Potentials and Limitations of Green Light Optimal Speed Advisory Systems

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***Abstract*—The reduction of CO_2 emissions is one of the most anticipated features of future transportation systems. Smart traffic lights are believed to contribute to achieving this by either adapting their signal program or by informing approaching drivers. In this paper we investigate the potentials and limitations of the latter, that is, Green Light Optimal Speed Advisory (GLOSA) systems in a realistic, large scale simulation study. We examine the impact of different equipment rates of both traffic lights and vehicles on environmental related metrics but also study how these systems can increase the comfort for drivers by reducing waiting times and the number of stops.**

We find that at low traffic densities these systems can meet all their goals and lower CO_2 emissions by up to 11.5 % whereas in dense traffic several side-effects could be observed, including overall longer waiting times and even higher CO_2 emissions for unequipped vehicles.

I. Introduction

Intelligent Transportation Systems (ITS), including the possibility to wirelessly exchange information among vehicles and between vehicles and various types of infrastructure, offer a broad range of applications [1]. While Car-2-X communication was shown to be able to help improve traffic safety [2], [3], the positive impact on comfort and on the environment is also an important factor in successfully bringing this technology onto the market.

In its Energy Roadmap 2050, the European Union has set a goal to reduce emissions of greenhouse gases by 80%-95% until 2050 (compared to 1990 levels). Decreasing the CO_2 emissions caused by internal combustion engine vehicles could substantially help reach this goal while at the same time improve air quality and thereby the quality of life – especially in urban environments. A great deal of these CO_2 emissions are caused by the constant stopping and starting at traffic light regulated intersections. Because optimization of traffic light programs can only help to a certain extent, automobile manufacturers as well as academic institutions investigate the possibility and benefits of providing this information to the vehicles [4]. In-advance knowledge about the traffic light program, that is, the duration of red and green phases, can enable vehicles to autonomously suggest certain driving strategies to drivers in order to avoid stops at traffic lights and hence reduce CO_2 emissions and (directly proportional) fuel consumption [5], [6]. The exchange of traffic light signal information has already been standardized and is achieved through the transmission of so called SPAT (Signal Phase and Timing) messages [7], [8].

Even though smart traffic lights were already field-tested within research projects such AKTIV [9] or CVIS [10], there exists no city-scale evaluation that shows overall benefits and limitations of these system. To the best of our knowledge, we are the first to investigate effects such a system has on unequipped vehicles while also varying equipment rates of both traffic lights and vehicles. Unlike most of the related work in this field, we deploy a nearly optimal driving strategy to identify the absolute potential of Green Light Optimal Speed Advisory (GLOSA) systems. Instead of only allowing vehicles to accelerate, brake or coast (i.e., not actively accelerating or braking), we account for the fact that freewheeling, i.e., when the clutch is disengaged, is often beneficial when it comes to fuel saving. All of these maneuvers have different characteristics regarding CO_2 emissions and fuel consumption, and (as we show in this paper) oftentimes a combination of them is the best strategy to approach a traffic light. We extended existing emission models to accurately reflect the effects of the chosen strategy and evaluated a traffic light assistance system in a large scale simulation while particularly focusing on the effects on unequipped vehicles and traffic flow in general.

In brief, the main contributions of this work can be summarized in four aspects:

- we measure the (best case) environmental impact (in terms of fuel consumption and CO_2) when using an optimal driving strategy
- we investigate the potential benefit as a comfort system (in terms of waiting time and stop count)
- we evaluate necessary preconditions for such systems (in terms of traffic density, percentage of equipped traffic lights, and fraction of equipped vehicles)
- we discuss possible limitations caused by traffic light assistance systems and identify necessary traffic densities in which operation can be beneficial.

The remainder of this paper is organized as follows: In Section II we give an overview of related work in the field of traffic light assistance systems as well as driving strategies. In Section III we discuss the envisioned system followed by the presentation of the used algorithm (Section IV). The setup and details of our extensive simulations along with the evaluation will be presented in Section V. Finally, Section VI concludes our work.

II. Related Work

In 1983 Volkswagen introduced the *Wolfsburger Welle*, the first driver assistance system to make use of traffic light information [11]. Infrared equipped traffic lights would inform approaching drivers whether their current speed allows them to benefit from synchronized traffic lights. A mechanical on-board display used this information to then give suggestions to the driver. Technical difficulties and low profit ratios led to discontinuation of the project.

In 2005 Richter proposed to optimize throughput at traffic light regulated intersections by giving each driver an individual speed recommendation [12]. This approach was evaluated using microscopic traffic simulation showing that total CO_2 emissions could be reduced by up to 15%. However, the used driving strategy was not optimal as deceleration was only achieved by actively braking the car. Furthermore, legal constraints were not accounted for, allowing vehicles to go below the minimum acceptable speed. In this work, we deploy a near optimal driving strategy while also considering maximum and minimum speeds.

Travolution, a research project situated in Ingolstadt, Germany, focused on improving traffic light programs and also on establishing an IEEE 802.11p [13] enabled communication to transfer traffic light information to vehicles [4]. Drivers were recommended a certain speed in order to avoid stopping at red lights. The study showed that such a system can also work with dynamic traffic lights (i.e, those that do not strictly follow a static program but adjust to current traffic measured by cameras or inductors). The amount of stops could be reduced by 17%, however, no information on emissions or fuel consumption was given.

Tielert et al. investigated which parameters have the biggest impact on fuel consumption using microscopic traffic simulation [5]. They identified that the impact of communication traffic lights depends on the information distance, that is, the remaining distance to the traffic light when the vehicle learns about the traffic light program. They state that an information distance higher than approx. 500 m to 600 m does not offer an additional benefit. From this they follow that the communication model in a simulative performance evaluation can be abstracted with the help of this information distance – a fact of which we make use in this paper. The deployed driving strategies, however, only included acceleration, active braking, and gear choice. We make use of all driving maneuvers to give more accurate information on possible fuel saving and therefore CO_2 reduction in a realistic scenario while also examining unequipped vehicles.

A computational approach to finding the optimal speed to approach a traffic light was presented by Alsabaan et al [14]. Their study includes the utilization of (idealized) multi-hop communication to disseminate traffic light programs and speed advisory information. Different driving strategies were neglected and CO_2 emissions were only based on braking and acceleration. Also, their system model only consisted of one intersection.

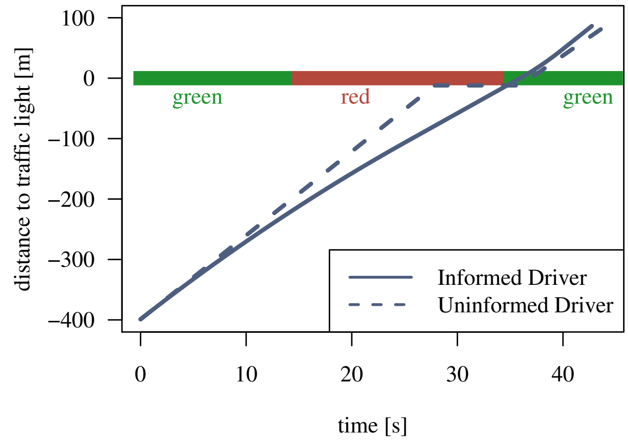


Figure 1. Trajectories of informed and uninformed drivers. The uninformed driver has to stop at the red light, while the informed driver arrives when the signal turns green.

Performance of GLOSA systems was also investigated in the scope of the PREDRIVE C2X project [15]. Authors present an algorithm for the computation of the advised speed and simulate the system using two simple small-scale scenarios. The small road networks with only two or four traffic lights respectively did not allow for a detailed analysis of the limitation of such systems. A realistic mix of regulated and unregulated intersections, however, can have a considerable impact on both informed and uninformed drivers as we will show in this paper.

The full potential of GLOSA systems through the choice of an optimal driving strategy was investigated by Raubitschek et al. [6]. They introduced two new strategies to the simulative performance evaluation, namely freewheeling (i.e., neutral gear) and coasting (any gear, no throttle). A submicroscopic evaluation and real life experiments showed that an average decrease of fuel consumption (and CO_2 emissions) of about 13% could be reached. However, only a single traffic light was investigated and vehicles did not influence each other in any way. In this paper we use these proposed driving strategies to conduct a large scale simulation to not only gain insights on the benefits of traffic light assistance systems but also on the implications such a system could have.

We contribute to the field of intelligent traffic lights by further investigating different traffic densities, equipment rates, and comfort metrics such as waiting times and the number of stops.

III. Intelligent Traffic Lights

Intelligent traffic lights are believed to play an important role in tomorrow's transportation system as they are a major factor in the optimization of traffic flows [16]. Dynamic traffic light programs can adapt to current traffic in order to lower waiting times and increase traffic throughput [4], [17].

Equipped with communication devices, traffic lights could also inform approaching vehicles of the current traffic light program to further reduce the amount of stops and starts in order to decrease CO_2 emissions and fuel consumption [5].

As shown in Figure 1, this information can be used by an approaching driver to alter his original trajectory through the use of certain driving maneuvers, such as braking, freewheeling, or coasting to avoid having to stop at the red light but arrive shortly after the signal turns green.

In this paper, we analyze the potential of GLOSA systems with the help of communicating traffic lights in terms of CO_2 reduction in a large scale simulation and also identify side-effects such a system could have on other vehicles. The used communication technology does not play an important role as long as an information distance (i.e, the distance to a traffic light at the time the driver is informed of the red and green phases) of about 500 m can be guaranteed [5]. In order to identify the maximum potential of communicating traffic lights we do not model communication but assume that equipped vehicles can always inform the driver about the next intelligent traffic light they are approaching 500 m in advance.

IV. The Optimal Driving Strategy

Given the traffic light program (i.e., duration of red and green phases) of the next traffic light a driver can approach the intersection in different ways. The vehicle can be in six different states which have specific CO_2 emission and (directly proportional) fuel consumption characteristics (N.B. we neglect emissions caused by auxiliaries such as air conditioning):

- **Constant Velocity**: The vehicle moves with constant speed when the driving force equals all resistances (air, friction, ...). Emissions are based on the sum of all resistances.
- **Acceleration**: The vehicle increases its speed. Emissions are highest in this state.
- **Braking**: Activation of the mechanical friction brake reduces the velocity of the vehicle. CO_2 is not emitted in this state.
- **Stopping**: The vehicle is not moving. The engine can be automatically turned off through the use of the start-stop system. When the engine is turned off no CO_2 is emitted. Restarting the engine will emit about as much CO_2 as if the engine was idling (neutral gear) for a few seconds.
- **Freewheeling**: When the gearbox is disconnected from the power-train the velocity of the vehicle will decrease over time. The distance possible to cover in this state is proportional to the initial speed. Drivers of vehicles with manual transmission have to enter this state by putting in the neutral gear. Modern automatic transmission vehicles can do this automatically. CO_2 emissions in this state are relatively low because the engine is idling.
- **Coasting**: The driver does not actively accelerate or decelerate and does not put in the neutral gear. The power-train remains connected to the gearbox and is driven by the kinetic energy of the vehicle. In general the vehicle does not emit CO_2 in this state but velocity will drop considerably faster. Figure 2 shows the difference between freewheeling and coasting in terms of reachable distance with an initial speed of 100 km/h.

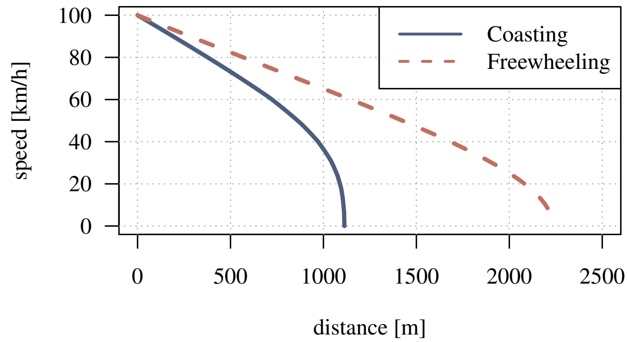


Figure 2. Coverable distances when coasting or freewheeling based on findings in [6]

Finding the optimal combination of strategies to minimize the amount of CO_2 emitted is an NP-hard problem and can only be found through evaluating all possible solutions. Authors in [6] describe an approach to find an optimum, however, this is computationally complex and was only done for a single vehicle at a single traffic light. This computation can hardly be done on an electronic control unit within a vehicle or in a large scale simulation for a high number of vehicles and traffic lights. We therefore try to approximate the optimal solution that not only prefers to arrive at the beginning of a green phase if possible but also accounts for legal constraints on German streets.

Depending on the type of street a minimum velocity v_{min} has to be maintained if possible. In relation to the maximum allowed speed v_{max} it holds that $v_{\text{min}} \approx 0.6 \times v_{\text{max}}$ on all German roads. From this it follows that the advised speed to a driver v_{adv} must always be in an interval:

$$0.6 \times v_{\text{max}} \leq v_{\text{adv}} \leq v_{\text{max}} \tag{1}$$

A simplified version of our algorithm is shown in Figure 3. The algorithm is called every time step and its outcome is a suggestion to the driver. In a first step we compute the virtual arrival time for v_{max} and check if the traffic light is green upon arrival. If this is the case, the system advises the driver to accelerate to/hold v_{max}. If the required speed to arrive at a green traffic light is greater than the current one the driver should accelerate unless this speed is greater than the speed limit. If it's lower, i.e., the driver is currently too fast and will arrive at a red light when maintaining the current velocity, it is checked if freewheeling is a possible solution. For this, deceleration and coverable distance in the freewheeling mode have to be computed based on individual parameters of the vehicle such as weight or the initial speed. We prioritized freewheeling over coasting because of its better energetic characteristics and the resulting considerably larger range (cf. Figure 2). In cases where freewheeling is insufficient, i.e., the vehicle arrives at the traffic light before it turns green, it is evaluated whether coasting offers a solution. Should this not be the case, the driver is advised to brake unless the required

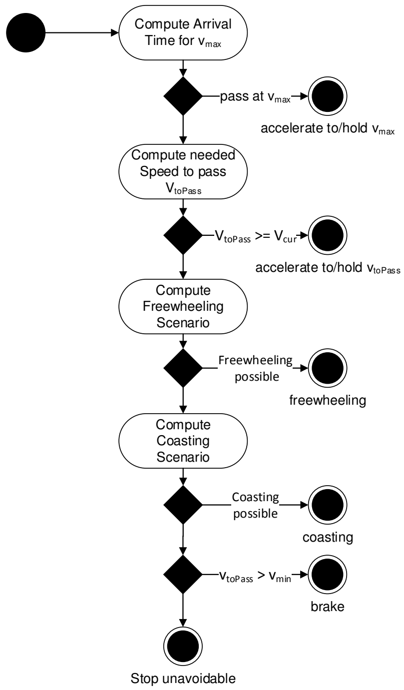


Figure 3. Overview of the driving strategy algorithm; some steps have been aggregated and checks for $v_{\text{toPass}} > v_{\max}$ have been omitted.

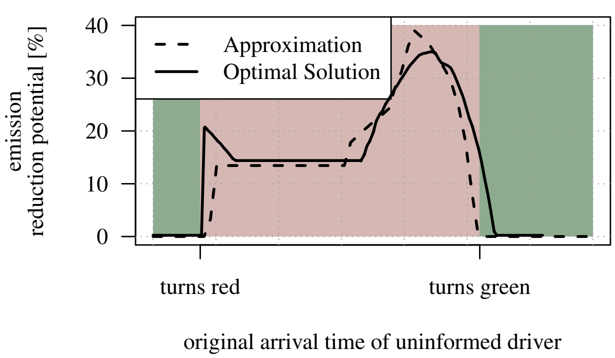


Figure 4. Relative fuel savings of informed drivers over uninformed drivers. Comparison of our algorithm to find an approximation of the optimal solution in comparison to the presented optimum in [6]

velocity is lower than the minimum speed – in this case a stop is unavoidable. Our algorithm never advises drivers to pass an amber traffic light.

Figure 4 shows our results compared to the optimal solution presented in [6]. We rebuilt the evaluated scenario and developed an approximative light-weight algorithm in order to find the best strategy. Differences in the graph can be explained by differing calibrations of the driving mode, i.e., their assigned fuel consumption. Fuel saving (and thereby CO_2 reduction) averaged at about 13.7% in our approximation and 13% in the solution presented in [6]; this shows that our simulation and algorithm produce sufficiently accurate results to conduct a large scale simulation.

Table I
SIMULATION SETUP

Parameter	Meaning/Value
ρ	vehicle equipment rate [0%-100%]
σ	traffic light equipment rate [0%-100%]
D	Traffic density, either Ia, Ib, II, or III
Number of Vehicles	169 – 3376
Area	5.6 km × 1.6 km
Information Distance	500 m
Regulated Junctions	80 %
TL Program	40 s red, 30 s green
Vehicle Types	VW Polo IV 1.4, BMW F10 535i, BMW E71 X6 M
Emission Model	EMIT (extended)
Simulator	Veins (SUMO)

V. SIMULATION

We conducted a large scale simulation to identify side effects and benefits of traffic lights equipped with communication devices. We used the simulation framework Veins [18] coupling OMNeT++ and the traffic simulator SUMO [19] which we extended to support driving modes such as coasting and freewheeling.

The plotted figures show the average values over all vehicles in the annotated sets, e.g., all equipped or non-equipped vehicles. To understand the meaningfulness of the presented results better, we also investigated box-plots for all traffic densities, and found that the notches were almost always non-overlapping for the lower traffic densities (Ia, Ib). For the higher densities, that is, density II and especially III, this was not always the case. These results must be understood as tendencies or indicators for the overall system performance instead of absolute values.

To fully explore the potential of GLOSA systems we assume that a driver always follows the suggested driving strategy; we note that in a real life scenario a driver might also choose not to. To account for these effects a psychological driver model [20] would have to be deployed, however, empirical data on the acceptance of speed recommendation of traffic light assistance systems was not available at the time of writing. It has been shown that such psychological behavior can be approximated using the vehicle equipment rate [20].

A. Setup

According to [21] and [22] traffic densities can be classified into four subregions (cf. Figure 5). These subregions give information about how independent a driver is, that is, to what extent driving maneuvers and decisions are influenced by other vehicles. Naturally, the more independent a driver is, the higher the possible benefit of GLOSA systems as driving strategies can then be chosen freely.

In the free flow subcategory (1), drivers can move freely within legal boundaries without being influenced by nearby vehicles. With increasing traffic density (semi-free flow, subcategory 2) drivers cannot always choose driving strategies arbitrarily as they are sometimes blocked by vehicles in front of them. This freedom is further decreased in the synchronized

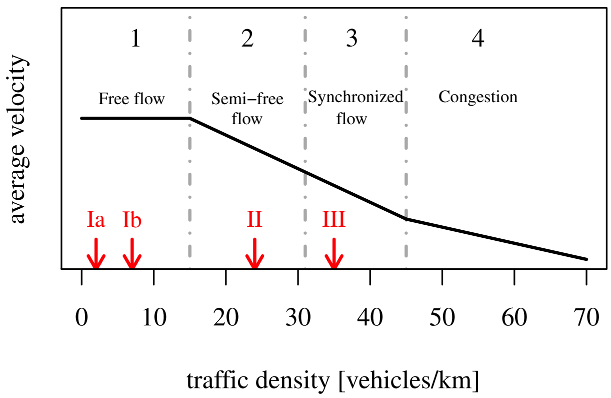
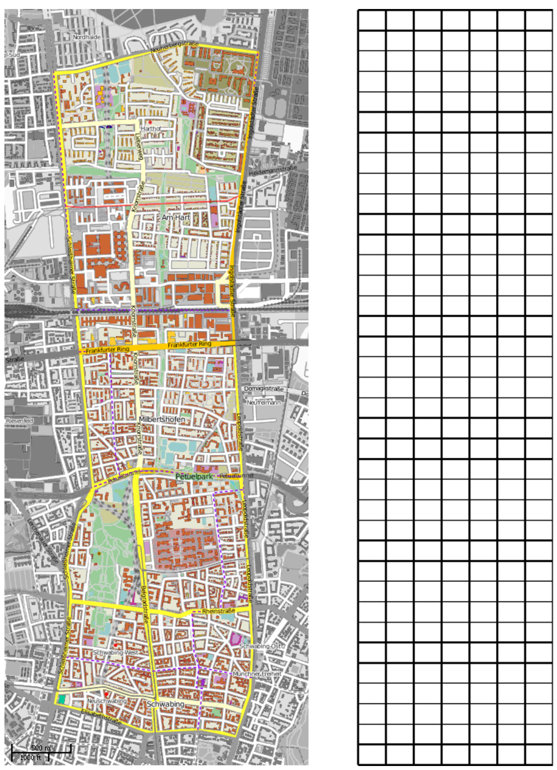


Figure 5. Relation of traffic density and average velocity according to [21]. Select traffic densities for the simulation are marked with red arrows.



(a) Original map Data[1] (b) Synthetic scenario

Figure 6. Conversion of map data to a synthetic scenario

flow subcategory (3) where acceleration or deceleration decisions almost always depend on other vehicles and in general only a low average velocity can be reached. On congested roads (subcategory 4) the movement of a vehicle entirely depends on the vehicles around it; in these cases individual driving strategies cannot offer a benefit due to the lack of space caused by the high volume of traffic. We therefore decided to select four traffic densities (annotated with Ia, Ib, II, and III in Figure 5) from the first three subcategories in order to evaluate benefits and side-effects of GLOSA systems.

Finding a suitable map for the performance evaluation is a critical task. The preferable solution would be to take real map data and convert it to be used in simulation [23]. However, intersections are often not converted properly and traffic light program information is missing or even wrong. We therefore decided to build a synthetic scenario with basing as many parameters as possible on map data taken from Munich, as shown in Figure 6. A total of 8 vertical and 38 horizontal roads with a speed-limit of 50 km/h cover an area of about 5.6 km $\times$ 1.6 km. A typical traffic light cycle in the selected area has a length of 70 s with a 40 s red phase. In the select area the percentage of unregulated intersection is approx. 82 %. The regulated intersections, however, are substantially busier than the unregulated ones. It was shown that in general about 20 % of all intersections control 80 % of traffic [24]. To account for this effect with uniformly distributed traffic, we equipped 80 % of all intersections with traffic lights in the simulation.

Results for potential fuel saving and CO_2 reduction heavily depend on the used emission models. We extended the EMIT emission model [25] to account for emissions during stopping for start-stop system enabled vehicles, freewheeling, and coasting. To analyse the absolute potential of traffic light assistance systems we did not model unequipped vehicles to be freewheeling or coasting as they were not informed about traffic light programs. We used three different types of vehicles and drivers to further increase the realism of our simulation: a cautious driver, a normal driver, and a sporty driver. Exact CO_2 emissions and physical parameters of the used vehicles were taken from real vehicles namely the VW Polo IV 1.4, the BMW F10 535i and the BMW E71 X6 M.

Table I gives an overview of all simulation parameters, their meanings, and their values.

B. CO_2 Emissions and Fuel Consumption

In a first step we investigated to what extent CO_2 emissions (proportional to fuel consumption) could be reduced in the whole network, not distinguishing between equipped and unequipped vehicles. Figure 7a and Figure 7b show our findings when altering the traffic light equipment rate σ or the vehicle equipment rate ρ respectively. As can be seen, both figures look very similar, showing that increasing either the vehicle equipment rate or the traffic light equipment rate has almost the same effect. This is an important finding as it indicates that both equipment strategies are valid approaches in decreasing CO_2 emission rates. A high ρ with a low σ leads to a low number of traffic lights whereas a high number of vehicles can potentially lower their emission rates, while in the inverse scenario a small number of vehicles can benefit from a high number of communicating traffic lights.

The figures clearly show that the benefit is considerably higher (up to 12 % fuel saving/emission reduction) at lower traffic densities (Ia and Ib, cf. Figure 5). The main reason for this is that in light traffic, vehicles can move more freely and do not interact with each other as often. Increasing the

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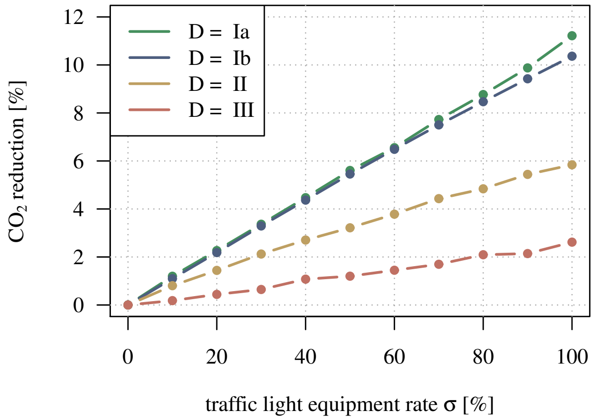
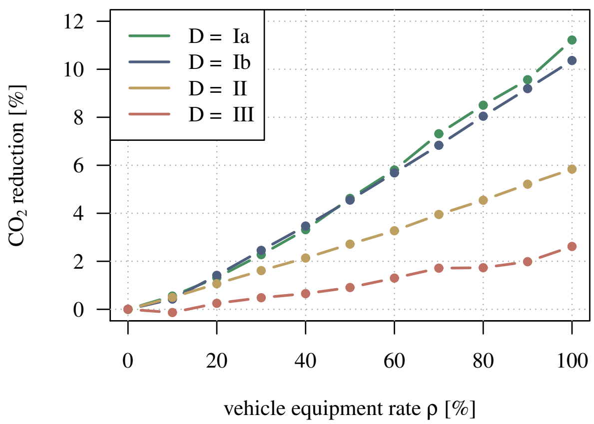
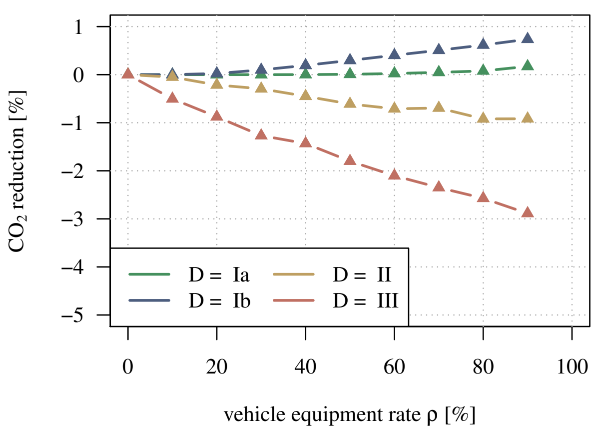


(a) Total CO_2 reduction for a fixed vehicle equipment rate $\rho = 100\%$ over different traffic densities



(b) Total CO_2 reduction for a fixed traffic light equipment rate $\sigma = 100\%$ over different traffic densities



(c) Effect on unequipped vehicles for a fixed traffic light equipment rate

Figure 7. CO_2 Reduction compared to a transportation system with no intelligent traffic lights

traffic density (II and III) directly leads to a lower benefit. Vehicles are affecting each other and the choice of driving strategies becomes more limited due to the now crowded streets and uninformed drivers blocking traffic lights. However, the positive effect of the system still increases linearly with the amount of equipped devices. Figure 7c shows that the overall reduction of CO_2 emissions is almost solely caused by equipped vehicles. Interestingly, unequipped vehicles can also marginally benefit at lower traffic densities as they are at times forced to drive behind an equipped vehicle and thereby sometimes avoid stopping at a red light. Note however, that unequipped vehicles were not modeled to be freewheeling or coasting and a lower CO_2 value for them is only caused by fewer acceleration and deceleration cycles. At higher traffic densities we observed a negative effect for unequipped vehicles, mainly caused by longer travel times, which will be discussed later on.

For the first time we were able to show that earlier findings for simpler scenarios (one vehicle, one intersection) [5], [6] can indeed be generalized under optimal conditions (low traffic density, fully equipped vehicles and traffic lights, and the use of a nearly optimal driving strategy). However, scenarios with higher traffic densities or lower equipment rates show that especially the interaction of non-informed drivers with their informed counterparts can have negative side-effects.

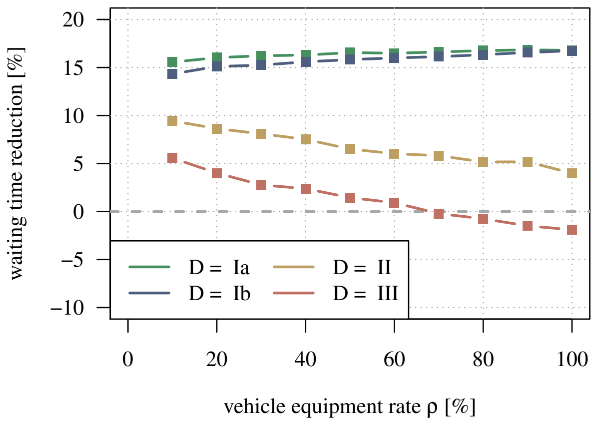
C. Waiting Time and Stop Count

Traffic light assistance systems are not only envisioned to be beneficial for the environment but to also serve as a comfort system for the driver by reducing the number of unnecessary stops at red lights or to decrease waiting times at traffic lights in general.

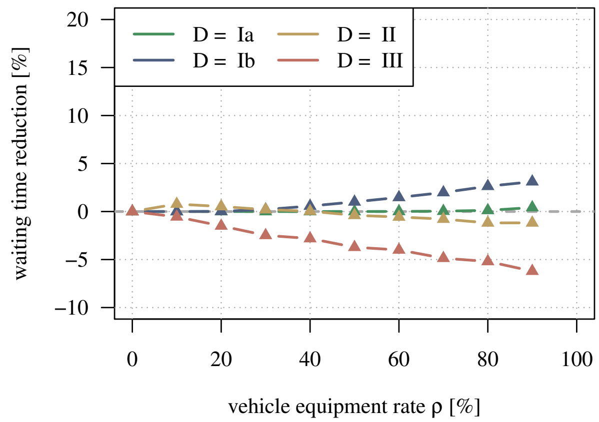
We investigated the effects on waiting times for both equipped and unequipped vehicles (Figure 8). As can be seen in Figure 8a the benefit for equipped vehicles is not dependent on the overall number of equipped vehicles at low traffic densities. Independent of the equipment rate, informed drivers could benefit from a reduction of waiting time of about 15 %. The slow increase with rising traffic density can be explained by unequipped cars blocking a traffic light because of their suboptimal approach, forcing an equipped vehicle to also stop.

For higher traffic densities we observed a different situation: When more vehicles used the traffic light assistance system, the benefit for the driver became less and less, eventually even resulting in longer waiting times. The reason for this is a suboptimal road utilization. When a traffic light turns green, assisted drivers might not fully accelerate (in order to pass the next traffic light without stopping), leading to a smaller number of vehicles to be able to pass the traffic light. This notably increases congestion at traffic lights and thereby the waiting time for all vehicles.

When looking at uninformed drivers (Figure 8b) we noticed that they could reduce their waiting time by a small percentage when forced to drive behind equipped vehicles in the low traffic density scenarios, but were also affected by the before mentioned problem of suboptimal road utilization. Stuck in traffic jams caused by slowly accelerating equipped vehicles, their waiting time increased in the higher traffic density settings, giving strong indication that naively following the optimal driving strategy for the own vehicle can have disadvantages for others. Our algorithm does not advise drivers



(a) Equipped vehicles only



(b) Unequipped vehicles only

Figure 8. Waiting Time Reduction in front of equipped traffic lights, shown for unequipped and equipped vehicles at a fixed traffic light equipment rate $\sigma = 100\%$ over different traffic densities

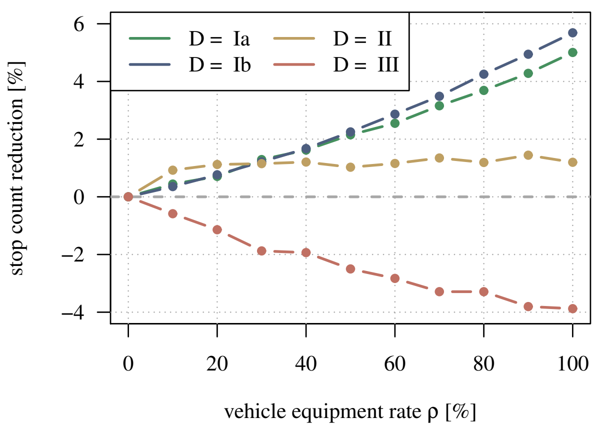


Figure 9. Total reduction of stops for all vehicles at a fixed traffic light equipment rate σ of 100 %

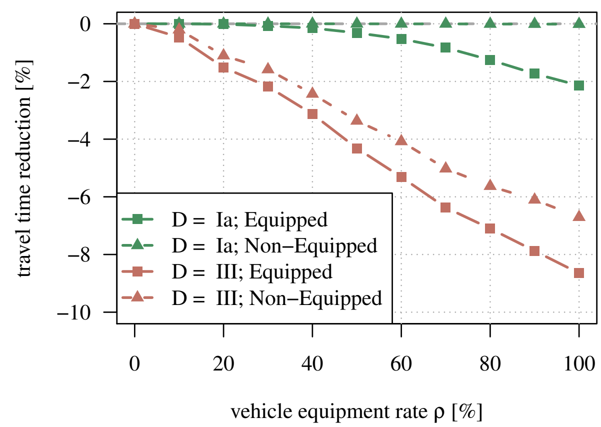


Figure 10. Travel Time at low and high traffic density, shown for equipped and unequipped vehicles

to pass an amber traffic light, causing unequipped vehicles that would otherwise pass the traffic light to also stop when driving behind an equipped vehicle.

We furthermore examined the number of stops vehicles had to make in front of equipped traffic lights and observed a linearly increasing benefit at low traffic densities (cf. Figure 9). With only a few equipped vehicles at the medium traffic density (II) we noticed a better performance caused by beneficial interaction of equipped vehicles with their unequipped counterparts. However, when the number of equipped vehicles increases the mentioned negative effects could be observed again, resulting in a lesser benefit, and even a negative impact for the highest simulated traffic density, where vehicles had stop multiples times in front of the same traffic light.

D. Travel Time

In general, we did not expect a reduced travel time for equipped or unequipped vehicles. The reduction of travel time caused by a vehicle passing a traffic light without having to stop is immediately canceled by the fact that our algorithm did not advise (and therefore disallow in our simulation) informed drivers to pass amber traffic lights. This can be seen in Figure 10 where we already noticed an increase of travel time at traffic density Ia. Unequipped vehicles were not affected by this, as interaction was minimal in this scenario. At the highest simulated traffic density we observed considerably longer travel times, not only directly caused by longer traffic jams at traffic lights but also by the resulting effect on other intersections: if the jam becomes long enough to block such an intersection, vehicles on the intersecting road are unable to cross or turn, forcing them to wait until the jam is resolved.

VI. Conclusion

Green Light Optimal Speed Advisory (GLOSA) systems are envisioned to be not only environmental friendly by reducing CO_2 emissions and fuel consumption but also to serve as a comfort system that is able to reduce waiting times and the number of stops at traffic lights.

In this work we investigated the benefits of informing approaching vehicles about traffic light programs. Our performance study showed that at low traffic densities ($\leq$ approx. 20 vehicles/km) all these goals could be reached. CO_2 emissions and fuel consumption could be reduced by up to 11.5 % in an ideal scenario, waiting times even by about 17 % and the amount of stops could be lowered by $\approx$ 6 %. We found that these benefits grow linearly with the number of equipped traffic lights *or* vehicles (or both).

However, with denser traffic the performance of such a system deteriorates. Vehicles affected by other vehicles can no longer choose an optimal driving strategy. In our simulation we could observe that self-serving drivers cause road utilization to become suboptimal, considerably contributing to the forming of traffic jams. The resulting congestions not only lead to higher CO_2 emissions for unequipped vehicles but also to longer waiting and travel times and more frequent stops for all vehicles in the scenario.

To solve this problem future work includes the investigation of more advanced approaches that account for surrounding traffic and traffic lights further ahead.

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