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Heavy Vehicle Fuel Economy Improvement Using Ultracapacitor Power Assist and Preview-based MPC Energy Management

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***Abstract*— A heavy hybrid vehicle is considered in which an electric motor and ultracapacitor energy storage are used in a parallel hybrid configuration as a power assist to improve fuel economy. The ultracapacitor's high power capabilities make it a good choice for this application. The optimal control technique of Dynamic Programming (DP) is applied to obtain the "best possible" fuel economy for the vehicle over the driving cycle under pointwise-in-time hard system constraints. Attainable fuel economy improvements are illustrated using a real-time implementable Model Predictive Control (MPC) method using a simple model for predicting future torque demands. The incorporation of simulated telematic future information is also investigated to further improve the the fuel economy of the MPC method close to the DP-calculated maximum.**

I. INTRODUCTION

This paper is concerned with the improvement of fuel economy in heavy duty vehicles through the use of high power ultracapacitors in a mild hybrid electric vehicle platform. Previous work has shown the potential for up to 15% improvement on the smaller hybrid SUV platform [1], but simulations have shown the potential improvement for larger vehicles is higher.

The power demands imposed on a heavy vehicle can be substantially higher than those seen in smaller vehicles due to its larger mass. The high power capability of ultracapacitors is well suited to assisting a heavy hybrid vehicle in meeting these high power demands in the most cost effective manner. A comparison of the initial investment costs show that ultracapacitors are 5 to 10 times less expensive than lithium batteries on a cost per kilowatt basis. Ultracapacitors, unlike many types of batteries, will retain an extraordinarily long lifetime of hundreds of thousands of cycles even at high power draw levels. As such, the lifetime energy costs of using ultracapacitors are vastly lower than lithium batteries; the author's calculations show 20 to 60 times less, a result corroborated by [2]. Further justifications for the use of ultracapacitors, and some examples of their implementations can be found in [1], [3], [4].

The control challenge explored in this paper is to effectively manage the very small energy buffer (around one hundred Watt-hours) of ultracapacitors in order to maximize the potential fuel economy. First, Dynamic Programming (DP) is used to obtain the "best possible" fuel economy for the vehicle over the driving cycles. However, the DP technique is not implementable since it requires predetermined vehicle demands to carry out the optimization calculations. The Model Predictive Control (MPC) method is an optimization-based receding-horizon control strategy which has shown potential as a powertrain control strategy in hybrid vehicles [5], [6]. A MPC strategy is developed for the heavy hybrid vehicle based on the same vehicle model and DP cost function which can achieve near-optimal fuel consumption even for very short prediction horizon lengths.

The prediction model of MPC is critical to the overall control performance. In this paper, simulated "future information" is used to aid in the MPC prediction method and improve the potential fuel economy of the vehicle, a result suggested by the works of [7], [8]. Examples of future information used here are speed limits, traffic conditions, and traffic signals along the desired route. The future information is able to improve the fuel economy above the promising results shown using the MPC method alone.

II. THE HYBRID POWERTRAIN CONFIGURATION

The ultracapacitor hybrid vehicle model is based on modeling techniques and component data from the high fidelity, forward-looking modeling and simulation program Powertrain Systems Analysis Toolkit [9].

A. Vehicle Configuration and Driving Demands

A heavy vehicle model is developed using available component data and then validated to known vehicle performance measures to ensure modeling fidelity [9], [10]. The chosen hybrid vehicle configuration is a parallel hybrid, which uses a 75kW peak motor and ultracapacitor pack of 56 Farads at 145 Volts. The primary driving cycle considered is the City Suburban Heavy Vehicle Route (CSHVR). The velocity and power demands of this cycle are shown in Figure 1 and the vehicle modeling equations are covered in the next section.

B. Powertrain Model

The vehicle driving force F is calculated as in [11]:

$$F = \alpha_A v^2 + \alpha_I a + \alpha_R + \alpha_S \tag{1}$$

where v is the velocity, a is the acceleration, α_A is a multiplying coefficient for aerodynamic forces, α_I is the coefficient for inertial forces(accounting for the vehicle's rotational and linear inertias), α_R is the coefficient for

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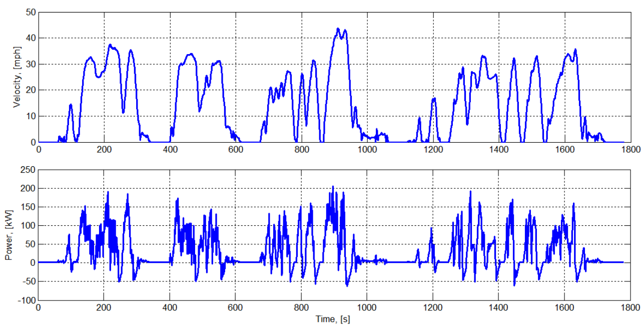

Fig. 1. Velocity and Power Profile for CSHVR Cycle

rolling resistance, and α_S is the coefficient for road grade forces. The α terms of Equation 1 are defined as follows:

$$\begin{array}{cc} \alpha_A = 0.5\rho C_D A_f & \alpha_I = 1.1m \\ \alpha_R = (C_{R,1} + C_{R,2}\omega)\, mg\cos\theta & \alpha_S = mg\sin\theta \end{array} \tag{2}$$

where ρ is the air density, C_D is the vehicle drag coefficient, A_f is the vehicle frontal area, m is the vehicle mass, $C_{R,1}$ and $C_{R,2}$ are rolling resistance coefficients, ω is the wheel rotational speed, g is the acceleration of gravity, and θ is the road grade angle. The rolling resistance definition used here is further detailed in [11]. The wheel torque then modified via component efficiencies and the selected gear ratio from the shifting strategy to become the torque demand at the engine:

$$\begin{array}{c} T_{dmd} = T_{dmd,wheel}\left(\frac{r_{gear}}{e_{gbx}e_{fd}}\right) \\ \omega_{eng} = \omega r_{gear} r_{fd} \\ T_{dmd,eng} = \max\left(0, T_{dmd}\right) \end{array} \tag{3}$$

where r_{gear} is the selected gear ratio, e_{gbx} is the efficiency of the gearbox in the selected gear, and e_{fd} is the final drive efficiency. ω_{eng} is the engine speed, determined from the wheel rotational speed ω, the gear ratio r_{gear}, and the final drive ratio r_{fd}. Engine braking effects are not considered, and all non-propulsion drivetrain components are assumed to have constant efficiencies. From the torque demand at the engine, the control decision of applied engine torque determines the motor assist torque as:

$$\begin{array}{c} T_{mot} = T_{dmd} - T_{eng} + T_{eng,loss} \\ \omega_{mot} = r_{TC}\omega_{eng} \end{array} \tag{4}$$

where T_{mot} is the motor demand torque, T_{dmd} is again the vehicle torque demand at the engine, T_{eng} is the commanded engine torque, $T_{eng,loss}$ is the torque loss to accessories and friction based on [12], ω_{eng} is the engine rotational speed, ω_{mot} is the motor rotational speed, and r_{TC} is the torque coupler ratio between the motor and engine.

The engine fuel rate $\dot{m}_f$ is also determined by the selection of engine torque and the given engine speed, based on mapped data from PSAT:

$$\dot{m}_f = f\left(T_{eng}, \omega_{eng}\right) \tag{5}$$

From the values of motor torque and speed, a lookup table is used to find the ultracapacitor electrical power:

$$\begin{array}{lll} P_{UC} = P_{mot}/\eta & for & P_{mot} > 0 \\ P_{UC} = \eta P_{mot} & for & P_{mot} < 0 \end{array} \tag{6}$$

where P_{UC} is the ultracapacitor power and η is the motor efficiency at a given operating point. The ultracapacitor pack current can then be calculated as given in Eq. (7). For more information on the derivation of these equations see [13].

$$I_{UC} = \frac{-SOC \cdot V_{\max} + \sqrt{\left(SOC \cdot V_{\max}\right)^2 - 4R_s P_{UC}}}{2R_s} \tag{7}$$

where I_{UC} is the ultracapacitor current, SOC is voltage-defined state of charge, $V_{\max}$ is maximum pack voltage, R_s is the ultracapacitor pack resistance, and η_{chg} is the ultracapacitor charging efficiency.

From the current demand out of the ultracapacitor, the rate of change of the state of charge can be found as:

$$S\dot{O}C = \frac{I_{UC}}{C_o V_{\max}} \tag{8}$$

where C_o is the pack capacitance. In implementing these equations the control input (commanded engine torque) determines the output state (the next SOC) of the system.

III. Control Problem Formulation

For fuel consumption minimization the cost function to be minimized is that of the integral of the fuel rate over the cycle time. However to avoid frequent engine on/offs, a small switching cost is added to the cost function to impose a 3-5 second engine on cycle time:

$$\begin{array}{c} J = \int_0^{t_f} \left(\dot{m}_f + q\Delta_e\right) dt \\ \dot{m}_f = f(\omega_{eng}, T_{eng}) \end{array} \tag{9}$$

where J is the cost function, which is integrated from the initial time to end of the cycle, q is the constant engine on-off cost, and Δ_e is the engine on-off switching signal. The fuel rate $\dot{m}_f$ is implemented as a lookup table in terms of engine speed and torque. This cost function is to be minimized subject to the following constraints:

$$\begin{array}{c} \dot{x} = S\dot{O}C = f(x,u,v) \\ SOC_{min} < x < SOC_{max} \\ P_{UC,max,charge} < P_{UC} < P_{UC,max,discharge} \\ I_{UC,min} < I_{UC} < I_{UC,max} \\ T_{mot,min} < T_{mot} < T_{mot,max} \\ T_{eng,min} < T_{eng} < T_{eng,max} \end{array} \tag{10}$$

where the state of the system is the state of charge of the ultracapacitor $x = SOC$, $S\dot{O}C$ is the rate of change of SOC which is a function of the state x, the control u, and the imposed velocity v. The other parameters $*_{min}$ and $*_{max}$ are the upper and lower limits on the state of charge x, the ultracapacitor power P_{UC}, ultracapacitor current I_{UC}, motor torque T_{mot}, and engine torque T_{eng}. The engine speed is constrained by the shifting strategy, and the constraint values are all defined with appropriate values for the component models specified.

IV. Potential Fuel Economy Improvements using Dynamic Programming

An optimal control problem can be solved numerically using the Dynamic Programming (DP) method, a numerical method of minimizing a functional originally developed by Richard Bellman [14]. The implementation of the DP method essentially reduces to an iterative calculation of a cost function at each time step of the form:

$$J^*(\mathbf{x},t) = \min_{\mathbf{u}} \{J(\mathbf{x},\mathbf{u},\mathbf{v}) + J^*(f(\mathbf{x},\mathbf{u},\mathbf{v}),t+1)\} \quad (11)$$

where $J^*(\mathbf{x},t)$ is the optimal cost-to-go from time t and any state in the state vector $\mathbf{x}$ to the end of the computational horizon, which is computed by a minimization over all admissible controls in the control vector $\mathbf{u}$ for the functional shown. The incremental cost for the current control decision, given the current state vector $\mathbf{x}$, control vector $\mathbf{u}$, and system input vector $\mathbf{v}$, is given by $J(\mathbf{x},\mathbf{u},\mathbf{v})$. The optimal cost for the future control decisions is based on the resulting state from the control vector, and is accounted for by the last term, $J^*(f(\mathbf{x},\mathbf{u},\mathbf{v}),t+1)$. The results of the DP method show the potential for up to a 40% improvement in fuel economy for the M1081 vehicle on the CSHVR cycle. Even higher fuel economy improvements are achievable if the vehicle is simulated on lower speed urban cycles such as the Manhattan Bus route.

V. The Model Predictive Control Algorithm

Model Predictive Control, or MPC for short, is an optimization-based receding horizon control strategy which, unlike Dynamic Programming techniques, has the potential to be implemented on a hybrid vehicle. In MPC a cost function is minimized over the prediction horizon and a set of optimal control actions over a finite control horizon (of length less than or equal to the prediction horizon) is calculated. Only the first input of the calculated control sequence is applied, the prediction horizon is moved forward one step and the process is repeated [15], [16], [17].

The previous section solved the nonlinear fuel minimization problem over the entire cycle length by assuming known future demands. In the receding horizon MPC framework, the DP solution method is still used for solving the fuel minimization problem at each time step. Of course, the MPC solution will be suboptimal when compared to that of a full horizon DP, but it is desired to explore the compromise made on fuel economy in order to reduce the computational effort and create a real-time implementable control strategy. Because of its receding horizon nature, the Model Predictive Control strategy can adapt to changing future demands, an advantage over DP. Since the typical MPC horizon length is a fraction of the whole cycle time, the nonlinear optimization problem can be solved much faster than a DP optimization solved over a whole cycle. If required for implementation in a fast process, the computational effort can be further reduced if the cost function is quadratic and the system constraints are linear or linearized [17], [15].

The cost function for MPC was initially chosen identical to that from the DP method. However, to avoid the simulation errors associated with the short-sighted nature of the MPC method, an SOC-based penalty cost has been developed to maintain the vehicle SOC within a narrow range. This "soft" SOC constraint has been created based on the results of the DP method, using the relative frequency of SOC values. A small penalty cost is used to influence the SOC and maintain it, but not to rigidly confine it, within the desired region. With this added SOC-based soft constraint cost, the performance index for the MPC is of the form:

$$J(k) = \sum_{i=1}^{N_p} \Big(\dot{m}_f(k+i|k) + q\Delta_e(k+i|k) + h\big(SOC(k+i|k)\big)\Big)\Delta t \quad (12)$$

where k is the current time step, N_p is the length of the prediction horizon, $\dot{m}_f$ is the engine fuel rate, q the constant engine on/off cost, Δ_e is the engine on/off switch signal, and $h(SOC)$ is the added SOC cost. Here $(k+i|k)$ denotes the i step prediction at step k.

When the vehicle is simulated under MPC control with a ten second prediction horizon, assuming fully known future demands, the potential fuel economy improvement is 38%, very close to the DP calculated maximum. Investigations in varying the horizon length between three and fourteen seconds results in improvements between 38-39%, as seen in the later Figure 5. In this case, however, the complete future torque demands have been assumed to be known over the prediction horizon, which is not realistically possible.

A. Prediction Method Development

It is impossible to be certain about future driving demands over the next 30 seconds or even the next two seconds. The critical part of MPC is the prediction method, to which a variety of methods have been proposed including the use of current speed/acceleration trends in [18] or the use of an exponential decay relationship for the driving torque in [5]. The use of a simple exponential decay relationship has shown promising results and will be explored as the prediction method in this study over the various short horizon lengths.

B. Exponential Decay Trending

In [5], it is assumed that the torque demand decays exponentially over the prediction horizon with a time constant that is a function of current torque demand. In this work, the time constant for the torque decay and penalty weights assigned to the fuel rate are all quantized functions of the current torque demand. Higher torque demands are assumed to decay much more quickly than lower demands, and the fuel cost is penalized more on lower torque demands since these are usually the less efficient operating region of the engine [5]. The heuristic governing equation for the exponential decay is given in Equation 13, where k is the current time step, i is the prediction step, and τ_d is the time

TABLE I

HEURISTIC METHOD: DISCRETE EXPONENTIAL DECAY VALUES

Torque Demand Range	Time Constant, τ_d	Decay Rate, $\lambda = 1/\tau_d$
$T_{dmd} \geq 7000$	$\tau_d = 0.1$	$\lambda = 10$
$7000 > T_{dmd} \geq 2500$	$\tau_d = 1$	$\lambda = 1$
$2500 > T_{dmd} \geq 0$	$\tau_d = 10$	$\lambda = 0.1$
$T_{dmd} \leq 0$	$\tau_d = 0.1$	$\lambda = 10$

constant for the decay rate:

$$T_{dmd}(k+i|k) = T_{dmd}(k)e^{-i\Delta t/\tau_d} \tag{13}$$

The torque decay method used in [5] will be applied here on the M1081 heavy hybrid vehicle using similar torque decay constants, with the torque regions modified of course for the difference in vehicle demands. An example of the results of the future torque prediction algorithm based on exponential decay is shown below in Figure 2. The

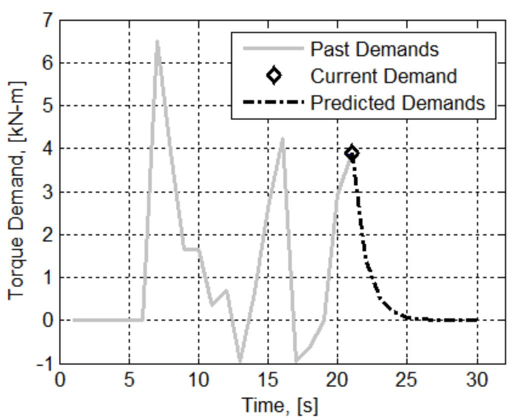

Fig. 2. MPC Prediction Method - Exponential Torque Decay

future torque demands over the MPC prediction horizon are assumed to start at the current "given" torque value and decay exponentially. The discretized torque regimes and associated time constants are given below in Table I. Simulations employing this heuristic method of exponential decay prediction are able to achieve potential fuel economy improvements between 29-34% over the original vehicle. Since the method determining these decay rates is largely heuristic, a more analytic way of tuning these parameters is presented next.

C. Decay Parameters Based on Expected Vehicle Demands

The particular parameter values used in [5] were largely determined based on experience and testing to determine suitable values and regions. A more analytic method for determining these decay parameters is presented here, based on the expected vehicle demands over the cycle. In practice, this method might be applied over the known future route, as given by GPS telematic data, or over a stochastic model-based prediction of the expected future driving demands. By plotting the vehicle torque demands for the CSHVR cycle against their relative temporal frequency (in terms of cycle time above a certain demand level), the relationship shown in the solid line of Figure 3 results. A very similar curve results for the vehicle demands imposed by other cycles.

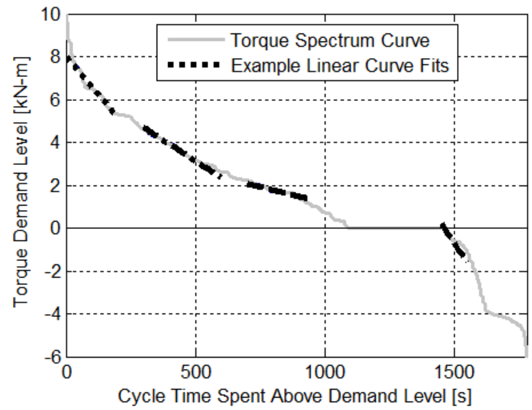

Fig. 3. CSHVR Torque Spectrum With Piecewise Linear Curve Fits

The slope of this line is essentially a piecewise linear estimation of the decay rate λ, or time constant τ_d, which can be numerically approximated to relate the current torque demand to the most likely decay rate. An example of a few of these linear fits along the curve (exaggerated for plotting) are also shown in Figure 3. Figure 4 plots the decay values for the heuristic method of [5] alongside these analytically derived demand-based values.

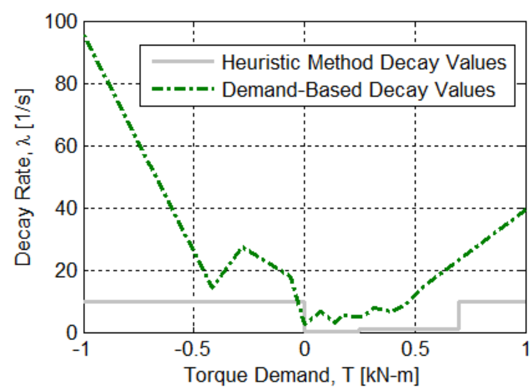

Fig. 4. Decay Rate Comparison, Heuristic vs. Demand-based Values

Similar to the assumptions in [5], at higher torque values (both positive and negative) the decay rate is larger. For comparisons, Figure 5 shows the MPC results for the different prediction methods over the short horizon lengths considered. A decrease in fuel economy with increasing horizon length can be seen for the heuristic torque decay prediction method, while the more robust demand-based method shows a consistent 36% improvement is achievable for all horizon lengths considered. It can be seen that there is only a small window for improvement here between the MPC and DP-established maximum. The potential gains in fuel economy through use of telematic future information are investigated next.

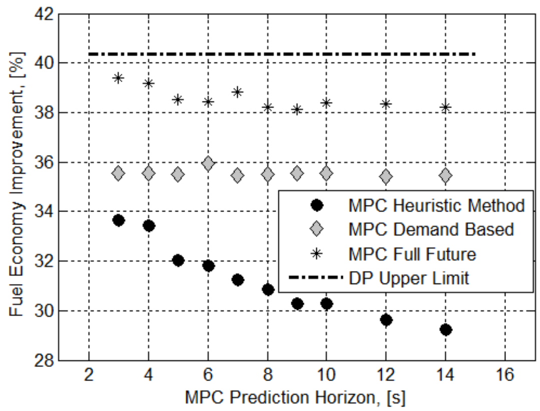

Fig. 5. MPC Horizon Variation - Comparison of Decay Methods

VI. MPC WITH TELEMATIC FUTURE INFORMATION

Only a small amount of research has focused on the use of future information to improve fuel economy in a hybrid electric vehicle. The research in [19] focused on the development of a driving behavior model to help predict future inputs based on a nonlinear driver model, recent driving statistics, and historical traffic information. [20] predicted vehicle velocity with the help of future road grade information in an ECMS online optimization routine over a relatively long (hundreds of seconds) horizon length. Optimal control methods have been applied on PHEV control simulations which use a simple driving model based on acceleration and deceleration trends from current and past traffic information to help predict future demands [21]. The potential fuel economy benefits from the use of future road grade information in a battery-based hybrid vehicle has been investigated in [8]. However, the focus of these research efforts were not on the types and character of the future information, but rather the simple application of this information to predict demands.

Here, simulated future information will be generated for the CSHVR cycle to aid in the prediction of future cycle demands. This information will be representative of that either currently available through commercial sources or from local government traffic authorities. The following types of information will be considered:

1) Speed limit information. This is already available in many places through commercial GPS receivers [22].
2) Traffic information. Currently only provided as a general "level of congestion" in many commercial GPS units, this could easily be made available as an average speed of traffic through an area [22].
3) Traffic signal information. In this case implemented as known "stop" and "go" locations, this type of information is sparsely available, and would depend highly on the local municipality.

A. Simulated Future Information for CSHVR Cycle

The CSHVR cycle speed profile is analyzed and simulated telematic future information is created using general knowledge about urban driving conditions. Figure 6 depicts this artificial information.

The suburban cycle speed limits given range from 25mph up to 40mph. The "general" traffic information is a level of traffic congestion, similar to that seen on modern GPS units [22]. In this study it is assumed that: low traffic means the expected traffic speed is the speed limit, for moderate traffic two-thirds of the speed limit, and for heavy traffic one-third of the speed limit. An "approximate" traffic speed is also considered and is based on a smoothed velocity curve. Stop and go signal information developed for the cycle is shown as well. These signals are based on the assumption that as the vehicle comes to a stop or accelerates there is an associated signal (from a traffic light, known stop sign, or otherwise) that is available for approximately 10 seconds before and after the stop. Portions of the suburban cycle are assumed to be spent waiting at a light in heavy traffic.

B. Future Information Benefits

These different types of future information are implemented using simple heuristic rules to improve the prediction method in the MPC framework. In shorter horizon lengths, mixed results were obtained for the benefits of the future information. However, the demand-based exponential torque decay method and longer horizon lengths (10, 12, 14 seconds) demonstrates a potential improvement of 1% above the previous case. Figure 7 shows the results of all the exponential torque decay-based MPC simulations using the various types of future information. As would be expected, the results show more detailed future information allow more potential improvement in fuel economy.

VII. SUMMARY AND CONCLUSIONS

This study has developed an ultracapacitor heavy hybrid vehicle model and demonstrated the potential fuel economy improvements attainable using a Model Predictive Control energy management strategy. After the upper limit to the potential fuel economy is calculated using Dynamic Programming techniques, a forward-looking Model Predictive Control (MPC) method is implemented which makes use of an exponential torque decay prediction method based on the work of [5]. The parameters of this MPC prediction

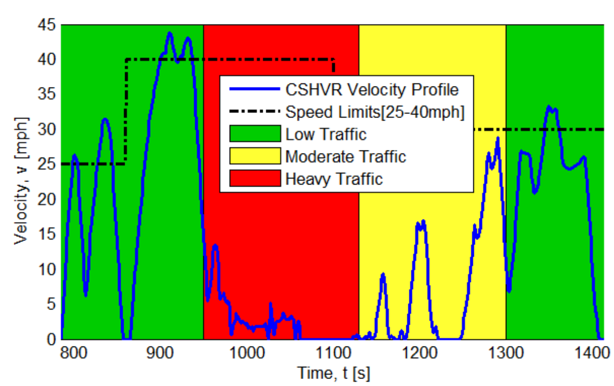

Fig. 6. Future Speed Limit and Traffic Information on CSHVR Cycle

model were tuned based on the vehicle cycle demands to better represent the future expected demands. A consistent improvement in fuel economy of around 35.5% has been shown for this demand-based prediction method with respect to the conventional vehicle, and compared to 29-34% improvement for the heuristically based method.

A variety of simulated telematic future information signals were used along with simple rules to improve the prediction of future torque demands. The use of this information showed the potential to improve the attainable fuel economy up to one percent more with the presence of relatively simple information currently available in telematic and GPS devices.

Table II gives a summary of the attainable fuel economy improvements demonstrated through this study. The overall benefits of the more robust demand-based tuning procedure for the MPC exponential decay prediction method are shown here along with the further benefits from the addition of simulated telematic future information.

TABLE II
SUMMARY OF ATTAINABLE FUEL ECONOMY IMPROVEMENTS COMPARED TO CONVENTIONAL POWERTRAIN

Control Method	% Improvement
Dynamic Programming Maximum	+40.5%
MPC Full Future Demands	+38-39%
MPC Exponential Decay using	
Heuristic Decay	+29-34%
Demand-Based Decay	+35.5%
Simulated Telematic Information	+35.5-36.5%

In order to improve the applicability of this work, future simulations should make use of a vehicle-specific velocity and road grade information. If possible, a real route should be used containing speed limits, traffic conditions, and signal locations and timings. This would allow for a more complete assessment of the potential benefits of future information in predicting future torque demands and

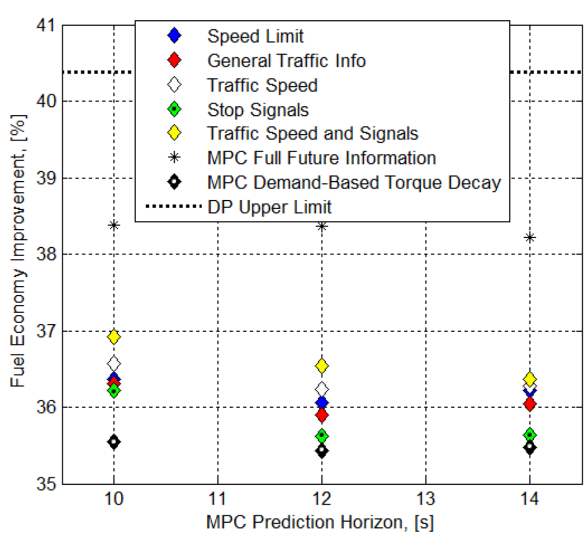

Fig. 7. MPC Results - Future Information Benefits on Longer Horizons

improving mileage.

VIII. ACKNOWLEDGEMENTS

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