VALIDATION OF A SYSTEM-LEVEL FUEL ECONOMY BASED CONTROL METHOD FOR AUTONOMOUS VEHICLES

M. Mamouei
University of Southampton

I. Kaparias
University of Southampton

F. Galatioto
Transport Systems Catapult

Abstract

The objective of the present study is to validate a new autonomous vehicle control method, whose purpose is to consider and reduce the total fuel consumption at the network-level. The method is based on the Intelligent Driving Model (IDM) car-following approach and on the VT-micro fuel consumption model. A test network from the city of Milton Keynes is chosen and two scenarios involving conventional and autonomous vehicles are simulated using the PTV VISSIM microscopic traffic simulation tool, whereby the method is implemented using VISSIM's External Driving Model add-on to enable automated vehicle features to be modelled. The results show that the proposed autonomous vehicle control method offers remarkable savings in terms of fuel consumption, as targeted, but also in terms of traffic flow-related performance measures. Indeed, significant fuel consumption reductions of the order of 8% and 16% are observed at the network-level and at the road/corridor-level (as monitored on a specific two-lane stretch in the network), respectively. These are accompanied by a 15% decrease in total network travel time and by a 38% decrease in total network delay.

1 Introduction

Fully automated vehicles are expected to have a significant share of the road network traffic in the near future. Several commercial vehicles with full-range Adaptive Cruise Control (ACC) systems or semi-autonomous functionalities are already available on the market. This provides a unique opportunity to change driving behaviour at a large scale in the short- to mid-term and consequently improve network efficiency in terms of important performance indicators, such as fuel consumption and traffic throughput.

However, the typical current approach to automated driving is to adopt highly conservative driving strategies, which are optimised for the safety and fuel efficiency of individual vehicles. The collective impacts of such strategies on the network level are usually not considered, and this is important, as they often include a deterioration of traffic flow and an increase in fuel/energy consumption for the network. As a result, much of the existing research in this area either targets driving conditions where there are no additional complexities caused by the interaction between vehicles, or makes simplistic assumptions about the dynamics of driving behaviour and its relationship with fuel consumption in order to formulate feasibly solvable optimisation problems.

In recent research (Mamouei, 2017) a new vehicle control approach enabling the consideration of the collective impacts of fuel-economy driving strategies for automated vehicles has been proposed. The approach uses car-following models and therefore allows comprehensive and feasible optimisations to be performed by limiting the search space for optimal strategies to the car-following parameter space. Initial validation tests on a motorway environment using a Matlab (Mathworks, 2017) implementation have demonstrated the benefits of the approach in terms of achieving system-level fuel economy without compromising traffic efficiency or safety and fuel consumption at the vehicle level.

The present study focuses on the more comprehensive validation of the developed vehicle control approach through its implementation in a real-world urban network using the PTV VISSIM (PTV Group, 2017) micro-simulation software. A test network from the city of Milton Keynes, previously developed and calibrated under the MK:Smart project by the Transport Systems Catapult, is chosen and two scenarios involving conventional and autonomous vehicles are simulated. The objective is to investigate the magnitude of the savings in terms of fuel consumption that can be achieved at the road/corridor level, as well as the associated impacts with respect to observed network travel times and delays.

The paper is structured as follows: Section 2 gives the background of the study by reviewing previous work on fuel economy based vehicle control. Section 3 provides the methodological background of the study, which relies on the Intelligent Driving Model (IDM) car-following approach (Treiber et al, 2000), a modification of the VT-micro fuel consumption model (Ahn, 1998), and a set of parameters derived from a macroscopic (system-level) optimisation process. Section 4 then presents the validation process using the PTV VISSIM tool and reports the results obtained. Finally, Section 5 draws conclusions and identifies areas of future work.

2 Background

In recent years, environmental concerns have placed the energy efficiency of vehicles at the centre of research efforts. Great leaps have been made in this area by employing a wide range of “hard” technological measures that improve fuel efficiency. Examples of such include the use of lighter materials in car manufacturing, the adoption of more aerodynamic designs, the utilisation of hybrid electric powertrains (Manzie et al, 2007), and the introduction of techniques such as pulse and gliding (Li et al, 2012). However, great potential also exists in the use of “softer” measures, which concentrate on the impact of the behaviour of drivers and of autonomous vehicle control strategies on fuel consumption, and while this is a well-acknowledged problem area, it appears to have received relatively little attention so far. A number of relevant studies from the literature are reviewed here.

2.1 Fuel consumption oriented driving strategies

Wu et al (2011) present an advisory system minimising fuel consumption in the acceleration phase before reaching desired velocities and the deceleration phase before coming to a standstill. The system is shown to deliver reductions of 12% to 31% in fuel consumption and the objective is defined as the minimisation of the cumulative fuel consumption, given by the VT-micro instantaneous fuel consumption model (Ahn, 1998), within the time interval of interest (deceleration/acceleration period). For this purpose, the objective function is discretised and the resulting optimisation problem is then solved using the Lagrange Multiplier Method (LMM).

Themann et al (2015) propose a control model for ACC systems that relies on the optimisation of the velocity profile with respect to fuel consumption; Dijkstra’s algorithm is used to find the optimal velocity profile for known road topography. Porsche’s Innodrive ACC also adopts a similar approach, resulting in about 10% reduction in fuel consumption (Markschläger et al, 2012). Correspondingly, Hellström et al (2010) present a fuel-optimal control model for trucks, using prior knowledge of road topography in order to optimise fuel consumption and gear-shifting, with the problem being formulated as a dynamic programming optimisation. In all these studies, fuel economy is obtained by producing a smooth velocity performance and avoiding unnecessary accelerations. Kohut et al (2009) achieve the same objective by adopting a Model Predictive Control (MPC) framework, highlighting the trade-off between fuel savings and trip time.

The development of optimal fuel economy control models in the car-following regime of driving is a more challenging task due to the highly unpredictable nature of driver behaviours. In one of the earliest studies by Zhang and Ioannou (2006), a Proportional-Integral-Derivative (PID) controller is designed for the car-following regime for trucks. The proposed method reduces fuel consumption by avoiding unnecessary accelerations and braking, and the objective of the controller is set to track the velocity of the preceding vehicle while maintaining a specified range of spacing. Correspondingly, in the study by Li et al (2008), cars’ tracking capabilities and fuel efficiency are considered in the development of ACC, and in order to ensure fuel efficiency, accelerations are penalised in the objective function. The problem is then formulated as an MPC optimisation, and the testing of the control model is carried out by considering its performance in an urban driving scenario and a motorway-driving scenario; fuel savings of 8.8% and 2% are obtained in each scenario respectively. In a similar manner, Kamal et al (2013) present an MPC-based controller for the car-following regime that saves an average of 13% in fuel consumption in urban driving scenarios. Similar approaches can further be found in other studies (Luo et al, 2015; Zhao et al, 2017).

Considering studies seeking more fuel-efficient driving behaviour, two categories can be defined. The first category includes studies seeking to optimise fuel consumption for simple scenarios, where there are no additional complexities caused by interactions between vehicles. In this case information about roadway topography or the position of traffic signals is used in order to formulate an optimisation problem and obtain the optimal velocity profile (Wu et al, 2011; Themann et al, 2015; Markschläger et al, 2012; Hellström et al, 2010; Kohut et al, 2009). As such, from a practical perspective, such approaches are limited. The second category, on the other hand, consists of studies targeting driving conditions, where interaction between vehicles is the defining factor in driving behaviour. In these studies, simplistic assumptions are often made about the relationship between fuel consumption and acceleration or driving dynamics in order to reduce the complexity of problem. More importantly, due to the computational cost of the methods used, these studies often narrow down the scope of the problem to a single follower-leader pair, and therefore overlook the potentially negative impacts of their proposed control strategies on the network (Li et al, 2008; Kamal et al, 2013; Luo et al, 2015; Zhao et al, 2017).

2.2 Car-following based fuel-economy vehicle control

In recent research work (Mamouei, 2017), a fuel economy based control algorithm addressing these limitations has been developed by adopting car-following models as its basis. The benefits of using car-following models as the basis of control have already been identified in the literature (Kesting et al, 2010), as car-following models have the ability to significantly reduce the complexity of simulation-based optimisation, which then allows the application of the latter to more comprehensive scenarios. Additionally, the provision of control based on car-following models benefits from the remarkable advantage of the extensive knowledge that exists on the collective properties of these models through the numerous studies that are available in the literature on aspects such as stability and traffic flow characteristics.

Two distinct approaches to the question of fuel efficiency are investigated by Mamouei (2017): a user-optimal approach, where individual vehicles are considered and their fuel consumptions are minimised; and a system-optimal one, where fuel efficiency is considered from a broader, network-level perspective. The study highlights the important and fundamental differences between the driving strategies produced by the two approaches, and finds that, while the “short-sighted” user-optimal approach is unable to deliver overall fuel efficiency, the system-optimal formulation is able to do so at both the network and the individual vehicle levels without compromising traffic flow efficiency. Hence, the study concludes by proposing the system-optimal fuel-economy vehicle control approach as the most suitable one.

However, while the advantages of the stated system-optimal vehicle control approach have been extensively elaborated (Mamouei, 2017), validation experiments have so far only concentrated on small examples relating to motorway environments. The approach has yet to be validated at the network-level using a real-world urban example, and this is the gap that the present study addresses. This is presented in the next sections.

3 Methodology

At the heart of the proposed methodology lie two key elements: a simplified formulation of the VT-micro fuel consumption model (Ahn, 1998); and the IDM car-following model (Treiber et al, 2000). These are then combined in a system-level optimisation approach, which, using a real-world vehicle trajectory dataset for calibration, results in a set of parameter values of the IDM, according to which autonomous vehicle control is carried out.

3.1 The simplified VT-micro fuel consumption model

The VT-micro fuel consumption model (Ahn, 1998) is specifically developed for investigations related to the operational level of driving for individual vehicles. Using instantaneous velocity and acceleration as input variables, it calculates instantaneous fuel consumption values, and so enables the estimation of the total fuel consumption over any time interval and across a single vehicle of sets of vehicles. According to VT-micro, the instantaneous fuel consumption F of a vehicle is calculated as:

$$\ln\big(F(x,y)\big) = \begin{cases} \sum_{i=0}^{3}\sum_{j=0}^{3} C^{acc}{}_{i,j} \times a^i \times v^j & if\ a \geq 0 \\ \sum_{i=0}^{3}\sum_{j=0}^{3} C^{dec}{}_{i,j} \times a^i \times v^j & if\ a < 0 \end{cases} \quad (1)$$

where a is the acceleration, v is the speed, and $C_{i,j}$ are the model coefficients.

VT-micro has the advantage of a relatively simple structure, especially when compared to other fuel consumption models, which are comprehensively reviewed and appraised by Faris et al (2011) and Zhou et al (2016). However, when it comes to its use in optimisation, as is done in the present study, VT-micro has limitations, as its dual regime, exponential structure, and large number of terms (16 for each regime), impose a significant computational cost. In order to address this issue, a simplified version of the model is adopted here, whereby only the first, second and third degree terms are retained. The simplified VT-micro is given by:

$$F_{NEW}(x,y) = C_{00} + C_{10}v + C_{01}a + C_{11}va + C_{02}a^2 + C_{12}va^2 + C_{03}a^3 \quad (2)$$

The simplified VT-micro is validated by Mamouei (2017) by comparing its estimates with the original model for the Federal Test Procedure (FTP) drive cycle, which is representative of urban driving. It is found that, in spite of the much simpler equation, estimates that are sufficiently close to the original VT-micro are produced (of the order of 10%), which, for the purposes of fuel-consumption-based optimisation, can be deemed acceptable.

3.2 The IDM car-following model

The modelling of car-following behaviour has been an active area of research for more than six decades. Simple models that effectively describe the microscopic and macroscopic features of traffic have been developed and have been widely studied, and some of them are also integrated in the control of partially automated vehicles. The IDM car-following approach is selected for the present study on the basis of its merits, which include good microscopic and macroscopic calibration performance (Treiber et al, 2000; Treiber and Kesting, 2013; Punzo and Simonelli, 2005; Wilson and Ward, 2011), as well as a simple mathematical form with a small number of parameters, each corresponding to a driving attribute.

The IDM car-following model is formulated as follows:

$$v' = a\left[1 - \left(\frac{v}{v^d}\right)^{\delta} - \left(\frac{s^*(v,\Delta v)}{s}\right)^2\right], \quad (3a)$$

with

$$S^*(v,\Delta v) = s_0 + s_1\sqrt{\frac{v}{v_d}} + Tv + \frac{v\Delta v}{2\sqrt{ab}} \quad (3b)$$

and

$$\Delta v = v - v_p \quad (3c)$$

where a is the maximum acceleration, v_d is the desired speed, δ is the acceleration exponent,

s_0 and s_1 determine the jam distances in fully stopped traffic and in high densities respectively, T is the safe time headway, and b is the comfortable deceleration rate. The input variables are the speed of the subject vehicle v, the speed of the preceding vehicle v_p, and the distance headway s. Finally, the output variable v' determines the acceleration of the subject vehicle.

3.3 System-level optimisation

Car-following models, including the IDM, have been primarily devised to describe car-following behaviour. However, when used as the basis of autonomous vehicle control, they can facilitate the implementation of different driving strategies simply by varying the values of the model parameters. As such, given a sufficient number of model parameters, one can reproduce a variety of driving strategies; for example, one set of parameters can represent a sporty driving style with intense accelerations and braking, while a different set of parameters can deliver a more conservative driving style that is less sensitive to the lead vehicle's braking by maintaining sufficient spacing.

In that view, a car-following model with $\mathbb{N}$ model parameters provides a $\mathcal{R}^{\mathbb{N}}$ space, in which each point may be regarded as a distinctive driving style. Therefore, one can seek to find the set of model parameters within $\mathcal{R}^{\mathbb{N}}$ that minimises an objective function of choice. In this study, this objective function involves finding the optimal set of parameters θ of the IDM, which minimise the total system-level fuel consumption for a stretch of length L over a certain time interval t, and given an inflow rate λ and a leading vehicle trajectory T_l. The system-level optimisation problem is, hence, formulated as:

$$J^*(T_l,\lambda) = \min_{\arg\theta\in\Theta} E\left[\sum_{i=1}^{n} F_i(\theta|L,T_l,\lambda,t)\right]$$

subject to
$$\text{Throughput} > \alpha\cdot\lambda\cdot t$$

where the operator $E[.]$ denotes expected value, $F[.]$ is the fuel consumption of the i-th vehicle following the lead trajectory T_l calculated by the fuel consumption model, n is the number of vehicles in the scenario, and α is a coefficient that sets a minimum threshold for the acceptable throughput as a percentage of the expected number of vehicles that enter the scenario, which is equal to t.

The leading vehicle trajectory comes from real-world observations or simulation, and this study, it is obtained from the trajectory dataset collected and analysed by Punzo et al (2005) from the city of Naples, Italy. The dataset has been obtained by instrumenting four vehicles and measuring their velocities and gaps while they drive through three different routes in Naples. Specifically, the dataset consists of five different sets of trajectories, three of which report spacing and velocity values of a platoon of vehicles while they drive along three different routes, and the remaining two of which are obtained from two previously examined routes on different dates.

In order to decrease the complexity of the optimisation by reducing the number of IDM parameters needing to be optimised, a sensitivity analysis is conducted to identify the parameters that have the highest impact on fuel consumption. The global sensitivity framework is adopted for this purpose, which has been applied to car-following models in the past (Ciuffo et al, 2014; Saltelli et al, 2010; Jacques et al, 2006; Punzo et al, 2015). Details on the application of the sensitivity analysis in this work are provided by Mamouei (2017), but the main finding is that parameters a, b and T have the highest impact on fuel consumption and are hence the ones selected for the optimisation; the remaining parameters are set to their default values, as outlined in the original study by Treiber et al (2000).

The optimisation is then carried out using a genetic algorithm, and it is found that over a time interval of t = 1 h, the optimal IDM parameter values with respect to fuel consumption are: a = 5 m/s^2, b = 0.5 m/s^2 and T = 5 s. Considering the practical implications, these values suggest a driving strategy that entails short headways (which results in higher traffic flow), high accelerations and low decelerations. This result is somewhat counterintuitive, as the driving behaviour produced using these parameter values is relatively agile, and this contradicts the assumption made by many studies in the past that fuel efficiency is best delivered by adopting a more sluggish driving style.

The proposed driving strategy can be implemented in autonomous vehicle control in order to ensure fuel efficiency at the network-level, but also at the road/corridor-level. This is demonstrated in the next section, where the approach is validated using a real-world urban network.

4 Experiment and results

In the study by Mamouei (2017) the proposed autonomous vehicle control algorithm is preliminarily validated by means of simulation of a single-lane highway and comparison of the fuel consumption in the simulated scenario with the NGSIM-I80 dataset (Halkias and Colyar, 2006). However, the stretch of motorway to which the NGSIM-I80 dataset relates consists of six lanes, and lane changes occur frequently, as opposed to the simulated scenario, where lane changing is absent. Additionally, the validation scenario demonstrates the potential of the proposed method in motorway driving, but does not investigate the impacts on urban driving. In the present study, hence, the proposed autonomous vehicle control method is applied to an urban network, and for this purpose, the PTV VISSIM microscopic traffic simulation software is used.

4.1 Simulation setup

The simulation consists of a large network encompassing the centre of the city of Milton Keynes, which has been developed by the Transport Systems Catapult. The model has been calibrated according to real values, and as a result offers a wide range of driving conditions. Thus, it provides a good opportunity to evaluate the effectiveness of the proposed autonomous vehicle control method in an urban scenario. The network is shown in Figure 1.

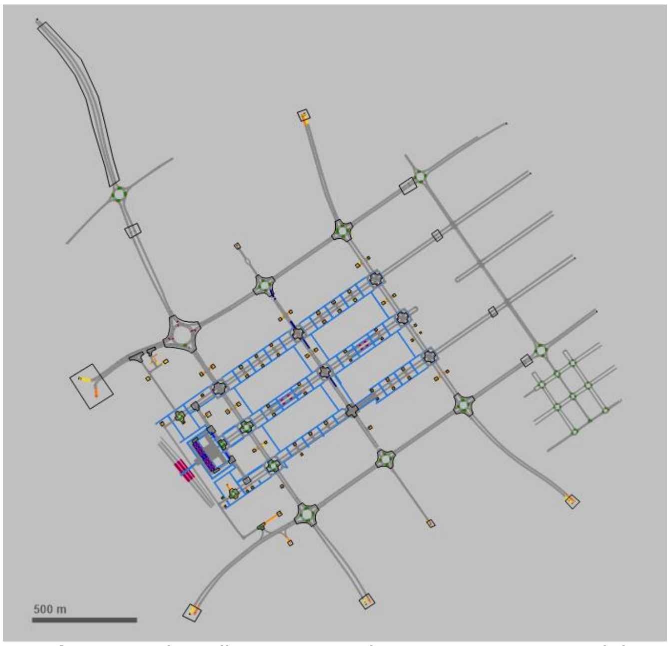

Figure 1: The Milton Keynes city centre VISSIM model

The proposed method is implemented in using VISSIM's External Driver Model add-on, which gives users access to the driving attributes that are necessary to define new car-following models. Building on previous experience of the Transport Systems Catapult as part of an Innovate UK funded LiFe project (Galatioto et al, 2017), a program is developed in C++ in order to bypass VISSIM's default car-following model and implement the proposed control method. VISSIM's default car-following model, on the other hand, which is the one of Wiedemann (1974) is used as the base case, against which the performance of the proposed method is compared.

An issue requiring particular attention is the treatment of lane changing manoeuvres and of the movement of vehicles around junctions. In the simulation these are handled by VISSIM's default models, and it is acknowledged that this may lead to some incompatibility, since these models are not fine-tuned to the proposed vehicle control method. For instance, the shorter gaps and increased velocities foreseen by the proposed autonomous vehicle control approach may lead to problems relating to gap acceptance behaviour when performing lane-changing manoeuvres, as the encountered gaps may not be long enough for such manoeuvres to take place, leading to queues in certain lanes. In order to address this, some further parameter fine-tuning is carried out (e.g. the jam distance parameter, s_0, initially set to the default value of 2 m, is increased to 5 m). It is understood that this fine-tuning will likely reduce the benefits of the proposed control method, and that the resolution of this issue would require the detailed consideration of the necessary tactical and strategic decision-making processes. This, however, extends beyond the scope of the present work.

Each simulation run has a period of one hour. The inflow of vehicles from the 17-vehicle input locations are increased in 5-minute intervals until they reach their maximum values halfway through the simulation. Vehicle inflows are then consecutively decreased until they reach the value of 0 at time, t = 3300 s or t = 3600 s. Figure 2 depicts the inflow rates from six of the vehicle input locations. The results of the simulation are presented next.

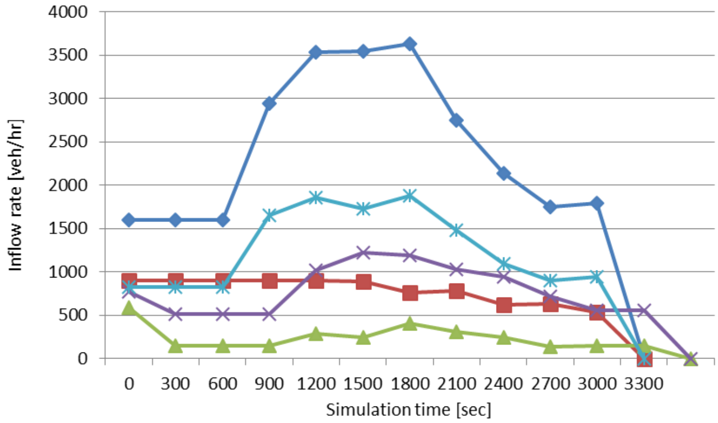

Figure 2: A representative sample of the inflow levels from six input section

4.2 Results

The results reported here are averaged over 10 independent simulations (using different seeds. The initial 300 seconds are considered as the warm-up period and only values relating to the remaining time intervals are reported. Results are reported for the whole Milton Keynes city centre network, but also for a 1.6 km stretch of a two-lane highway (Grafton Street – Figure 3). The reason why both levels (entire network and Grafton Street) are analysed is that, while at the network-level frequent lane-changes and multiple junctions are expected to reduce the benefits of the proposed autonomous vehicle control method, these phenomena are less present in Grafton Street.

Figure 3: Location of Grafton Street in the network

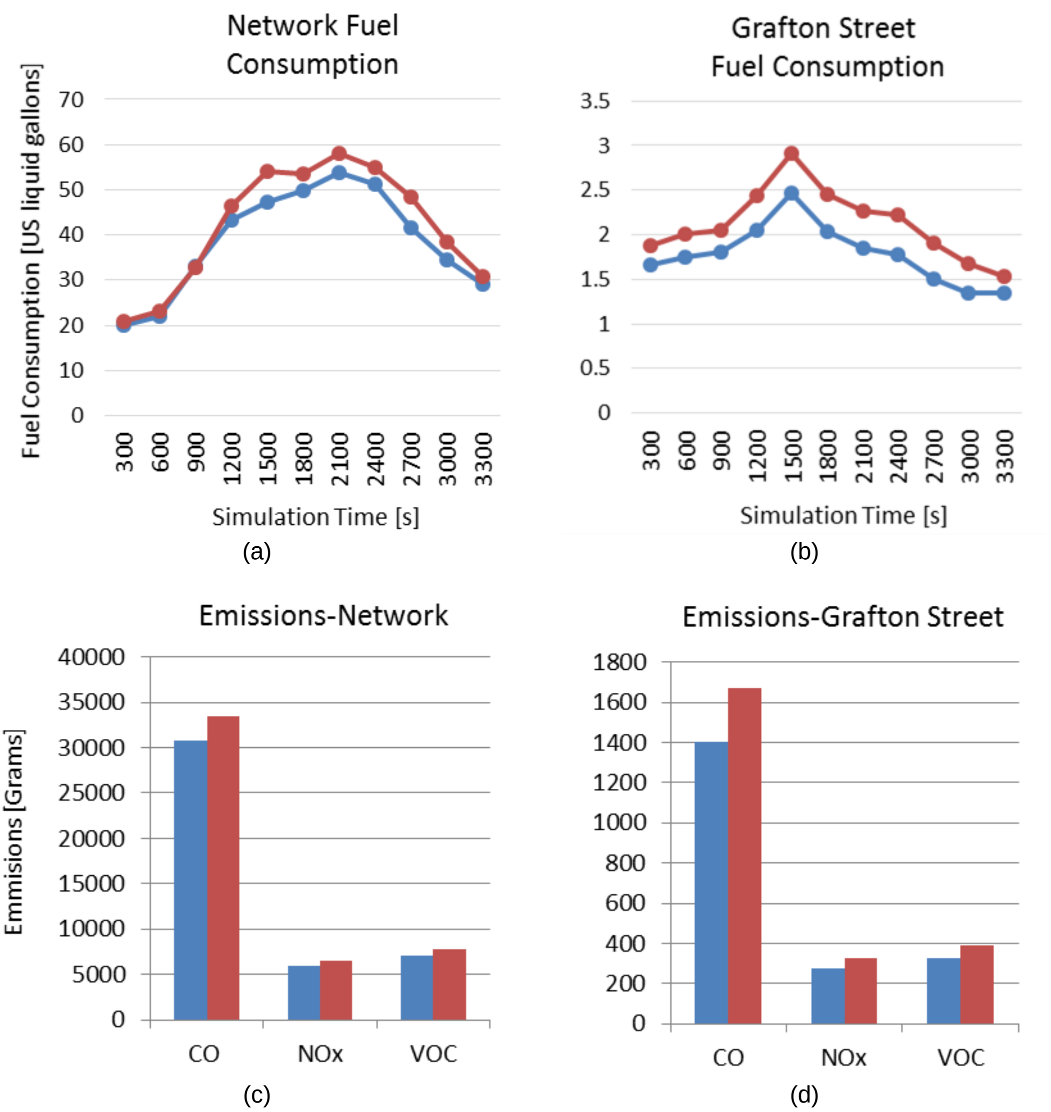

Figure 4: Fuel consumption and emissions results for the Milton Keynes case study under the base case (red) and the proposed autonomous vehicle control method (blue) scenarios

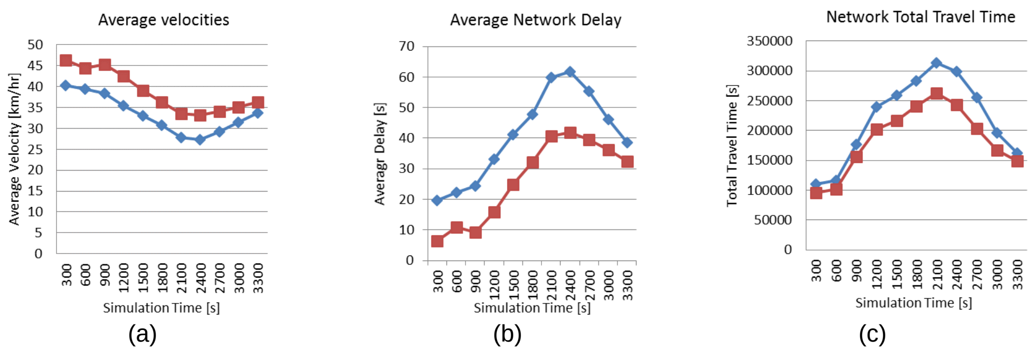

Figure 5: Traffic efficiency impacts in the Milton Keynes case study under the base case (red) and the proposed autonomous vehicle control method (blue) scenarios

From Figures 4a and 4b it can be seen that the proposed vehicle control method leads to significant savings in fuel consumption, and specifically 7.95% and 16.18% for the network and Grafton Street respectively. This also produces proportional reductions in emissions, namely Nitrogen Oxides (NO_x), Carbon Monoxide (CO), and Volatile Organic Compounds

(VOCs), as shown in Figures 4c and 4d. In addition, as discussed earlier, the proposed method achieves fuel savings by establishing a more efficient traffic flow, and this can be demonstrated by considering network performance measurements, such as average velocities, travel times and delays. Considering the relevant results shown in Figure 5, clear improvements compared to the reference case can be observed, of the order of 15% for total network travel time and of 38% for total network delay, on average.

5 Conclusions

In this paper, a new autonomous vehicle control method enabling the consideration of the collective impacts on fuel economy has been proposed. The method uses the IDM car-following approach as its basis and therefore allows comprehensive and feasible optimisations to be performed by limiting the search space for optimal strategies to the car-following parameter space. The method has been validated by means of a real-world case study, simulated in the PTV VISSIM microscopic simulation tool, in the form of a calibrated urban network from the city centre of Milton Keynes. The results have shown that the method offers remarkable savings in terms of fuel consumption, as targeted, but also in terms of pollutant emissions and of traffic flow-related performance measures. Indeed, significant impacts in terms of all these have been reported both at the network-level and at the road/corridor-level (as monitored on a specific two-lane stretch in the network, where traffic is relatively uninterrupted).

And while the study has thrown some light into the topic of energy-efficient network-level autonomous vehicle control, work in this direction continues. Specifically, the next step of the research entails the extension of the approach to encompass lane-changing models and traffic signal control strategies, both of which have not been addressed here. Moreover, future research will investigate the use of other suitable car-following models and the application of the method to different objectives, environmental settings and vehicle automation scenarios (e.g. different market penetration rates).

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