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Fuel Economy Improvement Strategy for Light Duty Hybrid Truck Based on Fuel Consumption Computational Model Using Neural Network

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Abstract: This paper describes a strategy for fuel economy improvement of light duty truck with parallel hybrid system. The main objective of this paper is to develop a new hybrid controller which optimizes the torque distribution among various running situations and driver's characteristics with on-line simulation, computing fuel and electric current consumption by using neural network models of the hybrid ECU. Then, fuel and battery current consumption computational models with respect to battery state of charge (SOC), engine and motor torque and engine speed are synthesized by using neural network, and the models are based on experimental data. Finally, the new hybrid controller including the above mentioned models is developed, and its effectiveness on fuel economy improvement is verified by using computer simulation.

1. INTRODUCTION

Nowadays, hybrid vehicles with diesel engine and electric motor as the target of this study will be one of the most efficient commercialized low emission vehicles to become wide spread in few years. The light duty hybrid truck which is target of this study can also reduce emissions and fuel consumption compared with conventional truck without hybrid system. The hybrid controller in the system determines torque distribution of the engine and the electric motor corresponding to the driver's required torque, under representative driving patterns in actual driving situation such as the expressway mode, suburban mode and traffic congestion mode etc. However, if the vehicle is used under completely different situation from the representative driving patterns for hybrid system design, satisfactory fuel economy performance as well as driveability cannot be achieved.

In recent researches, to optimize torque distribution between electric or hydraulic motor and internal combustion engine for fuel economy improvement, analysis by using dynamic programming (DP) method (Jin, et al., 2006; Wu, et al., 2004; Langari, et al., 2005) and hybrid system based on driving pattern recognition (Jeon, et al., 2002; Lin, et al., 2004; Won, et al., 2005) with computer simulation were proposed (Shimizu, et al., 2004; Morita, et al., 2004).

In this study, hybrid controller is developed to improve fuel economy under various driving situations. Its controller in the hybrid ECU includes fuel and electric current consumption models by using neural network, and it calculates optimal torque distribution to minimize fuel consumption and to control battery State of Charge (SOC) within the optimal range by on-line simulation.

First, the experiment with target vehicle is conducted to measure the teacher data set for training the neural network model, and fuel and electric current consumption models are identified by training the models with the set of experimental data. Second, the hybrid controller which embeds the neural network model is designed. Finally, the improvement of fuel consumption and the balance of electric current consumption are evaluated by using computer simulation.

2. TARGET VEHICLE

Target vehicle of this research is light duty truck with hybrid system, and its parameters are shown in Table 1. This hybrid system is composed of electric motor/generator, Ni-MH battery, inverter and diesel engine as indicated in Fig. 1.

Table 1. Target vehicle specification

Parameter	Value	Unit
Maximum load	2000	kgf
Maximum gross vehicle weight	4605	kgf
Tire model	205/70R 17.5	-
Engine displacement	4009	cm^3
Maximum output power	100kW/3000rpm	kW
Maximum output torque	353Nm/1600rpm	Nm
Motor max power	36	kW
Motor max torque	350	Nm
Transmission	5speed manual T/M	-

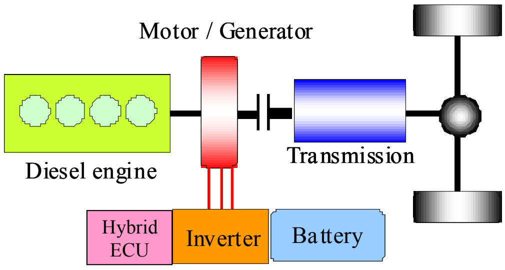

Fig. 1. Components of target vehicle with parallel hybrid system

Hybrid computer in this system requires assist torque to motor/generator during vehicle accelerating to reduce engine load. During vehicle decelerating, also, hybrid computer requires regenerative torque to motor/generator to accumulate vehicle kinetic energy and convert into electric energy for charging the battery. Hybrid computer calculates the effective assist and regenerative torques by using measured values such as vehicle speed, accelerator pedal stroke, engine speed and etc.

3. EXPERIMENT

Experiment with target vehicle was conducted to measure the teacher data set for training the neural network models. The measured variables are the fuel injection rate with respect to engine speed and engine required torque, the battery current with respect to engine speed, the motor required torque and the SOC. In this experiment, drivers were instructed to accelerate vehicle to the required speed from representative start to goal points. Transmission shift operations, longitudinal acceleration and deceleration were arbitrary of the drivers. The number of driver was 17. These variables were measured from vehicle Controller-Area-Network (CAN) information, and the data sampling was 10Hz as shown Fig. 2.

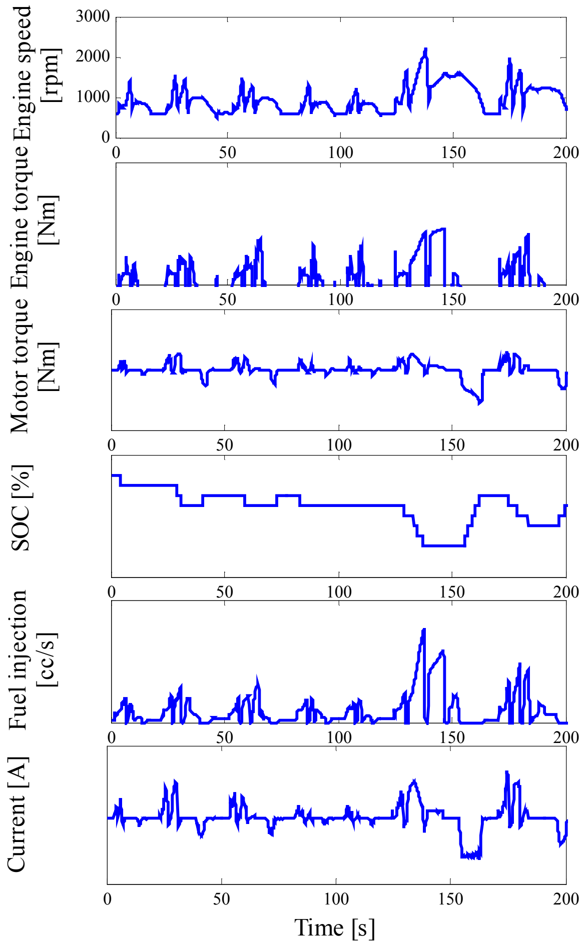

Fig. 2. Measured variables with experiment (Data sampling time ; 10 Hz)

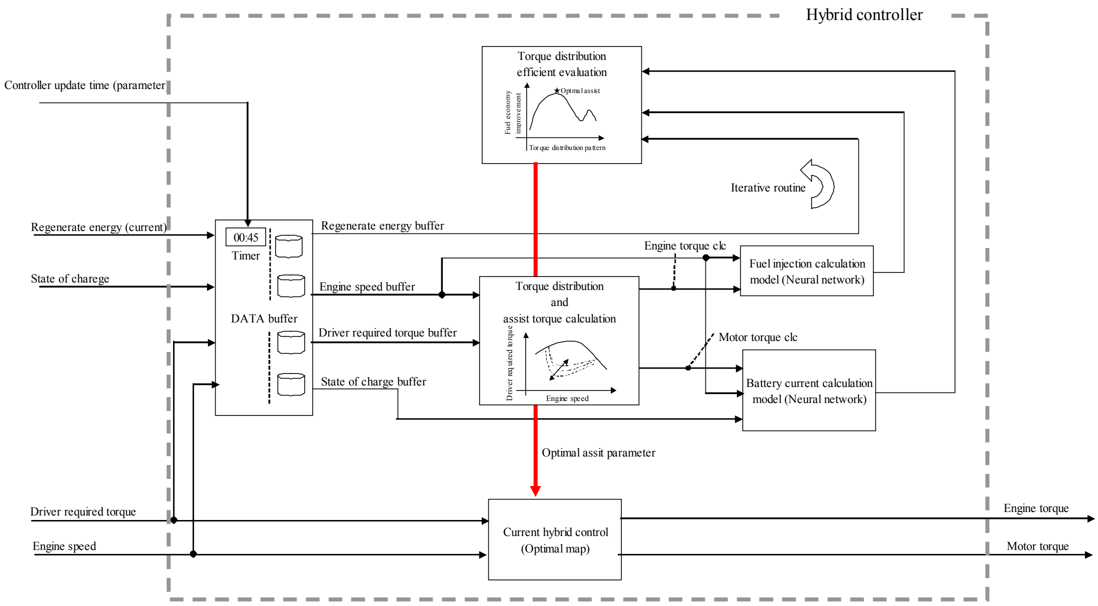

Fig. 3. New hybrid controller architecture

4. DESIGN OF HYBRID CONTROLLER

4.1 Hybrid Controller outline

Fig.3 shows the schematic diagram of the proposed hybrid controller architecture and Fig. 4. shows the flowchart of the hybrid controller algorithm. Controller sampling time, about several minutes, is defined as a parameter. During the sampling time, the CAN information of driver required torque, engine speed, regenerate current and SOC are buffered in temporary memory of the hybrid ECU. In the period of data by using on-line simulation of the hybrid ECU. Then, the assist torque map is updated to the optimal for the buffered data sampling time, hybrid controller starts iterative calculation to determine the optimal assist torque distribution for the buffered at the previous sampling time in the hybrid ECU. In this routine, as on-line simulation, the fuel and the electric current consumption models by using neural network are used. Details of them are described in the section 4.2.

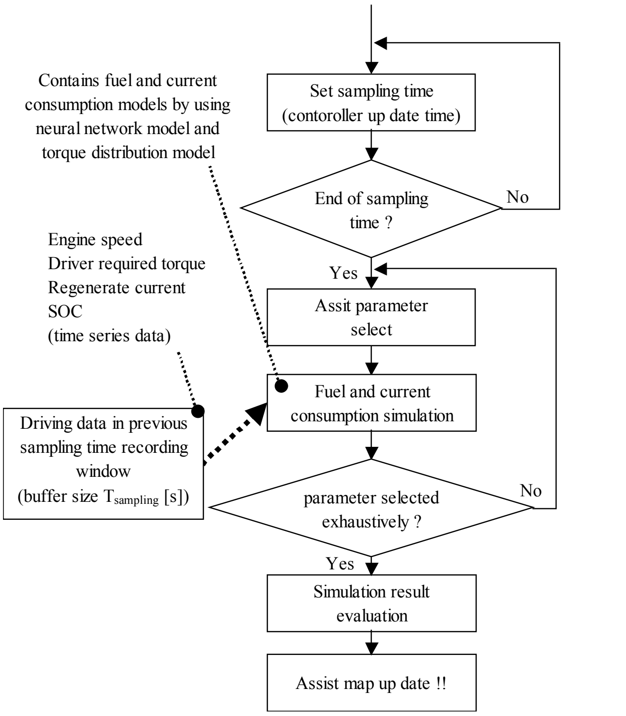

Fig. 4. Control flow chart to determine assist parameters

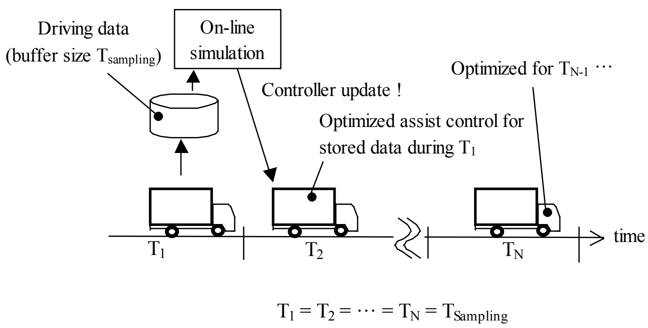

Fig. 5. Flow of controller parameter update algorithm

Assist map is updated to optimal with delay time as controller sampling time as Fig. 5. shown. In the figure, T_1....T_N indicate the sampling time duration and $T_{Sampling}$, the sampling time as a parameter. Then, the assist control is instantaneously optimized for driving mode.

4.2 Fuel and current consumption model by using neural network

According to the previous section, the proposed hybrid controller embeds the fuel and electric current consumption model which is synthesized by neural network model technique. This section describes the structure of the model and its validation. The neuron used in the model operation is shown as Fig. 6. and the sigmoid function is described as follows:

$$sigmoid(s) = \frac{1}{1+e^{-\alpha s}} \tag{1}$$

$$s = \sum_{n=1}^{N} w_n x_n \tag{2}$$

where, α indicates the sigmoid gain, x_n, the input values to the neuron, u, the output of the neuron, w_n, the associated weights, and N, the number of neuron. The both models, fuel and current consumption I/O and structure are indicated as Fig. 6. and Fig. 7. As learning procedure, these models are trained with back propagation method by using one of experimental data as shown Fig. 2. Model parameters and learning conditions are shown by Table. 2.

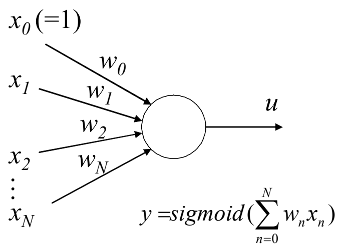

Fig. 6. A neuron operation in the network

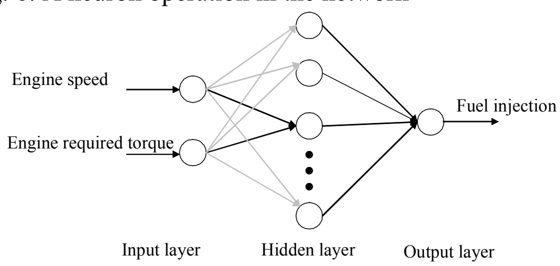

Fig. 7. Fuel consumption calculating model structure

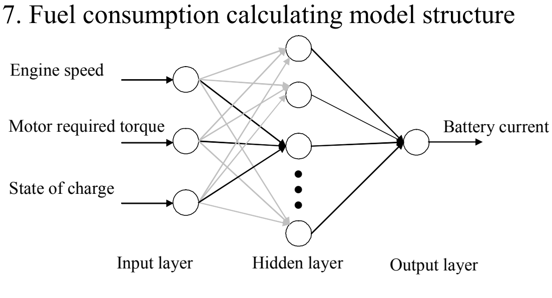

Fig. 8. Current consumption calculating model structure

Table 2. Neural network model parameters and conditions

PARAMETER	FUEL INJECTION	CURRENT
Hidden layer sigmoid gain	0.25	0.25
Output layer sigmoid gain	0.45	0.55
Hidden layer learning weithts	0.13	0.25
Output layer learning weights	0.55	0.55
Number of input layer neurons	2	3
Number of hidden layer neurons	15	20
Number of output layer neurons	1	1
Learning time	10000	5000
Data sets	1950	1950

Fig. 9 ～ Fig. 12 show the calculated result of neural network model trained with experimental data. Here, R^2 indicates the correlation coefficient between the experimental data and the calculated value by using the identified model.

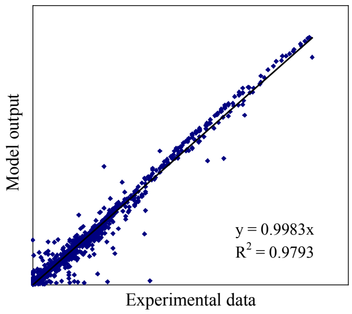

Fig. 9. Correlation coefficient between experimental data and identified fuel consumption model

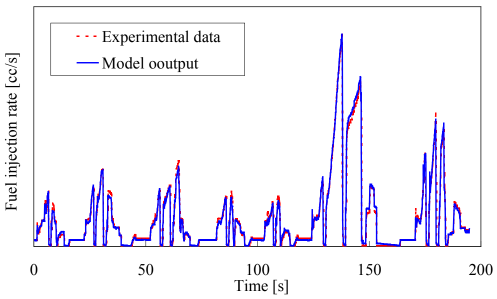

Fig. 10. Comparison of experimental data with identified fuel consumption model in time history

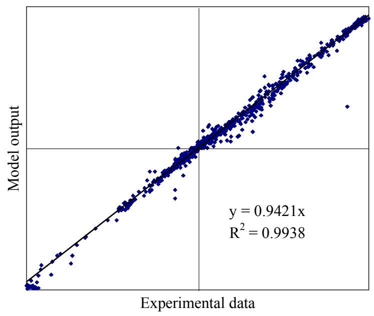

Fig. 11. Correlation coefficient between experimental data and identified current consumption model

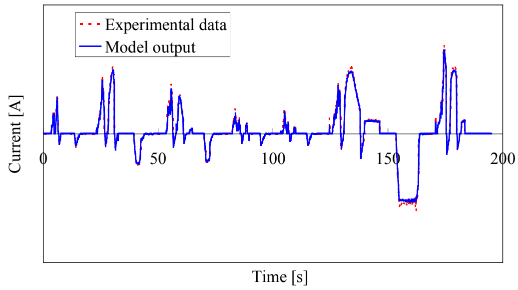

Fig. 12. Comparison of experimental data with identified current consumption model in time history

Model output values show good consistency with experimental data, as can be confirmed from the R^2 values and the gradient of linear approximation line. And then, generalization of identified models are evaluated by using other experimental data that are not used in model learning.

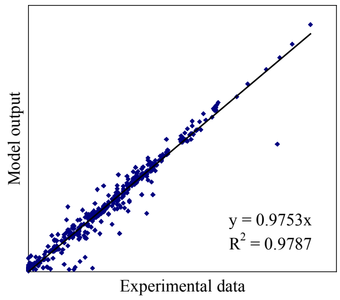

Fig. 13. Evaluation for generalization of identified fuel consumption model

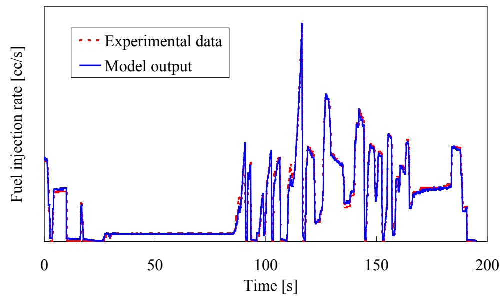

Fig. 14. Evaluation for generalization of identified fuel consumption model in time history

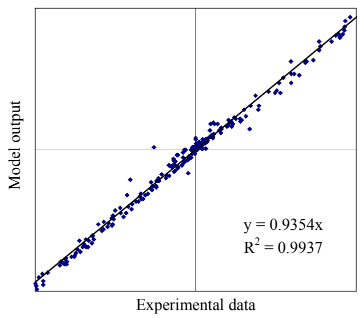

Fig. 15. Evaluation for generalization of identified current consumption model

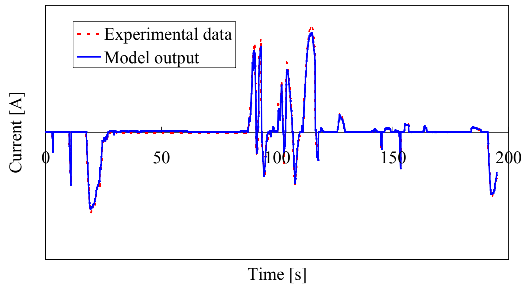

Fig. 16. Evaluation for generalization of identified current consumption model in time history

Fig. 13 ～ Fig. 16 show the result for model validation. The results show good consistency with experimental data. Therefore, it is proved that the fuel and electric current consumption models by using neural network have satisfactory effectiveness in predicting fuel consumption and electric energy consumption. For the next step, these models will be embedded in the hybrid system and utilized for computing the torque distribution.

4.3 Assist control parameters optimization

In this subsection, the assist torque control logic of new hybrid controller is described. The assist torque control is expressed as shown in Fig. 17. Here, T_{req} indicates the driver required torque, $T_{full}(\omega_e)$, the vehicle maximum torque and $T_{ass}(\omega_e)$, the assist start torque with respect to engine speed, T_{a_peak} and ω_{e_peak} , the parameter of $T_{ass}(\omega_e)$.

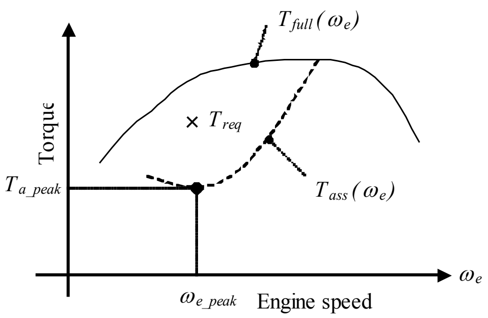

Fig. 17. Assist torque distribution control map

Then, the motor and the engine torques are described by the following equations.

$$T_m = \{T_{req} - T_{ass}(\omega_e)\} \times E_{trq} \tag{3}$$

$$T_e = T_{req} - T_m \tag{4}$$

where, T_m indicates the motor assist torque, E_{trq} , the assist weight from 0 to 1.0, and T_e , the engine torque. The assist torque $T_{ass}(\omega_e)$ which is a function of engine speed is assumed to be expressed as follows :

$$T_{ass}(\omega_e) = \gamma(\omega_e - \omega_{e\_peak})^2 + T_{a\_peak} \tag{5}$$

Then, the parameters of this assist control logic are T_{a_peak}, ω_{e_peak}, E_{trq} and γ. As shown in Fig. 18, the controller simulates fuel and current consumption from the buffered data, at the previous sampling time, with all parameter set patterns. Here, I_{regen_buf} indicates the buffered regenerated current, ω_{e_buf} , the buffered engine speed , T_{req_buf} , the buffered driver required torque, I_{b_s} , the calculated current , F_{c_s} , the fuel consumption by using neural network models, and ΔSOC indicates the current balance in the simulation for a parameter set. Hybrid controller calculates F_{c_s} and ΔSOC for all parameter sets by using the buffered data. And, the optimal assist control parameter set which satisfies the predetermined condition will be selected.

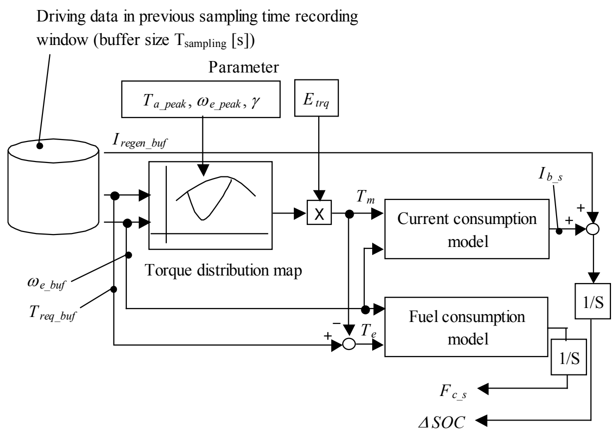

Fig. 18. On-line simulation with identified fuel and current consumption models.

The condition for select parameter are expressed as the following equations.

$$\Delta SOC_{\min}(SOC) \le \Delta SOC \le \Delta SOC_{\max}(SOC) \tag{6}$$

$$\Delta SOC(T_{a\_peak}, \omega_{e\_peak}, \gamma, E_{trq})$$

where, $\Delta SOC_{min}(SOC)$ and $\Delta SOC_{max}(SOC)$ respectively indicate the allowable minimum and maximum range with respect to current SOC for save Ni-MH battery, to prevent extraordinary charge or discharge as indicated in Fig. 19.

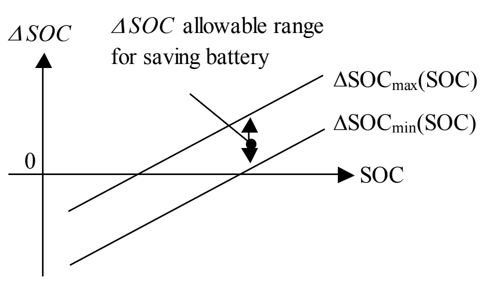

Fig. 19. ΔSOC allowable range with respect to current SOC for saving battery.

And the most important condition for parameter evaluation is fuel consumption as following equation.

$$\min[F_{c\_s}(T_{a\_peak}, \omega_{e\_peak}, \gamma, E_{trq})] \qquad (7)$$

Then, the hybrid controller is updated with the parameters selected on the above mentioned conditions, and distributes the driver's required torque to the engine and the motor based on the optimized parameters.

5. SIMULATION

Simulation was conducted to evaluate new controller described in the previous section for the improvement in the fuel economy as well as the SOC balance. As shown in Table 3, the proposed controller as control A selects and updates the optimal assist control parameter set in the 1008 pattern , and the fixed parameter set is used in conventional controller as control B. In addition, the running generating is started by using surplus engine torque if the battery SOC is less than the GenON_SOC as indicated in Fig. 20., and the parameter E_{trq} is fixed to 0.5 during generating mode.

Table 3. Assist control parameters

Parameter	unit	Control A			Control B
		min	max	step	fixed
T_{a_peak}	Nm	50	300	50	80
ω_{e_peak}	RPM	500	2000	250	500
γ	-	2.5×10^{-4}	5.5×10^{-4}	1.0×10^{-4}	2.5×10^{-4}
E_{trq}	-	0	1.0	0.2	1.0
Total pattern	-	1008			1

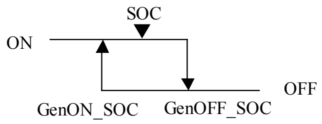

Fig. 20. Running generating mode range

Simulation was conducted in the condition of repeated driving pattern indicated in Fig. 21. The fuel consumption and the SOC balance for 13 cycles of the pattern were evaluated. Number of cycles, as repeating the driving pattern, was determined with the condition which recovers battery SOC to initial condition as Time = 0s. Here, the controller parameter of sampling time for the controller A was determined as $T_{Sampling}$ = 50s.

The results of simulation, the time history of the fuel consumption and the SOC balance, are shown in Fig. 22. The controller A was optimized in 1 cycle, and it held the balance of SOC. In contrast, with the controller B, SOC decreased less than the GenON_SOC, and the generating mode was started at about 400s. Generating mode is ineffective for the hybrid system, and the assist control is not optimized for the driving pattern with the controller B. Therefore, the fuel consumption with the controller A was improved about 7% compared with control B as shown Table 4.

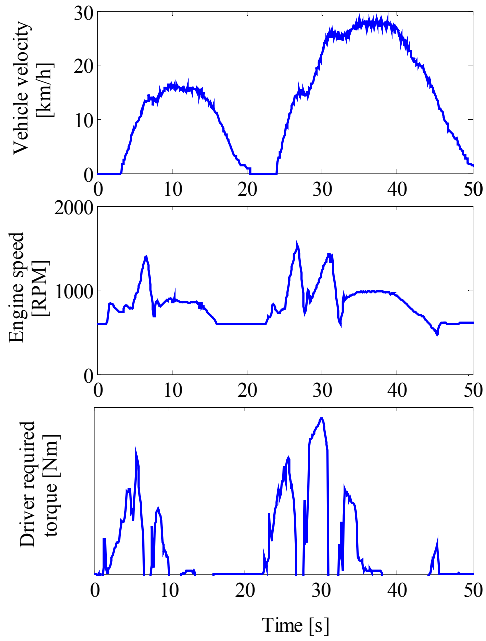

Fig. 21. Driving pattern for evaluate new hybrid controller

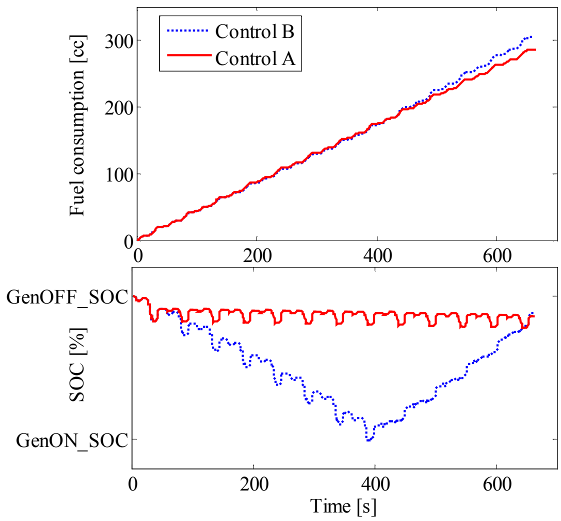

Fig. 22. Comparison of fuel consumption between the controller A and B

Table 4. Simulation results

HV controller	Control A	Control B	Improvement
Fuel consumption	308cc	331cc	Δ23cc

6. CONCLUSIONS

From the modelling of the fuel and the electric current consumption by using neural network, and the designed hybrid controller based on the models, the major conclusions to be drawn from the study can be summarized as follows:

- The fuel and the electric current consumption models are identified by using neural network, and the models show good consistency in time history and correlation coefficient when comparing the calculated results with the experimental data.

-The proposed assist controller is designed that selects optimal assist parameter under the running condition in real time and embeds the synthesized fuel consumption computational models. The effectiveness of the proposed controller is evaluated by using computer simulation under driving patterns. It was found that the fuel economy improvement can be achieved about 7% compared with the conventional hybrid system control algorithm.

In future works, the effectiveness of the proposed assist controller on fuel economy improvement will be verified under actual driving condition. Moreover, the relationship between the controller parameter update including sampling rate, and contribution to fuel economy improvement will be investigated.

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