THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING IN MACHINE AND VEHICLE SYSTEMS

# On Numerical Descriptions of Road Transport Missions

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Cover:
Plot of the longitude and latitude (in degrees) of all mission logs in the OCEAN-database.

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# Abstract

This thesis addresses some issues of current interest in energy consumption prediction through simulation. First, we review the situation for rating, regulation and legislation of $CO_2$-emissions for cars and heavy vehicles. We explain some of the problems with the current description (or lack thereof) of the road and surroundings for such tests, called driving cycles. With that in mind, two main research questions are formulated.

The first we call the 'representation problem': what to include in a numerical description of a transport mission, and how to represent it mathematically? In answer, a proposal for a format is derived; the operating cycle-format. It is a physical description of the transport mission that consists of four parts: road, weather, traffic and mission, with the important property that it is independent of both driver and vehicle. Furthermore, it is explained how to build a simulation model capable of using the new mission description. Next, this is applied in a case-study of a real-world cargo transport, and the simulation results are used in a product development situation to improve energy consumption. In this specific case, a fuel consumption improvement of 16% is achieved.

The second question we call the 'classification problem': how should a mission executed in a specific region be labelled (i.e. described on a high level) depending on its characteristics? In answer, two classification methods are discussed: the Global Transport Application (GTA) and stochastic models. The basic structure of GTA is explained, and it is applied to the same log file that was used in the case-study. The principles of classification through stochastic models is described by explicit construction of such a model for topography. An example of how the methods can be applied in sales-to-order is made, by investigating how to best choose buffer size for a hybrid truck.

Finally, a process for both efficient product development and sales-to-order is outlined, that combines the format proposal and the two classification methods. If the output of the process is used in an optimisation process, the result is a vehicle configuration tailored for the transport mission in question.

Keywords: Transport mission description, road format, energy consumption, energy efficiency, $CO_2$-emission, operating cycle, full vehicle simulation

*Canis meus id comedit.*
Latin proverb, explaining why the homework isn't done

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Pär Pettersson
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# Nomenclature

| Symbol | Explanation |
|---|---|
| $A_f$ | Vehicle frontal area |
| $C$ | Degree of unevenness (OC sub-parameter) |
| $C_1$, $C_2$ | Constants in speed bump associated speed function |
| $C_d$ | Drag coefficient |
| $CI$ | Cone index (OC sub-parameter) |
| $E_{bat}$ | Battery energy (state-of-charge) |
| $E_{conv}$ | Conventional vehicle energy from ICE |
| $E_{hybrid}$ | Hybrid vehicle energy from ICE |
| $E_{in}$ | Input energy |
| $F_{air}$ | Air resistance force |
| $F_{grade}$ | Slope (resistance) force |
| $F_{inertia}$ | (Fictive) force due to inertia |
| $F_{prop}$ | Propulsion force at the wheels |
| $F_{res}$ | Resistive force |
| $F_{roll}$ | Rolling resistance force |
| $F_{zd}, F_{zu}$ | Vertical force on driven and undriven axles |
| $G_t$ | (Ground) type (OC sub-parameter) |
| $L$ | Segment length |
| $L_h$ | Average hill length |
| $P_a$, $P_{ab}$ | Specified parameter values |
| $P_{aux}$ | Auxiliary power |
| $P_{ICE}$ | Power from ICE |
| $P_{in}$ | Input power (as OC-parameter: available charging power) |
| $P_{prop}$ | Propulsion power at the wheels |
| $P_{PTO}$ | Power take-off (OC-parameter) |
| T | Ambient temperature (OC-parameter) |
| $T_a$ | Times when $p$ is specified |
| $T_b$ | Brake torque |
| $T_b^{max}$ | Maximum brake torque |
| $T_d$ | Drive axle torque |
| $T_e$ | Engine torque |
| $T_e^{max}$ | Maximum engine torque |
| $T_{req}$ | Requested engine torque |
| $T_w$ | Wheel torque |
| $X_a$ | Positions where $p$ is specified |
| $a$ | AR(1)-model parameter |
| $a_p$ | Normalized accelerator pedal position |
| $a_{x0}$, $a_{y0}$ | Longitudinal and lateral acceleration limits |
| $b_p$ | Normalized brake pedal position |

| Symbol | Explanation |
|---|---|
| $c_f$ | Calorific value |
| $e_d$ | Intended travel direction (OC-parameter) |
| $e_k$ | Error term |
| $f_I$ | Driver interpretation function |
| $f_q$, $f_T$ | Fuel map and torque map functions |
| $f_r$ | Rolling resistance coefficient |
| $\mathbf{f}_R$ | Driver regulation function |
| $g$ | Gravitational acceleration |
| $h$ | Height of speed bump (OC sub-parameter) |
| $i_{FD}$, $i_g$ | Final drive and gearbox gear ratio |
| $k_t$ | Traffic density (OC-parameter) |
| $l$ | Length of speed bump (OC sub-parameter) |
| $l_d, l_u$ | Length from centre-of-mass to driven and undriven axles |
| $m$ | Total mass (GCW) |
| $m_c$ | Mass of cargo (OC-parameter) |
| $m_f$ | Fuel mass |
| $m_v$ | Kerb mass |
| $p$ | A generic operating cycle parameter |
| $p_{air}$ | Atmospheric pressure (OC-parameter) |
| $q$ | Mass of fuel injected every engine stroke |
| $\tilde{q}$ | Efficiency measure for hybrid vehicle comparison |
| $r$ | Wheel radius |
| $s$ | Arc length |
| $t$ | Time |
| $t_s$ | Standstill duration (OC sub-parameter) |
| $t_{trac}$ | Traction time ($t : F_{prop} > 0$ ) |
| $v$ | Longitudinal vehicle velocity |
| $v_b$ | Associated speed of speed bumps |
| $v_p$ | Associated maximum speed of $p$ |
| $v'_p$ | Predicted maximum speed of $p$ |
| $v_r$ | Relative speed between wind and vehicle |
| $v_{sign}$ | Speed from speed sign (OC-parameter) |
| $v_{stop}$ | Associated speed of the stop entries |
| $\mathbf{v}_w$ | Wind velocity (OC-parameter) |
| $v_{want}$ | The speed desired by the driver interpretation |
| $v_\kappa$ | Associated speed of the curvature |
| $w$ | Waviness (OC sub-parameter) |
| $x$ | Longitudinal position |
| $y$ | Road grade in percentage |
| $z$ | Vertical position |

| Symbol | Explanation |
|---|---|
| $\mathcal{OC}$ | The set of parameters in the operating cycle format |
| $\mathcal{P}$ | Probability |
| $\alpha$ | Speed bump deflection angle (OC sub-parameter) |
| $\gamma$ | Fuel conversion proportionality constant |
| $\zeta$ | Arbitrary road grade limit |
| $\eta_{bat}$ | Combined battery and electric motor efficiency |
| $\eta_{ICE}$ | ICE efficiency |
| $\eta_T$ | Overall (torque) transmission efficiency |
| $\theta$ | Angle of inclination |
| $\kappa$ | Curvature (OC-parameter) |
| $\lambda$ | GPS-longitude (OC-parameter) |
| $\rho$ | Air density |
| $\sigma_e$ | Standard error of the residual |
| $\sigma_y$ | Standard error of the grade |
| $\varphi$ | GPS-latitude (OC-parameter) |
| $\phi_{RH}$ | Relative humidity (OC-parameter) |
| $\omega_e$ | Engine speed |

All units are given in SI-units and radians, unless otherwise stated.

# Thesis

This thesis consists of an extended summary and the following appended papers:

| | |
|---|---|
| **Paper A** | P. Pettersson, P. Johannesson, B. Jacobson, S. Berglund, and L. Laine. *Influence of hill-length on energy consumption for hybridized heavy transports in long-haul transports*. Tech. rep. Presented at the 7th Commercial Vehicle Workshop Graz. Göteborg, Sweden: Chalmers Univ. of Technology, Applied Mechanics, May 2016 |
| **Paper B** | P. Pettersson, S. Berglund, H. Ryberg, B. Jacobson, G. Karlsson, L. Brusved, and J. Bjernetun. Use of Global Transport Application in development and selection of the I-Shift Dual Clutch transmission. *Int. J. Vehicle Design* (2016). Submitted for publication |
| **Paper C** | P. Pettersson, S. Berglund, B. Jacobson, L. Fast, P. Johannesson, and F. Santandrea. A proposal for an operating cycle description format. *European transportation research review* (2017). Submitted for publication |

In paper A, the text was mainly written by Pettersson, with valuable input from all authors. The simulation model was initially built by Professor Jacobson and the stochastic generation algorithm by Dr. Johannesson, while Pettersson made model adjustments and carried out the simulations. The ideas behind the paper belong to Professor Jacobson and Dr. Johannesson.

Paper B was based on the engineering solution by Karlsson, Brusved, Bjernetun, Ryberg and others at Volvo GTT. The text was written jointly by Pettersson, Dr. Berglund and Ryberg, with valuable input from Professor Jacobson. The experimental measurement was carried out by Ryberg, while the simulation model was built by Pettersson and Dr. Berglund. The ideas behind the paper belong to Dr. Berglund.

In paper C, the text was mainly written by Pettersson, with valuable input from all authors. The simulation model was built by Pettersson, and the experimental measurements were carried out by Dr. Fast and Pettersson. The ideas behind the paper belong to all authors, as well as the OCEAN-project members.

Other relevant publications by the author, not included in the thesis:

A. Odrigo, M. El-Gindy, P. Pettersson, Z. Nedělková, P. Lindroth, and F. Öijer. Design and development of a road profile generator. *Int. J. Vehicle Systems Modelling and Testing* **11**.3 (2016), 217–233

P. Pettersson, B. Jacobson, and S. Berglund. *Model for automatically shifted truck during operating cycle for prediction of longitudinal performance*. Tech. rep. Göteborg, Sweden: Chalmers Univ. of Technology, Applied Mechanics, Oct. 2016

# Contents

# Extended Summary

# 1 Introduction

This thesis is about vehicles. More specifically, it is about how and why vehicles operate on the roads, and how to describe it from a mathematical point of view.

Transportation is an integral part of society and improving its various parts provide a common benefit. Of course, there are some problems that need to be solved in a not too distant future, with the transport sector's contribution to global warming perhaps the most severe one. Since the amount of road transports are not likely to decrease (rather the other way around), the problem needs to be solved by technological advancement instead.

In past times, much of the product development was done by hand and new inventions, indeed complete vehicles, needed to be fully built to be tested and the performance evaluated. However, since the advent of sufficient computational power, this has changed. The field known as computer aided engineering has exploded, figuratively, and a large part of the product development can be done with various software that rely on mathematical modelling. Of course, for this to be possible it puts great requirements on the sophistication of those models: they must reflect the performance of individual components, control systems and the vehicle realistically. Naturally, a complete description of reality is impossible and a lower level of agreement needs to be acceptable. But even if that was not the case and the vehicle itself could be perfectly described, there is still no guarantee that a simulation would be able to predict accurate results unless it is also stimulated in the right way. The driver and the surroundings are the sources of that stimulation, and so both must also be represented mathematically. The mathematical description of the surroundings is the main topic of this thesis.

## 1.1 Background

Any thesis in the field of energy consumption of vehicles is, in some way, related to the environment: through the emissions of one chemical or the other. In this case, we are foremost interested in the emission of $CO_2$ due to its contribution to global warming. Often the total amount of greenhouse gases (GHGs) is given in official reports, which, apart from $CO_2$, is foremost made up by $H_2O$ (water vapour), $CH_4$ (methane), $N_2O$ (laughing gas), $O_3$ (ozone) and various CFCs (chlorofluorocarbons)[1]. Often the term '$CO_2$-equivalent' is used, to account for the different contribution of each gas to the greenhouse effect.

The latest complete set of data found at the writing of this thesis was from 2014. The Global Carbon Project reported that the total amount of $CO_2$-equivalent emissions was 36.2 gigatonnes [6], out of which Europe contributed with 4.4 gigatonnes (according to the European Environment Agency, EEA, [7]) and the U.S. with 6.9 gigatons (according to

[1]See, for example, the U.S. EPA: https://www.epa.gov/ghgemissions/overview-greenhouse-gases

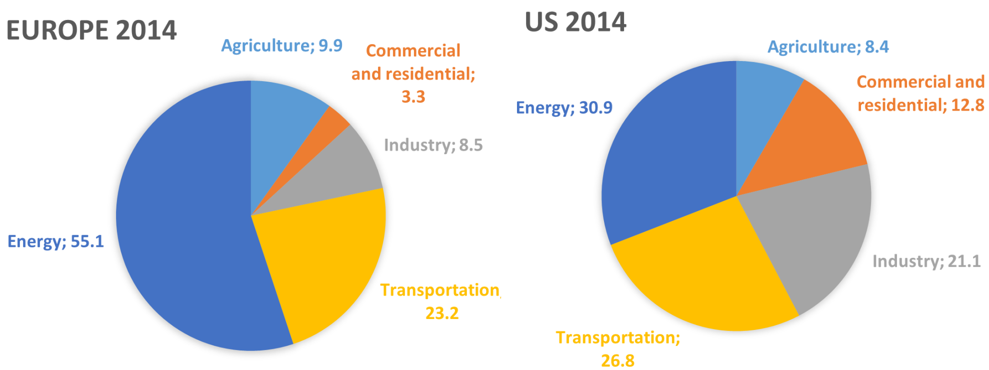


Figure 1.1: *$CO_2$-equivalent emissions by economic sector in percentage, for Europe (left) and the U.S. (right) in 2014. Data adapted from EEA [7] and EPA [8].*

the U.S. Environmental Protection Agency, EPA [8]). These two are mentioned especially, apart from the fact that they make up almost a third combined, because there are accurate estimates on how big a part each economic sector is responsible for, see Fig. 1.1. The transportation sector makes up about a quarter, so there is a lot of work to be done there to decrease the total amount.

Indeed, there has already been work done. Several international conventions have been agreed upon, starting with the United Nations conference on Climate Change in Rio de Janeiro in 1992, through the 1997 meeting in Kyoto that resulted in the Kyoto Protocol [9], and the Paris Agreement [10] in 2015. Both the Kyoto Protocol and the Paris agreement impose national limits on GHG-emissions. When it comes to the emissions from transportation, more detailed goals are set for example by the European Commission (valid in Europe) and the EPA (valid in the U.S.). There are similar requirements also in Japan, Canada and China.

For the European Union, the commission has set hard targets for emissions from cars [11] and light-duty vehicles [12]. For cars, the targets have been divided into several parts: in 2015, the average emissions should have been below 130 g $CO_2$/km (approximately 5.6 l/100 km of petrol or 4.9 l/100 km of diesel). Next target, in 2021, is 95 g/km (approximately 4.1 and 3.6 l/100 km, respectively). For light duty vehicles, the target is 147 g/km in 2020. At the time of writing, there are no hard targets for heavy-duty vehicles, but work is ongoing to introduce similar requirements [13], and the plan is to launch them in the near future.

In the U.S., there are requirements along the same lines. For cars, the emission in 2025 should be below 100 g/km and 127 g/km for light trucks [14]. There are also requirements for commercial vehicles, meaning buses and heavy-duty trucks [15]. The limits are given in g $CO_2$/(tonne·km) and different regulations based on various classes of vehicles: combination tractors (commonly called only tractors or semi-trailer truck), trailers (though technically not a vehicle) and vocational vehicles ('the rest' loosely

Table 1.1: *Combination tractor regulations in 2027.*

| Category | $CO_2$-emission (g/(tonne·km)) | | |
|---|---|---|---|
| | Low roof | Mid roof | High roof |
| Day cab class 7 | 60.0 | 64.5 | 62.4 |
| Day cab class 8 | 45.8 | 48.7 | 47.3 |
| Sleeper cab class 8 | 40.0 | 43.4 | 40.1 |
| Heavy hauler class 8 | 30.1 | - | - |

Table 1.2: *Engine standards for tractors in 2027.*

| Category | $CO_2$-emission (g/(bhp·hr)) |
|---|---|
| Medium heavy-duty | 457 |
| Heavy heavy-duty | 432 |

speaking: any other vehicle with total weight above 3.5 tonne)[2]. The regulations are further split into sub-classes depending on the general size of the vehicle within each truck category: Table 1.1 list the regulations that need to be met in 2027 for combination tractors. In addition, the engines have specific requirements, see Table 1.2 of regulations for tractor engines. As these tables show, the situation is more complex for commercial vehicles than for personal cars. The reason is that heavy-duty vehicles can be design for a vast variety of purposes and payloads, while cars are almost exclusively intended for personal transport.

Focusing on Europe, it seems that the requirements do have an effect. The EPA reported that the average amount of $CO_2$-equivalent emissions for new cars in 2016 was 119.5 g/km [16], meaning that the goal was achieved. But that brings up the question of how this number is found and what it means.

For cars, the official tests are done by putting the vehicle on a chassis dynamometer (a 'rolling road') and have a driver follow a specific target speed as a function of time, while the fuel consumption is monitored [11]. Such a target speed function is usually called a driving cycle (sometimes drive cycle or test cycle), and the specific one for the official test is the New European Drive Cycle (NEDC, see Fig. 1.2). It has long been criticised for being too unrealistic [18, 19, 20], and a cycle with higher levels of acceleration and higher average speed has been developed instead, the World-wide harmonized Light duty Test Cycle (WLTC, see Fig. 1.2) [21].

Naturally, the fuel consumption is heavily dependent on what the driving cycle looks like [22, 23, 24]: which implies that the reported fuel consumption is only applicable to trips that have similar characteristics as the NEDC or WLTC. The difference is further reinforced by the fact that the vehicles can be tailored to perform well on the official tests, as they serve as the benchmark for the manufacturer (the extremum of which is known as cycle beating). Thus, when comparing the official average fuel consumption to the

[2] A summary of these rules, that is a lot easier to read than the official federal regulation document, can be found at: `https://www.dieselnet.com/standards/us/fe_hd.php`.

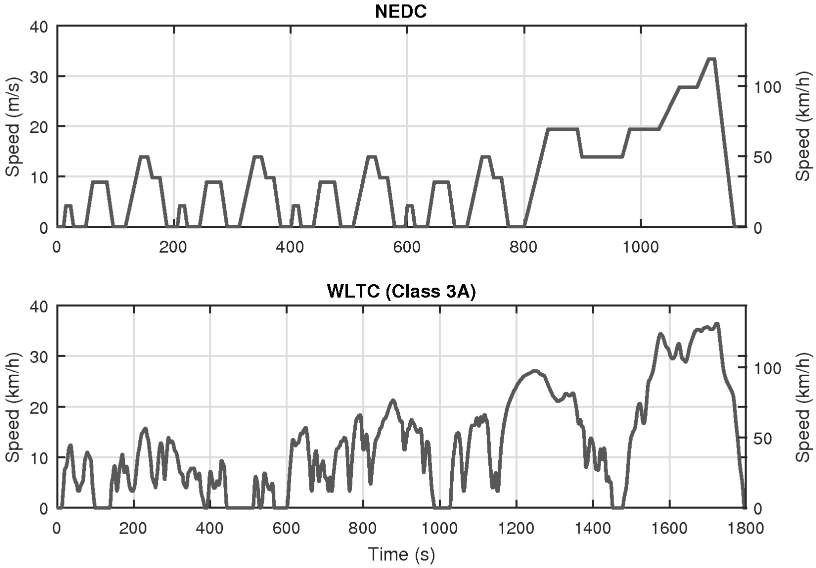


Figure 1.2: *Vehicle speed as a function of time for NEDC (top) and WLTC (bottom) [17].*

average from a collection of users[3] or academic studies [25, 26] there can be considerable differences.

For heavy-duty trucks the situation is more complicated, and so the solution is further simplified: there are no official driving cycles. Instead, the official way of testing emissions is by using engine load cycles: the percentage of total engine torque and (rotational) speed are specified as functions of time by the United Nations Economic Commission for Europe (UNECE) [27], and the fuel consumption (as well as many other emissions) measured while an engine is excited accordingly in a powertrain laboratory. The load cycles commonly used for official testing are known as the World Harmonized Steady state Cycle (WHSC) and the World Harmonized Transient Cycle (WHTC), shown in Fig. 1.3. Again, and to a greater extent than cars, the results are only applicable to missions where the engine follows cycles with similar characteristics.

In Europe, the plan is to launch legal requirements for complete vehicles based on a $CO_2$-rating method through simulation, using the software VECTO (Vehicle Energy Consumption Calculation Tool) [28, 29]. The situation is much the same independently of whether the rating comes from a simulation or an experimental test bench: for the results to be representative the setup must reflect the surrounding and the transport mission. What makes the question more complicated is that in simulation, the vehicle itself must be described together with all its control systems. In experiments, that comes

[3] There are many such databases available: U.S. Department of Energy (based in the U.S., `https://www.fueleconomy.gov/mpg/MPG.do?action=browseList`), True delta (based in the U.S., `https://www.truedelta.com/mpg`) and Honest John (based in the U.K., `https://www.honestjohn.co.uk/realmpg/`), though one has to keep in mind that the numbers are reported by the users themselves and are therefore not subject to any form of peer review.

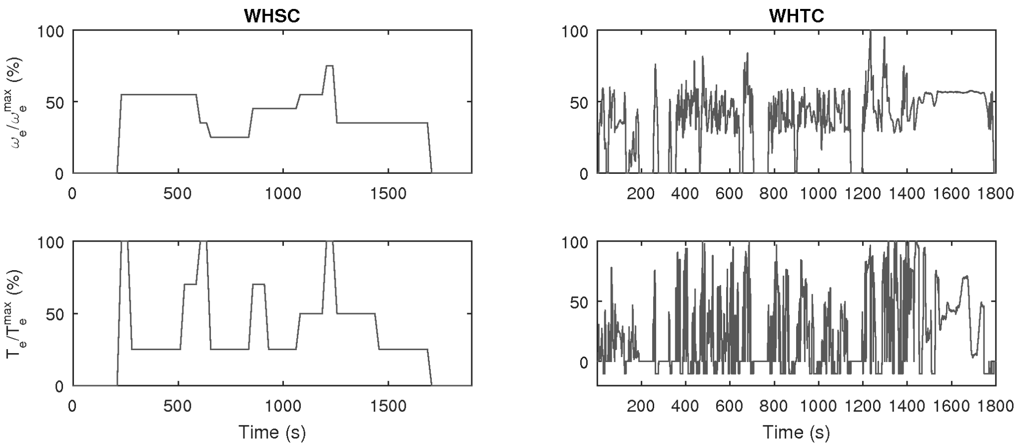


Figure 1.3: *The engine load cycles WHSC (left) and WHTC (right). Top row shows percentage of maximum engine rotational speed ($\omega_e/\omega_e^{\max}$) and the bottom row shows percentage of maximum engine torque ($T_e/T_e^{\max}$), both as functions of time.*

automatically.

For excellent product development, components and control strategies must be developed with specific applications in mind: different circumstances require different performances [30]. Therefore, there is no single component, setting or control strategy parametrization that is optimal for all driving conditions and transport missions. Instead, to achieve the best performance possible, each vehicle needs to be configured according to how and where it is used. The regulation processes described above reflects this badly because no such distinction is made. In addition, a more complete description of the transport mission than by a simple drive cycle is necessary, to let differences in surroundings have an impact and allow new inventions (like charging along the road) to influence the result. The discussion of these problems forms the core of the thesis.

## 1.2 Research questions

The outlined problems can be cooked down into two explicit questions and one implicit.

The first question is about how to describe transport missions in a good way. As explained, a driving cycle is not a sufficient description because it does not reflect any influence from the surroundings. In addition, the vehicle can be outfitted with many auxiliary devices (cranes, cutting equipment, digging tools, controllable body platforms, refrigerators, etc.) that require power both during driving and standstill: a proper mission description must detail when or where these are used. The question is: what to include in such a description of a transport mission, and how to represent it mathematically? We call this the ‘representation problem’ and it is the first research question.

The second question relates to the problem with only one mission (in the form of a driving cycle) being used for regulation and benchmarking. A change in mission often also results in a change of surroundings and driving conditions: a garbage truck driving inside a city core displays different characteristics (speed, traffic, number of stops) than a long-haul transport on a well-maintained highway between two cities, or a truck on a construction site. Likewise, the same mission executed in different surroundings - in a flat landscape or on hilly, curvy roads in a mountainous region - will impact how the configuration performs: this must be reflected. The question can be phrased: how should a mission executed in a specific region be labelled (i.e. described on a high level) depending on its characteristics? We call this the 'classification problem' and it is the second research question.

There is also a third, implicit problem: the solution from the two questions above must be useful. It is an obvious criterion, but really depends on the meaning of the word *useful*. In this case, it is not enough if the mission description is only explained in words or with equations, it must be possible to use in real product development and sales-to-order situations. Similarly, the classification must be able to capture the important characteristics, meaning differences that have a significant impact on energy consumption. The mission description (first research question) and parametrisation method (second research question) should be possible to combine, and use in a simulation environment to fairly evaluate different vehicle configurations with respect to energy consumption, and other measures connected to longitudinal dynamics. To show that this is possible and measure how well it works, it is necessary to have at least one example of a simulation model that can handle the new elements. Building such a model is not a trivial task. Therefore, a third question would be: what to model, and how to combine it with the solutions to the representation and classification problems? We refer to this as the 'simulation problem', and it a possible third question.

## 1.3 Limitations

For the mission description, the influence from traffic is largely neglected. Some ideas on how to deal with other vehicles are outlined, but a fully developed, systematic description is not attempted in this project.

When it comes to the classification problem, a complete description of case 1, 2 and 3 (see Section 4.5) for all variables in the operating cycle is never presented. Instead, a couple of prototype models show how it works.

In the following chapters only heavy-duty trucks will be used as examples. This is not really a limitation because the mission description is independent of the vehicle, and the variety of missions is much larger for trucks than for cars (the total weight for trucks can vary with several 100% of kerb weight, while in cars it is only some 10%). Nonetheless, the methods for what missions to parametrise are heavily biased towards heavy-duty vehicle operations.

The results from this thesis are intended to be used in an optimisation of the vehicle configuration with respect to energy consumption, but we will say very little about how the optimisation itself is done. This is a most interesting question that is not any way simple, rather the opposite, but it is not in the scope of the thesis. In the few examples that are made, the domain is so small that an exhaustive search is feasible. For an approach on how it can be done in a vast domain, see e.g. Nedělková [31] or Ghandriz et al [32].

## 1.4 Thesis outline

The thesis is structured as follows: Section 2 serves as a theory chapter and explains how to build a simulation model for predicting energy consumption. Some criteria that a transport mission description must satisfy are also derived. The solution to the representation problem is presented in Section 3 where a complete transport mission description (subject to the mentioned limitations) is formulated. An example of how it can be used is shown, as the result from two (slightly) different vehicles on two (slightly) different missions is presented and discussed. Next, Section 4 deals with the classification problem: two different forms of classification methods are presented and compared. Furthermore, a process for how to parametrise a representation on the form presented in the Section 3 is also explained. The extended summary finishes with discussion, conclusion and some words on future work, after which the appended papers can be found.

# 2 Prediction of energy consumption

A model whose purpose is to capture the energy consumption of a vehicle, must revolve around its longitudinal dynamics and the details of the longitudinal actuation: powertrain and brakes. For the purposes of this thesis, we start from Newtonian mechanics to describe that mathematics. A more in-depth description of the models in this section can be found in [5].

## 2.1 Model structure principles

There are many ways to build a simulation model whose purpose is to capture the energy use required by a vehicle, but they must all have a representation of the vehicle together with a postulate of how it should move. Generally, all such models can be divided into two categories: backward simulation (called non-causal or inverse-dynamic) or forward simulation (called causal or natural-dynamic).

A backward simulation is characterised by the fact that external stimuli, whatever the input (often only a speed is given), is used to compute required propulsion speeds and forces on the vehicle from the driven wheels to satisfy that stimuli. For example, if only a target speed as a function of time is given, then it is assumed to be followed exactly[1], including its time derivatives, and the necessary propulsion details computed. The resulting simulation is computationally effective, but the effect that a change of vehicle configuration - or an entirely different type of vehicle - results in a different behaviour cannot be reflected at all.

In a forward simulation, the input is again used as a reference, but it controls a natural interface, like the accelerator and brake pedals, and the dynamics of the vehicle model determines its final acceleration, velocity and position. This type of model is more physical because it follows the natural causality of reality [33]. However, it cannot reproduce a given speed profile exactly, in general, and it is more demanding computationally, because the number of states is greater than a corresponding backward simulation. On the positive side, it automatically reflects effects from changing vehicle configuration and type.

There are also cases where backward and forward simulation are combined. One way is to use the backward approach whenever possible, but if it breaks down the simulation switches to a forward approach until the propulsion system can follow the given speed profile again, then switches back (see [1, 34]).

A major difference between the two approaches, is that a forward simulation requires a driver model, while a backward simulation does not. Having a description of a driver is a considerable increase in complexity but allows for a more dynamic and realistic simulation. In reality, the vehicle behaviour is a result of the interaction between the driver and the environment [35]. An outline of a modular structure is shown in Fig. 2.1, and from this point on only forward simulation will be considered.

[1] Provided that the propulsion system can produce enough power to overcome the resistive forces and inertia, otherwise a strict backward simulation breaks down because the mathematical problem has no solution.

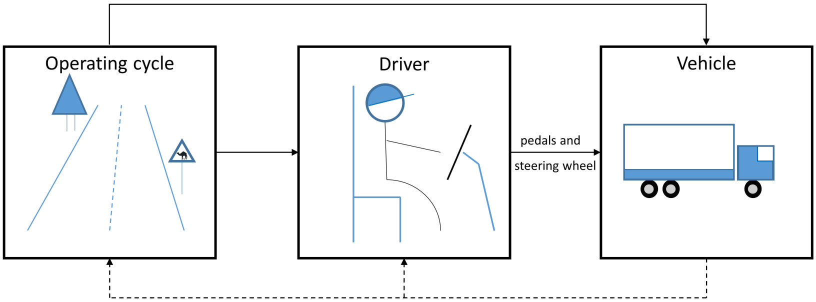


Figure 2.1: *The principles of a modular forward simulation with individual models for the mission (operating cycle), the driver and the vehicle. Arrows show signal flow.*

If we assume that the vehicle follows a trajectory, the most basic dynamics along the tangential direction (the longitudinal direction, in the vehicle frame of reference) can be written by using Newton's second law, Eq. (2.1),

$$m\dot{v} = F_{prop} - F_{grade} - F_{roll} - F_{air} \tag{2.1}$$

$$\left( F_{inertia} = m\dot{v}, \quad F_{prop} = \frac{P_{prop} - P_{aux}}{v} \quad \Rightarrow \right) \tag{2.2}$$

$$P_{prop} = v \cdot (F_{inertia} + F_{grade} + F_{roll} + F_{air}) + P_{aux} \tag{2.3}$$

The right-hand side of Eq. (2.3) is dependent on both how the vehicle and the mission are described, but the left-hand side only has a direct dependence on the vehicle.

## 2.2 A model for longitudinal dynamics

The purpose of the mathematical model of the vehicle, is to map the driver-vehicle input to the energy source, and transfer this energy from the source to the vehicle-road interface. The real-world equivalent would be, in the most common case of an internal combustion engine (ICE), to relate the accelerator pedal to a fuel injection, and from that an engine torque onto a tyre traction force. In the discussion below, only powertrain topology with a combustion engine is considered, as shown in Fig. 2.2. For details of hybrid-electric or full electric topology, see [36, 37, 38].

Here we assume that accelerator pedal position $a_p$ and brake pedal force $b_p$ are the only inputs from the driver to the vehicle. The steering wheel is neglected because it is assumed that the driver follows the road trajectory. Manual gear selection is avoided by requiring that there is an automatic gearbox. As shown in Fig. 2.2, the accelerator pedal goes into the engine. A simple model for transforming it onto an energy input and an engine torque would be: a linear mapping of the pedal input $a_p$ onto a torque request $T_{req}$, another map $f_q$ from request to fuel injection $q$, and finally through a steady-state

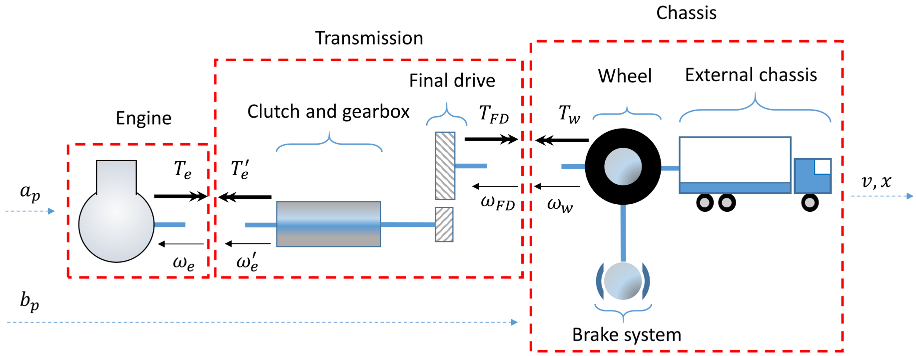


Figure 2.2: *A stylised high-level free body diagram of the different subsystems involved in the longitudinal dynamics.*

torque map $f_T$ to an output engine torque $T_e$,

$$T_{req} = T_e^{max} a_p \tag{2.4}$$

$$q = f_q(\omega_e, T_{req}) \tag{2.5}$$

$$T_e = f_T(\omega_e, q) \tag{2.6}$$

$$m_f = \int_{t_0}^{t_f} \gamma \omega_e q \, \mathrm{d}t \tag{2.7}$$

where $m_f$ is the fuel mass, $\omega_e$ is engine speed and $\gamma$ is a proportionality constant depending on engine type. The pedal map is one-dimensional and linear here, but is in reality a function of both pedal input and engine speed. An archetypical example of fuel and torque maps, $f_q$ and $f_T$, are shown in Fig. 2.3. The fuel mass flow is equivalent to an input energy $E_{in}$ given the calorific value $c_f$ of the fuel,

$$E_{in} = c_f m_f \tag{2.8}$$

When it comes to energy consumption, this is the metric for comparing different vehicle configurations. In cases where the total cost needs to be calculated, including e.g. driver salary, a fuel cost (€/g) needs to be introduced too.

The engine dynamics can be modelled with considerable more complexity, see [39, 40], and there should be at least one electric control unit (ECU). A slightly more complex model is used in paper B. Also, here we have said nothing about emissions or after treatment of the exhaust gases.

Next in Fig. 2.2, the torque flows through the transmission system. A simple model would be to approximate the gearbox with only a gear ratio $i_g$, another ratio $i_{FD}$ for the final drive, and an overall transmission efficiency $\eta_T$. A clutch can be disregarded if the gearshifts themselves are assumed to be instantaneous. The gear choice of the automated system may be based only on engine (or vehicle) speed thresholds with hysteresis, as in figure 2.4. Then the drive shaft torque $T_d$ becomes,

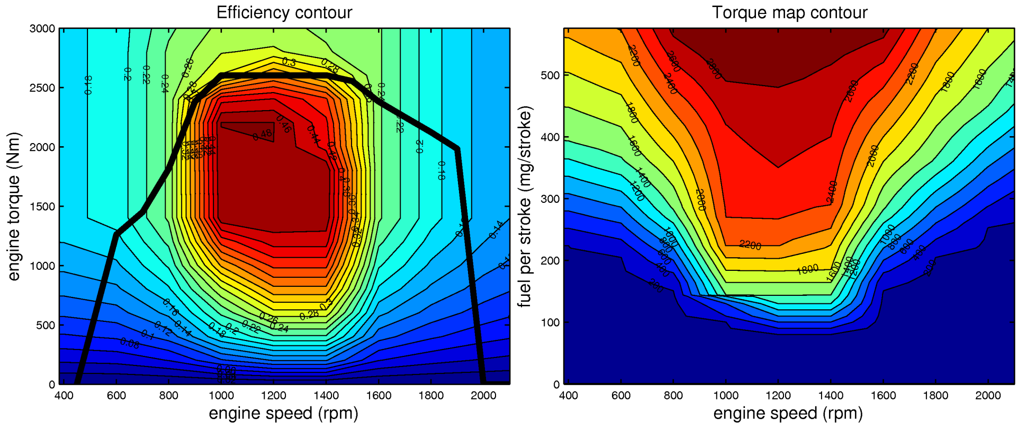


Figure 2.3: *Typical efficiency and torque maps (though synthetic) for heavy-duty diesel engines. The left contour shows the engine efficiency ($P_{out}/P_{in}$) and the right shows the steady-state torque output $T_e$ in Nm.*

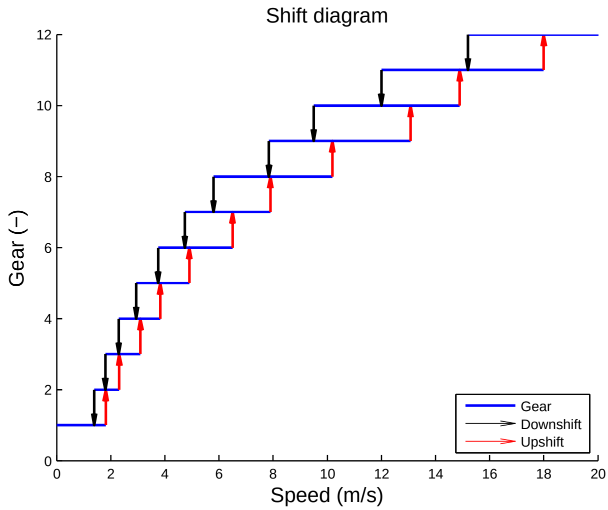


Figure 2.4: *Shift diagram for a 12-step, sequential, speed-based gear choice strategy.*

$$T_d = \eta_T i_g i_{FD} \left( T_e - \frac{P_{aux}}{\omega_e} \right) - f_r r F_{zd} \tag{2.9}$$

where we have also considered that the vehicle may be outfitted with some auxiliary equipment that requires a power $P_{aux}$ to function.

The situation for the transmission model is the same as for the engine: it can be modelled with considerably more complexity, see e.g. [41, 42]. There should be at least one ECU to handle all control, including the gear choice strategy, which is a hot topic for large savings in energy consumption[2]. Suffice to say, the simplest approach to such a strategy that was outlined above is a considerable simplification.

The final part in Fig. 2.2 is the chassis. A simple model would be to assume that the wheel with tyre is a rigid cylinder that does not slip, and that the chassis is a mass attached to the wheels through a rigid suspension. Also, let the brake pedal input $b_p$ be related to a (brake) torque with a linear map,

$$T_b = \text{sgn}(v) T_b^{max} b_p \tag{2.10}$$

then the wheel torque $T_w$ is,

$$T_w = T_d - T_b \tag{2.11}$$

Approximate all resistive force to those in Eq. (2.3): a grade, roll and air resistance,

$$F_{res} = mg \sin\theta + f_r F_{zu} + \frac{1}{2} \rho A_f C_d |v_r| v_r \tag{2.12}$$

with $F_{zd}$ the vertical force on the driven axles and $F_{zu}$ on the undriven. For a two-axle vehicle with distances $l_d$ and $l_u$ from respective axles to centre of mass, they would end up as,

$$F_{zd} = \frac{l_u}{l_d + l_u} mg \cos\theta, \quad F_{zu} = \frac{l_d}{l_d + l_u} mg \cos\theta \tag{2.13}$$

Newton's second law for the vehicle then takes form according to,

$$m\dot{v} = \frac{T_w}{r} - F_{res} \tag{2.14}$$

The speed $v$ of the vehicle is determined by integration in time of the equation above, and the position through a double integration. In practice, the system of differential equations listed in Eq. (2.4) to (2.14) is solved by successive iterations in small time steps, so the acceleration $\dot{v}_i$ in time step $i$ is used to compute the next speed $v_{i+1}$ in step $i+1$, similarly $x_{i+1}$ is computed from $v_i$. When coupled with a transport mission description in Section 3, the position $x_{i+1}$ leads to new values for the resistive forces (as well as accelerator and brake pedal inputs), and the loop closes.

The model structure that has been explained here is general and typical, but the detailed models are very simple. Nonetheless, provided that accurate numerical values are

[2]Like Volvo Trucks' I-See: `https://www.volvotrucks.us/powertrain/i-shift-transmission/i-see/`, Scania's Opticruise or Daimler's Predictive Powertrain Control.

attributed the various variables and mapping functions, the predicted energy consumption is of the correct order of magnitude compared to measurements[3] [3].

This section has established the basic simulation concept (forward simulation), and some details about how to describe the vehicle mathematically. For the complete model to predict anything at all, there still needs to be models for the transport mission and the driver.

[3]Depending on the realism of the input and provided that the model acts in its region of validity. For example, it cannot describe a trip with considerable tyre slip since it is assumed that the contact patch fully sticks - the curse of modelling physics.

# 3 A format for describing operating cycles for simulation

The representation question is the main topic of paper C, where it is treated in detail. This section will summarize that discussion; elaborate some things and simplify others.

Before going into details, we need to define what is meant by 'transport mission'. In this thesis, a transport mission means an enumerable number of tasks (the mission) that take place in certain surroundings (road, weather and traffic), independent of both driver and vehicle. For example, it could be a bus timetable and a number of passengers inside a city core; or a load of sand being picked up at a position, driven to a construction site and then distributed over a distance; or just a series of pickup and drop-off points with several parcels along a country road.

## 3.1 The format proposal

Up until this point, the need of a proper mission representation has been motivated only by qualitative reasoning. A more concrete reason can be found by looking at the right-hand side of Eq. (2.3). All the terms depend on the mission description:

- $F_{inertia} = m\dot{v}$

  The inertia term depends on the gross mass, and cargo transport is a major reason for transport altogether. The payload can be considerable compared to the kerb weight, especially for heavy-duty trucks where it commonly constitutes the main part of the total weight, so a complete description must include it in some form. In addition, it should also be allowed to vary; both during standstill (loading and off-loading while the engine is running) and driving (imagine a cement truck or a dumper that spreads its cargo over a distance).

  The other part of the inertia term is the acceleration. It is affected by e.g. speed limits and traffic. This is a complex problem to tackle.

- $F_{grade} = mg \sin\theta$

  The grade term is also mass dependent and for small angles the contribution to driving resistance is considerable. A description of the grade angle $\theta$ is therefore needed in some form.

- $F_{roll} = f_r mg \cos\theta$

  The rolling resistance coefficient $f_r$ depends both on the vehicle (mostly its tyres) and the ground surface. The vehicle dependent part should not be included, like a numerical value of $f_r$, but some kind of description of the ground is necessary to incorporate.

- $F_{air} = \frac{1}{2}\rho A_f C_d |v_r| v_r$

Both the air density $\rho$ and the relative air velocity $v_r$ have dependency on weather-related aspects such as: temperature, humidity, and wind velocity. These can have effects in other parts of the vehicle too and are important to include for many reasons.

- $P_{PTO}$

  A power take-off demand has a direct effect on the energy consumption, as in Eq. (2.9). There are many types of add-ons that require power, for example: refrigerators and freezers, garbage presses, lifts, cranes, pumps - the list is virtually endless. Any equipment must be allowed to function both during standstill and while driving. It might happen that a specific accessory needs to be triggered by an event, for example when the payload is above a certain limit. The description must allow for a dynamic treatment of the add-ons.

The mission description must treat all the aspects above to be useful in development. Besides the requirement that the format can represent the physics of the mission and its surroundings, there are some basic demands that must be satisfied:

1. **Computationally efficient**
2. **Easy to understand and update**
3. **Compact**
4. **Vehicle independent**

   This has been mentioned before: a description of a mission cannot require a certain vehicle if it is to reflect the performance of different configurations. This is the main problem with a conventional driving cycle, where $v = v(t)$ for all vehicles.

5. **Driver independent**

   Much the same as the criteria above, it should be possible to investigate how differences in driving style. To enable that, the description must be independent of the driver too. He or she can be considered a source of variation on the vehicle requirements, and a description that is driver independent grants control of that.

6. **Deterministic**

   This requirement stems from a practical point of view: if a simulation with the same vehicle, running the same mission with the same driver gives different output when run several times, it is very difficult to find a reason why one design choice works better than another. There is a risk of over-fitting, meaning that the randomness (noise) is fitted too. The overall consequence of stochasticity would be that optimisation will be difficult using the simulation results.

7. **Physically interpretable**

   The final criterion comes from the idea of a realistic description. It should be possible to interpret each parameter based on physics, to determine whether the effect on the vehicle energy consumption is large enough to motivate inclusion and assign a numerical value to it.

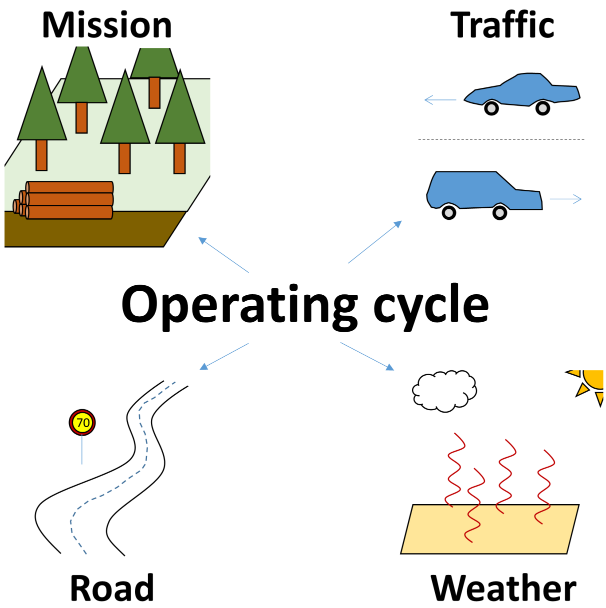


Figure 3.1: *The structure of the format proposal.*

Criteria 1-3 are matters of convenience, but if not fulfilled it would have the effect that the format was frustrating and troublesome to use. It should be the other way around; it should be quick, efficient and simple to work with.

The format proposal works by describing physical entities, called ‘parameters’. The complete description of the transport missions will be nothing more than a collection such parameters, together with a set of rules for how they act. A graphical representation is shown in Fig. 3.1, where a mission description on this form is called an operating cycle (OC). It consists of four independent parts: road, weather, traffic and mission, as shown in the figure.

The parameters that are included in the OC-format proposal are listed in Table 3.1, along with some properties. The dimensionality denotes how many sub-parts (or sub-parameters) that make up each (main) parameter. Each one must be given as a table[1] that is either specified at points in space: $X_a, P_a$, points in time: $T_b, P_b$, or both: $X_a, T_b, P_{ab}$. The tables are used in combination with the appropriate mathematical model, $f : (x, t, X_a, T_b, P_{ab}) \to p$, listed in Table 3.1, to find the value for any intermediary position $x$ or time $t$ by using interpolation. With equations (only shown with position

[1] Here we use tensor notation to write it in a compact way, see Goldstein [43] or Peskin and Schröder [44]. Letters from the start of the alphabet, $a, b, c$, denote dimensionality indices, while those in the middle, $i, j, k$, represent singular but generic values of the dimensionality indices. To separate tensor indices from notational ones, a comma sign is inserted. For example: a table of $v_{sign}$ values would be written $v_{sign,a}$.

Table 3.1: *The parameters defining the operating cycle format.*

| Parameter | Category | Math. model | Dim. | Unit | Symbol |
|---|---|---|---|---|---|
| Speed sign | Road | Constant | 1 | m/s | $v_{sign}$ |
| Topography | Road | Linear | 1 | m | $z$ |
| Curvature | Road | Linear | 1 | 1/m | $\kappa$ |
| Ground type | Road | Constant | 2 | -, kPa | $G_t, CI$ |
| Stop sign | Road | Discrete | 1 | s | $t_s$ |
| Roughness | Road | Constant | 2 | $m^3$, - | $C, w$ |
| Speed bump | Road | Discrete | 3 | m, m, deg | $l, h, \alpha$ |
| Longitude | Road | Linear | 1 | deg | $\lambda$ |
| Latitude | Road | Linear | 1 | deg | $\varphi$ |
| Ambient temperature | Weather | Linear | 1 | °C | T |
| Atmospheric pressure | Weather | Linear | 1 | kPa | $p_{air}$ |
| Wind velocity | Weather | Constant | 2 | m/s, m/s | $\mathbf{v}_w$ |
| Relative humidity | Weather | Linear | 1 | % | $\phi_{RH}$ |
| Traffic light | Traffic | Discrete | 1 | s | $t_s$ |
| Give-way sign | Traffic | Discrete | 1 | s | $t_s$ |
| Traffic density | Traffic | Constant | 1 | 1/m | $k_t$ |
| Mission stop | Mission | Discrete | 1 | s | $t_s$ |
| Cargo weight | Mission | Linear | 1 | kg | $m_c$ |
| Power take-off | Mission | Linear | 1 | kW | $P_{PTO}$ |
| Charging power | Mission | Constant | 1 | kW | $P_{in}$ |
| Travel direction | Mission | Constant | 1 | - | $e_d$ |

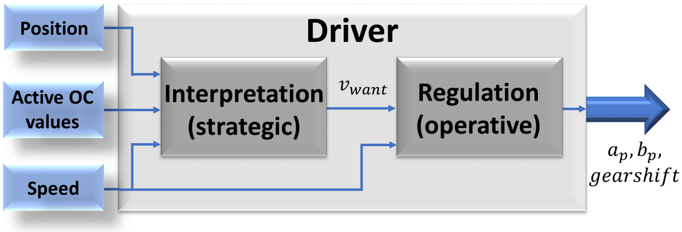


Figure 3.2: *Structure of the driver model. The composite model (light grey area) corresponds to the driver block in Fig. 2.1. Figure originally published in [3].*

dependence),

$$i : x \in [X_i, X_{i+1}] \tag{3.1}$$

$$p(x) = f(x, X_i, X_{i+1}, P_i, P_{i+1}) \tag{3.2}$$

analogous for $t$-dependence or both. In a complete vehicle simulation, such as the one in Section 2, $x$ is a state and therefore known in each time step while t is the prescribed variable: meaning that $p$ can always be computed using Eq. (3.2).

In principle, Eq. (3.2) can be implemented directly to serve as the model of the mission in Fig. 2.1. In practice, there are a lot of technical details that need to be handled, but they are treated in paper C and will not be further explained here.

As a side note: the parameters in Table 3.1 only have an effect in simulation if the interaction between them and the vehicle or driver is formulated in equations. For example, if a mission is run on sand, the ground type parameters is used to describe the surface, but an impact on the energy consumption will not show unless the interaction between the surface and the tyre is modelled. In Eq. (2.3) this is represented by the rolling resistance coefficient $f_r$, but in the case of soft surfaces the phenomenon is more complex than that [45]. However, those equations are a part of the vehicle model rather than the surroundings, since they depend on tyre properties.

## 3.2 Mission-driver interaction

The parameters in Table 3.1 are the proposed solution to the representation problem, together with the rules and considerations discussed in the previous section. However, at this point the format proposal is not *useful*: the interface to vehicle model in Section 2 are the accelerator and brake pedals and they are not included as parameters. Neither can they be, because of criteria 4 and 5. Therefore it is not possible to evaluate energy consumption and longitudinal performance with the format proposal by itself. Even though the mission description is the core of this chapter, a driver model is necessary to bridge information between the mission and the vehicle.

The driver model is divided into two parts: an interpretation and a regulation, as shown in Fig. 3.2. The interpretive part serves as a 'high-level' process, that receives information from the surroundings, interprets that and decides upon a wanted speed $v_{want}$, Eq. (3.3). The regulation is a 'low-level' process that compares $v_{want}$ with the current vehicle speed and formulates a suitable pedal input, Eq. (3.4). In equations,

$$v_{want} = f_I\left(x, v, \mathcal{OC}\right) \tag{3.3}$$

$$[a_p, b_p] = \mathbf{f}_R\left(v_{want}, v\right) \tag{3.4}$$

A straightforward way to implement the field $\mathbf{f}_r$ in Eq. (3.4) is by using a PID-regulator, hence the name of the model. It could be developed a lot more, though that is out of scope of the present work. We could model $\mathbf{f}_r$ as dependent on vehicle parameters, reflecting that the driver learns the pedal response of the vehicle. Such influence can involve physically interpretable transformations of $v_{want}$ to acceleration or force, then a reverse pedal map to the signals $a_p$ and $b_p$. Similarly, influence from road grade can be physically motivated.

The treatment of the interpretation entails some fundamental question and so needs a more careful handling: how does a driver make his or her choice of speed? For the reader blessed with a driving licence, an effective way to attack the question is to think about how you yourself choose speed when driving. There is probably a relation to the speed limits, though not necessarily very strict. Curves might make you decrease that speed, depending on how much fun you find lateral acceleration. Moreover, severe roughness, potholes and speed bumps may also make you want a lower speed, either for comfortability or to avoid causing damage your car. Other road signs, such as stop and give-way signs as well as traffic lights and intersections, require you to stop, sometimes depending on sight conditions. Finally, other vehicles will force you decrease the speed, unless you want to crash. Something quantitative can be derived from those ideas.

The basic rule is this: we imagine that the driver will want to travel as fast as possible, while remaining comfortable. Some of the parameters from the mission format, but not all, will impose boundaries on the speed by defining a threshold above which the person in question becomes uncomfortable. At any point in time, the lowest of those thresholds will define a static maximum wanted speed. In addition, we also imagine that the driver can see some distance ahead and predict that the speed may have to be decreased below the current static boundary, to reach the next one while remaining comfortable.

So, for each parameter $p$ that can be linked to a comfort criterion, there must be a related upper speed boundary $v_p(x)$ at position $x$. If $p$ is something that the driver can see from a distance (such as a road sign), there may also be a predictive threshold $v'_p$. We assume that the driver wants to brake the vehicle smoothly and not with full pedal actuation, therefore a deceleration threshold is suggested: $\dot{v} \geq -a_{x0}$, with $a_{x0} > 0$. Then, for a position $x \in [X_i, X_{i+1}]$, any $p$ with threshold $v_{p,i+1}$ at $X_{i+1}$ has the predictive upper speed limit such that,

$$\frac{dv}{dt} \geq -a_{x0} \quad \Rightarrow \quad v(x) \leq \sqrt{v_{p,i+1}^2 + 2a_{x0}(X_{i+1} - x)} = v'_p \tag{3.5}$$

From the basic rule, we can immediately write down an expression for the wanted speed for an arbitrary number of parameters,

$$v_{want} = \max\left(v_{p_1}, v_{p_2}, \ldots, v'_{p_1}, v'_{p_2}, \ldots\right) \tag{3.6}$$

To make use of Eq. (3.6), we must still find an expression for every $v_p$. Of the parameters listed in Table 3.1, the speed, stop and give way signs, traffic lights, mission stop, curvature, ground type, roughness, speed bumps and traffic density may potentially be linked to a comfortability criterion.

- The speed signs give a direct threshold, though a factor could be included to account for the variability in a driver's disposition to follow a given legal limit.
- The traffic lights, mission stop, give-way and stop signs also give direct limits: they are modelled to require a full stop. In reality, they do not always enforce stopping, but it is proposed to make the simulation deterministic.
- The roughness and speed bumps cause the vehicle to move in vertical direction and can be related to vertical acceleration and passenger ride comfort [46]. This can be linked to longitudinal velocity[2] and an upper limit found if a comfortability threshold is defined. The same thing can be done for speed bumps, but another way to do it is to look at their design criteria [47]: what maximum speed they were constructed for and use that as the upper limit.
- The curvature forces the vehicle to develop lateral acceleration. An expression can easily be found under the assumption that the vehicle can be treated as a particle. If a lateral acceleration limit $a_{y0}$ is defined, the vehicle speed threshold falls out nicely, Eq. (3.7). A problem is that the acceleration limit is difficult to assign a numerical value to. There is not much to be done for passenger cars, but for heavy-duty vehicles it can be taken one step further. Consider a wheel-lift threshold, and assume that the driver is sufficiently skilled or experienced that he or she has some feeling for it. Then the centre-of-mass height of the combination vehicle becomes the design parameter[3], which is more a corporeal parameter than a driver's lateral acceleration threshold.
- The ground type can affect the speed through rolling resistance and friction coefficient: driving on snow or ice tend to cause drivers to driver more carefully [48].
- The traffic density can have a profound effect on the vehicle speed: a highway queue, for example, forces all vehicles to a much lower speed, even standstill, than what is allowed. We do not attempt to make a connection between traffic density and vehicle speed here (though traffic flow theory [49] describes such relations), simply note that it should be done but is not easy.

We emphasize that different drivers will have different values of these, depending on skill and mindset.

[2]If a spatial wave component has a wavelength $\lambda$ and a particle travels over it with a (group) velocity $v$, the frequency in time would be $\omega = v/\lambda$, which enables the oscillation of the unsprung mass to be described in time. The ensuing vibration of a passenger can be computed using Newtons equations and a model of the suspension.

[3]In the simplest form, assuming the vehicle is a rectangle with centre-of-mass height $h_{cm}$ and track width $w$, the acceleration limit for wheel-lift is $a_y = wg/(2h_{cm})$

In the case study in Section 3.3, the effects from road roughness, ground type and traffic density are neglected. The static speed relation for the curvature $v_\kappa$ and speed bumps $v_b$ are taken as,

$$v_\kappa = \sqrt{\frac{a_{y0}}{\kappa}} \tag{3.7}$$

$$v_b(\alpha) = C_1 \frac{90 - \alpha}{\alpha} + C_2 \tag{3.8}$$

so Eq. (3.6) turns into,

$$v_{want} = \min\left(v_{sign}, v_\kappa, v_b, v_{stop}, v'_{sign}, v'_\kappa, v'_b, v'_{stop}\right) \tag{3.9}$$

where $v_{stop}$ represents all four stop kinds. This is but one example of an expression for Eq. (3.6), that works on well-maintained roads with light traffic. In case of bad road conditions, with respect to either roughness or road friction, it would not reflect how a driver choose his or her speed. Neither would it work in moderate to heavy traffic situations.

Equation (3.6) could include terms that are not strictly mission related: depending on vehicle type there may be additional legal considerations. In Sweden, buses are not allowed to drive above 90 km/h (with some exceptions); tractor-trailers, cars with trailer and articulated lorries not above 80 km/h [50] etc. Such thresholds are driver-vehicle interactions and not mission-related, but work in the same way.

## 3.3 Case study: city outskirt cargo transport

A case-study was made to test if the format proposal and the driver interaction works. The mission is a cargo transport, carrying goods from one destination to another (a part of a longer run, really) around the outskirts of a minor city (Göteborg, Sweden). The setting is based on a real transport mission coming from the OCEAN-project database, see Section 4. The route is about 17 km long and can be seen in Fig. 3.3. A special interest in this study was traffic, since it is not included in the format description. No such information was available in the log file of the original mission; therefore the same route was driven twice more using the Revere[4] truck. These two trips were filmed, so if traffic was the reasons for some variations in speed it could be determined.

### 3.3.1 Comparing measurement and simulation

The OC-parameters (Table 3.1) are straight forward to construct since the mission category is trivial. The signed speed, stop sign and traffic lights are shown in the top plot of Fig. 3.4 while the bottom shows the altitude and curvature. Apart from the speed bump-parameter that has one non-trivial entry (at position 158 m, $l = 2$ m, $h = 8$ cm, $\alpha = 7.1°$), all other parameters are trivial meaning that they only take their default values. The signed speed was estimated by GPS-speed together with the camera feed and

[4]Resource for vehicle research, the Chalmers vehicle laboratory

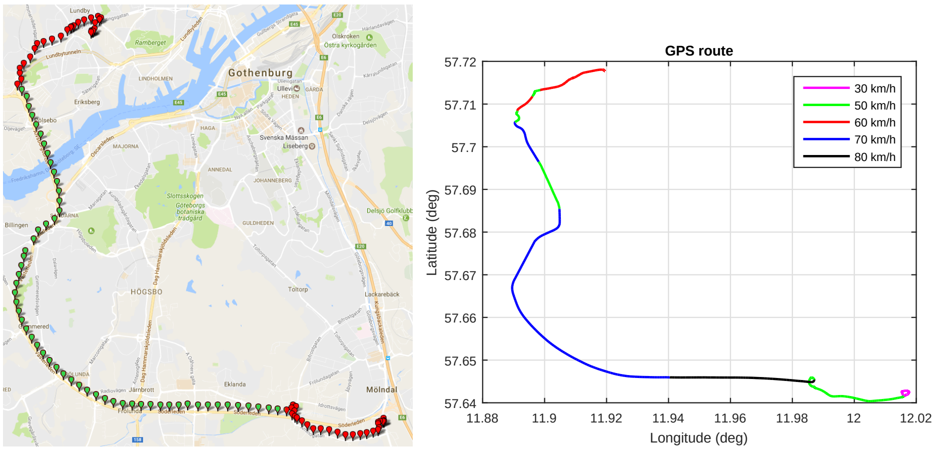


Figure 3.3: *Two perspectives of the transport mission in the case-study: the left figure shows the route on a map, while the figure on the right shows the speed limits. Originally published in [3].*

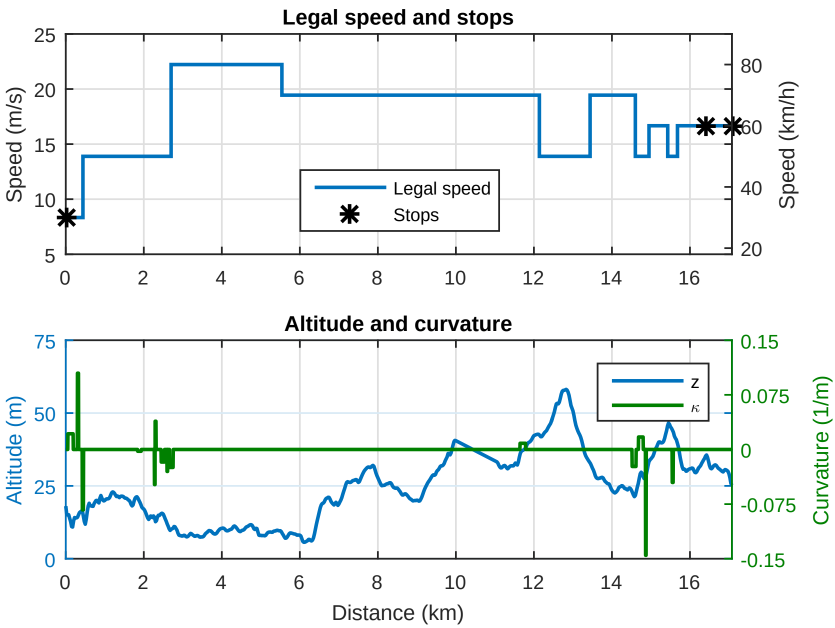


Figure 3.4: *Non-trivial parameters of the case-study OC, apart from the speed bump. Top figure shows the speed and stops, bottom figure shows the curvature and topography. Originally published in [3].*

an external database (NVDB [51]), and has 10 entries. The topography and curvature were both estimated from the GPS-data. The topography follows the ideas discussed in Section 4 and was specified at 25 m-intervals, giving 648 entries. The curvature was not continuously specified, but only in places with moderate or considerable turn radius. There were 13 such places in total, giving 57 entries.

Results from both measurements and simulations are shown in Fig. 3.5. The top plot shows the speed as a function of distance for the original log file (OCEAN), one measurement (M4) and two simulations. The driver in the new measurement was not the same as the driver in the log file.

Two vehicles are simulated, one (D16) is identical to the vehicle in the log file, while the other (D13) has a smaller engine. Otherwise both are Volvo FH-16 6x4RADD-tractors with basic parameters as in Volvo Trucks' specification sheet[5]. In the top plot, they carry a payload of 10 tonnes, same as the vehicle in the log file while M4 is unladen. In the two plots below, the route is the same but the cargo weight is 36 and 56 tonnes respectively.

All in all, the plots show that the mission-driver interaction seems to work well. The speed is decreased in the curves to levels that are in the same range as the log file, using a lateral acceleration threshold of $a_{y0} = 0.2g$. The speed bump works well too: it is the cause of the very first speed dip on the first part of the trip. The deceleration threshold was also set to $a_{x0} = 0.2g$ and it causes the speed to be decreased in a reasonable way: judging from the plots it may be that the real driver has a somewhat lower limit.

There are some places where there are considerable differences between measurement and simulation. In the initial 200 m, there is a difference of about a factor 2. The reason is that there was a recommended speed of 20 km/h here, but this type of sign is not present in the format proposal and therefore missing in the mission-driver interaction. The speed in the curves are everywhere lower in the measurement, but since the speed dips in the right place, it indicates either that the lateral acceleration limit should be lower or that the curvature estimation is too inaccurate. The positive acceleration is higher in the simulations, but that may be attributed to an inadequacy in the vehicle model: the real vehicle has a torque limiter to protect the engine from damage (which would be active when it is unladen), and of course the gearshifts come with a power disruption. Both lower the torque at the wheels.

There is a quite long piece at 13.8 km which displays considerable differences between the measurement and simulation. This is due to traffic, a tractor semi-trailer switching lanes in front of the subject vehicle.

Besides the two large deviations already mentioned, there are many other light-to-moderate variations that could be commented. But no quantitative metric will be used here: judging from the plots and with the analysis above, we conclude that the suggested approach seems to work well enough. It must be mentioned though, that the measurements were carried out in the late-morning on a Tuesday in the end of August: meaning a light traffic situation.

[5]See: `http://www.volvotrucks.co.uk/en-gb/trucks/volvo-fh-series/specifications.html`.

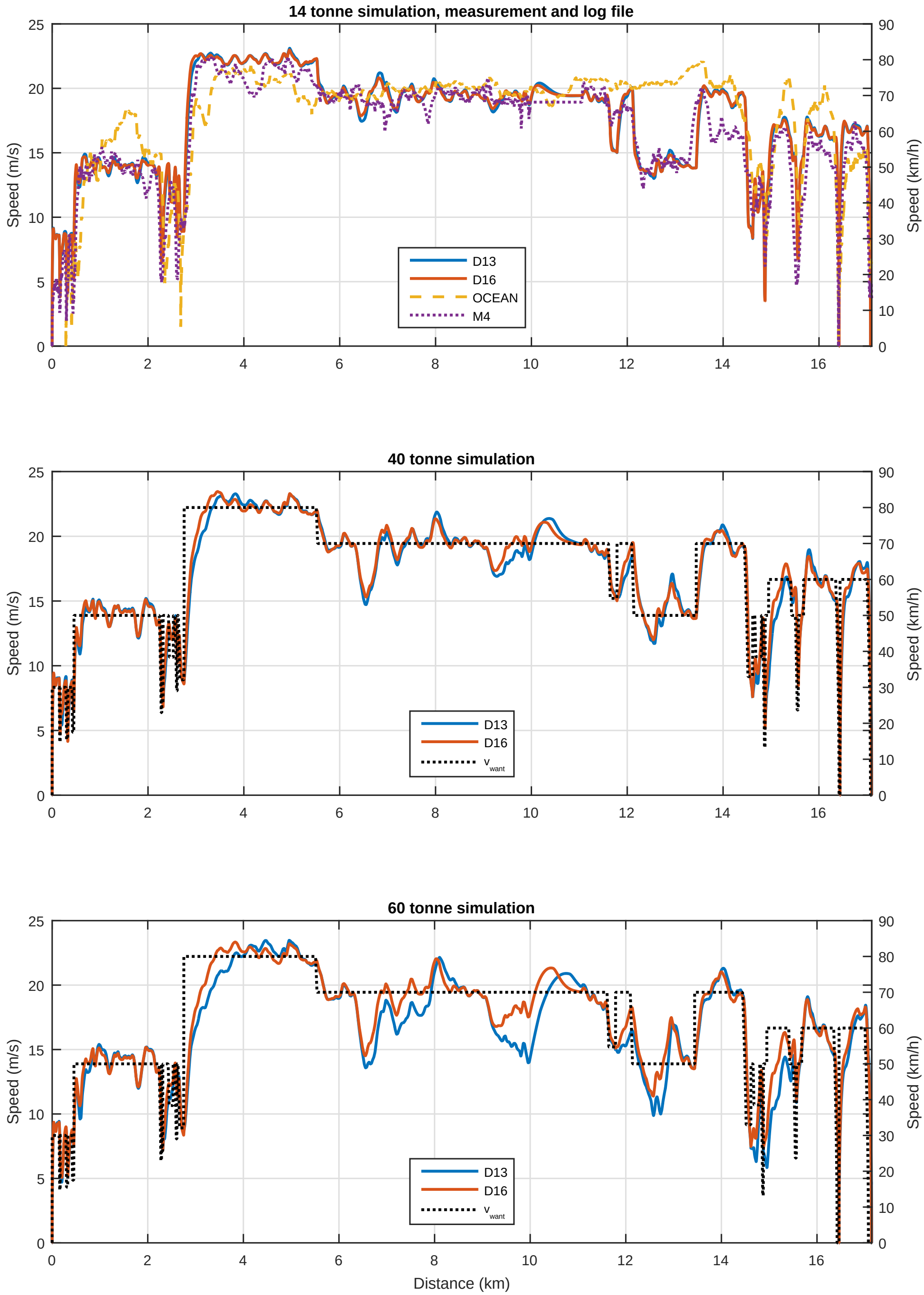


Figure 3.5: *Measurement and simulation results.*

Table 3.2: *Results for the extended transport mission.*

| Engine | Payload (tonne) | Fuel consumption (l/100 km) | (l/(100 km·tonne)) | Mission time (s) | (s/tonne) |
|---|---|---|---|---|---|
| D13 | 10 | 37 | 3.7 | 1079 | 108 |
| | 16 | 43 | 2.7 | 1085 | 67.8 |
| | 36 | 63 | 1.8 | 1104 | 30.7 |
| | 56 | 84 | 1.5 | 1162 | 20.8 |
| D16 | 10 | 44 | 4.4 | 1078 | 108 |
| | 16 | 50 | 3.1 | 1083 | 67.7 |
| | 36 | 67 | 1.9 | 1091 | 30.3 |
| | 56 | 88 | 1.6 | 1112 | 19.9 |

### 3.3.2 An application on vehicle selection

The point of this whole work is to propose a mathematical way to describe vehicle usage, that will make it possible evaluate energy consumption in a fair way. With this mission and vehicle as in the log file: D16 with 10 tonne cargo, it comes out as 44 l/100 km or 32 ml/(tonne·km). It is a relatively substantial number: the reason is that the engine often works at a low torque compared to its maximum, and hence has a low efficiency. The implication is that the engine is unnecessarily powerful and could be downsized. The fuel consumption for D13 turned out to be 37 l/100 km or 27 ml/(tonne·km), a fuel reduction of about 16%. Furthermore, the increase in mission time with the smaller engine is less than two seconds. So, in this mission the weight of the cargo is small enough that downsizing the engine has no disadvantage, and further size reduction could be investigated.

We may conclude that the larger engine is the wrong choice for this mission, and a vehicle with the D13 engine (or even smaller) is a better option. However, the increase in payload was done to see which kind of scenario would benefit the current vehicle configuration. The cargo weight takes four different values: 10, 16, 36 and 56 tonnes. The results in Table 3.2 show that for this route, the smaller engine achieves a better fuel consumption even up to 56 tonnes, but the difference gets smaller the larger the payload. At the largest cargo weight, the difference in mission completion time has become considerable. It needs to be pointed out that changing the transmission (gear choice strategy and gear ratios) offers potential for lowering the consumption and tailoring the configurations better for each load.

The reason that the D16 consumes more fuel is because the engine works at points with lower efficiency. Figure 3.6 shows the two-dimensional histograms for the 10 and 56 tonne missions with both engines, where the torque and speed has been averaged over 1 Hz. A detailed comparison can be done together with the efficiency map in Fig. 2.3, but a qualitative analysis like the one above (using the approximation that an ICE gets more efficient the closer its operates to its peak torque) can be done without too much effort. In this simulation, the two engines have the same mass, consequently there is no difference in total weight and therefore the resistive forces are the same for both vehicle

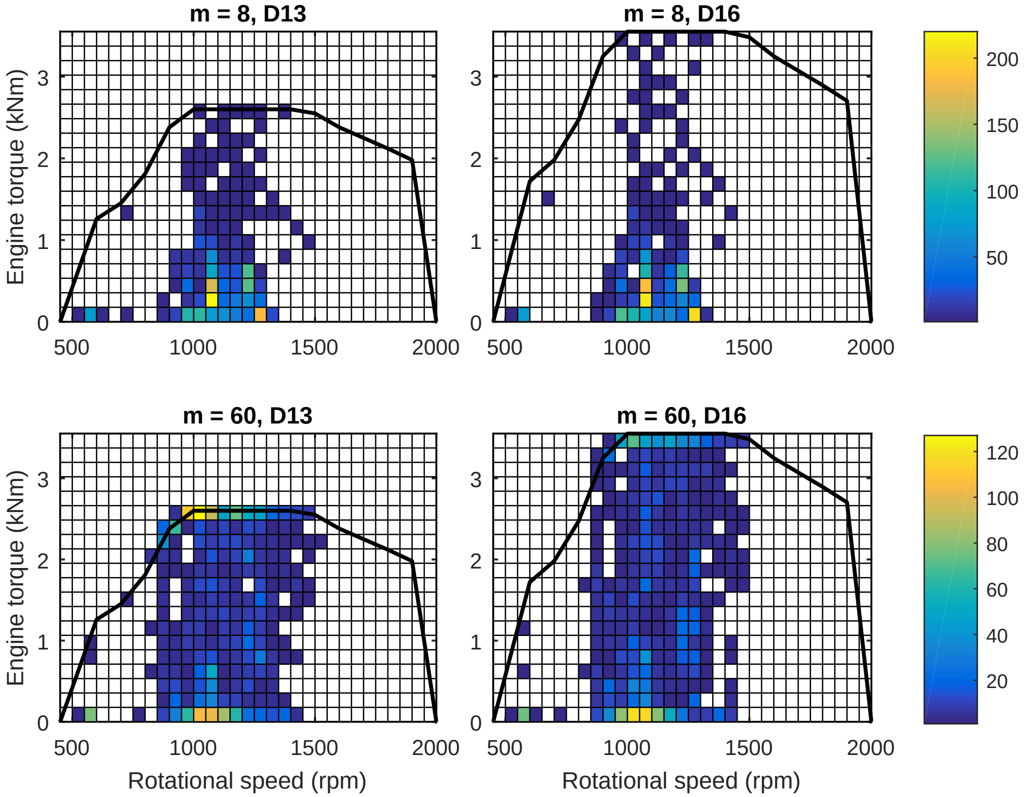


Figure 3.6: *Two-dimensional histograms of engine work points, with torque and speed averaged over 1 Hz. The colours show the total operation time (in seconds) in each area: the 10-tonne result in the top row and 56 tonnes in the bottom; left column shows the D13 engine and right shows D16. Note that the colours have been normalized within mission, i.e. the colour indicates the same numbers for equal masses but not equal engines.*

configurations. Thus, the resistive force causes a higher ratio of load for the smaller engine comparatively, allowing it to work at points of higher efficiency. The difference that does come about is because of inertia: the acceleration is generally higher for the D16, causing the load to be greater in absolute numbers. But the ratio may still favour the D13: if the acceleration is lower it is likely because the torque output is already at its peak, were the efficiency is high. Fig. 3.6 supports this reasoning: in the 56 tonnes case the D13 clearly operates at its maximum torque curve more frequently.

For the 10-tonne mission, none of the configurations work at peak torque more than occasionally. The work point frequencies look very similar in absolute numbers, which means that the output-to-peak ratio is higher for the D13.

# 4 Mission classification

The material in this section uses ideas and results from both paper A and B, but also Edlund and Fryk [30] and Johannesson et al [52].

## 4.1 The need for a classification system

The two previous sections presented a framework for how a complete model of the environment, driver and vehicle can be built and used for energy consumption evaluation. However, to apply it to a real product development or sales-to-order situation the OC must be filled with data. But how the final vehicle performs in reality depends on how well the data matched the actual transport conditions. If it matched the real use-case poorly, the final product will have been tailored for the wrong thing, and will likely be sub-optimal for its actual task. So even though the OC-format allows the transport mission to be fully described in terms of the relevant physical phenomena, the values of those parameters must be appropriately chosen depending on what each individual vehicle is supposed to do and where. In literature, this is sometimes called the 'representativity' of the dataset.

To select the appropriate data, one way to go is to figure out what things that are important to look at. This line of thought is similar to what was done when deciding on the parameters that should go in the OC. Equation (2.3) gives hints and much of the discussion in Section 3.1 can be used here too. For example: the mass enters in three of the five terms, and is therefore essential to consider. Depending on whether the mission specifies that the vehicle transports light, medium or heavy goods, we may predict that different vehicle configurations will be optimal for the three cases, as the result in Section 3.3.2 indicated. The same idea can be applied to the other terms in Eq. (2.3): we will need to know whether the terrain is flat or mountainous, whether the ground is soft or hard, and something about the frequency and amount of speed variation. Those four are examples of things that could make up the categories in a classification system.

The more detailed information that can be specified about the mission, the better selection of data can be made. However, there is always variation: a truck does not always run with the exact same amount of cargo; a bus does not always contain the same number of passengers and they do not always enter or exit at the same stops; a passenger car does not always stop at the same red lights, roundabouts or intersections. Because of the variation, there is a good point in taking the classification categories and dividing them into rough parts. An example of parts, or labels, was already made above, but the limits would need to be defined stringently if they are to be useful. Using mass as example again, the labels could be defined as:

- **Mass - light**: cargo weight is less than 10 tonnes for more than 90% of the distance, and never more than 15 tonnes.
- **Mass - medium**: cargo weight is less than 40 tonnes for more than 90% of the distance, and never more than 45 tonnes.

- **Mass - heavy**: if neither of the above apply

Those definitions make it easy to classify a mission. There are mainly three situations where it could be interesting to do so:

1. **In discussion with end-user**

   Firstly, when discussing with a customer who is interested in buying a new vehicle. Let's say that he or she wants a new truck for transporting timber. Then it is not a complex thing to pick which label that suits the application best, if dealing with an experienced truck driver. This way of doing a label selection, i.e. going from an application to a mission definition, can be called a *top-down* classification. To make sure that it can be done smoothly together with an end-user, the categories should have a set of labels that can be assigned based on questions like: 'what', 'where' or 'how often'.

2. **From log data**

   Secondly, when looking at driving data from, for example, logs from vehicles on the road. To be of most use, that data should contain information on all physical entities that the categories are based on, and be resolved in time. If the mass category is used as an example again, this could be achieved if the vehicle can estimate its payload, and the corresponding ECU-signal is stored with reasonable frequency. Then the correct mass-label can be assigned based on the distribution of the time series simply by counting the number of occurrences that corresponds to each label. This way of doing a classification, i.e. by looking at log data from a vehicle on a real mission, can be called a *bottom-up* classification.

3. **From OC**

   Thirdly, when looking at an OC. Obviously, if the classification system cannot be applied to a transport mission description on OC-format at all, then the whole idea with using that numerical description in simulations is useless and the labels or categories of the classification system are clearly flawed.

The reason that these three variants are mentioned, is that they fit into a product development and sales-to-order process in a natural way as shown in Figure 4.1.

For the sales-to-order process, a salesman discusses with the end-user and makes a top-down classification as per the first example, shown in the right-hand side of the figure. The information is used in the use-case compositor, whose purpose is to select several OCs that display the same characteristics. It can do that by choosing a subset that has the same category labels (or the most similar, if none with identical exist). Example three guarantees that is always is possible. Those OCs are used in simulations of energy consumption to find the most suitable configuration for the mission in question.

The left-hand side of the figure is connected to example two. Data from current vehicles on the road can form the basis from which operating cycles are constructed. In addition, since the log data is from real missions, they contain more detailed information than the rough labels of the classification system, or even things that it fails to consider altogether.

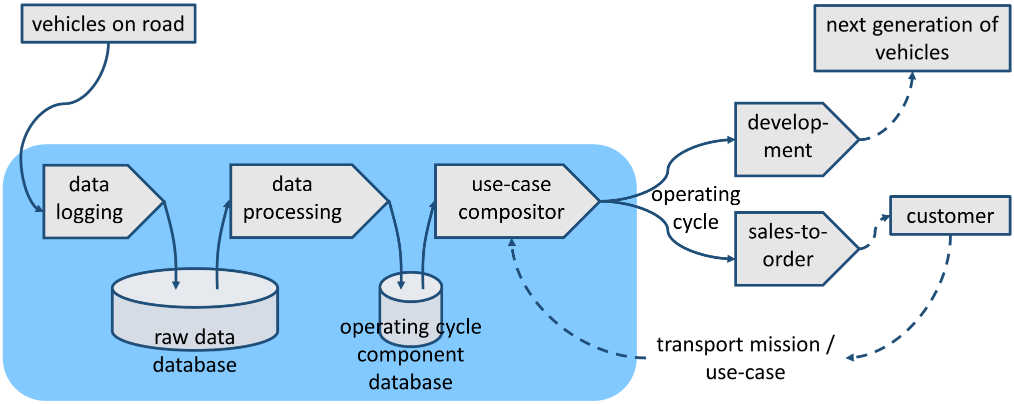


Figure 4.1: *A development process that shows how to choose appropriate OCs based on user application. See also Fig. 4.9.*

For development, an engineer can attain data with well-defined characteristics to use as input for simulation models to investigate or parametrise whatever he or she is developing. A top-down classification is made simply by selecting category labels, which go into the use-case compositor that finds relevant OCs.

The process above assumes the existence of a database of raw data. If the assumption is not fulfilled, then there is no data from which to construct OCs at all, hence there exists no selection problem and the line of question becomes irrelevant.

The discussion so far is applicable to both commercial vehicles and passenger cars, but it has the largest application in case of the former. Generally, cars have a much smaller variation in mission. There is more to be gained by looking at the driving style [21, 53] of the person using it, and that brings the question out of scope for this thesis: the driving style is not a part of the OC-format.

## 4.2 Classification using Global Transport Application

With the need of a system of classification clear, we may turn to the question of finding one. The topic is rarely mentioned in literature, but Volvo Trucks have developed a system called Global Transport Application (GTA) that is open and available to everybody. It was first mentioned by S. Edlund a P. O. Fryk in 2004 [30] who presented the idea and showed an example of categories, called (GTA) parameters, with labels, called (GTA) classes. Further details are found in [54] where 20 parameters[1] are defined, divided into three main groups. All are listed in Table 4.1, but the definitions will not be given here (see [54]). However, three examples are used to show how the classes of a parameter can be defined.

[1]The naming of some of them is unfortunate and clashes with what has been defined so far in this thesis. Whenever there is a risk of misunderstanding, it will be clarified by putting 'GTA' in front of the parameter.

Table 4.1: *The GTA-parameters.*

| Transport mission | Vehicle utilization | Operating environment |
|---|---|---|
| Vehicle type<br>Body and load handling equipment<br>Gross combination weight | Operating cycle<br>Speed changes<br>Manoeuvring<br>Yearly usage<br>Diesel fuel sulphur level | Road condition<br>Road type<br>Topography<br>Altitude<br>Ambient temperature<br>Curve density<br>Dirt concentration<br>Dust concentration<br>Bug concentration<br>Rolling resistance<br>Coefficient of traction<br>Load-bearing capacity of the ground |

Some of the definitions are based on statistics like the labels of the 'mass'-category in the previous chapter, while others are hard limits. The GCW-category (gross combination weight, the total mass of the truck and all trailers) takes the values: $\leq 32$ tonne, $\leq 36$ tonne, etc. and defines the technically allowed maximum gross weight. It does not say anything about the expectation value of the payload or its variation. While a weakness in a top-down description, the information could possibly be obtained by looking at the database of log data through a bottom-up classification. This is a typical example why it is a beneficial to work from both ends.

The topography-parameter is, unlike GCW, based on a statistical distribution. The classes are defined as follows:

- **Topography - flat (FLAT)**

  Grade $< 3\%$ during $> 98\%$ of driving distance, maximum grade $\leq 8\%$.

- **Topography - predominantly flat (PFLAT)**

  Grade $< 6\%$ during $> 98\%$ of driving distance, maximum grade $\leq 16\%$.

- **Topography - hilly (HILLY)**

  Grade $< 9\%$ during $> 98\%$ of driving distance, maximum grade $\leq 20\%$.

- **Topography - very hilly (VHILLY)**

  If other criteria are not fulfilled.

The grade $y$ is given in percentage here and relates to the road grade angle $\theta$ (see e.g. Eq. (2.12) and Section 3.1) by,

$$y = 100 \tan \theta \tag{4.1}$$

In a top-down classification, the correct topography class can either be assigned based on the geographic region where the vehicle will be operating or through special request from the end-user: if it is must be able to ascend a specific hill. In a bottom-up case, it can be found from the log data if the grade angle is measured by a sensor, or by GPS-data and a geographic database (such as NVDB [51], Here [55], Tomtom [56] or OpenStreetMap [57]).

A third example of a possible class definition can be found in the (GTA) operating cycle parameter. The classes are defined as follows:

- **(GTA) operating cycle - stop and go**

  Mean distance between delivery or pickup of goods or passengers is less than 0.5 km.

- **(GTA) operating cycle - distribution**

  Mean distance between delivery or pickup of goods or passengers is more than 0.5 km, but less than 5 km.

- **(GTA) operating cycle - regional**

  Mean distance between delivery or pickup of goods or passengers is more than 5 km, but less than 50 km.

- **(GTA) operating cycle - long distance**

  Mean distance between delivery or pickup of goods or passengers is more than 50 km.

The classes are based on an average value: easily obtained through log data or in discussions with the customer. Note that the relevant stop is pickup or delivery, which is equivalent to the mission stop in the OC-format.

The parameters show three separate ways of how the classes (labels) can be defined, though it can be done in many other ways too. All GTA-parameters in Table 4.1 have a definition, but some are vague and leaves the choice open to interpretation. That is contrary to the purpose and therefore the system can be improved.

GTA is an overall description of the mission, the operating environment and vehicle utilization, meaning that it can be used when looking at other properties than energy consumption (durability and fatigue, for example). Partly because of that, all categories in Table 4.1 are not relevant to consider when looking at a single mission in the log data: like yearly usage. Likewise, there are categories that are not relevant for classifying a mission on OC-format: vehicle type, yearly usage or diesel fuel sulphur level, for example. Additionally, there are parameters missing if GTA was to be able to completely classify an OC. Nevertheless, it can still be used for this purpose well enough.

To make an explicit example, we use the mission from the case-study in Section 3.3 and apply GTA to get a classification. The result is shown in Table 4.2.

It could happen that it is not possible to assign a class to a parameter due to lack of information. This is not ideal but manageable: recall that the main purpose is to find the right vehicle for the job. The six parameters: GCW, operating cycle, yearly usage, road condition, topography and load bearing capacity of the ground, are termed the ‘primary GTA parameters’. They are considered to contain the most essential information overall and the situation is good enough if a class can be assigned to each of those.

Table 4.2: *GTA-classification of the (logged) mission in the case-study.*

| GTA-parameter | Class |
|---|---|
| Vehicle type | Truck |
| Body and load handling equipment | 5th wheel |
| Gross combination weight | GCW $\leq 20$ |
| Operating cycle | Regional |
| Speed changes | Low |
| Manoeuvring | Low |
| Yearly usage | Not applicable |
| Diesel fuel sulphur level | $< 15$ PPM |
| Road condition | Smooth |
| Road type | City thoroughfare |
| Topography | PFLAT |
| Altitude | Altitude 1500 m |
| Ambient temperature | Upper limit $+40°$C, lower limit $-25°$C |
| Curve density | High |
| Dirt concentration | Low |
| Dust concentration | Low |
| Bug concentration | Low |
| Rolling resistance | $0.4 - 2\%$ (ROLR-2) |
| Coefficient of traction | $\mu \geq 0.8$ (FRIC-0.8) |
| Load-bearing capacity of the ground | Extremely hard |

Mission classification is only one of several applications that GTA can be used for. Another use is to make sure that the product terminology is the same in all parts of a company. Words like 'hot' and 'flat' can mean different things depending on which branch of engineering that is being discussed. A well-defined nomenclature according to the descriptions in GTA ensures that misunderstandings are kept to a minimum.

Another use that deserves to be mentioned is explained in paper B: to decrease the dimensionality of the space of components (the domain) in the optimisation process. Some parameters, especially the primary ones, may decrease the number of component choices considerably, or specify them completely based on fatigue considerations, gradeability etc. Any decrease in the number of dimensions spanned by the optimisation problem is good news indeed.

## 4.3 Classification through stochastic models

Another way of approaching the classification problem is by using stochastic models (Eqs. (4.3) and (4.4)). We would like to found the labels of a category on appropriate statistical measures, and a way to do that is to model the underlying phenomenon as a random process. The constants of such a model contain information on the statistical distribution it follows. If they can be interpreted physically, they would make for prime candidates to use in a classification system. To see how it works, we will use an example.

A very common way to generate driving cycles is by using a large set of driving data of vehicle speed sampled at some time interval, together with a stochastic process in the form of a Markov matrix (see [18, 23, 58, 59, 60]). Already in the introduction we argued that driving cycles are an obsolete way of describing a mission, so instead we choose to work with the topography, according to the article by Johannesson et al [52].

For convenience, we will work directly with road grade in Eq. (4.1). Consider the geometrical trajectory of the road and let it be discretized it into small parts $s_k$, $k = 1, 2, \ldots$, each with the length $L$. For each piece, we will model the road grade $y_k$ as constant. If the pieces are small enough, meaning that to describe a hill base-to-base many are needed, then we may observe that if the road starts to go uphill (for example), it tends to continue doing so for a while. Therefore, if the pieces are laid down one-by-one and we try to predict what the road grade looks like in the next step, a safe guess would be to assume it will be the same as the current piece, plus some small noise $e_k$, see Figure 4.2. That kind of behaviour is modelled using an autoregressive model (AR), also known as a Markov chain.

$$s_k = s_{k-1} + L \tag{4.2}$$

$$y_k = a y_{k-1} + e_k \tag{4.3}$$

$$e_k \sim \mathcal{N}\left(0, \sigma_e^2\right) \tag{4.4}$$

Here the model is based on the assumption that the grade has zero mean (i.e. the trip starts and ends at the same altitude) and a Gaussian noise term. There are two new constants introduced in Eq. (4.3): $a$ and $\sigma_e$, sometimes called the parameters of the AR-model. Depending on their physical interpretation, they may offer insight into the

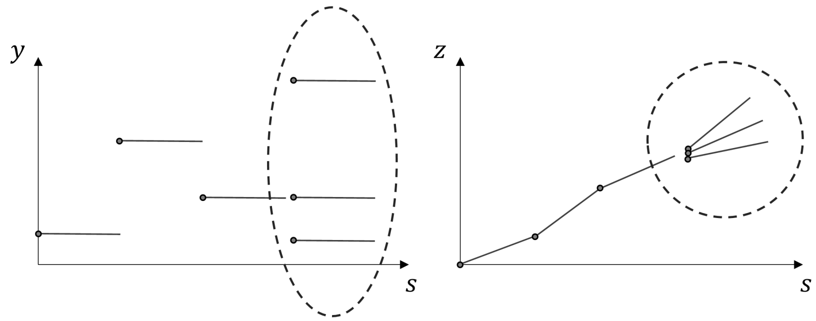


Figure 4.2: *The principle of the recursive model. Note that the altitude z corresponds exactly to the topography parameter in the OC-format.*

overall behaviour of the road grade and can be considered candidates for classification measures.

The constant $a$ determines how much the next step couples to the current, and therefore it says something about how fast the topography changes. The boundaries are $a \in [0, 1]$: $a < 0$ would mean that the slope had an inverse connection which makes no sense physically, and $a > 1$ yields a non-stationary process. A value close to 1 indicates a slow change (long slopes), while a value close to 0 means fast change and short slopes. The constant is easier to interpret physically through the mean hill length $L_h$,

$$L_h = \frac{L}{\frac{1}{4} - \frac{1}{2\pi} \arcsin a} \tag{4.5}$$

It is the mean distance of a crest or a valley, meaning half the wavelength if seeing the topography as wave-like.

The constant $\sigma_e^2$ is the variance of the noise, sometimes called the amplitude. It is a measure of how much the residual changes: the larger the variation the more the recursive model will change in each step. As it stands, the parameter is non-intuitive. However, we may note that since Eq. (4.3) is linear and the noise is Gaussian, the grade $y$ itself will also follow a Gaussian distribution,

$$y \sim \mathcal{N}\left(0, \sigma_y^2\right), \quad \sigma_y^2 = \frac{\sigma_e^2}{1 - a^2} \tag{4.6}$$

and $\sigma_y^2$ is simpler to interpret: it is the variance of the road grade itself. Therefore, it says something about how severe the topography is and that makes it an excellent choice of a classification category. The labels are continuous, so it is of a different kind than everything else so far.

It can be related to the four topography classes in GTA, if the criteria of maximum grade are neglected. For example, the FLAT-class says that the grade should be less than 3% for at least 98% of the distance. In terms of what we have written above, this is equivalent to saying that the probability of a grade less than 3% should be above 0.98, if the distance is long enough to invoke the law of large numbers. The only difference for the

Table 4.3: *Relation between $\sigma_y$ and the GTA topography classes.*

| | Variance limits | GTA topography class |
|---|---|---|
| $\sigma_y$ | $< 1.29$ | FLAT |
| | $\in [1.29, 2.58[$ | PFLAT |
| | $\in [2.58, 3.87[$ | HILLY |
| | $\geq 3.87$ | VHILLY |

other classes are the limiting grade values (6% and 9%), so to keep it general we consider a grade $\zeta$. Since $y$ is normally distributed, we know what the frequency function looks like: then we can write down the probability of having a grade (up or down) less than $\zeta$,

$$\mathcal{P}(-\zeta \leq y \leq \zeta) \geq 0.98 \tag{4.7}$$

$$\mathcal{P}(-\zeta \leq y \leq \zeta) = \sqrt{\frac{2}{\pi\sigma_y^2}} \int_0^{\zeta} \exp\left(-\frac{y^2}{2\sigma_y^2}\right) \mathrm{d}y \tag{4.8}$$

Setting these two equal, we can compute what value of $\sigma_y$ that corresponds to the limits of the classes. There is no point to continue analytically though, as the integral is not analytically solvable for an arbitrary $\zeta$. The numerical solutions are shown in Table 4.3.

$\sigma_y$ contains more information than the GTA-classification: it provides a continuous scale. So, given a log file, a classification can be made by estimating the variance. One weakness that should be mentioned, is that the stochastic model assumes that the topography follows a Gaussian distribution. The approximation holds up well enough, though it could be improved by using a Laplace distribution (see Johannesson et al [52]), but even so it is still an approximation. The GTA-classification, on the other hand, is based on the empirical distribution and does not display the same weakness.

In the same way that $\sigma_y$ is used as a classification measure, $L_h$ can be too. There is no similar category in GTA - no parameter mentions hill length - meaning that it spans a new dimension in classification space. That is only a good thing if there are situations where the new measure makes a difference. In this case, there are (see Section 4.4), the performance of several components may depend on the hill length as well as the magnitude of the grade: wear on friction brakes, clutches or tyres, and choice of battery size or electrical motor for a hybrid vehicle, for example.

The model parameters can be estimated from measurement data in several ways: via the least-squares method or the Yule-Walker equations to name two. In this thesis, the toolbox WAFO [61] for Matlab was used for that purpose. Using the mission in the case-study in Section 3.3 as an example again, the values compute to: $\sigma_y = 1.95\%$ and $L_h = 443$ m. Fig. 4.3 shows how the grade was distributed between GTA-classes.

Only a stochastic model for one physical parameter in Table 3.1 has been presented, but others that would work well are mentioned in literature. Karlsson [62] presents a model for the size of road curvature, Maghsood [63] has a method based on a hidden Markov model for estimating and generating where curves are along a road, Johannesson et al [64] defines a working example for road roughness, and Odrigo et al [4] shows that

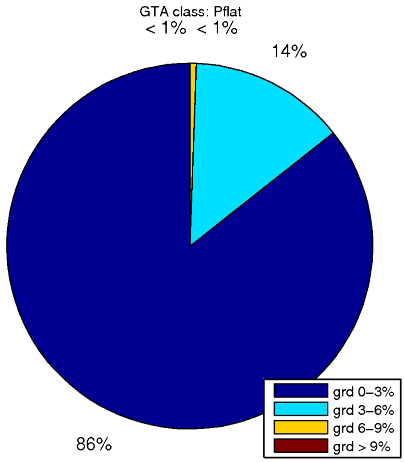


Figure 4.3: *The distribution of the topography for the case-study mission. The four colours can loosely be thought of as the GTA-classes themselves.*

these are possible to use for road generation. Nevertheless, much work remains to be done before there are models for all the OC-parameters, or even just the most important.

A great advantage of having a stochastic model is that it can be used to generate new time series of the physical variable it describes. It means that by using Eq. (4.3) an infinite number of new topographies can be constructed, all with the same statistical distribution as the mission from which the parameters were estimated. It implies that the process of finding suitable OCs in Fig. 4.1 can be done in another way. Instead of looking through the driving data for matching log files to convert, new OCs can be generated using the model parameters from the missions that are judged most similar (based on the classification method) for the application.

## 4.4 An example in a development process

Examples of how both GTA and the stochastic topography model can be used is found in both paper A and B. In this section, we use the results from the former to see how the methods from Sections 4.2 and 4.3 can be applied.

It was noted in the previous section that the stochastic model spans a dimension, the average hill length, that is not described by any category in GTA. Figure 4.4 shows an example of two roads that both belong to the PFLAT-class, but have very different average hill length. Some components could benefit if that was taken into consideration when choosing configuration.

The question of battery size and electric motor for hybridisation is one of them, if regenerative braking is possible. The size of the regenerated power in a downhill is only dependent on the road grade (according to Eq. (2.1), (2.3) and (2.12)), but the amount

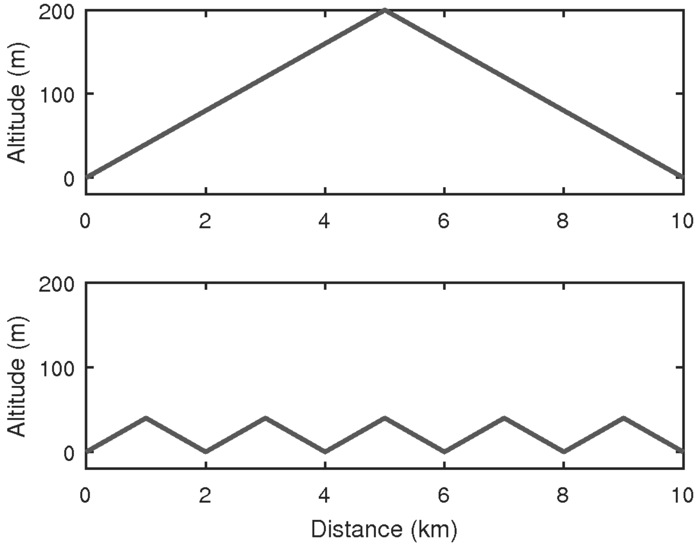

Figure 4.4: *Two examples of topographies that has the same GTA-class (PFLAT), but display distinctive characteristics. In the top plot* $L_h = 10$ *km, in the bottom one* $L_h = 2$ *km.*

of regenerated energy depends on the length of the hill,

$$E_{bat} = \int_{t_0}^{t_f} P_{EM}(t)\,\mathrm{d}t = \int_{s(t_0)}^{s(t_f)} \frac{\tilde{P_{EM}}(s)}{v}\,\mathrm{d}s \tag{4.9}$$

Returning to Fig. 4.4, it means that in these two cases the battery size would be the same if the decision was only based on the GTA-class, but the top figure has longer downhill and a vehicle should therefore benefit if equipped with a larger battery. Paper A tries to answer the question whether this is important or not.

The topography model from the previous section was used to generate a large number of missions, with varying values of the amplitude and average hill length according to Table 4.4. 400 roads for each of the 100 combinations of $\sigma_y$ and $L_h$ were generated, resulting in 40 000 missions in total. All of them had a travel distance of 20 km, but were run back-and-forth to ensure that the altitude was the same in the beginning and end. Each one was used in a simulation model[2] to compute the energy consumption for two vehicles: the first with a conventional ICE, the second a battery-electric hybrid equipped with both an electrical motor (capable of regenerative braking) and an ICE (with the same specification as in the conventional vehicle).

In the first study, two sets of missions are run on every road, transporting 40 tonnes and 80 tonnes in total. The vehicle setup was that the ICE engine had a maximum power of 450 kW, while the electric motor could produce 300 kW, and a maximum battery

[2]Not the model in Section 2.2, but an even simpler one. See paper A for the details.

Table 4.4: *Road topography values (left table) and vehicle parameters (right table).*

| $L_h$ (km) | $\sigma_y$ (%) |
|---|---|
| 0.3 | 0.50 |
| 0.4 | 0.90 |
| 0.6 | 1.29 |
| 0.8 | 1.60 |
| 1.0 | 2.00 |
| 1.2 | 2.35 |
| 1.4 | 2.60 |
| 1.6 | 2.90 |
| 1.8 | 3.21 |
| 2.0 | 3.50 |

| Parameter | Value |
|---|---|
| $m$ | 40/80 tonne |
| $\max P_{ICE}$ | 450 kW |
| $\eta_{ICE}$ | 0.45 |
| $\max P_{EM}$ | 300 kW |
| $\eta_{bat}$ | 0.75 |
| $\max E_{bat}$ | 12 kWh |

state-of-charge of 12 kWh. The comparison measure $\tilde{q}$ is taken as,

$$\tilde{q} = \frac{E_{conv} - (E_{hybrid} - \eta_{bat} E_{bat})}{E_{conv}} \tag{4.10}$$

$$\left.\begin{matrix} E_{conv} \\ E_{hybrid} \end{matrix}\right\} = \int_{t \in t_{trac}} P_{ICE}(t)\, \mathrm{d}t \tag{4.11}$$

It describes how much energy is saved by using the hybrid vehicle, in units of the conventional vehicle. For example, if $\tilde{q} = 0.2$ it means that the hybrid configuration uses 20% less energy than the conventional vehicle ($\tilde{q} \in [0, 1]$). The measure is easy to understand but some care is needed to avoid suffering Simpson's paradox.

The results from the simulations are plotted in Fig. 4.5, with the 40-tonne mission in solid and 80-tonne mission in dashed lines. In both settings, the hill length has little influence when the topography is flat but it grows as it gets hillier. For the class HILLY, there is a difference between saving 18% for shorts hills ($L_h = 0.40$ km) and 14% for long ones ($L_h = 1.8$ km). It proves that when it comes to hybrid vehicles and battery consideration, hill length has a non-negligible influence, and therefore using it as a classification measure has merit.

There is much more analysis that can be done with Fig. 4.5, but for most of it we refer the reader to paper A again. However, the fact that the energy saving starts to decrease in the upper range for the 80-tonne case deserves a comment. There are two main reasons:

1. When the battery is full, no more of the potential energy can be recovered. Then the hybrid vehicle operates identically to the conventional one and therefore the ratio between the difference starts to decrease. The effect comes from both dimensions: longer hills mean larger risk of saturation and larger inclination means quicker fill-up.

2. The amount of energy to be regenerated is mass dependent so in theory the heavier the cargo the better. But the electrical motor is only able to regenerate power up

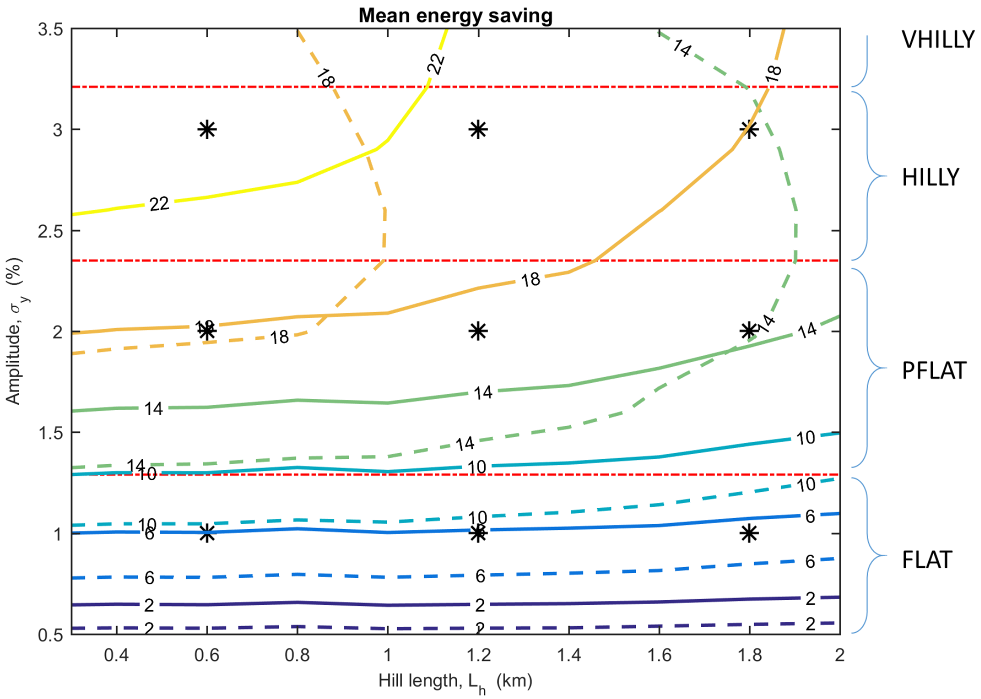


Figure 4.5: *Contour plot of the average energy saving ($\bar{\bar{q}}$ in percentage): with solid line showing the $m = 40$ tonne result and a dashed line for $m = 80$ tonne. Additionally, the limiting values of $\sigma_y$ for the GTA classes is shown in dotted red. Note that the efficiencies of the ICE and battery are different from the corresponding plot in [2].*

Table 4.5: *The recommended battery sizes (in kWh) based on the design criteria.*

| | $m = 40$ tonne | | | | $m = 80$ tonne | | |
|---|---|---|---|---|---|---|---|
| $\sigma_y \downarrow \setminus L_h \rightarrow$ | 0.6 | 1.2 | 1.8 | $\sigma_y \downarrow \setminus L_h \rightarrow$ | 0.6 | 1.2 | 1.8 |
| 1.00 | 0.2 | 1.0 | 2.7 | 1.00 | 0.5 | 1.9 | 5.8 |
| 2.00 | 0.7 | 4.1 | 8.2 | 2.00 | 1.2 | 6.1 | 12.6 |
| 3.00 | 2.4 | 8.0 | 12.6 | 3.00 | 2.9 | 9.5 | 15.5 |

to its maximum capacity, after which the friction brakes must be used to dissipate the rest. Since it is the same motor regardless of payload, it will saturate at a much lower grade angle when the cargo mass is large. The more the angle is increased above that limit, the less the difference between the hybrid and the conventional vehicle becomes. This effect has no dependence on hill length, only grade.

Both thresholds are disadvantageous for the heavier cargo, and they cause the saving to decrease at considerable $\sigma_y$ and $L_h$. The same thing happens for the 40-tonne case, but at larger amplitude and longer hills than what was investigated here.

At this point, any true vehicle dynamicist (or vehicle engineer) would start considering how the related design variables behave. Here we will only consider buffer size and leave the electrical motor fixed.

The battery size was varied from 0 to 24 kWh (twice as large as the nominal value) on three values of $\sigma_y$ and $L_h$, resulting in nine combinations with 400 missions in each. The variation and hill length values are marked with black asterisks in Fig. 4.5.

The behaviour of the $\tilde{q}$-value is shown in Fig. 4.6. Mission settings with the same hill length have the same line-type (solid, dashed and dotted) while settings with equal variance have the same colour. The energy saving increases with battery size, unsurprisingly, but the plots show that all settings have an approximate knee point, marked with asterisks at the very right edge. There is never a reason to increase buffer size beyond that point, as there is no longer any gain in energy saving. Quantitative recommendations of buffer size could be made if there was an explicit design criterion.

For example, let's say that the design criterion is that at least 90% of the maximum energy saving should be reached. Using Fig. 4.6 it becomes straight forward to find the buffer size that achieves that $\tilde{q}$-value. The setting is marked with a circle in the figure and can be found in Table 4.5. A look-up table like this can be used directly in a design process, provided that the typical GCW of the application is known along with the geographic region where the vehicle will operate.

The influence from the electrical motor could be evaluated in the same way, and design recommendations derived. Of course, the battery size and motor performance interact, so they should be varied together for the best result.

A final comment: it must be pointed out that it is not guaranteed that the hybrid vehicle is the better choice when total cost is considered. It is indeed more energy efficient, but the weight of the battery and motor could be replaced with cargo in the conventional vehicle. Moreover, the investment cost is higher for the hybrid and its battery has an expected life time. It is the total investment cost that determines which choice of

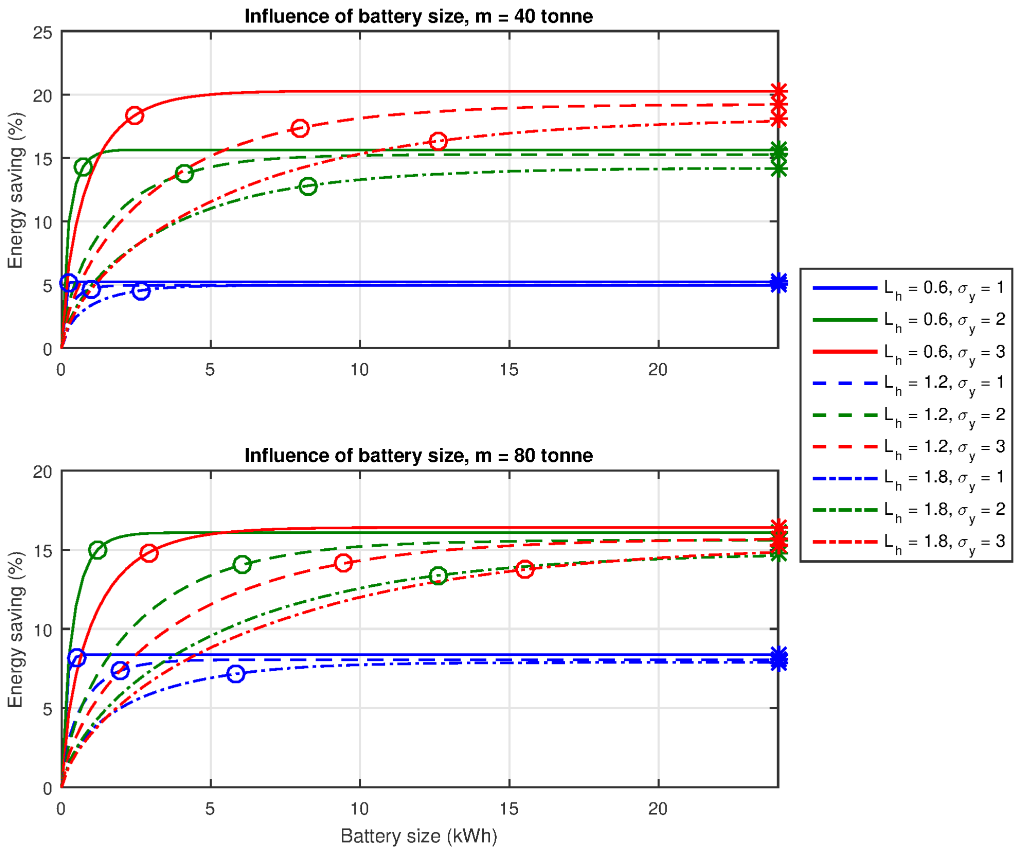


Figure 4.6: *Plots of energy saving as a function of battery size, for the nine road combinations. Note that the efficiencies of the ICE and battery are different from the corresponding plot in [2].*

configuration is the best from an economic point of view, see [32].

## 4.5 The advantage of combining methods

Two methods of classification have been described so far: GTA and using stochastic models, and it has been shown how they can be used. These are not mutually exclusive and can be used together to get around each other's weaknesses.

We remind the reader that there are two ways that OCs could be constructed for a transport mission: using GTA to find log files with similar characteristics and convert them into OCs, or by generation with the stochastic models. The former will be called *case 1* and the latter *case 3*.

### 4.5.1 Combining methods

One disadvantage of using GTA-classification only, is that the number of available OCs that have an appropriate combination of classes could be very few. The consequence is that predicted energy consumption has a large confidence interval: there is a lot of uncertainty in the value. From basic statistics: the more measurements (simulations) that can be obtained, the more the ensemble average approaches the real expectation value. The stochastic model remedies this, because it can generate an endless number of missions.

Another disadvantage of the GTA classification, is that it requires a conversion from log data into missions on OC-format and that transformation is non-trivial. For one thing, the data is contaminated by the choices made by the driver and limiting performance of the vehicle. Those influences should be removed. The speed is especially difficult to deal with, because it is a result of many interactions. The stochastic model avoids this to some extent because it generates missions based on the model parameters. Those parameters are estimated through the data though, and do suffer somewhat from the same thing.

A disadvantage of stochastic models is that there is a risk that fictional missions are used. The model parameters are estimated from data in general, but the model offers such an effortless way of obtaining (many) missions that they can be used in a way that the wrong conclusions are drawn. For example: Fig. 4.7 show a histogram of $L_h$ and $\sigma_y$-values from about 1000 real (logged) missions. In the energy contour in Fig. 4.5, 400 missions were used for each of the 100 combinations, but the histogram shows that only some combinations are relevant. For instance, there are no long hills with very large variation. It makes sense physically because the vehicle would travel far vertically which does not commonly happen, but it is not always easy to find all inconsistencies. Using GTA and case 1 OCs guarantees that only realistic values are chosen and used.

Another downside with a stochastic model is that it only describes what it was designed for. In reality, there may be dependencies between variables and unless those are explicitly modelled by the stochastic process, unrealistic roads will be generated. For instance: there are no speed bumps on highways, so the models for legal speed and speed bumps should be coupled. It is unlikely that all such dependencies (including exceptions, and exceptions to the exceptions. . . ) are found, and if so, the resulting model would be hideously complex.

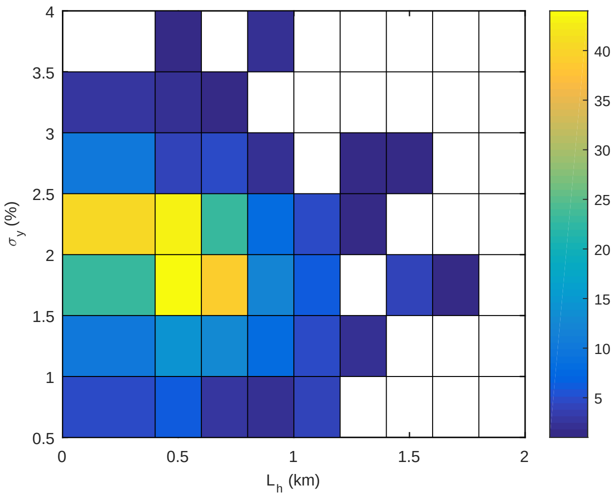


Figure 4.7: *Histogram of average hill length and amplitude on real roads. The data comes from the OCEAN-project and consists of about 1000 missions, mostly from Sweden but also some from Finland, Germany and the Netherlands. Only missions that were longer than 1 km have been considered.*

Using GTA and case 1 OCs avoids the problem, because the measured data is from real roads and do include all dependencies.

Using the two methods together may be a way to circumvent the downsides of each. This is by no means a done deal, it is simply an idea of what the result may look like, *if indeed it does work the way we hope it will.* Fig. 4.8 shows an outline of how the methods are intended to work together. In the figure, we imagine that energy consumption from nine vehicle configurations have been evaluated on a mission setup. The circles show the result from the only case 1 OC. The lines show the 90% confidence interval resulting from a batch of OCs from case 3. The case 1 simulation provides information on the energy consumption that is trustworthy. The case 3 simulations provide a value on the variation of the consumption. In the example, it is not obvious which configuration that is the best choice, options 3-6 are all good choices with 3 perhaps the best overall. However, we can note that if using only case 1 simulations, configuration option 4 would have been the choice, and using case 3 it would have been option 9 (where something clearly has gone wrong with the stochastic method). Again, we would like to emphasize that it is a constructed example.

### 4.5.2 The OCEAN-process

A process for product development was outlined in Section 4.1 using Fig. 4.1. We return to that now to discuss the parts in more detail. Figure 4.9 is another illustration of the same things, with another nomenclature. The green blocks constitute the parts of the bottom-up process, loosely corresponding to the left-hand side of Fig. 4.1. Log data is taken from vehicles on the road, and each one is classified using both GTA and by

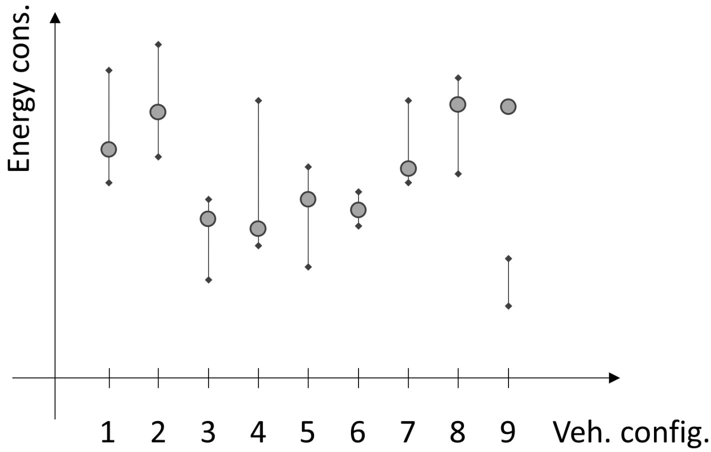


Figure 4.8: *Sketch of how case 1 and case 3 can be used together to evaluate energy consumption for real missions, and put a value to the variation and expected value of the overall performance.*

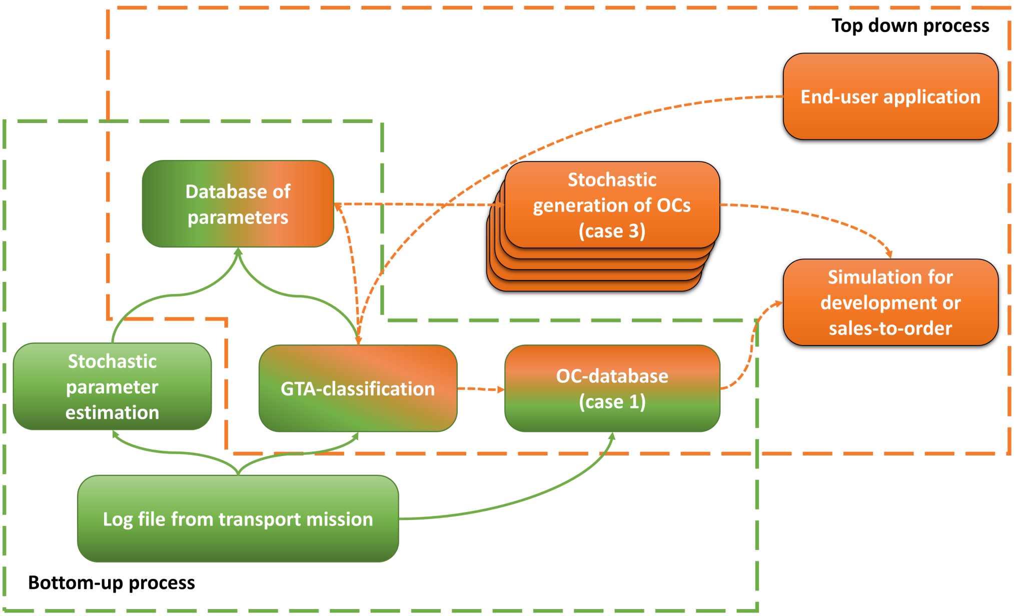


Figure 4.9: *Another way of seeing the OCEAN-process than in Fig. 4.1: here the various parts of the thesis are shown explicitly. It is also shown what methods and parts the bottom-up and top-down processes use and create.*

estimating the stochastic model parameters. This information is stored in a parameter database. Each log file, or parts thereof, are also converted into an OC and stored in a mission database.

The orange blocks constitute the top-down process, which is the right-hand side of Fig. 4.1. The user application block represents any user, whether from development or sales-to-order. Independently of the usage, a GTA-classification is made: through discussion or via analysis of relevant driving data. Based on the GTA-classes a selection algorithm is run in the parameter database that selects the OCs that are most similar in the mission database. Similarly, stochastic model parameters are selected based on the same premises and an ensemble of case 3 OCs are generated. All of them are used in simulations whose result form the basis for the optimisation process itself. If the objective is to find the most suitable vehicle configuration, the result could look something like Fig. 4.8. The same elements can be used for development of new products.

We call that the Operating Cycle Energy mANagement- or OCEAN-process.

# 5 Discussion, conclusion and future work

## 5.1 Discussion and conclusion

We return now to the research questions posed in the introduction:

I **The representation problem**: what to include in a description of a transport missions and how to represent it mathematically?

II **The classification problem**: how should a mission executed in a specific region be labelled (i.e. described on a high level) depending on its characteristics?

III **The simulation problem**: what to model, and how to combine it with the solutions to the representation and classification problems?

Roughly speaking, each chapter was dedicated to one of the questions: problem I was mainly discussed in chapter 3, problem II in chapter 4, and problem III in chapter 2. But the questions interact with each other, meaning that the solutions are not independent.

For the representation problem, a solution was proposed in the form of a set of parameters that were presented in Table 3.1. The description was divided into four categories: road, weather, traffic and mission, that together details the physics of the surroundings and the objective of the mission. A transport mission representation on this form was called an operating cycle (OC).

For the simulation problem, it was argued that a forward simulation is preferable for product development, to adequately reflect the differences between vehicle configurations. In addition, it is an advantage if the complete model is modular: examples of a top-level structure in the form of the operating cycle, a driver and a vehicle was shown in Figure 2.1; and a vehicle structure of the engine, transmission and chassis was shown in Figure 2.2.

Here we arrive at the first interaction: with a top-level model structure like that, the OC must talk to the driver model. The driver controls which speed the vehicle should travel at via the accelerator and brake pedals and the desired speed depends on, for example: speed limits and road trajectory. So, to make an OC fully useful, there must be a driver model that can interpret the information and transform it into pedal actuations. A simple example of such a model was given in Section 3.2. It was split into an interpretation and a regulation: the former took some of the information in the OC and translated the into a wanted speed, while the latter controlled the pedals based on that desire and the current vehicle speed.

The performance of the proposed OC-format together with the composite driver and vehicle models, was investigated using a case-study (Section 3.3). A simple mission was selected from a database of log files from real-world missions and an OC was constructed for the same thing. The simulation results showed that the information in the operating cycle described this mission and the surrounding well enough for it to be useful. The ensuing speed profile displayed similar characteristics as the measured one.

A weakness that deserves to be pointed out is that the case-study only tested some of the parameters in the OC-format: speed limits, road signs, curvature, topography and speed bumps. In paper C, much of the information in the mission matrix is also evaluated, while the weather parameters are based directly on physical variables and it should be safe to assume that they describe their respective phenomena well enough. However, the parameters roughness and, especially, ground type still need to be properly validated. Another weakness is traffic, a quantitative description is missing in the format proposal and therefore it cannot describe the driving conditions when the traffic situation becomes moderate or worse.

A fortunate consequence of using the recommended model structure (forward simulation), is that the mission completion time appears as an additional performance metric. The energy consumption should still be considered the most important, but the completion time is a good complement to assure that the vehicle configuration is an economically viable choice for the end-user. The conclusion from the case-study was that the vehicle in the log file would benefit from an engine downgrade, thereby saving at least 16% in fuel consumption while the decrease in mission completion time was negligible.

The simulation models used here are all available for download at the VehProp homepage[1]. We encourage interested parties in both academia and industry to use and improve them.

For the classification problem, two methods were explained and exemplified: Global Transport Application (GTA) and stochastic models. Furthermore, the basic idea of how those methods can be used for product development and sales-to-order was outlined using Fig. 4.1: the OCEAN-process.

GTA is an existing system originally developed by Volvo Trucks. It is built around 20 parameters that are ordered into transport mission, vehicle utilization and operating environment. Another interaction appears here: comparing these to the four categories of the OC-format, the OC's mission loosely corresponds to GTA's transport mission and vehicle utilization. Similarly, the OC's road, environment and traffic overlap with the GTA operating environment, though again the match is not perfect. Many GTA-parameters, but not all, can be used to label the characteristics of an OC.

It was briefly mentioned how OCs could be found from log data through GTA-parameters, but little was said of the methods of data analysis that are needed. While many are straight forward to find (topography, curvature etc.), others are much harder. For example, the driver and traffic influence must be removed to be able to estimate speed limits and it is highly non-trivial task. Some parameters will require the use of external databases. At the time of writing, the complete conversion from a log file into an OC does not exist and this is most certainly a weakness.

The method of classification using stochastic models was explained by using topography as an explicit example. In this case, it was shown how the parameters of the model can be used as classification measures: the variation (or amplitude) $\sigma_y$ and the mean hill length $L_h$. The former contains information on the severity of the grade, while the latter details the average length of a crest or valley.

The stochastic model of the road grade relates to the topography-parameter in the OC-format. If the model is used to generate a new grade profile, an integration of it yields the altitude, which is the OC-parameter. The grade is piecewise constant and so

[1]URL: `https://www.chalmers.se/en/departments/am/research/veas/Pages/VehProp.aspx`

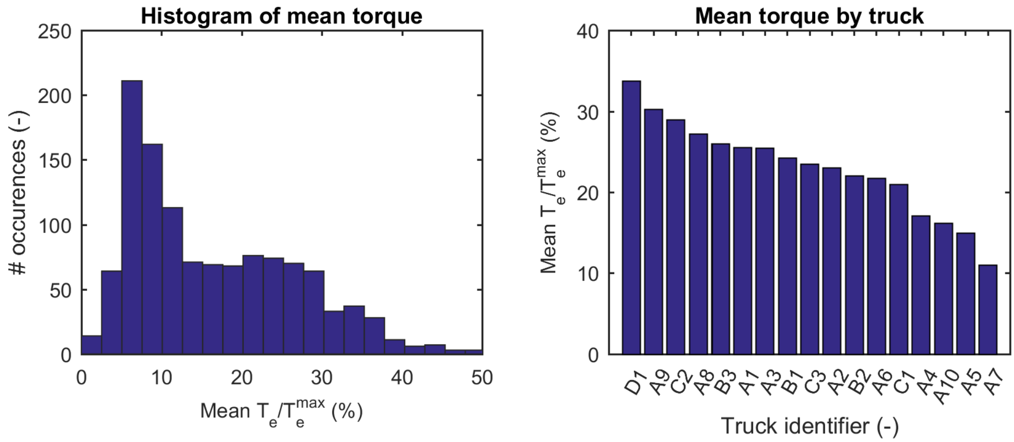


Figure 5.1: *Data of the mean torque ratio for the vehicles in the log file. The histogram on the left show how many of the logs have a certain mean torque ratio. The bar chart on the right show what the mean torque ratio is for each vehicle.*

its primitive is piecewise linear, precisely what is specified in Table 3.1. The conclusion is that a stochastic model can be used to parametrise operating cycles.

An obvious weakness is that only a model for topography has been presented. It was remarked in Section 4.3 that the literature contains work that describe similar models for curvature, roughness and speed limits, which fit well with the respective definitions in the OC-format. However, the work to implement them remains. Which points out another weakness.

It has not been rigorously proven that the overall energy consumption can be made to decrease if the proposed development process in Fig. 4.1 and 4.9 is used. It was motivated that by using GTA the most suitable configuration, which implies effective, can be chosen for an end-user. Similarly, the example of how to choose battery size in a hybrid truck in Section 4.3 shows how an estimation of the stochastic model parameters can lead to an appropriate choice of designs. Both arguments are fair, but they rely on the assumption that vehicles currently on the road are not already outfitted in the best possible way.

Here we can use the log data that is shown in the OCEAN-process. A quick analysis with the same simplified engine efficiency technique as in Section 3.3.2 is shown in Fig. 5.1, based on about 1000 log files from 17 vehicles. The mean torque ratio in the case-study with the original vehicle was 17%. Considering we could improve that with almost 20 % just by proposing a new engine, there is much that can be done by making other choices of vehicle functions and components. Hence, we draw the conclusion that the energy consumption can indeed be decreased by using the methods and processes proposed in this thesis.

## 5.2 Future work

All the weaknesses that were pointed out in the conclusion can be mended or removed:

- Improve and extend vehicle model.
- Validation of all parameters in the OC-format.
- A description of surrounding vehicles to include traffic in the OC-format.
- A standardization of the format would be beneficial.
- Improve GTA-parameter class definitions.
- A complete method for conversion of log file into an OC, including the use of external databases.
- Stochastic models for all parameters in the OC-format.
- A thorough study of all log files, using the OCEAN-process with both GTA-classification and stochastic models, that investigates how the vehicle specification in the log could be improved and what effect it would have on the energy consumption. A variant of Fig. 4.8 but with real values.

Apart from fixing the weaknesses in the work done so far, the methods that have been developed here can be applied. Problems with the current rating, regulation and legal requirements were discussed in the beginning, but after that little has been said about it. This thesis has built up a toolbox in the form of the OC-format and the OCEAN-process, and a most interesting line of study would be to use them to investigate how ratings and regulations could be formulated to better reflect reality.

The new software for rating the fuel consumption for heavy vehicles (VECTO) would be especially interesting to investigate, since the estimated $CO_2$-value is also computed through simulation.

Another interesting aspect to study, would be to make a pilot-project with OCEAN-process in a real product development situation. Thus, pick a customer who is looking to buy a new truck, use these methods to analyse the current missions that are run, suggest a vehicle specification based on that, and follow the new vehicle during some time to see how it performs.

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