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Identification of Driver Specific Parameters Using Real-Time Testing

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***Keywords*— ODE- Ordinary differential equation, S- Laplace domain, MISO- Multi-input single-output model, POF- Percentage of fit.**

***Abstract*— This paper emphasis on how to estimate the specific driver parameters corresponding to the human driver using the driver model approach. Subsequently, the specific driver parameters are defined based on the human driver under longitudinal driving conditions. To accomplish this, the mathematical description (Ordinary differential equation (ODE)) of the driver model is considered, representing the specific driver parameters.*

As stated before, the specific driver parameters are investigated for longitudinal driving conditions so, car following based model is selected this model determines how far the vehicle is in front of the other vehicle. Thereafter, the mathematical description of the driver model (ordinary differential equation) is transformed into the Laplace domain (S-domain) for estimating the specific driver parameters by using the input-output behaviour of the driver model.

In this research system identification method is used to obtain the higher order transfer function for the given input and output variable. In addition to it, the acquired higher order transfer function needs to be approximated to the theoretical transfer function of the driver model.

In a nutshell, it can be said that based on the defined goal the specific driver parameters were investigated using the driver model approach. In addition to it, one driver is analysed based on the identified specific driver parameters and correspondingly conclusions are drawn. Consequently, the same approach can be carried out for comparing different human drivers.

I. INTRODUCTION

In the automotive field, over the past decades, Advanced Driver Assistance Systems (ADAS) have been developed and implemented by the manufacturers. Such systems improve the shortcoming of human drivers, such as unavoidable reaction times, workload, low vigilance, etc. in recent years. Nowadays improving safety, comfort, and assistance to the driver is a major concern in the automotive industries and to do so new ADAS systems are developed. To develop the ADAS systems that are safe and comfortable for a human driver to use, it is necessary to understand real human driving behavior. Thus, the human driver behavior can be analysed and modelled using the existing driver models.

The modelling human driver behavior is challenging due to its imaginary nature and a high degree of human driver variability. As stated before, human behavior is analysed using the existing driver models as the driver model accounts for the human driver traits. To study the driver behavior first the driver parameters needs to be specified according to the selected driver model and the driving condition (longitudinal and lateral). Based on the recent advancements in the technology of automotive, electronics and communication, it is easy to collect real-time data during test using various sensors, control unit, etc. Later, on this real-time data is used for estimating the specific driver parameters corresponding to the human driver.

As the technology in the field of automation is improving day-by-day, a stepwise development of vehicle automation is shown in Fig. 1. Society of Automotive Engineers (SAE) has proposed 6 levels of automation ranging from 0 (Driver Only) to 5 (Full Automation).

Currently, more research is being done on level 3 and level 4 of automation but companies are working on to achieve level 5 also. Recently, Volvo has officially kicked *"Off Drive Me"*, the ambitious and advanced public autonomous driving experiment on their autonomous car (XC90 SUV).

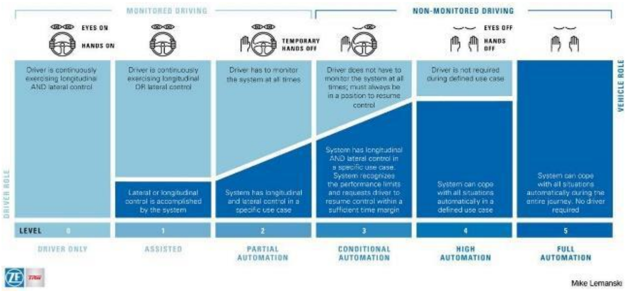

Fig 1: Levels of vehicle automation [4].

The modelling presents an economic and safe methodology for investigating various approaches. Every research is done first on the simulation level, later it moves into the production stage. In this project, the concept of the car-following model is used for estimating the specific driver parameters corresponding to the human driver. This model states that; how far the vehicle is in front of the other vehicle. Furthermore, estimating a suitable driver model is significant in the development of autonomous vehicles, as well as in simulation, evaluation, and optimization of a driver-vehicle closed-loop system. Thus, the schematic car following model is shown in Fig. 2. A large amount of real-time traffic data provide the potential to better calibrate and validate car-following models for more realistic traffic simulations [6].

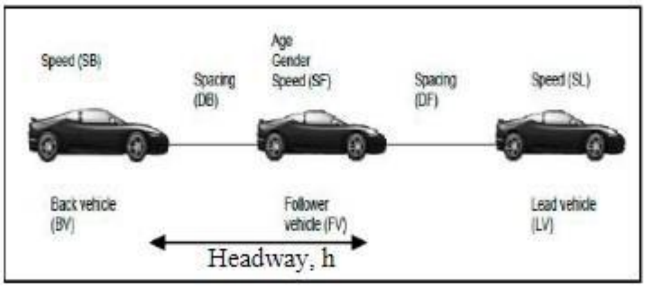

Fig 2: Car following model [6].

This project estimates the specific driver parameters corresponding to the human driver using the driver model approach. Here the problem is to identify the effects of the specific driver parameters on the driving conditions and how to solve the problems related to human factors. There are several human factors related to the human driver which are unique for everyone such as slow reaction time, fatigue, low vigilance, etc. This study is about, how the specific driver parameters (time delay, driver gain) affects the driving condition of the human driver which can be investigated as per the following approach shown in Fig. 3.

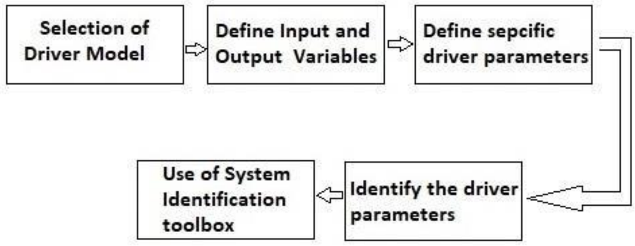

Fig 3: The project approach.

The rest of the paper is organized as follows. We first present the methodology in Section II. We then introduce the test description which explains the procedure of testing in Section III. Further, section IV deals with the approach towards the objective. The approach is subdivided into parts to elaborate the process of finding specific driver parameters. Section V deals with the results and discussion of the research. Conclusions are given in Section VI.

II. METHODOLOGY

This section is concerned about the different aspects of the research and the approach used to reach a satisfactory result. An explanation on the driver model, use of system identification toolbox and methods of estimating specific driver parameters have been discussed.

First, to start with the research, real-time test data is required which is gathered by conducting the test on HAN Automotive Test Vehicle BMW 320i, however, the driver details are anonymous. Thus, the test route was found by using the global coordinates of X and Y (GPS Longitude & Latitude), provided in the data set.

For understanding how the specific driver parameters are changed according to the driving conditions, a study was conducted and based on the analysis, results are presented. To accomplish this, the specific driver parameter are investigated using the driver model approach (see Fig. 3). Furthermore, in the sub-sections explanation is given for;

how and which specific driver parameters are identified corresponding to the human driver.

2.1 Driver Model

Generally, a driver model is defined by an ordinary differential equation (ODE) describing the complete description of the driver parameters, input and output variables which imitate the human driver. As stated before, in this research longitudinal driver behaviour is examined so it is decided to use car following model.

In this section, the car following based model is described. The car following model is selected in this research, due it is simplicity and ease of understanding the longitudinal driver behaviour. Fundamentally, this model considers a scenario where one car is following another car in front. In this condition, the human driver of the following car is observing errors in the desired headway distance, and the relative velocity, which is different for every human driver and changes accordingly [7].

The basic representation of the car following model is shown in Fig. 4. In this research, specific driver parameters; driver gain (K_D) and time delay (t_d) are estimated using the driver model approach.

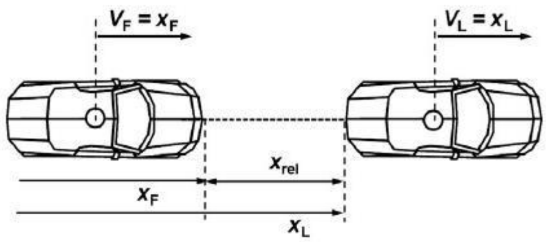

Fig 4: Schematic layout of the car following model [7].

Here the car following model is expressed in the terms of mathematical description assuming the desired time headway THW_{des} and considering a time delay $t_{d1,2}$ & driver gain $K_{1,2}$ [7].

$$P_a = K1 * \dot{X}_F * (t - \tau_{d1}) * (THW\big((t - \tau_{d1}) - THW_{des}\big) + K_2 * V_{rel} * \ (t - \tau_{d2}) \qquad (2.1)$$

Where;

P_a : Percentage of accelerator pedal depression,

K_1 & K_2 : Driver gains,

T : Reaction time delay,

t_d : Delay time,

THW : Time to headway,

THW_{des} : Desired time to headway,

V_{rel} : Relative velocity between the vehicles.

The mathematical description of the driver model (see Eq 2.1) is transformed into the Laplace domain (S-domain). Therefore, the above-mentioned driver model corresponds to the following transfer functions depending upon the input and output variables. In addition to it, the delay terms in transfer functions can be expressed as a power series eliminating higher order terms [3]. Fig. 5 represents the block diagram of the mathematical description of the driver model in the Laplace domain. Thus, the complete driver model results into a multi-input single-output model (MISO) and it is further elaborated in sub-sections.

$$G(s)_1 = \frac{P_a}{THW - THW_{des}} = K_1 e^{-\tau_{d1} s} \qquad (2.2)$$

$$G(s)_2 = \frac{P_a}{V_{rel}} = K_2 e^{-\tau_{d2} s} \qquad (2.3)$$

Fig 5: Representation of driver model in Laplace domain.

The above given transfer functions (see Eq 2.2 & 2.3) use different inputs for identifying the specific driver parameters corresponding to the human driver accounted in the driver model. The transfer function $G_{(s)1}$, formulates the input and output behaviour by using the output as throttle % (Pa) and input as the difference between the time to headway and the desired time to headway (error). The desired time to headway is assumed based on the literature [7]. The two-second rule (also known as the three-second rule) is a rule of thumb, in which a driver maintains a safe trailing distance at any speed [11, 9]. The rule states that a driver should ideally stay at least 2-2.5 seconds behind any vehicle which is in front of it.

Whereas, the transfer function $G_{(s)2}$, formulates the input and output behaviour by using the output as throttle % (P_a) and input as the relative velocity between the vehicles. From the given transfer function models $G_{(s)1}$ & $G_{(s)2}$, four specific driver parameters can be identified which corresponds to the human driver i.e., reaction time delay of the driver (time needed by the driver to analyse/percept the information from the vehicle and the road environment) and the driver gain (this quantity defines how attentive the driver is while driving) [8]. Therefore, the complete description of the driver model results in a multi-input single-output system (see Fig. 5). Finally, the schematic diagram is shown below in Fig. 6, explains about the vehicle and driver subsystems. From this closed-loop system of vehicle and driver, it can be stated that the driver provides input as throttle and brake to the vehicle according to the deviations from the reference set point to maintain the desired headway time (error).

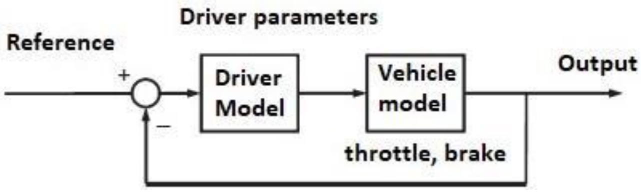

Fig 6: Vehicle driver system [[12, 5]

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2.2 Driver Parameters

As stated before, the driver gain (K_1, K_2) and reaction time delay (t_{d1}, t_{d2}) are the specific driver parameters which are being investigated in this research using the driver model approach (see 2.1). These human specific driver parameters physically vary from person to person, according to human traits such as age, gender, the experience of driving. Fundamentally, the reaction time delay (t_d) specifies the time needed to elaborate the information from the vehicle and the environment. Whereas, the driver gain (K_D) specifies, how attentive the driver is while driving the vehicle. Furthermore, in the subsequent section it is explained how to identify these specific driver parameters (K_1, K_2, t_{d1} & t_{d2}) using the driver model approach.

III. TEST DESCRIPTION

As mentioned in section II, the testing has been performed earlier with the HAN Automotive Test Vehicle BMW 320i as shown in Fig. 7, and the data set was used for analysis. The testing is used for gathering the input variables as per the requirement of the project mentioned above. Since the project is only specific to longitudinal driver behavior based on that the input variables are selected.

The vehicle was mounted with a VBOX 3i measurement system, through which the required data was recorded. Moreover, the vehicle was also equipped with the CAN Bus cable through which all the data coming from the vehicle CAN have been recorded within the flashcard. The variables which were obtained from the VBOX measurement system are:

- Longitudinal acceleration,
- Vehicle velocity,
- Collision front time,
- Brake,
- Throttle.

Along with these data variables, there are few more variables which were present in the data set. VBOX manager uses CAN-Bus cable (RLVBCABO5C) for communicating the data. On the other hand, RS232 was another connector used for VBOX configuration and also the output for real-time GPS data. Furthermore, IMU (Inertial Measurement Unit) was also equipped in the vehicle which acts as external equipment on the vehicle on which external sensors can be mounted if required. The serial port (SER) is connected to IMU which allows the system to retrieve the data through VBOX setup. The vehicle was also well-found with other sensors such as Steering Interface Unit, Radar, GPS Antennas and Mobil-Eye to collect most of the data. As the project is concerned with the longitudinal driver behaviour, therefore the respective data has been recorded.

Fig 7: Test vehicle.

Fig. 8 represents the test route which was obtained using the GPS data (Longitude, Latitude), readings provided in the data set. Therefore, the test was conducted on this specified route to collect the required variables for further analysis.

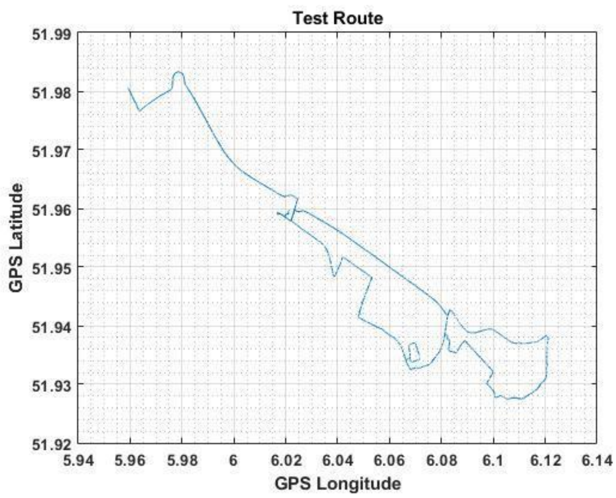

Fig 8: Test route.

IV. APPROACH

In this section, the approach towards the estimation of specific driver parameters is discussed. A general description of the approach was discussed earlier in section 2.1. As stated before, based on the driver model we need to define the input-output variables and identify the specific driver parameters respectively. Therefore, to build the mathematical model (transfer function) of a driver model, using the input-output variables (test data), system identification method is used.

Below in Fig. 9, represents the flow chart of the approach followed for estimating the specific driver parameters using the car following model. Thus, the flow chart is being elaborated in subsequent sections.

4.1 Analysis of the Test Data

This section describes the analysis/extraction of the test data. Since the gathered data has many readings therefore out of which arbitrarily data is selected and divided into a different number of sets based on the condition where one car is following the other car (car-following model). Therefore, the required data is categorized based on the driver model and used respectively for further steps.

Furthermore, the graphs (Fig. 11, 12) are plotted in which output variable (y) is shown as a function of input variable (x) for instance, y = f (x). From these plots, one can understand how the output variable varies with respect to the input variable. Therefore, these two figures are plotted as an example, which changes according to the data set.

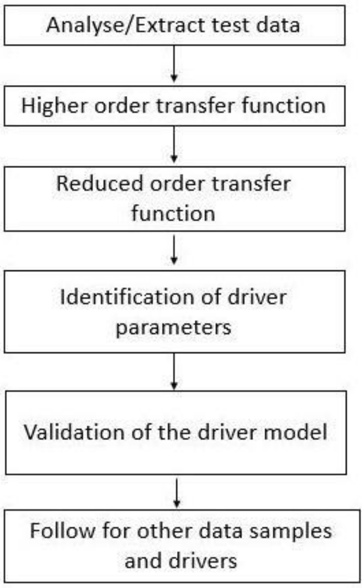

Fig 9: Flow chart.

From the graph shown below in Fig. 10, it is observed that the throttle output varies with the error in time to headway. Initially, when the error in time to headway is 0.5 secs the throttle output increases from 52 to nearly 60 %. Afterwards, the error in time to headway decreases from 0.5 secs to 0 secs, thus the value of throttle output increases in slight slope and later on, the throttle output is constant as given in test data.

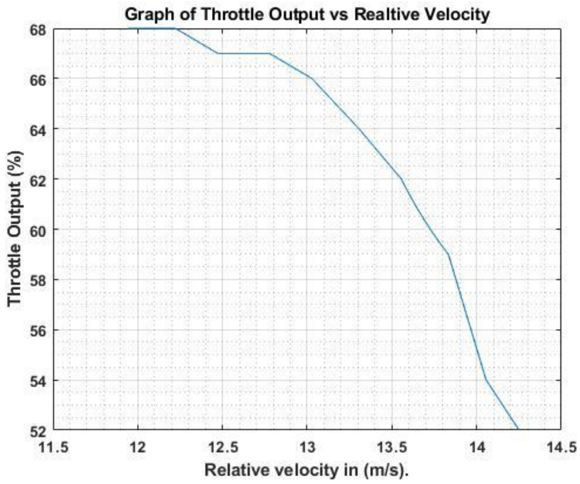

Fig 10: Graph representing Throttle vs Error in Time to Headway.

From the graph shown below in Fig. 11, illustrates throttle as a function of relative velocity. As the driver model is car following that means the cars are travelling in the same direction therefore, the relative velocity of the scenario is (V_F - V_L). Moreover, this quantity can be positive or negative (i.e., direction) depending upon the respective car velocities.

Where;

Velocity of following car: V_F (m/s)

Velocity of leading car: V_L (m/s)

From the graph shown below in Fig. 11, it can be observed that the value of throttle decreases with an increase in the relative velocity. The graph is plotted for a particular data set and from this it can be stated that when the relative velocity is less, throttle output is more to maintain the desired headway distance.

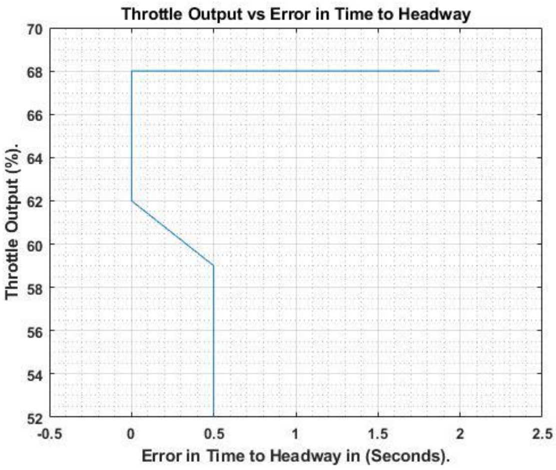

Fig 11: Graph representing Throttle vs Relative Velocity.

4.2 Estimation of Higher Order Transfer Function

According to the flowchart (see Fig. 9), the second step is to estimate the higher order function based on the input-output variables of the driver model by using system identification toolbox. To do so, the data set is already analysed before according to the objective i.e., where the following car follows the leading vehicle. Before estimating the higher order transfer function, the input-output data is pre-processed to remove the trends and disturbance.

Furthermore, the higher order transfer function is obtained for the complete driver model (two different transfer functions) given above (see 2.1), considering it as a MISO system. Hence, the obtained higher order transfer function is selected based on the maximum percentage of fit (less than 90% fit is rejected). As given before, there are two different transfer functions for the driver model (depending upon the input variable). An example for both the higher order transfer functions is given below:

The higher order transfer function $G_{(s)1}$, which is obtained using the system identification toolbox, for a particular set of data is given below.

$$G(s)_1 = \frac{-3.559s^3 + 458.5s^2 + 8749s + 2.494e04}{s^4 + 4.926s^3 + 432.5s^2 + 617.5s + 1.076e04} \quad (2.4)$$

The mathematical description of the estimated transfer function model $G_{(s)1}$ is given in equation 2.4. From the graph shown below in Fig. 12, it is observed that the test data sufficiently approximates the estimated transfer function model $G_{(s)1}$ with POF 95.39.

In following steps, this estimated transfer function model $G_{(s)1}$ is further reduced to the theoretical form (driver model) to identify the specific driver parameters (K_1 & t_{d1}) corresponding to the human driver.

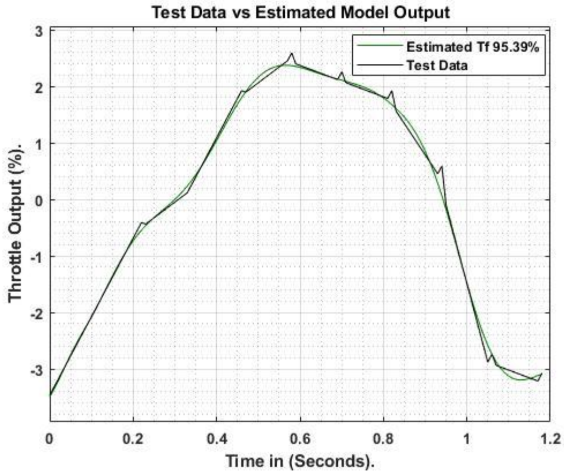

Fig 12: Response of test data vs estimated fit.

Similarly, the higher order transfer function $G_{(s)2}$, is obtained for a same set of data and is given below.

$$G(s)_2 = \frac{-4.292e08s^6 + 5.753e08s^5 - 5.67e11s^4 + 6.339e11 s^3 - 2.182e14s^2 - 2.119e14s - 1.618e16}{s^{11} + 47.59s^{10} + 5411s^9 + 1.414e05s^8 + 8.355e06s^7 + 1.267e08s^6 + 4.518e09s^5 \; 3.758e09s^4 + 8.245e11s^3 + 3.037e12s^2 + 3.331e12s + 1.565e13} \quad (2.5)$$

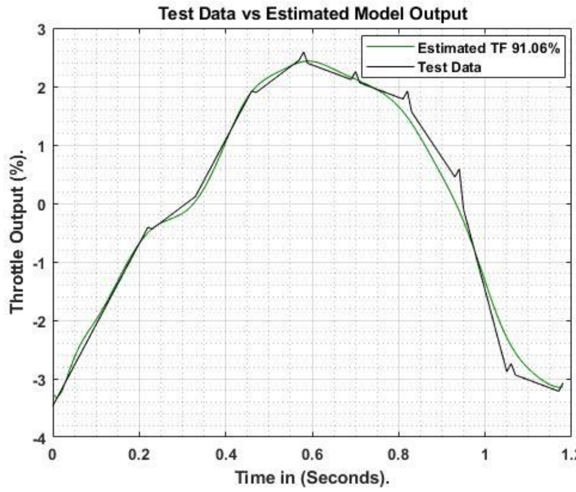

Fig 13: Response of test data vs estimated fit.

The mathematical description of the estimated transfer function model $G_{(s)2}$ is given in equation 2.5. From the graph shown below in Fig. 13, it is observed that the test data sufficiently approximates the estimated transfer function model $G_{(s)2}$ with POF 91.06. Furthermore, this estimated transfer function model $G_{(s)2}$ is reduced to the theoretical form (driver model) to identify the specific driver parameters (K_2 & t_{d2}) corresponding to the human driver.

4.3 Reduced Order Transfer Function

In this step, the obtained higher order transfer function for the specific set of data is approximated/converted to the lower order (FOPDT) using the process estimation method. The process/steps to estimate the specific driver parameters are presented in the flow chart as shown in Fig. 9. To start with this process, the initial step is to obtain the higher order transfer function according to the respective input-output variable of the driver model. As the complete driver model (see Fig. 5) is a multi-input single-output system (MISO) so, the higher order transfer function is found accordingly.

In addition to it, data object (in the time domain) is created by using the respective input variable with a specified sample time. Later on, this data object is used to reduce the higher order transfer function to the required form. As the test data was recorded at 100 Hz so, the sample time is used as 0.01 secs globally. Further, it is necessary to define the type of model based on the requirement such as P1D

=> one pole with delay, P1UZ => one undamped pole with the extra numerator, etc. Therefore, with the help of this process estimation method, specific driver parameters were identified in this research using the driver model approach.

Now the higher order transfer function for $G_{(s)1}$ & $G_{(s)2}$ (see Eq 2.4 & 2.5) is reduced to the theoretical transfer function which represents the driver model, using the above method (process estimation). The general form of the theoretical transfer function is given below which represents the $G_{(s)1}$ TF of the driver model.

$$G(s)_1 = \frac{K_1}{1 + \tau_{d1} s} \tag{2.6}$$

The above transfer function $G_{(s)1}$ (Eq 2.6), represents the driver model for output as throttle (%) and input as the difference between the time to headway & desired time to headway, which exemplify the driver gain (K_1) & reaction time delay (t_{d1}). Similarly, the general form of the theoretical transfer function $G_{(s)2}$ is given below.

$$G(s)_2 = \frac{K_2}{1 + \tau_{d2} s} \tag{2.7}$$

The transfer function $G_{(s)2}$ (Eq 2.7), represents the driver model for output as throttle (%) and input as relative velocity, which exemplify the driver gain (K_2) & reaction time delay (t_{d2}).

4.4 Identification of Driver Parameters

In this section, specific driver parameters are identified based on the reduced order transfer function model and are elaborated further. The approach towards the estimation of the specific driver parameters is already described earlier (see Fig. 9). Thus, here four different specific driver parameters (K_1, K_2, t_{d1} & t_{d2}), will be identified using the driver model approach.

In the previous step, the reduction/approximation of higher order transfer function is discussed. So, by following the same method higher order transfer function (see Eq 2.4 & 2.5) is reduced to the following.

$$G(s)_1 = \frac{7.8095}{1 + 0.141s} \tag{2.8}$$

$$G(s)_2 = \frac{6.654}{1 + 0.144s} \tag{2.9}$$

From the transfer functions are given above the specific driver parameters are tabulated and discussed respectively. The table presents the driver gain (K_D), reaction time delay (t_d) for a particular driver. However, the variation in the specific driver parameters is due to the different input variables, since the location (position) of the vehicle is the same.

Table 1: Illustration of driver parameters for a driver.

Driver	Specific Driver Parameters
K_1	7.8095
τ_{d1}	0.141
K_2	6.654
τ_{d2}	0.144

As mentioned before, the driver gain interprets the attention of the driver while driving. Whereas, the reaction time delay interprets that the driver responds t_d seconds later than the error input. Therefore, based on the parameters obtained it can be stated that the driver has a positive gain in both the cases (means the driver is responding to the error input sufficiently). Whereas, reaction time delay t_{d1} is less than t_{d2} which means the driver is more attentive in the second case and is correcting the error input quickly.

4.5 Validation of the Driver Model

In this section, the validation of the driver model approach is discussed. To validate the approach, a comparison of higher order transfer function model is presented with the lower order transfer function model (driver model) as shown in Fig. 16. From the graph shown in Fig. 14, it is observed that the combined estimated transfer function model (MISO system) sufficiently approximates the test data with POF 96.36. Whereas, Fig. 15 illustrates the reduced transfer function model of the complete driver model with POF 89.76.

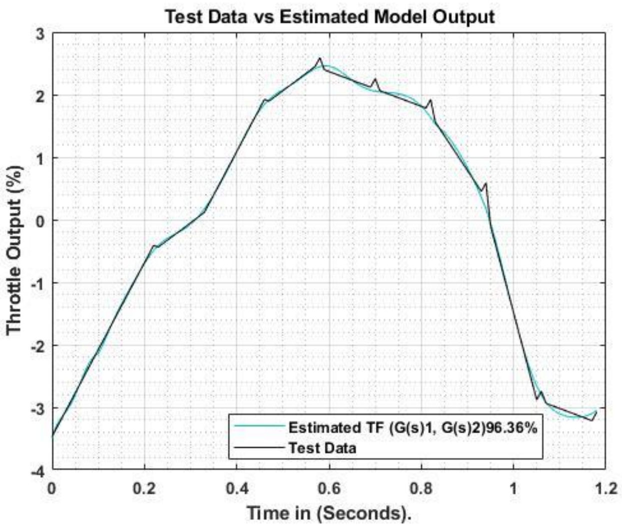

Fig 14: Response of estimated TF model.

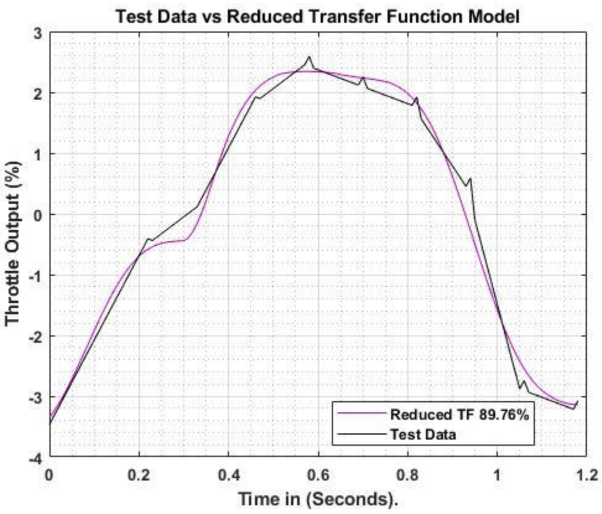

Fig 15: Response of reduced order TF model.

Fig. 16 shows the comparison of the driver model as a MISO system. The graph represents the test data, estimated driver model & reduced transfer function model. Overall, it can be stated that the various models (Higher order TF, Reduced Order TF), sufficiently approximates the input test data which is satisfactory. The reasons why the reduced transfer function model has less POF because every data sample of the higher order transfer function cannot be approximated to the required lower order transfer function model. However, the reduced transfer function model depicts a good relationship with the test data (POF as 89.76).

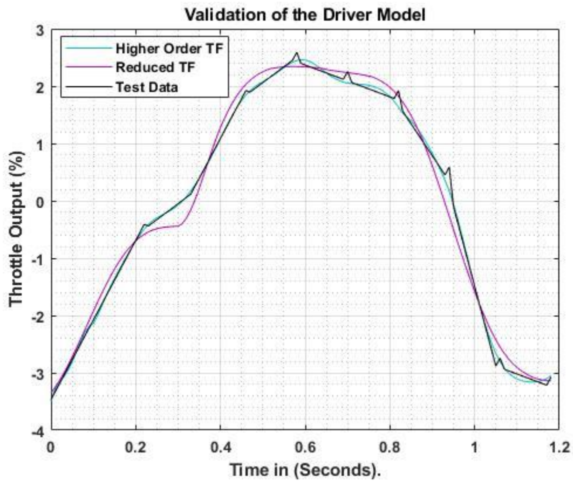

Fig 16: Validation of complete driver model as MISO system.

Therefore, the above comparisons were made for the same set of data to get an insight about the specific driver parameters corresponding to the human driver. Additionally, the driver model is compared with the test data and subsequently results are discussed in the next section.

V. RESULTS

In this section, results are being discussed based on the defined approach towards the estimation of specific driver parameters.

To start with this section of results, three different sets of data were used for a human driver and were analysed respectively. As the driver model is a MISO system therefore, two different transfer functions ($G_{(s)1}$, $G_{(s)2}$) results into four different specific driver parameters (K_1, K_2, t_{d1} & t_{d2}) which describes the human behavior. Although, the procedure for estimating the specific driver parameter is explained before (see IV).

Initially, one driver is taken into account and four different specific driver parameters are estimated by using the process estimation technique. Later on, these specific driver parameters are analysed and the conclusion is drawn based on the variations. However, the analysis of the four different specific driver parameters is done for the same location of the vehicle.

Thus, the variation in the specific driver parameters is due to the respective inputs being used for estimating the desired specific driver parameters as well as how the human driver is reacting to the deviations while driving. Moreover, these specific driver parameters describe the driver behavior which is unique and varies according to human traits such as age, gender, etc. Therefore, three different sets of readings were considered for a human driver and conclusion are drawn respectively.

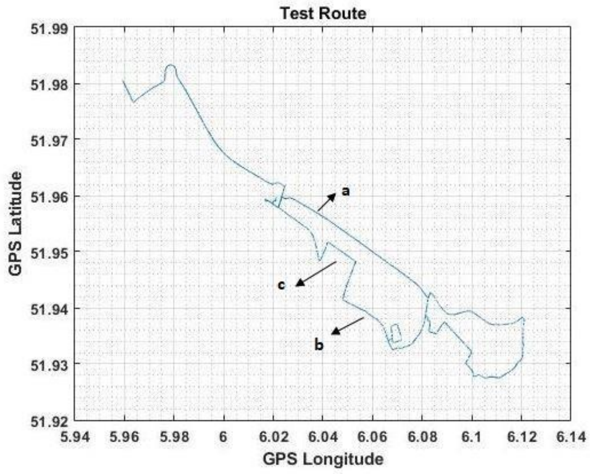

Fig 17: Representation of vehicle on the test route.

The graph is shown above in Fig. 17, represents the location of the vehicle for three different sets of readings taken into account. It can be observed from the graph that the vehicle is located at different locations that means the driver parameters are also being affected due to the road geometry.

Table 2: Representation of driver parameters for one driver.

S.No	Human Driver
1	$K_1 = 4.3671, \tau_{d1} = 0.685,\ K_2 = 5.6303, \tau_{d2} = 0.401$
2	$K_1 = 11.408, \tau_{d1} = 0.1857,\ K_2 = 4.867, \tau_{d2} = 0.0262$
3	$K_1 = 4.1461, \tau_{d1} = 0.734,\ K_2 = 4.3372, \tau_{d2} = 0.0362$

For this case, the four different specific driver parameter are estimated and listed below in Table 2. The analysis of the specific driver parameters is done based on the understanding and shown as follows.

Firstly, looking at the location of the vehicle on the test route (see Fig. 17), it is observed that the driver is on a completely straight road. Further, for case 1 the specific driver parameters (K_1, K_2, t_{d1} & t_{d2}) are listed in Table 2. While observing the value of the driver gains (K_1, K_2) it can be seen that the driver gain K_2 is slightly more and correspondingly the reaction time delay (t_{d2}) is less that is due the different input variable (relative velocity in the second case) as the location of the vehicle is same.

In other words, it can be stated that the driver is more attentive during the second case correcting the error input quickly compared to the first case K_1 (the driver showed reduced attention to the leading vehicle's behavior). Thus, the response of the driver model as a MISO system is shown below in Fig. 18, it represents a comparison of test data, higher order TF model & reduced order TF model.

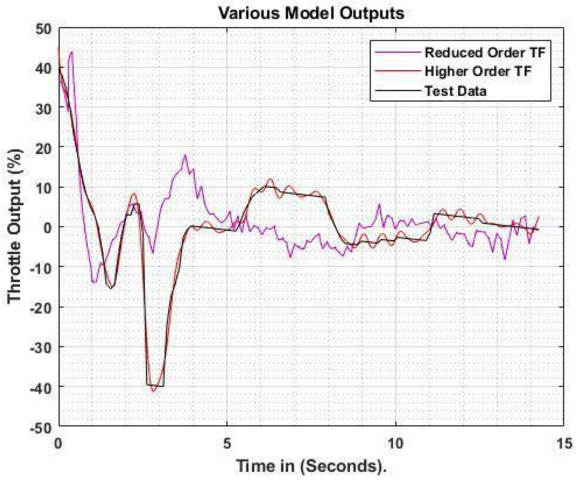

Fig 18: Response of the driver model (case 1).

Similarly for the second case 2, initially examining the location of the vehicle on the test route (see Fig. 17), it is observed that the driver is on a slightly curved path. In other words, the human driver is expected to be more attentive in this case compared to the first. The specific driver parameters (K_1, K_2, t_{d1} & t_{d2}) are listed in Table 2. While observing the value of the driver gains (K_1, K_2) it can be seen that the driver gain K_1 and K_2 are significantly more which is satisfactory and correspondingly the reaction time delays are less. Therefore, the human driver is more attentive during the curvy road and correcting the error input quickly so, the driver gains are comparatively higher. Below in Fig. 19, the response of the driver model as a MISO system is shown as well as it represents a comparison of test data, higher order TF model & reduced order TF model.

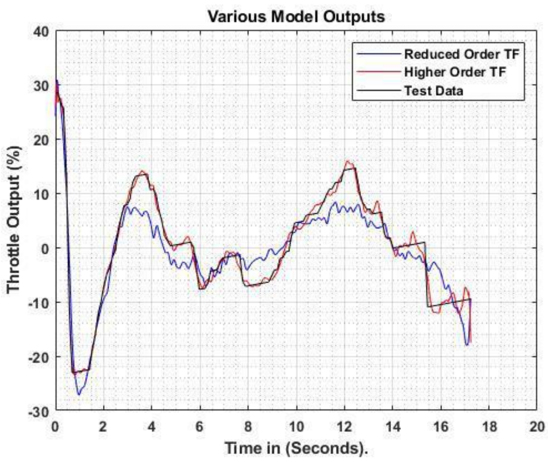

Fig 19: Response of the driver model (case 2).

Finally the last case 3, looking at the location of the vehicle on the test route (see Fig. 17), it is observed that the driver is on a completely straight road. The specific driver parameters (K_1, K_2, t_{d1} & t_{d2}) are listed in Table 2. While observing the value of the driver gains (K_1, K_2) it can be seen that the driver gains K_1 and K_2 are almost similar because the driving conditions are the same. Moreover, a minor change in the driver gains can be observed which is due to the response time of the driver (more response time, less driver gain). Thus, in this case, the driver is correcting the error input sufficiently and the parameters are estimated respectively. The response of the driver model as a MISO system is shown below in Fig. 20, it represents a comparison of test data, higher order TF model & reduced order TF model.

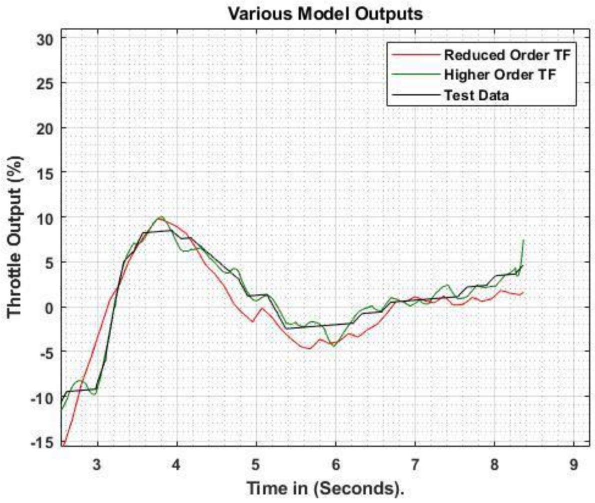

Fig 20: Response of the driver model (case 3).

Based on the analysis of the human driver it can be concluded that the driver is sufficiently correcting the error input i.e., attentive towards the driving. Therefore, the same approach can be followed for different human drivers. Additionally, a number of different human drivers can be compared to understand their behavior while driving in a specified test route.

VI. CONCLUSIONS

In this section, the conclusion were made based on the work. Following are some conclusions:

- Based on the defined goal specific driver parameters were estimated using the driver model approach.
- The driver model was considered as the first order system with a dead time (FOPDT) based on the research.
- The process estimation method was found to be a useful method/tool for obtaining satisfactory results.
- An approach has been created to estimate the specific driver parameters using the real-time test data, in where the steps are documented in the paper.

Future research can be followed for the improvement of the results and research methodology. The driver model can be extended which also considers external factors and driver traits. Some of the works are given below:

- Compare number of different drivers to have a comprehensive understanding of this key topic.
- Investigate different driver models for longitudinal driving behavior.
- Investigate lateral driving behaviour such as steering wheel angle, yaw, etc.
- Incorporate number of specific driver parameters corresponding to the human driver to understand the human driver preferably.
- Investigate different approach towards the estimation of the specific driver parameters (extended the given above).

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