Transportation Research Part D 16 (2011) 515–524

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

A fuel economy optimization system with applications in vehicles with human drivers and autonomous vehicles

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ARTICLE INFO

Keywords:
Vehicle fuel economy
Eco-driving
Human–machine interface
Autonomous vehicle
Driving simulator analysis

ABSTRACT

Motor vehicle powered by regular gasoline is one of major sources of pollutants for local and global environment. The current study developed and validated a new fuel-economy optimization system (FEOS), which receives input from vehicle variables and environment variables (e.g., headway spacing) as input, mathematically computes the optimal acceleration/deceleration value with Lagrange multipliers method, and sends the optimal values to drivers via a human-machine interface (HMI) or automatic control systems of autonomous vehicles. FEOS can be used in both free-flow and car-following traffic conditions. An experimental study was conducted to evaluate FEOS. It was found that without sacrificing driver safety, drivers with the aid of FEOS consumed significant less fuel than those without FEOS in all acceleration conditions (22–31% overall gas saving) and the majority of deceleration conditions (12–26% overall gas saving). Compared to relative expensive vehicle engineering system design and improvement, FEOS provides a feasible way to minimize fuel consumptions considering human factors. Applications of the optimal model in the design of both HMI for vehicles with human drivers and autonomous vehicles were discussed.

1. Introduction

A number of alternatives have been put forward to improve fuel economy of motor vehicles and recently driving behaviors and energy efficient technologies have been seen to offer considerable potential for reducing fuel consumption. Additional while the exploitation of energy efficient technologies may take time to implement and be costly in terms of continuously having to satisfy consumer demands for safety, comfort, space and adequate acceleration and performance encouraging changes in driving behavior can be accomplished relatively quickly.

One method to help drivers form appropriate driving behaviors is via the in-vehicle human–machine interface (HMI). For example, van der Voort et al. (2001) develop a fuel-efficiency support tool to present visual advice on optimal gear shifting to maximize fuel economy. Appropriate vehicle pedal operations, however, may contribute more than manual shifting operations to fuel economy (Brundell-Freij and Ericsson, 2005). Further pedal operations are applied for both manual-transmission and automatic-transmission vehicles with human drivers as well as autonomous vehicles, while gear shifting operations are only used for manual-transmission ones.

Fuel consumption models have been developed to quantify the relationship between fuel consumption and vehicle characteristics, traffic or road conditions but these, in general, are only able to provide approximate fuel consumption estimates. As the model accuracy increases by incorporating numerous variables affecting its outcome, however, the computational

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doi:10.1016/j.trd.2011.06.002

efficiency of these models dramatically decrease. Accordingly, some simplified models of fuel consumption and emissions were proposed in which outcomes can be expressed as a function of a few salient factors. For example, Ahn (1998) used non-linear multiple regression and neural network techniques to approximate vehicle fuel consumption and emissions as a function of speed and acceleration. Real traffic data collected at Oak Ridge National Laboratory containing 1300–1600 individual measurements for each vehicle were used to validate the modeling results. The models were able to estimate vehicle fuel consumption within 2.5% of their actual values, and could be further applied in the field of traffic simulation, transportation planning and intelligent transportation system design.

In addition to traditional vehicles with human drivers, those vehicles that can move autonomously and navigate in everyday traffic will become a reality in the next decades. Existing work mainly focuses on the development of technologies related to sensors, navigation, motion planning and control, and fuel economy of autonomous vehicle did not receive much attention. Consequently, a new fuel economy system that is able to provide engineers or manufacturers the optimal driving patterns by which they can develop better autonomous vehicles for the maximal fuel economy might be expected. Compared to human drivers, autonomous vehicles controlled via a computer could strictly follow the optimal driving patterns.

2. The new fuel economy optimization system

We develop a new fuel economy optimization system (FEOS), to help drivers reduce fuel consumption and vehicle-related emissions. The basic architecture of the system consisted of; vehicle variables and associated in-vehicle sensors, traffic/environmental variables and associated in-vehicle technology, data processing, redundant system components; and an application of optimal model in vehicles with human drivers and autonomous vehicles.

As illustrated in the Fig. 1, mechanical sensors, GPS, video and other technology installed in the vehicle measured the dynamic vehicle variables (current speed and acceleration), and environmental factors (such as the current speed limit, the headway spacing between a driver's vehicle and a leading vehicle or a traffic light). Filtered data were transmitted into an in-vehicle computer as model inputs. Data processing module in the computer could calculate optimal solutions in terms of contexts (for example acceleration, descending or ascending gradient) given vehicle and traffic inputs. These optimal solutions were further tested and compared to actual driving patterns. If optimal solutions were not correctly followed, data processing module updated optimal solutions according to the current vehicle and traffic situations. The information of the

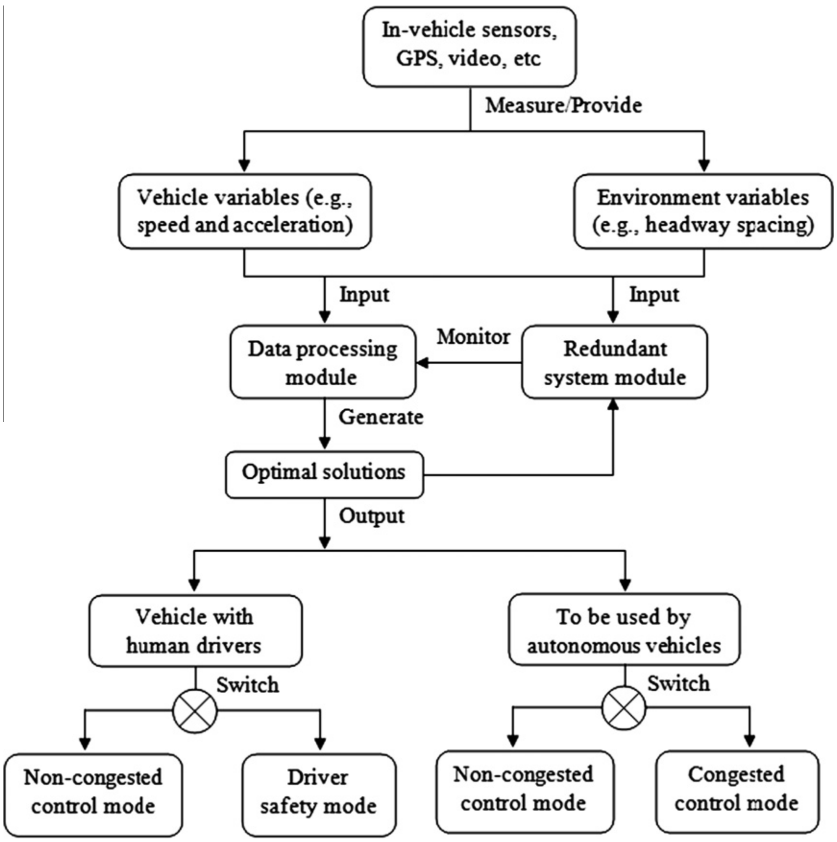

Fig. 1. System architecture of THE FEOS.

optimal pedal operation is displayed via an in-vehicle human machine interface for vehicles with human drivers. Such advice can either be presented online to help modify driver behavior in the real time, or provided offline for training purposes. Also, the information of desired pedal control can be processed and delivered for autonomous vehicles by mechanical means. In addition, two sets of switching algorithms for both traditional human-controlled vehicles and autonomous vehicles in non-congested and congested traffic conditions are developed.

2.1. Input variables

In accordance with Ahn, only speed (y) and acceleration (x) as inputs; both are available from existing in-vehicle sensors, which would avoid unnecessary costs related to installing additional sensors.

In addition to vehicle factors, environmental variables were regarded as important model inputs that affected the generation of optimal solutions related to pedal controls. These variables included the current posted speed limit, the headway spacing between a driver's vehicle and a leading vehicle or a traffic light (or other road signs), that a driver is supposed to react, and the duration of a traffic light (both red and green light). During the optimization process, environmental factors serve as a set of constraints or additional objectives to achieve besides minimizing fuel consumption. For example, when a driver decides to stop in front of a red traffic light, the headway spacing between the position of the subject vehicle and the traffic light has to be considered to develop optimal solutions for stopping within that distance.

2.2. Optimal model and data processing module in the free-flow regime

Vehicle longitudinal controls (or speed controls), in general, could be categorized into two regimes: free-flow and car-following. Free flow means that a driver's behavior of speed control is voluntary and unaffected by upstream or downstream driving conditions (Transportation Research Board, 2000). It can be applied in reality, where there is little interaction between vehicles (such as there are no other vehicles involved or there are other vehicles but far away from the driver's vehicle). Free-flow driving is critical in the capacity analysis procedures for basic freeway segments and multilane highways described in the *Highway Capacity Manual* (Transportation Research Board, 2000). In addition, the current system might become more applicable in the free-flow regime when considering human driving safety. In a free-flow condition, drivers are safer and have more freedom to control the car following the advice or commands derived from the system. While in a sophisticated driving condition (such as heavy traffic flow or congestion), drivers have to pay more attention on maneuvering the car within the flow of traffic (e.g., follow a leading vehicle and maintain a safe distance, change a lane, overtake, or cut in another lane). In this case, it is not valuable to provide advice for drivers because that may interfere with drivers' safety and driving performance. In a word, driver safety must receive higher priority than maximal fuel economy. The model could also be applied in a complicated driving condition for autonomous vehicles that are controlled via a computer.

Drivers maintain a constant speed most of the time, especially when they drive on a freeway or there is little interaction between vehicles. Advanced vehicle techniques (e.g., cruise control) have been developed and widely adopted to facilitate the process of maintaining a constant speed. Based on Ahn (1998)[1], fuel consumption rate (unit in gallon per hour), can be directly developed as a function of speed when the acceleration x is 0 (ft/s^2), with four constant parameters a, e, f and g.

$$F(y) = e^{a+ey+fy^2+gy^3} \tag{1}$$

The time t a driver spends driving at certain distance s is given by the Eq. (2):

$$t = \frac{s}{y} \tag{2}$$

Therefore, the cumulative fuel consumption G during a time period t (unit in s) is expressed as:

$$G(y,t) = \frac{1}{3600}\int_0^t F(y) \times dt \tag{3}$$

The primary objective is to minimize the cumulative fuel consumption to reduce gas consumption and emissions. The optimal speed y^* could be obtained as a result of Eq. (4) if y^* exists.

$$\frac{\partial G}{\partial y} = 0 \tag{4}$$

[1] Ahn (1998)'s Fuel Consumption Model and Parameters: Ahn (1998) proposed a mathematical model which described fuel consumption rate F (gal/h) as a function of vehicle's speed y (feet/s) and acceleration x (feet/s^2):

$$F(x,y) = e^{a+bx+cx^2+dx^3+ey+fy^2+gy^3+hxy+ixy^2+jxy^3+kx^2+y+lx^2y^2+mx^2y^3+nx^3y+nx^3y+ox^3y^2+px^3y^3} \quad \text{Ahn (1998)}$$

Where $a, b, \ldots, p$ are constants: a = −0.67944; b = 0.135273; c = 0.015946; d = −0.00119; e = 0.029665; f = −0.00028; g = 1.49E−06; h = 0.004808; i = −2.1E−05; j = 5.54E−08; k = 8.33E−05; l = 9.37E−07; m = −2.5E−08; n = −6.1E−05; o = 3.04E−07; p = −4.5E−09.

Several conditions can trigger the deceleration process. For example, a driver has to slow down and eventually stop at a signalized intersection according to traffic rules. The deceleration process could be developed into two stages. At the first stage, drivers released the throttle pedal, and applied the brake pedal if a higher level of deceleration is required, to slow down until the speed reached zero. Then, drivers waited for a while until it turned green.

At the decelerating stage, speed changed from v_0 to zero. To simplify this, the initial speed is divided into l ($l = -v_0/\Delta$), equal portions with interval Δ that refer to an infinitely small negative number (Eq. (5)). It is assumed that acceleration remains constant during each interval Δ.

$$v_0, v_0 + \Delta, v_0 + 2\Delta, \ldots, -\Delta, 0 \tag{5}$$

Given the constant acceleration, the time spent in reducing speed during the ith interval t_i is the ratio of the deviation of speed Δ divided by the constant acceleration x_i during the ith interval.

$$t_i = \frac{\Delta}{x_i} \tag{6}$$

In addition, the distance s_i driven during each interval is given by:

$$s_i = \frac{(v_0 + i\Delta)^2 - [v_0 + (i-1)\Delta]^2}{2x_i} \tag{7}$$

The time spent in decelerating and idle stages t_{dec_total} is equal to the sum of l time periods spent in slowing down plus idle time t_{idle} (Eq. (8)). Similarly, the headway spacing between the initial position of a driver's vehicle and the intersection s_{dec_total} is equal to the sum of l distances passed during each interval (Eq. (9)).

$$t_{dec\_total} = \sum_{i=1}^{l} t_i + t_{idle} \tag{8}$$

$$s_{dec\_total} = \sum_{i=1}^{l} s_i \tag{9}$$

Accordingly, the cumulative fuel consumption during a deceleration process can be described as:

$$G(x) = F(x_1, v_0) \times t_1 + F(x_2, v_0 + \Delta) \times t_2 + \cdots + F(x_l, -\Delta) \times t_l + F(0,0) \times t_{idle} \tag{10}$$

To minimize $G(x)$, the Lagrange multipliers method (LMM); a technique for solving optimization problems with multiple constraints. It is applied for not only differentiable functions, but also situations involving optimization of any type of function over any set of strategies, discrete or continuous, numerical or non-numerical, with constraints that can be represented as bounds on real valued functions over the same strategy set (Everett, 1963). The basic idea of LMM is to introduce a new variable, a Lagrange multiplier λ, to put the objective function together with multiple constraints. By adding this new component with respect to λ, the original n-dimensional gradient now has $(n + 1)$ dimensions. Because the new component of the gradient is zero, the old components of the gradient treat λ as a constant. As a result $(n + 1)$ equations in n dimensions result in a unique optimal solution. Moreover, multiple Lagrange multipliers can be added depending on the number of constraints.

One constraint regarding the headway spacing between the initial position of a driver's vehicle and the intersection is specified and thus, one Lagrange multiplier is added to formulate a Lagrange function based on the objective function (Eqs. (11) and (12)). In this case, Lagrange multiplier λ means the rate at which the optimal cumulative fuel consumption value changes if such constraint changes. Then $(l + 1)$, differential equations were developed: l components referred to acceleration and one is regard with the Lagrange multiplier (Eq. (13)). Eventually, optimal acceleration x_i^* during each interval Δ and optimal Lagrange multipliers λ^* are obtained.

$$Z(x) = \sum_{i=1}^{l} s_i - s_{dec\_total} = 0 \tag{11}$$

$$H(x, \lambda) = G(x) + \lambda \times Z(x) \tag{12}$$

$$\frac{\partial H(x,\lambda)}{\partial x_i} = 0, \frac{\partial H(x,\lambda)}{\partial \lambda} = 0 \tag{13}$$

Given the same example of stopping at a signalized intersection, when the traffic light turned green, drivers started to accelerate and eventually maintain at a constant speed v_l. Acceleration process is developed into two stages. At the first stage, drivers applied the throttle pedal until they reached the speed limit (accelerating stage). Then, drivers maintained that constant speed until the next intersection with a traffic light appears.

At the accelerating stage, speed increased from 0 to v_l. With the similar idea proposed in the deceleration process, v_l can be divided into l ($l = v_l/\Delta$), equal portions (Δ is an infinitely small positive number), and during each interval acceleration did not change. Then, the time spent in increasing the speed during the ith interval t_i is equal to the ratio of the deviation of speed Δ divided by the constant acceleration x_i during the ith interval. The time spent in both accelerating and constant stages t_{acc_total} is the sum of l time periods spent in speeding up plus the time drivers maintained a constant speed t_{cons}:

$$t_{acc\_total} = \sum_{i=1}^{l} t_i + t_{cons} \tag{14}$$

Consequently, the cumulative fuel consumption in an acceleration process can be described by:

$$G(x) = F(x_1, 0) \times t_1 + F(x_2, \Delta) \times t_2 + \cdots + F(x_l, v_l) \times t_l + F(0, v_l) \times t_{cons} \tag{15}$$

The Lagrange multipliers method is applied to generate the optimal solution of $G(x)$. One multiplier is added to reconstruct the objective function (Eqs. (16) and (17)). Then, a set of differential equations are developed (Eq. (18)), in general, resulting in optimal acceleration x_i^* during each interval Δ, optimal time spent in maintaining a constant speed t_{cons}^*, and optimal Lagrange multiplier λ^*.

$$Z(x) = \sum_{i=1}^{l} t_i + t_{cons} - t_{acc\_total} = 0 \tag{16}$$

$$H(x, \lambda) = G(x) + \lambda \times Z(x) \tag{17}$$

$$\frac{\partial H(x, \lambda)}{\partial x_i} = 0, \frac{\partial H(x, \lambda)}{\partial \lambda} = 0 \tag{18}$$

2.3. Redundant system components to enhance system reliability

The redundant module is independent of the data processing module and able to reconfigure the system in the presence of error/failure (Girard et al., 2001). It continuously received driving and environmental variables data from in-vehicle sensors as well as optimal solutions when they became applicable. In-vehicle sensors (or GPS, video, etc.), are assumed to measure and provide reliable inputs. Two potential system failures might create safety problems. First, the data processing module may generate wrong solutions and actual constraints $C_i = (C_1, C_2, \ldots, C_m$ for $i = 1, 2, \ldots, m)$ may be violated (i.e., the constraint with respect to the safe headway spacing between two vehicles or the distance to make a fully stop before a signalized intersection). This could lead to a forward vehicle crash or running a red light. To avoid such failure, the redundant module could examine if all constraints were satisfied based on the optimal solutions. Meanwhile, the reliability module randomly generates a number of non-optimal solutions and compares the corresponding cumulative fuel consumption G to the one with the optimal solution G^*. If optimal pedal operations lead to more fuel usage, or if any one of constraints C_i is not satisfied, data the processing module will recalculate optimal solutions.

Second, it is possible that human drivers fail to follow the optimal solutions. For those drivers who responded beyond the optimal recommendations, this would not create any driving safety problems but sacrifice maximal fuel economy. For example, drivers may step on the brake harder to slow down causing increased headway spacing between vehicles or stopping further from the signalized intersection. On the other hand, for those drivers who respond less than recommended, the reliability module compares the optimal to the actual speed recorded from the sensors. If the actual speed y exceeded the optimal y^* plus some tolerance θ during a deceleration process, the data processing module recalculates the optimal solutions based on recent driving and environmental variables (Eq. (19)). The reliability module can also play a warning to drivers if there is not sufficient time for them to correct their behavior. Similarly, there is a chance that autonomous vehicles do not follow the optimal solutions due to mechanical malfunction. If the reliability module detects differences between the optimal and actual speed, it will automatically slow down or stop the car to avoid collision or running a red light. Continuous and multiple recalculations will eventually cause the termination of the system. In this case, no advices/commands come out and human drivers or autonomous vehicles drive as normal.

$$\begin{aligned}&\textit{If any constraint } C_i \textit{ is violated } \textbf{OR } G < G^* \textbf{ OR } y - y^* > \theta,\\&\textit{then recalculate the optimal solutions}\end{aligned} \tag{19}$$

2.4. Application in vehicles with human drivers

After obtaining optimal solutions based on vehicle and environmental inputs, advice on speed controls, if applicable, is generated and presented to the driver who a driver is informed when to apply the throttle or brake pedal while the vehicle is in operation. Advice could be provided online to help a driver make necessary behavioral adjustments in real-time and offline to help familiarize them with optimal patterns of pedal control. Advice could also be presented as visual, auditory, or combined modality information.

Optimal pedal operations can be applied in non-congested or congested traffic conditions. The switching algorithm between congested and non-congested control modes (Fig. 1), can be determined based on the headway spacing between

Table 1
Two strategies of brake pedal operation during a deceleration process.

	Example 1	Example 2
Vehicle initial status		
Speed (ft/s)	30	60
Acceleration (ft/s^2)	0	0
Vehicle initial position		
Distance between vehicle and intersection (ft)	450	600
Duration of red light (s)	30	30
Duration of green light (s)	5	N/A
Optimal braking strategies derived from the FEOS	Light level → high level	Medium level

vehicles h^* (i.e., h^* = 50 m). This spacing may vary with factors such as travel speed, vehicle length and weight, weather, road condition and individual reaction times. When the actual headway spacing h is greater than h^*, the system automatically switches to the non-congested control mode (Eq. (20)), but when h is equal or less than h^*, the system temporarily becomes disabled and switches to the driver safety mode giving higher priority to driver safety than maximal fuel economy. When $h \leqslant h^*$ drivers have to pay more attention to maneuvering within the flow of traffic – follow the leading vehicle at a safe distance, changing lanes, overtaking, etc. – and may be unable to follow the advice given by the optimal model. It is not appropriate to provide advice to drivers in congested driving conditions because that may interfere with safety and driving performance. In addition to the headway spacing, the driver safety mode can be triggered due to levels of driving workload or fatigue.

$$\begin{aligned}&\textit{If } h > h^*,\ \textit{then switch to non}-\textit{congested control mode}\\&\textit{Else if } h \leqslant h^*,\ \textit{then switch to the driver safety mode}\end{aligned} \tag{20}$$

Advice generated by the in-vehicle computer system, and associated driving strategies, might vary in based upon certain vehicle and traffic conditions. Take a simple scenario for an example: suppose a driver is approaching an intersection, where the initial traffic light is green but will change to red after 5 s. The speed of the subject vehicle is 30 ft/s and remains constant; the distance between subject vehicle and intersection is 450 ft when the driver sees the traffic light; and the red light will last for 30 s (Table 1). The driver has to release the throttle and apply the brake pedal to fully stop the car. Given these parameter estimations (v_0 = 30, $s_{dec-totoal}$ = 450, $t_{dec-total}$ = 35, Δ = 1), the Lagrange multipliers method can be applied for the optimization process of minimal cumulative fuel consumption. At the end, the optimal strategy for pedal operation in this case is to lightly press the brake pedal (approximately – 1 ft/s^2) for about 10 s, and then to press harder (-5 ft/s^2) to slow the vehicle. Table 1 also described a case (Example 2) in which the driver is suggested to press the brake pedal consistently at a medium level (-3 ft/s^2) until the vehicle is stopped.

A new human–machine interface with color coding is designed and illustrated in the Fig. 2. The dash line represented the current acceleration, and numbers on the right side indicated the scale of the acceleration. The optimal acceleration is displayed with a dark green color, bordered by gradient colors. For example, if the current optimal acceleration is -1 ft/s^2, the area from 0 to -2 is highlighted. When the optimal strategy is first generated and presented, a tone is played to inform

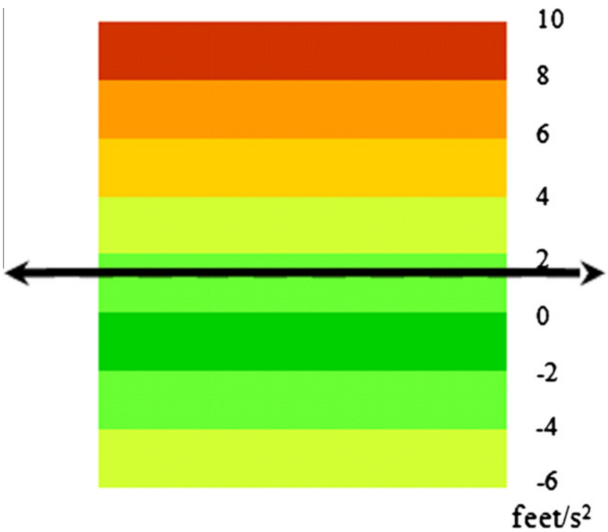

Fig. 2. The human–machine interface of the FEOS with color coding: The color of each bar: 10 to 8: red; 8 to 6: orange; 6 to 4: dark yellow; 4 to 2: light yellow; 2 to 0: light green; 0 to –2: dark green; –2 to –4: light green; –4 to –6: light yellow.

Table 2
Parameters on vehicle status and position.

Deceleration process:	Condition 1	Condition 2	Condition 3	Condition 4
Speed limit (mph)	20	20	40	40
Headway spacing between vehicle's initial position and intersection (ft)	900	900	900	900
Duration of red light (s)	30	30	30	30
Duration of green light (s)	20	15	5	0
Acceleration process:	Condition 1		Condition 2	
Speed limit (mph)	30		60	

drivers that it is the time to make behavioral adjustment. After practice, drivers were expected to move the dash line into the optimal area as accurately as possible by maneuvering vehicle pedals accordingly. Furthermore, if auditory function is enabled, the optimal strategies were played in accordance with the visual information.

2.5. Optimal model in autonomous vehicles

Compared to traditional vehicle with human drivers, the current mathematical optimal model might be better applied in autonomous vehicles that will become a reality in the next decades. The first and the most important reason is that autonomous vehicles avoid the potential hazard related to driving safety caused by the usage of such system. In general, when drivers use these in-vehicle HMIs, their attention might be distracted from driving. In other words, drivers may reach the maximal fuel economy by sacrificing their driving safety or performance. However, it is not the case for autonomous vehicles that requires no human interventions. Second, the optimal solutions were developed based on the immediate traffic and environmental inputs such as the posted speed limit or the headway spacing between the driver and a leading vehicle or traffic light. To obtain such information, sensors with a variety of modal (e.g., video, laser, radar, etc.), approaches are needed. Because these sensor technologies have becomes applicable in autonomous vehicles, immediate traffic and environmental measures can be easily obtained as inputs of data process module for the generation of optimal driving patterns. Third, the current system is developed based on a mathematical model of fuel consumption and all possible optimal solutions were generated relying on a set of mathematical equations. Therefore, it can be easily imbedded into an autonomous vehicle computer system. Finally, autonomous vehicles are controlled via a computer system. This allows the vehicle to achieve accurate motion by strictly following the instruction delivered by the computer. As a result, it is possible that the current system applied in autonomous vehicles help reach a higher level of fuel economy than traditional vehicles with human drivers.

Similar to vehicles with human drivers, optimal pedal operations could be applied by autonomous vehicles in both non-congested and congested traffic conditions. The switching algorithm between these two control modes (Fig. 1), could be decided by the same driving variable h^*: the FEOS remains the non-congested control mode unless the actual headway spacing h is equal or less than h^* in which the FEOS switches to the non-congested control mode (Eq. (21)). Because autonomous vehicles do not have the concern on driver safety, the FEOS becomes applicable in not only non-congested but also congested driving condition.

$$\begin{aligned}&\mathit{If}\ h > h*,\ \mathit{then\ switch\ to\ non-congested\ control\ mode\ Else\ if}\ h \leqslant h*,\\&\mathit{then\ switch\ to\ congested\ control\ mode}\end{aligned} \tag{21}$$

3. Model validation with a driving experiment

The fuel-economy human machine system is evaluated regarding its ability to reduce fuel consumption via a driving simulator experiment. A simulated urban driving condition with signalized intersections is chosen to investigate the vehicle fuel economy. Two reasons may support our selection. First, the speed limit in an unban area is usually low due to its high population and vehicle density. The US Energy Information Administration reported that when people drove at a speed between 5 and 25 mph, the fuel economy is less than 25 mpg. Therefore, urban driving condition should gain more attention on gas saving compared to other driving situations such as freeway. Second, urban driving condition involves a lot of intersections with either signalized traffic lights or stop/yield signs. This causes drivers to repeatedly speed up and slow down, which consumes more gas and produces more pollutant emissions than maintain at a constant speed.

Eight healthy participants (four males, four females), ranging from age 24 to 34 years of age took part, all had normal or corrected-to-normal vision and valid driver licenses. Written informed consent is obtained prior to the study[2].

[2] A STISIM® driving simulator (STISIMDRIVE M100K) is used in the experimental study. This simulator includes a Logitech Momo® steering wheel with force feedback a gas pedal, and a brake pedal. The driving scenario is presented on a 27 in. LCD with 1920 × 1200 pixel resolution. The FEOS provides participants with information about fuel consumption rates, cumulative fuel consumption and advice on vehicle pedal controls for the maximal fuel economy. The FEOS output is displayed on a 19 in Dell LCD (1098FP model) which is located 50 cm to the right of subjects, and 91 cm from their eyes. The visual angle of the touch screen is 13.1° vertically and the screen is controlled by a Dell PC (OPTIPLEX 745) connected to the driving simulator via a Labjack® system.

All participants were randomly divided into two groups: four individuals (two males, two females) drove with FEOS while the others drove without FEOS. More specifically, when participants who drove with FEOS were within 900 ft of an intersection with the traffic light ($s_{dec-totoal}$ = 900), this intersection appeared and the initial traffic light is green. The duration of such green light varied (Table 2). When the traffic light turned red, FEOS is aware of this change and generated the optimal pedal operations in terms of the level of acceleration. Following FEOS's visual advice on the HMI, drivers were able to fully stop ahead of the intersection with the maximal fuel economy. After waiting a red light for a while, drivers accelerated a car and finally maintained a constant speed following the speed limit. In this experiment, there were two levels of speed limits: 20 mph and 40 mph. The time for calculating the cumulative fuel consumption is 1 min ($t_{dec-total}$ = 60) and the speed interval is set equal to 1 ft/s (Δ = 1). As seen in Table 2, there are four deceleration and two acceleration conditions; each acceleration process being repeated twice.

All subjects first went through a practice session of four trials. Each practice drive of eight miles lasted 15–20 min with the session lasting 1–1.5 h. Participants were allowed to familiarize themselves with the driving simulator, including the steering wheel, speedometer, gas, and brake pedal. Also, participants who drove with FEOS are able to gain some feel of driving while following its guidance. These four participants are asked to follow the system's guidance as accurately as possible. After practice, all participants are required to complete two test blocks each of eight miles. The session lasted for 30–40 min. During the whole experiment, participants are asked to follow all traffic laws. The driving scenario for both the test and practice blocks are similar. An urban environment is simulated with two lanes, one lane in each direction. Eight randomly distributed intersections with traffic lights are designed and all participants had to stop at an intersection if the traffic light is red.

Several driving behaviors are automatically recorded by the driving simulator every 100 ms. There measurements included speed (unit in ft/s), acceleration (ft/s^2), time elapsed (s), traveled distance (ft) and lateral position (ft). Both acceler-

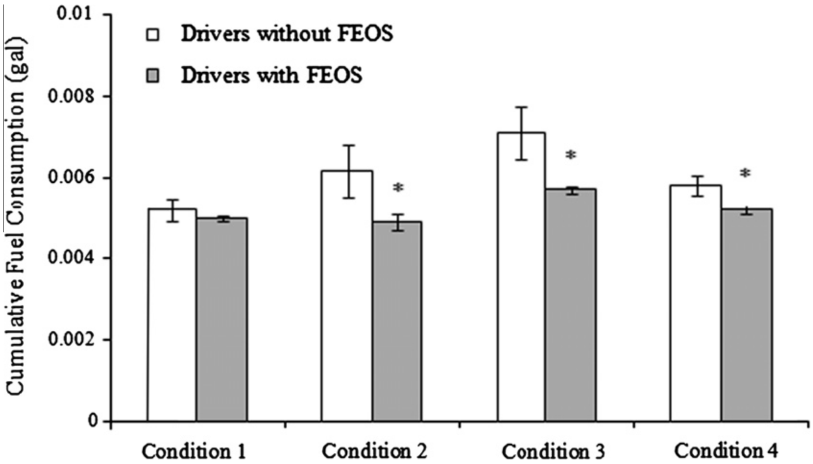

Fig. 3. The cumulative fuel consumption between drivers with and without FEOS. ∗ – significant difference between two groups of drivers at α = .05 level. Error bars indicated ±1 standard deviation.

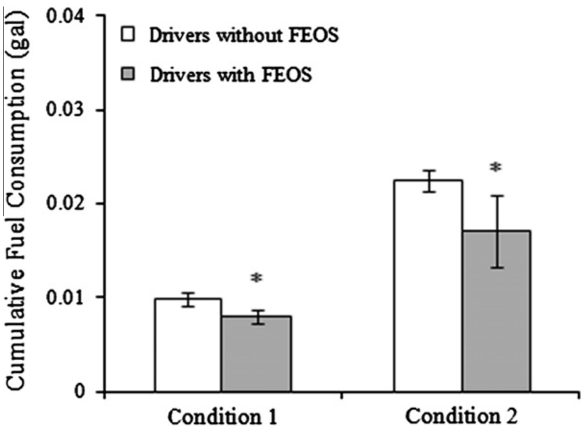

Fig. 4. Comparison of the cumulative fuel consumption between drivers with and without FEOS. ∗ – significant difference between two groups of drivers at α = .05 level. Error bars indicated ±1 standard deviation.

ation and speed are used to calculate real time fuel consumption rates. Adding another time elapsed, allows real time cumulative fuel consumption to be computed and displayed to drivers.

The cumulative fuel consumption is calculated in conditions according to Ahn's (1998) equation. One-way analysis of the variance (ANOVA) is performed to compare differences of the cumulative fuel consumption between two groups of drivers (with vs. without the FEOS) under different acceleration and deceleration conditions. Further, lateral position is also compared two groups of drivers to examine if the FEOS created safety problems.

Drivers with the FEOS consume less fuel than those without the system in Condition 2, Condition 3, and Condition 4 during the deceleration process (Fig. 3). There is no significant difference between two groups of drivers in Condition 1. Drivers with FEOS used 26% less fuel compared to those without FEOS in Condition 2 as well as 24% in Condition 3 and 12% in Condition 4 during the deceleration process.

Similarly, drivers with FEOS consumed less fuel than those without in Condition 1 and Condition 2 during the acceleration process (Fig. 4). Drivers with FEOS use 22% less fuel compared to those without FEOS during the first acceleration condition and 31% in the second acceleration process.

One-way ANOVA is also performed to compare the standard deviation of lane position from the central line at the road between two groups of drivers. No significant differences are observed, indicating that the usage of FEOS did not significantly add additional workload to drivers.

4. Extension of the model in the car-following regime

The FEOS can be extended and applied in the car-following regime when vehicle interactions are considered. In this case, the subject's vehicle is assumed to follow a leading vehicle and maintain a safe headway distance. Let v_0 be the initial speed of the subject's vehicle and v_f be the initial speed of the leading vehicle. Driving in a car-following condition is also divided into three subtasks: maintaining a constant speed ($v_0 = v_f$), acceleration ($v_0 < v_f$), and deceleration ($v_0 > v_f$). When maintaining a constant speed, the cumulative fuel consumption and optimal speed are expressed by the same equations developed in a free-flow condition. When changing speed from v_0 to v_f, the change is divided into l ($l = (v_f - v_0)/\Delta$), equal parts with interval Δ. The constraint in the car-following regime is:

$$\sum_{i=1}^{l} s_i = h_0 + v_f \sum_{i=1}^{l} t_i - h_f \tag{22}$$

where $\sum_{i=1}^{l} s_i$ is the distance passed by the subject's vehicle, h_0 is the initial headway spacing between two vehicles, h_f is the final headway spacing between two vehicles when they reach the same level of speed, $\sum_{i=1}^{l} t_i$ is the time spent. In dynamic driving situations, the leading vehicle may change speed frequently. Therefore, the model receives changes in of leading vehicle's speed at each time interval from sensors, the model can update its inputs and recalculate optimal solutions accordingly. In addition, the final headway spacing between the subject's vehicle and the leading vehicle could be predefined as a threshold to keep a safe distance between vehicles.

The cumulative fuel consumption during a deceleration process is:

$$G(x) = F(x_1, v_0) \times t_1 + F(x_2, v_0 + \Delta) \times t_2 + \cdots + F(x_l, v_f) \times t_l \tag{23}$$

Based on the Lagrange multipliers, one multiplier is added to reconstruct the objective function $G(x)$ (Eqs. (24) and (25)). Then $(l + 1)$, differential equations are developed (Eq. (26)), resulting in optimal acceleration x_i^* during each interval Δ and one optimal Lagrange multiplier λ^*:

$$Z(x) = \sum_{i=1}^{l} s_i - s_0 - v_f \sum_{i=1}^{l} t_i + s_h = 0 \tag{24}$$

$$H(x, \lambda) = G(x) + \lambda \times Z(x) \tag{25}$$

$$\frac{\partial H(x, \lambda)}{\partial x_i} = 0, \frac{\partial H(x, \lambda)}{\partial \lambda} = 0 \tag{26}$$

5. Conclusions

Modified driving behaviors may have a considerable influence on the consumption of vehicle fuel compared to technological improvement or regulations additional. When drivers follow fuel economy optimization system advice to control the level of acceleration they do not violate any traffic rules, such as speeding or running a red light. If advice is not followed, the data processing module will recalculate the optimal solutions according to current traffic and environmental inputs. In addition, FEOS can offer drivers not only online support but also offline training. Given the support of an in-vehicle computer with FEOS installed, drivers can receive the real-time fuel consumption information as well as instructions on the brake and/or throttle pedal controls while driving. FEOS can also help drivers, especially new drivers learn how to manipulate pedals according to traffic and environmental situations and eventually form an eco-driving style.

Acknowledgments

We appreciate the support for this research from National Science Foundation (NSF) (Award No.: 0916883) and UB2020 Grant at State University of New York.

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