Uncertainty Analysis as a Tool to Improve Corporate CO_2 Management

- A case study of Posten Norge AS' project to reduce CO_2 emissions

Sophie Davidsson

Department of Fire Safety Engineering and Systems Safety
Lund University, Sweden

Brandteknik och Riskhantering
Lunds tekniska högskola
Lunds universitet

Report 5378, Lund 2012

The report has been financed by Det Norske Veritas

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Title: Uncertainty Analysis as a Tool to Improve Corporate CO_2 Management
Titel: Osäkerhetsanalys som verktyg för förbättrad CO_2 hantering inom företag

Author: Sophie Davidsson
Tutor: Kurt Petersen

Report 5378
ISSN: 1402-3504
ISRN: LUTVDG/TVBB--5378--SE

Number of pages: 72

Keywords
Uncertainty analysis, GHG emissions, expert judgement, sustainable transportation, uncertainty propagation

Sökord
Osäkerhetsanalys, utsläpp av växthusgaser, expert bedömningar, hållbar transport, propagering av osäkerhet

Abstract
In the future an increasing number of industries will have to comply with greenhouse gas reduction directives. Plans and projects that aim to reduce CO_2-emissions are associated with multiple sources of uncertainty and the use of point estimates could lead to misjudgements and erroneous decisions. Within other fields of science uncertainty analysis is a commonly used tool to improve a decision basis. The aim of this report has been to assess the advantages of performing an uncertainty analysis of a corporate CO_2-reduction project

Well-applied theories and methodologies for uncertainty analysis have been applied to Posten Norge AS plan for reducing CO_2-emissions. The results gained by the uncertainty analysis were found to be more informative than the results obtained when only 'best estimates' were used to calculate the effect of the action plan. Explicit treatment of uncertainty increases transparency, quantification of a confidence interval for the outcome of the plan improves communication and the identification of the most sensitive input variables increases the corporation's possibilities to avoid risk scenarios and enables it to steer towards opportunities.

Brandteknik och Riskhantering
Lunds tekniska högskola
Lunds universitet
Box 118
221 00 Lund

brand@brand.lth.se
http://www.brand.lth.se

Telefon: 046 - 222 73 60
Telefax: 046 - 222 46 12

Department of Fire Safety Engineering
and Systems Safety
Lund University
P.O. Box 118
SE-221 00 Lund
Sweden

brand@brand.lth.se
http://www.brand.lth.se/english

Telephone: +46 46 222 73 60

Acknowledgements

Special thanks are extended to my academic supervisor Kurt Petersen (Department of Fire Safety Engineering and Systems Safety, Lund University) for valuable comments and guidance throughout the work with the thesis.

I would also like to express my sincere gratitude to everyone at the Risk Management and Corporate Responsibility department at Det Norske Veritas, Høvik; for encouragement and showing interest in the thesis. Special thanks are directed to Magnus Christiansen and Vibeke Binz, my supervisors at Det Norske Veritas, for engaging in discussions with me and helping me forwards. Thanks also to Pål Børresen for valuable help with the practical preparations that enabled me to write the thesis at DNV, Høvik.

Thanks also to Colin Campbell (Posten Norge AS), Mikael Lantz (Department of Environmental and Energy Systems Studies, Lund University) and Bengt Holmberg (Department of Technology and Society, Lund University) for taking time to answer my questions.

Lund, Sweden, February 2012
Sophie Davidsson

Summary

In the future an increasing number of industries will have to comply with greenhouse gas reduction directives. For a project to effectively and efficiently reduce emissions, relevant alternatives and their associated risks and opportunities needs to be analysed. A CO_2-reduction plan is associated with various sources of uncertainties, both related to the true value of activity data and conversion factors used to calculate emissions, and sources of uncertainty related to emission reduction projects in general. These may be categorized into parameter uncertainties and uncertainty drivers.

Parameter uncertainties represent the uncertainty in the most significant parameters that determine the effect of the measures included in the project plan.

Uncertainty drivers represent external and internal factors that may have an influence on the corporation's ability to implement the measures laid out in the project plan.

When the effect of a CO_2-reduction plan is calculated based on "best estimates" it results in an exclusion of possibly valuable information. Deterministic values could cause the decision maker to choose a less favourable option or to settle with a plan that is highly uncertain. An uncertainty analysis enables inclusion of information that would otherwise be lost and is frequently used as a tool to improve the decision basis within other fields of science. However, during this study no information was found of it ever before being used as a tool to improve corporate CO_2 management.

Posten Norge AS (Posten) has set an ambitious CO_2-reduction goal and developed action plans for how the corporation as a whole is to reduce their emissions. To assess the advantages of performing an uncertainty analysis of a corporate CO_2-reduction plan two models, in the report referred to as DNV's Uncertainty Analysis Model and DNV's Effect Calculation Model, were merged to create a model that enabled a quantitative uncertainty analysis of Posten's action plan.

DNV's Effect Calculation Model treats parameter uncertainties associated with the action plan. The model was developed by DNV to handle interaction between individual measures. It accounts for the interaction between individual measures, which ensures that interplay between uncertain input parameters is considered. The parameter uncertainties are propagated through the model by means of @Risk, which enables quantification of their effect on the project outcome.

DNV's Uncertainty Analysis Model enables explicit treatment of uncertainty drivers. Common practice is to evaluate their effect implicitly after a point value for the action plan's emission reduction has been calculated. Explicit analysis of external and internal factors increases the corporations understanding of how external actors may affect the project outcome.

This study shows that it is possible to perform an uncertainty analysis of a project aimed at reducing CO_2 emissions. The results gained by the uncertainty analysis are more informative than the results obtained when only 'best estimates' are used to calculate the effect of the action plan. Quantification of confidence intervals for the outcome of a project allows the decision maker to make informed decisions between alternatives and explicit treatment of uncertainty increase transparency. Most importantly, an uncertainty analysis enables identification of the most influential input variables which improves the corporation's ability to avoid risk scenarios and to steer towards opportunities.

Sammanfattning

I framtiden kommer ett ökat antal industrier att behöva rätta sig efter nya växthusgasdirektiv. För att ett projekt ska leda till effektiv reduktion av utsläpp så måste relevanta alternativ och associerade risker samt möjligheter analyseras. En handlingsplan för reduktion av CO_2-utsläpp är förknippad med flera källor till osäkerhet, dels relaterade till det verkliga värdet av de faktorer som används till att beräkna utsläppsreduktionen, och de som är kopplade till projekt i allmänhet. Dessa kan delas in i två kategorier, parameterosäkerhet och osäkerhetsdrivare.

Parameterosäkerhet representerar osäkerheten i de mest betydelsefulla ingångsparametrarnas verkliga värde. När effekten av en åtgärd beräknas används en eller flera parametrar som är osäkra

Osäkerhetsdrivarna representerar externa och interna faktorer som kan ha en inverkan på företagets möjligheter att implementera de åtgärder som ligger i handlingsplanen.

När effekten av ett CO_2-reduktionsprojekt beräknas med hjälp av deterministiska värden eller punktskattningar så utesluts information. Beslutsfattaren står då med ett bristfälligt beslutsunderlag och riskerar att ta felaktiga beslut. En osäkerhetsanalys möjliggör tillvaratagande på all tillgänglig information och är ett verktyg som allt oftare används för att förbättra beslutsunderlag. Vid genomförandet av den här studien hittades ingen information om att metodiken tidigare använts som verktyg för att förbättra CO_2 hantering inom företag.

Posten Norge AS (Posten) har satt ett ambitiöst mål för reduktion av CO_2-utsläpp innan 2015. För att undersöka fördelarna med att utföra en osäkerhetsanalys på ett företags plan för reducering av CO_2-utsläpp kombinerades två modeller, DNV's Osäkerhetsanalysmodell och DNV's Effektberäkningsmodell, och en kvantitativ osäkerhetsanalys utfördes på Posten's handlingsplan.

DNV's Effektberäkningsmodell hanterar parameter osäkerheter som är förknippade med åtgärderna i handlingsplanen. Modellen är utvecklad för att ta tillvara på samverkan mellan åtgärder och tar på så sätt även hänsyn till samverkan mellan parameterosäkerheter. Parameterosäkerheterna propageras genom modellen med hjälp av @Risk vilket gör det möjligt att beskriva deras effekt på projektets utfall.

DNV's Osäkerhetsanalysmodell möjliggör explicit hantering av osäkerhetsdrivare. I vanliga fall så evalueras effekten av externa och interna faktorer efter det att ett punktvärde har beräknats för handlingsplanens effekt. Explicit hantering av osäkerhetsdrivare ökar företagets förståelse för hur externa aktörer kan komma att påverka projektets utfall.

Det är möjligt att utföra en osäkerhetsanalys av ett projekt för reducering av koldioxid. Resultaten som fås genom osäkerhetsanalysen är mer informativa än när endast punktestimat används för att beräkna projektets effekt. Kvantifiering av konfidensintervall för projektets utfall förbättrar beslutsfattarens förutsättningar till att ta informativa beslut gällande alternativa åtgärder och explicit hantering av osäkerhet ger ökad transparens. Framförallt möjliggör osäkerhetsanalysen identifiering av de mest betydelsefulla ingångsvariablerna., vilket förbättrar företagets möjligheter att undvika risk scenarier och förbättrar deras förmåga att styra mot möjligheter.

Contents

1. Introduction

This master thesis comprises 30 hp, which corresponds to 20 weeks full time studies. It was carried out by a student from the Risk Management program at the Department of Fire Safety Engineering and Systems Safety at Lund University. The initiative to the thesis was taken by Det Norske Veritas (DNV) as DNV wanted to investigate the possibilities of strengthening corporate CO_2-reduction projects through uncertainty analysis. Currently, DNV are supporting Posten Norge AS (Posten) in the development and implementation of the corporation's plans to reduce CO_2 emissions. This thesis is based on information gathered through collaboration between DNV and Posten.

According to guidelines from the department of Fire Safety Engineering and Systems Safety the thesis must maintain a certain risk profile. In this context, the risk endpoint is defined as the CO_2-reduction project not reaching its carbon dioxide reduction goal. Possible risk sources are technologies not being as efficient as expected or that part of the organisation is incapable of fulfilling its commitments. The term uncertainty analysis is used to highlight that there also is a possibility that the risk sources might increase the chance of success, i.e. positive risks.

This introductory chapter will explain why it is interesting to perform an uncertainty analysis on an environmental plan. It will also be specifying the aim of the thesis.

1.1 Background

1.1.1 Posten Norge AS

Posten is owned by the Norwegian State through the Norwegian Ministry of Transport and is presently one of the largest shipping and logistical companies within the Nordic region. It comprises three divisions; Logistics, Logistical Solutions and Mail. Each division is divided into a number of smaller business units.

1.1.2 Posten's CO_2 reduction plan

In the fall of 2009 Posten to developed a revised environmental strategy. The most important objective of this strategy was to reduce carbon dioxide emissions by 30% from a 2008 baseline within 2015.

In 2010 corporate wide CO_2-reduction action plans were developed and implemented. The action plans were developed in each business unit, and comprised the following carbon dioxide reducing measures:

- Efficient energy use
- Route optimization
- Ecodriving courses for drivers
- Technical measures for vehicles
- Increased use of alternative vehicles
- Increased use of alternative fuel
- Modal shifts
- Decreased business travels

The action plans were consolidated for each division within Posten and contain information on the planned environmental measures that are to be implemented towards 2015, including their CO_2-reduction potential and Net Present Value (NPV). (Posten Norge AS, 2010)

To evaluate the effect of a project aimed at reducing CO_2 emissions it is necessary to develop an analytical model that can account for interaction between individual measures. For this purpose DNV has developed an Effect Calculation Model for Posten's CO_2 reduction project. Within the model point values ('best estimates') have been used to calculate the amount CO_2 reduced and net present value of the project. (Posten Norge AS, 2010)

The effect of the action plans was first calculated for each measure at the business unit level. Subsequently the effects of all the measures within the business units were summed up on to the divisional level. Finally, the effects on the divisional level were consolidated to show the effect and the cost of the CO_2-reduction plan at corporate level, see figure 1. (Posten Norge AS, 2010)

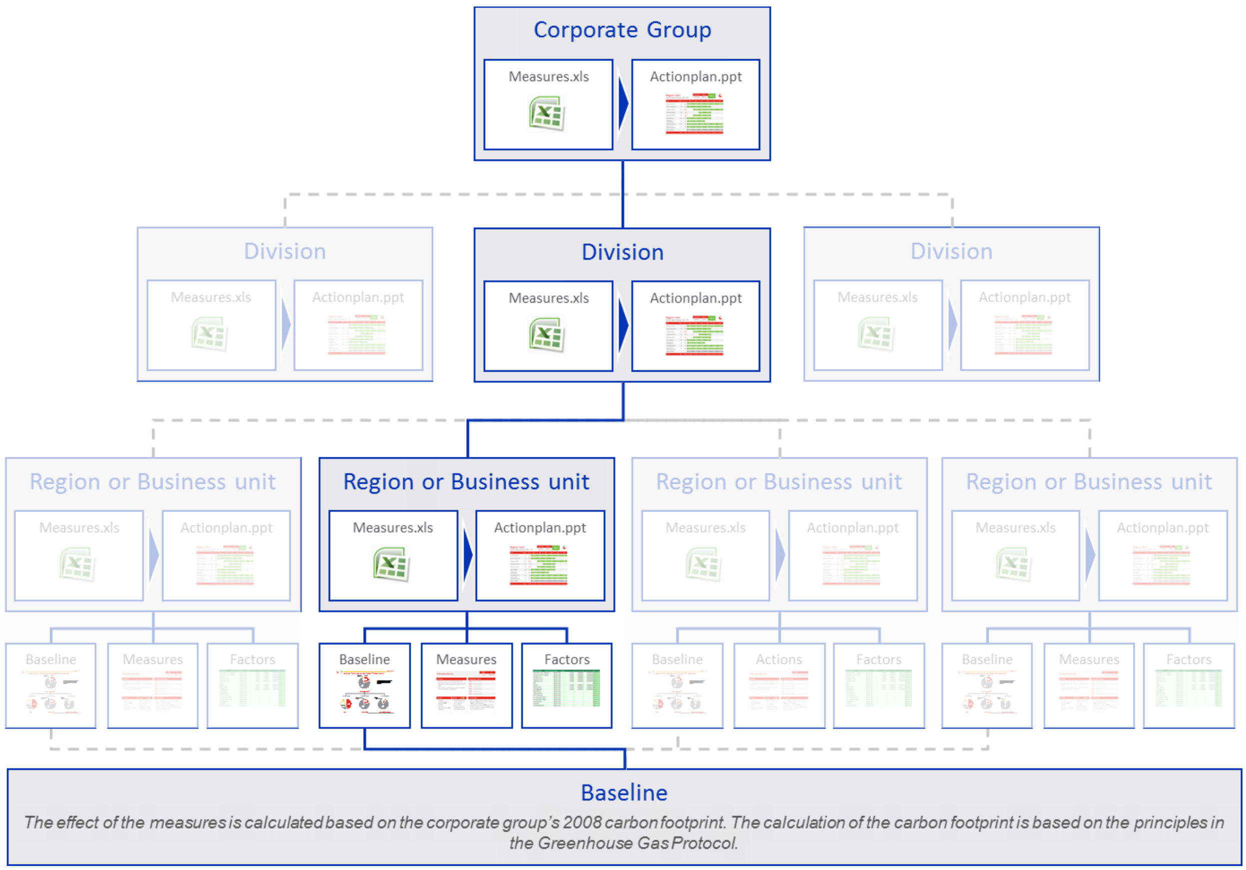

Figure 1 – Conceptual description of the action plan hierarchy in Posten Norge AS (Posten Norge AS, 2010).

1.1.3 The need to consider uncertainty

In the future, it is likely that an increasing number of industries will have to comply with greenhouse gas reduction directives. As an example, the transport sector within each Member State of the European Union should reach a 10% share of energy from renewable sources before 2020 (Renewable Energy Directive, 2009/28/EC). To effectively and efficiently reduce emissions a plan or project that is outlined to decrease GHG emissions needs to be thoroughly analysed, both with respect to relevant options and their associated risks and opportunities (Sentjens, Deakin, & Goudappel, 2011).

Historically, the most common means of handling uncertainty has been to use 'best estimates'. In recent years the field of uncertainty analysis has undergone large changes (Granger-Morgan & Henrion, 1990) and instead of ignoring uncertainty through the use of best estimates, different methods of uncertainty analysis have been developed; including qualitative, semi-quantitative and purely quantitative approaches (Austeng, Torp, Midtbø, Helland, & Jordanger, 2005b). In their book "Uncertainty – A guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis" Granger-Morgan and Henrion give four main reasons to why it is important to consider uncertainty:

- Considerable empirical evidence suggests that cognitive biases can cause errors in "best estimates" produced by experts. Subsequently, if 'best estimates' are used as a basis for calculation, the result could be erroneous. The 'best estimate' can be improved significantly if the expert is forced to consider uncertainty.
- A project or a decision process involves multiple actors and various decisions are made over an extended period of time. If uncertainty is treated explicitly it enables the actors to evaluate the conclusions and limitations of the analysis better than if uncertainty had merely been taken into account implicitly by the analyst.
- A separation of uncertainty due to disagreement over issues of value and issues of fact may help to improve the decision process.
- An analyst should state the implications and limitations of the results. An uncertainty analysis could help the analyst to detect external factors that should be taken into account during the decision process.

Lindley (2000) believes that it is necessary to consider uncertainty if good decisions are to be made. He argues that if it is possible, the combined uncertainty in reaching a desired goal should be quantified. An uncertainty analysis can be defined as a comparison of how the uncertainty in a models input parameters affect the uncertainty of the model output (Granger-Morgan & Henrion, 1990). By assigning probability distributions to uncertain input parameters all available information can be taken into account. It is then possible to propagate the uncertainty through the initial model by means of an uncertainty propagation method. Through quantification of uncertainty an uncertainty analysis of a CO_2-reduction project could lead to increased confidence in the strategy and may reveal new opportunities through better management of uncertainty (Sentjens, Deakin, & Goudappel, 2011).

1.2 Purpose and Objectives

The aim of this master thesis is to assess the advantages of performing an uncertainty analysis of a corporate CO_2-reduction project. For this purpose a quantitative uncertainty model for Posten's CO_2-reduction project was developed, where project success is defined as the achievement of a 30% reduction by 2015.

The following question formulations are to be answered:

- Is it possible to perform a quantitative uncertainty analysis of a CO_2-reduction project?
- What uncertainties are associated with the plans and how may they affect project success?
- What additional information is gained by performing an uncertainty analysis of a corporate CO_2-reduction project and how may this information improve the corporation's decision making process?

1.3 Specifications and Delimitations

The model and the analysis have been limited to only include the division Logistics within Posten. This division has the most and complex (in terms of number of measures) action plan for reducing CO_2-emissions and it is assumed that if the analysis can be performed for Logistics, it will be possible to expand the model to include the whole corporation at a later stage.

The action plans include planned measures that will be implemented during the period 2010 to 2020. Due to Posten's aim of reducing the corporations CO_2-emissions by 30% before 2015 the uncertainty analysis is only covering the measures performed during these five years

Posten's action plans are currently being revised. The analysis is thus performed on plans that are out of date. Consequently, the results should not be interpreted as an indication of Posten's upcoming environmental performance.

2. Methodology

This chapter give details upon the methods used to develop the uncertainty analysis model and to carry out the analysis of Posten's project to reduce CO_2-emissions. First it is explained how the literature review was carried out, then the uncertainty identification and estimation methodology is described. The chapter ends with a short description on how the uncertainty analysis model was developed.

2.1 Literature Review

The literature review was performed to develop ideas for how an uncertainty model could be designed as well as on how the analysis could be performed. Another important aim of the review was to gather information on key concepts that need to be considered during the analysis process. The model for uncertainty analysis of large public investment projects that DNV has developed (DNV's Uncertainty Analysis Model) in collaboration with the Norwegian Ministry of Finance and NTNU's Concept Research programme was given additional consideration. Understanding uncertainties related to other projects, as well as the various methods used for uncertainty analysis, was important input for performing an uncertainty analysis of a project aimed at reducing CO_2 emissions.

The literature review was conducted through searches of bibliographic databases as well as through general searches on the internet and library searches of books. The following search engines and libraries where searched: Lund University's search engine LibHub, the search engine SciVerse Scopus, the Civil Engineering Library at LTH and Malmö City Library. In the beginning of 2012 LibHub was replaced by a new search engine, Summons, which was also used. Summons enables literature searches through all of Lund University's digital resources, articles, databases, e-books and library text books.

In order to find relevant literature the following combinations of key words were used to limit the search results; 'uncertainty analysis', 'GHG emissions', 'expert judgement', 'sustainable transportation' 'uncertainty identification' and 'uncertainty propagation'. Information regarding the concepts related to uncertainty analysis was mainly gathered through library searches of books and the use of SciVerse Scopus. Information regarding DNV's Uncertainty Analysis Model was gained through discussions with experts at DNV, KGS reports and reports published by the Concept Research programme at NTNU.

2.2 Uncertainty Identification and Estimation

By gaining access to documentation concerning the CO_2-reduction project initiated by Posten, an uncertainty identification process could be initiated. Due to lack of data a subjective perspective on probability was taken, see chapter 3.2.

The uncertainty identification was conducted in 3 steps. Initially a small brainstorming session was held with experts at DNV. Different types of uncertainties with a potential to affect the outcome of the project were identified and subsequently divided into two groups; uncertainties related to external and internal factors (uncertainty drivers, in literature also commonly referred to as 'model uncertainty') and uncertainty in the true value of parameters employed within the effect calculation model (parameter uncertainty). The second step comprised of a more thorough identification of the uncertain parameters used in the effect calculation model. Each step of the calculation model was surveyed for parameters that were associated with a large degree of uncertainty and had a high potential to affect the outcome. Finally, the main uncertainty drivers which could have an effect on the outcome of the project were identified through a brainstorming session with the Corporate Environmental Manager at Posten Norge AS.

To find literature estimates (minimum, most likely and maximum values) of uncertainties transport statistics compiled in reports by Statistics Norway and the Norwegian Public Roads Administration were searched but also Norwegian and Swedish literature on sustainable transport. Expert judgements on uncertainties were gathered through discussions with experts within the fields of fuel technology and transport sustainability at DNV and LTH. To the extent possible, the 3-point expert elicitation method described in chapter 3.3 was used, but with a predefined confidence interval for the estimate. Posten provided information regarding the cost elements and a plus/minus 10% variation was put upon the original point estimates to account for parameter uncertainty. No information was available for the cost of modal shifts but to implicate their potential effect on the cost of the project these parameters were assigned large values and broad uncertainty intervals.

2.3 Development of Model and Uncertainty Analysis

The developed uncertainty analysis model is a based on DNV's well-applied Microsoft Excel and @Risk based Uncertainty Analysis Model that is used to conduct uncertainty analysis of public investment projects, described in chapter 3.7. It has been combined with the effect calculation model, previously used to calculate a single point value for the CO_2-mitigation effect of Posten's CO_2-reduction project. DNV's Effect Calculation Model designed for calculating the effect of Posten's CO_2-reduction project is briefly described in chapter 3.8.

During the value chain analysis for identification of uncertainties, interplay between measures that had not been accounted for was found. The Effect Calculation Model was expanded to account for this interplay and the expansion of the model is described in chapter 5.1.

The uncertainty analysis was performed in @Risk, a Risk Analysis and Simulation Add-In for Microsoft Excel, and the results are presented in chapter 6. Within the model each uncertain parameter was defined in a separate excel sheet to avoid sampling of different values for the same parameter. @Risk was used to assign probability distributions to the uncertain variables. All uncertain variables were estimated with a maximum, minimum and most likely value and assigned the non-parametric Trigen-distribution. Non-parametric distributions are discussed in chapter 3.4.1.

If nothing else is stated, @Risk treats all variables as independent. Therefore the parameter uncertainties and uncertainty drivers were reviewed to identify dependency relationships between variables. Correlation was built into the uncertainty model by means of conditional branching. The method used for building in correlation into the uncertainty model is described in chapter 6.4.

Parameter uncertainty was propagated through the model by means of Monte Carlo simulation. Based on the information gathered during the literature review, the sampling method Latin Hypercube sampling was used, see chapter 3.5. A sensitivity analysis on the output of interest was performed to identify the most significant input parameters and uncertainty drivers. The methodology of performing a sensitivity analysis in @Risk and the results gained is described in chapter 3.6.

3. Literature Review

How an uncertainty analysis is performed depends on the aim of the analysis and upon whom it is made for, but also on the sources of input available. A variety of different methods have been developed but all methods have some basic elements in common. It is thus possible to define a basic procedure for an uncertainty analysis:

1. *Define the aim of the analysis*
2. *Identification of uncertain elements* – a qualitative assessment of different factors that could introduce uncertainty to the project outcome.
3. *Quantification of identified uncertainties* – enables quantification of the effect of the identified uncertain elements.
4. *Propagation of uncertainty* – Calculation procedure to quantify the total uncertainty induced by the identified uncertain elements. Is often managed either through simulation or by means of statistical methods.
5. *Compilation of the results*

This chapter includes a literature study of theories related to step 2-4 of the uncertainty analysis procedure.

3.1 Uncertainty Identification

Uncertainty could be described as a measure that expresses our lack of knowledge about an event or an unknown quantity (Aven T. , 2011). Depending on what kind of knowledge we lack different kinds of uncertainty arise. For example, in project management, uncertainty could arise due to lack of information, overview of the project or be connected to planning and the ability of employees. Most projects are also affected by uncertainties caused by changes in the world such as the political situation or economic development. Project uncertainty can be divided into four main categories; conceptual uncertainty, operational uncertainty, contextual uncertainty and scenario uncertainty. (Austeng, Midtbø, Jordanger, Magnussen, & Torp, 2005a)

Conceptual uncertainty – Conceptual uncertainty is uncertainty associated with the methods used to solve the problem at hand. It could arise due to lack of knowledge of which model to use. It could also be uncertainty in if the model that is being used is applied correctly. When parameter values are estimated subjectively it is also a question of if the right tools are being used for elicitation of expert judgement.

Operational uncertainty – Operational uncertainty could be conceived as inner uncertainty and is mainly related to project execution. To improve operational uncertainty the organisation needs to expand its information basis or improve the methods used to gather information. This will help the organisation to create a clearer image of the true situation and will therefore improve the precision of the decisions that are made.

Contextual uncertainty – In contrast with operational uncertainty, contextual uncertainty arise due to factors that the organisation has little or no control over. Consequently it is often difficult to assess their effect on the project. Some external factors will be more important than others and it is important to identify and define those that could have the largest impact on the success of the project, these factors are also known as uncertainty drivers.

Scenario uncertainty – Scenario uncertainty arise due to the possibility of a change in project objectives and decision criteria owing to an unanticipated event. During the uncertainty identification process it is important to identify events that could have a significant impact on the success of the project.

There are several methods for uncertainty identification and they are built upon the same principles as the methods for risk or hazard identification (Aven T. , 2010). The aim is to identify all external and internal aspects that may affect the outcome of the project. A common identification method is to perform a brainstorming workshop with external experts and project participants. (Austeng, Torp, Midtbø, Helland, & Jordanger, 2005b).

It is impossible to ensure complete coverage of all uncertain elements but measures could be taken to structure and improve the identification procedure (Austeng, Torp, Midtbø, Helland, & Jordanger, 2005b). When identifying uncertainties in an organisation it is useful to survey its value chain. In a project, focus should instead be put on its processes and stages. In both projects and organisations a holistic approach is favourable and a checklist could help to maintain a holistic view. The checklist should consist of a wide spectrum of areas and elements to ensure an as complete identification procedure as possible. (Binz, 2011)

One way to structure the identification procedure is to place the identified uncertain elements in a matrix; the x-axis representing different aspects of the project and the y-axis describing the perspective. The advantage of placing the uncertain elements within different categories is that it makes it possible to identify if the brainstorming group has a skewed focus. If uncertainties are overrepresented in one area of the matrix it could be an indication of the need to invite additional individuals with expertise on the areas that are lacking. It is also important to define how the identified uncertain elements may affect the project in question. Arranging them into the four main categories of project uncertainty gives the analyst an indication of how the different uncertain elements should or could be modelled. (Austeng, Torp, Midtbø, Helland, & Jordanger, 2005b)

3.2 Uncertainty Representation

Most analysts consider probability to be the preferred mean of quantifying uncertainty. However, there is disagreement on the methodology for obtaining uncertainty estimations and on what the probability estimates should be based upon. The disagreement is caused by different views on the characteristics of uncertainty and can be divided into two main perspectives, an objective and a subjective. (Covello & Merkhofer, 1993)

3.2.1 The objective perspective

The objective perspective defines probability as a measure of the frequency with which an event will occur (Covello & Merkhofer, 1993). An uncertainty analysis that implements the objective perspective will rely on the classical theory of probability and statistics. The classical probability theory relates the probability of an event to its frequency in a large number of repetitions, a relation also known as the law of large numbers. The law of large numbers requires that an event can be repeated over and over again and that its frequency converges as the number of trials increases. With this perspective, probability is in fact a property of the physical system that generates the events. (Granger-Morgan & Henrion, 1990)

3.2.2 The subjective perspective

An analyst who adopts the subjective perspective will rely on the Bayesian theory of statistics. According to Bayes theorem, uncertainty about an event is dependent on the event itself as well as on the current information available to the analyst assessing it. It could be seen as a measure of the state of knowledge which depends on the information and experience of the analyst. These subjective probability estimates are not arbitrary but follow the same basic axioms as the classical probabilities. (Covello & Merkhofer, 1993)

3.2.3 Choosing perspective

The choice of perspective is critical since it affects not only the meaning assigned to a probability but also the interpretation of the results (Covello & Merkhofer, 1993). When empirical data is scarce, or the properties of the system are not well understood, the analyst who adopts an objective perspective will find it difficult to estimate uncertainty (Covello & Merkhofer, 1993). The subjective perspective is more flexible and allows for uncertainty representation also when there is lack of empirical data; it provides methods that make use of past experience and expert judgement (Megil, 1984). Many analysts and researchers avoid referencing to different types of perspective, instead they choose to consider all uncertainties as subjective (Aven T. , 2011).

3.3 Expert Judgement and Heuristic Biases

If the analysis contains an uncertain quantity, about which data or understanding is scarce, expert judgements can provide useful information (Granger-Morgan & Henrion, 1990). The larger part of the literature reviewed seem to agree that when performing an uncertainty analysis it is very difficult, if not impossible, to gather enough data to accurately determine the uncertainty of all variables. Conclusively, expert judgement is often necessary.

By definition the subjective perspective is able to make use of methods for elicitation of expert opinion. When using such methods it is necessary to understand how experts make judgements that involve uncertainty (Granger-Morgan & Henrion, 1990). Experts frequently employ heuristic procedures when trying to provide subjective estimates, these procedures may be assistive but they can also lead to biased outcomes or large errors (Vose, 2000).

One example of a heuristic procedure is availability, which means that the expert recalls past occurrences of an event and makes use of this information to provide an estimate. This heuristic is helpful when the experience of past occurrences correspond fairly well with the actual frequency of the event. Many factors can influence the availability heuristic and cause over- or underestimates of the events true probability. (Granger-Morgan & Henrion, 1990)

According to Vose (2000) the most important heuristic is adjustment and anchoring. It means that an individual who is trying to estimate a probability distribution usually starts with a single, often the most likely, value. Based on this value, adjustments are made to find the minimum and maximum value. Such a procedure frequently results in overconfidence in the estimate.

3.3.1 Strategies to minimize heuristic biases

There are several other heuristic processes and biases that cause inaccuracy in estimates and the elicitation process should be designed as to minimize their influence (Speirs-Bridge, Fidler, McBride, Flander, Cumming, & Burgman, 2010). The strategies put forward in the literature can be divided into three groups; motivational, technological and cognitive. Motivational strategies try to reduce biases by creating incentives for the expert to produce good estimates. Research suggests that these methods are inefficient and there is no proof that they would improve the elicitation process. Technological strategies try to reduce biases by the use of different technological means. Cognitive strategies are generally more effective than motivational strategies and are more frequently used than technological strategies. (Kirkebøen, 2009)

One extensively applied cognitive strategy is the Delphi-method which is a Bayesian structured group process. A panel of experts give numerical uncertainty estimates including the information upon which they have deduced these estimates. A facilitator gathers the results and provides the group of experts with an anonymous summary. The experts are then asked to reconsider their estimates in light of the new knowledge that they gained from the summary. This process is repeated until the experts answers converge towards a final estimate. Other cognitive strategies include; increasing the expert's awareness of heuristic procedures, to train the expert in logic and probability theory or to re-formulate the decision problem. (Kirkebøen, 2009)

One common way to elicit expert judgement is to ask the expert to provide an interval which he, with a specific confidence level, is certain contains the true value. There are several different ways for an analyst to elicit such an interval from an expert. For example, the analyst could specify a confidence level for which the expert should assign an interval or the analyst could specify an interval for which the expert should assign a confidence level. When only an interval is specified the elicitation process is sometimes referred to as a 2-step procedure, if the expert is asked to provide a most likely value as well, it is called a 3-step procedure. (Hammonds, Hoffman, & Bartell, 1994)

A simple cognitive approach to reduce heuristic biases when using a 3-step procedure is to ask the expert to provide the lowest or highest estimate first. If the expert gets to decide the order himself he tends to provide the most-likely value first, thus increasing the use of the availability heuristic. Studies have shown that by making the expert provide one of the other estimates first, overconfidence is reduced. (Vose, 2000)

Speirs-Bridge et al (2010) have developed a cognitive strategy called the 4-step procedure. It re-formulates the decision problem by decreasing the statistical information given to the expert. The expert is first asked to provide a 3-point estimate, including a best, worst and most-likely value, and then to provide a confidence level for that estimate. Studies have shown that a three point estimate clearly reduces the overconfidence of a two point estimate, which includes only a worst and best-case estimate. A study of the 4-point estimate procedure found it to be even more accurate. This suggests that the elicitation procedure improves by the number of considerations the expert has to make during the elicitation process. (Speirs-Bridge, Fidler, McBride, Flander, Cumming, & Burgman, 2010)

3.4 Assigning Probability Distributions to Expert Judgements

The precision of an uncertainty analysis is dependent on the appropriate use of probability distributions. When describing the uncertainty of a parameter using expert judgement one appropriate way of categorizing probability distributions is to divide them into parametric and non-parametric distributions. (Vose, 2000)

The shape of a parametric distribution is determined by one or more distribution parameters and its shape is generated by a mathematical function. Most probability distributions are parametric, including the lognormal, normal and beta distributions. If such a distribution is to be used to model expert judgment appropriately, both the analyst and the expert must have great knowledge of the underlying assumptions of the distribution. (Vose, 2000)

The shape of non-parametric distributions is instead directly determined by its parameters, its distribution function being a simple mathematical description of its shape. As a result these distributions are more intuitive and changes of one or more parameters create predictable responses. The most common non-parametric distributions are the uniform and the triangular distributions. (Vose, 2000)

Vose (2000) believes that it is more appropriate to use non-parametric distributions to model expert opinion. In his view, parametric distributions should only be used when one of the following statements is true:

- The theory behind the distribution applies to the problem at hand.
- It has been generally accepted that the distribution is very accurate for modelling that specific variable.
- The distribution represents the opinion of the expert and there is no requirement of high accuracy.

3.4.1 Non-parametric distributions

The uniform distribution requires two input variables, a minimum and a maximum value. All values within this range are assigned equal probability densities. Vose (2000) notes that it is rare that an expert only has an opinion about the minimum- and maximum values of an event and none on its most likely. He also states that the probability density function of a uniform distribution drops in an unnatural way at its endpoints and that this makes it a poor modeller of expert opinion.

The Triangular distribution is often used to model expert opinion due to its intuitive appeal and flexible shape. It is defined by three input parameters; a minimum (a), most likely (b) and maximum (c) value. From these parameters the mean and standard deviation of the distribution can be determined:

$$mean = \frac{(a+b+c)}{3} \qquad (1)$$

$$standard\ deviation = \sqrt{\frac{(a^2+b^2+c^2-ab-ac-bc)}{18}} \qquad (2)$$

The parameters a and c represents the estimated absolute minimum and maximum values of a variable. Equations (1) and (2) tell that the mean and standard deviation is equally sensitive to all input variables.

For some parameters it is difficult to estimate the maximum or minimum value since they could be virtually unbounded. In such cases it is more appropriate to use a distribution whose mean and standard deviation is less sensitive to the extreme estimates. The mean of the PERT distribution is four times more sensitive to the most likely estimate than to the extremes and its standard deviation is systematically lower than that of a Triangular distribution. It could therefore, in some cases, be successfully used to model expert judgement. The

PERT distribution is a modified version of the Beta-distribution which is a parametric distribution. It is not as intuitive as the Triangular and should therefore be used with care. (Vose, 2000)

The estimates a, b and c of a Triangular distribution represents absolute values and absolute values are often difficult for an expert to estimate. To avoid this problem a Trigen distribution, which is also triangularly shaped, can be used. It makes absolute estimates unnecessary by adding a confidence level [p, q] to the estimated values:

- the probability that the parameter value is below a (p)
- the probability that the parameter value is below c (q)

This distribution is compatible with the 4-step procedure developed by Speirs-Bridge et al (2010) which produces a 3-point estimate and a confidence level for that estimate.

Vose (2000) argues that a Triangular distribution's sharp peak and straight lines produce a definite shape that is inappropriate to use when there is little knowledge to base the estimation on. In contrast Granger-Morgan and Henrion (1990) consider the sharp edges of a Triangular distribution to appropriately communicate that the precise shape of the distribution is unknown. They argue that its unnatural shape help to reduce over interpretation of results and prevent a false sense of confidence.

3.5 Methods for Uncertainty Propagation

Methods for uncertainty analysis are used to compare the importance of the input uncertainties in terms of their relative contributions to uncertainty in the outputs (Granger-Morgan & Henrion, 1990). As mentioned in chapter 3.4 on uncertainty representation, there are two schools on how uncertainty should be represented. If a subjective perspective is taken, most probability distributions would be elicited directly from experts but some could also be generated from frequency data. In this way uncertainties due to natural variability and lack of knowledge are combined and a quantitative measure of the overall uncertainty in the output is obtained. Alternatively, an objective perspective is chosen where only probability distributions generated from frequency data are propagated through the model. Uncertainty due to lack of knowledge is instead superimposed on the output and is hence not propagated through the original model. (Covello & Merkhofer, 1993)

Several methods for uncertainty propagation have been developed and these can be divided into two main groups, analytical and numerical methods (Hammonds, Hoffman, & Bartell, 1994). Which method that is appropriate to use depends on the model, the problem at hand and the resources available. (Granger-Morgan & Henrion, 1990)

3.5.1 Analytical methods

Exact analytical methods for propagating uncertainty are applicable when all uncertainties in a model can be described with probability functions that can be combined algebraically (Vose, 2000). Such methods are applicable only to the simplest models; however a number of approximate analytical techniques based on Taylor series expansions have been developed. These are also known as Method of Moment techniques since they use the mean, variance and sometimes higher order moments to propagate and analyse uncertainty (Granger-Morgan & Henrion, 1990).

The Taylor series expansion techniques express the uncertainty in the output as a function of rates of change in input variables by exchanging the models functional relationship between input and output variables with a simpler form (e.g. a linear, quadratic, or cubic equation). For these relationships it is possible to express the mean and variance of the output in terms of the input moments. When the moments of the output have been calculated a probability distribution can be assigned to describe it. (Covello & Merkhofer, 1993)

First-order techniques are widely used in engineering and the physical sciences. Higher order approximations have been used to analyse more complex models. The Method of Moments technique has two important advantages:

- The necessary numerical calculations are often relatively simple once the algebraic analysis has been completed.
- It is an instinctive approach, providing a direct way of summing up the uncertainty contributions of the input variables to describe the total uncertainty of the output.
  (Granger-Morgan & Henrion, 1990)

However, Granger-Morgan and Henrion (1990) note that it has three disadvantages:

- The complexity of the algebraic analysis may increase rapidly with the complexity of the model.
- Because uncertainty in the output is described only by the moments of a distribution it is difficult to get reliable estimates of the tails of the output distribution.
- The approach uses deviations from the nominal value of the input variables to describe the uncertainty in the output. It is therefore a local approach and will not be accurate when the parameter is associated with large uncertainties.

3.5.2 Numerical methods

One way of overcoming the disadvantages of analytical methods is to use numerical methods for uncertainty propagation; Monte Carlo simulation being the most important (Hammonds, Hoffman, & Bartell, 1994). Monte Carlo analysis is a random sampling based method for uncertainty propagation. It computes a probability distribution for the output variable through simulation of multiple sets of different input combinations (Covello & Merkhofer, 1993). Several different random samplings methods have been developed through the years, of which Simple Random Sampling (SRS) and Latin Hypercube Sampling (LHS) are the most commonly applied (Hammonds, Hoffman, & Bartell, 1994).

Simple Random Sampling, also known as Monte Carlo sampling is the most basic Monte Carlo simulation approach. It allows input values to be drawn at random from the input value's specified distributions. For each run of the model, one value will be assigned to each input variable and these values will be used to calculate the corresponding output value. One run defines an input scenario and its corresponding output response. In a Monte Carlo analysis several runs are made and the input probability distributions will induce a probability distribution for the model output variable. (Covello & Merkhofer, 1993)

The Simple Random Sampling method is entirely random; this means that samples are more likely to be drawn from areas with a high probability. If too few runs are made, values in the outer ranges of the input probability distributions may be underrepresented or not represented at all. Stratified sample techniques, such as Latin Hypercube Sampling, have been developed to ensure the inclusion of extreme values. (Palisade Corporation, 1996)

In standard Latin Hypercube Sampling, each input distribution is divided into equally large and probable sections. Instead of sampling from the distribution as a whole, input values are obtained by random sampling from each of these sections. The number of sections that the distribution is divided into depends on the number of iterations that are to be made during the Monte Carlo simulation. If m iterations will be performed, the input distributions will be divided into *m* sections. Once a random number is selected from a section, no number will be drawn from that section again. (Hammonds, Hoffman, & Bartell, 1994)

Due to the stratification technique used in Latin Hypercube Sampling the input values created by this method tend to represent the input distributions better than those obtained through Simple Random Sampling. This makes the LHS technique more efficient and it requires less runs for the output distribution to become stable. However, in cases when there are many uncertain inputs contributing to the uncertainty in the output or when the model is highly nonlinear, the difference in efficiency between LHS and SRS is negligible. (Granger-Morgan & Henrion, 1990)

The advantage of using Simple Random Sampling instead of a stratified sampling method, such as LHS, is that the former technique ensures independence between the input variables (Granger-Morgan & Henrion, 1990). In @Risk independence between variables are maintained also for the Latin Hypercube Sampling method. For each input variable one interval is randomly selected and a value is drawn from within that interval. For example, when a value is drawn from interval *x* for variable *a* it does not mean that variable *b* is drawn from that interval; it is equally probable that variable *b* is drawn from any of the other available intervals. Thus, by letting the intervals be randomly selected unwanted correlation between variables is avoided. (Palisade Corporation, 1996)

3.6 Sensitivity Analysis in @Risk

In case of multiple uncertain parameters and factors it can be difficult to directly assess which of these that has the largest influence on the variance of the output. Sensitivity analysis is therefore an important part of the overall uncertainty analysis as it enables identification of the uncertain parameters or factors that drive the variability in the project outcome. (U.S. Environmental Protection Agency, 2001)

Several statistical techniques can be applied to a Monte Carlo simulation to evaluate the relative importance of different input parameters. These techniques are collectively known as correlation and regression analysis. (U.S. Environmental Protection Agency, 2001) In @Risk sensitivity analysis is either performed by multivariate stepwise regression or by calculating Spearman rank correlation coefficients (Palisade Corporation, 1996).

Multivariate stepwise regression is a technique for calculating regression values for multiple input data sets. The data sets are fitted to a planar equation that can generate the output data set. In @Risk, one normalized regression coefficient is calculated for each input variable. The regression coefficient can have any value between -1 and 1. A regression coefficient of 0 indicates no significant relationship between the input and the output. A regression coefficient of 1 (alternatively -1) indicates that 1 standard deviation change in the input causes a standard deviation change of 1 (alternatively -1) in the output. The goodness of fit can be tested by means of the squared multiple correlation coefficient (R^2), which in @Risk represents the percentage of variation in the output that can be explained by the linear relationship. If R^2 is lower than 0.60 the multivariate stepwise regression technique does not satisfactorily explain the relationship between the inputs and outputs. (Palisade Corporation, 1996)

If R^2 is less than 0.60 this is an indication of non-linearity. The use of Spearman rank correlation coefficients is often more robust when the relationship between the inputs and the output are non-linear (U.S. Environmental Protection Agency, 2001). By calculating Spearman rank correlation coefficients @Risk returns rank order correlation values ranging from -1 to 1. Zero indicates no correlation between the input and the output. Minus one indicates complete negative correlation and +1 complete positive correlation. The higher the correlation between the input and the output, the more significant is the input in determining the output's value. (Palisade Corporation, 1996)

3.6.1 Graphical representation of sensitivity

In @Risk scatterplots are used to display the relationship between the inputs and simulated output. Sensitivity results are presented graphically by means of tornado graphs. A tornado graph displays the input parameters that have the largest impact on the variability of the output results. @Risk version 5.0 allows for display of tornado graphs based on three different kinds of data sets – Regression coefficients, Regression (Mapped values) and Correlation coefficients. (Palisade Corporation, 2010)

Correlation coefficients are based on the Spearman rank correlation coefficients and the regression coefficients are calculated by Multivariate stepwise regression technique. The length of the bar in the tornado graph represents the size of the regression or correlation coefficient. A tornado graph that shows mapped values is also based on the multivariate stepwise regression technique but instead of displaying regression coefficients between -1 and 1 it shows the amount of change in the output due to a +1 standard deviation change in the input. (Palisade Corporation, 2010)

4. Introduction to the Two Underlying Models

This chapter gives an introduction to the two models upon which the uncertainty analysis of Posten's CO_2 reduction project is based. DNV's effect calculation model developed for calculating the effect of Posten's CO_2 reduction project is described and the chapter closes with an overview of Det Norske Veritas (DNV) methodology for uncertainty analysis of public investment projects.

4.1 Effect Calculation Model

The division Logistics is divided into three business units; Cargo, Supply Chain and PTT, see figure 2. Each business unit within Logistics has a separate action plan for how CO_2-emissions are to be reduced. The same general model is applied to each action plan creating one effect calculation model for each division. (Posten Norge AS, 2010)

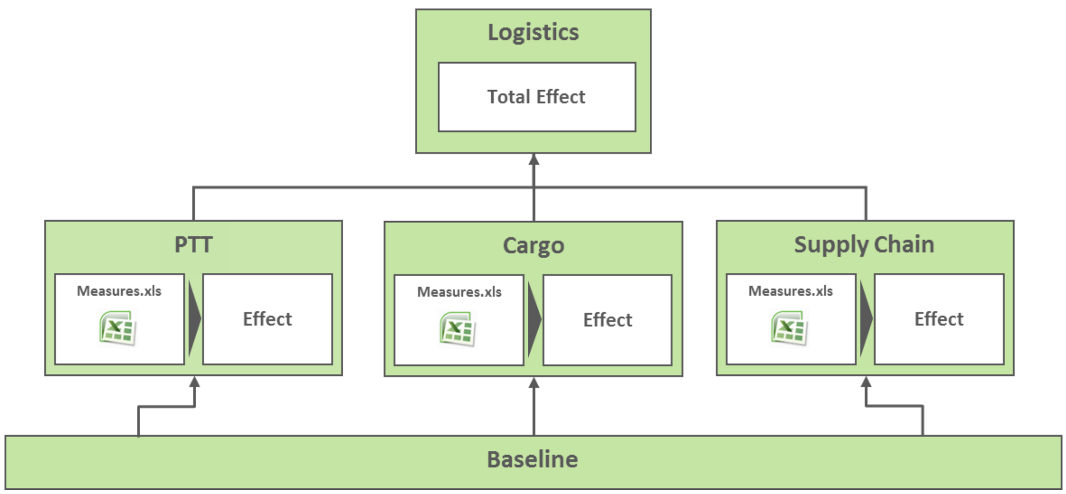

Figure 2 – General structure of the effect calculation model for Posten's project to reduce CO_2 emissions.

Initially, the effect is calculated for each respective business area. Calculations are performed in excel and a separate spread sheet is used to share input parameters to the model. The three models only differ in the planned degree of implementation. Finally, the amount CO_2 reduced within the division Logistics is gained by calculating the sum of the results for the three business areas. (Posten Norge AS, 2010)

4.1.1 General calculation procedure

Generally, the effect of the measures is calculated in the following order:

1. *Efficiency measures* that reduce the transport demand (eg. Route optimization)
2. *Optimization measures* that reduce the average fuel consumption (eg. Ecodriving)
3. *Operational or technological measures* that reduce CO_2 emissions (eg. Alternative vehicles)

Efficiency measures may either be assumed to reduce average fuel consumption or to decrease the number of vehicles in the vehicle fleet. The total effect of each measure is calculated as the difference between the baseline and the altered emission level after implementation of the planned measures. (Posten Norge AS, 2010)

4.1.2 Interplay between actions

The measures are implemented at different rates over a certain time period. To simulate reality as accurately as possible it is important to consider interplay between measures. By calculating the effect of each measure successively, co-variation between measures is accounted for and overestimation of effects is evaded. (Posten Norge AS, 2010)

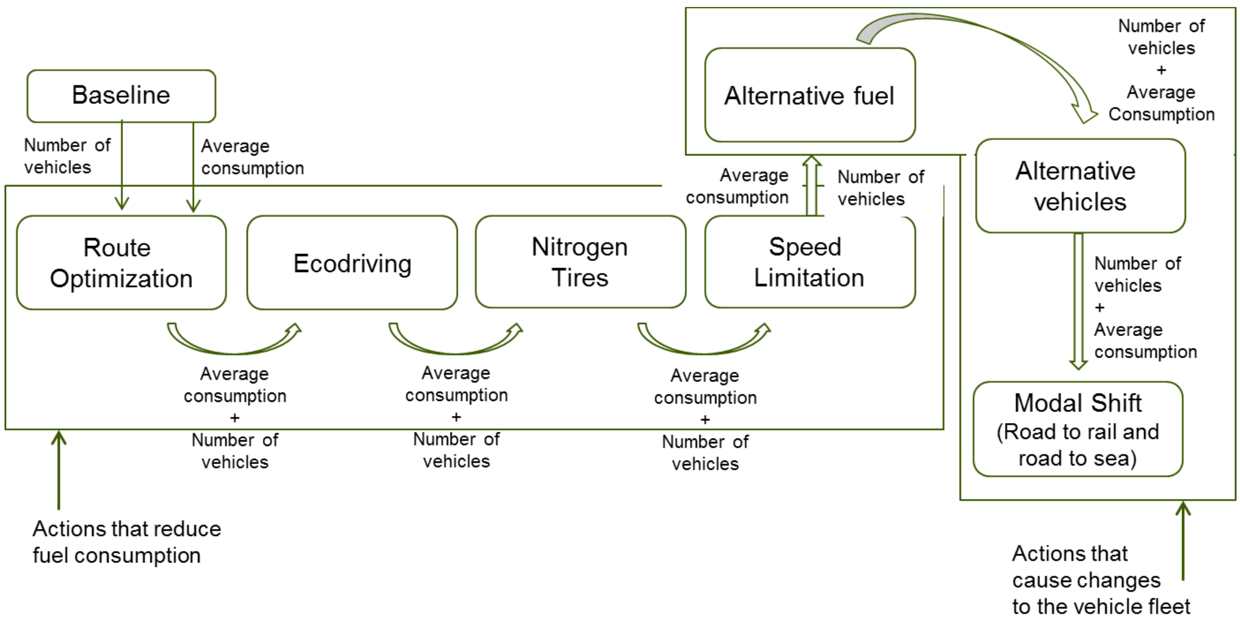

Figure 3 - Interplay between measures that reduce fuel consumption and measures that cause changes to the vehicle fleet. Baseline data is put into the first measure that decreases the average fuel consumption. The baseline data is then successively altered as it is used as an input for the upcoming measures.

The DNV Effect Calculation model is based on MS Excel and calculates the effect of the individual measures over a five year period. Figure 3 shows an example of how interplay between measures that reduce fuel consumption and measures that cause changes to the vehicle fleet have been accounted for. The effect of each measure is calculated successively, making continuous changes to the input parameters on average fuel consumption and the number of vehicles. This means that if the number of vehicles or the average consumption is changed by one measure, baseline data is re-calculated and used as input data for the next measure. As the baseline data is propagated through the model, overestimation of the effect of measures that cause changes to the vehicle fleet is evaded. The effect of the individual measures is summed up to calculate the effect on a business unit level. (Christiansen, 2012)

4.1.3 Net Present Value

In addition, the DNV Effect Calculation model accounts for operational and capital expenses. Profits and expenditures are estimated and calculated for each individual measure creating cash flows for the five year period. These are used as an input to calculate the Net Present Value (NPV) of the individual measures. The total NPV of the action plan is calculated as the sum of the NPV's of the individual measures.

4.2 Uncertainty Analysis of Public Investment Projects

Det Norske Veritas, Advansia and Samfunns- og næringslivsforskning AS (KSG) has entered into a framework agreement with the Norwegian Ministry of Finance regarding the performance of quality assurance assessments of major public investment projects (NTNU - Concept programme, 2012). In line with this agreement DNV has developed a MS Excel model for uncertainty analysis of project investments. The model can be adjusted to fit the project in question and treats uncertainty in three steps at two different levels of detail, see figure 4.

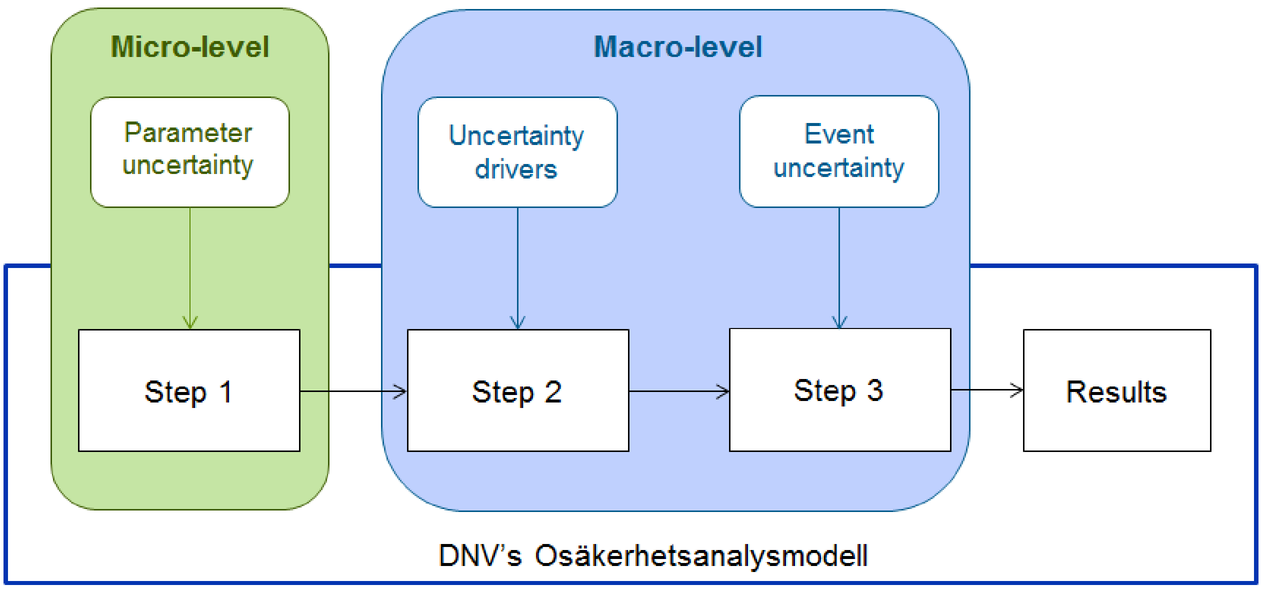

Figure 4 – General structure of the DNV's MS Excel model for uncertainty analysis of project investments.

Uncertainty is propagated through the model by means of two different methods; Monte Carlo simulation in @Risk and a simplified version of the Successive calculation method. The latter, an analytical method, is being used as a built in self-check of the model. The identified parameter uncertainties, uncertainty drivers and event uncertainties are assigned probability distributions and the size of the project investment is calculated as a sum of the contribution from the different uncertainty sources. (KGS, Rapport nr: 2009-0680)

4.2.1 Parameter uncertainty

Parameter uncertainty falls into the category of operational uncertainty described in chapter 3.3 and step 1 of the model accounts for uncertainty in input parameters. In the case of uncertainty analysis of project investments parameter uncertainty refers to the uncertainty in the true value of cost elements within the project budget. Each cost unit is assigned a 3-point estimate that is represented by a Trigen-distribution in @Risk. If the cost element is dependent on both the number of units and cost per unit, a 3-point estimate is assigned to each respectively. The total uncertainty in the cost element is obtained through multiplication of the two probability distributions. (KGS, Rapport nr: 2009-0680)

4.2.2 Uncertainty drivers

The cost of the defined cost elements is estimated under a set of assumptions about external and internal circumstances. These assumptions can be based on experience or on other sources of information that strengthens the belief that reality will behave in a certain way. Any uncertainty associated with the assumptions is simulated by means of uncertainty drivers. (KGS, Rapport nr: 2009-0680)

Uncertainty drivers represent external or internal factors that affect either the whole or parts of the project. It is certain that they will affect the project outcome but it is unknown how large the effect will be. The uncertainty drivers affect the cost elements with a percentage variation – an increase or a decrease depending on if there is a risk for going over budget or possibility to decrease project cost. (KGS, Rapport nr: 2009-0680)

To quantify the effect of an uncertainty driver it is important to thoroughly describe the external and/or internal factors it represents. A best, worst and most-likely scenario for each uncertainty driver should be described as well as its potential effect on the project. As an uncertainty driver may affect several cost elements simultaneously it is a way of modeling co-variation into the model. (Austeng, Midtbø, Jordanger, Magnussen, & Torp, 2005a)

4.2.3 Event uncertainty

Uncertainty drivers with low probability of occurrence are treated as events in the third step of the model. Event uncertainty represents events that would affect revenue or costs should they occur. The probability of the event occurring is described by a binary distribution while the uncertainty in consequence is described by a 3-point estimate, represented by a Trigen-distribution. Event uncertainty is not assumed to affect the cost elements directly but is instead evaluated through a possible total effect on the project. This value is then added to the total project cost. (KGS, Rapport nr: 2009-0680)

4.2.4 Correlation

The model may contain two or several input variables that are related to each other. For example, when a 'high' value is sampled from one distribution, another input variable is also likely to return a 'high' value. To avoid illogical results, it is important to correlate these input variables. @Risk provides methods for correlating probability distributions using rank-order correlation coefficient values. (Palisade Corporation, 2010) The methods provided often generate errors when simulations are run and correlations should therefore be built into the model to the extent possible. One method used at DNV to build correlation into a model is conditional branching. (Binz, 2012) This technique makes use of simple logical statements and variable input arguments to define an input distribution function that is correlated or dependent on another input. (Palisade Corporation, 2010)

5. An Uncertainty Analysis Model for Posten's CO_2 Reduction Project

This chapter describes the steps taken to merge DNV's Uncertainty Analysis model with DNV's Effect Calculation model to create an Uncertainty Analysis model for Posten's CO_2-reduction project.

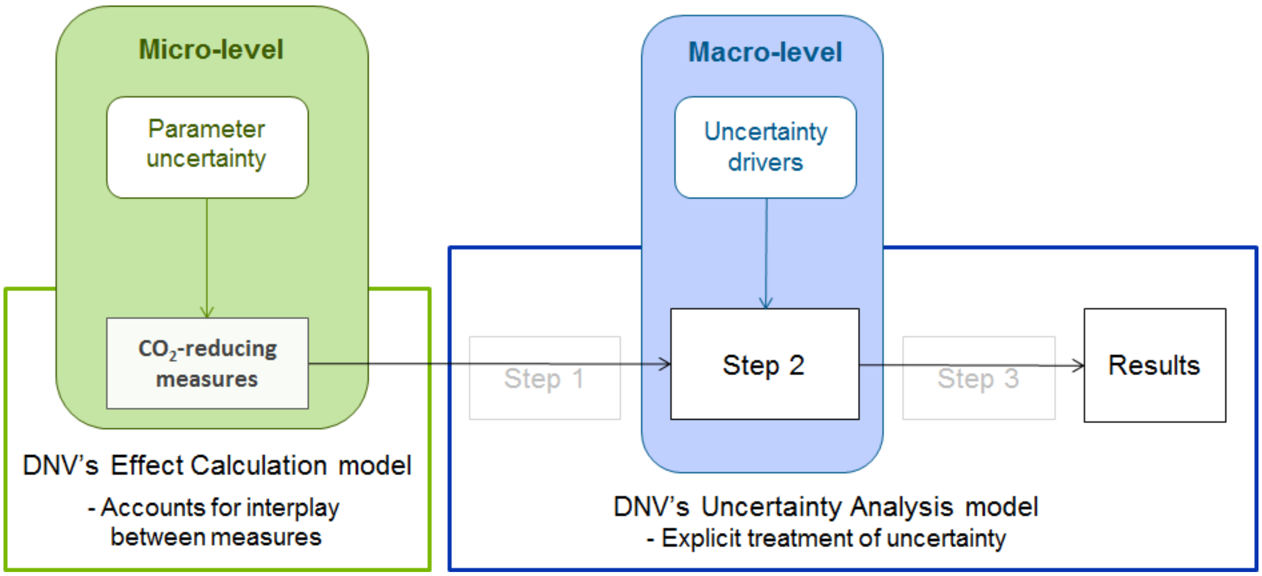

Figure 5 – Changed structure of the Uncertainty Analysis Model where the Effect Calculation Model replaces step 1 in the original model. Step 3 has been excluded and event uncertainties have instead been incorporated into the general uncertainty drivers.

The first section presents the identified uncertainties associated with the action plan, parameter uncertainties and uncertainty drivers. Section two describes the modifications done to DNV's Effect Calculation model to account for additional interplay. The last section describes how DNV's Uncertainty Analysis model has been adjusted to account for the identified uncertainties and how it has been combined with DNV's Effect Calculation model to account for interplay between individual measures.

5.1 Identification and Categorization of Uncertainties

Uncertainty associated with Greenhouse gas (GHG) reductions can be categorized into either "scientific uncertainty" or "estimation uncertainty". Scientific uncertainty could be described as lack of knowledge on the true value of an emissions factor or of the processes involved, while estimation uncertainty arises due to monitoring and/or quantification errors. (The GHG Protocol, 2003) In a CO_2-reduction project additional sources of uncertainty arise, these are connected to the corporation's and subcontractor's ability to implement measures as well as to various external factors.

Chapter 3.1 presents four different sources of project uncertainty which should be considered when identifying uncertainty related to a project. Considerable advantage could be gained by combining knowledge of uncertainty associated with GHG reductions with sources of uncertainty within project management. Due to the many sources of uncertainty the identification process has been performed in two steps; starting with an identification of key parameter uncertainties followed by an assessment of external and internal factors that could have an overall effect on the outcome of the project. The identified uncertainties have been summarized in table 1.

Table 1 – Summary of the identified parameter uncertainties and uncertainty drivers with a potential to affect the outcome of the project.

Effect calculation parameters (Estimate and Operational uncertainty)	Cost parameters (Estimate and Operational uncertainty)	Uncertainty drivers (Contextual, Operational and Scenario uncertainty)
Effect of Ecodriving	Course cost Ecodriving	Biofuel availability and infrastructure
Effect of Speed Limitation	Cost Nitrogen filling facility	Market structure
Effect of Nitrogen Tires	Fuel price Diesel	Technological development
Emission reduction B30	Fuel price B30	Infrastructure – Modal shift
Emission reduction B100	Leasing cost B30	Political framework
Emission reduction Biogas	Maintenance cost B30	Posten's ability to implement measures
Emission reduction Biogas hybrid	Fuel price B100	Subcontractors ability to implement measures
Emission reduction El-hybrid	Leasing cost B100	
Emission reduction Electric vehicles	Maintenance cost B100	
Emission reduction Modular Lorries	Fuel price Biogas	
Emission Electricity	Leasing cost Biogas	
Emission District Heating	Maintenance cost Biogas	
Emission Heating Oil	Fuel price Hybrid	
Emission Propane	Leasing cost Hybrid	
Emission per tonkm Air Domestic	Maintenance cost Hybrids	
Emission per tonkm Air European	Fuel price Electric	
Emission per tonkm Air International	Leasing cost Electric	
Emission per tonkm Rail Electric	Maintenance cost Electric	
Emission per tokm Rail Diesel	Cost Electricity	
Emission per tonkm Container ships	Cost District heating	
Increased consumption B30	Cost Heating Oil	
Increased consumption B100	Cost Propane	
Increased consumption Biogas	Capex Modal Shift	
Increased consumption Biogas hybrid	Opex Modal Shift	

5.1.1 Uncertain parameters in the effect calculation model

An example of a measure whose reduction potential is subject to multiple types of uncertainty is Ecodriving. Ecodriving is subject to operational uncertainty as the achieved effect is dependent on the driver's driving style before taking a course in Ecodriving and on the type of engine within the car. Additionally, it is dependent on contextual uncertainty since the reduction potential depends on whether or not the traffic conditions allow the driver to adapt its driving style, if the traffic density is high the reduction potential of Ecodriving decrease (Statens vegvesen, 2010). As it is difficult to measure the effect of Ecodriving it is also subjected to estimate uncertainty.

The effect calculations of each measure include one or several parameters subjected to scientific, estimation and/or operational uncertainty. Focus has been put into identifying key uncertain parameters that play a crucial role in determining the final effect of a measure. These parameters represent the parameter uncertainty within the model and include the scientific and estimate uncertainty as well as parts of the operational uncertainty. Parameter uncertainty may be reduced if the organisation expands its information basis. The input values for the identified parameter uncertainties are given in Appendix F.

5.1.2 External and internal factors that induce uncertainty

When assessing the probability of project success it is necessary to look beyond the parameter uncertainty and to make use of the current knowledge within the field of uncertainty analyses of project investments. Just as a political decision or the market structure can affect the profitability of a project investment, factors such as the availability of biofuels or future political decisions may have a large effect on the CO_2-reduction potential of a CO_2-reduction project. Contextual, operational and scenario uncertainty that affects implementation has been incorporated into uncertainty drivers with an overall effect on the project outcome.

Operational uncertainty connected to uncertainty drivers is made up by internal factors that determine the organisations ability to implement measures. By careful management, involvement and engagement of employees this uncertainty can be reduced.

External factors make up the contextual and scenario uncertainty related to the project. The organisation in charge of the CO_2-reduction project has limited or no control over the external factors and its ability to reduce such uncertainty is very limited.

The identified internal and external factors have been grouped into 7 generalized uncertainty drivers with a potential to impact different parts of the project plan, see Appendix E.

5.1.3 Uncertainty in implementation costs

The degree of implementation of any CO_2-reducing measure is also highly dependent on implementation costs. Consequently, parameter uncertainty and uncertainty drivers related to project costs have also been identified.

5.2 Modifications to the Original Effect Calculation Model

An analysis of interplay between measures was performed to investigate if any simplifications made during the development of DNV's Effect Calculation model could have a significant impact on the project outcome.

5.2.1 Analysis of Interplay between Measures

The analysis was performed through a semi-quantitative study of the results generated when the input parameters to one measure were altered. By changing the degree of implementation of one measure its effect with respect to each of the other measures was analysed. If it was found that there was an effect a number one (1) was set to indicate that interplay existed and had been accounted for, no effect was symbolized with zero (0) and interplay that had not been accounted for was instead assigned minus one (-1). The results of the analysis are shown in figure 6.

ID	Action	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14
A1	Ecodriving		1	1	1	-1	-1	-1	-1	-1	-1	0	-1	-1	0
A2	Speed Limitation	1		1	1	-1	-1	-1	-1	-1	-1	0	-1	-1	0
A3	Nitrogen Tires	1	1		1	-1	-1	-1	-1	-1	-1	0	-1	-1	0
A4	Route Optimization	1	1	1		-1	-1	-1	-1	-1	-1	0	-1	-1	0
A5	Biodiesel B30	1	1	1	1		0	0	0	0	0	0	0	0	0
A6	Biodiesel B100	1	1	1	1	0		0	0	0	0	0	0	0	0
A7	Biogas	1	1	1	1	0	0		0	0	0	0	0	0	0
A8	Biogas hybrid	1	1	1	1	0	0	0		0	0	0	0	0	0
A9	Electric hybrid	1	1	1	1	0	0	0	0		0	0	0	0	0
A10	Electric vehicles	1	1	1	1	0	0	0	0	0		0	0	0	0
A11	Energy Efficiency	0	0	0	0	0	0	0	0	0	0		0	0	0
A12	Modal Shifts	1	1	1	1	0	0	0	0	0	0	0		0	0
A13	Modular Lorries	1	1	1	1	0	0	0	0	0	0	0	0		0
A14	Business Travel	0	0	0	0	0	0	0	0	0	0	0	0	0	

Figure 6 – The results of the analysis of interplay between measures. The effect of each action was reviewed with respect to each of the other measures. If no interplay was found the coordinate in the matrix representing the relationship was assigned a zero. If interplay was found it was assigned 1 or -1 depending on whether or not the interplay had been accounted for in DNV's Effect Calculation model.

In the model it is assumed that efficiency measures and optimization measures related to the vehicle fleet decrease the average fuel consumption of vehicles. Column A1 in figure 6 indicate the effect of Ecodriving (A1) on measures A2-A14 respectively if the effect or degree of implementation of A1 changes. As the effect or degree of implementation of Ecodriving changes, the successive calculation methodology propagates the effect causing a lower (alt. higher) CO_2-emission reduction for the consecutive measures in the model. Figure 3 in chapter 4.1.2 describes how the effect calculation model accounts for the effect of reduced average fuel consumption (measures A1-A4) on measures that cause changes to the vehicle fleet (A5-A10 and A12-A13).

Similarly, column A5 in figure 6 examines the interplay between the introduction of B30 (A5) and measures A1-A4 and A6-A14. If additional vehicles are converted into B30 vehicles it would result in a decreased effect of the efficiency and optimization measures. In the DNV Effect Calculation model the baseline data on the number of vehicles and average fuel consumption is set as an input to the first efficiency measure within the action plan. This means that the effect of efficiency and optimization measures is calculated based on the initial number of vehicles in the vehicle fleet. As the operational and technological measures are implemented, the actual number of diesel vehicles in the vehicle fleet decreases with time. Hence, there is a risk that the effect calculation model causes misleadingly high results on the reduction potential of the project.

5.2.2 Modifications to Account for Additional Interplay

DNV's Effect Calculation model has been expanded to more accurately account for interplay between measures that cause changes to the vehicle fleet and measures that decrease average fuel consumption. Baseline data on the number of vehicles in the vehicle fleet has been set as an input to the first measure within the action plan that cause changes to the vehicle fleet, see figure 7.

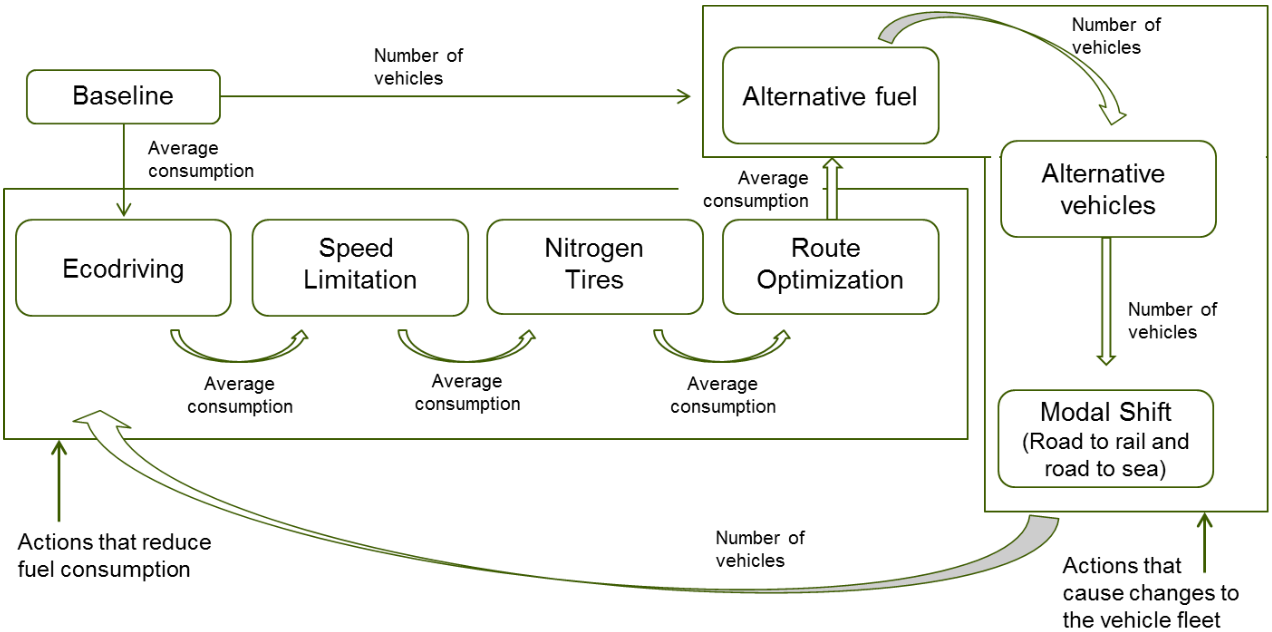

Figure 7 – Modified structure of the Effect Calculation model. The modified structure accounts for the effect of measures that cause changes to the vehicle fleet on measures that reduce fuel consumption.

Data on the number of vehicles is successivly altered as the following measures are implemented. The effect of the efficiency and optimization measures is then calculated based on the number of vehicles in the vehicle fleet after the implementation of measures that cause changes to it.

In order not to underestimate the effect of the efficiency and optimization measures the number of introduced alternative vehicles is summarised. The effect of the efficiency and optimization measures is then calculated for diesel and alternative fuels/vehicles separately. An example of the structure of the effect calculation procedure for a measure that reduces average fuel consumption is given in Appendix G.

5.3 The Structure of the Model

The general structure of the Uncertainty Analysis Model for Posten's CO_2-reduction project is described by figure 8. It is based on a merger of DNV's Effect Calculation Model, developed to calculate the effect of Posten's CO_2-reduction project, and DNV's Uncertainty Analysis model, a well-applied MS Excel model for uncertainty analysis in @Risk.

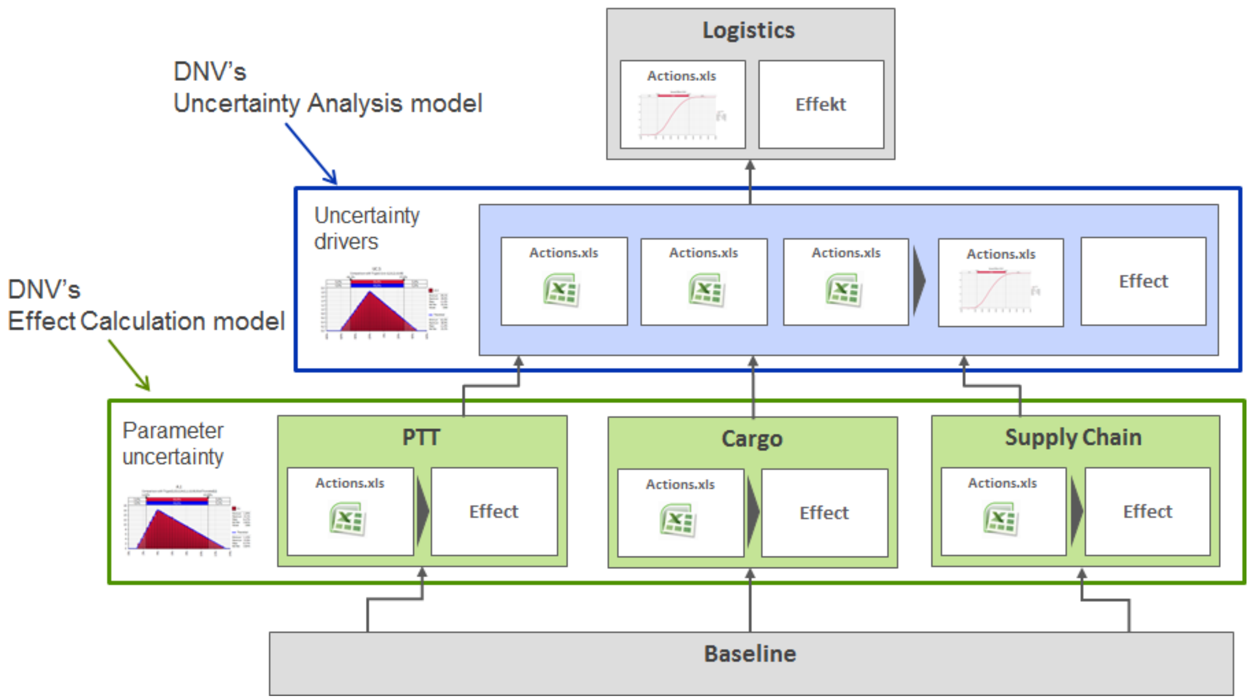

Figure 8 – The general structure of the uncertainty analysis model for Posten's CO_2-reduction project for the division Logistics. The effect is calculated based on baseline data in 2010. Parameter uncertainties are incorporated into the three effect calculation models, for the business units PTT, Cargo and Supply Chain respectively. The effect of the uncertainty drivers is superimposed on the calculated effect of the measure within the three Effect Calculation models.

At the first level of the merged model, parameter uncertainties are incorporated into the Effect Calculation Model for each business unit. The parameter uncertainties induce uncertainty into the effect of each individual measure and the output effect is represented by a distribution instead of a point value.

At the second level, the identified uncertainty drivers are superimposed on the effect distribution of each measure as calculated by the business unit's Effect Calculation Model. In contrast, when performing an uncertainty analysis of a project investment, the effect of the uncertainty drivers is directly superimposed on the parameter uncertainties.

Finally, the results of the measures and the uncertainty drivers are combined and an expression of the distribution for the CO_2-reduction potential of the division Logistics' action plan is derived.

5.3.1 Handling parameter uncertainty

The calculation of the CO_2-reduction potential of the action plan includes several uncertain parameters. To get an accurate image of the uncertainty connected to the outcome of the project, this uncertainty needs to be propagated through the effect calculation model. Instead of estimating the uncertainty of each measure, as is done with the cost elements in DNV's Uncertainty Analysis model for project investments, the uncertainty in each parameter is defined and then applied within the effect calculation model. The effect calculation model replaces step 1 in DNV's Uncertainty Analysis model. Thus, the effect calculation model treats parameter uncertainty at the lowest level practically possible. The parameter uncertainty is propagated through the model by means of Latin Hypercube sampling. By propagating parameter uncertainties through each Effect Calculation Model effects induced by interplay between uncertain parameters is accounted for.

5.3.2 Handling uncertainty drivers

Uncertainties that are not related to any specific parameter in the effect calculation model are superimposed on the results from the Effect Calculation Model; these represent the uncertainty drivers in DNV's Uncertainty Analysis model. An example of an uncertainty driver is 'Biofuel Availability and Infrastructure', which affects the implementation potential of alternative fuels and vehicles. The seven main identified uncertainty drivers and their relation to the different measures is summarized in figure 9. A more thorough description of each uncertainty driver and their potential impact on the different measures is given in Appendix E.

Action / Uncertainty driver	Ecodriving	Speed limitation	Nitrogen tires	Route optimization	Alternative fuel B30	Alternative fuel B100	Alternative fuel biogas	Biogas hybrid	Hybrids	Electrical vehicles	Modular Lorries	Modal shift	Energy efficiency	Business travel	U1	U2	U3	U4	U5	U6	U7
U1 -Biofuel availability and infrastructure	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
U2 - Market structure	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
U3 - Technological development	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
U4 - Modal shift infrastructure	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
U5 - Political framework	0	0	0	0	1	1	1	1	1	1	0	1	0	0	1	1	1	1	0	1	1
U6 - Posten's ability to implement	1	1	1	1	0,5	0,5	0,5	0,5	0,5	0,5	1	0,25	1	1	0	0	0	0	0	0	0
U7 - Subcontractor's ability to implement	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0

Figure 9 – The uncertainty drivers affect different parts of the project plan. The matrix describes which and to what degree the uncertainty drivers affect the different measures. Biofuel Availability and Infrastructure is for example assumed to have an effect on all measures that introduce alternative fuels and vehicles to the vehicle fleet.

As in DNV's Uncertainty Analysis model the uncertainty drivers are affecting the results from step 1 in the model by a percentage change. A matrix, see figure 10, containing the factors in figure 9 describes which and to what degree the different uncertainty drivers affect the implementation of a certain action.

Posts	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	Total GHG reduced per post @Risk(E)
PTT																
Ecodriving																
Year 0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
Year 1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
Year 2	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	266
Year 3	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	594
Year 4	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	1 039
Year 5	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	1 585
Speed Limitation																

Figure 10 – Extract from the Uncertainty Analysis Model for Posten's CO_2-reduction project. The matrix shows that the uncertainty drivers U.3 and U.6 may affect the implementation and effect of Ecodriving.

To calculate the projects total CO_2-reduction potential the percentage change induced by the uncertainty drivers is added to the results from the Effect Calculation Model, see equation 3.

$$Total\ CO_2\ reduction = A + A \cdot U \cdot f \qquad (3)$$

Where A represents the effect due to the implementation of an action, U is the percentage change induced by the uncertainty driver and f is the factor in the matrix describing to what degree the action is affected by the uncertainty driver.

5.3.2 Assigned probability distributions

According to Vose (2000) parametric distributions should only be used when information on the behaviour of a parameter comports with the theory behind the distribution. Information that supports the use of a specific parametric distribution has not been attained for any of the identified uncertainties. Consequently, non-parametric distributions have been used throughout the model.

The most commonly used non-parametric distribution is the triangular distribution. It sets the probability of occurrence for the estimated best and worst case to zero (Palisade Corporation, 1996). Hence, if input parameters are defined by the triangular distribution extreme values are not taken into account during simulation. To avoid this problem all of the identified parameter uncertainties and uncertainty drivers have been described by the non-parametric Trigen-distribution in @Risk.

As described in chapter 3.4 the Trigen-distribution complements the uncertainty estimate with a confidence interval. In addition to including best and worst cases the confidence interval takes height for the risk that heuristics biases has caused overconfidence in the attained expert judgements. Equation 4 describes how the Trigen-distribution is assigned to an estimate in @Risk. In this case, the first three entries into the @Risk Trigen-function represent the minimum, most likely and maximum effect of Ecodriving. The last two entries represent the confidence interval [p,q].

$$Effect\ of\ Ecodriving = RiskTrigen(1\%; 4\%; 6\%; 10; 90) \qquad (4)$$

A confidence level of 80% has been set to all of the attained uncertainty estimates. Thus, during simulation the Trigen-distribution will account for a 10% lower minimum and a 10% higher maximum value than would the triangular distribution. Estimates based on values found in the literature have been assigned the same confidence interval.

By means of the function RiskTruncate in @Risk, distributions within the model have been truncated not to include unrealistic values. For example, the effect of Ecodriving has been truncated not to include negative values since it is unlikely to increase CO_2-emissions, see equation 5.

$$Effect\ of\ Ecodriving = RiskTrigen\big(1\%; 4\%; 6\%; 10; 90; RiskTruncate(0;)\big) \quad (5)$$

A list of all parameter uncertainties taken into account and their input value into the effect calculation model can be found in Appendix F. Correspondingly, input values for the uncertainty drivers are found in Appendix E.

5.3.4 Handling correlation between variables

The developed model contains a number of parameters and uncertainty drivers that needs to be correlated. For example, the input parameter 'emission reduction B30' is dependent on the outfall of 'emission reduction B100' and the uncertainty driver 'Biofuel availability and infrastructure' (U1) is highly dependent on the uncertainty diver 'Political framework' (U5). For example, political decisions and subsidies can increase investor confidence by creating financial incentives for investments in biofuel production and infrastructure.

Correlation between parameter uncertainties and uncertainty drivers have been built into the model by means of conditional branching. The distributions for parameters that are dependent on another variable have been divided into two distributions, e.g. the uncertainty driver U1 has been divided into two distribution; U.1.1 and U.1.2, see figure 11. Distribution U.1.1 represents U1 when the political conditions are disadvantageous; U.1.2 on the other hand represents U1 when political conditions are favourable.

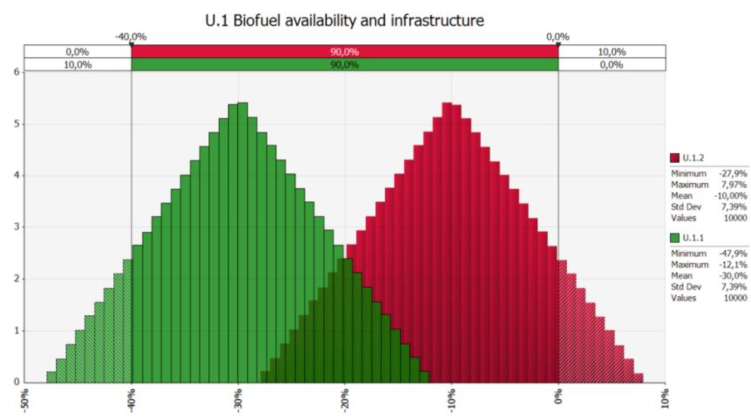

Figure 11 – The two distributions, U.1.1 and U.1.2, describing the uncertainty driver 'Biofuel Availability and Infrastructure' (U.1). Dividing the probability distribution in two enables conditional branching.

By means of an 'if statement' the two probability distributions are correlated to U5:

$$U5 = RiskTrigen(-40; -30; 20; 10; 90) \quad (6)$$

$$U1 = RiskMakeInput\big(IF(U.5 > 0\ ; U1.1; U1.2)\big) \quad (7)$$

When U5 (equation 6) is negative the cost of the measures it affects decrease. When implementation costs decrease it is likely that the degree of implementation increases. The 'if statement' implies that if U5 is positive then a value from distribution U.1.1 should be sampled, see equation 7.

6. Results and Analysis

The uncertainty analysis was performed in @Risk by means of Latin Hypercube Sampling. As Posten's aim is to reduce CO_2 emissions with 30% before 2015 the analysis endpoint has been set to be the percentage reduced emissions in 2015. The squared multiple correlation coefficient (R^2) was found to be above 0.6 for all outputs and throughout the analysis multivariate stepwise regression was used to analyse the sensitivity of input variables. This chapter presents the results of the uncertainty analysis and ends with a discussion about the possibilities of improving project efficiency and effectiveness.

6.1 Percentage Reduced Emissions in 2015

Inserting point estimates into the model results in an expected CO_2-reduction of 12.58% in 2015 while the total uncertainty model results in a mean of 10.4% reduced with a standard deviation of 3.5%. When only parameter uncertainties are considered the mean percentage reduced increases to 13.4%, with a standard deviation of 2.89%. Results of the partial and total uncertainty analysis respectively are shown in figure 12.

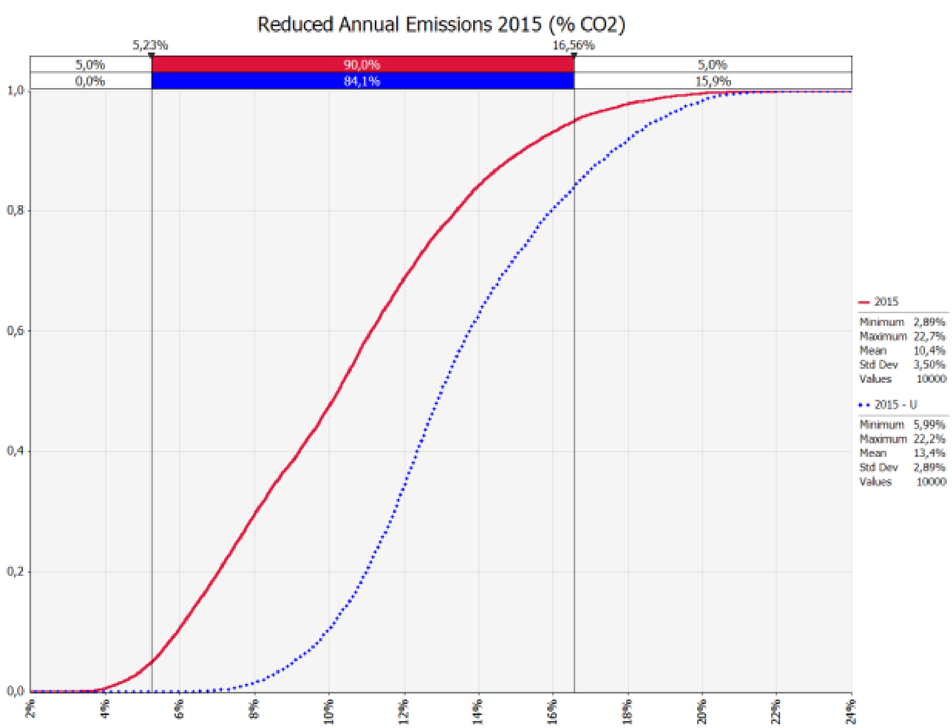

Figure 12 – The red full curve displays results of the uncertainty analysis when uncertainty drivers have been accounted for and the blue dotted line the results when only parameter uncertainty is considered. The red full line is statistically dominant over the blue dotted line. In this case it means that the uncertainty drivers have an overall negative impact on the results. To improve project results, Posten should strive to decrease the effect of external and internal factors.

The dashed line displays the result of the partial model, when uncertainty drivers are excluded, while the full line displays the result of the total model. A comparison between the partial and the total uncertainty analysis show that the uncertainty drivers have an overall negative impact on the CO_2-reduction potential of the project. Unless more efficient measures are developed or new political incitements for investments in green technology are created, the results of the project will not be higher than the results gained by the partial model.

6.1.2 Sensitivity analysis

To identify the most influential uncertainty drivers and parameter uncertainties a sensitivity analysis was performed on the output. According to the tornado diagram, see figure 13, the most sensitive input parameters and uncertainty drivers are 'Emission reduction B30' (E.1), 'Subcontractor's ability to implement measures' (U.7), 'Biofuel availability and infrastructure' (U.1), 'Technological development' (U.3) and 'Effect of Ecodriving' (A.1). A full list of ID's for the input parameters is found in Appendix E and F.

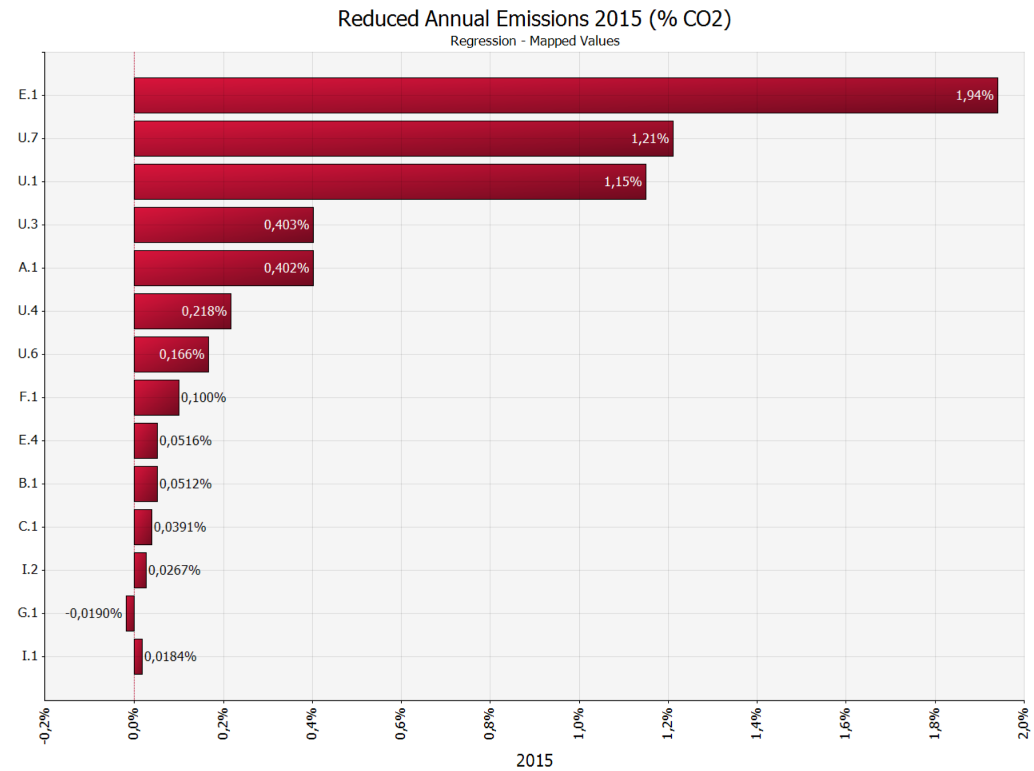

Figure 13 – The tornado graph displays the input parameters that have the largest impact on the variability of the percentage reduced emissions in 2015. The mapped regression value for E.1 means that if E.1 is changed with a +1 standard deviation the reduced emissions in 2015 will increase by 1.94%. If, on the other hand, the standard deviation of E.1 is changed by a -1 standard deviation the reduced emissions in 2015 will decrease by 1.94%. The same reasoning applies to all of the other variables in the tornado graph, except for G.1 (Emission reduction Electric vehicles). An increase in G.1 will instead cause a decrease in the percentage reduced emissions. The difference depends on how the variables have been defined in the model. E.1 is defined as the percentage reduced if a vehicle is converted; hence an increase of this factor would cause an increased reduction. G.1 is instead defined as the emissions per consumed kWh and an increase of this parameter will therefore cause a decreased reduction.

6.2.3 Output target scenario analysis

By looking at a worst and a best case scenario it is possible to get an idea of what makes the difference between project success and failure. This method of scenario analysis should not be confused with the way event uncertainty is modelled in the DNV Uncertainty Analysis model. It is simply a technique of finding out what parameters or uncertainty drivers to monitor and control in order to reach a desirable result or avoid a certain risk scenario.

The aim of the scenario analysis is to find the input variables that are significant if the output is to meet the entered scenario. Two scenarios were analysed; the first one setting the output target to below 7.50% and the second to above 12,73% reduced emissions in 2015, see figure 14.

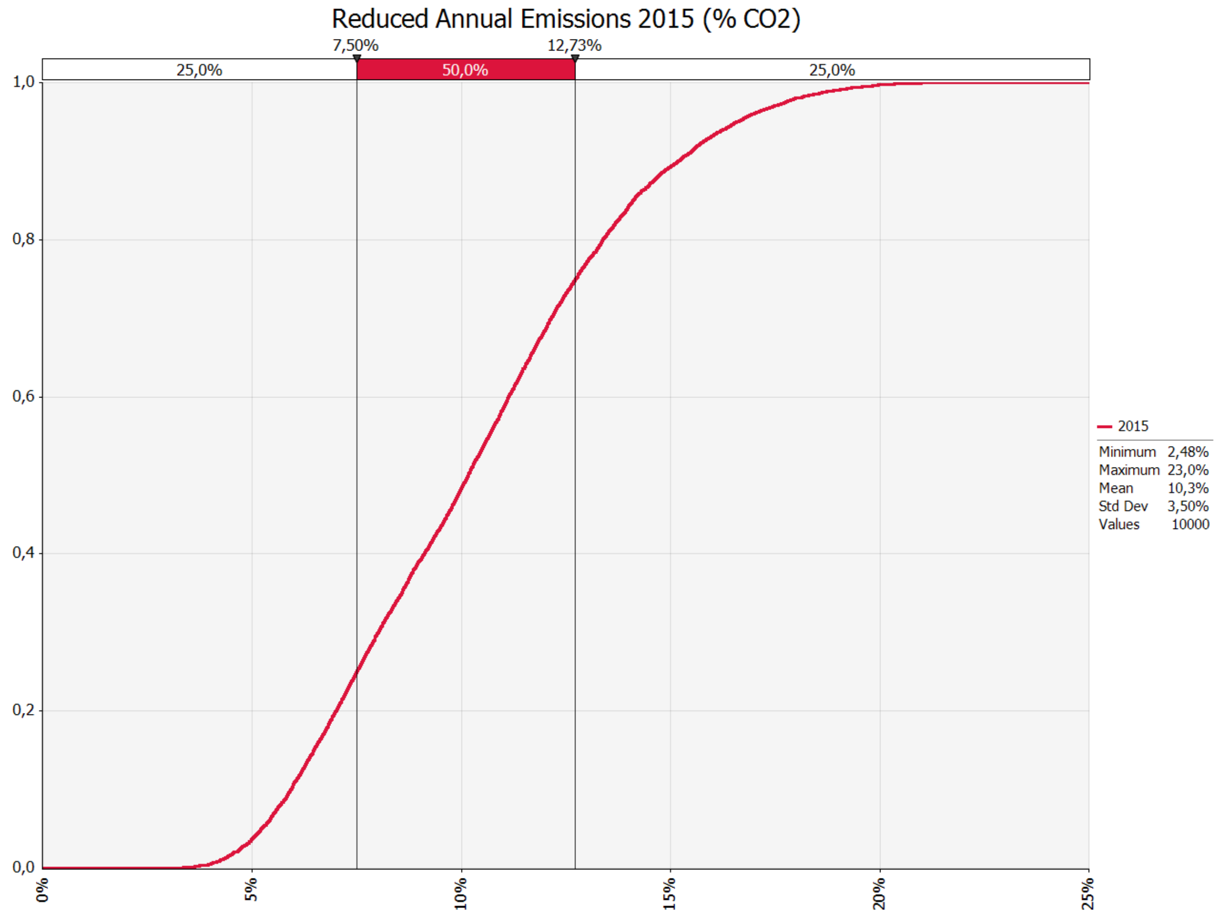

Figure 14 – The percentage reduced emissions in 2015 with the 25th and 75th percentiles marked. The 25th percentile is 7.50% while the 75th percentile is 12.73%. Two scenarios were analysed, one where the target was set to the output being lower than the 25th percentile (between 2.48% and 7.50% CO2 emissions reduced) and the other where the target was set to the output being higher than the 75th percentiles (between 12.73% and 23% emissions reduced).

The worst case scenario has been defined as the percentage reduced in 2015 being lower than its 25th percentile, which is equal to an emission reduction lower than 7.50%. Figure 15 shows the key inputs affecting the output in the worst case scenario. When the percentage reduced annual emissions is below 7.50% the key inputs affecting the output are the 'Subcontractors ability to implement measures' (U.7), 'Posten's ability to implement measures' (U.6), 'Biofuel Availability and Infrastructure' (U.1), 'Infrastructure – Modal Shift' (U.4) and 'Technological development' (U.3).

To avoid the worst case scenario Posten needs to ensure that the Subcontractors fulfil their commitments and that the own organization implement the measures that are in their control. It is also important that Posten communicates with external shareholders about their need of biofuel and modal shift infrastructure. The worst case scenario is also affected by technological development which is an uncertainty driver that Posten has very limited control over.

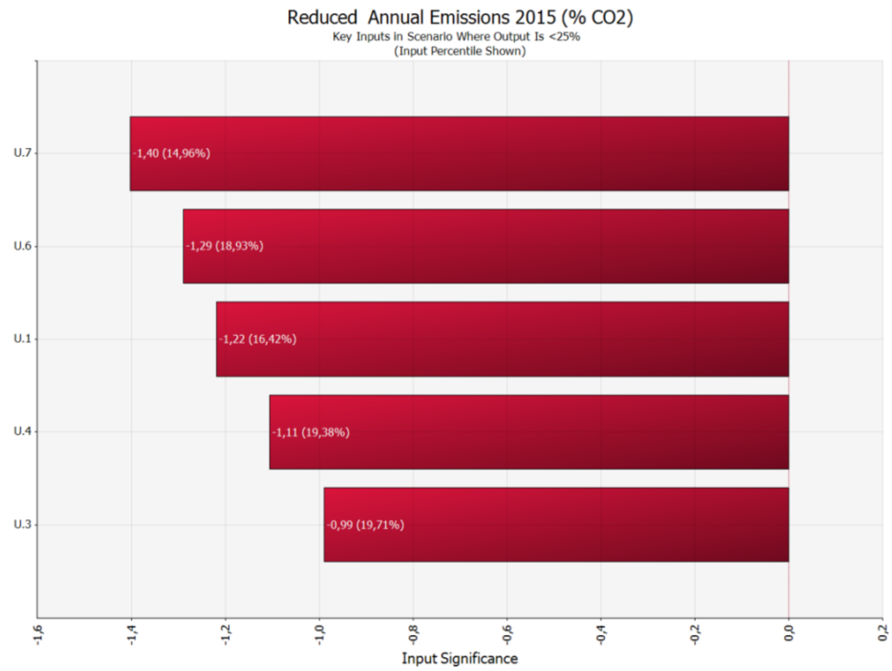

Figure 15 – Tornado graph for the worst case scenario where the output target has been set to result being lower than the 25th percentile value. The input percentiles that risk causing this scenario are a percentile below 14.96% for U.7, 18.93% for U.6, 16.42% for U.1, 19.38% for U.4 and 19.71% for U.3.

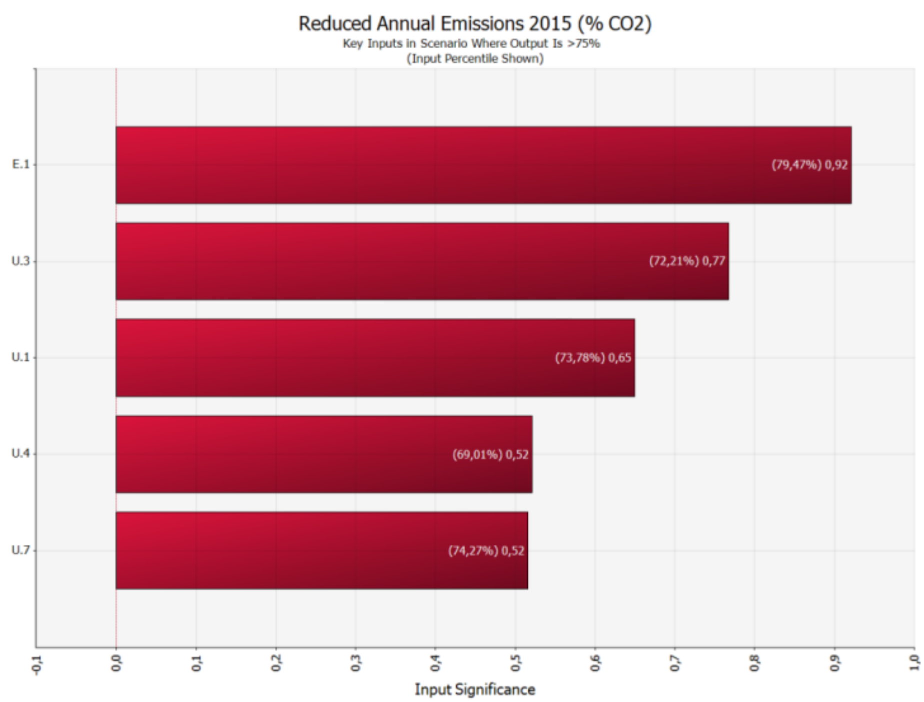

Figure 16 – Tornado graph for the best case scenario when the output target has been set to results being higher than the 75th percentile value. The input percentiles needed to create the scenario of an emission reduction between 12,73% and 23% are a percentile above 79.4% for E.1, 72,21% for U.3, 73.78 for U.1, 69,01% for U.1 and 74.27% for U.7.

The best case scenario has been defined as the percentage reduced emissions in 2015 being higher than its 75th percentile. Figure 16 shows the input variables which must attain values in their respective upper percentile if the percentage reduced emissions in 2015 is to be above 12.73%. The key inputs affecting the best case scenario are 'Emission reduction B30' (E.1), 'Technological development' (U.3), 'Biofuel Availability and Infrastructure' (U.1), 'Infrastructure – Modal Shift' (U.4) and 'Subcontractors ability to implement measures' (U.7).

6.2.4 Project costs

Costs are presented as negative values and profits as positive values. The mean cost per ton CO_2-reduced during the period 2010 to 2015 is -257 NOK, with a standard deviation of 2 456 NOK. The 90% confidence level for the cost per ton CO_2-reduced is -4 354 to 3 620 NOK, see figure 17.

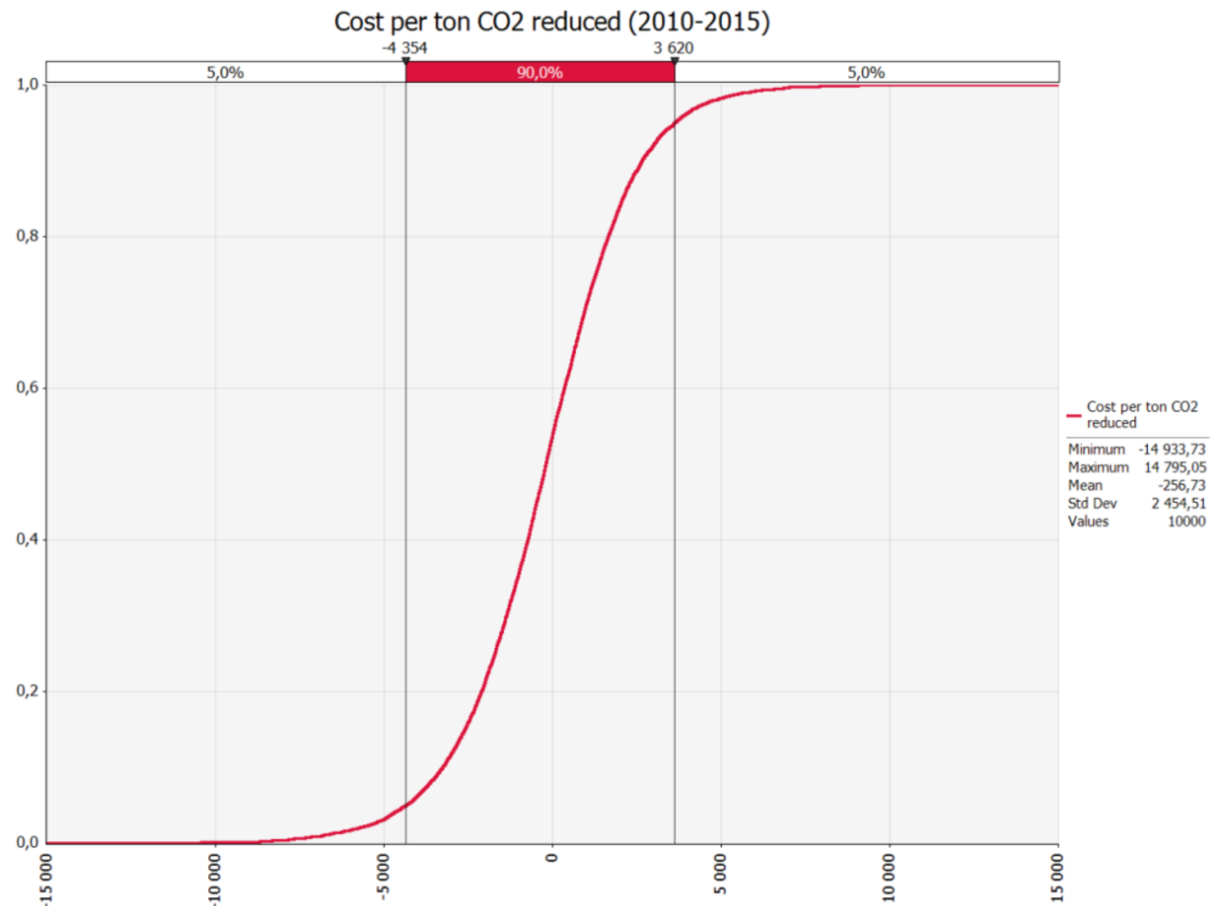

Figure 17 – Cost per ton CO_2-reduced during the period 2010 to 2015. The mean cost per ton CO_2-reduced is -256 NOK with a standard deviation of 2 456 NOK. The expected cost of the project is slightly shifted towards a net loss.

Sensitivity analysis results for cost per ton CO_2-reduced is shown in figure 18. The most sensitive factors are 'Fuel price Diesel' (CE.1), 'Fuel price B30' (CE.12), 'Effect of Ecodriving' (A.1), 'Capital Expenses Modal Shift Air to Road' (CI.4), 'Fuel price B100' (CE.23), 'Operational Expenses Road to Rail' (CI.7) and 'Effect of Nitrogen Tires' (C.1)

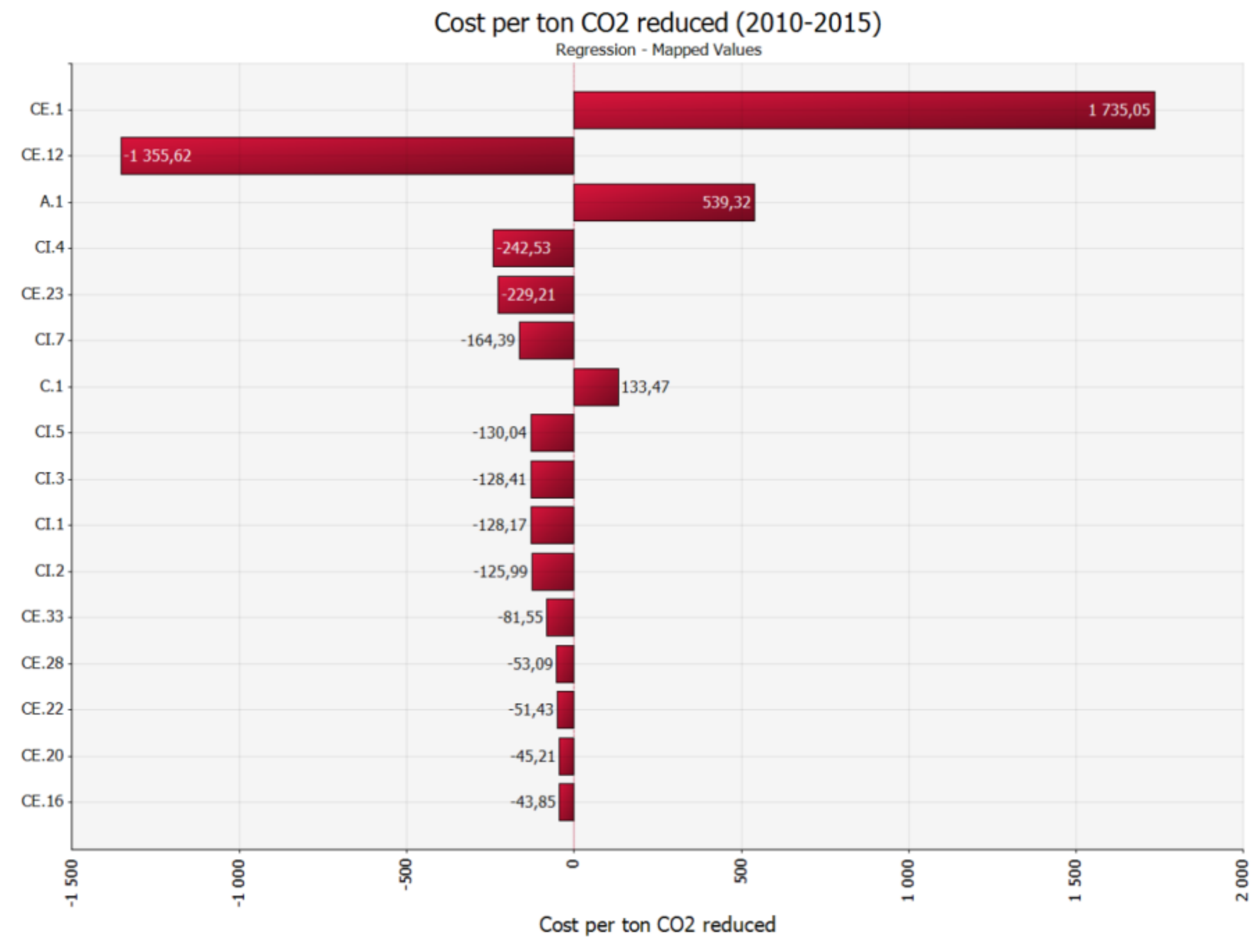

Figure 18 – The tornado graph displays the input parameters that have the largest impact on the variability of the cost per ton CO_2-reduced during the period 2010 to 2015. The most influential factors are the fuel price for diesel (CE.1), fuel price for B30 (CE.12) and the effect of Ecodriving (A.1). If the effect if Ecodriving is increased by one standard deviation the cost per reduced ton CO_2 is decreased by 539 NOK, resulting in a net profit per ton CO_2-reduced. If instead the fuel price for B30 is increased by one standard deviation the cost per ton CO_2 is increased by 1 356 NOK resulting in an increased net cost per ton CO_2-reduced.

The cost effectiveness of the project increases with the fuel price of diesel, the effect of Ecodriving and Nitrogen Tires. Cost effectiveness is instead reduced if the fuel price for B30, the capital expenses for modal shifts from air to road, the fuel price of B100 and the operational expenses for modal shifts from road to rail is increased.

6.1.1 Effect of uncertainty drivers

Table 2 shows the total effect of the uncertainty drivers that affect the amount CO_2-reduced.

Table 2 – The effect and standard deviation in ton CO_2 of the uncertainty drivers that affect the amount CO_2 reduced during the time period 2010 to 2015.

Uncertainty driver	Mean effect (ton CO_2)	Standard deviation (ton CO_2)
Biofuel Availability and Infrastructure (U.1)	-19 998	15 825
Technological Development (U.3)	7 660	6 644
Infrastructure – Modal Shift (U.4)	-4 073	2 843
Posten's ability to implement measures (U.6)	-1 150	2 560
Subcontractor's ability to implement measures (U.7)	-22 726	18 747
Total effect	**-40 287**	

Table 3 shows the total effect of the uncertainty drivers that affect project costs.

Table 3 – The total effect and standard deviation in NOK of the uncertainty drivers on project costs during the time period 2010 to 2015.

Uncertainty driver	Mean effect (NOK)	Standard deviation (NOK)
Market structure (UC.2)	-1 243 700	9 278 188
Political framework (UC.5)	3 133 410	11 910 149
Total effect	**1 889 710**	

6.1.3 Effect of B30 and Ecodriving

The tornado graph for the output 'Percentage reduced emissions in 2015' displayed E.1 and A.1 as the most sensitive parameter uncertainties. Both E.1 and A.1 are positively correlated with the output with Pearson Correlation coefficients of 0,956 and 0,361 respectively. In agreement with the sensitivity analysis results, the correlation coefficients imply that the percentage reduced emissions in 2015 is more dependent on E.1 than on A.1.

Figure 19 shows the total effect, in ton CO_2 reduced, of measures E.1 and A.1 during the period 2010 to 2015. The red and blue curves represent A.1 with and without the influence of uncertainty drivers, whereas the green and lilac curves show the effect of E.1 with and without the influence of uncertainty drivers.

The differences in effect between the two curves for A.1 and E.1, respectively, indicate that E.1 is affected by additional external and internal factors. Hence, the implementation of E.1 is associated with a higher degree of uncertainty and will be harder for Posten to steer than A.1.

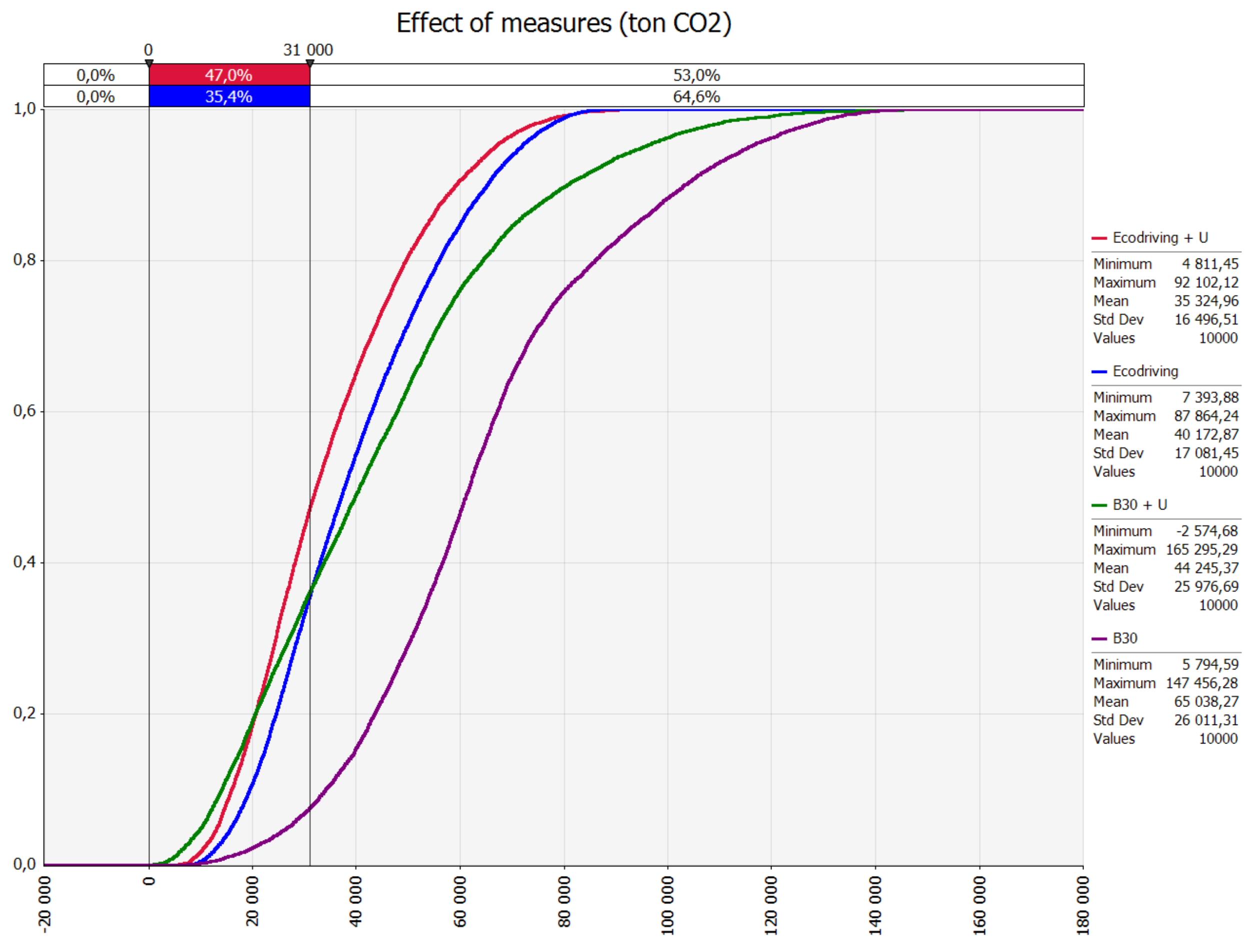

Figure 19 – Total amount of CO_2-reduced due to measures B30 (E.1) and Ecodriving (A.1). The red curve represents the effect of A.1 when influenced by uncertainty drivers as well as parameter uncertainties and the blue curve shows the effect of A.1 when only parameter uncertainties are accounted for. Similarly, the blue curve represents the total effect of E.1 when uncertainty drivers are accounted for while the lilac curve shows the effect of E.1 when only parameter uncertainties are taken into account.

6.2 A Biogas Scenario

The maximum percentage reduced emissions that can be achieved by the initial action plan is 22.7%, as indicated by figure 12. Posten's goal is to reduce CO_2 emissions by 30% in 2015. Hence, it is interesting to explore alternative designs of the action plan to see if there is a more effective way to reduce emissions.

The effect of B30 has been identified as one of the key parameters affecting the percentage reduced emissions in 2015. B30 has a relatively low reduction potential and the effectiveness of converting vehicles to use biodiesel as a fuel has been tested by altering the project plan. The number of vehicles converted to B30 in the initial project plan was converted to biogas hybrids and the vehicles previously converted to use B100 as a fuel was converted to biogas vehicles.

6.3.1 Percentage reduced emissions in 2015

The change of the action plan results in a mean of 17.6% reduced emissions in 2015 with a standard deviation of 7.02%. With a confidence level of 90% the reduced emission will be between 7.32% and 29.47%, see figure 20. This is an increase compared to the percentage reduced according to the initial project plan.

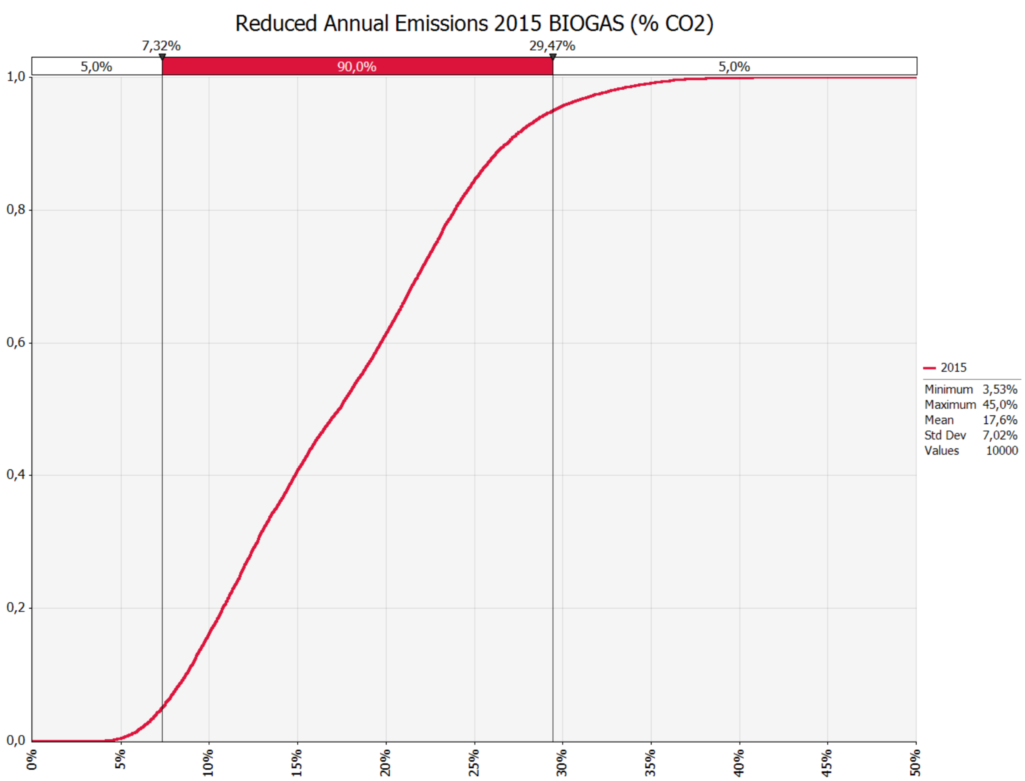

Figure 20 – Percentage reduced emissions in 2015 when the measures for biodiesel are repleced by biogas measures. The mean persentage reduced is 17.6% and the standard deviation is 7.02%. This corresponds to a 69% higher mean, a 98% higher maximum and a 22% higher minimum compared to the percentage reduced emissions in 2015 caused by the initial project plan (from 10.5% to 17.6%, 22,7% to 45% and 2.89% to 3.53% respectively).

Figure 21 shows the sensitivity analysis results for the biogas scenario. The most sensitive input parameters and uncertainty drivers are 'Emission reduction Biogas' (E.4), 'Subcontractors ability to implement measures' (U.7), 'Biofuel Availability and Infrastructure' (U.1), 'Technological development' (U.3) and 'Posten's ability to implement measures' (U.6).

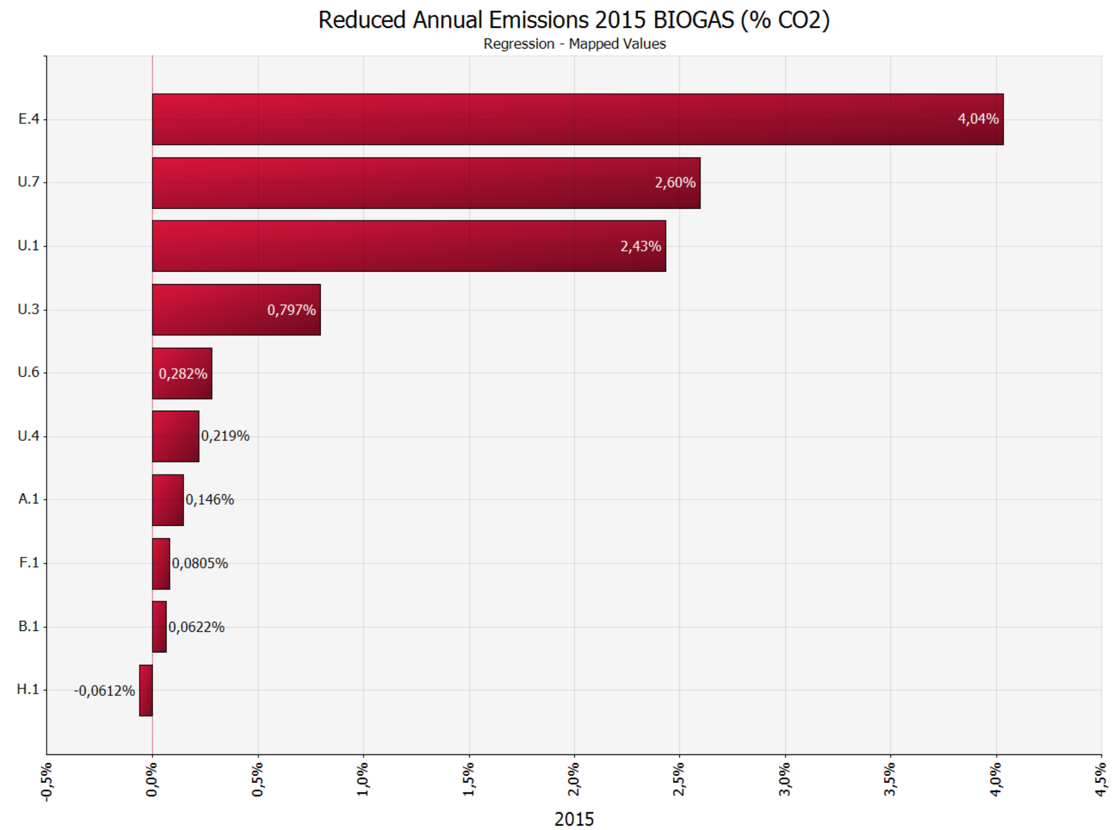

Figure 21 – The tornado graph displays the input parameters that have the largest impact on the variability of the percentage reduced emissions in 2015 for the Biogas scenario. E.4 is displayed as the most sensitive parameter. The mapped regression value for E.4 means that if E.4 is increased by one standard deviation the reduced emission in 2015 will increase by 4.04%. If, on the other hand, the standard deviation of E.1 is decreased by one the output will decrease by 4.04%. The same reasoning applies to all of the other input variables shown in the graph, except 'Emission electricity' (H.1) which if it is increased by one standard deviation causes a decrease instead of an increase of the output.

6.3.1 Project costs

The Biogas scenario results in a mean profit of 2 142 NOK per ton CO_2-reduced with a standard deviation of 1 974 NOK. With a confidence level of 90% the cost per ton CO_2-reduced is between -518 and 5 745 NOK, see figure 22. The confidence level represents both a decrease in loss and an increase in profit compared to the initial plan.

Sensitivity analysis results for cost per ton CO_2-reduced of the changed project plan is shown in figure 23. The most sensitive factors are 'Fuel price Diesel' (CE.1), 'Fuel price Biogas hybrid' (CE.45), 'Subcontractors ability to implement' (U.7), 'Emission reduction Biogas hybrid' (E.4), 'Biofuel Availability and Infrastructure' (U.1), 'Fuel price Biogas' (CE.34), 'Emission reduction Ecodriving' (A.1) and 'Capex Air to Road' (CI.4).

As the fuel price for diesel increases the cost effectiveness of the project increases, if instead the fuel price for biogas is increased this causes a higher cost, alternatively lower profit, per ton CO_2-reduced. The estimates for the capital and operational expenses for modal shift measures are very rough estimates and the tornado graph indicate the importance of specifying these costs further.

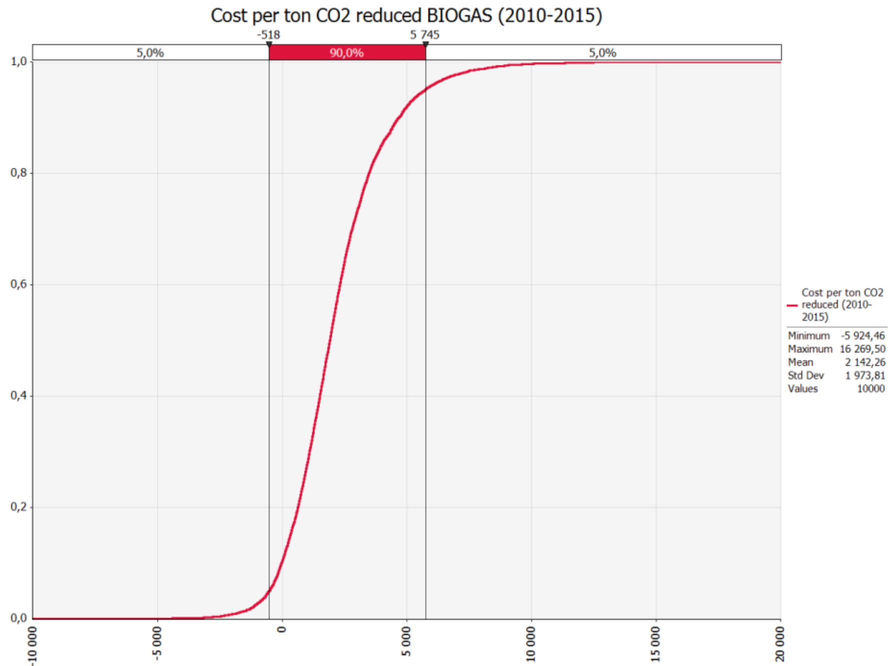

Figure 22 – Cost per ton CO_2 reduced for the Biogas scenario during the period 2010 to 2015. The mean cost per ton CO_2-reduced is a profit of 2 142 NOK with a standard deviation of 1 974 NOK. The expected cost of the project is shifted towards a net profit. The standard deviation for cost of the altered project plan is decreased by 482 NOK and the mean cost is increased by 2 399 NOK which results in a net profit per ton CO_2 reduced.

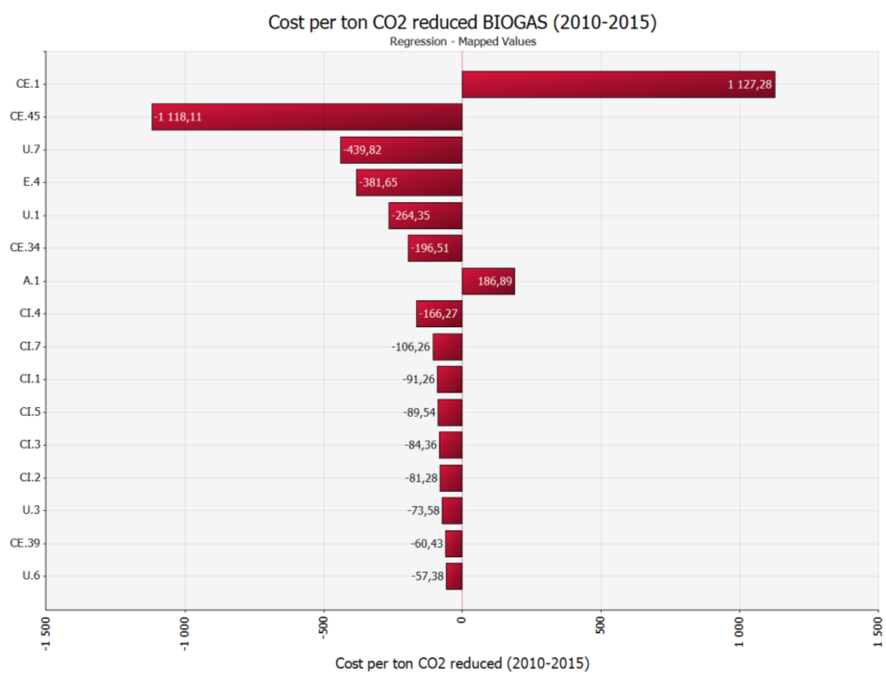

Figure 23 – The tornado graph displays the input parameters that have the largest impact on the variability of the cost per ton CO_2 reduced during the period 2010 to 2015. The most influential factors are the fuel price for diesel and biogas hybrids. If the fuel price for diesel is increased by one standard deviation it would result in an increased profit of 1 127 NOK per ton CO_2-reduced. An increase of one standard deviation of the fuel price for biogas hybrids would instead increase costs per ton CO_2-reduced by 1 118 NOK.

6.3 Analysis of Results

In contrast to a point estimate of the effect of the project, the uncertainty analysis gives additional information about the confidence of the estimate and of which factors that have the largest influence on the outcome of the project.

The comparison between the partial and the total model indicate that the uncertainty drivers induce a mean decrease of 3% on the overall project results. It is therefore important for Posten to identify the most influential uncertainty drivers and to monitor and steer them in the right direction. This observation is strengthened by the fact that throughout the uncertainty analysis the uncertainty drivers were displayed as influential factors with high potential to impact the outcome of the project.

Project efficiency could be improved by decreasing uncertainty in the results. To decrease uncertainty in the results Posten should focus on gathering more information about the parameter uncertainties and uncertainty drivers that the tornado graphs revealed to be the most significant. It could, for example, mean that Posten takes the following measures to reduce uncertainty:

- Sets demands for the Subcontractors environmental performance.
- Further engages employees in working towards overall enhanced environmental performance.
- Make efforts to influence the market by communicating their need for biofuel infrastructure.
- Investigate possible suppliers for biofuels to determine production pathway.

To improve project effectiveness Posten should monitor external factors and keep the project plan flexible. The gathering of more information is unlikely to improve the outcome by more than 3.5% (one standard deviation) while making changes to the project plan could have a far greater effect. As new information becomes available it is probable that the project plan needs to be reviewed in order to ensure that the measures that are implemented are effective.

The analysis showed that mean percentage reduced emissions in 2015 was 10.4% with a minimum percentage of 2.89 and a maximum of 22.7%. As Posten aims at reducing CO_2-emissions by 30% before 2015 the plan needs to be re-evaluated. When the initial project plan was altered to exclude biodiesel alternatives the overall effect of the project increased. The Biogas Scenario shows that there might be alternative options that both increase cost effectiveness and the probability that the CO_2-reduction goal for 2015 is reached.

It is important to monitor the implications of future environmental policies and directions, for example, it is possible that future policies for better air quality demands that Posten uses gas and biogas when active in city centres. By keeping track of which renewable alternatives that are likely to be subjected to future subsidies the effect of the external factors may be reduced.

According to the EU directive on renewable energy (2009/28/EC) biofuels will only be allowed to be counted as renewable if their GHG reduction is 35% or higher compared to fossil fuels. The EU directive will most probably affect local authorities in their decisions. To increase the probability of project success it is recommended that Posten evaluates EU's and the Norwegian government's long-term strategy for renewable fuels. As it is questionable whether or not B30 will be accepted as a renewable fuel it is of utmost importance for Posten to perform an analysis of alternatives and, if a more efficient alternative is found, to change the action plan accordingly.

7. General Discussion

In this chapter the added value of performing an uncertainty of a CO_2-reduction project is discussed.

7.1 Uncertainty Analysis of CO_2 Reduction Projects

When the effect of a CO_2-reduction project is calculated based on "best estimates" it results in an exclusion of possibly valuable information. An uncertainty analysis enables inclusion of information that would otherwise be lost. The four main reasons for performing an uncertainty analysis, as described by Granger-Morgan and Henrion (1990), applies to CO_2-reduction projects just as well as to decision and optimisation problems within other fields of science.

7.1.1 Increased transparency

Point estimates tend to be conservative as it is common that risks that are identified are incorporated into the estimate. This is indicated by the results from the case study of Posten's CO_2-reduction project where the point estimate showed a lower percentage reduced than the mean value gained by the partial uncertainty analysis model. The deterministic model fails to take positive risks into account.

It is important for a decision maker to know the assumptions upon which an analysis relies. Normally, it is not the decision maker who performs the analysis, but the analyst. This means that the decision maker is dependent on the analyst who must keep track of and communicate identified risks and opportunities. Assigning a distribution to each input parameter helps the analyst to keep track of this information. As the distributions are used as an input to the model the risks and opportunities will not disappear into a report, but will be shown clearly in the results of the analysis.

Explicit instead of implicit treatment of uncertainty increases transparency and enables the decision maker to evaluate the conclusions and limitations of the results. In addition, it will be easy for the analyst to update the results in light of new information.

7.1.2 Optimising the action plan

An uncertainty analysis can also be used to optimize an action plan. Two action plans may result in the same mean reduction potential but be associated to different degrees of uncertainty. If a deterministic model, with point estimates, was used to analyze the effect of the two action plans the difference in confidence level would not be apparent to the decision maker.

When the exact value of a parameter is unknown a lot could be gained by specifying the different sources of uncertainty affecting its value. Information on the sources of uncertainty could help in specifying an interval which most likely comprises the true value of the sought parameter. By identifying the most important parameter uncertainties and specifying the probability intervals for these, it is possible to take all available information into account.

Propagation of uncertainty through a model enables quantification of a confidence level for the emission reduction of the project. The quantification of confidence intervals for the percentage and total reduction in ton CO_2 will give a more accurate image of the effect that can be expected by the implementation of the planned measures. When choosing between two alternative actions plans, such information could be invaluable to the decision maker.

Project costs will have a huge effect on the degree of implementation of a measure and is subject to large uncertainties. It is thus of utmost importance to specify costs and profits related to the measures when designing an action plan. As most emission reduction measures are connected to a profit opportunity it should be possible to design an action plan which both meets the corporate reduction goal and agree with the corporation's financial risk appetite.

7.1.3 Communication

When an action plan has been chosen the confidence interval provides information of how certain it is that the project will lead to the targeted reduction. This in turn, could improve the corporation's ability to communicate their environmental strategy to customers, employees and other stakeholders. How successful the corporation is in communicating their strategy is dependent on their risk communication skills. Communicating statistics with the public can be difficult and the uncertainty analysis is probably more useful in improving internal communication and communication with authorities.

7.1.4 Strategic planning

A sensitivity analysis examines which input variables that matter the most in determining the value of a certain output parameter. It gives the decision maker information about which measures in the project plan that conduce the most to the uncertainty in the results. This enables the corporation to direct future efforts on the parts of the project plan that contribute the most to the uncertainty in the results, thereby, increasing the probability of achieving the target. In this way strategic planning is enabled and the analysis can be used as a basis for decisions as well as to give grounds for the efforts taken.

As illustrated for Posten's CO_2-reduction project it is possible to analyse which input variables matter the most if the project is to achieve a specific target. The results of such an analysis show what percentile values the input parameters must take on if the scenario is to be actualised. By looking at the percentile values needed for the different input parameters the decision maker gains additional information of the feasibility of the scenario.

7.1.5 A wider perspective

The success of a corporate CO_2 management plan is not only dependent on the technical reduction potential of the measures within the action plan. External and internal factors will have a large influence on the outcome as they influence the corporation's ability to implement the measures laid out in the plan. Common practice is to evaluate their effect implicitly after a point value for the project's emission reduction has been calculated, if their effect is evaluated at all. When performing an uncertainty analysis the effect of various external and internal factors is evaluated before the analysis starts. This makes it possible to take their influence into account explicitly, as uncertainty drivers.

In the analysis of Posten's action plan the uncertainty drivers had a large negative impact on the outcome but they affected certain measures more than others. Such, information can help the corporation to decide upon when the different measures are to be implemented. It could be a good idea to start implementing measures that the own corporation has a large influence over.

Knowledge about external and internal factors is also important when setting corporate reduction goals. Explicit treatment of uncertainty drivers increases the corporations understanding of how actors outside the own organization may affect the project outcome. It helps the corporation to avoid being dependent on external actors to succeed. It also enables the corporation to communicate how factors that they cannot influence affect their possibilities to succeed. If managed correctly such information could be used as leverage to influence authorities.

When the effect of both uncertainty drivers and parameter uncertainties is quantified the sensitivity analysis enables comparisons between all uncertainties affecting the output. A more holistic analysis is gained which further strengthens the decision maker's ability to steer the project in a direction which minimizes uncertainty and optimises the probability of success.

7.4 Simplified Model for Increased Usability

To perform an uncertainty analysis can be time consuming and costly and the added value must be weighed against the costs for the analysis. It is therefore interesting to look upon aspects of the uncertainty analysis that may be generalised or simplified.

What level of detail is needed for the analysis to be of aid in the decision process? It is in essence determined by what kind of questions the analysis is to answer. It may not be necessary to specify the uncertainty in the input parameters to the Effect Calculation Model. Instead, the Effect Calculation Model could be used, as before, to calculate the expected effect by means of 'best estimates'. The uncertainty in each measure could then be superimposed on the results from the Effect Calculation Model.

Such a simplified version of the model would not account for interaction between uncertain parameters and its ability to determine the effectiveness of different options would be weakened. However, the model would still provide the decision maker with valuable information on how external factors may affect project outcome.

8. Conclusions

Well-applied theories and methodologies for uncertainty analysis can be applied to CO_2-reduction projects. The results gained by an uncertainty analysis are more informative than if only point estimates are used to calculate the effect of the project. Three main sources of new information have been identified:

- *Increased transparency and a strengthened decision basis* – Conservative point estimates are avoided as the uncertainty analysis takes all available information into account and treats uncertainty explicitly. This increases transparency and enables the decision maker to evaluate the conclusions and limitations of the results.
- *Improved project control and steering* – Sensitivity analyses enable identification of the input variables that are the most influential in determining a certain project outcome. Knowledge of the most influential input parameters improves project control and steering as well as enhances multi-criteria decision making.
- *Enhanced credibility* – Uncertainty analyses enable quantification of confidence intervals for the expected emission reduction. Communication of results with quantified uncertainty leads to increased credibility and improves the corporation's ability to communicate their environmental strategy with employees and authorities.

It can be time consuming and costly to perform an uncertainty analysis. If the methodology is to be used as a tool to aid corporate CO_2 management, the added value must be weighed against the cost of performing the analysis.

9. Suggestions for Future Work

The uncertainty analysis model for Posten's CO_2-reduction project was established to review the additional information that could be gained by an uncertainty analysis of a CO_2-reduction project. During the development process five opportunities for improvement were identified:

Include modelling of trends – The uncertainty analysis model for Posten's CO_2-reduction project uses 3-point estimates to simulate the uncertainty in fuel prices. As the fuel price for diesel and the fuel prices for biofuels are likely to follow different trends this is not a very accurate way of modelling their effect on the cost of the project. Simultaneously, these parameters were displayed as the most sensitive in determining the cost per ton CO_2-reduced. The analysis of project costs could therefore be considerable improved if the 3-point estimates where replaced by projected price trends.

Modelling of Environmental policies – The uncertainty analysis displays that external and internal factors have a substantial effect on the project outcome. It is concluded that these factors are ultimately determined by the political framework. Further effort should therefore be put into modelling the effect of alternative political environmental strategies. For example, the three most likely strategies could be identified and their effect on the project could be simulated as three separate events.

Optimise model design for the analysis endpoint – How an uncertainty analysis model should be built depends on the analysis endpoint. The results of the sensitivity analyses show the influence of parameter uncertainties and uncertainty drivers on the selected output parameter. The parameter uncertainties are defined at a high level of detail and from the analysis results it is difficult for the corporation to see which measure, within the division's action plan, that is subjected to the largest degree of uncertainty. It should therefore be evaluated if it is preferable to display uncertainty in measures or in the parameters that determine the uncertainty connected to the measures.

Expand the scope of analysis - Environmental effect of other greenhouse gases than CO_2 has not been considered; neither does the analysis cover emissions of particulate matter. These emissions could have a profound effect on how the CO_2-reduction project should be designed. It is therefore recommended that the model is expanded to include these effects or that they are analysed implicitly.

Generalisation of model – To limit analysis costs the opportunities of developing a generalised model should be explored. One uncertainty analysis model, applicable to CO_2-reduction projects within different business categories, would improve efficiency and decrease analysis costs.

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11. Appendices

Appendix A – Abbreviations

GHG – Greenhouse gas

DNV – Det Norske Veritas

NTNU – Norges Teknisk-Naturvitenskaplige Universitet

KSG - Det Norske Veritas AS, Advansia AS and Samfunns- og næringslivsforskning AS

RED – The Renewable Energy Directive

Appendix B – Measures Included in the Project Plan

- Ecodriving
- Speed Limitation
- Nitrogen Tires
- Route Optimization
- Alternative fuel B30
- Alternative fuel B100
- Alternative fuel Biogas
- Biogas hybrids
- Electrical hybrids
- Electric vehicles
- Energy efficiency
- Modal Shift Road to Sea
- Modal Shift Road to Rail
- Modal Shift Air to Sea
- Modal Shift Air to Rail
- Modal Shift Air to Road
- Modular Lorries
- Business Travel

Appendix C – Calculation Example of Efficiency and Optimization Measures

Efficiency and Optimization measures reduce the average fuel consumption of vehicles. Table 4 show the measures belonging to this category (category 1).

Table 4 - Efficiency and Optimization measures.

Reduction of fuel consumption
Ecodriving
Speed limitation
Nitrogen Tires
Route Optimization

In the model the effect of these measures is calculated according to equation 8:

$$Reduced\ CO_2 = \Delta C \cdot number\ of\ vehicles \cdot \frac{CO_2\ emission}{l} \quad (8)$$

ΔC is the change in average consumption, see equation 9:

$$\Delta C = C_{in} - C_{out} \quad (9)$$

C_{in} is the average consumption per vehicle before the measure is implemented and C_{out} is the average consumption per vehicle after the measure has been implemented.

Because the measures in category 1 reduce the average consumption of a vehicle their implementation results in a lower average consumption input for the next measure. Consequently they are linked and the C_{out}-values for the first measure become the C_{in}-values for the next measure. The outgoing average consumption is calculated by equation 10.

$$C_{out} = C_{in} - (C_{in} \cdot degree\ of\ implementation \cdot effect\ of\ measure) \quad (10)$$

Where the degree of implementation represents the degree to which Posten has implemented the action. For the different measures in in category 1 this means; the percentage of drivers that has taken the course in Ecodriving, the percentage of vehicles not driving faster than a certain speed limit, the percentage of vehicles which have nitrogen filled tires or a percentage of the maximum possible distance reduction through route optimization.

Appendix D – Calculation Example of Technical and Operational Measures

Technical and Operational measures make changes to the vehicle fleet; either by the introduction of alternative types of fuel or by the exchange of vehicles into more environmentally friendly alternatives. Modal shifts from road to rail and road to sea are also included in this category as the implementation of these measures results in fewer vehicles in the vehicle fleet. Table 5 shows a list of the measures belonging to this category (category 2).

Table 5 - Technical and Operational measures.

Alternative fuel and vehicles
B30
B100
Biogas
Biogas hybrid
Hybrids
Electric vehicles
Modular lorries
Modal shift - Road to sea
Modal shift - Road to rail

The effect of the category 2 measures is calculated by equation 11:

$$Reduced\ CO_2 = \Delta V \cdot C \cdot \frac{CO_2\ emission}{l\ diesel} \cdot emission\ reduction \quad (11)$$

Where, ΔV is the change in vehicle fleet and C is the average consumption per litre fuel. The emission reduction is calculated differently dependent on which of the category 2 measures that is implemented. For example, if the vehicle fleet is decreased due to a modal shift from road to sea the emission reduction is estimated to be the difference in emission between transport by sea and transport by road.

The change in vehicle fleet is calculated by equation 12.

$$\Delta V = V_{in} - V_{out} \quad (12)$$

Where V_{in} represents the number of vehicles in the vehicle fleet after the previous measure has been implemented and V_{out} is the number of vehicles after the current action has been implemented. V_{out} is calculated by equation 13 and is used as an input to the next measure.

$$V_{out} = V_{in} - Vehicles\ converted \quad (13)$$

Appendix E – Uncertainty Drivers

U1	**Biofuel availability and infrastructure**		
Definition:	Irregular or uncertain supply of renewable fuel. The availability of renewable fuel and electricity is crucial if Posten is to introduce alternative fuels and vehicles to their vehicle fleet successfully. *Opportunities:* Increased production of renewable energy results in an increased availability at the market thus, lowering the implementation barrier. Increased production of biogas and biodiesel from waste could lead to an increased mitigation potential. *Risks:* Not enough renewable fuel available to implement all measures.		
Effect:	GHG		
Mean result:	-19 998	**Standard deviation:**	15 825
Estimate uncertainty:	P10	Mode	P90
	-40%	-20 %	0 %
	Risks	Most likely	Opportunities
Affects measures:	Alternative fuel (B30, B100, Biogas) and Alternative vehicles (Biogas hybrids, El-hybrids)		

U2	**Energy prices**		
Definition:	The energy prices for different fuels will have a large influence on the degree to which Posten will be able to implement measures that introduce alternative fuels; the measures must be financially viable. *Opportunities:* Technological development, refined procurement methods, extended infrastructure and increased resource availability results in a decreased cost for renewable fuels. An increase in cost for conventional energy will also increase cost efficiency. *Risks:* Increased cost of renewable energy/fuels due to increased demand and limited availability, decrease in cost for conventional energy/fuels: results in decreased cost efficiency.		
Effect:	Cost		
Mean result:	-1 243 700	**Standard deviation:**	9 278 188
Estimate uncertainty:	P10	Mode	P90
	-30 %	0 %	30 %
	Opportunities	Most likely	Risks
Affects measures:	Alternative fuel (B30, B100, Biogas) and Alternative vehicles (Biogas hybrids, El-hybrids), Energy Efficiency		

U3	Technological development				
Definition:	Technological development within the upcoming years could potentially have a large impact on the CO_2-reduction potential of alternative vehicles and other technological mitigation measures. *Opportunities:* More efficient biofuel production methods or the development of new renewable fuels and/or mitigation measures could further reduce carbon dioxide emissions. *Risks:* There is a slight risk that we find out that some measures are not as efficient as expected. This uncertainty driver could also reduce costs for technologies that are expensive today, but this is not accounted for in the model.				
Effect:	GHG				
Mean result:	7 660	**Standard deviation:**	6 644		
Estimate uncertainty:	P10	Mode	P90		
	-1%	3 %	10 %		
	Risks	Most likely	Opportunities		
Affects measures:	Ecodriving, Nitrogen Tires, Speed Limitation, Route optimization, Alternative Fuel(B30, B100, Biogas), Alternative Vehicles(Biogas hybrid, El-hybrid)				

U4	Modal Shift - Infrastructure		
Definition:	When the environmental plan was set up it was assumed that required infrastructure would be in place when needed. However, the required infrastructure might not be in place. Investments might be needed to provide new sea and rail infrastructure as well as to establish adequate infrastructure for the distribution of renewable fuel. *Opportunities:* It is possible to implement all of the planned modal shifts measures *Risks:* Inadequate transport infrastructure to implement modal shifts. Lack of infrastructure necessary to integrate and maintain new technologies. Results in measures being implemented to a lesser degree than expected.		
Effect:	GHG		
Mean result:	-4 073	**Standard deviation:**	2 843
Estimate uncertainty:	P10	Mode	P90
	-40 %	-20 %	0 %
	Risks	Most likely	Opportunities
Affects measures:	Alternative Fuel(B30,B100, Biogas), Alternative Vehicles(Biogas hybrids, El-hybrids), Modal shift (road to sea, road to rail, air to sea, air to rail)		

U5	Political framework		
Definition:	Transport and energy policies could have a large impact on capital and operational costs. Policies could also affect third party investment choices, hence affecting the uncertainty drivers: availability, technological development and infrastructure. *Opportunities:* Fee systems and biofuel tax systems that provide tax relief for biofuels would increase cost efficiency. By introducing biofuels mandates lack of fuel production and/or delivery infrastructure could be avoided. *Risks:* Market barriers or uncorrected market "failures" could impede the adoption of new technologies.		
Effect:	Cost/GHG		
Mean result:	3 133 410	**Standard deviation:**	11 910 149
Estimate uncertainty:	P10	Mode	P90
	-40 %	0 %	20 %
	Opportunities	Most likely	Risks
Affects measures:	Modal shift, Alternative vehicles, Alternative fuel, (Resource availability, Technological development, Infrastructure)		

U6	Posten's ability to implement measures		
Definition:	For measures to be implemented they must be prioritised within the organisation. Measures such as Ecodriving, Route optimization and business travel are more influenced by the organisation than others. The degree of implementation of these measures is largely dependent on the willingness of the management and employees to act according to the environmental plan. *Opportunities:* Posten implements more measures than planned *Risks:* Lack of trained personnel capable of maintaining, operating or managing a technology and lack of education or training resources. Aversion of high upfront costs or lack of awareness of benefits results in limited uptake of a product of service.		
Effect:	GHG		
Mean result:	-1 150	**Standard deviation:**	2 560
Estimate uncertainty:	P10	Mode	P90
	-10 %	0 %	2 %
	Risks	Most likely	Opportunities
Affects measures:	Ecodriving, Route optimization, Business travel, Energy efficiency, Speed Limitation, Nitrogen Tires, Subcontractors		

U7	**Subcontractor's ability to implement measures**		
Definition:	Subcontractors account for 79% of the corporate groups emissions. The degree to which the contractors implement their environmental plan will therefore be of great importance if the reduction goal is to be reached. *Opportunities:* Subcontractors implement more measures than planned *Risks:* Lack of trained personnel capable of maintaining, operating or managing a technology and lack of education or training resources. Aversion of high upfront costs or lack of awareness of benefits results in limited uptake of a product of service.		
Effect:	GHG		
Mean result:	-22 726	**Standard deviation:**	18 747
Estimate uncertainty:	P10	Mode	P90
	-50 %	-20 %	0 %
	Risks	Most likely	Opportunities
Affects measures:	Alternative fuel, Alternative vehicles, Ecodriving, Nitrogen Tires, Speed Limitation, Route Optimization		

Appendix F – Input Values for Parameter Uncertainties

CO_2 Reduction Parameters					
ID	**Parameter**	**Unit**	**P10**	**Mode**	**P90**
A	**Ecodriving**				
A.1	Effect of Ecodriving	%	3,00 %	4,00 %	10,00 %
B	**Speed Limitation**				
B.1	Effect of Speed Limitation	%	1,00 %	2,00 %	5,00 %
C	**Nitrogen Tires**				
C.1	Effect of Nitrogen Tires	%	1,00 %	2,00 %	3,00 %
E	**Alternative fuel**				
E.1	Emission reduction B30	%	5,70 %	13,50 %	24,90 %
E.2	Emission reduction B100	%	19,00 %	45,00 %	83,00 %
E.3	Emission reduction Biogas	%	53,00 %	80,00 %	90,00 %
E.4	Emission Biogas hybrid	%	15,90 %	40,00 %	63,00 %
F	**Hybrids**				
F.1	Emission reduction from hybrids	kg CO2/l fuel	30,00 %	50 %	70 %
G	**Electric vehicles**				
G.1	Emission Reduction Electric	kg CO2/kWh	0,089	0,099	0,109
H	**Energy Efficiency**				
H.1	Emission Electricity	kg CO2/kWh	0,09	0,10	0,11
H.2	Emission District heating	kg CO2/kWh	0,09	0,10	0,11
H.3	Emission Heating Oil	kg CO2/kWh	0,25	0,27	0,30
H.4	Emission Propane	kg CO2/kWh	0,19	0,21	0,23
I	**Modal Shift**				
I.1	Emission tonkm Air Domestic	kg CO2/tonkm	2,0034	2,226	2,4486
I.2	Emission tonkm Air European	kg CO2/tonkm	1,326501	1,47389	1,621279
I.3	Emission tonkm Air International	kg CO2/tonkm	0,551916	0,61324	0,674564
I.4	Emission tonkm Rail Electric	kg CO2/tonkm	0,000441	0,00049	0,000539
I.5	Emission tonkm Rail Diesel	kg CO2/tonkm	0,0378	0,042	0,0462
I.6	Emission tonkm Water Container ships	kg CO2/tonkm	0,014328	0,01592	0,017512
J	**Modular Lorries**				
J.1	Emission reduction Modular Lorries	%	11 %	12 %	13 %
M	**Joint parameters**				
M.1	Increased consumption B30	%	5,40 %	6,00 %	6,60 %
M.2	Increased consumption B100	%	5,40 %	6,00 %	6,60 %
M.3	Increased consumption Biogas	%	0,00 %	0,00 %	0,00 %
M.4	Indcreased consumption Biogas hyb	%	0,00 %	0,00 %	0,00 %
M.5	Increased consumption Hybrids	%	0,00 %	0,00 %	0,00 %
M.6	Increased consumption Electric	%	0,00 %	0,00 %	0,00 %
M.7	Increased consumption Modular Lorries	%	5,40 %	6,00 %	6,60 %

CO_2 Reduction Parameters	
ID	**Source**
A	
A.1	(Statens vegvesen, 2010)
B	
B.1	(Statens vegvesen, 2010)
C	
C.1	(Statens vegvesen, 2010)
E	
E.1	30% of the 3-point estimate for B100
E.2	Best estimate: rape seed biodiesel Estimates: typical values for biofuels if produced with no net carbon emissions from land-use change. (Renewable Energy Directive, 2009/28/EC)
E.3	Best estimate: municipal organic waste. Estimates: typical values for biofuels if produced with no net carbon emissions from land-use change. (Renewable Energy Directive, 2009/28/EC)
E.4	Mean 50% Min 30% and Max 70% of the 3-point estimate for Biogas
F	
F.1	A +/- 10% variation put upon the estimate used in the original Effect Calculation Model
G	
G.1	A +/- 10% variation put upon the estimate used in the original Effect Calculation Model
H	
H.1 - H.4	A +/- 10% variation put upon the estimate used in the original Effect Calculation Model
I	
I.1 -I.6	A +/- 10% variation put upon the estimate used in the original Effect Calculation Model
J	
J.1	A +/- 10% variation put upon the estimate used in the original Effect Calculation Model
M	
M.1 - M.3	A +/- 10% variation put upon the estimate used in the original Effect Calculation Model
M.4 M.5	Since posten has estimated the increansed consumption for biogas/electric vehicles to be 0%, it is assumed that biogas hybrid and el-hybrids vehicles have a 0% increase as well
M.6	A +/- 10% variation put upon the estimate used in the original Effect Calculation Model
M.7	Assumed to be the same as for B30 and B100

Costs Parameters	
ID	**Parameter**
CA	**Ecodriving**
CA.1	Course cost Ecodriving
CA.2	Drivers PTT
CA.3	Drivers Supply Chain
CA.4	Drivers Supply Chain (SC)
CA.5	Drivers Cargo
CA.6	Drivers Cargo (SC)
CB	**Speed Limitation**
CC	**Nitrogen Tires**
CC.1	Cost Nitrogen filling facility
CC.2	Nitrogen filling facilities PTT
CC.3	Nitrogen filling facilities Cargo
CC.4	Nitrogen filling facilities Cargo (SC)
CD	**Route Optimization**
-	-
CE	**Alternative fuel**
CE.1	Fuel price Diesel
CE.2	Leasing Cost Diesel Cars and vans (< 3.5 tons)
CE.3	Leasing Cost Diesel Trucks (< 7.5 tons)
CE.4	Leasing Cost Diesel Trucks (< 19 tons)
CE.5	Leasing Cost Diesel Trucks (< 27 tons)
CE.6	Leasing Cost Diesel Trucks (50-60 tons)
CE.7	Maintenance Cost Diesel Cars and vans (< 3.5 tons)
CE.8	Maintenance Cost Diesel Trucks (< 7.5 tons)
CE.9	Maintenance Cost Diesel Trucks (< 19 tons)
CE.10	Maintenance Cost Diesel Trucks (< 27 tons)
CE.11	Maintenance Cost Diesel Trucks (50-60 tons)
CE.12	Fuel price B30
CE.13	Leasing Cost B30 Cars and vans (< 3.5 tons)
CE.14	Leasing Cost B30 Trucks (< 7.5 tons)
CE.15	Leasing Cost B30 Trucks (< 19 tons)
CE.16	Leasing Cost B30 Trucks (< 27 tons)
CE.17	Leasing Cost B30 Trucks (50-60 tons)
CE.18	Maintenance Cost B30 Cars and vans (< 3.5 tons)
CE.19	Maintenance Cost B30 Trucks (< 7.5 tons)
CE.20	Maintenance Cost B30 Trucks (< 19 tons)
CE.21	Maintenance Cost B30 Trucks (< 27 tons)
CE.22	Maintenance Cost B30 Trucks (50-60 tons)
CE.23	Fuel price B100
CE.24	Leasing Cost B100 Cars and vans (< 3.5 tons)
CE.25	Leasing Cost B100 Trucks (< 7.5 tons)
CE.26	Leasing Cost B100 Trucks (< 19 tons)
CE.27	Leasing Cost B100 Trucks (< 27 tons)
CE.28	Leasing Cost B100 Trucks (50-60 tons)
CE.29	Maintenance Cost B100 Cars and vans (< 3.5 tons)
CE.30	Maintenance Cost B100 Trucks (< 7.5 tons)
CE.31	Maintenance Cost B100 Trucks (< 19 tons)
CE.32	Maintenance Cost B100 Trucks (< 27 tons)
CE.33	Maintenance Cost B100 Trucks (50-60 tons)

ID	Parameter
CE	**Alternative fuel (Continued)**
CE.34	Fuel price Biogas
CE.35	Leasing Cost Biogas Cars and vans (< 3.5 tons)
CE.36	Leasing Cost Biogas Trucks (< 7.5 tons)
CE.37	Leasing Cost Biogas Trucks (< 19 tons)
CE.38	Leasing Cost Biogas Trucks (< 27 tons)
CE.39	Leasing Cost Biogas Trucks (50-60 tons)
CE.40	Maintenance Cost Biogas Cars and vans (< 3.5 tons)
CE.41	Maintenance Cost Biogas Trucks (< 7.5 tons)
CE.42	Maintenance Cost Biogas Trucks (< 19 tons)
CE.43	Maintenance Cost Biogas Trucks (< 27 tons)
CE.44	Maintenance Cost Biogas Trucks (50-60 tons)
CE.45	Fuel price Biogas hybrid
CE.46	Leasing Cost Biogas hybrid Cars and vans (< 3.5 tons)
CE.47	Leasing Cost Biogas hybrid Trucks (< 7.5 tons)
CE.48	Leasing Cost Biogas hybrid Trucks (< 19 tons)
CE.49	Leasing Cost Biogas hybrid Trucks (< 27 tons)
CE.50	Leasing Cost Biogas hybrid Trucks (50-60 tons)
CE.51	Maintenance Cost Biogas hybrid Cars and vans (< 3.5 tons)
CE.52	Maintenance Cost Biogas hybrid Trucks (< 7.5 tons)
CE.53	Maintenance Cost Biogas hybrid Trucks (< 19 tons)
CE.54	Maintenance Cost Biogas hybrid Trucks (< 27 tons)
CE.55	Maintenance Cost Biogas hybrid Trucks (50-60 tons)
CF	**Hybrids**
CF.1	Fuel price Hybrid
CF.2	Leasing Cost Hybrid Cars and vans (< 3.5 tons)
CF.3	Leasing Cost Hybrid Trucks (< 7.5 tons)
CF.4	Leasing Cost Hybrid Trucks (< 19 tons)
CF.5	Leasing Cost Hybrid Trucks (< 27 tons)
CF.6	Leasing Cost Hybrid Trucks (50-60 tons)
CF.7	Maintenance Cost Hybrid Cars and vans (< 3.5 tons)
CF.8	Maintenance Cost Hybrid Trucks (< 7.5 tons)
CF.9	Maintenance Cost Hybrid Trucks (< 19 tons)
CF.10	Maintenance Cost Hybrid Trucks (< 27 tons)
CF.11	Maintenance Cost Hybrid Trucks (50-60 tons)

ID	Parameter
CG	**Electric vehicles**
CG.1	Fuel price Electric vehicles
CG.2	Leasing Cost Electric Cars and vans (< 3.5 tons)
CG.3	Leasing Cost Electric Trucks (< 7.5 tons)
CG.4	Leasing Cost Electric Trucks (< 19 tons)
CG.5	Leasing Cost Electric Trucks (< 27 tons)
CG.6	Leasing Cost Electric Trucks (50-60 tons)
CG.7	Maintenance Cost Electric Cars and vans (< 3.5 tons)
CG.8	Maintenance Cost Electric Trucks (< 7.5 tons)
CG.9	Maintenance Cost Electric Trucks (< 19 tons)
CG.10	Maintenance Cost Electric Trucks (< 27 tons)
CG.11	Maintenance Cost Electric Trucks (50-60 tons)
CH	**Energy Efficiency**
CH.1	Cost Electricity
CH.2	Cost District heating
CH.3	Cost Heating Oil
CH.4	Cost Propane
CI	**Modal Shift**
CI.1	Capex Road to Sea
CI.2	Capex Road to Rail
CI.3	Capex Air to Rail
CI.4	Capex Air to Road
CI.5	Capex Air to Sea
CI.6	Opex Road to Sea
CI.7	Opex Road to Rail
CI.8	Opex Air to Rail
CI.9	Opex Air to Road
CI.10	Opex Air to Sea
CI.11	Difference in freight costs
CJ	**Modular Lorries**
-	-
CK	**Business Travel**
CK.1	Investment in video conference equipment
CK.1.1	Savings due to reduced travel costs
CL	**Fossils phase out**
-	-

Appendix G – Extract from the Effect Calculation Model

	@Risk model												
Name of Action	Ecodriving	Effect (t CO_2)						Cash flow					
NPV (10 yrs)	kr 8 756 649	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Total effect (ton CO2)	2 349	269	445	432	427	397	378	926 396	2 000 361	2 062 110	1 851 002	1 110 360	806 421

Baseline	Bicycles	Mopeds or motorcycles	Cars and vans (< 3.5 tons)	Trucks (< 7.5 tons)	Trucks (< 19 tons)	Trucks (< 27 tons)	Trucks (50-60 tons)	
Fuel price Diesel		13,90	13,90	13,90	13,90	13,90	13,90	NOK/l
Emission per liter		2,32	2,66	2,66	2,66	2,66	2,66	kg CO_2/l fuel

Effect of Ecodriving	6 %
Percentage of drivers (Supply Chain)	100 %

Course cost Ecodriving	4 000
Drivers Supply Chain	200

Percentage drivers completed	År 0	År 1	År 2	År 3	År 4	År 5	År 6	År 7	År 8	År 9
Bicycles	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
Mopeds or motorcycles	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
Cars and vans (< 3.5 tons)	60 %	40 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
Trucks (< 7.5 tons)	60 %	40 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
Trucks (< 19 tons)	60 %	40 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
Trucks (< 27 tons)	60 %	40 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
Trucks (50-60 tons)	60 %	40 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
Capital Expenses	-480 000	-320 000	0	0	0	0	0	0	0	0
Operational Expenses	0	0	0	0	0	0	0	0	0	0

Percentage drivers completed	År 0	År 1	År 2	År 3	År 4	År 5	År 6	År 7	År 8	År 9
Bicycles	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
Mopeds or motorcycles	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
Cars and vans (< 3.5 tons)	60 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
Trucks (< 7.5 tons)	60 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
Trucks (< 19 tons)	60 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
Trucks (< 27 tons)	60 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
Trucks (50-60 tons)	60 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
Capital Expenses	-480 000	-800 000	0	0	0	0	0	0	0	0
Operational Expenses	0	0	0	0	0	0	0	0	0	0

Effects	År 0	År 1	År 2	År 3	År 4	År 5	År 6	År 7	År 8	År 9
Cost (Consumption)	1 406 396	2 320 361	2 062 110	1 851 002	1 110 360	806 421	806 421	806 421	806 421	806 421
CO2 (Vehicles)	269	445	432	427	397	378	378	378	378	378

Outgoing

Vehicles	År 0	År 1	År 2	År 3	År 4	År 5	År 6	År 7	År 8	År 9
Bicycles	0	0	0	0	0	0	0	0	0	0
Mopeds or motorcycles	0	0	0	0	0	0	0	0	0	0
Cars and vans (< 3.5 tons)	18	18	16	14	9	7	7	7	7	7
Trucks (< 7.5 tons)	2	2	1	1	1	0	0	0	0	0
Trucks (< 19 tons)	30	30	27	24	10	5	5	5	5	5
Trucks (< 27 tons)	11	11	10	9	6	5	5	5	5	5
Trucks (50-60 tons)	59	58	52	47	30	23	23	23	23	23

Average Consumption (liter)	År 0	År 1	År 2	År 3	År 4	År 5	År 6	År 7	År 8	År 9
Bicycles	0	0	0	0	0	0	0	0	0	0
Mopeds or motorcycles	0	0	0	0	0	0	0	0	0	0
Cars and vans (< 3.5 tons)	6 452	6 286	6 268	6 253	6 238	6 223	6 223	6 223	6 223	6 223
Trucks (< 7.5 tons)	16 552	16 128	16 080	16 042	16 004	15 966	15 966	15 966	15 966	15 966
Trucks (< 19 tons)	16 247	15 830	15 783	15 746	15 709	15 671	15 671	15 671	15 671	15 671
Trucks (< 27 tons)	21 438	20 889	20 827	20 778	20 729	20 679	20 679	20 679	20 679	20 679
Trucks (50-60 tons)	29 928	29 161	29 075	29 006	28 937	28 868	28 868	28 868	28 868	28 868

Incoming

Vehicles	År 0	År 1	År 2	År 3	År 4	År 5	År 6	År 7	År 8	År 9
Bicycles	0	0	0	0	0	0	0	0	0	0
Mopeds or motorcycles	0	0	0	0	0	0	0	0	0	0
Cars and vans (< 3.5 tons)	18	18	16	14	9	7	7	7	7	7
Trucks (< 7.5 tons)	2	2	1	1	1	0	0	0	0	0
Trucks (< 19 tons)	30	30	27	24	10	5	5	5	5	5
Trucks (< 27 tons)	11	11	10	9	6	5	5	5	5	5
Trucks (50-60 tons)	59	58	52	47	30	23	23	23	23	23

Average Consumption (liter)	År 0	År 1	År 2	År 3	År 4	År 5	År 6	År 7	År 8	År 9
Bicycles	0	0	0	0	0	0	0	0	0	0
Mopeds or motorcycles	0	0	0	0	0	0	0	0	0	0
Cars and vans (< 3.5 tons)	6 700	6 700	6 680	6 664	6 649	6 633	6 633	6 633	6 633	6 633
Trucks (< 7.5 tons)	17 189	17 189	17 138	17 097	17 057	17 016	17 016	17 016	17 016	17 016
Trucks (< 19 tons)	16 871	16 871	16 822	16 782	16 742	16 702	16 702	16 702	16 702	16 702
Trucks (< 27 tons)	22 263	22 263	22 197	22 145	22 092	22 040	22 040	22 040	22 040	22 040
Trucks (50-60 tons)	31 079	31 079	30 987	30 914	30 841	30 767	30 767	30 767	30 767	30 767

Emission reduction B30	16,91 %
Emission reduction B100	50,38 %
Emission reduction Biogas	72,67 %
Emission Biogas hybrid	31,72 %
Emission reduction from hybrids	50,00 %

Alternative vehicles

Increased consumption B30	6,00 %
Increased consumption B100	6,00 %
Increased consumption Biogas	0,00 %
Indcreased consumption Biogas hyb	0,00 %
Increased consumption Hybrids	0,00 %

Total	0,00	0,00	37,36	72,07	184,72	223,81	223,81	223,81	223,81	223,81

B30	År 0	År 1	År 2	År 3	År 4	År 5	År 6	År 7	År 8	År 9
Bicycles	0	0	0	0	0	0	0	0	0	0
Mopeds or motorcycles	0	0	0	0	0	0	0	0	0	0
Cars and vans (< 3.5 tons)	0	0	2	4	9	11	11	11	11	11
Trucks (< 7.5 tons)	0	0	1	1	1	2	2	2	2	2
Trucks (< 19 tons)	0	0	3	6	15	18	18	18	18	18
Trucks (< 27 tons)	0	0	1	2	5	6	6	6	6	6
Trucks (50-60 tons)	0	0	5	10	25	29	29	29	29	29
Effect CO2	0,00	0,00	37,36	72,07	175,07	207,30	207,30	207,30	207,30	207,30

B100	År 0	År 1	År 2	År 3	År 4	År 5	År 6	År 7	År 8	År 9
Bicycles	0	0	0	0	0	0	0	0	0	0
Mopeds or motorcycles	0	0	0	0	0	0	0	0	0	0
Cars and vans (< 3.5 tons)	0	0	0	0	0	0	0	0	0	0
Trucks (< 7.5 tons)	0	0	0	0	0	0	0	0	0	0
Trucks (< 19 tons)	0	0	0	0	0	0	0	0	0	0
Trucks (< 27 tons)	0	0	0	0	0	0	0	0	0	0
Trucks (50-60 tons)	0	0	0	0	2	4	4	4	4	4
Effect CO2	0,00	0,00	0,00	0,00	2,77	5,53	5,53	5,53	5,53	5,53

Appendix H – Extract from Uncertainty Analysis Model