A STUDY ON THE ECMS PARAMETER ADAPTION FOR THE DRIVER CHARACTERICSTIC VARIATION

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ABSTRACT
This paper proposes a novel supervisory control method for a parallel hybrid electric vehicle (PHEV) with a transmission mounted electric drive (TMED). An equivalent consumption minimization strategy (ECMS) is the supervisory control method and provides real-time sub-optimal energy management decisions by minimizing the "equivalent" fuel consumption of a hybrid electric vehicle (HEV). The equivalent fuel consumption is a combination of the actual fuel consumption an electrical energy use, and an equivalence factor is used to convert electrical power used into an equivalent chemical fuel quantity. In this study, the proposed ECMS parameter adaption focused on the driver characteristic variation. In the stage of development, the longitudinal driver model is developed and the represented driving patterns are defined. Results obtained in this research clarify the causal connection between the driver characteristic and the equivalence factor as the initial step of the adaptive ECMS implementable into microcontroller. The simulation results show that optimizing the control parameter is needed as the driver characteristic variation.

Keywords: Adaptive ECMS, Equivalence factor, Driving pattern, Driver model

1. INTRODUCTION
The advanced researches about the supervisory control algorithm of the HEV are heading to the parameter adaptation algorithm for global optimality. A research adapting the equivalence factor of the ECMS using past driving data has been done where the computational effort is too high. Another research proposed a pattern recognition algorithm to identify the drive cycle. However, that is insufficient to isolate the different driver on almost same drive-cycle. The purpose of this study is to clarify the causal connection between the driver characteristic and the equivalence factor as the initial step of the adaptive ECMS implementable into microcontroller.

Previous adaptive ECMS algorithm requires enormous computational effort to calculate the equivalence factor for stored driving data of past hundred seconds. However, the proposed algorithm calculates the combination of pre-calculated equivalence factor in offline so additional computation effort is only occurred for identifying the driver type and the drive cycle. Moreover, there was no research about analyzing the tendency of the equivalence factor according to the driver characteristic

In this paper, a forward simulator for the TMED type HEV is constructed based on the Cruise® and Simulink® including custom longitudinal driver model to imitate the characteristic of the actual driver. As a simulation group, some representative driver types are defined by the parameter set of the driver model. Each equivalence factor of these driver types for some drive cycles is calculated according to the conventional ECMS researches for the parallel HEV. These results are carefully analyzed in terms of the tendency of the equivalence factors. Operating points of actuators, the engine and the electric motor, are also depicted. Finally, the fuel economy of the conventional ECMS algorithm is simulated for the various combinations of the driving patterns and the equivalence factor to show the effectiveness of proposed adapting algorithm.

This paper introduces the target vehicle for the simulation (Chapter 2), and explains the used HCU (Chapter 3). Continually, the developed longitudinal driver model (Chapter 4) and the simulation result for the fuel economy (Chapter 5) is analyzed. Finally, the last chapter is the conclusion of this paper.

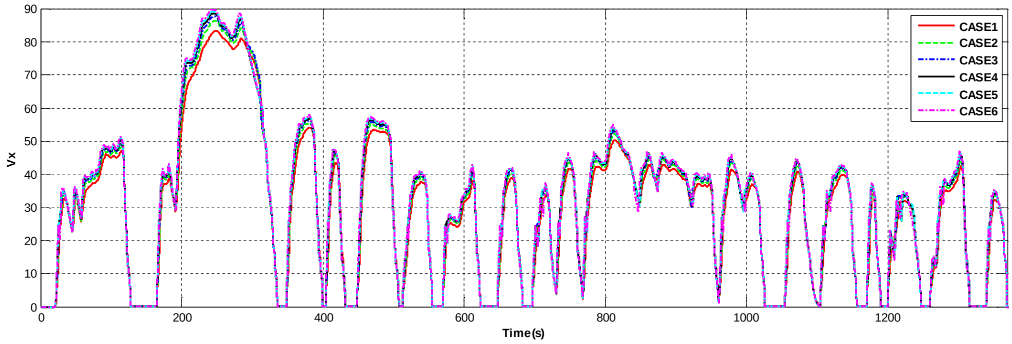
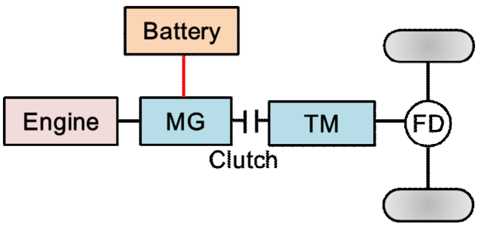


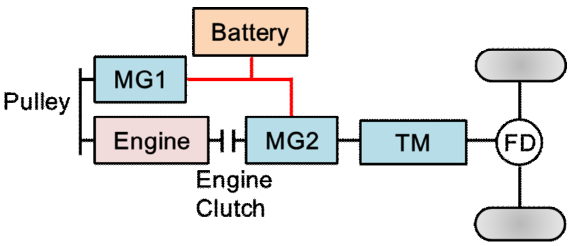
Figure 1: Example of the different 6 drivers driving almost same drive-cycle (FTP72: see the chapter 5.1)

2. TARGET VEHICLE

In this paper, target vehicle is the PHEV with the TMED type. This chapter introduces the configuration of the used PHEV with TMED type. There are many possibilities of configurations in a parallel hybrid powertrain. However, two different configurations are applied to the most of the parallel HEVs in production, which are shown in Fig. 2. The TMED can separate the traction motor (MG2) from the engine by the engine clutch. Therefore, the TMED can provide the electric vehicle mode which the practical parallel hybrid powertrain cannot support due to the engine friction. The TMED also offers a number of advantages such as flexibility to mix and match different sized electric motors and transmissions to suit different vehicles, and utilizing an existing off-the-shelf transmission. However, due to the additional complexity and the increased degree of freedom in the energy flow of the hybrid powertrain, the TMED requires more complicated and subtle supervisory control to take advantage of the advanced configuration. In general, the achievable improvements of fuel economy in HEVs depend strongly on the implemented energy management strategy, which is major part of the supervisory control. The next chapter will explain the HCU applied optimal supervisory control algorithm for a TMED in the sense of minimization of fuel usage.



(a) Practical parallel hybrid powertrain



(b) Transmission mounted electric drive (Target Vehicle configuration)

Figure 2: Parallel hybrid powertrain configuration

3. HYBIRD CONTROL UNIT (HCU)

In this chapter, The HCU and the ECMS algorithm are explained. The HCU is main controller to control the vehicle, in which energy management strategy that is the ECMS minimizing the equivalent fuel usage is implemented.

3.1. HCU

The hybrid control unit (HCU) is the main controller of the HEV which keeps the optimal driving condition as controlling each subsystem by observing the driving states of the vehicle for the optimal driving. Additionally, the subsystems are engine control unit (ECU), motor controller unit (MCU), transmission controller unit (TCU), battery management system (BMS) and voltage DC-DC converter (LDC). To be more concrete, the roles of the HCU are various and about 11s. First, starting a HEV with motor when turning ignition key or auto-stop or operating the starter-motor when no motor admitted, the next, assisting the engine torque by motoring when accelerating a HEV. Third, controlling the ratio of the transmission according to driving states, fourth, storing the electric energy by generation of the motor (regenerative breaking), fifth, stopping the engine when stopping with breaking after driving setting the D-range (auto-stop) or restarting the engine when non-zero accelerator pedal or zero decelerator pedal. Sixth, controlling the sliding at the slope, seventh, permitting the fuel cut and inject or not according to state of charge (SOC) and the ratio of the shift gears. Eighth, preventing the overcharging of the battery and limiting the motor torque. Ninth, control of the booster pressure, tenth, on/off control, generating of the LDC and voltage control. The last, inducing the eco-driving. Figure 3 is the block diagram of the HCU and subsystems.

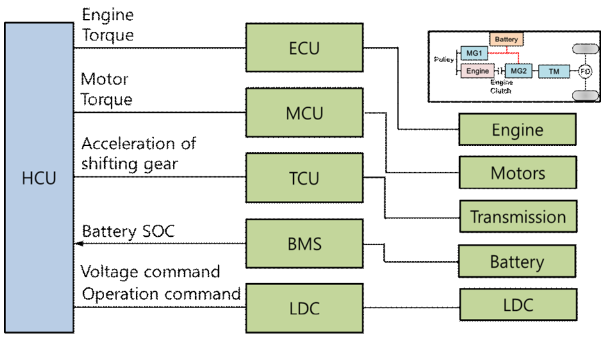


Figure 3: Hybrid control unit (HCU)

3.2. ECMS

A real-time control strategy based on an instantaneous optimization needs a definition of the cost function to be minimized at each instant. Such a function has to depend only upon the system variables at the current time. Since the main control goal is the minimization of the fuel consumption, it is clear that this quantity has to be included in the cost function. However, based on the requirements of electrical self-sustainability, the variations in the stored electrical energy (or state-of-charge, SOC) have to be taken into account as well. To deal with such aspects, various approaches have been proposed in this area. One-approach was used in the recently paper. It consists of evaluating the instantaneous cost function as a sum of the fuel consumption and an equivalent fuel consumption related to the SOC variation equivalent consumption minimization strategy (ECMS). In this case, it is clearly recognized that the electrical energy and the fuel energy are not directly comparable, but an equivalence factor is needed. The equivalence between electrical energy and fuel energy is basically evaluated by considering average energy paths leading from the fuel to the storage of electrical energy. If the overall efficiencies of the electrical and thermal paths were rigorously constant, such an equivalence would be theoretically exact. Since efficiencies vary with the operating point, this approach only allows the use of average values.

In the real-time control strategy, the equivalent fuel consumption is evaluated under the assumption that every variation in the SOC will be compensated in the future by the engine running at the current operating point. The equivalent fuel consumption therefore changes both with the operation point and with the power split control, and its evaluation requires an additional, inner loop in the instantaneous optimization procedure, or the prior storage of the results in a look-up table.

A control of the ECMS is presented at Sciarreta paper. This paper has the similar ECMS method. It is based on a new method for evaluating the equivalence factor between fuel and electrical energy. This method does not require the assumption of the average efficiencies of the parallel paths, and it is based on a coherent definition of system self-sustainability. The ECMS is valid for different system architectures and types of machines involved. The advantage includes good control performance with comparing that obtained with conventional control strategies, the robustness with respect to the variation of control parameters, and the system behavior in case of steady operating point.

4. LONGITUDINAL DRIVER MODEL

The longitudinal driver model is developed for imitating the real driver behavior. This driver model presents three driver tendency, flexibility, sensitivity and competence. Also, PI controller control the accelerator pedal (AP) and braking pedal (BP), and making the shape of AP, BP by driving maneuver mode.

Chapter 4.1 explains the behavior of the driver model and chapter 4.2 introduces the representative driving pattern in more detail.

4.1. The behavior of the driver model

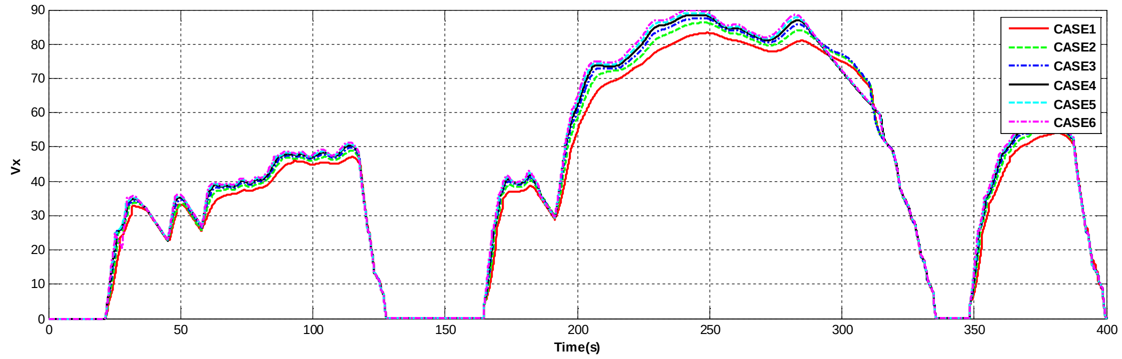
Figure 4 is the developing driver model. The driver model follows the reference driving cycle and makes the shape of AP signal (APS), BP signal (BPS). The red box of the figure 4 is reference driving cycle with FTP-72 speed profile. This model inputs are the vehicle speed, APS, BPS which have the blue line. The main control parameters have green, yellow, blue color box in the figure 4. The green box is making the APS delay (apdel). The figure 4 (g) depicts the vehicle speed graph changing the apdel. The behavior of the driver model is similar to competence of the drivers. The blue boxes are controller gains about AP, BP. Increasing the AP P_Gain (pa) effects the slope of the APS. This time, the behavior of the driver model is similar to flexibility of the drivers. Figure 4 (b) is APS example of the different flexibility. The yellow boxes are Bounds. The bounds related AP, BP control timing and vehicle speed error is reference. Bound1 is hb which decides activating AP, BP. If the hb is large amplitude, speed error is larger. Bound2 is lb which decides deactivating AP and Bound3 is blb which decides deactivating BP. Figure 4 (e) presents the APS graph of changing the lb. Moreover, driving maneuver mode is made with SR_latch and integrator reset designs the anti-winding.

4.2. The representative driving pattern

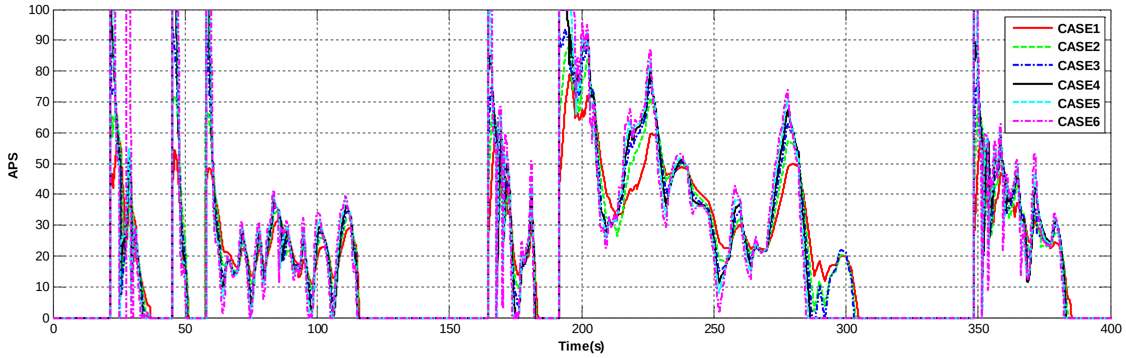
The driving pattern is defined as three. This paper assumes that various driver's characteristic are classified according to the flexibility, the sensitivity, the competence. These each patterns are orthogonal. Therefore, the each parameters of the driver model describes one pattern. Changing the pa describes Flexibility, changing the lb describes Sensitivity and changing the apdel describes competence. In this paper, parameter sets of the table 1 are used and its simulation results are figure 4.

Table 1: The parameter sets for the driver types used in the simulation

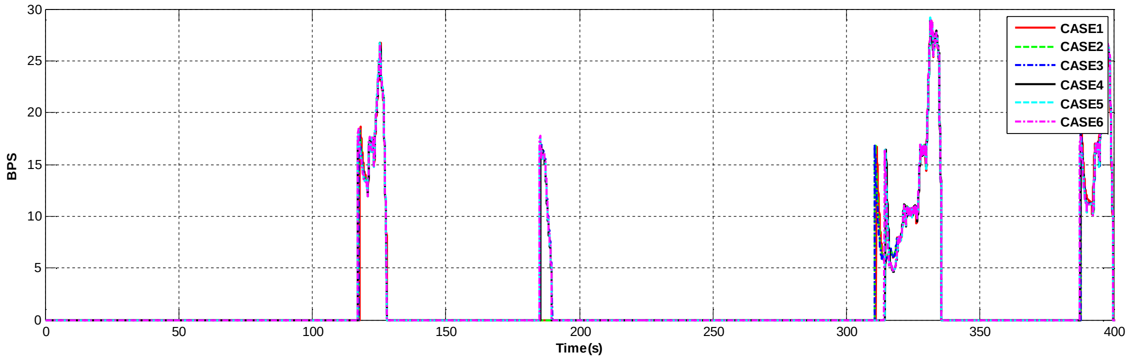
Flexibility	pa	lb	apdel
Case1	5	-1	0
Case2	8	-1	0
Case3	11	-1	0
Case4	15	-1	0
Case5	22	-1	0
Case6	30	-1	0
Sensitivity	pa	lb	apdel
Case1	20	-5	0
Case2	20	-1	0
Case3	20	1	0
Case4	20	2	0
Case5	20	3	0
Case6	20	5	0
Competence	pa	lb	apdel
Case1	20	-1	0
Case2	20	-1	0.5
Case3	20	-1	1
Case4	20	-1	1.5
Case5	20	-1	2
Case6	20	-1	2.5



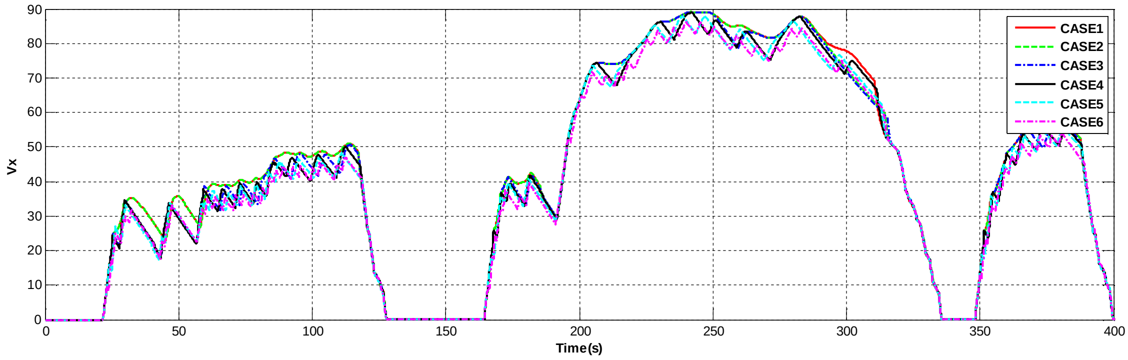
(a) Vehicle Speed (Flexibility)



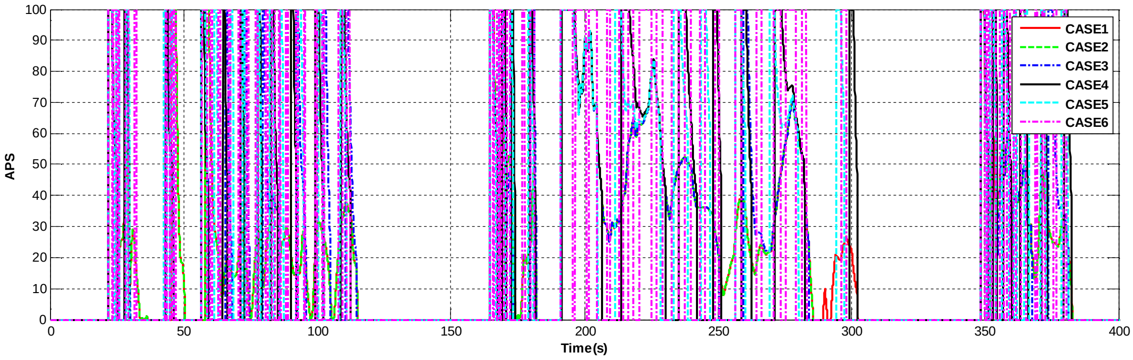
(b) APS (Flexibility)



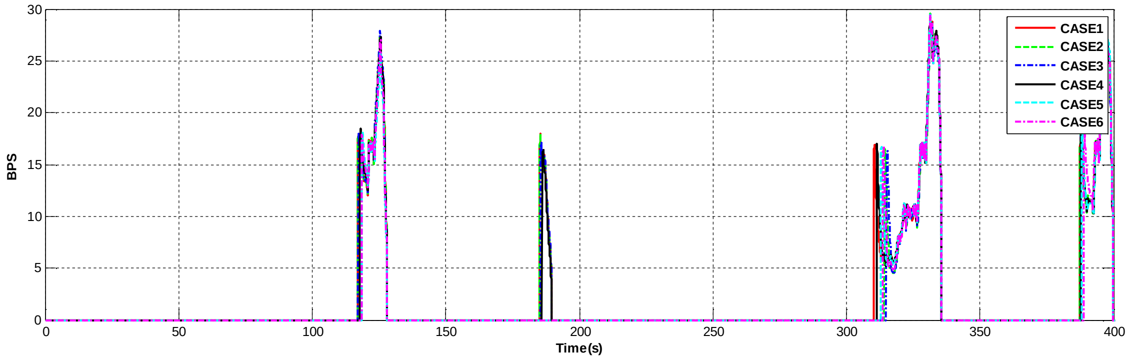
(c) BPS (Flexibility)



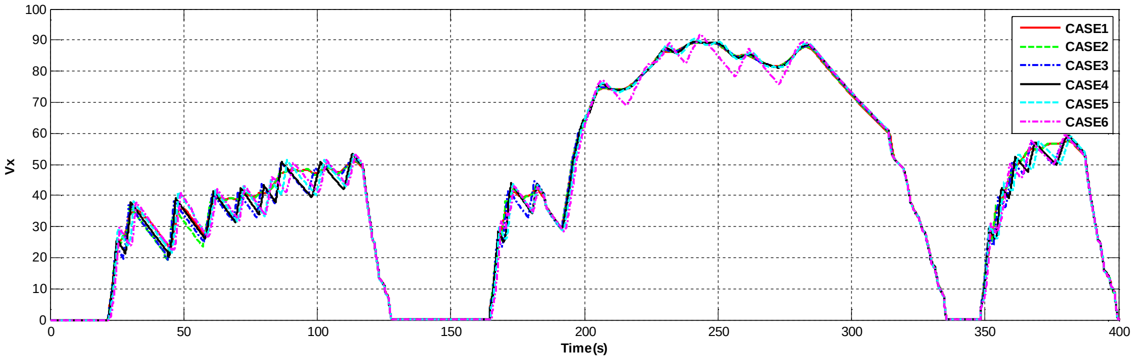
(d) Vehicle Speed (Sensitivity)



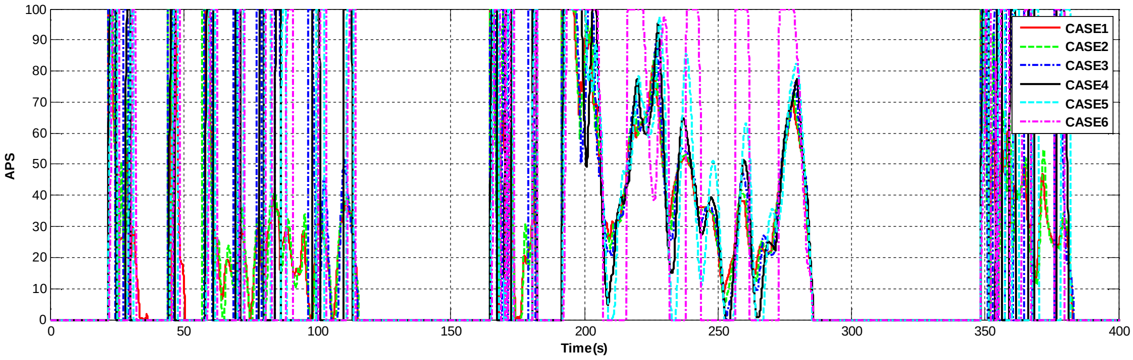
(e) APS (Sensitivity)



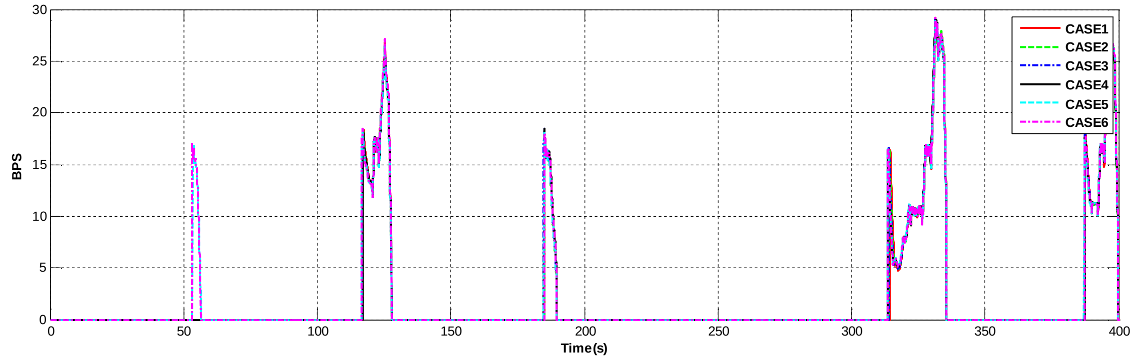
(f) BPS (Sensitivity)



(g) Vehicle Speed (Competence)



(h) APS (Competence)



(i) BPS (Competence)

Figure 4: Vx, APS, BPS of the each patterns (used parameter in the table 1)

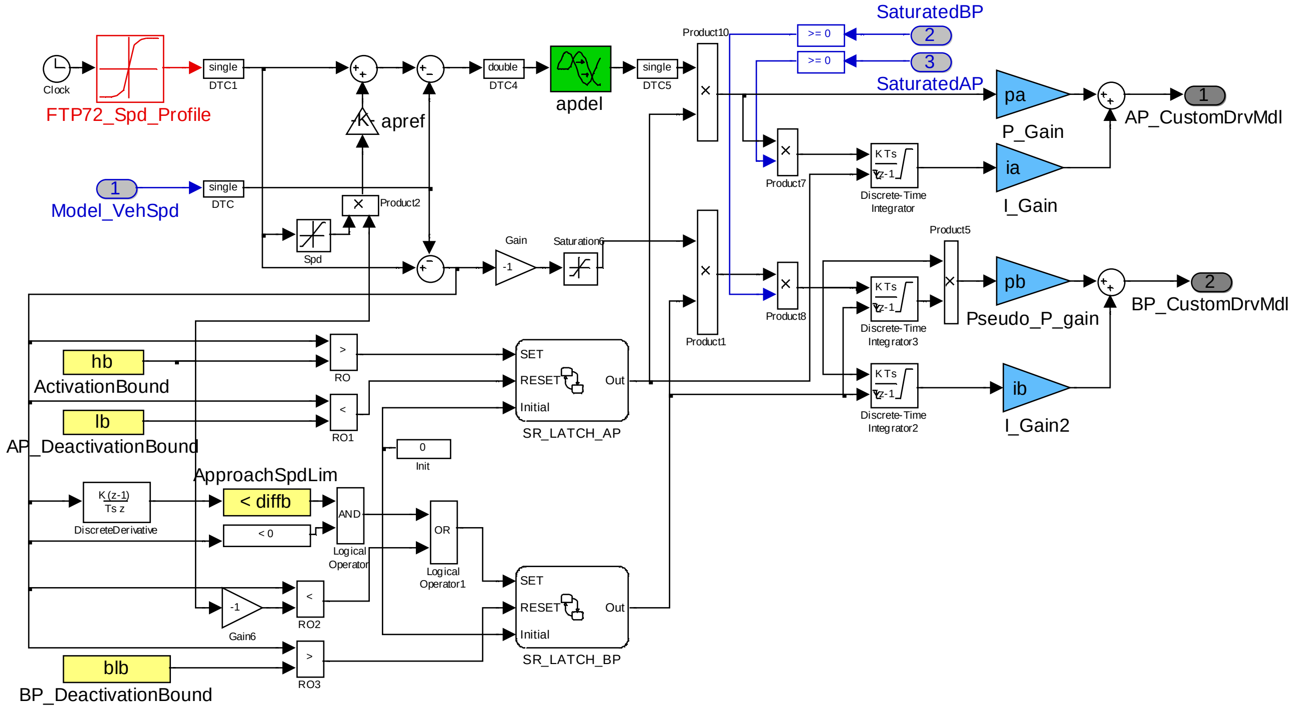


Figure 5: Longitudinal Driver Model

5. SIMULATION

The proposed Advanced HEV supervisory control algorithm adapts the equivalence factor according to driver characteristic variation. The different driving characteristic represents the driving pattern and driver type (Case1 ~ Case6) according to changing parameter pa, lb, apdel.

Chapter 5.1 depicts the simulation environment applied defined driving pattern, Chapter 5.2 shows the simulation results.

5.1. Simulation environment

The co-simulation environment configures with aforementioned (Chapter 2, 3) target vehicle and HCU control algorithm in the figure 5. The developed target vehicle by Cruise sends signals of EMS, MCU, GCU, LDC, BMS, TCU to the HCU logic, and the HCU calculates the each signals by control algorithm. As a result, the final calculated EMS, MG, ISG, LDC, TCU commands transmit the target vehicle. Above step repeat each sample time. This simulation has sampling time 0.005 sec and uses the FTP-72 profile among the driving cycles. Fuel consumption a constant speed cannot accurately represent real driving conditions. Various drive cycles have been developed to simulate real driving conditions. The drive cycles are usually represented by the speed along with the relative driving time. Legislation drive cycles – all mass produced cars are subjected to before being authorized for sale in a particular market. The total mass of emissions produced during a particular drive cycle must be below a set limit decided by the legislating authority. The most common – the cycles used by the US EPA and the European ECE. Light-Duty Vehicles (Chassis Dynamometer), FTP72 – A transient test cycle for cars and light duty trucks on a simulated urban route with frequent stops (Federal Test Procedure)

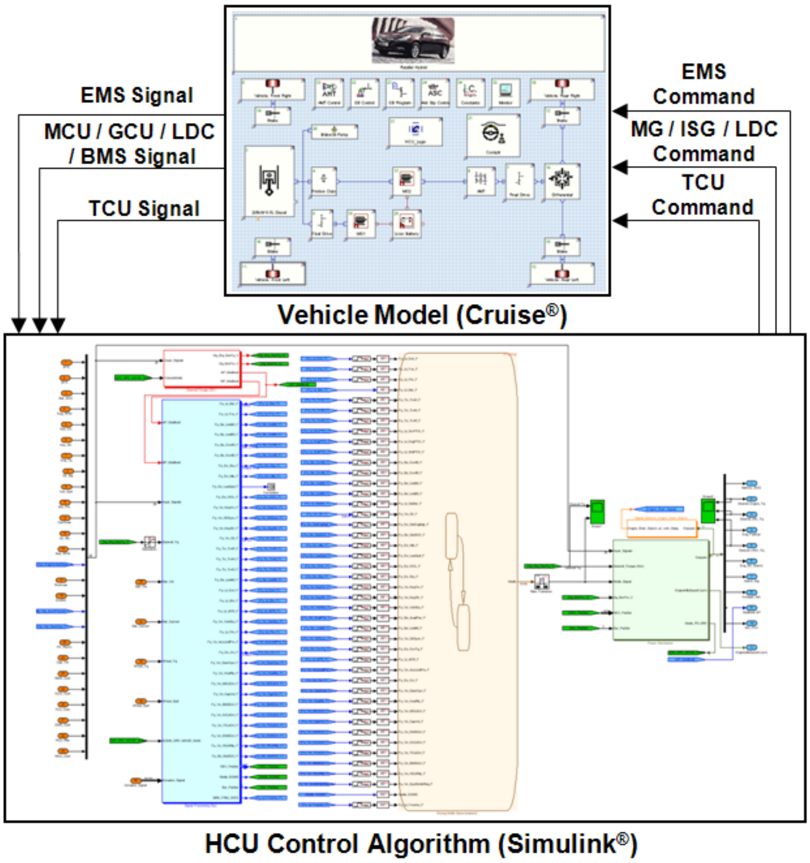


Figure 5: Simulation Environment

5.2. The simulation result for the fuel economy

The result of the driver characteristic variation works the fuel economy. This chapter shows the simulation result for the fuel economy according to changing the driving pattern. Chapter 5.2.1 is the case applied the optimal equivalence factor for each driving tendency. Chapter 5.2.2 is the case applied the non-optimal equivalence factor for each driving tendency. These two cases fuel economy made by table 2, 3.

5.2.1. The simulation for the optimal equivalence factor

The optimal equivalence factors are found for the one case selecting among Case1~6 of the each driving pattern. Case1 (Flexibility), Case6 (Sensitivity), Case4 (Competence) is simulated with it's the optimal equivalence factor and the fuel economy is calculated. In order, the fuel economy is 17.281km/l, 21.901km/l, 21.994km/l.

5.2.2. The simulation for the non-optimal equivalence factor

The equivalence factor sets selected in the chapter 5.2.1 are exchanged each other. The fuel economy appears in table 2. Comparing the table 1 and table 2, the gap of the Max and min fuel economy is the 5.831km/l in the Case1 (Flexibility), is the 0.991km/l in the Case6 (Sensitivity) and is the 1.846km/h in the Case4.

The fuel economy simulation result shows that the optimal fuel economy is made by adapting the optimal equivalence factor according to the driver characteristic.

Table 2: Optimal equivalence factor and fuel economy
*Fuel economy unit : [km/l]

Flexibility	S_{chg}	S_{dis}	Fuel economy
Case1	1.80	2.41	17.281
Sensitivity	S_{chg}	S_{dis}	Fuel economy
Case6	2.49	2.51	21.901
Competence	S_{chg}	S_{dis}	Fuel economy
Case4	1.78	2.87	21.994

Table 3: Non-optimal equivalence factor and fuel economy

Flexibility	S_{chg}	S_{dis}	Fuel economy
Case1	2.49	2.51	11.450
Case1	1.78	2.87	17.261
Sensitivity	S_{chg}	S_{dis}	Fuel economy
Case6	1.80	2.41	20.910
Case6	1.78	2.87	21.226
Competence	S_{chg}	S_{dis}	Fuel economy
Case4	1.80	2.41	20.148
Case4	2.49	2.51	20.190

*Fuel economy unit : [km/l]

6. CONCLUSION

This paper presented the concept of novel adaptive ECMS and defined the driver types in terms of the parameter set of the longitudinal driver model which is developed. The effectiveness of the equivalence factor adaptation according to the driver characteristic variation is verified through the fuel economy simulation. The simulation result shows that each driver using the optimal equivalence factor has better fuel economy than the non-optimal equivalence factor. In conclusion, the ECMS parameter adaption for the driver characteristic variation has validity.

In the future work, an algorithm identifying actual driver in real-time need to be developed, because this study analyzes the relationship between the offline-defined driver type and the equivalence factor as an initial step of novel adaptive ECMS algorithm. Taking a step forward, this study does not consider the road condition identification. Some pattern recognition algorithm for road condition identification can be combined with this study

REFERENCES

James, D.J.G., Boehringer, F., Burnham, K.J., and Copp, D.G., 2004. Adaptive driver model using a neural network. *Proceedings of artif life robotics, 7 4, 170-176.*

Majjad, R., Kiencke, U., and Körner, H., 2005. A-ECMS: An adaptive algorithm for hybrid electric vehicle energy management. *Proceedings of the 44th IEEE conference on decision and control, and the European control conference*, pp. 1816-1823. December 12-15, Seville, Spain.

Cheng, B., Fujioka, T., 1997. Hierarchical driver model. *Proceedings of the ITSC '97 IEEE conference on intelligent transportation system*, pp. 960-965. November 9-12, Boston, MA.

Gu, B., Rizzoni, G., 2006. An adaptive algorithm for hybrid electric vehicle energy management based on driving pattern recognition. *Proceedings of (ASME) international mechanical engineering congress and exposition*, pp. 249-258. November 5-10, Chicago, Illinois, USA.

Majjad, R., Kiencke, U., and Körner, H., 1998. Design of a hybrid driver model. *Proceedings of the 1998 society of automotive engineers international congress and exposition*, pp. 37-42. February 23-26, Detroit, Michigan.

McGordon, A., Poxon, J.E.W., Cheng, C., Jones, R.P., and Jennings, P.A., 2011. Development of a driver model to study the effects of real-world driver behavior on the Fuel. *Mechanical engineers, Part D: Journal of automobile engineering*, 225 11, 1518-1520.

Yang H.-H., Peng, H., 2010. Development of an errorable car-following driver model. *Vehicle sytem dynamics: International journal of vehicle mechanics and mobility*, 48 6, 751-773.

Inata, K., Raksincharoensak, P., and Nagai, M., 2008. Driver behavior modelling based on database of personal mobility driving in urban area. *Proceedings of international conference on control, automation and systems*, pp. 2902-2907. Octobor 14-17, COEX, Seoul, Korea.

Brundell-Freij, K., Ericsson, E., 2005. Influence of street characteristics, driver category and car performance on urban driving patterns. *Transportation research part D: Transport and environment*, 10 3, 213-229.

Sciarretta, A., Back, M., and Guzzella, L., 2004. Optimal control of parallel hybrid electric vehicles. *IEEE transactions on control systems technology*, 12 3, 352-363.

Hofman, T., Steinbuch, M., van Drutenm R.M., and Serrarens, A.F.A., 2008. Rule-based equivalence fuel consumption minimization strategies for hybrid vehicles. *Proceedings of the 17th world congress the international federation of automatic control*, pp. 5652-5657. July 6-11, Seoul, Korea.

Sciarretta, A., Chasse, A., 2011. Supervisory control hybrid powertrains: An experimental benchmark of offline optimization and online energy management. *Control engineering practice*, 19 11, 1253-1265.

Reñski, A., 1998. The driver model and identification of its parameters. *Proceedings of international congress and exposition*, pp. 1-8. February 23-26, Detroit, Michigan.

Macadam, C., 2003. Understanding and modeling the human driver. *Vehicle system dynamics: international journal of vehicle mechanics and mobility*, 40 1-3, 101-134.