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Abstract

An optimal energy management strategy (Optimal EMS) can yield significant fuel economy (FE) improvements without vehicle velocity modifications. Thus it has been the subject of numerous research studies spanning decades. One of the most challenging aspects of an Optimal EMS is that FE gains are typically directly related to high fidelity predictions of future vehicle operation. In this research, a comprehensive dataset is exploited which includes internal data (CAN bus) and external data (radar information and V2V) gathered over numerous instances of two highway drive cycles and one urban/highway mixed drive cycle. This dataset is used to derive a prediction model for vehicle velocity for the next 10 seconds, which is a range which has a significant FE improvement potential. This achieved 10 second vehicle velocity prediction is then compared to perfect full drive cycle prediction, perfect 10 second prediction. These various velocity predictions are used as an input into an Optimal EMS derivation algorithm to derive an engine torque and engine speed control strategy that improves FE compared to current vehicle operation. Dynamic programming is used as the Optimal EMS because it provides a globally optimal control which is preferable for this investigatory study. The vehicle model used is real world validated and represents a 2017 Toyota Prius Prime operating in charge sustaining mode. The results show that actual vehicle velocity prediction from the prediction model achieves 85% of the FE improvement from an Optimal EMS derived using perfect 10 second prediction.

Introduction

Transportation is the backbone of economic activity, connecting manufacturers with supply chains, consumers with products and tourism, and people with their workplaces, homes, and communities across both urban and rural landscapes. But, in 2016, the transportation sector became the top contributor to greenhouse gas emissions which eventually contribute to climate change [1]. Climate change is projected to significantly affect human health, the economy, and the environment in the world, particularly in futures with high greenhouse gas emissions and limited or no adaptation. Recent findings reinforce the fact that without substantial and sustained reductions in greenhouse gas emissions and regional adaptation efforts, there will be substantial and far-reaching changes over the course of the 21st century with negative consequences for a large majority of sectors, particularly towards the end of the century [2]. These accelerating emissions are putting the world on track to face some of the most severe consequences of global warming sooner than expected [3].

To mitigate the climate change, most recently, the Paris Agreement of 2015 took on the long-term aims of “holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels” [4]. Because of these issues, governments around the world have imposed various Fuel economy (FE) requirements that automotive manufacturers are required to meet [5]. Fuel economy (FE) is an important way to reduce the adverse effects of climate change. Therefore, the increase in FE would significantly reduce our energy footprint [6]. Electrification is a key technology to ensure FE compliance [2]. Benefits such as
increased energy security, improved fuel economy, and reduced emissions could be achieved by the use of Hybrid Electric Vehicles (HEVs), and Plug-In Hybrid Electric Vehicles (PHEVs) [8]. An internal combustion engine operated along with one or more electric motors powers the HEVs. Usage like this gives the benefits of high fuel economy with low emissions [9].

In addition to this FE trend, modern vehicles are incrementally incorporating self-driving technologies and transitioning to intelligent vehicles. Recent advances have enabled “Intelligent Vehicles” which utilize vehicle to vehicle communication (V2V), vehicle to infrastructure communication (V2I), camera data, radar data, and more [10]. Artificial neural networks (ANN) are computing systems inspired by biological neural networks where the algorithm is developed that can be used to model complex patterns and prediction problems [11]. ANNs has ability to model and extract unseen features and relationships. They are a very powerful tool to predict the future output of any system which enables utilization of optimal control principles to derive an optimal solution.

Numerous researchers have recognized the potential of using self-driving vehicle technologies to inform an ANN prediction model whose outputs can be used to derive a control strategy that improves FE [12, 13, 14, 15, 16, 17, 18, 19]. Recent advances in this field have demonstrated that adaptive Equivalent Consumption Minimization Strategy (adaptive-ECMS) yields better results when combined with an ANN model that predicts velocity [20]. Note that each of these studies incorporates “Intelligent Vehicle” technology inputs to a prediction model which informs optimal control. This is an article scope beyond the many hundreds of papers focusing on just the optimal control portion [21] which has been identified as an important research gap [22].

A mathematical optimization problem can be formulated by defining the mass of fuel used as a cost to be minimized over a fixed drive cycle. This mathematical optimization problem is formulated as either a second by second instantaneous optimization or as a global optimization which includes future vehicle operation prediction. The result from either of these schemes is the minimum fuel consumption strategy (Optimal EMS) which can be applied to the fixed drive cycle. For deriving a globally Optimal EMS using deterministic prediction, Dynamic programming (DP) has been the overwhelming favorite of researchers due to its ease of use, robustness, and that no derivatives or analytic expressions are required [23]. Therefore, a strategy can be developed where vehicle velocity predictions are formulated using a ANN, and an Optimal EMS is computed using dynamic programming.

This new research expands upon the previous work [24] in several ways. In the previous work, the number of signals used is limited while in this research we will be using alternate but more inclusive “intelligent vehicle” inputs. This study involves an improved perception model that uses a Long Short Term Memory (LSTM) deep ANN rather than the Nonlinear Autoregressive Shallow Neural Network with eXogenous inputs (NARX) used in previous work, new drive cycles from the Michigan area, and an updated and high accuracy vehicle model.

### Methods

The Baseline Energy Management Strategy (Baseline EMS) and an Optimal Energy Management System (Optimal EMS) need to be compared on urban/highway and highway focused drive cycles, to investigate the effectiveness of different prediction scenarios. The Baseline EMS should be adhering the current operation of our chosen vehicle which is 2017 Toyota Prius Prime. Our vehicle model must also validate against real world data. The Optimal EMS is comprised of multiple subsystems, which incorporate drive cycle prediction, Optimal EMS derivation, and Optimal EMS vehicle integration.

### Drive Cycle Development and SignalRecording

As described in part one of this research [28], two custom drive cycles are used to represent urban/highway driving and highway driving. The need for custom real-world drive cycles is necessitated by the numerous recorded sensors and signals required to develop the prediction model. The highway drive cycle is the drive cycle used in the highway dataset which is shown in Figure 1, and the urban/highway drive cycle is the drive cycle used in the urban/highway dataset which is shown in Figure 2. Each of these drive cycles was driven numerous times with all sensors and signals recorded. The different instances of each drive cycle may have different traffic conditions and different stop light states along the drive cycle.

Following are details about the drive cycles:

- Traffic condition:
  - Different time periods in a day; Highway & Urban

![Figure 1](drive_cycle_map.png)

Drive cycle map of the highway dataset (Created with: Google Maps)
Baseline Energy Management Strategy Simulation

The Baseline EMS represents the current operation of a 2017 Toyota Prius Prime which is shown in Figure 3 for reference. The Baseline EMS is a rules-based, non-predictive control strategy. A measured Baseline EMS in terms of engine speed and engine torque over the entire drive cycle is used as an input into a controls-oriented model developed in Matlab/Simulink. The controls-oriented model is used to evaluate FE and SOC as shown in Figure 4. The controls-oriented model is used with the Baseline EMS for consistency with the developed Optimal EMS which will be discussed in the next section.

This controls-oriented model was developed using previously documented Toyota Prius operation equations [25, 26] integrated with Matlab/Simulink but with updated vehicle parameters for the engine and electric motors to accurately represent a 2017 Toyota Prius Prime. This approach relies upon several assumptions to drastically reduce computation time; thus, it requires extensive validation. Validation was completed using real world chassis dynamometer data. This validation is shown in Figures 5. These plots show a linear relationship between this control-oriented model and the chassis dynamometer data for both fuel consumption and SOC across the industry standard U.S. Environmental Protection Agency (EPA) drive cycles which include the Urban Dynamometer Driving Schedule (UDDS), the Highway Fuel Economy Test (HWY), and more. Because there is a linear relationship between the controls-oriented model and the chassis dynamometer data over a variety of standard drive cycles, the model is considered to be validated.

Further, blending is an approach which utilizes the engine more during the charge depletion phase, thereby assisting the battery in meeting total power demand more often than...
charge depletion-charge sustenance (CDCS). Although in the blended case the engine operates at higher loads, therefore consuming more fuel, the engine efficiency is greater, and battery charge depletes more slowly. As a result, blending and charge sustenance incur nearly the same total energy costs through the depletion phase [27]. Therefore, charge sustaining approach is considered for this research.

Note that an individual adjustment to the accessory power load was made in the controls-oriented model to ensure that the Baseline EMS $\text{SOC}_f$ (final $\text{SOC}$) matched the Baseline EMS $\text{SOC}_i$ (initial $\text{SOC}$) for each instance of each drive cycle. This was made to ensure strict charge sustaining behavior which aids in the 10-second prediction Optimal EMS analysis. All adjusted accessory power loads to the Baseline EMS are also included in the Optimal EMS derivation and evaluation model to ensure that the Optimal EMS does not have an unfair advantage.

**Optimal Energy Management Strategy Simulations**

As demonstrated in previous research, an Optimal EMS system implementation can be broken down into discrete subsystems as shown in Figure 6. This model consists of subsystems for drive cycle prediction (perception), derivation of the Optimal EMS (planning), and implementation of the Optimal EMS in the vehicle. The following subsections describe each independent subsystem used in this study.

**Perception Subsystem Model** Rigorous details of the perception model are demonstrated in part one of this research which includes deterministic prediction approaches and stochastic prediction approaches [28]. Deterministic models include an Auto-Regressive Moving Average (ARMA) model, a Nonlinear Auto-Regressive with eXternal input (NARX) shallow neural network and a Long Short-Term Memory (LSTM) deep neural network. Stochastic models include a Markov Chain (MC) model and a Conditional Linear Gaussian (CLG) model. The velocity prediction is based on the highway dataset and the urban/highway dataset. The results indicate that deterministic models can give a more accurate performance on average while stochastic models may be less accurate in terms of the average velocity prediction.

This paper focuses on an objective of 1-10 sec prediction of vehicle velocity. Since the behavior of a vehicle operated in traffic by a driver is a complex dynamic system, the vehicle velocity may correlate with a large number of variables. Also, it was observed that there are instances where an increased prediction window results in a worse FE for the perfect prediction [29]. Furthermore, while the speed error reaches a saturation point, the distribution of the prediction errors continues to grow as the prediction window size grows [30]. The time shift, which reflects the time lag between the predicted value and the target value, is introduced to evaluate the prediction results. In the article [31], the FE of the scenario-controlled vehicles is demonstrated to be sensitive to prediction signal quality. Even when presented with imperfect information, the
scenario control predictive controllers were able to outperform the baseline controller for many of the scenarios investigated [31]. Overall for 10 seconds velocity prediction, LSTM demonstrates the best prediction accuracy with MAE of about 1 m/s and time shift of 0 to 4 seconds.

The perception subsystem inputs are the sensors and signals that are recorded along the drive cycle. The perception model gives output as vehicle velocity prediction for next 10 seconds into the future by computing 10 similar drive cycles in LSTM. An overall conceptual diagram of the perception subsystem model is shown in Figure 7.

The objective of future vehicle velocity prediction according to historical and current information can be formulated as a time series prediction problem. In part one of this research [28], it was shown that a deterministic model Long Short-Term Memory (LSTM) deep neural network model performs the best of the tested models. Now this LSTM perception model can be implemented into the Optimal EMS system. Figure 8 shows the general performance of the LSTM.

**Planning Subsystem Model** An overall conceptual diagram of the planning subsystem model is shown in Figure 9. The output of the planning subsystem is the Optimal EMS decision matrix, which provides the optimal engine power for any feasible timestep and battery SOC, also known as a 2-D lookup table. This output is then used in the vehicle to actuate the Optimal EMS.

To assess the potential FE improvements which can be achieved by incorporating vehicle velocity prediction into an Optimal EMS, a globally optimal solution is desired. If FE improvements can be realized with a globally Optimal EMS, future work using a real-time Optimal EMS is warranted and can be compared to the globally Optimal EMS. DP is chosen as an approach to derive the globally Optimal EMS because of its ease of implementation and because it guarantees a globally optimal solution (subject to the chosen discretization). Note that the DP solution provides an upper bound on achievable fuel economy by a real-time Optimal EMS.

The DP algorithm is implemented by setting the battery SOC as the state variable \(S\), setting the engine speed and engine torque as the control variables \(u_1\) and \(u_2\), and using the drive cycle velocity as a fixed input \(v\). The cost function is the summation of the mass of fuel used, plus a charge sustaining deviation penalty. Note that there are also restrictions on feasible engine speed, engine torque, engine power, generator speed, and battery state of charge that are used but not shown analytically here. Overall the formulation can be expressed as a dynamic equation of,

\[
S(k + 1) = S(k) + f(u_1, u_2, v)
\]  

(2)

which shows that the state variable changes according to a function of engine speed, engine torque, and velocity. Equation (2) is represented in Figure 10 which it shows the details of input and output, where \(SOC(k + 1)\) is the state of charge for time \(k+1\), \(SOC(k)\) is the current state of charge and \(f(u_1, u_2, v)\) represents the vehicle model.

The cost equation is given by,

\[
\text{Cost} = \sum_{k=1}^{N} m_{fuel}(u_1, u_2) + \frac{W}{2} (SOC_f - SOC_{f,Baseline \ EMS})^2
\]  

(3)

Where the mass of fuel \(m_{fuel}\) is a function of engine speed and engine torque and the penalty function weight is a constant set at 1000, which produces strict charge sustaining behavior between the initial SOC \((SOC_i)\) and the final SOC \((SOC_f)\).
Constraints for this problem include the relevant and feasible operation of the 2017 Toyota Prius Prime as,

\[ 10\% \leq \text{SOC}(k) \leq 20\% \quad (k = 0, \ldots N) \quad (4) \]

\[ P_{\text{ICE}} \text{min} \leq u_1 + u_2 \leq P_{\text{ICE}} \text{max} \quad (k = 0, \ldots N-1) \quad (5) \]

A summary of relevant variables is given as,

\- \( v \): fixed input velocity
\- \( u_1 \): engine speed
\- \( u_2 \): engine torque
\- \( m_{\text{fuel}} \): mass of fuel
\- \( k \): arbitrary timestep
\- \( N \): final timestep
\- \( \text{SOC}_i \): initial state of charge
\- \( \text{SOC}_f \): final state of charge
\- \( P_{\text{ICE}} \): Engine power
\- \( W \): penalty weighting factor set at 1000
\- \( f(u_1, u_2, v) \): represents the Matlab vehicle model.

Figure 10 shows the overview of the DP algorithm and an optimal control matrix. An example of the optimal control matrix for engine speed and the optimal control matrix for engine torque is shown in Figure 11(a) and 11(b). The example results of the application of these optimal control matrices which realizes FE improvement is shown in Figure 11(c).

Using full drive cycle prediction implemented with an Optimal EMS we can obtain a FE improvement in the full drive cycle. We also integrated the planning subsystem for use with a perfect 10 second prediction and an actual 10 second prediction from the LSTM perception model.

In case of Perfect prediction, velocity is known from full drive cycle, on the other hand, we predict velocity for actual 10 second results. These values are taken input to the planning subsystem, and then 2D Look up table is obtained. To obtain comparable results, the same planning subsystem model is used in both cases. This is further explained in the result section.

**Vehicle Subsystem Model**

Now that we have the optimal control, we again use the vehicle model to run the vehicle model over the drive cycle to measure \( \text{SOC} \) and FE. The input to the vehicle model is the Optimal EMS control request and disturbances attributed to the misprediction. The vehicle model used is the 2017 Toyota Prius Matlab/Simulink model described in the Baseline Energy Management Strategy Simulation section as shown in Figure 12.

The output of this vehicle model is fuel consumption, achieved engine power, and battery \( \text{SOC} \). 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 13.
Results

The FE results using actual prediction with an Optimal EMS must be put into proper context to understand the result. The context of the FE result can be determined by analyzing three results: (1) an Optimal EMS with perfect full drive cycle prediction, (2) an Optimal EMS with perfect 10-second predictions, and (3) an Optimal EMS with actual 10-second prediction. For the Perfect prediction, the DP programming uses full driving cycle, where we know the velocity of the vehicle at each instance. In the case of actual 10 second prediction, the velocity is predicted using the LSTM model. Hence at that time, DP programming does not require a full drive cycle. In perfect 10 second drive cycle, state of charge is maintained for the initial and final stage of 10 second prediction window for each instance. This is relevant to this research, as we are using 10 second prediction window for getting Optimal energy management. By computing each of these three results, we can understand if a significant portion of the maximum achievable FE is being realized with actual 10-second prediction and we can understand how much FE improvement our actual 10-second prediction realizes compared to the maximum achievable FE for perfect 10-second prediction. For both highway dataset and the urban/highway dataset, these 3 cases are simulated and presented in the separate graph. Each of these three Optimal EMS scenarios is presented next for both the highway dataset and the urban/highway dataset.

Perfect Full Drive Cycle Prediction

Perfect full drive cycle prediction implemented with an Optimal EMS provides the maximum possible FE improvement which is an important data point. This scenario was computed for both the highway dataset and the urban/highway dataset. An example drive cycle from each dataset is shown in Figure 14 and 15, respectively. The average FE improvement across all drive cycles in the highway dataset was 1.9%, and the average FE across all drive cycles in the urban/highway dataset was 3.8%.

When comparing the engine power from the Baseline EMS and the Optimal EMS in Figure 14, there are few points where the Optimal EMS has turned off the engine and operated the engine at a lower overall power resulting in the FE improvement. When comparing the engine power from the Baseline EMS and the Optimal EMS in Figure 15, the
Optimal EMS turns the engine on more frequently and also achieves lower overall engine power resulting in a FE increase.

**Perfect 10-Second Prediction**

We investigated the FE improvement from perfect 10-second prediction. This is an important data point because it reveals how much of the maximum possible FE improvement we can get using a 10-second prediction window. Example drive cycles from each dataset are shown in Figure 16 and Figure 17 respectively. The average FE improvement across all drive cycles in the highway dataset was 1.3%, and the average FE across all drive cycles in the urban/highway dataset was 2.7%.

When comparing the engine power from the Baseline EMS and the Optimal EMS in Figure 16, the Optimal EMS tends to operate the engine at lower power and a more consistent power resulting in the FE savings. When comparing the engine power from the Baseline EMS and the Optimal EMS in Figure 17, the Optimal EMS yields similar lower engine power behavior resulting in a FE increase.

**Actual 10-Second Prediction**

Lastly, we can investigate the Optimal EMS using actual 10-second prediction. Ideally, the FE result for this case will be very close to perfect 10-second prediction. Example drive cycles from each dataset are shown in Figure 18 and Figure 19, respectively. The average FE improvement for the one highway drive cycle was 1.1%, and the average FE across all drive cycles in the urban/highway dataset was 2.1%.

When comparing the engine power from the Baseline EMS and the Optimal EMS in Figure 18, there are similar trends from the perfect 10-second prediction case. The Optimal EMS tends to operate the engine at lower power and a more consistent power resulting in the FE savings. When comparing the engine power from the Baseline EMS and the Optimal EMS in Figure 19, there is again a similar trend to perfect 10-second prediction in that the Optimal EMS yields lower engine power behavior resulting in a FE increase.

It is also worthwhile to compare perfect 10-second prediction to actual 10-second prediction directly. This is shown in Figure 20 and Figure 21. Note that in both cases the engine power results are very similar indicating that the prediction fidelity achieved in this research works well for an Optimal EMS application.
Optimal Energy Management Strategy Fuel Economy Summary

Overall, the FE results shown in Table 1 line up with what one expects. The perfect full drive cycle prediction case has the largest FE improvement, followed by perfect 10-second prediction, and then actual 10-second prediction. But, what is significant is that the 10-second prediction provides a large chunk of the maximum possible FE improvement, and the actual prediction model provides most of the FE improvement from perfect 10-second prediction. These results are very encouraging and imply that the level of vehicle speed prediction fidelity achieved is useful for Optimal EMS applications.

Conclusions

In this study, we have simulated an Optimal EMS implementation in a 2017 Toyota Prius Prime for real world urban/highway and highway drive cycles. The urban/highway and a highway drive cycles were driven while GPS, current vehicle velocity, and radar data were collected. This data was used as an input for the perception subsystem which is modeled as an LSTM deep neural network. This perception model outputs a prediction of the velocity for the next 10 seconds as described in part one of this research [28]. The velocity prediction output of the LSTM is given to the planning model where we have used DP to derive the Optimal EMS. The Optimal EMS is then implemented in the vehicle plant subsystem which is a simulated 2017 Toyota Prius Prime. The output of the vehicle subsystem model is fuel consumption, achieved engine power, and battery SOC. This is compared with the Baseline EMS
which represents validated current operation of the 2017 Toyota Prius Prime. Using an LSTM deep NN to make 10 second predictions facilitated a 1.1% average FE improvement over highway driving and a 2.1% average FE improvement over urban/highway driving.

This study demonstrates that a significant FE improvement can be achieved in modern vehicles with an intelligent transportation system. In future work, we seek to develop additional rigorous tests of the FE improvement potential and possibly include other vehicle architectures, control strategies, different initial conditions such as SOC and physical vehicle implementation techniques. Also, the prediction method could be extended to allow optimization of blended energy management of the battery over the whole mission of the plug-in hybrid electric vehicle.

References

Definitions/Abbreviations

ANN - Artificial Neural Network  
ARMA - Auto-Regressive Moving Average  
CAN - Controller Area Network  
CDCS - Charge depletion-charge sustenance  
CLG - Conditional Linear Gaussian  
DP - Dynamic Programming  
ECMS - Equivalent Consumption Minimization Strategy  
EMS - Energy Management Strategy  
EPA - Environmental Protection Agency  
FE - Fuel economy  
GPS - Global Positioning System  
HEV - Hybrid Electric Vehicle  
HWY - Highway Fuel Economy Test  
MC - Markov Chain  
NARX - Nonlinear Auto-Regressive with eXternal input  
NN - Neural Network  
PHEV - Plug-In Hybrid Electric Vehicle  
SOC - State of Charge  
UDDS - Urban Dynamometer Driving Schedule  
V2V - Vehicle to Vehicle  
V2I - Vehicle to Infrastructure

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