Institutionen för systemteknik
Department of Electrical Engineering

Examensarbete

Parameter Estimation for a Vehicle Longitudinal Model

Examensarbete utfört i Fordonssystem
vid Tekniska högskolan vid Linköpings universitet
av

Robin Karlsson

LiTH-ISY-EX--15/4863--SE

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Titel
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Estimering av parametrar i en longitudinell fordonsmodell
Parameter Estimation for a Vehicle Longitudinal Model

Författare
Author

Robin Karlsson

Sammanfattning
Abstract

System modelling has an important role in vehicle development cycles. Hardware field tests are often replaced by simulations, especially during the preliminary design stages. Although system modelling is a time consuming task, significant amount of the overall development time and resources can be reduced if an accurate model is available.

In order to develop a good simulation model, a sound method for parameterising the model is desired. A favourable parameter identification not only provides an accurate model, but also requires less resources both time-wise and monetarily.

In this thesis, a model for the longitudinal dynamics of a passenger vehicle is presented. Unknown parameters in the model are estimated and the model is validated with measurements obtained experimentally. It is anticipated that the model will be used in a dynamometer, where the longitudinal forces on the vehicle are simulated and the corresponding torques are exerted on the driving wheels.

Nyckelord
Keywords

Vehicle dynamics, parameter identification

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Notation

Abbreviations

Abbreviation	Description
CAN	Controller Area Network
IMU	Inertial Measurement Unit

1 Introduction

1.1 Background

In the advent of affordable and rising computing power, system modelling now plays an important role in vehicle development cycles. Hardware field tests are often replaced by simulations, especially during the preliminary design stages. While system modelling is a time consuming task, it is a common consensus that significant amount of the overall development time and resources can be reduced if an accurate model is available.

Naturally, a sound procedure for parameterising the model is of paramount importance. The procedure not only directly affects the accuracy of the resultant model, but also relates to the associated costs (time and resources) for acquiring an accurate model.

In this thesis, a model for the longitudinal dynamics of a passenger car will be constructed. Unknown parameters in the model will be estimated and the model will be validated. The model is intended to be used for simulating the behaviour of a car during different driving scenarios.

The Department of Electrical Engineering at Linköping University has a dynamometer which has been operational for two years. This equipment allows the user to measure and generate torque on the four wheels of a car individually. This allows the user to perform realistic driving tests in a controlled environment. The dynamometer has two different modes, which are the constant speed mode and the road resistance mode. For the constant speed mode, the dynomometer outputs the required torque for keeping the wheels spinning at a constant speed chosen by the user. When the road resistance mode is activated, the system generates a torque that corresponds to the speed-dependant resistance experienced by a travelling vehicle. In order to perform a realistic road resistance simulations using the dynamometer, the software controlling the dynamometer needs information about the car and a model for the resistance so it can output the right amount of torque on the wheels.

1.2 Objective

The main goal of this project is to define a set of tests for determining vehicle parameters needed to run a road resistance test in the dynamometer. The set of tests should be general enough to be applied to most passanger cars. In order to perform the parameter identification, measurements from the car will be recorded using the equipments mounted on the car as described in Section 3. Additionally, the measurements collected from the dynamometer will also be used for the parameter identification.

1.3 Thesis outline

The outline of the thesis is as follow.

Chapter 2 provides an overview of the literature related to vehicle longitudinal dynamics model and parameter identification procedures. This provides a basis for model development and parameter estimation methods used for the later chapters.

In Chapter 3, experimental setup is described. The equipment used in the thesis include a VW Golf vehicle, a dynamometer and a pedal robot.

The main result of the thesis is provided in Chapter 4, where the method for identifying the vehicle parameters is proposed.

In Chapter 5, experimental results are presented and discussed.

Finally, Chapter 6 provides some concluding remarks and suggestions for further improvements.

2

Prestudy

In this section, literature survey on a model describing the vehicular longitudinal dynamics and methods for estimating the model parameters is presented. The vehicle model and estimation methods reviewed in this section will be used as the basis for further developments in the following sections.

2.1 Model for vehicle longitudinal dynamics

A low order model capturing the longitudinal dynamics of a vehicle is presented in [7]. The same model is also adopted in the ROTOTEST dynamometer, which is the dynamometer adopted in this work. The model is based on Newton's second law, which is given by

$$ma = F_e - F_{Ro} - F_{AD} - F_C, \tag{2.1}$$

where m is the vehicle mass, a is the longitudinal acceleration, F_e is the force contribution from the engine, F_{Ro} is the rolling resistance, F_{AD} is the aerodynamic drag and F_C is the climbing resistance. The latter three terms can be represented by:

$$F_{Ro} = C_r \cdot m \cdot g \tag{2.2}$$

$$F_{AD} = 0.5 \cdot \rho_{air} \cdot C_d \cdot A(v + v_0)^2 \tag{2.3}$$

$$F_C = 0.01 \cdot m \cdot g \cdot p, \tag{2.4}$$

where C_r is the rolling resistance coefficient, C_d is the aerodynamic drag coefficient, g is the gravitational acceleration constant, ρ_{air} is the density of air, A is the frontal cross section area, v is the vehicle speed, v_0 is the wind speed and p is the upgrade incline.

Note that the rolling coefficient C_r may be dependent on vehicle mass, however a constatnt value is typically adequate to capture the general dynamics of a passenger car [7]. However for a truck the rolling coefficient is shown to be dependant on vehicle speed [18], and its value is typically higher than a passenger car. More advanced model for rolling coefficient can be found in [16]

Since (2.4) uses p instead of an angle and the calculations will be done in degrees, (2.5) will be used instead.

$$F_C = m \cdot g \cdot \sin\theta, \tag{2.5}$$

where θ is the incline angle. The following terms F_e,C_r,C_d,A and m are considered unknown. In order to determine m a scale will be used to weigh the car. To determine the frontal area A a zoomed-in picture of the car will be taken from afar. After the picture is taken, calculations will be made to determine what area a pixel in the picture represent in reality and then software that can count the pixels will be used. This should give a good estimate of the front area. If a coasting test in neutral gear on a flat surface would be done, F_C can be neglected and F_e can be replaced by the resistance from the drivetrain in neutral gear.

An alternative method to the coasting procedure would be to construct a model for F_e. Then acceleration or constant speed tests can also be conducted in order to estimate C_r and C_d if the slip is neglected. An example of a model can be found in [17] and is written as

$$F_e = \frac{\eta_t \eta_f i_t i_f}{r_w} T_{qe}, \tag{2.6}$$

where i_t and i_f are the gear ratio and the final gear ratio. $\eta_t(i_t)$ and $\eta_f(i_f)$ are the efficiencies and T_{qe} is the engine torque. The efficiency of the gear ratio varies depending on which gear is engaged. Therefore an efficiency for each gear have to be estimated. The gear ratios and the final gear ratio in this project are considered to be unknown but the product of them can be estimated by comparing the wheel speed and the engine speed from the CAN bus. Therefore the model is changed to suit this project better. The new model is presented below

$$F_e = \frac{\eta i}{r_w} T_{qe}, \tag{2.7}$$

where i, η, and T_{qe} are the total gear ratio, total gear efficiency and engine torque respectively. The parameters η and i can be estimated by using the dynamometer measurements together with the CAN measurements, since the engine torque, engine speed, wheel speed and wheel torque are measured. Since there is no sensor for the engine torque, it is only an estimation done by the cars software, therefore it has to be evaluated before it is used. Since η is considered to vary with i and the car has five gears, five different values of i and η will be estimated. This model should be enough for this project, because the only thing needed is the conversion from engine torque to wheel torque. If movement and torque losses for individual parts is of interest, better and more advanced models can be found in [2].

2.2 Parameter identification

A working procedure for estimating the parameters in a vehicle longitudinal dynamics model is described in [1] and a similar approach will be adopted in this thesis. However, innovations will be introduced when estimating the parameters and a more structural procedure will be presented in this thesis.

Many articles concerning parameter estimation for vehicle models uses a simple least squares estimation or a recursive least squares method [23],[9],[10] and [3]. The other method used in many of the articles are Kalman filters [21], [20] or [17]. The recursive least squares and Kalman filter are used for online estimations in most of the articles.

One of the problems with estimating both states and parameters with Kalman filter is that the estimations will get worse when more are made [20]. In this article a solution is made where two Kalman filters are used, one for the parameters and one for the states. When the parameters have been estimated in a satisfying way, one can simply shut down that filter in order to get a better estimation for the states. Both of the articles [20] and [21] show that Kalman filter provides good results and during different driving manoeuvres.

The articles concerning the least squares methods also obtain results that are considered to be satisfactory, for example in [9] or [23]. Some of the estimations done with the recursive least squares method can take some time to converge, see [10].

In general both methods generate good results. Kalman filter seems to converge faster if the results from the above mentioned articles are compared. On the downside, Kalman filter can be a bit tricky to tune as mentioned in [20].

A simple least squares method will be implemented for parameter estimation in the model, as described in Chapter 4. If an online estimation procedure is of interest, the method can be expanded into a recursive algorithm instead. Examples on the least squares method are given in [12], [23], [10] and [11].

3

Experimental setup

In this chapter, the equipment that were used throughout the project will be described. The most important hardware is presented in the sections below. The software used for calculations and plot making during the project were Matlab. Inkscape was used for creating and editing pictures and all the documents were written in $\LaTeX$.

3.1 VW Golf

The car used for measurements was a Volkswagen Golf 2008, as shown in Figure 3.1. It has a 1.6 litre petrol engine, developing 100 horsepower. It is equipped with a manual gearbox and has a curb weight of 1250kg. The curb weight was not used in the calculations since the car was equipped with extra measurement equipment and a driver when the data collection was done. Instead the car was weighed as mentioned in Section 2. It was borrowed from the university for the thesis work. The data was collected from three individual systems, the CAN bus, an inertial measurement unit (IMU) and the Corrsys roll and pitch measurement system. The data collected from the different systems are stamped with an ID-number and time.

3.1.1 CAN bus

Data was collected from the CAN bus and written to a text file. The data was the processed and moved into Matlab where it was used for calculations. The identification of some of the signals had already been done by the university. The identified signals were considered to be adequate for the thesis work and therefore no effort was put into identifying more signals. A complete list of the

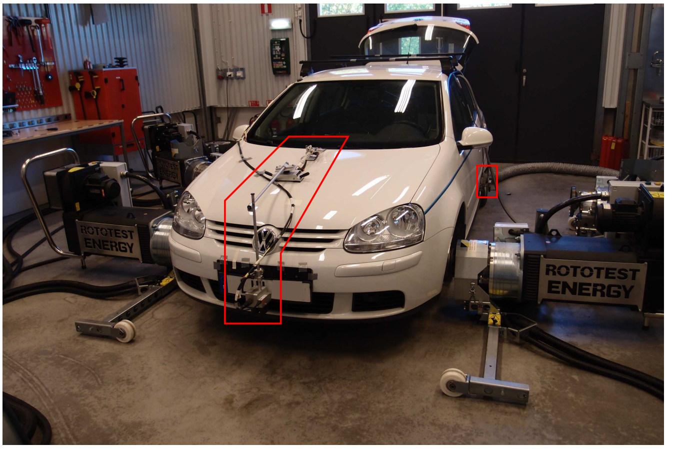

Figure 3.1: *The Golf attached to Rototest inside the vehicle lab. The Corrsys laser height sensors are marked with red.*

signals can be found in Appendix A. The CAN data was recieved with a frequency of 100Hz and 10Hz depending on the message that was being sent.

3.1.2 IMU

The IMU was placed at the center console and was held in place by duct tape. The measurement data was collected into the same text file as for the CAN data. The data was stamped with another ID so that it would be easy to tell the data apart. It was then imported into Matlab where it was used for the calculations.

The model of the IMU is MTi (Miniature Attitude and Heading Reference System) series by Xsens. The outputs given by the IMU sensor are the acceleration, magnetic field and rate of turn for 3 axes. The rate of turn values are given as $\pm 300\,\text{deg}$ with a deviation of $0.3\,\text{deg}$, the acceleration values as $\pm 17 m/s^2$ with a deviation of $0.034 m/s^2$ and the magnetic field as $\pm 750 mGauss$ with a deviation of $1.5 mGauss$. These values are converted into pitch, roll and yaw signals when the text file was imported to Matlab. The signals from the IMU was received with a frequency of 100Hz. The signals are also listed in Appendix. A picture of the IMU can be seen in Figure 3.2.

3.1.3 Corrsys

The Corrsys consists of three individual lasers with sensors. Two of them were mounted on the side of the car and the last one was mounted at the front of the car. The sensors are marked with red in Figure 3.1. The sensors mounted on the sides were HF-500C sensors from Corrsys-Datron and the one mounted at the front was a Correvit s-350 Aqua sensor, also from Corrsys-Datron. The side mounted sensors gives a height measurement with a resolution of $0.2mm$ and a deviation of $\pm 0.2\%$. The front mounted sensor also measures a height with

Figure 3.2: An IMU from Xsens.

a resolution of 2.47mm and also with a deviation of ±0.2%. The front mounted sensor is also equipped with a gyro which enables an automatic calculation of the sideslip angle. The sensors combined height measurements are feeded into an UC Processor, also of the Corrsys-Datron brand. This Processor uses the heights provided by the sensors to output pitch, roll and slip angle. All the information from the Corrsys system was written into the text file, similar to the CAN and IMU data, and then imported into Matlab. The signals provided by the Corrsys system are listed in Appendix. The signals from the corrsys system were recieved with a frequency of 250Hz.

3.1.4 GPS

The car was also equipped with a GPS which output a speed together with latitude and longitude. The frequency of the data collected from the GPS was 4Hz.

3.2 Dynamometer

The dynamometer system used in this thesis is manufactored by Rototest. The dynamometer setup consists of four individual electric motors. The motors are mounted on the driving wheels of the car. Since the car for the experiments in this project is a two wheel drive, only two of the electric motors were used. In Figure 3.1 the car was mounted to the Rototest equipment. The dynamometer can be used to perform two different tests. The first test is called the constant speed test, in which the dynamometer forces the wheels to rotate at a speed determined by the user. For instance, if the driver of the car has a gear engaged and press down the acceleration pedal, the wheel speed will start to increase. Since the constant speed mode is activated the electric motors will start to put out a braking moment in order to get the speed down to the desired level. Likewise is done for the opposite situation, if the driver is pressing down the accelerating pedal corresponding to an engine torque which will decelerate the car, the electric motors will put out an accelerating moment to keep the speed at the desired level.

The second mode is called the dynamic mode, where the motors output a moment corresponding to a model. The model used here is the longitudinal vehicle model as described in (2.1). With an altitude map, the motors will output the corresponding amount of torque. This mode is perfect for simulating a driving scenario where the road is not flat.

3.3 Pedal robot

The pedal robot is a device used for controlling the position of the acceleration pedal. It can be operated manually via a controller, or it can be fed with a signal describing the desired pedal position. By setting the dynamometer to dynamic mode and feeding a recorded pedal position to the pedal robot, a real driving scenario can be duplicated. A picture of the pedal robot mounted in the Golf can be seen in Figure 3.3.

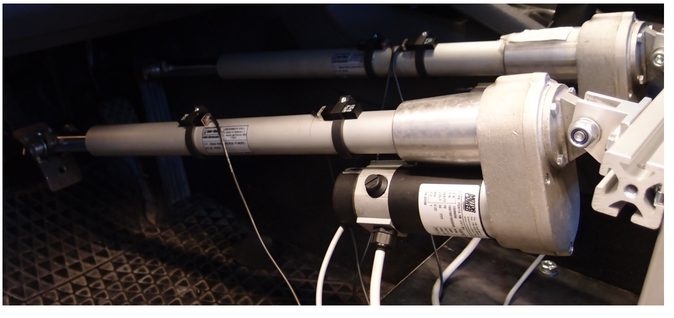

Figure 3.3: *Pedal robot mounted in car*

3.4 Complete setup

The complete setup consists of the IMU, Corrsys sensors, GPS, dynamometer and pedal robot. However when the car is mounted on the dynamometer the signals from the IMU, corrsys and GPS will not be of much interest, since the car is stationary. Nevertheless the CAN bus provides some interesting data, such as pedal position and rotation speed of the wheels. For example, tests described in 5.4, it was nessesary to run all the systems together. The signal flow between systems is depicted i Figure 3.4 and listed in Table 3.1.

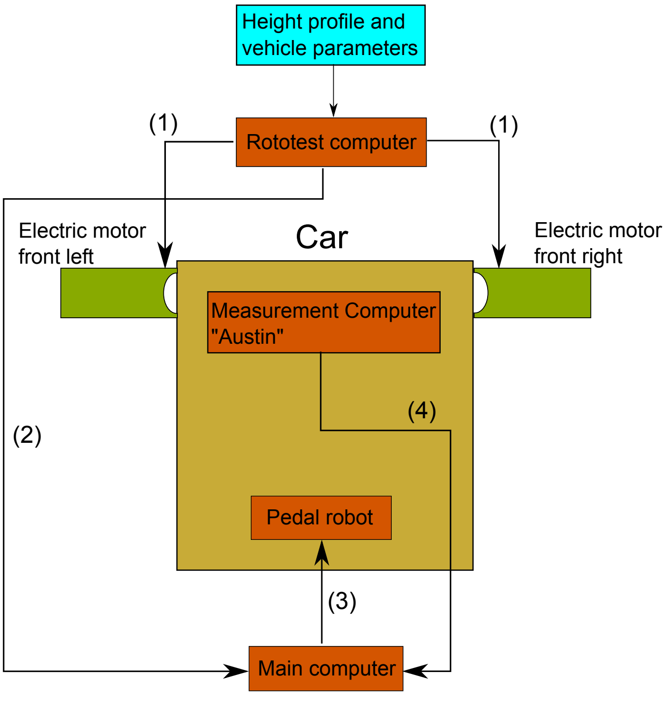

Figure 3.4: *Flow chart for the complete lab setup*

Note that the transmitted signals from the Rototest computer and the measurement computer can be saved by the main computer after the desired test has been done. However if the car is driven outside the lab, all the measurements (CAN,IMU,Corrsys,GPS) are saved on the measurement computer.

Signal number	Description
1	The Rototest computer outputs a control signal corresponding to a moment given by the model together with the height profile and vehicle parameters.
2	The Rototest computer outputs the measured wheelspeed to the main computer in real time.
3	The main computer outputs two control signals to the pedal robot, one for the accelerator pedal and one for the clutch pedal.
4	The measurement computer transmits desired signals given by the CAN bus back to the main computer.

Table 3.1: *Description of the signals in Figure 3.4*

4

Vehicle model parameter identification

As mentioned in the introduction, an accurate, simple and cost effective parameter identification procedure is desired. The parameters will then be used together with the model to simulate the behaviour the car in different driving scenarios.

In this section different procedures for estimating the parameters will be presented. First the model for vehicle longitudinal dynamics will be presented, followed by the identification of the gear ratio, road grade, rolling resistance and air drag.

4.1 Model and parameters

The model governing the longitudinal dynamics of a vehicle can be described by:

$$ma = F_e - F_{Ro} - F_{AD} - F_C \tag{4.1}$$

The forces contributing in the longitudinal direction of the car are illustrated in 4.1. F_e is the accelerating or decelerating force contribution from the car engine or brakes. Since there is a difficulty in measuring the brake force accurately, the tests were run without engaging the wheel brakes. Therefore F_e only consists of the force contributed from the engine. F_{AD} corresponds to the aerodynamic drag of the vehicle and F_{Ro} is the rolling resistance. When the car is travelling up or down a slope, the gravitational force has a component in the longitudinal direction which corresponds to:

$$F_C = mg \sin \theta, \tag{4.2}$$

Symbol	Description	Unit
C_r	Rolling resistance coefficient	-
C_d	Aerodynamic drag coefficient	-
g	Gravitational acceleration constant	$9.82 m/s^2$
ρ_{air}	Density of air	kg/m^3
A	Frontal cross section area	m^2
v	Vehicle speed	m/s
v_0	Wind speed	m/s

Table 4.1: *Table describing the parameters in the longitudinal dynamics model*

The rolling resistance and air drag can be respectively described by the following equations:

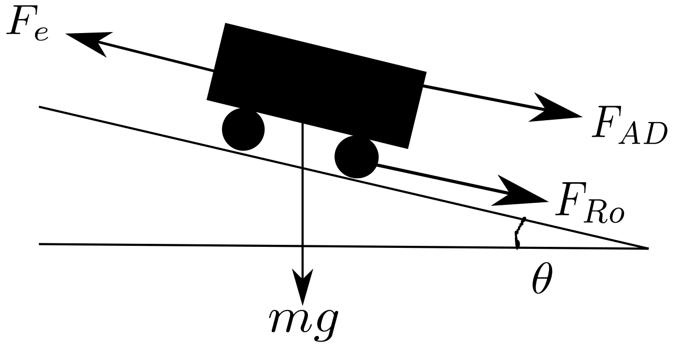

Figure 4.1: *Forces acting on a vehicle*

$$F_{Ro} = C_r \cdot m \cdot g \tag{4.3}$$

$$F_{AD} = 0.5 \cdot \rho_{air} \cdot C_d \cdot A(v + v_0)^2 \tag{4.4}$$

where the parameters are listed in Table 4.1

By neglecting the wind speed and substituting (4.2),(4.3) and (4.4) into (4.1) the following expression is obtained:

$$ma = F_e - C_r mg - 0.5 \cdot \rho_{air} \cdot C_d \cdot Av^2 - mg \sin\theta \tag{4.5}$$

Note that the mass, m, acceleration, a and velocity, v are measurable. The gravitational constant, g and air density ρ_{air} are known. The engine force F_e can be calculated from the measured engine torque. However the rolling coefficient, C_r, drag coefficient, C_d, frontal area, A and road grade, θ are unknown and therefore have to be estimated.

4.2 Test procedures for vehicle model parameter identification

As described in the objectives the main goal of this thesis is to find a set of tests needed to estimate the coefficients C_r and C_d. The tests will be done on open roads, which pose a few limitations to the tests. There are pedestrians, traffic and speed limits that must be considered when designing the test approaches. To this end, two different approaches were developed. The first method, Coasting Method, was developed to migrate the estimation difficulties of F_e. The car was driven on a high speed road and was then put in neutral gear. All pedals were released and the car was allowed to coast down to a low speed. The advantages of this method is that F_e can be estimated in the dynamometer after the coasting test. The downside with this method is that it is pretty difficult to perform this kind of test without disturbing the traffic.

To avoid causing major disturbance to the traffic, the second method (Constant Speed Method) was developed. The strategy is to drive the car at different constant speeds and estimate C_r and C_d from this data. The engine driving force can be represented by:

$$F_e = \frac{\eta_{1-5} i_{1-5}}{r_w} T_{qe} \tag{4.6}$$

where η is the current gear efficiency, i is the current gear and T_{qe} is the engine torque. The engine torque is given by the signals ENGINE_TORQUE and LOST_TORQUE, which are available from the CAN bus. These signals will be compared and validated using the dynamometer in the next section. The method for estimating the gear ratio and efficiency is also presented next.

4.3 Estimating gear ratios and efficiencies

The relation between engine speed and wheel speed can be described as

$$\omega_w = \frac{\omega_e}{i_{1-5}} \tag{4.7}$$

where ω_w is the wheel speed and ω_e is the engine speed. The dynamometer was used to drive the car at different speeds with different gears engaged. By measuring the wheel rpm with the dynamometer and the engine rpm measured by the car, it is possible to estimate the gear ratios using least square method and 4.7. The estimated gear ratios are presented in table 4.2.

Notice that these ratios are the total gear ratio, where the gearing in the rear axle is also included. Since it is not interesting for this thesis to split the ratio into

Gear	Ratio
1st	15.7035
2nd	8.8902
3rd	5.8229
4th	4.4370
5th	3.6974

Table 4.2: *Table describing the estimated gear ratios*

transmission and rear axle ratios the total ratio will be kept and used from here on.

Having found the gear ratios, the reported engine torque from the ENGINE_TORQUE CAN signal is compared with the dynamometer measurements. To this end, the wheel torque model is first investigated, given by:

$$T_w = \eta_{1-5} i_{1-5} T_{qe} \tag{4.8}$$

where T_w is the torque applied to the wheels, η is the gear efficiency, i is the current gear and T_{qe} is the engine torque minus the torque losses given by CAN. The gear ratios are now known so the only thing that needs to be estimated is the gear efficiencies η. By using the dynamometer and driving the car at constant speeds for different gears and loads, the efficiencies, η, can be estimated using least square method. However the results proved to not be good enough. The validation proved that the model with the newly calculated efficiencies was not accurate enough, especially for lower gears and high loads as shown in Figure 4.2. To mitigate the discrepancies between the estimated wheel torque $T\omega_1$ and the measured wheel torque from the dynamometer, a second wheel torque model is presented, i.e.

$$T_{w2} = \eta_{1-5} i_{1-5} T_{qe} + T_{bc_{1-5}} \tag{4.9}$$

where $T_{bc_{1-5}}$ is a bias value, dependent on the gear ratio. This method provided better results as can be seen in Figure 4.2 and therefore it was used in the estimation of the coefficients C_r and C_d. Note that this model only applies to positive driving torque, where engine brake is not used. This provides yet another restriction on the data collection. It may be possible to expand the model to include the engine brake as well, but this was not investigated here.

4.4 Estimating road slope angle

The cars longitudinal acceleration is affected by the gravitation when going up or down a slope. Therefore the angle of the slope is needed in order to estimate

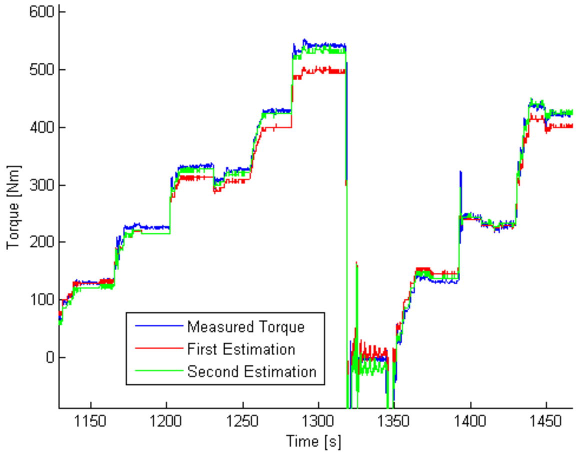

Figure 4.2: *A comparison with the two different methods to calculate the torque applied to the wheels for the different gears*

C_r and C_d. A comparison between the rolling resistance and the slope angle can be made to get an idea of the impact it has the longitudinal acceleration. As stated in [7] the value $C_r = 0.015$ is often close to the truth for regular passenger cars with radial tyres. This means that the slope angle needed for the gravitation to have the same decelerating force as the rolling resistance can be calculated as:

$$\theta = \arcsin \frac{C_r mg}{mg} = \arcsin(0.015) \approx 0.86^\circ \tag{4.10}$$

This means an angle of 1° is sufficient to affect the vehicle more than the rolling resistance. Since the effects are so big, a small error in the angle can cause a big error in the estimation of C_r and C_d.

Two different approaches were proposed for the angle estimation, a map based estimation and an estimation considering the accelerations measured by the IMU.

4.4.1 Map based method

Since the car is equipped with a GPS it was possible to log the coordinates. The coordinates were then used together with Google maps to find an altitude for all positions. The altitude was then used together with the distance to get the slope angle. This method worked very poorly and it took a lot of steps to get the altitude data. By comparing the result with rules of how Swedish roads are allowed to be constructed (according to the document 2012:179 krav for vagar och gators utformning) the measurement results sometimes gave results indicating that the road slope angle was as large as $8^\circ - 10^\circ$, which correspond to $14\% - 17,5\%$. These estimates were larger than the maximum angle allowed by the rules, which is 8%.

This could be due to the altitudes provided by Google maps were inaccurate. According to some sources (forums mostly), the altitude could be off by an order of 10-20 meters. The position of the GPS was inaccurate in some cases and contribute to the error. Therefore, a second method was designed, as described in the next section. A comparison between the methods is also provided next.

4.4.2 Accelerometer based method

As stated above a new method was needed because of the bad results from the map based method. A new method using the IMU was developed. In [14] an equation describing the slope angle is presented as below

$$\theta = \arcsin \frac{a_{sen} - a}{g}, \tag{4.11}$$

where θ is the slope angle, a_{sen} is the acceleration parallel to the road, measured by the IMU and a is the acceleration of the car. The IMU will pick up the longitudinal acceleration of the car as well as the gravitational acceleration, which makes it possible to estimate θ according to the equation. The acceleration of the car is derived from the measured speed, but the real problem is the IMU. It is not mounted so that it is parallel with the ground, which means some compensation needs to be done. The weight distribution will also affect the position of the IMU relative to the ground, which means the same compensation cannot be used when drivers are switched or the car is differently loaded between two test drives. When driving straight and accelerating, the lateral acceleration measured by the IMU, $\hat{y}$, was close to zero and when standing still on seemingly flat ground the acceleration was also close to zero. Therefore the mounting was considered to be good enough yaw and roll wise. The pitch mounting however was not done so that the IMU was parallel with the ground at standstill. The first solution tried was to put the car in the laboratory, since the ground there should be flat enough and a mean value of the $\hat{x}$ was removed from the signal as compensation. When later using the integrated speed as distance, together with the calculated slope angle there was a difference in altitude from the start point to the finishing point of an open road test. As a solution to this problem the compensation was changed so that the altitude at the start and end point of the run matched the altitude given by Google Maps in these coordinates measured by the GPS.

A comparison of the results with the IMU method and the Map based method can be seen in Figure 4.3. In this figure it is easy to see that the IMU method looks more "natural". The slope angle described by the Map method is very “bouncy” and its largest values are very high.

This method is not however flawless and a lot of errors can be introduced. For example when going around a corner the lateral acceleration is significant. Going around a corner will also make the car to move a bit roll-wise which means the gravitation will affect the measured acceleration in $\hat{y}$ as well.

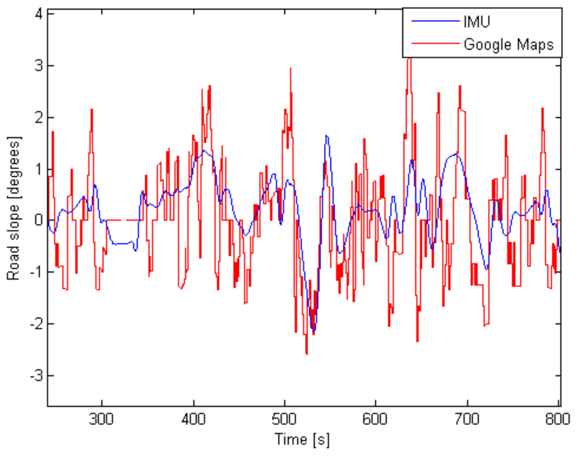

Figure 4.3: *A comparison between the two different methods of estimating the road slope angle*

4.5 Estimating frontal area using image processing method

In order to estimate the frontal cross section area a picture of the car is taken together with a smaller object which has a known height. The ratio between length and pixels is then calculated from the small object and applied to the car. In order for this to work the picture has to be taken from as far away as possible which require a camera with good zoom. The reason for the large distance is illustrated by Figure 4.6, which shows that with a shorter distance it is easier to lose some of the effective area because it is blocked by the car itself.

4.5.1 Validation of the method

In order to validate the method, a picture of a spray can and a board was taken. The spray can has a known height of 23cm and the board has a known size of $120cm \times 80cm$. The area of the board is $0.96m^2$. The validation result is shown in Figure 4.5 where the estimated area of the board is $0.9476m^2$. An estimation error of $0.0124m^2$ was obtained, corresponding to an 1.3% error. It is anticipated that the estimation error for the frontal area of a real car to be larger due to the extrusion of the car bonnet. However the estimation error of the car frontal area can be compensated by the estimated drag coefficient, as can be seen in (4.5).

4.5.2 Car frontal area

The estimation of car frontal area is shown in Figure 4.6. A fire extinguisher with a known height of $0.515m$ was used as the calibration object during the measurement. The frontal area of the car consists of both the vehicle body and the

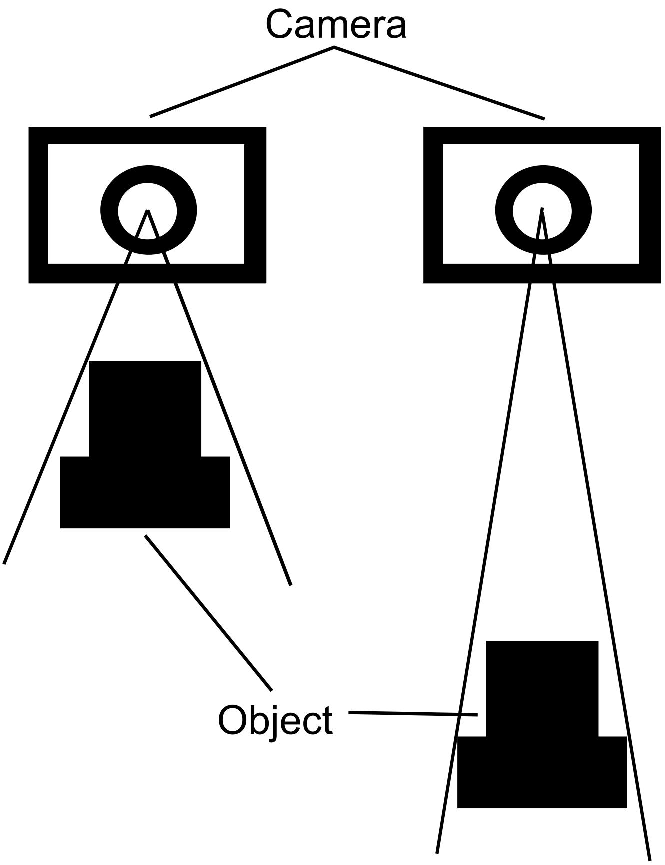

Figure 4.4: *Camera distance illustration*

mounting rack. Using the image processing method the estimated total frontal area of the car is $2.29m^2$.

4.6 Estimating rolling resistance coefficient and air drag coefficient

All the parameters needed to estimate the coefficients using the constant speed method are found. However the resistance from the drivetrain when coasting must also be found, since we are only interested in the rolling resistance and the drag. This resistance was calculated using the dynamometer. By putting the car in neutral gear and letting the dynamometer keep the car at different constant speeds the resistance was estimated to be a constant with a corresponding torque of $T_{cl} = 15Nm$. In Figure 4.7 one of these measurements can be seen. The parts marked with red squares are the parts where the car is put in neutral gear. The

Figure 4.5: *Validation picture with results*

Figure 4.6: *Car area estimation*

speed was varied between $20 - 100 km/h$.

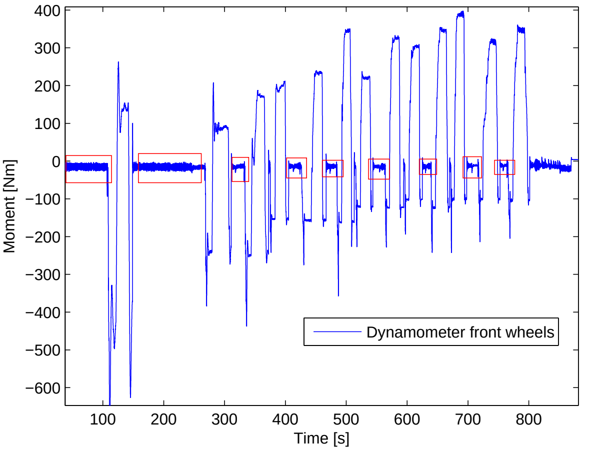

Figure 4.7: *Measurement of the driveline resistance while coasting, measured in the dynamometer*

Now all that is left is to estimate the coefficients. First the car was driven on the open road and the data was logged. After that all the parts where the coasting manoeuvre was identified by using the the signals for the pedals and also some comments were implemented in the logging file to mark when the coasting was done. These segments were merged into one which now only contains data for the coasting driving case with length n. After that Y and ϕ was created as;

$$\phi = \begin{pmatrix} -mg & -0.5A\rho v_1^2 \\ -mg & -0.5A\rho v_2^2 \\ \vdots & \vdots \\ -mg & -0.5A\rho v_n^2 \end{pmatrix}, Y_{coast} = \begin{pmatrix} a_1 m + mg\sin(\theta_1) + \frac{T_{cl}}{r_w} \\ a_2 m + mg\sin(\theta_2) + \frac{T_{cl}}{r_w} \\ \vdots \\ a_n m + mg\sin(\theta_n) + \frac{T_{cl}}{r_w} \end{pmatrix} \quad (4.12)$$

In the constant speed scenario the estimations will be done the same way except that the Y matrix is described as

$$Y_{constantspeed} = \begin{pmatrix} a_1 m + mg\sin(\theta_1) + \frac{T_{w1}}{r_w} \\ a_2 m + mg\sin(\theta_2) + \frac{T_{w2}}{r_w} \\ \vdots \\ a_n m + mg\sin(\theta_n) + \frac{T_{wn}}{r_w} \end{pmatrix} \quad (4.13)$$

where T_w is given by 4.9. When the matrices have been created the estimations of C_r and C_d is given by

$$C_{est} = R_N^{-1} F_N \tag{4.14}$$

$$R_N = \phi^T \cdot \phi \tag{4.15}$$

$$F_N = \phi^T \cdot Y \tag{4.16}$$

where $C_{est} = \begin{pmatrix} \hat{C}_r \\ \hat{C}_d \end{pmatrix}$.

The estimation results and comparison of the two test procedures will be presented in the next chapter.

5

Results and discussions

In this chapter estimations for the vehicle model parameters will be presented and the methods presented in Chapter 4 will be evaluated. To this end, the data collection procedure and typical filtering methods used in this work will first be described. Then using the coasting method and the constant speed method proposed in Section 4.2, the rolling coefficient and air drag coefficient are identified. The estimation results are validated and the difference in results obtained from these estimation methods are discussed. Furthermore, the identified model parameters are used as input to the vehicle model within the dynamometer system. The pedal robot is used to give accelerator command to the test vehicle to follow a speed trajectory.

5.1 Synchronizing the measurement signals

Once the data is collected it will need some processing before it can be used for the estimations. First of all the different measurement sources (CAN,corrsys,IMU,GPS and dynamometer) have different sampling frequencies as stated in Chapter 3. In order to use signals from two or more sources together for estimating a parameter they need to have the same timestamps. Therefore the matlab function 'spline' was applied to all the signals to create a common time vector for all the measurement signals. This function uses a cubic interpolation in order to find the value of the signal at desired timestamps. Therefore after using this function to obtain signals with an identical time vector for each of them it is possible to start comparing the signals.

When the dynamometer was used to collect data, synchronization of the collected data was needed. The data coming from the dynamometer was recorded in a different measurement file from the car and these two files contain measurements that are out of sync. In order to synchronize the data and make it useful, the measurement computers included the system time in the measurement files. After the computers were synchronized to the network time protocol, the system time was identical for both computers therefore it is possible to synchronise the data by looking at the time stamps of the two measurements.

5.2 Signal filtering

Apart from interpolation and synchronisation of the measurements, the signals provided from the sensors were noisy and therefore filtering was also required. The noise was assumed to be white and the Matlab function ’smooth’ was used. The smooth function applies a wandering mean filter to the signal. An example of the wandering mean with a window length of 3 is given by:

$$\begin{aligned} y_f(1) &= y(1) \\ y_f(2) &= (y(1) + y(2) + y(3))/3 \\ y_f(3) &= (y(2) + y(3) + y(4))/3 \\ y_f(4) &= (y(3) + y(4) + y(5))/3 \\ &\dots \end{aligned} \tag{5.1}$$

The window length of the filters varied depending on what signal that was filtered and what it was used for. If a signal is filtered with a large window, it will be much ’smoother’ than for a signal filtered with a smaller window. The trade off however is that for a larger window fast dynamics will not be detectable, but when a smaller window is used the noise will still affect the signal to create a oscillating behaviour. If for instance a velocity signal is filtered and to be derived into an acceleration signal it is better to use a larger window to get rid of the oscillating behaviour, otherwise the resulting derivation will result in an acceleration signal which will have large shifts in value because of the noise. An example of a derived velocity signal with two different windows can be seen in Figure 5.1. In this figure it is also possible to see that some fast dynamics have been lost due to the larger filter window. At the time 783 the red signal is increased dramatically whereas the blue signal is rather constant.

Apart from the wandering mean filter, low pass filters were also used. In the acceleration signal fast changes were sometimes detected when the car went over a bump. These resulted in an unwanted behaviour with high frequencies and therefore were handled by applying a low pass filter. The filters were created in Matlab and the cut-off frequency was chosen differently depending on the signals that were filtered. In Figure 5.2 a comparison between the low pass filter and the wandering mean filter is shown. In this case a cut off frequency of 5Hz was used. It can be seen here that the low pass filter better captures the fast changes at 1220-1230 s, but the signal is still too noisy to be derived into an acceleration

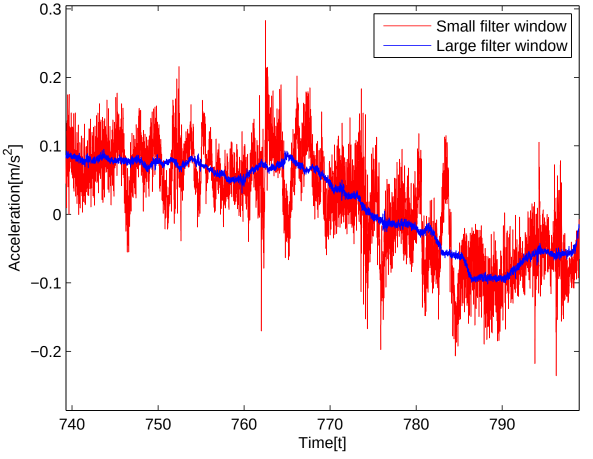

Figure 5.1: *Example of an acceleration signal derived from a velocity signal with two different filter windows*

signal.

The low pass filter was applied to the acceleration signals in order to get rid of fast disturbances from small holes and other irregularities on the road. The low pass filter was also applied to the speed measurement signals. In some cases the speed signals were derived into acceleration signals to create redundancy and to use in the IMU method, presented in Section 4.4.2. In these cases the smoothing filter was applied to create a smooth derivative.

5.3 Rolling resistance coefficient and air drag coefficient

Using the methods described in Chapter 4 the results of the estimations are given in Table 5.1. There is a significant difference in the obtained coefficients depending on the method used (coasting or constant speed). The results were validated by an independent coasting run and compared to the measured acceleration, which can be seen in Figure 5.3.

Method	C_r	C_d	MAE
Coast	0.0137	0.3387	0.0550
Constant speed	0.0077	0.4380	0.0291

Table 5.1: *Table displaying the results of the first set of estimated parameters*

As seen both in the plot and on the mean absolute error (MAE) from the table, it is obvious that the constant speed method provides smaller error. After taking

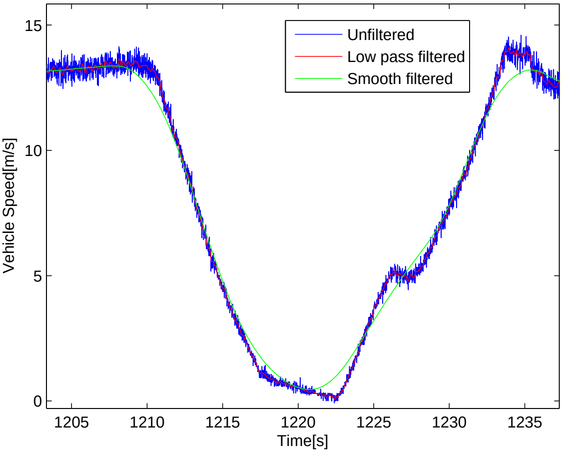

Figure 5.2: *Comparison between the two different filters*

a second look at the plot it seems that the coefficients provided by the coasting method better describes the behaviour of the the real measurement, but with a rather large bias. In order to improve the results, compensation for the initial road slope angle described in Section 4.4.2 was introduced. The road slope angle has a huge influence on the resistance and was likely to be a source of error. Therefore the method for estimating C_r and C_d was not changed but the estimation of θ was adapted. In order to get the coefficients estimated with the constant speed method to better describe the behaviour of the acceleration, the spread of speeds used was increased. A second test and estimations were done with these changes. The results from these estimations are given in Table 5.2. A similar validation was done as before with an independent coasting run. The results from this run is shown in Figure 5.4.

Method	C_r	C_d	MAE
Coast	0.0139	0.3955	0.0126
Constant speed	0.0096	0.4307	0.0327

Table 5.2: *Table displaying the results of the first set of estimated parameters*

There is a significant improvement to the result for the coefficients estimated using the coasting method, which can be seen both from the lower MAE and the plot. However the coefficients estimated with the constant speed method have an increased error compared with the first estimation set. Since both the estimation of road slope angle was changed for both coasting and constant speed method the error has to come from another source. The most likely source is the estimation of wheel torque, since this estimation uses a signal from CAN which is not measured as mentioned before. In order to improve the results from the

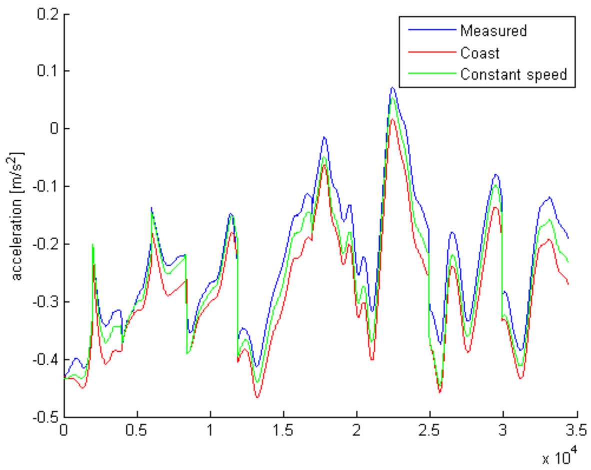

Figure 5.3: *Validation plot for the first set of estimated coefficients*

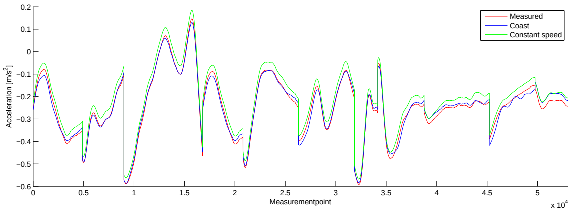

Figure 5.4: *Validation plot for the second set of estimated coefficients*

constant speed method, another method for estimating the torque is needed. It can also be noted that since the validation data was collected from a coasting run, the estimation results may be better for the coasting method compared to the constant speed method.

5.4 Dynamic dynamometer test

As mentioned in Section 1.2, the estimated coefficients will be used together with the dynamometer and the pedal robot to simulate a real driving scenario. Therefore a first test to do this was also included in the thesis, since this was the goal for the developed estimation methods. In order for this experiment to work, the setup presented in Chapter 3 was used, however the pedal position from the measurement computer was used as a feedback in controlling of the pedal robot. An error signal was created by taking the pedal position measured from an open road test and subtracting the pedal position measured in the car. This error was fed into a PID controller which controlled the pedal position. The height profile for the same open road test was loaded into the Rototest computer. The test scenario is shown in Figure 5.5. The test case starts off with small pedal movements in the beginning and larger pedal movements at the end. The test starts in a downhill position at an altitude of $100m$, but after approximately 60 seconds, the altitude is increased and reaches $105m$ at 300 seconds.

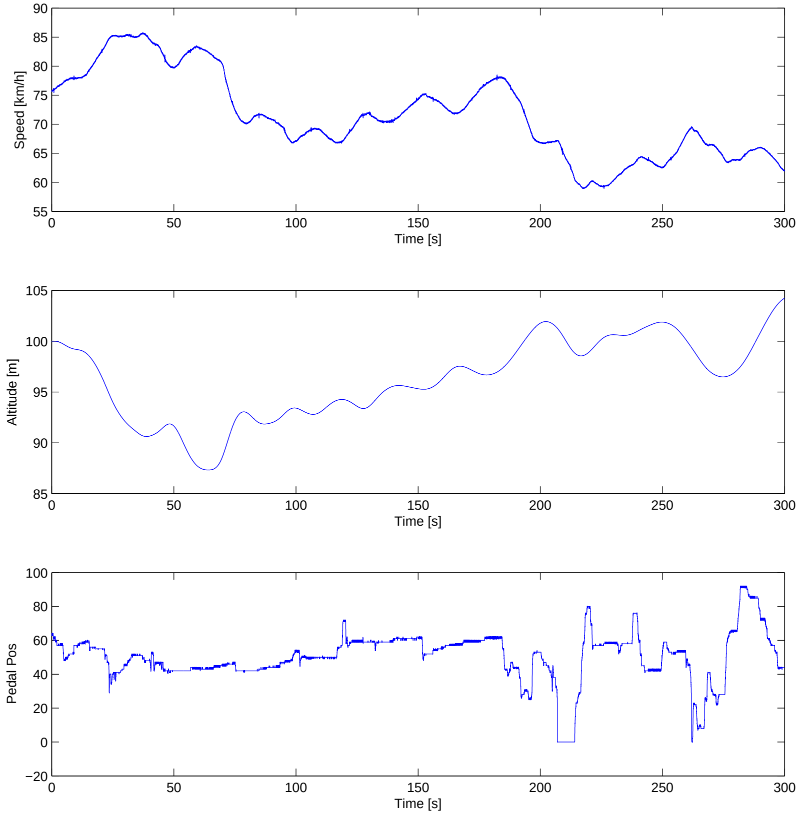

Figure 5.5: *Test case used in the dynamometer*

The goal of the test was to measure the vehicle speed in the lab, compared to the speed measured in the open road test. The results were very disappointing as can be seen in Figure 5.6. The speed started to diverge after approximately 50 seconds which made the distance between the test and the feeding signal to go off-sync. This led to a difference in altitude at different times, which made the speeds diverge even further. In the figure the open road measurement stops after approximately 300 seconds while the dynamometer goes on for another 50 seconds as a result of the difference in speeds.

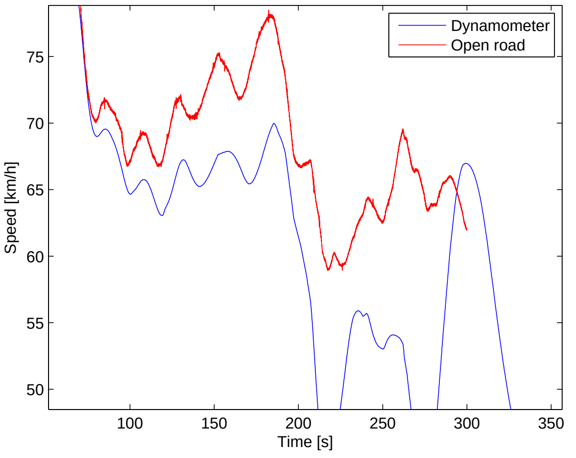

Figure 5.6: *Measured speed in the open road measurement together with the speed measured with the dynamometer.*

In order for this experiment to work the method was modified. Instead of using the pedal position as the reference signal, the speed was used instead to avoid the synchronisation problem. A feed forward link was added to the controller to improve the performance. Instead of comparing the speeds, the pedal positions were compared instead.

The results from this measurement can be seen in Figure 5.7. It can be seen here that the speeds are matched well. However the controller was aggressive and caused the pedal position to oscillate a lot at the beginning of the test where there were little dynamic in the pedal position. However at the end of the test when the pedal position is more dynamic, the pedal robot behaved in a very similar way compared with the open road measurement. There is a lot of work to be done here in order for the pedal robot to behave more like the real driving scenario. This will be discussed in the next Chapter.

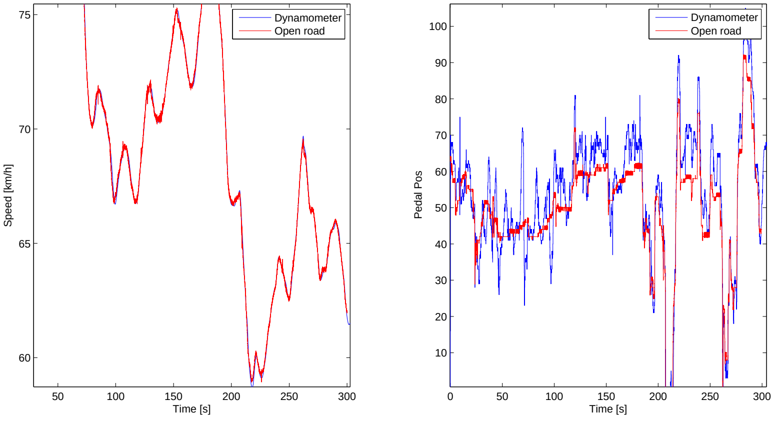

Figure 5.7: *Measured speed and pedal position in the open road measurement together with the speed and pedal position measured with the dynamometer.*

6 Conclusions

6.1 Applications

With the sensors equipped in the car and access to the vehicle CAN us it was possible to get a good estimation of the coefficients C_r and C_d using the coasting method (see Figure 5.4). The proposed method is useful for finding parameters for new cars when they are fitted to the dynamometer to run dynamic tests or to be used in a simulator. Since the method does not require many additional sensors, a test track or other expensive equipment, it is versatile for comparing the longitudinal dynamics of different vehicles. Another application for the dynamometer together with the coasting method for estimating the parameters, is to conduct vehicle testing in a controlled environment. An example is given by the development of cruise control. The only road test needed would be the coasting experiment, in order to determine the coefficients. After that, the testing can be done in the lab. There would be no need to find some good routes for trying the cruise. Instead, the route can be customised by feeding the dynamometer with the desired altitude map. This will also provide a perfect setup to try out the cruise controller with access to preview data. It may also be very easy to feed the controller with the same altitude map as the dynamometer, and then the cruise controller can be developed, tested and evaluated inside the lab. This is a hot topic among truck developers today since there is an opportunity to save fuel, which has become a very important feature in the cruise controllers for trucks.

6.2 Future work

The thesis has provided methods for parameterising a vehicle longitudinal model and the results are validated by experiments. However some further improvements on the methods may be made, which will be described in the following sections.

6.2.1 Road slope angle

An improvement to the road slope angle estimation may increase the quality of the estimation results. Obtaining a good road slope estimation was the most difficult task in this work and validating the obtained estimations was also difficult. New estimation algorithms incorporating the Corrsys measurement system may be needed in order to improve the result.

6.2.2 Constant speed method

The method was not effective and yielded poor results compared with the coasting method. However the constant speed method has some advantages over the coasting method, for example the driver is much less dependent on the rest of the traffic when collecting measurements. This method may be improved by equipping the car with a torque sensor. The torque signal used in this work was an estimation provided by the manufacturer. By equipping the car with a sensor, a better torque measurement may be obtained. If the car cannot be equipped with the sensor, then a better torque estimator may be needed.

6.2.3 Model

An extension to this work is to include the lateral dynamics. Since one of the future goals desired by the university is to use the model and dynamometer together with a simulator, the lateral dynamics will be needed for simulating both longitudinal and lateral movement.

6.2.4 Pedal robot

As seen in the results, the pedal robot behaved similar to the open road test when there was a lot of dynamic. However, when the reference pedal position was close to constant the controller was very aggressive which led to an oscillating signal. A development area would be to tune the controller so that consistent performance can be obtained over the whole operating range of the pedal.

Appendix

A

Appendix A

A.1 Measurement Signals

All the signals available in the measurements are listed here. In Table A.1 the car signals are listed. In Table A.2 the dynamometer signals are listed.

Signal	Source
BRAKE	CAN
CLUTCH	CAN
ENGINE_RPM	CAN
ENGINE_TORQUE	CAN
LOST_TORQUE	CAN
STATIC_ROT_SPEED	CAN
STEERING_WHEEL_ANGLE	CAN
THROTTLE_PEDAL_ANGLE	CAN
WHEEL_ANGULAR_VELOCITY_FL	CAN
WHEEL_ANGULAR_VELOCITY_FR	CAN
WHEEL_ANGULAR_VELOCITY_RL	CAN
WHEEL_ANGULAR_VELOCITY_RR	CAN
h1	corrsys
h2	corrsys
h3	corrsys
hc1	corrsys
hc2	corrsys
hc3	corrsys
pitch	corrsys
pitchrate	corrsys
roll	corrsys
roll2	corrsys
roll2rate	corrsys
rollrate	corrsys
slipangle	corrsys
vabs	corrsys
vlat	corrsys
vlon	corrsys
COG	gps
Lat	gps
Lon	gps
UTCTime	gps
vgps	gps
accX	imu
accY	imu
accZ	imu
gyrX	imu
gyrY	imu
gyrZ	imu
magX	imu
magY	imu
magZ	imu
pitch	imu
roll	imu
yaw	imu

Table A.1: *Table describing the measurement signals provided by the car*

Signal
Wheelspeed_FL
Wheelspeed_FR
Wheelspeed_RL
Wheelspeed_RR
Torque_FL
Torque_FR
Torque_RL
Torque_RR
Temp_FL
Temp_FR
Temp_RL
Temp_RR

Table A.2: *Table describing the measurement signals provided by the dynamometer*

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