

## Feasibility Risk Assessment of Transport Infrastructure Projects: The CBA-DK Decision Support Model

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This paper presents the final version of the CBA-DK decision support model for assessment of transport projects. The model makes use of conventional cost-benefit analysis resulting in aggregated single point estimates and quantitative risk analysis using Monte Carlo simulation resulting in interval results. Two special concerns in this paper is firstly the treatment of feasibility risk assessment adopted for evaluation of transport infrastructure projects, and secondly whether this can provide a more robust decision support model. This means moving away from a single point estimate to an interval result, and the determination of suitable probability distributions. Use is made of the reference class forecasting information, such as that developed in Optimism Bias for adjustments to investment decisions that relate to all modes of transport. The CBA-DK decision support model results in more informed decision support towards decision-makers and stakeholders in terms of accumulated descending graphs. The decision support method developed in this paper aims to provide assistance in the analysis and ultimately the choice of action, while accounting for the uncertainties surrounding any transport appraisal scheme.

*Keywords:* Decision Support System; Risk Analysis; Reference Class Forecasting; Cost-Benefit Analysis; Transport Assessment

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### 1. Introduction

Transport appraisal in many countries is primarily based on Cost Benefit Analysis (CBA), where the advantages and disadvantages of particular investment alternatives are assessed in terms of their relative importance for society. The principal elements concern the estimation of user

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benefits, mainly in terms of travel time savings, and the capital and operating costs of the scheme, all of which are discounted over the lifetime of the project. These elements are all given monetary values to allow comparison, and the preferred alternative is the one that achieves the highest net present value, or internal rate of return, or simply the benefit cost ratio. There is a huge literature on this well established and debated process in transport – see, for example Pearman et al. (2003), Grant-Muller et al. (2001), and Leleur (2000). These sets of deterministic single point output criteria are most often based upon “best guess” estimates of the input variables to the model. Although the CBA depicts in many ways a most likely “modal” value for the evaluation, there are many different ways in which more robust estimates can be obtained. This paper presents one such approach to modifying traditional CBA.

Traditionally, such modal values can be subjected to standardized sensitivity tests, where individual impacts are treated in order to determine how much the output might vary before the project is rejected (in terms of socio-economic viability). This is typically achieved by selecting various combinations for each input variable, such as running the model with a worst and best case scenario. These combinations of possible values around the best guess are commonly known as “what if” scenarios. However, the assessment of transport projects increasingly requires more analysis of the underlying assumptions in the CBA, and so the number of “what if” scenario combinations increase rapidly. In addition, the results presented to decision-makers are still reliant on single point estimates in terms of minimum and maximum values for each impact.

One way to accommodate the substantial increase in the number of scenarios is to use quantitative risk analysis (QRA). QRA makes use of Monte Carlo simulation (MCS), which is similar to the sensitivity analysis, as it generates a number of possible scenarios. However, the simulation procedure goes one step further by effectively accounting for every possible value that each input variable can take, and thereby weighs each scenario by the probability of occurrence. The QRA introduces probabilities into the decision-making process. Consequently, instead of receiving single point results, decision-makers receive interval results in terms of an output probability distribution.

This paper outlines one way of determining and handling the feasibility risk assessment (FRA) within decision-making concerning transport infrastructure projects. The key agenda is then to investigate whether the feasibility risk assessment adopted for the evaluation of transport infrastructure projects can provide useful decision support (by moving from single point estimates (CBA) to interval results (QRA)).

By adopting the two methodologies of CBA and QRA, a decision support model has been developed – the CBA-DK model (Salling 2008). The model is based on a Microsoft Excel platform embedding the deterministic calculations of CBA. The stochastic calculations as concerns the QRA are made by applying an add-in software: @RISK (Palisade 2007). This paper sets out to describe the CBA-DK modelling tool with a primary focus upon the FRA and the application of probability distributions within transport infrastructure appraisal.

The remainder of this paper presents the two methodologies, and lays out the theoretical foundation of the decision support model. The CBA-DK framework model is then presented in Section 3 together with the applied set of probability distributions. The final Section 4 presents a set of conclusions and a perspective.

## 2. Theoretical foundation

The proposed decision support system builds on conventional CBA where the costs and benefits of a transport project are considered in a unified framework, so that decision-makers can be informed about the social desirability of the project. The project is first defined and then the

relevant impacts are identified. It is necessary to quantify all costs and benefits in monetary terms, before aggregation takes place and the values are discounted over time. The alternatives being considered are then compared through a comparison of the total discounted benefits with the total discounted costs to give a net present value (NPV). If the NPV is positive, then the CBA test has been passed. Alternatively, information can be presented as a benefit-cost ratio (BCR – the ratio of the present value of the benefits to that of costs), or an internal rate of return (IRR), which is the discount rate that produces a zero NPV (Zerbe and Dively, 1994). Each of these evaluation criteria are produced through simple point estimates and they form the main outcome from CBA.

A key advantage of using CBA is its transparency, but this may also be considered as a weakness, as the method relies on empirical estimates, where all the considerations and calculations are reduced to just one aggregated value. Thus, the general public would most often see the methodology as a “black box” approach (Gissel 1999). Moreover, the sources of uncertainty embedded within the different unit pricing strategies are problematic. The CBA usually relies on first year impact values depicting the net change multiplied with a conversion factor to achieve the monetary input, and the impact is then discounted over the evaluation period. To set a “price tag” on an accident, the time saved in a vehicle or the emission of one tonne of CO<sub>2</sub> will vary according to time and location around the World. These average figures give clear estimates, but the levels of uncertainties around these values also need to be acknowledged.

In this paper, two sets of uncertainties will be presented within the context of transport infrastructure projects: First, there are the underlying uncertainties embedded within any traffic or impact model and secondly, there are the uncertainties inherent in any CBA pricing strategy. Prior studies (Vose 2002 and Walker et al. 2003) suggest separating these two issues into epistemic and ontological uncertainty. The epistemic uncertainty occurs when pricing strategies are defined as knowledge imperfections, which may be reduced by more research and empirical analysis. The ontological uncertainty (modelling deficiency) is due to inherent variability, which is especially applicable in human and natural systems, and it concerns social, economic, and technological developments (Salling and Leleur 2006a).

A schematic overview of the nature of uncertainty, related to transport infrastructure assessment, is given in Figure 1. The sources of uncertainty correspond to a combination of both the lack of knowledge and the inherent randomness in the system.

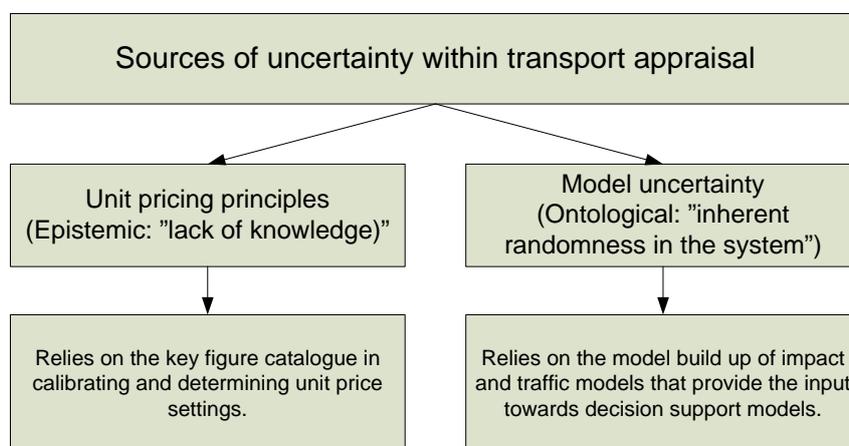


Figure 1. Schematically overview illustrating the two major sources of uncertainty embedded within transport infrastructure assessment (adapted from Salling and Leleur (2006a)).

The valuation of the various types of cost and benefits accruing from the project is the first major source of uncertainty within the unit pricing principles. These typical effects are non quantifiable in the normal sense, as they are not traded in any market, except for the investment and maintenance costs. For these non-market impacts, the valuation scheme set out relies on national standards in providing up-to-date unit prices. For example, in Denmark, a set of standard measures are comprised within a key figure catalogue published by the Danish Ministry of Transport (DMT 2006). Clearly, such measures are subjected to uncertainty and subjectivity, since no individual experiences the same discomfort of travelling or has the same value of time. So there is also a certain degree of ontological uncertainties embedded within the unit pricing principles. However, since both the key figure catalogue and the manual for socio-economic analysis propose the application of such standardized measures, the modelling scheme set out in CBA-DK assumes that the unit prices are fixed, and so it is assumed that there are no embedded uncertainties in the appraisal (Salling 2008).

The second major source of uncertainty relates to the embedded model uncertainty defined in context with the derivation of first year impacts and forecast scenarios. All models are an abstraction of a real life system, and they all contain some embedded uncertainty in both inputs and outputs (Law and Kelton 2000). The unit price principles depicts various shortcomings and deficiencies in determining the “correct” unit price values, whereas the model uncertainties depict shortcomings in prognosis, impact and transport models. Hence, to some degree epistemic uncertainties are embedded within the latter types of model applications. Two of the most important impacts when assessing transport projects (travel time savings and construction costs), both rely on prior modelling and the inherent uncertainties that may be embedded within those models. These model outputs are then input to the appraisal model, so that any embedded inaccuracies remain.

These two types of uncertainties have been subject to detailed scrutiny in Flyvbjerg et al. (2003), where it was concluded that in the case of Danish bridge and tunnel projects, on average, construction costs were 50% to 100% undervalued, whereas traffic forecasts, laying the foundation for the travel time savings effect, were about 60% overestimated (compared with the opening year traffic situation). The majority of the proposed transport systems cost is on average 50% more than their ex-ante estimates, while the ex-post demands within travel savings are about 50% below the estimated demand. This stems with an established *maxime* in transport CBA, stating that in order to derive benefit and cost values of an infrastructure project one should normally halve the predicted benefits and double the estimated costs (Banister and Berechman 2000, p. 187).

These more or less consistent overestimations of benefits and underestimations of costs within transport infrastructure appraisals have been named Optimism Bias. As discussed previously, decision-makers and analysts tend to be overly optimistic with respect to construction costs and future traffic. A technique developed for the UK Department for Transport provided a set of guidelines trying to cope with some of these shortcomings (Flyvbjerg & COWI 2004).

The Optimism Bias approach is dealt with by the use of a well-established technique named Reference Class Forecasting (RCF). The theoretical background of RCF is made up by prospect theory<sup>3</sup> developed by Kahneman and Tversky in 1979<sup>4</sup>. A reference class denotes a pool of past projects similar to the one being appraised. Past errors are systematically gathered for a range of projects, comparing the deficiencies in the modelling and forecasting stages to the actual values at outturn. The experience from past projects is then collected and compared so that “planning

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<sup>3</sup> In short prospect theory describes decisions between alternatives that involve risk, i.e. alternatives where the general outcome is uncertain but the associated probabilities are known.

<sup>4</sup> Daniel Kahneman received the Nobel prize in Economics in 2002 for his work in collaboration with Amos Tversky (1937-1996).

fallacy" can be avoided (Flyvbjerg 2007 and Cantarelli 2008). Relating Optimism Bias to the risk assessment scheme is made by the incorporation of probabilities of occurrence, where decision-makers can make use of their know-how expertise: this is denoted as *level of knowledge*. The strength of this procedure is revealed, when the experts' level of knowledge can be substituted with reference classes of past projects. The comparative procedure of Optimism Bias and risk analysis can assist in assigning the best and most suitable probability distribution. Risk is used to indicate the likelihood of selecting a "wrong" project in the sense that it would be non-viable, as seen from a societal point of view. Uncertainty, on the other hand, is defined as the degree of inaccuracy associated with the determination of the project's benefits and costs (Banister and Berechman 2000).

The technique used in this paper is Monte Carlo simulation (MCS), which involves a random sampling method concerning each different probability distribution selected for the actual model set-up (Rubinstein 1981). Several probability distributions have been tested (Salling 2008), in terms of their theoretical strengths and empirical justification, so that misspecification can be minimised. There has been a separation of actual data fit and "expert opinion" as illustrated above (Vose 2002, p. 273). This distinction has led to the conceptual interpretation in terms of *level of knowledge (LoK)* on the uncertain variables. If the uncertain variables are more or less defined in literature or by data, then parametric distributions should be applied, such as Normal, Gamma or Beta (high *LoK*). Conversely, if the uncertain variables rely on experts to judge the uncertainty, then non-parametric distributions should be assigned, such as Beta-PERT, triangular or uniform (low *LoK*) (Vose 2002). The application of non-parametric distributions allows for decision-makers to make entry values in the Monte Carlo simulation as they believe to be most appropriate. Thus, inputs are not dependent on prior data fitting and statistical testing, but more on intuition and experience. The set of probability distributions found valid and suitable within transport assessment are shown in Table 1.

**Table 1. Applied probability distributions within the assessment of transport projects (Salling 2008)**

Distribution	Category	Level of Knowledge (LoK)
Uniform	Non-parametric	Low
Triangular	Non-parametric	Low
PERT (beta)	Non-parametric	Medium
Normal	Parametric	High
Erlang (gamma)	Parametric	High

The five distributions, applied within the framework model developed here, are clearly not an exhaustive list of distribution functions. However, literature and data fitting have shown the applicability of the distributions illustrated (see Law and Kelton 2000 pp. 299-318 and Vose 2002 pp. 102-131). The idea is to apply "the best suitable" distribution to the uncertain variable within the decision support model, together with historically defined or expert based input parameters. Care must be taken in applying parametric distributions since they rely on mathematics to describe their shape. Vose (2002) proposes parametric distributions should be applied, if and only if, (1) the theory underpinning the chosen distribution applies to the particular problem, (2) the general acceptance of the specific problem, where it has been proven useful to apply the specific probability distribution, and (3) the distribution approximately fits the expert opinion being modelled and the required level of accuracy is not too high (Vose 2002, p. 102).

## 2.1 Implementation of Distribution Functions

The five continuous distributions shown in Table 1 are all applied to traditional transport assessment impacts. The following typology has been generated through a range of case studies conducted in Salling (2008). Typically, the uncertainty of the pricing strategies is assigned non-parametric distributions due to a relatively low *LoK*, whereas the embedded modelling uncertainties have parametric distributions, as there is a relatively high *LoK*. The range of case studies covers all three transport modes (road, rail and air), and for the more numerous examples of road transport both urban and inter-urban road projects have been tested (Salling 2008).

**The uniform distribution:** This is the simplest function to apply within the current modelling scheme. The uniform distribution is used as an approximate distribution where there is little or no available data. The reflection of the perceived uncertainty of a variable using the uniform distribution is rarely good, since the allowed range have the same constant probability of occurrence. Thus, the *level of knowledge* must be considered low, relying entirely on experts to judge the levels of uncertainty variable. Nevertheless, the uniform distribution has proven its usefulness, for example in the handling of accidents savings (Salling and Leleur 2006a). Another interesting application of this distribution type has been to estimate values for non-monetary impacts. These impacts are currently not covered within the decision support model, but there is often a need to include these non monetary factors in the CBA. For example, two non-monetary impacts have been treated with a uniform distribution, namely the network and mobility impacts and for the logistics and goods impacts (Salling et al. 2007).

**The triangular distribution:** This type of distribution function is applied where a minimum (*min*) and a maximum (*max*) limit are calculated together with a modal value (*mode*). The triangular distribution offers considerable flexibility in its shape, coupled with the intuitiveness of defining respectively the *min* and *max* values. The main pitfall of this distribution relates to the absolute *min* and *max* values used, as these are difficult to estimate (Vose 2002, p. 129). The modelling tool of CBA-DK offers the possibility of open ended tails, by defining a set of percentile overestimations and underestimations of the practical *min* and *max* values, referred to as the trigen distribution (Palisade 2007). During previous studies, the triangular distribution has been applied to the maintenance cost of road schemes (Salling and Leleur 2006a). Furthermore, a recent study used the trigen distribution to estimate values for accidents savings (Barfod et al. 2008).

**The beta-PERT distribution:** PERT (Program Evaluation and Review Technique) stems from 1958 where it was developed as a scheduling procedure within the American Military. PERT is derived from the Beta distribution which mathematically is fairly simple and covers a huge variety of skewness types (Lichtenberg 2000). The PERT distribution requires the same three parameters as the triangular distribution (Figure 2). However, the interpretation is made up of a smooth curve that places less emphasis to the *min* and *max* values. This distribution gives extra emphasis to the *mode*, making it ideal for modelling expert opinions of a variable (Vose 2002).

**The normal distribution:** The applicability of the normal distribution is extensively reported in the literature (Law and Kelton 2000 p. 306 and Vose 2002 p. 124). It is assumed that observed variations of a naturally occurring variable are approximately normally distributed. The central limit theorem states that averaging a large set of identically distributed independent random variables converges towards a normal distribution. The smoothness of the distribution around the mean, where the standard deviation (*std. dev.*) creates variation of occurrence is the main motivation for applying this type of distribution. The normal distribution is applied to the travel time savings effect, and it is used as a means to accommodate the uncertainty embedded within the development and performance of traffic models. Large-scale empirical and literature studies using the normal distribution have been conducted (Knudsen 2006 and de Jong et al. 2005) to

model traffic uncertainties. The use of this approach in evaluation models is made through the impact of travel time savings in terms of hours saved, for example for passengers in a new railway line or cars on a new high speed motorway. To implement a normal distribution, the *mean* is calculated as the first year impact, and the *std. dev.* relies on literature reviews. The *std. dev.* corresponds to the level of uncertainty in the embedded traffic models. These deviations have previously been found in the range of 10-20% of the *mean* value, which is considered relatively conservative (Salling et al. 2007 and Salling and Leleur 2006a), given the growing evidence of substantially larger variances.

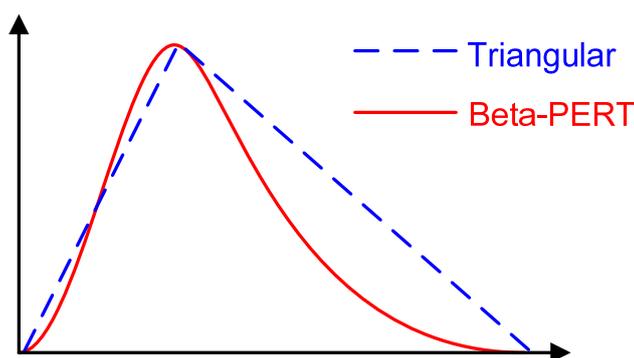


Figure 2. Illustration of the PERT distribution compared with a triangular distribution with the same input parameters

**The (Gamma) Erlang distribution:** The applicability of the Erlang distribution is large, especially in the context of the production processes and the uncertainty of production cut-offs. The uncertainties, as concerns production processes, relates to unforeseen production stops, for example by human interventions or mechanical shut downs. The process “dies” and “revives” after a certain period of time where the number of revivals can be described by the shape ( $k$ ) parameter. The Erlang distribution is a special case of the gamma distribution with integer values for the shape parameter. Moreover, the Erlang distribution needs a scale parameter  $\theta$  allowing for the shift of the distribution. The general implementation of a gamma distribution is considered parametric and high  $LoK$  (Lichtenberg 2000).

The Erlang distribution resembles the PERT distribution in terms of relevance and structure with respectively closed and open ended tails. Decision-makers are left with the same process of determining limits, in which an absolute *minimum* and an approximated *maximum* value is obtained. The difference lies in the interpretation of the mean value where a so-called triple estimation technique based upon successive calculation is applied (Lichtenberg 2000, p. 125). The triple estimation technique evaluates the extreme minimum and maximum limits as well as most likely values for each uncertain variable. The mean is calculated by: 
$$\mu = \frac{(\min + 2.9 \cdot ML + \max)}{4.9}$$

and the relationship to the shape and scale parameter is found by:  $\mu = k \cdot \theta$ . Hereby, the Erlang distribution is transferred from “parametric” to “non-parametric” in the sense, that to implement the distribution ex-ante, decision-makers have only to apply a minimum and maximum value to the analysis. Both the literature and the empirical data reveal that the use of the Erlang distribution can be applied within the construction costs derivation in transport appraisal (Lichtenberg 2000, Vose 2002 and Salling 2008).

## 2.2 Traffic demand forecasts of road projects

Demand forecasts in the transport sector make up a substantial part of any socio-economic analysis, as it provides the basis for calculating travel time savings stemming from transport infrastructure projects. The embedded uncertainty in deriving these traffic forecasts are dependent on the time and effort put into data collection and the traffic modelling. It is important to distinguish between the uncertainty involved in predicting future traffic and demand flows (epistemic), and the embedded modelling uncertainty corresponding to traffic models (ontological), see Figure 1.

A substantial literature and data study based upon hundreds of large-scale infrastructure projects has been conducted on traffic demand forecasts (Flyvbjerg et al. 2003). This comparative study relied upon reference class forecasting in collecting ex-ante based and ex-post based data sets from different transport related projects, covering rail, road and fixed link projects (Flyvbjerg 2007). It was concluded that traffic forecasts within road projects lie within a threshold of  $\pm 40\%$  accuracy, with an average of 9% underestimation. This contradicts the general rule of thumb, which states that demand forecasts are overestimated and construction costs are underestimated, as denoted by the use of Optimism Bias (MacDonald 2002 and Flyvbjerg and COWI 2004). These assumptions tend to increase the attractiveness of the transport scheme, giving a false sense of optimism in the decision-making process. This tendency is more valid for rail and fixed link projects, where the average overestimation within demand forecasts is approximately 50%, but with larger road scheme projects estimates are more accurate (Flyvbjerg et al. 2003). Figure 3 illustrates a sample of 183 road projects depicting respectively under- and overestimations of the traffic demand forecasts.

The inaccuracy of the traffic demand forecasts are clearly skewed to the right, which means that distribution functions which allows for skewness are needed to interpret this data set. Unfortunately, as the exact data material used is limited due to copyrights, the data depicted in Figure 3 is found by interpolation of data points from Flyvbjerg et al. (2003). It is also assumed that the inaccuracy from the traffic forecasts is directly translated into the travel time savings effect.

The software program used to perform the data analysis is @RISK from Palisade (Palisade 2007). This software allows for a basic data fitting by the use of Maximum Likelihood Estimators to estimate the distribution parameters (i.e. to determine the parameters that maximize the likelihood of the sample data). Secondly, the goodness of the data fit is performed by Chi-squared [ $\chi^2$ ] statistics, determining the sum of differences between the observed and expected sample outcomes (Palisade 2007). The 183 different road projects are described through a continuous probability density function within @RISK, and all data points are normalized, summing to 1.00.

The data sample illustrated in Figure 3 shows the inaccuracy in traffic forecasts skewed to the right. A lower sample limit is set to -78.5% whilst a modal value is calculated to 9.6% and an upper sample limit of 179% is set where the 90% confidence level lies between -48.7% and 105.7%. As described in Table 1, the PERT distribution is well-suited in describing the uncertainties involved in predicting future traffic flows. However, other distributions, such as the lognormal, would also be of relevance in this respect (Salling 2008).

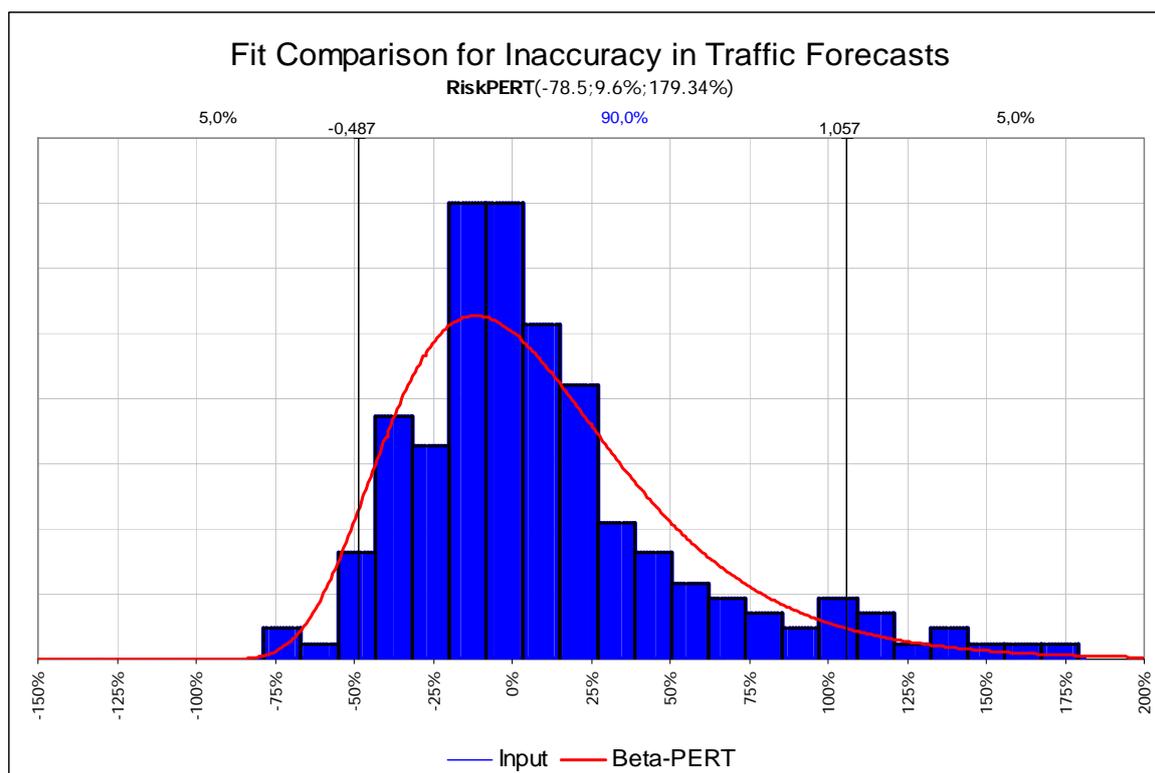


Figure 3. Inaccuracies of traffic forecasts in 183 road projects- calculated in percentage between ex-ante and ex-post analyses (adapted from Flyvbjerg et al. (2003), p. 27)

### 2.3 Construction costs for road projects

Construction costs for large public procurements tend to be underestimated, which means that appraisals seem to be over optimistic with regard to the project's costs. Misinterpretation of ex-ante based costs, deliberate or otherwise, results in budget overruns. Thus, projects especially with a longer time horizon tend to change according to site conditions, the nature and form of the project, legal requirements and political interference. During literature studies it is clear that estimating construction costs has assigned a relatively high degree of uncertainty. Studies conducted in the US, UK and Denmark all contribute to the evidence about interpreting and in some cases measuring the uncertainty of ex-ante based construction cost derivation (see Back et al. 2000, Lichtenberg 2000, MacDonald 2002, Flyvbjerg et al. 2003, Flyvbjerg and COWI 2004, the Danish Benchmark Centre 2007 and Priemus et al. 2008). These detailed studies contribute to the relatively high level of knowledge within the different studies in determining uncertainties of construction investments.

Flyvbjerg et al. (2003) has investigated cost overruns for 167 large-scale road infrastructure projects. The tendency is clearly right skewed where cost overruns are commonly occurring. In fact an average of 20% cost overrun among the 167 road projects are calculated with a worst project of 223% cost overrun and a -33.6% cost underrun, see Figure 4. The approach in which Optimism Bias exists for the estimation of construction costs ex-ante is also applicable where, for example rail projects on average are biased with 45% cost overruns, and fixed links on average is biased to other forms of transport with 34% cost overruns (Flyvbjerg et al. 2003).

The British Department for Transport (DfT) has approved the use of Optimism Bias in their assessment of transport projects, where for ex-ante based construction costs expenditure uplifts

in the range between 15-45% for roads projects are applied (Flyvbjerg and COWI 2004, Table 6). The uplift values have been derived from the reference classes built up by Flyvbjerg et al. (2003). By identifying a pool of similar past projects and comparing the construction costs before and after completion, a large database has been derived. Flyvbjerg and COWI (2004) adjusted the database by assigning distributions on the empirically identified cost overruns uncovering the share of projects with a given maximum cost overrun, which they called Optimism Bias uplifts. For instance, if the decision-makers allow a 50% threshold of budget overruns for a road project, the estimated cost should be increased by 15%. The threshold limit describes in many senses the risk aversion associated with the given evaluation scheme. Decision-makers who hold an 80% threshold needs to uplift the construction costs by 40% (Flyvbjerg and COWI 2004, p. 32). The document allows for decision-maker risk aversions between 50% and 90% dependent on their preferences. Flyvbjerg and COWI (2004) recommend that any shift should be between the 50 percentile and the 80 percentile, dependent on the type of project and risks involved.

Even though the data sample presented above is subjected to availability, it is the first major attempt to make such a classification based on past cost overrun tendencies. Several pitfalls exist, especially due the fact that many of the projects are funded publicly, where it is difficult to challenge funding and accounting procedures. For private funded projects, the major obstacle is the need to gather reliable data that are not available to the public. This means that many privately funded projects are not included in the database. The construction of valid and concise reference classes is a major challenge, where it is accepted that no two projects are ever "identical", and hence the allocation to a certain pool of projects is to some extent subjective. The use of Optimism Bias uplifts is therefore not risk free itself!

Figure 4 illustrates the fit of using the Erlang distribution of the data defined from the previous road type projects (*ibid.*). The distribution function is fitted with a shape parameter of  $k = 8$  and a scale parameter of  $\theta = 0.09$ . Normally, in order to apply the Erlang distribution ex-ante, the scale parameter is calculated on basis of the triple estimation technique as outlined earlier. It should be noted that the resulting standard error of  $k$  for relatively small fluctuations is found to be statistical insignificant compared with normal practical uncertainties (Lichtenberg 2000 p. 128). A small data analysis has been conducted in order to enhance the prospect of applying a shape parameter ex-ante. In Rosenstand (2007) tests were made for  $k$ -values in the range from 4-9 on a road project in Greenland. This study underpinned the statistical analysis from Lichtenberg (2000) revealing that the overall transport appraisal scheme was almost unaffected when changing the shape from 4 to 9.

The five distributions applied as concerns the decision support to be investigated are all found suitable and well documented through empirical studies and theory. However, as Lichtenberg (2000) points out, sources of error do not unambiguously stem from the above choice of distributions but likewise in the (1) lack of complete or accurate identification of all parameters and variables influencing the final result, (2) remaining and undetected dependencies, and (3) disputes between decision-makers and stakeholders despite using well-known evaluation techniques.

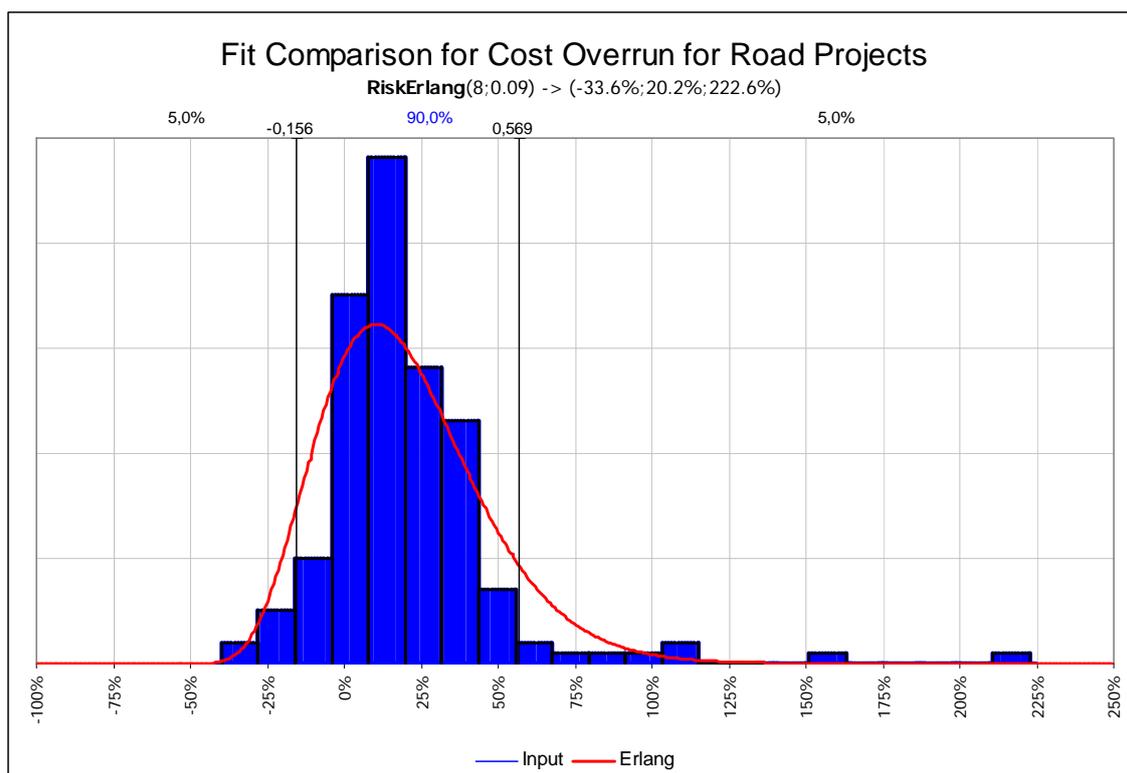


Figure 4. Inaccuracies of construction cost estimates of 167 infrastructure projects (from Flyvbjerg et al. (2003), p. 17)

### 3. The CBA-DK Decision Support Model

The CBA-DK decision support model is designed to bring informed decision support, both in terms of single aggregated estimates such as the BCR, and also in terms of interval results by accumulated probability curves (or accumulated descending graphs ADG). The current interaction between the deterministic and the stochastic parts of the CBA-DK model is made up by the feasibility risk to be investigated when assessing transport infrastructure projects. The analysis framework is shown in Figure 5.

The CBA-DK decision support model is comprised by two modules, namely a deterministic and a stochastic module as shown in Figure 5 (Salling 2008). Each of the individual boxes in Figure 5 denotes a separate worksheet within Microsoft Excel that forms the basis of the cost benefit analysis calculation procedure. The CBA part is based solely on the guidelines issued by the Danish Ministry of Transport in 2003 (DMT 2003). These guidelines concentrate on the use of cost-benefit methods, where future investments are calculated and assessed by the use of single point estimates. As described here, an important aim of this study is to examine whether the introduced feasibility risk assessment concept may be useful. The risk analysis is carried out by add-on software from Palisade named @RISK that uses a Monte Carlo simulation (Palisade 2002, 2007).

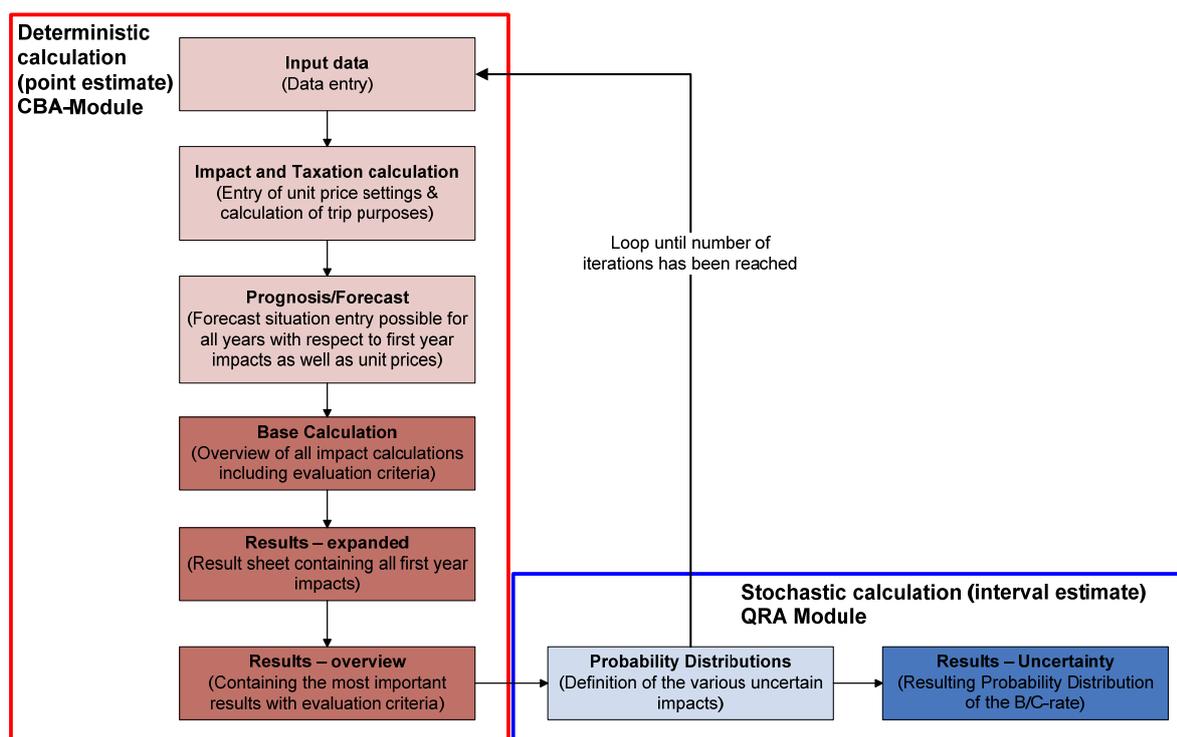


Figure 5. The feasibility risk assessment procedure composed by the CBA and QRA approaches to informed decision support (Salling 2008)

### 3.1 The CBA Module

The CBA module is comprised of 6 worksheets set out as a top-down approach (the left part of Figure 5). The entry sheet currently allows 27 entries to cover the range of user impacts. Additional entries are construction costs (investment costs), sequentially divided into operating and maintenance costs, evaluation period, and key parameters, such as discount rate, growth in the economy, gross domestic product and the net price index (DMT 2003). By calculating the net changes within the user impacts respectively with benefits and disbenefits measured against the investment costs and any follow-up cost, a set of decision criteria are determined. The two bar diagrams in Figure 6 depict the net present costs and benefits presented in the same absolute scale.

The case study involved an inter-urban alignment proposal relieving the town centre of Allerød from through traffic. Originally, the proposal was made up by four project alternatives where each proposal had varying degree of travel time savings, investment costs, accident savings and other costs. In the following analysis, use is made of the one project alternative alignment that formed the preferred option for investment in Allerød. The CBA-DK model is run for the three types of road modes namely, cars, vans and lorries. Furthermore, a group of external impacts are assessed containing accidents saved, local and regional air pollution and noise (Salling and Leleur 2006b). Each area in Figure 6 represents an impact group, so the various parts assist the decision-makers in interpreting the most influential impacts. The empirical interpretation in terms of decision criteria shows a generally low difference between costs and benefits. The BCR of the case is shown below, depicting a relatively narrow margin of approval (Figure 7).

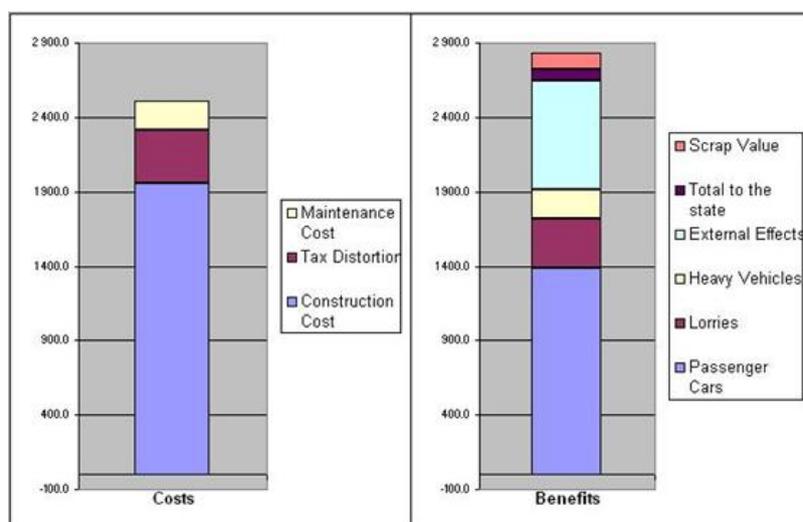


Figure 6. Deterministic run of CBA-DK illustrating a road infrastructure project in the northern part of Zealand, Denmark (Salling and Leleur 2006b)

Benefit-cost ratio (BCR)	1.16	
Internal Rate of Return (IRR)	6.71%	
Net Present Value (NPV)	323.0	
First Year Rate of Return (FYRR)	6.08%	

Figure 7. Aggregated rates of return (Salling 2008)

Benefit-cost ratio (BCR)	1.00	
Internal Rate of Return (IRR)	5.99%	
Net Present Value (NPV)	-5.2	
First Year Rate of Return (FYRR)	5.29%	

Figure 8. Aggregated rates of return including Optimism Bias uplifts (Salling 2008)

Including the Optimism Bias uplift where decision-makers allow for a 50% risk aversion towards a construction cost exceeding has been appraised. The 50% risk aversion leads to an uplift rate of 15% in terms of increasing the construction costs which again result in the decision criteria shown in Figure 8.

If a 50% Optimism Bias level is used in the framework model, there is a negative NPV and a BCR ratio of 1.00. Applying Optimism Bias uplifts gives the decision-makers an easy means by which to perform basic sensitivity tests. Figure 8 shows how robust the evaluation scheme is, and whether the project should be rejected in terms of socio-economic viability. In the example given here from the Allerød preferred route, the BCR reduces to 1.00 and the NPV is negative, so the case for the investment without the Optimism Bias adjustments is positive, but with the Optimism Bias it is negative.

The “alternative” investment cost produces decision criteria in which the uncertainty of cost overruns is embedded. Decision-makers are now presented with an interval in which to base their decisions. Performing sensitivity tests as shown in Figure 8 copes with some of the uncertainties within transport infrastructure assessment. However, the problem of the number of “what if” scenarios remain, as there are situations where combinations of one or more uncertain

impacts produce a large number of scenarios. Monte Carlo simulation is one way in which the complexity of combinations of uncertain impacts can be accommodated. This method uses combinatorial evaluations to perform uncertainty analysis. The simulation approach differs to the Optimism Bias that is heavily dependent on detailed empirical analyses to determine the values to be used.

### 3.2 The Quantitative Risk Assessment (QRA) Module

The QRA-module of CBA-DK (the right part of Figure 5) enables the analyst or modeller to *enhance* the deterministic results into probabilistic outputs. The main purpose of this module has been to incorporate risk and uncertainty within transport appraisal in a straightforward and comprehensive manner. Currently, the BCR is treated as the uncertain output parameter subjected to Monte Carlo simulation. Figure 6 illustrates the impact groups with the highest influence upon the overall decision-making process, namely construction costs, passenger cars and external effects. Table 2 shows an example of the aggregated point results from the CBA-DK model.

**Table 2. Aggregated single point limits from the QRA**

BCR	5% Quantile	0.91
	Mean	1.13
	95% Quantile	1.34
	Std. dev.	0.137

Empirical results can be seen in Table 2 where the probability mass in the 90% confidence interval between 5% and 95% denotes the new decision support foundation. It is important to bear in mind that the quantitative risk analysis technique of CBA-DK is a “tool” to assist the decision-makers to arrive at the best possible decision. Like any other tools, CBA-DK can be used to good advantage by skilled practitioners or to create “havoc” in the hands of the unskilled. It is especially important to keep in mind, that by changing a deterministic variable into a stochastic probability distribution, the possible errors are shifted. Ultimately, the risk associated with the analysis has to be interpreted by various decision-makers and analysts. The same results given to different individuals may be interpreted differently, and lead to different courses of action. Risk averse decision-makers, for instance, prefer a small spread in possible results with most of the probability associated with desirable results. On the other hand, if you are a “risk taker”, then you will accept a greater spread or possible variation in the outcome distribution.

### 3.3 Feasibility Risk Assessment

Substantial effort must be put on interpreting the parameters and variables within the cost-benefit analysis. The connecting arrow between CBA and QRA shown in Figure 5 depends solely on decision-maker involvement. Applying probability distributions on uncertain variables depends on communicable and validated input parameters (by minimum and maximum extreme values). These contributions to the feasibility risk assessment are all highly subjective of nature, particularly when data is not available (which unfortunately is often the case). Implicitly, pitfalls or bias is present and must be handled in order to make comprehensive judgments.

By making validated assumptions with regard to the input of probability distributions one common error is avoided within the FRA. Secondly, the feasibility risk assessment must be communicable to outsiders in terms of transparent and adoptable results. Thus, the second objective of FRA is the way it is communicated in terms of accumulated probability functions as depicted in Figure 9.

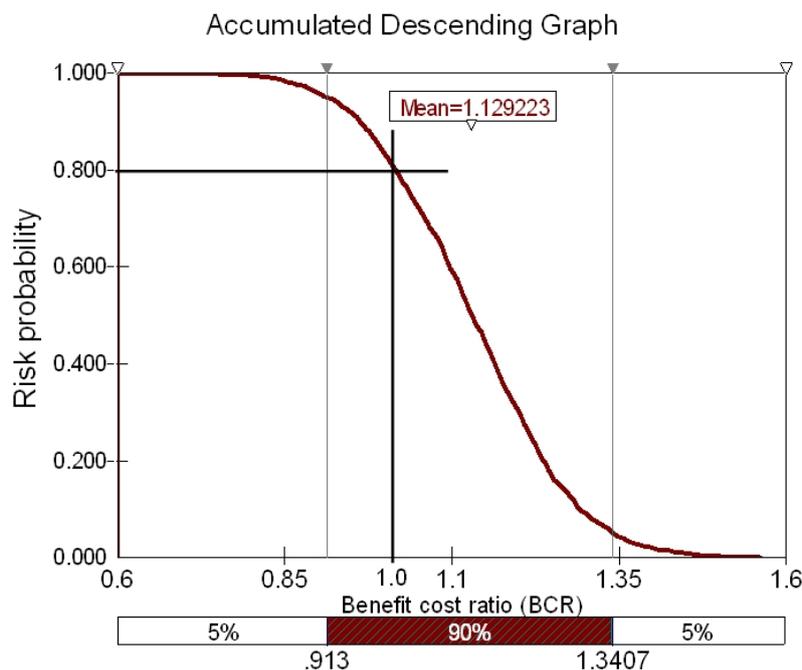


Figure 9. Resulting accumulated graph illustrating the variation of the BCR (Salling 2008)

The s-curve presented illustrates the output distribution from the QRA enabling the decision-makers to compare the overall associated risks within the modelling result. The advantage is the illustration of probability of occurrence, a relative measurement of each possible outcome. Figure 9 illustrates the benefit-cost ratio (BCR) depicting a socio-economic profitable project for values exceeding 1.0. The intersection between the vertical and horizontal line is where the BCR equals 1.0. By moving the horizontal line downwards lowers the risk and the corresponding rate of return increases. Decision-makers that allow high risks will “benefit” in higher rates of return and vice versa. Furthermore, the FRA allows for more than one impact to be assessed within the risk analysis. It should be further noted that for the accumulated descending graph with the probability on the y-axis and the BCR on the x-axis, more reliable data will lead to steeper curves. Hence, the input range would be narrower.

A cumulative frequency plot is traditionally used in project planning to determine the contract bid prices and project budgets, and this makes it useful in the context of transport appraisals. The major strength of this way of communicating the results is the possibility of adding a risk contingency to the budget or appraisal scheme. The risk contingency is typically the amount the decision-maker is prepared to see the budget exceeded (Vose 2002).

#### 4. Conclusion and Perspectives

Risk and uncertainty exists in practically all policy-making situations, and this is generally understood by most stakeholders, as well as the analysts providing the decision support. Nevertheless, studies and research programs still “avoid” the confrontation of uncertainties within decision support models, despite the awareness of these important factors. Decision support, as illustrated in this paper, aims to provide assistance in the development and ultimately the choice of action, by making the uncertainties surrounding a given issue more explicit.

Various strategies can be adopted to respond to high levels of risk and uncertainty. For example, decisions could be delayed if appropriate analysis has not been carried out, or if suitable data are not available, and in some situations (particularly in developing countries) variable discount rates have been used to reflect uncertain futures. In terms of modifying CBA, Optimism Bias is one empirical approach that balances uncertainty and risk through raising the cost estimates of a project, but this is really only a scaling exercise, and it is dependent on the availability of data on similar projects that have actually been implemented.

In this paper, two novel methods have been proposed to help decision makers make better judgements on transport projects. One makes use of a range of parametric and non-parametric distributions to help decide on alternatives, so the concern is not over one value but a range of probabilities – this is the QRA module. The other examines the means by which accumulated descending graphs can be used to communicate results to decision makers. This is the feasibility risk assessment which is concerned both with the interpretation of the analysis and with its presentation to decision-makers.

As an approach, the FRA and the QRA add to conventional CBA by moving away from the point distributions to interval distributions that reflect both risk and uncertainty. Yet there are still problems with the quality and the availability of the empirical data, and the distributions selected, particularly where choices being made between alternatives (as in the Allerød examples) are often marginal, and slight variations in the assumptions used can result in the scheme having a positive or a negative BCR or NPV, and a higher or lower IRR.

The feasibility risk assessment adopted in the CBA-DK software model has demonstrated that a combination of conventional cost-benefit analysis and quantitative risk analysis examination can increase the decision-makers' possibility of making informed decisions. The underlying modelling technique of Monte Carlo simulation provides comprehensive interval results of the given project alternatives replacing single value results. Thus, this modelling tool moves one step further than the proposed Optimism Bias method for the UK Department for Transport. The CBA-DK model should be seen as a useful tool that allows consideration to uncertainty in the appraisal of infrastructure projects, but with the limitation that the results are not better than the extent of the validity of the modelling assumptions, for example by the various probability distributions that can be used.

Future research tasks need to be undertaken, and these include the determination of non-monetary impacts, including long-range impacts, and the environmental and social effects, as well as the strategic impacts (Banister and Berechman 2000 p. 168-170). The handling of the interdependencies and correlations within the modelling framework also need further investigation. This would include an analysis of the possible correlations between transport related impacts, as well as the correlations between transport demand forecasts and construction cost forecasts. The model outlined here is being further developed, in a project for the Danish Strategic Research Council that focuses on the two key concerns of measuring travel time savings and construction costs through the identification of additional reference classes. The issues of risk and uncertainty in all project analysis are central to good decision making, as substantial sums of public (and private) capital are being committed to transport projects, and it is essential that more robust and flexible approaches are developed that can accommodate evidence from similar previous decisions to improve current decisions. This is a true learning process.

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