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Enabling Prediction for Optimal Fuel Economy Vehicle Control

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Abstract

Vehicle control using prediction based optimal energy management has been demonstrated to achieve better fuel economy resulting in economic, environmental, and societal benefits. However, research focusing on prediction derivation for use in optimal energy management is limited despite the existence of hundreds of optimal energy management research papers published in the last decade. In this work, multiple data sources are used as inputs to derive a prediction for use in optimal energy management. Data sources include previous drive cycle information, current vehicle state, the global positioning system, travel time data, and an advanced driver assistance system (ADAS) that can identify vehicles, signs, and traffic lights. To derive the prediction, the data inputs are used in a nonlinear autoregressive artificial neural network with external inputs (NARX). Two real world drive cycles were developed for analysis in the Denver, Colorado region: a city-focused drive cycle that passes through downtown as well as a highway-focused drive cycle that transitions across multiple interstates. A validated model of a 2010 Toyota Prius in Autonomie is used to determine the vehicle control fuel economy improvements that are possible from the NARX prediction. The optimal energy management control strategy is determined using dynamic programming due to its ease of use and that the solution produced is the globally optimal solution. The control strategies compared include the existing 2010 Toyota Prius control strategy as a baseline, the neural network prediction optimal energy management control strategy, and a 100% accurate prediction optimal energy management control strategy. Results show that inclusion of various sensors and signals enables a significant amount of the fuel economy improvement with respect to 100% accurate prediction. The conclusion is that prediction based optimal energy management enabled fuel economy improvements can be realized with currently available sensors and signals.

Introduction

There is a global need to increase automotive vehicle fuel economy (FE). An increase in FE would result in global decreases in energy consumption [1], petroleum importation costs [2, 3], greenhouse gas emissions [4], and air pollution [5]. A reduction of greenhouse gas emissions reduces the effects of climate change [6], while a reduction in air pollution reduces human deaths associated with air pollution [7]. Because of these issues, governments around the world have imposed various FE requirements that automotive manufacturers are required to meet [8].

A key technology to ensure FE compliance is vehicle electrification [9]. Hybrid electric vehicles (HEV) and plug-in hybrid electric vehicles (PHEV) are able to realize FE improvements due to the powertrain efficiency improvements enabled through intelligent use of mechanical power from the engine and electric power from the battery [10].

However, there is also a global need to improve vehicle safety. In the United States, 90% of vehicle crashes are due to driver error [11]. This has fostered significant development in commercially implemented driver assistance technology, known as Advanced Driver Assistance Systems (ADAS), over the past 30 years [12] that focus on safety [13]. ADAS sensing is achieved through a variety of sensors including cameras, radar, and ultrasonic detection [14]. A conceptual diagram of the potential sensing abilities of ADAS is shown in Figure 1. Note that connected and autonomous vehicle (CAV) technology further improves safety issues but has not currently experienced widespread commercial adoption [15].

In addition to the advancement of ADAS technologies, travel time technology has also improved significantly in recent years. Travel time calculations are currently used in routing software and programmable street signs shown in Figure 2. The travel time monitoring system records vehicles through a variety of sensors including Bluetooth, magnetic detectors, and cell phone signal monitoring and stores results in a database used by local state departments of transportation (DOT) [17]. Travel time information has widespread commercial adoption and is publically available.

FIGURE 1 A conceptual image of the sensing capabilities and scope of modern ADAS using a variety of sensors [14, 16].

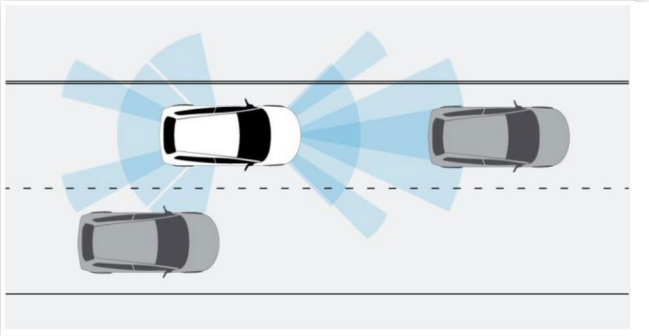
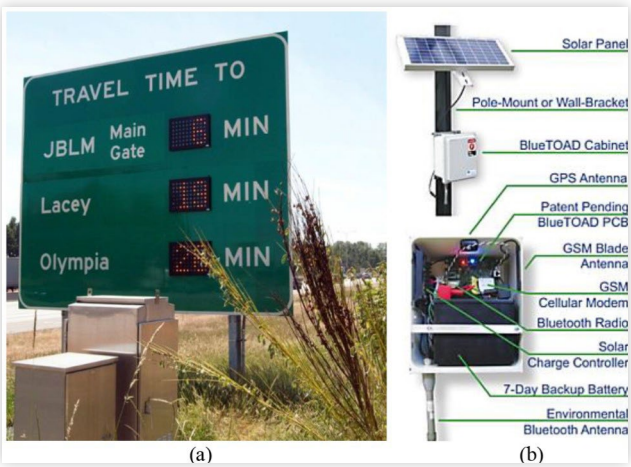


FIGURE 2 A conceptual image of the travel time calculation technology in deployment (a) and the basics of the sensing systems (b) [17].



The global need for increased FE and the trend of increasing sensing capabilities in the automotive industry have led to the development of improved vehicle control strategies. These strategies have the largest FE improvement in HEVs and PHEVs due to the optimization of engine power usage and battery power usage. For a fixed route, this can be accomplished through driver feedback to promote efficient driving habits (Eco-driving) [18, 19] as well as through optimal powertrain control to improve the powertrain efficiency [20]. Recent research suggests that the highest FE improvements are possible when Eco-driving is combined with optimal powertrain control [21]. The research in this paper is focused on improving FE through optimal powertrain control, which is typically discussed as an Optimal Energy Management Strategy (Optimal EMS).

For a globally optimal solution, an Optimal EMS must have perfectly accurate vehicle speed information along the entire route, then a computationally costly calculation must be made through either dynamic programming (DP) [22, 23] or Pontryagin's minimization principle [24, 25, 26]. To reduce the prediction requirement researchers have developed an alternative non-globally Optimal EMS that is stochastically robust using stochastic dynamic programming [27, 28, 29] and adaptive equivalent consumption minimization strategy [30, 31, 32]. To reduce the high computational cost, a non-globally Optimal EMS that is real time computable is realizable through optimized rules-based control [33, 34], model predictive control [35, 36, 37, 38], and equivalent consumption minimization strategy [39, 40, 41, 42]. But, despite the development of numerous alternate Optimal EMS, DP remains the overwhelming favorite due to its ease of use and that it provides the globally optimal control [43].

An existing research gap for commercial implementation of an Optimal EMS is the development of any type of prediction for use in an Optimal EMS [44]. From the limited research that does exist, initial results show that incorporation of traffic information improves prediction quality [45, 46] and that an artificial neural network may provide the most robust predictions [47]. Additionally, recent research suggests that using 15-30 second prediction windows may yield the best FE results when sensors and signals are limited [48]. None of these studies use ADAS technologies to enable prediction.

In this study, we seek to enable prediction for use in an Optimal EMS using a database of similar drive cycles [47, 48, 49, 50] but with the addition of commercially available ADAS and travel time technology. This novel incorporation of ADAS and travel time technology is then used to generate predictions for use in an Optimal EMS. A comparison of the FE improvements for each type of sensor-enabled prediction is the end result.

Methods

To analyze the effectiveness of various prediction scenarios, a baseline energy management strategy (Baseline EMS) and an Optimal EMS must be compared on city and highway focused drive cycles. The Baseline EMS should be reflective of the current standard and be validated against real world data. The Optimal EMS is composed of multiple subsystems, which include drive cycle prediction, Optimal EMS derivation, and Optimal EMS vehicle implementation.

Drive Cycle Development

Existing research in the prediction component of an Optimal EMS has been successful when a rigorous database of predictable drive cycles is used. Applications for this strategy include delivery or pick-up drive cycles or low traffic drive cycles. In order to make predictions difficult and demonstrate the potential of the prediction scheme, we seek to use high traffic and long drive cycles developed in a big city. We also seek to analyze and understand the application differences for city-focused driving and highway-focused driving.

The first drive cycle used is a city-focused drive cycle. Two of the busiest roads in Denver, CO USA were selected for the drive cycle, one of which passes directly through downtown. This downtown Denver drive cycle (shown in Figure 3) is ten miles long and was driven four times.

The second drive cycle used is a highway focused drive cycle. To complicate this drive cycle, it was modified to take place over two separate interstates and include a city driving

FIGURE 3 The city-focused drive cycle that passes through downtown in Denver, CO USA *source: Google Maps* (a), the velocity with respect to time of each of the four times the drive cycle was driven (b), and images of various driving encounters during the drive cycle (c).

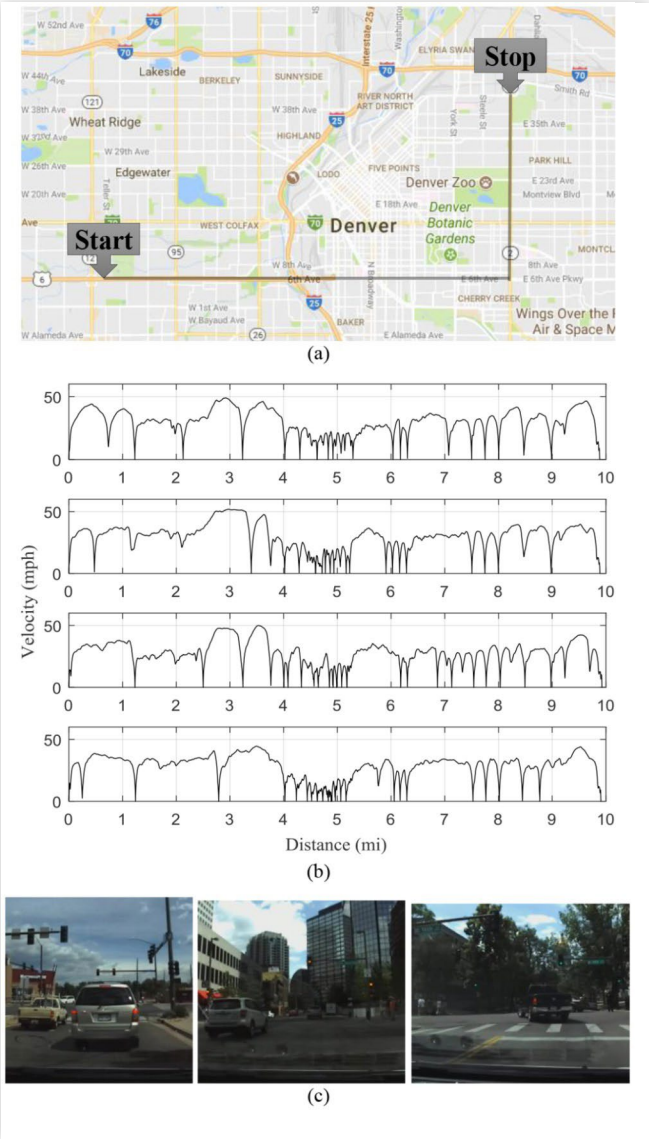
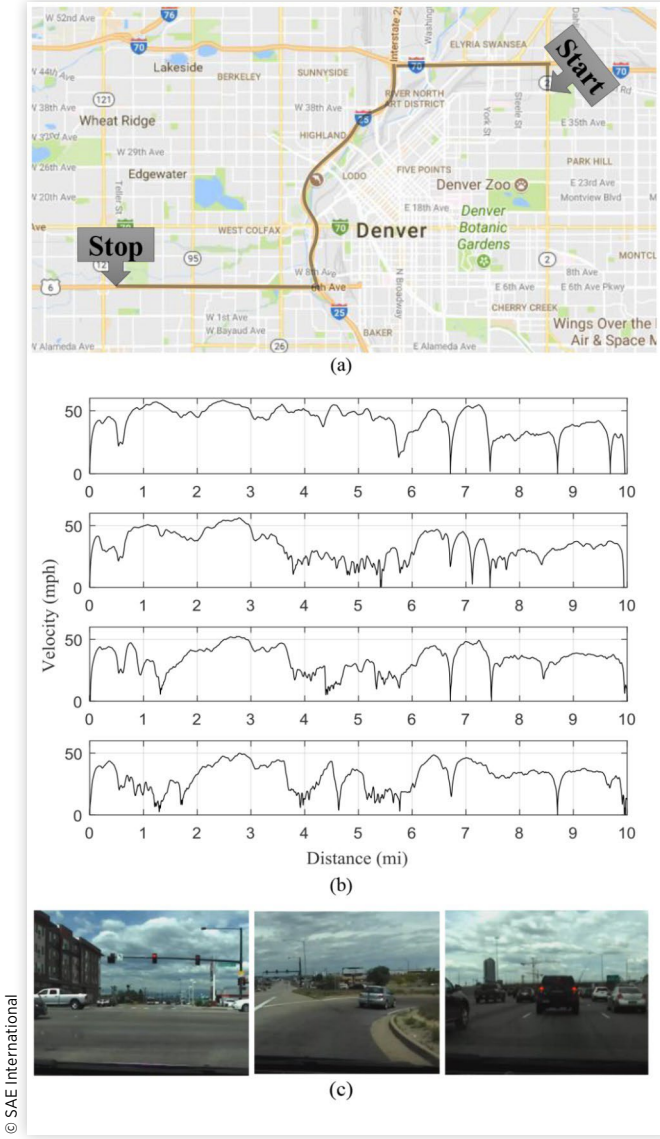


FIGURE 4 The highway-focused drive cycle that passes through two interstates in Denver, CO USA *source: Google Maps* (a), the velocity with respect to time of each of the four times the drive cycle was driven (b), and images of various driving encounters during the drive cycle (c).



portion at the end. The final drive cycle (shown in Figure 4) is also ten miles long and was driven four times. There are varying levels of traffic on each interstate for each drive cycle.

Baseline Energy Management Strategy Simulation

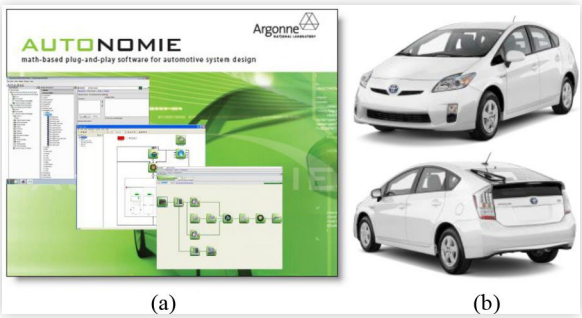
A 2010 Toyota Prius is selected as the vehicle model due to its commercial prevalence and that it has the highest FE in its class. The model used to represent the Baseline EMS is consistent with previous research in that it is a modification of the publically available 2004 Toyota Prius in the Autonomie modeling software to represent a 2010 Toyota Prius [51]. The Autonomie modeling software has demonstrated strong correlation with real world testing and is generally accepted as the standard among industry and research professionals.

The vehicle model must be validated against real world data. Table 1 shows the simulated FE over the industry standard U.S. Environmental Protection Agency (EPA) drive cycles of the Urban Dynamometer Driving Schedule (UDDS) drive cycle, the Highway Fuel Economy Test (HWFET) drive cycle, and the US06 drive cycle. A change in battery state of charge values must be taken in to account according to the SAE J1711 industry standard [52] and the adjust FE can be reported. These numbers can then be compared to real world measured values from Argonne National Labs [53]. When the numbers are compared, the simulation FE is within 3% of all of the physically measured FE numbers and the Baseline EMS is considered validated.

TABLE 1 Simulated and measured FE for the 2010 Toyota Prius HEV model developed using Autonomie.

EPA Drive Cycle	Simulated Fuel Economy	Measured Fuel Economy [53]	Percentage Difference
UDDS	76.9 mpg	75.6 mpg	1.7%
HWFET	68.8 mpg	69.9 mpg	-1.7%
US06	45.9 mpg	45.3 mpg	1.3%

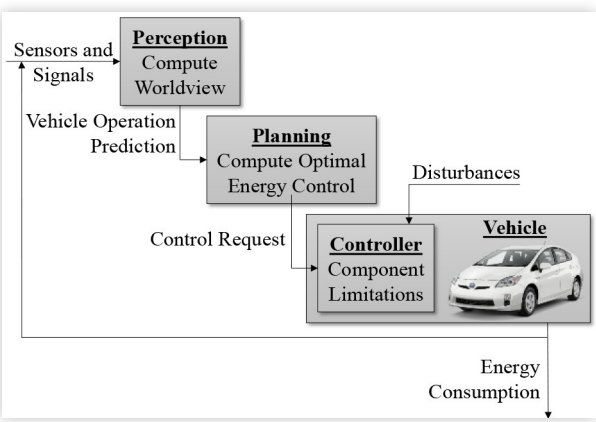
FIGURE 5 The high-fidelity Autonomie modeling software (a) was used to model the real world performance of a 2010 Toyota Prius (b).



Optimal Energy Management Strategy Simulations

Implementation of an Optimal EMS has been recently reviewed [44] and it was determined that a systems-level viewpoint consistent with autonomous vehicle control best captures Optimal EMS implementation. This system includes subsystems for drive cycle prediction (perception), derivation of the Optimal EMS (planning), and implementation of the Optimal EMS in the vehicle. This systems-level viewpoint is shown in Figure 6. The perception, planning, and vehicle plant subsystems can be developed and investigated independently, but the FE results are dependent on full system implementation and analysis.

FIGURE 6 The systems-level viewpoint of the optimally controlled vehicle model with subsystems for perception, planning, and a vehicle plant [44].



Perception Subsystem Model The perception subsystem utilizes outputs of the sensors and signals to generate a prediction of future vehicle operation. The commercially available sensors and signals chosen for the study were

- GPS Coordinates
- Current Vehicle Velocity
- ADAS Detection Ground Truth
- Travel Time Data

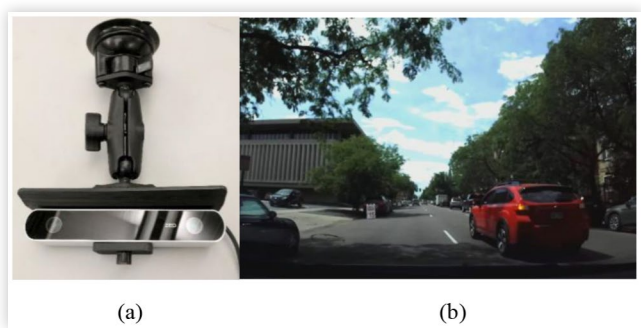
Each of these inputs is recorded independently and do not have a direct relationship to one another. Conceptually, GPS data locates the vehicle in the current drive cycle, which allows prediction of the upcoming drive speed based on previous drive cycles. ADAS detection serves to identify points of interest along a drive cycle that may affect unique driver behavior such as red traffic lights, slowing vehicles, or pedestrians in the road. Travel time data provides information about average vehicle velocities in 1-2 mile increments.

All of these inputs are recorded using 1 second timesteps and synchronized by atomic time. The GPS coordinates and current vehicle speed were recorded from the Controller Area Network (CAN) bus directly from the vehicle during the drive cycle. The ADAS detection ground truth (ground truth defined as a set of measurements that are provided by direct observation) was identified from recorded footage from the drive cycle using a camera, shown in Figure 7. The average travel time data along the drive cycle was recorded from the Colorado Department of Transportation (DOT).

The ADAS ground truth detection did not include the typical detection objectives that are required for safety focused ADAS implementation. Based on previous research identifying aspects of real-world driving that are most important for prediction [51], it was determined that the ADAS detection objective should only include identification of the state of the traffic light, identifying vehicle speed changes from the vehicle directly in front, identification of stop sign location, and identification of turn lanes. An analysis of automated ADAS detection algorithms and a comparison to ADAS ground truth is available in a separate article[54]. ADAS usage has the advantage of providing detailed drive cycle prediction information for the upcoming 1-100 seconds.

Travel time data in the Denver area does not provide drive cycle prediction details. Instead, it provides approximate drive

FIGURE 7 The camera used to record the drive cycle (a) and an example of the camera output (b). [44].



cycle speeds for the entire drive cycle before the trip has begun. These traffic levels for the entire drive cycle have demonstrated accuracy, as shown in Figure 8, but traffic information may not be as important for an Optimal EMS [51].

There are numerous methods to combine outputs from sensors and signals to generate a vehicle velocity prediction but initial research suggests that an artificial neural network may provide the best results [47]. For time series predictions used in control of dynamic systems, Nonlinear Autoregressive Neural Networks are typically used [55] since they have been demonstrated to be effective [56]. To predict future velocity using the sensor and signal outputs, a nonlinear autoregressive neural network with external input (NARX) is required. This neural network predicts future values of the vehicle velocity, $v(t)$, from past values of the vehicle velocity, $v(t-1)$, and from past values of each of the sensors and signals, $x(t-1)$. This network can be written mathematically as

$$v(t) = f\left[v(t-1), \ldots v(t-d), x(t-1), \ldots (t-d)\right] \quad (1)$$

where d is a time delay. Due to the success of neural networks, there are numerous toolboxes that can be used to design custom neural networks. Since other aspects of the Optimal EMS system must interface with the Autonomie Simulink model, the neural network was designed and implemented in Matlab. NARX networks were trained to predict both the Denver downtown drive cycle and the Denver highway drive cycle using three of the alternate versions of the drive cycle to be analyzed. After comprehensively studying the effect of all NARX parameters on the average FE results, it was found that 3 feedback delays, 1 hidden layer, 1 input delay, scaled conjugate gradient training, 90% data training, 2% data validation, and 8% data testing provided the best results. An overall conceptual diagram of the perception subsystem model is shown in Figure 9. The output of the perception subsystem is a prediction of vehicle velocity from which an Optimal EMS can be determined in the planning subsystem model.

FIGURE 8 Drive cycle predictions possible using travel time data for the highway-focused Denver drive cycle.

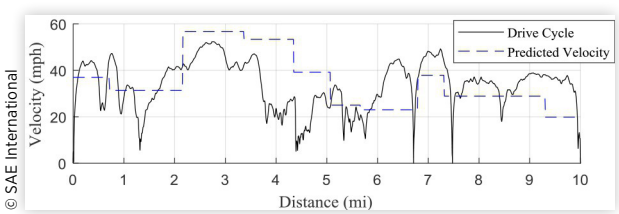
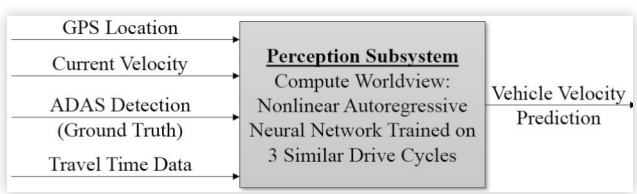


FIGURE 9 Details of the perception subsystem shown in Figure 6 that shows ADAS, GPS and Average Traffic Data as an input to a NNARX perception model to generate a vehicle velocity prediction.



Planning Subsystem Model The planning subsystem model receives a prediction of the future vehicle operation as an input, determines the globally optimal control using dynamic programming (DP) and issues a control request to the vehicle model. The DP formulation for an HEV Optimal EMS derivation uses the battery state of charge (*SOC*) as the state variable, the engine power (P_{ICE}) as the control variable, the vehicle velocity (v) as the external input, and the total mass of fuel required (m_{fuel}) as the cost function. This HEV Optimal EMS derivation can then be tailored to a 2010 Toyota Prius by using a power-split vehicle architecture relationship between these variables. A detailed description of this process can be found in previous research [51]. The final form used to derive the optimal control is

$$\mathrm{SOC}(k+1) = \mathrm{SOC}(k) - C_1 + C_2\sqrt{C_3 - C_4 v(k) + C_5 v(k)^3 + C_6 \dot{v}(k) v(k) - C_7 P_{\mathrm{ICE}}} \quad (2)$$

$$\mathrm{Cost} = \sum_{k=0}^{N-1} f(P_{\mathrm{ICE}}) + W\left[\mathrm{SOC}_f - \mathrm{SOC}(N)\right] \quad (3)$$

$$40\% \le \mathrm{SOC}(k) \le 80\% \ (k = 0, \ldots N) \quad (4)$$

$$0\,\mathrm{kW} \le P_{\mathrm{ICE}}(k) \le 73\,\mathrm{kW}\ (k = 0, \ldots N-1) \quad (5)$$

$$C_8\left[f(P_{\mathrm{ICE}})\right] + C_9 v(k) \le C_{10} \quad (6)$$

where C_{1-10} are constants, k is an arbitrary timestep, N is the final timestep, and W is a penalty weighting factor set at 10,000.SOC_f is the desired final state of charge of the battery. This value is typically set at 50% to encourage typical charge sustaining behavior of an HEV. Electric drivetrain component efficiencies were added to improve the fidelity of the Optimal EMS derivation from the previous publication [51].

The solution of the DP algorithm is a cost-to-go matrix, which is used to derive the optimal control decision matrix. This algorithm can be used to derive the globally Optimal EMS which assumed 100% accurate prediction data (shown in Figure 10) for the entire drive cycle as well as an Optimal EMS derived using time limited prediction data.

Results from existing research demonstrate that a 15 or 30 second prediction window is an ideal tradeoff between prediction accuracy and FE improvement potential [48]. Because ADAS technology provides near term prediction data such as identification of a red light or a slowing vehicle, a 15 second prediction window was used. An example of the Optimal EMS from 100% accurate prediction of a 15 second window that is then updated and actuated on a second by second basis is shown in Figure 11.

The technique used for sensing and prediction is a 15 second prediction that is recomputed every second. This implies that an Optimal EMS is calculated for every 15 second window but only the first second of operation is used. Thus, the key metric is not overall drive cycle prediction accuracy but a 15 second prediction accuracy for every second of the drive cycle. Therefore, presenting intermediate drive cycle results concerning velocity prediction accuracy does not provide meaningful insight. For a discussion on velocity prediction error analysis refer to other work [48,57].

FIGURE 10 The Optimal EMS solution for 100% accurate prediction of the downtown Denver drive cycle.

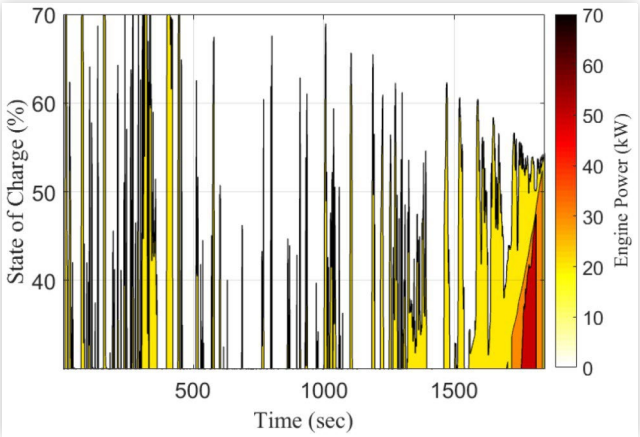


FIGURE 11 The Optimal EMS solution of a 15 second window within the first downtown Denver drive cycle for 100% accurate prediction (a) and sensor and signal output prediction (b).

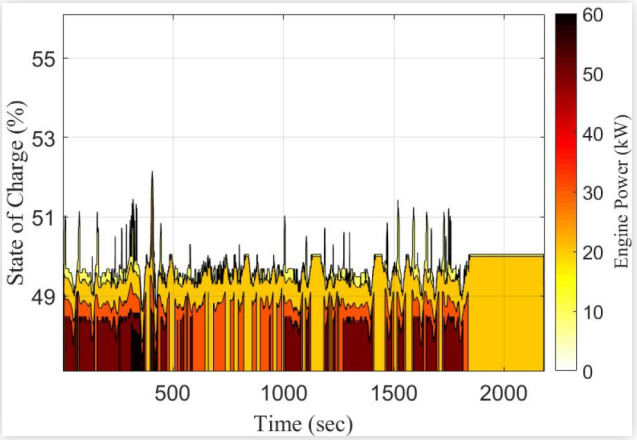
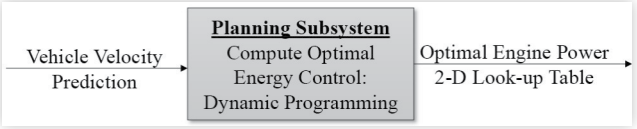


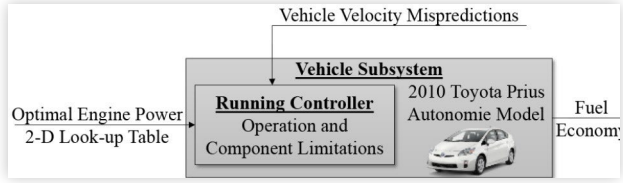
FIGURE 12 Details of the planning subsystem shown in Figure 6 that shows generation of a globally optimal solution for the provided vehicle velocity prediction.



An overall conceptual diagram of the planning subsystem model is shown in Figure 12. The output of the planning subsystem is the Optimal EMS decision matrix, which provides the optimal engine power for any feasible timestep and battery state of charge, also known as a 2-D lookup table. This output is then used in the vehicle to actuate the Optimal EMS.

Vehicle Subsystem Model The input to the vehicle model is the Optimal EMS control request and disturbances attributed to misprediction. The vehicle model used is a modified version of the baseline 2010 Toyota Prius Autonomie model that allows the desired engine power to be overwritten.

FIGURE 13 Details of the vehicle plant subsystem shown in Figure 6 that received the modified control request and implements it with the vehicle running control for FE measurements.



This model includes a running controller, which enforces individual component operation limitations. The recorded output of this model can be any variable inherent in the Autonomie software. Of particular interest is the fuel consumption, achieved engine power, and battery state of charge. These results can then be compared to the same outputs from Baseline EMS simulation.

An overall conceptual diagram of the vehicle subsystem model is shown in Figure 12. The main output of the vehicle subsystem is achieved charge adjusted FE which can be calculated according to the current SAE standard [52].

Results

There are several important data points required to gain insight into the prediction capabilities that are possible using the commercially available sensors and signals discussed. The first relevant data point is the globally Optimal EMS solution, which provides the FE improvement that is possible with 100% accurate prediction of the entire drive cycle. This data point is important because it identifies the absolute FE improvement ceiling. Next, since the chosen sensors and signals are being used to provide 15 second predictions, the 100% accurate 15 second prediction data point is required (prediction window optimal). This data point identifies the ceiling of the detection capabilities of the chosen sensors and signals in the 15 second window.

Next, to understand the relative importance of the chosen signals, three comparisons can be made

- Prediction using GPS and current velocity
- Prediction using GPS, current velocity, and ADAS
- Prediction using GPS, current velocity, ADAS, and travel time (traffic) information

For each of these prediction types, a unique NARX must be trained and implemented. The achieved FE improvement can then be compared to the ceiling value for 15 second prediction as well as the global ceiling. FE improvements are calculated as

$$Percent\ Improvement = \frac{FE_{Optimal} - FE_{Baseline}}{FE_{Baseline}} \tag{7}$$

To obtain information about general behavior of this technique, a unique NARX was trained using three drive cycle datasets and was then tested on the fourth drive cycle. This leads to four results from the four city drive cycles (for example: train using city drive cycles 1, 2, 3 then test on city

drive cycle 4; train using city drive cycles 2, 3, 4 then test on city drive cycle 1; etc.) and four results from the four highway drive cycles. This implies that results cannot be "cherry-picked" and that the final results will be representative of overall behavior of this technique.

City-Focused Drive Cycle

For the city-focused drive cycle, the FE results are shown in Figure 14, the engine operation is shown in Figure 15, and the battery state of charge results are shown in Figure 16.

The Baseline EMS for the city-focused Denver drive cycle was able to achieve 58.7 mpg on average, which was improved significantly by the globally Optimal EMS to 70.2 mpg; a total percent improvement of 19.6% as shown in Figure 14. Figure 14 also shows an 11.9% improvement for 15 second perfect prediction and a 5.3% FE increase for prediction using only GPS and current velocity. There is a 6.2% FE increase when using GPS, current velocity, and ADAS, which is the largest non-perfect prediction result. Lastly, there is a 4.8% FE increase when using GPS, current velocity, ADAS, and travel time information which is less than when travel time information is not included.

These results suggest that for city-focused driving, travel time information does not provide enough resolution to aid in prediction. In fact, excess or inaccurate information may hinder the prediction quality and thus the FE gain. Figure 15 shows two instances for which the addition of travel time data caused significant mispredictions of the engine power that was required. Meanwhile, the other prediction scenarios follow the prediction window optimal solution very closely. Figure 15 also shows the benefit of full drive cycle prediction since the global Optimal EMS is able to leverage operation over the entire drive cycle.

A drawback of the globally Optimal EMS is that the battery state of charge varies significantly over the drive cycle as shown in Figure 16. This may be due to the low cost of increasing battery charge in general since most optimal solutions follow a similar trajectory [51]. The Baseline EMS (shown in black) executes charge banking for the first half of the drive cycle while the globally Optimal EMS charge depletes over the first half of

FIGURE 14 Average FE improvement results for the four Denver downtown drive cycles.

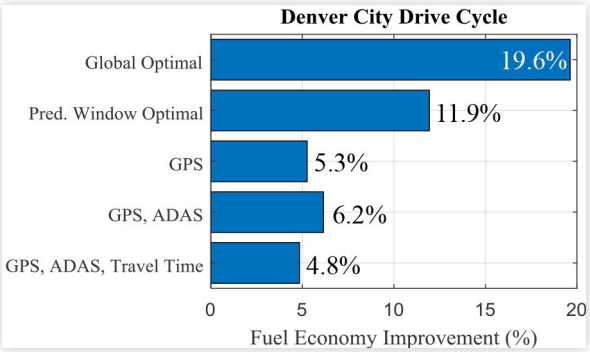


FIGURE 15 Engine power comparison for a Denver downtown drive cycle.

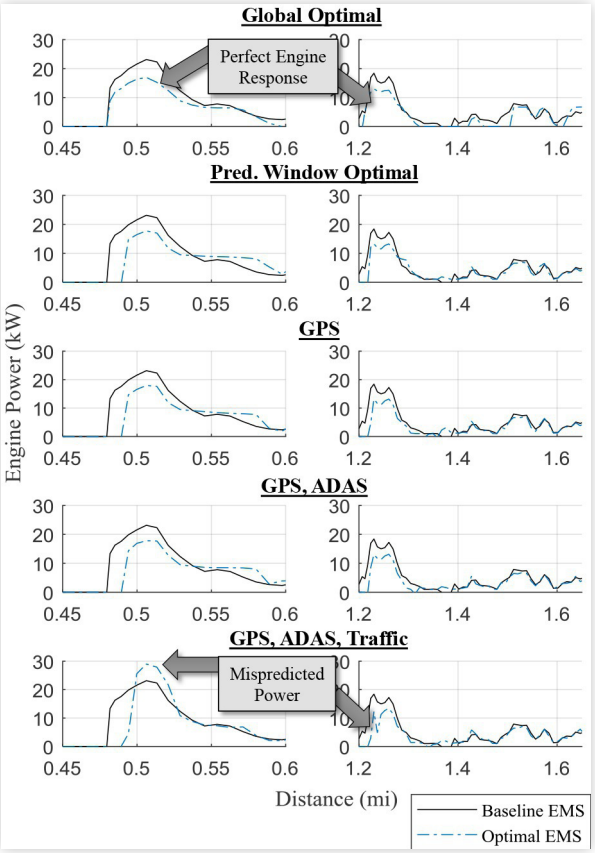
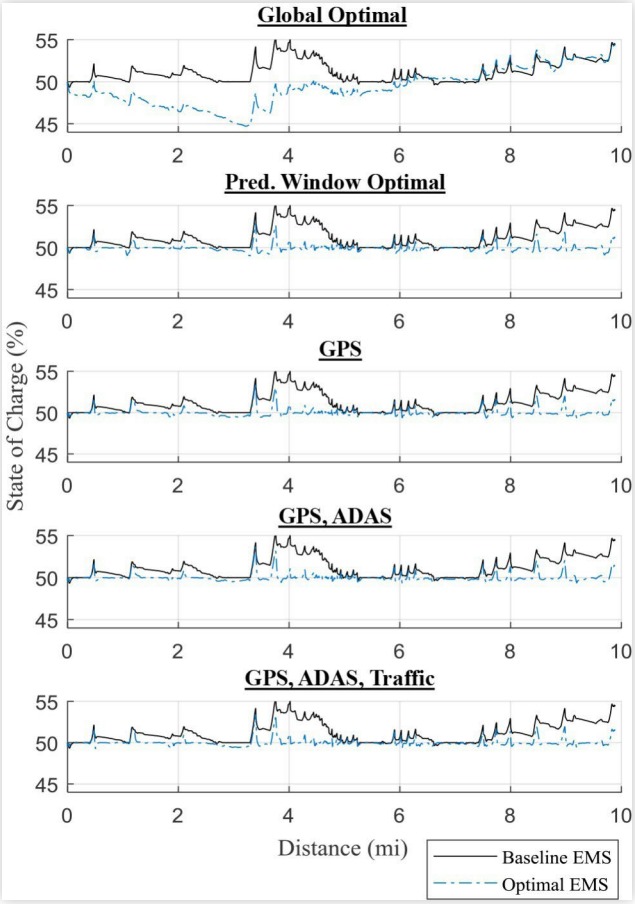


FIGURE 16 Battery state of charge comparison for a Denver downtown drive cycle.



the drive cycle to realize a FE improvement but still is able to end the drive cycle at the same value of final state of charge. All other cases use 15 second prediction windows and are constrained to end the 15 second prediction window at 50% state of charge. The result over the full drive cycle is a rigid charge sustaining operation that may improve battery longevity. The final FE numbers are computed using charge corrections [52].

Highway-Focused Drive Cycle

For the highway-focused drive cycle, the FE results are shown in Figure 17, the engine operation is shown in Figure 18, and the battery state of charge results are shown in Figure 19.

FIGURE 17 Average FE improvement results for the Denver highway drive cycles.

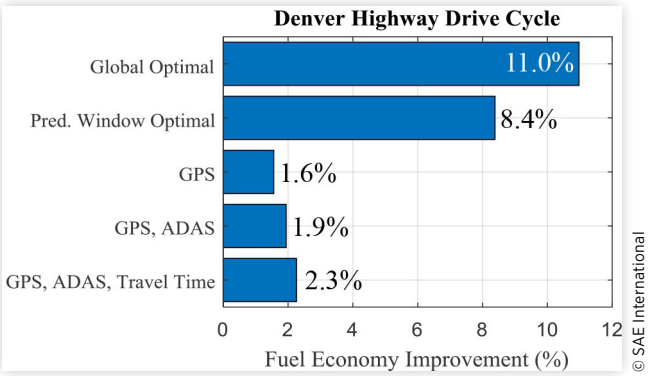
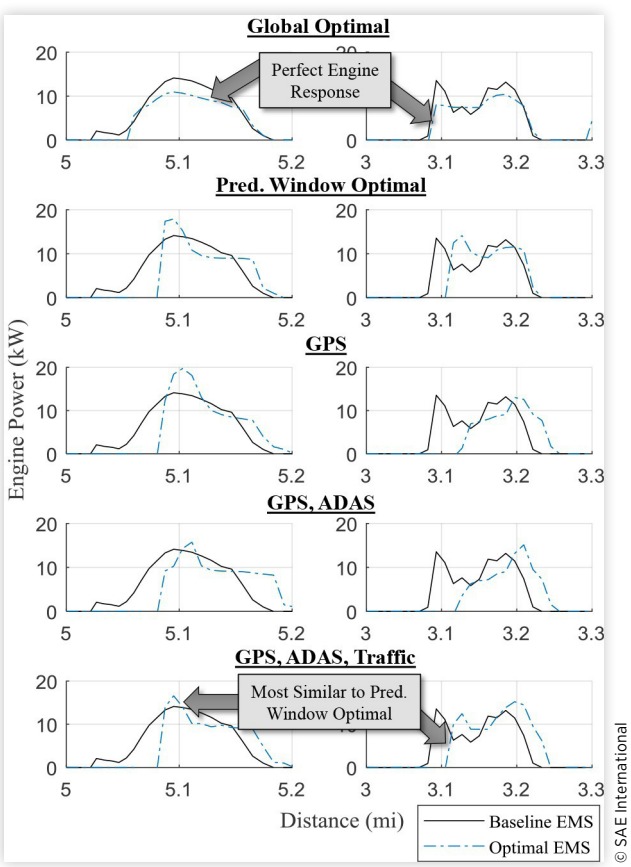


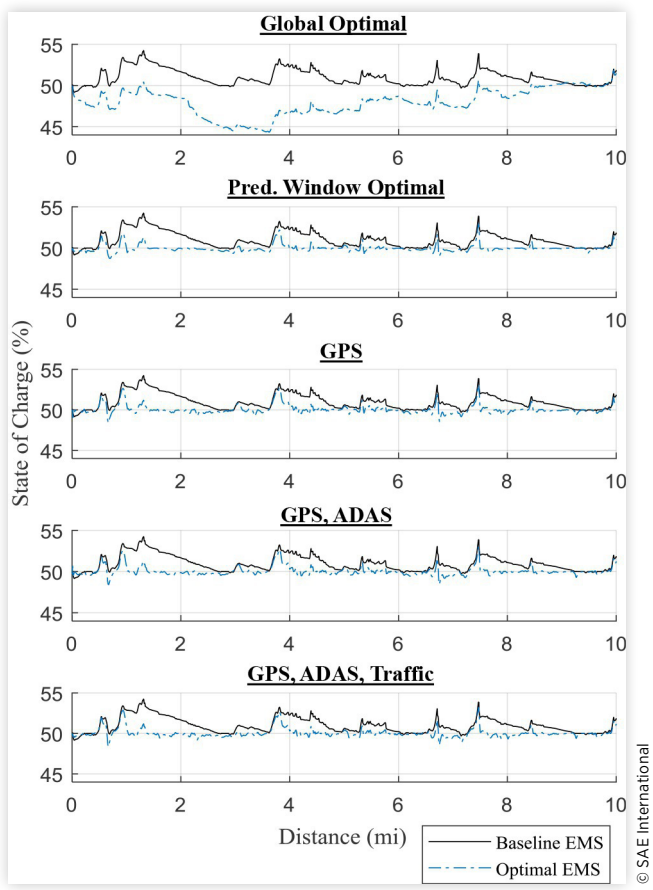
FIGURE 18 Engine power comparison for a Denver highway drive cycle.



The Baseline EMS for the highway-focused Denver drive cycle was able to achieve 64.0 mpg, which was improved by the globally Optimal EMS to 71.1 mpg; a total percent improvement of 11.0% as shown in Figure 17. Figure 17 also shows a 8.4% improvement for 15 second perfect prediction and reduced FE improvements for all sensor configurations. There is a 1.6% FE increase for prediction using only GPS and current velocity. There is a 1.9% FE increase when using GPS, current velocity, and ADAS. Lastly, there is a 2.3% FE increase when using GPS, current velocity, ADAS, and travel time information, which is the largest non-perfect prediction result.

These results suggest that for highway-focused driving, travel time information provides a significant prediction advantage and FE improvement. For highway driving, there is limited environmental information to aid in prediction therefore the current resolution of travel time data (shown in Figure 8) is useful. Due to the unpredictability of traffic induced slowdown regions on the highway, prediction using GPS and current vehicle velocity provide the lowest FE improvements. The evidence for the results in Figure 17 can be seen in Figure 18, which shows that prediction using GPS, current velocity, ADAS, and travel time (traffic) information provides the most similar engine response to the 15 second perfect prediction (prediction window optimal) engine response. Additionally, prediction using GPS and current velocity produces its own engine response.

FIGURE 19 Battery state of charge comparison for a Denver highway drive cycle.



As with the city-focused drive cycle, the globally Optimal EMS for the highway-focused drive cycle produces a battery state of charge that varies significantly over the drive cycle as shown in Figure 19. Also, similar to the city-focused drive cycle, all other cases that use a 15 second prediction windows achieve rigid charge sustaining behavior since each 15 second prediction window is constrained to end at 50% state of charge. This rigid charge sustaining operation may improve battery longevity. The final FE numbers are computed using charge corrections [52].

Conclusions

In this study, a unique set of sensors and signals was composed to investigate optimal vehicle control over ten mile long, busy drive cycles in a major capital city. City-focused and highway-focused drive cycles were driven during which GPS, current vehicle velocity, ADAS detection, and travel time data was recorded. These sensor and signal outputs were then input into a neural network perception model to determine future vehicle operation. The future vehicle operation was then used to derive the Optimal EMS using DP for 15 second prediction windows. The Optimal EMS was then implemented in a validated model of a 2010 Toyota Prius in the Autonomie software. The results show that for the city-focused drive cycle, large portion of the globally optimal Improvement can be achieved using GPS, current velocity and ADAS detection data in a prediction model coupled with optimal control. The results also show that for the highway-focused drive cycle, a large portion of the globally Optimal FE improvement can be achieved using GPS, current velocity, ADAS detection, and travel time data in a prediction model coupled with optimal control.

Adding future vehicle operation prediction to the existing safety objectives of ADAS is a viable method to enable and improve prediction for an Optimal EMS. In addition, travel time information significantly improves prediction for an Optimal EMS when driving on the highway. Exact and full prediction of the entire drive cycle is not required to obtain a significant FE improvement through implementation of an Optimal EMS which agrees with previous research [51]. Additionally, these sensors and signals are already in widespread commercial use, which suggests that it may be possible to implement an Optimal EMS in current vehicles. This could be achieved by either implementing the proposed methods in vehicles as they are manufactured, or via a retrofit kit for vehicles currently on the road. The retrofit kit would likely involve a software/firmware update and an external processor. The main costs associated with this FE improvement method are from development and testing. Once thoroughly developed, FE savings would quickly payback the retrofit cost. Exact payback would depend on vehicle use and architecture.

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Definitions/Abbreviations

ADAS - Advanced Driver Assistance System

DOT - Department of Transportation

DP - Dynamic Programming

EMS - Energy Management Strategy

EPA - Environmental Protection Agency

FE - Fuel economy

Ground Truth - A set of measurements that are provided by direct observation

HEV - Hybrid Electric Vehicle

HWFET - Highway Fuel Economy Test

NARX - Nonlinear Autoregressive Neural Network with External Inputs

PHEV - Plug-In Hybrid Electric Vehicle

UDDS - Urban Dynamometer Driving Schedule

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