Continuously Variable Transmission Vehicle Modeling and Control Algorithm Considering Fuel and Driveline Efficiency

Beomjoon Pyun, Chulwoo Moon, Changhyun Jeong, and Dohyun Jung

***Abstract*—From the perspective of vehicle driving, the relationship between driveline efficiency and fuel efficiency is a trade-off. Moreover, there are differences in each driver's preference in the ranges of driveline and fuel efficiency. For these reasons, the optimization between driveline efficiency and fuel efficiency is applied by considering personal driving characteristics. A study using a continuously variable transmission (CVT) control algorithm has advantages because continuous gears have a lot of freedom for control. Therefore, the target probability, which is related to the driving characteristics, is applied to the CVT gear shifting control algorithm based on a CVT vehicle model and verified.**

***Index Terms*—Controller, CVT, driveline efficiency, economy mode, fuel efficiency, modeling, personal driving characteristic, sporty mode.**

I. Introduction

From the perspective of powertrain system development, increases in driveline and fuel efficiency are the most important factors to satisfy intensified low pollution restrictions and the demands of customers [1]-[3]. In the powertrain research field, there are efforts to increase the driveline and fuel efficiency. Power management system (PMS) technology, an integration control technique for engine and transmission, provides a dramatic improvement of driveline and fuel efficiency through the control of engine speed and torque. In the study of PMS technology, the driver's driving characteristics are considered predominant factors in developing a control algorithm for the transmission-shifting ratio.

The problem is that there is a trade-off relationship between driveline efficiency and fuel efficiency regarding the control of the transmission-shifting ratio [4]. To optimize this relationship, a specific standard should be devised. However, it is difficult to select an optimum value that exactly fits the driving characteristics of all drivers. Before such a selection can be predicted, a transmission control algorithm that can apply driving characteristics should be developed based on a vehicular model.

To develop the transmission control algorithm, adaptive transmission control (ATC) is generally considered to reflect the driving characteristics. To develop an ATC, an evaluation of the driving characteristics, driving conditions, and environmental decisions are seriously considered indexes of the driving characteristics. However, such a scoring is not objective and the ATC standards can easily be changed when the target vehicle is changed because it also changes the driving characteristics. Therefore, a more exact and universal (generally applicable) control algorithm should be developed using a probability control algorithm.

In this study, a probability control algorithm is devised to increase the universality of a target probability. This is a proportion between driving with optimized driveline efficiency (sporty mode) and with optimized fuel efficiency (economy mode) that is used to apply the driving characteristics. The probability control algorithm, which is related to the shifting ratio control algorithm, was developed based on a continuously variable transmission (CVT) vehicle model that allows a designer to control the effect of optimization on driveline and fuel efficiency.

In Section II of this paper, the development of a CVT vehicular model based on a powertrain model and a vehicle and road loads model is described to verify the control logic in the simulation environment. In Section III, the target probability tracking controller (probability control algorithm), which allows the vehicle to reflect the driver's driving characteristics, is described.

II. Vehicular Model Based on a Vehicle Test

To study the control algorithm, a vehicular model was developed. The model comprises the powertrain model and vehicle and road load model because the major consideration is longitudinal dynamics [5]. An automatic transmission (AT) vehicular model was developed using dynamic formulas derived from the application of commercialized AT vehicle test results. Based on the AT vehicular model, a new CVT vehicular model was developed and verified.

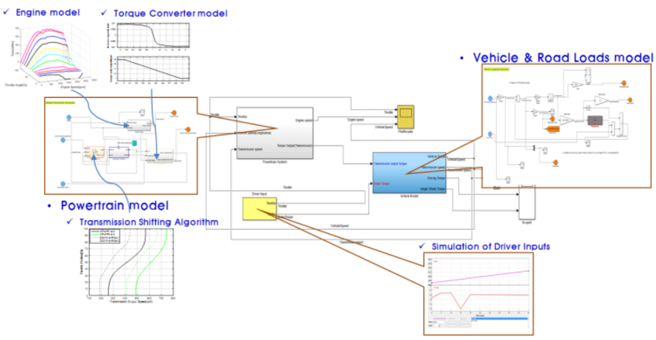

Fig. 1. Simulation environment of the AT vehicular model.

Fig. 1 shows the simulation environment of the AT vehicular model using Matlab/Simulink tool. In the figure,

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the top left block in the simulation environment is the powertrain model, which includes the engine map, torque converter model, and transmission-shifting algorithm based on the test results [6]. The right block in the simulation environment is the vehicle and road load model, which includes the surroundings and vehicle information. The formulas of the two models are as follows [7].

$$F_x = [-I_w\alpha_w - N_{tf}{}^2(I_e + I_t)\alpha_w + N_{tf}T_e - N_f{}^2 I_d\alpha_w]/r \quad (1)$$

$$\frac{W}{g}a_x = F_{xf} + F_{xr} - D_A - (R_{xf} + R_{xr}) - W\sin\theta \quad (2)$$

where $\alpha_e = N_{tf}\alpha_w$, I_e is the engine inertia [kgm^2]; α_e is the angular acceleration of the engine (rad/s); T_e is the engine torque (Nm); I_t is the transmission inertia (kgm^2); I_d is the differential gear inertia (kgm^2); N_f is the gear ratio of differential gear (-); I_w is the wheel inertia (kgm^2); α_w is the angular acceleration of the wheel (rad/s); r is the wheel effective radius (m); and F_x is the traction force (N). Here, F_x is the traction force (N); R_x is the rolling resistance (N); D_A is the drag force (N); a_x is the vehicle acceleration (m/s^2); θ is the road slope (rad); W is the weight of the vehicle (kg); and g is the acceleration of gravity (m/s^2).

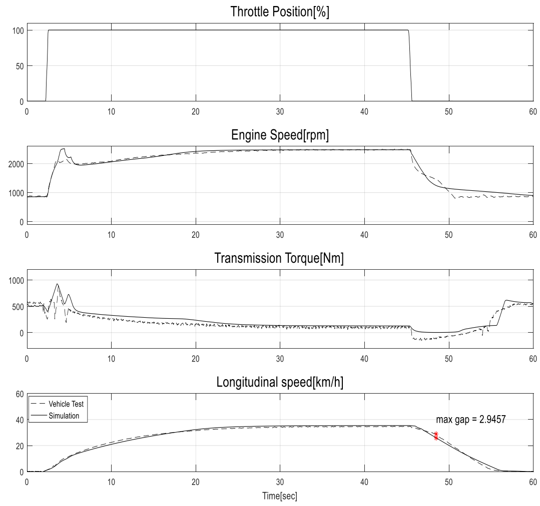
Formula (1) describes the powertrain dynamics. In this formula, the engine power is transferred to the drive wheels. Formula (2) describes the vehicle and road load dynamics. The formula shows how the power from the powertrain dynamics is used to calculate the actual acceleration of the vehicle. Therefore, in Fig. 1, the AT vehicular model using these formulas is described, and the specifications of an actual commercial vehicle are applied to the model. The specifications of the commercialized vehicle are as follows.

TABLE I: SPECIFICATIONS OF A COMMERCIAL VEHICLE

Component	Specifications
Engine	110/230 ps/rpm, 80.9 kW
Transmission	3-speed automatic transmission
	Ratio=[4.714, 2.341, 0.974]
Final Drive Ratio	10.544
Frontal Area	5.39 m^2
Wheelbase	2.3 m
Drag coefficient	1.06
Rolling resistant coefficient	0.01
Tire effective radius	0.405 m
Vehicle Mass	9930 kg

Table I shows the parameters of the vehicular model that describes the actual commercialized vehicle. As shown in Fig. 1, the parameters were applied to the model using the Matlab/Simulink tool.

To verify a longitudinal vehicle model, its maximum error and correlation of longitudinal speed are generally compared. Therefore, by comparing the vehicle test results, the vehicular model was verified using the output (the maximum error and correlation of the longitudinal speed) with the same input of throttle position corresponding to the accelerator position sensor.



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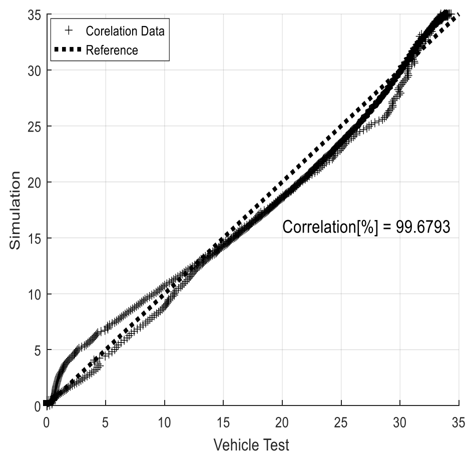


(b)

Fig. 2. AT vehicular model verification.

As shown in Fig. 2(a), the same input of throttle position, which was used in the vehicle test, is used in the simulation. From this condition, the graph shows that the longitudinal speed of the test result and that of the vehicular model simulation are similar. To show the quantitative results, the maximum error and correlation were used, and the correlation formula used is as follows.

$$r = \frac{\sum_{k=1}^{n}(x_k - \bar{x})(y_k - \bar{y})}{\sqrt{\sum_{k=1}^{n}(x_k - \bar{x})^2}\sqrt{\sum_{k=1}^{n}(y_k - \bar{y})^2}}, \quad (3)$$

where, $\bar{x} = \sum_{k=1}^{n}\frac{x_k}{n}$, $\bar{y} = \sum_{k=1}^{n}\frac{y_k}{n}$

Formula (3) is Pearson's product-moment coefficient of correlation (Pearson's r) [8]. In this formula, the r-square value is the correlation value. On the basis of these results, the AT vehicular model was developed with a maximum error of 2.93 km/h and correlation of 99.68%.

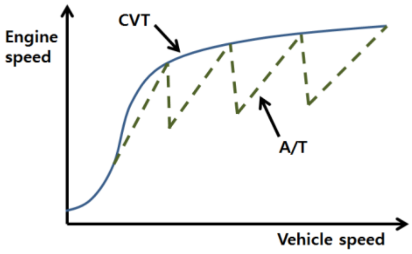
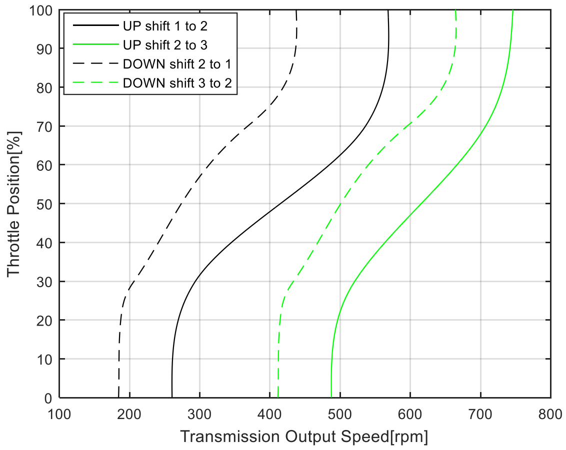


Fig. 3. Advantages of a CVT.

As shown in Fig. 3, a CVT can continuously change the gear ratio without shifting shock and shifting loss. Hence, CVT is more controllable than AT, and this makes it useful for taking an optimal value of driveline or fuel efficiency. The CVT vehicular model was developed based on the previously developed AT vehicular model, and the shifting schedule was created using the AT shifting schedule. Then, the CVT vehicular model was verified by comparing it with the AT vehicular model.



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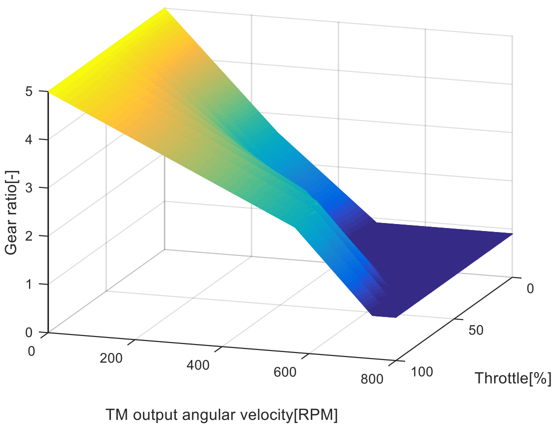
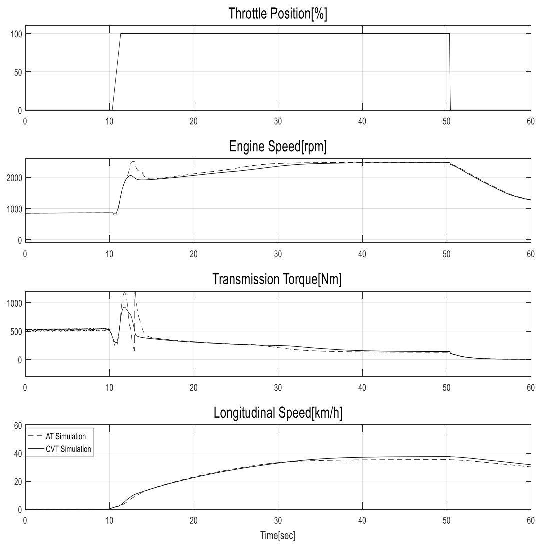


(b)

Fig. 4. Shifting scheduling of a CVT vehicle.

The AT shifting map is shown in Fig. 4(a). The gear ratio discretely changes at 4.714 (first gear ratio), 2.341 (second gear ratio), and 0.974 (third gear ratio). As shown in Fig. 4(b), the discrete shifting values were then interpolated to make them continuous because the CVT shifting map should be continuous.

To verify the reactions of the CVT vehicular model, the same input used for the AT vehicular model was applied, and the outputs of the AT and CVT vehicular models were compared (see Fig. 5). The current gear graph shows that the AT vehicular model is discretely shifting and the CVT vehicular model is continuously shifting. The engine speed and transmission torque graphs show that the shifting shock and shifting loss of the CVT vehicular model are lower than those of the AT vehicular model. In addition, the longitudinal speed of the CVT vehicular model is slightly higher than that of the AT vehicular model because of less energy loss. In this way, the CVT vehicular model was developed and verified.



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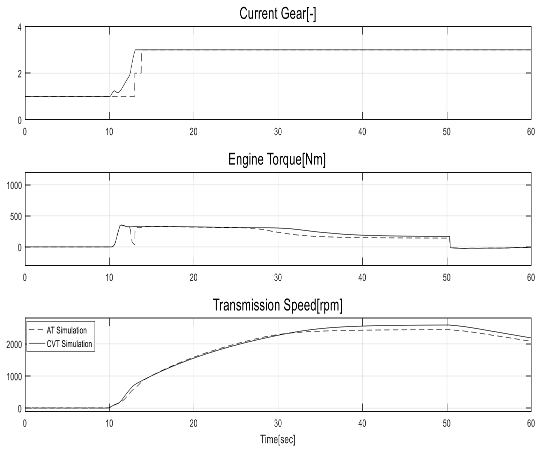

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Fig. 5. CVT vehicular model verification.

III. Probability Control Algorithm for the CVT Vehicular Model

Based on the CVT vehicular model, a probability controller that can select driving in the sporty mode (for driveline efficiency) or driving in the economy mode (for fuel efficiency) was developed. A maximum engine performance line and minimum fuel consumption line were drawn on each engine map, and a brake-specific fuel consumption map was the result of an engine test. Then, each line was optimized using “B. Bonsen’s CVT ratio control strategy optimization,” [9] which considers the physical limitations of the vehicle. To verify the tracking ability of the control algorithm, the optimized lines were used as reference lines. The target probability, which is a proportional line between the two optimized lines, was used as the ultimate reference line for the tracking control (probability control) algorithm. This control algorithm was verified using a case in which the personal driving characteristic was predicted.

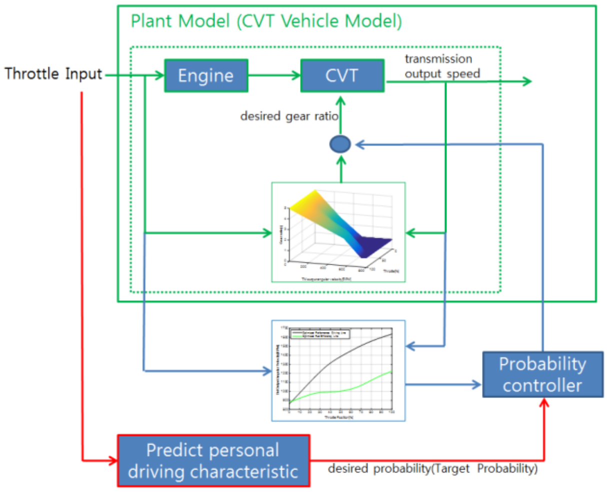
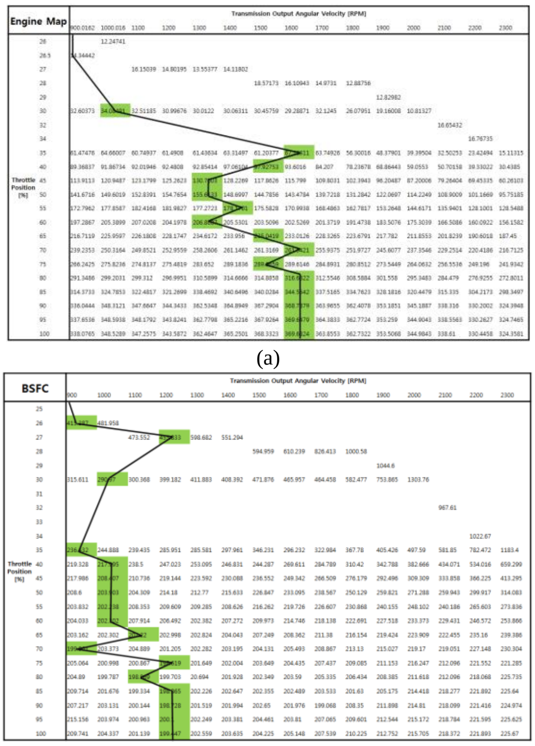


Fig. 6. Schematic block diagram of the CVT model control algorithm.

Fig. 6 shows the schematic block diagram of the probability control algorithm. On the block diagram, the green boxes and lines indicate the CVT vehicular model, which includes the CVT shifting map. The blue boxes and lines indicate the control algorithm, which is composed of the gear ratio feedback algorithm using the PI control. The red box and lines indicate the prediction algorithm, which transfers the target probability to the probability controller. In the prediction algorithm, data from a specific driver who tested the vehicle were used to apply the personal driving characteristic used for the verification.

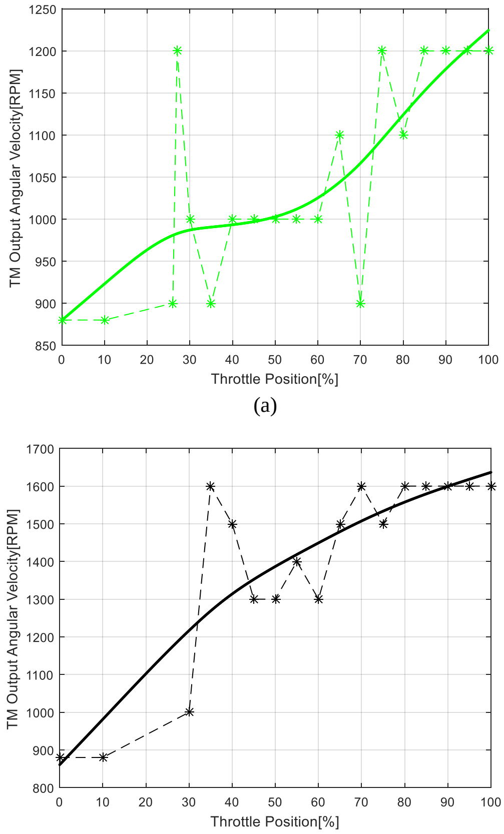


(a)

(b)

Fig. 7. Engine map table (a) and BFSC map table (b).

Fig. 7 shows the maximum engine performance and minimum fuel consumption lines drawn on each engine map, and the BFSC map, which is the result of an engine test. BFSC refers to the fuel consumption per hour ($B_e[g/h]$) in relation to 1 kW of power, and its unit is $b_e[Nm^3/kWh]$.

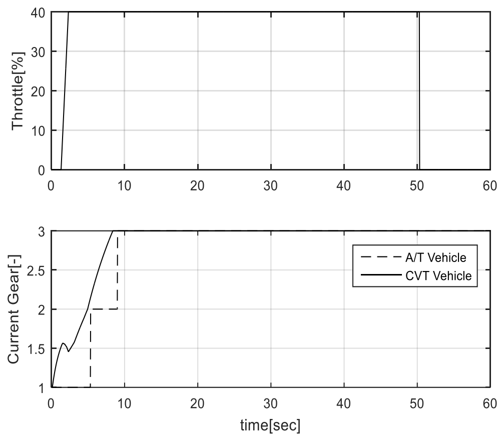


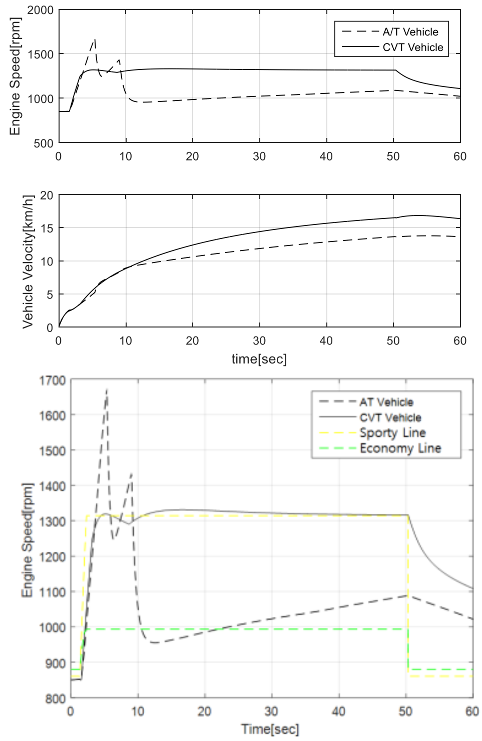
(a)

(b)

Fig. 8. Optimized driving efficiency (a) and fuel efficiency (b) line.

The lines in Fig.7 are plotted in Fig. 8 as dotted lines; however, there were physical limitations in applying the lines. For example, when the throttle position changed less than 5%, the transmission output speed should increase more than 300 rpm. However, this case is impossible. Therefore, using B. Bonsen's method, the dotted lines were optimized and shown as solid lines.





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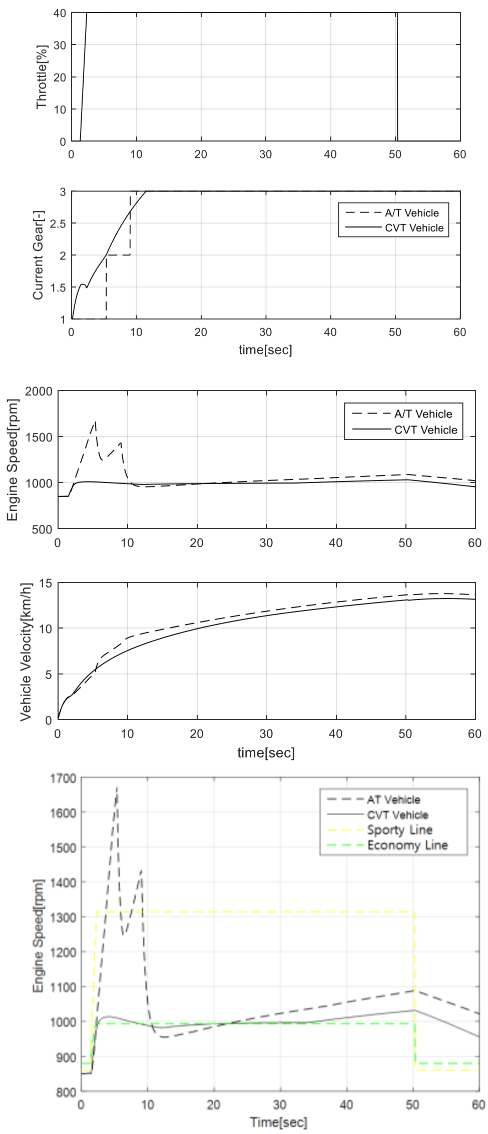

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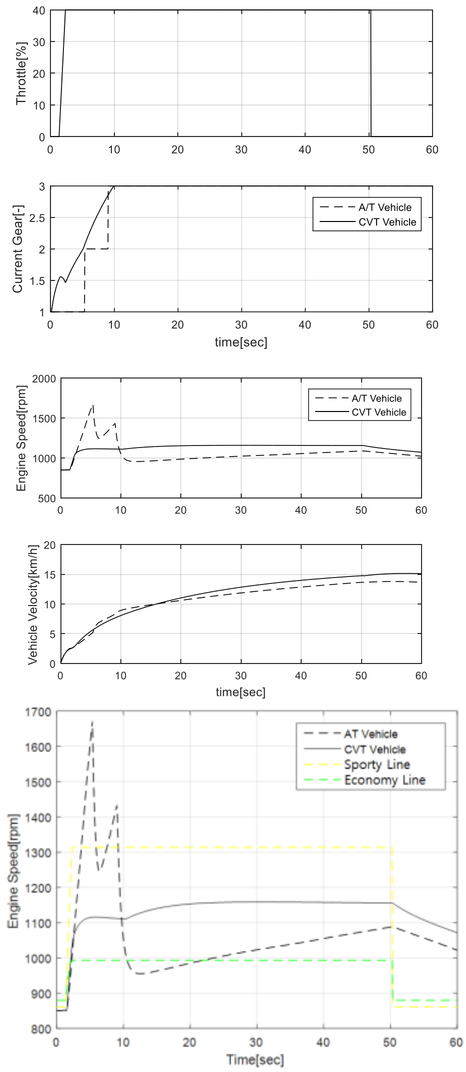
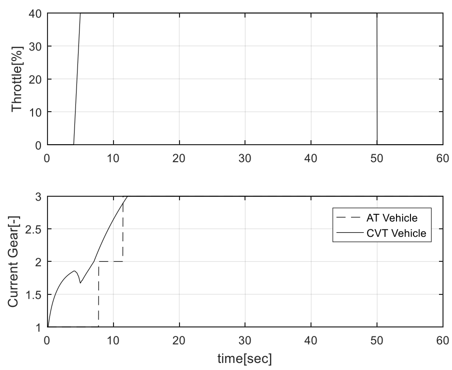
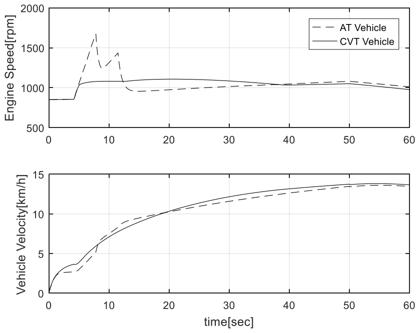


(c)

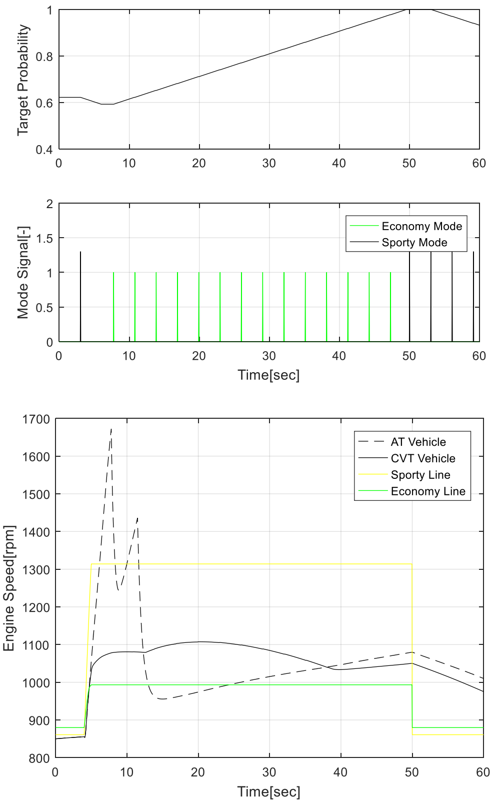
Fig. 9. Sporty and economy line traction control verification.

In conclusion, to track the targets in Fig. 8, a PI control algorithm was developed. In Fig. 9(a), the sporty line is traced by the CVT vehicular model simulation. In the top graphs of (a), the CVT vehicle is operating in the sporty mode. On the bottom graph of Fig. 9(b), the economy line is traced by the CVT vehicular model simulation. In the top graphs of (b), the CVT vehicle is operating in the economy mode. In Fig. 9(c), the probability target line is traced by the CVT vehicular model. Therefore, the tracking ability of the probability control algorithm is verified.





(a)



(b)

Fig. 10. Driver's intention traction control algorithm verification.

Fig. 10 shows the results from the probability controller with the prediction algorithm. To predict the target probability with the prediction algorithm, the driver's driving characteristic (driving in either the sporty or economy mode) should be decided. In the algorithm, accelerator-pedal input data was monitored every 3 s. In each 3 s of data, if the acceleration pedal increased more than 20% within 0.8 s or if the acceleration pedal was > 80%, then the driving characteristic selected was the sporty mode. If the acceleration pedal was not changing more than 10% for 3 s and the acceleration pedal was between 10% and 80%, then the driving characteristic selected was the economy mode. Once the sporty or economy mode was selected, the next mode selection would be after at least 3 s. Therefore, with the scenario in Fig. 10(a), the mode signal is shown in the left graph of (b). The mode signal causes the target probability to change, and the CVT vehicular model is affected by the controller, as shown in the right graph of Fig. 10(b). In conclusion, the driver's driving characteristic was applied to the probability control algorithm of the CVT vehicular model and was verified.

IV. Conclusions

In this study, a CVT shifting ratio control algorithm was developed that applied the personal driving characteristics of the driver as a proportion between the sporty mode and economy mode. For this, a seven-step process was used. On the basis of the test results of a vehicle with AT, an AT vehicular model was developed and verified. A CVT model was developed based on the AT model. The CVT vehicular model was developed and verified by comparing it with the AT vehicular model performance. The engine and BFSC map tables were derived from the engine test results. Optimized lines for driving for driveline efficiency (sporty mode) and fuel efficiency (economy mode) were developed using B. Bonsen's method. The CVT shifting ratio control algorithm (probability controller), which applied the traction control that could track each optimized line, was verified. The predicted driver's driving characteristic determined as a proportion between the sporty mode and economy mode was verified.

In future works, the prediction of a driver's driving characteristics will be specified, and PMS technology, including engine power control, will be considered. In addition, the PI controller will be changed to a machine learning control algorithm.

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