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Towards Intelligent Fleet Management: Local Optimal Speeds for Fuel and Emissions

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***Abstract*— In order to fulfill the policy requirements on increased transport energy efficiency and reduced emission impacts, smart control and management of vehicles and fleets have become important for the evolution of green intelligent transportation systems (ITS). The emergence of new information and communication technologies (ICT) and their applications, especially vehicle-to-vehicle and vehicle-to-infrastructure (V2I) communication, serves as an effective means for continuous management of real traffic fleet by providing vehicle driving support and guidance, and therefore affecting driver behavior. This study presents a recent Swedish R&D project for developing a dynamic fleet management system that incorporates real-time traffic information, eco-driving guidance and automated vehicle control in real-time heavy vehicle platooning. In addition to a general illustration of the main objectives of the project, the paper presents a methodological approach to developed local fleet control strategies so that the fuel and emissions of the managed vehicle fleet can be reduced. Speed trajectories minimizing predefined objectives are derived by applying a discrete dynamic programming method, and an instantaneous emission estimator is used for predicting fuel and emissions. Numerical examples show that the method is promising for real-time fleet management applications with support of V2I communication while the computational efficiency of the method needs to be enhanced. The adaptive speed control approach is implemented in a microscopic traffic simulation environment for further evaluation.**

I. Introduction

The environmental footprint of transport in the European Union (EU) corresponds to almost 25% of the total greenhouse gas emissions and 30% of the CO_2. The entire transport sector, especially road transport, has been targeted as a main policy area where further energy efficiency and environmental improvements are critical for a sustainable future of European transport systems.

A. Background

While the demand for road transport has been skyrocketing during the last decade, the impacts on mobility and air quality in cities, global climate change and other environmental aspects need to be significantly mitigated to satisfy the requirements for sustainable development. In comparison to the passenger transport, commercial transport has faster development during the recent years in EU countries. Commercial vehicles consumes more energy and produce higher emission level per vehicle. To ensure the sustainability on roads, new systems improving mobility and reducing environmental impacts of freight transport need to be emphasized and developed. For example, in the policy aspect one of the goals for 2030, set by the European Commission, is to reduce the green house gas emissions to 80% of the 2008 level [1], while the goods transport in Europe is projected to increase by 75% [2].

Information and communication technologies (ICT) when applied to road transport, e.g. intelligent control and advanced driver assistance systems (ADAS), have an enormous potential to impact fuel and emission levels, congestion and traffic safety. Recent advances in application of communication technology have opened up new perspectives for the development of ITS systems that utilize vehicle-to-vehicle (V2V) and/or vehicle-to-infrastructure (V2I) communication, so called cooperative ITS systems or C-ITS. The expectation of the industry and other stakeholders is that cooperative systems may improve safety, efficiency and reduce the environmental impacts of road traffic in an even more efficient way than the existing ITS systems in operation.

B. Vehicle platooning

Fuel efficiency and emission reduction can be achieved in many different ways such as improvements of engine and propulsion technologies, reduction of vehicle running resistance and active driving guidance. Research in vehicle platooning started in 1990s (e.g. [3]) because of its benefits for increasing road capacity, enhancing safety and saving fuel. The latest study and test show that platooning application can save up to 15% fuel usage and significantly mitigate carbon footprints of heavy trucks because of reduction of aerodynamic drag [4], [5]. Therefore, platooning becomes an important component in fleet management, especially for heavy duty vehicles (HDV) [6], and is an active research area that attracts interests from many transport stakeholders, especially HDV producers and owners of freight fleets. In Sweden, strong interests from vehicle industry have triggered extensive research efforts dedicated to vehicle and control technologies that allow vehicle platoons to operate on public highways with environmental, safety and comfort benefits (e.g. [5], [7], [8]). However, there is limited research effort to incorporate real-time traffic information and vehicle states into platooning operations. With the recent progress in ICT development, there is an increasing trend to develop intelligent fleet management system that integrates real-time traffic information and prediction with autonomous vehicle and platoon controls (e.g. in the recent EU FP7 projects, SATRE and HaveIT).

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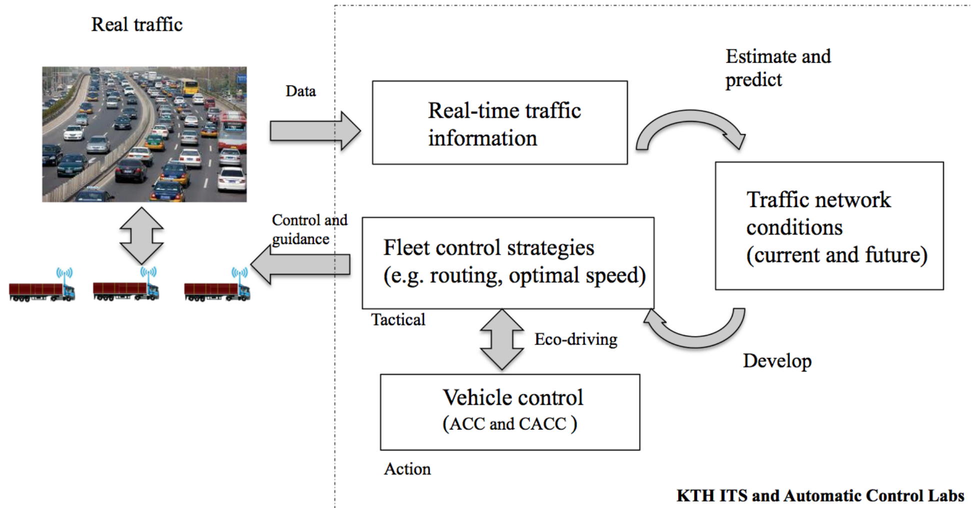

Figure 1. The concept framework of an intelligent fleet management system based on dynamic vehicle sensing and communications.

C. Research context and objectives

The technical boom of V2X communication has promoted a wide spectrum of interests in the current C-ITS development. Many completed and ongoing R&D projects have contributed to the state-of-the-art of cooperative systems while much attention are given to vehicle ad-hoc network (VANET) and V2V applications to improve road safety e.g. COOPERS [9]. Few infrastructure-based cooperative systems have been developed for fleet management on road, especially with purposes in energy and environment. Increasing demands are nevertheless being placed on developing intelligent systems capable to achieve fleet management purpose according to live traffic conditions.

This study is a part of the iQFleet project that is jointly initialized by Scania AB and KTH. The main objective of the project is to develop real-time fleet management systems for heavy duty vehicles. One part of the project extends the previous research in HDV controls (such as adaptive cruise control (ACC) and active braking systems (ABS)) based on on-board sensors (e.g. radar and lidar). Becasuse of the cooperation with neighboring vehicles and road-side units, both individual vehicle and fleet controls can be designed in smarter ways.

Among the versatile sensor technologies in current traffic applications, the emerging floating vehicle (FV) sensor can continuously capture live traffic states and predict traffic characteristics. In Stockholm, FV data gathered by taxis (equipped with GPS systems) is currently used for traffic prediction (the Mobile Millennium Stockholm project). In this project, Scania truck fleets provide complementary low-frequency GPS data for predicting traffic conditions on highways. Figure 1 shows a general diagram on how the real-time traffic state prediction (e.g. the congestion formulation and dissipation) can be processed and used for fleet management. An essential motivation is to use real-time traffic information to determine online fleet management strategies including pre-trip fleet planning, routing, real-time platoon formulation and dissemination and local speed control strategies. These strategies are mainly at the tactical level and should be implemented by detailed controls developed at the action level.

Under C-ITS, local traffic information can be transmitted to a central processing unit capable of creating local and regional view of traffic conditions. Traffic models are then enabled to predict real-time dynamic traffic conditions ahead, which will, in return, be applied for on-line guidance to drivers. Conventionally, such guidance is mainly through road-side messages or signs e.g. dynamic speed limits. C-ITS makes it possible to combine such guidance with in-vehicle systems, and simulation studies show good potential of the new speed measures [10]. Drivers therefore may receive more frequent guidance that is based on dynamic traffic conditions in Fig.1.

This study is mainly focused on developing tactical strategies that can continuously manage vehicle and fleet states (in particular speed profiles) through in-vehicle active guidance. A basic approach is derived for local vehicle speed management strategies according to traffic conditions and management objective in energy and environmental impacts. The paper illustrates the methodology by considering a case of individual vehicle, exploring the optimal speed control when the initial and expected final states in the prediction horizon are known.

II. METHODS

Optimal control of automobiles for fuel economy is not a new research topic. Since 1980s, several pioneer studies [11] [12] have been conducted to investigate the underlining principle of optimal driving with an objective of minimizing fuel consumption. Detailed vehicle dynamics was modeled while terrain variation of highway was also considered. However, the approach did not find wide applications in traffic management and in-vehicle systems because of the technical limitations in infrastructure, sensing technologies, and method and tool for traffic modeling and prediction at the time. The C-ITS development makes it technically possible to implement online guidance to drivers with benefits not only for system efficiency but also in fuel economy and environmental footprints. Thus, the eco-driving strategies become more than technical concepts. In this project, it is considered to obtain optimal controls for both individual vehicles and the whole fleet. Ideally, such type of controls can be disseminated to vehicles via infrastructure to vehicle (I2V) information and driver (or vehicle) will automatically follow the control messages received in real time. The objective is to minimize the total fuel or emissions of a fleet.

The rest of the section introduces the mathematical formulation of the control problem and proposes a solution using optimal control theory. The detailed vehicle trajectory control problem will be treated using a discrete dynamic programming formulation in the context of C-ITS.

A. Mathematical problem

General formulation: Consider a general optimal control problem that is described by the following ordinary differential equation system (ODEs):

$$\begin{cases} \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \boldsymbol{\alpha}(t)) & t \geq 0 \\ \mathbf{x}(0) = \mathbf{x}_0 \end{cases} \tag{1}$$

where $\mathbf{x}(t)$ is the state of the system controlled whereas $\boldsymbol{\alpha}(t)$ is the control input at time t. The initial boundary condition is given by $\mathbf{x}_0$. In a typical control problem, the target state $\mathbf{x}(\tau) = \mathbf{x}_1$ may be given and the control period τ is free. The control measure can be represented by a payoff function

$$J(\mathbf{x}, \boldsymbol{\alpha}) = \int_0^\tau r(\mathbf{x}(t), \boldsymbol{\alpha}(t))dt. \tag{2}$$

where $r(\mathbf{x}(t), \boldsymbol{\alpha}(t))$ is the general running payoff. The basic problem is to find an optimal control $\boldsymbol{\alpha}^*(\cdot)$ such that the control measure is optimized i.e.

$$J(\mathbf{x}^*, \boldsymbol{\alpha}^*) = \min_{\boldsymbol{\alpha} \in \Omega} J(\mathbf{x}, \boldsymbol{\alpha}). \tag{3}$$

where $\mathbf{x}^*$ is the optimal intermediate system states or trajectory.

This problem has been treated extensively in literature e.g. [13][14][15] and is often solved by reformulating optimal control as an optimization problem. That is, by defining the control theory Hamiltonian function

$$H(\mathbf{x}(t), \boldsymbol{\lambda}(t), \boldsymbol{\alpha}(t)) = r(\mathbf{x}(t), \boldsymbol{\alpha}(t)) + \boldsymbol{\lambda}^T(t)\mathbf{f}(\mathbf{x}(t), \boldsymbol{\alpha}(t)) \tag{4}$$

the Pontryagin Minimum Principle (PMP) is applied with the equations derived to satisfy the necessary condition to the infinite problem [14][15] . $\boldsymbol{\lambda}(t)$ is a vector of adjoint variables at each time instant t, which are indeed Lagrange multipliers (or co-states). It is shown that the optimal control problem formulated above can be solved by transferring the control problem to point-wise optimization problems at each time instant. When boundary conditions are defined, analytical or numerical solutions may exist [13][15].

Control of vehicle trajectory: In the application of vehicle trajectory control, instantaneous vehicle state can be represented by a vector

$$\mathbf{x}(t) = [s(t)\ v(t)]^T \tag{5}$$

where $s(t)$ and $v(t)$ are vehicle traveling distance and speed at certain time t. The control input is the acceleration itself

$$\boldsymbol{\alpha}(t) = a(t). \tag{6}$$

This formulation neglects the detailed vehicle dynamics model in previous studies [11] since our application is focused on driving guidance at the tactical level. However, it is convenient to extend with vehicle dynamics model in application of detailed vehicle control [8].

The objective of the control is to minimize certain impact measure such as fuel consumption or emission represented by

$$J(\boldsymbol{\alpha}) = \int_0^\tau \phi(\mathbf{x}(t), a(t))dt \tag{7}$$

with constraints to the state variables and control inputs

$$\dot{\mathbf{x}}(t) = [v(t)\ a(t)]^T \tag{8}$$

$$\mathbf{x}(0) = \mathbf{x}_0 \tag{9}$$

$$\mathbf{x}(\tau) = \mathbf{x}_T \tag{10}$$

$$a(t) \in (\hat{d}_{max},\ \hat{a}_{max}(v)] \tag{11}$$

where $\phi(\mathbf{x}(t), a(t))$ is instantaneous emission or fuel usage; $\hat{d}_{max}$ is the maximum deceleration and $\hat{a}_{max}(v)$ is maximum acceleration that vehicle engine can reach at the speed level.

B. Solution method using dynamic programming

Discrete formulation: The problem formulated by equation (7)-(11) is a two point boundary value problem (BVP) for a continuous ODE that needs to be solved numerically in applications. This paper, however, formulates the vehicle dynamics as a discrete system model as follows:

$$\mathbf{x}_{k+1} = \mathbf{f}(k, \mathbf{x}_k, \boldsymbol{\alpha}_k) = \mathbf{A} \cdot \mathbf{x}_k + a_k \mathbf{b} \tag{12}$$

where $\mathbf{x}_k = [s_k\ v_k]^T$ and a_k are the state of the vehicle and control input, the acceleration, at a time instant k respectively. $\mathbf{b} = [\Delta t^2/2\ \Delta t]^T$ is stationary in this problem and Δt is the time interval. $\mathbf{A}$ is also stationary, that is

$$\begin{pmatrix} 1 & \Delta t \\ 0 & 1 \end{pmatrix}.$$

The objective is to treat with the optimization below

$$\min_{\mathbf{X}, \boldsymbol{\alpha}} \{\hat{\phi}(\mathbf{x}_N) + J(k, \mathbf{x}_k)\} \tag{13}$$

$$J(k, \mathbf{x}_k) = \sum_{k=0}^{N-1} \phi(k, \mathbf{x}_k, a_k)\Delta t \tag{14}$$

with constraints

$$\mathbf{x}_0 = [0\ \hat{v}_0]^T \tag{15}$$

$$\mathbf{x}_N = [L\ \hat{v}_N]^T \tag{16}$$

$$a_k \in (\hat{d}_{max},\ \hat{a}_{max}(v_k)] \tag{17}$$

where $\phi(k, \mathbf{x}_k, a_k)$ is the instantaneous emission or energy usage; $\hat{\phi}(\mathbf{x}_N)$ is the final reward function and the equations (15) and (16) show the initial and final conditions.

Dynamic programming model*:* The discrete problem above can be treated as a backward dynamic programming recursion i.e.

$$J(k, \mathbf{x}) = \min_{a \in \alpha(k,\mathbf{x})} \{\phi_k(\mathbf{x}, a)\Delta t + J(k+1, \mathbf{x}_{k+1})\}, \quad k = N-1, ..., 0 \tag{18}$$

According to the principle of optimality [14], there exists an optimal control solution with feedback control in each stage obtained by

$$a_k^* = \arg \min_{a \in \alpha(k,\mathbf{x})} \{\phi_k(\mathbf{x}, a)\Delta t + J(k+1, \mathbf{x}_{k+1})\}. \tag{19}$$

The dynamic programming solution above is formulated based on the temporal discretization whereas the state variable has to be discretized at the same time. The time interval for the optimal control is unknown, though it is possible to find an optimal value by testing different feasible times.

Since the total distance of the controlled area is known in the two point BVP problem, a discretization on space is considered instead. Space discretization indeed simplifies the state transition dynamics i.e.

$$\mathbf{x}_{n+1} = \mathbf{f}(n, \mathbf{x}_n, \boldsymbol{\alpha}_n) = \mathbf{x}_n + \boldsymbol{\alpha}_n \tag{20}$$

where $\mathbf{x}_n = v_n$ is the state variable and the control input is

$$\boldsymbol{\alpha}_n = \Delta v_n \tag{21}$$

$$a_n = [(v_n + \Delta v_n)^2 - v_n^2]/2\Delta s \tag{22}$$

$$\Delta t_n = \Delta v_n / a_n \tag{23}$$

Δt_n is the time interval and a_n is the acceleration. While the time intervals are not equalized, the dynamic programming model in this case is similar to that of the temporal discretization case i.e.

$$J(n, \mathbf{x}) = \min_{a} \{\phi_n(\mathbf{x}, a)\Delta t_n + J(n+1, \mathbf{x}_{n+1})\}, \quad n = N-1, ..., 0 \tag{24}$$

C. Instantaneous emission estimator

In order to manage fuel consumption or other emission impacts induced by vehicle fleet, it is essential to accurately estimate the time-resolved emission quantity. The estimation is based on computational modeling of emissions using the inputs of traffic dynamics as well as individual vehicle information. Different emission models [16] were developed to predict fuel consumption and air pollutants including CO, HC, NOx and particulate matters (PMs) as well as green house gases (e.g. CO_2).

Similar to traffic models, an emission model can be either macroscopic, mesoscopic or microscopic in nature according to its characteristics. This study requires estimation of detailed instantaneous emissions of a vehicle or fleet. Therefore, microscopic emission models are most suitable for the application context. Taking vehicle operating conditions as inputs (e.g. instantaneous speed, acceleration, engine states etc.), microscopic emission models aim at calculating vehicular emissions at the second-by-second resolution. Two widely used approaches lead to the relatively simple statistical models and the complex physical load-based approaches, although other mixed approaches exist (e.g.[17]). Whereas statistical emission models use regression of input variables (e.g. speed and acceleration), load-based models are often built upon complex physical principles. In order to evaluate fuel and emissions of medium and heavy duty vehicles, the study adopts a load-based emission computational tool that implements the CMEM model [18].

III. Case study

This section illustrates a numerical example, to which the method presented above is applied. Let's consider the basic problem for the fleet speed management application, where control of vehicle trajectories are important for saving fuel and minimizing environmental footprints in terms of emissions (e.g. HC, NOx and CO).

A. Basic setups in an example

In the former study, four main scenarios were proposed when deriving optimal driving strategy for single vehicle fuel economy [12]. Here we simply consider a common scenario when vehicles in a fleet meet congestion downstream on highway. A central node of road-side ITS system can detect congestion formulation beforehand via communication and other sensors, and then predict traffic condition downstream, mainly flow speed, using relevant traffic information and models. Thus, the fleet management system needs to derive the optimal speed trajectory for vehicle or fleet, which can be disseminated to individual drivers. When the congestion is dispersed, vehicle may accelerate to its desired speed. This involves an acceleration process during which local pollutant emissions are heavily produced (e.g. HC and CO). Figure 2 shows a detailed case of the scenario with major parameters. Assume the downstream traffic flow speed is in a heavily congested mode with a speed level of v_2 while a heavy duty truck travels at a speed of v_1 upstream. There is a distance of D from the current position of the vehicle to the downstream traffic flow. The goal is to find a speed profile and control inputs that minimize the fuel produced in the procedure.

B. Numerical results

Applying the DP approach presented by Eq. (24) and the instantaneous CMEM emission estimator, we can derive a trajectory that fulfills the minimal fuel or emission objective set for a vehicle in each traffic information prediction horizon. However, the computational cost is very high due

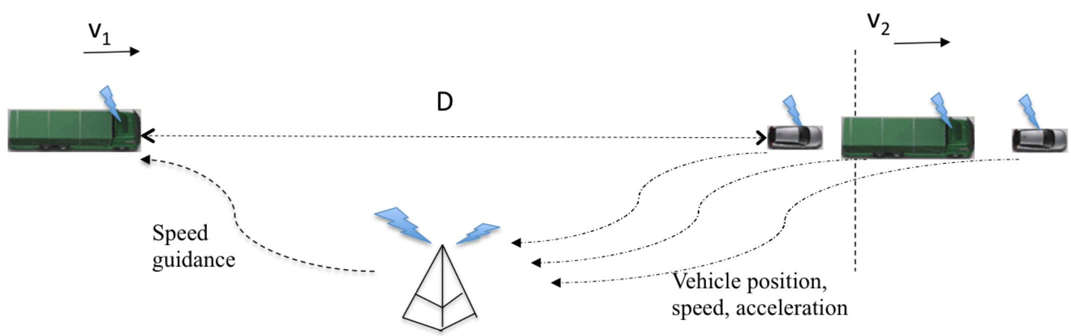

Figure 2. An example of the fixed boundary optimal control problem.

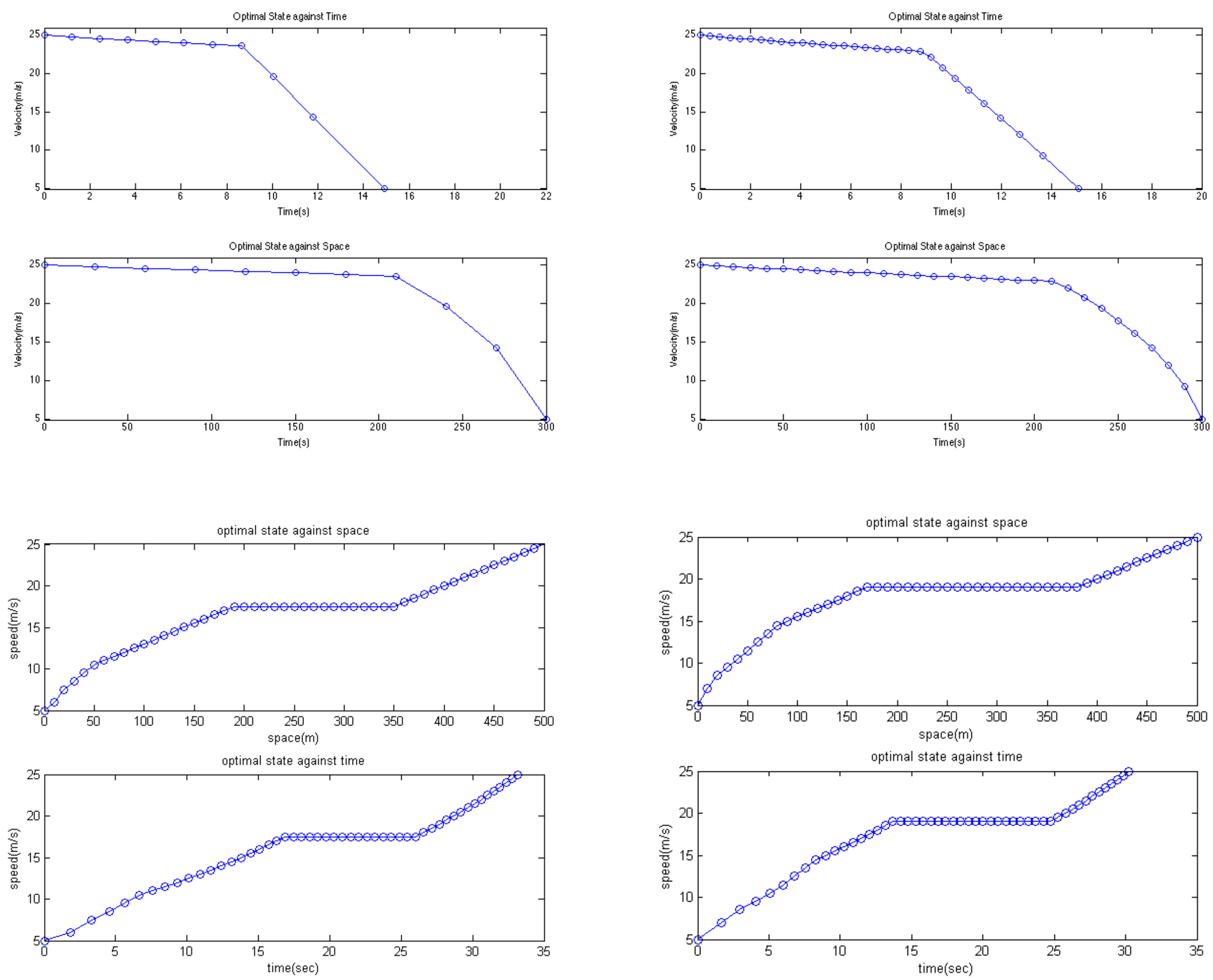

Figure 3. Comparisons of the performance under different DP step sizes during deceleration (upper) and optimal speed profiles when different objectives in fuel and CO emissions are applied during acceleration (lower).

to the external functional calls on the CMEM emission estimator running as a computer program that requires many IO operations. In the numerical tests, v_1 and v_2 are set to 25 and 5 m/sec and D varies from 300 to 500 m. A light duty truck is assumed in correspondence with the type-7 truck in CMEM. According to the results, the discrete step sizes on space and speed are directly related to the accuracy of the final trajectories derived. Higher resolutions will lead to results closer to the optimal solutions. The upper four graphs of Fig. 3 compare the trajectories (against time and space) when different spatial steps Δs (30 and 10 m) are applied. However, the computational time increase 50% when the space resolution increases from 30 to 10 m. In order to reduce the computational time, an approximate engine emission map was estimated offline by running the CMEM model in a detailed mesh of speed and acceleration. The CMEM emission outputs can be obtained by searching the final look-up table. The final optimal trajectory in this case can theoretically save more than 30% fuel when compared to a constant deceleration strategy $(-1m/s^2)$.

The similar problem in acceleration is also solved using the method. The lower four figures compare the speed trajectories optimal for fuel and the CO emissions when the truck accelerates from the congestion phase (5 m/sec) to its desired speed in free flow. While the two trajectories are obviously different, the trends of them share quite some similarities.

IV. Summary and further perspectives

This paper starts with the opportunities that cooperative systems based on V2I communication have brought to dynamic traffic management applications. The focus is mainly on the transport energy and negative emission impacts. The study is an important step towards developing an intelligent fleet management system using V2I-based ITS measure cable of minimizing local fuel consumption or other emissions produced by vehicle. We propose to derive the optimal trajectories by applying the optimal control theory. While a dynamic programming formulation is used for the fixed boundary control problem, a space discretization approach is developed to reduce computational cost. An emission look-up table generated from CMEM is applied in the calculation of the objective function using vehicle states. In the case study, a most common traffic scenario on highway, downstream congestion formulation (backward shockwave), is considered. By applying standard technique in backward recursion and forward recovery, optimal speed profiles and corresponding control inputs are derived for minimal environmental footprints in the braking and acceleration processes.

While the proposed method contributes to the generation of speed management strategies, a comprise of computational speed and accuracy in DP has to be considered. Meanwhile, large space exists to extend to the intelligent fleet management application. For instance, only a single truck is treated when deriving optimal trajectory. When a fleet of heavy vehicles is considered, it is necessary to treat the fleet as an entity that can interact with other vehicle and fleets. Since the ACC control within vehicle fleet has been already developed in several studies such as [8], the current work is to derive the optimal trajectory for a fleet where the vehicles are modeled as a whole fleet.

Besides the derivation of the fleet control strategies in different traffic scenarios, it is also important to test the performance of the derived trajectory control approach. Such evaluation requires real traffic situations and interaction with other traffic objects such as traffic light, traffic sign etc. Therefore, evaluation of the control strategies derived using traffic simulation is indispensable for the development of the dynamic fleet management system.

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