Estimation of Fuel Consumption for Real Time Implementation

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Degree project in
Automatic Control
Master's thesis
Stockholm, Sweden 2012

XR-EE-RT 2012:008
Abstract

With an unstable oil market and increasing prices, the focus has never been higher on reducing the fuel consumption costs. Using a navigation system that presents the fastest route, can today help a driver to reduce the fuel consumption by reducing the risk of not finding the target. A further development of such system is eco-routing: route optimization with regard to fuel consumption. Eco-routing is today being introduced to the market by several passenger car manufacturers.

An essential part of an eco-routing system is estimation of fuel consumption. The requirements of a fuel consumption model for trucks is studied in this thesis. Two estimation methods were evaluated and compared, one of the methods was estimating fuel consumption using look up tables consisting fuel consumption data. The other method was estimation doing real time calculations with a fuel consumption model. With a simplified real time model the modelling error was approximately lower than 5% for rural and highway driving, however for city driving the accuracy was significantly reduced. Eco-routing simulations for a truck showed a mean saving of 8.5% for a set of long haulage routes.
Acknowledgements

This work has been carried out at the Pre-development of Intelligent Transport Systems Department (REPI) at Scania CV AB in Södertälje, Sweden.

I have many persons to thank for the outcome of this master thesis. I would like to start with expressing my gratitude to my supervisor at Scania, Anders Johansson, for giving me the opportunity to do this master thesis. I would also like to acknowledge Rickard Lyberger at Scania for all the help with the measurements, a part of this work that has been essential in order to do validation tests. Frank Mohr and Mikael Curbo at Scania are acknowledged for all help in understanding and being able to use the simulation programs, Scop and Stars. Thanks also to Andreas Stenberg at Scania and my friend William Zhang for helping me with various programming challenges. Everyone at REPI and REPA at Scania are thanked for making my time at Scania enjoyable. For the simulation results and for many worthwhile discussions I would like to thank Christian Appelt and especially Patrick Bartsch at Volkswagen.

Last but definitely not least I would like to thank my supervisor at KTH, Christian Larsson and my examiner Håkan Hjalmarsson.

Daniel Macias
Stockholm, 2012
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Estimates by the European Environment Agency (EEA) show that greenhouse gas emissions keep increasing each year [12]. A possible effect of this is an increase of the overall average temperature of the earth, which could lead to drastic climate changes [25]. The fuel consumption of a truck is directly connected to greenhouse gas emissions and is also a significant cost for haulage companies. Even though there is a strong growth in the usage of renewable energy, fossil fuels are still the major energy source in the transport sector with a share of around 95% [13]. Trucks keep improving each year in reducing the fuel consumption by developing the engines and reducing weight, just to mention some of the areas. An average long haulage truck has for example reduced its fuel consumption with approximately 30% the last 20 years [4]. Although the requirements for vehicle emissions in Europe get stricter each year there are still improvements to be made in reducing fuel consumption by changing the way a truck is being driven [31].

To minimize the fuel consumption is today one of the most central challenges for the truck manufacturer Scania in order to be able to reduce the negative impact on the environment but also to improve operating economy. By using supporting systems such as look ahead cruise control and in the near future, possibly platooning, the fuel consumption could be reduced with more than 10% [16, 18]. Another possible way to reduce the fuel consumption is to optimize the choice of route with regard to fuel consumption, so called eco-routing.

Eco-routing is today being introduced by several passenger car manufacturers where some already have launched this supporting system. Increased availability of information on topography, real time traffic and road signs makes it possible for better prediction of the fuel consumption for a certain route. Availability of good predictions of fuel consumption makes it possible to see which route, among several, would consume less fuel. Even though eco-routing, intuitively, would make a difference in a city environment due to having more route options, studies show that when travelling on long distances the highway is not always the most fuel efficient route [3]. Therefore eco-routing could be a valuable system for both distribution
trucks and long haulage trucks.

1.1 Aim of the Thesis

To be able to do a route optimization, a cost to be optimized must be defined. The cost in an eco-routing optimization is the fuel consumed. This thesis focuses mainly on how to estimate the fuel consumption for trucks with sufficient accuracy for a route optimization system to give correct recommendation on which route is most fuel efficient. There are several methods to estimate the fuel consumption along a road, two possible methods will be investigated in this work. As a part of this work, a review of existing estimation methods of fuel consumption at Scania will be made.

Fuel consumption can be estimated using a look up table with information about the fuel consumption when driving at a constant velocity, accelerating and breaking at different road slopes. An advantage with look up tables is computational efficiency in real time. Tables of this kind will be created with existing modelling programs and validation tests will be done for these tables.

Another way to estimate the fuel consumption is to use a real time model with input parameters such as speed, acceleration and road slope. This method should have a higher accuracy than look up table estimation but a the cost of increased runtime. An investigation of which model would be suitable for this purpose will be conducted. Validation tests will be done for this model.

One of the main objectives for this thesis is to investigate how the accuracy problem should be tackled in order for a route optimization system not to give wrong recommendation about the most fuel efficient route.

Summary

Research questions to be answered by this thesis are:

- What accuracy is needed for a route optimization system to be able to give a correct recommendation on which route is the most fuel efficient?

- Investigate the possibilities of using look up table estimates and make validations test for this method. Is the accuracy satisfying?

- Investigate the possibilities of estimating fuel consumption in a route optimization system with the existing modelling programs at Scania. Can these programs be used in a route optimization system?

- Investigate the possibility of real time estimation with a simplified fuel consumption model and make validation tests. Is the accuracy satisfying?

- Can savings be done for trucks with eco-routing?
1.2 Structure of the Thesis

The next chapter describes the background for this work, which includes state of the art of modelling fuel consumption and a description of how widespread eco-routing is today. Route optimization is also described in the next chapter, where possible algorithms for this purpose are described and compared, a description of how networks needed for an optimizations are created, is also made.

Chapter 3 gives a presentation of existing fuel consumption models at Scania and compares these to each other with respect to accuracy and complexity. Chapter 4 describes how the fuel consumption can be estimated with two different methods, using look up tables and a real time model. This chapter also discusses how a driver uniquely influences the fuel consumption and how this is being taken into account with the two fuel estimation methods. A validation is made and results are presented in Chapter 6. In Chapter 7 and 8 conclusion are drawn and suggestions for future research are made.
Background

2.1 State of the Art

Research has been made concerning eco-routing and some companies have released such systems to the market. An essential part of an eco-routing system is to be able to estimate fuel consumption. Various parameters have a direct or indirect impact on the fuel consumption, therefore it is known that estimating fuel consumption is a difficult challenge that can be approached in many ways and consequently with varying accuracy. Fuel consumption models that are publicly available will be presented and compared in next section. In the sections that follows after that, Patrick Bartsch PhD-thesis [5] and other studies regarding eco-routing will be brought up.

2.1.1 Fuel Consumption Models

There are different methods to estimate fuel consumption along a road. However, the most common input variables to the models are the vehicles tractive power and speed [29].

A fuel consumption model for diesel vehicles based on road load and power train parameters is presented in [15]. The model consists of four major components: engine friction and efficiency, engine maximum torque map, vehicle transmission and vehicle road load parameters. Taking those parameters taken into account the fuel consumption is estimated according to,

\[ F = \frac{1}{H_d} \left( \frac{f_{mep}N V_d}{\eta_i 2000} + \frac{P}{\eta_i} \right), \]  

where \( F \) is the consumption rate (g/s), \( N \) is the engine speed (rps), \( V_d \) is the engine displacement (dm³), \( H_d \) is the energy density of diesel (kJ/kg), \( \eta_i \) is the indicated engine efficiency, \( f_{mep} \) is the friction mean effective pressure (kPa) and \( P \) is the sum of the vehicle tractive power and accessory power (kW). The sum of the required
instantaneous power demand \( P \) can be estimated according to,

\[
P = \frac{P_{\text{trac}}}{\eta_t} + P_{\text{acc}},
\]

where \( P_{\text{trac}} \) is the sum of the tractive power (kW), \( \eta_t \) is the total transmission efficiency, \( P_{\text{acc}} \) is the accessory power (kW), \( m \) is the vehicles mass (kg), \( g \) is the gravity acceleration (m/s\(^2\)), \( v \) is the speed of the vehicle (m/s), \( C_r \) is the rolling loss coefficient, \( A \) is the frontal area of the vehicle (m\(^2\)), \( C_d \) is the air drag coefficient, \( \rho \) is the air density (kg/m\(^3\)), \( m_j \) is the equivalent mass of the inertia of the moving parts (kg), \( a \) is the vehicle acceleration (m/s\(^2\)) and \( \theta \) is the road slope (rad).

A theoretical model for calculation of the fuel consumption rate has been developed in [26]. This model has been compared with results of an empirical model that has been derived through experiments. The purpose for this model was to evaluate the amount of exhaust emissions. The theoretical model is described by the following equations,

\[
F_w = (m + m_j)a + \frac{1}{2}c_dApv^2 + mgc_r \cos \theta + mg \sin \theta,
\]

\[
ft = ft_{\text{idle}} + \frac{\delta}{\eta \varepsilon H_g} (mg(c_r \cos \theta + \sin \theta) + (m + m_j)av + \frac{1}{2}c_dApv^3)
\]

where \( F_w \) is the total resistance (N), \( m \) is the mass (kg), \( m_j \) is the equivalent mass of the inertia of the moving parts in the power train (kg), \( a \) is the vehicle acceleration (m/s\(^2\)) , \( c_d \) is the air drag coefficient, \( v \) is the vehicle speed (m/s), \( c_r \) is the rolling resistance, \( \rho \) is the air density (kg/m\(^3\)), \( g \) is the gravity acceleration (m/s\(^2\)), \( \theta \) is the road slope, \( \varepsilon \) is the brake thermal efficiency of the engine, \( \eta_t \) is the total transmission efficiency, \( H_g \) is the heat equivalence of gasoline (J/cm\(^3\)), \( ft_{\text{idle}} \) is the idling consumption rate (cm\(^3\)/s) and \( ft \) is the instantaneous fuel consumption rate (cm\(^3\)/s). Equation (2.5) shows that this model assumes that the vehicle does not consume any fuel when \( F_w \) along the direction of movement is less than or equal to zero.

A model based on instantaneous power demand was developed from chassis dynamometer experiments [28]. This model is described by,

\[
F(t) = \begin{cases} 
\alpha_1 + \beta_1 P(t) & P(t) > 0 \\
\alpha_1 & P(t) \leq 0 
\end{cases}
\]
where $F(t)$ is the instantaneous fuel consumption rate ($\text{dm}^3/\text{s}$), $\alpha_1$ is the vehicle idling fuel consumption rate ($\text{dm}^3/\text{s}$), $\beta_1$ is the vehicle fuel consumption rate ($\text{dm}^3/\text{s}/\text{kW}$) and $P(t)$ is the instantaneous tractive power (kW). The vehicle parameters $\alpha_1$ and $\beta_1$ were found to vary with time as the vehicles condition and state of tune altered. A disadvantage with this model is the inability to describe the fuel consumption during stop and start maneuvers [28].

A model developed based upon the model presented in Equation (2.6) is the Australian Road Research Board fuel consumption model,

$$F(t) = \alpha_2 + \beta_{a} P_{a}(t) + \beta_{b} P_{c}(t),$$

(2.7)

where $F(t)$ is the instantaneous fuel consumption rate ($\text{dm}^3/\text{s}$), $\alpha_2$ is the vehicle idling fuel consumption rate ($\text{dm}^3/\text{s}$), $P_{a}(t)$ is the total engine and inertia drag power (kW), $\beta_a$ and $\beta_b$ are vehicle specific power parameters ($\text{dm}^3/\text{s}/\text{kW}$).

A model developed by researchers from Linköpings University estimates real time fuel consumption rates using control signals, such as a pedal, brake and gear signals, and engine speed [29]. The model is presented in the following equation,

$$F(t) = \begin{cases} \frac{N}{60000n_r}\omega_e(t)f_p(t)(a_\delta\omega_e^2 + b_\delta\omega_e + c_\delta) & G \neq 0, \\ F_{idle} & G = 0, \end{cases}$$

(2.8)

where $F(t)$ is the instantaneous fuel consumption rate ($\text{dm}^3/\text{s}$), $N$ is the number of engine cylinders, $n_r$ is the number of crankshaft revolutions per stroke, $\omega_e(t)$ is the engine speed at time $t$, $f_p(t)$ is the pedal control input [0,1] at time $t$, $G$ is the gear signal, $F_{idle}$ is the idling fuel consumption rate ($\text{dm}^3/\text{s}$) and $a_\delta$, $b_\delta$ and $c_\delta$ are experimentally derived constants.

Two models that can be calibrated using publicly available information of the fuel consumption and engine are the Comprehensive Power-based Fuel Consumption Models [29], CPFM-1,

$$F(t) = \alpha_0 + \alpha_1 P(t) + \alpha_2 P(t)^2,$$

(2.9)

and CPFM-2,

$$F(t) = \beta_0 + \beta_1 P(t) + \beta_2 P(t)^2,$$

(2.10)

where $P(t)$ is the instantaneous power demand (kW), $\alpha_0$, $\alpha_1$, $\alpha_2$, $\beta_0$, $\beta_1$ and $\beta_2$ are vehicle specific constants [29] The difference between the models is the calibration of the constant $\beta_0$ for CPFM-2, which is dependent of the engine speed, while the rest of the constants are calibrated using information from EPA and highway driving cycles. More detailed information on how these constants are derived can be found in [29].

The power demand $P(t)$ at time $t$ for both models is described by,

$$P(t) = \frac{R(t) + 1.04ma(t)}{3600\eta_d}v(t),$$

(2.11)
where \( m \) is the mass of the vehicle (kg), \( v(t) \) is the speed at time \( t \) (m/s), \( a(t) \) is the acceleration at time \( t \) (m/s\(^2\)) and \( \eta_d \) is the engine efficiency. \( R(t) \) describes the resistance force (N), on the vehicle at time \( t \),

\[
R(t) = \frac{\rho}{25.92} c_d C_H(t) A_f v^2(t) + 9.8066 m C_r [c_1 v(t) + c_2] + 9.8066 m G(t),
\]  

(2.12)

where \( c_d \) is the air drag coefficient, \( C_H(t) \) is a correction factor for altitude, \( A_f \) is the vehicles frontal area (m\(^3\)) and \( G(t) \) is the gravitation force as a function of time (N). \( C_r, c_1(t) \) and \( c_1(t) \) are rolling resistance parameters that vary as a function of the road surface type, road condition and vehicle type.

Summary

Most of the fuel consumption models presented have the vehicles tractive power or speed along with the acceleration and road slope as inputs. These models are relatively simple. Most of them are derived for passenger vehicles except one model, Equation (2.1) and (2.3). This model has been tested for 27 heavy duty diesel vehicles and diesel buses and is claimed to have an accuracy within 10% compared to measured values of fuel consumption [15].

The model in Equation (2.6) is derived for 177 in use Australian passenger vehicles and is said to have an accuracy within 2% for those vehicles [28]. The CPF models, Equation (2.9) and (2.10), can be derived for passenger vehicles, using public emission information and was demonstrated to have an accuracy within 10% [29]. Other models, for example Equation (2.8), requires detailed information of several control signals as input, such as gear and pedal signals.

2.1.2 Eco-Routing

Navigation systems today are usually built to find which route between point A and B is either the fastest or shortest. By using these systems, fuel can be saved by reducing the risk of not finding the target. But the fuel consumption can be additionally reduced by taking more factors into account than just the road distance. Different road slopes creates different power demands on a vehicle and there are studies that indicates that fuel consumption and emissions increases with 9% when increasing the road slope with 1% [27]. Another study showed that for a set of journeys where there was some kind of disturbance, for example a traffic congestion, there existed a more fuel efficient route for 76% of those journeys [14].

By using detailed information about the topography, road signs and real time traffic, it is possible to estimate the fuel consumption with relatively high accuracy. With more reliable information about the fuel consumption along a route it is possible to make better comparisons between several routes in order to find the most fuel efficient.

Navigation systems that optimize the route with regard to fuel consumption has recently been introduced into the market by passenger car manufacturers such as
Hyundai and Ford, where they claim that using their respective eco-routing systems offers between 6-15% reduced fuel usage [2,35]. Other companies such as VW and BMW have on going research projects within this subject [5,39].

Digital map providers such as TeleNav and NAVTEQ assist with information needed about the road and traffic. The information is usually divided to static information and dynamic information. Static information includes for example slopes, distances, speed limits and number of stops due to stop signs or traffic lights. Dynamic information includes for example information about where there are traffic congestions based on both historical data and real time data [2,37].

Research has been done where parts of a complete eco-route systems have been investigated [5,21]. These systems use a speed profile as one of the inputs to the fuel consumption model. The model that [21] used is described in Equation (2.9), (2.11) and (2.12), with small modifications. Findings of these research showed that the accuracy of the calculated fuel consumption varied when using a synthetic created speed profile using information from the digital map provider, NAVTEQ, compared to when using a speed profile measured in a field test. One of the reasons pointed out was that the synthetic speed profiles do not contain all the stop-start maneuvers.

2.1.3 Route Optimization in Energy Context

An investigation of the possibilities of eco-routing for passenger vehicles is found in the thesis [5], with the same title this section has. This thesis has investigated each component required in a complete eco-routing system. A driver model and a simplified vehicle model have been developed for this purpose and different shortest path algorithms have been presented and compared.

One conclusions drawn is that the mean savings potential is approximately 10%. The parameters that have most influence on which route is optimal with regard to fuel consumption is the road slope and especially the predicted speed profile. It is when using a real time model to estimate the fuel consumption that a good prediction of the speed profile makes a significant difference in the calculated fuel consumption.

2.2 Route Optimization

Route optimization is a well known shortest path problem that can be solved using dynamic programming algorithms to find the most optimal route among many, with regard to a predefined cost. For a route optimization for vehicles the cost could be time, distance or fuel consumption. The latter is being focused on in this thesis. Route optimization for vehicles with regard to fuel consumption is also known as eco-routing. An eco-routing system for trucks could be a similar system to the one described in [5]. In the following sections some of the components of this system are described.
2.2.1 Shortest-path Problem

The principles and methods for solving a shortest path problem are presented in this section. Different algorithms are being compared and a description of how a network suitable for eco-routing is created.

Network and Costs

A network needed to solve a shortest path problem contains of links and nodes, where a cost for passing through a link is defined and there could also be a cost defined to pass by a node. Route optimization for vehicles requires a network that describes relevant information about the road. What kind of road information that is needed is dependent on the cost the optimization is made upon. The complexity of this network can vary. For a simple route optimization with regard to time the information needed to create a network is the travelling time that a certain distance requires. An example of such a network is depicted in Figure 2.1, where there is a cost on each link that describes the travelling time along each specific link in a suitable unit.

![Figure 2.1: An illustration of a network with costs for all links.](image)

For a route optimization with regard to fuel consumption both nodes and links could have a cost. The cost for a link is defined by the fuel consumed when driving at a constant velocity with or without a varying slope profile. A node could describe a speed change, either an acceleration or a breaking maneuver [5]. The cost at a node is defined as the fuel consumed for making that speed transition. Since a speed change for each node is dependent on the link before and after, the node costs are dynamic. Which algorithms that have costs defined at the nodes are described in the next section.

To create a network for eco-routing the Most Probable Path concept is used, derived from ADAS (Advanced Driver Assistance Systems) horizon concept [30]. A digital map that contains attributes such as for example, slope, speed limits and traffic signs can with the Most Probable Path concept create street segments and for each of these segments estimate the route that has highest probability to travel
2.2. ROUTE OPTIMIZATION

along. With the information of all probable paths summarized, a network can be created and with the help of the Most Probable Path concept the selection of routes decreases. An illustration of how a network is created is depicted in Figure 2.2.

![Figure 2.2: For journey A to H there are several routes options. With digital map information it is possible to build a network describing a driver’s route options, where for example a congested road is translated to a road with a lower speed limit than ordinary. With a simplified network describing reality it is possibly to make a route optimization.](image)

A narrow turning during a driving is assumed to be conducted with a velocity that is predefined as a turning velocity suited for the vehicle in question. When entering a turn in reality the network describes this as follows: a node is first passed, since the speed usually needs to be reduced, the turning itself is thereafter described by travelling along a link with the turning velocity and thereafter a new node is passed, since an acceleration is needed to get back to the cruising speed.

Algorithms

Three algorithms were compared and tested in [5], the EPACO algorithm, a simple A*-algorithm and a model based A*-algorithm. The simple A*-algorithm is an extension of Dijkstra’s algorithm, with the difference that a heuristic guess is done for each new node which leads to less total calculations since fewer number of nodes will be required to be visited [38]. The costs for the simple A*-algorithm is based on hard and soft speed limits, where hard speed limits are determined by traffic signs and soft speed limits are determined by the topography and driving style, this algorithm will not take any costs at the nodes into account. The model based A*-algorithm will also take the fuel consumption at the nodes into account by adding a correction cost. The EPACO algorithm is able to customize the optimization to different driver styles. The impact of the costs on the algorithms presented are summarized in Table 2.1.
CHAPTER 2. BACKGROUND

Table 2.1: Influence on the cost function of the algorithms [6].

<table>
<thead>
<tr>
<th>Property</th>
<th>Simple A *</th>
<th>Model based A *</th>
<th>EPACO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Velocity (m/s)</td>
<td>stationary</td>
<td>stationary</td>
<td>dynamic</td>
</tr>
<tr>
<td>Dynamics (m/s²)</td>
<td>not included</td>
<td>not included</td>
<td>included</td>
</tr>
<tr>
<td>Driving style</td>
<td>partially included*</td>
<td>partially included*</td>
<td>included</td>
</tr>
<tr>
<td>Topography</td>
<td>not included</td>
<td>included</td>
<td>included</td>
</tr>
</tbody>
</table>

*Through the cornering limit acceleration

2.2.2 Vehicle Model and Driver Model

For the vehicle model that estimates the fuel consumption in [5], the required inputs are speed, acceleration and slope profiles. To be able to estimate the fuel consumption accurately with this model it is important to have a speed profile that mimics a real velocity profile as close as possible. The general principle of how the fuel consumption is calculated is depicted in Figure 2.3.

![Figure 2.3: Diagram of vehicle model and driver model.](image)

As described in Section 2.2.1 the network is built with information of the environment obtained from a digital map and real time traffic information, which is the first step in order to be able to estimate the fuel consumption. With the help from the environment, speed predictions can be made along the road. In the second step the information about the predicted speeds goes through a driver model that converts the discontinuous speed profiles into speed profile more like those of a real drivers, this is illustrated in Figure 2.4. With the new customized speed profile along with the slope profile, it is possible to estimate the fuel consumption.
Figure 2.4: Example of a speed profile before(left) and after(right) entering a driver model [21].
Chapter 3

Fuel Consumption Models at Scania

Today there exist two models for calculation and simulation of the fuel consumption of a truck at Scania. These models are called Stars and Scop, where Stars is the most accurate for estimating the fuel consumption. The models are described and compared in this chapter.

3.1 Stars

The most comprehensive simulation program at Scania is called Stars (Scania Truck And Road Simulation), used to calculate the fuel consumption on different types of roads [32]. The predecessor to Stars was named Strass, developed in the late 1970’s [22]. Stars is used internally, mostly to develop and examine engines and also new components to study the effect of these on the rest of the power train. Stars uses the component library SML in Dymola, previously called SHTL (Scania Heavy Truck Library) [22]. SML includes the models for the different components in the power train. An illustration of the major components included in Stars is illustrated in Figure 3.1.

During simulations with Stars several dynamic processes are being taken into account due to a variation of the engine temperature. This leads to an increase of fuel consumption and emissions during a short period right after start. Stars also has the can-bus modelled, where the can-bus makes it possible for the components to communicate with each other and also control the rest of the components. The can-bus makes it for example possible for the engine to know the reference speed right away and to act thereafter. Stars uses a longitudinal model to simulate the longitudinal behavior of the forces on a truck.
Figure 3.1: Overview of the major components modelled in Stars

Table 3.1: Description of the routes used for verification tests for Stars [23].

<table>
<thead>
<tr>
<th>Route</th>
<th>Date</th>
<th>Type of route</th>
<th>Distance[km]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Södertälje-Norrköping-Södertälje</td>
<td>110503</td>
<td>Long haulage</td>
<td>233</td>
</tr>
<tr>
<td>2. Södertälje-Norrköping-Södertälje</td>
<td>110402</td>
<td>Long haulage</td>
<td>233</td>
</tr>
</tbody>
</table>

Table 3.2: Comparison between total measured and estimated fuel consumption with Stars [23].

<table>
<thead>
<tr>
<th>Route</th>
<th>Unit</th>
<th>Measurement</th>
<th>Estimate</th>
<th>Difference[%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>dm³</td>
<td>80.5172</td>
<td>75.2581</td>
<td>-6.52</td>
</tr>
<tr>
<td>2.</td>
<td>dm³</td>
<td>74.1815</td>
<td>72.9328</td>
<td>-4.66</td>
</tr>
</tbody>
</table>

*Each route is described in Table 3.1

3.1.1 Accuracy

Verification tests have been executed where among other the simulated fuel consumption was compared for different routes. The routes driven for the verification tests are presented in Table 3.1. As can be seen a long haulage route of 233 km has been evaluated twice.

Part of the results of the verification tests are presented in Table 3.2, where focus is on fuel consumption. It must be noted that the estimated fuel consumption is affected by various simulation errors on some of the modelled components. Those could affect the estimated fuel consumption with approximately -2.4% [23]. With the simulation errors taken into account the estimated fuel consumption differs by 2-3% compared to the measurements for long haulage routes.
3.2 Scop

Scop was first developed in 1986 as a hobby program, however, today the program is used as a helping tool to compare different configurations of the power train when selling trucks. The comparisons are made to be able to give recommendations about which power train configuration is the most fuel efficient for the customers specific needs. Earlier the power train selection was based on experience and different comparison tables. Scop is written in C# and the simulation runs in steady state, that is, static calculations are executed \[10\]. An overview of the major components included in Scop is depicted in Figure 3.2.

![Figure 3.2: Overview of the major components modelled in Scop](image)

3.3 Comparison

Since the models at Scania are used for different purposes, the accuracy of calculating the fuel consumption varies. Therefore one of the major differences between Scop and Stars is the complexity and the environment on which the models are built in. Stars takes into account the temperature of the engine and Scop does not. This leads to an increased fuel consumption when the engine is cold as described in Section 3.1. Because of these differences the calculation times for a simulation differs by several minutes. Simulations in Scop are selected through the interface built in C#. There are different ways to run a simulation in Stars. It can run in Matlab, Dymola or in the same interface as Scop.

Stars has a high accuracy within approximately 2-3 %. Scop does an estimation with an estimated road, with a cruising speed defined and an assumption of how many stops the trip includes. The major differences between Scop and Stars are summarized in Table 3.3.

The three most significant parameters that have an impact on fuel consumption according to \[32\], are potential energy losses, rolling resistance and air resistance. Potential energy losses and air resistance are modelled in the same way for Stars and Scop. However the rolling resistance models for Scop and Stars are different. In the following section a presentation is made of the rolling resistance models used in Scop and Stars.
Table 3.3: Description of major differences between Scop and Stars

<table>
<thead>
<tr>
<th>Program</th>
<th>SCOP</th>
<th>STARS</th>
</tr>
</thead>
<tbody>
<tr>
<td>User</td>
<td>Used for sales</td>
<td>Used internally</td>
</tr>
<tr>
<td>Application</td>
<td>Optimizing power train config.</td>
<td>Develop engines</td>
</tr>
<tr>
<td>Language</td>
<td>C#</td>
<td>Modelica</td>
</tr>
<tr>
<td>Level of detail</td>
<td>Static calculations</td>
<td>Dynamic calculations*</td>
</tr>
<tr>
<td>Time</td>
<td>Short computing time</td>
<td>Time consuming calculations</td>
</tr>
</tbody>
</table>

*Engine temperature is modelled

3.3.1 Rolling Resistance

One of the parameters that could have an influence on the fuel consumption is the rolling resistance. Other parameters are the vehicle mass, the frontal area of the truck and the slope of the road. The rolling resistance is a part of the model that can be modelled in several ways. In Stars the rolling resistance is modelled in two ways, dependent on the tire type the user chooses to simulate. The first model is described by

\[ C_r = 0.006 + 0.23 \cdot 10^{-6} \cdot v^2, \tag{3.1} \]

where \( v \) is the velocity of the vehicle (km/h). This model is based on experimental data with radial-ply truck tires [40] and is claimed to be valid for speeds up to 100 km/h. The other rolling resistance model takes into account different rolling resistances for front and rear tires and is described by,

\[ C_r = C_{riso} + a(v^2 - v_{iso}^2) + b(v - v_{iso}), \tag{3.2} \]

where \( C_{riso} \) is a value from measurement according to ISO9948, \( v_{iso} = 80 \) km/h is the velocity during measurement according to ISO9948 and \( a, b \) are constants. This rolling resistance is developed by the tire manufacturer Michelin [32].

The rolling resistance model used in Scop is,

\[ C_r = C_{r1} + C_{r2}v \tag{3.3} \]

where \( C_{r1} \) and \( C_{r2} \) are tire and surface constants [36].
Chapter 4

Estimating Fuel Consumption

The most important steps in a route optimization with regard to fuel consumption are depicted and summarized in Figure 4.1. Before and while running the shortest path algorithm, the necessary costs, that is the fuel consumption must be estimated for each link and node. To estimate the fuel consumption, one of two methods can be chosen. Given these estimates the shortest path algorithm can be executed to obtain the most fuel efficient route.

**Figure 4.1:** When the destination is defined the costs for the links and nodes needs to estimated. This can be done with two methods, using a look up table or a real time model. Thereafter the shortest path algorithm can be executed.
This chapter will first describe the most significant parameters that influence fuel consumption for a truck. Thereafter two methods to estimate the fuel consumption will be presented. The first method presented is a method using a look up table to estimate the fuel consumption on different road sections. A look up table includes pre calculated information of the fuel consumption for different driving events. The second method is to use a real time model to estimate the fuel consumption. It has input parameters such as speed, acceleration and road slope.

The estimation accuracy for an eco-routing system and how this is evaluated for the two estimation methods will be presented. The influence of a driver will have an effect on the estimated fuel consumption and this will also be described in this chapter.

### 4.1 Impacting Parameters

There are a lot of parameters that have an impact on the fuel consumption. For a Stars simulation of a long haulage truck with the weight of 40 ton, the energy that the engine produces is distributed as shown in Figure 4.2 [33].

![Figure 4.2: Sources to energy losses for a long haulage truck [33].](image)

Almost 40% is used to overcome the gravitation when driving up hills and approximately 30% of the energy is used to overcome the rolling resistance. To overcome the air resistance, 23% of the energy is needed while the losses in the power train are only around 7% [32]. A lot of effort has been put into reducing the losses in the power train, which has resulted in these relatively small energy losses.

Figure 4.2 indicates that there are still improvements to be done in reducing the impact of potential energy on the fuel consumption. If a driver is able to choose a route where there are as few up hills as possible it could help the driver to save fuel.
4.2 Look up Table

To estimate the cost at specific nodes and links, a look up table can be used. The look up table used in this thesis is divided into two parts where the first part describes driving at a constant speed and the second part describes speed changes. The resolution of the table has been set for this work to include speeds between 10 and 100 km/h with the step of 10 km/h. The slope is described for slopes between -0.05 radians and 0.05 radians with a step of 0.005 radians.

The first part of the table describes driving at constant speed and as mentioned above, the topography is being taken into account by including fuel consumption data at different slopes. Input to the first part of the table is speed and slope, and output is the fuel consumption in (Wh/m).

The second part of the table describes different speed changes such as breaking and acceleration. In this part the environment is also being taken into account by including fuel consumption data at different slopes. The inputs for this part are a starting velocity, a target velocity and the assumed slope during this manoeuvre. The output is an energy difference and a manoeuvre distance that each specific manoeuvre requires. The look up table describes each acceleration and breaking for a road with a constant slope.

4.2.1 Estimating Fuel Consumption with Look up Table

Each time the cost for a link needs to be estimated, the first part in the table is entered. Since the information about the distance of the link and the road slope is known, it is possible to estimate the fuel consumption along the link with respect to the slope according to,

\[ F_{\text{stat}}(v, \alpha) = s_{\text{link}}(\alpha)C_e(v, \alpha), \]

where \( F_{\text{stat}}(v, \alpha) \) is the fuel consumed along a link (Wh), \( s_{\text{link}} \) is the distance driven (m), as a function of slope \( \alpha \), \( C_e(v, \alpha) \) is the energy consumed per meter (Wh/m), at a slope \( \alpha \) (rad) and velocity \( v \) (km/h). How many times the table needs to be entered when calculating the cost for a link is decided on the resolution of the slope profile.

The cost for a node is defined as the fuel consumed during a speed changing maneuver. Each node includes information about the current speed \( v_0 \), target speed \( v_1 \) and slope \( \alpha \). With this information an energy difference can be found in the look up table and also a maneuver distance that describes the distance needed to execute the speed change required. The fuel consumed during an acceleration \( F_{\text{acc}} \) (Wh), is calculated according to,

\[ F_{\text{acc}}(v_0, v_1, \alpha) = C_e\Delta(v_0, v_1, \alpha) - s_m(v_0, v_1, \alpha)C_e(v_0, \alpha), \]

and fuel consumption during a braking \( F_{\text{brake}} \) (Wh), is calculated according to,

\[ F_{\text{brake}}(v_0, v_1, \alpha) = s_m(v_0, v_1, \alpha)C_e(v_0, \alpha) - C_e\Delta(v_0, v_1, \alpha), \]
where $C_{e\Delta}$ is the energy difference (Wh) for a speed change from the current speed $v_0$ (km/h), to a target speed $v_1$ (km/h) during the slope $\alpha$ (rad). $s_m$ is the maneuver distance (m), and $C_e$ is the energy consumed per meter (Wh/m) at the slope $\alpha$ (rad), for the speed $v_0$ (km/h). The total fuel consumption for a trip can be calculated as,

$$F_{tot} = \sum_{i=1}^{k} F_{stat,i} + \sum_{i=1}^{m} F_{acc,i} + \sum_{i=1}^{n} F_{brake,i},$$  \hspace{1cm} (4.4)

where $F_{tot}$ is the total fuel consumption, $k$ is the total number of links, $m$ is the total number of acceleration nodes and $n$ is the total number of braking nodes.

### 4.3 Real Time Estimation

Fuel consumption for each node and link can be estimated using a real time model. Two models will be evaluated. The model presented in Section 2.1.1, Equation (2.4) and (2.5), will be evaluated and is denoted as the Oguchi model. The second model evaluated is based on the Oguchi model and on the model presented in Section 2.1.1 from [15]. This model will be denoted as the RT-model. Inputs to both models are acceleration, speed and road slope.

#### 4.3.1 RT-Model

![Equilibrium of the longitudinal forces acting on a truck.](image_url)

A longitudinal force equilibrium according to Newton’s second law and Figure 4.3 give,

$$F_w(a, v, \theta) = F_a + F_d + F_r + F_g = (m + m_j)a + \frac{1}{2} c_d A \rho v^2 + mgc_r \cos \theta + mgsin \theta, \hspace{1cm} (4.5)$$

where $F_w(a, v, \theta)$ is the total resistance (N), $m$ is the mass (kg), $m_j$ is the equivalent mass of the inertia of the moving parts (kg), $a$ is the vehicle acceleration (m/s$^2$), $c_d$
4.3. REAL TIME ESTIMATION

is the air drag coefficient, \( v \) is the vehicle speed (m/s), \( c_r \) is the rolling resistance, \( \rho \) is the air density (kg/m\(^3\)), \( g \) is the gravity acceleration (m/s\(^2\)) and \( \theta \) is the road slope (rad).

With Equation (4.5) the tractive power can be derived as a function of slope, acceleration and speed as,

\[
P(a,v,\theta) = F_w(a,v,\theta)v,
\]

where \( P(a,v,\theta) \) is the instantaneous tractive power (kW), as a function of \( a \), \( v \) and \( \theta \). The instantaneous fuel consumption can hence be estimated according to,

\[
ft(a,v,\theta) = ft_{idle} + \frac{\delta}{\varepsilon_b H_d} \left( \frac{P(a,v,\theta)}{\eta_t} + P_{aux} \right),
\]

with,

\[
\delta = \begin{cases} 
1 & F_w > 0 \\
0 & F_w \leq 0 
\end{cases},
\]

where \( \varepsilon_b \) is the brake thermal efficiency of the engine, \( \eta_t \) is the total transmission efficiency, \( H_d \) is the energy density of diesel (J/cm\(^3\)), \( ft(a,v,\theta) \) is the amount of fuel supplied to engine per second (cm\(^3\)/s) and \( P_{aux} \) is the power needed for auxiliary units (kW), such as for example cooling. Hence the total fuel consumption is estimated according to,

\[
F_{tot} = \int ft(a,v,\theta) dt,
\]

where \( F_{tot} \) is the total fuel consumed (cm\(^3\)).

Splitting the RT-Model into three blocks

Validation results that will be described in Section 6.3.1 showed that the accuracy for the RT-model was significantly reduced for city traffic estimates. The initial RT-model neglects the dynamics of gear changes and measurements showed that the actual gear varied for these types of drivings. Two parameters that were directly and indirectly dependent on the actual gear were the equivalent mass \( m_j \) and the total transmission efficiency \( \eta_t \). This lead to a modification of the model splitting it into three blocks were \( m_j \) and \( \eta_t \) changed in each block.

The actual gear is dependent on which engine speed and engine torque a certain situation requires. Since the validation result showed that the actual gear was most influenced on which speed the truck was keeping, an assumption was made where the gear was assumed to be dependent on the speed only. The conditions for each block are presented in Table 4.1.

With the measurements of the actual gear during the driving, a median value of the actual gear was calculated for each block described in Table 4.1. Using this value, \( m_j \) and \( \eta_t \) were calculated for each block using the real parameters value for the specific truck used during the experiments. A description of how \( m_j \) depends on the actual gear is described in Equation (4.12).
Table 4.1: Conditions for the different blocks, were $m_j$ and $\eta_t$ changes in each block.

<table>
<thead>
<tr>
<th>Block</th>
<th>$m_j$</th>
<th>$\eta_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$v \leq 30$</td>
<td>$m_{j3}$</td>
<td>$\eta_{t3}$</td>
</tr>
<tr>
<td>$30 &lt; v \leq 50$</td>
<td>$m_{j2}$</td>
<td>$\eta_{t2}$</td>
</tr>
<tr>
<td>$v &gt; 50$</td>
<td>$m_{j1}$</td>
<td>$\eta_{t1}$</td>
</tr>
</tbody>
</table>

4.3.2 Oguchi Model

The Oguchi model, Equation (2.4) and (2.5), is a simplified model compared to the more vehicle specific RT-model. There are various parameters that varies with different vehicles: $\eta_t$, $\varepsilon$, $c_d$ and $m_j$. The equivalent mass of the inertia of the moving parts $m_j$ is assumed to be described by Equation (4.13). The other parameters are roughly set by publicly available information.

4.3.3 Road Load Parameters

Assumptions were made regarding the road load parameters, air drag resistance and rolling resistance. The air drag resistance model used for both real time models is,

$$F_d = \frac{1}{2} c_d A \rho v^2,$$  \hspace{1cm} (4.10)

which is a simplified model dependent on the frontal area of the vehicle, the drag coefficient and the velocity of the airflow. The latter is assumed to be the same velocity as the vehicles. This model calculates the force on a body in the free stream direction [17]. In this work the drag coefficient is chosen from a look up table used in Scop, see Appendix A.1.

The rolling resistance model used for both real time models is one of the models used by Stars [40], which increases with the square of speed. The model is described by,

$$c_r = 0.006 + 0.23 \cdot 10^{-6} \cdot v^2,$$  \hspace{1cm} (4.11)

where $v$ is the velocity (km/h). As mentioned in Section 3.3.1, this model is claimed to be valid for speeds up to 100 km/h [40].

The equivalent mass is indirectly dependent on the slope and speed of the road since it increases at lower gears [24]. It can be described, according to [19], as,

$$m_j = \frac{J_w + i_t^2 i_f^2 \eta_t \eta_f J_e}{r_w^2},$$  \hspace{1cm} (4.12)

where $J_w$ is the wheel inertia (kgm$^2$), $J_e$ is the engine inertia (kgm$^2$), $i_t$ is the conversion ratio for gear $t$, $i_f$ is the final drives conversion ratio, $\eta_t$ the efficiency for gear $t$, $\eta_f$ is the efficiency for the final drive and $r_w$ is the wheel radius (m). This
model is used by the RT-model. The equivalent mass can also be described by the simplified expression in the following equation,

\[ m_j = 0.005 \frac{m}{r_w^2}, \]  

(4.13)

where \( m \) is the vehicle mass (kg). Equation (4.13) is used in Scop [36], and will also be used in the Oguchi model.

4.3.4 Comments on the Models

Equation (4.8) shows that both models assumes that the vehicle does not consume any fuel when \( F_w \) along the direction of movement is less than or equal to zero. When evaluating the model it is assumed that the thermal efficiency \( \varepsilon_b \) is constant. The total transmission efficiencies \( \eta_t \) are constant in three blocks for the RT-model and constant for all speeds in the Oguchi model. It is also assumed that the vehicle does not consume any fuel during braking manueuvres. The major difference between the RT-model and the Oguchi model is that the former is vehicle specific for some parameters and original data is used to set these.

4.4 Required Accuracy for Route Optimization

To be able to make a route optimization with regard to fuel consumption that is not misleading, the required accuracy needs to be studied. The possibility to make relative comparisons between various routes is critical for an eco-routing system. Two ways of studying the estimation error are described in this section, where the first step is to study the relative mean square error. The second is to study confidence intervals for a certain set of errors.

4.4.1 Relative Accuracy

Relative accuracy in this context refers to how accurate an estimate is compared to actual measurements. The error parameter studied for this purpose is the relative mean square error, denoted as \( r_{est} \). This parameter describes the relative mean square error of the total fuel consumption. How it is calculated is described in Appendix D.1.

When eco-routing optimization is executed from point A to B, the system compares several routes to each other with regard to fuel consumption. In most of the cases a comparison is made between the fastest and the most fuel efficient route. Considering such a case, the saving potential is assumed to be \( \delta_{save} = 10\% \) if choosing the most fuel efficient route. This generalized scenario of two route alternatives is depicted in Figure 4.4 with the corresponding costs. The dimension for the costs is a normalized unit.
CHAPTER 4. ESTIMATING FUEL CONSUMPTION

Figure 4.4: Generalization of two route alternatives, the fastest and the most fuel efficient route, from A to B.

The costs for these two route alternatives are assumed to describe the costs in reality. This information is in reality not available for the eco-routing system, hence these costs needs to be estimated. The estimated costs made for these route alternatives will be denoted $J_{fast}$ and $J_{eco}$. As long as condition,

$$J_{eco} < J_{fast},$$

is fulfilled the eco-routing system will do a proper recommendation to the driver.

Figure 4.5: Possible estimation intervals for an estimation method with $r_{est} = 5.0\%$ for the case when the saving potential is $\delta_{save} = 10\%$, see Figure 4.4.

Let's now consider the case when fuel consumption estimates for this scenario are done using an estimation method with $r_{est} = 5.0\%$. Since $r_{est}$ only describes an absolute error, the estimates could have an error between $\pm 5.0\%$. The possible estimation intervals for the two routes described in Figure 4.4 are depicted in Figure 4.5. Since these two intervals does not overlap each other, there is no risk for the eco-routing system to give wrong recommendations and Equation (4.14) will be fulfilled for all possible estimates.

For the same estimation method with $r_{est} = 5.0\%$, the potential fuel savings is now assumed to be $\delta_{save} = 9\%$. For such a case the generalized scenario describing this, along with the possible estimation intervals are depicted in Figure 4.6. In this case the possible estimation intervals overlap each other. There exists now a risk for wrong recommendations of which route that is most fuel efficient since for some cases, Equation (4.14) is not fulfilled. For smaller savings potential than $\delta_{save} = 9\%$, the range for the overlap increases and the risk of wrong recommendations increases.

Saving potentials $\delta_{save}$, that gives rise to a risk of overlapping of the estimation intervals were numerically derived for estimation methods with a certain $r_{est}$. The
4.4. REQUIRED ACCURACY FOR ROUTE OPTIMIZATION

Figure 4.6: Generalization of two route alternatives, the fastest and the most fuel efficient route, from A to B. The corresponding estimation intervals are also depicted for an estimation method with $r_{est} = 5.0\%$, when the saving potential is $\delta_{\text{save}} = 9\%$.

Overlapping boundaries $\delta_{\text{save}}$ as a function of $r_{est}$ are presented in Figure 4.7. The exact boundary is approximately linear for $r_{est}$ lower than $10\%$. The approximated linear boundary $\delta_{\text{save}} \approx 2 \cdot r_{est}$, is also plotted in Figure 4.7. For savings below these $\delta_{\text{save}}$ numbers there exists a risk of giving wrong recommendations since the possible estimation intervals will overlap each other.

With the results presented in Figure 4.7, a general rule of thumb can be assumed; for a model with the error $r_{est}$ recommendations should only be made for cases where the estimated fuel efficient route shows at least a saving potential of,

$$\delta_{\text{save}} \geq 2 \cdot r_{est}. \quad (4.15)$$
4.4.2 Confidence Interval

If the accuracy of an estimation method is too poor when considering the relative mean square error a further analyze of the errors is to study the corresponding two sided confidence interval. The confidence interval is given by,

\[ I = \left( \bar{e} \pm \frac{s}{\sqrt{n}} t_{\alpha/2}(f) \right), \tag{4.16} \]

where \( \bar{e} \) is the mean error (%), \( s \) is the standard deviation (%), \( n \) is the length of the vectors containing data and \( t_{\alpha/2}(f) \) is the quantile of a t-distribution with \( f = n - 1 \) degrees of freedom [9]. How these parameters are calculated is described in Appendix D.2. From Equation (4.16) the deviation is noted as,

\[ D = \frac{s}{\sqrt{n}} t_{\alpha/2}(f). \tag{4.17} \]

For the confidence interval the error is thus concentrated around the mean error with the deviation \( \pm D \).

The accuracy is as mentioned before only important to the extent that the eco-routing system recommends the correct route to the driver. If there exists a confidence interval with a significant offset from 0 it will give rise to \( r_{est} \) larger than \( D \). In this case it is more appropriate to study the confidence interval since the \( r_{est} \) show a larger estimation interval than the actual confidence interval. Considering for example the scenario described in the previous section, where an estimation is made for the fastest and the most efficient route. A larger estimation interval increases the risk for overlapping of these two estimation intervals. This will increase the risk of giving a wrong recommendation to the driver. Thus the accuracy requirement of an eco-routing system is dependent on how the modelling error is studied.

Let’s consider the same scenario that was presented in the previous section were the savings potential is assumed to be \( \delta_{save} = 10\% \). Let’s also consider an estimation method with a mean error of \( \bar{e} = -5\% \) and deviation, \( D = 5\% \). If the relative accuracy was considered instead, the relative mean square error would have been approximately \( r_{est} = 10\% \). The possible ranges for such an estimation method when considering the confidence interval and the estimation interval for \( r_{est} = 10\% \) are depicted in Figure 4.8. Considering the confidence interval for each route are concentrated around the red numbers, calculated according to the mean error \( \bar{e} = -5\% \). These intervals are distributed around the mean error with the deviation \( \pm D = 5\% \). If the relative accuracy is considered instead, the intervals are much wider as can be seen in Figure 4.8. The risk for overlapping of the intervals increases unnecessary when considering the relative mean square error instead of the mean error with the corresponding deviation. The rule of thumb of which recommendations to be done, Equation (4.15), can thus when studying the confidence interval be rewritten as,

\[ \delta_{save} \geq 2 \cdot D. \tag{4.18} \]
4.4. REQUIRED ACCURACY FOR ROUTE OPTIMIZATION

Figure 4.8: Generalization of the route alternatives from A to B, route u is the optimal route with the lowest cost, 0.9 e.u (energy units). Two estimation intervals are presented considering either the standard deviation or the relative mean square error.

4.4.3 Comments on Required Accuracy

The first step of studying the accuracy of a certain estimation method should be to study the relative mean square error. If the estimates of a certain method shows a too high relative mean square error then the confidence interval should be analyzed. This to conclude whether the accuracy is still for an eco-routing system in order to do correct recommendations.

The methodology of how to determine the required accuracy for eco-routing in this section is based on various assumptions and simplifications. This is a first step on treating required accuracy for an eco-routing system. To verify the rule of thumb, Equation (4.15), experiments should be executed. This rule of thumb helps the system to do a correct recommendation on which route that is fuel efficient but does not give the correct savings potential. The savings potential presented by the eco-routing system is based on the fuel consumption estimates and contains a certain error due the modelling error. Therefore the presented savings potential does not always describe the real savings potential.
4.5 Influence of the Driver

Different driving styles affect the fuel consumption in different ways. There are mainly four parameters that affect the fuel consumption for different drivers [8]. The first is delay for when to start changing the speed when for example a driver passes by a traffic sign that requires a speed change. How the longitudinal acceleration is made can also be driver dependent. This is the second parameter. The speed that the driver keeps on a highway is the third driver dependent parameter. The fourth is the tolerance for lateral acceleration, which sets a speed limit when the vehicle does different turns. For the two methods presented in this thesis the driver style influence on the fuel consumption is depicted in Figure 4.9.

Figure 4.9: Driver influence on a real time model(top), and on a look up table(bottom)

A look up table has more constraints describing the fuel consumption than a real time model for different drivers. The delay for when to start a speed change can be taken into account for different drivers but not the speed changing process itself. The look up tables include information about maneuver distance required for a speed change but that is fixed for each table. This is a drawback with using a table since a table only represents one type of driver when modelling the fuel consumption during a speed change. This is shown in Figure 4.9 where the road information directly goes to the look up table.

The real time model on the other hand has a speed profile as an input along with the slope profile. This speed profile is unique for different drivers, the delay for when to start a speed change and the speed change can be modelled for different drivers. The speed profile is created by a driver model, thus different speed profiles describes different driving styles as depicted in Figure 4.9. With these profiles as an input to a real time model, different driver styles can be considered.
4.6 Conclusions

Two different methods to estimate the fuel consumption have been presented. As mentioned in Section 4.5, the driver style affects these two methods in different ways. The real time model should be able to describe an individual driver style better than the look up table since the look up table describes the driving style of an average driver.

The models used as a real time models were chosen since these model are relatively simple and have a speed profile, acceleration profile and a slope profile as input and the necessary parameters can be derived. Most of the models presented in Section 2.1.1 require emission information about a certain vehicle and since Scania trucks are able to have many different power train configurations, the information needed to use these models cannot be found.

The methodology of how to determine the required accuracy for eco-routing, is based on various assumptions. The rule of thumb presented in Section 4.4, Equation (4.15), is suppose to help the eco-routing system mainly to do a correct recommendation on which route that is fuel efficient. The actual savings potential presented by an eco-routing system is based on estimates. Therefore, there is some uncertainty of how much fuel that is actually being saved in reality.
Look up tables were generated with different models. The methodology of how this was done will be described in this chapter. To be able to validate the estimation methods, measurements are needed. The approach of acquiring these measurements and how these were preprocessed will also be presented in this chapter.

5.1 Look up Tables

5.1.1 Creating Look up Tables

Two different look up tables were generated using Stars and Scop.

To be able to create look up tables in Stars, road files were created. The roads were defined by setting slopes and reference speeds along the road. Several roads were created to be able to simulate the fuel consumption for all the drive cases described in Section 4.2. Since the output data of a Stars simulation included continuous information along the simulated road a search code was written in Matlab, in order to be able to extract the relevant information needed for the look up tables.

Creating look up tables in Scop required modifications in the source code written in C#. Two different functions were used to build the first and the second part of the look up table, see Section 4.2. The first part of the look up table was created using a function that calculates the instantaneous fuel consumption when driving at constant speed at different road slopes. Scop is originally programmed to simulate accelerations from 0 km/h to the cruising speed, but the same functions could also be used to obtain the necessary values for different accelerations needed for the second part of a look up table, see Section 4.2.

5.1.2 Estimation Boundaries

A look up function was created in order to do a look up table estimation. This function was written in Matlab. This function searches through the look up tables
for the correct fuel consumption information at a certain slope for a certain maneuver, either acceleration, braking or driving at a constant speed. Since the look up tables only includes limited information, see Section 4.2, estimation boundaries were needed. The boundaries for the searching function are defined as follows,

- Estimations are only made for speeds between 10 and 90 km/h.
- Estimations are only made for road slopes between $-5\%$ and $5\%$.
- For estimations of integer speed numbers that are not described by the look up table, an upper and lower speed boundary are set by the speed numbers described in the look up table. These boundaries are defined by the specific interval the integer speed number is within. To approximate fuel consumption for this integer speed number, a linear interpolation was made between the boundary values.
- Acceleration and breaking maneuvers were only estimated for speed changes equal to 10, 20, $\ldots$, 90 and 100 km/h.

5.2 Measurements

Measurements from actual drivings were needed in order to be able to make validation tests for the two estimation methods.

A driving similar to the European Transient Cycle (ETC) was made to obtain measurements that described fuel consumption for the most common driving scenarios. Such a cycle is depicted in Figure 5.1. The ETC cycle is used for emission certification of heavy duty diesel engines in Europe and is divided into three parts where the first part describes city driving, the second part describes rural driving and the third part describes motorway driving [1].

![Figure 5.1: Velocity profile based on the European Transient Cycle [1].](image)
5.2. MEASUREMENTS

Measurements were also recorded during trips from Södertälje to Denmark and Karlstad respectively. Segments from these drivings were also used for validation, however, mainly for highway driving and rural driving.

Measurements were recorded for the altitude, distance driven, vehicle speed, gear and instantaneous fuel consumption with the sampling time, $T_s = 200$ ms. With the measurements of the altitude and the distance driven the road slope could estimated.

5.2.1 Equipment

To be able to measure vehicle speed and distance driven, a tachometer was used. The tachometer registers the time difference for passing each cog on a cogwheel in the power train, inserted just for measuring purposes. The vehicles altitude was measured using a GPS, GPS18x-5hz from Garmin.

![Figure 5.2: Implementation of flow meter in the engine system.](image)

To estimate the fuel consumption a flow meter system was used, 6000-Swissline from AIC. The flow meter was installed according to Figure 5.2, between the tank and the engine. This installation made it possible to measure all the fuel that was actually combusted. The fuel consumption was measured during each sampling with an accuracy and resolution of 1.25ml.

5.2.2 Preprocessing

Due to noisy measurements of the velocity and distance driven, preprocessing of measurement data was required. This section describes how the preprocessing was
done and how a numerical method was used to approximate the acceleration.

**Filter**

To be able to get smooth data of the noisy measurements of the velocity and distance driven, a low pass filter was constructed using the functions `fdesign` and `design` in Matlab with the cutoff frequency 0.1 Hz. The filtered velocity measurements are depicted in Figure 5.3.

![Filtered velocity measurements](image)

**Figure 5.3:** A part of the velocity measurements before and after being filtered

**Acceleration**

One of the parameters needed in the real time models, the RT-model and Oguchi model, is the acceleration. Since measurements of the velocity were recorded, the acceleration could be approximated using the numerical five point method for approximating the derivative according to the following equation [20],

$$a_i = \frac{-v_{i+2} + 8v_{i+1} - 8v_{i-1} + v_{i-2}}{12h}, (5.1)$$

where $a_i$ is the approximated acceleration (m/s$^2$) at sample $i$, $v_i$ is the velocity (m/s) at sample $i$ and $h$ is equal to the sampling time $T_s$.

**Road Slope**

Since the road slope was not measured, the measured altitude and distance driven were used to calculate the slope according to Figure 5.4.

By using previous and current information for the altitude and distance driven, the road slope could be estimated using trigonometry according to,

$$\alpha_i = \tan^{-1} \left( \frac{h_i - h_{i-1}}{s_i - s_{i-1}} \right), (5.2)$$
5.2. MEASUREMENTS

5.2.3 Sources of Errors

The measurements recorded must be regarded with some uncertainty, especially the measurements of the altitude and consequently the estimated road slope according to Equation (5.2). Measurements were recorded on a certain road segment several times using another vehicle with an Oxford GPS with a higher accuracy than GPS18x-5hz from Garmin. The Garmin GPS used for the measurements for this thesis also recorded the altitude for this same road segment, the differences are depicted in Figure 5.5.

As can be seen neither of the measured altitude curves are consistent. But the slope of the altitude curves are relatively consistent for the Oxford GPS measurements. While the slope of the altitude curve for the Garmin GPS measurements are not consistent compared to the Oxford GPS measurements. The critical parameter though for road slope estimations is not the altitude itself but the altitude difference, that is the slope of the altitude curve. If the slope of the measured altitude curves is consistent then the altitude difference should be accurate and therefore also the slope estimation.
Another possible source of uncertainty is the density of the diesel, that is the energy density of the fuel that the truck was fueled. The fuel consumption is dependent on density of the diesel and this could have an impact during validation tests. Since the density used for estimation could differ from the density of the fuel during the time when the measurements were taken.
This chapter begins with a comparison of Scop, Stars and the RT-model used in this thesis. Thereafter the validation results are presented. Validation tests were done to be able to draw conclusions from the two methods of estimating the fuel consumption presented in this thesis. Measurement data for the validation tests were recorded similar to the ETC-cycle, see Figure 6.1, in order to try to capture the most common driving cycles. Measurement data from drivings from Södertälje to Denmark and Karlstad were also used. The measurements of speed, acceleration and slope were used as inputs for the two estimation methods during the validation tests.

![Figure 6.1: Measurement data of speed according to the ETC cycle for a truck.](image)

This chapter mainly outlines the results of the validation tests for the different driving sections. In addition to the validation results, the result of the estimation accuracy from different perspectives is also presented. In order to see the impact of specific parameters on the fuel consumption, a sensitivity analysis is made. With the generated look up tables, eco-routing simulations were made for 36 long haulage routes. The results of these simulations are presented and evaluated. The last section describes implementation challenges with regard to computation time for Matlab and C++ and an evaluation of the estimation methods presented from an
6.1 Comparing Fuel Consumption Models

A comparison of the instantaneous fuel consumption for acceleration and braking maneuvers and driving at a constant speed, between Stars, Scop and RT-model was made. Since Stars is assumed to be the most accurate simulation program [23], Stars was used as reference in the comparison.

6.1.1 Constant Speed

<table>
<thead>
<tr>
<th>Vel [km/h]</th>
<th>Scop* [%]</th>
<th>RT* [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-5% 0% 2%</td>
<td>-5% 0% 2%</td>
</tr>
<tr>
<td>10</td>
<td>0 40.1 11.2</td>
<td>0 -32.7 -0.4</td>
</tr>
<tr>
<td>20</td>
<td>0 12.7 3.6</td>
<td>0 -24.3 10.4</td>
</tr>
<tr>
<td>30</td>
<td>0 12.8 -0.7</td>
<td>0 -6.6 11.6</td>
</tr>
<tr>
<td>40</td>
<td>0 11.8 0.8</td>
<td>0 -0.2 15.4</td>
</tr>
<tr>
<td>50</td>
<td>0 13.1 2.3</td>
<td>0 11.6 20.0</td>
</tr>
<tr>
<td>60</td>
<td>0 15.3 3.1</td>
<td>0 19.7 22.5</td>
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<td>70</td>
<td>0 16.2 4.6</td>
<td>0 12.5 5.9</td>
</tr>
<tr>
<td>80</td>
<td>0 18.0 4.3</td>
<td>0 15.7 9.3</td>
</tr>
<tr>
<td>90</td>
<td>0 14.6 5.5</td>
<td>0 15.9 7.5</td>
</tr>
</tbody>
</table>

*Comparison are made for Scop and the RT-model to results of Stars.

The results of the comparison when driving at a constant speed for road slopes of -5%, 0% and 2% are presented in Table 6.1. Since the truck is only able to keep 90 km/h at maximum 2%, this road slope was chosen as the upper value during the comparison. As can be seen both Scop and the RT-model show the same fuel consumption when the slope is -5% compared to Stars. For slopes of 0% the fuel consumption is significantly higher than Stars for Scop at all speeds. The RT-model shows a different behaviour at 0% slope. For speeds between 10-40 km/h it shows a lower fuel consumption than Stars and for speeds between 50-90 km/h a significantly higher fuel consumption than Stars. At 2% Scop estimates a fuel consumption that is relatively similar to Stars. Estimates with the RT-model deviates under 10% for speeds between 70-90 km/h. However for the lower speeds the fuel consumption is significantly higher than Stars.
6.1. COMPARING FUEL CONSUMPTION MODELS

6.1.2 Scop - Acceleration and Braking

A comparison of the percentage deviation and the difference between Stars and Scop was made for road slopes of -5% and 2%. The total fuel consumption for a certain acceleration or braking maneuver is evaluated.

Figure 6.2: Comparing the percentage deviation, between Scop and Stars when driving at -5% road slope. The vertical axis to the left describes starting speed and the horizontal axis on the top describes the target speed. Numbers below the white diagonal show the percentage deviation of total fuel consumption for braking maneuvers and numbers above the white diagonal show the percentage deviation of total fuel consumption for acceleration maneuvers.

Figure 6.3: Comparing the difference in liters between Scop and Stars when driving at -5% road slope. The vertical axis to the left describes starting speed and the horizontal axis on the top describes the target speed. Numbers below the white diagonal show the difference of total fuel consumption for braking maneuvers and numbers above the white diagonal show the difference of total fuel consumption for acceleration maneuvers.

The results of the comparison of the percentage deviation and difference between Stars and Scop for road slope -5% are presented in Figure 6.2 and Figure 6.3. As can be seen in Figure 6.2 Scop shows a higher fuel consumption than Stars for most of the acceleration maneuvers when considering the percentage deviation. However, the difference in liters does deviate noticeably, except for acceleration made to the highest velocities, which can be seen in Figure 6.3.
CHAPTER 6. VALIDATION AND RESULTS

For the braking maneuvers for road slopes of -5%, the total fuel consumption is almost the same for Scop and Stars during braking maneuvers, when considering the difference in liters. Figure 6.2 shows that the percentage deviation for Scop is far below compared to Stars for most of the braking maneuvers. This is because Scop assumes that there is no fuel consumption during a braking maneuver. A couple of braking maneuvers show exactly the same fuel consumption for Scop and Stars, for example the braking maneuvers; 40 to 30 km/h and 50 to 40 km/h. This is because there is no fuel consumption for both models.

Figure 6.4: Comparing the percentage deviation, between Scop and Stars when driving at 2% road slope. The vertical axis to the left describes starting speed and the horizontal axis on the top describes the target speed. Numbers below the white diagonal shows the percentage deviation of total fuel consumption for braking maneuvers and numbers above the white diagonal shows the percentage deviation of total fuel consumption for acceleration maneuvers.

Figure 6.5: Comparing the difference in liters, between Scop and Stars when driving at 2% road slope. The vertical axis to the left describes starting speed and the horizontal axis on the top describes the target speed. Numbers below the white diagonal shows the difference of total fuel consumption for braking maneuvers and numbers above the white diagonal shows the difference of total fuel consumption for acceleration maneuvers.

Comparisons of Scop and Stars for acceleration and braking maneuvers, for 2% road slope of the percentage deviations are presented in Figure 6.4. The difference is also presented for these maneuvers in Figure 6.5. Figure 6.4 shows that...
accelerations made by Scop in general shows a lower fuel consumption than Stars for acceleration up to 50 km/h. For higher acceleration maneuvers the total fuel consumption is close to Stars, when considering percentage deviation. The same pattern is also depicted in Figure 6.5 when considering the difference in liters, except for a couple acceleration maneuvers to 80 and 90 km/h that shows a much higher consumption than Stars.

Considering the braking maneuvers for road slopes of 2%, the total fuel consumption is almost the same for most of the braking maneuvers except for short brakings intervals above 50 km/h, when considering the difference in liters. Figure 6.4 shows that in percentage, Scop compared to Stars, is far below. This is because Scop assumes that there is no fuel consumption during a breaking maneuver.

### 6.1.3 RT-Model - Acceleration and Braking

Comparison of the percentage deviation and the difference between Stars and the RT-model was made for road slopes of -5% and 2%. The total fuel consumption for a certain acceleration or braking maneuver is evaluated.

![Figure 6.6: Comparing the percentage deviation, between the RT-model and Stars when driving at -5% road slope. The vertical axis to the left describes starting speed and the horizontal axis on the top describes the target speed. Numbers below the white diagonal shows the percentage deviation of total fuel consumption for braking maneuvers and numbers above the white diagonal shows the percentage deviation of total fuel consumption for acceleration maneuvers.](image-url)

The results of the comparison of the percentage deviation and difference between Stars and RT-model for road slope -5% are presented in Figure 6.6 and Figure 6.7. As can be seen in Figure 6.6, the RT-model shows a much lower fuel consumption than Stars for most of the acceleration maneuvers when considering the percentage deviation. This is because the RT-model estimates that there is no fuel consumption for road slopes where the gravitational force component is large enough to move the vehicle. As a consequence of this the difference in liters does deviate noticeably for most accelerations, except for short accelerations, which can be depicted in Figure 6.7.
CHAPTER 6. VALIDATION AND RESULTS

Figure 6.7: Comparing the difference in liters, between the RT-model and Stars when driving at -5% road slope. The vertical axis to the left describes starting speed and the horizontal axis on the top describes the target speed. Numbers below the white diagonal show the difference of total fuel consumption for braking maneuvers and numbers above the white diagonal shows the difference of total fuel consumption for acceleration maneuvers.

Considering the braking maneuvers for road slopes of -5%, the total fuel consumption is almost the same for the RT-model and Stars when considering the difference in liters. Figure 6.6 shows almost the same results for braking as Figure 6.2. As mentioned before this is due the assumption that there is no fuel consumption during braking. A couple of braking maneuvers show exactly the same fuel consumption for RT-model and Stars, and this is because there is no fuel consumption for both models.

Figure 6.8: Comparing the percentage deviation, between the RT-model and Stars when driving at 2% road slope. The vertical axis to the left describes starting speed and the horizontal axis on the top describes the target speed. Numbers below the white diagonal show the percentage deviation of total fuel consumption for braking maneuvers and numbers above the white diagonal shows the percentage deviation of total fuel consumption for acceleration maneuvers.

Comparisons of the RT-model and Stars for acceleration and braking maneuvers, for 2% road slope, of the percentage deviations are presented in Figure 6.8. The difference is also presented for these maneuvers in Figure 6.9. Figure 6.8 shows that
6.1. COMPARING FUEL CONSUMPTION MODELS

Figure 6.9: Comparing the difference in liters, between the RT-model and Stars when driving at 2% road slope. The vertical axis to the left describes starting speed and the horizontal axis on the top describes the target speed. Numbers below the white diagonal shows the difference of total fuel consumption for braking maneuvers and numbers above the white diagonal shows the difference of total fuel consumption for acceleration maneuvers.

the fuel consumption for all accelerations made by the RT-model are close to Stars estimations, when considering percentage deviation. However Figure 6.5 shows that the difference in litres is lower for the RT-model than Stars for long accelerations up to 90 km/h from almost all starting speeds.

Considering the braking maneuvers for road slopes of 2%, the total fuel consumption is almost the same for most of the braking maneuvers except for short intervals speeds above 60 km/h, when considering the difference in liters. The percentage deviation is far below for the RT-model compared to Stars also here, because of the assumption of no fuel consumption during braking.

6.1.4 Summary

The fuel consumption when driving at a constant speed and negative slope is for most cases the same for the RT-model, Scop and Stars. Since all models are based on longitudinal force equilibrium according to Newton’s second law, for sufficiently negative road slopes, these models assume that there is no fuel consumption since the gravity force component is sufficient large to move the truck. For drivings at a constant speed and 0% road slope, Scop always shows a higher fuel consumption. These results have also been noted in the validation tests made for Scop [11]. At 0% road slope the RT-model shows a negative percentage deviation of the fuel consumption compared to Stars for speeds between 10-60 km/h and a positive percentage deviation for speeds above 60 km/h. This clear boundary for different estimates is the result of dividing the RT-model in three blocks, as described in Section 4.3. For positive road slopes the fuel consumption deviation in percentage is relatively small for Scop while the RT-model still shows a significantly higher fuel consumption than Stars.
For most of the braking maneuvers the fuel consumption is similar for all three models. Both Scop and the RT-model show no fuel consumption during braking and Stars shows a small, almost negligible, fuel consumption. Accelerations during negative road slopes made with Scop show a higher fuel consumption than Stars. Accelerations during positive road slopes show a smaller fuel consumption for Scop compared to Stars. Considering accelerations made with the RT-model, it show a smaller fuel consumption at negative road slopes and almost the same fuel consumption during positive road slopes compared to Stars.

6.2 Validation of Look up Table

Look up tables were generated with the two models at Scania, Stars and Scop. This chapter will present results for estimation made with these look up tables. Validation tests were made using look up table estimates of fuel consumption compared to the measurements taken similar to the ETC cycle and during a trip from Södertälje to Denmark. Inputs to the look up table estimation were speed and slope profiles for each driving. Before estimation, those profiles were discretized to only include speeds of integer numbers and slopes which are included in the look up table, see Section 5.1.2. To study the error in estimation of total fuel consumption, the relative mean square error $r_{est}$ is used. How this is calculated is described in Appendix D.1.

<table>
<thead>
<tr>
<th>Section</th>
<th>Vel [km/h]</th>
<th>Mass [tonne]</th>
<th>Difference [%]</th>
<th>$r_{est}$ [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>ETC</td>
<td>61</td>
<td>39.2</td>
<td>-12.4</td>
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<td>32.2</td>
</tr>
<tr>
<td>Rural</td>
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<td>-9.2</td>
<td>9.5</td>
</tr>
<tr>
<td>Highway</td>
<td>79</td>
<td>39.2</td>
<td>-7.2</td>
<td>10.1</td>
</tr>
</tbody>
</table>

6.2.1 ETC cycle

The results of the estimates using a look up table generated by Scop for the entire ETC cycle and parts of it, are presented in Table 6.2. This table indicates that the accuracy is better for driving conditions with constant speed and few acceleration and breaking maneuvers. However all estimates are below the actual fuel consumption for each section.

The results of the estimates using a look up table generated by Stars for the entire ETC cycle and parts of it are presented in Table 6.3. This table shows the same characteristics as the look up table estimates made with a Scop generated table. However, these estimates show an even more pronounced bias.
6.2. VALIDATION OF LOOK UP TABLE

Table 6.3: Results of look up table estimates with table generated in Stars, compared to measurements of ETC cycle and parts of it.

<table>
<thead>
<tr>
<th>Section</th>
<th>Vel [km/h]</th>
<th>Mass [tonne]</th>
<th>Difference [%]</th>
<th>$r_{est}$ [%]</th>
</tr>
</thead>
<tbody>
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<td>-29.2</td>
<td>37.7</td>
</tr>
<tr>
<td>Rural</td>
<td>66</td>
<td>39.2</td>
<td>-20.6</td>
<td>18.4</td>
</tr>
<tr>
<td>Highway</td>
<td>79</td>
<td>39.2</td>
<td>-19.6</td>
<td>20.0</td>
</tr>
</tbody>
</table>

6.2.2 Sections of Driving to Denmark

Parts of measurements from a driving to Denmark were also used for validation tests. Estimates made by a look up table generated by Scop are presented in Table 6.4. The results differs from the results of estimates for the ETC cycle. The estimated values are here closer to the measured values though parts similar to city driving still show the highest deviation from measurements. But for one of the estimates, DK hw-2, it shows a larger fuel consumption than it actually was.

Table 6.4: Results of look up table estimates with table generated in Scop, compared to measurements from a driving to Denmark. Sections similar to city driving are denoted c while sections similar to highway driving are denoted hw.

<table>
<thead>
<tr>
<th>Section</th>
<th>Vel [km/h]</th>
<th>Mass [tonne]</th>
<th>Difference [%]</th>
<th>$r_{est}$ [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>DK c-1</td>
<td>31</td>
<td>39.2</td>
<td>-8.4</td>
<td>12.4</td>
</tr>
<tr>
<td>DK c-2</td>
<td>40</td>
<td>39.2</td>
<td>-13.0</td>
<td>16.8</td>
</tr>
<tr>
<td>DK hw-1</td>
<td>81</td>
<td>39.2</td>
<td>0.5</td>
<td>4.6</td>
</tr>
<tr>
<td>DK hw-2</td>
<td>84</td>
<td>39.2</td>
<td>13.2</td>
<td>13.8</td>
</tr>
<tr>
<td>DK hw-2</td>
<td>82</td>
<td>39.2</td>
<td>-1.9</td>
<td>8.6</td>
</tr>
<tr>
<td>DK hw-3</td>
<td>82</td>
<td>39.2</td>
<td>-4.6</td>
<td>7.7</td>
</tr>
</tbody>
</table>

Estimates made by a look up table generated by Stars are presented in Table 6.5. For these estimates the error lies in general between -17.7% and -14.1% except for DK hw-2 were the estimation error is significantly reduced.

6.2.3 Conclusions

There was a clear difference between the validations tests with the ETC cycle and sections from a trip to Denmark. One possible reason could be that the temperature on the day the measurements were collected, may have affected the result. During the day the measurements of the ETC cycle were recorded, the temperature was approximately $-10^\circ$C while the temperature during the trip to Denmark was approximately 0$^\circ$C.
CHAPTER 6. VALIDATION AND RESULTS

Table 6.5: Results of look up table estimates with table generated in Stars, compared to measurements from a driving to Denmark. Sections similar to city driving are denoted c while sections similar to highway driving are denoted hw.

<table>
<thead>
<tr>
<th>Section</th>
<th>Vel [km/h]</th>
<th>Mass [tonne]</th>
<th>Difference [%]</th>
<th>$r_{est}$ [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>DK c-1</td>
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<td>39.2</td>
<td>-16.2</td>
<td>13.3</td>
</tr>
<tr>
<td>DK c-1</td>
<td>40</td>
<td>39.2</td>
<td>-17.7</td>
<td>15.0</td>
</tr>
<tr>
<td>DK hw-1</td>
<td>81</td>
<td>39.2</td>
<td>-12.4</td>
<td>11.9</td>
</tr>
<tr>
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<td>84</td>
<td>39.2</td>
<td>-4.7</td>
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</tr>
<tr>
<td>DK hw-3</td>
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<td>15.0</td>
</tr>
<tr>
<td>DK hw-4</td>
<td>82</td>
<td>39.2</td>
<td>-17.5</td>
<td>18.2</td>
</tr>
</tbody>
</table>

In summary estimating fuel consumption with look up tables give in most cases an underestimate of approximately -10%. One reason for this could be that look up table estimation does not include accelerations for speed changes smaller than 10km/h. If a driver does small speed changes during the whole trip the additional fuel that is consumed because of this is neglected by look up table estimation.

6.3 Validation of RT-Model

Validation results for fuel estimation made by the real time models will be presented and described in this section. A study of how the estimation results vary with the simulation step size was done and these results will also be presented in this section.

To study the error in estimation of total fuel consumption, the relative mean square error $r_{est}$ is used. How this is calculated is described in Appendix D.1.

Table 6.6: Comparing estimates made with the RT-model to measurements from the ETC cycle and sections of it.

<table>
<thead>
<tr>
<th>Section</th>
<th>Vel [km/h]</th>
<th>Mass [tonne]</th>
<th>Difference [%]</th>
<th>$r_{est}$ [%]</th>
</tr>
</thead>
<tbody>
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<td>39.2</td>
<td>-16.2</td>
<td>32.0</td>
</tr>
<tr>
<td>Rural</td>
<td>66</td>
<td>39.2</td>
<td>-7.0</td>
<td>5.4</td>
</tr>
<tr>
<td>Highway</td>
<td>79</td>
<td>39.2</td>
<td>-1.1</td>
<td>3.6</td>
</tr>
</tbody>
</table>

6.3.1 ETC Cycle

The results of the estimates made for the ETC cycle and parts of it are presented in Table 6.6. All estimates showed an underestimate when studying the difference. However the city part of the cycle showed the lowest estimate compared to the measured value. Considering the relative mean square error, the rural and highway
part of the cycle showed best accuracy. While the city part of the cycle with \( r_{est} = 32.0\% \), showed poor accuracy. Considering the relative mean square error for the whole ETC cycle, it was significantly higher compared to the rural and highway part. Since the city part of the cycle had the highest relative mean square error, this seemed to affect the result for estimation of the whole cycle.

The following sections will give a more detailed description of the driving and the estimates of each part of the ETC cycle.

City

When driving in a city environment, speed changes were continuously done for velocities between 0 and 50 km/h as can be seen in Figure 6.10. Several stops due to for example traffic lights were executed and because of this, there were a lot of gear changes. As can be seen in Table 6.6, the relative mean square error is significantly higher compared to the other sections. The lower plot in Figure 6.10 shows that the estimated total fuel consumed always was lower than measurements.

![Figure 6.10: Measurements of speed and gears during city driving. Estimation and measurement of total fuel consumption can be seen in the lower plot. The numbers on the y-axis of the bottom plot are normalized units between 0 and 30.](image)

Rural

The cruising speed during rural driving was almost always kept around 70 km/h with few significant speed changes. This is depicted in the upper graph in Figure 6.11. Because of an almost constant cruising speed, the road slope had most influence on the instantaneous fuel consumption changes. The road slope and the instantaneous
CHAPTER 6. VALIDATION AND RESULTS

fuel consumption are depicted in the two middle plots in Figure 6.11. The relative mean square error for estimation made for the section of rural driving was relatively low, \( r_{est} = 5.4\% \) as can be seen in Table 6.6. The accumulated fuel consumption during the trip was slightly underestimated.

Figure 6.11: Measurements of speed and gears during rural driving. Estimate and measurement of total fuel consumption can be seen in the lower plot. The numbers on the y-axis of the second and bottom plot are normalized units between 0 and 30.

Highway

A constant speed of 80 km/h was kept during almost the whole highway driving part, as can be depicted in the upper graph in Figure 6.12. Comparing the slope and the instantaneous consumption plot shows that the instantaneous consumption follows the variation of the slope. This indicates that the fuel consumption during highway driving is strongly influenced by the road slope. Relative mean square error of total fuel consumed for the highway estimation is \( r_{est} = 3.6\% \), see Table 6.6.

6.3.2 Sections of Drivings to Denmark and Karlstad

Sections describing city and highway driving were used from measurement data of drivings to Danmark and Karlstad. The results of the estimation made for these sections are presented in Table 6.7.

Table 6.7 shows that for most highway sections the relative mean square error \( r_{est} \), lies within 3\% and 6\%. For estimates made for a truck with lower mass, 24.2
6.3. VALIDATION OF RT-MODEL

Figure 6.12: Measurements of speed, road slope and instantaneous consumption during highway driving. Estimation and measurement of total fuel consumption can be seen in the lower plot. The numbers on the y-axis of the second and bottom plot are normalized units between 0 and 30.

Table 6.7: Results of RT-model estimates, compared to measurements from drivings to Denmark and Karlstad. Sections similar to city driving are denoted c while sections similar to highway driving are denoted hw.

<table>
<thead>
<tr>
<th>Section</th>
<th>Vel [km/h]</th>
<th>Mass [tonne]</th>
<th>Difference [%]</th>
<th>r_{est} [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>DK c-1</td>
<td>31</td>
<td>39.2</td>
<td>-10.1</td>
<td>10.5</td>
</tr>
<tr>
<td>DK c-2</td>
<td>40</td>
<td>39.2</td>
<td>-6.5</td>
<td>5.8</td>
</tr>
<tr>
<td>DK hw-1</td>
<td>81</td>
<td>39.2</td>
<td>0.6</td>
<td>4.1</td>
</tr>
<tr>
<td>DK hw-4</td>
<td>84</td>
<td>39.2</td>
<td>0.2</td>
<td>3.4</td>
</tr>
<tr>
<td>KS hw-1</td>
<td>83</td>
<td>24.2</td>
<td>-4.8</td>
<td>9.2</td>
</tr>
<tr>
<td>KS hw-2</td>
<td>84</td>
<td>24.2</td>
<td>5.8</td>
<td>4.9</td>
</tr>
<tr>
<td>KS hw-3</td>
<td>81</td>
<td>24.2</td>
<td>4.0</td>
<td>4.7</td>
</tr>
<tr>
<td>KS hw-4</td>
<td>83</td>
<td>24.2</td>
<td>2.5</td>
<td>5.2</td>
</tr>
</tbody>
</table>

In tonnes, the relative mean square error, r_{est}, is below 6% for all sections except KS hw-1. For city drivings, r_{est} is up to 10.5%.
6.3.3 Modelling Error

For all types of drivings presented, the biggest difference between estimated and measured fuel consumption occurred for drivings in a city environment. The RT-model showed an estimate that deviated with -16.2% from the measured value. In this section one of the possible modelling errors that could be the reason for this is investigated.

![Figure 6.13:](image)

Figure 6.13: Segments of modelling errors highlighted of the measurements and estimates, when driving in a city environment. The numbers on the y-axis of the first plot are normalized units between 0 and 30.

When the truck was driving or changing to lower gears the estimated instantaneous fuel consumption was always lower than the measured. This can be seen in Figure 6.13. The difference between estimate and measurement of the fuel consumption during the highlighted segments in Figure 6.13 was therefore examined. The results are presented in Table 6.8.

As can be seen the RT-model showed an significant underestimate for all the highlighted segments, between -17% and -74%. If the differences for all highlighted segments are summed and added to the total fuel consumption estimate for the city part of the ETC cycle, it would give an increase of 11%. The total fuel consumption estimate would then differ with -6.1% from the measured number.

Table 6.8: Difference of RT-model estimates and measurements of fuel consumption for the highlighted segments in Figure 6.13.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Difference [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-74.2</td>
</tr>
<tr>
<td>2</td>
<td>-46.5</td>
</tr>
<tr>
<td>3</td>
<td>-35.0</td>
</tr>
<tr>
<td>4</td>
<td>-16.7</td>
</tr>
<tr>
<td>5</td>
<td>-59.4</td>
</tr>
</tbody>
</table>
6.3. VALIDATION OF RT-MODEL

Since input to the RT-model is the instantaneous tractive power demand, the model do not consider engine speed or engine torque. Therefore it does not consider which gear is activated, since this is dependent on engine speed and engine torque. During lower gears the equivalent mass of the moving parts in the power train, vary. This could affect the instantaneous fuel consumption. The impact of an increase of the mass that needs to be accelerated during different gears is presented in Section 6.5.

6.3.4 Varying Estimation Step Size

In order to reduce runtime during estimation, the estimation step size can be increased. This leads to less detailed information about the slope, speed and acceleration profile, and should lead to a less accurate fuel consumption estimation. A comparison of the fuel consumption estimates for different estimation step size were done and the results are presented in Table 6.9. For simulation step sizes up to 5s, the accuracy was maintained, though for a simulation step size equal to 10s the accuracy is significantly reduced.

<table>
<thead>
<tr>
<th>Section</th>
<th>$\Delta t_{est}=0.2s$</th>
<th>$\Delta t_{est}=1.0s$</th>
<th>$\Delta t_{est}=5.0s$</th>
<th>$\Delta t_{est}=10s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ETC</td>
<td>19.3</td>
<td>19.3</td>
<td>19.8</td>
<td>21.0</td>
</tr>
<tr>
<td>ETC city</td>
<td>32.0</td>
<td>31.9</td>
<td>33.2</td>
<td>36.3</td>
</tr>
<tr>
<td>ETC rural</td>
<td>5.4</td>
<td>5.2</td>
<td>5.9</td>
<td>13.2</td>
</tr>
<tr>
<td>ETC highway</td>
<td>3.6</td>
<td>3.5</td>
<td>3.4</td>
<td>9.3</td>
</tr>
</tbody>
</table>

6.3.5 Conclusions

The validation tests shows relatively high accuracy for highway and rural driving estimation, with relative mean square error of approximately $r_{est}=5\%$, but a significantly higher error for city driving where the relative mean square error lies between 6 and 19\%.

The section that showed lowest accuracy was the city part of the ETC cycle. This section, compared to the others, included several starts and stops from quiescent state, which could have an impact on the estimation. The results show that for sections with a large numbers of acceleration events the accuracy was significant reduced. One reason for this could be the assumption of a constant brake thermal efficiency, $\varepsilon_b$. For drivings in a city environment where a lot of braking maneuvers are made, the brake thermal efficiency varies and is in many cases significantly reduced. For the RT-model, $\eta_t$ is assumed to be constant. The assumption of a constant transmission efficiency in three blocks, $\eta_t$ could give rise to estimation
errors since in reality this parameter varies significantly for driving events that require a low engine torque and engine speed.

One of the modelling errors during city driving was the instantaneous increase of fuel consumption during gear changes to lower gears. The study of the relationship between low gears and lower estimate compared to measurement showed that approximately 11% of total fuel consumption was missed during low gears. In order to take the increased fuel consumption during low gears into account, a model that is dependent on the current gear would be needed.

Varying simulation step sizes for the RT-model, showed that the accuracy does not deteriorate for simulation step sizes up to 5 s. This indicates that high resolution information about the road slope and velocity is not always required to still preserve the accuracy.

6.4 Accuracy for Eco-Routing

The accuracy for the estimation methods have mainly been analyzed by studying the relative mean square error \( r_{est} \), described in Appendix D.1. In this section the distribution of the estimation errors are further analyzed to evaluate which method could be appropriate for an eco-routing system according to the rules of thumb presented in Section 4.4, Equation (4.15) or Equation (4.18).

6.4.1 Real Time Estimation

The results from the validation tests for the RT-model are in this section summarized along with real time estimation made with the Oguchi model \[26\], presented in Section 4.3.2. The distribution for the estimation errors by the RT-model is also presented.

Relative Mean Square Error

Estimation made with the RT-model and the Oguchi model are presented in Table 6.10. The results for city driving shows that \( r_{est} \) for city driving varies between 32.0% and 5.8% for the RT-model, and for the Oguchi model between 44.8% and 15.3%.

The comparison shows that during highway and rural driving, \( r_{est} \) is for the RT-model below 5.4% for all estimates for a heavy truck, and below 8.3% for the Oguchi model. This indicates on that relatively good estimation can be obtained with a simple model with several general assumptions, the Oguchi model described in Section 4.3.2. A vehicle specific model such as the RT-model, decreases \( r_{est} \) with approximately 1.7%. For a lighter truck the estimation errors are relatively low using the RT-model for most cases. However E estimation made with the Oguchi model show significantly lower accuracy than the model showed for a heavy truck.
Table 6.10: Comparing $r_{est}$ for estimation made with the RT-model and the Oguchi model.

<table>
<thead>
<tr>
<th>Section*</th>
<th>Vel [km/h]</th>
<th>Mass [tonne]</th>
<th>RT-model $r_{est}$ [%]</th>
<th>Oguchi $r_{est}$ [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>ETC city</td>
<td>34</td>
<td>39.2</td>
<td>32.0</td>
<td>44.8</td>
</tr>
<tr>
<td>DK c-1</td>
<td>32</td>
<td>39.2</td>
<td>10.5</td>
<td>21.9</td>
</tr>
<tr>
<td>DK c-1</td>
<td>40</td>
<td>39.2</td>
<td>5.8</td>
<td>15.3</td>
</tr>
<tr>
<td>ETC rural</td>
<td>66</td>
<td>39.2</td>
<td>5.4</td>
<td>8.3</td>
</tr>
<tr>
<td>ETC hw</td>
<td>78</td>
<td>39.2</td>
<td>3.6</td>
<td>4.7</td>
</tr>
<tr>
<td>DK hw-1</td>
<td>81</td>
<td>39.2</td>
<td>4.7</td>
<td>3.9</td>
</tr>
<tr>
<td>DK hw-2</td>
<td>84</td>
<td>39.2</td>
<td>5.1</td>
<td>5.3</td>
</tr>
<tr>
<td>DK hw-3</td>
<td>82</td>
<td>39.2</td>
<td>4.1</td>
<td>8.2</td>
</tr>
<tr>
<td>DK hw-4</td>
<td>82</td>
<td>39.2</td>
<td>3.4</td>
<td>5.0</td>
</tr>
<tr>
<td>KS hw-1</td>
<td>83</td>
<td>24.2</td>
<td>9.2</td>
<td>9.2</td>
</tr>
<tr>
<td>KS hw-2</td>
<td>84</td>
<td>24.2</td>
<td>4.9</td>
<td>7.6</td>
</tr>
<tr>
<td>KS hw-3</td>
<td>81</td>
<td>24.2</td>
<td>4.7</td>
<td>6.6</td>
</tr>
<tr>
<td>KS hw-4</td>
<td>83</td>
<td>24.2</td>
<td>5.2</td>
<td>7.6</td>
</tr>
</tbody>
</table>

*The sections that ends with c, describe city drivings. Similarly section that ends with hw, describe highway drivings.

With these results and the previously presented rule of thumb, Equation (4.15), estimates for city driving are not good enough to be used in an eco-routing system since the estimation error is too large. However recommendations for highway and rural driving are good enough to do recommendations where the saving potential is at least $\delta_{\text{save}} = 10\%$.

**Error Distribution**

The distribution of the errors for the RT-model during city drivings is presented in Figure 6.14. This figure shows that measurements errors for city traffic are very scattered and $r_{est} < 10\%$ for approximately 50% of the estimation errors during city drivings. This indicates on high uncertainty for real time estimation by the RT-model for city drivings. The presented error distribution confirms that the estimation accuracy for city driving with RT-model is too low to be used in an eco-routing system.

The distribution of the errors for real time estimation with the RT-model during highway and rural drivings is presented in Figure 6.15. It shows that $r_{est} < 5\%$ for approximately 80% of the estimation errors during highway and rural drivings. Thus relatively high certainty can be achieved for highway and rural drivings with the RT-model. These results confirms that the accuracy during highway and rural driving for the RT-model could be good enough to be used in an eco-routing system, as mentioned in the previous section.
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Figure 6.14: Distribution of estimation errors by the RT-model during city driving. The frequency of the error distribution can be seen in the graph to the left, the cumulative distribution of $r_{est}$ can be seen in the graph to the right.

Figure 6.15: Distribution of all errors for estimates made with the RT-model during highway and rural driving. The frequency of the error distribution can be seen in the graph to the right, the cumulative distribution of $r_{est}$ can be seen in the graph to the right.

Fastest and Fuel Efficient Route

Since $r_{est} < 5\%$ for most of the estimates during highway and rural driving, recommendations should be made for cases when the saving potential is 10\% according the rule of thumb, Equation (4.15). Therefore a similar scenario described in Section 4.4.1 where the saving potential is $\delta_{save} = 10\%$ is considered. Possible estimates were approximated using error data from the validation tests. Cost estimates using these errors were calculated according to,

$$J_{est} = J_j \cdot (1 + e_i).$$

(6.1)

where $J_j$ is assumed to describe the real fuel cost for route $j$ and $e_i$ is the estimation errors $e_i = e_1, e_2, \ldots, e_n$. 
6.4. ACCURACY FOR ECO-ROUTING

Figure 6.16: Frequency for RT-model estimates for the fastest route and fuel efficient route using the error data from validation tests, when the saving potential is $\delta_{\text{save}} = 10\%$. The estimation intervals overlap each other for approximately 11% of the estimates.

Using Equation (6.1), the distribution of the estimates for the fastest route and the most fuel efficient route are calculated and depicted in Figure 6.16. Approximately 11% of the estimation intervals overlapped each other and a risk of wrong recommendations exists. This indicates on that rule of thumb is a relatively good assumption of which recommendations that should be done by the eco-routing system. Also that the RT-model can be used for the cases when the saving potential is equal or larger than 10%, according the rule of thumb, Equation (4.15).

6.4.2 Look up Table Estimation

The relative mean square error for look up table estimates are in this section analyzed from an eco-routing point of view. The distribution of the estimation errors are also studied and presented.

Relative Mean Square Error

Estimation made with look up tables generated by Scop and Stars are presented in Table 6.11. With the relative mean square error as an accuracy parameter, the accuracy is very low most of the estimates, in particularly for city drivings. Taking the rule of thumb into account, Equation (4.15), recommendations should only be done for the few cases when the saving potential is very high due the low accuracy. Therefore the error should be further analyzed by studying the error distribution, this is done in the next section.
Table 6.11: Comparing $r_{est}$ for look up table (LT) estimates made with tables generated by Scop and Stars.

<table>
<thead>
<tr>
<th>Section*</th>
<th>Vel [km/h]</th>
<th>Mass [tonne]</th>
<th>LT Scop $r_{est}$ [%]</th>
<th>LT Stars $r_{est}$ [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>ETC city</td>
<td>34</td>
<td>39.2</td>
<td>32.2</td>
<td>37.7</td>
</tr>
<tr>
<td>DK c-1</td>
<td>32</td>
<td>39.2</td>
<td>12.4</td>
<td>13.3</td>
</tr>
<tr>
<td>DK c-2</td>
<td>40</td>
<td>39.2</td>
<td>16.8</td>
<td>15.0</td>
</tr>
<tr>
<td>ETC rural</td>
<td>66</td>
<td>39.2</td>
<td>9.5</td>
<td>18.4</td>
</tr>
<tr>
<td>ETC hw</td>
<td>78</td>
<td>39.2</td>
<td>10.1</td>
<td>20.0</td>
</tr>
<tr>
<td>DK hw-1</td>
<td>81</td>
<td>39.2</td>
<td>4.6</td>
<td>11.9</td>
</tr>
<tr>
<td>DK hw-2</td>
<td>84</td>
<td>39.2</td>
<td>13.8</td>
<td>8.4</td>
</tr>
<tr>
<td>DK hw-3</td>
<td>82</td>
<td>39.2</td>
<td>8.6</td>
<td>15.0</td>
</tr>
<tr>
<td>DK hw-4</td>
<td>82</td>
<td>39.2</td>
<td>7.7</td>
<td>18.2</td>
</tr>
</tbody>
</table>

*The sections that ends with c, describe city drivings. Similarly section that ends with hw, describe highway drivings.

Error Distribution

The distribution of the errors for estimates by a Stars generated look up table, is presented in Figure 6.17. As can be seen in the graph to the left, the estimation errors are spread out between -40% and 40%. The graph to the right confirms this by showing that almost 60% of the $r_{est}$ are within 10% and 40%. This confirms the low accuracy of the estimates during city drivings.

![Error distribution graph](image)

**Figure 6.17:** Distribution of estimation errors by a look up table generated in Stars, during city driving. The frequency of the error distribution can be seen in the graph to the left, the cumulative distribution of $r_{est}$ can be seen in the graph to the right.

The distribution of the estimation errors by a look up table generated by Stars
for highway and rural driving is presented in Figure 6.18. Even though the relative
mean square error were relatively high for these drivings, \( r_{est} \geq 8.4\% \), the errors
seem to be concentrated around a certain mean error. The graph to the right also
shows that almost 90\% of the errors were within -10\% to -20\%.

\[ \text{Figure 6.18: Distribution of estimation errors by a look up table generated in Stars, during}
\text{highway and rural driving. The frequency of the error distribution can be}
\text{seen in the graph to the left, the cumulative distribution of } r_{est} \text{ can be seen}
\text{in the graph to the right.} \]

In order to study how the error data during highway and rural drivings were
distributed, confidence intervals for the ETC drivings and Denmark drivings were
defined according to Section D.2. The results are presented in Table 6.12. The

\[ \text{Table 6.12: Parameters of confidence intervals for drivings during highway and rural traffic}
\text{with a truck of 39.2 tonnes.} \]

<table>
<thead>
<tr>
<th>Section</th>
<th>( r_{est} ) [%]</th>
<th>( D ) [%]</th>
<th>( \bar{e} ) [%]</th>
<th>C-level* [%]</th>
<th>( t_{\alpha/2}(f) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>ETC</td>
<td>9.5 to 10.1</td>
<td>0.8</td>
<td>-19.0</td>
<td>99</td>
<td>2.62</td>
</tr>
<tr>
<td>DK</td>
<td>4.6 to 13.8</td>
<td>1.4</td>
<td>-13.0</td>
<td>99</td>
<td>2.62</td>
</tr>
</tbody>
</table>

*Confidence level

relative mean square error for all drivings were higher than the deviation parameter
\( D \). In this case it could be misleading setting up the possible estimation ranges
using \( r_{est} \), described in Section 4.4.2. The width of the estimation intervals would
be within \( \pm r_{est} \). Therefore the estimation intervals would be far greater than the
distribution of the estimation errors actually were according to the confidence in-
tervals in Table 6.12. Thus it is more appropriate to study the confidence interval
when comparing estimation intervals.
Fastest and Fuel Efficient Route

Considering look up table estimation for a similar scenario as described in Section 4.4.1 with the saving potential $\delta_{save} = 10\%$, estimation costs were approximated. Using Equation (6.1) with the error data from validation tests for a look up table generated by Stars, cost estimates were calculated. The distribution of estimates for the fastest route and the most fuel efficient route are depicted in Figure 6.19. Approximately 13% of the estimation intervals overlapped each other, and a risk of wrong recommendations exist. This result along with the maximum deviation $D = 1.4\%$ and the rule of thumb, Equation (4.18) indicates on that recommendations for saving equal or larger than 10% can be achieved with relatively high certainty for highway and rural drivings.

6.4.3 Conclusions

Real time estimation with the RT-model during city driving showed that the errors were scattered and that accuracy indicated by the relative mean square error gave a correct description of the low accuracy. Therefore the RT-model is not appropriate for city driving estimation for an eco-routing system. The study of the error distribution for estimates during highway and rural driving showed that these errors were concentrated around $r_{est} = 5\%$. The distribution of these estimation errors indicated on that the relative mean square error showed a correct description of the accuracy. It showed that the rule of thumb, Equation (4.15), could be used when the saving is equal or larger than 10% for highway and rural drivings.

Comparing real time estimation with the RT-model and the Oguchi model for rural and highway driving, showed that a relatively simple model was good enough to
do estimates with an error lower than \( r_{est} = 9\% \) for both a light and a heavy truck. Using a model with vehicle specific parameters, the RT-model, showed an error lower than \( r_{est} = 6\% \) for both a light and a heavy truck. This is a mean decrease of approximately 2\% of the error compared to the simplified Oguchi model. The error distribution by the Oguchi model was not studied. But assuming that those estimation errors shows same distribution as the RT-model, the Oguchi model could be used in an eco-routing system. With the rule of thumb, Equation (4.15), it could in that case be used when the saving are equal or larger than 18\% for highway and rural drivings.

Estimation made by a look up table generated in Stars showed during validation tests poor accuracy with \( r_{est} > 10\% \) for most cases. Therefore confidence intervals for these errors were studied and showed that the relative mean square error showed a higher estimation uncertainty from an eco-routing point of view, than it actually was. The deviation parameters for highway and rural drivings were significantly lower compared to the relative mean square errors. For these estimates it is therefore more suitable to use the rule of thumb presented in Equation (4.18) along with the deviation parameter \( D \) instead of Equation (4.15) for which recommendations that should be given by an eco-routing system. The rule of thumb with along with the error distribution results for an possible eco-routing scenario showed that recommendations can be given when the saving is equal or larger than 10\% for highway and rural drivings.

6.5 Sensitivity Analysis

An sensitivity analysis was made for the RT-model for some parameters. The speed \( v \), road slope and rolling resistance, \( c_r \) that is a function of the vehicle speed, varies during a driving and were therefore analyzed. While the vehicle mass \( m \) and the frontal area \( A \) are static parameters that needs to be approximated with a proper method. The results are presented in Table 6.13 and are compared to the results from an sensitivity analysis that was made for Stars in [34].

The sensitivity analysis for the RT-model is similar in the sense of the order of which parameter has the largest influence on the fuel consumption, except the rolling resistance. The vehicle speed has for both models highest impact on fuel consumption. This could because fuel consumption because of several parameters are implicit dependent on the speed, such as \( c_r \), Slope and \( A \). However there is clear difference of the impact on the fuel consumption of the speed parameter between the RT-model and Stars. A reason for this could be that the vehicle speed and acceleration has direct impact on the fuel consumption for the RT-model. While in Stars, the fuel consumption is also dependent on the actual engine speed that is dependent on both vehicle speed and road slope.
CHAPTER 6. VALIDATION AND RESULTS

Table 6.13: Relative sensitivity for the RT-model and Stars on fuel consumption for mass, rolling resistance, frontal area and road slope. The values for Stars are taken from [34].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>RT-model</th>
<th>Stars</th>
</tr>
</thead>
<tbody>
<tr>
<td>±10% fuel consumption</td>
<td>±[%] fuel consumption</td>
<td>±[%] fuel consumption</td>
</tr>
<tr>
<td>$v$</td>
<td>16.0</td>
<td>6.2</td>
</tr>
<tr>
<td>$m$</td>
<td>7.4</td>
<td>5.3</td>
</tr>
<tr>
<td>$c_r$</td>
<td>4.1</td>
<td>2.9</td>
</tr>
<tr>
<td>Slope</td>
<td>2.5</td>
<td>2.2</td>
</tr>
<tr>
<td>$A$</td>
<td>2.4</td>
<td>3.6</td>
</tr>
</tbody>
</table>

6.5.1 Impact on Fuel Consumption by Activated Gear

Dependent on which gear is activated the equivalent mass that needs to be accelerated by the power train varies. An analysis of how this mass varies with the activated gear is presented in Table 6.14. As can be seen $m_j$ is very high at the lowest gear which normally is rarely activated, especially during highway and rural driving. Gears below the fourth gear are activated around 10% of the total time when driving in City environment, shown in Figure 6.13. When the fourth gear is activated it gives an increase of the total mass of approximately 6%.

Table 6.14: Variation of the equivalent mass, $m_j$, with regard to the activated gear.

<table>
<thead>
<tr>
<th>Gear</th>
<th>$m_j$ [kg]</th>
<th>Fuel consumption [%]*</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>9230</td>
<td>11.1</td>
</tr>
<tr>
<td>4</td>
<td>2426</td>
<td>2.7</td>
</tr>
<tr>
<td>8</td>
<td>477</td>
<td>0.3</td>
</tr>
<tr>
<td>12</td>
<td>163</td>
<td>-</td>
</tr>
</tbody>
</table>

*Fuel consumption difference is compared to the case when 12th gear is activated.

The sensitivity analysis shows that the mass is one of the parameters that has highest influence on the fuel consumption, where an increase of 10% in mass gives an increase of fuel consumption of approximately 6%. The results in Table 6.14 shows that the variation of mass is significant at low gears, especially for light trucks. Around 10% of the total time during city driving of the ETC cycle was in the fourth gear or lower. This leads to an increase of fuel consumption that is not modelled by the RT-model nor the Oguchi model.

6.6 Eco-Routing Results

Eco-routing simulations were made with the look up tables generated by Scop and Stars. During the simulations the fastest route was compared to the most fuel effi-
6.6. ECO-ROUTING RESULTS

cient route. The results of eco-routing for a set of long haulage routes are presented in Figure 6.20. These simulations were made with look up tables generated in Scop and Stars. It can be seen that there existed a route with 10% or larger fuel saving alternative compared to the fastest for approximately 45% of the simulations. The mean saving for all 36 simulated routes when such routes were chosen was equal to around 8.5%.

Figure 6.20: Results of ECO-routing simulations between cities. The y-axes show percent of the driving (left) and mean saving potential (right) for all routes were the savings per route is equal or larger than the value on the x-axis.

Table 6.15: Share, mean saving and mean time increase for cases when there exists a more fuel efficient route than the fastest of \( \delta_{\text{save}} \geq \) for some numbers.

<table>
<thead>
<tr>
<th>( \delta_{\text{save}} \geq )</th>
<th>Share of simulations</th>
<th>Mean saving*</th>
<th>Mean time increase*</th>
</tr>
</thead>
<tbody>
<tr>
<td>[%]</td>
<td>[%]</td>
<td>[%]</td>
<td>[%]</td>
</tr>
<tr>
<td>5</td>
<td>58</td>
<td>-23</td>
<td>11</td>
</tr>
<tr>
<td>10</td>
<td>45</td>
<td>-27</td>
<td>13</td>
</tr>
<tr>
<td>20</td>
<td>20</td>
<td>-35</td>
<td>12</td>
</tr>
</tbody>
</table>

*These are the mean values only for the cases were a recommendation is given according to the column to the left.

Figure 6.20 shows that savings can be done for a significant part of the simulations. However, taking a fuel efficient route alternative may lead to an increased travelling time. Therefore the travelling time and mean saving for the certain simulations were a saving \( \delta_{\text{save}} \geq 5\% \), 10\% and 20\% are compared in Table 6.15. Taking into account routes were the saving is high, leads to a larger mean saving for those sets of simulations, as expected. However, the mean time increase is approximately the same for all the presented sets of simulations, around 10%. The set of simulation were the saving is at least 20% are therefore more economic than the other.
sets, when taking the time increase into account. However, this set is only 20% of all 36 simulations. Example of three simulated routes regarding increased travelling time are presented in Appendix C.

6.6.1 Conclusions

The eco-routing results shows that there are significant savings that can be done according to the rule of thumb, Equation (4.15), and the accuracy analysis made in Section 6.4 for rural and highway drivings. It can be concluded that estimates by the look up tables and the RT-model were good enough to be used in a eco-routing system for recommendations where there exists a 10% more fuel efficient alternative. Therefore, the simulation results with the look up tables can be used as an indication of what savings can be achieved with the RT-model as well. Taking this into account the mean saving for the 36 simulation routes is equal to approximately 8.5%.

Even though a more fuel efficient alternative than the fastest route exists, for most of these cases it leads to an increased travelling time. For the certain set were there existed a 10% more fuel efficient route than the fastest route the approximated time increase was 10%. The costs for an increased travelling time needs to be further studied, taking into account for example; drivers salary, wear costs and delay costs.

6.7 Implementation

In this section computation time for the different estimation methods are compared. An evaluation of the methods is done regarding which method would be suitable to use in an eco-routing system.

6.7.1 Computation Time

Most of this work has been done in Matlab. To implement the RT-model in a similar eco-routing system as the one presented in Section 2.2, it needs to be written in C++. Therefore an evaluation was done regarding computation time between Matlab and C++. The results are presented in Table 6.16. Exactly same calculations

<table>
<thead>
<tr>
<th>Cycle</th>
<th>Size*</th>
<th>Matlab/step</th>
<th>C++/step</th>
<th>Matlab tot</th>
<th>C++ tot</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>21 246</td>
<td>0.1359</td>
<td>0.0046</td>
<td>2 887</td>
<td>97</td>
</tr>
<tr>
<td>City</td>
<td>6 207</td>
<td>0.0842</td>
<td>0.0047</td>
<td>523</td>
<td>29</td>
</tr>
<tr>
<td>Rural</td>
<td>7 648</td>
<td>0.0904</td>
<td>0.0047</td>
<td>691</td>
<td>36</td>
</tr>
<tr>
<td>Highway</td>
<td>7391</td>
<td>0.0904</td>
<td>0.0049</td>
<td>668</td>
<td>36</td>
</tr>
<tr>
<td>Söd-Jön</td>
<td>129 114</td>
<td>1.1513</td>
<td>0.0047</td>
<td>148 650</td>
<td>605</td>
</tr>
</tbody>
</table>

*Number of rows(step) that the input vector contains of
were done in Matlab and C++. As can be seen in Table 6.16 the calculation time for each step is consistent in C++, but in Matlab the calculation time for each step increases with an increased input vector. The biggest difference is the calculation time for large input vectors, where C++ is approximately 246 times faster than Matlab for the largest vector, Söd-Jön.

<table>
<thead>
<tr>
<th>Route</th>
<th>RT-model [s]</th>
<th>Scop [s]</th>
<th>Stars* [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Söd-Jön</td>
<td>1</td>
<td>1</td>
<td>180</td>
</tr>
</tbody>
</table>

*This value was recorded with an external counter compared to the RT-model and Scop.

Assuming that the RT-model runs in C++, a comparison was made between the RT-model, Scop and Stars. The results are presented in Table 6.17. There is a clear difference between calculations made in dymola, where Stars is programmed in compared to the RT-model and Scop that is programmed in C#.

### 6.7.2 Conclusions

When a user executes a route optimization in an eco-routing on board a truck, it cannot be too time consuming. Therefore fuel consumption estimation needs to be fast in an eco-routing system, since there are other needed calculations that are time consuming. For an fuel consumption model to work in an eco-routing system like the one described in Section 2.2 it is preferable to be written in C++.

The saving potential by an eco-routing system for highway and rural drivings for different methods is presented in Figure 6.21. The conclusions that follows are made with the assumption that the results from the look up table simulations during highway and rural driving are representative for other estimation methods with higher accuracy. The savings that can be achieved with each estimation method is with regard to the previous presented rule of thumb, Equation (4.18).

Using Stars as an estimation method in an eco-routing shows that mean saving of least 9.5% can be achieved. However this method is time consuming and built in an unsuitable environment. The RT-model shows a mean saving of 8.5% and has a fast computational time when implemented in C++. The simplified Oguchi model implemented in the same environment as the RT-model shows a mean saving of 6%. However no conclusions can be drawn regarding Scop, since the accuracy requirement needs to be further investigated. Another drawback with Scop is fuel consumption is not estimated using a predefined speed profile. Scop estimates the fuel consumption with an estimated cruising speed and estimated number of stops during the trip.
**Figure 6.21**: Comparing estimation models with each other regarding expected savings potential and adequacy.
It was concluded that savings should only be made according to one of the rules of thumb presented in Section 4.4, Equation (4.15) or Equation (4.18). This dependent on whether the relative mean square error or the confidence interval of the method in question is considered. These rules of thumb are based on if the estimation intervals of two route alternatives that are compared, overlap or not. If the intervals do overlap, there exists a risk of giving the wrong recommendation. Therefore, no recommendation should be given by an eco-routing system for these cases.

Two estimation methods have been presented and validated, look up table estimation and real time estimation. Look up tables showed, when studying the relative mean square error, a poor accuracy. Estimation for city driving are concluded to be too poor to be used in an eco-routing system. The main reason is most probably the inability to take different accelerations into account. However, the width of confidence intervals were relatively small for highway and rural driving estimates. Simulation results showed that fuel savings of approximately 8.5% can be done by look up table estimation for highway and rural traffic. However, look up tables is not a proper method to use in an eco-routing system for trucks. The mass of a truck varies and the power train can be configured in many ways. In addition to this, different driving styles requires additional look up tables. This leads to an endless number of look up tables that needs to be generated. Therefore this method is concluded as an unsuitable estimation method for an eco-routing system for trucks.

Fuel consumption during city drivings were not possible to estimate with sufficient accuracy with neither the RT-model nor the Oguchi model. As with the look up tables, these models showed a poor accuracy when estimating fuel consumption during acceleration maneuvers. The varying equivalent mass of the power train lead to an increase of fuel consumption in low gears and this was not taking into account by these models. In order to do that, the models must also include the engine speed and the engine torque to be able to model which gear that is activated. However, real time estimates showed a good accuracy for highway and rural drivings, with a relative mean square error equal or lower than 5%. One reason for this could be the
absence of acceleration maneuvers during these type of drivings. If the simulation results of 36 long haulage routes by look up tables are used as an representative indication of which fuel savings that can be done, the RT-model shows significant saving potential. The accuracy of the RT-model, taking the rule of thumb into account, showed that fuel savings could be made of approximately 8.5% for highway and rural drivings.

An notable advantage with real time estimation is that a varying mass easily can be taken into account, by just changing some of the predefined parameters in the models. However, the accuracy of real time estimation is dependent on a good driver model that generates realistic speed profiles dependent on driving style.

The existing fuel consumption modelling programs at Scania, Scop and Stars were studied. Even though the accuracy for Stars is high for rural and highway drivings, Stars is built in an unsuitable environment, Dymola, and is too time consuming. Therefore it is not suited to be used in an eco-routing system. Scop, on the contrary, is built in an appropriate and fast environment, C#. But on the other hand, the accuracy needs to be studied further. A modification of Scop is also needed in order to have a speed and slope profile as an input.

Summing up the conclusions, the vehicle specific RT-model and the simplified Oguchi model can be used in an eco-routing system for highway and rural drivings. With the current accuracy, fuel savings can be done of at least 8.5%. A more fuel efficient alternative to the fastest route existed for 48% of the simulated 36 routes.
Future Work and Extensions

There exists more route alternatives for a distribution truck in a city environment compared to long haulage trucks. Hence, possibly higher fuel saving potential. In order for an eco-routing to able to work in a city environment, the RT-model, Scop or a new model needs to be improved when estimating the fuel consumption during accelerations. A detailed study to map the significant parameters that affect the fuel consumption during such a maneuver should be done.

Scop has been developed for many years and is already implemented in C#. Furthermore, Scop does take the actual gear into account unlike the RT-model. The accuracy of Scop should therefore be further studied, in order to be able to see if this estimation can be used for comparing routes with regard to fuel consumption. The required modifications should be further defined.

Several factors, including this master thesis, indicates on that real time estimation is the best way to estimate the fuel consumption in an eco-routing system. In order to achieve good accuracy for such a method, a good driver model is necessary. In order to define the requirements of a driver model, the variation of driving styles among truck drivers should be identified.

Fuel consumption estimation is dependent on good information provided by a digital map. The recommendations by an eco-routing system are dependent on the reliability of this information. A study should be done whether the information by the available digital map is good enough.

In order to make proper estimates of fuel consumption, a good estimation of the vehicle mass is needed. The possibility of making such estimation should be further analyzed.

In order to reduce the load on hardware in the trucks that needs to do heavy calculations an alternative could be doing these calculations off board. Meaning that all calculations are done in a stationary computer and are transmitted wireless to the truck. Such a method could be further analyzed to see what the challenges
and advantages are.

This master thesis showed that for most of the more fuel efficient alternatives to the fastest route, there was an increase of travelling time. In order to evaluate if eco-routing is advantageous economically the costs of increased time regarding driver salaries, wear costs and delay costs should be further studied.
Bibliography


Appendices
Truck Parameters

A.1 Defining Parameters

Several parameters were needed to be defined before the RT-model could be used: the power required for auxiliary units $P_{aux}$ (W), air drag coefficient $C_d$, idle fuel consumption $f_{idle}$ (cm$^3$/s), brake thermal efficiency $\varepsilon_b$, total transmission efficiency $\eta_t$ and diesel energy density constant $H$ (J/cm$^3$). For comparison purposes the same parameters were also defined for the Oguchi model.

A.1.1 RT-Model

To be able to define within which boundaries the brake thermal efficiency should be, simulation results from Stars were used. These results from include information about the fuel consumption, $f_{stars}$ (g/h), engine torque $M_e$ (Nm) and engine speed $n_e$ (RPM). With this information the input power to the engine can be calculated according to,

$$W_{in} = \frac{f_{stars}}{3.6 \cdot 10^6} D_e,$$

where $W_{in}$ is the input power (kW) and $D_e$ describes the energy density of diesel, which was assumed to be $D_e = 43.1 \cdot 10^3$ (kJ/kg). The output power of the engine can be calculated according to,

$$W_{out} = \frac{M_e \cdot n_e}{9550},$$

where $W_{out}$ is the output power (kW). With Equation (A.1) and (A.2) the brake thermal efficiency could be approximate according to,

$$\varepsilon_b = \frac{W_{out}}{W_{in}}.$$
Approximations were made for the same engine that the vehicle used for the measurements had. An upper and a lower bound could thereafter be defined with Equation (A.3) for city driving and highway driving.

To be able to define $P_{aux}$ (W), simulation results from Stars where also used since this parameter included in the simulation results. A mean value of this parameter from simulation results were used for the RT-model. The air drag coefficient, $C_d$ were defined through a table describing this coefficient for different vehicles used in Stars.
Driving Route for ETC cycle

The route driven for the measurements similar to the ETC cycle is depicted in Figure B.1.

Figure B.1: Driving route used for measurements similar to the ETC cycle.
Appendix C

Increased Travelling Time

Simulation results for three route optimizations are depicted in Figure C.1. The numbers of increased travelling time and fuel saving for these routes are presented in Table C.1.

Figure C.1: Three simulated long haulage routes with the fastest route and fuel efficient route highlighted.

Table C.1: Difference regarding length, time and fuel between fastest route and fuel efficient route for three simulated routes.

<table>
<thead>
<tr>
<th>Route</th>
<th>Length [%]</th>
<th>Time [%]</th>
<th>Fuel [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lübeck-Chemnitz</td>
<td>+11</td>
<td>+12 (+40 min)</td>
<td>-28 (-58 liter)</td>
</tr>
<tr>
<td>Heidelberg-München</td>
<td>+3</td>
<td>+4 (+10 min)</td>
<td>-8 (-9 liter)</td>
</tr>
<tr>
<td>Bremen-Waren</td>
<td>+0.6</td>
<td>+14 (+30 min)</td>
<td>-23 (-26 liter)</td>
</tr>
</tbody>
</table>
The estimation accuracy was analyzed by either studying the relative mean square error or the confidence interval for a set of errors.

**D.1 Relative Mean Square Error**

Estimated results, $S$, were compared to measured results $M$, for this the relative mean square error was used [5]. Measurements and estimates were registered with a constant time discretization $\Delta t$ (s). The length of the vectors containing measurements and estimates is,

$$n = \frac{t_{sim}}{\Delta t},$$  \hspace{1cm} (D.1)

where $t_{sim}$ is the total simulation time (s). The percentage deviation for each pair of measured and estimated values along the entire course were calculated with,

$$e_n = \frac{E_n - M_n}{M_n},$$  \hspace{1cm} (D.2)

where $e_n$ is the error at the $n$:th pair of measured and estimated value, this is depicted in Figure D.1.

With $e_1, \ldots, e_{n-1}$ and $e_n$, the relative mean square error could be calculated according to,

$$r_{est} = \sqrt{\frac{1}{n} \sum_{j=1}^{n} e_j^2}.$$  \hspace{1cm} (D.3)

This value was used to compare the results to each other. An ideal estimation would be described by $r = 0$. 

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**D.2 Confidence Interval**

The confidence interval is defined by,

\[ I = (\bar{e} \pm \frac{s}{\sqrt{n}} t_{\alpha/2}(f)) \]

where \( \bar{e} \) is the mean error (%), \( s \) is the standard deviation (%), \( n \) is the length of the vectors containing data and \( t_{\alpha/2}(f) \) is the quantile of a t-distribution with \( f = n - 1 \) degrees of freedom [9]. The quantile parameter is defined according to Table 3 in [9]. An interval with the quantile \( t_{\alpha/2} \) has the confidence level \( 1 - \alpha \).

The mean error \( \bar{e} \) and standard deviation \( s \) was calculated according to,

\[ \bar{e} = \frac{1}{n} \sum_{i=1}^{n} e_i, \]

\[ s = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (e_i - \bar{e})^2}, \]

where \( e_i \) is calculated according to Equation (D.2).

---

*Figure D.1:* Characteristic curves of total fuel consumption as a function of time, with the error \( e_n \), for all registered measured and estimated values [5].