Abstract—From the perspective of vehicle driving, the relation between driveline efficiency and fuel efficiency is a trade-off. Moreover, there are differences in each driver’s preference in the ranges of driveline efficiency and fuel efficiency. For these reasons, the optimization between driveline efficiency and fuel efficiency is applied considering personal driving characteristics. Study using a Continuously Variable Transmission (CVT) control algorithm has advantageous 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 of driveline efficiency 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 efficiency and fuel efficiency. Power Management System (PMS) technology, an integration control technique for engine and transmission, provides dramatic improvement of driveline efficiency and fuel efficiency by 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 the 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, ATC (Adaptive Transmission Control) is generally considered to reflect the driving characteristics. To develop an ATC, an Evaluation of Driving Characteristics, Driving Conditions, and Environmental Decisions are seriously considered as indexes of the driving characteristics. However, such scoring is not objective and the ATC standards can easily be changed when the target vehicle is changed. This is 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 paper, 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 efficiency 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 loads model because the major consideration is longitudinal dynamics [5]. An automatic transmission (AT) vehicular model was developed using dynamics 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,
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 test results [6]. The right block in the simulation environment is the Vehicle and road loads model, which includes the surroundings and vehicle information. The formulas of the two models are as follows [7].

\[
F_x = [-I_w \alpha_w - N_{st}^2(I_e + I_i)\alpha_e + N_{st}^2T_e - N_{st}^2I_d\alpha_w] / r \tag{1}
\]

\[
W / g = F_x + F_{sw} - D_A - (R_{sf} + R_{sw}) - W \sin \theta \tag{2}
\]

wherein, \( \alpha = N_g \alpha_w \), \( I_e \) is engine inertia [kgm^2]; \( \alpha_w \) is angular acceleration of the engine (rad/s); \( T_e \) is engine torque (Nm); \( I_i \) is transmission inertia (kgm^2); \( \alpha_e \) is differential gear inertia (kgm^2); \( N_g \) is gear ratio of differential gear (-); \( I_w \) is wheel inertia (kgm^2); \( \alpha_w \) is angular acceleration of wheel (rad/s); \( r \) is wheel effective radius (m); and \( F_x \) is traction force (N). Here, \( F_x \) is traction force (N); \( R_v \) is rolling resistance (N); \( D_A \) is drag force (N); \( \alpha_w \) is vehicle acceleration (m/s^2); \( \theta \) is road slope (rad); \( W \) is weight of vehicle (kg); and \( g \) is the acceleration of gravity (m/s^2).

Formula (1) describes the Powertrain dynamics. In this formula, 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>
<thead>
<tr>
<th>TABLE I: SPECIFICATIONS OF A COMMERCIAL VEHICLE</th>
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<tr>
<td>Component</td>
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<tr>
<td>Engine</td>
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<td>Transmission</td>
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<td>Ratio</td>
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<td>Final Drive Ratio</td>
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<td>Frontal Area</td>
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<td>Wheelbase</td>
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<td>Drag coefficient</td>
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<td>Rolling resistant coefficient</td>
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<td>Tire effective radius</td>
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<td>Vehicle Mass</td>
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Table I shows the parameters of the vehicular model that describe 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 comparison with the vehicle test results, the vehicular model was verified using output (the maximum error and correlation of longitudinal speed) with the same input of throttle position corresponding to the Accelerator Position Sensor (APS).

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 quantitative results, the maximum error and correlation were used, and the correlation formula used is as follows.

\[
r = \frac{\sum_{k=1}^{n} (x_k - \bar{x})(y_k - \bar{y})}{\sqrt{\sum_{k=1}^{n} (x_k - \bar{x})^2} \sqrt{\sum_{k=1}^{n} (y_k - \bar{y})^2}} \tag{3}
\]

wherein, \( \bar{x} = \sum_{k=1}^{n} x_k \), \( \bar{y} = \sum_{k=1}^{n} y_k \).

Formula (3) is Pearson’s product-moment coefficient of correlation (Pearson’s r) [8]. From this formula, the r-square value is the correlation value. From these results, the AT vehicular model was developed with a maximum error of 2.93 km/h and correlation of 99.68%.
As shown in Fig. 3, a CVT can change the gear ratio continuously 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 efficiency 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, CVT vehicular model was verified by comparison to the AT vehicular model.

In Fig. 4(a), the AT shifting map is shown. The gear ratio changes discretely at 4.714(1st gear ratio), 2.341(2nd gear ratio), and 0.974(3rd 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 shifting discretely and the CVT vehicular model is shifting continuously. 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.

III. PROBABILITY CONTROL ALGORITHM FOR THE CVT VEHICULAR MODEL

Based on the CVT vehicular model, a Probability Controller that could select driving in Sporty Mode (for driveline efficiency) or driving in 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 (BSFC) map was the result of an engine test. 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. 7 shows the maximum engine performance and minimum fuel consumption lines drawn on each engine map, and the Brake Specific Fuel Consumption (BFSC) map, which is the result of an engine test. BFSC refers to the fuel consumption per hour \( (B_f [g/h]) \) in relation to 1 kW of power, and its unit is \( b_f [Nm^3/kWh] \).

Fig. 6 shows the schematic block diagram of the CVT model 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 feed-back algorithm using 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.

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 is impossible. Therefore, using B. Bonsen’s method, the dotted lines were optimized and shown as solid lines.
In conclusion, to track the targets in Fig. 8, a PI control algorithm was developed. In Fig. 9(a), it is shown that the Sporty Line is traced by the CVT vehicular model simulation. In the top graphs of (a), it is shown that the CVT vehicle is operating in Sporty Mode. On the bottom graph of Fig. 9(b), it is shown that the Economy Line is traced by the CVT vehicular model simulation. In the top graphs of (b), it is shown that the CVT vehicle is operating in Economy Mode. In Fig. 9(c), it is shown that the Probability Target line is traced by the CVT vehicular model. Therefore, the tracking ability of the probability control algorithm is verified.
In this paper, a CVT shifting ratio control algorithm was developed that applied the personal driving characteristic of the driver, as a proportion between Sporty Mode and Economy Mode. For this, a seven-step process was used. From the test results of a vehicle with Automatic Transmission (AT), an AT vehicular model was developed and verified. A Continuously Variable Transmission (CVT) model was developed based on the AT model. The CVT vehicular model was developed and verified by comparison with the AT vehicular model performance. The Engine map table and Brake Specific Fuel Consumption (BFSC) map table were derived from 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 traction control that could track each optimized line was verified. The predicted driver’s driving characteristic determined as a proportion between the Sporty and Economy Mode, was verified.

In future work, prediction of the driver’s driving characteristic 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.

REFERENCES


Beomjoon Pyun was born in the Republic of Korea in 1985. He received the bachelor degree in mechanical engineering from Hanyang University in 2013 and the master’s degree in automotive engineering from Hanyang University in 2015. His research interests are system modeling, control algorithms, and machine learning for vehicles.

Chulwoo Moon obtained a B.S. degree in mechanical engineering from Hanyang University (Republic of Korea) in 2006, and his M.S. and Ph.D. from the Korea Advanced Institute of Science and Technology (KAIST) in 2018. He joined the Korea Automotive Technology Institute in 2007, where he is currently a Senior Research Engineer in the Driving Efficiency & Safety Systems R&D Center. His current research interests include control system development for intelligent vehicle systems considering driving efficiency and the emotional factors of human drivers.
Changhyun Jeong received B.S. and M.S. degrees in mechanical engineering from Yonsei University, (Republic of Korea) in 1997 and 1999, and his Ph.D. from Seoul National University in 2014. He was a research engineer at Korea Delphi Automotive Systems Corporation from 1999 to 2002. He joined the Korea Automotive Technology Institute in 2002, where he is currently a director in the Driving Efficiency & Safety Systems R&D Center.

Dohyun Jung received a B.S. degree from Seoul National University (Republic of Korea) in 1992, and the M.S. degree in mechanical engineering from the Korea Advanced Institute of Science and Technology (KAIST) in 1994. He received a Ph.D. in mechanical engineering from KAIST in 2001. He is currently a vice president of Convergence Systems R&D Division at the Korea Automotive Technology Institute.