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# Hybrid powertrain control based on the prediction of driver's acceleration intention

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**Summary**

Driver's acceleration intention is one of the most important variables in determining the powertrain operating state such as the target gear step of the transmission and the engine operating mode. The driver's intention acquired through the accelerator pedal and the brake pedal can be changed rapidly in a short period of time and it may interfere with deciding the appropriate powertrain state. This study tried to predict the driver's intention using various information and machine learning algorithms. The prediction model was employed for making proper decision in turning on the engine of the HEV. The study also addressed the method to manage the inaccuracy of the prediction as well as issues in implementing the prediction model on the embedded controller. Actual road test results were also presented to demonstrate the feasibility of the proposed method.

*Keywords: control system, GPS, HEV, intelligent, user behaviour*

## 1 Introduction

HEVs improve Fuel Economy (FE) and meet drivability requirements by shifting internal states of the powertrain corresponding to the driving condition properly. The powertrain states include engine on or off state, target gear of the transmission and target mode of a multi-mode hybrid powertrain configurations. In most cases, switching between the states and the modes requires a certain amount of time and energy. So, it is important to determine the appropriate target state and trigger the transition to the target state by examining all the different variables collected by sensors deployed inside and outside of the vehicle. The driver's acceleration intention is one of the most important variables in determining the powertrain operating state. However, the driver's intention can be changed rapidly in a short period of time and the target state can be evaluated inappropriate when the transition is completed.

There have been studies to improve the FE of HEVs by predicting driving conditions and optimizing the energy management strategy with the predicted information. Some researches tried to predict vehicle operating conditions such as vehicle speed, battery SOC and torque command from environmental knowledge such as traffic conditions, traffic signals, road types and grade [1, 2, 3, 4, 5]. These methods didn't reach on-board implementation due to the difficulty of obtaining and communicating accurate environmental information to the vehicle.

D. Baker suggested a dynamic programming derived engine controller using a nonlinear autoregressive artificial neural network with exogenous inputs [6]. The study also addressed that 30 seconds is the most effective prediction for the Energy Management Strategy (EMS) in its application. There also have been approaches to employ Neural Network (NN) as a part of the intelligent online EMS [7, 8, 9].

This study tries to predict the driver's intention for short time horizon by utilizing heterogeneous information to solve the problem brought by the rapid change of the driver's intention. The data required in the learning process of the prediction model can be acquired through the navigation, telematics and radar systems. The conventional rule based prediction method needs a plenty of time and effort in building a hypothesis of the relation between various data and driver's behaviour, and in validating it with experiments. Hence, a prediction model based on machine learning is developed. This paper also covers the optimization of the prediction model in terms of hardware resource such as memory usage and computation load as well as the issues to improve the accuracy of the prediction. Several different variable selection methods, proper learning models, and parameter tuning are considered to build the effective prediction model.

# 2 Mode shifting control for parallel HEV powertrains

HEVs and PHEVs are equipped with a high voltage battery which enables preserving surplus energy for later use. Therefore, its EMS needs to be optimized by taking account not only instantaneous efficiency of the powertrain but also future driving conditions. All the studies introduced above are based on this perspective. However, there are also transient control problems that cannot be covered by the mid to long range prediction based EMS. Driver's acceleration intention can be changed rapidly in response to different kind of events encountered during real road driving. The rapid change can decrease system operating efficiency by affecting the powertrain transient controls. In this chapter, the subject HEV system is introduced and the requirements for the prediction model are addressed to improve the transient control for the system.

## 2.1 Impact of transient acceleration intention

The degree of impact of the rapid intention change on FE can vary depending on the system configuration and its transient control characteristics. If the system has discontinuous operating states which can be changed in response to the driver's acceleration demand, it could be more sensitive to the transient intention in terms of FE since the state transition requires additional energy consumption. From this perspective, multi-speed transmissions could be exposed to greater impact than continuous variable transmissions since ineffective gear changing can be triggered. As shown in Fig. 1, if the driver's Accelerator Pedal Stroke (APS) value fluctuates greatly and exceeds the predetermined threshold within a short time, the transition from the first mode to the second mode can be triggered. However, before the actual mode transition is completed, the APS value may fall back below the threshold. In this case, the transition process can be considered unnecessary, and it needs to return to the original state, and the energy used in all of the process may degrade overall operating efficiency.

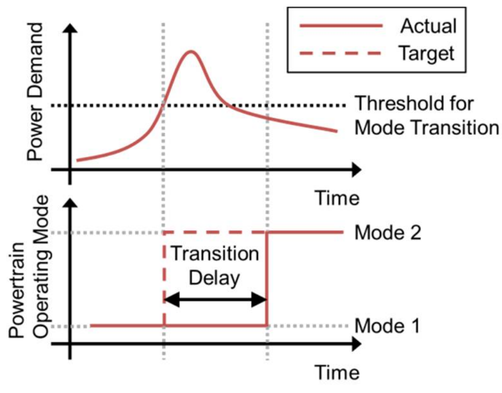


Figure1: Inappropriate mode transition due to rapid change of driver's intention

The problem can be partially mitigated by applying appropriate filtering to the signal processing of the driver's APS and Brake Pedal Stroke (BPS) value, but this may delay the transition to the optimal state in most cases. Fig. 2 presents a parallel hybrid powertrain configuration to improve its control through this study. This system employs an engine clutch to disengage the engine from the driveline to realize the EV mode, and a six-speed transmission to change the speed of the engine and motor. In this system, engine start up and gear shifting from the first gear to the second gear are carried out consecutively in most vehicle launching conditions. These characteristics can be seen in Fig. 3 which presents the engine start up threshold, shifting line and vehicle acceleration demand profile on the speed and torque plane in a typical case. Since these consecutive state changes need to be conducted promptly to achieve the benefits that can be obtained in the appropriate state, any delay in filtering the ineffective state change triggering can distort the optimal operation of the system.

## 2.2 Conventional mode transition strategy

There has been the conventional state transition method which adjusts the efficiency optimal engine start up threshold in positive or negative direction by monitoring driver's input and vehicle behaviour to avoid ineffective engine starting or to increase convergent speed to the optimal engine operating point, respectively. This compensation method consists of two different algorithms as summarized in Fig. 4. The first compensation logic recognizes low speed travel pattern which can be observed in the parking lot or traffic congestion based on the APS and vehicle speed profile and increases the engine start up threshold to be insensitive to transient torque demand to avoid inefficient engine operation. Another compensator observes the gradient of vehicle speed and determines whether the torque demand stays stable within the rapid acceleration range to advance the timing of engine start up by lowering the threshold.

These compensation methods are developed using limited information and they are only applicable to specific driving condition due to the limitation in its developing process. Building the algorithm requires an iterative process that involves setting hypotheses that depend on human experience and intuition, evaluating through vehicle testing, and modifying the hypotheses. And since all of this is done with human effort, it can be difficult to increase the type of input signal or to broaden the scope of application.

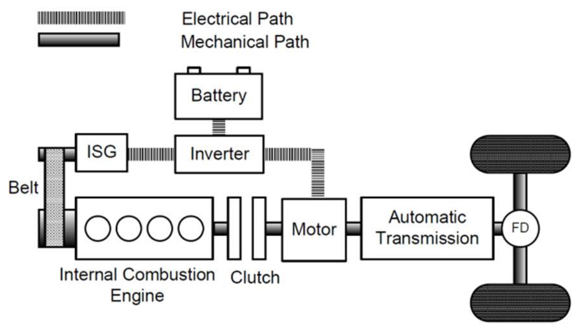


Figure2: Parallel HEV configuration

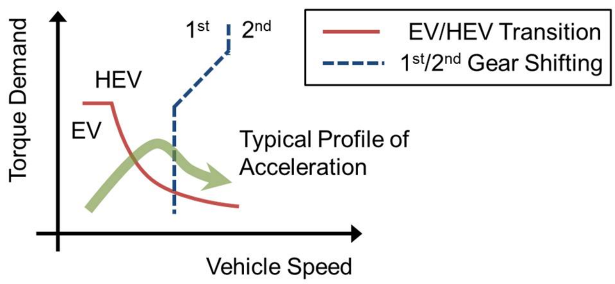


Figure3: Typical acceleration profile which induces consecutive mode changes

## 2.3 Predictive mode transition strategy

Nowadays, the number of sensors and controllers mounted on vehicles for various purposes is continuously increasing. This study utilizes machine learning in order to develop predictive algorithms that can be used more universally by using the information of the sensors and controllers. If a model for predicting the driver's acceleration or deceleration intention is implemented, it is possible to utilize not only the present but also the future driver's intention to decide the engine-on, so that inappropriate engine starting can be reduced or the engine starting can be reacted faster when it is needed.

Considering the time it takes to start the engine, the minimum time to keep the engine running to protect the engine components such as catalyst, and the time it takes to turn the engine off again, the minimum engine run time is about 5 seconds. Therefore, this study tries to avoid ineffective engine on request which is shorter than the minimum engine operation time by predicting driver's near future acceleration intention after 5 seconds. Forecasting further could have potential for additional improvement in terms of energy efficiency. However, as the prediction horizon is expanded, prediction uncertainty can also be increased.

Figure 5 shows the control flow employing the prediction model and the compensation mechanism. In this control scheme, the predictive compensator overrides the decision made by the conventional logic only when the probability is greater than a certain level. Therefore, the mode transition can be improved with reliable predictions and the risk of side effects, due to prediction errors, can be minimized.

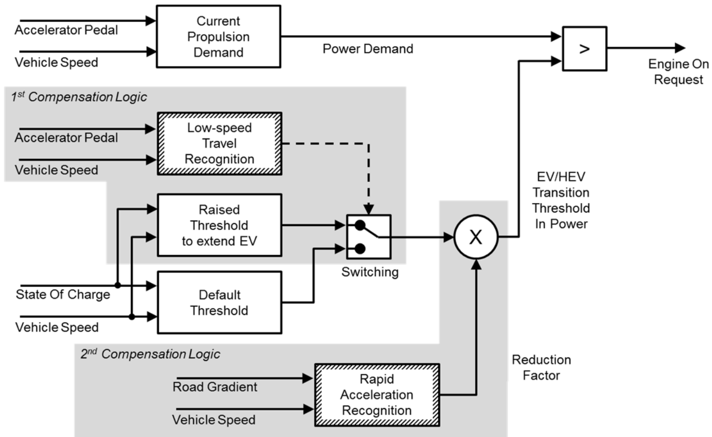


Figure4: Conventional mode transition control flow

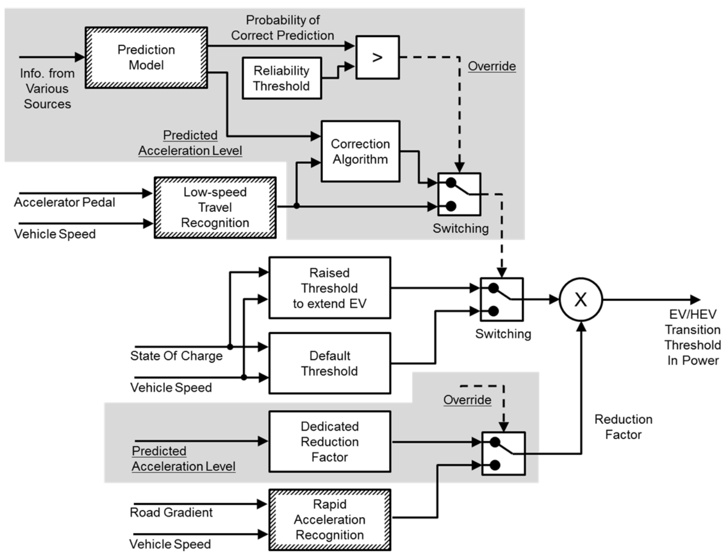


Figure5: Mode shifting control flow utilizing the acceleration prediction

# 3 Prediction model

A single-layer NN is selected as the predictive model to be implemented inside the embedded controller, which is responsible for EMS and has limited resources reserved for the other functionalities. The network is trained with the signals data from a certain point in time as inputs and the acceleration intention of the driver after 5 seconds from such point as the output. This chapter introduces the process of data acquisition, learning and model optimizations.

## 3.1 Data acquisition

Different types of communication modules and sensors such as Radar, Lidar and camera have been applied to current vehicles in order to implement Advanced Driver Assistant System (ADAS) and connected car applications. Among the variety of information, this study utilizes the information of the roads and the distance from the front vehicle acquired by the GPS navigation system and the front mount radar, respectively. The types of signals considered in this project are summarized in Table 1. Data acquisition for machine learning has been conducted twice. The first was obtained from 20 drivers from April to September 2016 and the second was obtained from 25 drivers from September to December 2017 for several routes.

## 3.2 Feature selection

Among the acquired vehicle information data, input variables having a high degree of influence on the prediction of acceleration are selected. Using all the acquired variables increases the complexity of the model, which is not only disadvantageous to the implementation in the embedded system but also hinders effective learning of the model. Before reducing the input variables, the structure of the input variables is simplified by exerting efforts to signal processing such as excluding the unused area of the quantitative variable, reducing the label of the qualitative variable or grouping the variables with high negative or positive correlation. We choose some input variables to apply the model construction using VIP (Variable Importance on partial least square Projection), Anova (Analysis of Variance), CCF (Cross Correlation Function), and VIF (Variance Inflation Factor) [10, 11, 12, 13]. After training, MOI (Maximum Output Information) is used to rank the input variables with respect to their influence into the prediction accuracy [14]. As a result of repeating the above feature selection process under conditions satisfying the weighted precision of 98% of the existing model, the number of input variables was reduced from 40 to 20.

Table1: Data acquired to predict the near future acceleration

| No. | Variable | Source | Property |
|---|---|---|---|
| 1 | Road class (Freeway, County, Local, …) | Navigation | Discrete category |
| 2 | Vehicle speed | Powertrain | Continuous signal |
| 3 | Form of the junction (Roundabout, U-turn, …) | Navigation | Discrete category |
| 4 | Degree of traffic congestion | Navigation | Discrete category |
| 5 | Speed limit | Navigation | Discrete category |
| 6 | Road gradient | Navigation | Discrete category |
| 7 | Distance to the vehicle ahead | Radar | Continuous signal |
| 8 | Accelerator pedal stroke | Powertrain | Continuous signal |
| 9 | Turn angle | Navigation | Discrete category |
| 10 | Brake pedal stroke | Powertrain | Continuous signal |
| 11 | Torque demand | Powertrain | Continuous signal |
| 12 | Relative speed of the vehicle ahead | Radar | Continuous signal |
| 13 | Yaw rate | Chassis | Continuous signal |
| 14 | Current gear step | Powertrain | Discrete category |
| 15 | Latitudinal acceleration | Chassis | Continuous signal |
| 16 | Longitudinal acceleration | Chassis | Continuous signal |
| | … | … | … |

### 3.3 Neural network structure

The prediction model was originally designed to output one of seven steps from deceleration to acceleration. However, in the training process, the result was observed to be biased on the intermediate output step because there are a large number of data corresponding to constant speed driving. In order to alleviate the data imbalance problem, oversampling method and weighted cost function are considered to be applied. Furthermore, even though the versatility is weakened, the outputs are reconstructed in 3 classes and their thresholds are adjusted to respective proper values. However, the prediction result for the 3$^{rd}$ class (rapid acceleration) was below acceptable levels. Hence, we developed a 2-steps model to first predict whether or not the output corresponds to the 1$^{st}$ class, and if not, a second model classifies it as the 2$^{nd}$ or 3$^{rd}$ class as shown in Fig.6.

Model compression methods are also applied to reduce the model size to fit into embedded boards with limited storage. Furthermore, the energy consumption can be reduced in the compressed small model. The first method, pruning reduces the model by keeping only the most informative connection. Another method, quantization allows shared weights to be used with a codebook containing the corresponding indices [15].

### 3.4 Training and validation

We trained and validated the NN using 5-fold cross validation. In order to guarantee the reliability of the predictions we only considered output from the softmax layer which are above a certain confidence threshold (in our case 70% or higher). Figure 7 shows the prediction accuracy for each class by sequentially applying the improvements such as variable selection method, output class re-definition, 2-steps structure and model compression. This result shows that the accuracy of the output class is improved, and especially in the third model with 2-stages, the predictive reliability of output 1 and 3, which are closely related to engine-on or engine-off judgment, is improved significantly. Under these conditions, sample retention associated with predictive control is close to 40%.

Figure 8 shows the code size and calculation load for each model. As the input has been reduced due to the variable selection methods and the output class has also been reduced, the second model has been greatly reduced in size and can be mounted on the embedded controller. We can see the benefits of execution time in the third model by applying pruning and weight sharing, but we can see that the code size itself has increased slightly due to the 2-step structure.

## 4 Experiment and result

The predictive model was applied to the hybrid control unit for the parallel hybrid vehicle in the same manner as proposed in Chapter 2. And it was confirmed whether the engine-on decision was properly compensated in the evaluation test route focused on low - speed driving in the city.

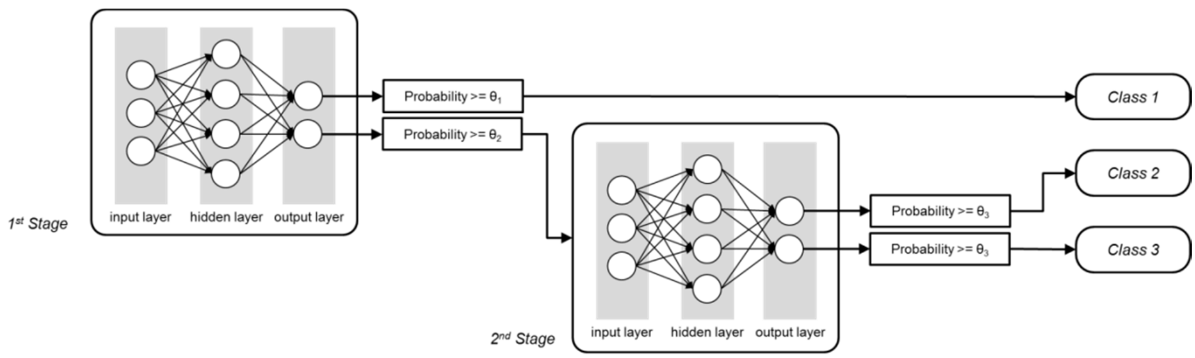


Figure6: 2-stage neural network structure for acceleration prediction

In the test, three improvement cases were observed as shown in Fig.9. In the first case, the model predicted a smooth driving of class 1 with a prediction probability of 70% or more, and activated the low-speed travel correction logic to suppress engine starting. Next, the existing low-speed travel correction logic operated to raise the engine-on threshold, but in the predictive model, the acceleration of class 3 was predicted, and the threshold correction was recovered. The last case shows that the rapid acceleration judgment logic was activated, but it was suppressed according to the prediction result. Observing the changes in the torque demand before and after the predictive model intervention, the second case was improved to allow the engine to be started in continuous acceleration situation and in the other two cases intermittent acceleration input was filtered to suppress unnecessary engine starting.

Among the three improvement cases, the first low-speed travel case was applied to the vehicle fleet test and the result is shown in Fig.10. In the entire test period, there were 237 acceleration events where torque demand input exceeds the engine-on thresholds, of which 42.6% were intermittent demand torque patterns that could cause ineffective engine operation. Of these, 27.7% inhibited by conventional logic, and the predictive model could suppress ineffective engine-on in 8.9% of cases, except in cases where the probability of prediction was low or not operated by interference from other control logic.

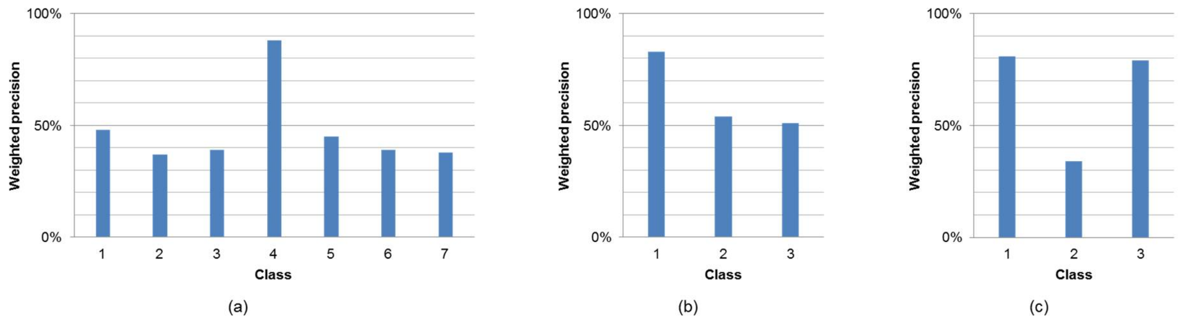


Figure7: Weighted precision for each class; (a) initial model, (b) model with enhanced variable selection method and output class re-definition and (c) model with 2-step structure and model compression

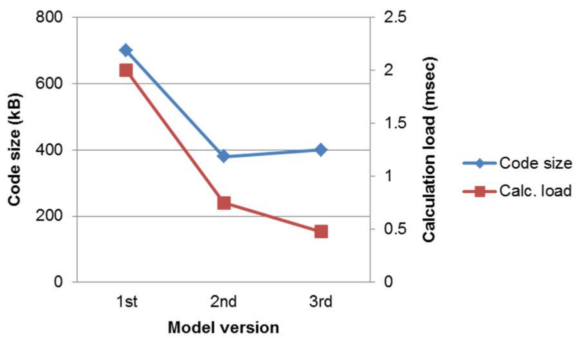


Figure8: Code size and calculation load for each model

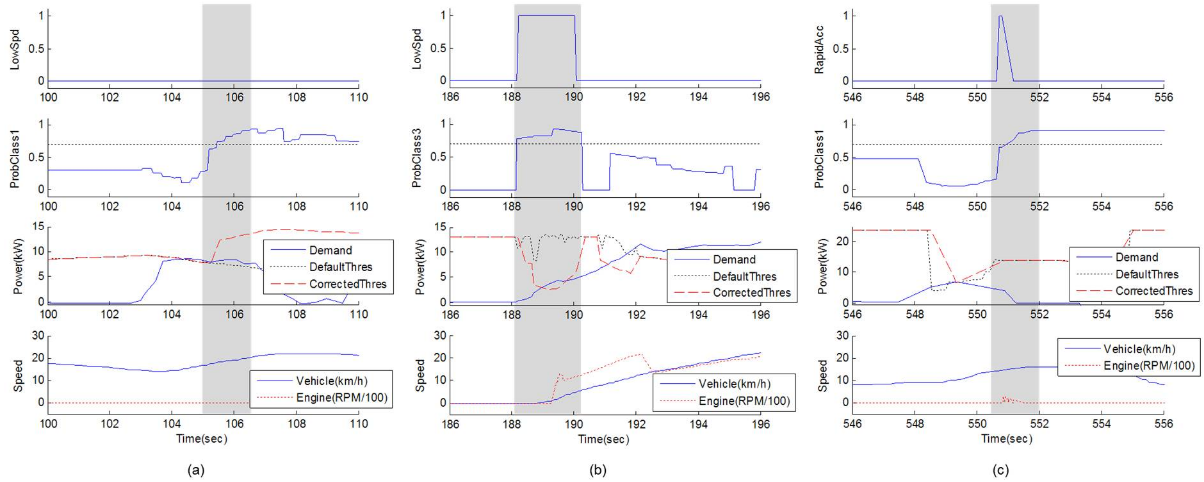


Figure9: Correction result of the engine on-off judgement based on the proposed prediction model; (a) Class1 prediction to raise the threshold, (b) Class3 prediction to override the low-speed travel recognition and lower the threshold and (c) Class1 prediction to override the rapid acceleration recognition and raise the threshold

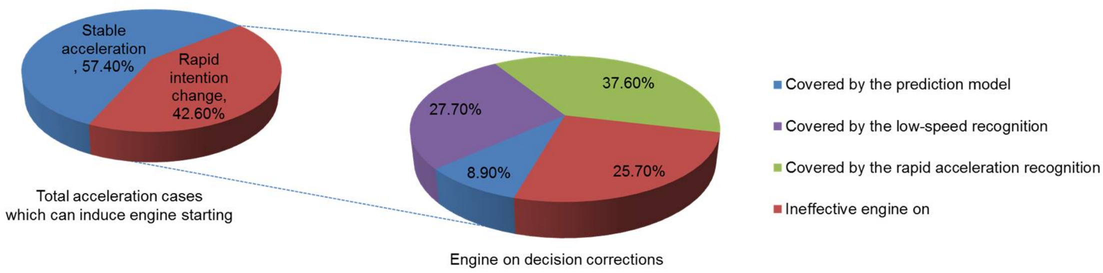


Figure10: Overview of the vehicle fleet test result

# 5 Conclusion

In this study, we tried to suppress ineffective engine start by predicting the acceleration / deceleration of the driver in the near future and using this prediction information in the engine-on decision process of the hybrid vehicle.

Using machine learning algorithms and various information available in the vehicle, we developed the predictive model that outputs the acceleration after 5 seconds with their respective probabilities.

The data bias of the constant speed range of data for accelerating / decelerating prediction and the lack of data of the high acceleration region could be improved by redefining the acceleration / deceleration output class in the way appropriate for the application, and by using the two-stage model structure.

By using methods such as VIP, Anova, CCF, and VIF, we selected candidate input variables for model construction, and we used MOI for feature selection. Furthermore, model compression methods such as pruning and weight sharing were applied to reduce the code size and computation load for embedded system implementation.

The effectiveness of the predictive model and compensation logic was evaluated in real road conditions of low speed congestion zone where the driver's acceleration / deceleration change is prominent.

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