A Dissertation

On

Mass and Grade Estimation of Commercial Vehicle using Kalman Filter

Submitted in partial fulfilment of requirements for the degree of

Master of Engineering

in

CAD / CAM Engineering

Submitted by

Ashwin Dhawad

Registration No.: 801784003

Under the Supervisions of

Mr. Chaitanya Tiwari
Senior Manager
Engineering Research Centre, CV-Engineering
Tata Motors Ltd.

Dr. Sivakumar Palanivelu
General Manager
Engineering Research Centre, CV-Engineering
Tata Motors Ltd.

Dr. Ashish Singla
Associate Professor
Department of Mechanical Engineering
TIET

Mechanical Engineering Department
Thapar Institute of Engineering and Technology
(Deemed to be University)
Patiala-147004, India
July 2019

DECLARATION

*I hereby declare that the work done in thesis report entitled, " **Mass and grade estimation of commercial vehicle using Kalman filter**" submitted towards partial fulfilment of award of **Master of Engineering degree in CAD/CAM Engineering in Mechanical Engineering Department of Thapar Institute of Engineering and Technology, Patiala** is an authentic record of work carried out by me under the supervision and guidance of **Mr. Chaitanya Tiwari, Senior manager, TATA Motors Ltd., Pune, Dr. Sivakumar Palanivelu, General manager, TATA Motors Ltd. and Dr. Ashish Singla, Associate Professor, Mechanical Engineering Department of Thapar Institute of Engineering and Technology, Patiala.***

Date: 02/07/19

Ashwin Dhawad

This is to certify that above declaration made by the student concerned is correct to the best of our knowledge and belief.

02/07/2019

Mr. Chaitanya Tiwari
Senior Manager
New Technology Development
& Simulation
Engineering Research Centre, CV-Engineering, Tata Motors Ltd.
Pimpri, Pune 411018, India
chaitanya.tiwari@tatamotors.com

Dr. Sivakumar Palanivelu
General Manager
Head - Ultra Platform, New Technology development & Simulation
Engineering Research Centre, CV-Engineering, Tata Motors Ltd.
Pimpri, Pune 411018, India
sivakumar.p@tatamotors.com

3/7/19

Dr. Ashish Singla
Associate Professor
Mechanical Engineering Department
Thapar Institute of Engineering & Technology
(Deemed to be University)
Patiala – 147001, India
ashish.singla@thapar.edu

Acknowledgement

It is my great fortune to have the opportunity to work on this exciting and inspiring project. The learning and experience I have received here is of inexplicable value. It gives me immense pleasure to express my paramount gratitude to each one of those who made this possible.

I would like express my profound exaltation and gratitude to Mr. Chaitanya Tiwari, Senior Manager, TATA Motors Ltd. for sharing his priceless experience in the field of simulation and vehicle level Knowledge with me. I thank him from the core of my heart for standing by me through all highs and lows of the process and at times steering the research in right direction for me to achieve my objectives.

I sincerely thank Dr. Sivakumar Palanivelu, General Manager, TATA Motors Ltd. for providing me with this unique opportunity of carrying out my project under his guidance. His advice, persistent support and patience have helped me get through difficult times.

Also, I would like to heartily convey my gratitude to TATA MOTORS LTD., Pune, for providing me with this amazing opportunity and company facilities for my research.

I express my heartfelt thanks to Dr. Ashish Singla, Associate professor, Department of Mechanical Engineering, Thapar Institute of Engineering and Technology for his continuous support throughout the project. I thank him for sharing his expertise and all the learnings that I have received over the years. Along this journey, I find myself immensely fortunate to spend many opportune moments under his guidance.

Finally, I would like to thank all those who directly or indirectly helped me complete my thesis report.

Abstract

In today's world, everyone is in race to make efficiently performing vehicles. For this performance improvement, it is important to know real-time vehicle parameters. This thesis presents a method to achieve some of those parameters. In this thesis, the considered parameters for estimation are mass of vehicle and slope of the road on which vehicle is present.

Extended Kalman Filter (EKF) is a nonlinear estimator which has been used to estimate mass and road slope simultaneously. Use of any additional sensors to collect this information will be costly. So, EKF is used with already existing sensors in the vehicle to achieve the desired result.

For virtual testing, co-simulation was carried out between Simulink and AVL Cruise. The input data to Simulink model was supplied from AVL cruise. The vehicle model was also verified through this co-simulation, by suppling all inputs for known mass and slope of road to satisfy the mathematical governing equation. The mass estimated is more than 80% accurate, which is enough for performance enhancing applications on the vehicle. If the algorithm runs for longer time. It corrects itself in the background so that all estimation reach above 90% accuracy with time, but due to constraint of convergence time, the mass estimation needs to be locked within certain time limit.

Nomenclature

ILCV - Intermediate And Light Commercial Vehicle

M&HCV - Medium And Heavy Commercial Vehicle

KF - Kalman Filter

EKF - Extended Kalman Filter

UKF - Uncented Kalman Filter

C_d - Co-efficient of drag

A_f - Front projected area of vehicle

v - Velocity of vehicle

ρ_{air} - Density of air

$\mathbf{x}$ - State vector

$\mathbf{a}$ - Noise in system

$\mathbf{P}$ - Covariance matrix

$\mathbf{F_j}$ - Jacobian matrix

$\mathbf{W_j}$ - Jacobian matrix

$\mathbf{Q}$ - Process noise covariance matrix

$\mathbf{K}$ - Gain of estimator

$\mathbf{C}$ - Output matrix

$\mathbf{R}$ - Measurement noise covariance matrix

$\mathbf{x_{updated}}$ - State vector updated

$\mathbf{Y_i}$ - Sensor readings

$\mathbf{P_{updated}}$ - Covariance matrix updated

List of Figures

List of Tables

Table of Content

1.1 Background and Motivation

In today's world, the advancement in vehicle technology is increasing day by day. This thesis is an attempt to get a step closer to this. To achieve this two parameters have been estimated viz. mass of vehicle and grade of road. These are obtained in real-time. It has different applications like automatic gear shifting resulting in improvement of fuel economy of vehicles. Also, co-relation of fuel economy data from telematics with exact loading condition can give better enlightenment on fluctuation of fuel economy in vehicle if any. If vehicle mass and slope of road are available in real-time, then it can be used to have better results in decision making algorithms of automatic driver assistance systems and active dynamic control systems.

To achieve these parameters, there are majorly 2 methods viz.:

- Use of additional vehicle mass and road grade measurement sensors
- Use of numerical algorithms

In case of using sensors, the overall cost of vehicle will increase. This makes it difficult for the any vehicle manufacturer to compete in the business market. Value addition to the product without increase in its cost is very much important for any business unit. Also accuracy of sensor may vary with time due to different reasons depending on type of sensor used. Therefore, it is better option to use numerical algorithms with available data from ECU to estimate vehicle mass and road grade.

1.2 Introduction to Parameter Estimation

Parameter estimation is very useful and economical way to get the desired data. In certain practical applications it is not possible to measure each and every variable. In such situations, variables has to be determined through this approach. The estimator to be selected for parameter estimation depend on the system on which it has to be applied. Estimator selection and construction will vary depending on linearity or nonlinearity of problem, number of measured data available from sensor, number of parameters to be estimated, etc.

1.2.1 Linear and Nonlinear Systems

For a system to be linear it has to satisfy property of homogeneity and superposition principle [1].

The property if homogeneity can be stated as, for a system with function, z, and input variable, p,in domain of z then for any real number, r,

$$z(rp) = rz(p) \tag{1.1}$$

Super position principle can be stated as, for a system with function, z, and multiple inputs say p and q, in domain of z,

$$z(p + q) = z(p) + z(q) \tag{1.2}$$

If any of the above mentioned properties are not satisfied, then, the function is considered as nonlinear. A system with nonlinear function say

$$\dot{x} = z(p, q) \tag{1.3}$$

is nonlinear, if z is nonlinear.

1.3 Introduction to Extended Kalman Filter

Different Numerical algorithms like recursive least square, extended Kalman filter (EKF), unscented Kalman filter (UKF), etc. are available for parameter estimation. It is important to select robust method which is accurate for all different engines and road conditions. In this thesis extended Kalman filter has been selected to obtain mass of vehicle and road grade in real-time.

Extended Kalman filter is an extension of Kalman filter. Kalman filter is used to solve linear systems. To handle nonlinear system, the concept of EKF came into picture. EKF linearizes the system and solve it in similar manner as that of linear Kalman filter problem. This is done with the use of Jacobian matrices, which have to be solved in each iteration. In this algorithm it is important to construct process noise matrix and measurement noise matrix to get best possible results for estimation. It is important to have Gaussian distribution of noise to use this algorithm.

The EKF requires different inputs of vehicle attributes and engine parameters. Since the implementation of Bharat Stage – 4, electronics engines have been used. These vehicles consist of electronic control unit (ECU) which provides with required input data for the estimation. To get this data for testing the algorithm, AVL Cruise software is used.

1.4 Software-In-Loop Testing

In this thesis, the developed algorithm was tested in software in loop (SIL) by co-simulation of AVL cruise and Simulink. The vehicle system model is created in AVL Cruise which had been incorporate with actual vehicle data. When the co-simulation between AVL Cruise and Simulink takes place, the vehicle data from AVL Cruise is supplied as input to algorithm created in Simulink for parameter estimation. The type of road, engine, constant inputs and weight of vehicle can be selected in AVL Cruise, for which it will accordingly supply the input data like torque, velocity, etc.

1.5 Research Methodology

In this thesis work, at first, the physical system was converted to mathematical model. This was done using the Newton's second law of motion, considering the forces acting on the vehicle in dynamic condition. To solve this mathematical equation was the objective. The equation formed contained two unknowns *i.e.* mass of running vehicle and slope of road on which vehicle is moving.

To tackle the above problem, estimation method was adopted instead of using any additional sensors. To estimate these parameters different estimators were available. Different filters were reviewed and extended Kalman filter was selected for estimation. To conduct the estimation, the mathematical model was converted to state-space representation.

Initially, an algorithm was developed for step input torque, estimator performance was noted and basic structure of algorithm was created. This exercise also helped in learning the effect of different parameters of extended Kalman filter on the estimation.

After this, actual vehicle data was to be tested. This testing was done with the assistance of AVL Cruise software. The real-time data was give as input to Simulink and estimation was obtained. Different trials for process noise matrix and measurement noise matrix were taken to see their effect on estimation for actual vehicle data.

The estimator has to estimate the mass in certain time constrain and then lock its value. After this, only the grade estimation is carried on. To achieve good accuracy in mass estimation within a short period, the algorithm restarts after some period keeping the previous learning. This helps to get to the desired accuracy and also reduce the convergence time.

1.6 Outline of Thesis

The Chapter 2 discusses the literature on the thesis topic. In Chapter 3, mathematical model of the system is constructed using Newton’s second law of motion and also validated the same. In chapter 4, the mathematical model is converted to state space representation and the observability analysis is conducted. Working of EKF is explained along with estimation of input parameters. Chapter 5 describes methodology of testing, test condition and their results. Sensitivity analysis is conducted and observations are discussed. In Chapter 6, conclusion of thesis and future work is discussed.

2.1 Modelling of System

For estimation the system model has to be created based on governing equations and physical laws. Detailed forces and their modelling has been discussed in book by Thomas Gillespie [2]. Similar method has been used by Holm [3]. Here, the body is considered as lumped mass. Newton's 2nd law of motion was applied and a mathematical model was generated. This considers the resistance of aerodynamic drag, rolling resistance and self-weight of vehicle under the acceleration of gravity. This system when modelled gives two unknowns in single equation.

2.2 Estimation Theory

Lot of applications in parameter estimation field has been done over the years. Sometimes, in many practical applications, it is not possible to measure the desired parameter using sensors. This is either due to physical constrains or inaccuracies generated in data due to presence of noise. Even the parameter required at the output may be a combination of different states which are not measurable directly through single sensor.

Three important estimation theory has been discussed by Mohan *et al.* [4]. The first one is known as equation error method. In this the process noise is not specified until the differential equation of the state is balanced. In the second type, the measurement noise is specified with all the measurement in combination with state. This is known as Output error model. The third one is most general one, where both measurement and process noise are present during the formulation of equation.

Different methods have been developed for estimating parameters in linear models and nonlinear models. In real life most problems are nonlinear. Linear model is the one which satisfies the principle of superposition and homogeneity [1]. Any model which does not satisfy any of this condition is considered as nonlinear model. The estimation for both linear and nonlinear cannot be carried out in similar way. For *e.g.* Kalman filter was initially developed for linear models only. Same could not be applied to nonlinear systems. Later, to solve this issue extended Kalman filter was developed. If the system is highly nonlinear then unscented Kalman can also be used.

2.2.1 Estimation of Vehicle Mass and Road Grade

Different methods and approaches have been tried along the years to estimate mass and grade of the vehicle. Also the use of different filters have been conducted. Following is the discussion on the work undertaken in relation to vehicle mass and road grade estimation using different methods.

In the past, people have tried vehicle mass and road grade estimation. Various methods are suggested for this in different thesis work. In thesis by Ritzén [5], the problem statement was converted to estimate a line using desired filter. It shows estimation of mass during acceleration and during gear shift. Here, the oscillation in driveline were not modelled, but instead strong filtering was used. In thesis by Ghotikar [6], both mass and grade were estimated simultaneously. Before this, only single parameter used to be estimated. The estimation was on hold during braking and clutch disengagement to reduce noise in the estimation. Two different algorithms were used to present the estimation results. Results of both were filtered using low-pass filter. In thesis by Holm [3], Kalman fiter was used to conduct simultaneous estimation of vehicle mass and grade. It described the mathematical model, state-space model and Kalman filter working to obtain mass and road grade. The master's thesis by Paulsson and Asman [7], estimates vehicle mass using recursive least square method. The algorithm was tested on different vehicles to check the robustness of the estimation. Here, the road grade was estimated using longitudinal accelerometer.

There have been different methods to estimate the mass by recursive least squares (RLS) with multiple forgetting factors, dynamic grade observer (DGO) and parallel mass and grade (PMG) estimation using a longitudinal accelerometer [8]. Many test were conducted on the constructed model and method of estimating the parameters. The forgetting factor in the above mentioned method cannot be same for different rate of variation in the estimating parameter. The accuracy in depends on the guesses made for initial values for parameters to be estimated. To avoid this, EKF algorithm is used to get the initial mass value, helping the estimation reach better accuracy. PMG was the most effective than other methods discussed.

Winstead and Kolmanovsky [9] proposed a method for mass estimation of road grade and mass by model predictive method. They have used EKF for the estimation purpose.

In this paper, the combination of extended Kalman filter and model predictive controller (MPC) has been used. They have optimised the cost function by penalizing the estimated parameter’s variance. For considering the traffic condition in simulation, they have constrained the vehicle speed under certain limit.

2.3 Kalman Filter

Rudolf Emil Kalman discovered Kalman filter in 1958 [10]. It helps in achieving the true value of desired parameters by removing the noise in them. This means Kalman filter algorithm detects anonymous measurement and filter them out. Modern control system has lot of applications of Kalman filter. It was a great achievement in estimation theory. But, this filter was useful for linear system models. Kalman filter was initially used for linear systems. It works on the balance of process noise and measurement noise. As the measurement noise increases, the estimation shifts away from sensor readings and as the process noise increases, more weightage is given to measured readings.

One of the Paper by Akesson *et al.* [11] and other paper by Ge and Kerrigan [12] presents the methods of tuning process noise matrix of Kalman filter has been elaborated, which is one of the major concerns in designing Kalman filter algorithm. The measurement noise can be obtained from sensor specifications. But determination of Q becomes the task during estimation. A method for Kalman filter tuning was presented in paper by Akesson; *et al* [13]. The method uses process data to estimate process noise. It applies autocovariance least-squares method to the model with mutually correlated noise. To manage least-square estimation problem few regularization were included in the algorithm.

In the paper by Gunda *et.al* [14], the use of Kalman filter is used for harmonic estimation. Also, the modelling of load impedance has been done. This was for validating the algorithm. Here, the Kalman filter helps in dealing with noise in current signal and voltage signal. To find out the behaviour of system under harmonics, calculation of impedance for the model was done.

Singh *et al.* [15], describes that Kalman filter has two famous extensions namely extended Kalman filter and unscented Kalam filter. In wireless sensor network the data has to be passed through noise reduction process for which extended Kalman filter has been used in this paper. Number of samples were taken to reach correct value of estimated error covariance. Error covariance of measurement values and estimated values will have more difference if sample numbers are more.

To find solution to nonlinear problems, Kalman filter algorithm was modified by Schmidt. It was initially known as Kalman-Schmidt filter and later as Extended Kalman filter (EKF). EKF linearizes nonlinear relations using partial derivatives. Kalman filter estimation is very robust and is useful for linear models. To conduct estimation for nonlinear model use of Unscented Kalman filter or Extended Kalman filter can be preferred. A simple nonlinear problem was taken to apply both UKF and EKF. EKF on the other hand is simple to apply and gives almost the same accuracy as UKF. Almost similar results were obtained. UKF is useful when model is highly nonlinear.

2.3.1 Extended Kalman Filter

It the extension of Kalman filter to solve nonlinear problems. EKF is applied in lot of application. Its process contains development of Jacobian matrices which helps in linearizing the system and then solving it. The covariance and estimate calculated in the previous step is reused in the next step. One of the major advantages of this method is that, it is not required to save all the previous data, only the estimation obtained in last iteration has to be given further. Also, EKF is very robust.

Mohan *et al.* [4] gave their input on extended Kalman filter (EKF) algorithm. The augmented state variables can gain good accuracy through recursive learning if choice of initial covariance matrix. A comparative study has been conducted on three adaptive estimation technique viz. extended Expectation Maximisation, Maximum Likelihood and Covariance matching. At zero process noise, estimation was conducted with both Newton Raphson and Kalman filter with efficient tuning of measurement noise and covariance matrix.

The paper by Blanchard *et al.* [16] proposes a method for parameter estimation. The approach taken consist of polynomial chaos theory which is quicker than Monte Carlo simulations. Polynomial chaos has been applied on different systems like structural mechanics, fluid mechanics, etc. Here, it has been applied on mechanical systems. One of the drawbacks pointed by this paper is that EKF diverges if sampling frequency is high. In case, low sampling frequency is required, it will not be able to generate accurate results. The truncation error accumulation happens at faster rate in EKF. All this has been shown with an example of roll plane model with 4 degree of freedom. It is a nonlinear model used for illustration. The estimation obtained here are in the form of probability density function and not as definite numerical values. It is recommended to check EKF on various sampling rate.

2.3.2 Unscented Kalman Filter

The major drawback of EKF was linearization of nonlinear model and then solving the linearized model. This creates lot of inaccuracies when system is highly nonlinear. To overcome this, Julier and Uhlmann [17] developed a new method. The accuracy was equivalent to Kalman filter for linear models. In case of nonlinear models, the performance was good. This method estimates without linearization of the system as done in EKF.

The paper by Wan *et al.* [18] shows the drawbacks and inefficiency of EKF against the unscented transformations. Dual estimation has been conducted using different estimators. The same order of computational complexity has been maintained as that of EKF. Also, an alternative to dual estimation has been shown *i.e.* the joint EKF and joint UKF. Another alternative applied to nonlinear-dynamics was expectation maximization (EM) which allows unscented smoothing. The performance gain was shown on different dual estimation methods along with standard regression model.

The authors Wan and Van der Merwe [19] shows the downsides of EKF and proposed improvements to UKF proposed by Julier and Uhlmann [17]. It states that EKF results can diverge from true value as Gaussian random variable (GVR), which propagates through system dynamics, propagates through first order linearized model. This causes errors in mean and covariance of the Gaussian random variable which is transformed. UKF does not allow this to happen. This is due to deterministic sampling approach taken by UKF algorithm.

2.4 Testing with AVL Cruise

The AVL Cruise is comprehensively designed software package for vehicle system simulation [20]. In this paper the power drive train was developed. Software forms innovative tool using different design principles. It describes different components of

AVL Cruise in detail. Also, dynamics of multi-body system involving coupling connections, structure variant systems and degree of freedom has been explained. Along with mechanical systems, AVL Cruise can also be used to construct electrical components like battery, motor, etc.

The paper by Sangtarash *et al.* [21] used AVL Cruise to conduct vehicle simulations for the study of effect of regenerative braking on vehicle. The model of hybrid bus was created in the software. Even brake analysis was performed. For simulation, different drive cycle can be made in AVL Cruise. The performance is tested on these drive cycles. Using this, fuel and energy saving was evaluated at the end.

AVL cruise helps in early stages of development [22]. Vehicle attributes like coefficient of drag, vehicle weight, frontal area, etc. In the paper by Srinivasan [22], the test data from AVL cruise is compared with actual vehicle data. It proved that the accuracy of software is reliable. It was useful to determine the modifications required in the engines and vehicle to improve fuel economy and performance.

Wang and Luo [23] created an AVL based model for simulation and then compared the results with experiment. Acceleration performance and fuel economy were tested to get the accuracy of simulation. Two buses were taken for testing namely simulation and conventional public bus (CPB) and hybrid electric bus (HEB). From this activity it was concluded that, simulation results and experimental results are close.

Yang *et al.* [24] used AVL Cruise and Matlab-Simulink for modelling and simulation. Fuel consumption, acceleration and maximum velocity were calculated. All test were conducted on hybrid and conventional buses. The results from simulation fits the on road results.

Simulation is useful to know functionality of system and carry out proper tuning of parameters much before the actual product is developed [25]. The authors Sundaravadivelu *et al.* [25] have co-simulated AVL Cruise and CarMaker in real-time to conduct analysis of vehicle systems. It also suggest that, direct on road testing have the potential to cause great damage and loss to the product owner.

2.5 Observations from Literature Survey

- In construction of vehicle model, driveline oscillations were not included and instead an efficiency factor was multiplied with torque
- To consider the on road traffic conditions, only the velocity parameter is changed.
- Initially assumed values of the EKF affect the accuracy of the results
- In recursive least squares (RLS) method, different forgetting factors are required when rate of variation in parameters is different.
- Simulations from AVL Cruise gives very close results to actual vehicle testing

2.6 Objectives of Present Work

- Development of the algorithm for estimation of vehicle mass and road grade using extended Kalman filter.
- Conduct sensitivity analysis to check the robustness of algorithm when vehicle attributes undergo changes.
- Reduce convergence time of estimation.

3.1 Forces Acting on Vehicle

To construct mathematical model Newton's 2nd law of motion is used. Applying this to longitudinal dynamics of vehicle, the governing equation of system is obtained. This gives the forces acting on vehicle as shown in Figure 3.1. It is required to solve this governing force balance equation of vehicle in dynamic state. The governing equation consists of real-time input viz. Engine torque, vehicle velocity, vehicle acceleration and current vehicle gear. Additional inputs such as gear ratio of each gear, wheel and axel inertia, co-efficient of rolling resistance (C_{rr}), co-efficient of drag (C_d), vehicle frontal area (A_f), engine efficiency and transmission efficiency etc. are constants depended on vehicle type.

Before constructing the mathematical model. It is important to know about the different forces acting on the vehicle.

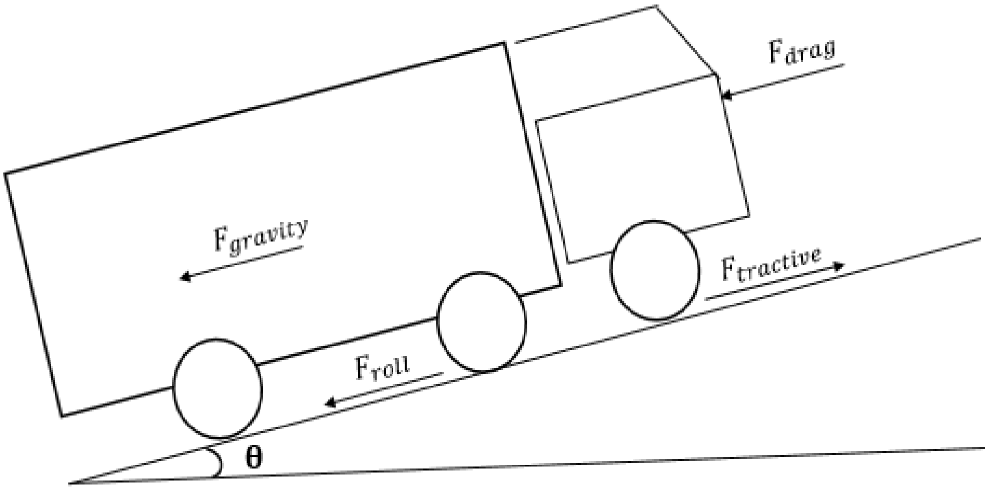


Figure 3.1 Forces on vehicle

3.1.1 Tractive Force:

Engine is the source of power in vehicle. It gives engine torque as the output. Passing it through different gear ratios along the driveline of vehicle gives torque at the wheels.

The engine torque passes though clutch assembly. From clutch, the torque is transmitted through gear box. The output of gearbox is dependent on the gear selected in current state, which may vary depending on driver selection.

This wheel torque in relation with dynamic load radius of wheel, gives the tractive force ($F_{tractive}$) at the vehicle. More detailed explanation is in a book by Gillespie [2].

- **Transmission Effect:**

The torque generated from engine (T_e) has inertial losses ($\dot{\omega}_e I_e$). Disengagement of clutch will stop any further transmission of power. Through clutch torque transmitted moves to gear box, where it is modified. The output torque of transmission is given by,

$$T_t = ((T_e - \dot{\omega}_e I_e) - \dot{\omega}_e I_t)Gr_t \tag{3.1}$$

Where,

$\dot{\omega}_e$ is rotational acceleration of engine

And

I_t is transmission rotational inertia and I_e is engine rotational inertia.

Here, the engine torque is modified by gear ratio of transmission (Gr_t) and it is reduced due inertia losses ($\dot{\omega}_e I_t$). Gear ratio (Gr_t) changes depending on driver gear selection.

- **Final Drive Effect:**

The transmission torque passes through final drive (differential) which has fixed gear ratio (Gr_f). It is used to turn the power supply by 90° to reach the wheels. Differential is also useful when vehicle is taking a turn, as the speed of inner wheel and outer wheel is different.

The output of final drive is given by,

$$T_f = (T_t - \dot{\omega}_p I_f)Gr_f \tag{3.2}$$

Where,

$\dot{\omega}_p$ is rotational acceleration of propeller shaft

And

I_f is inertia of final drive

- **Final Drive to Wheels:**

The torque at wheel is delivered by axle shafts. The torque from final drive is reduced due to inertial losses. It is given by,

$$T_w = (T_f - \dot{\omega}_w I_w) \tag{3.3}$$

Where,

$\dot{\omega}_w$ is rotational acceleration of wheel

And

I_w is Inertia of wheel and axle

Now, consider the following substitution in the above equation,

$$T_w = F_{tractive} R_w \tag{3.4}$$

$$F_{tractive} R_w = (T_f - \dot{\omega}_w I_w) \tag{3.5}$$

The angular acceleration of engine and propeller shaft can be expressed in terms of angular acceleration of wheel.

$$\dot{\omega}_p = Gr_f \dot{\omega}_w \tag{3.6}$$

$$\dot{\omega}_e = Gr_t Gr_f \dot{\omega}_w \tag{3.7}$$

Also, express angular acceleration can be expressed in terms of linear acceleration in relation with radius of wheel.

$$\dot{v} = R_w \dot{\omega}_w \tag{3.8}$$

Combining the above equations, following equation is obtained,

$$F_{tractive} = \frac{T_e Gr_f Gr_t}{R_w} - (I_e + I_t + \frac{I_f}{{Gr_f}^2} + \frac{I_w}{Gr_f Gr_t}) \frac{(Gr_f Gr_t)^2 \dot{v}}{{R_w}^2} \tag{3.9}$$

The term $\frac{Gr_f Gr_t}{R_w}$ is represented as K_0 and $(I_e + I_t + \frac{I_f}{{Gr_f}^2} + \frac{I_w}{Gr_f Gr_t}){K_0}^2$ as m_r in further discussion for simplicity. When torque is transmitted through the driveline, it undergoes some mechanical losses. To consider that loss, it is required to modify above equation considering the efficiency of torque transmission in transmission and final drive combined (η_{torque}).

$$F_{tractive} = T_e \eta_{torque} K_0 - m_r \dot{v} \quad (3.10)$$

3.1.2 Aerodynamic Drag:

Whenever an object moves with certain velocity within the atmosphere, the air resistance will act on it. Similarly, when a vehicle moves, it is acted upon by aerodynamic drag or air resistance [2]. The amount of aerodynamic drag (F_{air}) acting on the vehicle depends on the following parameters:

C_d - Co-efficient of drag
A_f - Front projected area of vehicle
v - Velocity of vehicle
ρ_{air} - Density of air

Aerodynamic drag is given by,

$$F_{air} = \frac{1}{2} \rho_{air} A_f C_d \dot{v}^2 \quad (3.11)$$

3.1.3 Rolling Resistance:

Rolling resistance occurs as soon as wheel starts moving. At lower velocity this is the dominating resistance on the vehicle. At higher velocities aerodynamic drag also plays an important role. Rolling resistance act at contact patch of tire. Even though it is present at tire contact patch, the distribution of load on axles does not have much effect on it. Instead the total vehicle weight affects the magnitude of rolling resistance [2]. This is assuming that there is no lift.

Consider a two axle vehicle with total weight W_{Total}, co-efficient of rolling resistance C_{rr}, and weight on front and rear axle W_f and W_r respectively.

Rolling resistance force at front axle wheels,

$$R_{rf} = C_{rr} W_f \quad (3.12)$$

Rolling resistance force at rear axle wheels,

$$R_{rr} = C_{rr} W_r \quad (3.13)$$

Therefore, total rolling resistance obtained is,

$$R_r = R_{rf} + R_{rr} \quad (3.14)$$

$$= C_{rr}(W_f + W_r) \tag{3.15}$$

$$R_r = C_{rr}W_{Total} \tag{3.16}$$

3.1.4 Self-weight:

The complete weight of the vehicle act downwards unless the vehicle is travelling along a grade. The downward force gets distributed in two components. One acting perpendicular to road surface (F_{normal}) and other parallel to the road surface ($F_{gravity}$). The force $F_{gravity}$ can help the vehicle motion or resist it. This will depend on whether the vehicle is travelling uphill or downhill.

$$F_{normal} = mg\cos(\theta) \tag{3.17}$$

$$F_{gravity} = mgsin(\theta) \tag{3.18}$$

Where, θ is slope of road.

3.2 Mathematical Modelling

Considering Figure 3.1, which is showing forces acting on vehicle in dynamic state at certain slope (θ) and mass (M).

From Newton's second law,

$$\sum \mathrm{F} = m\dot{v} \tag{3.19}$$

Therefore,

$$F_{tractive} - F_{drag} - F_{roll} - F_{gravity} = m\dot{v} \tag{3.20}$$

From equation (3.10), (3.11), (3.16) and (3.18), the following is obtained,

$$F_{tractive} = T_e\eta_{torque}K_0 - m_r\dot{v} \tag{3.21}$$

$$F_{drag} = \frac{1}{2}\rho_{air}C_dA_fv^2 \tag{3.22}$$

$$F_{roll} = C_{rr}mg\cos(\theta) \tag{3.23}$$

$$F_{gravity} = mgsin(\theta) \tag{3.24}$$

On substitution of equations (3.21) to (3.24) in equation (3.20), following equation is obtained,

$$m\dot{v} = T_e\eta_{torque}K_0 - m_r\dot{v} - \frac{1}{2}\rho_{air}C_dA_fv^2 - C_{rr}mg\cos(\theta) - mgsin(\theta)$$

...(3.25)

On rearranging the above equation, following equation is obtained,

$$(m + m_r)\dot{v} = T_e \eta_{torque} K_0 - \frac{1}{2}\rho_{air} C_d A_f v^2 - mg(sin(\theta) + cos(\theta)C_{rr})$$

… (3.26)

Considering above equation,

Let,

$$\alpha_1 = \frac{1}{2}\rho_{air} C_d A_f \tag{3.27}$$

$$\alpha_2 = \frac{g}{\cos(\arctan(C_{rr}))} \tag{3.28}$$

$$\xi_m = \frac{1}{m} \tag{3.29}$$

$$\xi_g = \mathrm{Sin}(\theta + \arctan(C_{rr})) \tag{3.30}$$

On rearranging, the equation obtained is as follows,

$$\dot{v} = \frac{\xi_m (T_e \eta_{torque} K_0 - \alpha_1 v^2) - \alpha_2 \xi_g}{1 + \xi_m m_r} \tag{3.31}$$

$$(m + m_r)\dot{v} = T_e \eta_{torque} K_0 - \frac{1}{2}\rho_{air} C_d A_f v^2 - mg(sin(\theta) + cos(\theta)C_{rr})$$

…(3.32)

3.3 Mathematical Model Validation

The model constructed in section 3.1 was checked and verified with the help of AVL Cruise and Simulink co-simulation (discussed in chapter 5). All the attributes of the vehicle model for 25,000Kg M&HCV vehicle were given as input to check if the value of mass obtained from equation (3.32) matches 25,000Kg.

As seen in Figure 3.2 there are many instances where model without any execution constraints is failing. It was important to find correct execution condition for the mathematical model, so that the estimation is accurate. During the simulation following conditions were discovered:-

- Stop estimation when Clutch is engaged
- Stop estimation when Brake is engaged

- Stop estimation when Torque is less than 100Nm

From simulation results it can be observed that, at certain instances the value of mass is also coming to be negative. Such unnecessary values are filtered directly using the execution conditions.

In the above mentioned testing, the road inclination was given as input, but in actual case, even the grade is an unknown parameter. This leads to the problem statement of estimation of multiple parameters for nonlinear model.

4.1 State-Space Modelling

The state-space model consist of 2 parts. First is the process equation and second is the measurement equation. To understand the concept of state-space it important to know about phenomenon of state variables. State is collection of set of system attributes that define behaviour of the system. Behaviour of any system can be known at any particular instant the state of the system at that particular instance is known. Quantities that consist of these state are known as state variables. These state variables form a hypothetical space which is known as state-space [26].

Considering the mathematical model, from equation (3.32), the differential equation is converted to difference equation, to get the following equation,

$$V_{\mathrm{i}} = V_{\mathrm{i-1}} + (t_s)\frac{\xi_{\mathrm{m}}(T_e \eta_{torque} K_0(1 + a_t) - \alpha_1 v^2) - \alpha_2 \xi_{\mathrm{g}}}{(1 + \xi_{\mathrm{m}}\, m_{\mathrm{r}})} \tag{4.1}$$

Here, the first state variable *i.e.* velocity is obtained. a_t is the noise in torque.

Also, the augmented state variables ξ_{m} and ξ_{g} is to be used in the state-space. Following format of augmented state variable has been used,

$$\mathrm{x}_i = \mathrm{x}_{i-1} + t_s f(\mathrm{x}_{i-1}, \omega_i, u_i) \tag{4.2}$$

In the model shown, the state variables ξ_{m} and ξ_{g} are augmented state variables. They are represented in first order differential.

$$\dot{\xi_{\mathrm{m}}} = 0 + a_m \tag{4.3}$$

Where,

a_m is additive white noise in state variables ξ_{m}

In the above model it is considered that mass of vehicle does not change until the vehicle has stopped. But in real cases such as buses where passengers may get in or out even though engine is still in running condition, so it is needed to recalculate the mass depending on certain conditions.

Different approaches has been suggested by Lingman *et al.* [27] and Sahlholm *et al.* [28] for modelling road dynamics. But due to complexity they have considered slope of road to be changing very slowly. In this thesis road dynamic is model based on similar approach. Where change in road slope is very slow. This means derivative of slope is almost equal to zero [3]. As per the road model selected,

$$\dot{\xi}_{\mathrm{g}} = 0 + a_g \tag{4.4}$$

Where,

a_g is additive white noise in state variables ξ_{g}

From above equation state space model has been developed with state variables as velocity, ξ_{m} and ξ_{g},

$$\begin{bmatrix} \mathrm{V_i} \\ \xi_{\mathrm{m(i)}} \\ \xi_{\mathrm{g(i)}} \end{bmatrix} = \mathbf{X_i} \tag{4.5}$$

$$\mathbf{X_i} = \begin{bmatrix} \mathrm{V_{(i-1)}} + (t_s)\dfrac{(\xi_{\mathrm{m(i-1)}}(T_e\eta_{torque}K_0(1 + a_t) - \alpha_1 {\mathrm{V_{(i-1)}}}^2) - \alpha_2\xi_{\mathrm{g(i-1)}})}{(1 + \xi_{\mathrm{m(i-1)}}m_{\mathrm{r}})} \\ \xi_{\mathrm{m(i-1)}} + t_s a_m \\ \xi_{\mathrm{g(i-1)}} + t_s a_g \end{bmatrix}$$

…(4.6)

$$\mathbf{Z_i} = [1\ 0\ 0]\ \mathbf{X_i} + \mathbf{e_k} \tag{4.7}$$

4.2 Observability Analysis

To estimate state of any system, it is important to check if it is observable or not. It is an essential characteristic of the system. It helps to know, if the output of the system can be useful to estimate any initial state of the system. In nonlinear system, the observability can be checked using the method specified by Holm [3] and Ritzen [5]. This thesis uses the same method. For more details theory from book by Kiencke and Nielsen [29] can also be referred.

Consider the following equations matrix obtained from Lie derivative method,

$$\mathbf{O} = \begin{bmatrix} \frac{\partial v}{\partial x_1} & \frac{\partial v}{\partial x_2} & \frac{\partial v}{\partial x_3} \\ \frac{\partial \dot{v}}{\partial x_1} & \frac{\partial \dot{v}}{\partial x_2} & \frac{\partial \dot{v}}{\partial x_3} \\ \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \frac{\partial f_1}{\partial x_3} \end{bmatrix} \tag{4.8}$$

Where

$$f_1 = \dot{v}\frac{\partial \dot{v}}{\partial x_1} \tag{4.9}$$

Therefore, the following matrix is obtained

$$\mathbf{O} = \begin{bmatrix} 1 & 0 & 0 \\ \frac{\partial \dot{v}}{\partial v} & \frac{\partial \dot{v}}{\partial \xi_\mathrm{m}} & \frac{\partial \dot{v}}{\partial \xi_\mathrm{g}} \\ \frac{\partial f_1}{\partial v} & \frac{\partial f_1}{\partial \xi_\mathrm{m}} & \frac{\partial f_1}{\partial \xi_g} \end{bmatrix} \tag{4.10}$$

To make sure the system is observable, it is important to have maximum rank of the above mentioned matrix. To obtain maximum rank, the determinant of above mentioned matrix should not be zero.

Considering the determinant of matrix O,

$$D = 1\left(\left(\frac{\partial \dot{v}}{\partial \xi_\mathrm{m}}\frac{\partial f_1}{\partial \xi_g}\right) - \left(\frac{\partial \dot{v}}{\partial \xi_\mathrm{g}}\frac{\partial f_1}{\partial \xi_\mathrm{m}}\right)\right) + 0 + 0 \tag{4.11}$$

$$D = \left(\left(\frac{\partial \dot{v}}{\partial \xi_\mathrm{m}}(0)\right) - \left(\frac{\partial \dot{v}}{\partial \xi_\mathrm{g}}\frac{\partial f_1}{\partial \xi_\mathrm{m}}\right)\right) \tag{4.12}$$

$$D = \left(-\left(\frac{\partial \dot{v}}{\partial \xi_\mathrm{g}}\frac{\partial f_1}{\partial \xi_\mathrm{m}}\right)\right) \tag{4.13}$$

On calculation, equation obtained is,

$$\frac{\partial \dot{v}}{\partial \xi_\mathrm{g}} = \frac{-\alpha_2}{(1 + \xi_\mathrm{m} m_\mathrm{r})} \tag{4.14}$$

$$\frac{\partial f_1}{\partial \xi_\mathrm{m}} = \frac{-2\alpha_1 \dot{v} v}{(1 + \xi_\mathrm{m} m_\mathrm{r})^2} \tag{4.15}$$

On substitution of equation (4.14) and (4.15), the following equation is obtained,

$$D = \frac{-2\alpha_1\alpha_2 v\dot{v}}{(1+\xi_{\mathrm{m}} m_{\mathrm{r}})^3} \tag{4.16}$$

The above mentioned equation will not be equal to zero if acceleration is not zero. Remaining constants and variables cannot become zero during vehicle running condition. So, the system is observable until it has constant or zero velocity.

4.3 Extended Kalman Filter Working

EKF algorithm executes in two steps. The first one is the prediction step and second one is the correction step [30].

In the first step, it calculates the covariance matrix (**P**) and state variables of state vector (**X**) using given input and estimated values from the previous iteration. In second step, the gain (**K**) of the estimator is calculated which helps to correct the state vector.

EKF conducts comparison between measured value and estimated value, and choses the best possible estimation for the desired parameter. To achieve this, it is important to tune the process noise covariance matrix (**Q**) and the measurement noise covariance matrix (**R**). Also, the Jacobian matrices need to be computed in each iteration, this increases computation time in each step in EKF algorithm. Consider the following algorithm of EKF:

Prediction Step

$$\mathbf{x}_i = f(\mathbf{x}_{i-1}, \mathbf{u}_{i-1}, \boldsymbol{a}_{i-1}) \tag{4.17}$$

$$\mathbf{P}_i = \mathbf{F}_j \mathbf{P}_{i-1} \mathbf{F}_j^{\ T} + \mathbf{W}_j \boldsymbol{Q} \mathbf{W}_j^{\ T} \tag{4.18}$$

Correction Step

$$\mathbf{K} = \frac{\mathbf{P}_i \mathbf{C}^{\mathrm{T}}}{\mathbf{C}\,\mathbf{P}_i \mathbf{C}^{\mathrm{T}} + \mathbf{R}} \tag{4.19}$$

$$\mathbf{x}_{\boldsymbol{updated}} = \mathbf{x}_i + \mathbf{K}\,(\mathbf{Y}_i - \mathbf{C}\mathbf{x}_i) \tag{4.20}$$

$$\mathbf{P}_{\boldsymbol{updated}} = (\mathbf{I} - \mathbf{KC})\,\mathbf{P}_i \tag{4.21}$$

Where

X - State vector

$\boldsymbol{a}$ - Noise in system

$\boldsymbol{P}$ - Covariance matrix
$\mathbf{F}_j$ - Jacobian matrix
$\mathbf{W}_j$ - Jacobian matrix
$\boldsymbol{Q}$ - Process noise covariance matrix
$\boldsymbol{K}$ - Gain of estimator
$\boldsymbol{C}$ - Output matrix
$\boldsymbol{R}$ - Measurement noise covariance matrix
$\mathbf{x}_{\mathbf{updated}}$ - State vector updated
$\mathbf{Y}_i$ - Sensor readings
$\mathbf{P}_{\mathbf{updated}}$ - Covariance matrix updated

- **Jacobian Matrix Calculation:**

The Jacobian matrices can be calculated as follows,

$$\mathbf{F}_j = \begin{bmatrix} \frac{\partial X_1}{\partial x_1} & \frac{\partial X_1}{\partial x_2} & \frac{\partial X_1}{\partial x_3} \\ \frac{\partial X_2}{\partial x_1} & \frac{\partial X_2}{\partial x_2} & \frac{\partial X_2}{\partial x_3} \\ \frac{\partial X_3}{\partial x_1} & \frac{\partial X_3}{\partial x_2} & \frac{\partial X_3}{\partial x_3} \end{bmatrix} \qquad \mathbf{W}_j = \begin{bmatrix} \frac{\partial X_1}{\partial a_t} & \frac{\partial X_1}{\partial a_m} & \frac{\partial X_1}{\partial a_g} \\ \frac{\partial X_2}{\partial a_t} & \frac{\partial X_2}{\partial a_m} & \frac{\partial X_2}{\partial a_g} \\ \frac{\partial X_3}{\partial a_t} & \frac{\partial X_3}{\partial a_m} & \frac{\partial X_3}{\partial a_g} \end{bmatrix} \tag{4.22}$$

Therefore, following matrix is obtained,

$$\mathbf{F}_j = \begin{bmatrix} 1 + 2t_s \frac{\alpha_1 V_i \xi_\mathrm{m}}{1 + \xi_\mathrm{m} \mathrm{m_r}} & t_s \frac{T_e K_o \eta_{tf} - \xi_\mathrm{m} {V_i}^2}{(1 + \xi_\mathrm{m} \mathrm{m_r})^2} & -t_s \frac{\xi_\mathrm{m}}{1 + \xi_\mathrm{m} \mathrm{m_r}} \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{4.23}$$

$$\mathbf{W}_j = \begin{bmatrix} t_s \frac{T_e K_o \eta_{tf} \xi_\mathrm{m}}{1 + \xi_\mathrm{m} \mathrm{m_r}} & 0 & 0 \\ 0 & t_s & 0 \\ 0 & 0 & t_s \end{bmatrix} \tag{4.24}$$

These matrices has to be calculated in each iterations. This consumes execution time which is not a problem in unscented Kalman filter (UKF).

- **Q and R Matrix:**

The process noise matrix (**Q**) and the measurement noise matrix (**R**) create a balance between measured value and estimated value. It is important to consider how they affect the estimation in relation to each other. **Q** determines how much to trust calculated values and **R** determines how much to trust values of the sensor readings. Powell [31] suggested a tuning methodology for Q and R matrix using the downhill simplex algorithm. To apply this, highly accurate true data should be available for reference. Different implementation challenges has also been discussed by Powell [31].

In this thesis different trials were taken for **Q** and **R** matrix. The effect of both on the final estimation was noted and accordingly values of both were fixed. In all the test cases discussed in chapter 7, the values of **Q** and **R** remain the same.

As the value of **R** decreases, the measurement is valued more by the algorithm and as it increases towards infinity the measured value is trusted less [30]. As per the problem statement, only velocity is the measured value. Mass and theta are not available from sensor. Therefore, **R** is a scalar. **Q** is a diagonal matrix of order 3. It represents the process noise in the model.

Consider the following representation for linear state-space model [32]:

$$\mathrm{x}_i = \boldsymbol{A}\mathrm{x}_{\boldsymbol{i-1}} + \boldsymbol{B}\boldsymbol{u}_{\boldsymbol{i-1}} + \boldsymbol{e}_{\boldsymbol{q}_{i-1}} \tag{4.25}$$

$$\boldsymbol{y}_{\boldsymbol{i-1}} = \boldsymbol{C}\mathrm{x}_{\boldsymbol{i-1}} + \boldsymbol{e}_{\boldsymbol{r}} \tag{4.26}$$

Here, e_q and e_r represent process noise and measurement noise in the system with variance **Q** and **R**, both having zero mean. **A** is state transition matrix, **B** is input matrix and **C** is output matrix. For Kalman filtering noise should be normally distributed.

$$\boldsymbol{e}_{\boldsymbol{q}} \sim (0, \mathbf{Q}) \tag{4.27}$$

$$\boldsymbol{e}_{\boldsymbol{r}} \sim (0, \mathbf{R}) \tag{4.28}$$

Similarly, for nonlinear model also, **Q** and **R** are the variance of process noise and measurement noise respectively.

4.4 Input Parameter Estimation

In this section, different parameter estimation methods have been discussed. Figure 4.1 shows the real-time inputs required for estimation algorithm. In actual vehicle the gear ratio and acceleration are not directly available. So, along with mass and grade it is important to calculate gear and acceleration using engine speed and vehicle velocity as available input.

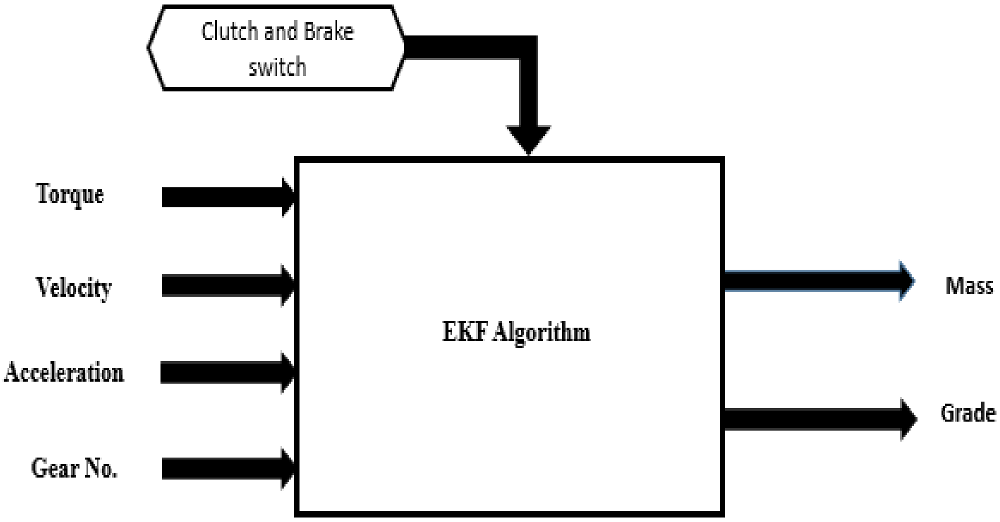


Figure 4.1 Representation of various real-time inputs and outputs of the algorithm

4.4.1 Gear Estimation

Velocity of vehicle is given by,

$$V = \frac{2\pi N_{engine} R_{DLR}}{60 G_r RAR} \tag{4.29}$$

Where

N_{engine} - Engine Speed(rpm)
V - Vehicle Velocity(m/s)
R_{DLR} - Dynamic Load Radius(m)
G_r - Gear Ratio
RAR - Rear Axle Ratio

In the above equation, only the gear ratio is unknown. Remaining inputs are available for calculation. Velocity and engine rpm are real-time inputs from ECU. The Dynamic load radius and real axle ratio remains fixed for vehicle.

4.4.2 Acceleration Estimation

Acceleration of vehicle is not directly available from ECU. But, velocity of vehicle is available which has been used to estimate actual vehicle acceleration. Different differential algorithms of estimating acceleration can be used as shown below:

$$\dot{v} = \frac{v(t) - v(t-1)}{t_s} + O(h^2) \tag{4.30}$$

$$\dot{v} = \frac{-v(t+2) + 8v(t+1) - 8v(t-1) + v(t-2))}{12t_s} + O(h^4) \tag{4.31}$$

Initially the first equation was used to calculate the acceleration because of its simple nature. It has a truncation error of order 2 [33]. Here only the velocity in the previous iteration and current iteration is required. But, this was not giving correct answers for the acceleration. Then, equation (4.31) was used which has truncation error of order 4 [33].

The acceleration obtained from this approach was matching in magnitude but was not in phase with actual acceleration. As observed from the equation (4.31), velocity at time $t + 1$ and $t + 2$ are required. This delays the acceleration input. To match the input of acceleration with other real-time inputs, it is required to delay all the remaining real-time inputs [5]

4.5 Mass and Grade Estimation

The mass of vehicle can be estimated using one of the method described by Ritzen *et al.* [5] which says that the rate of change of grade is very small. Due to which it can be assumed that grade change between 2 consecutive iterations is zero. To estimate the mass it is important to bridge the gap between filter and the mathematical model. Considering the mathematical model and rearranging the denominator following equation is obtained,

$$a_i = \frac{\xi_\mathrm{m}}{1 + \xi_\mathrm{m} m_r}(T_e \eta_{torque} K_0 - \alpha_1 v^2) + \frac{-\alpha_2 \xi_\mathrm{g}}{1 + \xi_\mathrm{m} m_r} \tag{4.32}$$

From this it can be observed that above equation is in the form of $y = mx + c$. This forms a line with slope ‘m’ and y-intercept ‘c’. From equation (4.32) following equation is obtained,

$$m = \frac{\xi_\mathrm{m}}{1 + \xi_\mathrm{m} m_r} \tag{4.33}$$

$$c = \frac{-\alpha_2 \xi_g}{1 + \xi_\mathrm{m} m_r} \tag{4.34}$$

It is important to estimate this line correctly to get the mass of the vehicle. This is difficult as the assumption of rate of change of grade may not be true on actual roads. Also the input data will have noise in it. It is important to handle such difficulties in the filtration process.

Once the mass of the vehicle is known it is possible to estimate grade. In grade estimation if noise in acceleration and torque is high then even though mass is known, accurate estimation for grade is difficult to obtain.

4.5.1 Locking of Mass Estimation

When the estimator is continuously giving different mass values as output, it cannot be used to make any decision in any of the applications. So, it is important to lock the value of mass after certain period. This is done based on following condition:

1. Minimum number of calculations has to take place before locking. This is not time dependent constraint as clutch, brake and torque conditions may not be satisfied for any period of time. So, a set number of minimum mass outputs has to be obtained before making the decision of locking the mass.

2. The standard deviation of output estimated mass has to be below a certain value. This value can be defined based on the number of output values considered for standard deviation calculation.

4.5.2 Correction in Mass Estimation after Locking

Due to constraint on convergence time, it is needed to lock the mass on its convergence for the first time. If the algorithm is allowed to run for longer period it will push the estimation in more accurate direction. But this takes very long time. To avoid this delay, after locking the mass for the first time, algorithm was allowed to calculate in the background. If the new value achieved has certain amount of difference, it will unlocks the estimator and allows it to recalculate. The recalculation happens with stronger filtering as, a close enough value of mass is already present within the algorithm. This is allowed only once from the start of the estimation. Then the value obtained is locked until vehicle velocity reaches below certain limit.

Estimation under any situation will give 80% accuracy as shown in chapter 9. But, it improves even more in certain cases due to above method applied. In some cases, the estimation is already above 90% accuracy, so if the algorithm recalculation starts and estimation accuracy decreases due to this recalculation, it will still maintain itself above 90%.

5.1 Testing Methodology

During the development of algorithm, it was important to check if the path of followed is correct. Also, to confirm the working and effect of filtration on data is correctly working or not. To achieve this, step input torque and the acceleration were supplied as input. This was checked for two different conditions of constant acceleration and variable acceleration. This helped to understand how parameters of Kalman filter were affecting the estimation. This was initial stage of project. Later the algorithm was modified based on actual data handling requirements.

After this actual data was to be tested. Actual vehicle data can be tested in following ways:

- Software in Loop
- Hardware in Loop
- On Vehicle testing

Due to availability of resources at TATA Motors Ltd., SIL (software in loop) method was adopted. Advantages of this method is that it gives the opportunity to test the algorithm on different road cycles, different range of mass, different engine type and different vehicle type. After each test and new learnings obtained, changes has to be made accordingly making the algorithm robust for different conditions. This task is very time consuming to perform on actual vehicle.

For this SIL testing, AVL cruise software has been used. AVL cruise is a simulation software for vehicle systems and driveline analysis. By providing vehicle attributes to the software the desired vehicle model in AVL cruise can be developed, on which simulations are conducted.

Initially, the data of vehicle velocity, engine speed and torque was obtained from AVL cruise and sent as an input to Simulink algorithm through data reading from Microsoft excel. Later, Simulink model was developed which was co-simulated with AVL cruise.

Co-simulation between AVL cruise and Simulink was conducted for actual vehicle data. The real-time inputs to Simulink viz. Engine torque, vehicle velocity and engine speed were obtained directly from AVL cruise during runtime. These inputs vary depending on mass of vehicle and road gradient. Simulation results are obtained for different routes, engines, vehicle type (M&HCV, ILCV) and loading conditions. Results are discussed in next chapter.

5.2 Testing on Actual Vehicle Data

To apply the algorithm in actual vehicle application it was not enough to consider only one specific route or one specific vehicle. Such testing does not show behaviour of estimator in different real life scenarios. Thus to check robustness of algorithm, testing has been conducted on different conditions.

Actual vehicle data testing has been done on different conditions as specified below:

Table 5.1 Different test conditions

Test No.	Engine	Route	Route Type	Vehicle Weight	Vehicle Type
Test 1	Cummins 5.9 L	Pune-Bangalore	Highway	18 ton, 26 ton and 32 ton	M&HCV
Test 2	TATA 5 L	Pune-Bangalore	Highway		
Test 3	Cummins 5.9 L	Wakad-Satara	City		
Test 4	TATA 5 L	Wakad-Satara	City		
Test 5	Cummins 5.9 L	Jamshedpur Track	Off Road		
Test 6	Cummins 5.9 L	Talcher Mines Track	Off Road		
Test 7	TATA 3 L	Pune-Bangalore	Highway	5 ton, 7.5 ton and 10 ton	ILCV

The range of estimation in above testing conditions for M&HCV is 12 ton to 40 ton. In ILCV the range is from 3 ton to 12 ton. If the estimation goes above or below this range then the algorithm will reflect maximum value or minimum value of range respectively.

The above mentioned tests in Table 5.1 under M&HCV section are conducted on18 ton, 26 ton and 32 ton vehicles. These values are kept same in all testing conditions as to see the effect on comparative basis, to have maximum learnings without any discrepancies in observations. The ILCV vehicle type is tested on 5 ton, 7.5 ton and 10 ton.

5.2.1 Results of Test No. 1: Cummins 5.9 L Engine - Pune Bangalore Highway

Test 1.1: Vehicle Mass - 18 ton

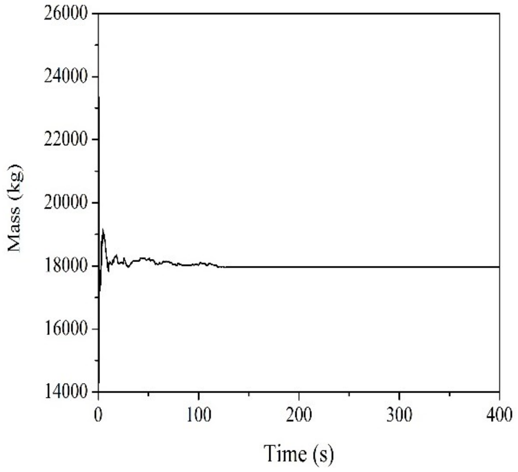


Figure 5.1 Mass estimation of Test 1.1 – 18 ton vehicle

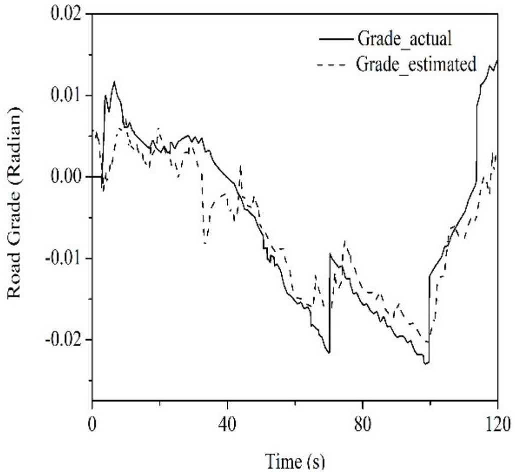


Figure 5.2 Grade estimation of Test 1.1 – 18 ton vehicle

Test 1.2: Vehicle Mass - 26 ton

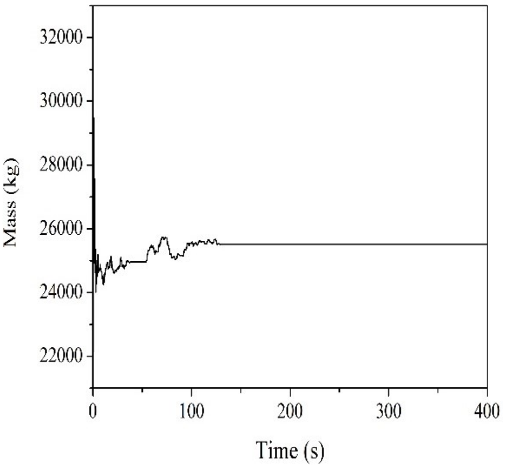


Figure 5.3 Mass estimation of Test 1.2 – 26 ton vehicle

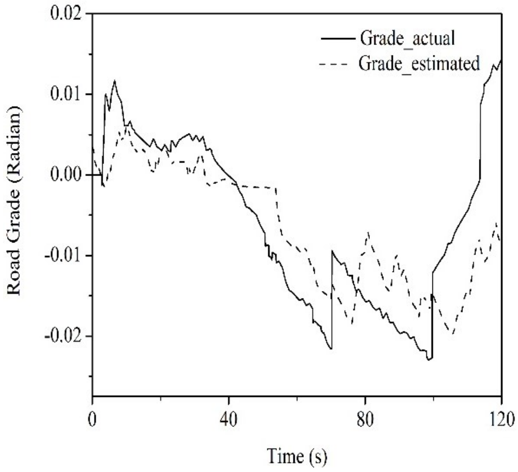


Figure 5.4 Grade estimation of Test 1.2 – 26 ton vehicle

Test 1.3: Vehicle Mass - 32 ton

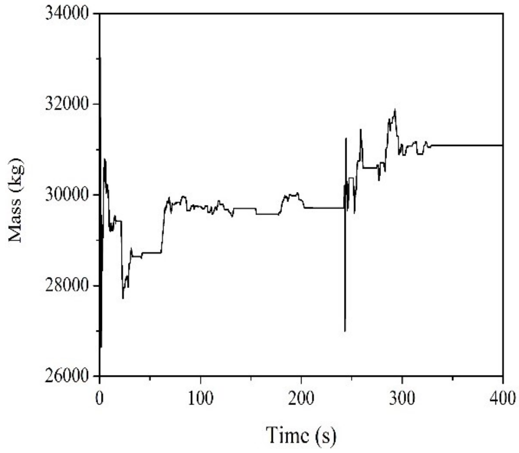


Figure 5.5 Mass estimation of Test 1.3 – 32 ton vehicle

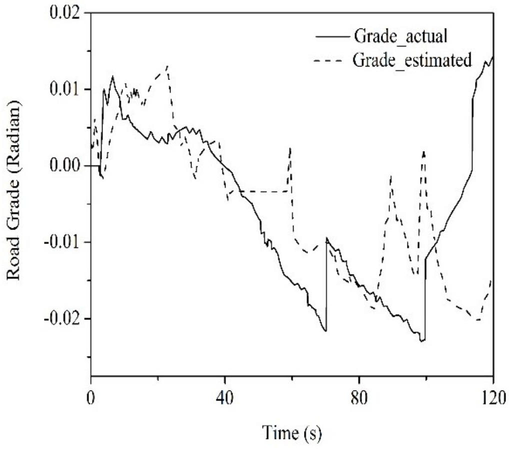


Figure 5.6 Grade estimation of Test 1.3 – 32 ton vehicle

The accuracy of the mass estimation is shown below:

Table 5.2 Results for mass estimation of Test 1

Test No.	Actual Mass	Estimated Mass	% Accuracy
Test 1.1	18 ton	17.95 ton	99.72%
Test 1.2	26 ton	25.51 ton	98.11%
Test 1.3	32 ton	31.09 ton	97.15%

5.1.2 Results of Test No. 2: TATA 5 L Engine – Pune Bangalore Highway

Test 2.1: Vehicle Mass - 18 ton

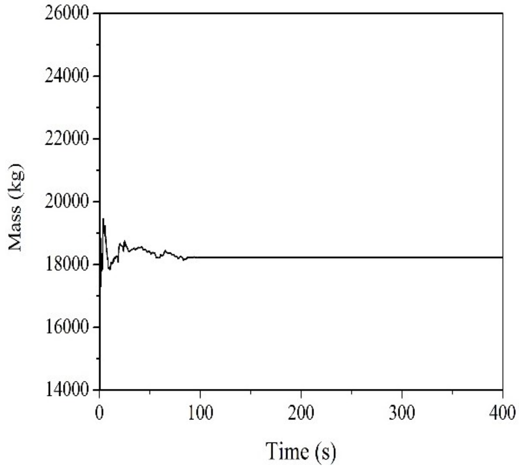


Figure 5.7 Mass estimation of Test 2.1 – 18 ton vehicle

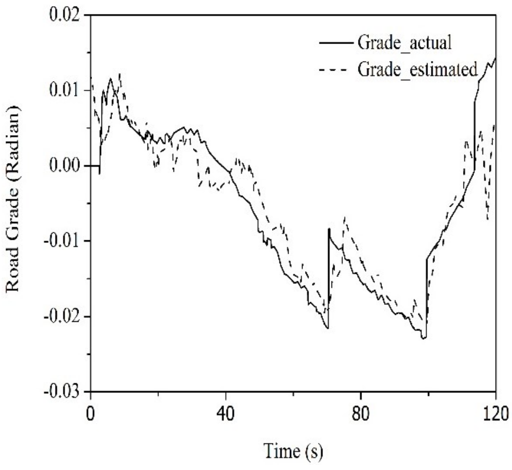
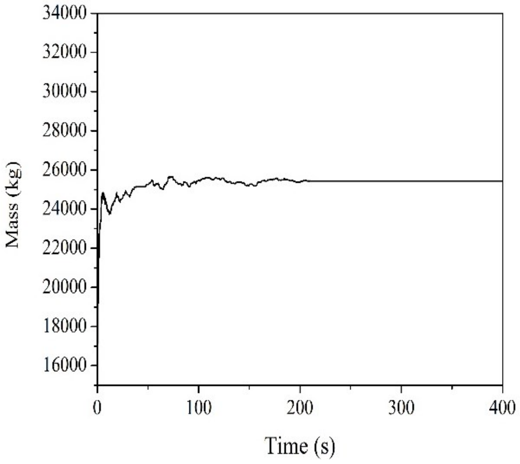


Figure 5.8 Grade estimation of Test 2.1 – 18 ton vehicle

Test 2.2: Vehicle Mass - 26ton



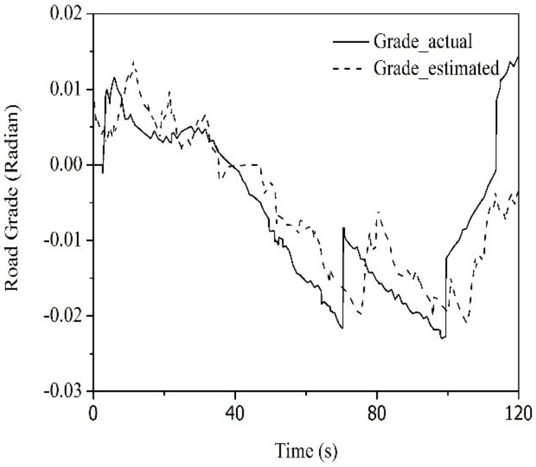
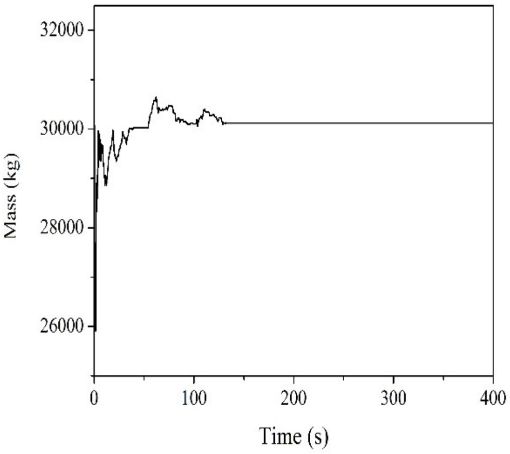


Figure 5.9 Mass estimation of Test 2.2 – 26 ton vehicle

Figure 5.10 Grade estimation of Test 2.2 – 26 ton vehicle

Test 2.3: Vehicle Mass - 32 ton



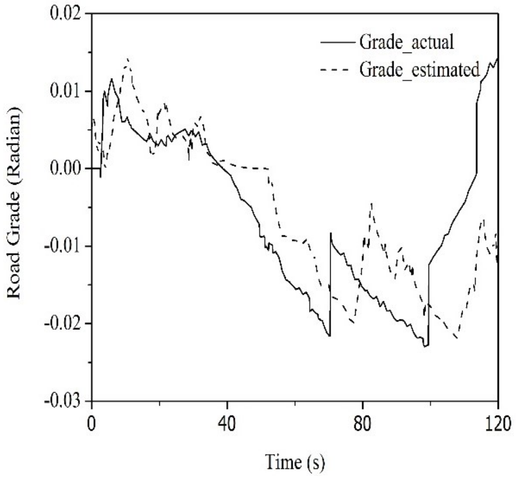


Figure 5.11 Mass estimation of Test 2.3 – 32 ton vehicle

Figure 5.12 Grade estimation of Test 2.3 – 32 ton vehicle

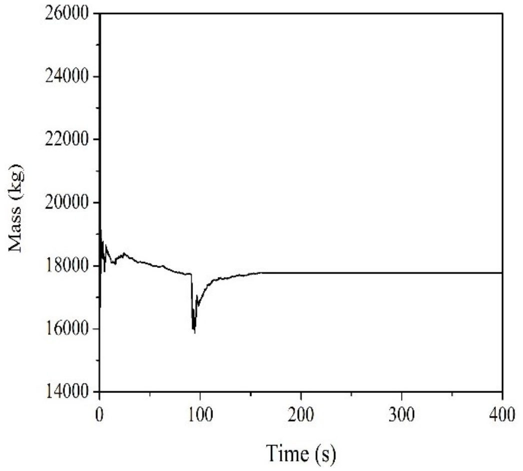
The accuracy of the mass estimation is shown below:

Table 5.3 Results for mass estimation of Test 2

Test No.	Actual Mass	Estimated Mass	% Accuracy
Test 2.1	18 ton	18.22 ton	98.77%
Test 2.2	26 ton	25.43 ton	97.80%
Test 2.3	32 ton	30.12 ton	94.12%

5.1.3 Results of Test No. 3: Cummins 5.9 L Engine – Wakad Satara - City

Test 3.1: Vehicle Mass - 18 ton



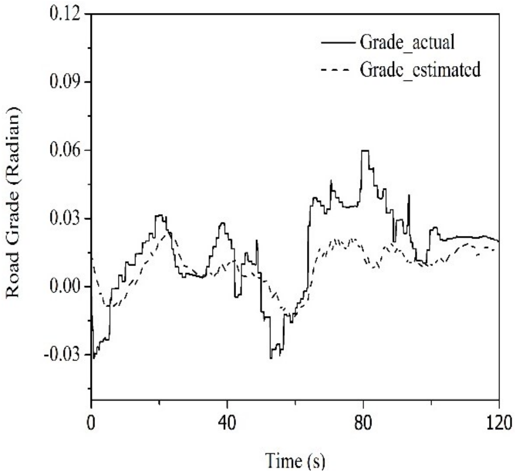
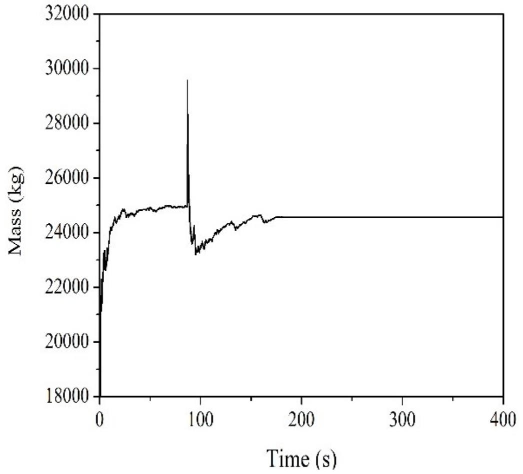


Figure 5.13 Mass estimation of Test 3.1 – 18 ton vehicle

Figure 5.14 Grade estimation of Test 3.1 – 18 ton vehicle

Test 3.2: Vehicle Mass - 26 ton



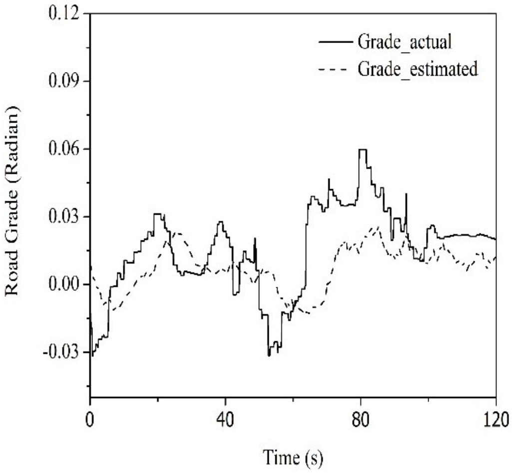


Figure 5.15 Mass estimation of Test 3.2 – 26 ton vehicle

Figure 5.16 Grade estimation of Test 3.2 – 26 ton vehicle

Test 3.3: Vehicle Mass - 32ton

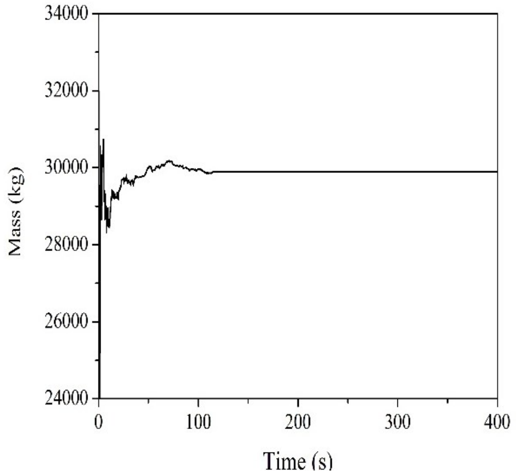


Figure 5.17 Mass estimation of Test 3.3 – 32 ton vehicle

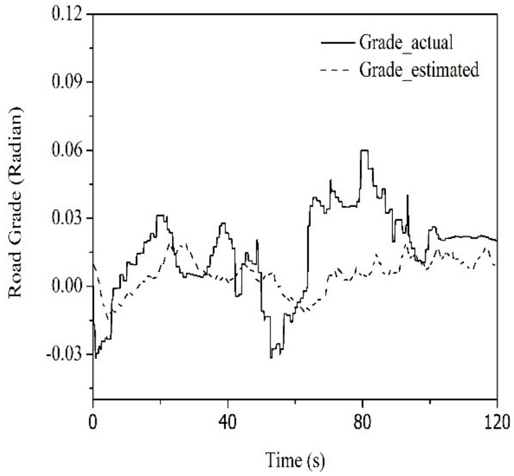


Figure 5.18 Grade estimation of Test 3.3 – 32 ton vehicle

The accuracy of the mass estimation is shown below:

Table 5.4 Results for mass estimation of Test 3

Test No.	Actual Mass	Estimated Mass	% Accuracy
Test 3.1	18 ton	17.77 ton	98.72%
Test 3.2	26 ton	24.55 ton	94.42%
Test 3.3	32 ton	29.90 ton	93.43%

5.1.4 Results of Test No. 4: TATA 5 L Engine – Wakad Satara – City

Test 4.1: Vehicle Mass - 18 ton

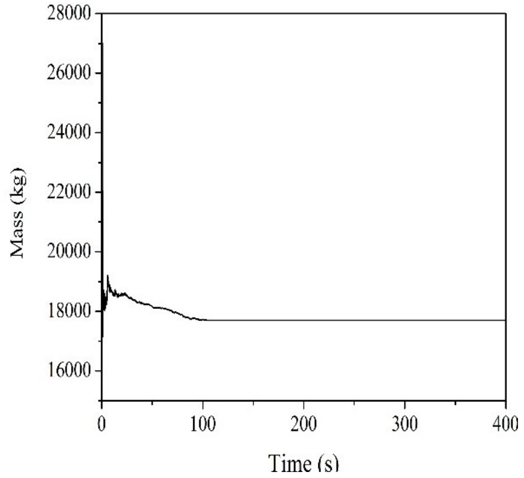


Figure 5.19 Mass estimation of Test 4.1 – 18 ton vehicle

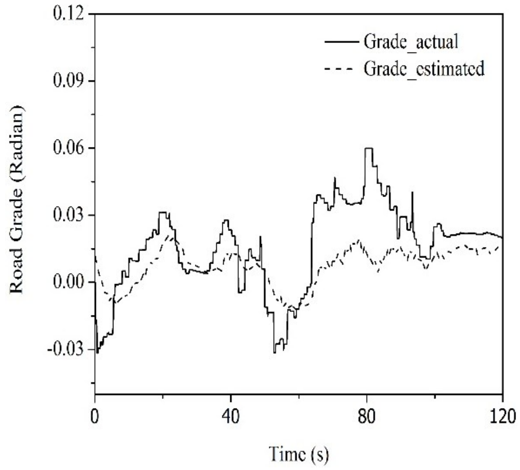
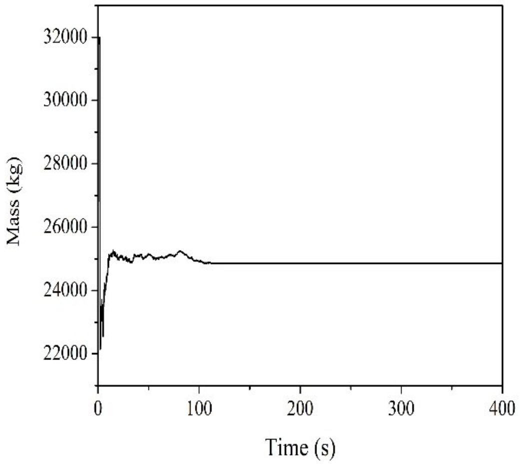


Figure 5.20 Grade estimation of Test 4.1 – 18 ton vehicle

Test 4.2: Vehicle Mass - 26 ton



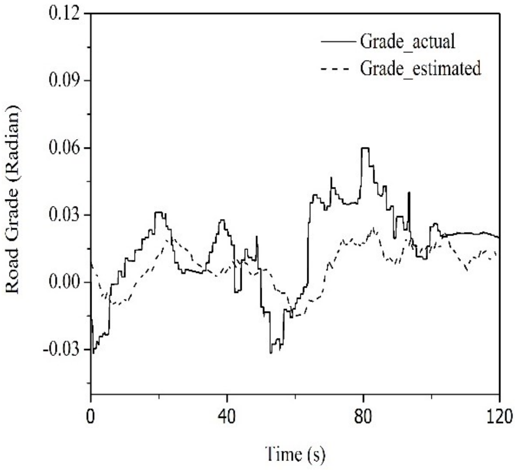
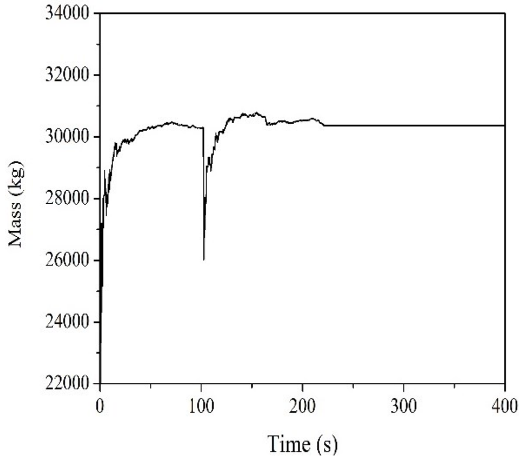


Figure 5.21 Mass estimation of Test 4.2 – 26 ton vehicle

Figure 5.22 Grade estimation of Test 4.2 – 26 ton vehicle

Test 4.3: Vehicle Mass - 32 ton



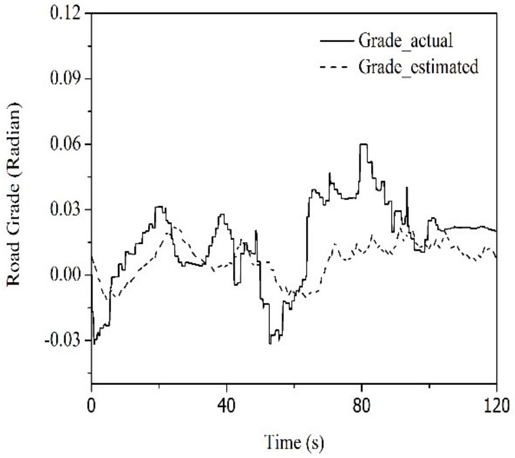


Figure 5.23 Mass estimation of Test 4.3 – 32 ton vehicle

Figure 5.24 Grade estimation of Test 4.3 – 32 ton vehicle

The accuracy of the mass estimation is shown below:

Table 5.5 Results for mass estimation of Test 4

Test No.	Actual Mass	Estimated Mass	% Accuracy
Test 4.1	18 ton	17.69 ton	98.27%
Test 4.2	26 ton	24.86 ton	95.61%
Test 4.3	32 ton	30.36 ton	94.87%

5.1.5 Results of Test No. 5: Cummins 5.9 L Engine – Jamshedpur - Off Road

Test 5.1: Vehicle Mass - 18 ton

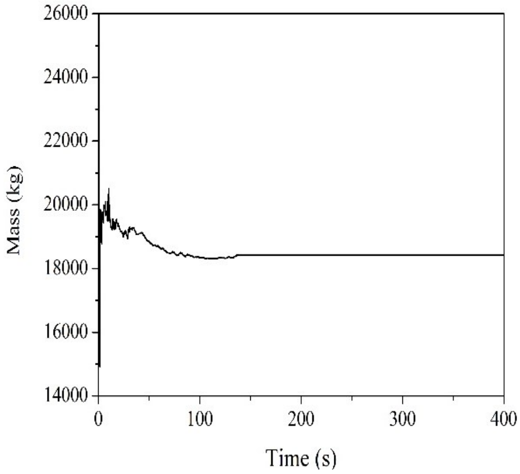


Figure 5.25 Mass estimation of Test 5.1 – 18 ton vehicle

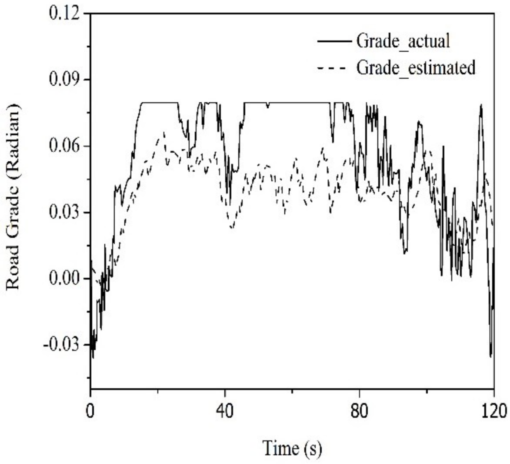


Figure 5.26 Grade estimation of Test 5.1 – 18 ton vehicle

Test 5.2: Vehicle Mass - 26 ton

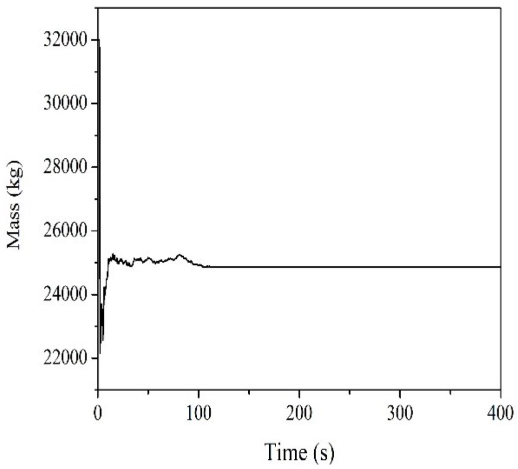


Figure 5.27 Mass estimation of Test 5.2 – 26 ton vehicle

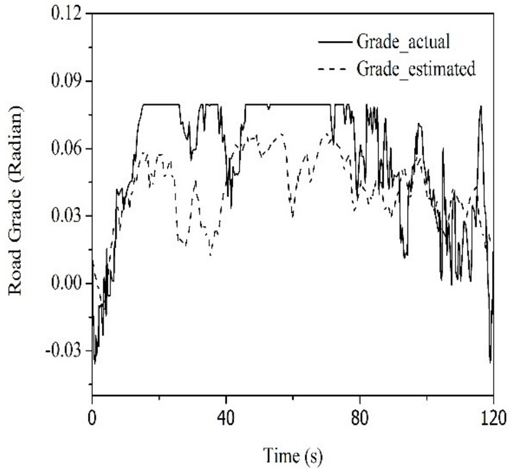


Figure 5.28 Grade estimation of Test 5.2 – 26 ton vehicle

Test 5.3: Vehicle Mass - 32 ton

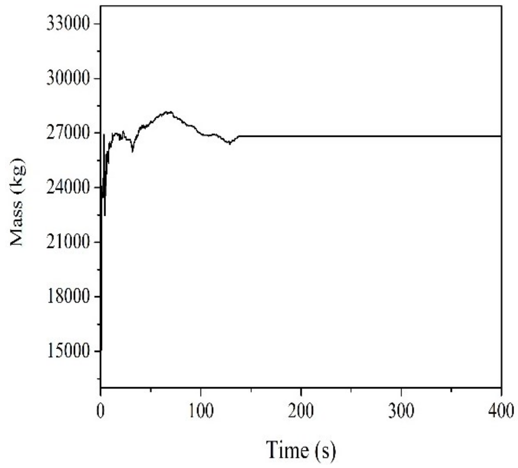


Figure 5.29 Mass estimation of Test 5.3 – 32 ton vehicle

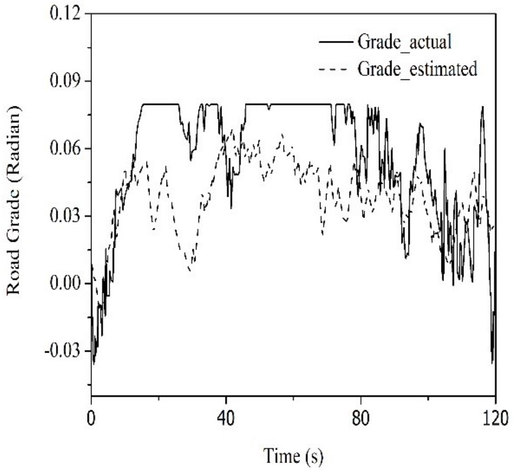


Figure 5.30 Grade estimation of Test 5.3 – 32 ton vehicle

The accuracy of the mass estimation is shown below:

Table 5.6 Results for mass estimation of Test 5

Test No.	Actual Mass	Estimated Mass	% Accuracy
Test 5.1	18 ton	18.41 ton	97.72%
Test 5.2	26 ton	23.86 ton	91.76%
Test 5.3	32 ton	26.80 ton	83.75%

5.1.6 Results of Test No. 6: Cummins 5.9 L Engine Talcher Mines - Off Road

Test 6.1: Vehicle Mass - 18 ton

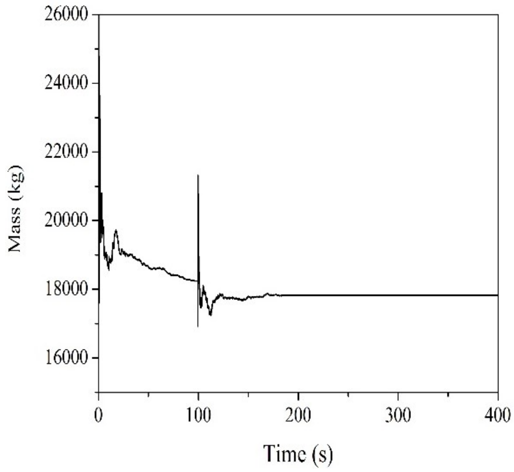


Figure 5.31 Mass estimation of Test 6.1 – 18 ton vehicle

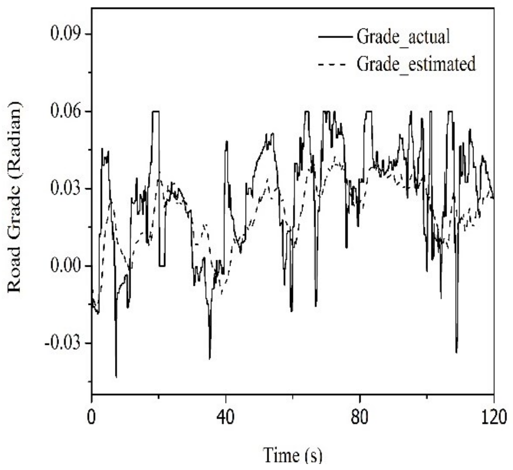


Figure 5.32 Grade estimation of Test 6.1 – 18 ton vehicle

Test 6.2: Vehicle Mass - 26 ton

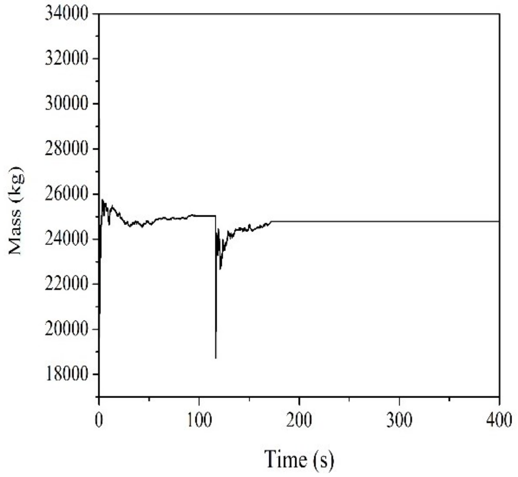


Figure 5.33 Mass estimation of Test 6.2 – 26 ton vehicle

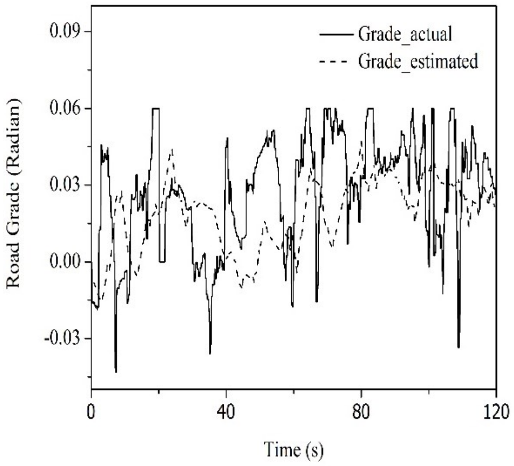


Figure 5.34 Grade estimation of Test 6.2 – 26 ton vehicle

Test 6.3: Vehicle Mass - 32 ton

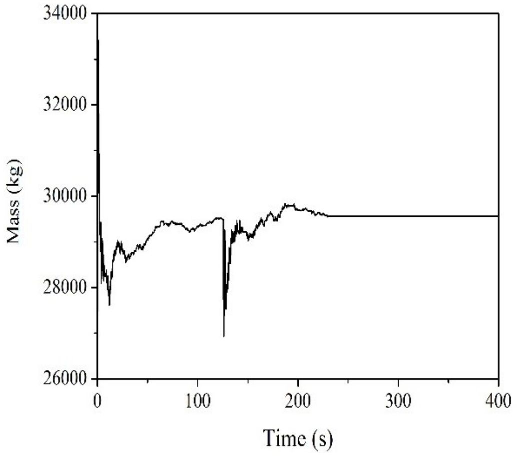


Figure 5.35 Mass estimation of Test 6.3 – 32 ton vehicle

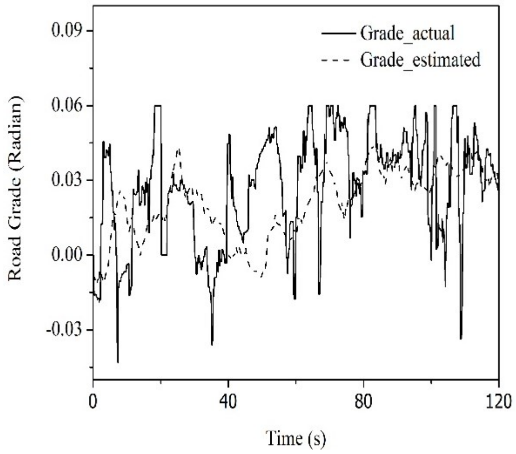


Figure 5.36 Grade estimation of Test 6.3 – 32 ton vehicle

The accuracy of the mass estimation is shown below:

Table 5.7 Results for mass estimation of Test 6

Test No.	Actual Mass	Estimated Mass	% Accuracy
Test 6.1	18 ton	17.83 ton	98.05%
Test 6.2	26 ton	24.77 ton	95.27%
Test 6.3	32 ton	29.55 ton	92.34%

5.1.7 Results of Test No. 7: TATA 3 L Engine Pune-Bangalore – Highway

Test 7.1: Vehicle Mass - 5 ton

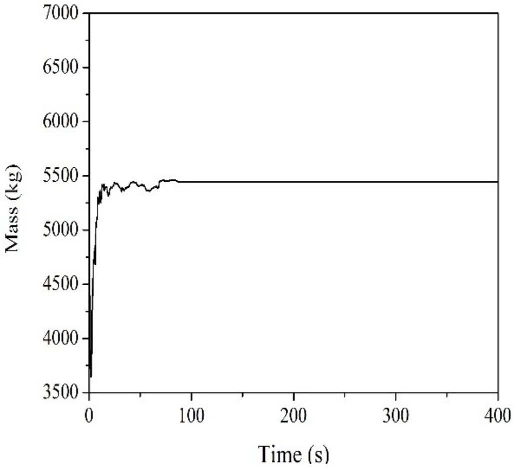


Figure 5.37 Mass estimation of Test 7.1 – 5 ton vehicle

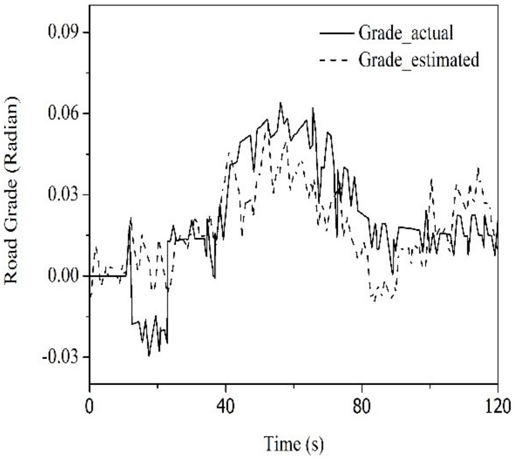


Figure 5.38 Grade estimation of Test 7.1 – 5 ton vehicle

Test 7.2: Vehicle Mass - 7.5 ton

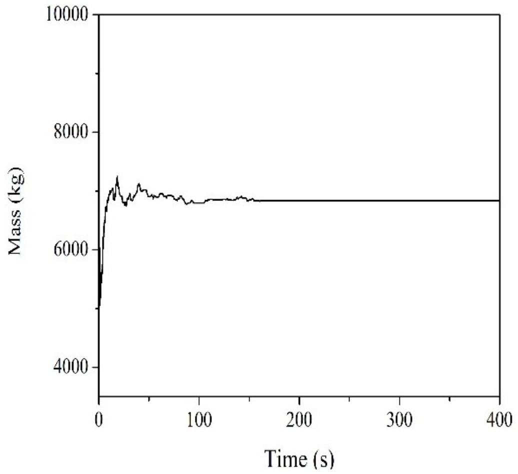


Figure 5.39 Mass estimation of Test 7.2 – 7.5 ton vehicle

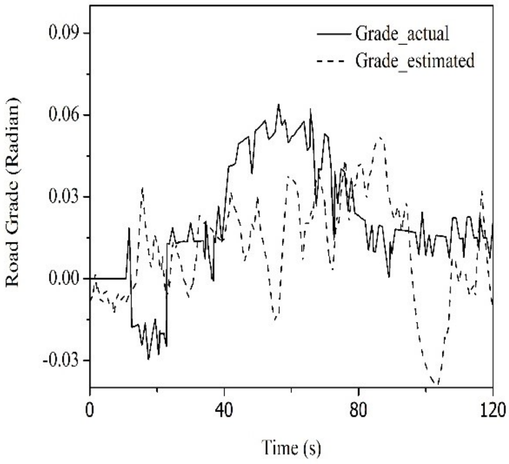
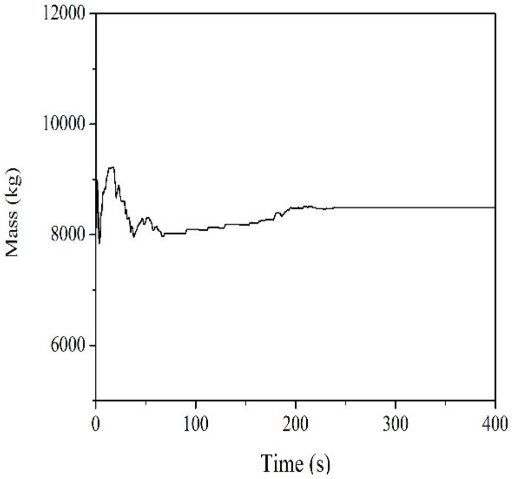


Figure 5.40 Grade estimation of Test 7.2 – 7.5 ton vehicle

Test 7.3: Vehicle Mass - 10 ton



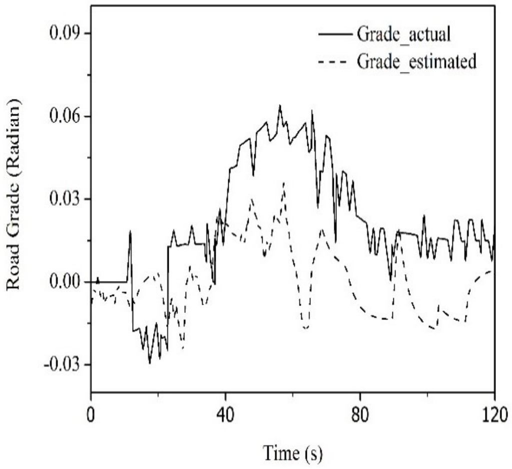


Figure 5.41 Mass estimation of Test 7.3 – 10 ton vehicle

Figure 5.42 Grade estimation of Test 7.3 – 10 ton vehicle

The accuracy of the mass estimation is shown below:

Table 5.8 Results for mass estimation of Test 7

Test No.	Actual Mass	Estimated Mass	% Accuracy
Test 7.1	5 ton	5.57 ton	88.6%
Test 7.2	7.5 ton	6.83 ton	91.06%
Test 7.3	10 ton	8.48 ton	84.80%

5.3 Sensitivity Analysis

In this section, different vehicle attributes were changed and their effect on the estimation was studied. This process was carried out mainly to know if the algorithm is robust to any changes in vehicle properties. The attributes on which this was carried out are coefficient of drag, front area of vehicle and coefficient of rolling resistance. The Figures 5.43–5.45 shows the amount of percentage error caused due to variation in, dynamic load radius, coefficient of rolling resistance and coefficient of drag respectively.

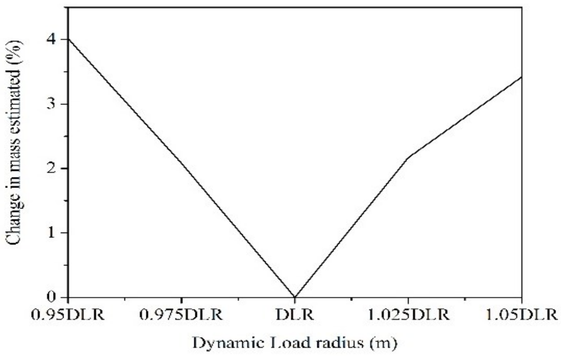


Figure 5.43 Effect of dynamic load radius

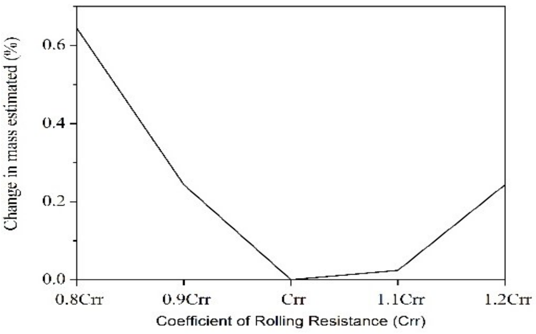


Figure 5.44 Effect of coefficient of rolling resistance

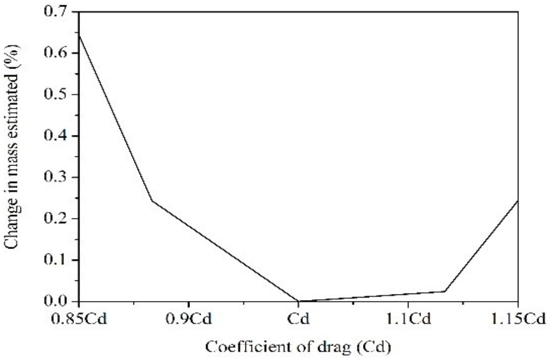


Figure 5.45 Effect of coefficient of drag

It can be noted that, effect of coefficient of drag and coefficient of rolling resistance is very less compared to dynamic load radius. Even though there is change in estimation accuracy, the algorithm is fairly robust to these changes.

5.4 Observations

1. Mass estimation accuracy is less in city roads and off road conditions compared to highways as driving input from driver changes.
2. Fluctuation of estimated mass and road grade values from the actual values is more when vehicle is heavily loaded.
3. Different types of engines results in different estimation accuracy.
4. M&HCV and ILCV are different segments of vehicles. Estimation algorithm is equally robust for both types of vehicle.
5. In certain estimation cases, the estimation is suddenly fluctuating. This is due to the correction done in estimation algorithm after mass is locked.
6. The grade estimation drops its accuracy when there is very sudden change of high magnitude in grade. It takes some time to regain the accuracy.

6.1 Conclusion

Extended Kalman Filter has been implemented successfully to simultaneously estimate mass and grade. Sensitivity analysis shows that the algorithm is very robust to variations in coefficient of rolling resistance, coefficient of drag and dynamic load radius. SIL testing with co-simulation of AVL Cruise and Simulink is giving acceptable results. Mass obtained from estimation is more than 80% accurate. Multiple conditions under which constructed mathematical model is valid has been determined. The convergence time required is more if there is requirement of higher accuracy in the estimation.

6.2 Future Work

1. Filter development for all input parameters, to obtain better results.
2. Actual vehicle testing has to be carried out.
3. Improvement in acceleration and torque signals through better modelling and filtration should be focused on.

REFERENCES

[1] Hedrick J. K. and Girard A., 2005. Control of nonlinear dynamic systems.

[2] Gillespie T. D., 1992. Fundamentals of vehicle dynamics. Vol. 400. Warrendale, Society of automotive engineers.

[3] Holm E. J., 2011. Vehicle mass and road grade estimation using Kalman filter. Linköping University.

[4] Mohan M. S., Naik N., Gemson R. M. O. and Ananthasayanam M. R., 2015. Introduction to the Kalman filter and tuning its statistics for near optimal estimates and cramer rao bound. arXiv preprint arXiv:1503.04313.

[5] Ritzén E., 1998. Adaptive vehicle weight estimation. Linköping University.

[6] Ghotikar T., 2008. Estimation of vehicle mass and road grade. Clemson University.

[7] Paulsson E. and Åsman L., 2016. Vehicle mass and road grade estimation using recursive least squares. Lund University.

[8] Kidambi N., Harne R.L., Fujii Y., Pietron G.M. and Wang K.W., 2014. Methods in vehicle mass and road grade estimation. SAE International Journal of Passenger Cars-Mechanical Systems, 7(2014-01-0111), pp.981-991.

[9] Winstead V. and Kolmanovsky I. V., 2005, August. Estimation of road grade and vehicle mass via model predictive control. In Proceedings of IEEE Conference on Control Applications. pp. 1588-1593.

[10] Grewal M.S. and Andrews A.P., 2001. Theory and practice using MATLAB. Wieley-Interscience, Canada.

[11] Åkesson B. M., Jørgensen J. B., Poulsen N. K. and Jørgensen S. B., 2007. A tool for kalman filter tuning. In Computer Aided Chemical Engineering. Elsevier Vol. 24, pp. 859-864.

[12] Ge M. and Kerrigan E.C., 2014. Noise covariance estimation for time-varying and nonlinear systems. IFAC Proceedings Volumes 47(3), pp.9545-9550.

[13] Akesson B. M., Jorgensen J. B. and Jorgensen S. B., 2007, July. A generalized autocovariance least-squares method for covariance estimation. American Control Conference IEEE pp. 3713-3714.

[14] Gunda, S.K., Kumar, T.R. and Sarma, D.S., 2012. Implementation of Kalman filtering algorithm for Harmonic Load Impedance modelling of Electrical

loads with Experimental Verification. Annual IEEE India Conference pp. 847-852.

[15] Singh R., Mehra R. and Sharma L., 2016, January. Design of Kalman filter for wireless sensor network. International Conference on Internet of Things and Applications (IOTA). IEEE. pp. 63-67.

[16] Blanchard E., Sandu A. and Sandu C., 2009. Parameter estimation for mechanical systems via an explicit representation of uncertainty. Engineering Computations, 26(5), pp.541-569.

[17] Julier S.J. and Uhlmann J.K., 1997, July. New extension of the Kalman filter to nonlinear systems. International Society for Optics and Photonics. In Signal processing, sensor fusion, and target recognition VI Vol. 3068, pp. 182-193.

[18] Wan E.A., Van Der Merwe R. and Nelson, A.T., 2000. Dual estimation and the unscented transformation. In Advances in neural information processing systems, pp. 666-672.

[19] Wan E.A. and Van Der Merwe R., 2000, October. The unscented Kalman filter for nonlinear estimation. In Proceedings of the IEEE 2000 Adaptive Systems for Signal Processing, Communications, and Control Symposium, Cat. No. 00EX373, pp. 153-158.

[20] Hasewend W., 2001. AVL Cruise—Driving performance and fuel consumption simulation. ATZ worldwide, 103(5), pp.10-13.

[21] Sangtarash F., Esfahanian V., Nehzati H., Haddadi S., Bavanpour M.A. and Haghpanah B., 2009. Effect of different regenerative braking strategies on braking performance and fuel economy in a hybrid electric bus employing CRUISE vehicle simulation. SAE International Journal of Fuels and Lubricants, 1(1), pp.828-837.

[22] Srinivasan P., 2009. Performance Fuel Economy and CO 2 Prediction of a Vehicle using AVL Cruise Simulation Techniques, No. 2009-01-1862. SAE Technical Paper.

[23] Wang B.H. and Luo Y.G., 2010. AVL cruise-based modeling and simulation of EQ6110 hybrid electric public bus. IEEE, International conference on computer application and system modeling, Vol. 7, pp. V7-252.

[24] Yang Y., Zhao H. and Jiang H., 2010. Drive train design and modeling of a parallel diesel hybrid electric bus based on AVL/Cruise. World electric vehicle journal, 4(1), pp.75-81.

[25] Sundaravadivelu K., Shantharam G., Prabaharan P. and Raghavendra N., 2014. Analysis of vehicle dynamics using co-simulation of AVL-CRUISE and CarMaker in ETAS RT environment. International conference on advances in electrical engineering, pp. 1-4.

[26] Tewari A., 2002. Modern control design. NY: John Wiley & sons, pp.283-308.

[27] Lingman P. and Schmidtbauer B., 2002. Road slope and vehicle mass estimation using Kalman filtering. Vehicle system dynamics, 37, pp.12-23.

[28] Sahlholm P., 2008. Iterative road grade estimation for heavy duty vehicle control, Doctoral dissertation, KTH.

[29] Kiencke U. and Nielsen L., 2000. Automotive control systems: for engine, driveline, and vehicle.

[30] Welch G. and Bishop G., 2006. An introduction to the Kalman filter.

[31] Powell T.D., 2002. Automated tuning of an extended Kalman filter using the downhill simplex algorithm. Journal of Guidance, Control, and Dynamics, 25(5), pp.901-908.

[32] Simon D., 2010. Kalman filtering with state constraints: a survey of linear and nonlinear algorithms. IET Control Theory & Applications, 4(8), pp.1303-1318.

[33] Rade L. and Westergren B., 1998. Mathematics Handbook for Science and Engineering. 4th edition, Springer.

Ashwin Dhawad

ORIGINALITY REPORT

5%	2%	2%	4%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Narayanan Kidambi, R. L. Harne, Yuji Fujii, Gregory M. Pietron, K. W. Wang. "Methods in Vehicle Mass and Road Grade Estimation", SAE International Journal of Passenger Cars - Mechanical Systems, 2014 Publication	1%
2	www.atelierlibros.es Internet Source	1%
3	Submitted to Middle East Technical University Student Paper	<1%
4	repository.tudelft.nl Internet Source	<1%
5	d-nb.info Internet Source	<1%
6	open.uct.ac.za Internet Source	<1%
7	Submitted to Universiti Sains Malaysia Student Paper	<1%
	Submitted to University of the West Indies	

8	Student Paper	<1%
9	Submitted to University of Newcastle upon Tyne Student Paper	<1%
10	Nabil Nassif. "The impact of air filter pressure drop on the performance of typical air-conditioning systems", Building Simulation, 2012 Publication	<1%
11	Submitted to Technische Universiteit Delft Student Paper	<1%
12	Submitted to The Scientific & Technological Research Council of Turkey (TUBITAK) Student Paper	<1%
13	Submitted to Deakin University Student Paper	<1%
14	Submitted to University of Lancaster Student Paper	<1%
15	Liu, Hongmei, Dawei Liu, Chen Lu, and Xuan Wang. "FAULT DIAGNOSIS OF HYDRAULIC SERVO SYSTEM USING THE UNSCENTED KALMAN FILTER : Fault Diagnosis of Hydraulic Servo System Using the Unscented Kalman Filter", Asian Journal of Control, 2014. Publication	<1%
16	docplayer.com.br Internet Source	

		<1%
17	Submitted to Cranfield University Student Paper	<1%
18	Submitted to Oxford Brookes University Student Paper	<1%
19	Submitted to University of Southern California Student Paper	<1%

Exclude quotes	On	Exclude matches	< 10 words
Exclude bibliography	On		