

THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY IN MACHINE AND  
VEHICLE SYSTEMS

Operating cycle representations for road vehicles

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A polar bear in a snow storm.

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## ABSTRACT

This thesis discusses different ways to represent road transport operations mathematically. The intention is to make more realistic predictions of longitudinal performance measures for road vehicles, such as the CO<sub>2</sub> emissions. It is argued that a driver and vehicle independent description of relevant transport operations increase the chance that a predicted measure later coincides with the actual measure from the vehicle in its real-world application. This allows for fair comparisons between vehicle designs and, by extension, effective product development.

Three different levels of representation are introduced, each with its own purpose and application.

The first representation, called the bird's eye view, is a broad, high-level description with few details. It can be used to give a rough picture of the collection of all transport operations that a vehicle executes during its lifetime. It is primarily useful as a classification system to compare different applications and assess their similarity.

The second representation, called the stochastic operating cycle (sOC) format, is a statistical, mid-level description with a moderate amount of detail. It can be used to give a comprehensive statistical picture of transport operations, either individually or as a collection. It is primarily useful to measure and reproduce variation in operating conditions, as it describes the physical properties of the road as stochastic processes subject to a hierarchical structure.

The third representation, called the deterministic operating cycle (dOC) format, is a physical, low-level description with a great amount of detail. It describes individual operations and contains information about the road, the weather, the traffic and the mission. It is primarily useful as input to dynamic simulations of longitudinal vehicle dynamics.

Furthermore, it is discussed how to build a modular, dynamic simulation model that can use data from the dOC format to predict energy usage. At the top level, the complete model has individual modules for the operating cycle, the driver and the vehicle. These share information only through the same interfaces as in reality but have no components in common otherwise and can therefore be modelled separately. Implementations are briefly presented for each module, after which the complete model is showcased in a numerical example.

The thesis ends with a discussion, some conclusions, and an outlook on possible ways to continue.

Keywords: operating cycle, transport operation description, road format, energy usage, CO<sub>2</sub> emissions, full vehicle simulation



*I don't like it and I'm sorry I ever had anything to do with it.*

Erwin Schrödinger, about his wave formulation of quantum mechanics upon realising it did not make the (microscopic) world predictable and deterministic: it still had to be interpreted through probabilities.

## ACKNOWLEDGEMENTS

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Finally, thank you mom, dad, Jon, Sivert and Benji. For everything.



## NOMENCLATURE

Symbol	Explanation
$A$	Frontal vehicle area projected in the transverse plane
$C$	Curvature
$C_d$	Aerodynamic drag coefficient
Exp	Exponential distribution
$F_{air}$	Aerodynamic resistance force
$F_{grade}$	Longitudinal component of the gravitational force
$F_{inertia}$	Inertial force (fictive)
$F_{ix}$	Longitudinal traction force on axle $i$
$F_{iz}$	Vertical normal force on axle $i$
$F_{roll}$	Rolling resistance
$J_i$	Rotational inertia of component $i$
$L$	Total length (also called mission distance)
$L_h$	Hill length
$L_m$	Mean length
$L_s$	Segment length
$\mathcal{M}$	The set of mission parameters
$\mathcal{N}$	Normal distribution
$\mathcal{OC}$	The collection of the road, weather, traffic and mission sets
$P_{aux}$	Auxiliary power
$P_d$	Drive axle power
$P_{PTO}$	Power take off
$P_{tot}$	Total power from the prime mover
$R$	Wheel radius
$\mathcal{R}$	The set of road parameters
$R'$	Modified road radius
$\mathcal{T}$	The set of traffic parameters
$T_i$	Torque at component $i$
$\mathcal{U}$	Uniform distribution
$W$	Work
$\mathcal{W}$	The set of weather parameters
$a$	Topography regression coefficient
$a_p$	Accelerator pedal actuation
$b_p$	Brake pedal actuation
$e_i$	Noise term of property $i$
$f, F$	Fuel consumption
$f_{ij}$	Number of transitions from state $i$ to $j$
$f_r$	Rolling resistance coefficient
$g$	Gravitational acceleration
$h_{air}$	Aerodynamic centre height

Symbol	Explanation
$h_{cm}$	Centre of mass height
$l_f$	Distance from the centre of mass to the front axle
$l_r$	Distance from the centre of mass to the rear axle
$m, M$	Mass
$m^*$	Effective mass (including rotational inertia)
$n_i$	Number of states of property $i$
$p$	A generic dOC parameter
$p_{ij}$	Transition probability from state $i$ to $j$
$q$	Energy carrier injection rate
$r_t$	Road type
$r_{turn}$	Minimum road radius
$t, T$	Time
$v$	Vehicle speed
$v_i, V_i$	Speed of property $i$
$x, X$	Position
$y, Y$	Road grade
$\Phi$	Cumulative distribution function of the standard normal distribution
$\gamma$	Distance proportion
$\eta$	Gradient limit
$\theta$	Road gradient angle
$\lambda$	Event intensity
$\mu_i$	Expectation value of property $i$
$\xi$	First element of an ordered pair, either position or time
$\rho$	Density of air at standard atmospheric pressure
$\sigma_i$	Standard deviation of property $i$
$\omega_i$	Rotational speed of component $i$
$\dot{x}$	Time derivative of $x$
$\bar{x}$	Arithmetic mean of $x$
$X \sim f_X$	$X$ distributed according to $f_X$
$\mathbb{P}(A)$	Probability of event $A$
$\mathbb{P}(B A)$	Conditional probability of event $B$ given event $A$
$\mathbb{E}(X)$	Expectation value of $X$
$\text{Cov}(X, Y)$	Covariance of $X$ and $Y$
$\text{Var}(X)$	Variance of $X$

All units are given in SI-units and radians, unless otherwise stated. For random variables, upper case ( $X$ ) denotes the variable itself while lower case ( $x$ ) denotes particular realisations.

## ABBREVIATIONS

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<b>Abbreviation</b>	<b>Explanation</b>
dOC	Deterministic operating cycle
FBD	Free body diagram
GPS	Global positioning system
GTA	Global transport application
LCV	Long combination vehicle
OC	Operating cycle
PTO	Power take-off
RAD	Rear axle drive (axle configuration specifier)
SD	Standard deviation
SE	Standard error
sOC	Stochastic operating cycle
VECTO	Vehicle energy consumption calculation tool
WGS	World geodetic system
WLTC	World wide harmonised light duty test cycle

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# THESIS

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

- Paper A** P. Pettersson, S. Berglund, H. Ryberg, B. Jacobson, G. Karlsson, L. Brusved, and J. Bjernetun. Comparison of dual and single clutch transmission based on Global Transport Application mission profiles. *International Journal of Vehicle Design* 77.1/2 (Mar. 2019), pp. 22–42. DOI: 10.1504/IJVD.2018.098263
- Paper B** P. Pettersson, S. Berglund, B. Jacobson, L. Fast, P. Johannesson, and F. Santandrea. A proposal for an operating cycle description format for road transport missions. *European Transport Research Review* 10.31 (June 2018), pp. 1–19. DOI: 10.1186/s12544-018-0298-4
- Paper C** P. Pettersson, P. Johannesson, B. Jacobson, F. Bruzelius, L. Fast, and S. Berglund. A statistical operating cycle description for prediction of road vehicles' energy consumption. *Transportation Research Part D: Transport and Environment* 73 (Aug. 2019), pp. 205–229. DOI: 10.1016/j.trd.2019.07.006
- Paper D** P. Pettersson, B. Jacobson, F. Bruzelius, P. Johannesson, and L. Fast. *Intrinsic differences between backward and forward vehicle simulation models*. Submitted to 21st IFAC world congress. Oct. 2019

In all papers, the author of the thesis wrote the vast majority of the text and was responsible for the modelling, simulation and data analysis.

Paper A was based on the engineering solution by Karlsson, Brusved, Bjernetun, Ryberg and others at Volvo trucks. Ryberg provided the experimental measurements and contributed to the text together with Dr Berglund and Professor Jacobson. The ideas behind the paper belong mostly to Dr Berglund. In Paper B, Dr Fast and Pettersson carried out the experimental measurements. In Paper C, Dr Johannesson was the architect behind the stochastic operating cycle format and wrote the generation software.

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

- I P. Pettersson, B. Jacobson, P. Johannesson, S. Berglund, and L. Laine. “Influence of hill length on energy consumption for hybridized heavy transports in long haul transports”. *7th Commercial Vehicle Workshop Graz*. Graz, Austria: TU Graz, May 2016. URL: <https://research.chalmers.se/publication/236668> (visited on June 18, 2018)
- II A. Odrigo, M. El-Gindy, P. Pettersson, Z. Nedělková, P. Lindroth, and F. Öijer. Design and development of a road profile generator. *International Journal of Vehicle Systems Modelling and Testing* 11.3 (Dec. 2016), pp. 217–233. DOI: 10.1504/IJVSMT.2016.080875



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# Extended Summary

## 1 Introduction

This thesis is one of many that involve the CO<sub>2</sub> emissions from road vehicles. But unlike most, it is not directly aimed at developing something for the vehicles themselves. Rather, it is discussed how vehicles are used in practice and how this can be described mathematically. The outcome is (applied) theoretical methods, similar to a box of abstract tools. These can be used for improved transportation research or vehicle technology development.

This idea may seem strange, and one might wonder: ‘How could there be a practical use for a mathematical description of vehicle operations, to reduce CO<sub>2</sub> emissions?’. In the vehicle industry, much of the technological development and research are based on mathematical modelling and numerical simulation. This applies to both software functions and mechanical components; whose design have to be thoroughly evaluated before being built as physical prototypes. Many of these strive to reduce CO<sub>2</sub> emissions. To design vehicle systems in the best way imaginable, it must be possible to represent how they are used in reality. Therefore, the effects that component designs and software functions have on the full vehicle must be understood, which requires that the interactions between the vehicle and the surroundings are represented. To do so, a realistic mathematical description of the surroundings is needed. Hence, this thesis.

### 1.1 Background

This summer (the months of June and July 2019) broke the record for the hottest ever measured both in Europe [7] and worldwide [8, 9]. Although single seasons are difficult to attribute to global warming, there are overwhelming scientific evidence that this is the reason for the overall climate change, with increasingly extreme weather and the trend with rising temperatures [10–12]. Many greenhouse gases<sup>1</sup> contribute to global warming to different extents, but they can be bunched together into one single term called the ‘CO<sub>2</sub> equivalent’ emissions. When the term CO<sub>2</sub> emissions is used throughout the thesis, this is what is referred to.

In the year 2017, we humans released about  $36.3 \pm 1.8$  gigatons (1 gigaton = 1 billion tonnes =  $10^{12}$  kg) of CO<sub>2</sub> [15]. Road transports are responsible for a substantial part of these, mostly from combustion of fossil fuels. To get some idea of how much of the total these constitute, we will consider Europe by itself (which contributes with about 10% to the global emissions [15]), because here there are estimates of the respective contributions from different economic sectors [16]. These are shown in Fig. 1.1a. All transports combined are responsible for about a quarter of the total. Furthermore, this piece can be divided

---

<sup>1</sup>The majority of the of these are: CO<sub>2</sub> (carbon dioxide), CH<sub>4</sub> (methane), N<sub>2</sub>O (laughing gas), O<sub>3</sub> (ozone) and various CFSs (chlorofluorocarbons). The individual contributions to the greenhouse effect are different. For example, CH<sub>4</sub> traps heat in the atmosphere about 30 times more efficiently than CO<sub>2</sub> does [13]. This is accounted for in the term CO<sub>2</sub> equivalent. See [14] for an overview.

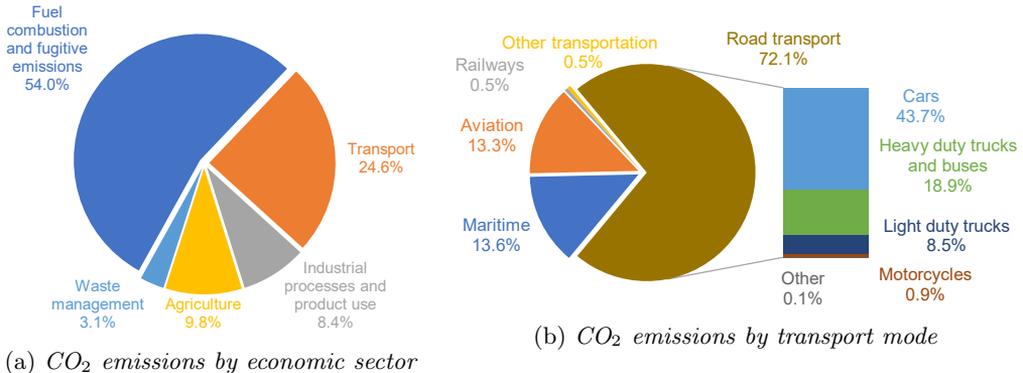


Figure 1.1: *Distribution of  $CO_2$  emissions per economic sector in 2017 (left) and the fraction belonging to each transport mode in 2014 (right), both in Europe [16, 17].*

into different transport modes, as shown in Fig. 1.1b. The majority, about 72% [17], comes from road transports. Digging deeper, the road transport emissions can be split into those coming from cars (43.7%), light duty vehicles (8.5%), heavy-duty trucks and buses (18.9%) and motorcycles (0.9%). The numbers change somewhat depending on which part of the world that is considered [18], or if a global perspective is taken, but the situation in Europe gives some idea of the scale of the emissions coming from road vehicles.

To deal with the problem, several international agreements have been made. The most famous are perhaps those in Rio de Janeiro, Kyoto and Paris, where specific national limits [19, 20] were decided upon. For vehicles in Europe, legal emission limits are imposed by the European commission and it is up to the manufacturers to make certain that these are fulfilled. Limits are set separately for cars [21], light duty vehicles [22] and heavy-duty vehicles [23]; the latter which has only been active since August 2019 and specifies target values for 2025 and onwards.

Official tests have been devised to ensure that the limits are respected, although the procedures are not the same for all three categories. Cars and light duty vehicles are tested experimentally using a chassis dynamometer (a ‘rolling road’) [21, 22]. The physical vehicle is placed in the testing equipment and a driver controls the accelerator and brake pedals to exactly follow a specific target speed whilst the emissions are monitored. Such a target speed as a function of time is called a driving cycle (sometimes drive cycle, testing cycle or test cycle) and the specific one for the official test is called the World Wide Harmonised Light Duty Test Cycle [24] (WLTC). One of its variants is shown in Fig. 1.2. The driving cycle concept is the first example of a mathematical representation of how a vehicle should operate. As it only specifies a speed, it is not difficult to see that this is a highly simplified description compared to driving on the road, where there are curves, hills, bumps, weather, different surfaces, other vehicles, and a driver at the helm, with his or her own preferences of how to drive. Moreover, we will call this kind of driving cycle, where the target is a direct representation of the vehicle speed (meaning that it should be followed exactly at all times), a conventional driving cycle.

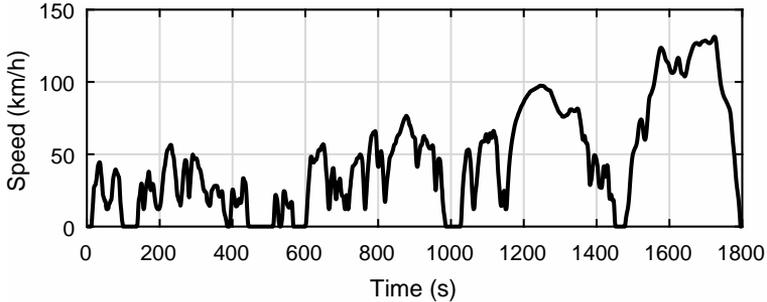


Figure 1.2: *The WLTC class 3 driving cycle.*

Another way to describe vehicle operations shows up when looking at the official tests of heavy-duty trucks and buses. These are not tested experimentally (though individual components, like the engine, still are) because of the vast number of different variants<sup>2</sup>. Instead, each specification receives an emission rating from a numerical simulation in a dedicated software called the Vehicle Energy Consumption Calculation Tool (VECTO) [28, 29]. This is a simulated reality, hence both the vehicle itself and its operation are described by mathematical models. The operation consists of a road gradient, several auxiliary power requests, and a target speed of another kind. Thus, this second example is more complex than a conventional driving cycle. Furthermore, there is not one but five cycles, shown in Fig. 1.3, where each is meant to represent a certain kind of operation, such as: long haul or urban delivery.

Compared to the direct target speed in Fig. 1.2, it can be seen that this target is of a different nature. The description does not exactly specify how a vehicle should behave, because it changes abruptly, in steps. Therefore, it contains more freedom in how a vehicle is allowed to operate: the description sets thresholds but does not say how to transition between these. This way of describing a vehicle’s operation has been called a target speed cycle [26], and we will do likewise, to make a distinction with conventional driving cycles.

The heavy-duty vehicle testing procedure is especially interesting, because it is virtual. This way is both faster and cheaper [32]. Therefore, virtual modelling is used for product development too, and has been for quite some time, for both cars and trucks [33, 34]. Then entire concepts can be evaluated and compared early in the development phase, long before any physical prototype exists. However, for a virtual approach to be useful it must be able to predict a vehicle behaviour that is both accurate and realistic.

By *accurate* behaviour, we mean that the virtual model yields the same results as a real-world measurement of a physical prototype when operated in the same way. This requirement implies that the mathematical model of the vehicle must be sophisticated enough. Modelling the components and the algorithms that control the software is complicated but straightforward. Many books introduce the topic [35–41] and there are

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<sup>2</sup>The main reason that virtual testing is used for trucks but not for cars, is that the former has a great number of applications and are therefore highly specialised [25, 26]. There exist more variants by many orders of magnitude [27]. Building all of them and testing experimentally is simply not feasible. In comparison, the majority of all cars have the same application, personal transport, and so there are much fewer variants in each manufacturer’s range.

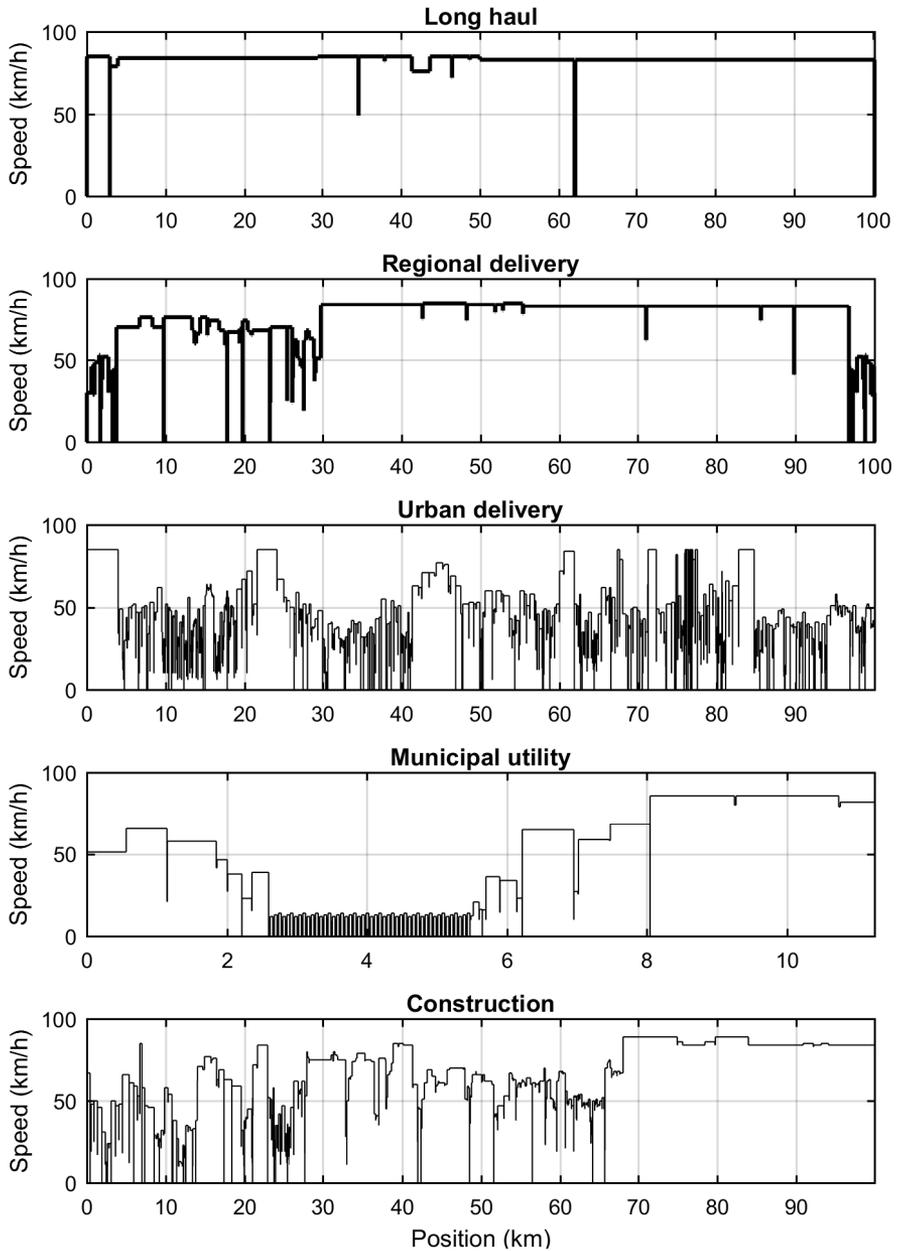


Figure 1.3: *The target in VECTO's target speed cycles [30, 31]. Note that the scales on the horizontal axes are not identical.*

entire journals dedicated to the subject.

By *realistic* results, we mean that the virtual model yields the same behaviour when used in the virtual setting as a physical vehicle does when used in the real world. This is a very strict requirement and challenging to achieve. It could be relaxed to instead state that the influence from the studied design parameters on the studied vehicle should be similar between the virtual setting and the real world. Unlike the requirement on accuracy, the requirement on realism includes not only the vehicle but also the things that stimulate it, such as: the driver, the road and the surroundings. Therefore, these must be described in the virtual setting, for it to be capable of predicting realistic results.

Comparing this need to the two examples of virtual descriptions encountered so far, there are three problems:

1. Real driving is complex. In some cases, describing it as just a target speed is an oversimplification [42–55]. What would be a more comprehensive description?
2. All vehicles are not operated in the same way. Different applications mean different driving conditions [5, 25, 27, 56–59]; a garbage truck typically drives short distances, stop frequently and carries a light payload, while a timber truck may drive long distances, sometimes in poor road conditions, and often carries a heavy payload. How can such differences be measured and how can applications be compared to assess the similarity?
3. Road and driving conditions change from day to day and induce variation in the vehicle operation [60–70]. Such daily differences disappear when using singular realisations, no matter what the virtual description looks like. How can this variation be addressed?

These three problems are necessary to treat to ensure fair comparisons between different vehicle concepts in a virtual environment. Then the most effective solutions for lowering the CO<sub>2</sub> emissions could be found. That is an excellent setting for product development. On the other hand, if the problems are not considered, technical solutions become more difficult to develop as the predicted effect may not match the actual one.

This is the background and motivation to the problems that the thesis concerns. Each problem deserves a more thorough and scientific inspection than the vague, hand waving description above. Therefore, a short literature survey is presented in Section 1.1.1, that relates to the first point, and in Section 1.1.2, that relates to the second and third points.

### 1.1.1 The inadequacy of driving cycles

What are the concrete problems with using a driving cycle as a mathematical description? An obvious shortcoming is that several physical properties that have a direct effect on the vehicle are missing. The topography (road gradient) is one example, often treated in the literature [42–49], which has a major impact on energy usage. There are also effects from the horizontal geometry (road curvature) [50], the road roughness [51], and the ground conditions: the texture and load bearing capacity [35] (meaning whether it is soft or hard). Apart from the road itself, the surroundings and the mission also affect the energy usage. The weather impacts through wind and temperature [52–54], for example. For

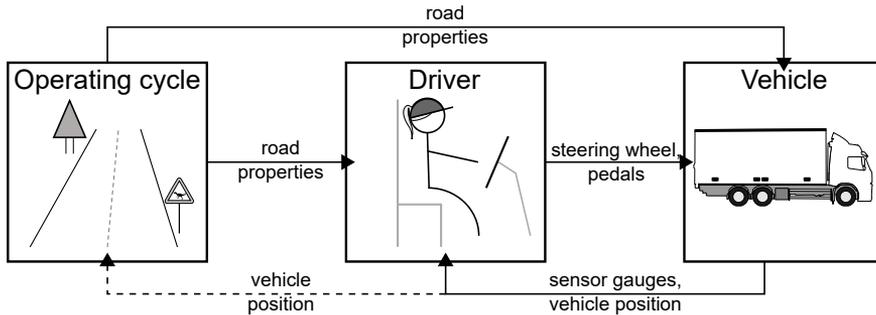


Figure 1.4: A perspective of the driving situation with a vehicle travelling on a road, controlled by a driver who reacts according to the situation.

the mission, there are effects from equipment fitted to the vehicle, like pumps and cranes, that require power to actuate [55].

For a mathematical description of vehicle operations to be realistic, these effects should be considered. But such weaknesses are easy to remedy, at least in theory, by simply including a description of each property along with the speed in the driving cycle. The description in VECTO's target speed cycle [26, 29, 71] is a good example, where a road gradient and several auxiliary power requests from various sources are included together with the target speed [72].

A more subtle problem is the idea itself of an exact target speed. In reality, the speed is a result of a driver controlling the vehicle based on the current driving situation, depicted in Fig. 1.4. The exact target speed of a conventional driving cycle is a considerable simplification of the actual situation, which gives no reason for why the speed takes a certain value. As an example, assume that we pick a road, a driver and a vehicle, and we measure the speed when it drives. Let this be the target speed of a conventional driving cycle. Now if we let the road and the driver be the same but switch the vehicle and rerun the experiment, the resulting speed profile may not be the same. Depending on the road and the properties of the vehicle, some may be able to keep to the legal speed limit (or above, depending on the preferences of the driver), while others cannot. The type of ride may have an influence: a sports car encourages a different driver behaviour than would a multi-purpose vehicle; an articulated vehicle may require more care when manoeuvring than a rigid one; a fully laden vehicle may need a more careful driving style than an empty one. Likewise, different propulsion systems have different abilities: an electrical propulsion system has a rapid torque response [73, 74] that allows a vehicle to accelerate quickly, compared to a turbocharged diesel engine where the transient torque response is much slower [75]. These differences in vehicle systems would result in different speed profiles, but if the longitudinal action is completely specified by a target speed they would not be reflected.

From this point of view, the speed thresholds provided by a target speed cycle are a better approach. Then the vehicle that can reach the limit will do so, while the one that cannot is still allowed to follow according to its own capabilities. Furthermore, the acceleration is unspecified and, therefore, different powertrain concepts are not forced to

work in the same way.

To point out a second problem with a target speed, independently of whether it comes from a conventional driving cycle or a target speed cycle, we come back to the road properties that were mentioned before. Take the road curvature as an example: it was mentioned that the curvature has an effect on the energy usage, but the contribution is twofold. There is a direct effect from energy dissipation due to tyre side slip, but this is generally negligible [76]. The greater contribution comes from the indirect effect that the driver reduces the speed when negotiating a curve [50]. When a target speed is defined by a driving cycle, the indirect (but greater) effect disappears. The road roughness, speed bumps and potholes have similar twofold effects [77].

A third problem appears when considering predictive control systems. There are functions that use the vehicle itself as an energy buffer by controlling the speed in a clever way. For example, systems that can lower the CO<sub>2</sub> emissions quite dramatically when negotiating hills [78–81]. A conventional driving cycle has no freedom in its target speed and therefore no speed variation is possible, rendering any predictive system ineffectual. Clearly this does not allow for a fair comparison between vehicle concepts. In the worst case it could even be detrimental for product development, as there is little point in spending resources on developing solutions that go uncredited, even though they have a real effect.

A final point to make, is that there is no driver in a driving cycle. The road, the weather and the traffic influence people differently [82] and the person who controls the vehicle has a major impact on its energy usage [83–86].

Most of the cited studies are aware of the weaknesses in using driving cycles to represent vehicle operations. Indeed, many suggest techniques to remedy the problems. But the idea of a target speed is still used, though it is patched, changed and extended in different ways. What this thesis tries to do differently, is to step away from the entire concept. Instead we go in another direction and make a new description; one that is firmly based on the idea that, if we want realistic vehicle behaviour, we need a realistic mathematical description of what affects it.

### **1.1.2 The differences in application and the variation therein**

These issues are quite separate from the driving cycle problem, as they do not concern the details of the mathematical transport description but rather the data that it contains. We will start by discussing the difficulty with differences in application, and then transition into the problem with variation.

The core of the application issue is that a vehicle is not operated in the same way for all missions and geographies [25, 56, 57]. One example of such differences has already been given: a low speed, frequently stopping garbage truck compared to a heavily laden timber truck travelling long distances. As an example of the influence from a geographic feature, consider the topography. It has already been commented that the road gradient impacts the energy usage [42, 43], so a vehicle mostly operating on flat roads is stimulated differently than one that operates mostly in hilly regions [5, 46].

Developing an individual product for every single road and application is not possible in practice [27]. Instead, a statistical viewpoint is often used. Products and technology

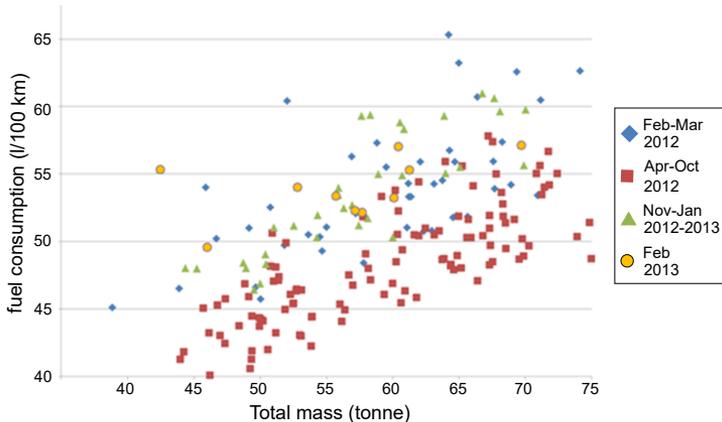


Figure 1.5: *Fuel consumption data from a specific truck on a route between Malmö and Göteborg, Sweden. The figure is reproduced with data from [95, 96].*

are developed for a typical application and a typical geographical region [25, 58, 59]. For example: regional distribution in a mostly flat landscape. This line of thought is a common topic in scientific literature, where there are many methods for tailoring a driving cycle to particular region [62, 87–93]. Though the methods differ (statistical analysis and selection from small trip segments in [62, 87–90]; short piecewise linear pieces as building blocks in [91]; linear discriminant analysis in [92]; a discrete Markov model based on data resolved per second [93]), all of them rely on an assortment of scalar measures to assess the similarity between different cycles. Those measures are often based on vehicles that operate on the road, like: mean speed, mean positive and negative acceleration, duration spent cruising, mean traction force, and others [93, 94]. Like the driving cycle, vehicle independent measures would be more appropriate from a development perspective [25], because then there are no prior assumptions about the product. Therefore, we want a way to measure and compare applications and regions without using metrics that directly rely on a vehicle, but that can still capture the important physics that influence the longitudinal vehicle dynamics.

To understand the problem with variation, consider the data in Fig. 1.5. Here, the fuel consumption of a heavy-duty truck is shown as a function of the total combination weight. This data comes from the DUO2 project [95, 96], where a special long combination vehicle<sup>3</sup> was driven between Malmö and Göteborg, Sweden. The truck and the route were fixed, though both driving directions are shown. There were several drivers involved.

One thing that the figure shows is that the total combination weight has a large influence on the consumption, as expected. However, even with a fixed weight the consumption can vary considerably, up to about 50%. The route and the vehicle are

<sup>3</sup>Here a long combination vehicle (LCV) means a tractor with two semitrailers. These are not allowed on public roads in Sweden and the project was a pilot to test the concept. The total length of an LCV is 32 m and they are allowed to weigh 80 tonnes in total. In Sweden, the largest combination currently allowed is 25.25 m in length and may weigh up to 60 tonnes, while the largest in the rest of the EU is the standard tractor-semitrailer of 16.5 m and 40 or 44 tonnes. See also [97, 98].

fixed so this variation appears due to differences in road conditions, traffic, weather and driving style. To have realistic use cases when developing vehicles, that variation should be considered [60, 61]. The scientific literature offers many ways to introduce variation in vehicle operations using statistical methods [59, 62–70], but these target conventional driving cycles.

Both the problems with application and variation need to be approached from a statistical perspective. Whatever solution that is suggested must allow for different technical concepts to reflect their own advantages and disadvantages. Therefore, driving cycles cannot be a large part of the process. Certainly, they cannot be what the statistical measures are based on, nor the centrepiece of whatever method that is used to introduce variation. Something else is needed.

## 1.2 Research questions

The three problems can be formally stated as research questions. A fourth question will also be formulated, to make certain that the solutions to the other three are useful in practice.

- I. How should a transport operation be described mathematically to enable a realistic vehicle usage?

This question refers to the problem of how to make a detailed and comprehensive mathematical description of the driving conditions; one that does not suffer from the problems that a conventional driving cycle does. The main question can be broken down into several smaller ones, such as: what physical features should be included? Are there any important nonphysical features that should be considered? What do the mathematical details look like? How can changes in speed be included without using an explicit target function? Are there any specific principles that the description should follow?

The question intends to deal with transport applications on a basic level but in great detail: useful to describe individual roads and missions. We call this ‘the representation problem’, and it is the first research question.

- II. How can transport applications be compared, with respect to geographical and operational features, in a way that is both vehicle and driver independent?

This question refers to the problem of differences in application, and how to find typical similarities. It requires comparing operations with each other, which implies that scalar metrics are needed to measure aspects such as: the terrain, the climate, and the mission. Again, the problem can be broken down to smaller questions: what mission features need to be considered? Which ones are the most important for energy usage? How can suitable metrics be found? Can these be connected to more detailed operation descriptions? How can suitable groupings be found?

This question intends to describe transport missions on a high level with few details. We call this ‘the classification problem’, and it is the second research question.

- III. How can variation in operation be measured for transport operations, and how can it be reproduced mathematically?

This question refers to the problem with variation in everyday usage, and it has two parts. The measurement part has some connection to the second research question: if there are metrics that can describe transport operations, then a variation could be computed using elementary mathematical statistics. At least between operations, but not within. The second half of the question, the reproduction part, is very different. Assuming that a variation is known, the question implies that there would need to be a connection from the abstract, high-level description that the classification problem concerns, to the concrete, low-level description that the representation problem addresses. How can this be done? We call this ‘the variation problem’, and it is the third research question.

- IV. How should a complete model for dynamic simulations be built to use the detailed mathematical representation of a transport operation, and are there any basic principles it should follow?

Simulation has not been discussed in detail so far, but the question is included as a way to make certain that the solutions to the other problems are useful and robust in practice. Especially the detailed mathematical description in the first research question: this must be runnable in a virtual simulation environment so that the energy usage of a vehicle design can be evaluated. The question concerns technical details surrounding how to implement the mathematical representation. Whether the problem should be called a research question when it really is about technical implementation is a matter of opinion. Nevertheless, we call this ‘the simulation problem’, and it is the fourth and final question.

## 1.3 Limitations

The thesis concerns problems that are a part of the product development process, that typically deal with tailoring vehicle components and software functions. Therefore, optimisation is a part of the process too, although located further down the work chain. In fact, the solutions to the research questions are pieces that would go into an optimisation problem. To really show that the ideas presented here work in practice for the entire development process, the optimisation part would be needed too. This is a very challenging problem because the domain is immense, and it has not been attempted in this work. For ideas on how to approach such problems in a vast domain, see [98–100], for example.

The methods that the thesis presents are constructed mostly with heavy-duty trucks in mind. This may not be a severe limitation, since the road is independent of the user. However, some features, like lane width, could be of different relevance depending on whether the description is used for heavy-duty trucks, passenger cars or motorcycles. Therefore, there may be features of some importance that were overlooked because they were deemed as less influential for heavy-duty vehicles.

The driver is something else that must be mentioned. It has been explained that for a realistic vehicle behaviour in a virtual model, there needs to be some kind of description of the driver. Modelling this is not trivial. To solve the simulation problem, we will have to construct a driver model, but it needs to be emphasised that this is not the main point of the exercise.

## 1.4 Scientific contribution

The main scientific contributions of this work are as follows (listed in order of the papers):

- A case study of the effects of a dual clutch transmission as opposed to a single clutch transmission on heavy-duty trucks in long haul applications.
- A proposal for a deterministic operating cycle description, independent of the vehicle and the driver, that can include the road, the weather, the traffic and the mission.
- A proposal for a statistical road description, using a framework easily extended to include other properties that influence the vehicle operations.
- Insights concerning differences and similarities between the backward method and the forward method in vehicle simulation models of energy usage.
- Executable models and scripts, written in MATLAB/Simulink, that are public and free<sup>4</sup>.

## 1.5 Thesis outline

The thesis is structured as follows: Chapter 2 outlines what features that need to be included in a transport operation description. Three such representations are discussed. It is also shown how these can be connected to each other. The suggested solutions to the first, second and third research questions are all found here. In Chapter 3, the simulation model approach is discussed. The suggested solution to the fourth research question is found here. An example with a goods distribution mission and a heavy-duty truck is also made to showcase how the complete simulation model works in practice. The extended summary finishes with a discussion, some conclusions and possible ideas for future extensions. The scientific papers on which the thesis is based are appended afterwards. Figure 1.6 shows how they are related to each other.

Paper A discusses two transmission technologies, a single clutch gearbox and a dual clutch gearbox, and what effects these have on heavy-duty trucks. Some basic principles are laid down for how to build a complete simulation model in a forward scheme. These return throughout all other papers, and that is why the paper has a loose connection (dashed line in Fig. 1.6) to all. Moreover, Volvo trucks' classification system, the global transport application, is discussed. This is an example of a bird's eye view representation (see Section 2.2).

Paper B introduces the deterministic operating cycle format: the suggested solution to the first research question. It is also described how to implement the road, mission and driver models, so it treats a part of the solution to the fourth research question too.

Paper C introduces the stochastic operating cycle format, which is a possible solution to the second research question. It is also explicitly shown how variation can be introduced through simulation, and so it contains the suggested solution to the third research question.

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<sup>4</sup>Available through [www.chalmers.se/vehprop](http://www.chalmers.se/vehprop) or directly from <https://chalmersuniversity.app.box.com/s/f5ejzj18bh3c6z057ri71nf04er8g469>.

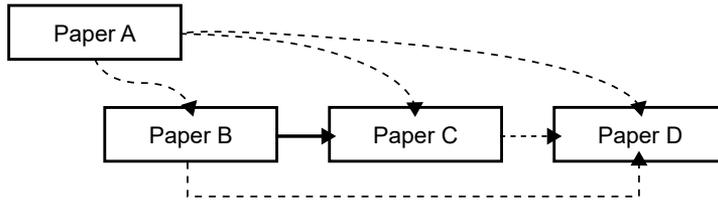


Figure 1.6: *A map of how the papers in the thesis are connected. A solid line indicates a strong connection while a dashed line means a loose connection.*

There is a strong connection to Paper B, because the relations between the deterministic and stochastic descriptions are explained in detail. In addition, the methods and models developed in Paper B are used for the numerical experiments, and the data from the real-world measurement is reused.

Paper D discusses some technical details that are relevant for vehicle simulation models of longitudinal vehicle dynamics and energy usage. It uses the methods developed in both Paper B and Paper C but does not extend them further. Therefore, it is only loosely connected to what has been done previously.

## 2 Representing transport operations

The main focal point in this chapter is how to describe transport operations. It will be done in three ways: a high-level view with a modest amount of detail, a low-level view with a great amount of detail, and something in between, an intermediate view with a moderate amount of detail. All three serve as representations of transport operations, but they are used in different ways. Before getting into the representations though, there are a couple of expressions that need to be defined.

We define the *transport application* as the overall purpose of a vehicle during its lifetime. This refers to a very broad, rough way of talking about everything a certain vehicle does. Examples of transport applications would be: long distance cargo transport, recycling and garbage transport, regional distribution, city bus, intra city bus, and many others. Unfortunately, the definition cannot be made much more rigorous than that, because the concept itself is vague, as the examples above show.

We define the *transport operation* as an enumerable number of tasks along a specific route. Typically, the concept refers to the driving that a vehicle does during singular instances, like a day. It could be interpreted as shorter parts too, like the driving between a pick up and drop off location. If all transport operations that a vehicle executes during its lifetime are collected, then this would correspond to the transport application. Moreover, a transport operation can be broken down into the road, the surroundings, the weather, other vehicles and the tasks themselves, which we come to next.

We define the *transport mission* as the details surrounding the tasks of a transport operation. This include their position, the payload, the flow of power, the direction of driving, and similar features that relate to the purpose of the transport. Thus, each transport operation comes with a mission. Of course, it could be very simple and only consist of the starting and ending positions.

The material in this chapter is, for the most part, already explained in the papers. Paper A mentions a particular example of the bird's eye view, the main topic in Paper B is the deterministic view and the main topic in Paper C is the statistical view. All perspectives are also mentioned in [101] to some extent.

### 2.1 What features need to be included?

Independently of which level of detail that is considered, we first need to figure out what features, meaning either physical phenomena or assumptions, and actions of the transport environment that need to be included. Plenty of examples are mentioned by the scientific works referenced in Chapter 1, although it is not too difficult to motivate them mathematically, by applying the laws of classical mechanics to a vehicle moving on a road.

Consider the free body diagram (FBD) of a two-axle truck in Fig. 2.1 (left) and a generic axle (right). For the vehicle, the aerodynamic resistance, gravitational force, front and rear traction forces, and front and rear normal forces are shown. For the generic axle, a total external torque (combined propulsion and brake torque) is drawn and the normal force is offset by small distance  $f_r R$ . The suspension has been approximated as

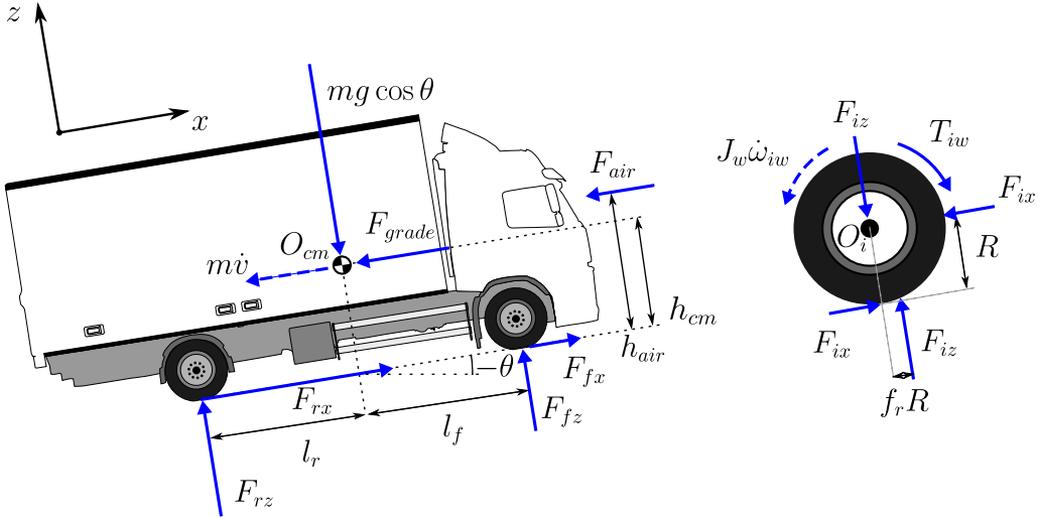


Figure 2.1: Free body diagrams of a truck (left) and a wheel axle (right).

rigid, so there is neither pitch motion nor any difference in motion between the sprung and unsprung masses (meaning that the energy dissipation in the suspension damping will not show up).

The equations of motion, for vehicle and axle respectively, are:

$$x : 0 = -m\dot{v} - F_{grade} - F_{air} + F_{fx} + F_{rx}, \quad (2.1)$$

$$z : 0 = F_{fz} + F_{rz} - mg \cos \theta, \quad (2.2)$$

$$\widehat{O}_{cm} : 0 = l_r F_{rz} - l_f F_{fz} - h_{cm} (F_{fx} + F_{rx}) - (h_{air} - h_{cm}) F_{air}, \quad (2.3)$$

$$\widehat{O}_i : 0 = T_{iw} - R F_{ix} - f_r R F_{iz} - J_w \dot{\omega}_{iw}, \quad (2.4)$$

where Eq. (2.4) can be applied to both the front and rear axles;  $i = f, r$ . Note that the inertia terms from the axles have been neglected in the vehicle FBD, and so do not appear in Eq. (2.3). Rearranging the terms in Eq. (2.1) and using Eq. (2.4) for both axles

$$\frac{T_{fw} + T_{rw}}{R} = m\dot{v} + \frac{J_w}{R} (\dot{\omega}_{fw} + \dot{\omega}_{rw} + F_{grade} + F_{air} + f_r mg \cos \theta), \quad (2.5)$$

with  $f_r mg \cos \theta$  what is usually called the rolling resistance  $F_{roll}$ . A prerequisite for Eq. (2.5) to hold is that the traction is great enough to sustain the wheel torques without fully slipping.

Arranged in this way, the right-hand side only contains external influences, while the left-hand side contains all the dependences on the internal workings in the vehicle (powertrain and brakes). We are interested in energy usage, so next step is to connect the above torques to the power that comes from the prime mover.

To stay general, we split the wheel torque for axle  $i$  in two parts: one from the brakes  $T_{ib}$  and one from the prime mover  $T_{id}$  (via some transmission, but that does not need to

be resolved at the moment)

$$T_{iw} = T_{id} - T_{ib}. \quad (2.6)$$

In which case we can write the power needed to move the vehicle  $P_d$  as

$$P_d = \omega_{fw}T_{fd} + \omega_{rw}T_{rd}. \quad (2.7)$$

The prime mover may also need to supply a power  $P_{aux}$  to the auxiliary equipment, meaning things that are intrinsic to the vehicle, such as air condition, and a power  $P_{PTO}$  to any mission specific equipment, like a crane or a refrigerator. The total power that needs to be supplied is

$$P_{tot} = P_d + P_{aux} + P_{PTO}. \quad (2.8)$$

Note that we have tried to stay fairly general here, so the expressions in Eqs. (2.5) to (2.7) are slightly messy. They could be made clearer (and probably more familiar) by making some approximations. If it is assumed that there is a propulsion torque  $T_d$  on one axle only (which one does not matter, for this argument), that the brake torques are zero, and neglect any longitudinal tyre slip so that  $\omega_{fw} = \omega_{rw} = v/R$ , then Eqs. (2.5) to (2.7) reduce to

$$P_{tot} = v(F_{inertia} + F_{grade} + F_{air} + F_{roll}) + P_{aux} + P_{PTO}. \quad (2.9)$$

Where term  $F_{inertia}$  contains the mass as well as the inertia of the axles (the effective mass  $m^*$ ).

For a description of the surroundings to be realistic, a fundamental requirement is that it must excite the vehicle with the right things. We can understand that quantitatively by looking at the right-hand side of Eq. (2.9). Let's interpret these in terms of the physical properties of the road, the surroundings and mission actions.

- The inertia term:  $F_{inertia} = m^* \dot{v}$ .

This term depends on mass and the change in speed. The mass is straightforward to deal with: apart from the vehicle itself, it includes the payload which is a part of the mission. We will need to know what the payload is and how it changes. The speed changes are a much more complicated subject, because they arise from a multitude of sources. On the road, the speed signs, stop signs, give way signs, traffic lights, speed bumps, potholes, curves and road surface all require the driver to adapt the speed. Likewise, other vehicles can cause rapid changes in the speed.

- The road gradient:  $F_{grade} = mg \sin(-\theta)$ .

Another mass dependent term, this time coupled with road gradient angle  $\theta$ . Since both the mass and the gravitational acceleration are included, the term is large in magnitude and the road gradient often has a great influence on the energy usage. Thus, the angle needs to be included in some form. The choice of direction is in accordance with the convention in ISO 8855 [102].

- The rolling resistance:  $F_{roll} = f_r mg \cos \theta$ .

The mass and road gradient angle have been mentioned already, but the rolling resistance coefficient  $f_r$  depends on the ground properties. These need to be included in some form. Additionally, the weather can have an impact, by changing the surface layer: making it wet, or covering it with ice or snow.

- The aerodynamic resistance:  $F_{air} = \rho C_d A |v_r| v_r / 2$ .  
The new parts here that depend on the external influences are the density of air  $\rho$  and the relative speed  $v_r$  between the vehicle and the air. The air density depends on the weather through the atmospheric pressure, ambient temperature and humidity. The wind is a weather effect, while the road properties that are the greatest influence on the vehicle speed were already mentioned under the inertia term.
- The power terms:  $P_{aux}$  and  $P_{PTO}$ .  
The power terms are direct parasites on the vehicle energy source. The power take-off is mission dependent, so any external equipment needs to be considered. The auxiliary power term is more questionable, it is rather a property of the vehicle itself than a result of external influences. We therefore refrain from including an auxiliary power in the description of the mission. Note though that there could be indirect dependences, for example the ambient temperature could affect the power by changing the need for cooling or heating. Such influences should still be accounted for.

The above list of features is not exhaustive by any means and there are more influences than those described by Eq. (2.9). For example, there are direct effects from the curvature due to side slipping and from the road roughness due to energy dissipation in the suspension damping. These appear when the vehicle motion is treated more comprehensively than with the planar, two-dimensional model in Eqs. (2.1) to (2.4).

The travel distance did not show up under any of the terms in the above list, though it influences the total work  $W$

$$W = \int_0^L F_{dx} ds, \quad (2.10)$$

with  $F_{dx}$  the propulsion force on whichever axle (or the sum, if both) that is propelled and  $L$  the mission distance.

Now we know of a number of properties that should be taken into consideration when constructing a road description, independently of its level of detail. It is also important that there is no dependence on the vehicle itself, and preferably not the driver either. Vehicle independence is central to the idea of making a description of the operation that allows for realistic behaviour, no matter what vehicle that is used. Driver independence is also desirable, because then the impact from the environment and that from the driver can be varied independently.

## 2.2 A high-level description for classification

The first description that we will discuss is a very rough and highly generalising one, almost colloquial in nature. We call this a *bird's eye view*, because the purpose is to give an overview of entire transport applications, without going deeply into details. The material connects to the second research question.

One reason for why this kind of description is needed has already been mentioned: it

is not feasible to develop products for singular roads or individual users<sup>1</sup>. Instead, one would want to develop products for applications that are similar with respect to their tasks and the landscapes in which they are set. Therefore, there is a need for some way to compare applications and determine what is similar and what is not. This could be done with a high-level description than gives a rough overview.

A second reason for why a broad description is needed, is when discussing with a user how to outfit a vehicle. In that case, it is not a question of product development but selection: to choose the best combination of components and functions. To do so, something must be known about what kind of application the user has in mind. This is why the tone should be colloquial: all users cannot be expected to have full insight into complicated models and parameters. Rather, the language should be familiar and intuitive, if possible. Still, clear definitions are vital, and could be supplied by a high-level description.

A broad description is thus a kind of classification system, where a transport application is labelled with respect to different categories and grouped with those of a similar nature. Three things are needed for a system like that:

1. A list of categories that make up the classification system.

For a classification connected to the energy usage of a vehicle, the relevant categories would be the features mentioned in Section 2.1. However, there are more vehicle properties than energy usage that are of interest for product development, like fatigue. Therefore, a broad classification system would rather target the complete longitudinal vehicle behaviour. It can later be clarified which categories that impact which vehicle property the most.

2. A number of labels (i.e. values, classes or groups) for every category.

How many labels and what they should be would have to depend on the category in question. If a low resolution is enough, then two groups would be sufficient: separating between high and low values. If a higher resolution is needed, then more groups are simply added.

3. A method to measure a transport application with respect to the categories.

This implies that each category must be associated with some kind of distance function: a metric. What this should be would again have to depend on the category in question. Moreover, once a metric has been found, it must be used to find suitable criteria for the labels.

Constructing such a system is quite an undertaking. Furthermore, it is far from obvious how to satisfy points 2 and 3 above for every category listed in Section 2.1. To show one possible approach, we can make an example with a single feature. This ad hoc approach will have many weaknesses, which will be commented on afterwards.

Let's say that we want to construct a classification parameter for the mission distance. First of all, we should think about what impact the feature has and what the classification parameter actually says about the transport application. The mission distance affects

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<sup>1</sup>Although there are exceptions, like the research project in [103].

the total energy through Eq. (2.10), but energy usage is usually considered per distance unit, just like fuel consumption and CO<sub>2</sub> emissions, in which case the total distance is unimportant. There are some cases where it has a secondary effect, for instance: if a vehicle has an energy buffer that is relatively limited in size (like a battery), but overall the distance is not of primary importance for energy consumption. However, when it comes to longitudinal vehicle behaviour in general, it can be expected that the mission distance is characteristic for certain groups of applications. For example, it could be used to separate between applications resembling long-haul and applications resembling urban distribution. Therefore, a mission distance parameter could have some usefulness.

Next, the labels need to be invented. The terminology should be familiar, therefore say that we decide on using three distance classes and call them: ‘short’, ‘medium’ and ‘long’. The third step is to find the metric, preferably one that is easy to work with. One option is to use the mean travel distance per operation: it is a simple concept to understand and a user should have some idea of how long a distance they usually go. Furthermore, if it is a matter of replacing a truck, there could be data available. It seems likely that the travel distance would be available as a signal and the average distance could then be estimated.

The last step is to find suitable limits for the classes in terms of the metric. It is unlikely that this could be done from first principles, so instead we can look at data from real transport applications. Figure 2.2 shows data of 1684 transport operations from 32 trucks, all driving in Europe. The top left shows a histogram of the travel distance, where each bar covers 20 km. About 27% of the operations are below 20 km, while another 65% are between 20 km and 200 km. In the bottom left the cumulative distribution is shown in two ways: a standard histogram to the left, and the distance as a function of the cumulative probability to the right.

One way to choose the limits for the classes is to base them on the cumulative distribution. Specific percentiles could be chosen, based on convention, and the corresponding distances would serve as the limits for the groups. In the plot, lines are shown for the 30th and 70th percentiles, and the corresponding distances are 18 km and 137 km. Then the short class would contain the lowest 30% of the operations, the long class would contain the highest 30% and the medium class would contain the 40% in between. This process would result in the following definition:

**Mission distance** The mission distance parameter of a transport application is defined as the mean travel distance of all its transport operations. It may take three values:

- *short*, if the mean travel distance is below 18 km.
- *medium*, if the mean travel distance is above 18 km, but below 137 km.
- *long*, if the mean travel distance is above 137 km.

The top right plot of Fig. 2.2 shows the mean distance of the trucks, which is also shown in Table 2.1. With the newly invented classification parameter, truck 1 and 2 would be labelled as having short mission distance, truck 3-25 as medium and 26-32 as long.

Some caution is advised when working with measurement data like this. If the classes are defined as above, then it is vital that the data includes many different applications. If it is not statistically representative, the limits would likely be biased and that would

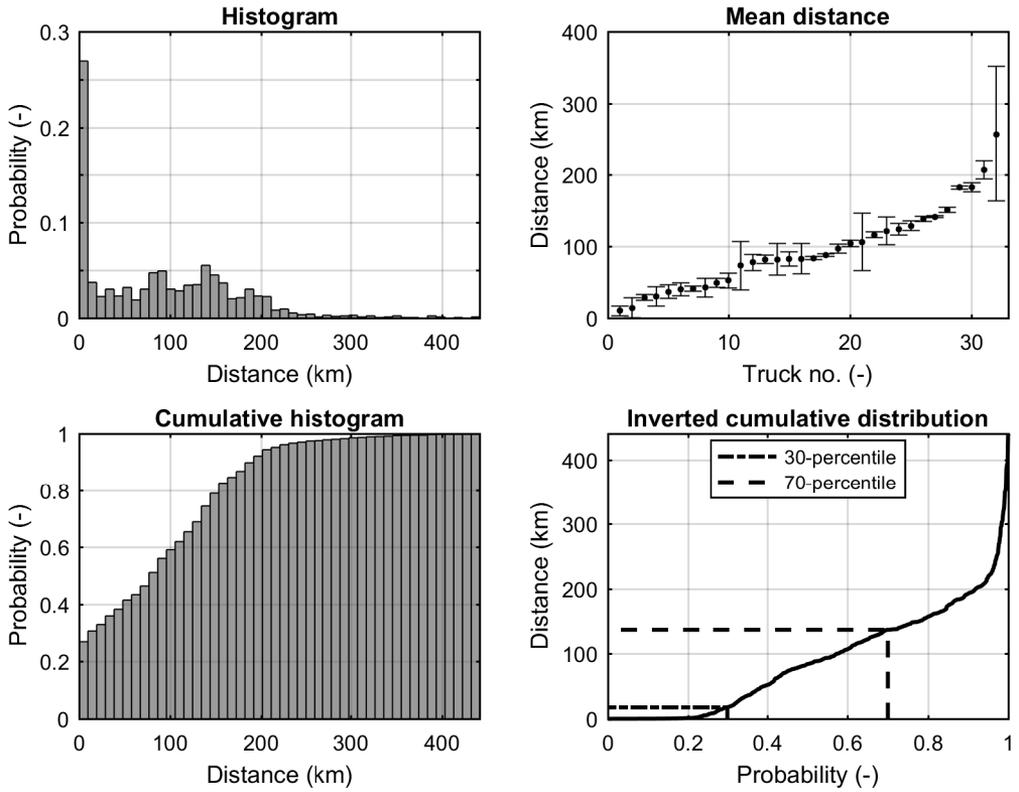


Figure 2.2: *Travel distance from 1684 transport operations. Top left: a histogram of the distribution; top right: the mean distance of each truck, with uncertainty; bottom left: a histogram of the cumulative distribution; bottom right: inverted cumulative distribution.*

Table 2.1: Mean travel distance from the 32 trucks (SE: standard error).

Truck	Mean (km)	SE (km)	Truck	Mean (km)	SE (km)
1	10	6.8	17	84	2.3
2	14	13.9	18	88	1.8
3	29	4.2	19	97	6.5
4	30	13.6	20	104	4.5
5	37	9.2	21	106	40.0
6	40	8.6	22	116	4.2
7	41	3.7	23	122	19.6
8	42	13.2	24	124	8.0
9	49	6.4	25	128	6.8
10	52	10.8	26	138	3.9
11	73	33.8	27	141	1.0
12	78	11.4	28	151	3.5
13	82	5.7	29	182	2.5
14	82	22.4	30	182	6.6
15	82	9.6	31	207	12.6
16	83	21.1	32	257	94.2

ruin the grouping. In the example, 32 trucks are too low a number to make an informed selection.

The above process may work as an example of how to form a classification parameter, but it leaves much to be desired. Metrics and limits can be chosen in many ways: by using other statistical measures, by cluster analysis, or with different choices of conventions. A more scientific method for finding suitable metrics and corresponding limits should be possible, but we do not know how. This leads to a couple of new research questions: how can a metric be chosen in a scientific way? How can it be verified that the choice is sound? Once a suitable metric is found, how can the limits be chosen systematically? These questions are not answered in the thesis, though we will return with some ideas in Section 2.5.1.

We end this section with a summary of what was actually achieved. It was explained what is meant by a bird’s eye view representation: a classification system in which transport applications can be compared. However, no such system was presented. Some ideas for an ad hoc approach to the construction of classification parameters were outlined, although they gave rise to more questions than they answered.

### 2.2.1 The global transport application

An easier option than constructing a new classification system, is to choose one that is already available. One such system is the global transport application (GTA), introduced by Volvo trucks and used in their product development and sales to order processes [25, 104].

The system is shown in Table 2.2. It is built around three main categories: transport

Table 2.2: *The parameters in GTA.*

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

mission, vehicle utilisation and operating environment. Each category contains a number of parameters, 20 in total, and every parameter can take a number of values (classes). Also, each parameter is connected to some kind of metric, that can measure which class a given transport application belongs to.

In GTA, the closest resemblance to the mission distance of previous section, is the operating cycle parameter in the vehicle utilisation category. Its definition, given in [104], is the following:

**(GTA) Operating cycle** An operating cycle reflects how often the vehicle stops to load or unload goods or passengers. GTA specifies four basic operating cycles:

- *stop and go*, if the mean distance between delivery or pickup of goods or passengers is shorter than 0.5 km.
- *local*, if the mean distance between delivery or pickup of goods or passengers is shorter than 5 km but longer than 0.5 km.
- *regional*, if the mean distance between delivery or pickup of goods or passengers is shorter than 50 km but longer than 5 km.
- *long distance*, if the mean distance between delivery or pickup of goods or passengers is longer than 50 km.

The metric here is also a mean: the mean distance between stops. Also note the colloquial nature of the terminology. A vehicle user would not have too much trouble with answering what kind of application he or she has in mind, with these definitions. However, no explanation is given for why the mean distance between stops was chosen as a metric or why this choice of class limits was made.

Two other examples of classification metrics show up in the topography and the ambient temperature parameters (from [104] again).

**(GTA) Topography** GTA specifies four levels of topography:

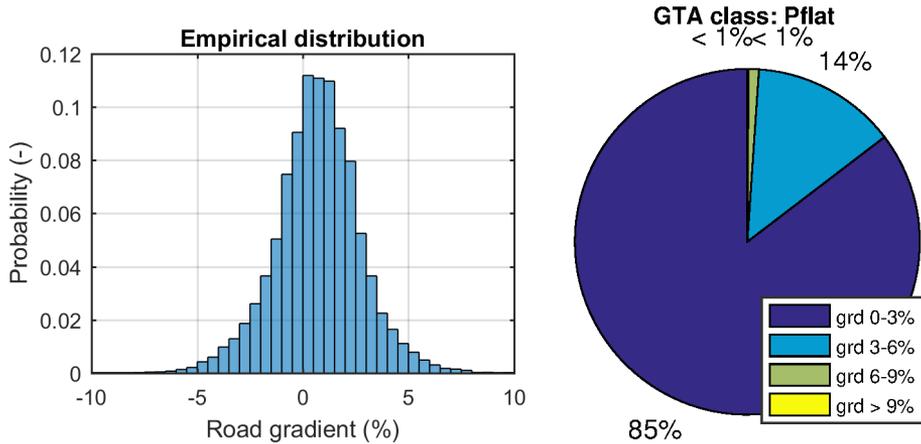


Figure 2.3: A histogram of the empirical distribution of the road gradient (left) and a pie chart with the GTA classes (right) for truck 15 in Table 2.1.

- *flat*, if slopes with gradient of less than 3% occur during more than 98% of the driving distance, and the maximum gradient is 8%.
- *predominantly flat*, if slopes with gradient of less than 6% occur during more than 98% of the driving distance, and the maximum gradient is 16%.
- *hilly*, if slopes with gradient of less than 9% occur during more than 98% of the driving distance, and the maximum gradient is 20%.
- *very hilly*, if the criteria for hilly are not met.

**(GTA) Ambient temperature** GTA specifies six levels of ambient temperature:

- warmer than +40 °C.
- upper limit +40 °C.
- lower limit -15 °C.
- lower limit -25 °C.
- lower limit -40 °C.
- colder than -40 °C.

The topography parameter is classified in terms of what fraction of the distance that is set between certain road gradients, based on where the vast majority of the transport application takes place. Three boundaries are mentioned, and these can loosely be thought of as the classes themselves. Figure 2.3 shows a diagram from all transport operations for truck 15 in Table 2.1. Looking at the pie chart, about 85% of the distance has a road gradient below 3%, and another 14% between 3% and 6%. Since 99% in total is set below a road gradient of 6%, the application would be classified as predominantly flat. The metric is clearly more complicated than a mean, but it also gives more useful information. Again, little information is given about why the bounds for the classes have been chosen as they are.

The classification method in the ambient temperature parameter is of a different kind: it is not statistical in nature but just a fixed limit. A reason why could be that the physical influence of the parameter (temperature, in this case) is rather weak. A simple choice of metric could be a good idea just to avoid spending unnecessary time and effort.

GTA is one example of a bird's eye view classification system, but there are others: topography in [44], curvature in [105], or [106] for a combination. Other vehicle manufacturers may have their own systems, although they are not public. For instance, Scania has a system based on what they call user factors, briefly mentioned in Chapter 4 of [107].

Before leaving GTA, it should be pointed out that many of the parameters in Table 2.2 are more or less irrelevant for energy consumption, for example: yearly usage. This is because GTA is an overall description of the transport application, that can be used when considering many vehicle properties. This was mentioned before but is worth to emphasise with this functional classification system as an explicit example.

## 2.3 A mid-level description for variation

Now we turn to a more comprehensive statistical description of either individual transport operations or several in a collection. The material in this section is a summary of the study in Paper C and connects to the third research question.

While the classification system of a bird's eye view can be based on metrics that are statistical in nature, like the mean travel distance, these are meant to describe entire transport applications. Its metrics are supposed to be rough tools only. Furthermore, the variation problem in the research question cannot be solved with a bird's eye view system that leans on mean values, because those say nothing about variation. Something else is needed.

Many of the approaches found in scientific literature that deal with uncertainty and variation of CO<sub>2</sub> emissions use stochastic processes [59, 62–70]. These studies have mostly focused on driving cycles, whereas we need to consider the properties mentioned in Section 2.1. The approach with stochastic processes holds merit though. If modelling something as a random process, then probability and variation appear naturally. That trait would suit our needs perfectly.

### 2.3.1 Modelling individual road properties

To limit the scope, we will not consider all properties that were mentioned in Section 2.1, but only the ones that are associated with the road itself. These are: stop and give way signs, traffic lights, speed bumps, speed signs, ground type, topography, curvature and road roughness. For some, suitable stochastic models have already been designed by others.

The road curvature (horizontal geometry) was modelled by Karlsson [108, 109] as a marked Poisson process and by Maghsood et al [110–112] as a hidden Markov model. The application was not energy usage but fatigue assessment of steering components, but the characteristics of the road remain the same. The topography was treated statistically by Rouillard and Sek [113] and more recently by Johannesson et al [114, 115], who modelled it as a first order autoregressive relation with either a Gaussian or Laplacian

signature. When the road roughness is treated through the spectral power density of the vertical profiled, as recommended by ISO 8608 [116], stochastic models have been used for quite some time [117]. Bogsjö [118] and Johannesson et al [119] noted that the common approach with a Gaussian process could be improved over longer distances and suggested a model with a Laplacian signature. In summary: the curvature, topography and road roughness do not need to be modelled from scratch.

To model the others, let's say that a transport operation of length  $L$  is given. Now consider only the road itself. Let the road properties be individually described by a sequence of variables, discrete or continuous, just like what one would get if measuring at given points. We will see these sequences as containing random variables<sup>2</sup> and model them by the simplest stochastic process that fits the behaviour. At first, we will assume that the sequences are mutually independent, so that, for example, the speed signs are not affected by curvature and vice versa. The assumption will be revised later in Section 2.3.2.

### Stop signs, give way signs, traffic lights, and speed bumps

These are all discrete entities that behave somewhat similarly, and so we deal with all of them at the same time. They are modelled in three parts: location, recommended speed and standstill time, though all are not equally important for every property. The recommended speed for stop signs is always zero, while a standstill time has no meaning for a speed bump. Nevertheless, the four properties are similar in nature with respect to how they appear on the road.

Consider the locations first. Model these as a sequence of random variables  $\{X_k\}$  and treat them as events that are scattered randomly between the start and end points. Now, if the road is split into small segments, then the probability of a piece containing an event would not depend on what happened before reaching it. Only its length would matter. The simplest stochastic model with this property is the Poisson process (see e.g. [120]). An easy way to characterise the positions are by considering the difference between two consecutive ones:

$$X_{k+1} - X_k \sim \text{Exp}(\lambda), \quad (2.11)$$

where  $\lambda$  is the intensity (sometimes called rate) of the process, which can be interpreted as the mean number of events per distance unit. Naturally, there is one intensity for each property.

At any given location, say  $k$ , the event has two additional properties, recommended speed  $V_k$  and standstill time  $T_k$ . The simplest nontrivial model is used for both, a random number from a uniform distribution. The recommended speed would be uniform between a minimum speed  $v_{min}$  and maximum speed  $v_{max}$

$$V_k \sim \mathcal{U}(v_{min}, v_{max}), \quad (2.12)$$

while the standstill time would be uniform between a minimum time  $t_{min}$  and maximum time  $t_{max}$

$$T_k \sim \mathcal{U}(t_{min}, t_{max}). \quad (2.13)$$

---

<sup>2</sup>A sequence of random variables is just a family  $\{X_k : k \in K\}$ , indexed by some set  $K$ , where each  $X_k$  is a random variable that takes value in some set  $S$  (called the state space). We will use the shorthand notation  $\{X_k\} = \{X_k\}_{k=0}^N = \{X_0, X_1, \dots, X_N\}$  to denote the sequence, where it could be the case that  $N = \infty$ . The notation follows that of Grimmett and Stirzaker in [120].

The five numbers describing the intensity, recommended speed and standstill time bounds, fully parametrise the model. Again: the stop sign and speed bump models only use three.

## Speed signs and ground type

These properties will also be treated simultaneously, because both change stepwise along the road. Mathematically, they behave as piecewise constant, right-side continuous functions of position. For simplicity, the speed signs are used as the canonical example.

Let the speed signs be a random process  $V = V(x)$  along the position  $x$  on the road. There are only a few different speed limits<sup>3</sup>, say  $n_s$ , so  $V(x)$  may take values in the set  $\{v_1, \dots, v_{n_s}\}$ . However, it may change anywhere on the road,  $x \in \mathbb{R}$ . We split the process in two parts again and treat it as a sequence of positions  $\{X_k\}$ , with the locations of the signs, and a sequence of speeds  $\{V_k\}$ , with the speed limit given by the signs.

When it comes to the speed limits, make the approximation that the current limit exerts the majority of the influence on the upcoming limit:

$$\mathbb{P}(V_{k+1} = v_{i_{k+1}} | V_1 = v_{i_1}, V_2 = v_{i_2}, \dots, V_k = v_{i_k}) \approx \mathbb{P}(V_{k+1} = v_{i_{k+1}} | V_k = v_{i_k}). \quad (2.14)$$

This is called the Markov property, and it means that the sequence can be modelled as a Markov chain. This is a well-known model that has applications in many fields (see [120], or [121] for an introduction). Like the continuous process  $V(x)$ , the state space of  $\{V_k\}$  is the possible speed limits mentioned above. Furthermore, the model is embedded in that of the sign locations, because there cannot be a new speed limit without a sign to announce it, so  $k \in \mathbb{N}$ .

An  $n_s$ -by- $n_s$  matrix of probabilities, called the Markov matrix or transition matrix, is enough to fully characterise such a chain. An entry  $p_{ij}$  describes the probability of jumping from state  $i$  to state  $j$ . However, we can reduce the description further. Since the speed limit model is embedded in that of the locations, there are no self-transitions: if the speed limit is already fifty, it does not change if another sign appears saying fifty. Therefore, all diagonal elements vanish:  $p_{ii} = 0$ . Then the off-diagonal elements can be described as the observed number of changes  $f_{ij}$  between states  $i$  and  $j$

$$p_{ij} = \frac{f_{ij}}{n_s \sum_{j=1} f_{ij}}. \quad (2.15)$$

Therefore,  $f_{ij}$  is the simplest parametrisation possible.

The speed sign locations can be modelled as in Eq. (2.11). However, different states cannot be expected to have the same intensity, and for  $n_s$  states there will be  $n_s$  intensities:  $\lambda_1, \dots, \lambda_{n_s}$ . Also, it may be more intuitive to think about the mean length  $L_{m,i}$  of a certain speed limit  $v_i$  than its intensity,

$$L_{m,i} = \frac{1}{\lambda_i}. \quad (2.16)$$

---

<sup>3</sup>Though they would differ from country to country. All speed limits on the planet could be accounted for in every single application, but it would be a cumbersome solution. A better way is to only include the speed limits in the country (or countries) where the application is set, and explain what these are.

The complete description thus consists of the matrix  $f_{ij}$  and the  $n_s$  mean lengths  $L_{m,i}$ .

The ground type works the same as the speed signs, but it has a different number of states  $n_g$ , with types  $\{g_1, \dots, g_{n_g}\}$ , where  $g_1$  could be tarmac,  $g_2$  gravel, and so on. Each state is also associated with a load bearing capacity, but this can be taken as a property of the states themselves and does not need a random process.

### Topography, curviness and road roughness

The models used for road curvature and topography are taken from [109] and [115] but written here in brief anyway. The model for road roughness can be found in [119].

For the topography, partition the road into short segments (say 25 m or so) and let the road gradient  $\{Y_k\}$  be a random variable on each segment  $k$ . Then a first order autoregressive model is used

$$Y_k = aY_{k-1} + e_k, \quad e_k \sim \mathcal{N}(0, \sigma_e^2), \quad (2.17)$$

where the two characteristic parameters are  $a$  and  $\sigma_e$ . The autoregression parameter  $a$  can be written as a hill length  $L_h$ :

$$L_h = \frac{4\pi}{\pi - 2 \arcsin a} L_s. \quad (2.18)$$

The error amplitude  $\sigma_e$  can be rewritten as a topography amplitude instead:

$$\sigma_y^2 = \frac{\sigma_e^2}{1 - a^2}. \quad (2.19)$$

The parameters  $L_h$  and  $\sigma_y$  parametrise the topography model.

The curves are modelled as independent events that have a location, a curvature (inverted radius) and a length. Call this description the curviness of the road and denote the sequence as  $\{X_k, C_k, L_k\}$ . The locations  $X$  are modelled as a Poisson process and obey Eq. (2.11), with an intensity  $\lambda_c$ . The curvature  $C$  is modelled as a modified log-normal distribution

$$R' = 1/C - r_{turn}, \quad \ln R' \sim \mathcal{N}(\mu_c, \sigma_c), \quad (2.20)$$

with parameters  $r_{turn}$  (minimum curve radius),  $\mu_c$  and  $\sigma_c$ . The curve length  $L$  is modelled as a log-normal distribution

$$\ln L \sim \mathcal{N}(\mu_L, \sigma_L) \quad (2.21)$$

with parameters  $\mu_L$  and  $\sigma_L$ . These six values parametrise the curviness model.

### 2.3.2 The stochastic operating cycle format

When constructing the above models, we assumed that they were mutually independent. This is convenient, but not realistic. Real roads are built using specific guidelines depending on their function, see, for example, [122–125]. Streets in the heart of a city may have sharp curves, plenty of traffic lights and low speed limits, while highways have shallow curves, few traffic lights (if any) and high speed limits. The statistical characteristics

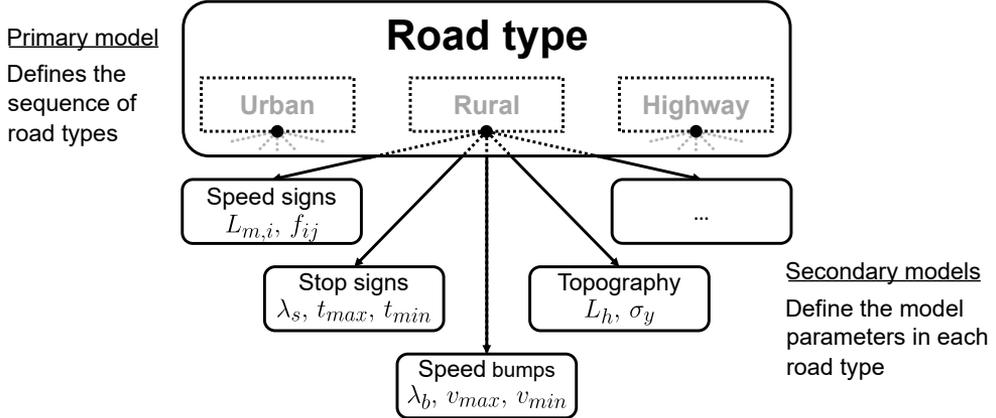


Figure 2.4: A graphical view of the hierarchical structure (adapted from Paper C).

are different between these two roads and some correlation between property behaviour should be expected.

The models in Section 2.3.1 can describe both types of roads above, but not at the same time. The structure of the stochastic processes does not change, but the parameters' numerical values would be different. If a transport operation stretches over many types, then a statistical description based on a single value for each parameter may result in a poor representation, as the characteristics are clumped together and mixed.

To capture such interaction, we include the road type as a property, model it as a stochastic process, and impose a hierarchical structure. The road type becomes a primary model, while all those in Section 2.3.1 become secondary models. The structure is shown graphically in Figure 2.4. Each distinct type (urban, rural and highway, in the figure) gets its own set of parameters for all secondary models. For instance, there will be one stop intensity on urban roads, another on the rural roads and a third on the highway.

In this way, it can be guaranteed that characteristics that often go together, like speed bumps and low speed limits, appear without any risk that speed bumps are also scattered all over sections with very high speed limits. The interaction takes the shape of a grouping.

There are a few downsides. Firstly, the number of parameters that we need to keep track of are tripled (assuming three road types, otherwise increased by the same factor as the number of road types). Secondly, the stochastic models must be handled sequentially when used in practice, always starting with the road type. Before, they could be taken in any order. Thirdly, we need to define what a road type actually is and, fourthly, present a model for it.

Compared to the road properties in Section 2.1, which are all physical and experimentally measurable, the road type is a vague concept. Here we use a working definition in terms of the speed limits, much like [126]. If there are  $n_r$  road types, called  $\{r_1, \dots, r_{n_r}\}$ , there needs to be  $n_r - 1$  characteristic speeds, called  $\{v_1, \dots, v_{n_r-1}\}$ , ordered in rising magnitude. Then the road type  $r_t$  at any point  $x$  would be given by the speed limit  $v(x)$

Table 2.3: A summary of the models in the sOC format (adapted from Paper C).

Road property	Model type	No. of states	No. of parameters
Road type	Markov process	$n_r$	$n_r^2$
Stop signs	Marked Poisson	Continuous	3
Give way signs	Marked Poisson	Continuous	5
Traffic lights	Marked Poisson	Continuous	5
Speed bumps	Marked Poisson	Continuous	3
Speed signs	Markov process	$n_s$	$n_s^2$
Ground type	Markov process	$n_g$	$n_g(n_g + 1)$
Topography	Gaussian AR(1)	Continuous	2
Curviness	Marked Poisson	Continuous	6
Road roughness	Laplace AR(1)	Continuous	2

at this point through

$$r_t(x) = \begin{cases} r_1, & v \leq v_1, \\ r_i, & i : v_{i-1} < v \leq v_i, \quad i = 2, \dots, n_r - 1, \\ r_{n_r}, & v_{n_r-1} < v. \end{cases} \quad (2.22)$$

In Fig. 2.4 we have that  $n_r = 3$ , which were also given the names: urban, rural and highway. We will continue using these three throughout the rest of the thesis.

With this definition, it is easy to construct a stochastic model. The road type is a piecewise constant function of the speed limit, and the speed signs are a piecewise constant function of the position: then the composition is also a piecewise constant function. Therefore, it can be modelled as the same kind of marked Poisson process with an embedded Markov chain as the speed signs and ground type in Section 2.3.1. This is fully parametrised by the  $n_r$  mean lengths  $L_{m,i}$  and the  $n_r$ -by- $n_r$  hollow matrix  $f_{ij}$ .

Finally, we define the full statistical description as the composition of the models for stops signs, give way signs, traffic lights, speed bumps, speed signs, ground type, topography, curviness, road roughness, and the road type, arranged in a hierarchical structure. We call this the *stochastic operating cycle* format or sOC format. A transport operation described in this way is a stochastic operating cycle or an sOC (pronounced ‘ess oh see’). Table 2.3 contains a summary of the format. This is the suggested solution to the first half of the third research question.

A final remark: we introduced and used the road type because we had to. It is a necessary evil to get an interacting model. If we would want to avoid introducing the road type concept, the alternative would be to work with joint probability distributions and mix the stochastic models for the road properties. That would very quickly become very complicated.

## 2.4 A low-level description for simulation

The third and final representation is a highly detailed description that is meant to realistically reflect the physics of the world in a virtual setting. This concerns individual transport operations only. This section connects to the first research question, and the material is a summary of Paper B.

Before presenting the description itself, there are a few guiding principles that it should obey.

- *Driver and vehicle independent.*

From a realistic point of view, the transport operation, the driver and the vehicle are all separate entities. In a virtual environment, they should be too. At least for vehicle engineering purposes, the influences from the vehicle design should not be contained in the driver or the transport operation. Therefore, the description should not contain anything that has explicit dependence on either a specific driver or a specific vehicle.

- *Modular.*

It should be expected that the description needs changing in the future. It may happen that there is new technology that rely on properties that we do not consider relevant today. It may happen that more properties need inclusion because greater accuracy is required. Or it may happen that we overestimate the influence of some properties and could remove them without any negative consequence. Whatever the reason, if the description is built in modules then it is easy to make changes to some parts without affecting anything else. Simply stated: it is good practice.

- *Compact and easy to understand.*

There is no point in making things more difficult than they are. On the contrary: making something as easy as possible is one of the cornerstones of science, sometimes called principle of parsimony [127] or Occam's razor. Therefore, we will try to keep the description as simple as possible (but not simpler)<sup>4</sup>, which makes it easier to use and modify. Moreover, it should be compact in the sense that it does not need more (data) storage space than necessary, to ensure that superfluous information is avoided.

- *Physically interpretable.*

This criterion relates to the idea of a realistic description. The intention is to use the description to represent the physics in a virtual environment. A basic requirement is therefore that we can understand and interpret its content in terms of physics and even make experimental measurements when needed.

- *Deterministic.*

This condition originates from a practical point of view. The main reason behind the description is for use in simulation. It is important that the influence from the environment does not have a random component, because then it would be very

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<sup>4</sup>The quote "everything should be made as simple as possible, but not simpler" has been attributed to Albert Einstein, though the evidence is questionable: <https://quoteinvestigator.com/2011/05/13/einstein-simple/> (visited on 2019-10-01).

difficult to find the cause of a result: was the increase in performance due to a change in vehicle design or did the vehicle not stop at as many traffic lights? A deterministic description avoids this question.

### 2.4.1 The deterministic operating cycle format

The properties listed in Section 2.1 is a good starting point. These can be grouped in four categories depending on their origin: the road, the weather, the traffic and the mission. Table 2.4 shows the content of the representation.

Like its statistical counterpart in Section 2.3, we call this way of representing a transport operation an operating cycle, but to make a difference between the two formats, this one will be called the *deterministic operating cycle* format or dOC format. A transport operation described in this way is called a deterministic operating cycle or dOC (pronounced ‘dee oh see’).

A property in the dOC format is called a parameter. The parameters are defined mathematically as sequences of ordered pairs  $\{\xi_k, p_k\}$  (conveniently implemented as an array or a table, in a computer). The first object in the pair  $\xi$  is either position or time; which one depends on the parameter in question. The second object  $p$ , which can itself be an ordered pair (see the dimensionality in Table 2.4), describes the physical quantity. In plain language: the pair describes a location (in space or time) and a physical property’s value. Any value between pairs can be computed by interpolation using the mathematical function in Table 2.4. The motivation behind the choice of mathematical model for the individual parameters can be found in Paper B.

Three parameters in Table 2.4 deserve some extra attention: longitude, latitude and travel direction. They were not mentioned in Section 2.1 because they are of a different nature.

The longitude and latitude are the WGS 84 (world geodetic system) coordinates of the trajectory. They are useful primarily because that is the reference system used in GPS (global positioning system) receivers. There are systems that use the coordinates to either store data about the road or fetch it from a database, to use for vehicle control, often energy management [78]. Therefore, the coordinates are included in the dOC format to allow such systems to function.

The travel direction is included to describe vehicle manoeuvring. For heavy-duty trucks in particular, reversing is common and often required when on or off loading. Therefore, it should be included to enable a realistic mission description. This part of a transport scenario may not be the largest contributor to the energy usage but could be of importance to other longitudinal measures: like transport time or component fatigue. Unfortunately, the travel direction introduces some extra difficulties, but these are explained and solved in Paper B.

There are several parameters that may need to be included in the near future. For example, the road category may need to be extended with number of lanes, lane width, banking angle, super elevation, or ground moisture content. The weather category could list surface conditions (e.g. dry, wet, ice, snow, etc.) or sight conditions (rain, snow, mist, etc.). The traffic could include the speed of a lead vehicle, measured mean traffic flow speed, or jam density. The mission could include type of transport (e.g. cargo or

Table 2.4: *The parameters that define the dOC format, adapted from Paper B. ‘Linear’ refers to a piecewise linear model and ‘Constant’ refers to a right-side continuous piecewise constant model.*

<b>Parameter</b>	<b>Category</b>	<b>Type</b>	<b>Math. model</b>	<b>Dim.</b>	<b>Quantity</b>
Speed signs	Road	Function	Constant	1	Speed limit
Altitude	Road	Function	Linear	1	Vertical coordinate
Curvature	Road	Function	Linear	1	Curvature
Ground type	Road	Function	Constant	2	Surface type, cone index
Roughness	Road	Function	Constant	2	Waviness, roughness coef.
Stop signs	Road	Event	Dirac delta	1	Standstill time
Traffic lights	Road	Event	Dirac delta	1	Standstill time
Give way signs	Road	Event	Dirac delta	1	Standstill time
Speed bumps	Road	Event	Dirac delta	3	Length, height, angle of approach
Longitude	Road	Function	Linear	1	WGS84 longitude
Latitude	Road	Function	Linear	1	WGS84 latitude
Ambient temperature	Weather	Function	Linear	1	Temperature
Atmospheric pressure	Weather	Function	Linear	1	Pressure
Wind velocity	Weather	Function	Constant	2	Velocity vector
Relative humidity	Weather	Function	Linear	1	Humidity
Traffic density	Traffic	Function	Linear	1	Density
Mission stops	Mission	Event	Dirac delta	1	Standstill time
Cargo weight	Mission	Function	Linear	1	Payload
Power take-off	Mission	Function	Linear	1	Output power
Charging power	Mission	Function	Constant	1	Input power
Travel direction	Mission	Function	Constant	1	Driving direction

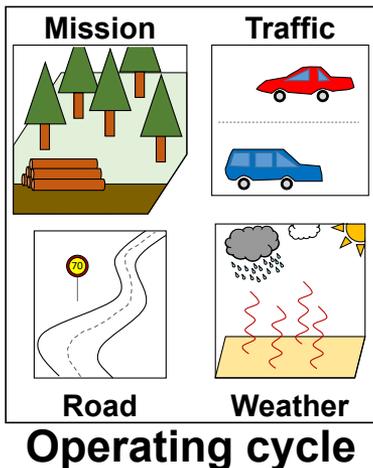


Figure 2.5: *A graphical overview of the dOC format (adapted from Paper B).*

people), a mission related speed limit, or more detailed descriptions of the task, like the geometry and weight of individual quanta of cargo. This is the reason why modularity is required: new things can be included without affecting what is already there. Furthermore, the principle of compactness ensures that unnecessary parameters are not included, like the colour of the road. It is certainly a physical property but unlikely to be of great importance for the longitudinal vehicle behaviour.

To formalise the dOC format mathematically, the four categories can be defined as the sets that contain the parameter sequences:  $\mathcal{R}$  is the set that contains all sequences marked as road in Table 2.4,  $\mathcal{W}$  is the same but for the weather,  $\mathcal{T}$  for traffic, and  $\mathcal{M}$  for mission. Then the dOC format can be formally defined as the collection of those sets:

$$\mathcal{OC} = \{\mathcal{R}, \mathcal{W}, \mathcal{T}, \mathcal{M}\}. \quad (2.23)$$

Interpolation can be defined as an operator that acts on the elements of these sets. However, the algebraic structure does not get deeper than that; it is just a bunch of elements, where those belonging to different sets are defined on different spaces, and an operator that acts on these. Another way to think about the dOC format, and considerably more relaxed, is offered by Fig. 2.5.

The dOC format is our suggested solution to the first research question, the representation problem. It gives a detailed view on individual transport operations, that makes no assumptions about the vehicle or the driver. Furthermore, it is built in a way such that the parameters can easily be modified, removed or added to. Note though that, at this point, it has only been explained why the dOC format should be expected to work. It has not been shown whether it actually does.

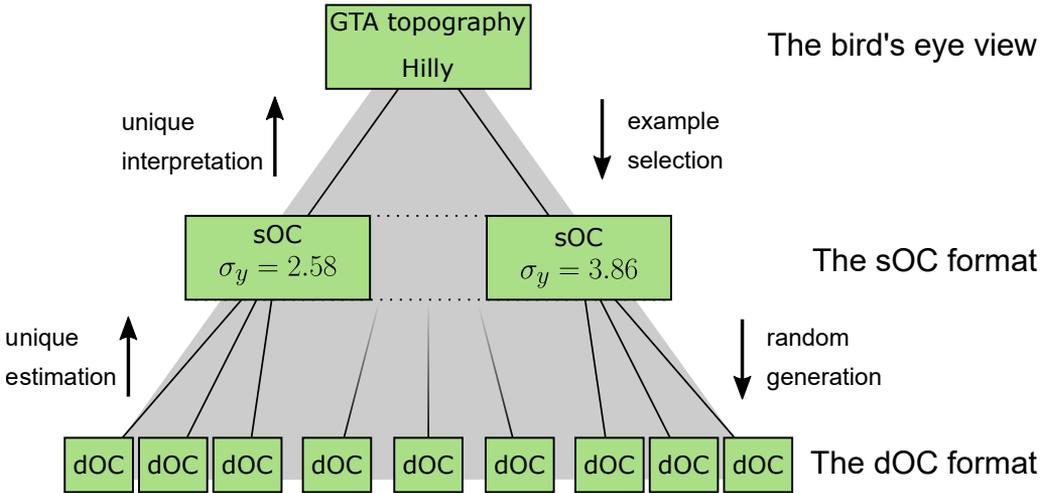


Figure 2.6: A view of the relations between the different levels of representation. From the bottom: all roads are physically different, but many can have (approximately) the same stochastic parameter values. Moreover, entire intervals of values in the sOC format may belong in the same bird's eye view class (GTA is used in the figure).

## 2.5 Relations between representations

So far, three descriptions have been discussed: the rough, high-level perspective of the bird's eye view, the statistically comprehensive, mid-level perspective of the sOC format, and the detailed, low-level perspective of the dOC format. The representations are clearly different: they are not used in the same way and do not serve the same purpose. Yet they can still be related to each other, which is very useful. The idea in this section is to clarify and explain those connections. Figure 2.6 gives a graphical idea of how the representations are related to each other.

### 2.5.1 Stochastic model parameters as classification measures

We start by looking at the connection between the bird's eye view and the sOC format. These descriptions are both statistical in nature, but on different levels: the bird's eye view is a broad representation that encompasses an entire transport application, while the sOC format is a more comprehensive representation that can be applied to individual operations, entire applications or anything in between.

A clear connection can be formed as (some of) the stochastic model parameters of the sOC format can work as classification metrics. As an example, a connection can be found between the GTA topography parameter and the sOC topography amplitude  $\sigma_y$ . As described in Section 2.2.1, the GTA parameter is based on the proportion of the distance with a road gradient below a certain limit. To keep it general, denote the distance proportion by  $\gamma$ , the gradient limit by  $\eta$  and the road gradient by  $Y$ . Then the

Table 2.5: *The relation between the sOC topography and the GTA topography.*

Amplitude	GTA class
$\sigma_y < 1.29$	flat
$1.29 \leq \sigma_y < 2.58$	p-flat
$2.58 \leq \sigma_y < 3.87$	hilly
$3.87 \leq \sigma_y$	v-hilly

above statement can be formulated in terms of a probability:

$$\mathbb{P}(|Y| < \eta) \geq \gamma. \quad (2.24)$$

The equation says that, for a small road segment, the probability that the road gradient is below the limit must be equal to or greater than the required distance proportion. The entire road consists of many such small road segments, and the (Borel's) law of large numbers then guarantee that the total proportion coincides with this probability.

A probability is something that can be connected to the sOC format, where a stochastic model for the road gradient was given in Eq. (2.17). It was formulated as an autoregressive relation and we do not yet know what distribution the gradient follows. However, since the equation is linear and the noise Gaussian, the road gradient itself will also follow a Gaussian distribution (because the normal distribution is stable). The variance was given in Eq. (2.19), while the expectation value can be computed from Eq. (2.17)

$$\mathbb{E}(Y) = \mathbb{E}(aY) + \mathbb{E}(e_k) \quad \Rightarrow \quad \mathbb{E}(Y) = 0, \quad (2.25)$$

which means that

$$Y \sim \mathcal{N}(0, \sigma_y^2). \quad (2.26)$$

With the probability density function known, the left-hand side of Eq. (2.24) can be written explicitly

$$\mathbb{P}(|Y| < \eta) = \mathbb{P}(-\eta/\sigma_y < Y' < \eta/\sigma_y) = 2\Phi(\eta/\sigma_y) - 1, \quad (2.27)$$

with  $\Phi(t)$  the cumulative distribution function of the standard normal distribution. By writing out the equality in Eq. (2.24), we can formulate a condition that links the topography amplitude of the sOC format to the boundaries of the bird's eye view metric:

$$\Phi(\eta/\sigma_y) = \frac{\gamma + 1}{2}. \quad (2.28)$$

Unfortunately, the equation cannot be solved analytically.

In GTA,  $\gamma = 0.98$  for all classes while  $\eta = 3\%$ ,  $6\%$ , and  $9\%$  for flat, predominantly flat and hilly respectively. The numerical solution to Eq. (2.28) with these limits is shown in Table 2.5, rounded to two decimals. This is the connection between the sOC parameter and the GTA parameter: each class corresponds a continuous span of sOC values. So, while the GTA parameter takes categorical values; the sOC parameter gives continuous values, making it a much more precise tool for comparing the topography on roads.

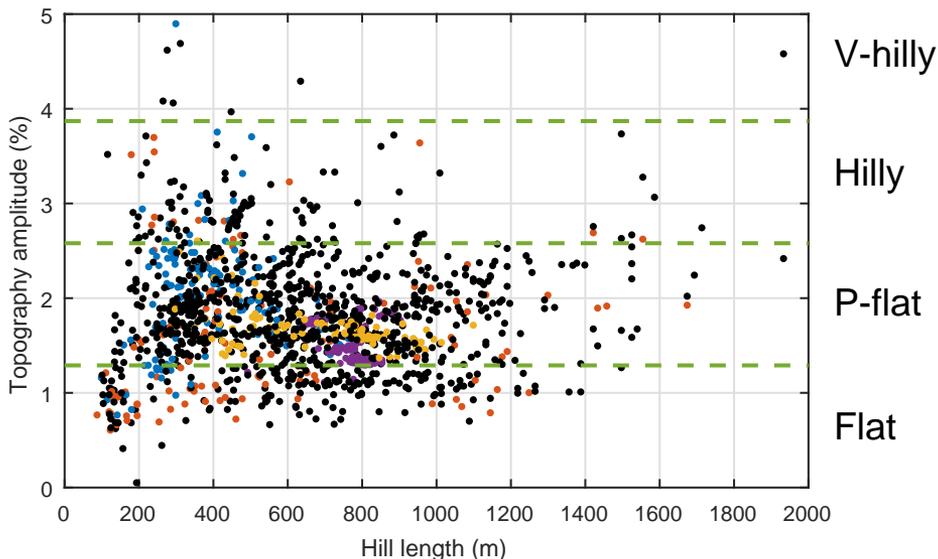


Figure 2.7: *The sOC topography parameters computed for 1429 operations, with the GTA class limits in dashed lines. The black dots come from 29 different trucks, while the coloured dots belong to one specific truck each.*

To see the difference more clearly, assume that the topography is measured on two roads, and that their GTA class and  $\sigma_y$  are computed. Comparing the classes tell us whether the roads are roughly similar (if the labels are the same) or not (if they are not). By comparing the  $\sigma_y$  values, it can be determined *how* similar they are. Additionally, blind luck could play in as it may happen that the roads are in fact very similar topographically, but one ended up right below a class limit and the other right above. They would receive different labels. If looking at the  $\sigma_y$  value, this would not happen as the comparison is a difference between values, and therefore independent of where it is computed.

However, we would like to emphasise that in discussions with users, suppliers or even between different product development departments, the topography amplitude can be difficult to understand. Also, finding its numerical value requires measurements (or data from another source), it is not intuitive and guessing its value is not feasible. The GTA parameter is easy to understand and use in discussions. Guessing what class a certain road belongs to is fully possible, though not without uncertainty. The GTA parameter is much easier to use in a non-technical setting or when data is not available.

A real-world example of the relation between the GTA parameter and the sOC parameter can be seen in Fig. 2.7, where the class and  $\sigma_y$  value have been estimated for about 1500 individual transport operations. Four trucks are shown with coloured dots, to show the spread across their transport operations. Note that the GTA classes have no relation to the hill length.

The connection between the two levels of representation offers a solution to one of the questions that were left as open in Section 2.2: how can suitable classification measures be found? As shown here, one option is to use the model parameters of the sOC format.

This would guarantee that a well-defined measure is used, one that has a firm connection to a probability distribution and all the mathematical machinery, and that it can be interpreted physically on the transport operation.

## 2.5.2 Generating transport operations from an sOC

The second connection to be discussed is the one between the sOC format and the dOC format. Some explicit examples can be found in Paper C and Paper D.

Going from the dOC format to the sOC format (upwards in Fig. 2.6) is a question of how to estimate the stochastic model parameters. A dOC contains data that can be interpreted as the sequences that were used when the sOC format was designed in Section 2.3.1. All physical properties that the models in the sOC format describe, exist as parameters in the dOC format. The process of estimating the model parameters can be done by standard methods (although that does not mean it is easy), see, for example, Rice [128] for a general treatment, or [108, 115] for some of the models used in this thesis.

Figure 2.8 shows a dOC of about 32 km in length, coming from a transport operation in the northern parts of Sweden (from Skellefteå to Byske). The parameters that are shown are the speed signs, altitude, curvature and stop signs. All others were left as trivial because they could not be estimated from the vehicle’s log data. The corresponding sOC can be found in Table 2.6. The road type limits were 50 km/h for urban, and 80 km/h for rural, shown as colours in Fig. 2.8. It should be pointed out that the road type is not a parameter in the dOC format (and should not be included either, as it is not a physical property), but shown to illuminate the sOC estimate.

Looking at the figure, it seems that using the road type concept as a grouping mechanism was a good idea. It is quite clear that the magnitude of the curvature is different between the rural and urban sections compared to the highway ones. Likewise, the stops are considerably more frequent on the urban (four on a distance of 1.7 km) and rural (one on 2.8 km) parts, than on the highway (one on 27 km). The  $\lambda_s$  parameter in Table 2.6 confirms this. In the altitude, it is difficult to discern any difference, and the table shows that the amplitudes are fairly similar. The hill lengths  $L_h$ , however, are quite different. Looking back at the figure when knowing this, it does indeed seem to be the case.

As a side note, there seems to be many small, short curves on the highway section, which is neither expected nor realistic. The vehicle’s own GPS was used for the estimation and it has a fairly slow sample rate of 1 Hz. This may be the source of error as the measurement points are rather far apart at higher speeds. Alternatively, it could be the crude estimation algorithm.

There are some comments to be made about the sOC in Table 2.6. Firstly, all model parameters are not included. The give way signs, traffic lights, speed bumps, road roughness and ground type are missing. The reason is that the corresponding parameters in the dOC are missing, and therefore the sOC parameters could not be estimated. It is not a big problem though, because the modular structure means that the parts that are present suffer no negative consequences. Secondly, the states in the speed sign model in the highway are degenerate: the 110 km/h speed limit did not appear in the dOC (see the top left of Fig. 2.8) and it could be dropped from the sOC altogether. Nevertheless,

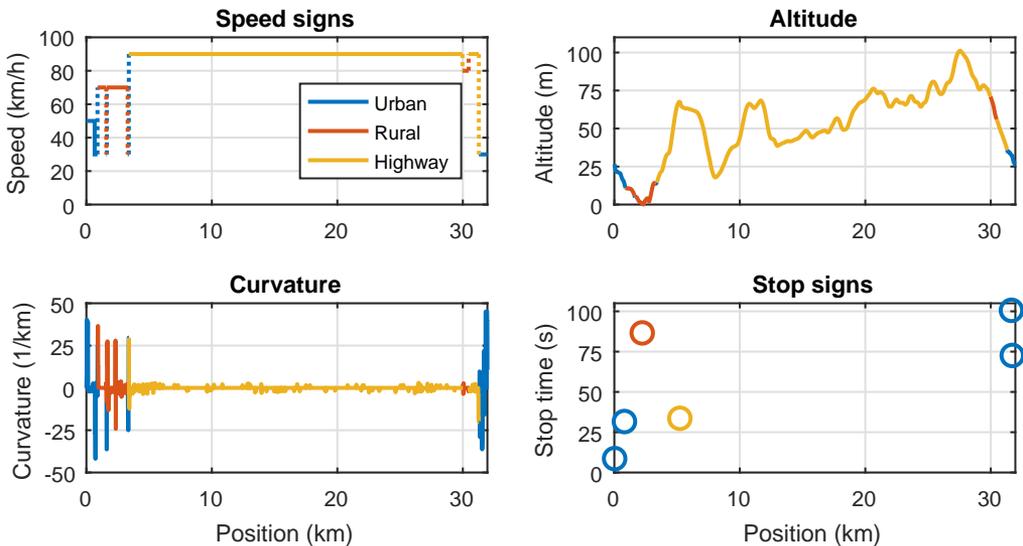


Figure 2.8: An example of the nontrivial road parts of a dOC.

Table 2.6: The sOC estimated from the dOC in Fig. 2.8.

Model	Parameter	Value (per road type)			Unit
		Urban	Rural	Highway	
Road Type	$L_{m,i}$	0.4	1.0	13.7	km
	$f_{\cdot j}$	$[0 \ 2 \ 1]$	$[2 \ 0 \ 1]$	$[1 \ 1 \ 0]$	-
Speed signs	States	30, 50	70, 80	90, 110	km/h
	$L_{m,i}$	$[1.0 \ 0.7]$	$[2.4 \ 0, 5]$	$[27.4 \ -]$	km
	$f_{ij}$	$\begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}$	$\begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}$	-	-
Stop sign	$\lambda_s$	2.30	0.35	0.04	1/km
	$t_{min}, t_{max}$	8, 100	77, 95	29, 37	s
Curviness	$\lambda_c$	8.8	5.3	3.4	1/km
	$\mu_c$	5.3	5.7	6.2	ln(m)
	$\sigma_c$	1.2	0.9	0.3	ln(m)
	$r_{turn}$	12.5	12.5	12.5	m
	$\mu_L$	4.2	4.1	3.7	ln(m)
	$\sigma_L$	0.6	0.5	0.3	ln(m)
Topography	$L_h$	170	450	1010	m
	$\sigma_y$	1.47	1.99	1.88	%

this is an explicit example of how to go from a dOC to an sOC.

This connection makes it possible to characterise the sequences of the dOC parameters in terms of the scalar model parameters of the sOC format: a classification with a continuous metric. Comparing scalar values is trivial and therefore obviously much simpler to use when assessing similarities between operations, than the sequences in the dOC parameters are.

The connection in the other direction, from an sOC to a dOC, is theoretically easy yet can be of great practical use. Stochastic models are the building blocks of the sOC format, meaning that new sequences can be created by generating random numbers<sup>5</sup> from the respective probability distributions. The sequences that pop out are the same as those in Section 2.3. Some of them are exactly the kind of ordered pair as the corresponding parameter in the dOC format, like the stop signs, while others need modification before becoming a valid member, like curviness to road curvature. The mathematical details surrounding the necessary conversion are given in Paper C.

Figure 2.9 shows two dOCs generated from the sOC in Table 2.6. The road type is generated first (shown in colour), since it decides what values the other stochastic parameters take at all points. The grouping is seen in the curvature plot, as the curves come out with different characteristics on the urban, rural and highway parts. Similarly for the stops. In the dOC on the left, there is only one stop, on a highway section, and the reason is likely that only a very short urban section appeared: 380 m in length. This might seem odd, but given the urban stop intensity, the likelihood of this happening is about 0.4, meaning that the event is nothing out of the ordinary.

Figure 2.9 is an example of the connection from an sOC to a dOC. While the results are not overly exciting, the practical implications that they have, are more so. The two generated dOCs are obviously different physically, as the two columns in Fig. 2.9 are not identical. However, they originate from the same processes and distributions, which means that they are statistically equivalent in this regard. Therefore, those dOCs can be seen, together with the original one in Fig. 2.8, as different transport operations that are set in the same kind of environment (the same landscape, in some sense): they are variations of one another. In other words, given a transport operation, a dOC can be estimated first, and an sOC second (though it could be estimated straight from the data too). Then we can generate as many new dOCs as we want, all of which are variations of the original. This is exactly what was asked for in the second half of the variation problem: ‘how can variation be reproduced mathematically?’, to which we suggest the solution: ‘by generating new operations from an sOC’.

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<sup>5</sup>A probabilist or a statistician may refer to this as ‘simulation’ or ‘simulating random numbers’. We use ‘generation’ instead, to avoid confusion with the word simulation as used in the context of dynamical systems, where it means computational evolution of a system over time.

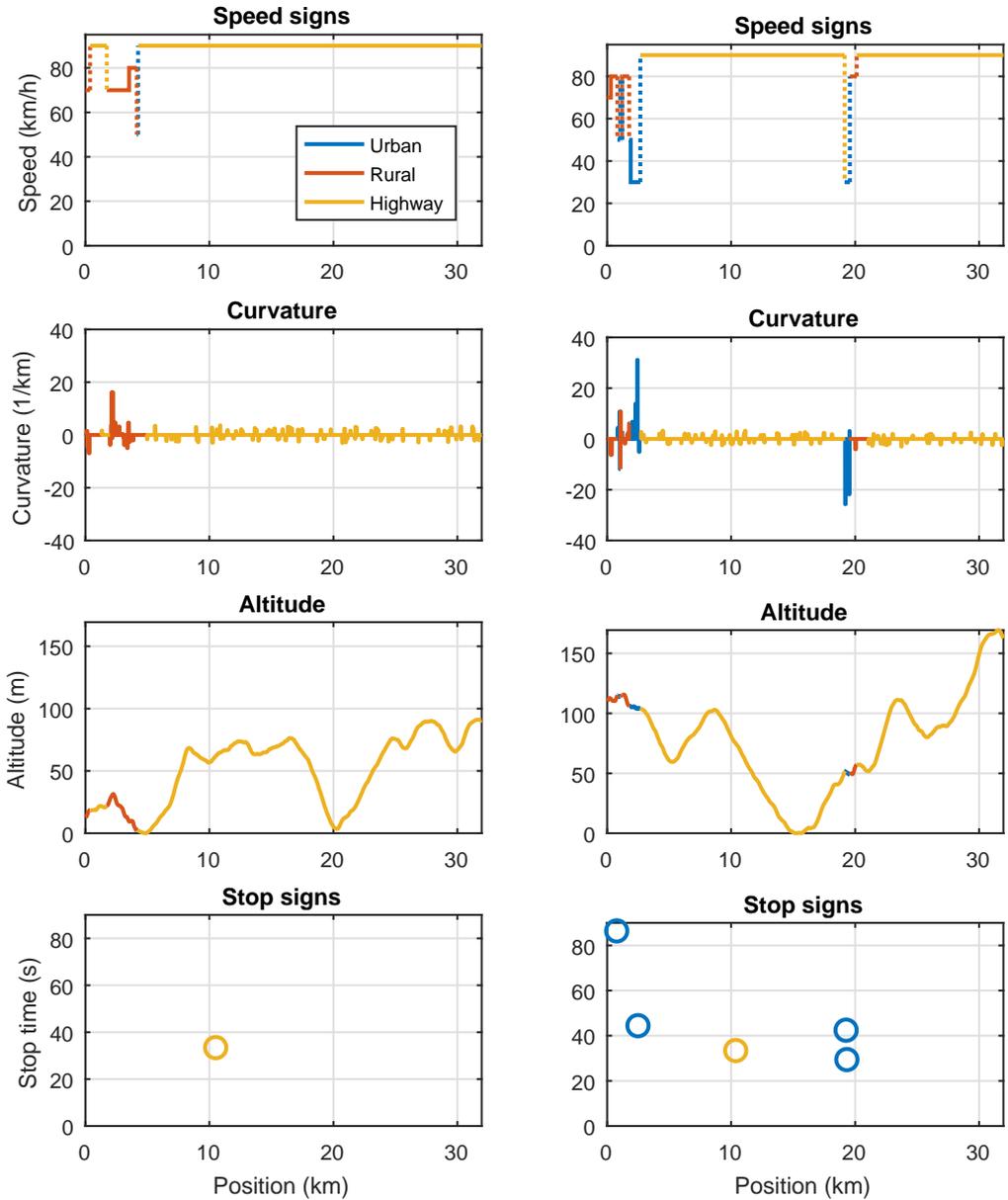


Figure 2.9: The speed signs, curvature, altitude and stop signs in two generated dOCs.



## 3 Modelling and simulation

The main topic of this section is the fourth research question, the simulation problem, the core of which is to conceptually explain how to build a dynamic model for simulation that can use the data contained in a dOC. This is explained in some detail in Paper B, with additional information in [101]. Meanwhile, some basic modelling principles were laid down in Paper A, which also contains the most sophisticated vehicle model, although that may actually be the least interesting part from the thesis' point of view. Paper D uses these ideas and compares two ways of approaching the simulation process but does not dig deeper into the functional modelling itself.

An in-depth description of the advanced vehicle model used in Paper A can be found in [129]. In addition, vehicle modelling is a huge topic and there are many books that introduce the topic [35–41].

### 3.1 Model topology

To start out, we will have to discuss some principles that are needed in the virtual environment that is about to be constructed. These introduce requirements that lead to what parts that the model must consist of at the very top level.

In the introduction, the need for realism in a virtual environment was argued, to increase the chance that the developed products work as predicted. This was the reason why the dOC format was designed. To use road data (and other data) given on such a form, a corresponding dynamic model of the operating cycle (OC) must be constructed. A dynamic model of the vehicle is also necessary, since this is the system under test for an original equipment manufacturer. However, these two parts alone are not enough. Unlike the target speed in a conventional driving cycle, the data in the dOC does not stipulate how a vehicle should move. It does provide the speed limit, which is the (legal) upper bound, but there are many situations where it does not make sense to keep this: in curves, around bumps, on rough ground, on slippery surfaces, around other vehicles, and more. In reality, there is a driver inside the vehicle who reacts to the situation on the road and controls the vehicle to the best of his or her ability. As long as the vehicle is not fully automated, some kind of driver model is needed. The more automated the vehicle becomes, the simpler the driver model can be and the more extensive the flow of information from OC to vehicle has to be.

With these three models in mind: the OC, the driver and the vehicle, a fair idea of how the environment could look at the top level was already provided by Fig. 1.4. The three models have no components in common but share information through their interfaces. A modular structure like this is advantageous, because a component can be switched out (or just the data inside it) without affecting the others. This is convenient in practice, because then the, say, vehicle can be replaced while the driver and OC remain the same. That is precisely what one would want if trying to find the best vehicle design for a particular transport operation and driver, for an entire transport application, or for a class of drivers.

The interfaces between the models should correspond to their physical counterparts in

the real world. For a given position, the forces on the vehicle are decided by the properties of the road through the contacts with the ground and air as taught by the basic laws of physics, as in Fig. 2.1. The interface between the driver and the road is the optical flow: the driver can see, for example, the road's signs and signals, its geometry and the surface condition. This gives the person information both about the moment and some distance ahead, depending on what the visibility is like. The interface between the driver and the vehicle are the actuators: the accelerator and brake pedals, the steering wheel, possibly a gear stick, and various buttons, like cruise control activation. Sensor information, like the speedometer, is also available.

With these principles in mind, we can start discussing individual models for the OC, the driver and the vehicle.

### 3.1.1 An operating cycle model

The first model to be discussed is that of the OC. Note the difference between the dynamic model and the dOC format itself. A dOC contains static data, and the idea is to build a dynamic model that can be parametrised by such data (meaning that the model takes the data as input before any simulation starts and keeps it constant), to work together with the driver and vehicle models. The dynamic OC model sends out the current value of the physical quantities in the data based on the position of the vehicle, and some upcoming values depending on how far the driver can see.

The purpose of the model is to provide a value for all dOC parameters at any given time instant during the simulation. The road category contains physical parameters that describes the trajectory, signs and signals. These only vary by position, so one input to the OC model must be the position of the vehicle  $x$  along the trajectory, measured at some convenient reference point, like the centre of mass, the front bumper, or the front axle. The weather, traffic and mission categories can obviously change with position too, but they may also have an explicit time dependence, for example: when using a mounted crane to load or unload cargo. Thus, the current time  $t$  must also be an input. In addition, the vehicle speed  $v$  will be needed, not for the parameters themselves but for purely technical reasons: to separate between a vehicle at standstill and at motion.

A stylised idea of what an implementation may look like is shown in Fig. 3.1. Here, each category in the dOC format has its own module, to adhere to the principle of modularity. The road, traffic and weather modules are uncomplicated; each parameter  $p$  has an underlying (suggested) mathematical model  $f_p(x, x_i, \dots, p_i, \dots)$ , listed in Table 2.4. Then it is only a problem of interpolation to find the value of  $p$  at any position  $x$  between the points  $(x_i, p_i)$  and  $(x_{i+1}, p_{i+1})$  where its value is tabulated:

$$i : x_i \leq x < x_{i+1}, \tag{3.1}$$

$$p = f_p(x, x_i, x_{i+1}, p_i, p_{i+1}). \tag{3.2}$$

Interpolation in time works equivalently.

The mission module is more complicated because it can be active both when moving and during standstill, and it needs to consider which variable that governs the simulation. Of course, time is always an independent variable in a dynamic simulation. However, when the vehicle is moving, the explicit dependence in Eqs. (3.1) and (3.2) is position

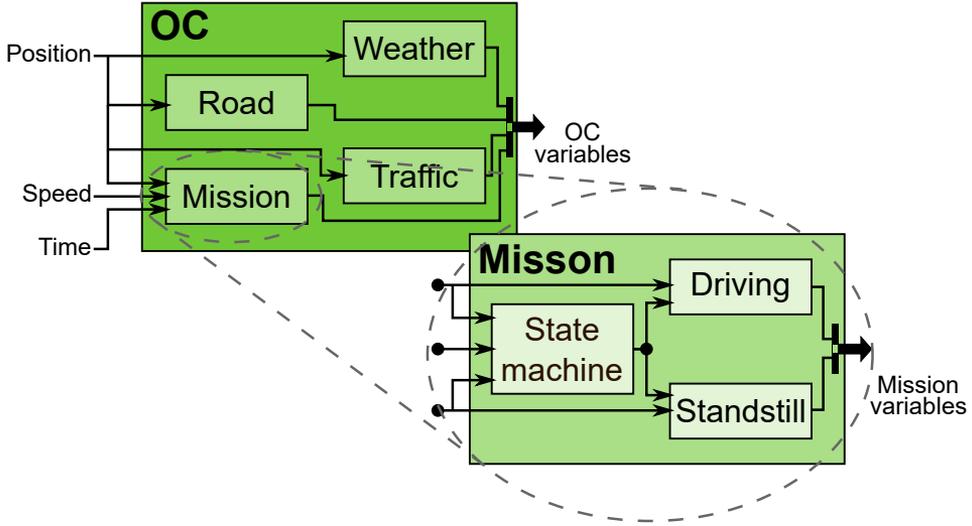


Figure 3.1: A stylised example of a dynamic OC model (adapted from Paper B). The main module is shown top left, in which the mission module, bottom right, is one part.

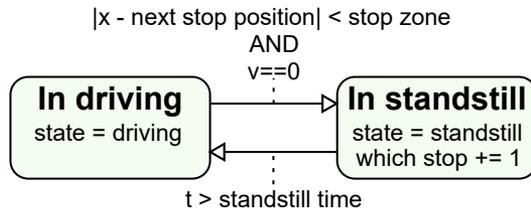


Figure 3.2: The mission state machine (adapted from Paper B).

and the time dependence is implicit (the position changes over time). During standstill, the time dependence is modelled as explicit in Eqs. (3.1) and (3.2).

The ambiguity can be resolved by separating the model behaviour during moving and standstill with a state machine and some pre-processing. The latter involves scanning through the dOC mission parameters and extracting all standstill events into a sequence of matrices (action matrices), one for each stop position, that describe what to do during that event. Then the resulting lean mission parameters only have an explicit position dependence while the action matrices only have an explicit time dependence.

In the implementation, both a moving module and a standstill module are present. The state machine in Fig. 3.2 decides which one of these should be active and keeps track of which action matrix to use. The **standstill time** is just the sum of the duration of all actions at the stop, and the **stop zone** is a constant that defines the effective area (length really, since the trajectory is one dimensional) of the site.

This OC model design was used in Paper B, Paper C, Paper D and [101]. The examples in Paper B were the most challenging, as they included manoeuvring and fairly complicated actions in both driving and standstill.

### 3.1.2 A driver model

The driver model is next to be discussed. Its main purpose here is to serve as a connection between the OC and the vehicle, to interpret the information on the road and transform it to vehicle actuation requests. In general, driver modelling is a complex topic that is often treated in research problems [130–135]. Therefore, it should be made clear that the driver model presented here is built with the primary purpose of making the virtual environment function, rather than to perfectly represent or recreate how a human driver controls a vehicle.

It was earlier argued that the input to the driver model must be the OC parameter values (though all may not be needed), and the vehicle’s position and speed. The output should be control of the vehicle actuators. This will split this into two parts: a tactical part that interprets the road information and decides what action to take, and an operative part that transforms the decision into vehicle control signals. Figure 3.3 shows what the model could look like. These ideas are similar to those of Eriksson [136], although the terminology is adapted to that of contemporary vehicle automation research and development (see Michon [137]).

To get some idea about where to begin, we may look at other simulation environments. Usually when a conventional driving cycle is used, the driver model is little but a speed controller [61, 138, 139] based on the error between the current vehicle speed and the target speed. In our case, this would work nicely for the operative part (where the controller algorithm could be made more or less sophisticated) provided that the tactical part could interpret the driving situation into some kind of wanted speed.

So, we need to think about how a driver chooses his or her speed. A reader fortunate enough to have a driving licence can think about how they themselves decide on a suitable speed at a given moment. There is probably some relation to the current speed limit. Curves may make you decrease that speed, depending on how fun you think lateral acceleration is. Furthermore, severe roughness, low friction conditions, potholes and speed bumps may also make you want to reduce the speed, either for comfortability or to avoid causing damage to your car. Other road signs, like 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 to decrease the speed to avoid crashing. Something quantitative can be derived from these ideas.

The main idea for a tactical module is that a driver will want to travel as fast as possible while remaining comfortable. Some features on the road can 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 provide a static maximum wanted speed. Additionally, we imagine that the driver can see some distance ahead and predict that the speed may have to be decreased below the current maximum static boundary, to reach the next limit without becoming severely uncomfortable.

For each parameter  $p$  that can be linked to a comfort criterion, there is a related upper speed boundary  $v_p(x)$  at position  $x$ . This is the static threshold. If  $p$  is something that the driver can see from a distance, there is also a predictive threshold  $v'_p(x)$ . The wanted speed  $v_w$  then

$$v_w = \min(v_{p_1}, \dots, v'_{p_1}, \dots). \quad (3.3)$$

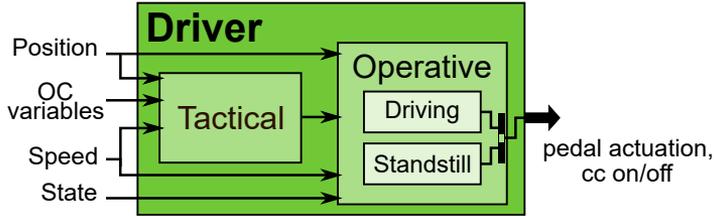


Figure 3.3: A stylised example of a driver model (adapted from Paper B). The ‘State’ input is the current mission state, originating from the state machine in Fig. 3.2.

Some examples of comfort criteria and predictive speed threshold are given in Paper B and [101].

In the operative module, we can then choose some control design  $\mathbf{f}_c$  to relate the current vehicle speed and the wanted speed to an accelerator  $a_p$  and brake pedal  $b_p$ ,

$$[a_p, b_p] = \mathbf{f}_c(v, v_w). \quad (3.4)$$

The pedal variables are assumed to be continuous but bound in some interval, because they can neither be less than unactuated nor more than fully actuated. Without any restriction, we can let this interval be  $[0, 1]$ .

An effective and fairly simple choice of control algorithm is a PID design based on the speed error. If so, another useful simplification is to say that the pedals cannot be used at the same time. The equations are

$$a_p = f_{PID}(v_w - v), \quad b_p = 0, \quad \text{if } f_{PID} \geq 0, \quad (3.5)$$

$$a_p = 0, \quad b_p = -f_{PID}(v_w - v), \quad \text{if } f_{PID} < 0. \quad (3.6)$$

In Fig. 3.3, the state from the mission state machine is also shown as an input. This is not a necessity but a convenience: to enable a switch to a different control strategy in standstill (always fully actuated brake pedal, for example) to avoid winding up the algorithm used for driving.

This driver model design was used in Paper B, Paper C, Paper D and [101] to good results.

### 3.1.3 A vehicle model

The third and final model to be discussed is that of the vehicle. This part can be made complex in the extreme if, for example, the powertrain components are resolved in detail together with any control strategies in a companion control unit. However, the more complicated a model gets, the more effort is required to analyse the results and the more parameters are needed to describe the vehicle. Finding their values require much data and great effort spent on calibration. Therefore, the discussion here will be kept simple and very general, only outlining what parts that are needed to capture variation in propulsion energy from changes in dOC or vehicle design parameters. More detailed equations on the implemented model can be found in Paper B, [101] and [129].

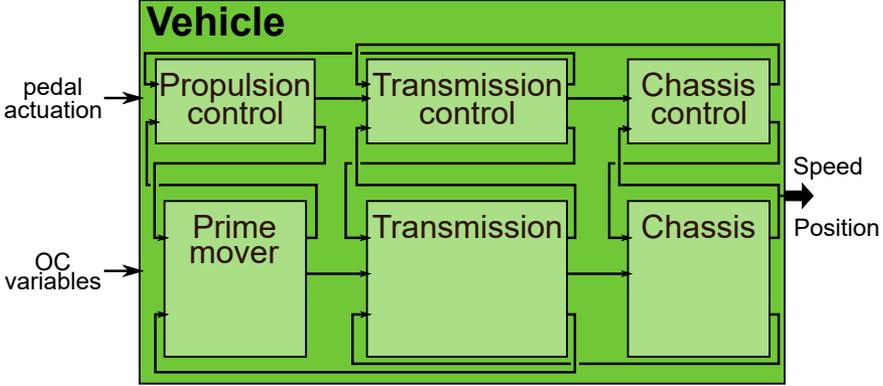


Figure 3.4: A stylized example of a vehicle model.

The driver model's pedal actuations are the input to the vehicle (possibly together with other buttons), as are the physical variables from the OC model. The output should be the vehicle speed and position. An outline of a vehicle model is shown in Fig. 3.4. Only modules for a prime mover with its energy well, a transmission and a chassis are drawn, each with its own control unit. All of them could contain many submodules.

The model would work as follows: imagine that the propulsion control unit receives the accelerator pedal actuation  $a_p$ , interprets it as torque request and computes the right way to tickle the prime mover. This could be a fuel mass flow, an electric current, something else, or a combination: simply referred to as the energy carrier  $q$

$$q = g_1(a_p, \omega_e, \mathcal{OC}, \dots). \quad (3.7)$$

With the injected energy, the mechanical components in the prime mover produce a torque  $T_e$ . The angular speed  $\omega_e$  evolves according to how much torque  $T_c$  that passes onward to the transmission

$$\dot{T}_e = f_1(q, \omega_c, \omega_e, T_e, \dots), \quad (3.8)$$

$$J_e \dot{\omega}_e = f_2(\omega_e, T_c, T_e, \dots), \quad (3.9)$$

$$T_c = f_3(\omega_c, \omega_e, \dots). \quad (3.10)$$

If the prime mover consists of more than one power source, they would have one each of Eqs. (3.8) and (3.9). Furthermore, if an energy buffer is present, we would need to add some relation that keeps track of its energy level. For more complex prime mover structures, see [75, 140, 141].

Next is the transmission. Its control unit decides which gear  $k$  to use

$$k = g_2(a_p, b_p, \omega_c, \omega_e, \omega_t, v, T_e, T_t, \dots). \quad (3.11)$$

The mechanical components rescale the input torque to  $T_t$  and the angular speed to  $\omega_t$ . The cut with the chassis is here called  $T_w$ , which can be interpreted as the torque at the

wheel hub

$$\dot{T}_t = f_4(k, \omega_c, \omega_t, T_c, \dots), \quad (3.12)$$

$$\omega_c = f_5(k, \omega_t, T_c, T_t, \dots), \quad (3.13)$$

$$J_t \dot{\omega}_t = f_6(\omega_t, T_t, T_w, \dots), \quad (3.14)$$

$$T_w = f_7(\omega_t, \omega_w, \dots). \quad (3.15)$$

For more complex transmission structures, see [142–145].

Next is the chassis, including the wheels. Its control unit is in charge of the brake torque  $T_b$

$$T_b = g_3(b_p, \omega_w, v, \dots). \quad (3.16)$$

Usually all wheels have brakes, but only a total torque is shown here. The mechanical chassis and wheel equations were already written in Section 2.1 for a two-axle vehicle, but they can be written on the same general form as the other two systems

$$J_w \dot{\omega}_w = f_8(\omega_w, T_b, T_w, F_x, \dots), \quad (3.17)$$

$$F_x = f_9(\omega_w, v, T_b, T_w, \dots), \quad (3.18)$$

$$m \dot{v} = f_{10}(v, F_x, \mathcal{OC}, \dots). \quad (3.19)$$

With  $\omega_w$  the angular speed of the wheels,  $F_x$  the traction force and  $v$  the longitudinal speed. Note that Eq. (3.17) only contains one axle. Similar equations for the other axles, or the individual wheels, could be added on the same form. For a more complex take on the chassis equations, see [146–148].

We would once again like to emphasise that the relations in Eqs. (3.7) to (3.19) are nothing but an outline of a vehicle model. The reason it is done this way, is to describe what is needed from a vehicle model without going deeply into the mathematical details: these can be found in the references. Also, a framework written like this can be made to host many different models of varying complexity. The examples in Section 3.2 use the same model as in Paper C.

## 3.2 Predicting CO<sub>2</sub> emissions through simulation

With an overview of a simulation model framework given, we may start thinking about the application. In this section, an example is made to show what happens when a dOC is used as input to a complete model. An sOC is also used to show how an uncertainty in CO<sub>2</sub> emissions can be found, and the influence of the mission distance is discussed. The examples in this section have not been presented before, although they are similar to those in Paper B and Paper C. The results concerning the mission distance appear here for the first time.

The main fitness measure is the mass of emitted CO<sub>2</sub> normalised by the travelled distance. This is simply by referred to as the CO<sub>2</sub> emissions of a transport operation and given in units of g (or kg) per km. For trucks, the emissions are often given in units of g per km and tonne of cargo. Only one combination of vehicle and payload is used here, and the normalisation by cargo weight is therefore disregarded.

Table 3.1: *Basic vehicle information.*

Parameter	Value	Unit
Mass	7360	kg
Final drive ratio	2.85	-
Maximum engine torque	2600	Nm
at engine speed	1000-1450	rpm
Maximum engine power	540	hp
at engine speed	1450-1800	rpm
Tyres	315/70 R22.5	-
Aerodynamic drag coefficient	0.6	-
Rolling resistance coefficient	0.0056	-

### 3.2.1 An example in goods distribution

An example of a dOC was introduced in Fig. 2.8, Section 2.5.2. We continue with that example here and use it as input to the simulation model. It is run as an out and return operation, to force the altitude at the start and end to be the same and simplify the analysis. The mission distance is thus 64 km. To emulate the run being (a part of) a distribution mission, the payload is initially 15 tonnes. The cargo is unloaded at the mission stop in the middle, after 32 km, and the vehicle returns empty along the same route.

The truck is a rigid 4x2RAD with a 13 l diesel engine and an automated, stepped gearbox of 12 gears, much like what was used in the FBD in Fig. 2.1. Some basic information about the vehicle is shown in Table 3.1.

Figure 3.5 shows a selection of plots from the simulation: vehicle speed, engine torque and gear. The resulting CO<sub>2</sub> emissions are 974 g/km (equivalent to a fuel consumption of 36.9 l/100 km). The total mission time is 1.12 h (4018 s), although this includes the standstill duration from the mission itself (330 s) and the stop signs (702 s). The resulting average speed is 57 km/h.

A good sign that the simulated longitudinal behaviour is reasonable, is that the vehicle speed displays less disturbances after the payload has been dropped off (after 32 km and 2000 s respectively). The disturbances appear because of a varying topography in combination with the operative driver model. The resistance force is mass dependent, Eq. (2.1), and when the total weight decreases the influence from the gravitational force decreases as well. The speed trajectory grows smoother because the hills cause less acceleration, and the operative driver does not have to react as much.

The novel part of the simulation concept is the OC model in combination with the tactical driver model. Figure 3.6 shows how the road interpretation works. The top plot shows the speed that the driver wants, Eq. (3.3), in solid blue. The actual vehicle speed (same as Fig. 3.5 top left) is shown in dotted red. On the long highway sections, between 5-31 km and 33-59 km, the speed signs set the lowest limit exclusively.

On the urban and rural sections, there are also influences from the curves and the stops. This can be seen from the plots on the second and third rows: the middle row

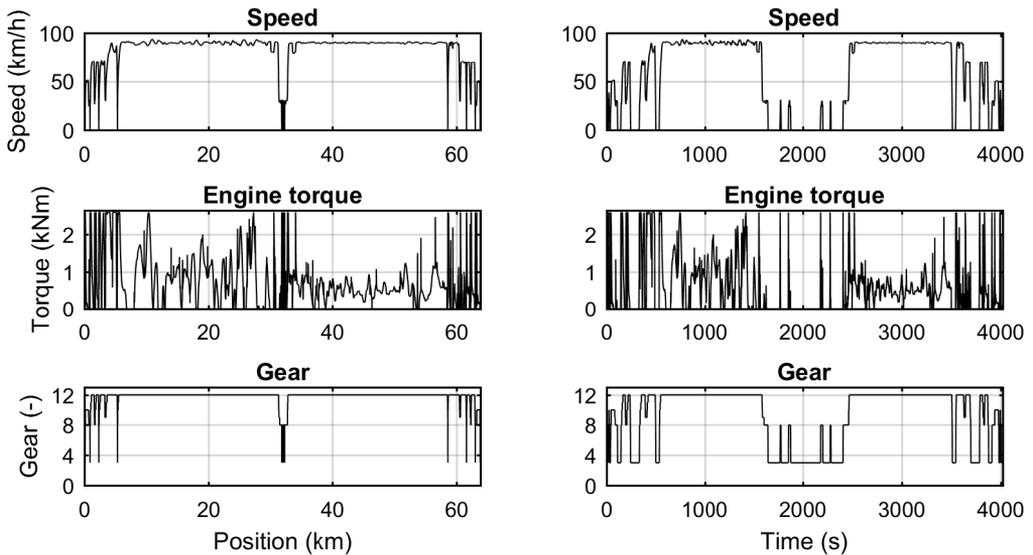


Figure 3.5: *Simulation results. Top row: vehicle speed, middle row: engine torque, bottom row: current gear, left column: versus position, right column: versus time.*

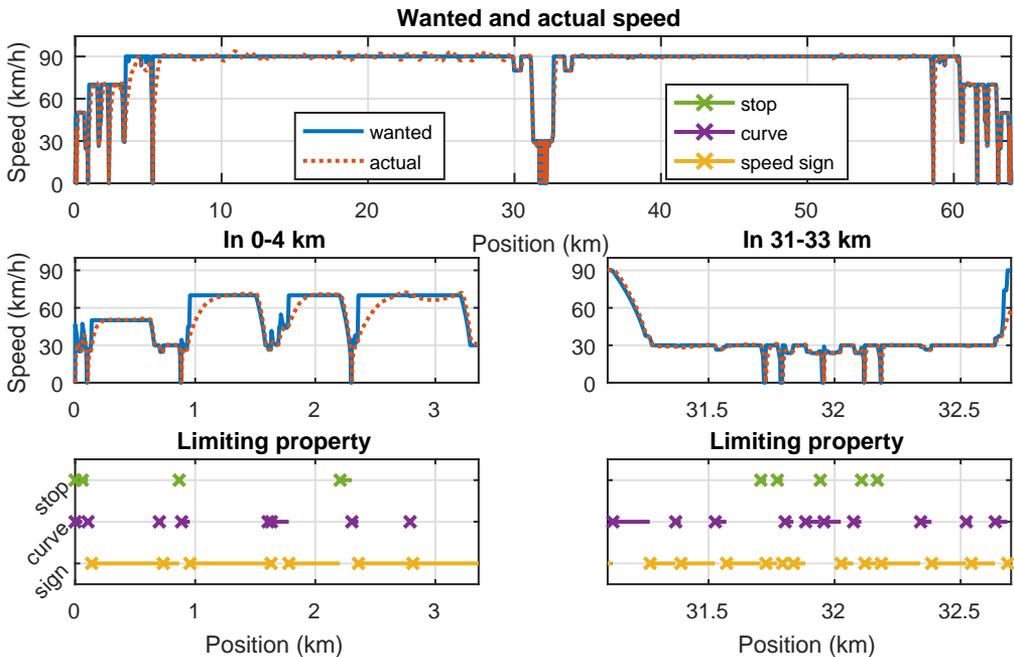


Figure 3.6: *A comparison of the output from the tactical driver module and the vehicle speed. The second row shows a zoomed in view of two instances (between 0 km and 4 km to the left, and between 31 km and 33 km to the right), and the third row shows which property that is responsible for the limiting speed value.*

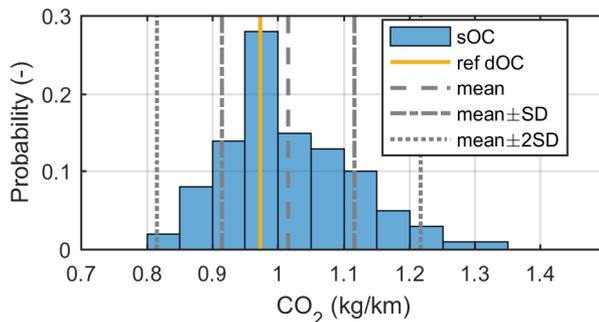


Figure 3.7:  $CO_2$  emissions from 100 dOCs generated with the sOC in Table 2.6 over the nominal distance.

shows a magnified view of the section between 0 km and 3.4 km (left) and 31.1 km and 32.7 km (right). The bottom row shows what road feature that sets the current lowest limit. By looking at these, it can be observed that, at least for this operation, the speed signs set a main limit while the curves cause small variations around this threshold (e.g. the spikes at the left plot around 1.6-1.8 km) and the stops cause large variations. This makes sense intuitively. The physical road properties can be seen in Fig. 2.9.

For the larger decreases in speed threshold, the transition follows a smooth shape, like the first transition from 90 km/h to 30 km/h in the right plot, middle row. This is because of the predictive speed threshold, where the comfortability deceleration limit has the value  $0.2g$  ( $1.96 \text{ m/s}^2$ ). No corresponding (positive) acceleration limit has been used, and therefore all increasing speed thresholds are shaped as steps.

Next, the sOC in Table 2.6 is used to create 100 dOCs. These are generated over the original mission distance of 32 km and then mirrored to 64 km in the same way as the reference was. The 100 new operations are simulated in the same way as before. Figure 3.7 shows the histogram of the  $CO_2$  emissions. Much like the result of the case study in Paper C, the distribution displays a positive skew with a tail towards higher emissions. The mean is  $1017 \text{ g/km}$  and the median is  $995 \text{ g/km}$ . The spread, measured by the standard deviation (SD), is  $100 \text{ g/km}$ . The  $CO_2$  emissions from the reference, shown as a vertical line, ends up in the lower half of the distribution, in the very bulk. It is well within one SD away from the mean, as well as the 95% confidence interval (approximately two SDs from the mean) for belonging to the distribution. Therefore, the reference dOC can be declared to be a typical operation for this sOC. This is good news, since the dOC was used to estimate the stochastic parameters from the very start. If this was not the case, something would have been very wrong.

With these results, we have shown that the simulation concepts with an OC model, a driver model in two parts (a tactical and an operative part), and a vehicle model, can be made to work in practice. The longitudinal behaviour that they predict seems reasonable for this specific case. We also demonstrated that an sOC can be used to get an idea of what kind of spread in emissions that can be expected.

### 3.2.2 About expected consumption, variance and mission length

The CO<sub>2</sub> emissions are one measure of a vehicle's energy efficiency, the used mass per distance. Fuel consumption is another. One could even be more general and define 'energy usage' as the required input energy per distance unit, to remove any dependence on what medium said energy comes from. Whichever one of these are used, an sOC could be used to predict a mean and a spread. However, the mission distance has a curious effect on these. To see it, consider the following situation, where the fuel consumption is used as the canonical example.

Let's assume that we have been given an sOC, generated a bunch of dOCs over a mission distance  $L$  and simulated these. Both the total fuel mass  $m$  and the fuel consumption  $f$  can be computed for each operation. These form some distribution (unknown which) and a mean mass  $\bar{m}$  and variance  $\sigma_m^2$  can be computed, likewise a mean consumption  $\bar{f}$  and variance  $\sigma_f^2$ . If we then treat the fuel mass as coming from a sequence of random variables  $\{M_k\}$ , we can write down a stochastic model as just a random value that varies around a mean

$$M_k = \bar{m} + e_k, \quad \mathbb{E}(e_k) = 0, \quad \text{Var}(e_k) = \sigma_m^2, \quad (3.20)$$

although we have absolutely no idea what distribution the error term  $e_k$  follows. The stochastic fuel consumption  $\{F_k\}$  is then the above normalised by the distance

$$F_k = \frac{M_k}{L} = \bar{f} + \varepsilon_k, \quad (3.21)$$

where

$$\mathbb{E}(F_k) = \bar{f} = \frac{\bar{m}}{L}, \quad \text{Var}(F_k) = \frac{\sigma_m^2}{L^2} = \sigma_f^2. \quad (3.22)$$

Now let's say that we double the mission distance  $L' = 2L$  but otherwise keep the sOC parameters unchanged: what happens to the mean and variance of the fuel consumption? The landscape is the same, which means that the vehicle would behave similarly. We can formulate a stochastic model for the new fuel mass  $\{M'_k\}$  by using the old one in Eq. (3.20): for twice the distance we would just need to pick two of the original dOCs and put them together, one after the other. For ease of notation, drop the  $k$ -index in the analysis

$$M' = M_1 + M_2 = 2\bar{m} + e_1 + e_2. \quad (3.23)$$

The new expected value and variance then

$$\mathbb{E}(M') = 2\bar{m}, \quad \text{Var}(M') = \text{Var}(e_1 + e_2) = 2\sigma_m^2, \quad (3.24)$$

where the last equality comes about because the errors are uncorrelated,

$$\text{Cov}(e_1, e_2) = 0, \quad (3.25)$$

since the landscape is statistically equivalent on both halves of the new operation. The new fuel consumption  $F'$  would be

$$F' = \frac{M'}{L'} = \frac{M'}{2L}, \quad (3.26)$$

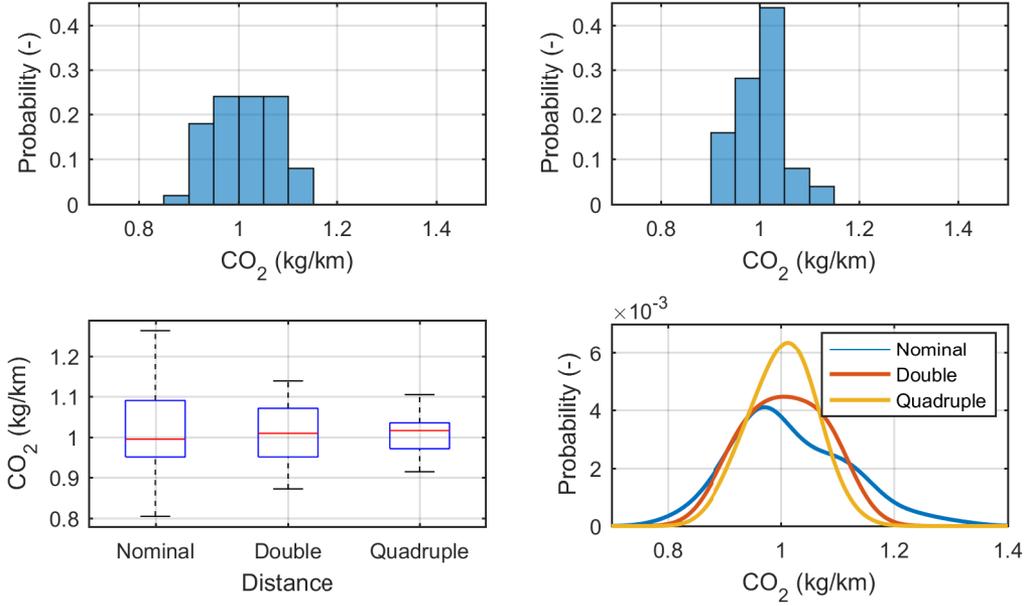


Figure 3.8:  $CO_2$  emissions of the sOC in Table 2.6 when generated with different mission distances. Top left shows the histogram for twice the nominal distance; top right shows the histogram for four times the nominal distance; bottom left shows a boxplot of the three cases; bottom right shows an estimate of the probability density for the three cases.

and its expectation and variance

$$\mathbb{E}(F') = \frac{\bar{m}}{L} = \bar{f}, \quad \text{Var}(F') = \frac{\sigma_m^2}{2L^2} = \frac{\sigma_f^2}{2}. \quad (3.27)$$

Comparing the expected value and variance of Eqs. (3.22) and (3.27) yields a peculiar result: the mean fuel consumption is the same independently of the distance, but the variance decreases. This is very interesting, because fuel consumption is normalised by distance and is therefore generally considered to be independent of this variable. For the specific case of doubling the distance, the variance is reduced by a factor  $1/2$ . The spread, usually interpreted as the SD, is then reduced by  $1/\sqrt{2}$ .

The results can be verified numerically by simulation, see Fig. 3.8. Here the sOC has been used to generate dOCs over twice and four times the distance instead, 128 km and 256 km respectively (out and return, as before), compared to those in Fig. 3.7. The mean and spread are shown in Table 3.2.

The mean is virtually the same, a difference of less than 0.2% in both cases, but the spread reduces by a factor 0.67 and 0.49 respectively. The predicted theoretical factors are  $1/\sqrt{2}$  and  $1/2$ , so the experimental values deviate by 4.8% and 3.1% in the same direction. A boxplot of the three cases is shown in the bottom row of Fig. 3.8, left: the median is shown as a red line, the blue box shows the data between the 25th and 75th percentiles, and the black lines encompass the whole distribution. To the right, estimates

Table 3.2: *Resulting CO<sub>2</sub> emissions from the simulations.*

Simulation	Distance (km)	CO <sub>2</sub> (g/km)	
		Mean	SD
Reference dOC	64	974	-
Nominal sOC	64	1017	100
Double sOC	128	1008	68
Quadruple sOC	256	1003	49

of the probability densities are shown. Both graphs show that the spread decreases in magnitude as the distance increase: the boxes shrink and the distribution estimates grow thinner.

In general, if the distance is increased by  $\Delta L$  instead, the fuel consumption variance goes as

$$\text{Var}(F) = \frac{\sigma_f^2}{1 + \Delta L/L}. \quad (3.28)$$

What does this imply in practice? It is an important question, because one of the reasons that the sOC was constructed was to have some method to introduce variation in simulations: what does it mean when this has a distance dependence?

The short answer is that we must be careful when interpreting the predicted variation. For a given vehicle, a specific sOC cannot be directly associated with a variation in energy usage. Not unless a mission distance is known. If we do have a distance, we can still compute a spread and trust it, just as before. Furthermore, if the variation is measured, we can say how the spread changes when the length changes, through Eq. (3.28). The interpretation for a real vehicle is that the sOC predicts the spread in energy usage when driving on missions a with certain length, which are all set in a similar landscape.

The obvious follow up question is then: which distance should be used when running simulations with an sOC? This would have to depend on some knowledge of the application in question. However, when using a reference dOC in combination with an sOC, as in Section 3.2.1, the mission distance in the dOC can be taken as a baseline. If there is no detailed knowledge about the application and no reference dOC, another option would be to use a rule of thumb. Each property in the sOC format has an associated characteristic length: hill length for the topography, the inverse of the intensity for the stops, the mean lengths of the speed signs, and similarly for the others. An appropriate mission distance would be a couple of times (say ten) longer than the longest characteristic length. That should give a typical operation, as all the properties have had long enough to vary and are thus unlikely to display uncharacteristic behaviour.

A final remark: Eq. (3.28) says that the spread goes to zero as the distance goes to infinity. This can be understood intuitively. The longer the operation is, the greater is the chance that the parts with below average consumption are exactly balanced by the parts with above average consumption. Another way to see it is as a consequence of the law of large numbers. This theorem tells us that with an infinite distance, the computed fuel consumption for any generated dOC would always coincide with the mean. The spread is therefore zero.



## 4 Discussion, conclusion and outlook

In this chapter, we will summarise what has been done in the thesis. We will also say something about what has not been done, by giving an outlook on possible ways to continue.

### 4.1 Discussion and conclusion

We return to the research questions posed in the introduction

- I. **The representation problem:** how should a transport operation be described mathematically to enable a realistic vehicle usage?
- II. **The classification problem:** how can transport applications be compared, with respect to geographical and operational features, in a way that is both vehicle and driver independent?
- III. **The variation problem:** how can variation in operation be measured for transport operations, and how can it be reproduced mathematically?
- IV. **The simulation problem:** how should a complete model for dynamic simulations be built to use the detailed mathematical representation of a transport operation, and are there any basic principles it should follow?

Questions I-III were all discussed in Chapter 2, while question IV was the topic of Chapter 3.

In Chapter 2 three kinds of representations were presented. We started by motivating what aspects of the transport operation that should be considered when talking about energy usage. These were sorted into four categories: the road, the weather, the traffic and the mission.

Next, the classification problem was discussed in conjunction with the first representation: the bird's eye view. This was defined as a highly generalised description that only gave a rough outline of an entire transport application, sparse with details. The mission distance was used as an example to construct a classification parameter with three classes. The framework used by a vehicle manufacturer (Volvo trucks used as an example), the global transport application (GTA), was mentioned as an existing classification system. Three of its parameters were disseminated as to how they were defined, their metric and their classes.

The bird's eye view representation is our suggested solution to the second research question. It is a solution that leaves much to be desired though, because an explicit classification parameter was only given for a single operational property. Furthermore, an ad hoc method was used to find the metric and the classes, but a more scientific way should be possible. Therefore, while the question of how to make comparisons between transport applications may have been solved in theory, it was not solved in practice. Three new questions appeared during the construction of the classification parameter: 'how can a metric be chosen in a scientific way?'; 'how can it be verified that the choice

is sound?'; and 'how can the classification limits be chosen systematically?'. A possible solution to the first of these new questions was found later: the sOC parameters. Then the second question is automatically answered too, by the arguments that were used to motivate the stochastic processes in the first place. The last question, however, remains to be answered.

The second representation that was discussed, in connection with the variation problem, was the stochastic operating cycle (sOC) format. This was a comprehensive yet abstract description that could treat transport operations individually or in a collection. It was said to have an intermediate level of detail, because of the one-to-many correspondence with physical roads: each road on the planet corresponded uniquely to one sOC, but a given sOC could describe many roads. The road properties were treated as sequences of random numbers and then modelled individually by a stochastic process, depending on how each sequence behaved. The parameters of those models had a firm statistical background as they were related to the probability distributions that modelled how the road properties manifested physically. In other words, the parameters encompassed the (modelled) characteristics of said properties. The sOC format was defined as the composition of the models for the stops signs, give way signs, traffic lights, speed bumps, speed signs, ground type, topography, curviness, road roughness and road type, arranged in a hierarchical structure. The format was summarised in Table 2.3 and a graphical perspective was given in Fig. 2.4.

The variation problem has two parts, and the sOC format itself is the solution to the first half: 'how can variation be measured?'. Many (but not all) of the parameters in the sOC format are connected to the probability distribution that model the properties' characteristics. If the probability distribution is fully known, the variance is just the second central moment and can be computed. Then the variation, which is often interpreted as the standard deviation (also called spread or dispersion), is also known. Hence, we have found a way to measure the variation of individual road properties, which embody the variation of the transport operation itself when taken together. There is also variation from the driver, in how he or she chooses to drive. This is something different, which has not been treated in this work.

The second half of the research question: 'how can variation be reproduced?', required some more work and the solution was not presented until the very end of Chapter 2. It was shown that the sOC format can be used to generate new transport operations described on the dOC format. The generated operations are all statistically equivalent because they originate from the same processes and distributions, but the individual realisations are different physically. When used in simulation together with a vehicle and a driver, the longitudinal actions are different for each operation. Thus, by using this method, we have found a way to introduce variation too.

The third and final representation that was discussed, was the deterministic operating cycle (dOC) format. This was a highly detailed description of the transport operation, that divided into the road, the weather, the traffic and the mission. It worked by specifying values of the operational features at points on the trajectory and explaining their behaviour between those points. It had a one-to-one correspondence with the roads on the planet: each physical road could be associated with one dOC, which was unique for that road in question. The weather, the traffic and the mission could still change of course. The

format was summarised in Table 2.4.

The dOC format is the suggested solution to the first research question. It was argued that the representation allows for a realistic vehicle usage because it describes the physical surroundings where the vehicle drives and the mission actions. But it does both these things without making any assumption about the vehicle or the driver: there is no prior knowledge of what speed or acceleration a vehicle should have. The included parameters are some of the (most important) properties that influence the physics of a vehicle or information that a driver can sense. We claim that a realistic description of a road transport operation, independent of the vehicle and the driver, offers the possibility for a realistic vehicle usage when employed in a virtual simulation environment.

The fourth question, the simulation problem, was quite different. It was a practical issue whose essence was to make certain that the solutions to the other three, especially the representation problem, could be used in a virtual environment for simulation with a dynamical model. It was explained and exemplified how a dynamic operating cycle (OC) model could be built, such that it could be parametrised by the data in a dOC. In combination, a dynamic model of the driver was presented in two parts, that could interpret the information sent from the OC model and transform it into control of the vehicle actuators. Furthermore, a framework for a very general vehicle model was briefly discussed. The complete model, consisting of OC, driver and vehicle, was used in an example with a dOC to show that the concept worked. The method with using an sOC to generate new dOCs and thereby estimate a variation in CO<sub>2</sub> emissions was also showcased. In addition, the influence of mission distance on the expected value and variation of the fuel consumption was treated in some detail. These results, which can be generalised to any measure of energy usage per travel distance, have not been previously presented.

The research question mentioned what principles that were needed, but these were never summarised. The first principle is the model structure, as in Fig. 1.4, with separate modules for the operating cycle, the driver and the vehicle. The dOC format says nothing about how a vehicle should be controlled and therefore neither does the dynamic OC model. However, for the very same reason it cannot be used in practice without a driver there to interpret the information. At least not until there are fully automated vehicles, in which case the automation system takes the place of the driver. The second principle is that the simulation should work in a forward scheme. This question has not been treated in the thesis, and so it is somewhat unfair that we simply postulate the principle. It is, however, treated in Paper D.

In summary, we have treated all four of the research questions and attempted to offer a solution to each. However, it must be pointed out that the thesis is a theoretical treatment of (small parts of) an applied problem: how to reduce CO<sub>2</sub> emissions from vehicles by improving their development process. Some methods and tools have been developed, and we have attempted to motivate why these should be expected to work in practice, but little has been tested rigorously and next to nothing has been proven. Paper B, Paper C and [101] contain more examples and case studies, but nowhere have the methods with classification, matching, sOC generation and dOC selection, dynamic simulation and optimisation, been combined in a working chain. In all honesty, the thesis delivers a box of theoretical tools that are largely untested. Practical application to the real-world problem is necessary to find out whether the tools work as intended or not.

## 4.2 Outlook

After having looked back at what was done, it is time to look in the opposite direction and outline some ways to continue.

There are suggested solutions for all research questions, but the one in the classification problem can be particularly improved. Three new questions appeared when solving the problem, concerning how to choose classification metrics and labels in a systematic and scientific way. We later returned to these to comment that the parameters of the sOC format would be suitable choices of metrics, which may be an answer to one or two of the new questions. However, the remaining one ('how can the classification limits be chosen systematically?') has not been solved. It offers an interesting problem whose solution is not obvious. In some sense, it is a matter of finding patterns and, therefore, employing machine learning algorithms may be a direction to explore. Another way to continue with the classification problem is to explicitly construct a bird's eye view classification system that is open and available to everybody. This could be valuable both for the scientific community and original equipment manufacturers.

The third research question and the sOC format have obvious extensions: stochastic models were only presented for properties in the road category. None were presented for the weather, the traffic or the mission. A stochastic approach is common for the two former, but not for the latter. How to construct such models is an interesting and unexplored question. It could also be quite challenging, because the mission category can have a dependence both on time and space. Modelling this may require an innovative approach.

The first research question and the dOC format have similar extensions. The weather and traffic categories have not been used to any larger extent, and very likely need more work before they are useful in practice. This is also true for some of the parameters in the road category, especially the roughness and ground type. At the very least, examples of driver interaction (the tactical part of the driver model) and vehicle modules that can use these concepts should be presented. That being said, the truly innovative part of the dOC format, compared to other comprehensive road descriptions (like OpenDRIVE [149], the unofficial standard used in vehicle simulators), is the mission category. Considering the vast variety of different vehicle applications, there are bound to be many opportunities to develop this further.

As far as the simulation problem is concerned, implementation can always be improved but that does not mean it is a research opportunity. However, the question was included to serve as an insurance that the solutions to the other problems were useful in practice. With that mindset, the question can be expanded to a larger setting that concerns the entire development process: 'what should a product development process look like to be effective and are there basic principles it should follow?'. This was discussed in [101], but the topic has been avoided in the thesis because too many tools were missing to continue working with it at the time. With the development of the sOC format and the connections between the three levels of representation, those tools are now available and the research (presented in Fig. 4.1) can be continued. Especially, the development idea must be tested in practice; both numerically with dynamic simulations and experimentally with real users and vehicles. This is what was referred to with the final remarks in Section 4.1.

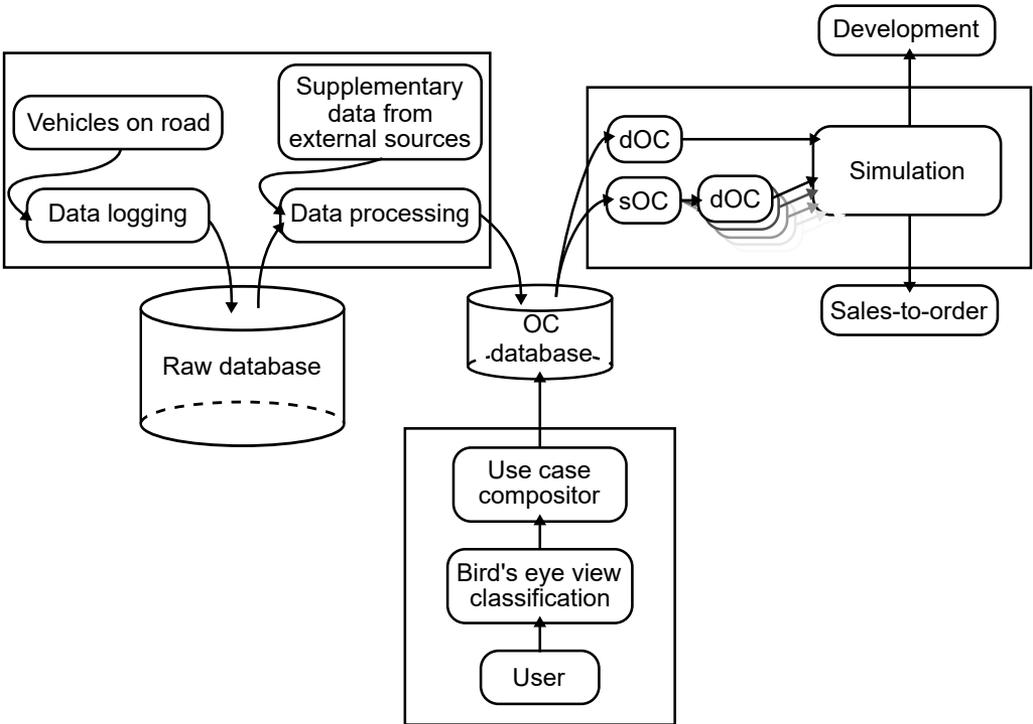


Figure 4.1: An outline of a development process using the new representations. The leftmost box shows how logged data is used to form the component database that contains transport operations described with both the sOC format and dOC format. The bottom box shows how a user makes use of the bird's eye view classification to formulate use cases and fetch matching sOCs and dOCs from the component database. The rightmost box shows how these go into a simulation environment that gives results on which to base either development or sales-to-order decisions.

Another thing that we have not brought up in detail is logged data from vehicles in normal operation. We have used it for some analysis, like Figs. 2.2, 2.3, 2.7 and Table 2.1, and the dOC in Fig. 2.8. Such data is a central part when working with the representations in practice. It tells us where a vehicle drives and what it does, giving the details to the operations of many transport applications. Logged data is the pool of information from which sOCs and dOCs can be estimated, as indicated by the left box of Fig. 4.1. Although such data contains much information, it is contaminated by the driver and the vehicle it originates from. This is a problem, because both the sOC format and the dOC format are fundamentally driver and vehicle independent. One possible solution to filter unwanted influences is to use supplementary data from external sources, that do not contain such contaminations. External data would also make it possible to find information that is not stored (like weather and traffic). There could be interesting questions regarding the coupling between logged data and that from external sources: how to approach uncertainties and what data to trust; how to fuse information in a good way; what to actually measure; and more.

The driver is the final thing that we will discuss. This was mentioned as one of the limitations, and it was stated that the problem of how to model this person was not a part of the research questions. Then the representations and the dynamic OC model were constructed as driver independent. But there must still be a driver model in practical simulation, because something needs to interpret the road and convert this information into control of the appropriate vehicle interfaces. Subsequently, a driver in two parts was presented: a tactical module and a control module. This idea could be thoroughly investigated, especially with experimental measurements in a driving simulator. For instance, one could design dedicated studies to find values for the parameters in the tactical module or investigate whether the simple relations between road properties and the speed a driver wants hold.

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