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MASTER'S THESIS

In-Vehicle Prediction of Truck Driver Sleepiness

Lane Position Variables

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Preface

This is the final report of the master thesis project "In-Vehicle Prediction of Truck Driver Sleepiness – Lane Position Variables", made at Scania CV AB for Luleå Technical University (LTU) between September 2006 and February 2007. It was carried out for the department of Computer Science and Electrical Engineering at LTU with supervisor/examiner professor James P. LeBlanc. The work was conducted and carried out at Scania Technical Centre in Södertälje, in the department RCIS (cab electrical system development), with company supervisor Fredrik Ling and Maria Lundin. The project was done in collaboration with Jens Berglund from Linköping University and is a continuation of a master thesis project done by Lena Kanstrup and Maria Lundin for Scania in 2005-2006.

I would not have been able to carry out this project without the help and assistance from a number of people:

Jens Berglund	Master degree student and co-worker, Linköping University
Fredrik Ling	Supervisor, Scania CV AB
Maria Lundin	Supervisor, Scania CV AB
Anders Wikman	Group manager, RCIS, Scania CV AB
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Eva Enqvist	Professor at the department of Mathematics, Linköping University
Göran Henriksson	Library and information services, Scania CV AB

Test truck drivers, Scania CV AB

Test leaders and staff at VTI

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Södertälje, February 2007

Kristina Mattsson

Abstract

Drivers falling asleep behind the steering wheel are the cause of many traffic accidents, and the statistics show that the number of sleepiness related accidents are escalating. Commercial drivers represent a large part of the sleepiness accident statistics, probably depending on much time spent on the road, long driving hours and the monotonous character of the roads traveled. Systems for sleepiness detection exist but the evidence to judge their applications and performance is inadequate. Sleepiness detection from cameras monitoring the driver and other driver related measures can be hard and expensive to implement. A system only using variables that could be measured from the vehicle itself, preferably using already existing sensors, would be desirable.

The assignment of this master thesis project, commissioned by Scania CV AB in Södertälje, was to investigate the possibility to develop an algorithm that detects a sleepy driving behavior, using in-vehicle variables only. This project is a continuation of a previous master thesis project that investigated a patent claiming to be able to detect inattentive driving. The authors came to the conclusion that two of the variables in the patent showed promising results that should be further investigated. These were to be tried out in this project, along with other variables proved to predict driver sleepiness, by performing extensive tests.

Quantitative testing, where 22 subjects drove a simulator while sleep deprived, enabled the collection of ten *raw variables*, measured from either the steering wheel or lane position. Examples of raw variables are steering wheel torque, yaw angle rate and lateral acceleration. These were combined in different ways to form 17 *transformed variables* that according to literature had shown to be correlated with a sleepy driving behavior, like the number of lane exceedances or the variance of lateral position. To be able to judge the performance of the different transformed variables, a reliable measure of the driver's actual sleepiness was needed. A subjective measure called Karolinska Sleepiness Scale (KSS) was chosen, where the drivers estimate their own sleepiness on a 1-9 scale. Each transformed variable exists in different versions depending on what limits and thresholds are used. The best version of each transformed variable was optimized compared to the KSS and forward selection with regression analysis was used to extinguish which variables should be combined to make the best formula to detect sleepiness. Since some transformed variables were not defined for all time intervals, different formulas had to be created depending on which variables that was available. This created a selection model where six different formulas were used.

The algorithm performance was judged and it proved to give good results. The formulas combined in the algorithm make correct classifications, sleepy or alert driver, in more than 87 % of the cases when sleepiness threshold was set to eight, with a low false alarm rate of less than one percent. This is a promising result considering that only in-vehicle variables were used. A better performance would probably come from combining the detection from in-vehicle variables with another sleepiness measure.

The project is done in collaboration Jens Berglund from Linköping University. The work was divided during the literature study and the identification of the transformed variables, where this report focused on the lane position measurements and frequency analysis of the raw variables and Berglund (2007) addressed the steering wheel related measurers. The result and conclusion came from the combination of the steering wheel variables, lane position variables and frequency analysis variables.

Keywords: Sleepiness detection, lane position, raw variables, transformed variables, truck drivers

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1 Introduction

The following introduction will provide a background to the master thesis project. The background leads to the problem with assignment, purpose, goal, limitations and difference from earlier work in the area. A summary of the preceding master thesis project that constitutes the base for this project is presented in 1.3. This project is, as mentioned, done in collaboration with Jens Berglund and 1.4 will explain how the work is divided. The closing part of the chapter is an outline for the report.

1.1 Background

Sleep deprivation in drivers is suspected to cause more and more accidents on our roads. “Official” figures claim that driver fatigue is estimated to cause 1-3 % of the traffic accidents but this number is generally considered to be much higher. According to Åkerstedt and Kecklund (2000) the correct figures for light traffic are rather in the approximate size of 10-20 % and presumably even higher for heavy traffic. There are significant concerns that statistics are inadequate since no systematic accident analysis has been carried out where accidents caused by fatigue are distinguished from those caused by other factors like alcohol or drugs. (Dinges, 1995) The National Transportation Safety Board (NTSB) in USA has also stated, in repeated reports, that fatigue related accidents constitute a much larger portion of the accidents than official figures claim. As early as 1990 they withheld that fatigue was the single most important cause to fatal accidents in heavy traffic. (NTSB, 1990)

The problem of sleepy driving has existed for as long as there have been cars and trucks. In the beginning, most research resources were focused on how to diminish the effect of accidents in general and did not address prevention or detection of sleepy driving in particular. Dr David F Dinges has studied sleep deprivation, night work and the relation between fatigue and performance. He coined the phrase “power napping”[1] and has studied how the sleepiness of a driver affects the driving performance. (www.humanities.sas.upenn.edu, 2005). His work has constituted the base for several other studies where the sleepiness/performance trade-off was put in the context of driving. The vehicle industry has taken an interest in this area of research and the area is now expanding.

[1] A shorter nap that could help manage fatigue.

Time is nowadays expressed in 24 hour operations and more and more people are conducting vigilance-based activities at times other than the traditional daytime work hours. Starting at the end of the last century, night-time has become an opportunity for production, and there is evidence that these tendencies will escalate over time. (Dinges, 1995) The numbers of accidents caused by sleepiness is increasing due to the tendency that sleep is being less prioritized; hence more people are sleep deprived. Commercial drivers are no exception. Tight schedules and time pressure makes drivers drive for longer hours and during night time to avoid traffic. (NTSB, 1990) Individual differences on how to handle sleepiness and to which extent it affects performance exists but they are limited. There is no evidence that the need for sleep of "professionals" is different from what observed in other persons. Motivation, commitment and extra pay could only prevent sleepiness for transient periods of time. People in general tend to overestimate their own ability to handle their sleepiness. They often consider the risk of reduced performance less when it comes to their own driving, with the argument that precedent ensures an adequate safety margin (i.e. they have performed sleepy in the past and not had a catastrophe). "Every time the citizen manages to drive sleepy without having an accident, it reinforces his or her perception of control and safety" (Page 10, Dinges, 1995). The circadian rhythms[2] are low in the early morning hours as well as in the mid-afternoon. Driving during these hours could in combination with other factors like sleep loss or driving for long periods of time be the cause of sleepy driving, independent on the professionalism of the driver. (Tijerina et al., 1999) Hence, drivers are not always good judges of their own sleepiness. Even if they are aware of their sleepiness, they could be unaware of the risk of falling asleep. (Stutts et al, 2001)

Populations that have been known to be at higher risk for involvement in sleep-related crashes include young people, especially young males, persons with sleeping-disorders or those who have taken soporific medications and night time or shift workers. Commercial vehicle operators are also at increased risk for sleep-related crashes due to factors like extended driving times, irregular work and sleep schedule, higher frequency of night-time driving and inadequate sleep. (Stutts et al., 2001) This opinion is also shared by Sagberg et al. (2004) who have looked at several crash statistics from different references and come to the conclusion that the problem with fatigue related crashes seems to be larger among truck drivers than drivers in general, probably due to that truck drivers mainly drive on large monotonous roads and often during night-time. The accidents associated with sleepy driving are therefore more often fatal since the speeds are higher on highways, main roads and motorways combined with a delayed reaction time of the driver. Dinges (1995) claims that statistics, although inadequate, indicates that the sleepiness-related accidents are common on long stretches of motorway, perhaps accounting for 40 % or more of the fatal crashes. According to him, NTSB (1990) has implicated that fatigue is the most frequent contributor to crashes in which a truck driver was fatally injured.

Stutts et al. (2001) made a population-based case-control study where drivers involved in accidents in North Carolina were interviewed over the telephone. They compared a group of drivers that had been reported (by the police) to be asleep or fatigued by the time of the crash with a control group where drivers had either been in a recent crash not related to fatigue or not in a crash at all. Results showed that drivers in the sleep-related crashes were more likely to work multiple jobs, night shifts, or other irregular work schedules, more likely to have used soporific medications, had been driving for longer time and had slept fewer hours the night before. They also reported poorer quality of sleep (and averaged less sleep per night), drove more often late at night, and had more prior instances of sleepy driving.

Dinges (1995) states that a low level of vigilance gives risk to a dangerous driving style in terms of steering wheel movements, lane keeping and speed variation. Referenced in Kanstrup & Lundin (2006) are Vincent et al. (1998) who studied changes in steering wheel activity associated with decreased alertness. Their study showed that small magnitude steering wheel movements decreased in frequency when the driver was getting sleepier, while large magnitude steering wheel movements increased in frequency. Also referenced in Kanstrup & Lundin (2006) are Haworth & Heffernan (1989) showing possible warning signs of a sleepy driver:

- no memory of the last few miles driven
- zigzag driving, lane drifting, hitting rumble strips, keeps jerking the vehicle back into the lane
- wandering or disconnected thoughts
- repeated yawns
- difficulty to keep eyes open
- tailgating[3]

[2] Circadian rhythm means an innate, daily, fluctuation of behavioral and physiological functions, which include sleeping and waking. (Sleep Terms, Definitions and Abbreviations, 1995-2004 in Kanstrup & Lundin, 2006)
[3] American expression for driving too close to the vehicle in front of you.

- misses traffic lights
- has trouble keeping head up

Regulations in the Swedish law permit the driver to drive for four and a half hours before taking a brake of at least 45 minutes. These rules are the same in the European Union and apply to vehicles registered in EU that weighs over 3500 kg, buses included. The driver can not drive for more than nine hours a day, although this can be extended to ten hours a day two times a week. After driving six days in a row the driver has to have a week-rest of normally 45 hours. The driver is not allowed to drive more than 90 hours in a two-week period. (Vägverket, 2006) All of these rules aim to prevent sleepy driving and similar regulations exist in most countries. The economic needs of the industrialized countries of America and Europe are changing. Also, the scientific data of the consequences of sleepy driving has accumulated during the last 30 years. This combined with the publics perception of what should be regulated constitutes the base for the revision of regulations in many countries. Dinges (1995) warns that governments need to take these factors in to account when changing regulations or they will be doomed to be ineffective in the prevention of fatigue-related accidents.

Governments try to approach the problem of sleepy driving by tightening regulations and improving or changing road design. One such road design change is the installation of rumble strips[4] along the shoulder of selected roadways to alert drifting drivers, another is to diminish the outcome of the accident by building fences or roads with separated lanes to avoid oncoming traffic. Also, educating the public about the risks of sleepiness when driving may reduce the number of sleepy drivers. There are also biobehavioral countermeasures to fatigue like application of preplanned naps, caffeine consumption and bright light. (Dinges, 1995) Airbags and seat-belts to protect passengers in the event of an accident are also a kind of secondary prevention that traditionally has been the focus of safety development in the vehicle. Nowadays the vehicle industry investigates other countermeasures where the aim is to predict sleepiness and prevent the driver from falling asleep by monitoring the driver and give some kind of warning when sleepiness is detected. Other systems aiming to assist the driver in the vehicle are called ADAS (Advanced Driver Assistance Systems) and include parking aid, night vision, lane departure warning systems and adaptive cruise control. Some of these systems are implemented and others will assumingly be implemented in trucks in the near future. (Kanstrup & Lundin, 2006) For example, Scania CV AB has introduced the LDWS (Lane Departure Warning System), which is meant to hinder the driver from making a non deliberate lane departure.

In-vehicle sleepiness detection measures uses variables from the vehicle itself. These systems are based on the idea that a driver goes through different stages as he/she is getting sleepier. Before the sleepy stage there is usually a period of degraded driving which can be detected by measuring different in-vehicle variables. (Knipling & Wierwille, 1994) Such a system would gather signals in real-time that are then passed through an algorithm that is trained to detect a sleepy driving behavior. If the outcome from the formulas of the algorithm is higher than the set threshold, the system should produce a warning. It is important to notice the difference between detection and prediction. A system should preferably be able to predict driver sleepiness, although this is harder to achieve. Detection of driver sleepiness could be sufficient but it could also mean that the system discovers the sleepy driving behavior too late and the accident can not be avoided.

1.2 Problem

Inattentive driving is a growing problem due to longer transportation and tight schedule for both private and commercial drivers. Different kinds of warning systems have been or are being developed to prevent the driver from falling asleep while driving. Some of these systems are based on body signals from the driver like EEG[5], eye movements and blinking rate. To be able to receive these signals, special sensor equipment like wiring or cameras is needed that could be obstructive or disturbing for the driver[6]. Using cameras to read signals from either eye movement or blinking rate could, except from being a quite expensive method, be difficult to use in a non heterogeneous environment where different lighting and other factors like usage of glasses complicates the gathering of information. A system that measures in-vehicle signals, like steering wheel variance or lateral lane position drift variables, would be preferable. According to Dinges (1995) there are existing in-vehicle systems

[4] Rumble strips are grooves or rows of raised pavement markers placed perpendicular to the direction of travel to alert inattentive drivers. (www.wsdot.wa.gov, 2007)
[5] Electroencephalogram measures aims to detect brain waves typical for fatigue.
[6] Renner and Mehring did research on automated sleepiness detection systems for Daimler Benz. They found that in a successful warning system it is not feasible to expect the driver to wire up with electrodes or sensors every time she/he goes on the road, hence they worked by the clear directive to "never bother the driver". (Commission of the European Communities, 1998)

meant to detect driver sleepiness in commercial and noncommercial driving but the evidence to judge its application and efficiency is insufficient. In a study made of Vincent et al. (1998) where behavioral adaptation of drivers to Fatigue Warning Systems (FWS) was evaluated, they concluded that their findings suggested that FWS as currently conceived may not contribute to reduce fatigue induced collisions. This implies that systems known today do not live up to the expectations of FWS and that further studies are needed.

1.2.1 Assignment

The assignment of this project, which is commissioned by Scania CV AB, is to continue where Maria Lundin and Lena Kanstrup finished off and investigate the possibilities to develop an algorithm to detect driver sleepiness, using only in-vehicle variables. Kanstrup and Lundin (2006) found correlations between driver sleepiness and two variables, reaction time and degree of interaction. These should be explored as well as other variables that are shown to be correlated with driver sleepiness. To be able to develop an algorithm relying on only in-vehicle variables, extensive experiments needs to be done to collect adequate information from real situations. This means that quantitative tests have to be performed in a simulator. Through these tests, proper variables could be identified that shows when a driver is sleepy. The best variables should be combined to create a formula that, if shown to be effective, might be implemented in future systems.

1.2.2 Purpose and goal

The purpose of this master thesis project is to try out a way to prevent truck drivers from falling asleep behind the wheel, hence reducing the number of dead or injured in traffic and making the Scania truck a safer work environment for commercial drivers.

The goal is to develop an algorithm that predicts when a driver is falling asleep or is about to fall asleep, independent of conditions like lighting, weather or curvature of the road. The algorithm should be applicable in a real truck and should not give false alarms that would be disturbing to the driver.

1.2.3 Limitations

- The algorithm should be created for real-time usage in trucks, driving on motorways, highways and main roads with a speed over 65 km/h. The differences between driving behaviors depending on road types is not considered in this report.
- This project will focus on sleepiness, even if other inattentive conditions like drug influence *maybe* could be measured in a similar way.
- Legal and ethical issues will not be treated.
- This project will not focus on if the driver is disturbed/suffers from an illness.
- The tests will be conducted in a Swedish environment with Swedish roads and weather conditions.
- Implementation of the algorithm into a system is not considered in this project.
- The evaluation of driver sleepiness is done after the tests are performed and the project will discuss but not consider how the algorithm should be implemented in real time.

1.2.4 Difference from earlier work

It exist in-vehicle systems today that claim to detect or predict driver sleepiness from one or several variables. However, no system is generally accepted since there are difficulties with all different methods. Also, the empirical proofs for the systems are missing or protected in most cases. According to Åkerstedt & Kecklund (2000), many research projects are ongoing at the moment in this area but no system has proved to give an accurate and safe warning system. Therefore, the difference from earlier work is the usage of only in-vehicle variables in the detection of driver sleepiness.

1.3 Previous thesis project

This master thesis project is a continuation of Maria Lundin and Lena Kanstrup's master thesis project for Scania CV AB during autumn 2005 and spring 2006. They investigated if an existing patent for sleepiness detection, belonging to Cesium AB, could be useful in Scania's trucks. They performed two day-time and two night-time tests in a simulator to test the patent algorithm and also a validation test in a real truck to see if the results from the simulator were applicable to a real truck environment. In the case that they found the patent to be useful they should specify which variables that is best combined in an algorithm. (Kanstrup & Lundin, 2006)

The patent belonged to Hans Eriksson at Cesium AB and describes a method for measuring the status of the driver's vehicle control. The purpose was to identify variables which could be used as indicators of the driver's wakefulness. The patent method introduces the term *micro communication* which is considered to be the subconscious interaction between the truck and the driver, in a certain frequency range. Typically this micro communication is usually no more than 0.1% of the maximum steering wheel rotation of a private car. (Eriksson, 2005) The *degree of interaction* in this micro communication indicates if the driver is alert or not. This together with the other variables reaction time, answered question frequency and variation of amplitude are then combined into an algorithm that is said to be able to detect a sleepy driver. According to the method, the interaction between the driver and the truck can be measured through how well the truck's lateral acceleration corresponds with the torque that the driver puts on the steering wheel. This interaction is measured through different variables which is the combined into an algorithm. (Eriksson, 2005; Björkman, 2005)

The different variables were evaluated and the conclusion made by the authors was that two of the four variables in the patent algorithm showed correlation with the sleepiness of the driver. This was the reaction time and degree of interaction and were therefore of interest for further studies. Kanstrup & Lundin suggested that further studies with more night-time simulator tests needed to be conducted to be able to continue developing an algorithm for sleepiness detection.

1.4 Division of work

This master thesis project is as stated before a collaboration between Kristina Mattsson and Jens Berglund. The assignment, purpose and goal of the project are the same but the work will be partly divided. Two approaches is used, lane position variables and steering wheel variables, where this report will focus on the former one. The literature study is conducted in either area although the testing is combined. The analysis is then performed according to what variables that are looked upon. Table 1 shows a schematic view how the work is divided.

Table 1 Division of work

	Kristina Mattsson	Jens Berglund
Literature review	Mainly lane position but also steering wheel variables.	Mainly steering wheel but also lane position variables.
Simulator testing	The testing in the simulator was performed by both.	
Analysis	The lane position variables, reaction time and frequency components of the raw variables were analyzed.	The steering wheel variables and degree of interaction were analyzed.
Formula	In the final formula the variables were combined to create the optimal result.	

1.5 Outline of the report

This report is divided into 8 main chapters, starting with an introduction to the background to the problem which leads to and the purpose, goal, limitations and the difference from earlier work. The final thesis project preceding this one is presented in subchapter 1.3 and in 1.4 a table shows how the collaborating authors divided the work between them. The theoretical frame of reference in chapter two contains the necessary theory later used in the project and the chapter following that presents the technical issues. In chapter four the method is described where extensive simulator experiments were conducted. Results from these experiments are shown in chapter five with following discussions in chapter six. A conclusion of the project finishes the report part followed by the references and appendixes.

2 Theoretical frame of reference

This chapter comprises information and theory needed for the realization of this project. Terms and definitions to define sleepiness, factors that could enhance the driver sleepiness and the measure used in this report to estimate sleepiness are presented in the first subchapter. The second and third subchapters present the different independent variables that were found in literature to indicate sleepiness. A method is needed to find out which of these variables that should be included in the final formula. Different statistical methods for this are evaluated in subchapter four. The theoretical frame of reference finishes of presenting a way to judge the performance of the final formula.

2.1 Sleepiness

Driver sleepiness is generally associated with loss of vigilance and vehicle control. According to Dinges (1995), even moderately sleepy persons can contribute to severe traffic accidents since they show increased periods of non-responding or delayed responding. The underlying problem when trying to prevent sleepiness-related accidents is of course the sleepiness of the drivers. To understand the complexity of sleepiness is hard and no definite measure exists to tell if a person is sleepy or not. This subchapter will define the sleepiness terms used in this report.

2.1.1 Definitions

Tiredness, fatigue, exhaustion, drowsiness, inattention, distraction and drug influence are all human conditions that have similar effect on the driving behavior. Some of these expressions describe a human condition that is caused by outer circumstances, such as drug-use or physical or mental work. This project aims to detect when a driver is about to fall asleep behind the steering wheel, *not* depending on outer circumstances. According to Åkerstedt (2000), the term sleepiness describes an inability to stay awake. Sleepiness is often used synonymously with drowsiness but the latter term has a wider meaning in the sense that the cause of the condition is not as defined. Drowsiness can be caused not only by exhaustion and lack of sleep but also by drug-use. In this report, sleepiness will be used for the human condition “ready or inclined to sleep”. (Dictionary.com, 2007)

2.1.2 Sleepiness factors

There are different reasons why drivers become sleepy and fall asleep behind the steering wheel. Some are related to the cab and road environment, some to the condition the driver is in. Some of the issues addressed by authors in the literature review are presented in this section. Knowing what causes fatigue and sleepiness was important when planning and executing this project.

Pack et al. (1995) noticed in a study that being awake for more than 20 hours drastically increases the risk of an accident. NTSB (1995) stated that the most important factors to 58 % of the fatigue related accidents were the length of the drivers last sleep, total amount of sleep the last 24 hours and fragmented sleeping patterns (several short sleep intervals). (Åkerstedt & Kecklund, 2000) Studies also show that the circadian rhythm has an effect on the level of sleepiness. Analysis of police-reports in both the USA and Europe shows a pattern where sleepy driving accidents elevates during night-time and mid-afternoon. (Dinges, 1995)

Referenced in Åkerstedt & Kecklund (2000) is SCB/SIKA (1999) who shows Swedish statistics that 41 % of the accidents where only one vehicle was involved in Sweden 1998 happened in darkness. Åkerstedt and Kecklund (2000) performed their own studies but they saw no significant proof that darkness as a single factor made drivers fall asleep but rather that the circadian rhythm makes the body want to sleep at night-time. They looked at fatigue induced accidents on Swedish highways[7] hour by hour and noticed that most accidents occur at three or four in the morning during week-days, independent if is was summer or winter, hence indicating that the darkness was not the main reason for falling asleep. They also saw that during the week-ends the peak of accidents appeared later in the morning, around eight or nine, which indicates that it has more to do with lack of sleep than the lighting conditions.

The results from tests where driving-time were measured as a possible factor for sleepiness are hard to separate from the effects of time of day or the amount of sleep that driver have had lately. Fell (1995) showed that 59 % of all fatigue-related accidents occurred within two hours from start, the average was between two and three hours from start. There are no convincing proofs that the length of driving time is essential concerning the risk of accidents. (Åkerstedt & Kecklund, 2000)

Cab environment, gender and age of driver and time of year are other factors that might add to the risk of falling asleep. Also, the amount of noise in the cab environment could be a factor that increases the sleepiness of the driver. Löfstedt et al. (1988) showed that the level of performance goes down when the continuous average intensity noise goes up. The character of the road is another factor that has been mentioned by several authors, although no extensive studies have been made. (Åkerstedt & Kecklund, 2000) An obvious and important sleepiness risk factor is sleep disorders and Dinges (1995) recommends that this area should be addressed in a work/accident arena.

2.1.3 Sleepiness measure

To be able to extract variables that indicate sleepiness when performing simulator tests, a reliable definitional measure of the driver’s actual sleepiness is required. Such a measure may be based on different attributes such as physiological, performance or subjective measures. It need not be obtained operationally but it must be available in the experiments so that the final formula can be “trained” to indicate a sleepy driver. (Knipling & Wierwille, 1994) Sleepiness is possible to assess both objectively, with wiring and sensors, and subjectively, by for example Stanford Sleepiness Scale or Karolinska Sleepiness Scale. (Kanstrup & Lundin, 2006) All of the known techniques of measuring sleepiness are limited in some way. There is a trade-off between the difficulty to perform the measurements and the correlation between the actual sleepiness and the measure. This indicates the complexity of sleep and that it is individually changing.

PERCLOS is a well-known objective measure that uses cameras and image processing to determine how large proportion of a time interval that the eyes of the driver are 80-100 % closed (exclusive of blinks). This measure is generally accepted as a reliable way to measure fatigue but is hard to implement. Well-placed cameras with high resolution is needed as well as advanced image processing software. The driver can not move around too much in the cab and the use of glasses can complicate the measurement and make it impossible to assess data at

[7] Swedish: Europavägar

all times. The Karolinska Sleepiness Scale[8] (KSS) is a subjective sleepiness measure that is much easier to use since the subject rates his/her own sleepiness on a scale. It has been validated in several studies, for example in a study by Kaida et al. (2006) where the KSS were compared to EEG and the behavior of the test subject. There are several methods for subjective assessment of a person's sleepiness. When using the KSS the person is asked about his/her tendency, intention or potential for falling asleep at that particular moment. (Sagberg et al., 2004) The KSS is a nine grade subjective scale where rate one indicates a very alert driver and nine a very sleepy one. The different steps are defined as in Table 2:

Table 2 Karolinska Sleepiness Scale

Rate	State
1	extremely alert
2	very alert
3	alert
4	somewhat alert
5	neither alert nor sleepy
6	slightly sleepy
7	sleepy, but not strenuous to stay awake
8	sleepy, somewhat strenuous to stay awake
9	very sleepy, great effort to stay awake, fighting sleep

According to Åkerstedt (2006) the scale is linear compared to a base scale, i.e. the distance between for example KSS value one and two is equal to the distance between KSS value eight and nine. The main focus for this project is to predict or at least detect when a person is an eight or a nine on the scale, this is when the sleepiness is becoming hazardous for continuous driving. Åkerstedt (2006) have made studies where it is shown that persons that rank themselves to be a nine are estimated to drift off the lane in as much as 17 % of the cases.

The KSS is easy to use compared to objective measurements but there are also drawbacks with the method. According to Tijerina (1999) research shows that the problem with subjective sleepiness ratings is that the subject might not always be good at gauging how drowsy they are or when they are likely to fall asleep. The authors discusses in their report (page 3) that "Drowsy driver detection algorithms and approaches have been a topic of considerable research in recent years. A key ingredient in the development of such algorithms is selection of and appropriate 'criterion' measure for drowsiness. Such a measure of drowsiness should ideally be valid and reliable." This kind of discussion is found in several reports and the dilemma is finding a good way to measure sleepiness that is reliable and that could be relatively easy implemented.

2.2 Independent variables - lane position measures

This chapter will describe different lane position variables that in the literature is shown to be correlated to driver sleepiness and that is later used in the formula. These variables will be called *transformed variables* in this report. To compute a transformed variable, one or more *raw variables* are used (they are further presented in chapter 4.1.3). The raw variables are the variables collected from the real vehicle using line tracking cameras, gyro meters and accelerometers.

As mentioned in the last subchapter, PERCLOS is a well-known and accepted independent measure of sleepiness and is closely related to driving patterns and performance. When the eyes are closed due to sleepiness, visual inputs to the driver are temporarily halted. This means that the driver might hold the steering wheel still or almost still and the vehicle will continue in a straight path. During this period of driver inattention, variations in the road geometry and other disturbances as wind gusts may make the vehicle drift out of the lane. When (or if) the driver opens the eyelids again to assess the driving situation, a more or less sudden correction will be needed to keep the vehicle in the lane. (Tijerina, 1999) This will be shown in lateral acceleration of high amplitude or relatively large lane drift and can therefore be measured with in-vehicle variables. Measuring in-vehicle variables therefore show great potential for prediction of driver sleepiness. For example, Tijerina et al. (1999)

[8] The KSS was developed by Professor Torbjörn Åkerstedt and his group in 1979.

finds that those measures related to steering inputs and lane-keeping appear to be the most promising indicators of sleepiness or impaired driving performance.

Research shows that the lateral lane position of the vehicle contains a lot of information about the driver's vehicle control and therefore it is a promising measure for detection of sleepy drivers. The most common lane position measures are different lane drift variables and Time-to-Lane Crossing (TLC, presented in subchapter 2.2.4). There are different ways of measuring the lane drift, such as lane position variation, mean lateral position and vehicle path deviation. The lane drift measures are usually closely related since they are describing the same behavior but in different ways. The general opinion is that the vehicle control diminishes as the driver gets sleepier; hence the vehicle lateral position varies more. Åkerstedt & Kecklund (2000) found that tests in a truck simulator during night time involves an increase of variation in lateral position i.e. the truck "wobbles" over the lane more with a tired driver. Referenced in Tijerina et al. (1999) is Allen, Parseghian, and Stein (1996) who reported that as the standard deviation of the lane position increased beyond about 0.8 ft[9] (relative to lane centre), the probability of a lane departure goes up drastically. In an experiment in a simulator done by Sagberg et al. (2004) changes in the lateral deviation was measured when the driver drove non-stop for six hours. The lateral deviation started to increase considerably after the fourth hour of driving. This also showed a correlation with the driver sleepiness, measured with EEG, which implicated that the driver was becoming more and more sleepy.

Some of the in-vehicle related measurers have been proven to show no signs of driver sleepiness and will not be used in this report. Wierwille et al. (2001) refers to Huntley and Centybear (1974) who states that brake usage did not significantly change with sleep deprivation. Also, speed and longitudinal acceleration was not shown to be correlated with sleep deprivation and fatigued driving. This is also the conclusion of Kircher et al. (2002) who says that the speed of the vehicle shows no correlation with the sleepiness of the driver.

There are some problems with measuring only lane position variables. The idea of a sleepiness prediction or detection system where only in-vehicle variables are used is based on the fact that an experienced driver, subconscious and under normal conditions, handles the vehicle as an extension of the body. (Kanstrup & Lundin, 2006) This means that each driver will show an individual driving style which will cause problems in the automatic recognition of sleepiness through measurement of variables such as lateral position. (Kircher et al., 2002) There are actually stated cases where the driver takes small "naps" on long straight sections of the road. In this state he/she will hold the steering wheel still and will therefore drive straight if the lateral influences are small or moderate. Measuring only one road position variable will then give a misleading result since the thought is that the driver's vehicle control diminishes when the driver is getting sleepier.

To solve the problem with adapting a general formula to drivers with different driving styles Knipling & Wierwille (1994) introduced the term "baselining". They state (page 10) that "A 'baselining' procedure will be used to tailor detection formulas to the individual driver. It will record each driver's performance measures on-line initially and then subtract such values from all subsequent values. Accordingly, measures obtained are actually deviations from the driver's own baseline."

2.2.1 Theory - lateral position variance and standard deviation

Maybe the most straight-forward lane drift measure is the standard deviation[10] and variance[11] of the lateral position, i.e. how much the vehicle "wobbles" over the lane. Following the discussion from previous subchapters a sleepy driver would be characterized by larger fluctuations from the lane path and this would show in an increase of standard deviation and variance of the lateral position as the driver is getting sleepier. The variance is calculated as the squared standard deviation and is therefore only a 2nd order scaling. Referenced in Kircher et al. (2002) are two studies that showed that the standard deviation of lateral position increased as the driver got sleepier. (Allen & O'Hanlon, 1979; Stein et al., 1995)

[9] About 25 centimeters.

[10] Standard deviation is defined as the square root of the average of the squares of deviations about the mean of a set of data. More generally, a measure of the extent to which numbers are spread around their average. (interstorwords.com, 2007; childrens-mercy.org, 2007)

[11] A measure of the average distance between each of a set of data points and their mean value; equal to the sum of the squares of the deviation from the mean value. (investorwords.com)

2.2.2 Theory - mean lateral position

There are theories and studies that suggest that the mean position of the road could be used as an indicator of driver sleepiness. Driving on a motorway where the lanes are separated by fences or ditches makes the driver (subconsciously) keep to the left of the lane since a lane exceeding to the right probably would cause more damage. On the other hand, when there is on-coming traffic, tired drivers tend to keep to the right since a head-on collision is more dangerous than drifting off the road. Within the SAVE-project[12] the mean of the lane position over a time interval was used to predict driver sleepiness. It showed that the driver kept further to the right of the lane with prolonged driving. This means that the driver, consciously or subconsciously, keeps to the part of the lane where the damage from an accident would be the least. They also studied the time preceding the vehicle drifted of the road. This showed that the average lateral position tended to move to the right, some time before drifting of the road.

2.2.3 Theory - vehicle path deviation

Following the discussion of detection of sleepiness from diminished vehicle control, another driving behavior measure could be to assess the area of vehicle deviation. Computing the vehicle mean lateral position over a time interval would enable the measurement of the deviation from this path. The area would increase when the driver becomes more and more tired. An example illustration of this is shown in Figure 1.

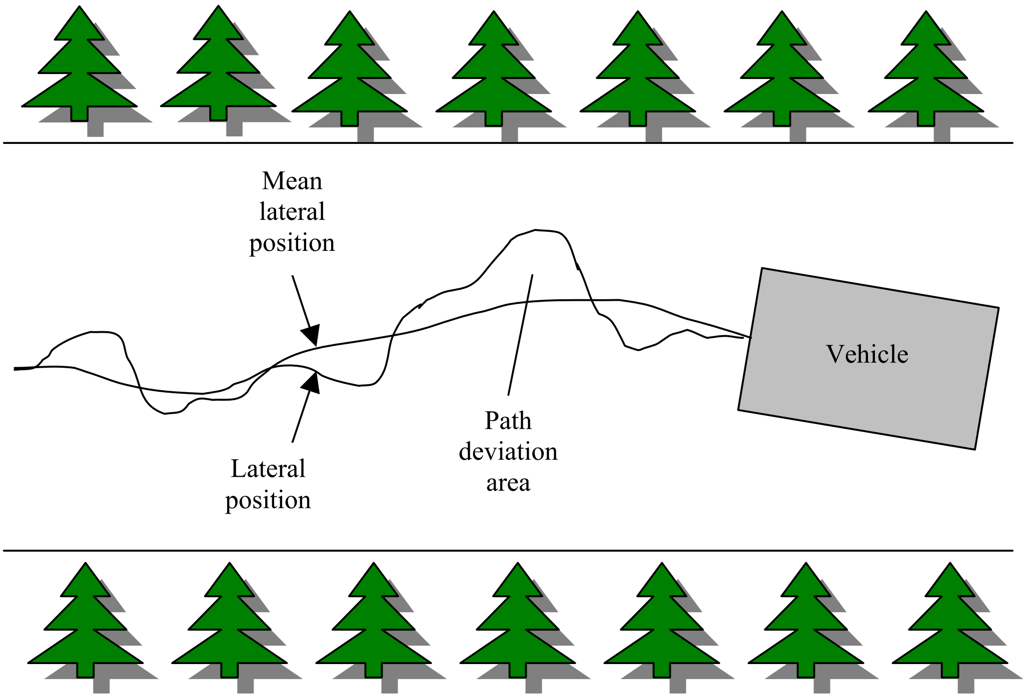


Figure 1 Vehicle path deviation

2.2.4 Theory - Time-to-Lane Crossing

Time to Lane Crossing (TLC) was first proposed by Godthelp in 1984 and is by definition the time available until any part of the vehicle reaches one of the lane boundaries, following the trajectory given by the present vehicle direction and velocity. (Batavia, 1999) According to Kircher et al. (2002), TLC can help prevent diminished performance and warn the driver before the vehicle actually drifts of the lane. This is also supported by van Winsum et al. (1999) who states that accidents where the driver inadvertently moves of the road often are preceded by a period during which the TLC minimum[13] is low. This suggests that lane control of the vehicle

[12] System for effective Assessment of the driver state and Vehicle control in Emergency situations. A European traffic safety program.
[13] A TLC minimum is when the vehicle is close to crossing the lane boundary but the driver avoids the lane exceeding by a steering correction. A TLC minimum will therefore not occur prior to a lane exceeding.

diminishes as the sleepiness of the driver increases and TLC minimum could therefore indicate driver sleepiness. A simple TLC-estimation algorithm would give reliable results for systems that detects when the driver has fallen asleep and is in danger of drifting out of lane. (van Winsum et al., 1999) To calculate the TLC a simplification can be made where two assumptions are used. The first assumption is that the lateral velocity is constant, determined by state measurements of the road. The second is that the road is locally straight. The yaw angle, lateral position and forward velocity can then be used to calculate the time before that first wheel crosses a lane boundary. A schematic view of this is shown in Figure 2. A more thorough presentation of the algorithm used to calculate the TLC is presented in appendix A.

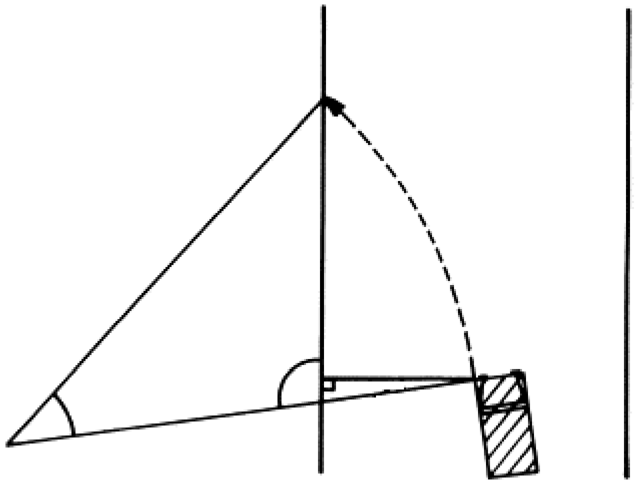


Figure 2 Time-to-Lane Crossing

The TLC could potentially be delayed if there is a curvature on the road. However, this is not a big problem in practice due to the shallow nature of most highway and motorway curves. (Batavia, 1999)

2.2.5 Theory - lane exceeding

Unwanted lane exceeding incidents are another indication of diminished vehicle control. There are different ways of how to measure the lane exceeding to give the best indication of driver sleepiness. Wierwille et al. (1994) presents LANEX, which is the proportion of time that any part of the vehicle exceeded either lane boundary. To get a weighted measure they also use LNERRSQ which is the mean square of the horizontal difference between the outside edge of the vehicle and the lane edge when the vehicle exceeded the lane. When the vehicle did not exceed the lane, the contribution to the measure was zero. They found that LANEX showed good correlation to driver sleepiness (measured by PERCLOS[14]) and LNERRSQ also showed some potential.

2.2.6 Theory - frequency analysis

Some authors have made attempts to get information about the driving behavior from frequency analysis of the raw variables. For example, Kircher et al. (2002) analyzed the Fourier transformations of the lateral position of data from a driver sleepiness study performed in a simulator. The authors experienced quite a lot of variations and noise in the signals, probably depending on the small amount of data in each interval from their examined data. They tried to reduce the noise using Burg[15] and MUSIC eigenvector[16] methods when estimating the power spectral density[17] (PSD). These methods did not show any significant correlations with driver sleepiness and were therefore abandoned.

Ordinary Fourier transform would fail to discover some steering patterns that other methods might catch since the specific time for the frequency components is not revealed. Short-time frequency transform were discussed

[14] Presented in appendix A.
[15] A parametric method for estimation of power spectral density. The method tends to produce better results than a classical nonparametric method when the data length is relatively short. (www.mathworks.com, 2007)
[16] A subspace method for estimation of power spectral density. The method is effective in detection of sinusoids buried in noise, especially when the signal-to-noise ratio is low. (www.mathworks.com, 2007)
[17] The power spectral density is the region in the frequency domain where power of the process exists and the relative proportion of the power at each frequency. (Ludeman, 2003)

by Kircher et al. (2002) as an alternative possible method to solve this problem. This transform works in two dimensions and compromises between the time and the frequency view of a signal. Non-stationary signals[18], as the signals that will be used in the algorithm, are better analyzed by short-time frequency transform since it could reveal single "high" one-time frequencies at a certain time. (Kircher et al., 2002; Kircher, 2007)

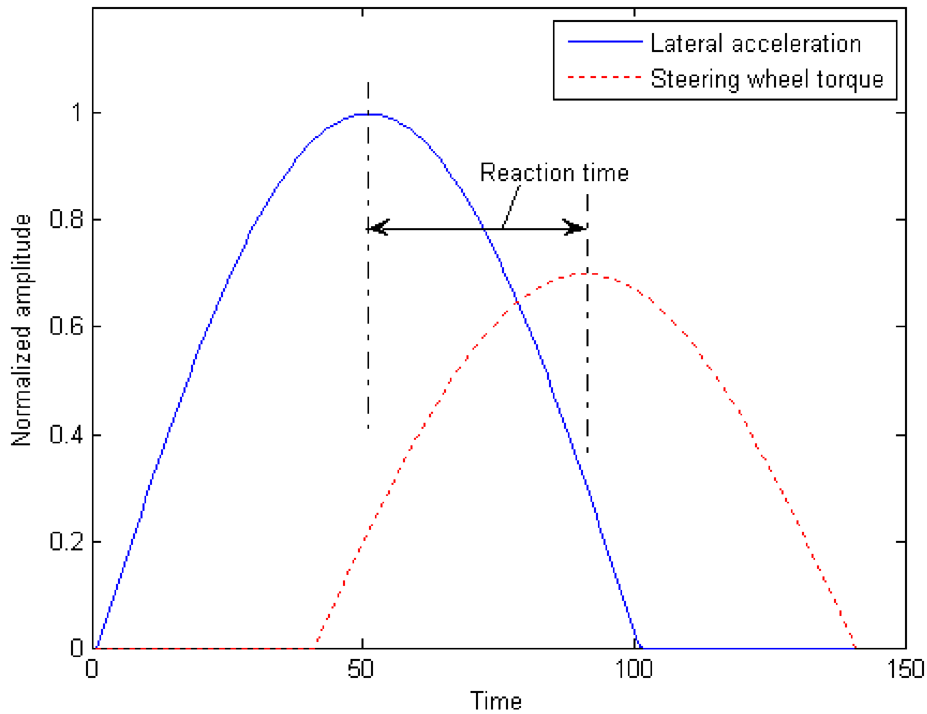
One way of estimating the PSD on the non-stationary raw variables would be to use windowing, where each interval is assumed to be stationary. Using time windows for an "ordinary" Fourier transform is like making a short-time Fourier transform. The Welch method is a nonparametric method that estimates the PSD from the signal itself by using averaged periodograms of overlapped, windowed signal sections. Implemented in MATLAB[19] is a function called `pwelch` that by default divides the data into eight segments with 50 % overlap between them. A Hamming window[20] is then used to compute the periodograms of each segment. This function can be used when analyzing the frequency components of the raw variables.

The reason why frequency analysis is only performed on the raw variables is that when variables are transformed the number of data points from the raw variables drastically diminishes, from 25 million data points to 418. This is too few to make a reliable frequency analysis.

2.2.7 Theory - reaction time

The reaction time in this report refers to the time needed for the driver to react to lateral pulses to the vehicle, like wind gusts or bumps in the road. The authors of the precursor of this project, Lundin & Kanstrup (2006), studied a patent that used the reaction time as one of the variables to estimate driver sleepiness. They came to the conclusion that reaction time is correlated with a sleepy driving behavior and recommended further studies with more test subjects.

To calculate the reaction time both lateral acceleration and steering wheel torque are used. An extreme value of the lateral acceleration will be followed by an extreme value of the steering wheel torque since the driver will compensate for the lateral movement with the steering wheel. Figure 3 shows both of the two raw variables in the same diagram. The reaction time is the difference between an extreme value of the lateral acceleration and the consecutive extreme value of the steering wheel torque.



[18] The raw variables used to calculate the transformed variables are non-stationary since the probability distribution changes over time. A more thorough explanation of stationary signals is found in appendix A.
[19] The software program used for computations on the raw data.
[20] Properties of the Hamming window are found in appendix A.

Figure 3 Reaction time

2.2.8 Theory - degree of interaction

Knowing the reaction time, the degree of interaction can also be computed. The degree of interaction shows, according to the patent explored in the project before this one, how well the driver and the truck interact with each other and showed promising correlation with driver sleepiness. A high degree of interaction indicates an alert driver with high vehicle control and a low degree of interaction means that the driver is sleepy, under the influence of drugs or distracted. (Kanstrup & Lundin, 2006)

Lateral acceleration and steering wheel torque signals are normalized before the torque signal are delayed with the value of the present reaction time. The degree of interaction is then defined as the inverse absolute values of the difference between the integrated versions of the two signals. The equation will be:

Equation 1 Degree of interaction

$$\text{Degree of interaction} = \frac{1}{\left|\int f_a - \int f_b\right|}$$

where f_a is the lateral acceleration and f_b the steering wheel torque. The transformed variable is illustrated in Figure 4.

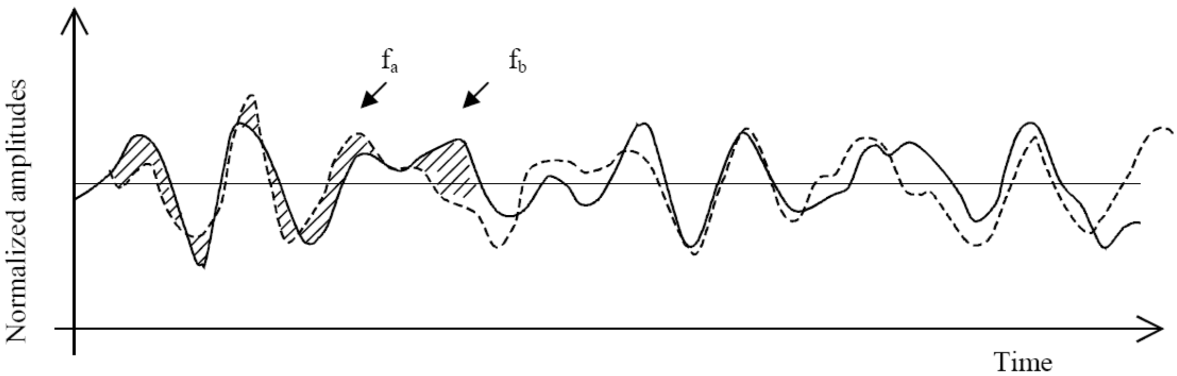


Figure 4 Degree of interaction (Kanstrup & Lundin, 2006)

2.3 Independent variables - steering wheel measures

Steering wheel measures uses the raw variables steering wheel angle, angle velocity and torque to calculate different transformed variables. An advantage of steering wheel measures compared to eye blink rate and lane position variables is that no camera is needed in real-life to assess the signals and it is therefore easy and cheap to install. (Kircher et al., 2002) The variables that could be measured from the steering wheel are further explored in the report “In-vehicle prediction of truck driver sleepiness – steering related measures” (Berglund, 2007) and will only shortly be presented here. The steering wheel variables constituting the base of further development are listed in Table 3 with a short description of the theory behind them.

Table 3 Steering wheel measures found in literature

Variable	Description
Ellipse	The distance to the origin from the points in the plane of wheel angle and wheel angle velocity.
STEXED	The proportion of time the wheel angle velocity exceeds a certain threshold.
NMRHOLD	The proportion of time the wheel is held still.
SDEV	The standard deviation of the wheel angle.
STVELV	The variance of the wheel angle velocity.
SWDR	The number of times the wheel changes direction over a time interval.
Amp_D2_Theta	Describes how the wheel diverges from its own mean.

2.4 Optimization of transformed variables

Each transformed variable described in the previous subchapters will be available in many different versions depending on if there are any thresholds that could be altered and if baselining[21] is used. Trying all these variables in the final formula would be too time consuming and is not plausible. A way of determining which version of each variable that is the best is needed. The best version would be the one that gives the least error when trying to estimate the KSS value. This error can be computed in different ways. Least-square error estimation sums the squared difference between the estimated KSS value and the real one, showing which version would produce the least error. This method is straight forward and is also used in regression analysis, presented in the next chapter, and will therefore be used as error estimator. The MATLAB-function polyfit could be used, which makes least-square error estimation with a stated polynomial order. The relation between the variables and KSS values are assumed to be of first order and linear.

When plotted, some variables could show large peaks in the data that will not add any further information about the state of the driver and therefore can be excluded. These peaks, called outliers, will create a big error using the least-square error estimation and to compensate this, the whole curve would be "lifted". Patterns showing good correlation with the KSS values in the smaller amplitudes could therefore be missed. The large peaks could be cut off since these already show an extreme value, the question is where to lay the incision to make it optimal. One way would be to use trial and error and lay a large number of incisions, compare each of the outcome curves with the KSS values and choose the curve that produces the least error.

2.5 Statistical method

The best transformed variables are to be combined in a formula to predict driver sleepiness. A statistical method is needed to find out which variables gives the best result and also decide their corresponding coefficients. There are different available methods to estimate a dependent variable from one or several independent variables, commonly used are regression analysis and discriminant analysis. By using these methods one can distinguish which transformed variables that combined gives the best sleepiness predictor. The question is which statistical method to use.

Performing a discriminant analysis in this project would mean dividing the KSS into a nominal scale where two groups are formed, tired drivers and alert drivers. The method aims to discriminate the different variables used into the two groups, where the probability of one variable value ending up in the wrong container is minimized. The method assumes that the transformed variables are normally distributed and that the covariances[22] of the two

[21] See appendix A and subchapter 2.2.

[22] Definition: a statistical measure of the variance of two random variables that are observed or measured in the same mean time period. This measure is equal to the product of the deviations of corresponding values of the two variables from their respective means. (The American Heritage® Dictionary of the English Language, 2004)

groups are identical. This is not the case in this project and the transformed variables would have to go through a non-linear transformation, if one can be performed at all, before the method could be used. Regression analysis aims to express one dependent variable as a linear combination of other independent features or measurements (the transformed variables). Multiple linear regression refers to regression on more than two variables and is useful when trying to find the best coefficients for the transformed variables to estimate the level of sleepiness from the KSS. (Enqvist, 2001) In an extensive report from 1994, Wierwille et al. performed multiple regression analysis and discriminant analysis on their collected data. Their results showed that multiple regression analysis was as accurate as discriminant analysis in classifying levels of sleepiness. They discussed that since multiple regression analysis have some inherent advantages over discriminant analysis when dealing with detection algorithm development and use, they decided to use multiple regression when developing their algorithms. The regression analysis seems to fit this project goal the best and will therefore be the statistical method used.

To perform a regression analysis the first step is to set up the general multiple regression statement. For N number of independent variables (x) the statement will be:

Equation 2 General regression statement

$$\overline{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_N x_N$$

where $\overline{y}$ is the estimated dependent variable and $\beta_0 \ldots \beta_N$ the coefficients to the transformed variables. In this project the regression statement could for example look like:

Equation 3 Example regression statement

$$\overline{KSS} = \beta_0 + \beta_1 \cdot LANEX + \beta_2 \cdot NMRHOLD + \beta_3 \cdot TLC$$

where $\overline{KSS}$ is the estimated KSS value and LANEX, NMRHOLD and TLC are examples of transformed variables.

2.4.1 Residual sum of squares

After obtaining the regression statement, the objective is to minimize the difference (error) from the stated KSS value and the estimation from the transformed variables. This error can be estimated with a least-square method called residual sum of squares. For the example above this will mean minimization of:

Equation 4 Example residual sum of squares

$$Q_{RES} = \sum \left[KSS - \left(\beta_0 + \beta_1 \cdot LANEX + \beta_2 \cdot NMRHOLD + \beta_3 \cdot TLC\right)\right]^2 = \sum \left[KSS - \overline{KSS}\right]^2$$

where Q_{RES} is the residual sum of squares. This is also illustrated in Figure 5.

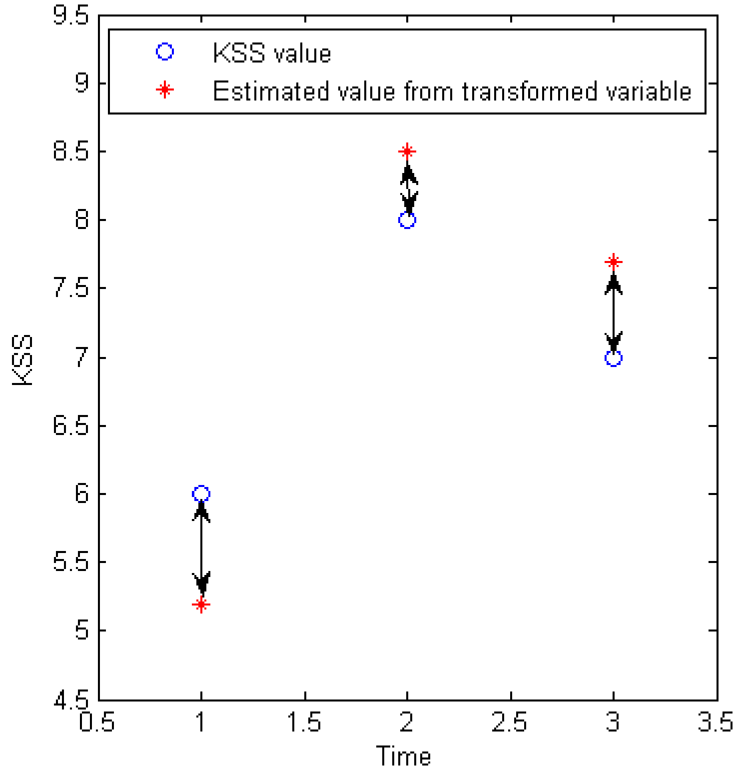


Figure 5 Error computation with residual sum of squares

2.4.2 Forward selection

Forward selection is a method to distinguish which independent variables that contribute enough information, without increasing the uncertainty, to be included the formula. Having two highly correlated independent variables in the same equation is redundant and will create multicollinearity[23] which increases the uncertainty and error of the estimation. Ideally, the transformed variables each correlates highly with the dependent variable (the KSS values) but correlate minimally with each other. (Körner & Wahlgren, 1998)

Forward selection performs repeated iterations to pick out the best variable at all times and include that in the formula. The first iteration of the forward selection process differs from the others. Here, the first variable to be used in the final formula is chosen by computing the correlation coefficient ρ between the KSS and each of the transformed variables with the equation:

Equation 5 Correlation coefficient

$$\rho_{KSS,\mathrm{var}iable} = \frac{\lambda_{KSS,\mathrm{var}iable}}{\sigma_{KSS}\sigma_{\mathrm{var}iable}}$$

where λ is the covariance between the KSS and the variable and σ is the standard deviation. (Ludeman, 2003) The variable that has got the highest correlation coefficient will constitute the base of the formula.

After the selection of the first variable a regression analysis is made with the chosen variable together with each of the remaining. In this second iteration the pair that gives the least residual sum of squares error compared to the KSS is chosen to be in the formula. The third iteration will select the triple that gives the least error, and so on. This continues until the adding of another variable not improves the formula any further. The error of each

[23] Any relationship between independent variables in a regression model which can lead to overfitting of curves in the regression analysis.

iteration in the forward selection is a normally distributed random variable[24]. When the new error has been computed, it is to be compared to the last error to see if it improves the formula or not. Since the error is stochastic, the smallest error can never be identified with a certainty of 100 %. To determine if the new variable improves the formula the F-test is performed.

2.4.3 F-test

To use the F-test a null hypothesis is decided, in this case it was decided to be "adding a new variable will not improve the formula". A test quantity is needed that can decide if the null hypothesis is true or not. This test quantity is based on the residual sum of squares since this shows how good the regression model is. Enqvist (2001) gives this test quantity w as:

Equation 6 Test quantity for F-test

$$w = \frac{Q_{RES}^{(1)} - Q_{RES}^{(2)}}{Q_{RES}^{(2)} /(n-k-2)}$$

where $Q_{RES}^{(1)}$ is the residual sum of squares of the model before a new variable has been added, $Q_{RES}^{(2)}$ is the residual sum of squares of the model after the new variable has been added, n is the number of variables that is tried and k is the number of observation points. If the null hypothesis is true, then the stochastic variable w has an F-distribution. A critical boundary a, for when to reject the null hypothesis, can be calculated for a specific significance level, knowing the F-distribution. The significance level is set to 95 % which means that in this case, if w is bigger than a, the null hypothesis is false. Therefore, the new variable is not redundant with a certainty of 95 % and the forward selection iterations continue. When the null hypothesis is true the iteration will stop and the outcome is the final formula with optimized coefficients.

2.6 Algorithm appraisal

To judge the performance of an algorithm the terms sensitivity and specificity could be used. The sensitivity is the probability that a sleepy driver is detected as sleepy by the final formulas in the algorithm and the specificity is the probability that an alert driver is detected as alert. (Kircher et al., 2002) The different possible outcomes are shown in a contingency table in Table 4.

Table 4 Contingency table (revised version from Kircher et al., 2002)

	Sleepy driver	Alert driver
Detection by algorithm	True Positive (TP)	False Negative (FN)
No detection by algorithm	False Positive (FP)	True Negative (TN)

The aim would be to get sensitivity[25] and specificity[26] to 1, which means that the formula made correct detections in all cases. This is generally not the case, and there is a trade-off between sensitivity and specificity. Setting limits and thresholds to detect as many sleepy drivers as possible will also make the formula detect an alert driver as sleepy more often. This will cause reduced acceptance of the system and drivers might disconnect such a system. More eligible would be a system that has a low False Negative rate but still detects as many sleepy drivers as possible, hence creating a specificity value close to one. Wierwille et al. (1996, referenced in Tijerina, 1999) expressed the opinion that, although it is not desirable to have a system that misses detections; it is less desirable to have a system that produces a large number of false alarms since this erodes driver acceptance.

[24] See appendix A for definition.

[25] $Sensitivity = TP/(TP + FP)$

[26] $Specificity = TN/(TN + FN)$

2.7 Alternating formulas

Some of the transformed variables will not be accessible at all times depending on if certain thresholds are exceeded or not. For example, a driver that drives in a straight path and keeps away from the right side line will not get values for the Time-to-Lane Crossing variable in all intervals. Lacking one or more of the variables originally computed to be in the formula will make the outcome more uncertain. One possible way to get around this problem is to compute a formula for each combination of variables and the final system will choose formula depending on which variables are available. A schematic view of the course of events is shown in Figure 6. Alternating formulas is also more adjusted to a real time environment, for example when driving with snow on the road might make it impossible to detect the lane marker lines with cameras hence the lateral position, velocity and acceleration will not be available for transient periods of time.

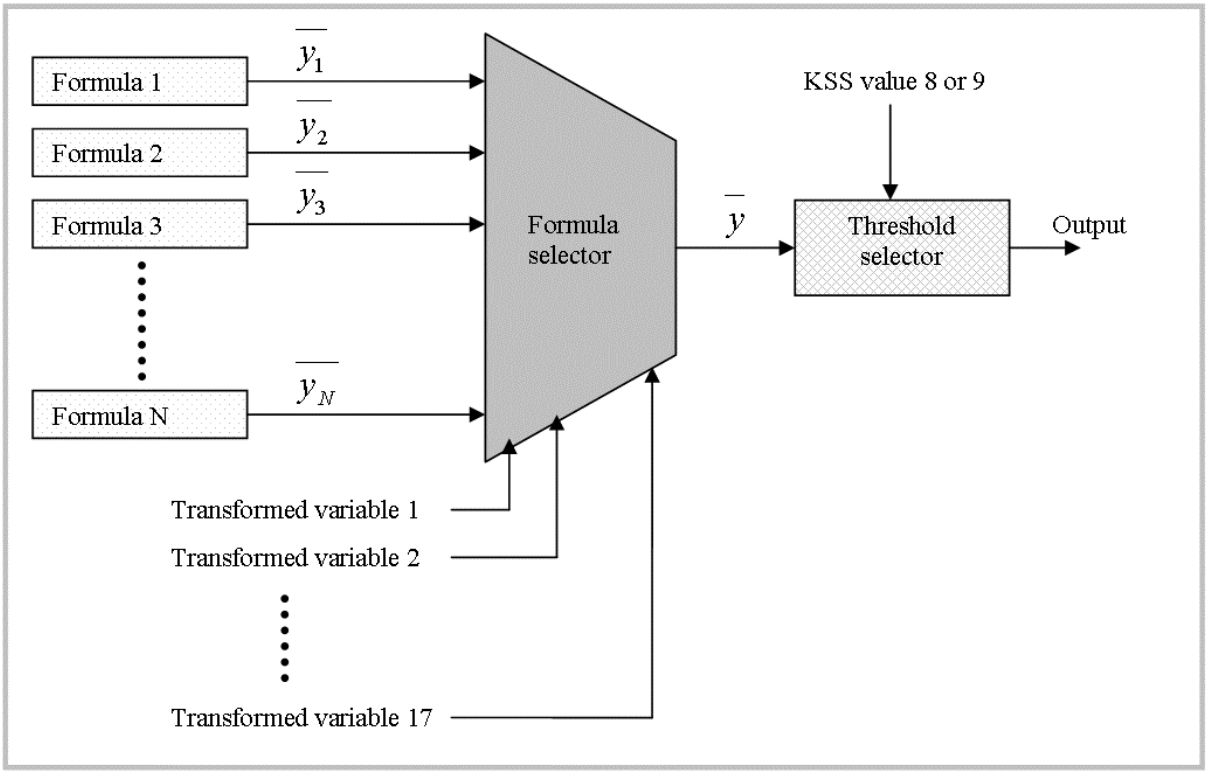


Figure 6 Model for formula selector

3 Technical frame of reference

This chapter will describe the test driving devices, such as simulator technical facts and cab environment, and software needed in the project.

3.1 Simulator

The tests were performed in a simulator at VTI[27] in Linköping, Sweden called Simulator II. This is a full motion simulator that imitates all aspects of a real vehicle and the environment. Jolts simulating road structure and wind gusts enhances the feeling of driving in a real truck. The sound system also adds to the experience by generating noise and infrasound that resembles the internal environment of a truck. Outside of the simulator the test leaders can supervise the test through three cameras showing the driver in different angles, speakers and microphones for communication and computer screens that shows the same visual output as in the simulator cab (Figure 7).

Figure 7 Control room for monitoring the tests

[27] Swedish National Road and Transport Research Institute (Statens Väg- och Transportforskningsinstitut)

After the tests were all done, VTI provided DVDs with recordings from the simulator cameras and data from the corresponding tests.

The simulator needs to significantly resemble a real truck to be able to be used in real situation experiments. Simulator II at VTI has been validated against trucks on several occasions. Kanstrup & Lundin (2006) refers to Hakamies-Blomqvist et al. (2001) who found that some of the most important differences between the simulator and a real truck are:

- the variation in speed, lateral position and steering wheel movements was greater in the simulator compared to a real truck
- the test subjects drove further to the right on the carriageway in the simulator
- familiarization effects such as higher speed and less variation in speed and lateral position occurred to a much greater degree in the simulator than in the real vehicle

These differences could have effect on the final formulas of this report since only in-vehicle variables are used. However, all the differences were according to the authors relatively small. Hakamies-Blomqvist also made the study on a test group all aged over 65 years old which could be misleading for this project. Kanstrup & Lundin (2006) made a validation test between Simulator II and a Scania truck and came to the conclusion that it is possible to collect exact and accurate data from the lateral acceleration and steering wheel torque when using the simulator. The difference is that noise is present in the real vehicle signals and they therefore have to be filtered. In the simulator there is no noise to consider and signal processing before using the data is superfluous.

3.1.1 Technical facts

The simulator is built around a real Scania truck chassi and uses a sophisticated motion system to simulate acceleration, vibration and road contact. The motion system has three degrees of freedom and a simulated lateral and longitudinal acceleration of 0.4g. The environment is simulated on two rear-view mirrors and a screen covering a 120°x 30° field of view. Figure 8 shows a picture of Simulator II at VTI. More hard facts about the simulator and pictures are found in appendix B.

Figure 8 The simulator used in the experiments (VTI, 2006)

Settings for disturbing lateral pulses could be set by the test leader during the tests. These pulses were supposed to imitate wind gusts, bumps etc. that is normal in a real truck environment. The amplitude value of the pulses was set to 4 on a 1-10 scale where one scaled the pulses with small amplitudes and ten maximum amplitudes.

3.1.2 Test environment

Following the discussion in chapter 2.1.2, driving on a broad and straight road with little traffic creates a monotonous environment that increases the risk of falling asleep behind the steering wheel, hence causing an accident. (Åkerstedt & Kecklund, 2003) People tend to use physical activity and/or dietary stimulants to cope with sleep loss, masking their level of sleepiness. However, when they sit still and get bored, like when driving long distances, sleep comes quickly. (Mitler et al., 1988; National Transportation Safety Board, 1995 in NHTSA, 2006) This was desirable when performing the experiments since the objective was to study the driving behavior of sleepy drivers. Therefore, the test environment in the simulator was chosen to be a broad, straight, road with fog limiting the field of vision to 150 meters. There were two lanes going in each direction, separated by a low fence. No buildings, creatures, vehicles or other attributes other than trees and fields were seen in the rural landscape, either on or by the side of the road. Also, the drivers had no access to any stimulants (for example radio) other than the ones directly connected to the driver environment such as the screen, rear-view mirrors, gas pedal and steering wheel. The gear was disabled and the watch and trip gauge concealed so that the driver could not know for how long he/she had been driving. A sheet showing the KSS was placed in the middle of the steering wheel so that the driver could remember the different steps of the scale.

3.2 Software

The tests were performed with a sampling frequency of 100 Hz and ten different raw variables were extracted for approximately 70 hours of simulator testing. This meant a lot of data that had to be processed to make the transformed variables. Scripts were formed in the mathematical programming tool MATLAB 7.1 for this particular reason. The simulations were often time consuming because of the size of the data and they had to be run over several days. Some calculations and diagrams were also made in Microsoft Excel.

4 Method

This chapter describes the methods used in the project. The simulator experiments and the subjects, the raw and transformed variables and how they were extracted and after that how the transformed variables were optimized are explored. Finally, a presentation of how the statistical analysis and formula selection were performed finishes the chapter.

The work of this project can be divided into three main parts. In the planning stage the project plan and goal of the project was set up. A rough time-plan was made in collaboration with staff at VTI and the supervisors of the project at Scania. The second stage was the empirical testing which contained 22 simulator tests at VTI in Linköping. In the third and final stage the data was analyzed and conclusions drawn.

The idea was to use the raw data from the simulator tests to compute measures (transformed variables) that were correlated with the driver sleepiness. The best measures would be combined in the final formulas. A schematic view of the whole development process is shown in Figure 9, where examples of raw variables are used.

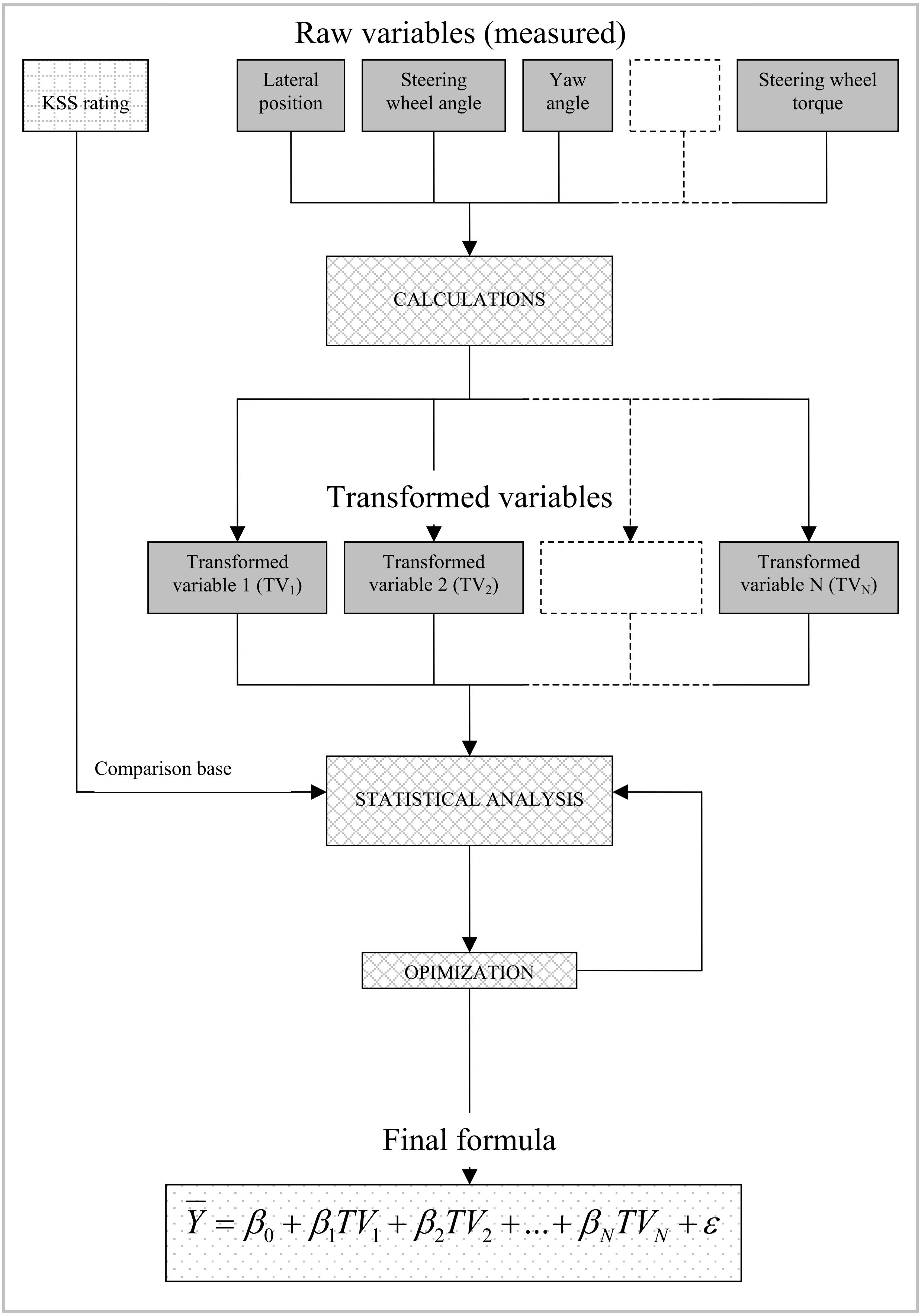


Figure 9 Schematic view of the algorithm development of the formulas

4.1 Simulator testing of sleepy drivers

In order to get in-vehicle variables that implied driver sleepiness, testing of fatigued drivers needed to be performed. This is not easily and safely done in real traffic (and is also prohibited by Swedish law), therefore a simulator was used. The simulator settings are described in chapter 3.1. This chapter describes how the sleepiness experiments were performed in the simulator. The measured variables, called the raw variables, were transformed into different known variables, called the transformed variables, which according to the literature could imply sleepy driving. The raw variables are presented in the final part of this subchapter.

4.1.1 Test procedure

The tests were first scheduled and planned in collaboration with experienced test leaders from VTI. Their staff is well acquainted with the simulator and has great experience in performing these tests. It was decided that the test persons were to do the test night-time after a normal day at work. Tests performed by Kanstrup & Lundin (2006) and VTI (2005) showed that two hours would be a suitable length of the tests to ensure that the driver became sleepy during the test. To be able to correlate certain in-vehicle variables with a sleepy driver, the drivers driving pattern when *not* sleepy also needed to be recorded. Therefore, each test was preceded by a one hour reference test earlier the same day. With each test (reference and real test) taking totally three hours to perform, this meant that three tests could be performed each night. The schedule for the nightly tests for both pilot tests and ordinary tests are shown in appendix F. The first four tests were pilot tests where the driving-time and settings were checked and verified. After that 18 more tests were performed. A few problems occurred, for example the rear-view mirror screen went black or the simulator temporarily halted, but the problems were worked out and all tests could be completed as planned. In the test leader's opinion, the driver reactions to these problems were not so big that it would affect the results of the tests. Some data had to be cut off and was not used when the simulator halted unprovoked or if the driver fell asleep and drifted out of the lane.

When arriving at VTI and the simulator the driver was asked to fill in a questionnaire and was given information of what to expect during the test. Before the test the drivers performed a 10 minute pre-test to ensure they did not suffer from simulator sickness and that they felt comfortable in performing the test. Instructions were given that they could stop the test at any time, without having to give a reason. They also got training in how the simulator worked and answered, by orally stating a KSS value, to the question "sleepy?" as it appeared on the screen. During this pre-test the question came up every second minute compared to every ten minutes in the real test[28]. No data was recorded during the pretest. The drivers were asked to drive as they normally do and obey the Swedish driving rules, for example to drive in the outer (right) lane. The maximum speed of the simulator was set to 90 km/h. During the pre-test the test leaders spoke to the driver through speakers in the cab. This communication stopped when the real test started since that could have a stimulating effect on the driver. When the test was completed the driver was asked to stop the vehicle and was asked to complete another questionnaire. The driver was then driven to a hotel by taxi.

4.1.2 Subjects

All 22 subjects recruited for the test were employees of Scania, seven of them as professional truck drivers that work as long-time testers (LP-drivers) of Scania trucks. The LP-drivers were scheduled for the test quite early and the rest of the group was employed by asking random people at Scania if they were interested in participating. Criterions for participating in the test were that the subject should not suffer from any sleep disorders and they had to have a truck driver license. The test persons were aged between 24 and 57 with a mean age of 35 years, fifteen men and seven women. The driving experience over the test group differed a lot, both between men and women and between LP-drivers and others. This was expected since the women participating were generally younger than the men and the LP-drivers (all men) had been working as truck-drivers for several years.

A couple of weeks before the test the participants got an information letter containing practical information as well as the background and purpose of the tests in general terms. No specific details were revealed about the detection algorithm or what variables that were measured. The LP-drivers worked their regular night shift week and were therefore asked to limit the sleep on the day before the test. Restrictions regarding caffeine consumption or other stimulants before and during the tests were made, as well as naps during the day prior to the test.

[28] In a study made by Anund et al. (2005) the test subjects were asked if they were sleepy every five minutes. She saw no indication that such a short interval would inflict the sleepiness of the driver and the ten minute interval was therefore chosen. (Anund, 2006)

The subjects were asked to fill out a questionnaire before and after the test drive. These were meant to give an overview of the drivers sleep habits, sleep problems, driving experience etc. The questionnaires were given in Swedish but translated and shortened versions are shown in appendix C and D. A summary of the answers to the questionnaires is found in appendix E.

One part of the questionnaire was the questions of Epworth Sleep Scale (ESS) that is a test for helping to recognize narcolepsy. According to the inventor of the scale, Dr Murray Jones, the test can give an indication of a sleep disorder. (narcolepsyfacts.com, 2006) When scoring 10 or more, he suggests that you should see a physician and take part in a sleep study. The average of the test group scored 8, with quite a big difference between the averages of women (9.6) and men (7.3). Four persons scored ten or higher with one test subject that scored as much as 15. In a study made by Anund et al. (2005) the ESS mean of the test group was 7.5. This was compared to other control group studies made by Johns (1991) who showed an ESS mean of 5.9. This indicates that the subjects within this study reported higher sleep latency compared to "normal" people.

When summarizing the question about sleep problems, all answers where the test person stated that he/she had the problem often or always were counted. More men than women had sleep problems. Only two women stated that they had problems regularly (got too little sleep) while the largest proportion of regular sleep problems for men (five test persons) were snoring. Twenty test subjects had been awake for eight and a half to eighteen and a half hours since their last coherent sleep when performing the test. Most of them, 75%, found the latest sleep to be of good or fairly good quality. The two remaining subjects had had less than four hours coherent sleep the preceding night and were therefore not counted in the statistics for that part of the questionnaire.

After the test another questionnaire were filled in by the test participants regarding the experience of driving in the simulator. 20 out of 22 test drivers stated that they once or more during the test were so tired that they under normal circumstances would have stopped to rest. 13 fell asleep behind the wheel, but it did not always result in a lane exceeding. 68% thought that the simulator environment was very realistic. Estimating your own level of sleepiness did not seem to be a problem since 17 out of the 22 drivers stated that it was quite easy or very easy to do. One person felt nauseous during the drive but could still complete the test. The simulator environment were as stated before chosen to be very monotonous which also lead to the drivers feeling bored, 82% said that they were quite bored or very bored while driving.

4.1.3 Raw variables

Ten different in-vehicle variables were extracted during the simulator tests. They were each sampled with a frequency of 100 Hz and put in a separate file for each test driver. These time-discrete variables were later used to calculate transformed variables used in the final formula. The raw variables are shown in Table 5.

Table 5 Raw variables

Variable	Unit
Time	Seconds (sec)
Speed	Meters per second (m/sec)
Lateral position	Meters (m) (measured from the central line)
Lateral velocity	Meters per second (m/sec)
Lateral acceleration	Meter per square second (m/sec^2)
Yaw angle	Degrees (deg)
Yaw angle rate	Degrees per second (deg/sec)
Wheel angle	Degrees (deg)
Wheel angle rate	Degrees per second (deg/sec)
Wheel moment	Newton (N)

The variables are available from the simulator system. In a real truck these signals needs to be collected with different sensors like cameras (lane tracking system) and gyro sensors (yaw rate).

4.2 Identification of transformed variables

The ten raw variables described in chapter 4.1.3 were combined in different ways to get good predictors of driver sleepiness. These predictor variables were a mix of literature studies (chapters 2.2 and 2.3) and alterations of, or new variables thought of by the authors. The alterations of the literature variables and the method to calculate them are presented in this chapter. After using the raw variables there were 17 transformed variables that could be tried in the formula.

All the 22 test files provided by VTI were combined into one big file to contain 418 data points. Each point generally represented ten minutes of data, being either a KSS value or some variable value. If all data were to be plotted in the same figure, each ten minute period would have one discrete KSS value and 17 corresponding continuous values belonging to each of the transformed variables. In this way, when trying to minimize the error it will include all drivers and therefore be more general.

Each driver has an individual driving style. To diminish the effect of different driving styles when trying to do a general algorithm a reference was made for each driver. The first ten minute interval of each driver were recorded and saved. All remaining intervals for that driver were then divided by the reference to get a relative variable that could be compared between drivers. This method, called baselining, is presented in chapter 2.2 and is used for each of the variables.

4.2.1 Method - lateral position variance and standard deviation

According to the literature study presented in 2.2.1, both the variance and standard deviation of the lateral position showed potential as predictors of driver sleepiness. They are closely related but this is by a second order relationship which will not be detected when performing the regression analysis later. Therefore, both of the measurements were computed and tried out and the one producing the least error were chosen to be the transformed variable tried in the formula. A baselined version were computed for each of the two variables, hence four variables came out of the computation. The one containing the least error was given the abbreviation LATVAR.

When computing the lateral position variance and standard deviation the raw variable lateral position was used together with MATLAB functions `std` (standard deviation) and `var` (variance). The lateral position was buffered during the ten minute intervals and the variance, standard deviation and the referenced version of the same were computed when a KSS value appeared.

4.2.2 Method - mean lateral position

The mean lateral position, called MEANPOS, was computed in a similar way to the lateral position variance and standard deviation. The raw variable buffered was lateral position and instead of using the MATLAB functions `std` and `var`, the function `mean` was used. A baselined version was also computed and two versions were therefore the outcome of the computation.

4.2.3 Method - vehicle path deviation

The mean lateral position is needed when computing the area of the vehicle path deviation discussed in subchapter 2.2.3. In real-time processing this mean will have to be computed from former positions but in this case the mean could be computed over both former and future lateral positions. This is done with a sliding window that could be set to different lengths; hence several versions of the variable will be the outcome. The interval length from which to compute the mean could also be set to different thresholds, which means that the variable will have quite a few versions that should be tried to find the one with the least error. These variables are also doubled since a baselined version is computed for each of them. The variable that is found to be the best is called PATHDEV.

Looking at the first preliminary results from the vehicle path deviation it was obvious that another measure showed potential as a driver sleepiness predictor. It was noticed when plotting the variable against the KSS that the variance of the variable over time could be used as a measure. This means that an alert driver will keep about the same level of deviation area over time while a tired driver will vary from small areas to large ones. The variance over time of all the versions presented above was calculated, thus doubling the number of versions one more time.

4.2.4 Method - Time-to-Lane Crossing

The TLC calculations found in literature proposed to set the time threshold until the vehicle crosses the line to one, three and six seconds. After setting the threshold, the amount of time the vehicle was computed to be less than this threshold away from crossing the line was summed up and presented every time a new KSS value showed up. The three thresholds suggested in literature were tried out as well as a reference for the baseline, creating six versions of TLC variables. Computing the TLC is done by using the raw variables lateral position, yaw angle and longitudinal speed together with the road width and vehicle width. The TLC computation assumes that all the variables measured will stay constant. A thorough presentation of the TLC algorithm used is presented in appendix A.

4.2.5 Method - lane exceeding

The lane exceeding variables used, in this report called LANEX, are extensions of the variables found in literature. More than measuring the proportion of time and the distance from the outside edge of the vehicle to the line when lane exceeding, as proposed by the studied literature, the maximum distance and area of the lane exceeding is measured. Since no traffic occurs in the simulator environment and the driver was asked to stay in the right lane, lane exceeding over the left line (central line) is also measured. Together with baselining this will create 16 different versions of the LANEX variable. The transformed variable can be calculated knowing the lateral position and the width of the road.

4.2.6 Method - frequency analysis

As described in chapter 2.2.6 a function in MATLAB called pwelch could be used to estimate the PSD of the raw signals by using windowing. The order of the filter was chosen after some testing to be four[29]. Six raw variables were frequency analyzed to see if they showed any patterns of energy content that differed between alert and tired drivers. The raw variables analyzed were lateral acceleration, lateral position, speed, steering wheel angle, steering wheel torque and yaw rate. The PSD vectors that were the outcome of the pwelch function were ordered after the corresponding KSS value and stacked after each other to produce a three dimensional plot. This plot would show the frequency, time and energy of the signal and from that plot any patterns of energy contents could be observed. Figure 10 shows an example of this, the figure showing the plot of the yaw rate. The values belonging to tired drivers are in the back of the figure and the alert ones in the front. To the right in the figure there are large peaks. They represent the low frequencies and show that the most common frequencies are the ones just above zero. These peaks are quite similar for alert and tired drivers and the focus will therefore lie in larger frequencies, between 0.05 and 0.4. The energy content between these frequencies are assimilated for all time periods and the result is a threshold value that is used as a transformed variable. The abbreviation for the variable will be FREQANA and the six raw variables are baselined creating twelve versions of the transformed variable.

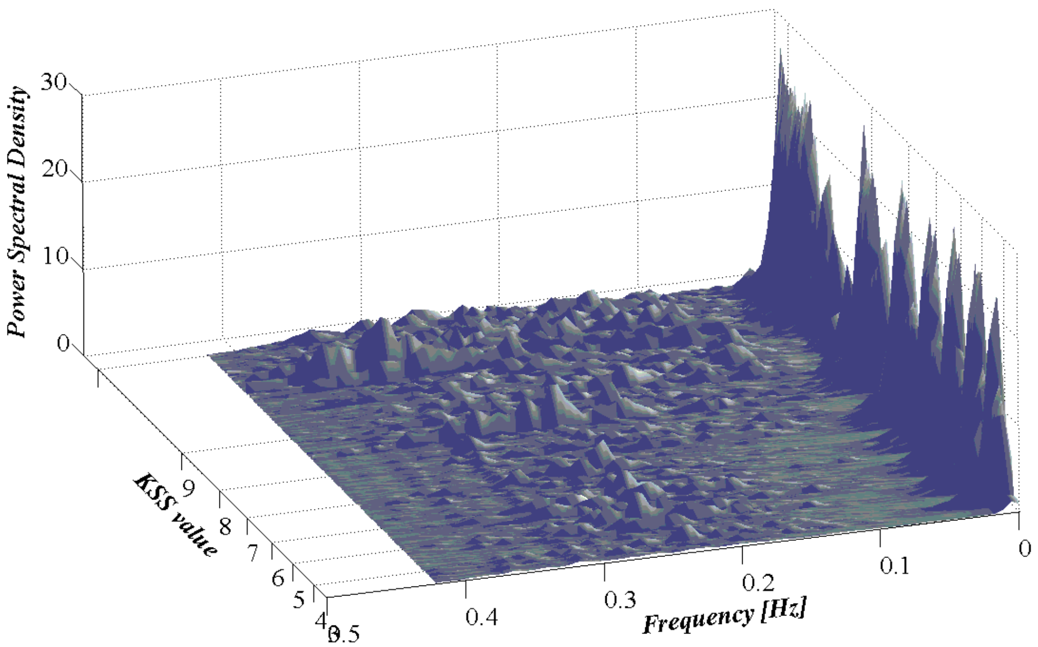


Figure 10 Example 3D plot of the energy contents of the yaw rate

[29] The trial and error technique were used, trying to get a clear result from an order that was as low as possible.

4.2.7 Method - reaction time

Two raw variables are needed to compute the reaction time: lateral acceleration and steering wheel torque. To be able to extract the reaction time discussed in subchapter 2.2.7, several methods had to be tried. The one that proved most successful was using the MATLAB command `xcorr` that makes a cross-correlation between the two curves and plots a diagram for how correlated they are for each time lag. In this correlation diagram the extreme values are considered since the largest one will occur at the time when two curves correlates the most. This will happen when one of the curves is delayed with the reaction time. The reaction time extracted from this computation was baselined in the same way as the other variables and will be called REACTIM.

4.2.8 Method - degree of interaction

The degree of interaction was extracted using Equation 1 described in chapter 2.2.8. Before the computation, the steering wheel torque was delayed by the reaction time for that time interval (the reaction time was computed as stated in the previous subchapter). The two raw variables steering wheel torque and lateral acceleration were normalized to get similar amplitude so that the area between the two signals was representative and general. The outcome, called DEGOINT, was referenced with a baseline and tried in the final formula.

4.3 Optimization of transformed variables

As discussed in chapter 2.4 and seen in the previous subchapters, there are different versions of each transformed variable. A method was needed to distinguish which version was the best. The least-square error was calculated for all different versions of these variables and the ones producing the least error were used in the regression analysis to obtain the final formulas. The best versions are presented in the result chapter (chapter 5).

Also discussed in chapter 2.4 is the procedure of cutting of the extreme values of the variables. The trial and error technique was used where the maximum amplitude were divided into 100 equally sized sections. An incision was laid at each of these points and then the error was calculated. The one with the least error was picked and cut accordingly. Figure 11 shows an example of a transformed variable before any alterations. Figure 12 shows how the same variable as in Figure 11 looks when the extreme values has been cut of. The version with cut extreme values constituted the new and improved transformed variable.

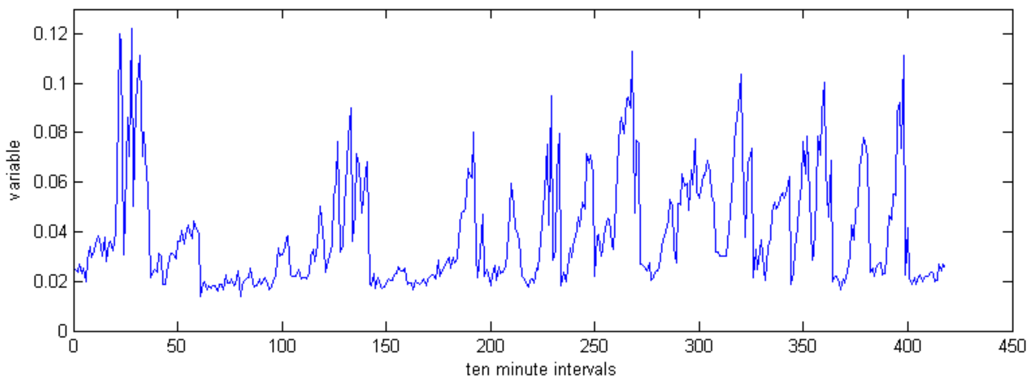


Figure 11 Example of transformed variable

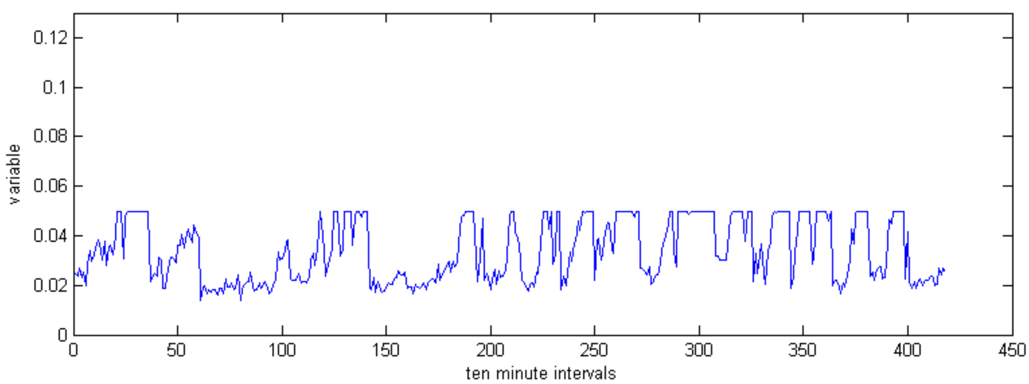


Figure 12 Example of transformed variable where the extreme values has been cut

4.4 Statistical analysis

Special statistical computer programs exist that perform regression analysis. In these programs it is hard to survey the course of events and conclusions made from their results can hide generalizations that were not meant to be made. Therefore, scripts calculating the forward selection with regression analysis were formed manually from scratch in MATLAB. These scripts were used to form formulas depending on the different constellations of transformed variables, as discussed in subchapter 2.7. In this project there are only a limited number of variables that is defined for less than the total data set. For example, the TLC variable will only have values when the threshold for time to lane exceeding has been exceeded, with this test data it will be defined for 187 of the total amount of intervals. The different formulas will therefore not be as many as if all combinations had to be tried. An example is shown in Figure 13 where four different formulas would be needed. The transformed variables (TV) 1-7 have values for all intervals and can therefore be included in the forward selection process of all formulas. The other two variables, TV 8 and TV 9 are defined only for certain time periods. The four different formulas for the example would be:

- Formula 1 - selecting from transformed variables 1-7
- Formula 2 - selecting from transformed variables 1-8
- Formula 3 - selecting from transformed variables 1-7 + 9
- Formula 4 - selecting from transformed variables 1-9

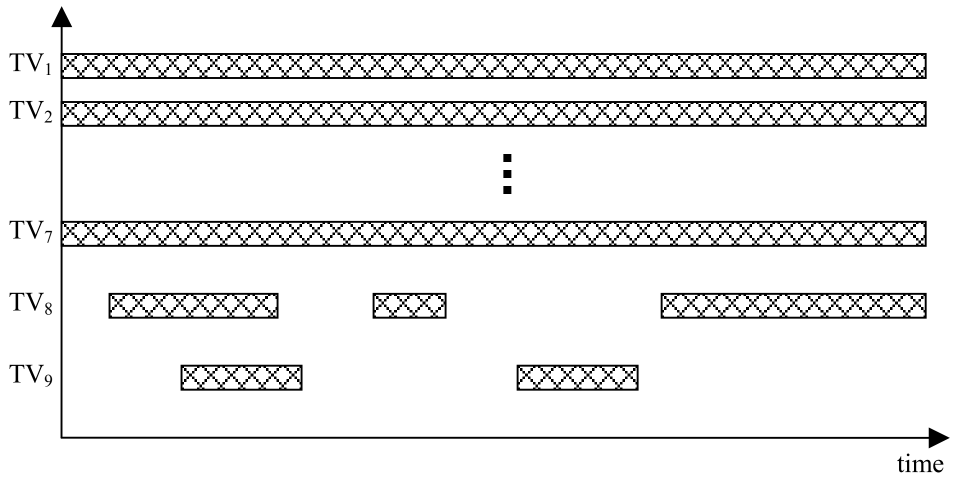


Figure 13 Formula selection

The difference from the example to this project is that one of the variables, the FREQANA, has a threshold above which the driver can be detected to be sleepy with 100 % certainty[30]. This means that a check is made before the formula selection process, and if the threshold is exceeded the driver shows a sleepy driving behavior, hence the formula selection is superfluous.

In this project the variables that were not defined for all values were TLC and LANEX; this meant that four different formulas were needed. It was discovered that one of the raw variables needed for the steering wheel variable "ellipse" was missing from the pilot studies. This meant that this variable were also lacking some values and had to be considered when setting up the formula selection process, meaning that the number of formula versions went up to eight. Some of these formulas were defined in very few intervals and it was not possible to make a reliable regression analysis. To avoid this, three formulas were combined to one, leaving six formulas as a result. The outcome formulas are presented in the result chapter.

[30] In reality this certainty is less since the threshold is calculated from an experimental study.

5 Results

The results coming from the simulator testing and statistical analysis is presented in this chapter. Each of the transformed variable results is presented separately as well as the results from the sleepiness measure (KSS). The chapter is finished with a summary over the most important results of the chapter. The results are given shortly and will be further discussed in the next chapter.

5.1 Sleepiness measure

During the tests the KSS values stated by the drivers were assessed and recorded by the test leaders. They each corresponded to about ten minutes[31] of simulator testing. The drivers stated KSS values spanned from 3 to 9, hence no driver was extremely alert (KSS value 1) or very alert (KSS value 2) even though the reference tests are included. The total number of KSS intervals was 418 and counting the number of intervals corresponding to each KSS value gives Figure 14. The figure also shows that the drivers were generally sleepy during the tests since the intervals of KSS value 9 accounts for a large amount of the intervals.

The KSS values of all 22 test files were put together into one big file that would work as a template and comparison base for extracting the best transformed variables. A plot showing the total file of KSS values are shown in Figure 15.

[31] If the driver fell asleep and drove of the road the file was cut, creating a shorter file. Also, in a few of the pilot tests the interval for which the sleepy-question appeared were set to 15 minutes instead of 10, creating a longer interval.

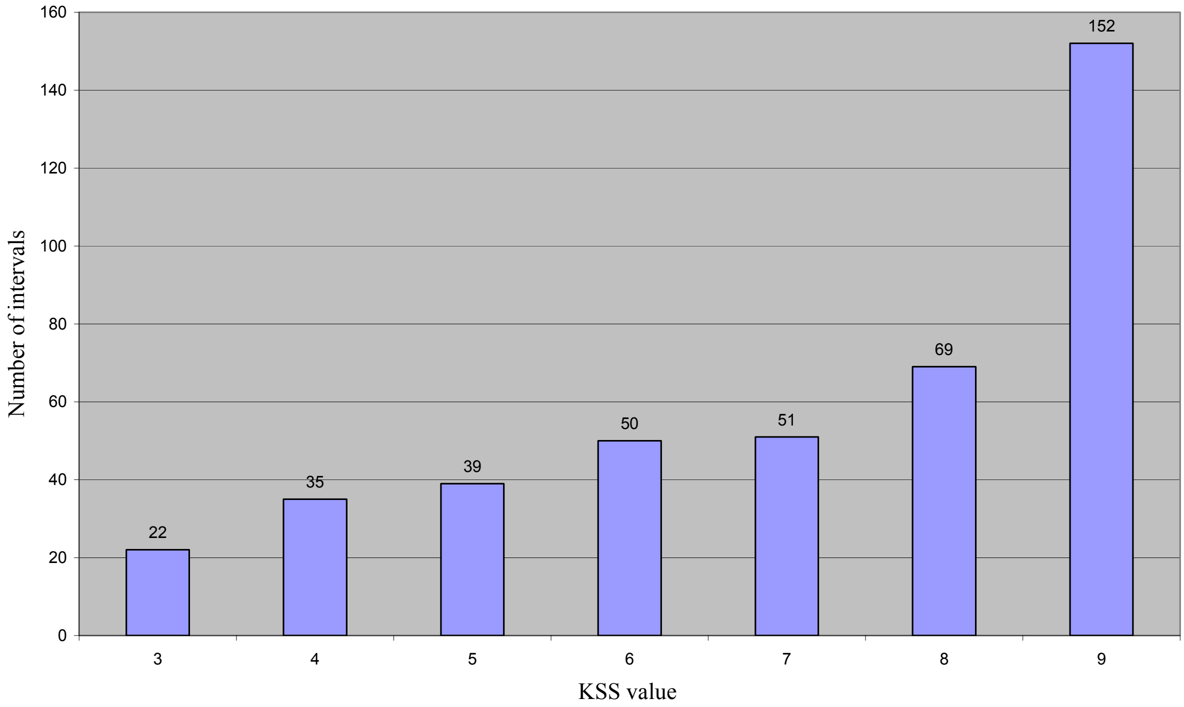


Figure 14 Number of intervals corresponding to each KSS value

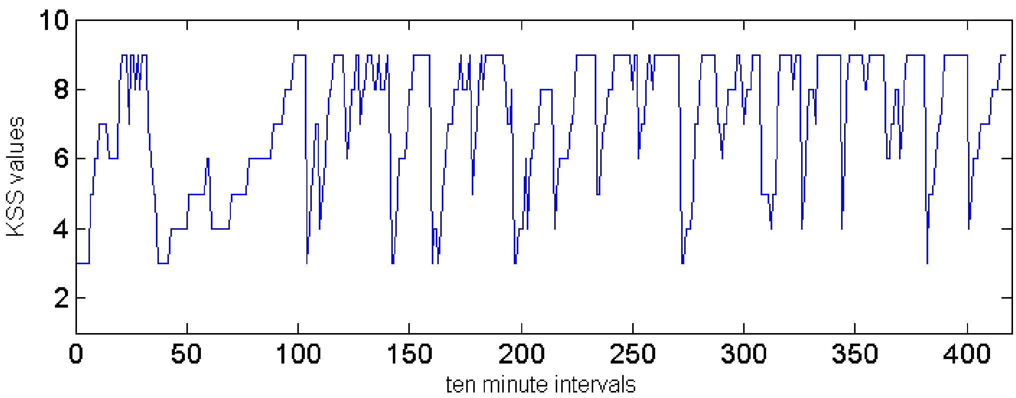


Figure 15 KSS values for all tests

5.2 Identified transformed variables

The results from each variable transformation are presented in this subchapter. First the best version of all variables was computed and then all of the transformed variables were cut according to chapter 2.4. The specific point where the curves were cut will vary depending on what raw data is available and is not specified in the report.

5.2.1 Result - lateral position variance and standard deviation

The variance is defined as the squared standard deviation and the two variables have therefore a second order relationship. Figure 16 shows a plot over the variance and standard deviation over the whole file containing 418 values, their appearance are quite similar. After optimizing the two variables together with their baselined versions, the results showed that the baselined standard deviation produced the least error and was therefore chosen as the variable later used in the regression analysis.

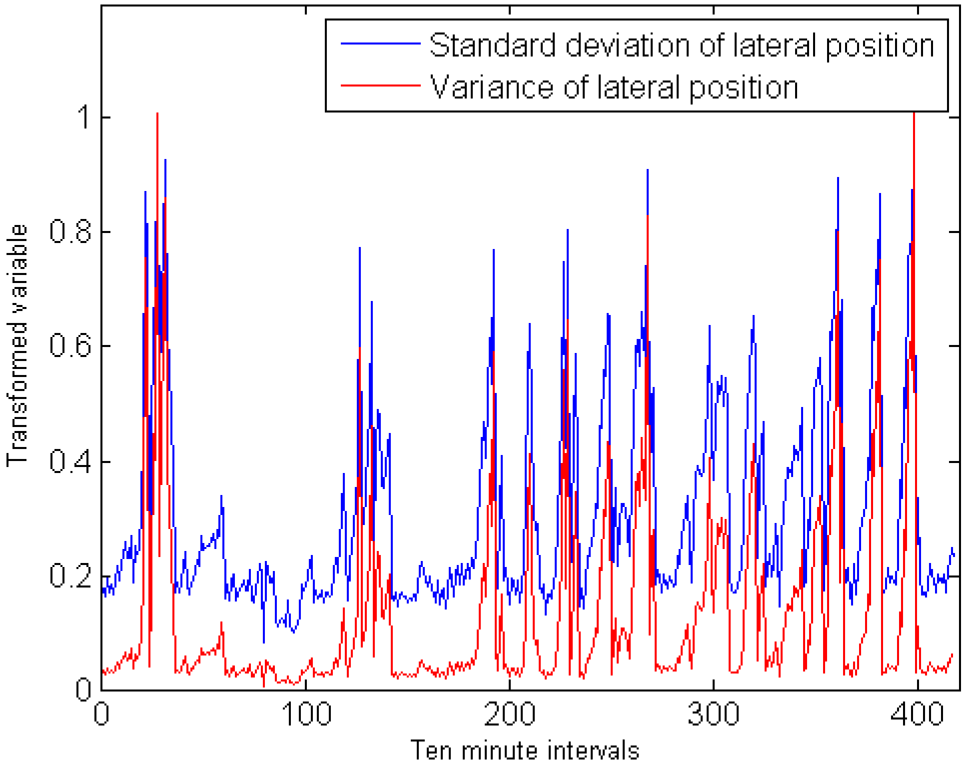


Figure 16 Standard deviation and variance of lateral position

5.2.2 Result - mean lateral position

The mean position of the lateral position showed some correlation between a sleepy driver and keeping to the right of the road. The error was smaller for the version of the variable that was not baselined and was therefore picked as the one to be tried in the final formula.

5.2.3 Result - vehicle path deviation

Different window sizes and buffer sizes were tried as well as baselining and variance over time. These computations showed that the best window size from the ones tested was of 2000 samples and the best buffer size was 100 samples long. The preliminary results presented in chapter 2.2.3 proved to be correct and the version giving the least error was the one where the area variance over time had been computed when no baselining was used.

5.2.4 Result - Time-to-Lane Crossing

Six different versions of the Time-to-Lane Crossing were computed, time limits set to six, three and one second until lane exceeding and their baselined versions. The results showed that the TLC where the proportion of time the vehicle was less than a second from exceeding the lane (given the same lateral velocity, speed and yaw angle) showed closest correlation to the driver sleepiness. The baselined version proved to produce a larger error than the one without.

5.2.5 Result - lane exceeding

A lot of variable versions came out of the computation of lane exceeding. The results were somewhat surprising, showing that the version producing the least error was the one where the maximum distance from the edge of the vehicle to the left line when exceeding the lane to the left was computed. According to the literature, lane exceeding to the right was the variable correlated with driver sleepiness. The baselined versions also proved to give more errors than the ones without reference.

5.2.7 Result - frequency analysis

Six plots over power spectral density were analyzed to see if some of them showed to be a good predictor of driver sleepiness. Studying the frequency analysis plot[32] over the lateral position (Figure 17), a special pattern could be identified. In the plot, the axis labeled KSS value contains 418 vectors, each representing the PSD of a ten minute interval. They are grouped according to their corresponding KSS value, the intervals indicating an alert driver (KSS value 3) in the front and the sleepy (KSS value 9) in the back. The figure shows that the sleepy intervals have energy contents in the approximate frequency range of 0.020 to 0.15 Hz that is not present in the alert driver intervals.

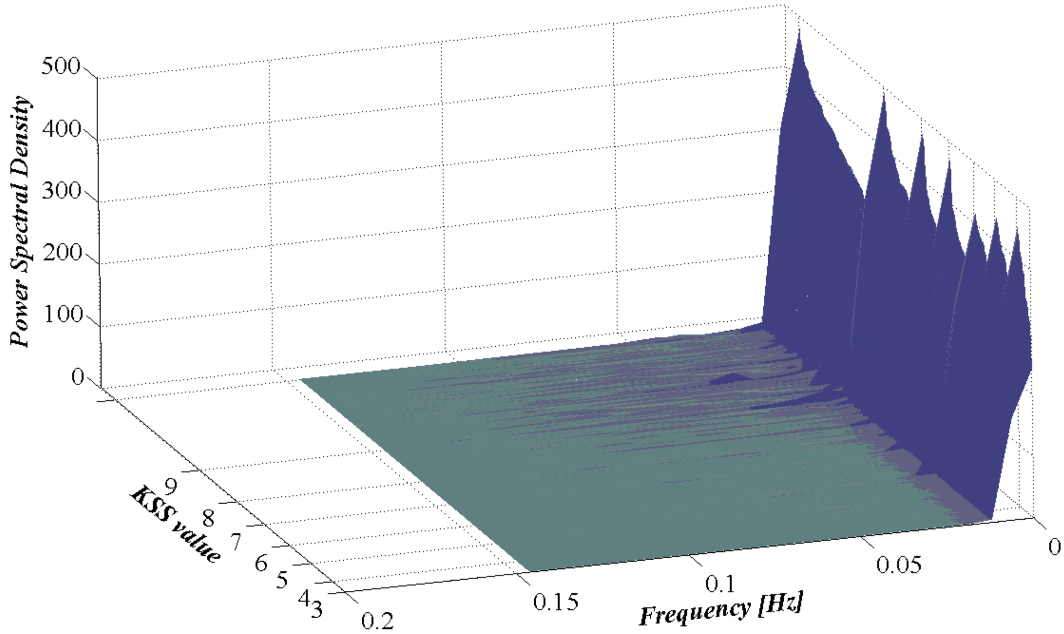


Figure 17 Power spectral density of lateral position

The energy content in the above mentioned frequency band was summed up for each interval and is shown in Figure 18. To illustrate where the different KSS value groups are situated, a line is also plotted with the different KSS steps starting at three on the left and up to nine at the right in the figure. This clearly shows that large energy contents in this frequency band are very specific for intervals where the driver was sleepy. From the figure a threshold could be set above which the driver could be detected as being sleepy (within groups with KSS value 8 or 9) with high certainty.

The baselining process could be executed for this variable as well, using the summed energy content for each interval. This version proved to give more intervals that could be detected as belonging to a sleepy driver, hence indicating that it should be a better measure since it leaves fewer intervals to be detected by the more insecure formulas. Surprisingly, this was not the case, the version without baselining showed less error compared to the KSS values. Figure 19 shows the baselined version; note that the size of the energy content is sorted within each KSS value group which makes the figure have a slightly different appearance than the example above.

[32] The five remaining plots are shown in appendix G.

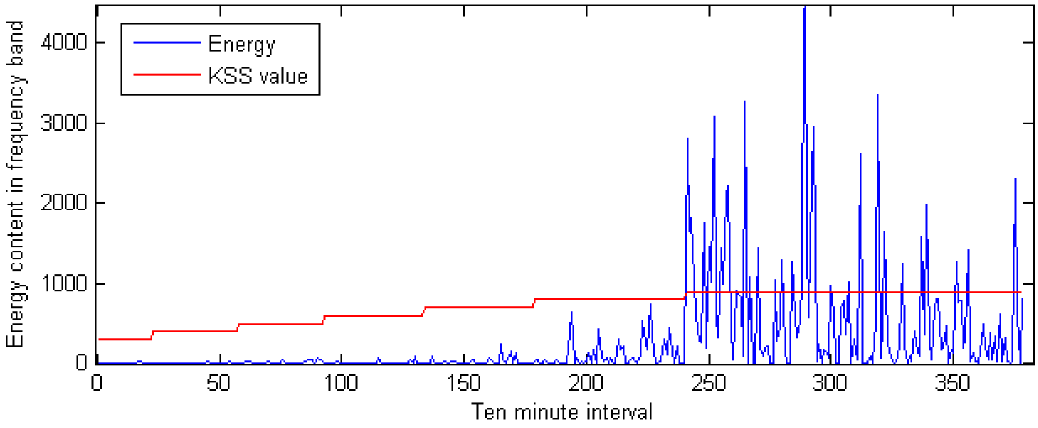


Figure 18 Energy content in a certain frequency band (0.02Hz - 0.15Hz)

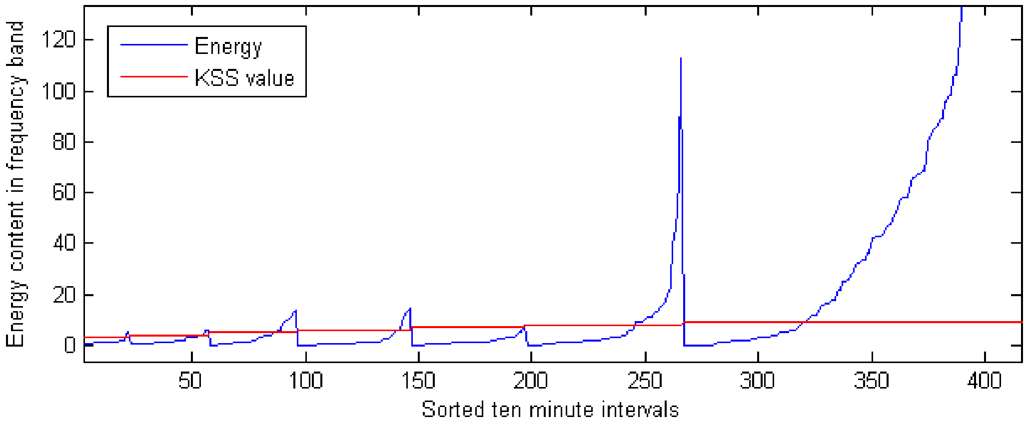


Figure 19 Baselined energy content in a certain frequency band (0.02Hz - 0.15Hz)

5.2.7 Result - reaction time

The reaction time computed showed approximately the same pattern that Kanstrup & Lundin (2006) discovered. The average reaction time was around 0.8 seconds which the histogram in Figure 20 also implies. The baselined version turned out to be the one producing the least error.

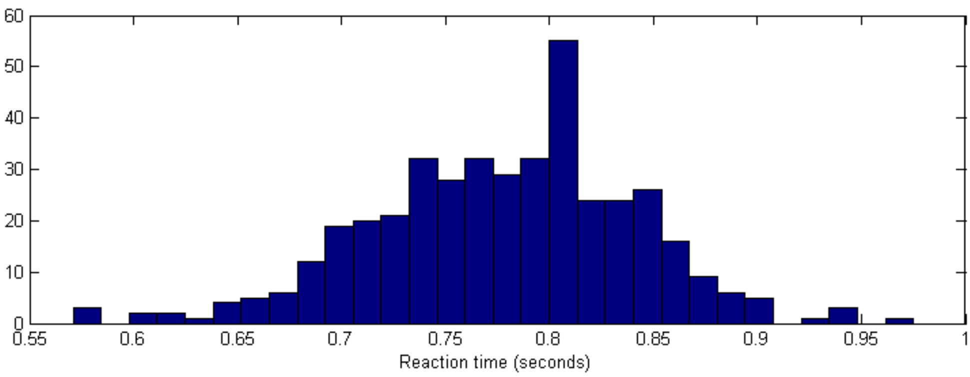


Figure 20 Histogram of the reaction time

5.2.8 Result - degree of interaction

Using the results from the reaction time computations, the degree of interaction could also be computed. The baselined version was computed but produced more error than the one with no alterations made.

5.2.9 Result summary for transformed variables

A compilation of the best versions of each of the transformed variables are shown in Table 6. Here, the variables measured from the steering wheel (studied in Berglund, 2007) are included for completion; they are marked with a star in the table. The different versions are not presented for the steering wheel variables, other than if variance over time and baselining is used. The steering wheel variables found in literature and presented in Table 3 chapter 2.3 has been extended in some cases. A thorough presentation of the modifications made can be found in Berglund (2007).

Table 6 Variable versions tried in the formulas

Transformed variable	Best version
LATVAR	Baselined lateral position standard deviation
MEANPOS	No alterations
PATHDEV	Variance over time
TLC	TLC with one second until lane exceeding with no other alterations
LANEX	The maximum distance the vehicle exceeded the left line
FREQANA	No alterations
REACTIM	Baselined
DEGOINT	No alterations
* STEXED_1 (literature version)	Baselined
* STEXED_2 (modified version)	Baselined
* Amp_D2_Theta	Variance over time and baselined
* Ellipse	Variance over time and baselined
* NMRHOLD_1 (literature version)	Baselined
* NMRHOLD_2 (modified version)	Baselined
* SDEV	Baselined
* STVELV (modified version)	No alterations
* SWDR	No alterations

5.3 Statistical analysis and formula selection

The eight variables accounted for in the previous subchapters were optimized and added to nine transformed variables extracted from the steering related measures studied by Berglund (2007). The 17 variables were then used as independent variables in the forward selection process to obtain the final formulas. As explained in chapter 4.4 there will be six different formulas depending on which transformed variables are available at each time interval and KSS value. The final outcome formulas when the sleepiness threshold has been set to eight are presented below. This means that a driver that is estimated as an eight or over will be detected as sleepy.
Note that the coefficients have been rounded of to two significant digits.

Output formula 8-1

$$\overline{Y}_{8-1} = 7.8 - 2.4 \cdot SWDR + 10000 \cdot PATHDEV + 0.64 \cdot LATVAR$$

This formula is a combination of three variable constellations since two of them had too few intervals to make a reliable regression analysis. The first constellation included is defined when all full-length variables are present but none of TLC, LANEX or ellipse. The second is used when all full-length variables and TLC have values. If TLC, LANEX and the full-length variables exist at the same time the third variable constellation is used.

Output formula 8-2

$$\overline{Y}_{8-2} = -18 - 1.6 \cdot SWDR + 1.0 \cdot LATVAR + 25 \cdot MEANPOS$$

If all the ground variables and LANEX is defined, this formula is used.

Output formula 8-3

$$\overline{Y}_{8-3} = 2.5 - 4.3 \cdot NMRHOLD\_1 + 470000 \cdot DEGOINT + 0.71 \cdot ellipse + 7.7 \cdot REACTIM - 3.8 \cdot SDEV$$

This formula is used when all the ground variables are available together with the ellipse variable. Note that this formula is specific for this project and will not be needed in real-life since the raw variables needed will be present at all times.

Output formula 8-4

$$\overline{Y}_{8-4} = 0.71 - 0.57 \cdot STVELV + 1.4 \cdot LATVAR - 2.6 \cdot SDEV + 7.7 \cdot REACTIM$$

The variables constellation where ellipse, LANEX and ground variables are present will enable the use of this formula. As stated above, this formula will not be needed in real-life but only in this project.

Output formula 8-5

$$\overline{Y}_{8-5} = 8.1 - 4.7 \cdot NMRHOLD\_1 + 9900 \cdot PATHDEV$$

This is the third formula only used for this project since it is defined when only the ground variables, TLC and ellipse are available.

Output formula 8-6

$$\overline{Y}_{8-6} = 6.5 + 210000 \cdot LANEX + 0.43 \cdot LATVAR$$

This formula is used when all the variables are available at the same time. This is the fourth and final formula that will not be used in real-time.

The final outcome formulas when the sleepiness threshold has been set to nine are not very different from them where the threshold is eight, only a few parameters are changed. The variable constellations are the same as the previous formulas.

Output formula 9-1

$$\overline{Y}_{9-1} = 7.8 - 2.4 \cdot SWDR + 10000 \cdot PATHDEV + 0.64 \cdot LATVAR$$

Output formula 9-2

$$\overline{Y}_{9-2} = -17 - 1.6 \cdot SWDR + 1.0 \cdot LATVAR + 25 \cdot MEANPOS + 3.0 \cdot NMRHOLD\_1$$

Output formula 9-3

$$\overline{Y}_{9-3} = 2.5 - 4.3 \cdot NMRHOLD\_1 + 470000 \cdot DEGOINT + 0.71 \cdot ellipse + 7.7 \cdot REACTIM - 3.8 \cdot SDEV$$

Output formula 9-4

$$\overline{Y}_{9-4} = 1.1 - 0.58 \cdot STVELV + 1.4 \cdot LATVAR - 2.6 \cdot SDEV + 7.3 \cdot REACTIM$$

Output formula 9-5

$$\overline{Y}_{9-5} = 8.1 - 4.7 \cdot NMRHOLD\_1 + 9900 \cdot PATHDEV$$

Output formula 9-6

$$\overline{Y}_{9-6} = 5.6 + 0.43 \cdot LATVAR + 160000 \cdot LANEX + 0.59 \cdot SWDR$$

5.4 Algorithm appraisal

In chapter 2.6 a way of judging the performance of the algorithm was presented. Using the model with six different formulas that are presented in the previous chapter to estimate all 418 KSS values will give the result presented in Table 7 when setting the sleepiness threshold to eight.

Table 7 Algorithm appraisal for threshold eight

	Sleepy driver	Alert driver
Detection by algorithm	40.9 %	0.717 %
No detection by algorithm	12.0 %	46.4 %

This gives:

$$Sensitivity = \frac{40.9}{40.9 + 12.0} = 0.774 \qquad Specificity = \frac{46.4}{46.4 + 0.717} = 0.985$$

The estimated value of the formulas is plotted in the same figure as the KSS values to show the accordance between the curves (Figure 21). For clarification, the plot has been divided into four subplots. In the figure, the KSS curve is red and the estimated curve is blue and a line marks the sleepiness threshold value eight.

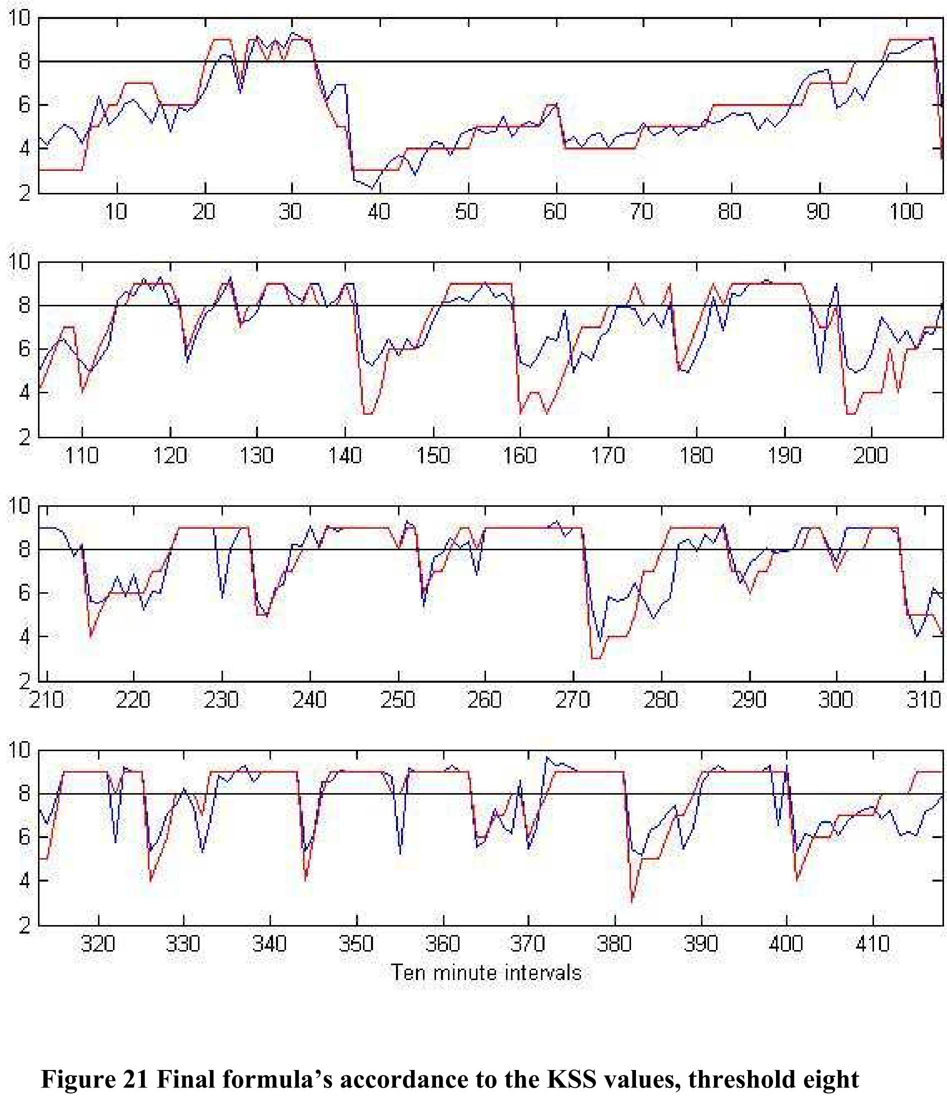


Figure 21 Final formula's accordance to the KSS values, threshold eight

The same procedure as above is used but with nine as a sleepiness threshold. This will give Table 8.

Table 8 Algorithm appraisal for threshold nine

	Sleepy driver	Alert driver
Detection by algorithm	16.7 %	0.956 %
No detection by algorithm	19.6 %	62.7 %

Which gives:

$$Sensitivity = \frac{16.7}{16.7 + 19.6} = 0.460 \qquad Specificity = \frac{62.7}{62.7 + 0.956} = 0.985$$

Figure 22 shows, same as the last example above, the KSS value as a red line and the estimated curve as blue. The threshold value nine is marked by a line above which the driver is said to be tired and below which he/she is said to be alert.

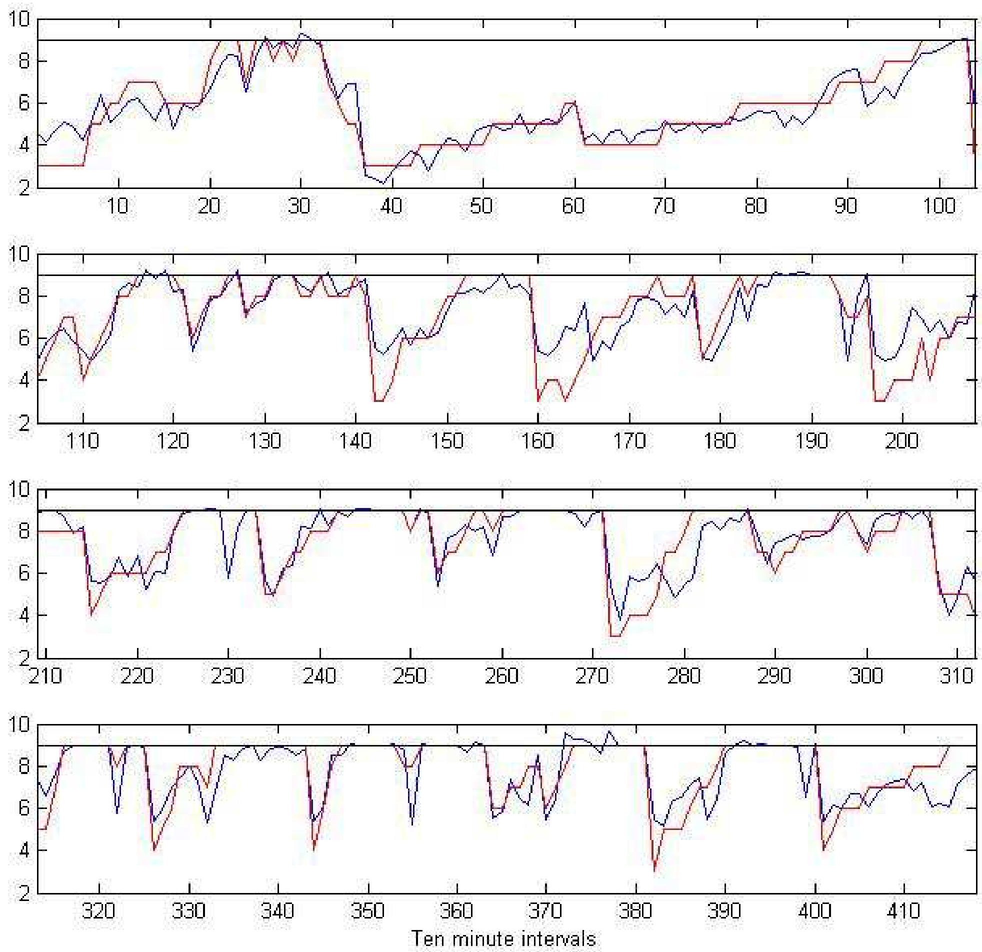


Figure 22 Final formula's accordance to the KSS values, threshold nine

6 Discussion

The results and method presented in the previous chapters will be discussed and analyzed here. Conclusions made from this are presented in the next chapter.

6.1 Sleepiness measure

The Karolinska Sleepiness Scale used as a measure of sleepiness has both its advantages and disadvantages as discussed in chapter 2.1.3. It is hard to say how much error is included in such a measure since it is subjective assessment of the state of sleepiness. Individual differences may be too large to be ignored and would make the algorithm misleading. At the simulator tests, the test leaders observed that different drivers seemed to judge their own sleepiness in different ways. Some drivers that stated that they were a nine on the scale had real big troubles staying awake and made several lane exceedances while others that stated nines looked surprisingly alert. This indicates that other measures could be needed, or at least as a complement to the KSS.

In the results the algorithms are appraised when the sleepiness threshold is set to eight and nine. Surprisingly, the algorithms work better when setting the threshold to eight than setting it to nine. It seems likely that it would be harder to *predict* the sleepiness (given that an eight is always followed by a nine) than to *detect* a driver that is already sleepy. This does not seem to be the case. The problem would instead be that no studies have been made on when the driver is dangerously sleepy and when it is safe to keep on driving. It might be the case that alarming when the driver is an eight might be too early and the driver will find the system annoying.

Setting the threshold to exactly an eight or a nine can also give misleading results. If the prediction is smaller than the KSS value exactly on the threshold, but still very close, the algorithm appraisal would still say the algorithm made a false detection, even though the error is very small. Setting the threshold to seven and a half or eight and a half will enable a more correct round off of the estimated values. When trying this the results showed that the correct detections went up to almost 90 % when the threshold was at seven and a half but the false alarms also went up to around three percent. This trade-off in correctness versus false alarms will have to be discussed by developers of future systems.

6.2 Transformed variables

Some of the transformed variables used could be hard to measure in reality. For example all the lane position measures require a camera that could detect the side lines. Even with those raw variables available, the version of LANEX used in the formulas, where the maximum distance to the left line when exceeding the line to the left, would be restricted. In the simulator, no other vehicles than the one driven is on the road, which makes it less dangerous to wobble over to the left lane. With on-coming traffic the driver would probably keep more to the right. This is a problem that has to be considered if trying to implement the algorithm in real life.

Using lateral position to detect driver sleepiness can also cause problems when overtaking other vehicles. Since the line will be exceeded while doing so, the action is seen as a big lane drift. This problem can be helped by ignoring the lane position variable when the directional indicator is used. Road curvature could also be a problem if the lane position is calculated from gyro sensors or accelerometers. A curve will be seen as an unintentional lane drift. However, the formulas are limited to work on motorways, highways and main roads. These are usually not that curvy and with few exceptions they could be assumed to be locally straight when using for example TLC.

The energy content in a certain frequency band extracted from the frequency analysis proved to give a reliable measure of driver sleepiness. The draw-back when using frequency analysis on lateral position is that it could be hard to implement in a real truck. The energy contents were small and could drown in noise or be restricted from the resolution of the sensors measuring the position. Another problem is that when using windowing to calculate the PSD, the window size is non-dynamic. A better alternative would be to use wavelets. This could be a subject for future studies.

6.3 Method

Was the choice of method appropriate for this project? How could it have been done in another? This subchapter will address and discuss these questions.

6.3.1 Simulator testing

When developing an algorithm it is important that the result could be generalized. In this case, the results from the simulator testing would need to be applicable to a real environment. The tests were performed in a simulator which means that the drivers knew that the consequences of their driving errors could not affect their safety. This could influence their driving behavior which would make the results misleading. However, the simulator was validated against a real truck by the authors of the precedent to this project. In addition, the simulator offers a number of advantages like the absence of noise and the possibility to choose the environment the driver is in.

When performing the tests, effort was made so that the drivers were sleepy when driving. This was desirable for measuring different variables when the test person was sleepy but the KSS values corresponding to the intervals were not proportional to real life driving. As seen in Figure 14 in chapter 5.1, the number of intervals with KSS value eight or nine constituted a large part of the total amount of intervals. Performing statistical analysis, where the least square error is computed as a measure, on this set of data could give misleading results. The curve will be “lifted” since the intervals with low KSS values are few hence their error does not contribute that much to the total error. On the other hand, the focus when detecting sleepiness is determining if the estimated value is above or below a set threshold. This threshold is normally eight or nine and it is most important for the curve to be correct in the area around this threshold.

The test persons were not randomly picked but were limited to Scania employees only, and could therefore not be said to be statistically representative to all truck drivers. The question is what would be representative in this project? Since the goal with the project was to develop an algorithm that should help prevent truck drivers from falling asleep behind the steering wheel, maybe the test should only be performed on truck drivers? The LP-drivers of Scania were limited to nine drivers and this meant that the number of simulator tests would decrease radically. Also, the group would be even more homogenous and the individual differences would be small. The gender perspective can also be discussed. In the test group, the women constituted a much larger proportion of the total number of drivers than it does in reality. This might give misleading results for the present truck driver population, but it is a danger with developing a system that only fits to a certain group of drivers. The goal was to make the algorithm as general as possible and a broad range of test persons assured this.

The drivers did not get any restrictions for the use of nicotine while driving and at least two drivers used moist snuff during the simulator test. This could have a bracing effect which was not desirable. The alternatives were to restrict the nicotine use with risk of the drivers suffering from abstinence instead or not to employ persons that would want to use nicotine during the test. None of these alternatives seemed to work in favor of the project and it was therefore decided to go through with the original plan. However, the use of nicotine was recorded but did not show any signs of alerting the driver more than marginally.

As presented in chapter 4.1.2, three of the subjects scored 10 or higher on the Epworth Sleep Scale and could be suffering from narcolepsy or similar sleeping disorder. This might affect the driving style of the driver and make the results misleading. On the other hand, the algorithms are developed to detect or predict a sleepy driving behavior and not the cause of the sleepiness. If a sleeping disorder only makes the driver sleepy and does not give other side effects then it should not be a problem. The problem would be if the person suffering from a sleeping disorder would have side effects making the driving style change in a deviant way from what they normally would. The ESS is not a final proof of a sleeping disorder but should be looked upon as an indication. All subjects stated that they had no sleeping disorders and this will have to be the foundation of the conclusions.

6.3.2 Statistical methods

Regression analysis was used to perform the statistical analysis. Discriminant analysis was discussed as an alternative way, but the method has some disadvantages that could not be ignored. To use discriminant analysis a linearization would have to be performed, that still did not assure the results. Regression analysis was found to be as good method for analysis as discriminant analysis from several authors and was therefore chosen. The method is easy to use and proved to give good results. Logistic regression is a continuation of the regression analysis that has several advantages. The method works in similar way to discriminant analysis in terms of a focus on detecting group membership. This could have been an advantage in this project since the goal was to be able to detect or predict if the driver were sleepy or not, hence making it superfluous to estimate every step in the KSS. Some kind of stepwise selection would still be needed to know which of the variables to include. There are methods to do this with logistic regression but the time deadline of the project did not allow this method to be tried out. Logistic regression as method of analysis could be the subject of further studies in the future.

6.4 Result

Looking at a plot of the DEGOINT variable, it does not seem to be much correlated with the KSS. Still, in one of the resulting formulas (Output formula 8-3 and 9-3); the variable is used with a large corresponding coefficient. This indicates that the variable contains information that is lacking in the other variables; hence it could be useful in the formula. Generally, the remaining variables seem to be correlated to a high extent since the forward selection process only includes two to five variables in the formulas. According to literature, the best formulas generally contain four to seven variables. This means that the transformed variables in this project are different measures of the same driving behavior. All variables more or less measure the level of the drivers' vehicle control and how straight he/she is driving. The exception could be the frequency analysis, where the energy content is used as an indicator of sleepiness, that adds another dimension and measures patterns that is not so straight-forward as the other measures.

The baselining process helps generalize the results. The surprising conclusion from the optimization of the transformed variables is that the baselined version did not always produce the least error for each variable. An explanation for this could be that some of the measures are general over the whole group while other measures are very individual for each driver.

The specificity and sensitivity measures used to appraise the formulas of the algorithm shows one way to judge the performance of the model. Another way would be to compute the mean square error, as done in the regression analysis, and pick the one that gives the least error. The latter alternative would give equal weight to the error of a driver being really alert (KSS value 1-3) as to one being really tired (KSS value 7-9). This is not desirable since the main focus is detection close to the set threshold, therefore the first method was chosen. As discussed in previous chapters, the level of correct detections should be high and the number of false alarms few to make a good sleepiness prediction algorithm. This means that the specificity should be close to one. Both of the results presented in the last chapter showed specificity values between 0.98-0.99 which can be considered to be very good.

7 Conclusion

The project is concluded in this chapter, going back to the assignment, purpose and goal to see if they have been fulfilled. Counsels for future sleepiness detection algorithm development are given as well as advises for system design based on the algorithm.

7.1 Project conclusion

The assignment of this project was to investigate the possibilities to develop a sleepiness detection algorithm, using in-vehicle variables only. The simulator testing showed promising preliminary results and a model with different formulas was therefore developed. The finished model could correctly classify more than 87 % of the drivers as sleepy or alert. This result can be considered to be very good, especially knowing that the rate of false negative[33] classifications is small.

Making the Scania truck environment safer was the purpose of the project and the results can be seen as a step towards achieving this. The first goal has been successfully fulfilled, making an algorithm with formulas that prevents drivers from falling asleep behind the steering wheel, independent of outer conditions like lighting, weather and curvature of the road. The second goal was to make the algorithm applicable in a real truck and that false alarms were minimized. No real truck tests have been performed but the false alarm rate can be considered to be low (less than one percent of the classifications).

7.2 Future prospective and system design

This project shows promising results and could be the subject of future system development. Alterations in the development process might improve the algorithm even more. The transformed variables could be extended to contain better optimization process, more transformed variables could be added, tests in a real truck could be performed and another statistical analysis could be used. The author of this report believes that real truck testing,

[33] The driver is alert but the algorithms detect the driver as being sleepy.

investigating logistical regression as a statistical method and further studies in the area of frequency analysis would give the best improvements.

The one-dimensional complexity of this project is discussed in previous chapters, i.e. the problem that all in-vehicle variables are measurements of the same driving behavior. This creates uncertainty in detecting sleepiness and could give an unacceptable level of false alarms. To avoid this problem another measure can be added. This could either be an objective measure (for example a camera that measures eyelid drops) or a secondary task that the driver has to perform when the first algorithm spotted driver sleepiness. An alternative to the secondary task approach could be to use the same algorithms again, as a validation test, when the formulas have detected the driver as sleepy once. Looking at the future system development in sleepiness detection, it is likely to be the case that the best in-vehicle driver sleepiness monitoring system will use a multiplicity of approaches which are collectively better that any single approach alone.

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Appendix

List of figures

A. Terms and definitions

Algorithm
An algorithm is defined as the procedure for accomplishing a task. In this case the algorithm means the whole procedure from measuring the raw variables until the final formulas has predicted the state of the driver.

Baselining
Baselining tries to diminish the effect of different driving styles in different drivers by taking a reference in the beginning of the driving session. In this way, the measures obtained are deviations from the drivers' own baseline.

Hamming window
A window function is a function that is zero-valued outside of some chosen interval. Another function that is multiplied by the function will also be zero-valued outside the interval; hence all that is left is a "view through the window". The Hamming window has the properties illustrated in Figure 1.

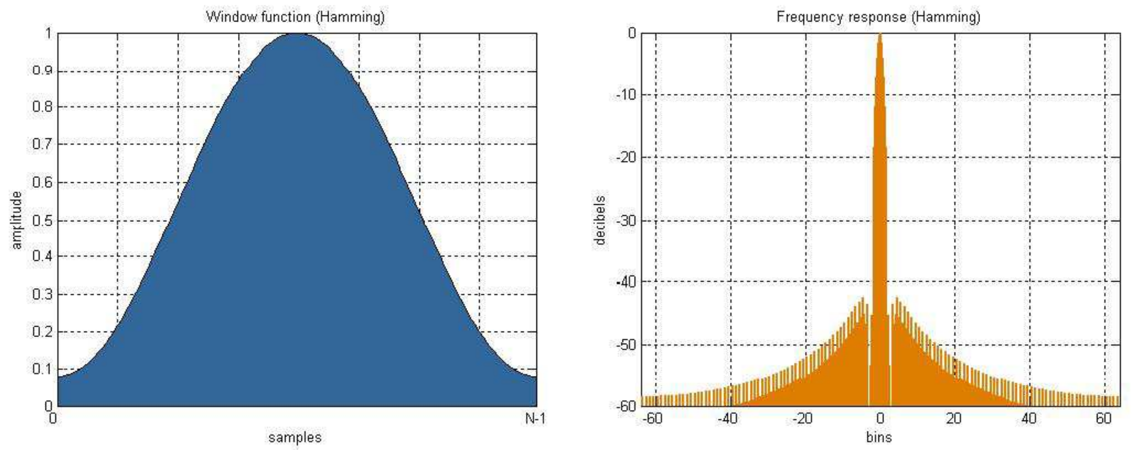

Figure 1 Hamming window (Wikipedia.org, 2007)

In-vehicle variables
Variables available in the truck and directly connected to the driving behavior, commonly used in-vehicle variables are the position of the vehicle on the road or the steering wheel angle.

Karolinska Sleepiness Scale (KSS)
Subjective measure of sleepiness.

Normal distribution
A normal (or Gaussian) random variable have probability density function

$f_X(x) = \frac{1}{\sqrt{2\pi\sigma_X}} \exp\left\{-\frac{(x-\eta_X)^2}{2\sigma_X^2}\right\}$ where σ_X and η_X is the standard deviation and mean of the random variable. (Ludeman, 2003) The distribution can be visualized according to Figure 2.

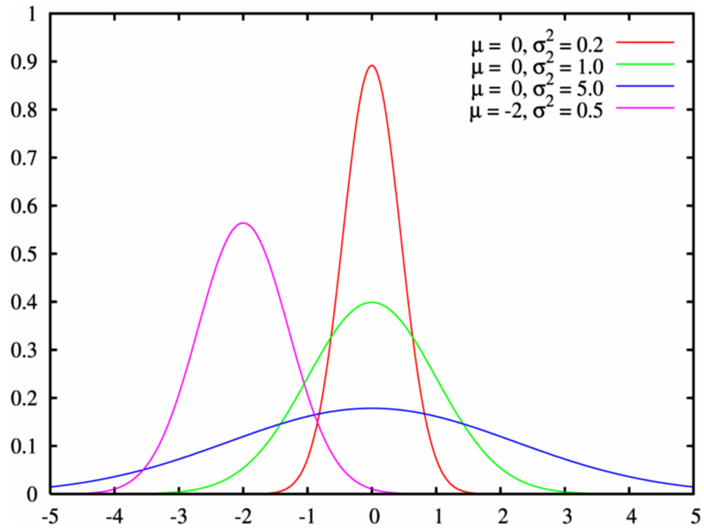

Figure 2 Normal distribution (Wikipedia.org, 2007)

PERCLOS
Percentage of eye closure. The amount of time the eye is 80-100% closed.

Stationary signals
Stationary signals are constant in their statistical parameters over time. You can explain this as if you look at a stationary signal for a few moments and then wait an hour and look at it again, it would look essentially the same, i.e. its standard deviation and amplitude distribution would be about the same. (www.dliengineering.com, 2007)

Time-to-Lane Crossing (TLC)
TLC is the time available until any part of the vehicle crosses a lane boundary. The TLC is calculated from the equations below. The figure shows the variables needed.

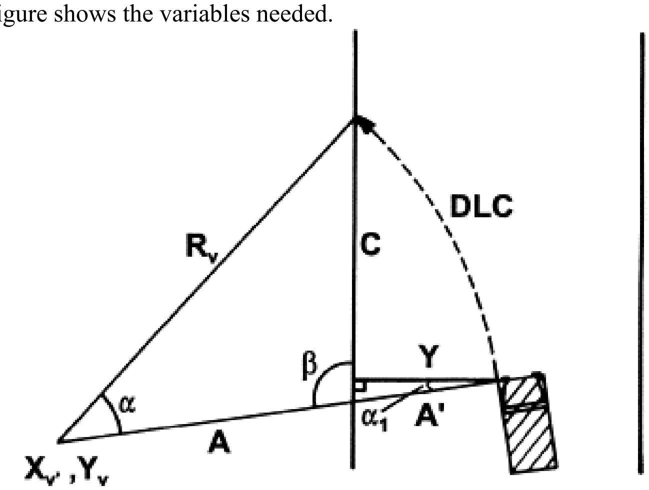

Figure 3 Illustration of Time-to-Lane Crossing

1. $TLC = \frac{DLC}{v}$

where v is speed of vehicle

2. $R_v = \frac{v}{r}$

where r is yawrate

3. $DLC = \alpha * R_v$

4. a) $\alpha = \arccos\left[\frac{A^2 + R_v^2 - C^2}{2 * A * C}\right]$

b) $A = R_v - A'$

c) $A' = \frac{Y}{\cos(\alpha_1)}$

where α_1 is the yaw

d) $C = \frac{2A\cos(\beta) + \sqrt{2A\cos(\beta)^2 - 4(A^2 - R_v^2)}}{2}$

B. Hard facts about the simulator

Motion system:	Pitch angle: -10 degrees to +15 degrees Roll angle: ±24 degrees
External linear motion:	Maximum amplitude: ±3.75 m Maximum speed: ±2 m/s Maximum acceleration: ±4 g
Vibration table:	Three vertical hydraulic cylinders: ±7.5 cm One horizontal hydraulic cylinder: ±7.5 cm
Visual system:	Forward view 120 degrees Rear-view in two mirrors PC-based graphics

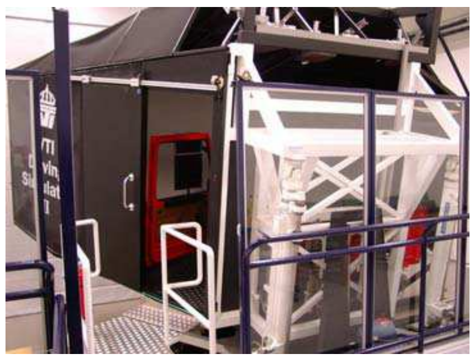

Figure 4 Simulator II

Figure 5 Simulator motion system

C. Questionnaire before simulator test

Name:____ Age:_________

O Woman
O Man

Years with car driver license:________________ Driving experience (km/year):_________________

Years with truck driver license:_______________ Driving experience (km/year):_________________

……………………………………………………………………………………………

Question 1 – sleeping behavior
How likely is it that you fall asleep when you perform the specified activities below? Please answer how you normally would act/react even if you haven't performed the activities for some time.

	Would never dose	**Slight chance of dozing**	**Moderate chance of dozing**	**High chance of dozing**
Sitting and reading	O	O	O	O
Watching television	O	O	O	O
Sitting inactive in a public place, e.g. a theater or a meeting	O	O	O	O
As a passenger in a car for an hour without a break	O	O	O	O
Lying down to rest in the afternoon	O	O	O	O
Sitting and talking to someone	O	O	O	O
Sitting quietly after lunch when you've had no alcohol	O	O	O	O
In a car while stopped in traffic	O	O	O	O

Question 2 – sleeping disorders
Have you had any of the following problems the last year?

	Never	**Rarely**	**Sometimes**	**Often**	**Always**
		A few times per year	A few times per month	A few times per week	Every day
Hard to fall asleep	O	O	O	O	O
Hard to wake up	O	O	O	O	O
Snoring	O	O	O	O	O
Short breathing breaks during sleep	O	O	O	O	O

Fighting to stay awake while driving car/truck	O	O	O	O	O
Gets too little sleep (less than 6 hours per night)	O	O	O	O	O

Question 3 – circadian rhythm

a) What time do you prefer to wake up when you work full-time (8 hours) day-time if you could choose?

O before 6:30 a.m.
O 6:30 a.m. – 7:29 a.m.
O 7:30 a.m. – 8:29 a.m.
O 8:30 a.m. – or later

b) What time do you prefer to go to bed when you work full-time (8 hours) day-time if you could choose?

O before 9:00 p.m.
O 9:00 p.m. – 9:59 p.m.
O 10:00 p.m. – 10:59 p.m.
O 11:00 p.m. – or later

Question 4 - tobacco

Have you during the day used any form of tobacco?

O yes If yes, how many hours ago: ________________
O no
O don't know

Question 5 - caffeine

Have you during the day used any form of bracing substances (tea, coffee, caffeine beverages etc.)?

O yes If yes, how many hours ago: ________________
O no
O don't know

Question 6 - alcohol

Have you during the last 72 hours (3 days) drunk alcohol?

O yes If yes, how many hours ago: ________________________
How much and what: ______________________________
O no
O don't know

Question 7 – sleepiness state

a) How many hours ago did you begin your latest coherent sleep (more than four hours) and for how long did it last?

A fell asleep: _____________ hours ago. The sleep lasted for: _______________ hours.

b) How would you rate the quality of the latest coherent sleep?

O bad
O fairly bad
O fairly good
O good

c) Have you after the latest coherent sleep slept shorter periods of time?

O yes If yes, I fell asleep: ___________ hours ago.
The sleep lasted for: __________ hours.
O no
O don't know

D. Questionnaire after simulator test

Question 1 – sleepiness during the test
a) Did you experience that you during the test were so tired that you under normal circumstances would have stopped driving?
O yes, several times
O yes, once
O no
O don’t know

b) Did you fall asleep some time during the test?
O yes, several times
O yes, once
O no
O don’t know

Question 2 - realism
How realistic did you find it driving in the simulator?
O not realistic at all
O quite realistic
O very realistic
O felt like driving a real truck

Question 3 - KSS
How hard did you find it to estimate your sleepiness on the Karolinska Sleepiness Scale?
O very difficult
O quite difficult
O quite easy
O very easy

Question 4 - feeling
a) Did you feel nausea when driving the simulator?
O not nauseous at all
O a bit nauseous
O quite nauseous
O very nauseous

b) Did you feel bored during the test?
O not bored at all
O a bit bored
O quite bored
O very bored

c) Did you feel worried during the test?
O not worried at all
O a bit worried
O quite worried
O very worried

E. Summary of questionnaire for test drivers

Before the test

General
All 22 test drivers are employees of Scania. Seven of them work as long-time test drivers for Scanias trucks, 15 were men and 7 women. Three had driven the simulator before. The first four tests were pilot studies.

Age

Men: 52, 37, 46, 57, 33, 28, 46, 49, 35, 27, 27, 27, 31, 30, 53	Average: 38.5 years
Women: 26, 29, 31, 27, 24, 27, 28	Average: 27.4 years
Total:	Average: 35 years

Driving experience

Number of years with private car driver license

Men: 34, 19, 28, 39, 14, 10, 28, 31, 17, 10, 7, 9, 13, 12, 35	Average: 20.4 years
Women: 6, 11, 13, 9, 6, 9, 10	Average: 9.1 years
Total:	Average: 16.8 years

Estimated driving experience in private car (kilometers/year)

Men: 25', 20', 30', 17.5', 15', 20', 15', 15', 15', 0.5', 15', 30', 8'	Average: 17.4'
Women: 7', 10', 20', 3', 2', 2', 5'	Average: 7'
Total:	Average: 13.8'

Number of years with truck driver license

Men: 32, 1, 25, 37, 8, 3½, 23, 29, 6, 0, 2, 1, 2, 3, 31	Average: 13.6 years
Women: 0, 1, 6, 1, 1, 0, 3½	Average: 1.8 years
Total:	Average: 10.0 years

Estimated driving experience in truck (kilometers/year)

Men: 20', 3', 40', 50', 65', 10', 67', 130', 3', 0.7', 1', 0.5', 4', 2', 35'	Average: 28.8'
Women: 65, 300, 50, 300, 400, 100, 350	Average: 2.2'
Total:	Average: 20.3'

Sleep behavior

Score on the Epworth Sleep Scale (can indicate narcolepsy if scored 10 or higher)

Men: 5, 8, 10, 4, 8, 8, 9, 9, 1, 8, 8, 8, 5, 7, 12	Average: 7.3
Women: 9, 10, 9, 8, 9, 15, 7	Average: 9.6
Total:	Average: 8.0

Sleep problems

(number of test persons that experiences the problem often or always)

	Men	*Women*	*Total*
Hard to fall asleep	0	0	0
Hard to wake up	1	0	1
Snoring	5	0	5
Short breathing breaks during sleep	1	0	1
Fighting to stay awake while driving	1	0	1
Gets to little sleep	3	2	5

Sleepiness state

(hours since the last coherent sleep)

	Men	*Women*
The sleep was of good or quite good quality	14, 17, 7½, 14, 14½, 18½, 14½, 17, 12	13, 16½, 14½, 14, 16½, 17½
The sleep was of bad or quite bad quality	9, 8½, 13½, 15	16

Two test persons slept less than four hours in the last coherent sleep and are therefore excluded from the statistics of this question.

After the test

During the test:	*Men*	*Women*
I was so tired that I would have stopped under normal circumstances. *(Yes, one or several times)*	13/15	7/7
I fell asleep behind the wheel. *(Yes, one or several times)*	8/15	5/7
How realistic did you find the simulator? *(Very realistic/felt like I drove a real truck)*	9/15	6/7
How hard was it to estimate your sleepiness on the KSS? *(quite easy/very easy)*	12/15	5/7
Did you feel nauseous during the test? *(quite nauseous/very nauseous)*	0/15	1/7
Did you feel bored during the test? *(quite bored/very bored)*	12/15	6/7
Did you feel worried during the test? (quite worried/very worried)	0/15	0/7

F. Schedule for tests

<table>
<tr><th>Time</th><th>Test</th></tr>
<tr><td>20:00</td><td rowspan="4">Reference test 2, 1h</td></tr>
<tr><td>20:15</td></tr>
<tr><td>20:30</td></tr>
<tr><td>20:45</td></tr>
<tr><td>21:00</td><td></td></tr>
<tr><td>21:15</td><td></td></tr>
<tr><td>21:30</td><td rowspan="4">Reference test 3, 1h</td></tr>
<tr><td>21:45</td></tr>
<tr><td>22:00</td></tr>
<tr><td>22:15</td></tr>
<tr><td>22:30</td><td></td></tr>
<tr><td>22:45</td><td></td></tr>
<tr><td>23:00</td><td rowspan="4">Reference test 1, 1h</td></tr>
<tr><td>23:15</td></tr>
<tr><td>23:30</td></tr>
<tr><td>23:45</td></tr>
<tr><td>00:00</td><td rowspan="8">Test 1, 2h</td></tr>
<tr><td>00:15</td></tr>
<tr><td>00:30</td></tr>
<tr><td>00:45</td></tr>
<tr><td>01:00</td></tr>
<tr><td>01:15</td></tr>
<tr><td>01:30</td></tr>
<tr><td>01:45</td></tr>
<tr><td>02:00</td><td></td></tr>
<tr><td>02:15</td><td></td></tr>
<tr><td>02:30</td><td rowspan="8">Test 2, 2h</td></tr>
<tr><td>02:45</td></tr>
<tr><td>03:00</td></tr>
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<tr><td>05:00</td><td rowspan="8">Test 3, 2h</td></tr>
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<tr><th>Time</th><th>Pilot-test</th></tr>
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<tr><td>22:00</td></tr>
<tr><td>22:15</td></tr>
<tr><td>22:30</td><td></td></tr>
<tr><td>22:45</td><td></td></tr>
<tr><td>23:00</td><td rowspan="4">Reference pilot-test 1, 1h</td></tr>
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<tr><td>23:30</td></tr>
<tr><td>23:45</td></tr>
<tr><td>00:00</td><td rowspan="12">Pilot-test 1, 3h</td></tr>
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<tr><td>06:30</td><td></td></tr>
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G. Frequency analysis plots

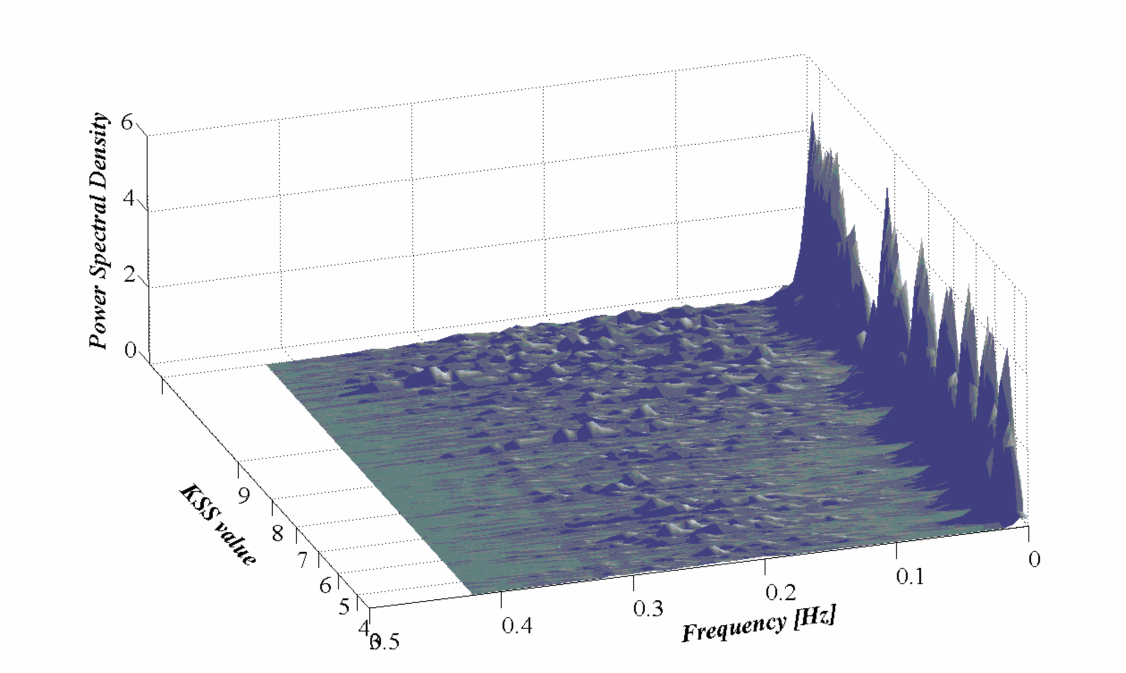

Figure 6 PSD of lateral acceleration

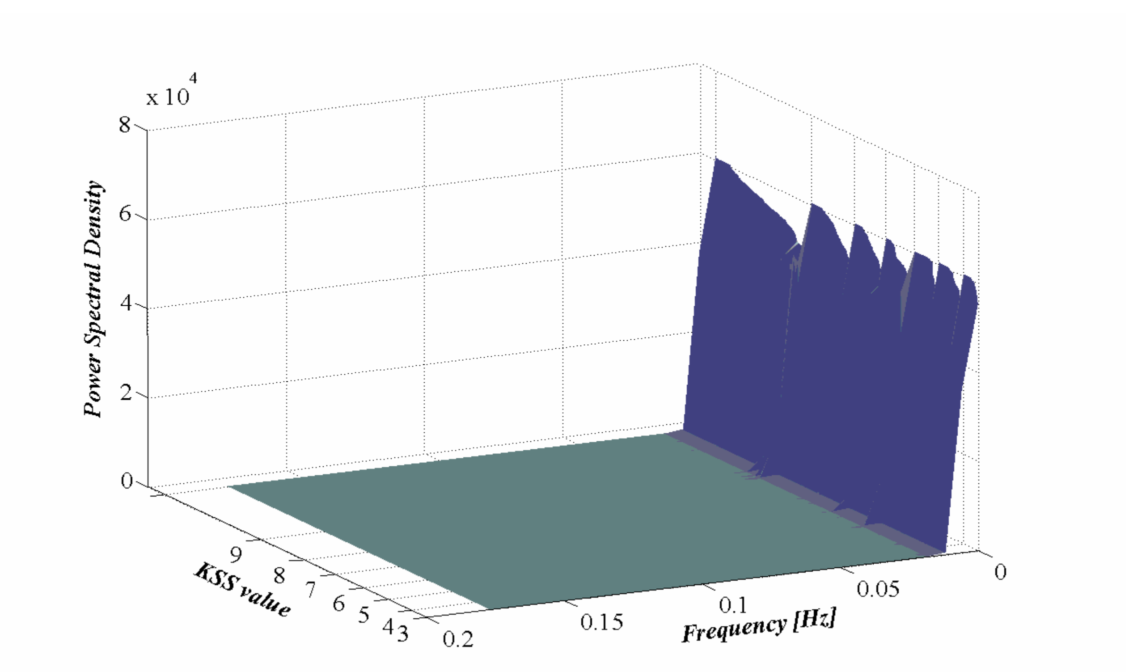

Figure 7 PSD of speed

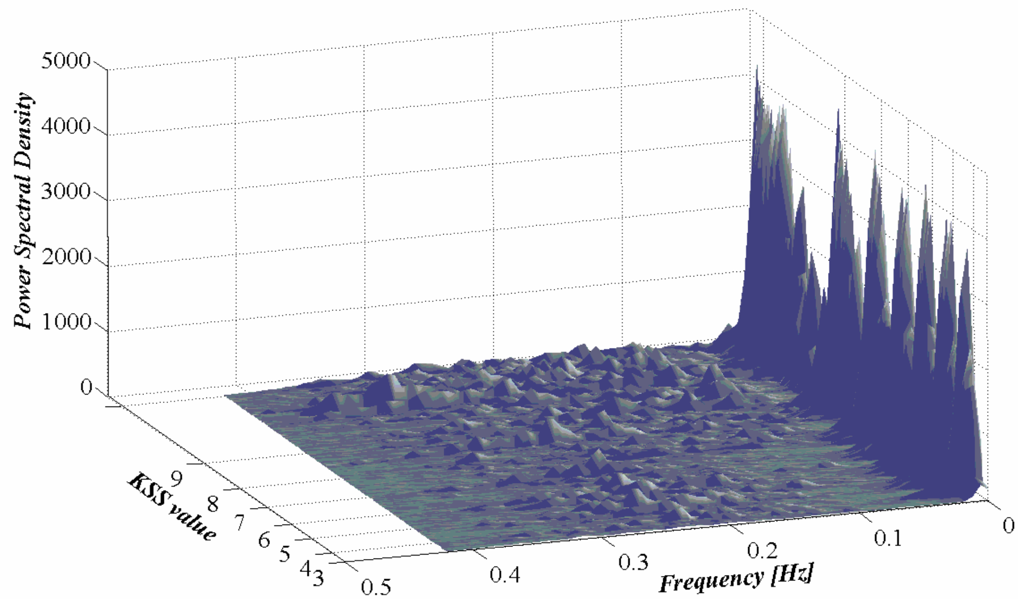

Figure 8 PSD of steering wheel angle

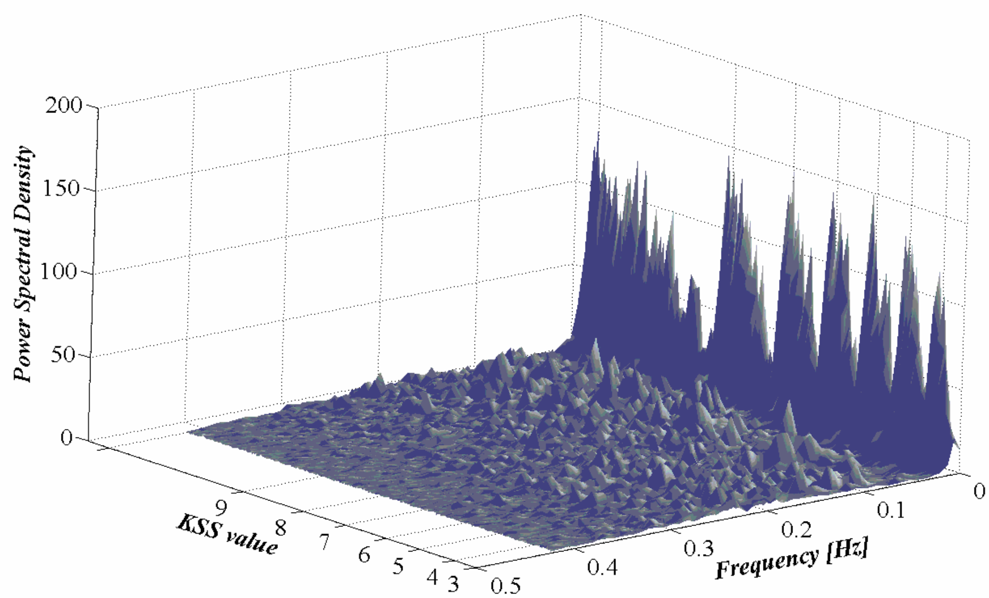

Figure 9 PSD of steering wheel torque

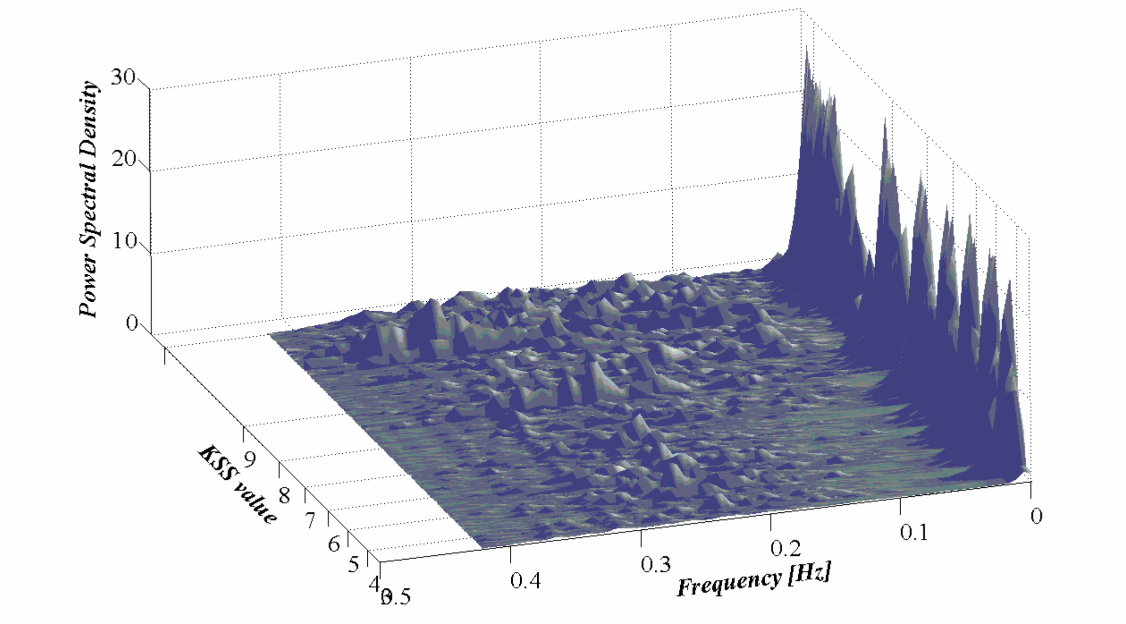

Figure 10 PSD of yaw rate