İSTANBUL TECHNICAL UNIVERSITY ★ INSTITUTE OF SCIENCE AND TECHNOLOGY

VEHICLE MASS ESTIMATION WITH LONGITUDINAL DYNAMICS FOR A LIGHT DUTY VEHICLE

M.Sc. Thesis by
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Department : Mechatronics Engineering

Programme : Mechatronics Engineering

OCTOBER 2010

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

HAFİF TİCARİ BİR ARAÇ İÇİN BOYLAMSAL DİNAMİK MODEL İLE ARAÇ KÜTLE TAHMİNİ

YÜKSEK LİSANS TEZİ

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KASIM 2010

to my Family,

FOREWORD

Vehicle powertrain plays an important role in vehicle dynamics. The customers expect much better driveability for their vehicles each day. In order to have a fine tuned driving feel, vehicle dynamics should be studied. One of the main contributors to this work is the vehicle mass. Knowing the vehicle mass, calibrating the torque output will lead to superior driveability of the vehicle. In order to refer to this issue, a light duty vehicle longitudinal dynamics is studied and with related simulations, a vehicle mass estimation algorithm is developed.

I would like to thank to Prof. Dr. Levent Güvenç for sharing his experience and knowledge with me throughout my thesis study. I would also like to thank to FORD OTOSAN for supplying me with the testing resources and information.

May 2010 Ozer Oztop

Mechanical Engineer

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ABBREVIATIONS

ECU	: Electronic Control Unit
ABS	: Anti-lock Braking System
ESP	: Electronic Stabilization Program
TCS	: Rapid Pro Control Unit
NVH	: Noise Vibration Harshness
LDV	: Light Duty Vehicle
CAN	: Controller Area Network
HDV	: Heavy Duty Vehicle
PSD	: Power Spectral Density
MPC	: Model Predctive Control
RLS	: Recursive Least Square
1D	: One Dimensional

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NOTATIONS

$\mathbf{m}$	: Vehicle mass
$\mathbf{g}$	: Gravitational acceleration
$\mathbf{v}$	: Vehicle speed
$\mathbf{F_{roll}}$	: Rolling resistance force acting on the vehicle
$\mathbf{F_{air}}$	: Aerodynamic force acting on the vehicle
$\mathbf{F_{slope}}$	: Gravitational force acting on the vehicle
$\mathbf{F_{wheel}}$	: Longitudinal force acting on the wheel
$\mathbf{C_{r1}}$	: Rolling resistance coefficient 1
$\mathbf{C_{r2}}$	: Rolling resistance coefficient 2
α	: Road slope angle
$\mathbf{i_f}$	: Conversion ratio final drive
$\mathbf{r_w}$	: Wheel radius
$\mathbf{i_t}$	: Conversion ratio transmission
$\boldsymbol{\theta_w}$	: Angular position wheel
$\boldsymbol{\theta_t}$	: Angular position transmission
$\boldsymbol{\theta_m}$	: Angular position engine
$\boldsymbol{\theta_f}$	: Angular position final drive
$\mathbf{T_d}$	: Torque at drive shaft
$\mathbf{T_b}$	: Braking torque
$\mathbf{T_c}$	: Torque at clutch
$\mathbf{T_m}$	: Engine torque
$\mathbf{T_p}$	: Propeller torque
$\mathbf{T_{fr:m}}$	: Engine friction torque
f()	: Function of
$\mathbf{b_d}$	: Viscous friction coefficient drive shaft
$\mathbf{b_c}$	: Viscous friction coefficient clutch
$\mathbf{b_w}$	: Viscous friction coefficient wheel
$\mathbf{k_d}$	: Drive shaft stiffness
$\mathbf{k_c}$	: Clutch stiffness
$\mathbf{J_m}$	: Mass moment of inertia engine
$\mathbf{J_t}$	: Mass moment of inertia transmission
$\mathbf{J_f}$	: Mass moment of inertia final drive
$\mathbf{J_w}$	: Mass moment of inertia wheel
$\mathbf{F}$	: Force applied
$\mathbf{a}$	: Acceleration of the vehicle
$\mathbf{C}$	: Air resistance coefficient
$\mathbf{A}$	: Frontal area of the vehicle
ρ	: Air density

VEHICLE MASS ESTIMATION WITH LONGITUDINAL DYNAMICS FOR A LIGHT DUTY VEHICLE

SUMMARY

In this thesis, a mass estimation system for a light commercial vehicle is designed. First of all, brief information is given on the vehicle dynamics. Later, a mathematical model for the vehicle longitudinal dynamic has been derived. Moreover, actual data from a LCV has been acquired and the developed model has been supplied with these data. Finally, discussions on model validation, mass estimation and gear estimation along with the simulation results are presented in the thesis.

This thesis consists of the following sections. In the first chapter, the purpose and the already completed works in the literature have been reviewed. In the second chapter, some information regarding the vehicle dynamics has been provided. Besides the forces acting on a vehicle are explained. In the third chapter, the longitudinal dynamic model is proposed. In the next chapter, real data from the vehicle along with the simulation results are presented. Finally, the thesis concludes up with the discussions and the recommendations.

During this thesis, computer simulations are performed using MATLAB/Simulink[1] and ATI VISION[2].

[1] MATLAB/Simulink, is the registered trademark of Mathworks.
[2] ATI VISION, is the registered trademark of Accurate Technologies.

HAFİF TİCARİ BİR ARAÇ İÇİN BOYLAMSAL DİNAMİK MODEL İLE ARAÇ KÜTLE TAHMİNİ

ÖZET

Bu çalışmada hafif ticari bir araç için ağırlık tahmin etme sistemi geliştirilmiştir. Öncelikle, araç dinamiğiyle ilgili temel bilgiler verilmiştir. Sonrasında, araç boylamsal dinamiği için bir matematiksel model çıkarılmıştır. Bunun üstüne bir hafif ticari araçtan alınan datalar, geliştirilen modele beslenmiştir. Son olarak model validasyonu, kütle tahmini ve vites tahmini simülasyonlarının sonuçları yayınlanmış ve üzerine tartışmalar yapılmıştır.

Bu çalışmanın bölümleri şu şekilde ayrılmıştır. Öncelikle çalışmanın amacı ve yapılmış çalışmalarla ilgili literatür taraması yapılmıştır. İkinci bölümde araç dinamiğiyle ilgili bilgiler sunulmuştur. Araca etkiyen kuvetler açıklanmıştır. Üçüncü bölümde aracın boylamsal dinamik modeli çıkarılmıştır. Bunu takip eden dördüncü bölümde gerçek data ve simülasyon sonuçları verilmiştir. Daha sonra tez tartışma ve öneriler ile son bulmuştur.

Bu çalışmada, bilgisayar simülasyonları MATLAB/Simulink[1] ve ATIVISION[2] kullanılarak gerçekleştirilmiştir

[1] MATLAB/Simulink, Mathworks firmasının ticari bir ürünüdür.
[2] ATI VISION, Accurate Technologies firmasının ticari bir ürünüdür.

1. INTRODUCTION

In this first chapter of the thesis, a general overview to the topic the thesis covers is given and the borders of this study have been drawn. A lot of previous studies on the topic are examined and the necessity and importance of the topic, vehicle mass estimation, has been highlighted. Improvement chances on a commercial vehicle have been put forward and the outline of the thesis is given. Considering the investments in automotive technology, the study contributes in why and how the vehicle mass estimation algorithms should be implemented.

1.1 Purpose of the Thesis

Throughout the 21st century, the vehicle technology has vastly improved. Electronics has taken control over nearly all commercial vehicles and passenger cars. Controlling the engine outputs with ECU, considering the vehicle safety with ABS, ESP and TCS like modules are just some part of the novelty, the technology has yet to provide. Everyday the technology pushes the limits searching further improvements mainly based on engine emissions, fuel economy, vehicle safety, driveability and NVH concerns.

The environment, driver and the vehicle are of utmost interest for transportation. Powertrain is the major contributing factor in improving the relation between these areas. Development on the powertrain is an on-going process, and there has been a lot of research to enlighten on which way to go. With the aid of the electronic control, firms invest much more each day in developing new technologies for vehicle dynamics. One of the main concerns which yet to be improved is the driveability of the vehicle. Generally, it is linked directly with the longitudinal dynamics of the vehicle. The scope behind these research is to create an optimised driving feel according to the environmental conditions and the driver requests. As stated in [1], owners of the vehicles are waiting for a more sensitive torque response from the powertrain. Characterization of the drive train differs in HDVs and LDVs due to the varying loading properties.

From manufacturer's point of view, adding sensors, actuators or any new components to the current system brings complexity and is expensive. Therefore, an algorithm that is capable of fulfilling its defined functionalities with the current equipments on the vehicle is expected. As LDVs have larger mass variances according to being loaded or unloaded like HDVs, predicting the mass online will have a big contribution in the vehicle dynamics. Thus, accurate estimation of the mass for LDVs will lead to new developing areas for vehicle safety, fuel economy and driveability based topics. Mass feedback approach is shown in the below figure.

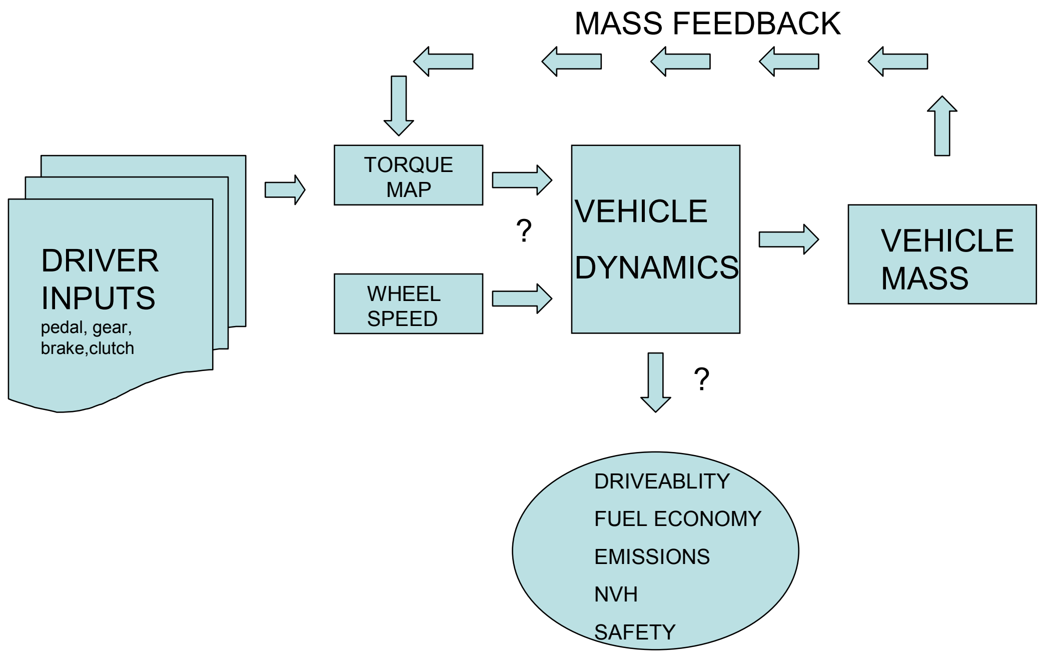

Figure 1.1 : Mass Feedback Effect

In vehicle dynamics, the system performance is directly effected with the difference in mass. Besides, it is a matter of fact that disturbances on the torque flow through the powertrain causes the mass to be calculated harder. Moreover, there are parameters which are unknown in the dynamic equations, like the gradient of the road, drag coefficient, rolling resistances, etc... However, it is always possible to make assumptions, prior to begin calculations. In order to follow the mass effect, the mass of the vehicle could be left as the only unknown in the equations, which will lead and force us to make controlled experiments that are not considering the other effects on the longitudinal dynamics. From the paper [2], it is seen that the major contributors to longitudinal dynamics are engine braking and inertial forces.

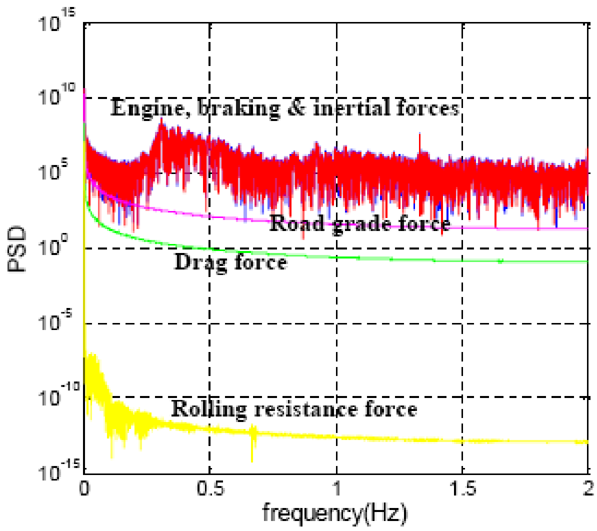

Figure 1.2: Comparison of Longitudinal Force Spectral Densities [2]

The experimental conditions and the entry conditions for the algorithm to estimate the mass will be selected as to minimize the exterior effects on the calculations. These exterior effects on torque calculations could be; torsional vibrations in drive shaft, noise factors in the signals, uncertain dynamic of the engine torque, etc... To improve the accuracy of the system these exterior effects will be excluded. To not to overcomplicate the system, time periods for the algorithm to enable will be chosen and conditioning of the signals will be handled. With an engaged drivetrain, the system will be able to estimate the mass during an acceleration move.

In this study, as explained above, estimating the mass of a LDV from the longitudinal dynamics is aimed. For the purpose of this thesis MATLAB/Simulink™ and ATI VISION™ software are used along with the vehicle's present CAN line in order to collect real data and to run the model simulation. Afterwards commenting on the performance of the system for estimating the vehicle mass will be possible. It will be further beneficial to determine how it could be possible to introduce the algorithm on the vehicle. For estimating the LDV mass, longitudinal vehicle dynamic model is used and validated. Performance reviews are given after processing the data.

1.2 Literature Review

Vehicle mass estimation can be realized with add-on equipment as well as the on-board ready hardware. It is aimed to realize a model based approach for estimation. Below some of the current already developed and applied mass estimation techniques can be found.

Stated in the Toyota R&D review, Toyota have chosen a way to simplify the longitudinal dynamics and has omitted the road grade effect from the equation with a smart identification of the road slope from the vehicle speed and the road profile, realizing the mass estimation with a 15% accuracy according to the road data collected. It is aimed to reduce the necessity for further instrumentation in order to calculate the vehicle mass. This approach only utilizes the current hardware equipped on the vehicle. As the models created in the simulations are effected adversely by the disturbances caused by the unknown inputs and due to interactions with the surroundings, for controlling the signal disturbances, some signal processing filtering the noise had been done. An integral calculation method in estimating the mass is developed. One contributor to the algorithm is the vehicle speed and the second contributor is the acting torque. To calculate the acting torque filtered engine out turbine speed is utilized, whereas for the output vehicle speed, a speed feedback signal is filtered. [3]

In their paper, Vinstead and Kolmanovsky benefits from the approach of using an extended Kalman filter and the model predictive control. Emphasizing the request of the drivers, that an improved powertrain response is expected, a vehicle mass estimation algorithm is put forward by the authors as the Ford Motor Company Powertrain Research and Advanced engineering division. It is stated that lots of the signals on the vehicle are estimates and there are no sensors taking measurements. Engine torque is one of the signals being estimated and experiments are conducted in cruise control mode in order to control the torque actively. This leads a better identifiability for the vehicle mass and road grade estimation; whereas a vehicle speed trajectory planning is required for the close loop speed control. The approach in model predictive control depends on persistent excitations in calculations. The mass estimation is carried out by the extended Kalman Filtering and a receding horizon optimization with model predictive control is used to amend the parameter environment. Using the extended Kalman filter brings computational advantage in estimating the dynamic equations. Estimating the unknown, Kalman filter provides reduced calculation load due to the fact that it utilizes just the last known value of the estimate in order to calculate the next value. As the Kalman filter is settled on linear systems, extended Kalman filtering offering a useful application for the system in discussion is used. In the tests realized, vehicle speed limitation constraint is added and it is seen that the deviation in estimating the mass is higher in the given speed trajectory. Moreover, it is highlighted that one of the main disturbances is the uncertainties in engine output torque for the model dynamics. [1]

In the study [4] by Mcintyre et all., a two stage based estimator has been developed. In order to estimate the mass of the vehicle, a least square method is used. Ready-to-use available sensors on the vehicle are preferred and estimations are based on the outputs of the current sensors. It is emphasized that for a better vehicle longitudinal control and transmission control, vehicle mass estimation is desired by the automotive industry. As the road grade itself is varying during estimation, a non-linear estimator pointing this variation is studied as a second step. The following assumptions within the study are made; clutch accepted always in engaged position, brakes are never applied during calculation period, the coefficients in the dynamic longitudinal dynamic equation are constant with time, the input signals are accepted to be measurable and road slope is taken as zero. It is aimed not to overcomplicate the system as a whole. Gear shifting and braking is handled with care by processing the signals. Whereas the actual coefficient values present in the longitudinal dynamic equation are changing in time and can not be known all the time, the basic model equations are straightforward. The model created is validated via the engine speed, net engine torque and vehicle speed signals taken from the CAN line. One of the issues raised is due to clutch engagement in calculations. Before the disengagement, latest known estimations are taken and even to enhance the estimation, preventing the spikes due to gear change, after the engagement 0.4s of data is neglected. Experiments conducted with 12400kg and 14000kg weighing vehicles. As the road grade estimation is handled as well with the mass estimation, a deviation to the mass estimation is constantly added to the simulations in order to determine the sensitivity of the model due to the fact that mass estimation depends on the road grade estimation. A significant influence is not seen. Finally a robustness check is realized by simulating a trip, beginning with a loaded case and then unloading the weight. It is seen that an accurate estimation can be made with the model with the aforementioned experimental setups.

In the papers [5] and [6], Vahidi et all. uses a recursive least square method with multiple forgetting in order to overcome the disturbance added due to road grade variance in time. Based on the linear relationship in the torque equation function with the vehicle mass and road grade, a recursive leas square method is sufficient for mass estimation. The forgetting method approach is decreasing the weight of the older information used in the estimations, due to time-varying dependability of the mass estimation. It is seen that with a single forgetting factor, it is possible to face blow-ups and wind-ups in the mass estimation during the gear shifts. This is found to be due to the fact that the sum of the errors in the calculations of the vehicle mass and road gradient is taken into account as a lumped single scalar term. In return, a separation of the errors with the multiple forgetting algorithm is proposed. The performance is found to be quite satisfactory. Additionally, the noise factor is tested via adding noisy data onto the engine speed and engine out torque data. A second method, a Lyapunov function is used to design a dynamic observer for estimation. An upper and lower bound for this approach has to be defined for improved convergence. It is highlighted that for improved emissions, increase safety and better driveability, online parameter estimation is a key contributor. It is stated that the mass estimation algorithms running during gear shifting may defeat due to low speed variances between gear changes causing low signal to noise ratio. An adaptive filter design is desired, as there can be variances on the requested parameters. Experiment data with decreasing vehicle load is acquired. Vehicle speed and engine torque data is available and taken from the CAN line of the vehicle. It is added that, if the brakes are to be applied, acting pressure on the wheels need to be measured in order to convert the force and implement into torque equations. For sensitivity analysis of the system on rolling resistance, drag coefficient and the wheel radii, simulations are carried out.

Kober and Hirschberg creates a method benefiting from the idea that the mass can be estimated with the air-sprung pressure sensors on HDVs. Measured pressures of the vehicle's air springs utilized with the suspension dynamics can lead to good estimates of the mass. As the driving safety in lots of the overturning situations comes into first place, it is aimed to inform and help the driver by means of any modules within the vehicle by providing the load mass data and by defining the center of mass information. The adverse effect of the accidents to public economy due to uncontrolled vehicles is also stressed. [7] Basic structure of the payload identification system can be seen in the below figure. Roll dynamics of the vehicle is utilized for the identification process. A recursive least squares method is implemented and various J-turn manoeuvres reveals a fine performance during steady state periods.

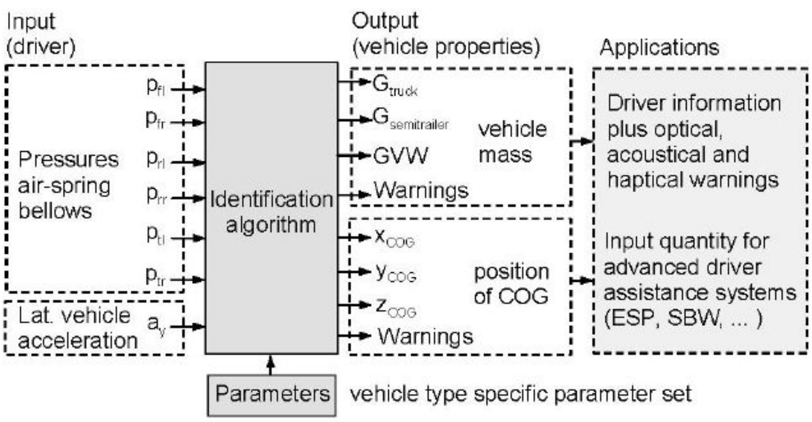

Figure 1.3: Payload Parameter Identification [7]

Pence et all. [8] also uses quarter car suspension model for mass estimation and from the linear dynamics of the suspension, they estimate the sprung mass with RLS method. Off-road terrain conditions bring uncertainties and adversely affect the performance of the mass estimation techniques commonly in use. The paper differs from the other studies by the applied base excitation concept. Also, for active and semi-active suspension systems, suspension actuator forces are taken as input to estimate the mass. Two acceleration signals with the spring displacement characteristics are utilized to develop a mass estimation algorithm. Quarter car suspension model composes of an unsprung mass and a sprung mass as seen in the figure below. Taking the unsprung mass acceleration as the system input, the algorithm differs from the ones using the ground displacement signal as the input. The acceleration signal is integrated along with the developed filter. The recursive least square method estimates vehicle sprung mass and the suspension damping coefficient continuously. Various simulations are carried out with the model. Tests with signal noise addition for linear suspension dynamics, with changing natural frequencies for the filter, with changing damping coefficients for the filter, with varying vehicle speed and with varying signal-to-noise ratios are conducted. The proposed system is able to offer feasible mass estimation for off-road vehicles.

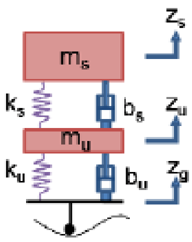

Figure 1.4: 2 DOF Quarter Car Suspension Model [8]

In the thesis by Johansson and Höglund [16], an approach analyzing the frequency response of the driveline system is utilized to estimate the mass of the vehicle. The idea is to model the driveline as a spring mass system for mass estimation. Torsion of the springs and the velocity of the inertias are taken as the states of the model. A representative scheme for the modelling can be seen in the below figure, where some simplifications are to be made later on.

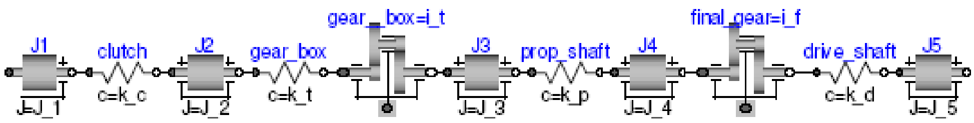

Figure 1.5: Stiffness and Moments of Inertia of the Driveline System [16]

Solving the natural frequency of the system for the acquired data from CAN line, a rough mass estimation is possible and it is stated that the method is no good than the existing methods. The main difficulty is defined as lower gears having low resonance frequencies, resulting in low engine speed necessity for estimation, whereas engine speed less than idle may be required. On the other hand, higher gears have less natural frequency sensitivity to vehicle mass making it harder for estimation.

Lingman and Schmidtbauer further explain the difficulties in calculations in their study. Caused by the discontinuous propulsion force due to gear change, high frequency oscillations are seen on the flexible driveline. On the other hand, estimating the vehicle mass during gear change is not possible for the automatic transmission, as the driveline is engaged all the time. Another fact is the inconsistent torque maps for the engine out and brake torque. The propulsion torque needs to be filtered as well. The input torque to the system is gathered by the engine out speed and knowing the fuelling quantity. Having considered these, in the paper it is suggested that the acceleration is measured with filtered accelerometer data and an extended Kalman filtering is used to estimate the vehicle mass apart from the road slope. On top of these, other than gathering reasonable mass estimate with just the vehicle speed, introducing an accelerometer is found to be improving the calculations. The estimations are stated to be robust and the method applicable. [9]

In the study carried out by Fathy et all., minimum instrumentation is desired. It is stated that over certain types of maneouvers, the vehicle dynamics will be lead by the inertial dynamics most depending on the perturbation theory. The properties of an industry desired mass estimator is given as follows; being simple to run the algorithm in real time, being accurate enough to rely on, being responsive to loading as fast action is required on varying loads, being robust to road disturbances and variance and finally being inexpensive. A mass estimation literature in terms of being event-seeking or averaging is given in the paper. Based on suspension dynamics, lateral dynamics, powertrain dynamics, longitudinal dynamics many methods can be developed being event based or averaging to estimate the vehicle mass. The aim is to estimate the mass without direct measurement of the road grade and the aerodynamic force. It is seen that the inertial dynamics contributes the most in to the longitudinal behaviour with increasing frequencies and the absence of the road grade data definitely changes the speed of mass estimation as well. The algorithm is in place when the inertial dynamics dominates the vehicle's motion. For the online mass estimation experiments, Fathy et all. uses the recursive least square method based on the longitudinal dynamics excluding the effects of the road gradient from the equations. It is shown that the lack of road grade estimations can lead to slower speeds of mass estimation. Therefore without the road slope data, it is aimed to estimate the mass. Based on the vehicle yaw rate info, the decision if the vehicle motion is longitudinal or not is made. Some entry conditions for the vehicle includes minimum exerted longitudinal force, minimum velocity and acceleration and slip ratio as well. A lead lag band pass filter is utilized for the high frequency components. Lower and upper bounds for mass estimation are also introduced as to be benefited in practical implementation. The mass estimation is found to be viable. [2]

The study carried out in Korea [15] by Lee et all., enlightens the interaction and the side benefits of mass estimation to other control modules on the vehicle. This paper directly deals with the enhancement of the ESP module. An adaptive approach for the ESP module is utilized by means of online mass estimation. Longitudinal dynamics along with the empirical rolling resistance and empirical drag force calculations gives the estimated mass within 2% accuracy, where the frictional losses in the powertrain model were neglected. To further improve the results, frictional losses are mapped through tests at different gears. For the mass estimation, operating conditions are defined, including min engine speed, min acceleration and being between specific gear ratios. Reliable mass estimation could be observed within the predefined conditions. In accordance to the mass estimation, the ESP algorithm gathers the mass change information simultaneously and changes the vehicle reference model parameters as related. An overview of the enhanced ESP system is in the below figure.

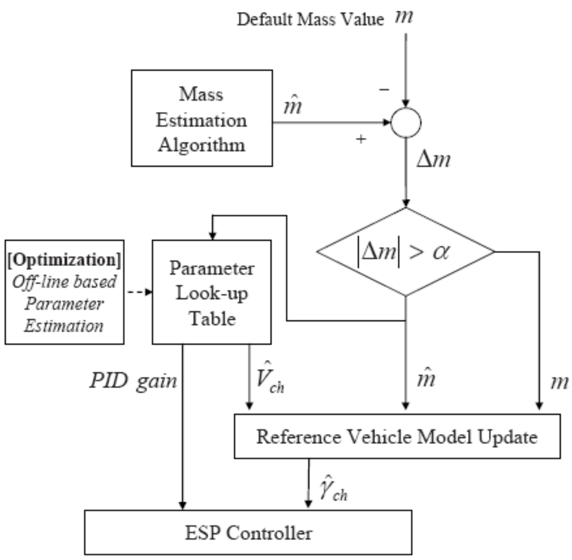

Figure 1.6: Overview of the Enhanced ESP system [15]

Also a PID gain controller is developed with a look-up table in order to adapt the parameter variations. A trajectory optimization is utilized offline for determining the gains. Having testing the ESP algorithm in simulation environment, it is seen that the vehicle stability can be improved.

Finally, in the study realized for the roll stability by Huh et all. [17]; longitudinal, lateral and vertical dynamics are combined in order to estimate the vehicle mass and the height of the center of mass of the vehicle. A unified algorithm of RLS for longitudinal estimation, Kalman filtering for lateral estimations with the help of the vehicle kinematic equations and a dual RLS method for vertical estimations based on the sprung mass is used. Three of the techniques are combined in order to estimate the mass in different maneuvers. Also disturbance observer technique is desired for the increasing robustness. To get performance from the vehicle control modules, as much info of the vehicle inertial parameters as possible should be known. It is also stated that lot's of the vehicle mass estimation methods present are based on definite vehicle running conditions and much of these require big vehicle models. Modelling the longitudinal dynamics, a lumped disturbance term is added and a recursive least square with a disturbance observer method is utilized. During acceleration without steering, the filter designed is able to estimate mass against the disturbances. Lateral velocity is estimated with a Kalman filter using a 2 DOF bicycle model. Due to the proposed system being able to estimate based on cornering stiffness coefficient and the longitudinal velocity, it is mostly reliable for low-slip range conditions. Finally, a multiple forgetting recursive least square estimation is used along with the vertical dynamics for estimating the unsprung mass. A state flow chart decides which algorithm to take control for mass estimations according to the vehicle driving conditions. All three algorithms have some limiting conditions to take start estimations. These include the raw rate, steering angle and the acceleration limiting conditions. The simulations are run for a road having bumpers, corners and a straight path. The resulting estimates for different driving conditions are in good coherence to vehicle mass.

1.3 Outline

Within this thesis study, parallel to the studies explained above, mass estimation for a light duty vehicle is carried out. Within the first chapter an entrance to the topic vehicle mass estimation has been made. Besides the purpose of the thesis and a literature review including industrial and academic examples has been given in this chapter. In the second chapter, information regarding the basic vehicle dynamics is provided. Third chapter deals with the mathematical model derivation described in the literature. In the fourth chapter, there is the experimental study represented from the data taken from a LDV at FORD OTOSAN. Acquiring data from the vehicle and detailing the principles for the model validation is carried out in this chapter. Also a gear estimation algorithm is presented aiming to help mass estimation in future. The thesis ends with the conclusions and recommendations section. It should be noted that the theoretical studies combined with the practical approach leads to good results in terms of improving the vehicle control.

2. VEHICLE DYNAMICS

In automotive industry shortening the response time for new designs to meet the market needs is always an important point to success. In order to meet the demands, engineers rely on the simulations run by high technology computers where the actual vehicle can be represented by dynamic models. As the modelling needs to be practically applicable, it needs to be kept as simple as possible while being as real as possible. In terms of the effort that will be needed, it is not necessary to capture every subsystem during modelling the vehicle dynamics. [10] Mainly it is possible to divide the contributors to the dynamics to four: Environment, Driver, Vehicle and Loading.

2.1 Environment

The environment is in an interactive relation with the vehicle dynamics. It effects the vehicle in via road profiles, friction and air resistance. Besides it directly affects the driver via traffic density and from visibility point of view. As stated in [11], some of the key issues in modelling and simulation of the vehicle are the changing road gradient; the friction forces appearing between the road and the tyres and the aerodynamic forces acting on the vehicle due to vehicle speed and cross winds. [12] The environmental forces on the vehicle are seen in the figure below.

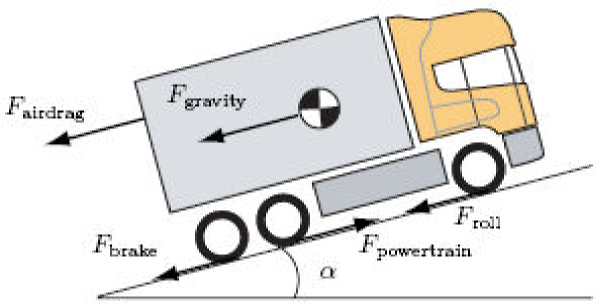

Figure 2.1: External Forces [13]

From the figure, the rolling resistance, the air resistance and the road slope resistance is seen. Rolling resistance is due to the tyre and road contact while the vehicle is in motion and can be characterized as;

$$F_{roll} = m(c_{r1} + c_{r2}v) \quad (2.1)$$

In the equation 2.1, m is the vehicle mass, F_{roll} is the total force exerted to the vehicle, v is the speed of the vehicle and c_{r1} and c_{r2} are the rolling resistance coefficient depending on the tyre and road properties.

The air resistance is due to the shape of the vehicle and can be formulated as follows;

$$F_{air} = \frac{\rho}{2} CAv^2 \quad (2.2)$$

In the equation 2.2, F_{air} is the aerodynamic force acting on the vehicle, ρ is the density of air, C is the air resistance coefficient, A is the frontal area of the vehicle and v is the vehicle speed.

The road slope resistance is due to road gradient affecting the gravitational force.

$$F_{slope} = mg \sin \alpha \quad (2.3)$$

In the equation 2.3, F_{slope} is the force occurring as a result of gravitational force on the vehicle; m is s the vehicle mass and α is the slope angle.

2.2 Driver

The driver supplies the model with lots of inputs. He has the access to acceleration pedal, break pedal, clutch pedal and gear shifting. Along with the longitudinal dynamics, the driver interferes with the lateral dynamics via steering command. In accordance to this relation, driver gets feedback for the vertical, longitudinal and lateral dynamics of the vehicle. The driver instinctively gets the sounds from the tires, engine and environment as well as temperature and speed data, which in return changes his control inputs over the powertrain.

In order to eliminate subjective results which could occur due to the driver characteristics, it is provided that the tests have been conducted several times obeying the driving profiles.

2.3 Vehicle

Regarding the ISO 3833 regulations, there are types of vehicles including HDVs, passenger cars and LDVs. Creating the equations of motion for any of these single type, with validating via real data collected from the vehicle, is an invaluable asset to develop technology.

Vehicle dynamics is affected directly by the vehicle type to be considered as the dynamics, including longitudinal, vertical and lateral inevitably depends on the vehicle mass distribution and the height of the center of mass.

The vehicle model will include subsystems, consisting of the components; engine, clutch, transmission, propeller shaft, final drive, drive shafts and wheel. In the figure below for one dimensional longitudinal dynamics of a vehicle, each component within the drive line from engine out to wheels can be seen.

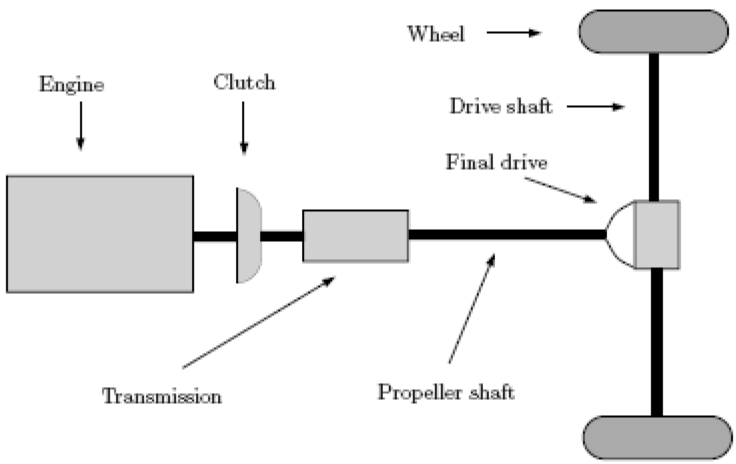

Figure 2.2: A Vehicular Driveline [14]

The effect of each component for the LDV differ from other vehicles, as the inertias, stiffnesses and frictions in the system changes with changing size of the vehicle.

The accuracy of the engine output torque, the spring dynamics on the clutch, the propeller shaft and drive shaft flexibilities add uncertainties to the model and need to be worked out in order not to create big disturbances on the model.

After all of the components are modelled and simplified according to the purpose of this thesis, it will be possible to realize further studies on the driveline. The mathematical model to be used in simulations will be driven in the next chapter.

2.4 Loading

Talking about commercial vehicles, they are able to carry loads of four or five times their mass for HDVs. There is not such a difference for LDVs as well. The LDVs can carry loads of one third or nearly half of their weights. This significantly affects the driving behaviour of the vehicles.

The center of mass along with the mass of the vehicle is a major parameter in driveability of the vehicles in terms of dynamics. Knowing the mass of the vehicle can lead engineers to improve driving feel of the vehicles by implementing adaptive torque management algorithms. A LCV to be considered for the rest of the thesis is presented below with courtesy of FORD OTOSAN.

Figure 2.3: *Ford Transit Connect*

2.5 Performance Criteria

As per every physical system, vehicle dynamics has limitations. There are control authorities limitations, safety module limitations, in fact there are lots of subsystems limitations effecting the torque management.

Therefore, the simulations run by the data collected from the vehicle needs to be valid that the model can be used for mass estimation purposes.

Discrepancy in the engine out maps and flexible powertrain based elements' oscillation problems should be considered. Whereas the purpose is to estimate the vehicle mass with minimum equipment needs, it should be noted that the systems stability and robustness should be provided. In order for that, system performance criteria should be defined:

- Being simple, reliable and cheap
- Able to estimate accurate
- Being active when the clutch is engaged
- If necessary, having the high frequency components filtered
- Working under no brakes applied condition
- Firstly, working under no road slope condition
- There is no steering in place.
- Determine if the method could be applied

It will be aimed to meet these criteria as much as possible. Having a simple system and a responsive accurate system could be difficult to maintain in the same time. Simplifying usually derates the responsiveness and the accuracy. Thereof, the study will continue to create an optimum model in an iterative way.

In the end, it will be understood if good estimates of mass can be done without the measurement of the road grade and aerodynamic force.

3. MATHEMATICAL MODELING

For the mass estimation of the LDV Ford Transit Connect, the vehicle's longitudinal dynamics will be studied with model based approximation. The parameters representing the current model will be provided by FORD-OTOSAN and will be entered in the simulations that will be run in MATLAB™ software along with the input data acquired by ATI VISION™ software.

3.1 Longitudinal 1D Vehicle Model

Below are the subsystems that will be used in characterization of the dynamic equations to obtain the complete driveline model are presented. Stiffnesses and damping coefficient are taken into account for the subsystems accordingly. Every single subsystem will then be merged with each other in order to get the 1D longitudinal vehicle model.

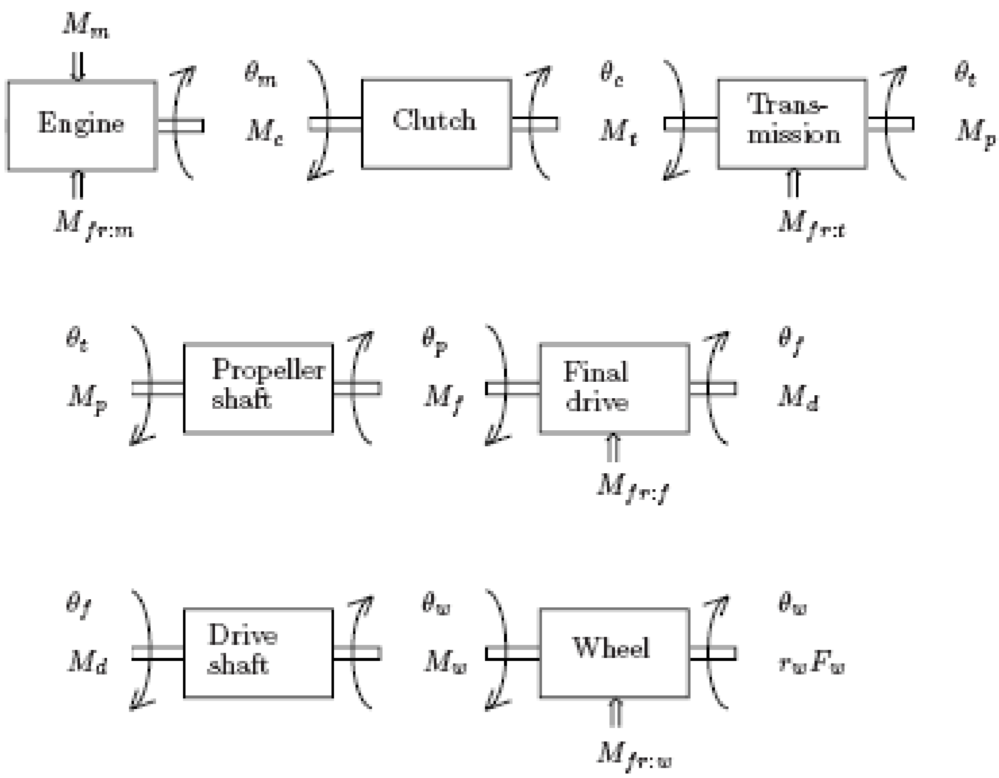

Figure 3.1: Powertrain Subsystems [14]

For the engine characterization,

$$J_m \ddot{\theta}_{\boldsymbol{m}} = T_m - T_{fr:m} - T_c \tag{3.1}$$

For the clutch characterization,

$$T_c = T_t = f_c(\theta_m - \theta_c, \dot{\theta}_m - \dot{\theta}_c) \tag{3.2}$$

For the transmission characterization,

$$T_p = f_t(T_t, T_{fr:m}, \theta_c - \theta_t i_t, \dot{\theta}_c - \dot{\theta}_c\, i_t, i_t) \tag{3.3}$$

For the propeller shaft characterization,

$$T_p = T_f = f_p(\theta_t - \theta_p, \dot{\theta}_t - \dot{\theta}_p) \tag{3.4}$$

For the final drive characterization,

$$T_d = f_f(T_{f,} T_{fr:m}, \theta_p - \theta_f i_f, \dot{\theta}_p - \dot{\theta}_{ft}\, i_f) \tag{3.5}$$

For the drive shafts characterization,

$$T_w = T_d = f_d(\theta_f - \theta_w, \dot{\theta}_f - \dot{\theta}_w) \tag{3.6}$$

For the wheels characterization,

$$F_{wheel} = m\dot{v} + F_{air} + F_{roll} + F_{slope} \tag{3.7}$$

Taking into account all the above subsystems and deriving their equations in detail which could be found in [14], the following generalized linearized longitudinal dynamic model equations can be used:

For the engine speed,

$$J_m \ddot{\theta}_{\boldsymbol{m}} = T_m - T_{fr:m} - (k_c(\theta_m - \theta_t i_t) + b_c(\dot{\theta}_m - \dot{\theta}_t\, i_t)) \tag{3.8}$$

For the transmission speed,

$$
\begin{aligned}
&(J_t + J_f / i_f^2)\ddot{\theta}_t = i_t(k_c(\theta_m - \theta_t i_t) + b_c(\dot{\theta}_m - \dot{\theta}_t\, i_t)) \\
&- (b_t + b_f / i_f^2)\dot{\theta}_t - \frac{1}{i_f}(k_d(\theta_t / i_f - \theta_w) + b_d(\dot{\theta}_t / i_f - \dot{\theta}_w))
\end{aligned}
\tag{3.9}
$$

For the wheel speed,

$$
\begin{aligned}
&(J_w + m r_w^2)\ddot{\theta}_w = k_d(\theta_t / i_f - \theta_w) + b_d(\dot{\theta}_t / i_f - \dot{\theta}_w) \\
&- (b_w + CA\rho r_w^3 + c_{r2} r_w)\dot{\theta}_w - r_w m(c_{r1} + g\sin(\alpha))
\end{aligned}
\tag{3.10}
$$

Finally, the general mass equation will be,

$$
m = \frac{k_d(\theta_t / i_f - \theta_w) + b_d(\dot{\theta}_t / i_f - \dot{\theta}_w) - T_b - J_w\ddot{\theta}_w - \dot{\theta}_w(b_w + CA\rho r_w^3)}{m r_w^2\ddot{\theta}_w + c_{r2} r_w \dot{\theta}_w + r_w c_{r1}}
\tag{3.11}
$$

With the deriving of the mathematical model for the mass estimation, the road map to follow will be to validate the model with the actual inputs and outputs. Afterwards, the mass will be estimated in simulation via feeding the actual values to the model.

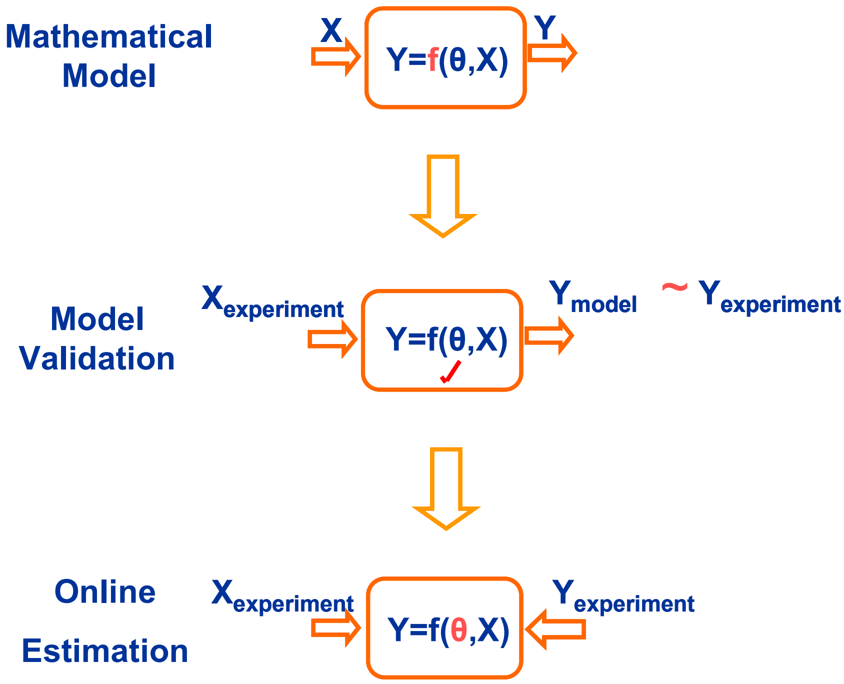

Figure 3.2: Model Based Estimation Process [18]

4. MASS ESTIMATION SIMULATION

In this fourth chapter, the simulations will be carried out based on the data gathered from the vehicle. Related hardware and software will be presented, real world data will be acquired, the data will be processed in the computer environment, the developed model will be validated and simulations will take place in order to estimate the vehicle mass along with a gear estimation algorithm. Combining the gear estimation and the mass estimation methods, a supervisory system deciding when and how to estimate the vehicle mass will have been derived. The performance discussions are also covered within the chapter.

4.1 Experimental Setup

The vehicle mass estimation directly deals with the vehicle longitudinal dynamics, a system composed from the engine out torque to the vehicle speed. As the system input is the engine out torque, with a system output of the vehicle speed and all the measurable quantities within the system are all gathered by the electronic control module on the engine, it is valuable to take a look at the engine control system as a mechatronic system composing of mechanic, electrical and computational parts

The system can be defined as the plant, controller, actuator, sensors and the CAN line carrying the information. Plant is the engine itself which is the controlled system. The engine has itself subsystems consisting of the air path control, fuel path control,... etc. Controller is the system producing the controlling and commanding signal according to the feedback coming back from the sensors, which reveal the plant's response to the commanding signal. Actuators are the generators of the controlling signal whether it is force or pressure or what is needed to derive the system. Hydraulic valves, electrical actuators and hydraulic pumps are the current examples of the actuators present on the engines. Lastly sensors are the measurement system informing the controller about the plant output and the state variables. On an engine exists the pressure measurements, temperature measurements, position measurements, velocity measurements, flow rate measurements and acceleration measurements.

An example schematic of the engine control system can be seen below. The engine control unit here is defined as powertrain control unit, the actuator in place is the fuel pressure pump, the plant is the engine itself and the sensor carries the fuel pressure information back o the controller.

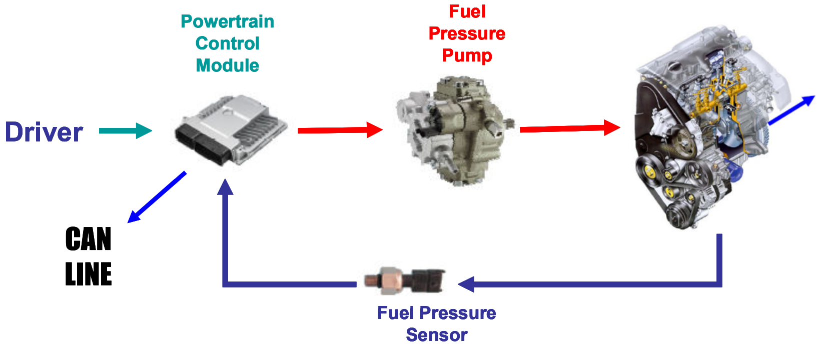

Figure 4.1: Engine System CAN Line

The communication within and outside of the electronic control unit on the vehicle is currently handled mostly by the controller area network systems. Knowing the addresses of the required labels one can gather the necessary info from the CAN line. The CAN line already carries all the information going to actuators and all the signals coming back from the sensors. In this study, listening the CAN line will enable to record the experimental data desired.

Experiments are carried out in Gölcük FORD OTOSAN test track on dry conditions. Tests are conducted on the part of the track that has no inclination, which will ease the calculation of the mass, independent from the road grade estimation factor.

The vehicle is already equipped with an on-board diagnostic port available due to the regulations. The CAN lines are available through the pins on the port. Therefore, acquiring data from the vehicle system will be realized via the pins available on the diagnostic port. Accurate Technologies hardwares will be used to transfer the data from the engine ECU to our MATLAB environment along with their ATI VISION software. The network hub hardware is seen below.

Figure 4.2: Accurate Technologies Network Hub [19]

The ATI Vision software is able to provide the data in MATLAB mat format simplifying the processing of the data. The software is triggered to record the pedal input, clutch position, gear position, brake position, vehicle speed, indicated engine out torque value and engine speed with a sampling time of 20ms. All of the channels are already found on the engine control unit.

4.2 Model Validation

The required parameters in the longitudinal dynamic equation are gathered from the related departments and from the suppliers where necessary. Isolating the model for specific parameters, the model is validated.

There are lots of parameters contributing to the model verification that need to be considered. From these, the efficient wheel radius is one of the important ones for our model to match the actual vehicle speed data and needs to be validated.

Isolating the wheel radius equation leads to a reduced relation between the engine speed and the vehicle speed. Below the efficient wheel radius equation is seen.

$$r_w = \frac{n * \pi * i_t * 3,6}{v * 30 * i_f} \qquad (4.1)$$

Running the simulations for estimating efficient radius results in the following figure.

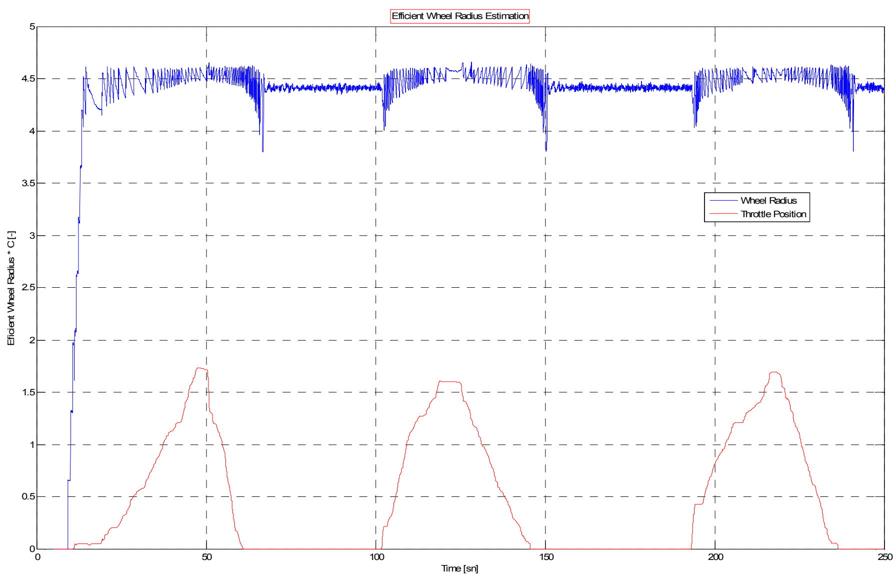

Figure 4.3: Efficient Wheel Radius Estimation

The results are multiplied by a constant due to FORD OTOSAN confidence policies. Here it is seen that the resulting value converges to 4.5 which is the number given by the supplier. Therefore, the wheel radius is validated and estimations can rely on the current model. Leaving the desired parameter on the left side of the equation provides us to validate each parameter we are interested in. Thus, the approach is used to validate the constants in our model as needed.

Validating the whole model, simulations will be carried out in two ways. The two cases will be the clutch being engaged and disengaged. The accuracy of the model is tested in these two phases.

With the simulations carried out, fed with the data clutch being disengaged, the results for the engine speed and torque produced can be seen in below figures with the pedal input on them.

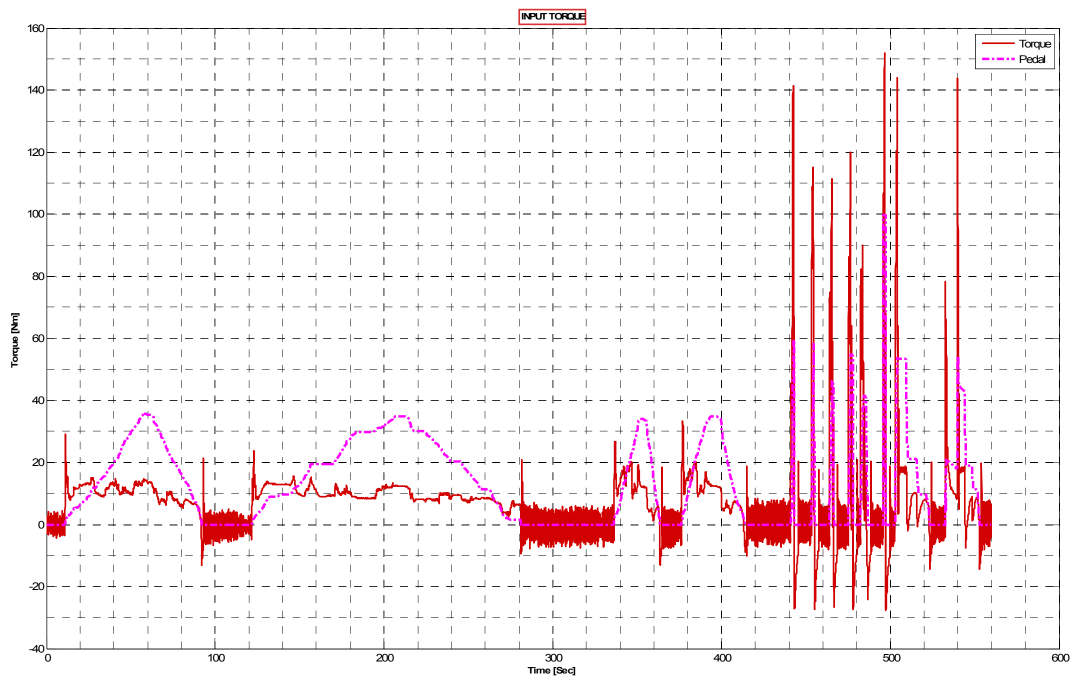

Figure 4.4: Neutral Gear Torque Produced

Simulating the disengaged clutch model will obviously isolate the engine out torque and will aid in matching the engine related parameters like the engine inertia and the friction term. On the other hand, current electronic control modules on the engines drive the engine wisely, that there is an idle speed governor algorithm in place. This algorithm automatically increases the desired engine out torque request in order to overcome the internal friction and auxiliary torque requests.

From figure 4.4, it is seen that the torque output fluctuates outside the ramp pedal input periods. This is directly related with the idle governor algorithm discussed. Therefore, saturation to the engine speed output is introduced to the system in order to simulate the idle governor algorithm as it is in the vehicle. Other than that, during the ramp pedal input, there is still some torque mismatch, especially at the beginning of the input. This can be explained by the torque discrepancies and not correlated friction torque losses. Friction torque is known to be calculated as a function of engine speed and temperature.

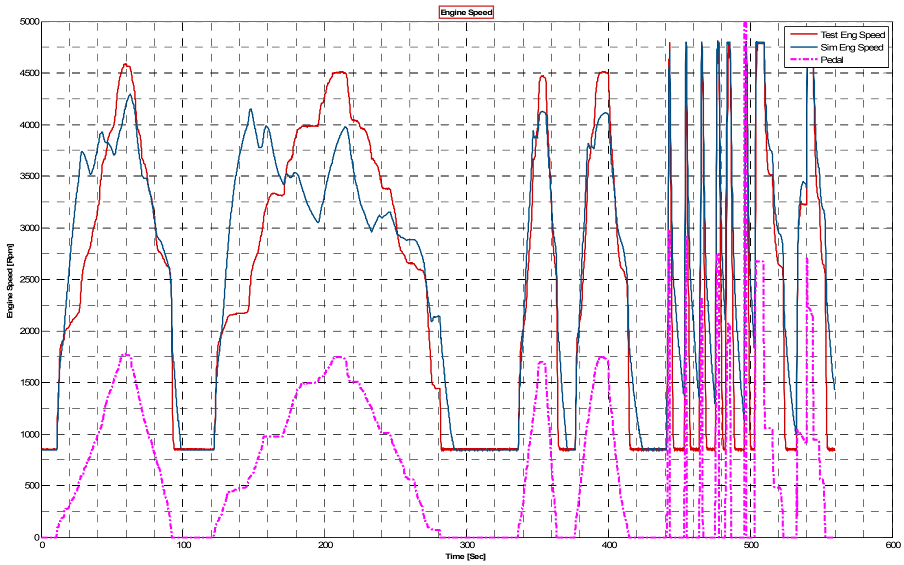

Figure 4.5: Neutral Gear Engine Speed

Next in figure 4.5, the engine speed response is seen. The engine speed saturation on 800 rpm can be seen to simulate the idle governor algorithm in the vehicle. Also engine overspeed protection can be seen as well for the engine speeds over 4750 rpm in the figure. It is observed that the deviation in the beginning, effects the rest of the curve in smooth ramp pedal inputs, whereas for impact like pedal inputs, the model is more bias to follow the actual values. However, the response is found reasonable to continue.

It is considered to create a sequence of tests if needed, in order to determine whether this mismatch is linear and the difference could be added to the model as an input changing with changing speed. This could also be realized by creating torque maps according to the engine speed, throttle position and temperature values.

For the second phase, in gear tests are carried out to simulate drive train model dynamics. The current model has the clutch, transmission, propeller shaft, final drive and drive shaft with wheel dynamics modelled. All of the components of the system bring some complexities and difficulties to the system. It is proposed to simulate the real world dynamics as much as possible, trying not to eliminate any of the components. In the model studied, there exists a linear assumed clutch model and also for the drive shaft exists one torsional flexibility.

Conducting the tests in first gear, no brakes applied, clutch continuously engaged, the driveline dynamics state variables are observed and validated. Below the resulting torque output of the engine can be seen according to the pedal input given to the electronic control unit.

Figure 4.6: First Gear Torque Produced

From the figure 4.6, there occur several blow-ups in the torque output of the system with respect to the pedal input. This is simply due to overcome inertial and resistive forces in order to move and accelerate the vehicle. Nonetheless, the torque signal has lots of fluctuations. This is the result of the engine maps providing the indicating torque. Further signal processing and filtration may be considered if necessary. The trend for the torque is reasonable.

Calculating the vehicle speed, transmission, shafts and wheel dynamics all need to be considered. To provide real world conditions, transmission and wheel dynamics have saturation limits to simulate mechanical operating ranges.

For the vehicle in first gear, figure 4.7 shows the vehicle actual speed with simulation results. It is seen that due to unknown rolling motion friction coefficients, the simulated vehicle speed reveals a lag in both accelerating and decelerating. In this thesis, proposed numbers from the literature will be used. Regarding the delays in the simulated vehicle speed, further discussions are focused on the modelled clutch and signal filterization lags.

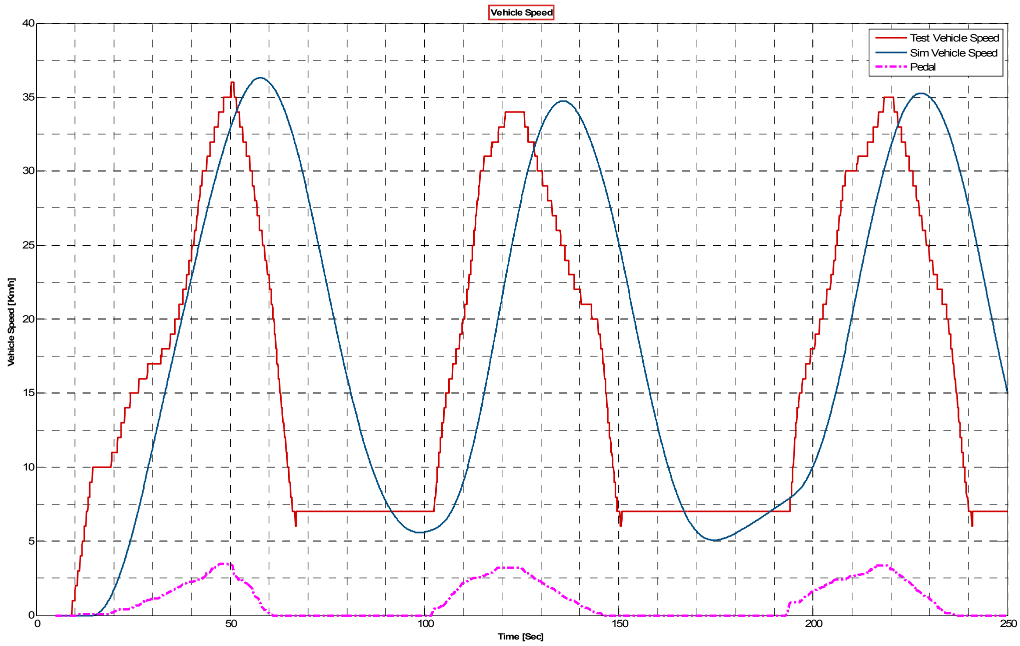

Figure 4.7: First Gear Vehicle Speed

The response will be accepted as reasonable to continue for mass estimation.

Running some tests with the clutch being disengaged to simulate and validate the engine dynamics, and running some tests with the clutch being engaged to simulate and validate driveline dynamics have been conducted. The results reveal that the simple longitudinal vehicle dynamic model derived has reasonable figures in order to continue with the estimation of the vehicle mass. Besides, the discrepancies in the simulation results are found to be acceptable for mass estimation and are not considered as road blocks for an initial estimation of the mass. The trends and limits of the outputs of the simulations are found to be reasonable. It should also be noted that the mass estimation will be done for pre-defined conditions, which will further improve the estimation of the mass.

4.3 Mass Estimation

Vehicle mass estimation with the longitudinal dynamics of a light duty vehicle will be carried out in this section. The mass estimation will take place during acceleration in 1st gear, where the road gradient is zero and no steering occurs.

With the model validated, the mass will be estimated with the equation derived in 3.1. The simulink diagram of the process is given below in the figure 4.8.

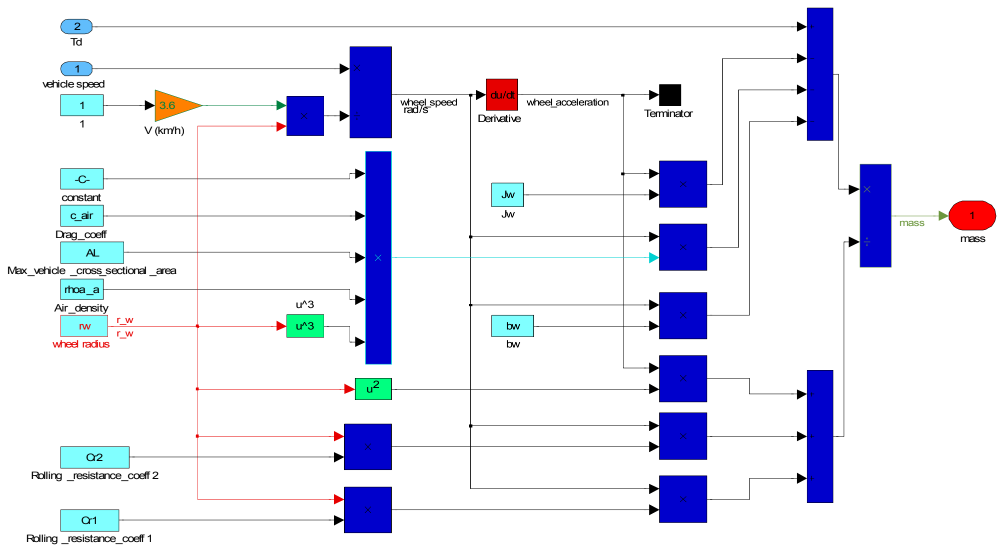

Figure 4.8: Mass Estimation Simulink Diagram

In order to estimate the mass, the in gear vehicle's acceleration is followed and mass calculation took place in the time period of acceleration.

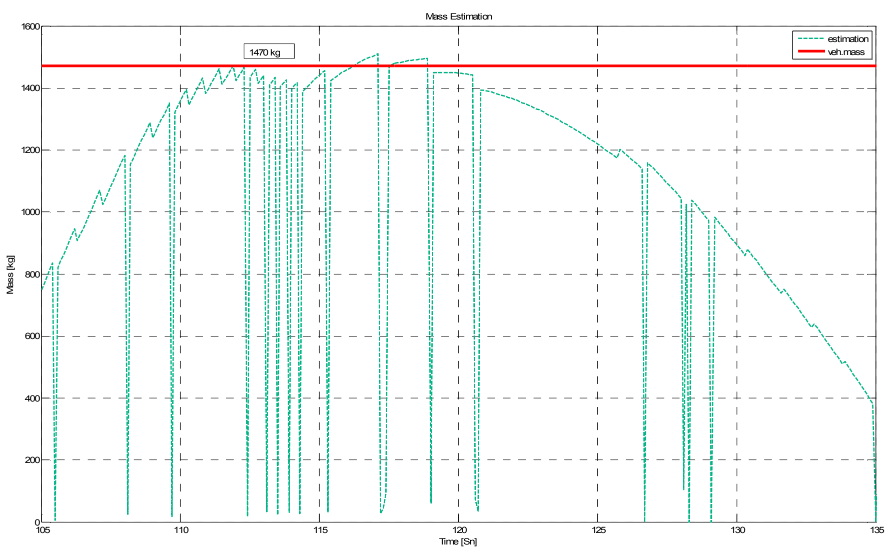

Figure 4.9: First Gear Acceleration Mass Estimation Results

When the acceleration transients come to a steady state, the mass is observed to be estimated. The actual mass of 1470 kg can be calculated for the period between the beginnings of the peak in the pedal till the time the pedal begins going to zero position. However, there are big jumps in the response which need to be handled.

Having seen the derivative term effects on the output mass estimate, it is studied to exclude the effects of the derivative term. Hence, the resulting mass estimate is seen to be a continuous and an accurate estimation for the engine speed above 3000 rpm on the 1st gear while a ramp throttle input was applied. The proposed model is within a 5% accuracy error for the below operating conditions.

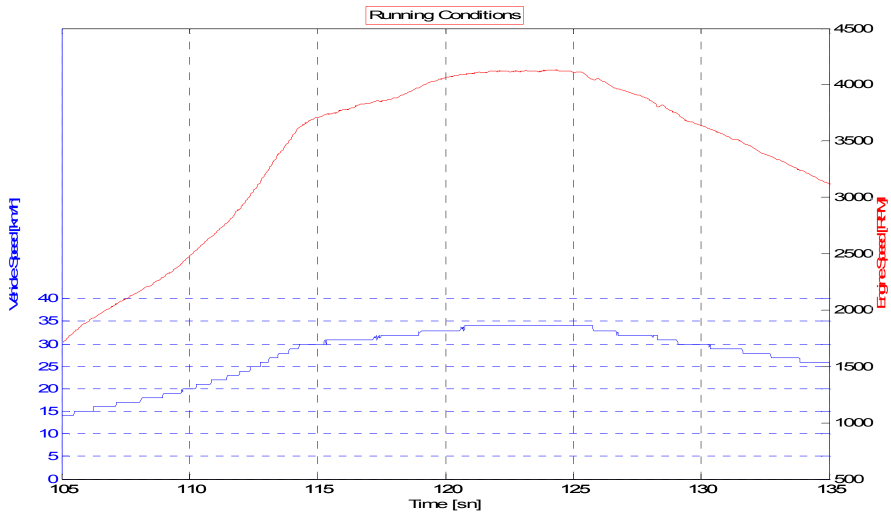

Figure 4.10: Running Conditions

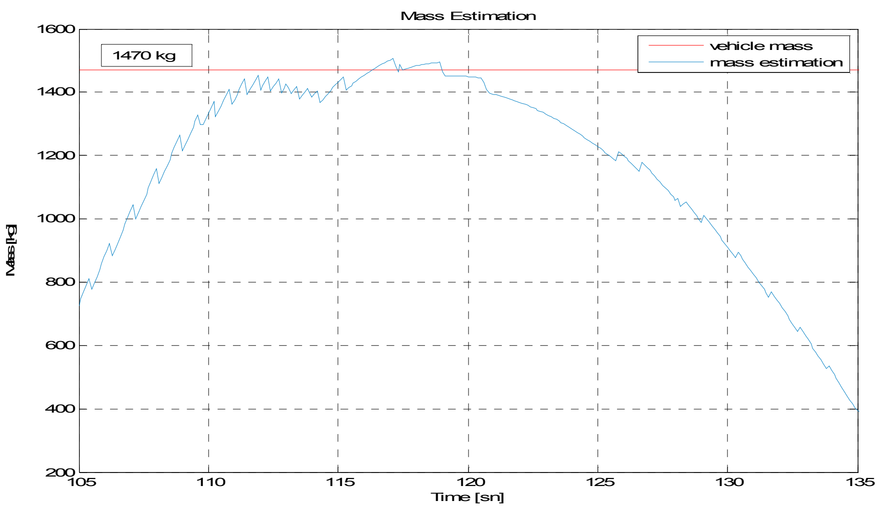

Figure 4.11: First Gear Acceleration Mass Estimation Results

From the estimation, it is seen that, the derivative term effect is handled while there is a significant fluctuation on the mass is seen. This is aimed to be referred by simply implementing a filter on the output. Introducing a first order low pass filter to the system brings a lag along with a smoothened estimation. It is seen in the below figure 4.12, that the steady state value of the estimation is shifted to the right due to the time delay of the first order filter

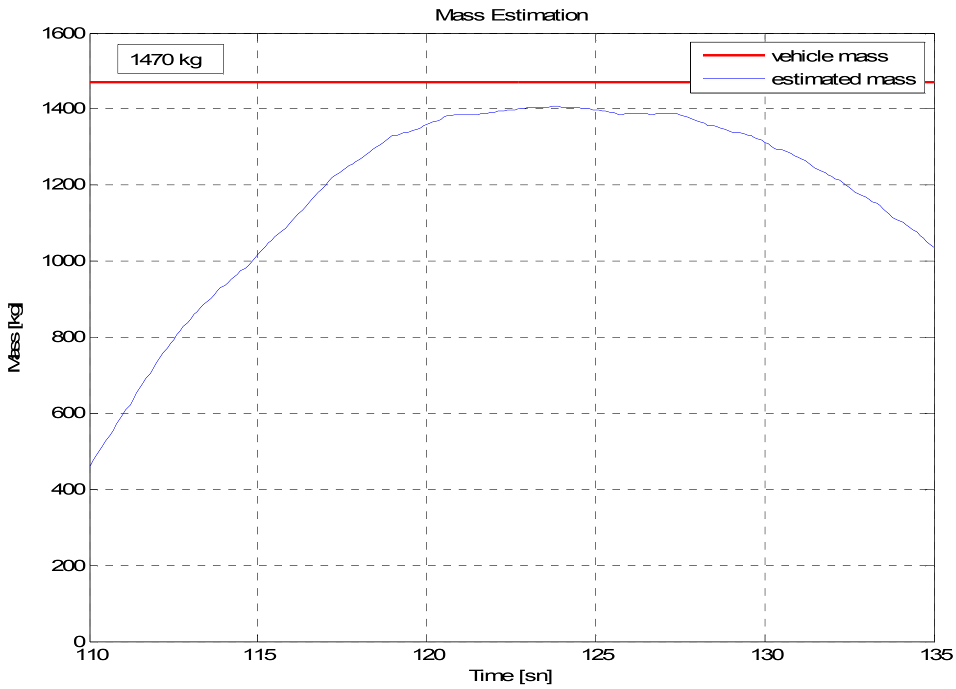

Figure 4.12: Low Pass Filtered Mass Estimation Results

Experiments carried out and having validated the model with the data acquired, the proposed mass estimation algorithm is found to be able to determine the vehicle mass within the predefined operating conditions with a low-pass filter.

Conducting further tests with different loading weights will reveal the proposed approach's convergence accuracy better. Therefore, with different scenarios observing the system response should be the next step.

4.4 Gear Estimation

It is aimed to gather the gear number during the vehicle operation in order to decide when to run the vehicle mass estimation. No extra vehicle instrumentation is desired. Thereby, estimating the gear number from a model is preferred.

Simply deriving the speed conversion equations from engine out to the wheel speed, and leaving the gear ratio on the left side of the equation as the unknown, one finds the following gear ration equation in 4.2

$$i_t = \frac{\dot{\theta}_m * r_w * 3.6}{v * i_f} \tag{4.2}$$

A smart gear selection system is placed in the model. It is possible to include all the constant terms in the upper and lower limits as multipliers as well. Also a curve can be defined, whose output could give us the gear selected. In here, a wise addition block is used in order to detect in which gear the vehicle is. The principle depends on the fact that in the same time just one gear may be selected, so that just one of the outputs of the system will be a non-zero value providing the current gear.

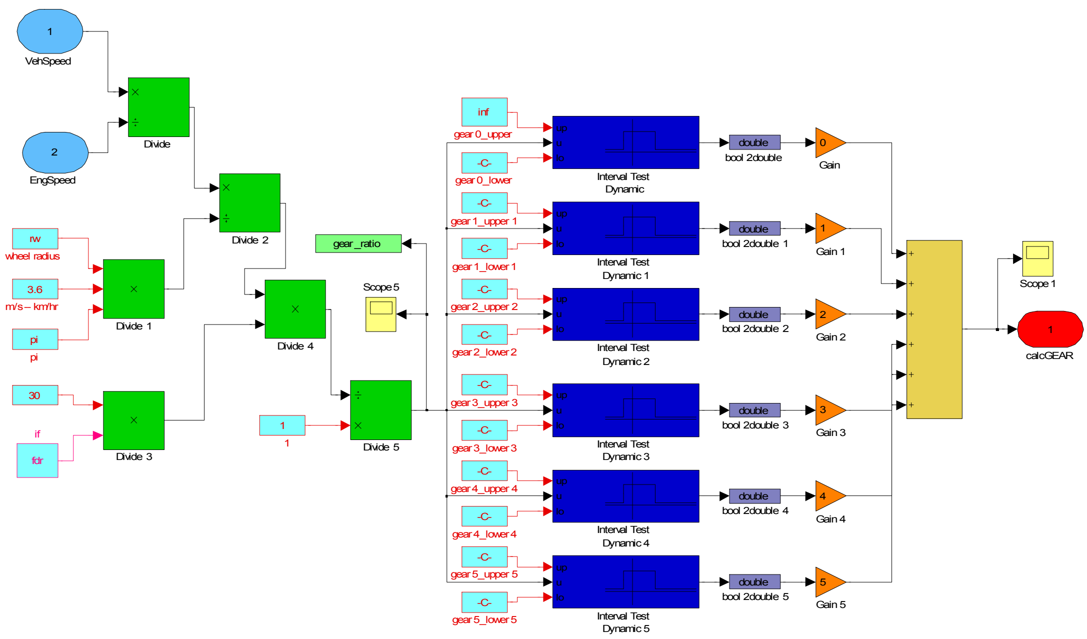

Figure 4.13: Initial Gear Estimation Algorithm Simulink Block

Simulations show that the results are affected by the inertia of the system, as the gear selection directly depends on the engine and vehicle speed.

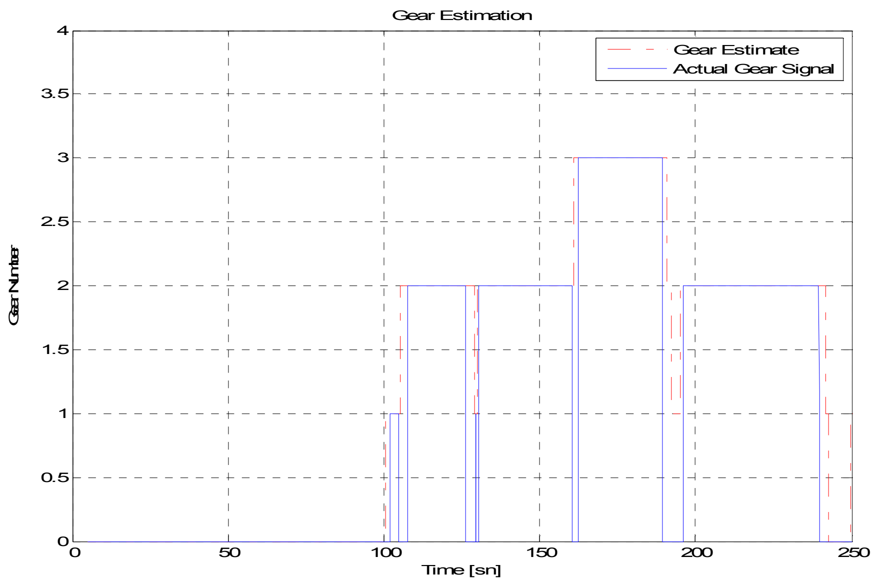

Figure 4.14: Gear Estimation Results

It is seen that during the gear shifts, the model continues to calculate and seems to perceive the selected gear wrongly. Selecting the gear between the gear shifts is found to be faulty. Thus, if a clutch switch is added to the system, a more accurate estimate of the gear position could be obtained, which in return brings complexity to the system. It is proposed not to run the estimation during gear shifts. The updated algorithm can be found in figure 4.15

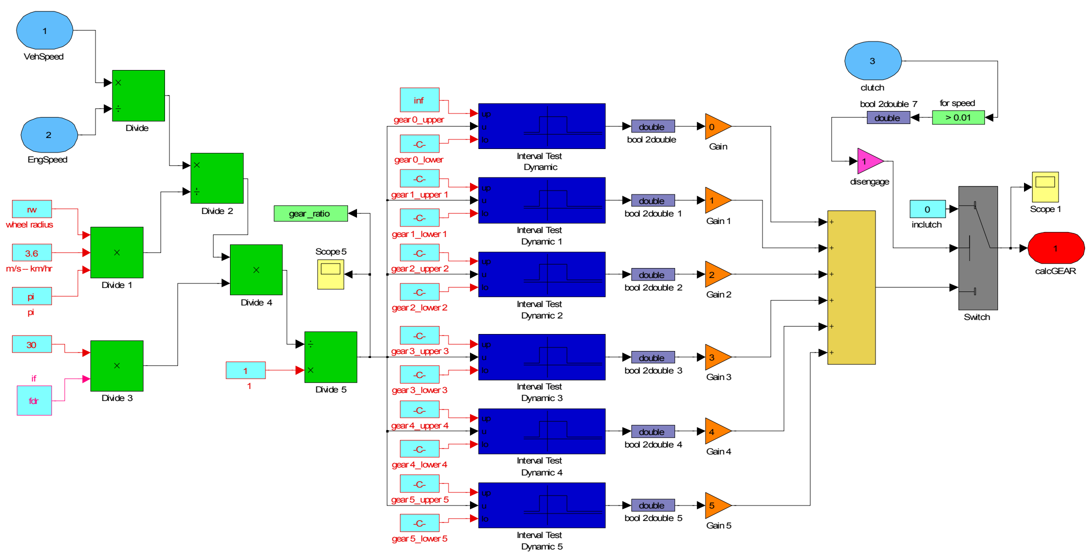

Figure 4.15: Enhanced Gear Estimation Algorithm

Running the clutch added model, the gear estimation is found to be accurate and reliable. The results can be seen in the below figure 4.16. In the results seen in the figure 4.17, the actual gear position is even recalculated during the clutch being depressed. Therefore, it can be said that the proposed algorithm is able to provide the current gear while the vehicle is running in a robust and simple way.

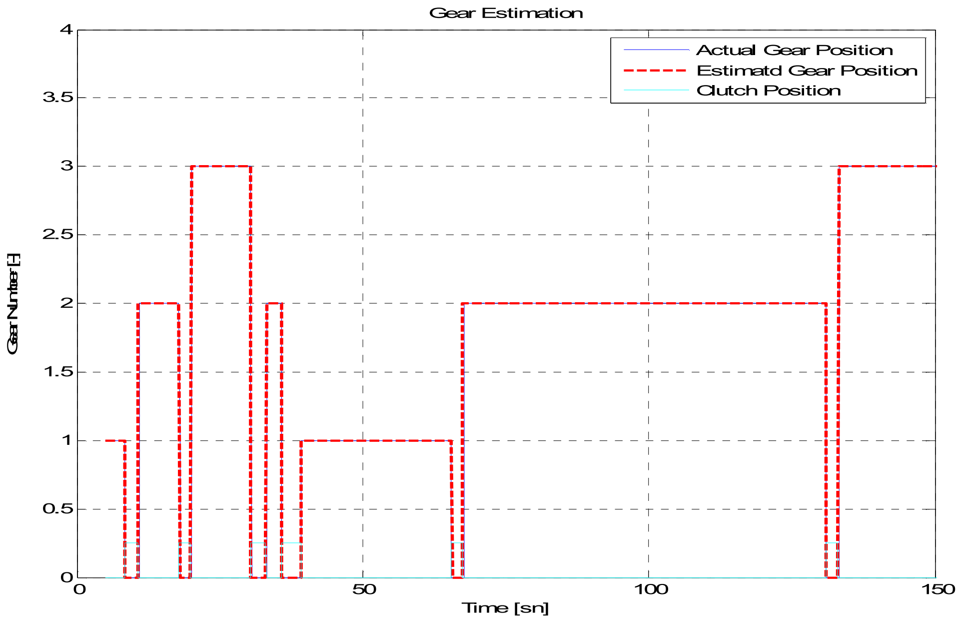

Figure 4.16: Gear Estimation Results

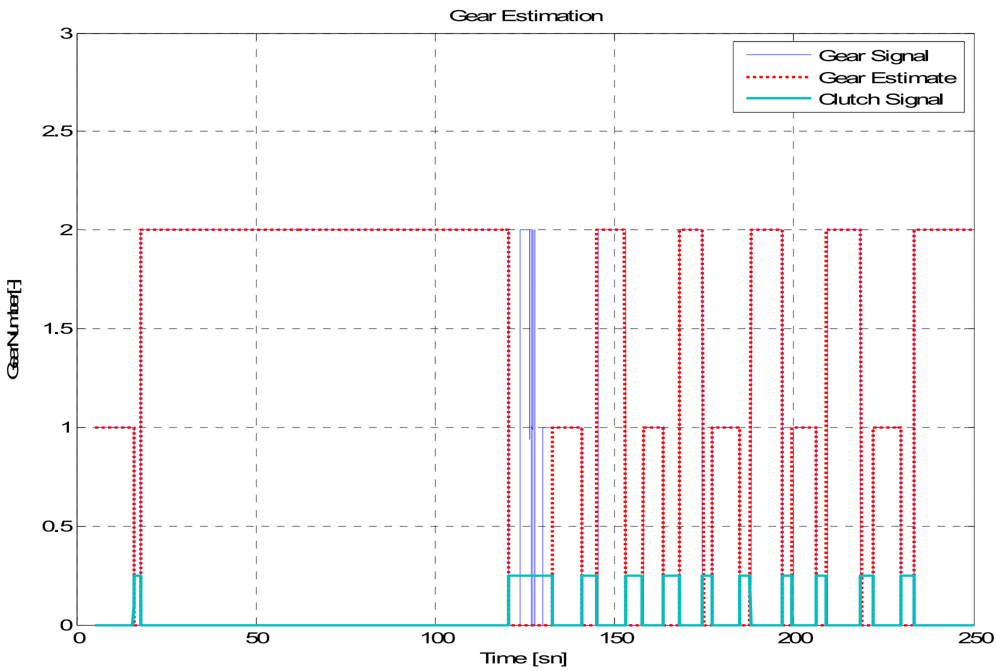

Figure 4.17: Gear Estimation Results

5. CONCLUSIONS AND RECOMMENDATIONS

In this study, for a light duty vehicle, the mathematical model for the longitudinal dynamics has been given. The model has been validated with real data taken from a FORD Transit Connect. The results show that, due to the uncertainties in engine output torque and signal noises and delays with the high frequency driveline dynamics, the model could be further studied. For these grounds, filterization needed to be done and the driveline dynamics has been simplified.

Using the obtained model, the mass estimation for the predefined condition has been realized without any instrumentation. Although the mass estimation for a certain period is acceptable, further designs and improvements will be better to have a more reliable algorithm. It should be stated that the study is beneficial for the realization methodology of vehicle mass estimation. A gear estimation algorithm is also provided successfully. Studying different driving scenarios and conducting sensibility and robustness checks are needed before the implementation of the algorithm into the on vehicle software for conducting online tests along with the simulations. Trying developing softwares like this one on the vehicle controlling unit can be realized with rapid prototyping like embedded softwares.

Having compared the actual test data results and the simulation results, it should be stated that a more accurate estimation can be realized. Introduction of the algorithm to the vehicle control methodology needs to be studied and further driving scenarios should be validated. During the thesis, vehicle mass estimation methodology for a light duty vehicle has been developed successfully and acceptable results of vehicle mass have been obtained.

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