Simulation Scenario Map #1

decreased due to the fact that when the vehicle passes the traffic light it has an initial speed greater than zero.

5. *ARC* 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 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 GCCG [23]. This message includes information related to the road that the congestion has occured. 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] is used for the communications and finally the application simulator described in section 3 which 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 centre in United Kingdom as depicted in Fig. 4. It consists on 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 in order to gather sufficient data in terms of time and number of independent vehicles to get statistically accurate results. The travel distance is approximatelly 0.6miles (0.965km). 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 seconds, 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 2x2 grid with four traffic lights as depicted in Fig.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 15m/s (54km/h) which is near the usual limit in an urban area. The minimum advisory speed is set to 6m/s (21.6km/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 500m and use IEEE 802.11p communication as access mechanism to broadcast their messages.

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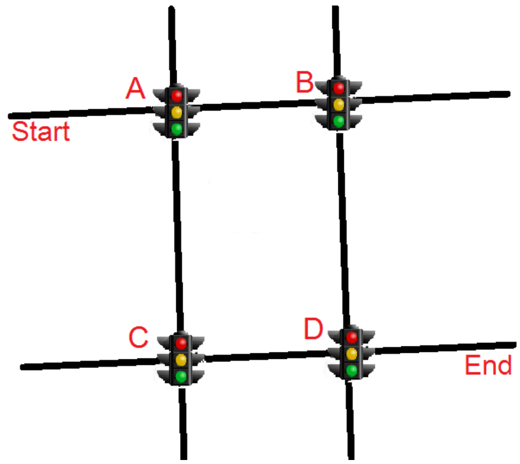

Figure 5. Simulation Scenario Map #2

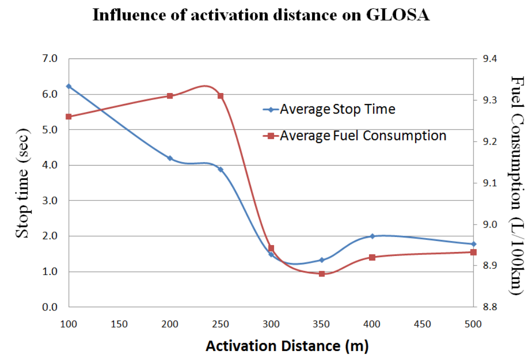

Figure 6. Influence of activation distance on *GLOSA* performance

6.1. *GLOSA* 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, in order 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 in order to have equal red and green phases. The results of the two performance metrics can be seen in Fig. 6. An optimal point of activation is found at a distance near 350m. 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 due to 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 400m between them (Fig. 4), shift this optimal point to a shorter distance of 250m 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 better resource allocation and less collisions in the communications. Compared with the work in [12], where the minimum activation distance is found near 500m, 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 λ = 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 Fig. 7, 8 and 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 which - if equipped with *GLOSA* - forces them to adjust their speeds accordingly since 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 in order 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

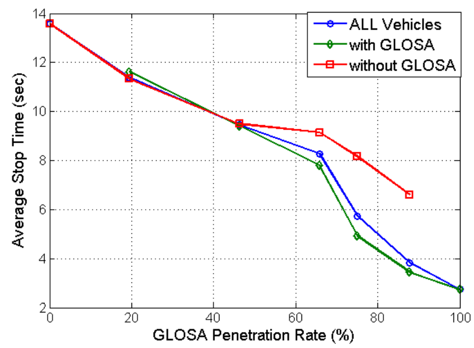

Figure 7. Influence of *GLOSA* penetration rate on average stop time

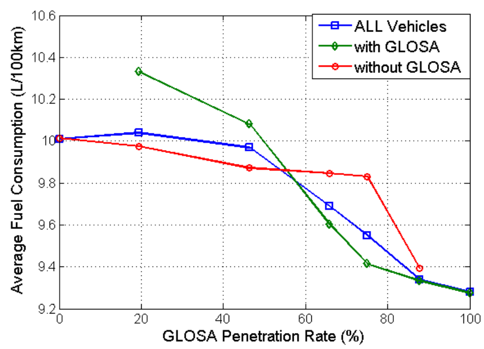

Figure 8. Influence of *GLOSA* penetration rate on average fuel consumption

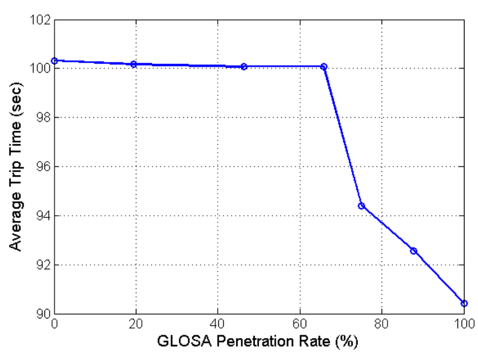

Figure 9. Influence of *GLOSA* penetration rate on average trip time

the *GLOSA* algorithm. Driver's behaviour 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 adivsed speed as described previously. We simulated a scenario where all vehicles are equipped with the *GLOSA*

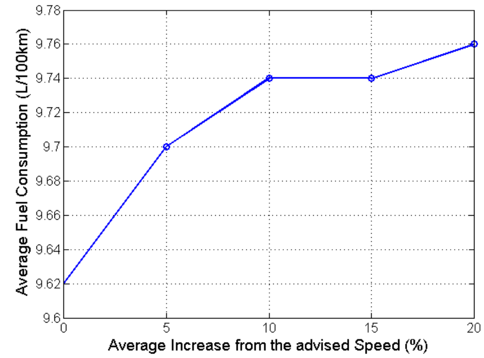

Figure 10. Influence of driver's compliance to the advised speed on fuel consumption

application and we vary the maximum deviation from the advisory speed. The results presented in Fig. 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 stop time and trip time.

$$U_{driver} = (1 + a)U_t \tag{4}$$

where U_{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 which 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) in order to capture the influence they have on the overall performance of the *GLOSA* application. The results shown in Fig. 11 suggest that the higher the traffic density (moving from left to right in the plot), the more benefits we have regarding in 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. *ARC* 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

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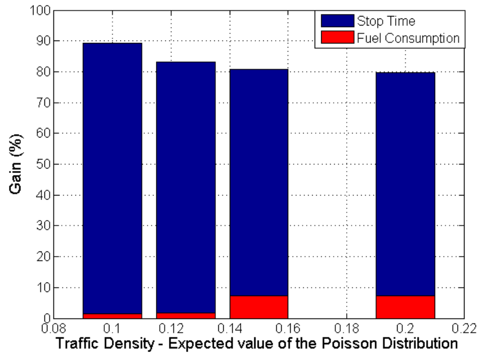

Figure 11. Influence of vehicle traffic density on the *GLOSA* performance

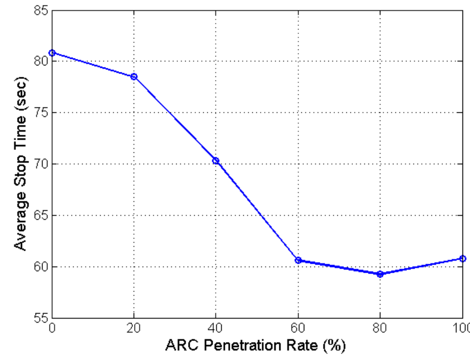

Figure 13. Influence of *ARC* penetration rate on average stop time

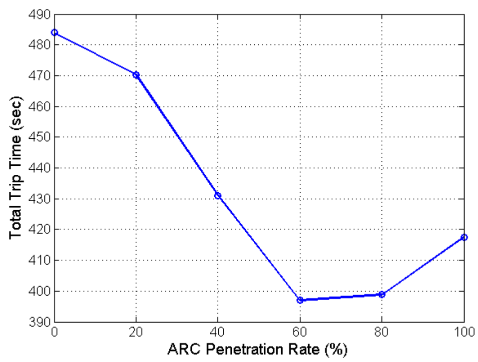

Figure 12. Influence of *ARC* penetration rate on average trip time

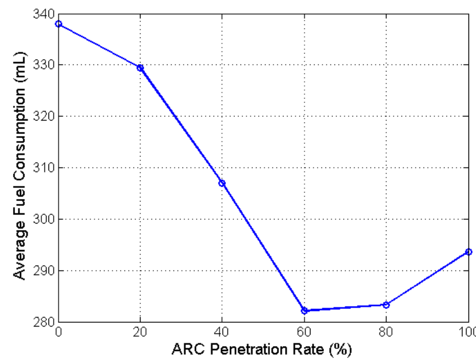

Figure 14. Influence of *ARC* penetration rate on average fuel consumptio

for the geo-broadcast messages. As presented in Fig.12 and 13, the average trip time is reduced up to 18% and the average stop time up to 26.7%, respectively. In addition, fuel consumption is also reduced by 15.86% as depicted in Fig.14. The minimum values are observed not at 100% penetration, but at 60-70%. 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 not-equipped 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}) and 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 50 and 100 vehicles running and the results presented in Fig.15 and 16 suggest that the maximum and average queue size are decreased as *ARC* penetration is increased.

$$Q = \frac{D_{tl} - D_0}{L} \tag{5}$$

7. CONCLUSIONS AND FUTURE WORK

The results suggest that both *GLOSA* and *ARC* application 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

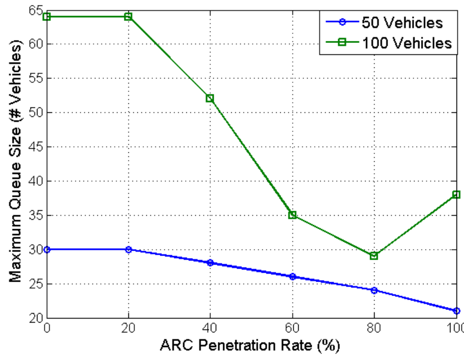

Figure 15. Influence of *ARC* penetration rate on maximum queue size

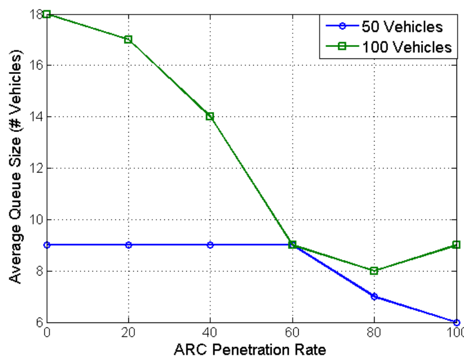

Figure 16. Influence of *ARC* penetration rate on average queue size

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 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 to 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 and this is near 300m from the traffic lights but it depends slightly on the road network. Closer to this distance, the time to react is limited and 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 efficiency. We observe a 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 efficiency 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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