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# Development of enhanced ESP system through vehicle parameter estimation †

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**Abstract**

In this research, an enhanced lateral stability control system has been developed for a vehicle. The system consists of a vehicle parameter estimation part and an enhanced ESP control logic part. The vehicle parameter estimation was conducted by considering the physical relationship among the longitudinal dynamic components. The enhanced ESP logic was designed so that the controller gains change adaptively to the vehicle parameter variation. All the system components were tested in a simulation environment, while the vehicle mass estimation algorithm was also tested in the field. The results indicated that the lateral vehicle stability limit can be improved with the designed ESP system.

*Keywords*: ESP (Electronic Stability Program); Load adaptive control; Optimization; Parameter estimation

## 1. Introduction

ESP (Electronic Stability Program) is an electronic chassis control system whose objective is to maintain lateral vehicle stability during critical cornering [1]. At the beginning of its control logic, the ESP algorithm computes the reference yaw rate as the target to follow, using a lateral vehicle model. The parameters of the vehicle model, however, can change significantly due to many passengers or heavy loads. The amount of vehicle mass variation, for example, can be bigger than the vehicle's curb weight for some vehicles. Hence, it is very important for the ESP logic to account for any significant change in the vehicle parameters, since otherwise, the ESP logic can worsen vehicle lateral stability by setting an improper target in dangerous cornering maneuvers.

Many previous studies in the area of the vehicle parameter estimation have adopted the recursive least square method [2, 3]. This online version of the unconstrained least square method is reliable in determining the parameters of a mathematical function that matches the vehicle performance in its transient motion. However, due to the possibility of non-unique minimum solutions, the algorithm may have difficulty in the process of extracting the physical parameters from the mathematical solution. The recent work of Bosch states that through vehicle mass estimation, ESP could improve the braking efficiency and performance of stability control [4].

In this research, an enhanced ESP system has been developed for a passenger vehicle. The system consists of two parts: a vehicle parameter estimation part and an enhanced ESP control logic. The vehicle parameter estimation was conducted by considering the physical relationship among the longitudinal dynamic

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components of the vehicle. The enhanced ESP logic was designed using a proportional-integral-derivative (PID) controller, and for a feasible range of the vehicle parameter variation, a lookup table for the PID gains was made using trajectory optimization. All the system components were validated in a simulation environment where the CarSim vehicle model was used in place of the actual vehicle. The vehicle mass estimation algorithm, however, was also tested in the field after proper modification was made so that it could work only with the sensor signals available in real vehicles.

## 2. Model-based mass estimation

A vehicle mass estimation algorithm was first developed using the powertrain model in Fig. 1.

This model consists of the engine, torque converter, transmission, final drive, and wheels. Their equations are as follows:

$$T_{Eout} = T_{Ein} - \dot{\omega}_E J_E \tag{1}$$

$$T_{TMout} = (T_{TMin} - \dot{\omega}_{TM} J_{TM})\, i_{TM} \tag{2}$$

$$T_{FDout} = T_{FDin}\, i_{FD} \tag{3}$$

$$F_w = \frac{T_{FD_{out}}}{r_{eff}} - \frac{a_x}{r_{eff}^2} J_w \tag{4}$$

In the engine model in (1), $T_{Ein}(T_{Eout})$ is the engine input(output) torque, $\omega_E$ is the engine speed, and $J_E$ is the rotational inertia. The torque converter was modeled by a lookup table for its characteristic curve. In the transmission model in (2), $T_{TMin}(T_{TMout})$ is the transmission input(output) torque, $\omega_{TM}$ is the rotational speed, $J_{TM}$ is the rotational inertia, and $i_{TM}$ is the gear ratio. In the final drive model in (3), $T_{FDin}(T_{FDout})$ is the final drive input (output) torque, and $i_{FD}$ is the gear ratio. In the wheel model in (4), $F_w$ is the tire traction force, $r_{eff}$ is the effective tire radius, $J_w$ is the tire inertia, and $a_x$ is the vehicle longitudinal acceleration.

Once the tire traction force is found, the vehicle mass $m$ can be estimated by the following equation:

$$ma_x = F_w - R_{rolling} - R_{aero} \tag{5}$$

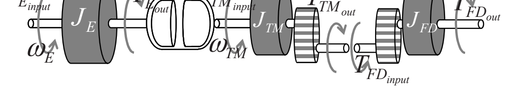



Fig. 1. Powertrain model.

In the above, $R_{rolling}$ is the rolling resistance, and $R_{aero}$ is the aerodynamic drag. They were computed using empirical functions in this study. Fig. 2 shows their contributions in different vehicle velocities. This figure indicates that at a low speed, the rolling resistance which remains almost constant becomes a dominant resistive force.

The model-based mass estimation algorithm of this chapter was tested using the CarSim vehicle model. The maximum estimation error remained within 2%.

## 3. Mass estimation from sensor signals

This chapter introduces another mass estimation algorithm developed in this research. It is based on the previous algorithm but modified for application in real vehicles. In the CarSim vehicle model used in Chapter 2, the frictional loss in the powertrain mechanism was neglected, and the rotational inertia of the powertrain was not accurately modeled. To improve the accuracy of mass estimation in real vehicles, these quantities were first found through vehicle tests.

When the vehicle is cruising at a constant speed, a small throttle is needed to produce a traction force that can balance all resistive forces present. This can be represented as follows:

$$R_{total} = \frac{T_{Eout} R_{TC} i_{TM} i_{FD}}{r_{eff}} \tag{6}$$

In (6), $R_{TC}$ is the torque gain in the torque converter, and $R_{total}$ is the total resistive force that consists of the rolling resistance, the aerodynamic drag, and the powertrain's frictional loss. Using this equation, the frictional loss was found at different gear shift positions.

Once the powertrain frictional loss is computed, the powertrain inertia can be found in a constant acceleration test as indicated by (7). Here, $T_I$ represents the powertrain inertia in the form of an equivalent torque.

$$T_I = (T_{Eout}\, R_{TC}\, i_{TM}\, i_{FD} - r_{eff} R_{total}) - ma_x r_{eff} \tag{7}$$

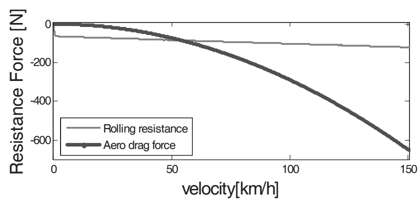



Fig. 2. Resistive forces.

Table 1. Operating condition for mass estimation.

| Parameters | Operating condition |
|---|---|
| gear shift | 1 ~ 3 |
| rotational gain in torque converter | 0.5 ~ 0.8 |
| engine rpm | above 1500 |
| longitudinal acceleration | above 0.1g |

Table 2. Mass estimation by field test data.

| total weight (extra load) | number of tests | estimation average | min absolute error | max absolute error |
|---|---|---|---|---|
| 1810 kg (0 kg) | 4 | 1819 kg | 6.5 % | 11.0 % |
| 2110 kg (300 kg) | 6 | 2092 kg | 0.2 % | 8.9 % |
| 2310 kg (500 kg) | 4 | 2278 kg | 1.1 % | 4.0 % |

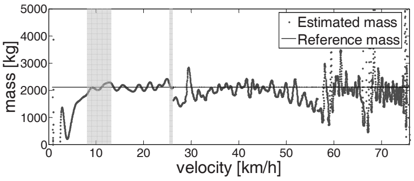



Fig. 3. Estimated mass in the field test.

The mass estimation algorithm of this chapter requires some specific transient motions in the vehicle's longitudinal dynamics. Therefore, detection of the right time for mass estimation becomes a key component of the algorithm. Table 1 lists the operating conditions for activating mass estimation in the algorithm.

Fig. 3 shows the mass estimation results from the field test. The vehicle, loaded with a weight of 300kg in the trunk, was accelerated with a step input of throttle from a stop position. In the test, the maximum longitudinal acceleration was about 0.2g.

In Fig. 3, the two shaded areas are the periods when all operating conditions in Table 1 are satisfied. Table 2 gives the estimation results for different extra loads.

Table 2 indicates that the mass estimation algorithm of this paper gives a very reliable result for a wide range of mass variations. It can be observed that the error of the estimation average did not exceed 1.5%.

## 4. Enhanced ESP system

Fig. 4 shows the configuration of the enhanced ESP system developed in this research. When the estimation of the vehicle mass change is greater than a certain threshold, the reference vehicle model, which is used for computing the target yaw rate for ESP, is updated with a new mass and a new characteristic speed. The ESP control gains are also updated from the PID gain lookup table.

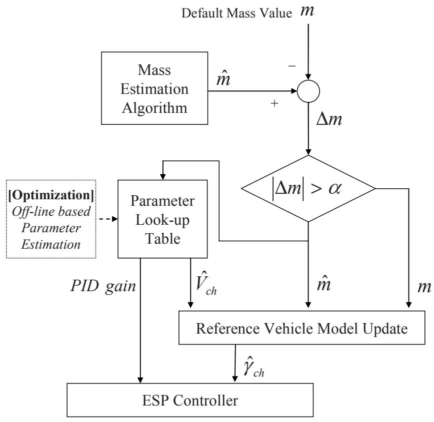



Fig. 4. Configuration of the enhanced ESP system.

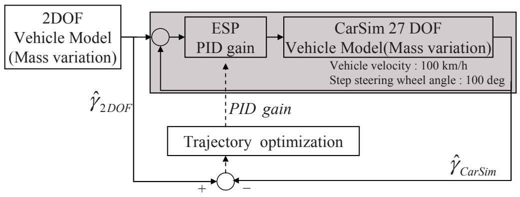



Fig. 5. PID gain by trajectory optimization.

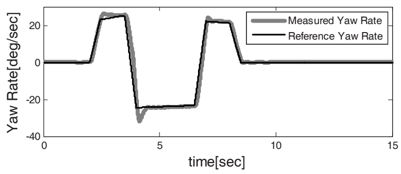



Fig. 6. ESP without LAC with no extra load.

To determine the characteristic speed and PID control gains for different vehicle weights, trajectory optimization was performed offline, and a lookup table was made from this result. Fig. 5 shows the block diagram for finding the optimal PID gains of the ESP logic for different values of the vehicle mass by trajectory optimization. The characteristic speeds for different vehicle masses were also found similarly so that the steady state yaw rate error between the CarSim model and the 2DOF bicycle model is minimized.

## 5. Simulation results

Presented in this chapter are the results of the simulation conducted to evaluate the performance of the

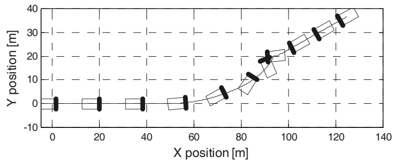
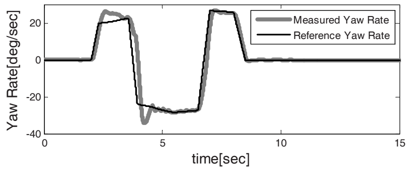
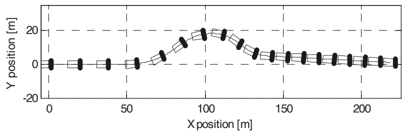



Fig. 7. ESP without LAC with a 500kg load.




(a) Yaw rate




(b) Trajectory

Fig. 8. Enhanced ESP with a 500kg load.

enhanced ESP system developed in this research. A double lane change test was performed on the road with a friction coefficient of 0.9. The vehicle speed was 80km/h, and the steering wheel angle was changing by $\pm 120°$. For performance validation, the enhanced ESP system was compared with the normal ESP system without any load adaptive control (LAC).

Fig. 6 shows the simulation result for an ESP vehicle without LAC when there is no extra load. It shows that the controller is tracking faithfully the reference yaw rate.

Fig. 7 shows the vehicle trajectory for an ESP vehicle without LAC when it is loaded with the weight of 500kg. It shows that the vehicle cannot make any lane change. This is because the reference yaw rate and the controller gains are based on the vehicle model without any additional load.

Shown in Fig. 8 are the simulation results for a vehicle with enhanced ESP when there is a load of 500kg. It shows that the vehicle successfully follows the reference yaw rate, and as a result, it can make double lane change without losing lateral stability.

## 6. Conclusions

An enhanced lateral stability control system for a vehicle has been developed in this paper. The system consists of a vehicle parameter estimation part and an enhanced ESP control logic part. The vehicle parameter estimation was conducted by considering the physical relationship among the longitudinal dynamic components. The enhanced ESP logic was designed so that the controller gains change adaptively to the vehicle parameter variation. All the system components were tested in a simulation environment, while the vehicle mass estimation algorithm was also tested in the field. The results indicated that the lateral vehicle stability limit can be improved with the designed ESP system.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