1 Introduction

Self-driving cars are expected to hit the road before 2020 and dominate the vehicle market by 2030. A review of expert opinion in Ref. [1] predicts that between 2018 and 2020, self-driving vehicles would become commercially available. They predict that by 2040 almost 75% of the vehicles in the UK could be fully automated. Recent announcements by major car manufacturers in the U.S. seem to be consistent with these predictions. A more recent survey and analysis in Ref. [2], found that an average U.S. household is willing to pay up to $3500 and $4900 premium for partial and full automation, respectively, thus indicating significant customer willingness to pay for the technology. With the inevitable advent of autonomous vehicles, drive cycle optimization is an important topic. This presents a unique opportunity and a challenge as vehicle-embedded but infrastructure connected vehicle controls would now be able to remove the driver from the loop and drive their own drive cycle. Such drive cycles can be optimized to improve multiple objectives such as commute time, fuel consumption, or passenger comfort, or even to perform an optimal tradeoff among all.

One approach to optimizing a drive cycle is velocity smoothing (reducing acceleration and deceleration) which improves passenger comfort by reducing jerk and, in turn, reduces fuel consumption, but this method does not guarantee an absolute minimum of fuel consumption [3–5]. This solution is attractive as it is independent of vehicle characteristics such as vehicle mass, road load and aerodynamic resistances. Moreover, the two state velocity model can be formulated as a simple linear model with quadratic costs, allowing for faster computation. In our previous work, we showed that this methodology can be effectively employed for online implementation with model predictive control. Using just 1.5 s preview for some drive cycles, we could get as much as 66% of the improvements from an entire drive cycle preview [6].

Another approach is tractive energy minimization; here, the penalized variable is tractive or propulsion energy demand at the wheels, and hence is more closely related to fuel consumption. Such an approach should in theory reduce fuel consumption to beyond acceleration optimization [7–9]. In Ref. [10], a continuously variable transmission (CVT) was assumed and engine torque minimized. However, as the analytical solution in the same paper shows, the result of any energy optimization strategy is a pulse and glide velocity trace. Indeed, in this report similar results were shown for energy optimization. Any attempt at reducing total energy demand at the wheels will result in a pulse and glide operation, where an initial heavy acceleration is followed by a steady speed or slow rate deceleration gliding before finally coming to a stop. A fuel optimization, where the fueling rate is a linear function of propulsion power, will also result in a similar optimized velocity trajectory.

In the literature reviewed for this paper, the comparison is always between human and optimized driving, where improvements are so substantial that the gains derived by the correct choice of the optimization function become obscure. Note here that the reduction in fuel economy shown in this investigation can be as high as 17% for the optimized drive cycles over the standard U.S. environmental protection agency (EPA) drive cycles. However, between the two optimization techniques, there is also a difference in fuel consumption. This difference comes out only in comparison between the two optimization problems with differing cost functions. Our work compares the two approaches for various engine sizes in a conventional powertrain and also against an all-electric powertrain, in time-varying position constrained simulations, to better understand the characteristics of each optimization strategy.

It is common practice in the literature to assume that a reduction in propulsion power or engine torque would yield a reduction in fuel consumption [9,11,12]. Translating vehicle power demand to an engine power demand is difficult for both offline and online optimization as complex powertrain dynamics cannot be accurately modeled without using a high-fidelity software, which, in turn, increases computational time. Hence, optimal control designers rely on simpler vehicle models. Several complex algorithms have been developed to minimize energy demand. Even...
when an engine fueling map is included, important powertrain dynamics such as gear shift strategy and torque converter clutch slipping are typically ignored. Hence, the real engine operation region is unknown to the optimizer and a pseudotraactive energy minimization strategy is implemented.

This paper, by utilizing full vehicle simulations from Ref. [13] shows that reduction in active energy does not guarantee a reduction in fueling rate. These results were shown to be valid across three different engine sizes in a conventional gasoline powertrain. This result is fairly well known in the powertrain community, but its implications on fuel efficient driving are not well understood. We show that velocity smoothing that has a higher tractive energy demand is able to match if not improve fuel economy over tractive energy minimization.

This paper is organized as follows: Sec. 2 introduces the drive cycle optimization based on velocity smoothing and energy minimization. Section 3 explains the urban and highway cycles chosen for this study and their optimized cycles. In Sec. 4, a full vehicle simulation model used to evaluate fuel consumption is explained. Sections 5–8 provide detailed analysis of results obtained from the full vehicle simulation over the optimized drive cycles for a 1.6L downsized boosted engine, a further downsized engine, a full size 4.3L engine and an all-electric vehicle, respectively. A summary discussion on the implications of these results is presented in Sec. 9, while the conclusions are noted in Sec. 10.

2 Optimal Control Problem

As mentioned earlier, improvements in velocity trajectory or driving patterns result in the reduction in fuel consumption for autonomous vehicles. The two optimization objectives considered here are velocity smoothing and tractive energy minimization. The end objective of these velocity optimization approaches is to minimize fuel consumption; hence, the resulting optimal velocity trajectory will be evaluated later in full vehicle simulations to determine individual fuel consumption. In this section, the two approaches to optimizing drive cycles including the models, cost functions, constraints, and optimization strategy used are provided in detail.

2.1 Velocity Smoothing by Acceleration and Deceleration Minimization. For velocity smoothing or minimizing the total acceleration and deceleration in the velocity profile, a simple point linear time-invariant model in Ref. [7] is adopted, with position ($x_p$) and velocity ($x_v$) as states and acceleration ($a$) as the only input

$$x_{p,k+1} = x_{p,k} + x_{v,k} T_s + 0.5 a_k T_s^2 \quad (1a)$$

$$x_{v,k+1} = x_{v,k} + a_k T_s \quad (1b)$$

where $T_s = 1$ s is the sampling time. The optimization cost function chosen here is the square of acceleration and deceleration. The sum of the cost function is minimized; hence, a smoother drive cycle is produced by minimizing the total changes in velocity. Define $A, X_p$, and $X_v$ as polyhedral sets of constraints on inputs and states, respectively. Thus, the optimal control problem is formulated as

$$\min_{a_k} \sum_{k=1}^{N_f} a_k^2 \quad (2a)$$

s.t. $a_k \in A, x_p \in X_p, x_v \in X_v \quad (2b)$

where $N_f$ is the final time-step, and constraints $X_p$ and $X_v$ are defined later in this section. The acceleration and deceleration constraints are time-invariant. For this paper, they have been derived from the EPA drive cycles to be $a_{min} \equiv -6 \text{ m/s}^2$ and $a_{max} \equiv 6 \text{ m/s}^2$. The same is true for the state of velocity $x_v$ where $x_{min} \equiv 0 \text{ m/s}$ and $x_{max} \equiv 40 \text{ m/s}$. Constraints on the state of position $x_p$, however, are time varying as the position of the autonomous vehicle is determined by the position and velocity of a lead vehicle and hence a speed-dependent gap. The cost function used earlier is a squared term, ensuring that larger accelerations and decelerations are penalized more, and hence, it results in a smoother drive cycle. We shall now describe the second approach to drive cycle optimization.

2.2 Tractive Energy Minimization. For the second approach of tractive energy minimization, the total propulsion energy at the wheels is minimized. This optimization takes into account vehicle characteristics such as road load coefficients and vehicle mass. The optimization, however, does not take into account the internal powertrain dynamics such as the engine fuel map and gear selection strategy. Instead, it is assumed that a minimization of energy demand would lead to a reduction of fuel consumption, which is a common assumption in the literature as previously mentioned in the introduction. To have the power demand at the wheels as the input, the acceleration term $a$ in Eq. (1) is calculated by the net force on the vehicle, by Newton’s second law of motion. The external resistive forces on the vehicle, the rolling and the aerodynamic drag forces are modeled using the well-known coast down parameters [14]. Detailed description about this coast down test is given in Sec. 4. The model and cost function for the second approach are given as follows:

$$x_{p,k+1} = x_{p,k} + x_{v,k} T_s + 0.5 \frac{P_k - (A + B x_{v,k} + C x_{v,k}^2) x_{v,k}}{M} T_s^2 (3a)$$

$$x_{v,k+1} = x_{v,k} + \frac{P_k - (A + B x_{v,k} + C x_{v,k}^2) x_{v,k}}{M} T_s (3b)$$

where $P_k \in P$ is the total power delivered at the wheels by the engine; $A$, $B$, and $C$ represent the road load coefficients determined from a vehicle coast down test [15]; and $M$ is mass of the vehicle in kilogram. The total available power for propulsion and braking is limited as $P_{min} \equiv -60 \text{ kW}$ and $P_{max} \equiv 60 \text{ kW}$; these are the minimum and maximum power applied by the selected vehicle while executing the standard US06 drive cycle. The formulation for the optimization is given by

$$P_k^+ = \begin{cases} P_k & \text{if } P_k > 0 \\ 0 & \text{if } P_k \leq 0 \end{cases} \quad (4a)$$

$$\min_{P_k} \sum_{k=1}^{N_f} P_k^+ \quad (4b)$$

s.t. $P_k \in P, x_p \in X_p, x_v \in X_v \quad (4c)$

Since the objective of this formulation is to minimize only the total tractive energy and is not concerned with the braking energy, the cost function only considers the positive input. In our previous work, we have shown that the optimal policy even with regenerative braking is to avoid braking as much as possible as there are losses in energy conversion [16]. This is unlike the previous case where both the positive and negative input, i.e., the acceleration and braking were minimized for a smooth velocity profile. Also, the cost function for the tractive energy minimization case does not use a squared term, unlike the velocity smoothing case. This is because, the attempt is to minimize the total energy demand at the wheels and instantaneous high-power demand is acceptable. For acceleration optimization where the objective is velocity smoothing, the harsher acceleration and deceleration are penalized more by using a squared term.
2.3 Velocity and Position Constraints. After defining the formulations for both the velocity smoothing and tractive energy minimization cases, we shall now define the constraints on the optimal control problems. The constraints on the drive cycle optimization assumed in this paper are time-varying position limits based on the lead vehicle’s velocity for safe and close following. These constraints are different from the certification limits imposed by the EPA for their fuel economy testing. According to their constraints, only ±2 MPH deviation within 1 s from the certification velocity trace is allowed. These constraints are very restrictive and in the case of autonomous vehicles the extra degree-of-freedom of staying within safe distance can be used. The resulting profile would completely change from an average human thus resulting in a very different velocity profile beyond the EPA limits.

Specifically, the gap between the lead and the following vehicles is constrained by a lower and an upper bound. The lower bound, a safety limit, is the closest that the follower vehicle can follow the lead vehicle. This is derived from being one car length behind the lead vehicle for every 10 MPH, a common safety length recommended [17]. The upper bound is the longest distance that the autonomous vehicle can fall behind the lead. This is derived from assuming a distance that would prevent safe cut-ins from adjacent lanes and is kept at 2.7 m/m/s(4 ft/MPH). The spacing function comes from results presented in the U.S. Department of Transport study on traffic flow theory [18]. The constraints are further relaxed at low speeds of less than 20 MPH to 2.7 m/m/s (10 ft/MPH). Indeed, at such low speeds, cut-ins are not expected and a longer gap reduces frequent starts and stops. Since the position constraints are dependent on the lead vehicle’s velocity at that instant, these constraints are time-varying. The constraints on position and speed are selected according to

\[ x_{p,k}^{\min} = x_{L,k} - v_{L,k} L/10 \]

\[ x_{p,k}^{\max} = x_{L,k} - \begin{cases} v_{L,k} d_{\max} & \text{if } v_{L,k} < 20\text{MPH} \\ v_{L,k} d_{\min} & \text{otherwise} \end{cases} \]

\[ v_{p,k}^{\min} = 0 \]

\[ v_{p,k}^{\max} = 40 \]

where \( x_{L} \) is the position of the lead vehicle, \( v_{L} \) is the velocity of the lead vehicle, \( L \) is one car length or 4.5 m, \( d_{\max} \) is 3 m (10 ft) and \( d_{\min} \) is 1.2 m (4 ft). The stationary distances are defined as 2 m as the lower bound and 15 m as the upper bound. The time-invariant limits on the speed between 0–90 MPH or 0–40 m/s are reasonable on almost all U.S. roads [19]. The bounds for the distance from the lead are shown in Fig. 1 as well as the actual distances resulting from the optimization problems.

In this paper, the universal lead velocity trace \( v_{L} \) was determined by introducing a hypothetical lead vehicle. When followed by a human it results in EPA standard drive cycles, and when followed by the optimization algorithms, it results in the optimal drive cycles. Through this approach, human and autonomous optimized driving can be compared with the same baseline lead. The concept of the hypothetical lead and its derivation from the standard cycles are explained in detail in Ref. [20].

2.4 Optimization Methodology. In optimizing drive cycles, dynamic programming (DP) is considered in this study. DP utilizes the Bellman principle to minimize an objective cost function by computing a global input sequence [21]. Specifically, the DP formulation for the drive cycle optimization is solved by using dpm function in Ref. [22].

3 Drive Cycle Optimization

In Sec. 3, the selected urban and highway drive cycles are described as well as the reasons for their selection. We will then discuss the resulting optimized velocity traces before switching to vehicle simulation software in Sec. 4 and results in Sec. 5.

The urban drive cycle selected for this paper is the LA92 dynamometer driving schedule, as it has higher maximum speed and maximum acceleration/deceleration as compared to the urban dynamometer driving schedule. For similar reasons, the US06 drive cycle was selected as the highway cycle over the highway fuel economy driving schedule (HWFET).

The selected drive cycles were optimized using the DP algorithm as mentioned before with two approaches: velocity smoothing and tractive energy minimization. A part of the resulting drive cycles are shown in Fig. 2 and they are explained as follows. The standard drive cycle obtained from human driving has frequent changes in velocity. On the other hand, the velocity smoothing algorithm produces a cycle with gentler propulsion and braking thus beneficial to passenger comfort.

The tractive energy minimization case, however, shows very interesting behavior. The initial acceleration is very harsh, followed by a very low power cruising phase which also features low rates of deceleration before finally decelerating to complete the hill.\(^2\) This result is very similar to pulse and glide [23] and previous analytical solutions have also predicted that pulse and glide results in least energy consumption [24]. Another attempt at engine torque minimization in Ref. [10] also resulted

\(^2\)A section of drive cycle featuring an acceleration, cruising and braking in sequence is referred to as a velocity hill for this paper.
in a pulse and glide velocity profile. In effect, any attempt at tractive energy minimization results in a pulse and glide velocity profile.

4 Full Vehicle Simulation

To assess the impact of the optimized drive cycles on fuel consumption, a full vehicle simulation model is required. In this study, the advanced light-duty powertrain and hybrid analysis (ALPHA) tool was used. The ALPHA model was developed by the U.S. EPA for full vehicle simulation over a drive cycle with the stated aim of evaluating the fuel economy of the vehicle. The ALPHA is a physics-based, forward-looking, detailed vehicle simulator built on MATLAB/SIMULINK environment.

The input to the model is any velocity trace in time and a driver system integrated within the model utilizes feedforward and feedback control schemes to maintain the desired speed. Detailed description of ALPHA is provided in Ref. [13]. This model has shown to be robust over a range of very different drive cycles and has physics based models for different components, thus leading to a high confidence in the resulting fuel economy numbers. In published validation for different standard EPA drive cycles, the maximum reported error in fuel economy was 2% against experiment [25].

This simulation model is of a higher fidelity than the models used for optimization, as it takes into account the inertial and other delays in the engine and powertrain while executing a velocity change, thus ensuring that simulated vehicle velocity is realistic. Detailed engine, transmission and vehicle systems within the model provide a sophisticated and comprehensive method of estimating fuel efficiency as the modeled vehicle traverses a drive cycle.

The model also accounts for the rolling and aerodynamic resistances. This is accomplished by utilizing the well-known vehicle coast down test, where the vehicle is sped up to a high speed of 80 MPH and then put in neutral and allowed to slow down by the various road and aerodynamic drag forces [14]. The resulting velocity decrease over short time periods can be translated to an absorbed power using the kinetic energy equation. From there, the drag force at each velocity is found and fit using the linear least squares method to obtain the coefficients $A$, $B$, and $C$, of the following equation:

$$ F = A + Bv + Cv^2 $$

where, $F$ is the drag force, and $v$ the velocity at the force. This method is used to simulate the drag forces in a chassis dynamometer test as well. We use these experimentally determined parameters in Eq. (3) for calculating the resistive forces [15]. The software is simply evaluating the fuel required to maintain a given velocity trajectory.

For the drive cycles simulated in this paper, the driver model in ALPHA was able to achieve desired speeds very accurately. The root-mean-squared error between the desired and actual velocity traces for the velocity smoothed LA92 drive cycle was only 0.12 m/s and the mean absolute error was only 0.09 m/s. For the tractive energy minimized cycle, the root-mean-squared error was 0.17 m/s and mean absolute error was 0.08 m/s. Considering that the average speed for LA92 was 11.0 m/s, these small errors show that ALPHA is able to simulate the velocity accurately and also that a vehicle is capable of traversing these optimized velocity traces. Figure 2 shows the close following of the simulated velocity trajectories to the desired trajectory.

The results from vehicle simulations presented in Secs. 5–7 indicate that the drive cycle found from tractive energy optimization can in some cases lead to higher fuel consumption than that found through velocity smoothing. Previous comparisons were made between standard and optimized cycles, where these smaller differences were obscured by the significant reduction in fuel consumption. Hence, the remainder of the paper will focus on comparisons between the two optimized drive cycles. For comparisons with the standard cycles, readers are referred to Ref. [20]. The findings of this paper would aid future work on the choice of the cost function when the full fuel optimal computation cannot be performed in real time and a simplified metric might be needed. The results obtained in this paper are computed through full vehicle simulations in a well validated ALPHA model. The simulation results are explained in detail in Secs. 5–8.

5 Case Study I: Downsized Boosted Engine

In this section, full vehicle simulation results and analysis are detailed for both urban and highway cycles. The baseline vehicle is a 2013 Ford Escape powered by a 1.6 L Ford Ecoboost engine. The low-displacement boosted engine is considered, as it is a commercially available advanced technology that delivers high efficiency in typical federal test procedures.

5.1 LA92 Drive Cycle Optimization.

The complete LA92 drive cycle with both the optimized cycles is shown in Fig. 3. Clearly, both the optimized drive cycles are much smoother than the standard cycle as they are able to utilize the flexibility in position constraints to avoid frequent accelerations and decelerations. This smoothing of the drive cycle significantly reduces the fuel consumption of the vehicle as it traverses the velocity trajectory. As shown in Table 1, while the fuel economy of the standard LA92 cycle is 26.0 MPG, those for the velocity smoothing and tractive energy minimization trajectories are 30.7 MPG and 30.6 MPG, respectively. This produces almost an 18% increase in fuel economy, showing the significant benefits of optimized driving.

However, the small difference in fuel economy between the two optimized drive cycles is interesting. One would assume that a reduction in total tractive energy demand at the wheels would have resulted in a reduction of fuel consumption when compared with the plain velocity smoothed method. It turned out that, in a comparison between the two optimized cycles, a 6.9% reduction in total tractive energy at the wheels conversely results in a 0.3% increase in fuel economy.

To understand this phenomenon, a particular velocity hill from 850 to 950 s was studied closely. In Fig. 2, at 850 s, the power optimization case applies a 76% higher instantaneous propulsion.
power leading to an 80% increase in fuel consumption. However, for the entire event from 850 to 950 s, the overall propulsion energy is reduced by 5.6%. The corresponding fuel consumption reduces by only 2.1%. Clearly, a decrease in total tractive energy demand did not lead to a correspondingly proportional decrease in fuel consumption.

The underlying cause for this difference can be explained by Fig. 4, which shows the engine operating points in the selected region. The reasons for smaller reduction in fuel consumption are not clear from operating points alone and so the map is divided into several regions, where the energy demand and fuel consumption within the confines of the region can be calculated. The regions are created as approximate zones of operation in different modes as follows:

1. Region 1: the low-speed high-power region which is only visited during transient fast accelerations.
2. Region 2: the approximate region of operation for the acceleration optimization case where the power demand is relatively smaller.
3. Region 3: the region with higher power potential that is accessed by the higher power demand of the tractive energy optimization case.
4. Region 4: the region of operation for engine idling.
5. Region 5: the low-torque high-speed region, which is accessed while decelerating slowly, where the vehicle speed is high and the tractive power demand almost negligible. When the vehicle decelerates at a higher rate, brakes have to be applied and there is no tractive power demand.

Within a region, a positive number indicates a higher energy demand or fuel consumption for the tractive energy minimization case while a negative number, a higher energy or fuel demand for the velocity smoothing case. In region 2, velocity smoothing is optimizes energy use.
Table 2: Comparison between optimized drive cycles in different models for LA92 and US06 drive cycles

<table>
<thead>
<tr>
<th>Mode</th>
<th>Energy minimization time (s)</th>
<th>Velocity smoothing time (s)</th>
<th>Fuel percentage difference</th>
<th>Energy percentage difference</th>
<th>Time percentage difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acceleration</td>
<td>7.04 (6.77)</td>
<td>7.77 (8.09)</td>
<td>-6.1 (1.3)</td>
<td>0.0% (0.0%)</td>
<td>-6.1 (1.3)</td>
</tr>
<tr>
<td>Deceleration</td>
<td>2.03 (2.45)</td>
<td>N/A</td>
<td>0.2 (0.1)</td>
<td>0.0% (0.0%)</td>
<td>0.2 (0.1)</td>
</tr>
<tr>
<td>Inertial acceleration</td>
<td>0.75 (1.10)</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Vehicle idling</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Note: US06 results are in parentheses.

The previous analysis explains for the entire drive cycle that the presence of these gliding regions increases fuel consumption substantially for slightly higher energy demand and thus lower the
Interestingly, in the first case, a reduction in energy shown in Fig. 6. The results for each of the parts are presented in cycle are chosen as 490–525 s, 525–540 s, and 540–560 s as and minimizing fuel, three consecutive parts of the US06 drive cycle. However, in this case, the energy minimized drive cycle demand leads to an increase in fuel consumption; in the second case, a similar reduction in energy leads to a slight reduction in fuel consumption; finally for the third case, a significant reduction in energy demand does not lead to a proportional reduction in fuel consumption.

The difference in results is explained in Fig. 7, where the engine map is divided into ten equally spaced grids. For reference, regions similar to the ones in Fig. 4 are also demarcated. The difference in energy demand as well as fuel consumption between velocity smoothing and tractive energy minimization are shown in each of those grids as squares and circles, respectively.

(1) The width of a square is proportional to the percent difference in energy demand in that grid. A pink solid square indicates a higher energy demand for the velocity smoothing case while a black dashed square indicates a higher energy demand for the energy optimization case.

(2) The radius of a circle is proportional to the percent difference in fuel consumed in that grid. A green solid circle indicates a higher fuel consumption for the velocity smoothing case while a yellow dashed circle a higher fuel consumption for the energy optimization case. Different colors are necessary to show positive and negative differences.

Clearly in all cases region 5 is where all the gains from the tractive energy minimization are lost. The tiny black dot indicates a slightly higher power demand and large dashed concentric yellow circle shows the much higher fuel consumed. The length of operation in the high speed low torque zone dictates the increase in fuel consumption and can explain the contradictory results of the three selected parts. For all three selected cases the continued operation in the low torque high speed domain can be clearly seen in Fig. 7 with black dots indicating more power sought in those regions by the energy optimization case. This occurs when the vehicle velocity is decreasing at a very low rate of deceleration between 505–525 s, 535–540 s, and 540–555 s. The elevated fuel consumption based on the length of operation in these low efficiency regions reduces all gains made from lowered energy demands. Hence, the nonlinearity of the engine map plays a significant role in determining the overall fuel consumption.

### 5.2 US06 Drive Cycle Optimization

The standard and optimized US06 drive cycles are shown in Fig. 5. For the US06, the optimized cycles showed a 17% improvement over the standard cycle. However, in this case, the energy minimized drive cycle had a better fuel economy than the velocity smoothed one. Over the US06 drive cycle, the tractive energy demand was reduced by 4.2% and the fuel economy by 1.4% as shown in Table 3. The interesting results were found in shorter sections of the drive cycles demarcated by the solid vertical lines in Fig. 5. In the first section from 0 s to 131 s, the energy demand was reduced by 11.1% but the fuel by only 3.5%. In the second section from 131 s to 490 s the total energy demand decreased by only 1.9% and the corresponding fuel consumption by 0.6%. The most important case was the last section from 490 s to 600 s where even though the total power demand reduced by a significant 18.1% the fuel consumption increased by 0.2%.

To illustrate the difference between minimizing tractive energy and minimizing fuel, three consecutive parts of the US06 drive cycle are chosen as 490–525 s, 525–540 s, and 540–560 s as shown in Fig. 6. The results for each of the parts are presented in Table 4. Interestingly, in the first case, a reduction in energy overall fuel economy of the energy optimization case. This difference in fuel consumption is significant only in the comparison between the two optimized drive cycles. In case of the standard cycle the difference in fuel economy is 18% and hence the increased fuel consumption at inefficient regions gets obscured.

### 6 Case Study II: Further Downsized Engine

In Sec. 5, the optimized cycles were simulated for the baseline engine which was already a downsized boosted engine. However,
the optimized drive cycles had a much lower power demand than the standard drive cycles. The maximum engine power demanded for a standard US06 drive cycle was 93.6 kW, while those for the velocity smoothed and energy minimization ones were 60.8 kW and 47.1 kW, respectively. Clearly, a smaller engine with lower peak power could be used to meet the demands of these optimized drive cycles.

Since the ALPHA model was built at the EPA to account for a range of engine loads, it also has a function that provides the capability to generate fuel consumption maps by varying the engine size. Details of the function are provided in Ref. [27], where it takes into account the changes in heat transfer, friction and knock sensitivity as an engine is downsized. The 1.6L Escape engine was downsized to 75% of the original maximum power and the drive traces simulated through ALPHA. With a smaller engine, and a reduced torque range, the difference in operation between the velocity smoothing and energy optimization velocity traces was studied.

It was found that between the two drive cycles at a same reduction of power, for the entire drive cycle the smaller engine showed a 2.3% decrease in fuel consumption as compared to 1.3% in the standard engine. The cause of the reduction in the energy minimization case was however, not from the absence of operation in the inefficient regions. In fact the reason was that at some acceleration events the smaller engine operated in more efficient regions.

In Fig. 8 the difference in vehicle speeds between velocity smoothing and energy minimization are shown. Engine operation regions for acceleration from 75 to 90 s are also plotted on the respective engine maps in Fig. 8. The plots clearly show that the smaller engine has a higher engine speed as compared to the standard engine for the power optimization case. The limited torque range for the smaller engine drives the operating region to a higher speed to generate the same amount of power. This forces the engine to operate in more efficient regions. The result does make sense as the smaller engine is able to meet the comparatively smaller peak power demand more efficiently. However, this approach of further downsizing the engine does not overcome operation in the inefficient regions during the low deceleration cruising that still occur and increase fuel consumption for the energy minimization case.

For the selected period of 0–130 s, the energy minimization case shows a 1.3% reduction in fuel consumption for the standard engine but a 2.3% reduction in fuel consumption for the smaller engine. Similar effects were observed in the period of 130–490 s a 1.8% reduction in power resulted in a 0.6% reduction in fuel consumption for a full size engine but a double or 1.2% reduction in the smaller engine. Again the reason for improvement was more efficient operation during the acceleration phase. The effect was particularly visible in the last 40 s of the drive cycle where the full engine showed a 5.9% reduction in fuel consumption but the small engine a significantly higher 9.6% reduction. However, it must be noted that the gain in fuel consumption is not proportional and the inefficient operation at low rates of deceleration remains for all cases.

After exploring the downsized engine in this section, we shall now show simulation results for the full-size engine in case study III as it traverses the two optimized drive cycles.

7 Case Study III: Naturally Aspirated Full Size Engine

To understand whether the conclusions on tractive energy optimization were specific to turbocharged engines or would hold for naturally aspirated ones as well, in this section a 4.3 L Chevrolet Silverado EcoTec engine map was used to run the optimized drive traces. This particular engine is used to power large Chevrolet pick-up trucks and does incorporate an aggressive deceleration fuel cutoff strategy.

It was interesting to observe that the aggressive cutoff actually affected the velocity smoothing case more positively than the energy minimization one. For the entire US06 drive cycle, the total tractive energy demand reduced by 4.1% but the reduction in total fuel consumption was only 0.1%. As shown in Fig. 9, the higher rates of deceleration allow for longer durations of fuel cutoff in the acceleration optimization case. On the other hand for

![Fig. 7](https://asmedigitalcollection.asme.org/dynamicsystems/article-pdf/141/7/071011/6029846/ds_141_07_071011.pdf) Three consecutive parts of US06 drive cycle with the operating regions demarcated. A pink square and a green circle shows a higher energy and fuel demand, respectively, for the velocity smoothing case, while a black square and a yellow circle shows a higher energy and fuel demand, respectively, for the tractive energy minimization case. The size of the square and circle are proportional to the percentage gain over the other drive cycle.

![Fig. 8](https://asmedigitalcollection.asme.org/dynamicsystems/article-pdf/141/7/071011/6029846/ds_141_07_071011.pdf) US06 drive cycle for a production 1.6L EcoBoost engine and a downsized version of the engine. For the downsized case, the available torque is reduced and to generate equivalent power, a higher engine speed is required. The full-size engine fuel maps are experimentally determined from Ref. [26].

Transactions of the ASME
power optimization, the low rates of deceleration that require very small amounts of engine power reduces the duration through which the fuel cutoff can be initiated, thus increasing fuel consumption. In the period shown in Fig. 9, the fuel cutoff occurs for 19.3% of the time for velocity smoothing and only 7.8% of the time for energy minimization. Hence, for that period, a reduction of only 0.2% is achieved in fuel consumption, even though the total energy required decreased by 10.8%.

Obviously, there was no explicit term for deceleration fuel cutoff in either of the optimization cases, but the point of running these drive cycles with this technology is to highlight the several ways in which fuel consumption might not be proportional to energy demand. Any optimization to reduce fuel by minimizing energy demand has to take into account the effect of these technologies and how they change fuel consumption. Another important point is the low rate of deceleration that is the main culprit in increasing fuel consumption. While these cases require a very low amount of power to traverse, they disproportionately consume large amounts of fuel to operate in these regions.

By disabling the fuel cutoff strategy for this large engine, the effect of only changes in the drive cycle could be studied. It was found that the decrease in fuel consumption for the entire drive cycle in the power optimization case was now 0.5% as compared to 0.1% with the cutoff enabled. The improvement can be attributed to a higher increase in fuel consumption in the acceleration optimization case with idle fuel consumption instead of a complete fuel cutoff. The corresponding increase in the energy minimization case was obviously smaller as the length of time fuel cutoff was engaged was less in this case.

The reason for much lower decrease in fuel consumption of 0.5% as compared to the 1.6L EcoBoost, which showed a 1.3% decrease is during the period of 490–560s. Recalling that this is the region with longest operation at the low-torque–high-speed range, it can be understood that the fueling rate is much higher for this large engine and it leads to significantly higher fuel consumption. An interesting technology that can be applied in this case would be cylinder deactivation which can be engaged if the desired engine torque is below 150 N·m and engine speeds are between 100–250 rad/s.

In the previous three sections, this paper covered the engine performance of three different engine sizes, encompassing almost all the engine displacements available commercially for light duty vehicles. The three case studies showed that energy minimization leads to a pulse and glide operation, and for conventional vehicles powered by an internal combustion engine, the glide portion operates in a highly inefficient region of engine operation consuming a disproportionately higher fuel thus lowering the overall fuel economy. While the previous analysis hold true due to the fuel map of a conventional vehicle, for an all-electric vehicle powered by only an electric motor should always show a reduction in energy consumption with a reduction in energy demand. This assumption was tested in Sec. 8 on electric vehicles.

8 Case Study IV: Electric Vehicles

Since the issues with minimizing energy not leading to a minimization of fuel consumption were derived from the nonlinear fuel map and low power cruising causing the engine to operate in inefficient regions, electric vehicles were analyzed to understand their behavior. The electric motor efficiency map is much flatter and does not include enormous efficiency penalties at high speed and low torque as compared to a conventional engine. This should mean a proportional gain for the power optimization case. On the other hand, electric vehicles have regenerative braking which ensures that some of the lost energy is regained through braking. These effects are studied in this section. Simulations were carried out using the ALHPA model for a 2013 Tesla Model S.

From 0 to 130s of the US06 drive cycle, it was found that a 9.7% decrease in tractive energy was accompanied by a 9.0% decrease in total battery energy demand. As expected the battery discharge demand was 12% less indicating a greater gain in energy consumption than energy demand due to operation in more efficient regions. However, there was lesser battery charging in the power optimization case of ~3.0% which lead to a net battery demand of 9.0%. Even though the drive cycles operated in the low-torque high-speed region, the slight change in efficiency did not decrease the overall gain in the energy minimization case.

The velocity smoothing case did have a much higher braking power demand, and some of this was regained by the charging of the battery. But the regained charge was much less as compared to the discharge during propulsion, leading to a net gain for the energy minimization case. In all cases studied, it was found that the battery energy regained in braking was not proportional to the braking energy. The more aggressive braking in the power optimization case was able to regain more energy through regen braking than the acceleration optimization case even though the total braking energy was much larger for the latter.

Figure 10 shows the distribution of operating points in engine and motor efficiency and the power demand from the engine and motor. Looking at the efficiency distribution it can be seen that both the engine and the motor operate for longer periods of time in less efficient regions for the power optimization case. However, to compare the efficiencies of a conventional engine to an electric motor, both have been normalized. As expected, the maximum engine efficiency is around 35% for the 1.6L EcoBoost, Ford Motor Company, Dearborn, MI, but the electric motor has a maximum efficiency of almost 90%. So, while the shapes of distribution are very similar between the two, due to the much lower efficiency of the engine, the inefficient regions are far worse than the motor. This leads to a smaller increase in battery energy consumption for the motor.

In the case of the power demand, it can be seen that the conventional engine has a far higher demand for low power between 1–3 kW, than the electric motor where this demand is comparatively less. This discrepancy can be explained by the lack of gears in an electric vehicle, where the motor speed directly commands the engine speed without several transmission losses. In Fig. 11, the increased demand of fueling power as compared to the battery power for the 490–560s of the US06 drive cycle is shown. The
inefficiency of the engine forces the required fuel power to be much higher than the equivalent battery power. During the low-speed deceleration and idling it can be clearly seen that fuel power required is much higher. The maximum to idling fuel power ratio is 6.5. On the other hand, the electric motor is able to operate with much lower demands of battery power, proportional to the wheel power demand. The maximum to idling battery power ratio is 12.9 indicating almost double the efficiency during the phases of low rate deceleration. Moreover, it is much easier for the motor to go to a zero power case than a conventional engine and a part of the braking energy can also be recovered.

For these reasons the electric vehicle showed a straightforward proportional decrease in battery energy demand for a decrease in wheel energy request on account of an energy minimized drive cycle. Some of these gains were overturned due to regen braking and energy regained in the velocity smoothing case owing to its substantially higher braking energy. Still, the more aggressive gains in the tractive energy minimization case were able to reduce the deficit, and in all cases, the net battery energy consumed was always lower for energy minimization. This shows that the tractive energy minimization strategy works much better for an electric vehicle where a reduction in battery power consumption can be guaranteed unlike a conventional vehicle where this cannot be conclusively stated.

9 Discussion

From the literature review, it is clear that the fuel minimization problem is addressed, either as a simple energy minimization at the wheels or by using a linear function of wheel power that estimates fuel. In both cases, the energy at the wheel is minimized. It was analytically shown in Ref. [10] that such minimization results in a pulse and glide velocity trajectory. Therefore, it is not surprising that whatever the assumed model might be, most attempts at velocity manipulation for minimum fuel consumption lead to a pulse and glide velocity trajectory. Similarly, in this paper, minimizing the power demand at the wheels, resulted in a pulse and glide velocity trajectory. This result is consistent with those presented in the literature.

The main contribution of this paper is twofold. First, the fuel economy improvement achieved by the two optimization approaches is compared and analyzed rigorously. Second, the effectiveness of the approaches for different powertrain options, i.e., downsized turbocharged engine, further downsized engine, naturally aspirated engine, and all-electric vehicles is investigated. The comparison in this paper reveals that velocity smoothing works as well, or better in some cases than tractive energy minimization for conventional gasoline vehicles. A well-validated ALPHA model is used to evaluate the fuel economy of both drive
cycles. The detailed comparative analysis of the resulting velocities as shown in Fig. 6 clearly reveals the differences. As an optimization problem, the tractive energy minimization case with the cost function as the tractive energy experienced at the wheels reduces it over the velocity smoothing case. However, a similar reduction of fuel consumption was not found. Utilizing ALPHA’s detailed simulation, it was shown that during the gliding phase, to maintain the optimal velocity, a slightly higher energy demand led to a significantly higher fuel consumption. This was due to the engine efficiency at the high speed low torque operating points which wipes out all the gains from the lower energy demand.

The significance of this result, is that a simple optimal control problem with a linear model and quadratic costs could deliver comparable results to a more complex nonlinear optimization requiring more computational time and power. For instance, the cloud based DP algorithm in Ref. [8] can be replaced by a quadratic programming solver that can be implemented online; or the nonlinear function in the formulation used in Ref. [9] can be replaced by a linear function to reduce the computational burden. This method would significantly simplify the optimal control problem in Ref. [11].

Further, the resulting pulse and glide profile can be unsatisfactory from a passenger comfort point of view. Hence, in the literature, implementation of pulse and glide has to manipulate the optimal velocity to account for passenger comfort [10]. The switching in Ref. [24] can be implicitly removed in the velocity smoothing formulation delivering superior smoothness. Therefore, it is much easier to persuade customers to implement the velocity smoothing algorithm that does both, improve passenger comfort without compromising on fuel economy. It should be noted that these results are only valid in a conventional gasoline vehicle and as shown are not valid for an electric vehicle.

10 Conclusion

From the initial attempt at minimizing fuel consumption by minimization of energy demand at the wheels, this work has shown that in some cases the assumption might not hold. The energy minimization algorithm decreased the total energy by initially applying a high power at the start of any velocity hill and then moving to a low power cruising mode. This ensured a lesser energy demand than the velocity smoothing case under all circumstances. However, the presence of the low power cruising part forced the engine to operate in an inefficient low torque—high speed region, significantly increasing fuel consumption for a slight demand of power. This behavior was observed in a larger as well as smaller engine. Additional technologies such as deceleration fuel cutoff reduced the gains from energy minimization further. Finally, in a comparison with electric vehicles, owing to the more efficient electric motor and a lack of gears, it was shown that reducing energy demand at the wheels guaranteed a decrease in battery energy consumption.

From this work, it is clear that the easily solvable velocity smoothing algorithm, which does not require any vehicle information and is more conducive for passenger comfort can deliver almost the same improvements as a more complex energy minimization algorithm. Hence, in a conventional vehicle, the engine operating region has to be taken into account while reducing propulsion power to result in a proportional decrease in fuel consumption.

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References


