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Optimization of Driving Styles for Fuel Economy Improvement

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Abstract—**Modern vehicles have sophisticated electronic control units, particularly to control engine operation with respect to a balance between fuel economy, emissions, and power. These control units are designed for specific driving conditions and testing. However, each individual driving style is different and rarely meets those driving conditions. In the research reported here we investigate those driving style factors that have a major impact on fuel economy. An optimization framework is proposed with the aim of optimizing driving styles with respect to these driving factors. A set of polynomial metamodels are constructed to reflect the responses produced by changes of the driving factors. Then we compare the optimized driving styles to the original ones and evaluate the efficiency and effectiveness of the optimization formulation.**

I. INTRODUCTION

Fuel consumption and emission can be improved by 40% by altering the driver's driving style [1, 2]. Developing a means of improving driver behavior to maximize fuel economy is a significant opportunity to reduce fuel consumption in existing fleets. Dam [3] conducted a survey about the perception of the achievable automobile fuel economy indicating that significant fuel economy enhancement can be achieved with a few driving adjustments. In recent research, the inverse problem was addressed; namely, the theoretical framework and algorithms [4, 5] were developed for making the engine of a vehicle into an *autonomous intelligent system* capable of learning its optimal operation in real time while the driver is driving the vehicle. Through this new approach, the engine progressively perceives the driver's driving style and eventually learns to operate in a manner that optimizes fuel economy and emissions.

A significant research effort has been focusing on investigating the impact of driving behavior on fuel consumption. Van Mierlo *et al.* [2] studied how driving styles and traffic measures can affect fuel consumption and vehicle emissions. The study consisted of evaluating driver behavior and fuel economy over specific driving routes, before and after supplying the drivers with tips on fuel efficient driving practices, to determine whether a change in driver behavior had an impact on fuel economy. Ericsson [6] focused on independent factors to describe driving patterns and behaviors and to investigate their effects on fuel consumption. Hooker [7] conducted a study aimed at generating reliable advice concerning the optimal driving style to maximize fuel economy.

Simulation-based models that can provide fuel consumption by considering driving factors have been another research focus. Ross [8] investigated the factors that affect the fuel economy of light vehicles and can be used to estimate the effect of driving styles and vehicle characteristics. Using data gathered at Oak Ridge National Laboratory [9], Ahn *et al.* [10] introduced a method for estimating fuel consumption based on driver-related factors such as instantaneous speed and acceleration. Hybridization of conventional powertrain systems allows elimination of the impact of driving styles on fuel economy because the power management controller separates the coupling between the driver and the engine. Manzie *et al.* [11] examined the possible fuel economy benefits that can be achieved with emerging technologies such as hybrid electric vehicles and *intelligent* vehicles that use telematics. The latter allow the vehicles to communicate with the road infrastructure and other vehicles to obtain information about their environment. Langari and Won [12] proposed an intelligent energy management system for parallel hybrid vehicles that incorporates driving style identification.

This paper has two main objectives: (a) to investigate those driving factors that have a major impact on fuel economy and (b) to optimize driving styles with respect to these driving factors. In this context, we formulate an optimization framework that aims to modify driving styles with respect to key driving factors. A set of polynomial metamodels is constructed to reflect the responses produced by changes in these driving factors. Finally, to evaluate the efficiency and effectiveness of the optimization formulation, we compare the optimized driving style with the original one. The proposed optimization framework could be used in future research aimed at developing real-time feedback systems to enable drivers to alter their driving styles in response to actual driving conditions to be more fuel efficient and environmentally friendly.

The remainder of the paper proceeds as follows. In Section II we develop the general framework for identifying

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the driving factors. In Section III, we formulate a constrained optimization problem with respect to these driving factors. In Section IV, we evaluate the fuel economy benefits of using the optimized driving factors on a new driving style, and we draw concluding remarks in Section V.

II. Driving Style Factors

A. Engine Operation and Fuel Consumption

To evaluate the impact of a driving style on fuel economy through simulation, standard dynamometer driving schedules (DDSs) (or simply driving cycles) were used [i.e., vehicle speed profiles established by the U.S. Environmental Protection Agency (EPA) for testing and measuring fuel economy and emissions]. These driving cycles provide a good representation of typical urban and highway commutes and represent a situation in which the driver desires a particular vehicle's speed profile deemed characteristic of his/her driving style. The belief implicit here is that if the impact of the driving factors on fuel economy can be successfully captured by means of driving cycles, then it should also be possible to capture their impact by means of individual driving styles.

Transient operation constitutes the largest segment of engine operation over a driving cycle compared to the steady-state one [13]. Fuel consumption and emissions during transient operation are extremely complicated, vary significantly with each particular driving cycle, and are highly dependent upon the engine calibration. State-of-the-art engine calibration methods generate a static correlation between the values of the engine variables and the corresponding steady-state operating points. This correlation is incorporated into the ECU of the engine to control engine operation. While the engine is running, these correlations are being interpolated to provide values of the engine variables for each operating point.

To overcome the limitations imposed by the engine calibration schemes, it is always preferable to operate the engine over steady-state operating points (e.g., highway driving) that are well optimized through the engine calibration and thus avoid transient operation (e.g., stop-and-go driving) [14]. Furthermore, elimination of near idle engine operation enables direct fuel economy enhancement since at idle the efficiency is zero as no usable work is being drawn from the engine. Consequently, two factors, formally defined below, that have a major impact on engine operation and thus on fuel economy are (a) the *stop factor* (i.e., the percent of time over a driving cycle that the vehicle is stopped) and (b) the *coefficient of power demand,* which is directly related to transient engine operation.

B. Stop Factor and Coefficient of Power Demand

The *stop factor* is defined as the amount of time during a driving cycle that the vehicle is stopped (i.e., time that the vehicle's velocity is zero divided by the total duration of the driving cycle). This factor provides a convenient indication of idle engine operation over a driving cycle. When a vehicle is stopped during a drive cycle, the engine is idling. In this situation, fuel is consumed but the distance traveled is zero, so the fuel economy is reduced to 0 MPG.

The *stop factor* is calculated for several driving cycles; its effect on fuel consumption per meter is shown in Fig. 1. It seems that there is a linear correlation between the *stop factor* and fuel consumption; as the stop factor increases, the fuel consumption also increases. Namely, the more the engine is idling the higher the fuel consumption per meter. The Highway Fuel Economy Test (HWFET) driving cycle, for instance, is a representation of highway driving and contains the least amount of time stopped. This cycle shows the lowest amount of fuel consumption per meter. On the other hand, the Japan 10-15 and Federal Test Procedure (FTP) cycles have the highest percentage of time stopped compared to other cycles and, as a result, demonstrate higher fuel consumption per meter.

The second driving factor considered here is called the *coefficient of power demand.* It provides an indication of the transient engine operation since it is proportional to power demanded by the driver. This power is the work done by the vehicle over time, which is equal to the total force, F_{total}, acting on the vehicle multiplied by the distance traveled, d:

$$P = \frac{W}{t} = F_{total} \cdot \frac{d}{t}. \tag{1}$$

The forces acting on the vehicle in the longitudinal direction are shown in the free body diagram of a vehicle in Fig. 2. These forces consist of (a) the tractive force, F_x; (b) the drawbar force, R_{hx}; (c) the aerodynamic force, D_A; (d) the rolling resistance force, R_x; and (e) the component of vehicle weight in this direction. By Newton's second law, the total force, F_{total}, is equal to the inertial force, namely

$$M \cdot \alpha = F_{total} = F_x + R_{hx} - D_A - R_x - M \cdot g \cdot \sin\theta, \tag{2}$$

where M is the vehicle mass, α is the vehicle acceleration in the longitudinal direction, and g is the gravitational constant.

Eqs. (1) and (2) yield

$$P = M \cdot \alpha \cdot \frac{d}{t} = M \cdot (\alpha \cdot v), \tag{3}$$

where v is the vehicle speed.

Consequently, the power demanded from the driver is proportional to the product of the vehicle speed, v, and acceleration, α. This product is defined as the *coefficient of power demand*.

To investigate the impact of the *coefficient of power demand* on fuel consumption, it was normalized and compared to the normalized fuel consumption rate over a given driving cycle. It turns out that there is a linear correlation between the *coefficient of power demand* and fuel consumption. This correlation is illustrated in Fig. 3 for the Japan 10-15 driving cycle. To further investigate the relationship between this factor and fuel economy, the parts of the Japan 10-15 driving cycle that correspond to a high fuel consumption rate are identified. High fuel consumption rate is defined as the values of the fuel consumption rate that are equal to or greater than the high fuel point, which was specified as two standard deviations above the mean fuel consumption rate. These high fuel consumption rate points are then mapped onto the graph of the driving cycle to find what parts of the driving cycle correspond to high fuel consumption rates. Then, the values of the *coefficient of power demand*, which are equal to or greater than the high fuel points, are plotted along the driving cycle as illustrated in Fig. 4.

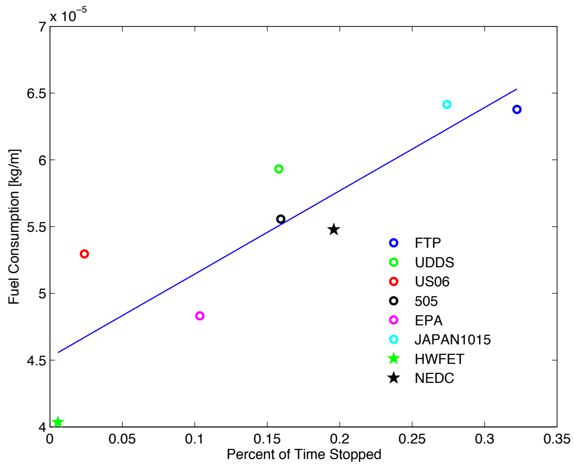

Fig. 1. Fuel consumption versus the percent of time the vehicle is stopped in various driving cycles.

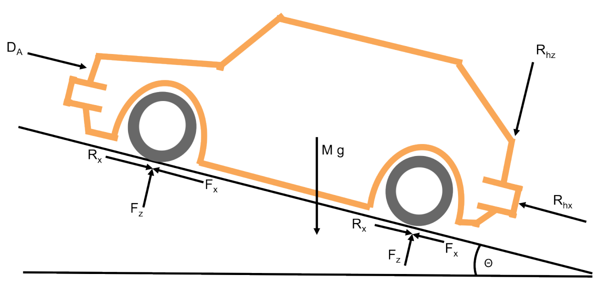

Fig. 2. Forces acting on a vehicle.

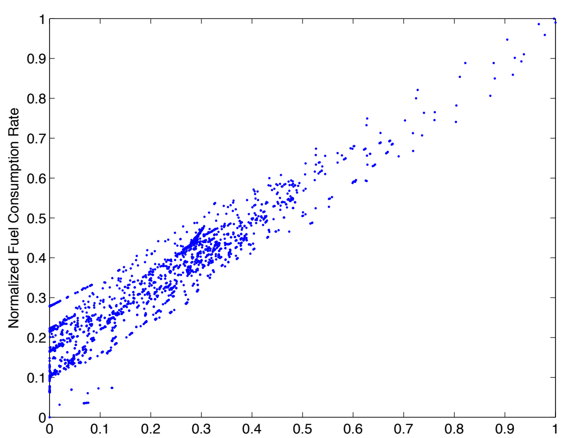

Fig. 3. Normalized fuel consumption rate with respect to the *coefficient of power demand* for the Japan 10-15 driving cycle.

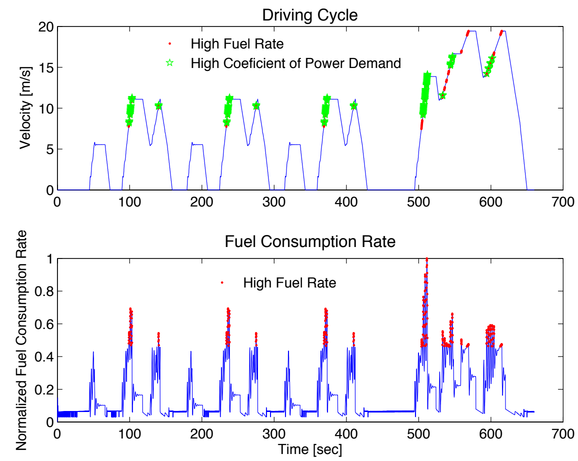

Fig. 4. High fuel rates over the normalized fuel consumption rate for the Japan 10-15 driving cycle.

It appears that both the *coefficient of power demand* and the high fuel consumption rate are provide the same information; thus, the *coefficient of power demand* constitutes a suitable indicator for aspects of a driving cycle that have a strong influence on fuel consumption. The same qualitative results were observed for other standard DDSs established by EPA.

Although the conjoint attributes of these two factors entail a comprehensive intimation of fuel consumption, the *stop factor* constitutes a commute aspect rather than a driving one. As such, it cannot be altered by changing driving behavior but only by modifying the route. However, hybridization of vehicles has aimed to address the *stop factor* by shutting off the engine when the vehicle is at stop and thus eliminating near idle engine operation. Thus in our optimization problem formulation the objective is to optimize a driving cycle with respect to the *coefficient of power demand* only.

III. Optimization Problem Formulation

Autonomie [15] was used to evaluate the various performance indices required for the optimization study. Autonomie is a Matlab/Simulink simulation package for powertrain and vehicle model development developed by Argonne National Laboratory.

A. Polynomial Metamodel for Fuel Consumption

To formulate the optimization problem analytically and reduce computation time, a set of polynomial metamodels are constructed to reflect the responses produced by changes in the *coefficient of power demand*. A metamodel is a "model of a model," which is used to approximate a usually expensive analysis or simulation process; metamodeling refers to the techniques and procedures to construct such a model [16]. In this optimization framework, a set of polynomial metamodels is used to express the objective function in the problem formulation. For example, fuel economy is evaluated though simulation in Autonomie over a grid of values for vehicle speed and acceleration for a particular driving cycle. Then multivariate polynomial functions are fit to the data using the least squares method.

The least squares method is a fundamental approach for parameter estimation. If the model has the property of being linear in the parameters then the least squares estimate can be calculated analytically. It was assumed that the model to be identified was in the form

$$\hat{y}(i) = \varphi_1(i) \cdot w_1 + \varphi_2(i) \cdot w_2 + \cdots + \varphi_n(i) \cdot w_n \,, \quad (4)$$

where $i = 1,2, \dots, n, n \in \aleph$ indexes the number of simulation data points; $\hat{y}$ is the output of the model; $w_1, w_2, \dots, w_n$ are the parameters of the model to be determined; and $\varphi_1, \varphi_2, \dots, \varphi_n$ are known functions that may depend on other known variables. The simulation data points derived from Autonomie correspond to pairs of the measured and regression variables $\{(y(i), \boldsymbol{\varphi}(i)), i = 1,2,\dots,n, n \in \aleph\}$. The problem is formulated so as to minimize the following least squares cost function with respect to the parameters of the model $w_1, w_2, \dots, w_n$

$$R(w,n) = \frac{1}{2}\sum_{i=1}^{n}[y(i) - \hat{y}(i)]^2. \quad (5)$$

The measured variable y is linear in parameters w_i, and the cost function is quadratic. Consequently, the problem admits an analytical solution.

For the optimization problem formulation, it is necessary to derive a polynomial metamodel of fuel consumption with respect to *coefficient of power demand* that will be the objective function. A quadratic function of the form

$$f(v,\alpha) = w_1 \cdot v^2 + w_2 \cdot \alpha^2 + w_3 \cdot v^2 \cdot \alpha + w_4 \cdot v \cdot \alpha^2 + \\ + w_5 \cdot v \cdot \alpha + w_6 \cdot v + w_7 \cdot \alpha + w_8 \quad (6)$$

provides an appropriate fitting to the discrete simulation data points of fuel consumption, $f(v,\alpha)$, with respect to vehicle speed, v, and acceleration, α. A higher order polynomial metamodel appears to "overfit" the data, whereas a lower order polynomial is not adequate to estimate fuel consumption accurately.

Different sets of discrete simulation data points consisting of a grid of vehicle speed and acceleration for three driving cycles, Japan 10-15, combined FTP and HWFET, and FTP, are derived by running the vehicle model in Autonomie. These sets are used to compute the polynomial fitting coefficients, **w**. To assess the polynomial fitting with the discrete simulation data points, the norm of residuals given by the following equation were evaluated:

$$||r|| = \left|\left(\mathbf{f}_{f.c.}(t) - \mathbf{f}(\boldsymbol{v}(\mathrm{t}), \boldsymbol{a}(\mathrm{t}))\right)^2\right|^{1/2} \,, \quad (7)$$

where $\mathbf{f}_{f.c.}(t)$ is the vector fuel consumption values over time derived from Autonomie and $\mathbf{f}(\boldsymbol{v}(\mathrm{t}), \boldsymbol{a}(\mathrm{t}))$ is the vector of fuel consumption over time estimated by the polynomial metamodel. Table 1 lists the values of the polynomial coefficients of the metamodel of each driving cycle and the norm of residuals. The latter yields an indication of a satisfactory curve fitting.

B. *Optimal Acceleration Profile*

This paper poses an optimization framework to determine the optimal values of the *coefficient of power demand* to improve fuel economy. This framework must maintain the original shape of a driving cycle (i.e., vehicle speed profile). Consequently, the objective of the optimization problem is to minimize fuel consumption, (6), only with respect to the vehicle acceleration. Deceleration is not a concern because the fuel cutoff controller in modern vehicles can successfully handle rapid deceleration.

Although a new acceleration profile will yield a new vehicle speed profile, the original driving cycle must somehow be preserved. To avoid the trivial solution (i.e., zero acceleration), a constraint is imposed on the difference between the resulting and the original vehicle speed profile. More specifically, the optimal acceleration profile is constrained to yield a new vehicle speed profile that is no more than 5 kph less than the original one. However, this hard constraint could result in reducing significantly the feasible domain of the optimal solution. To overcome this posterior technicality, the constraint is formulated as the norm of the difference between the original and the new speed profile. This norm should be less or equal to another norm formulated as the difference between the original and the speed profile that is 5 kph less than the original. The inherent modularity of the proposed constraint circumvents the hard limit of the derived speed profile to be no more than 5 kph less than the original one. However, it preserves the average discrepancy to be within these limits, and thus, it enables the feasible space of the acceleration profile to include solutions resulting in smooth shaping of the speed profile. Consequently, the following nonlinear constrained optimization problem is formulated:

TABLE 1
POLYNOMIAL COEFFICIENTS OF FUEL CONSUMPTION METAMODELS FOR DIFFERENT DRIVING CYCLES

	JAPAN 10-15	COMBINED FTP AND HWFET	FTP
w_1	$0.208 \cdot 10^{-6}$	$0.442 \cdot 10^{-6}$	$0.222 \cdot 10^{-6}$
w_2	$40.899 \cdot 10^{-6}$	$-5.670 \cdot 10^{-6}$	$4.332 \cdot 10^{-6}$
w_3	$-0.532 \cdot 10^{-6}$	$1.166 \cdot 10^{-6}$	$1.250 \cdot 10^{-6}$
w_4	$45.419 \cdot 10^{-6}$	$39.269 \cdot 10^{-6}$	$36.217 \cdot 10^{-6}$
w_5	$86.518 \cdot 10^{-6}$	$58.284 \cdot 10^{-6}$	$57.877 \cdot 10^{-6}$
w_6	$23.923 \cdot 10^{-6}$	$19.279 \cdot 10^{-6}$	$24.245 \cdot 10^{-6}$
w_7	$26.602 \cdot 10^{-6}$	$82.426 \cdot 10^{-6}$	$77.482 \cdot 10^{-6}$
w_8	$160.640 \cdot 10^{-6}$	$185.360 \cdot 10^{-6}$	$171.200 \cdot 10^{-6}$
$\|\|r\|\|$	0.004	0.014	0.015

$$\min_{\boldsymbol{a}} \mathbf{f}(\boldsymbol{v}(\mathrm{t}), \boldsymbol{a}(\mathrm{t}))$$
$$\text{subject to } \|\boldsymbol{v}(t) - \boldsymbol{v}^*(t)\| \leq \|\boldsymbol{v}(t) - \boldsymbol{v}_{5\,kph}(t)\|\ , \quad (8)$$

where $\boldsymbol{v}(t)$is the vector of the original vehicle speed of the driving cycle; $\boldsymbol{v}^*(t)$ is the optimal speed profile from the optimal acceleration profile, $\boldsymbol{\alpha}^*$; and $\boldsymbol{v}_{5\,kph}(t)$ is the vehicle speed profile, which is 5 kph less than the original one.

The optimization problem in (8) was solved iteratively until convergence employing the Matlab function *fmincon*, based on sequential quadratic programming (SQP) [17]. SQP proceeds by computing an approximate solution of a sequence of quadratic programming subproblems in which a quadratic model of the objective function is minimized subject to the linearized constraints.

IV. Optimized Driving Cycle

A. Construction of Optimized Driving Cycle

The acceleration profile, $\alpha(t)$, yields a vehicle speed profile, $v(t)$. This speed profile will be used in the constraint of the optimization problem iteratively until convergence to the optimal acceleration, $\alpha^*(t)$, and speed, $v^*(t)$, is achieved. In this iterative process, the construction of the vehicle speed profile needs to preserve the total distance that the vehicle travels as well as the instances where the vehicle has to stop. In other words, the desired route of the driver and the speed limits must be preserved. Integrating the acceleration is not enough to accurately obtain a new driving cycle, as some route-related information is not described by the acceleration profile (e.g., when the vehicle is stopped and duration of time that the vehicle is stopped). This information is available, however, from the original drive cycle. Therefore to preserve the total distance, Δs should remain constant and can be computed as follows. The total distance that the vehicle travels is given by

$$\mathrm{S} = \sum_{k=0}^{n} (v_k \cdot (t_{k+1} - t_k) + \tfrac{1}{2} \cdot (v_{k+1} - v_k) \cdot (t_{k+1} - t_k)) \quad (9)$$

The time interval, $\Delta t = (t_{k+1} - t_k)$, is not constant, however, and depends on the acceleration, α_k, at time k. The time interval, Δt, is computed by (9) using each interval of distance, Δs, of the original driving cycle. For each Δs covered, both initial velocity and initial time are known, so the time Δt to travel the distance Δs is computed by (9). The optimal speed profile, $v^*(t)$, is derived at each time through the following equation:

$$v_{k+1}^* = \sum_{k=0}^{n} \left(v_k^* + \alpha_k^* \cdot (t_{k+1} - t_k)\right). \quad (10)$$

This process is repeated over all of the distance intervals, and new velocity and time vectors are constructed.

B. Simulation Results and Discussion

The optimization framework described above was applied to three driving cycles, Japan 10-15, combined FTP and HWFET, and FTP. The Japan 10-15 was selected as suitable for this analysis because of its inherent engineering shape. The other two are well known standard DDSs established by EPA for testing and measuring fuel economy and emissions. In the case of the Japan 10-15 driving cycle, a new optimized driving cycle was obtained depicted in Fig. 5. The optimal driving cycle is 28% longer than the original one as the new acceleration profile aims to smooth out the vehicle speed, and thus resulting in minimizing the overall average speed. The speeds for both the original and optimized driving cycles versus distance are illustrated in Fig. 6. Although the optimized speed profile in some instances falls below the bound of the speed profile, which is 5 kph less than the original Japan 10-15 driving cycle, the optimal solution is bounded by the active constraint in (8). For the optimized cycle, it should be noted that the total distance traveled and intermediate stops have been preserved (i.e., the route has been preserved). Smoothing out the speed profile to eliminate transient engine operation results in significant fuel economy enhancement, as shown in Fig. 7. A more conservative driving style that delays destination arrival time has a major impact on fuel economy; in this particular case, a 22.3% improvement in fuel consumption was observed.

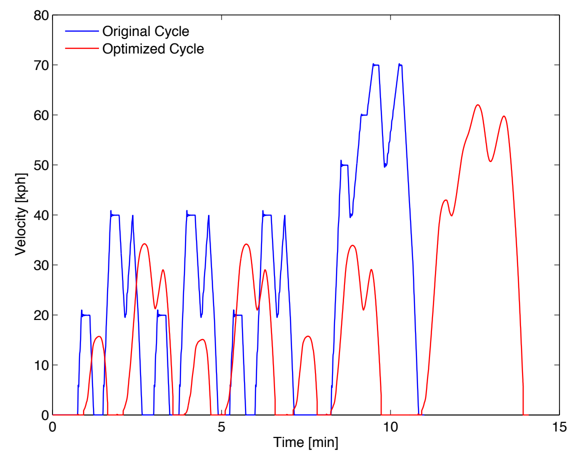

Fig. 5. Optimized vehicle speed profile of the Japan 10-15 driving cycle with respect to time.

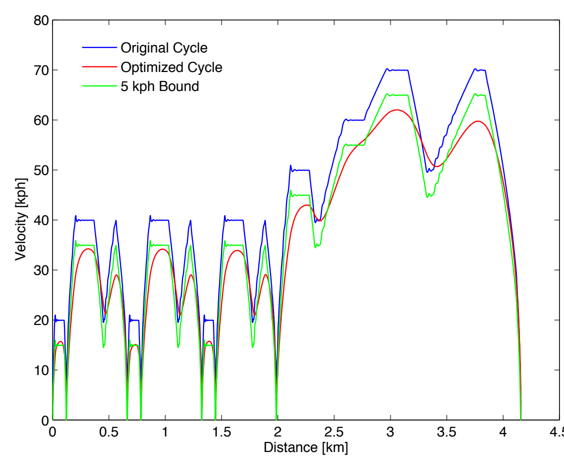

Fig. 6. Optimized vehicle speed profile of the Japan 10-15 driving cycle with respect to distance.

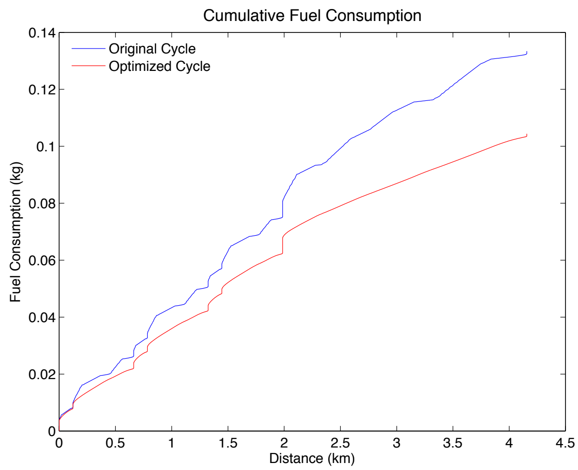

Fig. 7. Cumulative fuel consumption of the original and optimized Japan 10-15 driving cycle.

TABLE 2
SUMMARY OF OPTIMIZATION RESULTS

DRIVING CYCLE	ADDITIONAL TRAVEL TIME [%]	FUEL CONSUMPTION IMPROVEMENT [%]
JAPAN 10-15	28.0	22.3
COMBINED FTP AND HWFET	9.8	15.9
FTP	14.1	23.2

Similar qualitative results are observed for the combined FTP and HWFET, and FTP driving cycles. Table 2 provides a summary of the results for the three driving cycles. It is important to note the significant fuel consumption savings that can be achieved if a more conservative driving is employed.

The problem could be modified by attempting to maintain the same average speed of both the original and the resulting driving cycles. In this case, however, it would be over-constrained ending up with no feasible solution, unless the constraint initially imposed of preserving the route was relaxed. In the alternative formulation, the optimized driving cycle would just simply imply change the route. In this paper, however, the requirement is that the original route needs to be preserved (e.g., traffic lights, stop signs) and we are interested in investigating the impact of a more conservative driving style on fuel economy.

V. CONCLUSION

In the research reported here we investigated those driving style factors that have a major impact on fuel economy. An optimization framework was proposed with the aim of optimizing driving styles with respect to these driving factors. Individual driving styles are different and rarely meet the driving conditions posited in testing (e.g., engine optimization with respect to steady state operating points or vehicle speed profiles for particular highway and city driving). The optimization framework adopted here facilitates better understanding of the potential benefits from employing a more conservative driving. Future research should investigate the use of the proposed optimization framework in developing real-time feedback systems to enable drivers to alter their driving styles in response to actual driving conditions to be more fuel efficient and environmentally friendly.

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