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Uncertainty in life cycle costing for long-range infrastructure. Part I: Leveling the playing field to address uncertainties

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Abstract

Purpose

Life cycle costing (LCC) is a state-of-the-art method to analyze investment decisions in infrastructure projects. However, uncertainties inherent in long-term planning question the credibility of LCC results. Previous research has not systematically linked sources and methods to address this uncertainty. Part I of this series develops a framework to collect and categorize different sources of uncertainty and addressing methods. This systematization is a prerequisite to further analyze the suitability of methods and levels the playing field for Part II.

Methods

Past reviews have dealt with selected issues of uncertainty in LCC. However, none has systematically collected uncertainties and linked methods to address them. No comprehensive categorization has been published to date. Part I addresses these two research gaps by conducting a systematic literature review. In a rigorous four-step approach, we first scrutinized major databases. Second, we performed a practical and methodological screening to identify in total 115 relevant publications, mostly case studies. Third, we applied content analysis using MAXQDA. Fourth, we illustrated results and concluded upon the research gaps.

Results and discussion

We identified 33 sources of uncertainty and 24 addressing methods. Sources of uncertainties were categorized according to i) its origin, i.e. parameter, model, and scenario uncertainty, and ii) the nature of uncertainty, i.e. aleatoric or epistemic uncertainty. The methods to address uncertainties were classified into deterministic, probabilistic, possibilistic, and other methods. With regard to sources of uncertainties, lack of data and data quality were analyzed most often. Most uncertainties having been discussed were located in the use stage. With regard to methods, sensitivity analyses were applied most widely, while more complex methods such as Bayesian models were used less frequently. Data availability and the individual expertise of LCC practitioner foremost influence the selection of methods.

Conclusions

This article complements existing research by providing a thorough systematization of uncertainties in LCC. However, an unambiguous categorization of uncertainties is difficult and overlapping occurs. Such a systemizing approach is nevertheless necessary for further analyses and levels the playing field for readers not yet familiar with the topic. Part I concludes: First, an investigation about which methods are best suited to address a certain type of uncertainty is still outstanding. Second, an analysis of types of uncertainty that have been insufficiently addressed in previous LCC c is still missing. Part II will focus on these research gaps.

Keywords

Life cycle costing (LCC); Whole-life costing; Cost of ownership; Uncertainty; Data variability; Infrastructure

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1 Introduction

Almost 40 years ago, Sullivan and Claycombe (1977) stated that “no forecast should be accepted as final”. An illustrative example of a rising uncertainty and misestimation is the current phase of low interest rates. In fact, these uncertainties challenge cost planners. Tools and skills to thoroughly estimate future costs are undeniably important for the performance of companies and projects (Goh et al. 2010). Life cycle costing (LCC) aims for such comprehension over the entire life span of a project (Dhillon 1981) by analyzing dynamic cash flows related to life cycle stages, for example, design, manufacturing, operating, and end-of-life (Swarr et al. 2011). LCC ideally supports long-term and sustainable investment decisions if applied appropriately. Projects within infrastructure face particularly large uncertainties due to their extended time frames (Gluch and Baumann 2004; Cole et al. 2005; Kayrbekova et al. 2011). Indeed, results of LCC evaluations related to infrastructure have been proven inaccurate in the past and were significantly influenced by uncertainties (Cole and Sterner 2000; Greenberg et al. 2004).

Uncertainties are not a singular problem of LCC, but inherent in any forecasting method (Emblemsvåg and Bras 1997) and other life cycle-based concepts such as life cycle assessment (LCA) and life cycle sustainability assessment (LCSA) (Björklund 2002). Ignoring the uncertain environment (Lindholm and Suomala 2007) or limiting the scope of uncertainty quantification in LCC fosters misguided decisions (Budnitz et al. 1997). If uncertainties cannot be reduced, one should systematically consider the impact of uncertainties on LCC results (McDonald and Madanat 2012). This article, as Part I of a series of two, aims to provide a comprehensive systematization and characterization of uncertainties in LCC and is a prerequisite for further analyses, for example, the suitability of methods. In addition, Part I intends to level the playing field around understanding concepts and terms of uncertainty for readers not yet familiar with the topic.

Generally, uncertainty results from a lack of knowledge and cannot be measured (Boussabaine and Kirkham 2004; Levander et al. 2009). In other words, it is the difference between the amount of information required and the amount of information available (Tatikonda and Rosenthal 2000) or any deviation from the unattainable ideal of complete determinism (Walker et al. 2003). We use the term “uncertainty” broadly and encompass all uncertainty and variability in LCC, unless indicated otherwise. Sources of uncertainty include anything that occurs in an experiment, calculation, or research project that could lead to uncertainty in the results. These sources are categorized depending on their origin. A more detailed definition of uncertainty is provided in Section 2, as well as Section 3.1.

Various efforts have already been made to systematize uncertainty and to find methods to improve LCC methodology (e.g. Isukapalli 1999; Levander et al. 2009; Xu et al. 2012a). These efforts resulted in various diverging classifications without a general consensus (Goh et al. 2010) and little standardization concerning the definition and modeling of uncertainty (Xu et al. 2012a). Levander et al. (2009) reviewed the concept and applicability of LCC for the case of multi-dwelling timber frame housing to identify the perceived uncertainties of building owners. Their results suggest that long-term financial cost is the most crucial source of uncertainty. Schmidt (2003) suggested to apply sensitivity or scenario analysis to address uncertainty in LCC. For cases where sufficient historical data is available, they suggested more sophisticated probability analyses.

In an attempt to close to this series, Goh et al. (2010) classified uncertainties in the engineering literature in combination with “through life costing”, a formerly used synonym of LCC. They criticized current uncertainty modeling approaches in LCC and suggested a separation of uncertainty in epistemic and aleatory uncertainty to draw attention to epistemic uncertainties within LCC.

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The present series aims to provide a comprehensive overview of sources of uncertainty and methods to deal with them within LCC. Thus, this series is guided by the following three research questions:

1) What are potential sources of uncertainty in LCC for infrastructure?

2) What methods are appropriate to address uncertainties in LCC calculations?

3) What methods to deal with uncertainty have been insufficiently addressed in previous LCC cases?

Part I focuses on research question one, Part II answers research questions two and three. Part I comprehends a systematic literature review to identify, analyze, and evaluate sources of uncertainties and methods to address them. The sources were categorized according to three different schemes. First, we categorized parameter, model, and scenario uncertainty. Second, we differentiated between aleatoric and epistemic uncertainty. We then mapped them in a third step according to whether they were on an analytical, hierarchical, or life cycle level. The methods to deal with uncertainty were classified into deterministic, probabilistic, possibilistic, and other methods. Additionally, we discuss the advantages and disadvantages of the presented methods and illustrate their applicability. More detailed definitions of all categorization and classification schemes are provided in Section 3.1.1.

The results of this series aim to enhance the quality of LCC and similar costing techniques for planners, users, and builders of infrastructure. Our systematic overview of the subject is a guidance to improve the reliability of LCC calculations and applications. However, the consideration of uncertainties related to human behavior such as overconfidence or strategic, deliberate undervaluation (Kostka and Anzinger 2015) was not in the scope of our research. The method and empirical basis of this systematic literature review are described in Section 2. Results and discussion of the review are presented in Section 3. Finally, in Section 4, conclusions are drawn.

2 Methods

Similar to Ilg et al. (2016), LCC is defined rather broadly as “an economic method for assessing all (direct, indirect, internal, and external) costs and revenues (cash flows) arising within a defined life cycle considered important to the investment decision and project evaluation”. Some authors frame LCC as a third pillar of LCSA alongside LCA and Social LCA (Swarr et al. 2011; Klöpffer and Ciroth 2011; Zamagni 2012; Pesonen and Horn 2013). Another way to differentiate LCC is classifying a conventional, an environmental, and a societal type of LCC (Hunkeler et al. 2008; Swarr et al. 2011). This review focuses on applications of LCC for “hard” infrastructure as defined by Jochimsem (1966) and the American Society of Civil Engineers (ASCE 2015): building and constructions, energy supply, transportation, waste treatment, and water infrastructure. In this context, infrastructure is characterized by long life spans, complex interdependencies between system, subsystems, and components, high material usage, and large externalities (ISO 15686-5: 2008).

Uncertainty within LCC modeling is “a potential deficiency in any phase of activity […] due to lack of knowledge which causes the model-based predictions to differ from reality” (Xu et al. 2012a). This lack of knowledge generally refers to existing or non-available data, model context, and modeling structure (Björklund 2002; Heijungs and Huijbregts 2004), which is adapted to parameter, model, and scenario uncertainty in this review. Uncertainty is present in every life cycle stage (Asiedu and Besant 2000), but alters in and over each stage depending on accumulated knowledge (Xu et al. 2012a).

Variability is a measure of the random nature of specific inputs, where well-described differences among data sets exist, whereas risk is characterized by uncertain (i.e. not known with certainty) outcomes but good probability information (Park and Sharp-Bette 1990). Uncertainty, in a narrower sense, refers to outcomes that even lack sufficient probability information (Park and Sharp-Bette 1990). For a detailed discussion of the terms

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uncertainty, variability, and risk, we refer to Apostolakis (1990) and Boussabaine and Kirkham (2004). An overview of all expressions and concepts is given in Table 1.

[Insert here Table 1]

We carried out a systematic literature review to explore and synthesize relevant studies on LCC, uncertainty, and infrastructure. In this review, four steps were completed as suggested by Mayring (2015) or Fink (2013): i) selection of research questions and bibliographic databases, ii) practical screening, iii) methodological screening, and iv) synthesis of results. Existing reviews provided necessary input to assess the practiced and academic status quo.

In step one, research questions were selected, bibliographic databases and websites were chosen, and search terms were defined. The search engines of major publishers (Elsevier, Emerald, Springer, and Wiley) and established bibliographic databases (EBSCOhost and Thomson Reuters' Web of Science) were screened. Google Scholar and SSRN were used to broaden the scope and to include grey literature in order to avoid a publication bias as explained by Tranfield et al. (2003). We used keywords and expressions for uncertainty ("uncertain*", "data quality", "variability") and synonyms for LCC ("life cycle cost*", "cost of ownership*", "whole life cost*"). All search terms were applied to title, abstract, and keywords in the bibliographic databases. As advised by Töpfer (2012), cross references that include relevant articles from the studies identified in the systematic search completed our empirical basis.

In step two, relevant literature in English was identified by applying previously determined criteria for the inclusion in a practical screening. Language bias is not a concern as it is unlikely to miss important differences in meta-analyses when concentrating on English literature (Moher et al. 2000). We considered both empirical and methodical studies in this paper. The screening was performed by three authors. To ensure that all relevant articles were included, the screening was repeated after the coding of all papers. In step two, only title and abstract were examined to identify valuable articles (Becheikh et al. 2006). We included only those empirical articles that assessed infrastructure and included concrete cost data for the life cycle stages. We identified 1,235 studies, of which 825 were excluded during the first screening, 275 were excluded during the second, and 11 were not available. Using ResearchGate and direct contacts to authors, we reduced the number of unavailable studies to five. We also included 13 studies that were cross-referenced in the identified literature. As a result, 115 case studies and 14 methodical articles were part of our analysis.

In step three, the methodological screening, a coding scheme was applied to all identified articles in an iterative process. Following El-Diraby and Rasic (2004), the coding scheme was validated and discussed in expert groups. MAXQDA, a qualitative data analysis software program, was used to execute the coding. The screening was done by three authors. Double coding, the usage of a precise review protocol, and communicative validation were carried out to ensure high intercoder reliability (Kvale 1995; Seuring and Müller 2008).

The fourth step summarizes and presents syntheses of the findings (see Sections 3 and 4).

3 Results and discussion

In this section, we present the results of the systematic literature review. First, the identified sources within the 115 articles are categorized (Section 3.1) using two categorization and three mapping schemes simultaneously (see Figure 1). In this series, the term "categorization" is used if sources of uncertainty are systematized.

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Methods to address uncertainties are then presented and classified into deterministic, probabilistic, possibilistic, and other approaches (Section 3.2). Accordingly, the term "classification" is used for this systematization.

[Insert here Figure 1]

3.1 Sources of uncertainty

3.1.1 Categorization schemes for sources of uncertainty

Swarr et al. (2011) stressed that, in the area of LCC, only a few articles deal with a stringent categorization of uncertainty. Thus we applied two categorization schemes to sources of uncertainty in this section (see Figure 1). In contrast to LCC, various categorization schemes of uncertainty are proposed in life cycle assessment (e.g. Björklund 2002; Heijungs and Huijbregts 2004; Geisler et al. 2005) and other life cycle approaches (Isukapalli 1999; Ayyub 2001; Goh et al. 2010; Xu et al. 2012a). Thus, sources were first categorized according to a scheme common in LCA literature (Huijbregts et al. 2003; Johnson et al. 2011) that differentiates between parameter uncertainty, model uncertainty, and scenario uncertainty (PMS). Second, this article distinguishes between aleatoric and epistemic uncertainty (A&E) according to the verification and validation approach from engineering (Goh et al. 2010). In contrast to previous reviews (Asiedu and Gu 1998; Cavalieri et al. 2004), PMS and A&E uncertainty are not analyzed as exclusive categories, but are considered concurrently.

Categorization according to PMS

With regard to the PMS categorization, parameter uncertainty encompasses sources that are typically based on limited datasets, or biased empirical, subjective, ambiguous, and qualitative information (Goh et al. 2010). "Empirical inaccuracy (imprecise measurements), unrepresentativity (incomplete or outdated measurements) and lack of data (no measurements) are common sources of parameter uncertainty" (Huijbregts 1998). LCC practitioners could rephrase parameter uncertainty by asking: *"Is the available data appropriate and sufficient for the chosen model?"*

Model uncertainty originates from modeling errors such as assumption, approximation, or lack of definition (GAO 2007), the wrongly chosen level of detail or model resolution (Yoner 2001), and reducing complexity and ignoring (auto-)correlation between cost elements (Book 1999). Thus, the reduction of model uncertainty often requires further information (Xu et al. 2012a). In this context, the dependency between model and parametric uncertainty is important. For instance, if new parameters are introduced to reduce the scatter in the predictions, there will be additional parametric uncertainty, thereby transferring some modeling uncertainty into parametric uncertainty, without varying the total level of uncertainty (Budnitz et al. 1997). LCC practitioners could rephrase parameter uncertainty by asking: *"Is the model appropriate and robust enough to depict the object of investigation?"*

Scenario uncertainty refers to the choices of a researcher that lead to uncertainty. For example, choices are made about the functional unit, weighting of factors, system boundaries, or during allocation (Huijbregts 1998). LCC practitioners could rephrase parameter uncertainty by asking: *"What influence does the researcher (or their choices) have on the investigation?"*

Categorization according to A&E

With regard to the aleatoric and epistemic uncertainty categorization, aleatoric uncertainty or statistical uncertainties are derived from the Latin word "alea", which means the "rolling of dice". Thus, the source of aleatoric uncertainty is intrinsic randomness in samples and parameters. Consequently, either the modeler does not

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foresee the possibility of reducing them (Der Kiureghian and Ditlevsen 2007) or they are inherent and cannot be eliminated by more accurate measurements (Saassouh and Lounis 2012).

Epistemic or systematic uncertainties origins from a lack of knowledge about fundamental phenomena (Saassouh and Lounis 2012). Consequently, it can be reduced by improving the models or adding more explanatory variables to the model (Der Kiureghian and Ditlevsen 2007).

Table 2 summarizes the classifications and shows selected authors within the life cycle modeling community that apply the same. Scenario uncertainty only contains epistemic uncertainty, whereas parameter and modeling uncertainty contain both aleatory and epistemic uncertainty (Budnitz et al. 1997).

[Insert here Table 2]

3.1.2 Mapping schemes for sources of uncertainty

We applied three mapping schemes: mapping according to the analytical level, subject hierarchy, and addressed life cycle stages. In the first mapping, analytical aspects related to data quality, data availability, modeling, and scenario parameters are used. In the second mapping, LCC drivers within the project's context (e.g. regulation and taxation), its organizational level (e.g. budget restrictions), and product level (e.g. life time) were identified. The third mapping sorts articles according to the life cycle stages that were addressed in the calculation and in the uncertainty analysis.

Mapping based on the analytical level

The analytical mapping, i.e. analytical aspects related to data quality, data availability, modeling, and scenario parameters, closely follows the PMS scheme. Parameter uncertainty dominates the section and is mentioned in 77 articles, while model uncertainty and scenario uncertainty are mentioned in 60 and 61 articles, respectively.

Parameter uncertainty is important because LCCs require high-quality data and the reliability of outcomes depend on the accessibility, quality, and accuracy of input data (Cole and Sterner 2000). For instance, uncertainty rises if data and parameters are obtained from various sources (Sanyé-Mengual et al. 2015) because comparability might be difficult due to different assumptions and starting points. Associated with data quality issues are uncertainties due to data collection errors, such as direct measuring errors or the measurement of a quantity through a proxy (Saassouh and Lounis 2012). In particular for future projects, the lack of experience in applying LCC is important (Sterner 2000), and vague descriptions or linguistic uncertainties may hamper a precise LCC calculation (Battke et al. 2013). Finally, general variability and inherent randomness in data and processes increase uncertainty (Morcous and Lounis 2005). Missing data is categorized in *no data* (Kishk 2004), *lack of data* (Hinow and Mevissen 2011), and *unrepresentative data* (Moore and Morrissey 2014). It is difficult to distinguish the first two sources, as lack of data by linguistic terms may also refer to no data. However, in statistical terms, a distinction is important so that the different sources of uncertainty can be considered appropriately. Additionally, inaccurate data, as suggested by (Huijbregts 1998), is encoded within *data collection errors*.

Sources of model uncertainties can be divided into seven subcategories: *model structure*, *approximation in computer coding*, *extrapolation errors*, and four types of *simplifications* (by averaging, reduced observations, reduced variables, and functional form). Uncertainties in *model structure* might rise because different data is used, explanatory variables vary, or assumptions regarding the functional form differ (Budnitz et al. 1997). Extrapolation uncertainties occur as some events, for example large earthquakes, do not happen very often and thus effects of

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these situations are lessened (Shin and Singh 2014). Further uncertainties occur as models are simplified by deliberate action of the modeler, for example changes in the climate data or system improvements, while replacement is neglected (Mata et al. 2014).

Subcategories for sources related to scenario uncertainty refer to different kinds of choices. First, the choice of cost allocation is important. Different category systems exist in different companies or countries, for example uncertainties arise if costs from US and European companies are aggregated (Swarr et al. 2011). Second, the choice of cost definition is important because often it is not clear what are the costs, revenues, or transactions within the system (Reich 2005). Comparing results that base on different definitions leads to faulty conclusions due to different starting points. Third, the selection of the input parameters or system boundaries influences the result as these parameters are a subjective selection by the researcher (Aissani et al. 2014). Only models with the same system boundary can be compared accurately. Similarly, the choice of methodology, depending on the researcher's preference and aim, impacts the results (Mitropoulou et al. 2011). Finally, the choice of weighting between multiple criteria has a high influence on the results, as has been concluded by Mavrotas et al. (2010).

Mapping based on the subject hierarchy

Subject mapping relates to LCC spheres or drivers on context (mentioned in 108 studies), organizational (35), and product (75) levels.

The context level includes sources of uncertainty referring to macroscopic spheres surrounding an organization. Derived from the PESTEL[1] analysis, it is divided into an *economic*, *sociopolitical*, *technological*, and *natural level*. The *economic level* consists, inter alia, of labor rates (Asiedu and Besant 2000), competitors (Schmidt 2003), market demand (Kantola and Saari 2013), inflation and cost development (Cole and Sterner 2000), and discount rate (Hong et al. 2007). The *sociopolitical level* includes demographic and social factors (Lai et al. 2013), public acceptance (Troldborg et al. 2014), and the influence of regulation and taxation (Greenberg et al. 2004). The *technological level* summarizes future technological development (Lee et al. 2009), capacity forecast (Li 2015), and infrastructure conditions (Durango-Cohen and Tadepalli 2006). The *natural level* includes the availability of resources such as fuel (Russell 1981), wind (Kavousi-Fard et al. 2014), solar radiation (Kumar et al. 2009), heat (Robert and Gosselin 2014), and occupied area (Menikpura et al. 2012). It also comprises environmental conditions such as earthquakes (De Leon et al. 2013), weather conditions (Willuweit and O'Sullivan 2013), climate conditions (Aissani et al. 2014), and flooding (Francis et al. 2011).

Sources of uncertainty on the organizational level are divided into *funding and budget restrictions* (Patra et al. 2009), *operating processes* i.e. energy use (Russell 1981), insulation (Aissani et al. 2014), and workmanship (Mullard and Stewart 2012), as well as *project and red-tape complexity* (Boussabaine and Kirkham 2004).

Finally, on the product level, sources of uncertainty relate to *life time prediction* (Butry 2009), *product performance* (Kavousi-Fard et al. 2014), and *failure rates and product reliability* (Wen and Kang 2001). Figure 2 summarizes the two mapping schemes discussed above.

[Insert here Figure 2]

[1] Political, economic, social, technological, environmental, and legal aspects

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In Table 3 the identified sources of uncertainty related to the two presented mapping schemes (analytical level and subject hierarchy) are presented with additional information: number of articles for each source (in total 115), its explicit assignment to both mappings, and its categorization into aleatoric and epistemic uncertainty.

[Insert here Table 3]

Mapping based on the life cycle stage

When LCC is used as a planning tool ex ante, uncertainties in LCC rise with a progressive time horizon, i.e. its life cycle stages (Ammar et al. 2013). Uncertainties therefore increase time-dependently. As a planning tool, project properties that predefine (future) life cycle costs are set at early stages with the lowest levels of information. However, a large share of life cycle costs in infrastructure projects occurs in the usage stage. Thus, it is particularly important in infrastructure LCCs to revise LCC estimates after a project has been realized and is already in operation. If LCC is applied iteratively over time within one project, information levels about the project will augment with each life cycle stage, i.e. uncertainties will diminish. This approach would enable an improvement of the accuracy of life cycle costs which are influenced by different user behaviors (Roy 2003).

The life cycle stage mapping encodes what life cycle stage is examined within the LCC calculation. The usage stage is the most frequently modeled stage (102 times), followed by the construction stage (79), and the production stage (62). End-of-life (30) and raw material extraction (4) were considered less often (see Figure 3). Interestingly, only a few of the LCCs conduct an uncertainty analysis in the construction stage (22%) and the production stage (13%). For the usage stage, an uncertainty analysis is almost always conducted within the LCC cases as the usage stage often represents the largest share in total life cycle costs. We see potential for improving LCC by studying uncertainties in early and late life cycle stages of the study object as confirmed by previous research (Ilg et al. 2016).

[Insert here Figure 3]

3.2 Methods to address identified uncertainties

Methods reduce, evaluate, or illustrate uncertainties. We classify the methods applied in previous research in four groups: deterministic, probabilistic, possibilistic, and other methods. Similar categories were applied by Boussabaine and Kirkham (2004), who distinguished between deterministic, qualitative, and quantitative uncertainties; or Goh et al. (2010), who distinguished between qualitative and quantitative techniques.

We define deterministic methods as techniques that use point estimates and assume a singular outcome. Uncertainty is modeled by ignoring or excluding uncertain parameters. Probabilistic methods encompass stochastic approaches that include randomly selected parameters in a variety of sampling methods. These methods presume multiple possible outcomes with varying degrees of likeliness. Probabilistic methods are suitable for addressing aleatory uncertainty. However, probabilistic methods cannot effectively handle ambiguous uncertainties and use expert knowledge (Chen 2007). Possibilistic methods use much weaker statements of knowledge in these cases, for example fuzzy values are assumed for previously unknown or largely missing parameter values (Xu et al 2012a). These methods are suitable to address data gaps or epistemic uncertainty, such as lack of knowledge. Other methods contain, for example, different measurement, analogy, or documentation regimes.

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In total, 91 articles mention or apply deterministic methods, 90 articles use probabilistic methods, and a minor proportion, 42 articles, address uncertainties by using possibilistic methods. 61 articles apply other methods. An overview of applied methods is presented in Table 4.

[Insert here Table 4]

3.2.1 Deterministic methods

The most frequently applied deterministic methods are scenario analysis, mentioned or used in 44 articles (38%), and sensitivity analysis, mentioned in 61 articles (53%). Further deterministic approaches are cost-benefit estimation, break-even analysis, risk-adjusted discount rate, and the certainty equivalent technique (Boussabaine and Kirkham 2004; Xu et al. 2012a).

Scenario analyses usually encompass at least two scenarios (23), one worst-case scenario (11), or Delphi scenarios (6). The most common type of scenario analysis is using at least two different scenarios that are then subsequently compared. Another type of scenario analysis is the application of worst-case scenarios, for example high deterioration rates (Li and Madanu 2009). They are very common in deterministically handling uncertainties and are probably the most simple ones (Domínguez-Muñoz et al. 2010). Apart from a worst-case scenario, further scenarios are usually developed depending on their relevance on the overall results, for example by assuming different discount rates, lifetimes, or energy prices (e.g. Val 2007; Fernandes et al. 2011; Francis et al. 2011). The most sophisticated application is a Delphi scenario analysis, which combines scenario planning with the Delphi approach, i.e. the systematic development of expert opinions (Dalkey and Helmer 1963). The Delphi scenario analysis contains the elaboration of various scenarios, including the associated probability of each scenario, leading to a risk tree analysis (Emblemsvåg and Bras 1997). The amount of scenarios varies broadly, from five (Danaher 2012) to 324 (Mishalani and Gong 2009a). However, more scenarios do not necessarily lead to a higher quality of a scenario analysis.

Sensitivity analysis determines the influence of assumptions on results. Parameters are varied over a range of values, often based on their assumed distribution (Boussabaine and Kirkham 2004). In the present sample, one-at-a-time (35) and advanced sensitivity analysis (11) were applied most frequently. Further variations are regression analysis (3), scatter plots (6), screenings (6), and variance-based methods (1). Sensitivity analysis is mainly used to identify the effect that certain parameters have on the result (Walls and Smith 1998; Halog 2004). A sensitivity analysis is performed by altering one parameter at a time and monitoring the impacts of this alteration. While it is also possible to change more than one parameter simultaneously, this kind of sensitivity analysis is applied less frequently (Patra et al. 2009). Typically a sensitivity analysis focuses on parameters such as lifetime, discount rate, fuel prices, or maintenance routines and frequencies. A disadvantage of standard sensitivity analyses is the equal weight that is given to the input value assumptions (Walls and Smith 1998). Parameters with low volatility but high influence on the results get the same weight as parameters with high volatility and low impact. Consequently, a more sophisticated approach to sensitivity analysis was developed that is called uncertainty importance analysis. This approach weights each input parameter by its standard deviation (for further discussion see Part II of this series).

In summary, deterministic methods are the most easy-to-use and, thus, most frequently applied methods to address uncertainties. However, their simplicity also limits the extent to which they can provide insights into the uncertainty of a LCC. Deterministic methods are not able to trace uncertainty within the input variables of LCC

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(Tighe 2001). They ignore information that could improve the LCC results. Even when applying sensitivity analysis with various combinations of input values, this technique rather conceals uncertainty important to the decision than questioning the validity of LCC results (Chen 2007).

3.2.2 Probabilistic methods

In probabilistic methods, an objective or subjective probability distribution function is assigned to each or selected uncertain parameters (Walls and Smith 1998). For probabilistic methods, it is important to distinguish between probability distributions and sampling methods. In contrast to deterministic approaches, where parameters are altered, probabilistic methods assess the uncertainty of parameters based on different sampling methods. Typical parameters that are considered in infrastructure analyses are unit rates of construction, rehabilitation and maintenance treatments, traffic growth rates, and discount rates (Li and Madanu 2009). Probability distributions can be either parametric or nonparametric. The difference is that nonparametric probability distributions do not require stringent model assumptions and, thus, are useful when data availability is limited (Fernandes et al. 2011). The easiest solution to determine a probability distribution is on the basis of historic data (Boussabaine and Kirkham 2004), i.e. empirical or measured distributions. The data is grouped to form a frequency histogram that is then used for simulations. In case of a theoretical distribution, this approach helps to smooth irregularities as present in historic data and so provides the possibility of sampling the extreme values of the distribution (Emblemsvåg and Bras 1997). The most frequently used types of distributions are the Gaussian or log-normal distribution (20), the Weibull distribution (11), and the linear or triangular distribution (12). Other applied distributions are the uniform distribution (9), the risk-based distribution (7), and the Poisson distribution (5). The Gaussian distribution is mainly applied if little historical data is available (Jung et al. 2009), whereas linear, i.e. triangular distributions, are commonly selected when a questionnaire study is the source of data and the sample size is small (Walls and Smith 1998; Jung et al. 2009; Settanni and Emblemsvåg 2010). Although often applied, a major problem with triangular distributions is that the probability precipitously drops to zero outside of the minimum and maximum values (Walls and Smith 1998). The Weibull distribution is sophisticated because it is a stretched exponential function. It is mainly applied to life expectancy, life-cycles, future forecasting, and deterioration of elements (Boussabaine and Kirkham 2004). Thus, it is commonly used for the simulation of electricity cost forecasts in buildings (Kirkham et al. 2002), to represent the wind speed character (Rathore and Roy 2014), or to model the ageing of bridges (van Noortwijk and Klatter 2004). The Poisson distribution is used in infrastructure projects and disaster research to predict the probability of occurrence (Xu et al. 2012b).

A risk-based distribution is favorable for highly uncertain input parameters. It was first used to evaluate pavement systems and bridges (Ehlen and Marshall 1996; Walls and Smith 1998; Jung et al. 2009) and has recently been also applied by electricity distribution companies.

Monte Carlo Simulation (MCS) is the most frequently applied sampling method (59). Latin Hypercube Simulation (9), design of experiment (5), and subset sampling (3) are applied less often. MCS is a statistical method "by which a quantity is calculated repeatedly, using randomly selected "what if" scenarios for each calculation" (Boussabaine and Kirkham 2004). MCS is based on random sampling of selected input parameters (Budnitz et al. 1997). Often, only the most relevant input parameters are considered in an MCS to reduce the simulation time and required processing power. In such an approach, also referred to as importance sampling, a sensitivity analysis is carried out to detect the most influencing input parameters. The simulation then focuses

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only on the parameters that materially contribute to variations in results (Budnitz et al. 1997). Latin Hypercube sampling uses a different approach known as stratified sampling (Guo et al. 2012). It generates a sample that is smaller but with plausible distribution of all parameter values. For it, the probability distribution is split into n intervals of equal probability, and each of the n intervals is sampled only once (Guo et al. 2012; Budnitz et al. 1997). This approach assures that the entire range of each parameter is still represented in the sample (Iman and Shortencarier 1984). Moreover, the resulting sampled distribution more precisely fits to the initial distribution as compared to Monte Carlo samples.

Probabilistic methods help to assess uncertainty in the input variables. However, LCC analysts face difficulties in collecting all necessary information for these models (Chen 2007). It is important to know that probabilistic methods may be less useful for epistemic uncertainty, i.e. when data is lacking or uncertainties are caused by a lack of knowledge (Xu et al. 2012a). Additionally, all probabilistic methods are highly sensitive to the shape of the input distributions (Boussabaine and Kirkham 2004).

3.2.3 Possibilistic methods

In possibility theory, a possibility function represents uncertainty by expressing the degree of possibility for a certain situation to occur. This class of method mostly includes approaches that use Bayesian statistics. Possibilistic approaches can represent uncertainty with much weaker statements of knowledge compared to probabilistic methods (Oberkampf et al. 2001). In LCC, available data is often incomplete and ambiguous. Retrieved from expert opinion and existing databases, fuzzy logic techniques as an example, possibilistic methods provide a formal treatment of these types of information (Chen 2007).

Bayesian models consider parameters as random variables that follow a prior distribution. This distribution is combined with a likelihood that leads to a posterior distribution of the parameters of interest (Andrade and Teixeira 2012). Within Bayesian approaches, different types of expert systems have been developed and include rule-based, model-based, and case-based systems (Walls and Smith 1998; Fernandes et al. 2011). Bayesian statistics have become popular in uncertainty modeling since powerful computers became widely accessible in the early 1990s (Andrade and Teixeira 2012). Since then, further versions have been developed, such as Latent Markov decision process / Hidden Markov chain or Markov chain Monte Carlo. The Latent Markov decision process addresses uncertainty by incorporating the measurement error model into the decision-making framework and is often used for maintenance modeling (Mishalani and Gong 2009b). Being dependent on strong computational power, Latent Markov decision process is more difficult to apply if multiple technologies are used simultaneously to measure different distresses, for example investments in maintenance and repair of transportation infrastructure (Durango-Cohen and Tadepalli 2006).

Fuzzy set theory was originally introduced by Zadeh (1965). A fuzzy logic system offers a balance between a qualitative-based simulation and an analytical simulation (Fernandes et al. 2011). Fuzzy logic is characterized by representing qualitative linguistic expressions numerically with fuzzy sets. The quantitative part characterizes every fuzzy set by a membership score, which varies from 0 to 1 (Boussabaine and Kirkham 2004). LCC is fully compatible with fuzzy logic (Chen 2007). That allows replacing existing scenarios within LCC, for example related to M&R strategies, with fuzzy set models. Moreover, fuzzy systems are fault-tolerant related to minor changes in system parameters or input values. The main advantage of fuzzy logic is introducing rules from heuristics, experience, and intuition that create a functional transparency (Chen 2007). Additionally, fuzzy set theory is often combined with MCS, for example uncertainty is modeled as fuzzy numbers and the model solved

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numerically by employing MCS techniques (Rodríguez Rivero and Emblemsvåg 2007; Settanni and Emblemsvåg 2010).

Other artificial intelligence techniques similar to the ones mentioned above include ant colony optimization (Stützle and Hoos 2000), artificial neuro networks (Chien et al. 2002), and evolutionary programming such as genetic algorithm (Fwa et al. 1994). It is important to acknowledge that although genetic algorithm techniques produce “good” solutions for specific optimization problems, they may not find the true optimum solution (Chen 2007). Not surprisingly, hybrid techniques exist. For example, soft computing defines an “umbrella of artificial intelligence techniques” (Chen 2007) that combines some of the presented techniques to an improved decision-support tool able to handle numeric data values and linguistic expressions. It includes three main principles: probabilistic reasoning, neural networks, and fuzzy programming. Chen (2007) applies such hybrid soft computing as a combination of artificial neuro networks, fuzzy sets, and genetic algorithm to study optimal M&R strategies for road pavement. Chen (2007) also offers an evaluation of this technique’s applicability regarding the five required analysis steps for M&R, such as condition assessment, performance prediction, need analysis, prioritization, and optimization. In LCC for infrastructure, soft computing techniques may offer a powerful way to “achieve tractability, robustness, and better rapport with reality” (Zadeh 1973).

Expert opinions (20), Markov chain (9), and Bayesian distributions (3) are the most frequently applied methods in the present sample. Reservations and resistance to change among LCC analysts seem to be the largest barrier for implementing possibilistic methods (Chen 2007). Besides, the integrating of new methods within existing decision systems also poses a challenge.

3.2.4 Other methods

Apart from these three main classes, several other less statistical methods are identified. Often, the LCC modeling or data is checked by comparison to prior literature. In this sample, data sets were checked 34 times (e.g. Allacker 2012; Liu 2014), models were checked 18 times (e.g. Kim and Frangopol 2011; Battke et al. 2013), and the outcome of a model seven times (e.g. Rathore and Roy 2014; Terzi and Serin 2014). Furthermore, models are checked with modified deterministic models (9), by multiple cases (3), or by tests within the model (10). The last one includes quality criteria such as R^2, the Watson test, or level of significance. Moreover, standardization processes are used referring to commercial databases (e.g. Han et al. 2014; Shin and Singh 2014), public databases (e.g. Mavrotas et al. 2010; Simões et al. 2013), official standards (e.g. Aissani et al. 2014; Mata et al. 2014), and software packages (e.g. Morcous and Lounis 2005; Anwari et al. 2012). A different way to reduce uncertainty is by providing additional data to increase the overall transparency, for example via electronic supplementary materials (e.g. Sanyé-Mengual et al. 2015; Zakeri and Syri 2015).

Along with the three other classes (deterministic, probabilistic, possibilistic), these less statistical methods are useful in addressing different kinds of uncertainties in LCC modeling. The identified methods should not be applied exclusively, but reveal their maximum effectiveness in combination with each other. Figure 4 presents an overview of these methods.

[Insert here Figure 4]

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4 Conclusions

Uncertainties in LCC have a strong influence on the results. When LCC is applied as a planning tool¸ these uncertainties increase for parameters with longer time horizons (Ammar et al. 2013). Infrastructure projects are characterized by long lifetimes; therefore, the impact of uncertainties is particularly significant. The ignorance of uncertainty is then inadvisable as unforeseen internal and external shifts results in jeopardizing circumstances (Budnitz et al. 1997; Lindholm and Suomala 2007). Infrastructure projects require long-term thinking and robust estimation methods in order to support decision-makers when applying LCC (Hellweg 2001; Klauer et al. 2013). To the best of our knowledge, no holistic framework exists which systematically collects and combines sources of uncertainty and methods to deal with them in LCC related to infrastructure (Swarr et al. 2011). Thus, a systematization was necessary to provide a basis for quality improvements of LCC or similar costing techniques. In Part I of this series, we provide a comprehensive overview of uncertainties in LCC. Part I therefore levels the playing field for readers that are not yet familiar with uncertainty in LCC. This paper contributes to previous literature in various ways. First, we apply a rigorous approach to identifying and reviewing relevant literature. As a result, this paper is based on a comprehensive empirical basis, consisting of 115 articles that deal with LCC, uncertainty, and infrastructure. Second, we systematized the sources and types of uncertainty. One conclusion is that the variety of uncertainties makes it difficult to provide a meaningful and simple categorization. Consequently, we looked at uncertainties from several perspectives by applying two different categorization and three mapping schemes. Third, we provide a detailed overview of methods to deal with uncertainty, including a discussion of their general advantages and disadvantages. We contribute to the scholarly discussion by combining all schemes in order to improve visibility, awareness, and applicability of methods.

A limitation of this paper is the omission of uncertainties related to human behavior, such as overconfidence or strategic, deliberate undervaluation (Kostka and Anzinger 2015). These aspects play a role in infrastructure project planning, but are not within the scope of this review. Consequently, their influence should be investigated in further studies.

Part I, nevertheless, provides a comprehensive inventory of the status quo of uncertainty analysis in LCC. The next logical step is to use this basis for an evaluation of which method is sufficient to address a certain type of uncertainty. Consequently, we discuss this topic in Part II of this series to also provide practical guidance for LCC applications in infrastructure projects. Furthermore, Part II evaluates learning potentials from other life cycle-based concepts such as LCA and LCSA. Part II also provides guidance on how to integrate uncertainty analysis results into management routines.

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Figure Captions

Fig. 1: Applied system of categories in this review

Fig. 2: Categorization of sources of uncertainty

Fig. 3: Examined life cycle stages and uncertainty analyses in the review articles

Fig. 4: Guiding classification of methods to address uncertainty in LCC

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Table captions

Table 1 Overview of applied definitions

Table 2 Categorization of sources of uncertainty

Table 3 Overview of sources of uncertainty mentioned in the articles

Table 4 Comparison of the applied categories

Table 5 Overview of reviewed articles and applied uncertainty analyses