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# V2V Communication Based Real-World Velocity Predictions for Improved HEV Fuel Economy

**David Baker, Zachary D. Asher, and Thomas Bradley** Colorado State University

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## Abstract

Studies have shown that obtaining and utilizing information about the future state of vehicles can improve vehicle fuel economy (FE). However, there has been a lack of research into whether near-term technologies can be utilized to improve FE and the impact of real-world prediction error on potential FE improvements. In this study, a speed prediction method utilizing simulated vehicle-to-vehicle (V2V) communication with real-world driving data and a drive cycle database was developed to understand if incorporating near-term technologies could be utilized in a predictive energy management strategy to improve vehicle FE.

This speed prediction method informs a predictive powertrain controller to determine the optimal engine operation for various prediction durations. The optimal engine operation is input into a validated high-fidelity fuel economy model of a Toyota Prius. A tradeoff analysis between prediction duration and prediction fidelity was completed to determine what duration of prediction resulted in the largest FE improvement.

This study concludes that speed prediction and prediction-informed optimal vehicle energy management can produce FE improvements with real-world prediction error and drive cycle variability. This Optimal Energy Management Strategy (EMS) achieved up to a 6% FE improvement over the Baseline EMS and up to 85% of the FE benefit of perfect speed prediction. Additionally, the results from this prediction method are compared to the results of a previous study that incorporates only local vehicle information in speed predictions.

## Introduction

Climate change is well understood and acknowledged in the scientific community [1, 2]. The burning of fossil fuels is accepted as one of the largest contributors to climate change and poor air quality [3, 4, 5]. The United States Environmental Protection Agency (EPA) and National Highway Traffic Safety Administration (NHTSA) have implemented Corporate Average Fuel Economy (CAFE) standards that automakers are required to meet. The current standards state that by 2025, the minimum standard for domestically manufactured passenger cars, which burn fossil fuels, will be 51.3 MPG [6]. These standards allow automakers freedom to determine which technologies they utilize to reach the required fuel economy and GHG emissions standards. Many studies have concluded that hybrid electric vehicles (HEV) and plug-in hybrid electric vehicles (PHEV) are the best means to improving near-term sustainability and vehicle FE [7, 8, 9]. The FE of hybrid vehicles is strongly influenced by their energy management strategies [10]. To achieve an Optimal EMS, it is necessary for vehicles to shift from the current, reactive EMS, towards a predictive EMS that can take into account the power needs of the vehicle in the future [11].

### Integration of Advanced Technologies

The continuous, incremental integration of advanced driver assistance systems (ADAS) and intelligent transportation systems (ITS) is making it possible to shift towards a predictive EMS, and higher FE. There are two main considerations for using ADAS and ITS for an Optimal EMS: 1) obtaining future information, and 2) utilizing that information to achieve optimal (or near optimal) energy management. Relevant future information includes things such as future vehicle speed, road grade, road speed limits, traffic signals, traffic flow and density. Some of the technologies that are either currently available, or are expected to be available in the near future, include GPS location, geographic information system (GIS) information, vehicle-to-vehicle communication and vehicle-to-infrastructure (V2I) communication. GPS information is currently available on most cars today, GIS information is not readily on cars today, but the information is available on off-vehicle networks. V2V and V2I communication is not commercially available. V2V communication will be commercially available near-term, although it will still be years before the majority of vehicles on the road are V2V capable. Toyota released vehicles in 2015 [12] with V2V capabilities and the National Highway Traffic Safety Administration has proposed a mandate that all light duty vehicles have V2V capability by 2019 [13].

Many researchers are investigating ways to utilize information obtained by V2V to make vehicle speed predictions. However, they are assuming that V2V and V2I are both mature and provide detailed vehicle information [14, 15, 16].

## Prediction Error Simulation

Vehicle speeds are transient, random, and are dependent on many factors such as traffic, road type, weather, driver style, etc. [26]. Thus, vehicle speed predictions are bound to have random and bias errors. There is a range of different procedures for dealing with these errors when investigating speed predictions. Many acknowledge that the predictions will be erroneous and different magnitudes of stochastic error are added into their predictions because error quantification is out of their scope of study [15, 17, 18]. A more realistic way of handling prediction errors is to use real-world data to derive the speed predictions, which inherently includes realistic errors of both driving-derived and random types [19, 20, 21].

## Optimization of EMS

Dynamic programming (DP) as a means of deriving the optimal control for a given state space is well understood [22] and its application to the an HEV Optimal EMS is well documented in literature articles [23, 24, 25, 26, 27] and textbooks [28], [29]. The drawback of DP is that it is computationally costly and thus difficult to implement in real time HEV energy management [30] and because of this, research has moved towards more implementable versions of this theory such as stochastic dynamic programming [31, 32, 33, 34, 35] and model predictive control [36, 37, 38, 39]. Because of the difficulties of real world implementation of DP researchers now mainly use it as a convenient measure of the globally optimal results [21].

## Novel Aspects of this Study

This study takes a data-driven and systems-level approach to understanding the impact of real-world prediction error on vehicle fuel economy. The speed prediction method developed in this study focuses on utilizing current and near-term technology (V2V) communication. This method incorporates real-world driving data, thus prediction errors are representative of real-world prediction errors. Instead of using only standard RMSE (Root Mean Square Error) quantifications of prediction accuracy, a system level metric of accuracy (FE) is used.

Through this study, it is intended to understand and quantify the impact of real-world prediction error on potential FE improvements, as well understand if current and near-term technology can be incrementally implemented to transition from reactive to predictive energy management. This paper expands on the concepts from previous research [40].

# Methods

Prediction-based Optimal EMS aims to maximize FE by predicting the vehicle speed for an upcoming segment of time and optimizing engine control for that prediction horizon. This prediction method utilizes limited V2V communication and previously recorded driving data to predict future vehicle velocities. To investigate the tradeoff between prediction horizon and prediction error, a range of prediction horizons is evaluated for their effect on vehicle FE.

The goal of this study is to compare the predictive EMS vehicle FE for differing prediction horizons, to a Baseline EMS with no speed prediction, and to an idealized case with perfect speed prediction. These comparisons will allow for a better understanding of the impact of real-world prediction errors on potential FE benefits.

## Baseline Vehicle Fuel Economy Modeling

The Baseline EMS and vehicle plant model operate on an equation-based algorithm. The vehicle plant and Baseline EMS are a high fidelity FE model of a generation three Toyota Prius, previously developed in our research group [41]. A model of a driver receives the velocity trace (velocity vs. time) and outputs a wheel torque request, i.e. the torque that is required at the wheels to propel the vehicle at the desired velocity. The running controller model (sometimes referred to as a hybrid supervisory controller) obtains the wheel torque request from the driver model. Based on the current vehicle states and the desired wheel torque request, the running controller model determines what the engine, motor and generator torques and speeds should be. The running controller model passes these requests to the vehicle plant model, which simulates the physical components of the vehicle. The vehicle plant model then outputs - among other things - the vehicle speed, Energy Storage System State of Charge (ESS SOC), and fuel consumption. Figure 1 depicts the information flow through the FE model.

To ensure this model is a valid representation of a generation three Toyota Prius, simulations of three EPA drive cycles are developed. The FE results of these simulations are compared to actual driving data on these drive cycles for a 2010 Toyota Prius [42]. Table 1 demonstrates this comparison. Based on the similarities to real-world FE, the model is considered validated for predicting FE of a real-world Toyota Prius.

## Drive Cycle Development

Existing EPA standard drive cycles aim to capture a mixture of generic stop-and-go and constant velocity driving. In order to capture a similar mix, through a shortened drive cycle, a custom cycle in Fort Collins, Colorado is developed. A shorter drive cycle is desired because the route needs to be driven multiple times. The route was developed in a previous study [41]. It is used again in this study so the two prediction methods can be compared. Vehicle speed and GPS location

**FIGURE 1** Information flow through reactive Baseline EMS FE model

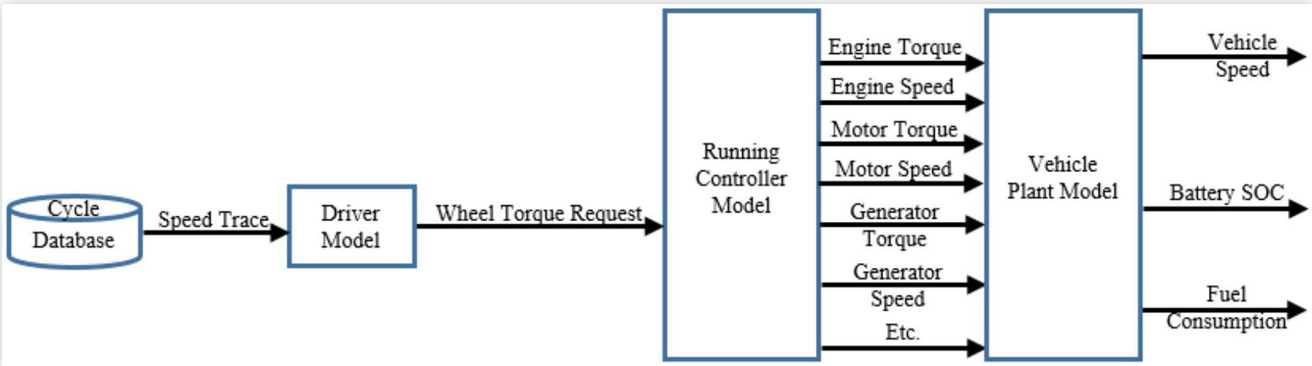





**TABLE 1** Comparison of baseline model and experimental FE

| | UDDS | HWFET | US06 |
|---|---|---|---|
| Experimental | 69.6 mpg | 67.3 mpg | 43.5 mpg |
| Simulation | 71.8 mpg | 67.9 mpg | 44.0 mpg |
| Percent Difference | 3.2% | 0.9% | 1.0% |



are recorded from the Controller Area Network (CAN) bus during each trip along the route. An example of the speed trace is shown in Figure 2.

To collect data for vehicle velocity predictions and FE simulations, this drive cycle is driven 11 times, on different days and at different times of day to capture as much variation as possible. A Baseline EMS was developed to compare to a speed prediction Optimal EMS using simulations of the custom drive cycles. These simulations provide an important baseline comparison for the optimized FE results.

Data from three drive cycles were utilized for FE simulations in this study. One drive cycle was recorded during relatively low traffic, mid-morning on a weekday in Fort Collins, CO (referred to as Cycle 1). The other two were recorded at times with high traffic in Fort Collins, CO, during the evening weekday rush hour (referred to as Cycles 2 and 3). All three cycles were during normal weather conditions, as all of the training data was also recorded during normal weather conditions. Investigating the effects of adverse weather is out of the scope of this study.

## V2V Communication Simulation

In order to make vehicle speed predictions based on V2V communication using real-world data, a method of simulating V2V communication while obtaining driving data is necessary. To simulate this, the drive cycle was driven with two vehicles closely following each other. The vehicle in front will be considered the "lead vehicle" and the second vehicle will be considered the "ego vehicle" which is consistent terminology from other prediction studies [43, 44, 45]. Speed predictions will be made for the ego vehicle. Each was equipped with data logging equipment; vehicle speed and GPS location information was recorded for both. From these two sets of recorded data, a common GPS location was used to set an adjusted start time and from this, the spatial and temporal relationship of these two datasets is extracted. Figure 3 is an overlay of the two velocity traces for one of the drive cycles investigated after the start time adjustment.

The adjusted speed traces are used to simulate V2V communication between the two vehicles. In this study, we assume the lead vehicle communicates its vehicle velocity and GPS location information to the ego vehicle. This experimental setup allows for different amounts of information exchange to be explored. However, this was not in the scope of this study. It is assumed the ego vehicle obtains information from the lead vehicle that is 5 seconds in the future from the ego vehicle's current state.

Discussion on the assumption of being able to obtain information from a vehicle that is 5 seconds ahead is as follows.

**FIGURE 2** Example speed trace from custom drive cycle in Fort Colins, CO

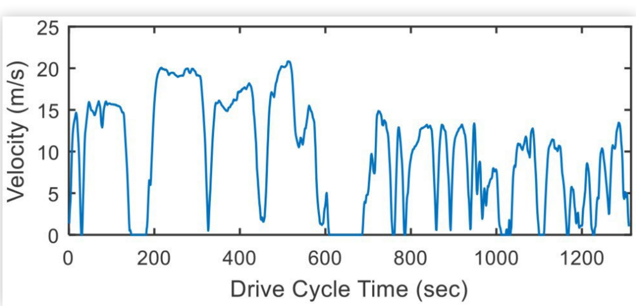
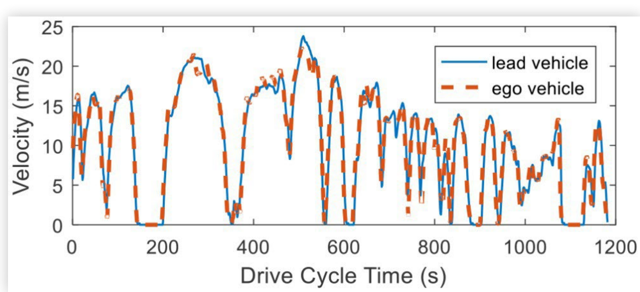





**FIGURE 3** Ego and lead vehicle speed trace overlay with time synchronization for simulated V2V communication



Digital Short Range Communication (DSRC) is accepted as the form of initial V2V communication. Some model-year 2017 vehicles are equipped with DSRC in America [46] and Toyota already released some vehicles in Japan with DSRC capabilities [12]. The NHTSA has proposed a mandate that all light duty vehicles have V2V capability by 2019, with all new vehicles having it by 2023. Information that is proposed to be broadcasted are things such as location, speed, braking, etc. [13]. Thus, this study aims to simulate DSRC-type communication. DSRC has a range of 200-300m. Under the assumption that vehicles will be traveling at a maximum speed of 35 m/s (~75 mph), and that 200m is a reliable range for DSRC, then even when traveling at this maximum speed, a vehicle 200m away will be about 5.8 seconds away. Thus, vehicles more than 5 seconds ahead of the ego vehicle will be able to communicate with it through DSRC.

There are other assumptions that are important to note about this method of simulating V2V communication. The study of simulating and investigating the impacts of communication errors (poor signal, invalid data, etc.) is out of the scope of this study, so it is assumed the information communicated is accurate. Additionally, this study assumes that there is always a vehicle broadcasting its velocity and location 5 seconds ahead of the ego vehicle.

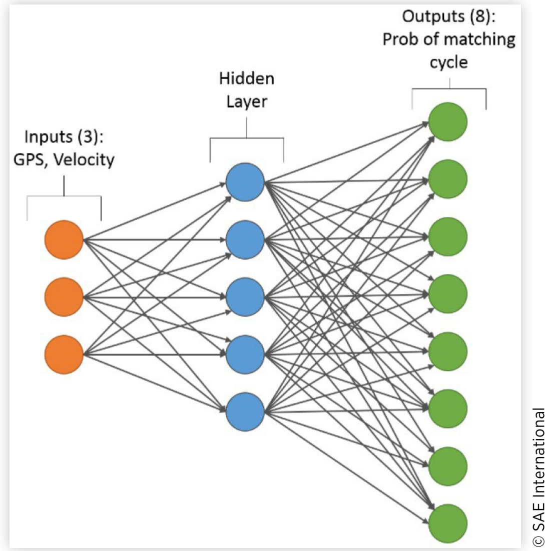
## V2V Vehicle Velocity Predictions

The ego vehicle utilizes the obtained information to make vehicle speed predictions. Many researchers have investigated making speed predictions based on V2V communication alone, but this research combines limited information communicated via V2V with previously recorded driving data. The general process of this speed prediction method is to obtain future information from the lead vehicle, use this velocity and location information to identify which previous driving route is most similar to the current driving route, and, finally, use the most similar route to predict future vehicle velocities. This method can predict further ahead than the 5 seconds of information obtained from the lead vehicle. However, again, this relies on the assumption that the route has been driven before by the ego vehicle.

A two-layer feedforward NN is used to classify which drive cycle from the database of previously recorded drive cycles is most similar to the one that is currently being driven. The inputs to this NN are the lead vehicle's broadcasted velocity, longitude and latitude information. The output is which drive cycle from the database of cycles is most similar to the inputs and there is one hidden layer. The output of the NN is not an actual speed prediction, just the drive cycle that is the most similar to current driving conditions. Figure 4 depicts the structure of the pattern recognition NN used in this research. It should be noted that only five neurons are depicted in the hidden layer of Figure 4 for clarity.

Data from eight recorded drive cycles are used to train, test and validate the pattern recognition NN. The pattern recognition NN has one hidden layer and is trained using scaled conjugate gradient backpropagation. This training method uses backpropagation to calculate the derivatives of the performance function with respect to weights and biases.

**FIGURE 4** Structure of pattern recognition NN used to classify most similar drive cycle from lead vehicle information




These derivatives are used to update the weights and biases of the NN [47]. Performance of the pattern recognition NN is calculated by the cross-entropy method. This is used over a more general error calculation such as mean square error because it has a high penalty for extremely inaccurate outputs and low penalties for close to correct outputs [48]. This behavior is standard with pattern recognition algorithms.

The number of neurons in the hidden layer affects how well the NN can model the desired behavior. To determine the optimal number of neurons for this application, a range of different numbers of neurons in the hidden layer from 2 to 30 were explored. For each, a new NN is created and trained via the method described above. Since the NN's training process stochastic in nature, each time a NN is trained it will result in slightly different weights and biases, thus potentially affecting performance. To account for this, 10 NNs with the same number of neurons in the hidden layer were trained and the performance was averaged. However, there was essentially no cross-entropy performance difference between 5 and 20 neurons in the hidden layer from the training routine. Thus, we 10 hidden layer neurons was selected to be used.

As described above, the output of the NN is simply the drive cycle from the database that is the most similar to the information obtained from the lead vehicle. This drive cycle is referred to as the most similar cycle and is used to make velocity predictions. To make a velocity prediction, the location information from the lead vehicle is related to the corresponding location of the most similar cycle. From this, the most similar cycle is used to predict velocity for the prediction horizon.

## V2V Vehicle Velocity Prediction Refinements

There were multiple refinements made to the original velocity prediction method. The first refinement was to incorporate a "low speed shutoff" for the prediction. The need for this was driven by the fact that since the speed prediction was merely the most similar drive cycle, there were times when the ego vehicle stopped in locations that were not captured in the drive cycle database (i.e. stoplights). This caused the speed prediction to be non-zero when the ego vehicle was stationary. To correct for this, once the lead vehicle reached a minimum threshold velocity, the speed prediction was changed to be zero until the lead vehicle accelerated past the velocity threshold an example of this is shown in Figure 5.

The second refinement incorporated V2V communicated velocity information into the velocity prediction, rather than solely the most similar cycle. This is desirable because it incorporates information from the lead vehicle as part of the prediction. However, this can lead to a discontinuity in the velocity prediction when switching from the V2V velocity to the most similar cycle information. To correct for this discontinuity, an offset to the most similar cycle portion is applied. This offset is calculated by taking the difference between the last V2V velocity point and the corresponding velocity from the most similar cycle. This shifts the most similar cycle portion of the prediction to the lead vehicle velocity while still allowing for the same trend (acceleration/deceleration) from the most similar cycle to remain. Instances where this offset could be helpful could be during bad weather or traffic causing the flow of traffic to be generally lower, or an occasion where traffic is lighter than usual so the flow of traffic is higher. An example of this method reducing error in the prediction is displayed in Figure 6 (a). Figure 6 (b) displays that the offset does not significantly affect when the prediction is close to the driving conditions. It is ensured that prediction of negative velocities does not occur because of this offset.

To evaluate the effectiveness of these refinements, a design of experiments (DOE) was developed. For each of the three drive cycles investigated, every combination of the low speed shutoff on/off, incorporating lead vehicle information as prediction on/off were investigated. For each combination, a velocity prediction was produced at each second along the drive cycle and the RMSE was calculated for the prediction horizon. Thus, there was a RMSE produced every second. The mean and variance of the RMSEs over the entire drive cycle was calculated as the metrics of accuracy for this DOE. Since training methods of NNs are stochastic, this entire process was completed 3 times. It was observed that incorporating the lead vehicle velocity with the offset to the most similar cycle was superior to using only the most similar cycle.

**FIGURE 5** Example of low speed shutoff making better prediction when most similar drive trace did not come to complete stop.

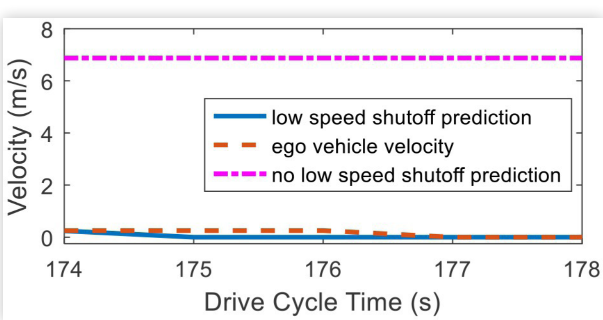
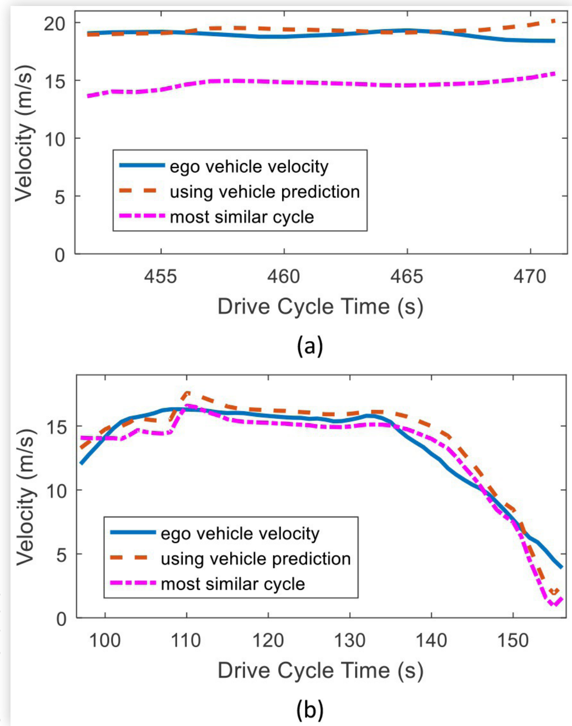





**FIGURE 6** Example of where incorporating V2V information and offset into prediction improves prediction fidelity (a). In (b) the offset does not significantly affect prediction when most similar cycle is not erroneous.



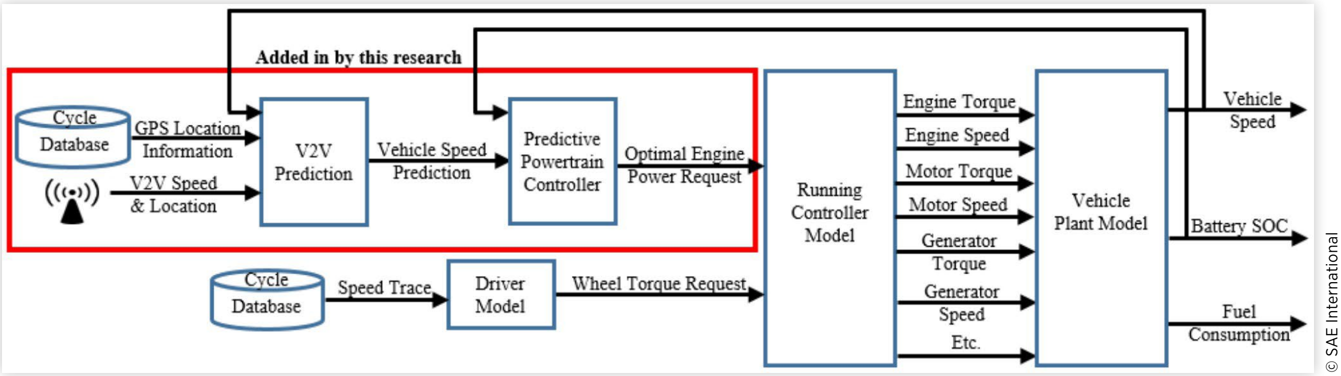



The results of this DOE demonstrate that predictions without the low speed shutoff were more accurate. Two driving factors cause this. First, predicting velocities of zero for the long prediction horizons is not realistic, as it is not often that a vehicle remains idle for up to 90 seconds (one of the longer prediction horizons). Second, the velocity offset when transitioning from the lead vehicle velocity prediction to the most similar cycle, corrects for the instances when the lead (and hence ego) vehicle is stopping but the most similar cycle does not stop. This offset still allows the acceleration phase to be predicted, resulting in predictions that are more accurate.

# Development of Predictive Powertrain Controller

A predictive engine controller that was developed in previous research at Colorado State University [21] is leveraged as a foundation in this research to determine optimal engine control based on predicted vehicle speeds. The controller uses DP to evaluate all possible states and determine the optimal engine power for each state. The states are the ESS SOC and the time over the prediction horizon. The input of the DP algorithm is the speed trace and the output is a table of optimal engine power for all combinations of SOC and time steps. The optimal engine power is found by minimizing the fuel consumed over the prediction horizon. One important constraint of the algorithm is that the SOC at the end of the speed trace is set to be a constant (50%), to simulate a charge-sustaining situation.

**FIGURE 7** Information flow through FE model, including the V2V prediction method and predictive powertrain controller




## Implementation of Prediction and Predictive Powertrain Controller into FE Model

To evaluate the benefit of predicting future vehicle speeds, the prediction and predictive powertrain controller are implemented into the running controller of the FE model so that speed predictions and engine control can be developed as the simulated vehicle is driving. The Baseline EMS in the model is adapted to have the capability to use the pattern recognition NN to make speed predictions of the upcoming vehicle speed using previous vehicle speed and GPS location. The predicted speed is then input into the predictive powertrain controller to calculate the optimal engine power for each SOC and time for the upcoming prediction horizon.

This routine is repeated at 1 Hz to ensure that the maximum realizable FE is achieved. Repeating this routine at 1 Hz ensures vehicle information is as up to date as possible and this routine is utilized for the idealized cases of perfect speed predictions. It should be noted that this does not diminish the benefits of having a longer prediction horizon as the DP algorithm in the predictive powertrain controller is run over the entire prediction horizon at each time step. Figure 7 shows the flow of information between the V2V prediction algorithm, the predictive powertrain controller, the modified running controller and the vehicle plant model. This can be compared to the Baseline EMS in Figure 1.

In addition to this prediction based FE model, idealized cases are explored. Simulations where the speed prediction algorithm is removed and instead the actual speed trace is used as an input to the predictive powertrain controller are developed for the same array of prediction horizons. These represent cases in which perfect speed predictions could be made.

## Results and Discussion

We seek to develop a simulation-based quantification of the FE benefit as a function of prediction horizon. This will provide insight into the tradeoff between increasing prediction horizons and prediction fidelity. This tradeoff can only be understood via a systems level analysis by incorporating the predictive powertrain controller and FE model.

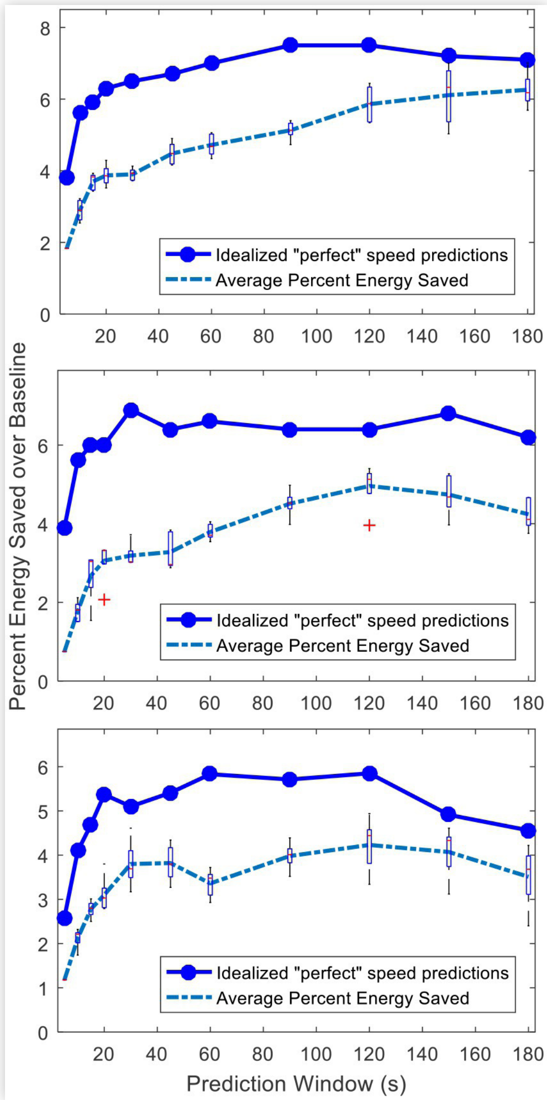
## FE Benefit of Different Prediction Horizons

Simulations for each prediction horizon studied (5, 10, 15, 20, 30, 45, 60, 90, 120, 150, and 180 seconds) are developed and compared to the Baseline EMS simulation, as well as the idealized case where perfect predictions over the same prediction horizon are possible. These comparisons provide two insights: first, the comparison to the Baseline EMS provides insight if prediction method and predictive powertrain controller are robust to real-world prediction errors. Second, by comparing to the idealized case we seek to understand how effective current and near-term technologies are in making vehicle velocity predictions.

After each simulation, the final ESS SOC, fuel consumption and distance traveled are extracted. The SAEJ1711 Jun. 2010 Recommended Practice for Measuring the Exhaust Emissions and Fuel Economy of Hybrid-Electric Vehicles, Including Plug-in Hybrid Vehicles is used to calculate the Charge-Sustaining (CS) miles per gallon equivalent (MPGe). Since NN training is stochastic, each prediction horizon is simulated five times to capture the variation that is incorporated with training differences. Additionally, with a short drive cycle such as this, variations in the ending SOC have a noticeable effect on CS MPGe. By running multiple simulations, these variance effects can be explored.

Figure 8 captures the variance in each prediction horizon by incorporating box plots for percent energy increased over the Baseline EMS simulation. These also show the perfect prediction scenario as well. This represents a ceiling for the percent energy that could be saved over the Baseline EMS for this drive cycle. Note that there are instances where an increased prediction horizon results in a worse FE for the perfect prediction (and, often, similarly for the V2V prediction simulations as well). At the end of the drive cycle, prediction is stopped one prediction horizon length from the end of the cycle and the Baseline EMS is used for the rest of the cycle. Thus, predictions are ended at different times along the drive cycle. Ending predictions at the same time for all prediction horizons was considered, however prediction horizons up to

**FIGURE 8** Box plot of percent energy (total vehicle energy) saved over the Baseline EMS, and comparison to perfect prediction simulations for Cycles 1-3

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180 seconds were investigated and on an eight-mile drive cycle, the 180-second prediction window is a significant portion of the cycle and it would limit the amount of FE benefit shorter prediction horizons could achieve. Instead, the perfect prediction simulations are stopped at the same time as the corresponding V2V predictions, so that an even comparison is drawn.

Up to about 6% CS MPGe improvement over the Baseline EMS is achieved and up to about 85% of the potential FE benefit that could be derived with perfect prediction can be achieved by this speed prediction method. It should be noted that this research differs from predicting the entire drive cycle and optimizing the SOC trace over the full cycle. This research focuses on short-term predictions that are realizable with current technology.

Additionally, few trends can be extracted from this study. First, only utilizing information from the lead vehicle (the 5-second prediction horizon) does result in increased FE, but only marginally. Incorporating only that information is not fruitful, a prediction method is also necessary to achieve significant FE improvements. Second, as the prediction horizon increases, so does the FE benefit. The point where FE benefit begins to decrease for long prediction horizons are where the benefit from gaining more future information is offset by the prediction being too erroneous. This tipping point was seen to be at 120-second prediction horizon for cycle 2 and 3. For cycle 1, the FE continued to increase for each prediction horizons investigated. There are a few possibilities for this. Cycle 1 was the cycle that was driven in non-rush hour traffic, whereas cycles 2 and 3 were in driven in rush hour traffic. Also, the prediction method is completed by identifying the most similar cycle from a database of previously recorded drive cycles. If the database contains more cycles that are more similar to lower traffic periods, that could cause Cycle 1 to increase FE more in comparison to Cycles 2 and 3.

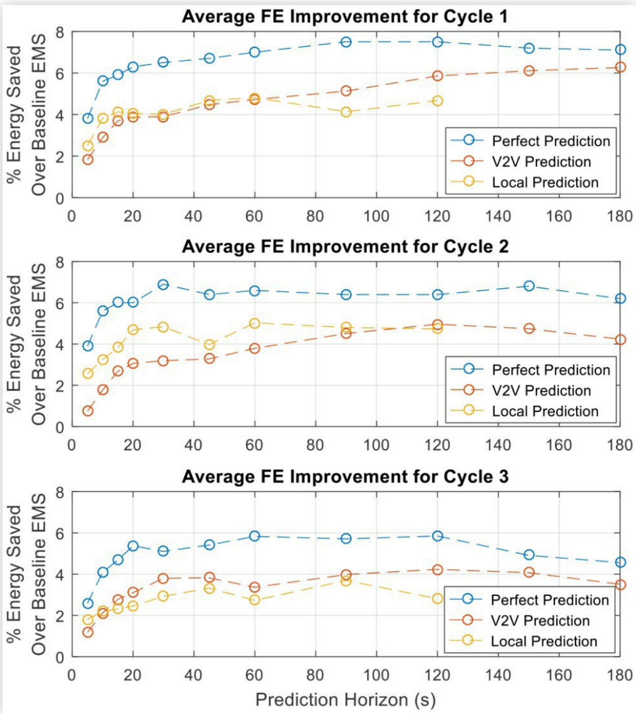
## Comparison of Prediction Methods

The vehicle velocity prediction method developed in this study - which utilizes limited V2V communication information and incorporates that with local, previously recorded driving data - is compared to another velocity prediction method developed in previous research. The other method utilizes only local, previously recorded driving data to make future velocity predictions [41]. The FE benefit over the Baseline EMS for both prediction methods over the same cycles is compared. Additionally, the first 5 seconds of both prediction methods is explored further to provide insight into differences between information obtained locally and from other vehicles.

**Prediction Method FE Comparison** To gain a better understanding of the costs and benefits between these two prediction methods, a systems level analysis is completed. By evaluating the prediction methods through the metric of FE, we can determine which prediction method is superior. Figure 9 illustrates the average FE benefit over the Baseline EMS for each of the three cycles investigated. In general, the local prediction is more accurate at shorter prediction horizons, although, those do not gain as much FE as longer prediction horizons do. It should be noted that for the 5-second prediction horizon, the local prediction actually performed better than the V2V prediction in all three cycles. This indicates that the local prediction method produces more accurate predictions than the lead vehicle's velocity.

For longer prediction horizons, the V2V method consistently realized a higher FE improvement over Baseline EMS than the local prediction method. This indicates that choosing one drive cycle as the prediction is, overall, more accurate than the prediction produced by the NARX NN. It should be noted that the local prediction method had issues with not achieving a charge-sustaining state. Additionally, for long prediction horizons (greater than 120 seconds) the local prediction would sometimes produce predictions that were so erroneous that the predictive powertrain controller could not find a solution. Thus, simulations greater than 120-second prediction horizons were not completed for the local prediction method.

**FIGURE 9** Comparison between local and V2V prediction methods of average FE improvement over Baseline EMS for Cycles 1-3



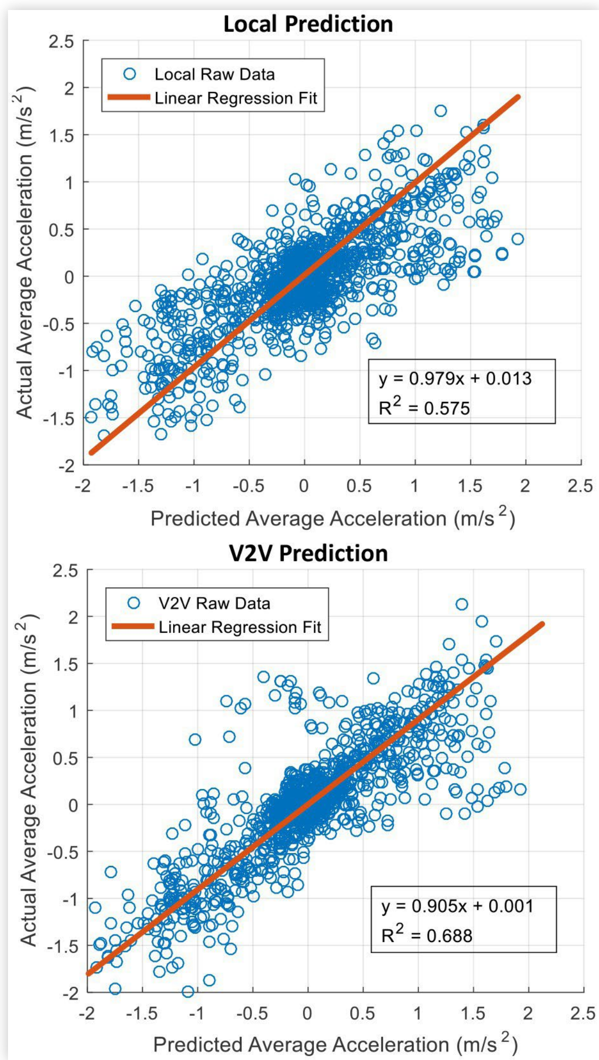



While the local prediction method is limited in its prediction horizon, it is able to achieve significant improvements over the Baseline EMS, and only utilizes technology that is readily available on vehicles today. This suggests that prediction methods such as this can be implemented into today's vehicles to switch from reactive to predictive energy management strategies. Looking into the near future, DSRC V2V communication will become commercially available in the next few years. The V2V prediction method proved to produce predictions that are more accurate for longer horizons, and is only utilizing information that will be communicated over initial V2V communication. This method also has the ability to utilize more information that might be shared between vehicles in the future, such as the lead vehicle broadcasting its own velocity prediction, which could be utilized to further improve both prediction accuracy and achievable prediction horizon lengths.

**5-Second Prediction Horizon Comparison** Figure 9 illustrates that, in all three cases of the 5-second prediction horizon, the local prediction method realized a larger FE benefit than the V2V prediction method. This is particularly interesting because for the V2V prediction method, the 5-second prediction horizon is simply the V2V communicated information. This ascertains that the local prediction method for 5 seconds is actually more accurate than velocity information obtained from a vehicle traveling directly in front of the ego vehicle. We hypothesize that this could be a result of the local prediction method being trained on driving data from the ego vehicle, so the driver's driving characteristics (i.e. accelerations and braking aggressiveness) are learned by the local prediction method. In the V2V method, there is no relation between the drivers in the lead and ego vehicles. To test this hypothesis, a comparison of the predicted and actual vehicle accelerations for both prediction methods is completed. The average acceleration for each 5-second prediction and the corresponding 5 seconds of actual vehicle acceleration were plotted on x and y axes, respectively. This is illustrated in Figure 10.

A linear regression of the raw data provides insight into the relationship between the actual and predicted vehicle accelerations. Figure 10 illustrates that the linear regression slope of the local prediction method is closer to one than the V2V prediction method - 0.979 compared to 0.905. Thus, the predicted accelerations derived from the local prediction method have less bias than those of the V2V method. This explains why the local prediction method produced a higher FE for the five-second prediction horizon. It should be noted that the coefficient of determination ($R^2$) is lower for the local

**FIGURE 10** Comparison of predicted and actual vehicle accelerations for cycle 2 with linear regression. This shows there is less bias in the local prediction method, providing insight into why it realizes a larger FE benefit than the V2V prediction method for the 5-second prediction.



prediction method, indicating there is more variance in the local prediction method. Similar trends is be seen for the other two individual cycles.

## Conclusions

In this study, we developed a method of making vehicle velocity predictions using V2V communication with the purpose of understanding if a shift from reactive to predictive EMS can be implemented with today's technology. The results of this study allow us to conclude that this prediction method - which incorporates V2V communication and a drive cycle database with previously recorded driving data to make velocity predictions - does result in significant FE benefits, even with real-world prediction errors. This demonstrates that a shift to predictive EMS is possible with current (vehicle speed, GPS, etc.) and near-term (V2V) technologies.

There is a competing relationship between prediction horizon length and prediction fidelity. The prediction horizon that best balanced these opposing forces for this drive cycle was 120-second prediction horizon, which resulted in up to a 6% MPGe increase over the Baseline EMS. This study also sought to understand if FE improvements gains could still be achieved in the presence of real-world variability (traffic, prediction error, NN training, etc.). All prediction horizons for each of the three individual cycles produced FE improvements over the Baseline EMS. This allows us to conclude prediction and Optimal EMS are, indeed, robust to real-world prediction errors and drive cycle variability.

This prediction method developed in this study uses 5 seconds of V2V communicated information to make a velocity prediction. However, that 5 seconds of V2V communicated information was compared to a prediction method that uses only local vehicle information to make a 5-second prediction. It was determined that the local prediction method produces predictions that are more similar to the actual driving data. This suggests that information that can be obtained locally can be utilized to produce short-term predictions that are more accurate than what information will be exchanged during initial iterations of V2V communication.

## Future Work

Several aspects of this study warrant further research to understand fully the impact of velocity predictions for FE improvement. Investigating different drive cycle lengths would allow for an understanding of the impact of drive cycle length on FE improvement potential. Additionally, investigation into the sensitivity of prediction fidelity to the number of cycles in the drive cycle database and the driving conditions captured in the training dataset could provide valuable insight into how many training cycles are needed to produce predictions with high enough fidelity to provide FE improvement. Also, it would be intriguing to modify the V2V prediction method by replacing the 5 seconds of V2V information with a locally predicted 5 second prediction to see if it would produce a larger FE improvement than the V2V method.

## References


[1]. Cook, J., Nuccitelli, D., Skuce, A., Jacobs, P. et al., "Quantifying the consensus on anthropogenic global warming in the scientific literature," *Energy Policy* 73:706-708, 2014.

[2]. Carlton, J.S., Perry-hill, R., Huber, M., and Prokopy, L.S., "The climate change consensus extends beyond climate scientists," *Environ. Res. Lett.* 10(9):94025, 2015.

[3]. International_Energy_Organization, "CO2 emissions from fuel combustion," 2016.

[4]. U.S. Environmental Protection Agency, "EPA and NHTSA Set Standards to Reduce Greenhouse Gases and Improve Fuel Economy for Model Years 2017-2025 Cars and Light Trucks," no. August 2012, 1-10, 2012.

[5]. J. Rogelj, M. den Elzen, N. Höhne, T. Fransen, H. Fekete, H. Winkler, R. Schaeffer, F. Sha, K. Riahi, and M. Meinshausen, "Paris Agreement climate proposals need a boost to keep warming well below 2 °C," *Nature*, vol. 534, no. 7609, pp. 631-639, 2016.

[6]. U.S. Environmental Protection Agency, "Final Rule for Model Year 2017 and Later Light-Duty Vehicle Greenhouse Gas Emissions and Corporate Average Fuel Economy Standards," 2012.

[7]. Romm, J., "The car and fuel of the future," *Energy Policy* 34(17):2609-2614, 2006.

[8]. Bradley, T.H. and Frank, A.A., "Design, demonstrations and sustainability impact assessments for plug-in hybrid electric vehicles," *Renew. Sustain. Energy Rev.* 13(1):115-128, 2009.

[9]. Hannan, M.A., Azidin, F.A., and Mohamed, A., "Hybrid electric vehicles and their challenges: A review," *Renew. Sustain. Energy Rev.* 29:135-150, 2014.

[10]. Ates, Y., Erdinc, O., Uzunoglu, M., and Vural, B., "Energy management of an FC/UC hybrid vehicular power system using a combined neural network-wavelet transform based strategy," *Int. J. Hydrogen Energy* 35(2):774-783, 2010.

[11]. Asher, Z. D., Wifvat, V., Navarro, A., Samuelsen, S., and Bradley, T. H., "The Importance of HEV Fuel Economy and Two Research Gaps Preventing Real World Implementation of Optimal Energy Management," SAE Techical Paper 2017-26-0106, 2016, doi:10.4271/2017-26-0106.

[12]. IEEE, "First Toyota cars to include V2V and V2I communication by the end of 2015," 2015. [Online]. http://sites.ieee.org/connected-vehicles/2015/09/30/first-toyota-cars-to-include-v2v-and-v2i-communication-by-the-end-of-2015/, accessed 07 Jul. 2017.

[13]. USDOT, "NHTSA Issues Notice of Proposed Rulemaking and Research Report on Vehicle-To-Vehicle Communications," 1-4, 2016.

[14]. Zhang, F., Xi, J., and Langari, R., "Real-Time Energy Management Strategy Based on Velocity Forecasts Using V2V and V2I Communications," *IEEE Trans. Intell. Transp. Syst.*1-15, 2016.

[15]. Zulkefli, M.A.M., Zheng, J., Sun, Z., and Liu, H.X., "Hybrid powertrain optimization with trajectory prediction based on inter-vehicle-communication and vehicle-infrastructure-integration," *Transp. Res. Part C Emerg. Technol.* 45:41-63, 2014.

[16]. Valera, J.J., Heriz, B., Lux, G., Caus, J., and Bader, B., "Driving cycle and road grade on-board predictions for the optimal energy management in EV-PHEVs," . In: *EVS27 International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium*. (2013), 1-10.

[17]. Zulkefli, M.A.M. and Sun, Z., "Real-time Powertrain Optimization Strategy for Connected Hybrid Electrical Vehicle," *ASME 2016 Dynamic Systems and Control Conference*1-10, 2017.

[18]. He, Y., Chowdhury, M., Pisu, P., and Ma, Y., "An energy optimization strategy for power-split drivetrain plug-in hybrid electric vehicles," *Transp. Res. Part C Emerg. Technol.* 22:29-41, 2012.

[19]. Fu, L., Ozguner, U., Tulpule, P., and Marano, V., "Real-time energy management and sensitivity study for hybrid electric vehicles," *American Control Conference (ACC)* 2011:2113-2118, 2011.

[20]. Bender, F.A., Kaszynski, M., and Sawodny, O., "Drive Cycle Prediction and Energy Management Optimization for Hybrid Hydraulic Vehicles," *IEEE Trans. Veh. Technol.* 62(8):3581-3592, 2013.

[21]. Asher, Z.D., Baker, D.A., and Bradley, T.H., "Prediction Error Applied to Hybrid Electric Vehicle Optimal Fuel Economy," *IEEE Trans. Control Syst. Technol.*1-14, 2017.

[22]. Bellman, R., "Dynamic Programming and Lagrange Multipliers," *Proc. Natl. Acad. Sci. U. S. A* 42(10):767-769, 1956.

[23]. Sciarretta, A. and Guzzella, L., "Control of hybrid electric vehicles," *IEEE Control Syst. Mag.* 27(2):60-70, Apr. 2007.

[24]. Sundström, O. and Guzzella, L., "A generic dynamic programming Matlab function," *Proc. IEEE Int. Conf. Control Appl.* (7):1625-1630, 2009.

[25]. Lyshevski, S.E. and Yokomoto, C., "Control of Hybrid Electric Vehicles," *Control*, no. June, 1998.

[26]. Brahma, A., Guezennec, Y., and Rizzoni, G., "Optimal energy management in series hybrid electric vehicles," *Proceedings of the 2000 American Control Conference*. ACC (IEEE Cat. No.00CH36334), 1(6):60-64, 2000.

[27]. Lin, C.-C., Kang, J.-M., Grizzle, J. W., and Peng, H., "Energy management strategy for a parallel hybrid electric truck," *Am. Control Conf. 2001*. Proc. 4(D):2878-2883, 2001.

[28]. Rajamani, R., "Vehicle Dynamics and Control," Second Edition (Springer, 2006).

[29]. B. de Jager, T. van Keulen, and J. Kessels, "*Optimal Control of Hybrid Vehicles*," 2013.

[30]. Zhang, P., Yan, F., and Du, C., "A comprehensive analysis of energy management strategies for hybrid electric vehicles based on bibliometrics," *Renew. Sustain. Energy Rev.* 48:88-104, Aug. 2015.

[31]. Moura, S.J., Fathy, H.K., Callaway, D.S., and Stein, J.L., "A Stochastic Optimal Control Approach for Power Management in Plug-In Hybrid Electric Vehicles," *IEEE Trans. Control Syst. Technol.* 19(3):545-555, May 2011.

[32]. Opila, D.F., Wang, X., McGee, R., Gillespie, R.B. et al., "An energy management controller to optimally trade off fuel economy and drivability for hybrid vehicles," *IEEE Trans. Control Syst. Technol.* 20(6):1490-1505, 2012.

[33]. Wang, Y. and Sun, Z., "SDP-based extremum seeking energy management strategy for a power-split hybrid electric vehicle," *Am. Control Conf.*553-558, 2012.

[34]. Opila, D.F., Wang, X., McGee, R., and Grizzle, J.W., "Real-Time Implementation and Hardware Testing of a Hybrid Vehicle Energy Management Controller Based on Stochastic Dynamic Programming," *J. Dyn. Syst. Meas. Control* 135(March 2013):21002-1-21002-11, 2012.

[35]. Moura, S.J., Stein, J.L., and Fathy, H.K., "Battery-health conscious power management in plug-in hybrid electric vehicles via electrochemical modeling and stochastic control," *IEEE Trans. Control Syst. Technol.* 21(3):679-694, 2013.

[36]. Di Cairano, S., Bernardini, D., Bemporad, A., and Kolmanovsky, I.V., "Stochastic MPC With Learning for Driver-Predictive Vehicle Control and its Application to HEV Energy Management," *IEEE Trans. Control Syst. Technol.* 22(3):1018-1031, May 2014.

[37]. Borhan, H., Vahidi, A., Phillips, A.M., Kuang, M.L. et al., "MPC-based energy management of a power-split hybrid electric vehicle," *IEEE Trans. Control Syst. Technol.* 20(3):593-603, 2012.

[38]. Yan, F., Wang, J., and Huang, K., "Hybrid electric vehicle model predictive control torque-split strategy incorporating engine transient characteristics," *IEEE Trans. Veh. Technol.* 61(6):2458-2467, 2012.

[39]. Poramapojana, P., and Chen, B., "Minimizing HEV fuel consumption using model predictive control," *Proc. 2012 IEEE/ASME 8th IEEE/ASME Int. Conf. Mechatron. Embed. Syst. Appl.*, 148-153, 2012.

[40]. Baker, D., "Development of Predictive Energy Management Strategies for Hybrid Electric Vehicles," (Colorado State University, 2017).

[41]. Baker, D., Asher, Z., and Bradley, T. H., "Investigation of Vehicle Speed Prediction from Neural Network Fit of Real World Driving Data for Improved Engine On/Off Control of the EcoCAR3 Hybrid Camaro," SAE Technical Paper 2017-01-1262, 2017, doi:10.4271/2017-01-1262.

[42]. A. N. Laboratory, "2010 Toyota Prius | Argonne National Laboratory," [Online] www.anl.gov/energy-systems/group/downloadable-dynamometer-database/hybrid-electric-vehicles/2010-toyota-prius.

[43]. Sun, C., Sun, F., and He, H., "Investigating adaptive-ECMS with velocity forecast ability for hybrid electric vehicles," *Appl. Energy* 185:1644-1653, 2017.

[44]. Morton, J., Wheeler, T.A., and Kochenderfer, M.J., "*Analysis of Recurrent Neural Networks for Probabilistic Modeling of Driver Behavior*," (2016), 1-10.

[45]. Jing, J., Kurt, A., Ozatay, E., Michelini, J., Filev, D., and Ozguner, U., "Vehicle Speed Prediction in a Convoy Using V2V Communication," *IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC*, 2015(Octob):2861-2868, 2015.

[46]. "V2V Safety Technology Now Standard on Cadillac CTS Sedans," 2017. [Online], https://www.gm.com/mol/m-2017-mar-0309-v2v.html, accessed: 07 Jul. 2017.

[47]. Møller, M.F., "A scaled conjugate gradient algorithm for fast supervised learning," *Neural Networks* 6(4):525-533, 1993.

[48]. M. H. Beale, M. T. Hagan, and H. B. Demuth, "*Neural Network ToolboxTM Getting Started Guide How to Contact MathWorks*," 2015.

## Contact Information

**Thomas H. Bradley, Ph.D.**
Colorado State University, Fort Collins, CO 80523 USA
Thomas.Bradley@Colostate.edu

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## Abbreviations

**ADAS** - Advanced Driver Assistance Systems

**CAFÉ** - Corporate Average Fuel Economy

**CAN** - Controller Area Network

**CS** - Charge Sustaining

**DOE** - Design of Experiment

**DP** - Dynamic Programming

**DSRC** - Digital Short-Range Communication

**EPA** - Environmental Protection Agency

**EMS** - Energy Management Strategy

**ESS** - Energy Storage System

**FE** - Fuel Economy

**GIS** - Geographical Information System

**GPS** - Global Positioning System

**HEV** - Hybrid Electric Vehicle

**ITS** - Intelligent Transportation Systems

**MPGe** - Miles Per Gallon Equivalent

**NHTSA** - National Highway Traffic Safety Administration

**NN** - Neural Network

**PHEV** - Plug-in Hybrid Electric Vehicle

**RMSE** - Root Mean Square Error

**SOC** - State-of-Charge

**V2I** - Vehicle-to-Infrastructure Communication

**V2V** - Vehicle-to-Vehicle Communication



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