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USING INTELLIGENT TRAFFIC LIGHTS TO REDUCE VEHICLE EMISSIONS

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Abstract. *Cars with petrol driven internal combustion engines are constant sources for air pollution. As alternative car engines have not yet replaced the petrol-driven engines, road transportation is today still responsible for large emissions of carbon monoxide, carbon dioxide, hydrocarbons, and many other organic compounds into the environment. These chemicals produce great damage to our health (e.g., respiratory diseases, irritation to the eyes), and to the environment (e.g., global warming, acid rains). There is a direct relation between the car's emissions and its acceleration: an accelerating car will pollute more than a non-speeding car. Imagine a car approaching an intersection with the traffic lights showing green color. The driver can accelerate (hoping that she/he will be able to pass) or not (bring the car to a safe speed, but risking missing the green). In this paper we present an ITS-based system capable of guiding the driver's decisions with the goal of reducing vehicle emissions. The system considers parameters ranging from the car's characteristics to human reactions. In this we present results demonstrating the capability of the system to produce decisions that reduce pollution in urban traffic environments.*
Keywords: Intelligent traffic lights, Urban traffic, Pollution, Wireless communication

1. **Introduction.** The number of cars has grown to approximately 1.1 billion of cars on road today [1]. Experts predict that by 2030 the number of cars will double [1]. Even today cars are already major sources for air pollution, with negative effects on the environments and health [9]. Cars emit tons of pollutants in the air every day, with negative impact on health and environment. Ground level ozone (O_3) produces smog, which causes visibility and lung-health issues. And carbon dioxide leads to Global Warming.

Today various measures are taken to reduce air pollution, including the manufacture of hybrid cars, and the creation of new environmentally friendly fuels [9]. Unfortunately we are not there yet, and the reality is that cars still pollute. Even though manufacturers try to reduce as best as possible the problem, the people behind the wheel are also responsible for creating a better future for themselves and their children. The solution to environmental degradations involves unselfish and compassionate behavior, a scarce commodity.

In this we propose a system designed to assist drivers in adapting their behavior and take informed decisions to minimize the fuel consumption (and, implicitly, air-pollution). *We consider the special case of minimizing fuel consumption as drivers approach an intersection.* The car's fuel consumption increases when the car accelerates. In case of an intersection equipped with traffic lights, previous studies showed that drivers tend to accelerate more than usually to catch the green light [20]. This is also a major cause of over 5,000 fatal crashes that occur each year in intersections with traffic signals or stop signs (according to the National Highway Traffic Safety Administration [12]).

"Smart" vehicles of the future are envisioned to aid their drivers to reduce fuel consumption and emissions by wirelessly receiving phase-shifting information of the traffic lights (TL) in their vicinity and computing an optimized speed in order to avoid braking and acceleration maneuvers. As communication technology continues to become more and more affordable, an increasing number of everyday objects participate in today's interconnected world. In the future, the interaction of physical objects is envisioned to facilitate new services that improve our everyday lives. This Internet of Things society is facilitated by advances such as the wireless communication from and to vehicles, aiming at increasing comfort and safety of the driving experience as well as at reducing fuel consumption and emissions to mitigate the environmental impact. In this we propose an application which uses traffic-light-to-vehicle communication ($TLVC$) to present the use with personalized driving recommendations [2]. The traffic light periodically broadcasts its scheduling information over the wireless medium to the vehicles in its vicinity. From this information, vehicles compute their required speed in order to hit a green light and offer this information to their drivers who can in turn adapt their speed accordingly.

This idea is today feasible, as studies show that cars equipped with processing and wireless transmission capabilities are becoming reality [5]. The objective of the proposed system is to constantly guide the drivers through intersections equipped with traffic lights, and recommend optimal speeds to reduce the number of stop-starts due to red lights and the number of vain accelerations to catch green lights. The TLs constantly inform the approaching cars about the current state of the intersections. For each road segment controlled by the traffic light, the broadcasted message contains the current color and the time until it changes. The cars are equipped with radio devices that enable the communication with the traffic light. They are also equipped with computing systems that are able to run complex software. Being equipped with such devices, the cars form a vehicular ad-hoc network through which they can forward the messages received from the traffic lights to other cars that are out of the traffic light's communication range.

A secondary objective of this paper is to present a methodology for evaluating the impact on the reduction of pollution, using modeling and simulation. While field tests so far have focused on a technical proof of concept, simulation is still the means of choice for an estimation of the achievable large-scale benefits of applications designed for complex vehicular-based scenarios. We present large-scale simulation studies that were performed to evaluate the overall benefit of the proposed application. Our evaluation results provide insights on the positive impact that such a small change in driver's behavior can bring on the environment.

The rest of this paper is organized as follows. Section 2 presents related work. In Section 3, we present the theoretical model for predicting fuel consumption, based on the car's characteristics. Section 4 describes the solution, and presents the proposed model to estimate vehicle emissions. We also present the proposed system that uses a prediction algorithm to recommend the cruising speeds to the driver. In Section 5, we present an analysis and experimental results and, finally, in Sections 6 we give conclusions and propose future work.

2. **Related Work.** Similar work to the one presented in this paper were previously considered by different authors. A generic solution to reducing air-pollution using vehicular networks was previously presented in [2]. The authors propose an adaptive traffic light system that uses wireless communication with vehicles and fixed controller nodes deployed in intersections to improve traffic fluency in intersections. They show that traffic fluency has an impact on the pollution caused by cars. A similar solution is presented in [14, 19].

Here we also propose the use of "smart" traffic lights, but with the objective of reducing car emissions in the particular situation of an intersection equipped with traffic light. Changes in speed require acceleration or deceleration. Emissions tend to be highest during acceleration. They lead to large increases in CO and HC emissions as well as increased fuel consumption. The vehicle acceleration contributes significantly to fuel consumption, and consequently to emissions. The driver's decisions regarding acceleration or deceleration influence greatly the amount of car emissions. Aggressive accelerations, or accelerations under heavy load (e.g., when driving up a hill) can produce higher emissions than do moderate accelerations. Unlike generic solutions to reducing air pollution ([2, 14, 21]) we concentrate on a concrete case study, and identified key influencing factors on the level of detail and characteristics required for real-world implementation of such a system.

Regarding the emission model, previous studies that included environmental impact assessments rely on mathematical formulae, calibrated for average personal cars, to compute fuel consumption and emissions [15, 16]. Others used more detailed emission models [14], with studies that addressed particular aspects like cold/warm start, gear shifting and different vehicle and emission types. In this we present a more generic model that considers all these aspects combined. The authors in [3] relate speed to fuel consumption and emissions rate. They emphasize on the importance of the driver's behavior on reducing car emissions. Estimating fuel consumption and pollutant emissions is a necessity when evaluating traffic management applications. Similar to our approach, the authors use the method proposed by Akcelik and Besley [4] to model fuel consumption and emissions (CO_2, CO, HC, NOx). However, unlike our work, the authors willingly simplified the model to consider only light vehicles. We present a more complex model, similar to the theoretical one, which we believe to more accurately reflect real-world traffic situations.

The authors of [13] show that Traffic-light-to-vehicle communication ($TLVC$) has the potential to reduce the environmental impact of vehicular traffic by helping drivers to avoid braking and accelerating maneuvers at traffic lights. However, the focus is not on the algorithm to be used for speed recommendations, but rather on a methodology to use modeling and simulation to evaluate such solutions. The motivation is that equipping traffic lights with communication technology requires significant financial expenditures. Thereby, credible large-scale simulation studies are an important means to assess the return on investment. In this we also propose a complex simulation model to evaluate the proposed solution. In addition, we propose a solution that uses TLVC to disseminate information, and an algorithm to make recommendations considering the characteristics of the car that optimize fuel consumption. Our solution also considers the driver's behavior.

Authors of [17] find fuel consumption to be lowered by up to 47% for a traffic-light scheduling based cruise control algorithm when evaluating 9 traffic lights in a row and having vehicles consider the phases of the subsequent traffic lights. [18] states a maximum of 35% and an average of 14% for a single road and traffic light. Providing hard figures on how much fuel/emissions can be saved is difficult, since simulation results depend highly on the simulation setup, models and implementations used as well as on the way of evaluation. For example, when analyzing a single road and traffic light, the ratio of fuel saved depends on the length on the evaluated road segment. Thus, it is not the objective of this paper to provide hard figures, but to identify key influencing factors and to quantify the degree of their influence.

3. **Computational Model for Fuel Consumption.**

To estimate fuel consumption we first developed a model that takes as input the car's characteristics, and estimates an optimal cruising speed based on the distance to the traffic light. The prediction of the car's movement is based on a model of the mechanical physics involved. Figure 1 illustrates the forces that act on the car. The force of gravity F_g pulls the car towards the earth. The total normal force, F_N, is the sum of the forces on the front and rear tires and it is equal to the mass of the car multiplied by the acceleration due to gravity and the cosine of the slope angle, θ.

$$F_N = F_{Nf} + F_{Nr} = mg\cos\theta \tag{1}$$

The engine generates torque, which when applied to the wheels causes them to rotate. The force applied to the tires, F_T, is equal to the torque applied to the wheels, T_w, divided by the wheel radius, r_w. When the car is in motion, an aerodynamic drag force develops. This drag force can be modeled as a function of the air density, ρ, frontal area, A, the square of the velocity magnitude, v, and a drag coefficient, C_D. The last important force in the car diagram (see Figure 1) is due to rolling friction. This force acts on all four wheels and resists the rolling motion of the car. The total rolling friction force, F_R, is equal to the total normal force, F_N, multiplied by the coefficient of rolling friction for the vehicle, μ_r.

The total force that acts on the car parallel to the direction the car is driving, F_{total}, is equal to the sum of the forces due to engine torque, gravity, aerodynamic drag, and rolling friction (Equation (2)).

$$F_{total} = \frac{T_W}{R_w} - \mu mg\cos\theta - mg\sin\theta - \frac{1}{2}C_D\rho v^2 A \tag{2}$$

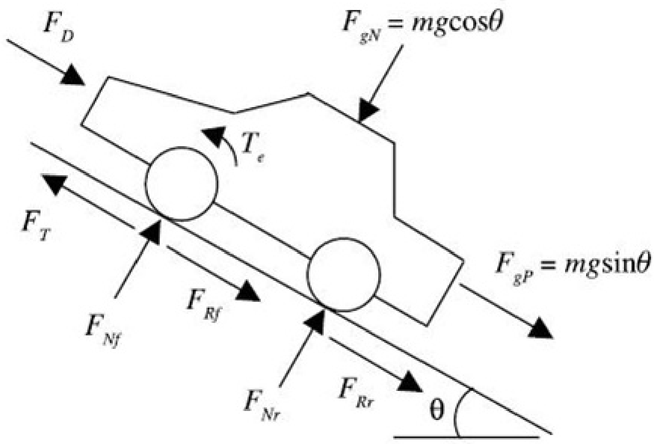

FIGURE 1. Force balance on a car

The acceleration of the car at any given time is equal to the net force on the vehicle divided by the mass of the vehicle, m.

$$a = \frac{T_W}{r_w m} - \mu g\cos\theta - g\sin\theta - \frac{1}{2}\frac{C_D\rho v^2 A}{m} \tag{3}$$

The engine generates a torque that is used to move the car. The torque generated by the engine is not the same as the torque applied to the wheels (the engine is not coupled directly to the wheels, but to some set of gears). The engine torque is a function of the rate at which the engine is turning over. The engine turnover rate is expressed in revolutions per minute, rpm. There is a relation between the engine torque and the engine's turnover rate, which vary from car to car and can be obtained from the manufacturer or from different sources. One characteristic of engine torque is that it does not always increase with the increase of the engine turnover rate.

The torque applied to the wheels of a car determines its acceleration. Generally the torque applied to the wheels is not the same as the engine torque. Before the engine torque is applied to the wheels, it passes through a transmission. The gears inside a transmission change the angular velocity and torque transferred from the engine. This can greatly increase the acceleration of a car. The gear ratio between two gears is the ratio of the gear diameters. Car transmissions will typically have between three and six forward gears and one reverse gear. There is also an additional set of gears between the transmission and the wheels. The gear ratio of this final gearset is known as final drive ratio.

The wheel torque, T_w, is equal to the engine torque, T_e, multiplied by the gear ratio, g_k, of whatever gear the car is in and the final drive ratio, G, of the car. Using the previous equations, the car's acceleration can be computed as:

$$a = \frac{T_e g_k G}{r_w m} - \mu g \cos\theta - g \sin\theta - \frac{1}{2}\frac{C_D \rho v^2 A}{m} \tag{4}$$

Transmission gears also change the angular velocity of the wheel relative to the turnover rate of the engine (the factor "60" is to transform from rpm in $revolutionspersecond$):

$$\omega_w = \frac{2\pi\Omega_c}{60 g_k G} \tag{5}$$

If the tires roll on the ground without slipping (the "burn rubber" effect), the translational velocity of the car, v, can be related to the angular velocity of the wheel, and therefore to the engine turnover rate:

$$v = r_w \omega_w = \frac{r_w 2\pi\Omega_e}{60 g_k G} \tag{6}$$

In order to estimate the movement of a car, it is necessary to determine the acceleration and velocity of the car at any point in time. The starting point for this analysis is Equation (4). If the slope angle, frontal area, and air density are known, the only unknown quantity in this equation is the wheel torque, T_w. As explained, the wheel torque is the product of the engine torque, T_e, the current gear ratio, g_k, and the final drive ratio, G. The engine torque, T_e, can be obtained from the torque curve of the engine. The torque curve can generally be modeled by three equations. The units for engine torque in all three equations are in $N - m$.

$$\begin{aligned} &T_e = 220, \quad \Omega_e \le 1000 \\ &T_e = 0.025\Omega_e + 195, \quad 1000 < \Omega_e < 4600 \\ &T_e = -0.032\Omega_e + 457.2, \quad \Omega_e \ge 4600 \end{aligned} \tag{7}$$

The general equation for the three previous ones is:

$$T_e = b\Omega_e + d \tag{8}$$

Using Equations (8), (6) and (4), the expression for the acceleration of the car as a function of the current velocity of the car becomes:

$$a = \frac{60 g_k^2 G^2 b v}{2\pi m r_w^2} + \frac{g_k G d}{m r_w} - \mu g \cos\theta - g \sin\theta - \frac{1}{2}\frac{C_D \rho v^2 A}{m} \tag{9}$$

Knowing this equation that expresses the car motion equation, and some typical parameters for the rolling friction coefficient (0.015), the average frontal area of a car ($1.94m^2$), the wheel radius (0.3186), etc., we solved this differential equation using the fourth-order Runge-Kutta method.

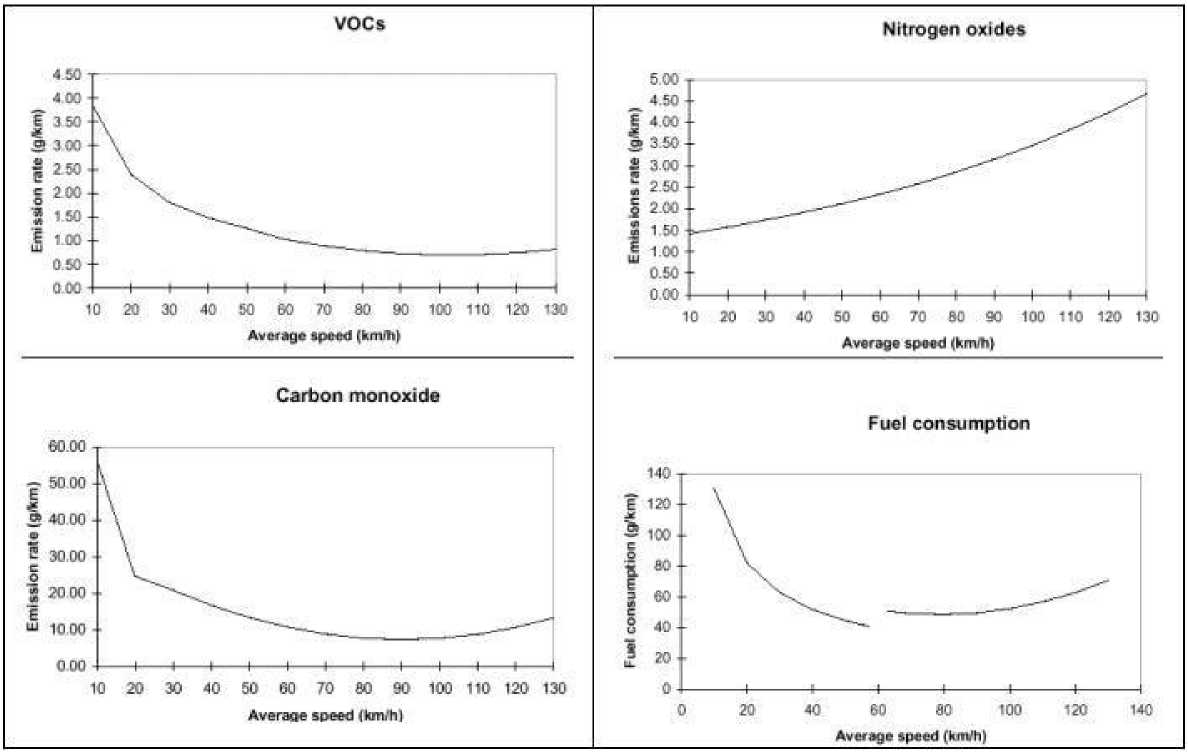

FIGURE 2. Typical emission rates for volatile organic compounds ($Hydrocarbons - HC$), carbon monoxide, nitrogen oxides and fuel consumption as a function of average speed for passenger cars conforming to ECE 15-04 regulations [5]

The relation between speed and fuel consumption and emission rate is given by the Haworth and Symmons model [3]. These are results relative to the car's characteristics. However, they clearly show that by accelerating or decelerating a car consumes relatively larger or smaller fuel quantities than it would consume normally (in such a model the normal value is defined depending on the type of car and its characteristics).

A number of curves relating emissions to fuel consumption, and to the average cruising speed have been developed in the related literature. Figure 2 presents the typical car emission and fuel consumption rates as a function of average speed [6]. Emissions of Volatile Organic Compounds ($VOCs$ or HCs) and carbon monoxide (CO) generally decrease as average speed increases and then increase somewhat over $100km/h$. Emissions of nitrogen oxides increase more than proportionally with average speed. The relationship between fuel consumption and average speed is somewhat more complex. It appears to decrease as average speed increases to about $60km/h$ to $80km/h$, and then it increases.

Other authors have presented curves of similar shapes, but with different gradients or minima. For example, Andre and Hammarstrom [7] report that CO emission reaches a minimum at about $70km/h$, similar to Figure 2, whereas CO emissions decrease monotonically with speed. These previous studies show a clear relation between acceleration and the car's emissions. Emissions tend to be higher during acceleration, when the fuel to air ratio is higher. This leads to an increase in the amount of CO and HC emissions; in fact, the emissions of pollutants during acceleration are five to ten times higher, on average, than the emissions resulted while driving at a constant speed. Also, how the driver accelerates influences greatly the amount of emissions. Very hard or aggressive accelerations or accelerations under heavy load (e.g., when driving up a hill) can produce higher emissions than do moderate accelerations. In addition, other driving issues also affect the car's emissions. One such example is the so-called "cold start" effect. If a car is started with a cold enough catalytic converter, the chemical reactions that convert pollutants to water vapors, nitrogen and carbon dioxide will not take place.

The conclusion of this analysis is that the driver can greatly influence the emissions rate through smooth accelerations (i.e., no rapid speed changes), constant speed at cruising, and reduced number of cold starts (by combining several shorter trips into one longer trip).

This conclusion was the starting point for the proposed solution presented in this paper. It aims to help driver controlling his/her car's emissions by recommending specific actions to follow regarding the optimum cruising speed.

4. **A Recommending Solution to Decrease Vehicle's Emissions.** We first make the assumption that the intersection is equipped with intelligent traffic lights ($ITLs$), which are semaphores equipped with sensors, and wireless communication capabilities [2]. They can send information to approaching vehicles, to servers, to other traffic lights. They were first introduced as a solution to monitor approaching vehicles and make smart decisions that can smooth traffic flow [2].

In this paper we extend the original ITL approach, and propose a system that uses these semaphores to minimize pollution and assist the driver find the optimum cruising speed as he/she approaches the intersection. We consider that messages are constantly exchanged between ITL and vehicles, and also between vehicles (see Figure 3). We assume that ITLs and the vehicles are equipped with short range communication devices and computing capabilities. The ITL periodically broadcast data about the color and the time until it changes, for each segment of road it controls. The broadcasted package contains in addition the local time, which is used for synchronization. The problem of short range communication is resolved by letting cars re-broadcast further all received messages for a limited time period.

The vehicle uses the received information as input for an algorithm that outputs a recommendation speed that optimizes the quantity of car's emissions. To run the algorithm cars are equipped with computational devices. The algorithm is based on the computation of both speed, movement, as well as fuel consumption.

4.1. **Computing fuel consumption.** First we developed a solution to estimate fuel consumption and pollutant emissions. To model fuel consumption and emissions (CO_2, CO, HC, NOx), we extended the work of Akcelik and Besley [4]. The qualities of their model are better reflected by the extensive study conducted in [8]. The method to estimate the value of fuel consumed (mL) or emissions produced (g), in a time interval (Δt), is given by:

$$\Delta F = \left(f_i + \beta_1 R_T v + \left[\frac{\beta_2 M_v a^2 v}{1000} \right]_{a>0} \right) \Delta t, \quad R_T > 0 \tag{10}$$

$$\Delta F = f_i \Delta t, \quad R_T \leq 0 \tag{11}$$

where ΔF [mL or g] is the quantity consumed or gas emitted (HC, CO, NOx) during a time interval, $v[m/s]$ is the vehicle's instantaneous velocity, $a[m/s^2]$ the acceleration, M_v [kg] is the mass of the vehicle ($1400kg$ on average for light vehicles in a city environment), and R_T [kN] represents the total force acting on a car, including air drag and rolling resistance. For the values of f_i, β_1, and β_2 we used the results from [4]. Figure 4 presents results for fuel consumption, related to speed and acceleration for vehicles passing through an intersection.

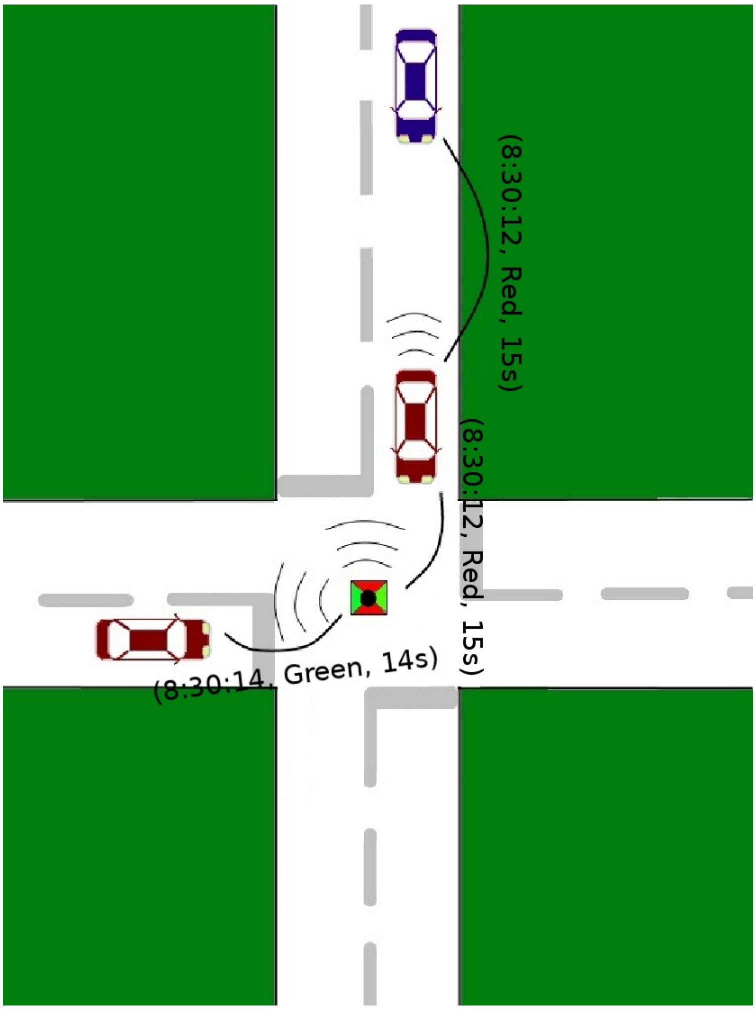

FIGURE 3. The intelligent traffic system

4.2. **The decision algorithm.** In order to determine the optimal speed when approaching an intersection, we consider that cars are equipped with computational devices. Various experts, in fact, predict this will be a reality on a general-scale in the near future [1]. In this section we present the algorithm that runs on the computational device inside a car.

a. Car Movement Prediction The most important part of the algorithm, which can greatly affect the accuracy of the recommended speed, is the prediction of the movement of the car on a given distance, or in a given amount of time. To make an accurate decision, the algorithm needs to estimate with relatively high precision the future speed and position of the car. For that we use parameters such as the delay to reach a certain speed, the acceleration style of the driver, the characteristics of the road (curves, slopes). The implementation of this part of the algorithm (method "updateSpeedAndLocation" below) is based on the equations for the car's motion previously presented, which consider the forces that act on the car.

b. Green Lights When the car approaching the intersection is informed that the current traffic light color is green, the device inside the car executes the algorithm described in this section. The algorithm simulates two scenarios: (1) the driver accelerates to catch the green light, and (2) the driver slowly decelerated to stop at the red light. The first case may not even be possible (considering the car's characteristics, the acceleration might not be possible for example). If it is possible, that the algorithm estimates the quantity

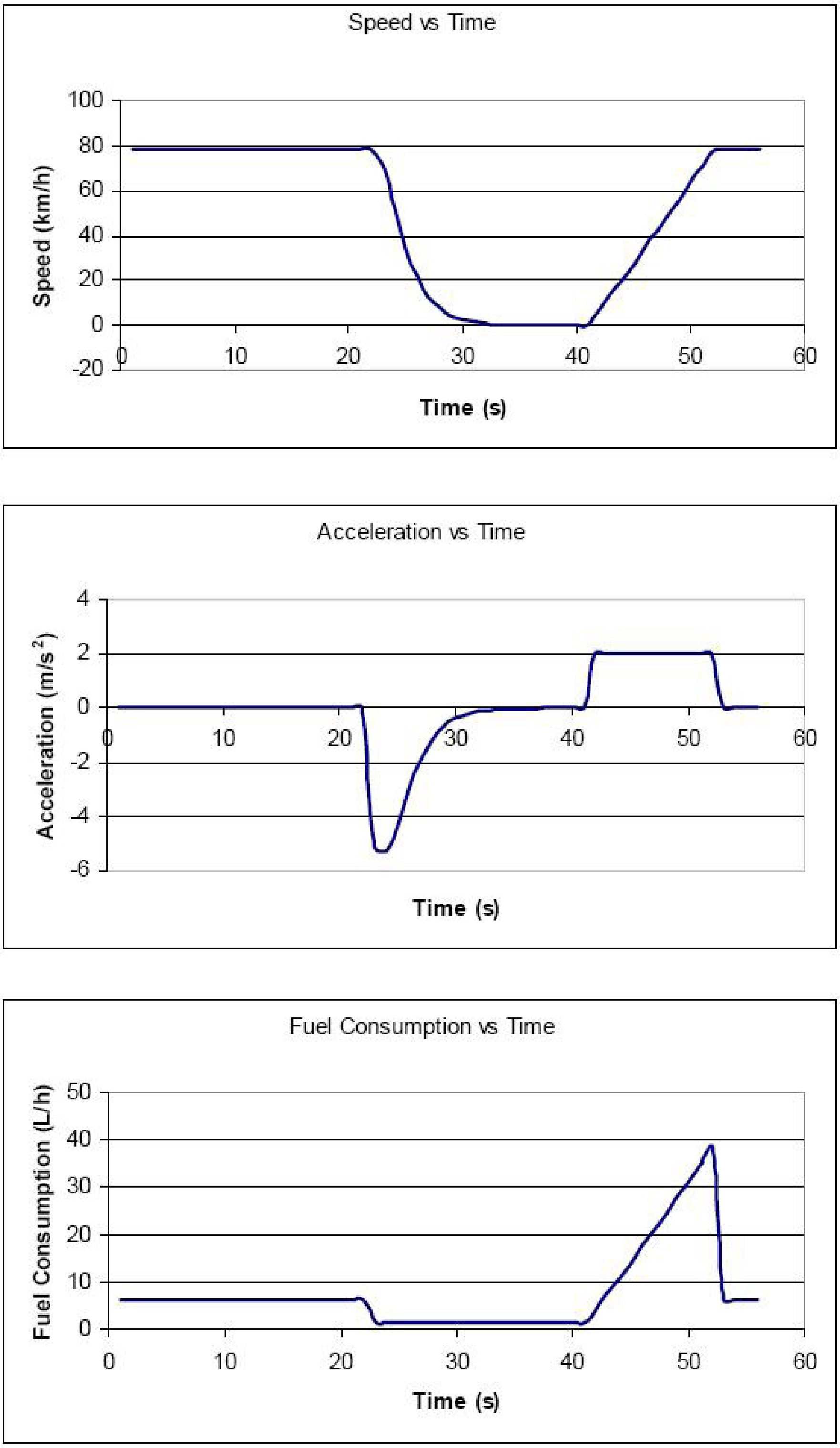

FIGURE 4. Fuel consumption for vehicles passing through an intersection

of emissions for these two cases. If the quantity of gases is smaller in the first case than in the second, it will recommend the accelerating speed to the driver. Otherwise, it will recommend a full stop at the red light.

The application starts by first predicting the movement of the car when we assume the driver will try to catch the green light (*case 1*). In this case the driver's intention is to accelerate until the speed he/she anticipates is needed to catch the green light. The pseudocode for this algorithm is the following:

THE ALGORITHM FOR GREEN LIGHT, CASE 1.

```
car.distance = 0                        //the total distance traveled by the car
car.time = 0                            // the total time the car traveled
timeIncrement = 0 : 06                  // the time increment to apply runge-kutta
car.setMode("accelerate")               // the driver accelerates
while car.distance < distanceToTrafficLight
      neededSpeed = (distanceToTrafficLight − car.distance) ÷ (greenTime
      −car.time)
      if neededSpeed > MaxSpeedAllowed
            return          // the driver cannot catch the green light
      if neededSpeed ≤ car.speed
            car.setMode("cruise")
      car.updateSpeedAndLocation(timeIncrement)
            // this updates car.time, car.speed and car.distance
      car.estimateEmissions()
```

The application further estimates the emissions of the car, assuming the driver maintains a constant speed, stops at the red color, then accelerates to the speed he/she previously had before stopping (*case 2*). The pseudocode for this algorithm is:

THE ALGORITHM FOR GREEN LIGHT, CASE 2.

```
car.distance = 0                        // the total distance traveled by the car
car.time = 0                            // the total time the car traveled
timeIncrement = 0 : 06                  // the time increment to apply runge-kutta
car.setMode("cruise")                   // the driver maintains a constant speed
while car.distance < distanceToTrafficLight − 100
      // assume the driver starts to break 100m before the intersection
      car.updateSpeedAndLocation(timeIncrement)
      car.estimateEmissions()
car.setMode("break")                    // the driver breaks to stop at the red light
while car.distance < distanceToTrafficLight
      car.updateSpeedAndLocation(timeIncrement)
      car.estimateEmissions()
car.setMode("accelerate")     // the driver accelerates to the speed he had before
stopping
while car.speed < WantedSpeed
      car.updateSpeedAndLocation(timeIncrement)
      car.estimateEmissions()
```

In the end the application compares the results obtained in these two cases and recommends a speed to the driver that will lead to the least fuel consumption.

c. Red Lights

When the car approaches an intersection and is informed that the current color of the traffic light is red, it executes an algorithm that decides to (1) reduce the speed to enter the intersection when the light color is turning green, or (2) continue to a full stop using the same constant speed. The decision depends on the smaller quantity of emissions when comparing the estimated for these two cases. Again, the algorithm involves two steps.

First the application runs an algorithm to predict the movement of the car, assuming the driver reduces the speed in an attempt to avoid the red light – by the time he/she would reach the intersection the current light will have changed to green in this approach. In this case the algorithm estimate the quantity of emissions. The pseudocode for this case is:

The algorithm for Red Light, case 1.

```
car.distance = 0                    // the total distance traveled by the car
car.time = 0                        // the total time the car traveled
timeIncrement = 0 : 06              // the time increment to apply runge-kutta
car.setMode("accelerate")           // the driver accelerates
while car.distance < distanceToTrafficLight
      neededSpeed = (distanceToTrafficLight − car.distance) ÷ (redTime
      −car.time)
      if neededSpeed < MinSpeedAllowed
            return           // the driver cannot avoid stopping at the red light
      if neededSpeed ≥ car.speed
            car.setMode("cruise")
      car.updateSpeedAndLocation(timeIncrement)
            // this updates car.time, car.speed and car.distance
      car.estimateEmissions()
```

Next, it runs an algorithm to predict the movement of the car, assuming the driver maintains constant speed, stops at the red color, then when the color changes he/she accelerates to the speed needed to catch the green light (and possible avoid a new change to red light). The pseudocode for this case is:

The algorithm for Red Light, case 2.

```
car.distance = 0                    // the total distance traveled by the car
car.time = 0                        // the total time the car traveled
timeIncrement = 0 : 06              // the time increment to apply runge-kuttag
car.setMode("cruise")               // the driver maintains a constant speed
while car.distance < distanceToTrafficLight − 100
            // assume the driver starts to break 100m before the intersection
      car.updateSpeedAndLocation(timeIncrement)
      car.estimateEmissions()
car.setMode("break") // the driver breaks to stop at the red light
while car.distance < distanceToTrafficLight
      car.updateSpeedAndLocation(timeIncrement)
      car.estimateEmissions()
car.setMode("accelerate")
      // the driver accelerates to the speed he had before stopping
while car.speed < NeededSpeed
      car.updateSpeedAndLocation(timeIncrement)
      car.estimateEmissions()
```

In the end the application compares the results obtained in these two scenarios and recommends the optimal speed to the driver, depending on the least fuel consumption.

5. **Results.**

The evaluation in terms of the environmental impact of the proposed solution was done using modeling and simulation. This cost-effective method of evaluation required us to model at least four components: vehicular traffic, communication from traffic lights to vehicles, driver behavior (speed adaption) and finally fuel consumption and emissions. Such and other components were integrated into VNSim [2], a VANET simulator which is able to model complex traffic conditions, with real-world mobility assumptions and state-of-the-art networking protocols [11]. Its extensibility allowed us to implement the models for the estimate of fuel consumption and pollutant emissions proposed in this paper. In fact, extensive simulation experiments validating the fuel consumption and pollution model using VNSim were previously presented in [10].

We were first interested in how acceleration relates to pollutant emissions. These experiments were conducted as a calibration stage, to verify that the simulation model corresponds in known-cases to the expected mathematical results (see Section 3). In these experiments we considered the case of an average car. Following the analysis presented in Section 3, the entry values for our experiments were similar to the ones presented in Figure 2.

We conducted two experiments that evaluate the fuel consumption for the typical driver behaviors. In the first experiment the driver keeps accelerating until the car reaches $30m/s$ (or $108km/h$). This speed was chosen based on the theoretical estimated Haworth and Symmons model (looking at Figure 2, for speeds higher that this value the pollution slope continues to increase relatively constant) and ECE 15-04 regulations (a car would not cruise with a higher speed in an urban area – official regulations limit speeds in such situations to much lower values). Figure 5 shows how speed and acceleration change in time. In the second scenario, the driver accelerates until the car reaches $15.22m/s$ (or $54.8km/h$, a speed which is more acceptable for urban areas [1, 5]) and then he/she maintains a constant speed (see Figure 6).

Looking at the acceleration curves in Figures 5 and 6, two observations can be made: 1) the very steep slopes (three in Figure 5 and two in Figure 6) are due to gear shifting and 2) acceleration is decreasing in time, due to the gear ratio (and this concurs to the mathematical estimations previously presented, and the increasing drag force). The quantity (in grams) of emitted CO_2 and CO in the first scenario is shown in Figure 5 and the results of the second scenario can be visualized in Figure 6 (in which the car traveled for the same amount of time as the one in the first scenario). Comparing the results of the two scenarios, it can be noticed that the quantity of gases emitted by the car in the second scenario ($\approx 129g$ of CO_2), is smaller than the one obtained in the first scenario ($\approx 360g$ of CO_2). Based on the slope of the emissions curve in Figure 6, we can compute the total distance the car can travel until its emissions reach the ones in Figure 5.

5.1. **Case 1 – Green light.** We next experimented with the proposed algorithms. We started with the case of the green traffic light. The algorithm has been used in two relatively different scenarios.

In the first scenario, a car traveling at $40km/h$ ($\approx 11m/s$) has 15 seconds to catch the green light. This corresponds to the case when a car cruising at a relatively high speed in town approaches the intersection. Also, to avoid potentially dangerous situations, the driver has sufficient time to cross the intersection. The distance between the traffic light and the car is $200m$. According to the proposed algorithm, the car predicts the speed and acceleration of the car until it crosses the intersection, and it estimates the quantity of emissions in the two possible scenarios: 1) the driver tries to catch the green light and accelerates until the needed speed is reached and 2) the driver maintains a constant speed, stops and waits at the red light, and then he/she accelerates until the previous speed is obtained. The estimated quantity of emissions is illustrated in Figure 7 – for the first situation ($\approx$ 54 grams of CO_2 emitted) and in Figure 8 – for the second situation ($\approx$ 96 grams of CO_2 emitted). Based on these results, the system advises the driver to accelerate to catch the green light. By doing this, the driver could reduce the quantity of

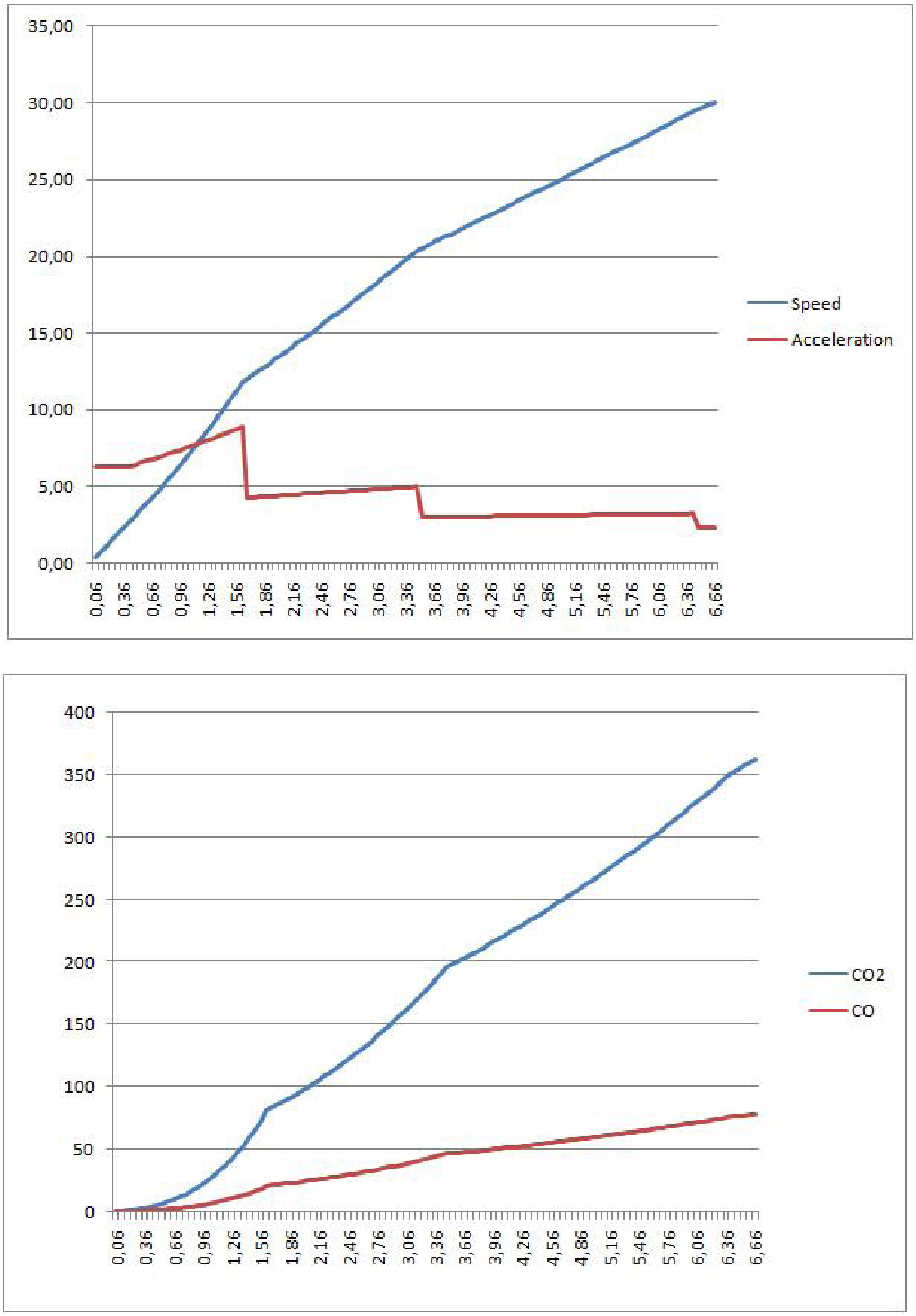

FIGURE 5. The case of a car that accelerates from $0km/h$ to $108km/h$

CO_2 by approximately 42 grams (going at high speed, but this higher limit depends on the maximum speed imposed by legislation in that particular location).

In the second experiment, the same car, now traveling at $22km/h$ ($\approx 6m/s$), has to catch the green light, given the same conditions as in the previous scenario. This corresponds to a slower car approaching the same intersection. As before, the algorithm

FIGURE 6. A car that accelerates from $0km/h$ to $54.8km/h$ and then maintains a constant speed

predicts the speed and acceleration of the car until it passes the intersection, and it estimates the quantity of emissions in the two scenarios previously described. The estimated quantities of emissions are presented in Figure 9 ($\approx$ 110 grams of CO_2 emitted). Based on these results the system advises the driver not to accelerate, in the attempt to catch the green light. If the driver complies with this suggestion, he/she would reduce the quantity of CO_2 by $\approx$ 52 grams.

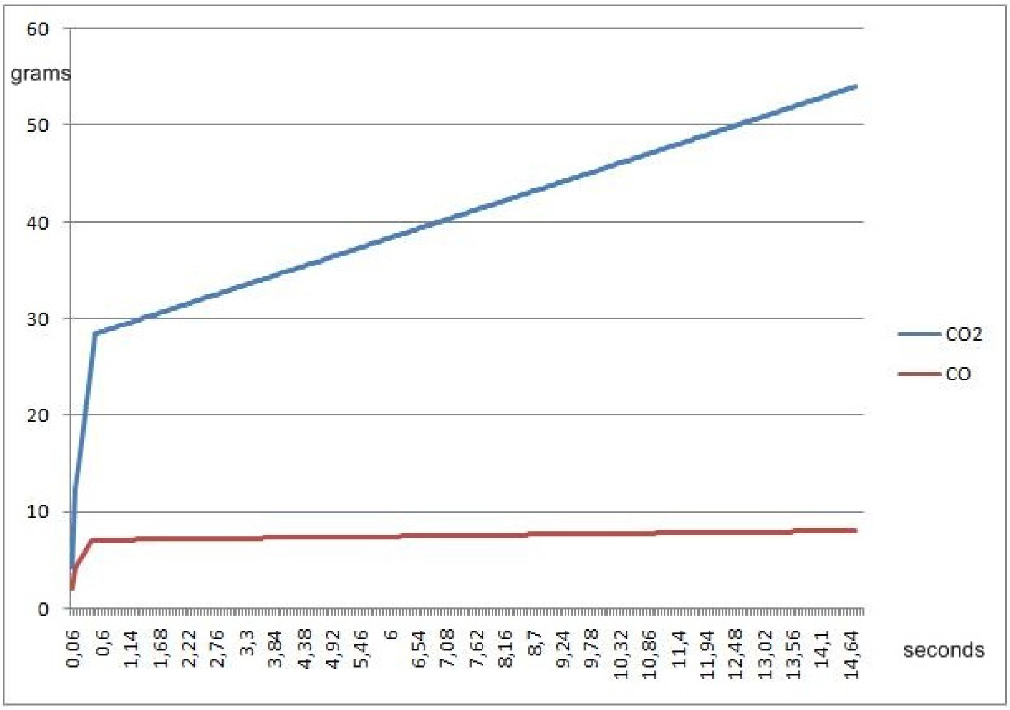

FIGURE 7. Quantity of emissions in scenario 1, situation 1

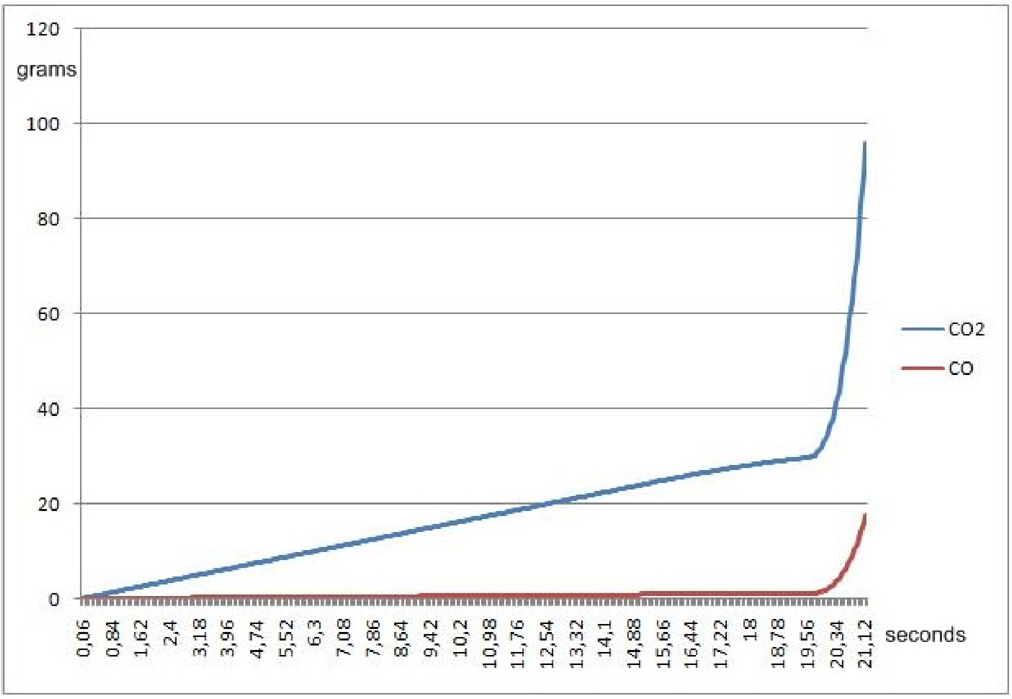

FIGURE 8. Quantity of emissions in scenario 1, situation 2

5.2. **Case 2 – Red light.** This section presents the experimental results obtained with the use of the proposed algorithms applied in case of red traffic light. Again we experimented with two situations.

In the first case, a car traveling at $60km/h$ ($\approx$ $16.6m/s$) approaches a traffic light showing a red color, which will change after 20 seconds. This corresponds to a high-speed

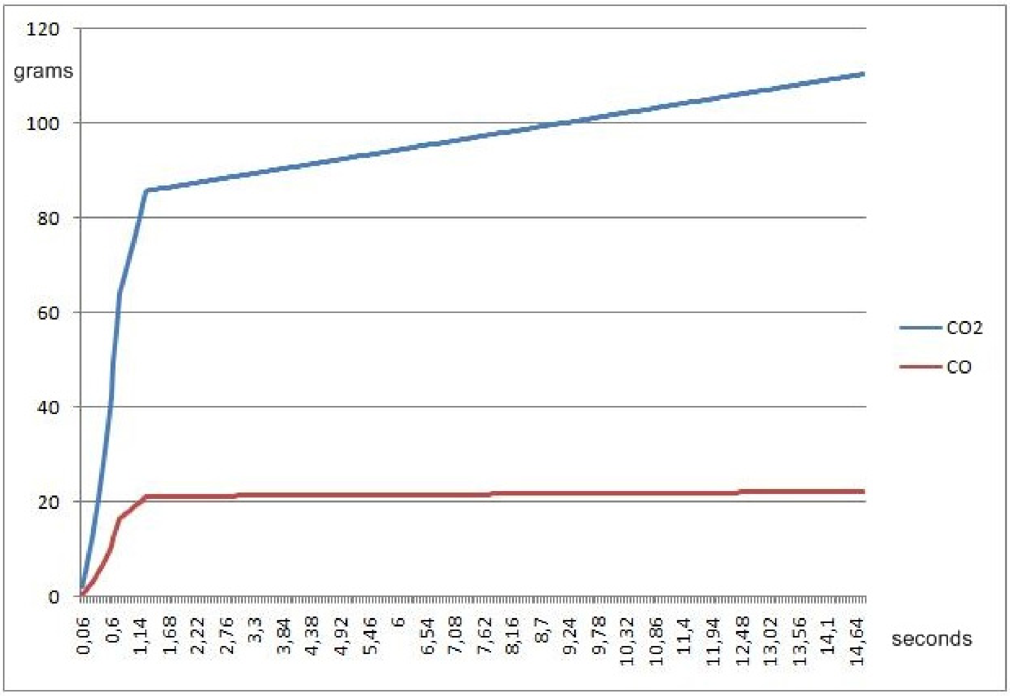

FIGURE 9. Quantity of emissions in scenario 2, situation 1

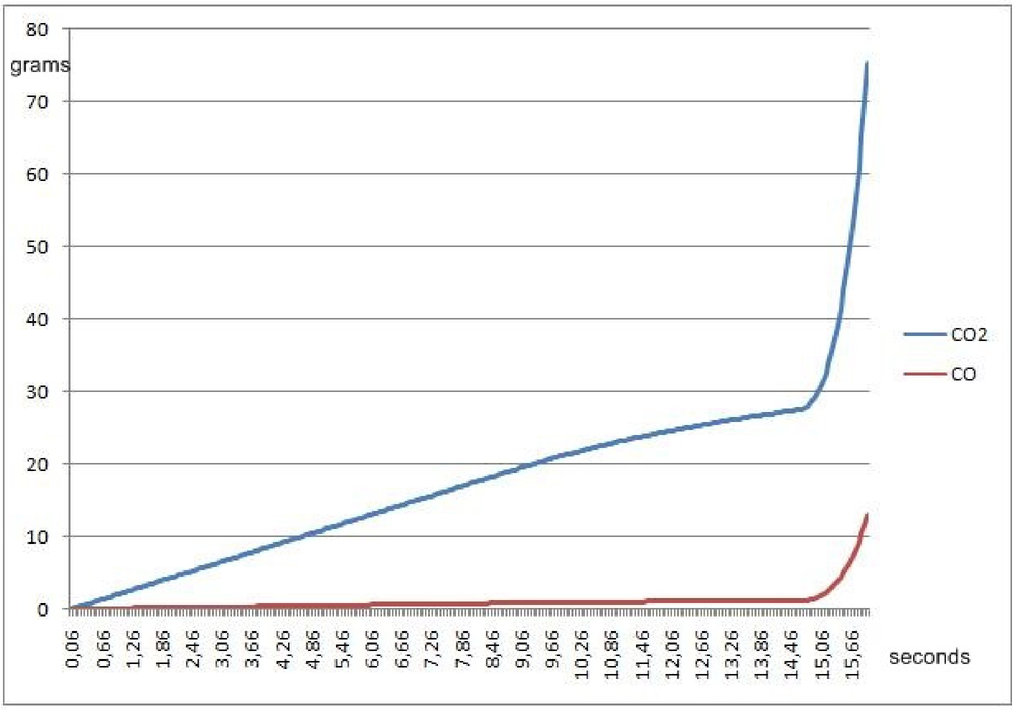

FIGURE 10. Quantity of emissions in scenario 1, situation 1

car approaching the intersection. Again, the distance between the traffic light and the car is $200m$. The algorithm predicts the speed and acceleration of the car until it passes the intersection, and it estimates the quantity of emissions in two possible situations: 1) the driver tries to reduce the speed to avoid the red color and 2) the driver maintains a constant speed, stops waits at the red light, and when the color changes back to green

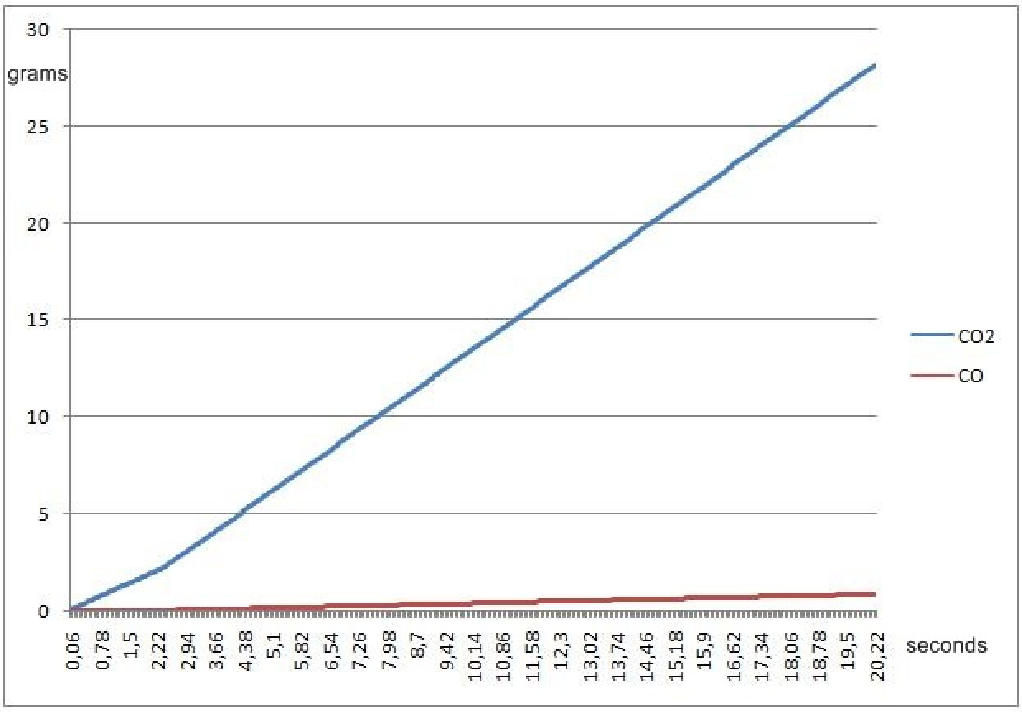

FIGURE 11. Quantity of emissions in scenario 1, situation 2

accelerates until the speed needed to avoid the next change to red color is obtained. The estimated quantity of emissions is illustrated in Figure 10 – for the first case ($\approx$ 28 grams of CO_2 emitted) and in Figure 11 – for the second case ($\approx$ 75 grams of CO_2 emitted). Based on these results, the system advises the driver to reduce the speed until he reaches approximately the speed of $34km/h$ ($\approx 9.47m/s$), such that to avoid waiting at the red light color. By doing this, the driver reduces the quantity of CO_2 by $\approx$ 47 grams.

In the second scenario, the same car, traveling at the same speed ($60km/h$), approaches a red traffic light color which, this time, will last for the next 40 seconds. As before, the algorithm predicts the speed and acceleration of the car until it passes the intersection and estimates the quantity of emissions in the two cases described earlier. The estimated quantities of emissions for the two cases are shown in Figure 12 ($\approx$ 46 grams of CO_2 emitted), and, respectively, Figure 13 ($\approx$ 37 grams of CO_2 emitted). Based on these results the system advises the driver not to reduce the speed, in an attempt to avoid the red light. If the driver complies with this recommendation, he/she will reduce the quantity of CO_2 by $\approx$ 9 grams.

The obtained results show good progress towards decreasing the amount of fuel being consumed. The scenarios consider several parameters which might change depending on the local legislation, characteristics of cars, etc. However, in the different considered scenarios we showed that our recommendations can lead to significant changes in the fuel consumption, with positive results on the environment on the long term.

6. **Conclusions.** In this we presented a solution that uses intelligent traffic lights, mobile devices and wireless communication to reduce car emissions. The solution minimizes the number of stop-starts due to the red light and the accelerations needed to catch the green light (happening quite frequent and having an important influence on the emissions rate). Periodically the traffic lights broadcast information about the status of the current traffic light color. This information is used by a decision algorithm. The role of this algorithm is

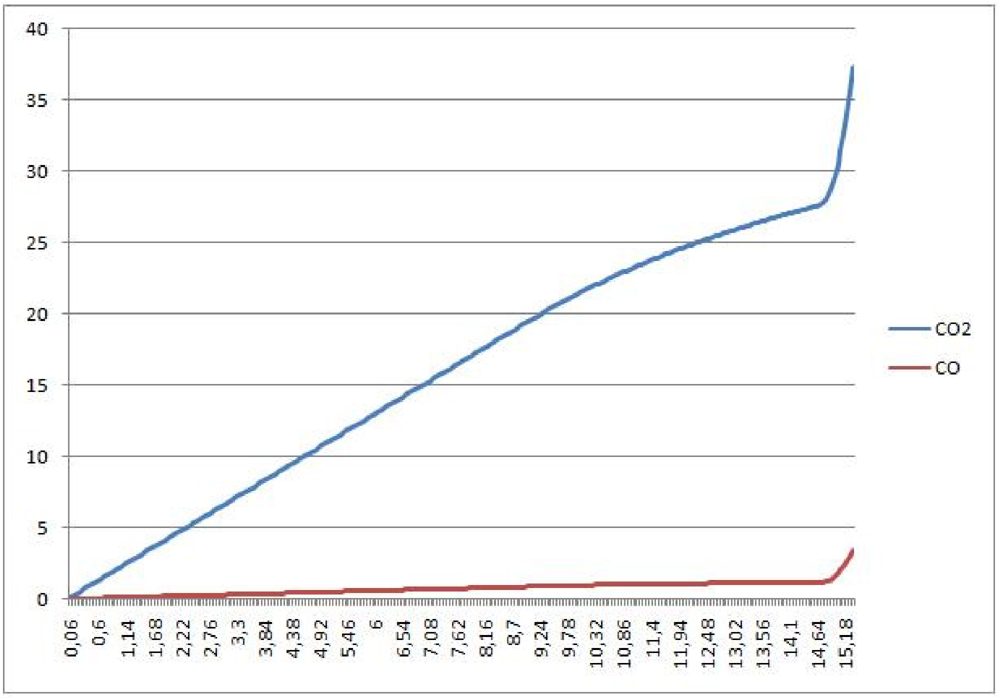

FIGURE 12. Quantity of emissions in scenario 2, situation 1

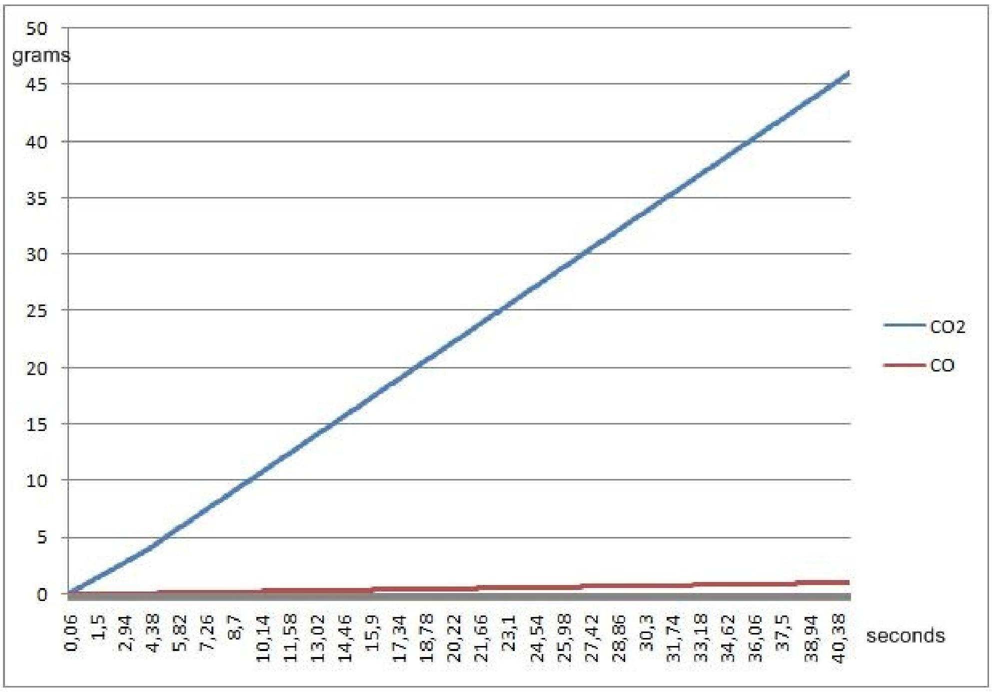

FIGURE 13. Quantity of emissions in scenario 2, situation 2

to assist the driver make informed decisions to 1) avoid the red traffic light and 2) catch the green traffic light, if possible, and reduce the quantity of emitted gases.

In order to decide whether the driver's action of catching the green light leads to less fuel consumption, by recommending accelerate/decelerate, we devised a method to predict the car's movement. For this we use the motion equation of a car to predict its speed and position at any time. The prediction of the movement of the car is among the most challenging part. To estimate a specific driver's behavior and predict how the car is going to move in different situations is a difficult task, because of the number of parameters to be considered: all forces that act on the car, coupled with the human factor. In the end we proposed a solution that was evaluated in an implementation on top of the VNSim simulator. The obtained results are promising and show that the proposed algorithm can recommend speeds that, in fact, lead to a decrease in the emissions of a car.

In the future we plan to further optimize the models and the solution, mainly because of several simplifications made in this current version. They are due mainly to the lack of information: in determining the motion equation, just the x-axis was considered. The weather was also ignored (this means that the slopes and the curves of the roads were ignored – 3D maps are needed to obtain complete information about the roads).

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