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Panenka, Andreas; Nyobeu Fangue, Francois Marie; Rabe, Rolf; Schmidt-Bäumler, Heike; Sorgatz, Julia

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Reliability assessment of ageing infrastructures: an interdisciplinary methodology

Andreas Panenka[a], François Marie Nyobeu Fangue[b], Rolf Rabe[a], Heike Schmidt-Bäumler[a], Julia Sorgatz[c]

[a] Structural Engineering, Bundesanstalt für Wasserbau (BAW), Karlsruhe, Germany

[b] Bridges and Structural Technology, Bundesanstalt für Straßenwesen (BASt), Bergisch Gladbach, Germany

[c] Geotechnical Engineering, Bundesanstalt für Wasserbau (BAW), Karlsruhe, Germany

Abstract: This article presents an interdisciplinary methodology that provides decision makers with key figures on the reliability of ageing structures in transport infrastructures. The methodology is closely connected to ongoing discussions about proactive and sustainable maintenance strategies under increasing economic and ecological pressures. Since the infrastructures of the main modes of transport in Germany, that is, roads, railways and waterways, pose similar challenges to the responsible governmental authorities and administrations, the development of the methodology presented in this article is embedded in the research programme 'BMVI Network of Experts'. Under the premises of the research programme, the methodology provides a step-by-step approach to creating a profound knowledge base which is required for the reliability assessment of ageing infrastructures. The methodology aims at generating meaningful key figures about the structural condition of an assessed asset for a risk-informed maintenance strategy. The examples of a condition assessment procedure based on a fuzzy criticality recommendation and a screening tool for ranking a large number of structures using operative reliability indices illustrate how the interdisciplinary methodology allows the development of user-friendly tools to support and facilitate the management of infrastructure maintenance in the responsible governmental entities.

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1 Introduction

A sustainable and future-oriented maintenance strategy for transport infrastructure is of general interest, as the economic success of a country depends on uninterrupted goods traffic and passenger services. Developing a maintenance strategy involves meaningful key figures about the condition of the transport infrastructure and its structures. Reliability-based methods are suitable for assessing existing structures that are inspected at regular intervals and maintained as necessary (cf. Straub, 2018). The use of the concept of structural reliability requires a high level of knowledge of the relevant deterioration mechanisms, their effects on a structure and their causes.

In this regard, the applicability of existing standards, such as the Eurocodes, is limited, because the detailed requirements and comprehensive recommendations concern the design and construction of new buildings. The interdisciplinary methodology presented in this article uses proven methods of understanding a problem, analysing collected data and assessing reliability in order to successively replace the generic assumptions in the standards with systematically compiled knowledge about the assessed structure. The generated meaningful key figures support an effective, risk-informed maintenance management for transport infrastructures from a cross-modal perspective.

The methodology is developed within the framework of the research programme 'BMVI Network of Experts' (NoE), initiated by the Federal Ministry of Transport and Digital Infrastructure (BMVI). Although well-known and established in the academic world, research networks are a considerable novelty in the context of collaborative work of German authorities and agencies. Therefore, Section 2 describes the general goals of the NoE and explains the premises of the research and development (R&D) process for the assigned projects. Section 3 presents the step-by-step approach to the gathering of the relevant knowledge about the reliability of existing structures while Section 4 describes the interdisciplinary methodology and explains its application. The benefits of the methodology are illustrated in Section 5 with the aid of two examples taken from the maintenance management of transport infrastructures. In Section 6, the article concludes with a discussion of the essential findings of the development work to date and an outlook on the next phase of the research programme.

2 Premises of the integrated research format 'BMVI Network of Experts'

German infrastructure assets have a capital value of around 430 billion Euros. In addition to passenger services, goods traffic with its approximately 655 billion ton-kilometres plays a key role. The investment strategy of the German government prioritises rehabilitation and upgrading measures over the extension of the existing transport network. However, the investment backlog is significant and enforces a prolonged operation of structures which may have already reached the end of their theoretical service life. (Bundesministerium für Verkehr und digitale Infrastruktur [BMVI], 2016) The combination of ageing infrastructure (Figure 1), significantly increasing traffic loads (Figure 2) as well as drastically changing ecological circumstances and socio-economic demands requires the development of sustainable and future-oriented solutions.

In Germany, large parts of the transport infrastructure are owned by the public sector. The responsible entities of the BMVI are organised according to the modes of transport road, railway and waterway. The R&D format 'BMVI Network of Experts' (NoE) enables the participating institutions to cooperate across institutional borders, thus overcoming the strict separation of spheres of responsibility (Figure 3). In currently more than 70 interdisciplinary projects across administrative borders, the NoE is developing tools and guidelines that will allow the BMVI to respond efficiently to five distinct challenges affecting the infrastructure of all three modes of transport (Figure 4). Methods and techniques to support a safe and reliable operation of ageing infrastructures are investigated and developed in Topic 3 with its four key topics (KT; Figure 5). The interdisciplinary methodology for the assessment of reliability at object level is developed in KT 302.

The research period of the NoE is subdivided into the phases 'investigation', 'integration' and 'implementation' and ends in the year 2030. Primarily devoted to basic investigations and conceptual studies, the first phase also aims to establish shared working processes across agency borders and to develop an interdisciplinary glossary (cf. BMVI, 2017a). The premises for R&D work under the NoE may be summarised as follows:

- flexibility to meet the needs and requirements of the three modes of transport road, rail, waterways;
- versatility to cover the wide variety of challenges associated with the different structures in the transport infrastructures;
- comprehensive and expressive results;
- conclusive methodology;
- scalability for use at different levels of decision making;
- accuracy for sound decision-making support but user-friendly application.

3 Step-by-step approach to gaining knowledge about the reliability of existing structures

In the context of civil engineering structures, Eurocode 0 defines reliability as the 'ability of a structure or a structural member to fulfil the specified requirements, including the design working life, for which it has been designed. […]' (Deutsches Institut für Normung e. V. [DIN], 2010b, p. 17). The definition implies characteristics that determine structural reliability:

- structural as well as functional requirements;
- structural behaviour under actual load scenarios;
- limit states and corresponding possible failure modes;
- possible deterioration mechanisms.

Consequently, the step-by-step approach to the reliability assessment of existing structures involves the analysis, modelling and simulation of these relevant characteristics. The assessment process requires a specific methodology to establish a conclusive understanding of the actual problem, to collect and analyse necessary data and to produce meaningful key figures on the reliability of the assessed structure (Figure 6).

The methodology at the level of problem understanding concerns the compilation of knowledge about system behaviour, relevant limit states, required input parameters as well as the definition of an appropriate 'accuracy to usability' ratio. At the level of data collection and analysis, the methodology aims at gaining the knowledge needed to build a factual model of the real-world situation. Based on this knowledge, the methodology for the compilation of meaningful key figures supports the reliability-based condition assessment of existing structures.

4 The interdisciplinary methodology

With regard to the reliability assessment of existing structures, the elicitation of knowledge requires an interdisciplinary methodology to establish a fundamental understanding of the problem to be analysed, to cover the wide range of available data sources and to generate meaningful key figures based on reliability assessment procedures.

4.1 Problem understanding

For the design of new structures, information about technical requirements and safety regulations is provided by national standards (e.g. Eurocodes) or probabilistic model codes (e.g. www.jcss.byg.dtu.dk/Publications/Probabilistic_Model_Code; Vrouwenvelder, 1997). In contrast, the reliability assessment of existing structures involves an elaborate understanding of the actual system behaviour, limit states, input parameters and the necessary resolution level of the analysis to enable the preliminaries and methods for subsequent data collection and data analysis to be specified. The presented methodology for this assessment step encompasses expert interviews, system analyses and physical model tests.

4.1.1 Expert interviews

Expert interviews are an experience- and knowledge-based scientific method aiming at understanding hitherto unknown context and hidden processes. In human and social sciences, expert interviews are a widely accepted method of analysing knowledge about the social context of

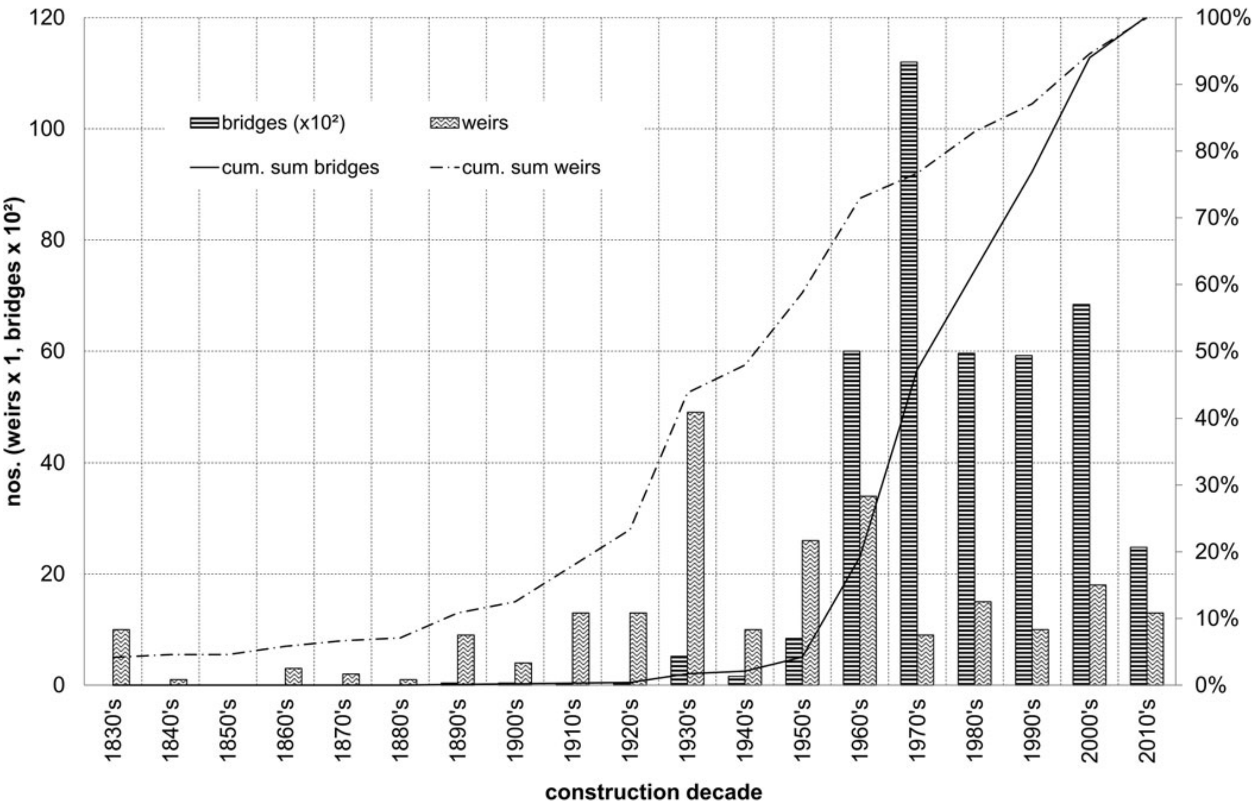

Figure 1: Age distributions of bridges and weirs in the German transport infrastructure (sources: BASt, BAW).

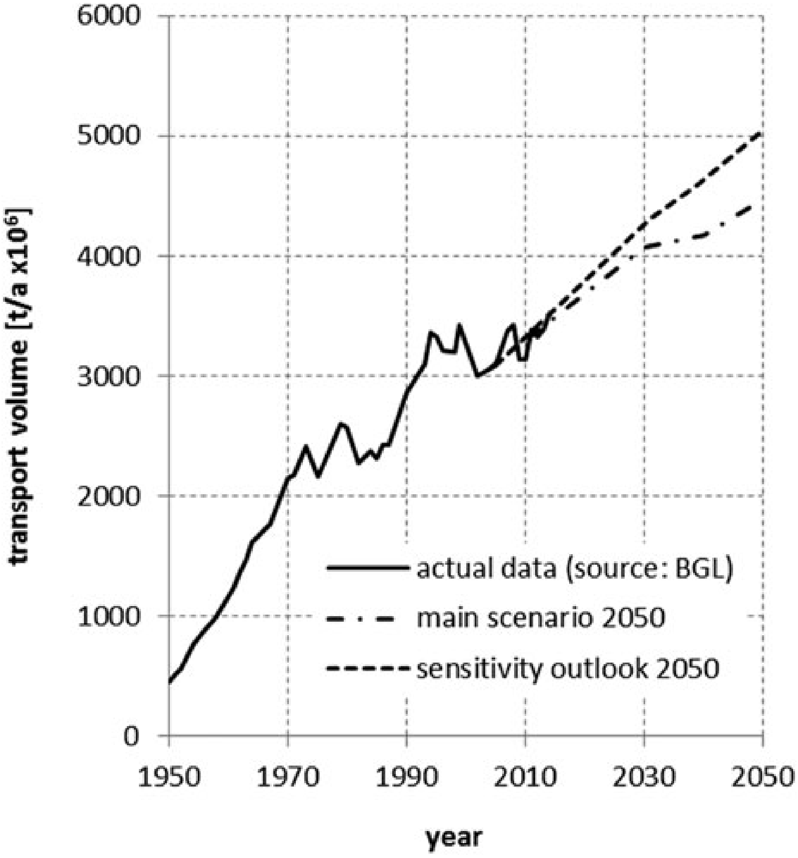

Figure 2: Development and prognoses of the transport volume between 1950 and 2050 in Germany (source: BASt, BGL).

actions and social structures (cf. Bogner, Littig, & Menz, 2009; Gläser & Laudel, 2010; Meuser & Nagel, 1991). In civil engineering, eliciting expert knowledge becomes attractive when quantitative data are not available in sufficient quality (cf. Kuhnert, Martin, & Griffiths, 2010; McBride & Burgman, 2012; Schuttrumpf, Kortenhaus, Fröhle, & Peters, 2008).

Various aspects have to be taken into account when conducting expert interviews (Figure 7). In the preparation phase, the research questions are collected and experts to be interviewed are selected. A semi-quantitative questionnaire sent out in advance can help to ask detailed questions for which the experts need to prepare and which can be answered before the actual interview. In expert interviews, possible ambiguities in answering the questionnaire are clarified by discussing some aspects of the questionnaire in detail. Moreover, the use of what are known as 'guided expert interviews' is recommended in which the interviewer uses a catalogue of key subjects and questions that are summarised in a guideline.

With respect to civil engineering structures, conducting an additional on-site inspection together with the expert contributes to validating the received information. In the subsequent data analysis, the general key subjects are subdivided into sub-categories to give the interviewer a better overview of the data content (Miles, Huberman, & Saldaña, ~ 2014). If a general key subject is, for example, 'documentation', possible sub-categories may be 'documentation of damage', 'documentation of maintenance measures', 'widely accepted damage classes' and 'data management'. Sub-categories can also be compiled over several key subjects. The results of the first level of expert interviews may lead to a second level investigation, for example, a group discussion.

Expert interviews contribute to an improved problem understanding by eliciting available (field) knowledge. They support the description and identification of critical elements

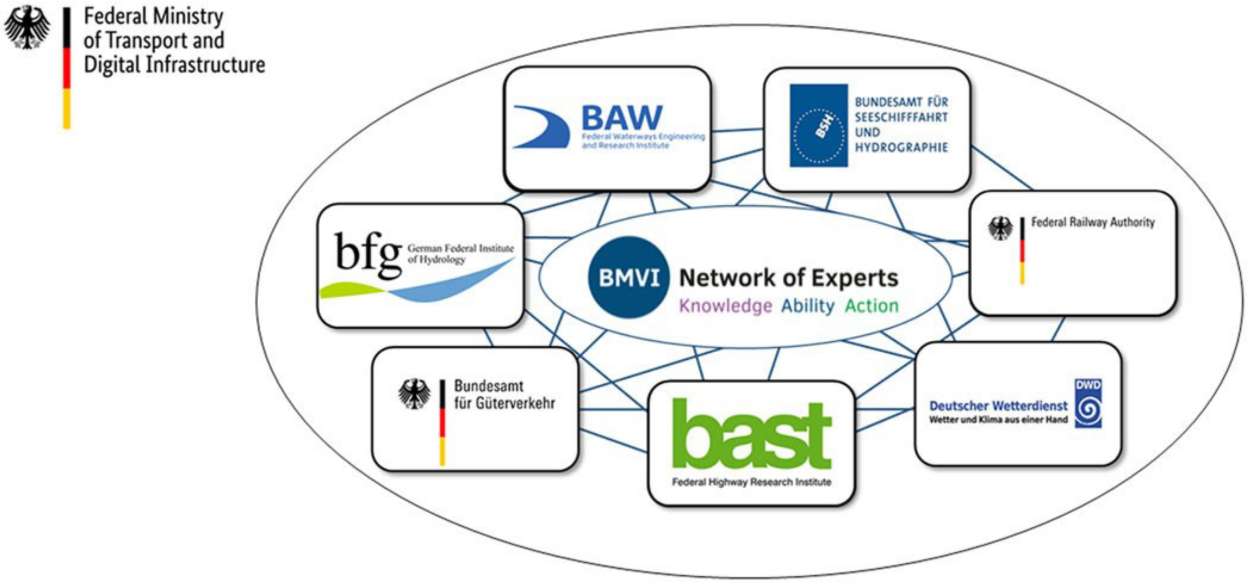

Figure 3: The seven departmental research units composing the NoE.

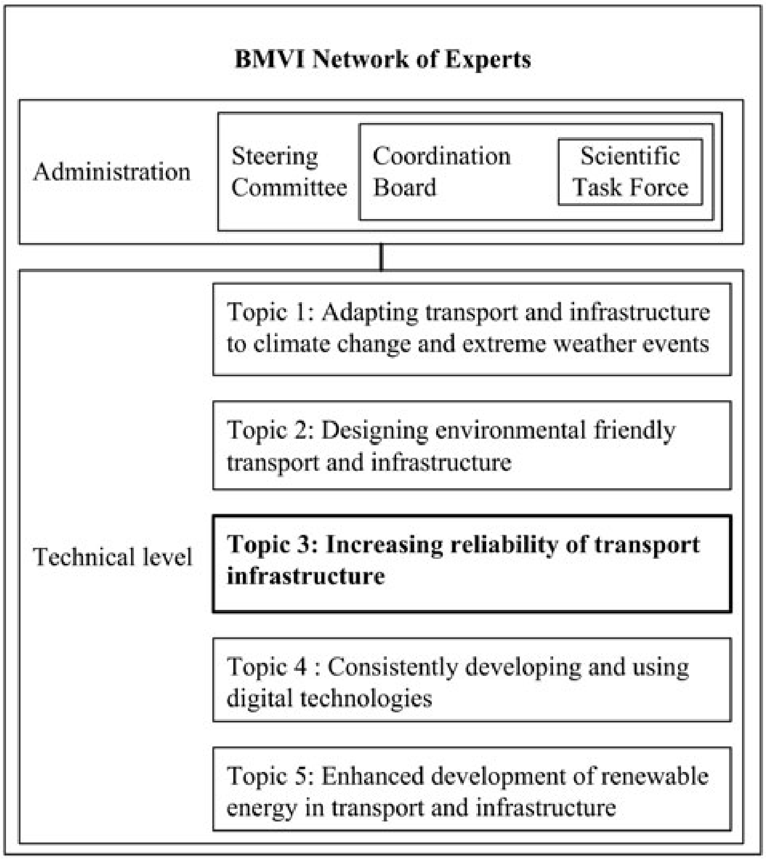

Figure 4: Organisation chart of the NoE.

at object or system level and thus also provide information about an adequate resolution level for the subsequent data collection and model concept. As a result, deficits in the understanding of investigated problem may become obvious, and can subsequently be elaborated by further investigations. A comprehensive explanation of how to conduct expert interviews is available in (Sorgatz, Kayser, & Schüttrumpf, 2018).

4.1.2 System analysis

Complex technical systems, such as civil engineering structures, are composed of a multitude of different components, each with a specific contribution to the overall functionality of the system. Thus, the causes for failure may not be obvious at first sight. There are various methods of analysing complex systems that aim to determine hazard scenarios describing potential failure modes, their consequences and causes (cf. DIN, 2010a). For the analysis of technical systems, which are organised hierarchically, the USA military developed the Failure Mode, Effects and Criticality Analysis (FMECA) in the 1940’s (United States Department of Defense, 1949). Soon after, the method was adapted and improved by NASA (National Aeronautics & Space Administration [NASA], 1966) and various productive sectors, such as the automotive and aviation industry (Matsumoto, Matsumoto, & Goto, 1975; S-18 Aircraft & Sys Dev & Safety Assessment Committee, 1967). Nowadays, the FMECA is an essential tool in the field of quality engineering for the risk assessment of systems, products and processes.

The FMECA is an inductive method, which supports the determination and mitigation of potential risk scenarios arising from technical items (i.e. products, systems or processes). After defining the relevant components (i.e. functional units required for the overall functionality of the assessed item) and their hierarchical organisation, the corresponding cause–effect chains leading to system failure are identified. Failure is defined as non-compliance with a specified requirement. Each cause–effect chain consists of a potential failure mode, its consequences and respective causes. Following the hierarchical organisation of the components, the failure consequence at a certain hierarchy level may be regarded as the failure cause at the next higher level. In a subsequent criticality assessment, the cause–effect chains are prioritised for mitigation measures based on their risk priority number (RPN). The RPN is determined by three or more risk criteria, which assess the severity of the impact of a failure sequence on achieving a predefined objective (e.g. customer satisfaction, reliance on a product, etc.), the occurrence of the corresponding failure cause and

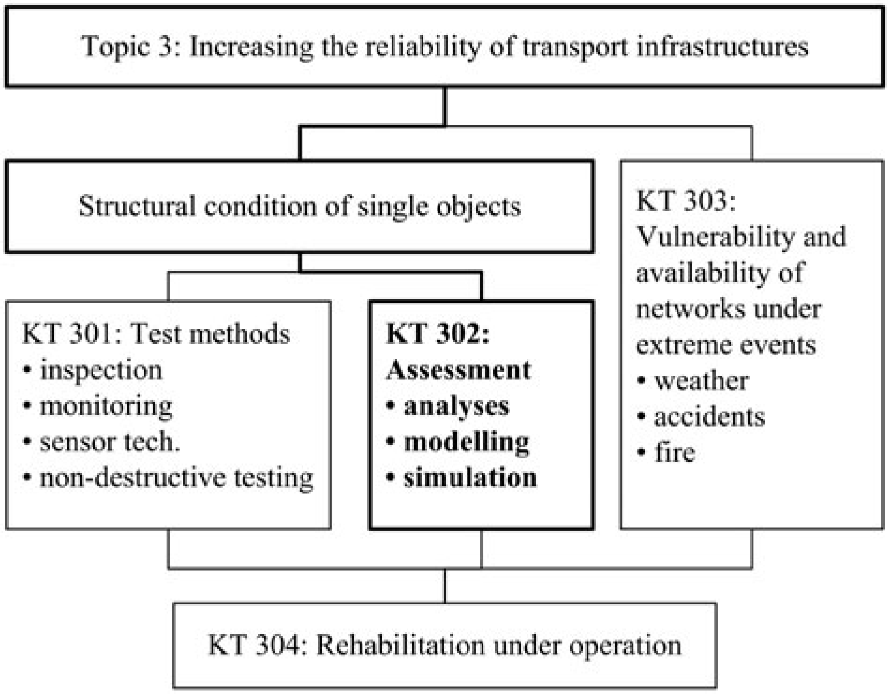

Figure 5: Topic 3 of the NoE and assigned key topics.

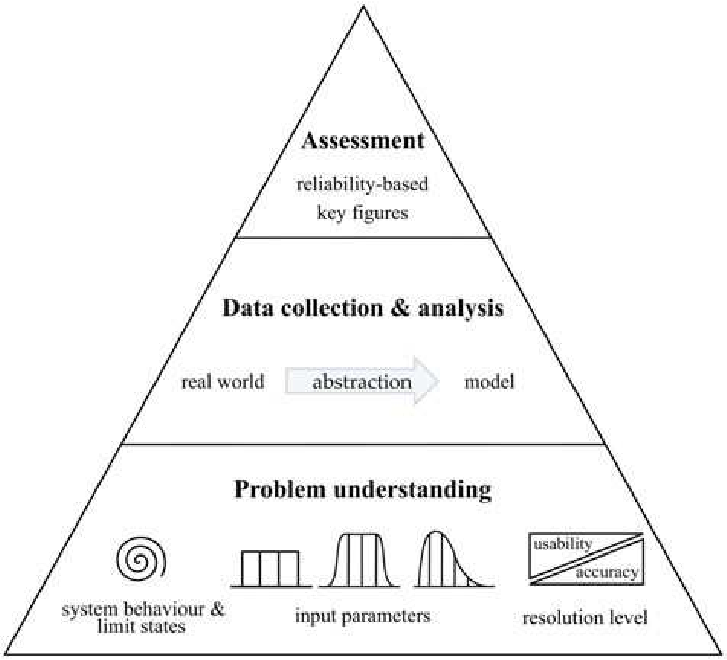

Figure 6: Step-by-step approach to gaining knowledge about the structural reliability of an existing structure.

the chance to avert the impact of the failure mode (Figure 8). The risk criteria may be evaluated by assessing information derived from expert interviews or by analysing quantitative data obtained from QA/QC-procedures. (Stamatis, 2003)

Due to its systematic approach, a FMECA supports the gathering of knowledge as well as knowledge transfer. The FMECA is particularly suitable for defining an appropriate resolution level of subsequent analyses by reducing the extent of an assessment to components of high criticality. The cause-effect chains qualitatively describe the system behaviour in relation to the functional requirements and their limit states. The formalised description of hazard scenarios by means of failure mode, failure consequence and failure causes serves as a system of categorising elicited knowledge about an assessed item. Linking the failure causes with the corresponding limit states facilitates the definition of requirements for a subsequent data collection. The use of representative risk criteria allows the qualitative or semi-quantitative assessment of the risk of non-compliance with a specified limit state. Thus, the result of the assessment could be seen as a measure of the reliability of the item.

4.1.3 Physical model tests

Physical model tests are a third relevant method of achieving an improved understanding of problems which cannot be achieved by in-situ observation or monitoring. Sorgatz et al. (2018) use expert interviews to identify the most significant causes of damage, relevant damage patterns and the critical maintenance state of bank revetments on inland waterways. Based on the elicited knowledge, the experimental set-up for physical model tests in a wave basin is adjusted so that only the relevant deterioration mechanisms are observed and the number of tests is reduced. A full-scale embankment model is erected that specifically allows real-world observations of armour stone displacements in a controlled environment (Figures 9–11). The critical maintenance state, substantiated by expert knowledge, can be approached through successive wave loading. Close monitoring of the deterioration occurring during the tests leads to an improved understanding of the underlying mechanisms. First results of the tests are expected at the end of 2019.

Physical model tests contribute to a better understanding of the behaviour of a technical system. They can be used to validate and complement expert knowledge and to refine limit states. Parameter studies enable significant input parameters and the adequate resolution level to be defined. Furthermore, physical model tests enable the need for additional field measurement campaigns, including scope, structure and technical set-up, to be determined. Yet technical and economic reasons demand that the model test design should be carefully chosen. In this regard, experienced maintenance staff are an important source of expert knowledge supporting the design process.

4.2 Data collection and analysis

The development of a factual model, which represents an informative abstraction of a real-world situation, requires sufficient information on the relevant parameters. The information is generated by analysing collected data. The methodology for collecting and analysing data depends on the data requirements and the availability of data.

4.2.1 Qualitative elaboration of causal relationships

Qualitative data constitute expert knowledge about a subjective perception of a real-world situation which is otherwise hard or even impossible to detect or to describe (e.g. unique or rare random events, slowly progressing deterioration, etc.). Eurocode 1, for example, includes unexpected deterioration in the accidental actions and proposes the use of qualitative methods to identify and describe related unforeseeable hazards, hazard scenarios and possible consequences (DIN, 2010a). Tools for collecting expert knowledge in the context of maintenance management include, inter alia, guided expert interviews and inspection report

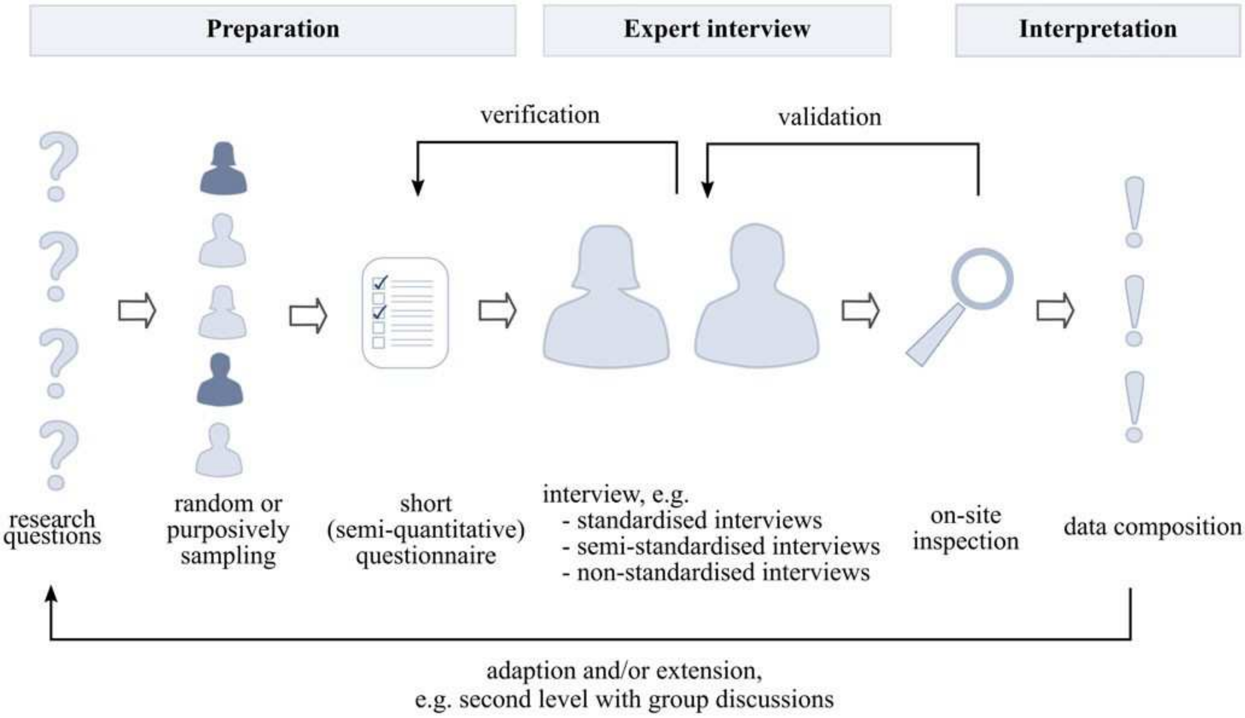

Figure 7: Essential elements of expert interviews from preparation to data interpretation.

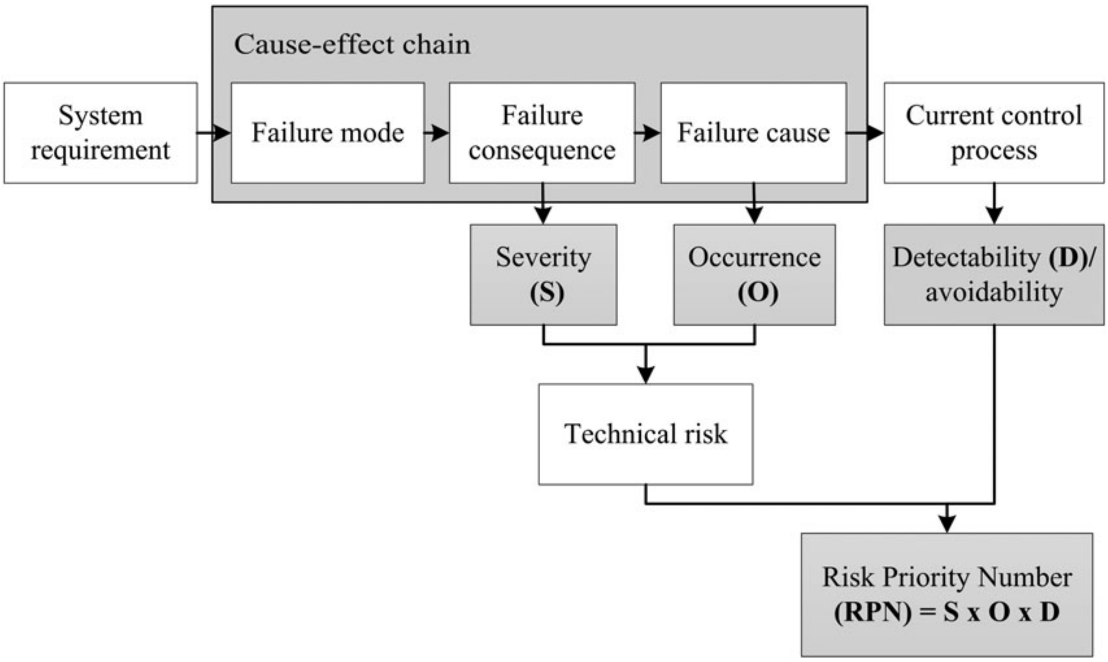

Figure 8: Schematic overview of a FMECA including aggregation of the RPN.

repositories provided by maintenance management systems (MMS).

Data sets of expert knowledge may contain statements using linguistic terms or judgments based on an ordinal grading system (cf. Urban, 1998). Analysing data sets from multiple sources may be difficult because of a different use of language or incompatible grading formats. Therefore, the analysis process consists in the a priori determination of relevant categories of information and a corresponding classification of the content of the available data sets. During the analysis, the category system is iteratively adjusted to the actual content of the data sets. The categorisation then serves to determine causal relationships between data sets, to present information derived from different data sources in a comparable format and to analyse the assigned data sets quantitatively. (Miles et al., 2014)

System analysis using FMECA supports the categorisation of expert knowledge in qualitative data sources without

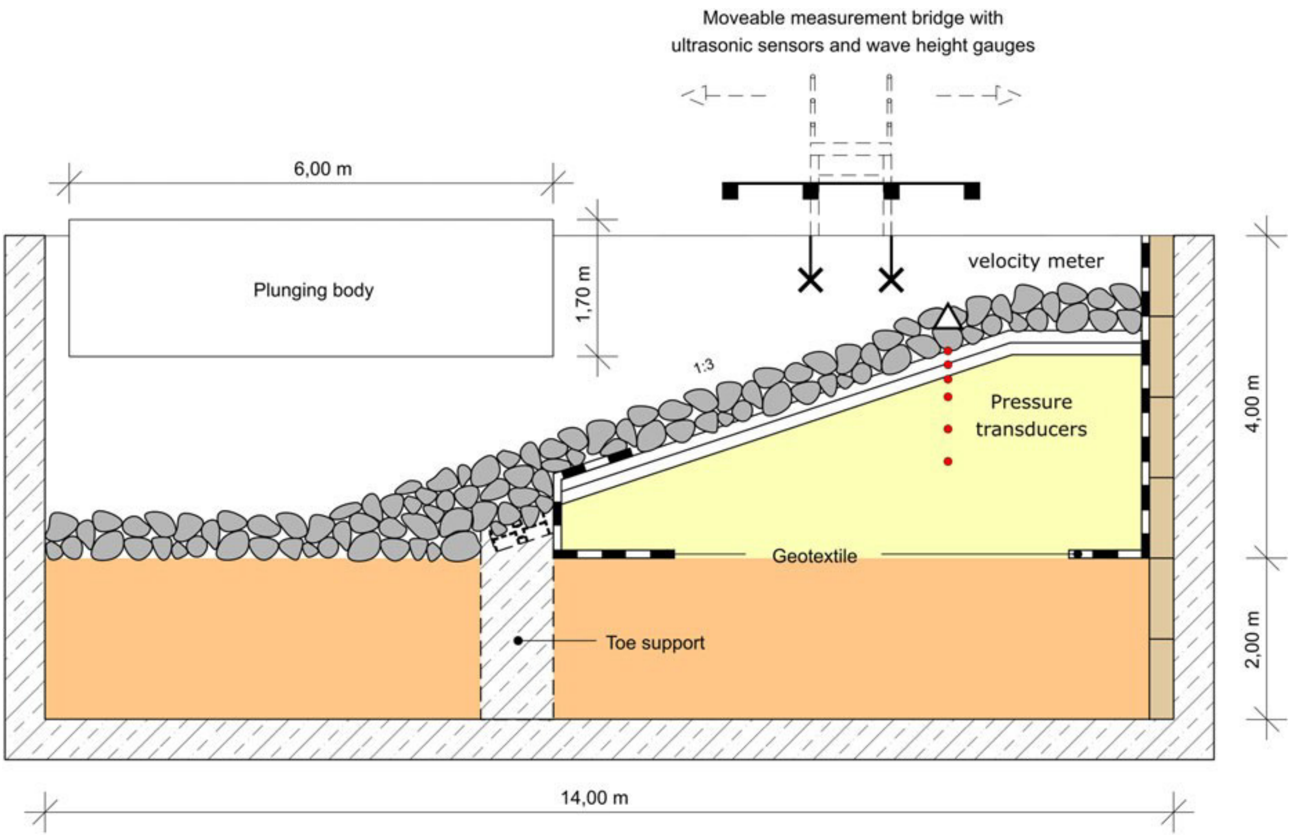

Figure 9: Model test design using a wave basin.

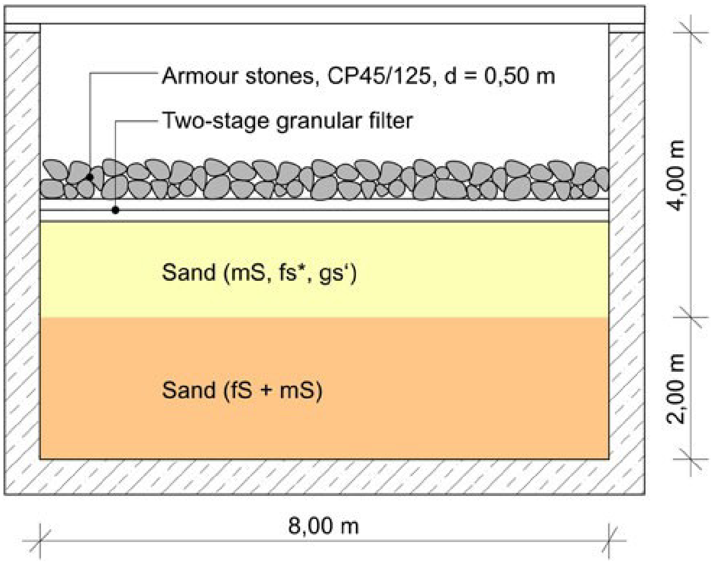

Figure 10: Section view of the model test design.

interfering with the existing data sets themselves. The data sets containing the expert knowledge are categorised on the basis of their implicit statement regarding the cause–effect chains elicited during the system analysis. The comparison of inductively derived cause–effect chains with the available data sets validates the FMECA and may lead to an iterative adaptation process until the cause–effect chains sufficiently represent the statements of the available data sets. The use of the cause–effect chains of a FMECA as a superordinate category system, which is independent of the original data formats and the individual use of language, allows a joint analysis of data sets from different sources.

The criticality assessment within a FMECA is based on expert knowledge about the risks associated with the assessed item. Using expert knowledge introduces uncertainty, which derives from the vagueness in the description of the semantic meaning of a statement or judgment (Zimmermann, 2001). Various authors recommend the application of Fuzzy Set Theory (FST) and Fuzzy Logic (FL) when vague information is included in an assessment procedure (e.g. Bowles & Peláez, 1995b; Cai, 1996; Rommelfanger, 1994; Urban, 1998). The theoretical foundations of the FST go back to the work of Zadeh (1965). Mamdani and Assilian (1975) succeeded in developing the first technical implementation, a FL-controlled steam engine. Since then, there has been widespread implementation of FST and FL in various industrial sectors and applications (Bai, Zhuang, & Wang, 2006).

In traditional set theory, an element x of the universe X either is, or is not, member of a set A. The basic idea of capturing imprecision is to define that elements in a fuzzy set Ã have a continuum of degrees of membership ranging from complete membership to complete non-membership. This is done by membership functions ($\mu_A(x)$) that assign each element x of the universe X a number from the real-valued interval between 1 and 0. This number specifies the degree of membership of each element x to the fuzzy set Ã. Thus, each element x becomes member of each fuzzy set, but with different degrees of membership. (Bowles & Peláez, 1995b) A FL-based aggregation of the RPN in a FMECA provides the possibility of considering vagueness in the criticality assessment and, consequently, in the prioritisation of the cause-effect chains.

In the context of maintenance management of ageing infrastructure, data analysis by means of a FMECA-based

Figure 11: Wave basin with the model of the embankment and some sensors.

category system builds a model of causal relationships between observed damage and failure of the assessed structures. The categorisation facilitates a quantitative assessment of expert knowledge taken from inspection reports. Using the cause–effect chains as links between functional requirements and observed damage allows data material to be reassessed using a different perspective from the one originally implied. The criticality assessment based on the fuzzy RPN provides a useful tool for the consideration of uncertainty in a qualitative condition assessment of deteriorating structures (Panenka & Nyobeu, 2018b).

4.2.2 From real-world data to mathematical models through quantitative data assessment

In the assessment of existing structures, quantitative data commonly derive from measurements. A measurement is a 'quantitatively expressed reduction of uncertainty based on one or more observations' (Hubbard, 2014, p. 31). Methods and technologies for assessing existing structure by means of measurement techniques and monitoring systems are covered by KT 301 of the NoE (cf. Figure 5). This involves the evaluation of the efficiency and benefits of non-destructive testing methods, the methods for the long-term monitoring of engineering structures and the integration of inspection and monitoring measures in rehabilitation strategies (www.bmvi-expertennetzwerk.de/EN/Projects/TF3/301).

Processing quantitative data is necessary in order to mathematically describe the relevant variables of the observed real-world situation and to translate the data into a mathematical model. Variables derived from measurements are realised within a range of possible, but random values. Probability functions transfer these random values into a mathematical model. A discrete random variable is described by its probability mass function; a continuous random variable by its probability density function (Ang & Tang, 2007).

Provided that the data are quality-assured and validated, the use of parametric distributions and their approximation by Maximum Likelihood Estimate (MLE) and Method of Modified Moments (MME) is considered the most robust and, above all, most reproducible way of determining the probability functions, taking into account the fluctuating sample sizes of data sets. The Goodness-of-Fit (GoF) of a distribution is assessed either by visual tools, such as the probability function plot, the cumulative density function plot, the Q–Q plot and the P–P plot or by hypothesis tests such as the Anderson–Darling test and the Kolmogorov–Smirnov test for continuous data; and the Chi-Square test for discrete or categorical data (Ang & Tang, 2007).

Where the assessment of a real-world situation involves the consideration of more than one input variable, the mathematical model includes the description and implementation of the dependence between these variables. An unconditional dependence of multiple variables can best be described by multivariate probability functions. However, as these are difficult to construct and data on multivariate correlation is sparse, the correlation is commonly reduced to bivariate observations. Most frequently, a linear relationship of two variables is evaluated by the Pearson's correlation coefficient (Ang & Tang, 2007).

For example, physical considerations imply an unconditional dependence between the relevant input variables for a revetment design. The results of field observations indicate that the height of the return flow velocity and the slope inflow depends on the height of the sternal wave. Mathematical formulations of the underlying relationships do not exist. The revetment design is currently based on the parameters of the vessel producing the wave (size, velocity, draught, etc.; Bundesanstalt für Wasserbau [BAW], € 2010)

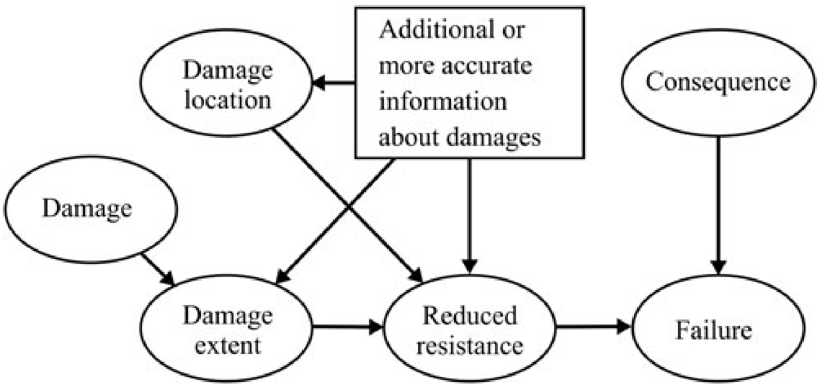

Figure 12: Consideration of additional damage data through a Bayesian network in an assessment of existing structures; adapted from Hajdin, Büchel et al. (2018).

instead of the actual wave load parameters (i.e. sternal wave height, return current velocity and slope supply flow).

Therefore, a new design concept currently under development envisages specifying actual hydraulic loads on the basis of field measurements to avoid the present extreme value design caused by a conservative assumption of the design vessel passages. In this case, correlations allow the relationship between the measured load parameters to be exploited, thereby avoiding physically implausible assumptions. Consequently, in a subsequent reliability analysis, the occurrence of large wave heights increases the probability of high flow velocities and vice versa. The complete design model including a short discussion on correlations is presented by Sorgatz, Kayser, and Schüttrumpf (2019).

A conditional dependence is modelled, inter alia, by Bayesian networks, a probabilistic directed acyclic graphical model. This type of graphical model consists of a set of nodes indicating variables, edges indicating dependencies and a conditional probability distribution corresponding to every node and conditioned to its parent node, hence providing a distribution over all variables. Based on Bayes' Theorem, the prior knowledge of a variable is used to calculate the posterior probability of this variable given that new data has been observed. This process is called Bayesian inference (Box & Tiao, 1992).

Within the framework of planning the maintenance of civil engineering structures, a Bayesian network allows the integration of new data, for example, data collected during inspections or monitoring campaigns, in the reliability assessment of a structure (Figure 12). By taking the new data into account, the prior calculated reliability of a structure is updated into a posterior reliability in view of the observed data (Hajdin & Fastrich, 2019).

Finally, Annex B of Eurocode 1, Part 1 (DIN, 2010a) recommends quantifying the variability of the model output with regard to the input parameters. A sensitivity analysis can assist in this process. Common methods of sensitivity analysis are listed in Table 1. When conducting a sensitivity analysis, a two-level approach is often helpful, especially for models with numerous input parameters. Firstly, the method of Morris is used to screen a large number of variables in order to identify the most significant ones. Subsequently, a comprehensive sensitivity analysis is conducted, featuring only the variables that have been shown to make a significant contribution to the variance of the model during the screening procedure. In this analysis, the mean value may be used for parameters that were found negligible during screening.

A quantitative data assessment captures the randomness and dependencies of the observed real-world data with the aid of mathematical models. This is necessary in order to generate comparable key figures in the next step. Methods such as GoF and sensitivity analyses support the assessment of the model quality in order to find a satisfactory mathematical description of the data as well as a suitable model resolution. Examples developed within the framework of NoE can be found in Sorgatz et al. (2019) and Hajdin, Büchel, Novák, and Bunz (2018).

4.2.3 Assuring data quality

Regardless of the methodology for collecting and analysing data, Annex B of Eurocode 1, Part 1 (DIN, 2010a), recommends implementing data quality assurance measures. Currently, various data quality assessment frameworks are being assessed for future application in the presented methodology. For example, a hierarchy concept specifically designed for flood defences by Klerk, Van Der Hammen, Wojciechowska, and Pot (2018), the Data Quality Assessment Framework (DQAF) by Sebastian-Coleman (2012) and a data quality matrix by Weidema and Wesnaes (1996).

4.3 Reliability assessment

In the context of the methodology presented in the article, reliability assessment is conducted to generate comparable key figures that can assist in an effective and risk-informed maintenance management for transport infrastructure.

4.3.1 Qualitative criticality assessment of causal relationships between damage and failure

The qualitative criticality assessment of the causal relationships between damage and failure of a structure by means of a fuzzy-FMECA is based on expert opinion about the three risk criteria severity, occurrence and detectability/avoidability. Traditionally, each of the risk criteria is assessed on the basis of an ordinal scale between 1 and 10. The RPN is then calculated by multiplying the resultant integer values and thus ranges between 1 and 1000. In a fuzzy-FMECA, the RPN is aggregated by means of FL, remedying some of the aspects of the traditional approach which have been the subject of much criticism (Bowles, 2004; Liu, 2016).

Generally, the term 'fuzzification' may refer to the introduction of FL into a traditionally deterministic procedure. In the context of a FMECA, fuzzification specifically means to map 'crisp', i.e. precise, values onto linguistic variables. Each linguistic variable is defined by a term set (e.g. [high; medium; low] or [fast; moderate; slow]) with a defined number of members. A rule-based procedure allows the aggregation of the linguistic input to a linguistic conclusion. The rule base contains m^n conditional rules for n linguistic variables with m members per term set. The defuzzification

Table 1: Sensitivity analysis methods for different types of parameter.

Correlated parameters	Local methods	Global methods
No	One-at-a-time Morris method (Morris, 1991)	Sobol indices (Sobol, 1993, 2001) Fourier amplitude sensitivity analysis (FAST) (Cukier, Fortuin, Shuler, Petschek, & Schaibly, 1973; Saltelli, Tarantola, & Chan, 1999; Schaibly & Shuler, 1973) Derivative-based Global Sensitivity Measure (DGSM) (Sobol & Kucherenko, 2009)
Yes	n/a	ANCOVA (Caniou, 2012)

finally determines a crisp expression of the linguistic conclusion, if required. A detailed description of the procedure is provided in Bowles and Peláez (1995a). The use of FL regarding general multi-criteria decision problems is presented in Rommelfanger (1994).

The FL-approach has several advantages over the traditional way of determining the RPN. FL allows working with linguistic variables instead of only assumedly precise values, and considering more than one possible interpretation of a numerical value. Also, the FL-based approach provides a more flexible structure for combining the risk criteria of a FMECA. In addition, the use of a rule base instead of arithmetic allows quantitative data and qualitative data to be combined in a uniform manner. Furthermore, a rule base determined by means of expert knowledge implicitly contains a weighting of the different criteria, which is not included in the traditional approach. Additionally, the fuzzified procedure provides different representations of the assessment results. Depending on the application, the resulting criticality recommendation may be expressed in different formats (Figure 13): numerically (e.g. 'RPN ≈ 700'); linguistically (e.g. 'rather high with a tendency to high') and graphically (e.g. fuzzy output sets). Panenka and Nyobeu (2018a) give an illustrative example in the context of condition assessment of existing structures.

4.3.2 Quantification of the probability of failure

The assessment of the probability of failure permits the generation of meaningful key figures based on quantitative data. Using probabilistic methods, the reliability index β serves as a key figure for the probability of failure (P_f) over a given reference period and under the assumption of a normal distribution. Since assessing the exact value of P_f is mathematically complex, if not impossible, the application of approximate methods, for example, the first-order reliability method (FORM), or fully probabilistic methods, for example, the Monte-Carlo simulations (MCS), is recommended. With FORM the probability of failure $\phi(-\beta)$ can be derived from the reliability index β.

FORM was introduced by Hasofer and Lind (1973) who proposed a geometric definition of the reliability index β_{HL}. In standard space, β_{HL} is defined as the minimum distance between the design point P* and the origin O with P* as a point on the limit state surface characterised by the maximum probability density. FORM finds P* by solving a constrained optimisation problem with methods such as

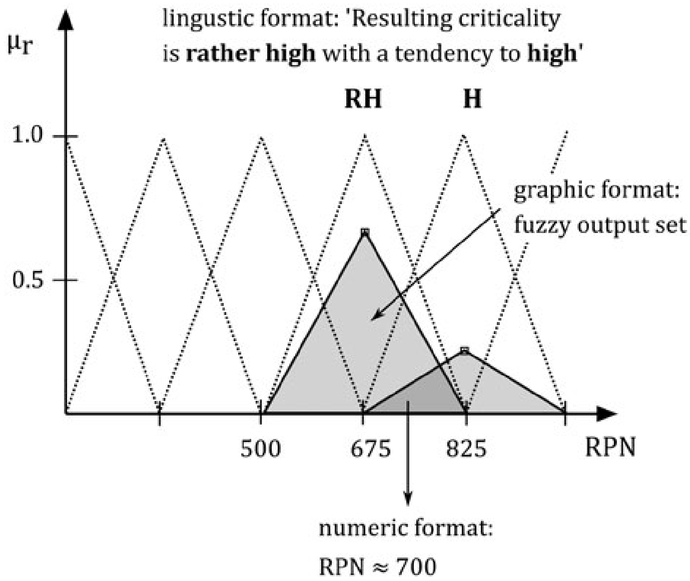

Figure 13. Formats of a fuzzy criticality recommendation (exemplary).

Lagrangian Multiplier, Taylor Series or the Fiessler–Rackwitz approach (Abdo & Rackwitz, 1991; Rackwitz & Fiessler, 1978). The methods proposed by Rosenblatt (1952) or Nataf (1962) may be utilised for the transformation of non-Gaussian distributions into standard space. Correlated variables may be incorporated, for example, by means of the Cholesky matrix or eigenvectors and eigenvalues (Baecher & Christian, 2005). FORM assumes P* to be unique in standard space. This assumption may lead to erroneous results, in particular for highly non-linear limit state functions. In these cases, more advanced methods, such as MCS, may be applied.

MCS refers to a broad class of statistical sampling methods that solve mathematical problems whose analytical solutions are biased or impossible to achieve. Its origins lie in the research on nuclear technology during the Second World War, where various mathematicians and physicists worked on a method of describing neutron diffusion (Fermi & Richtmyer, 1948; Metropolis, Rosenbluth, Rosenbluth, Teller, & Teller, 1953; Metropolis & Ulam, 1949). A random sample of the uncertain parameters is generated and the problem is solved analytically. Following the Central Limit Theory (CLT), the sample average approaches a true value as the number of simulations approaches infinity. The probability of failure and thus the reliability index β are derived directly from the statistics of the simulation. MCS rely heavily on the number of simulations performed and the algorithm used for the random sampling process, such as the Wichmann–Hill algorithm (Wichmann & Hill, 1982) and the SIMD-Oriented Fast Mersenne Twister algorithm (Saito & Matsumoto, 2008).

5 Implementation of the interdisciplinary methodology in the condition assessment of German transport infrastructures

In Germany, the BMVI and its subordinate administrations are responsible for the overall safety of the transport infrastructure and the ease of traffic. The safety of a structure is important not only for daily users but also for staff ensuring the smooth operation and maintenance of the structure. Therefore, the MMS for structures in road networks ('SiB-Bauwerke'; BMVI, 2017b) and waterways ('WSVPruf'; BAW, 2015) are designed to treat damage as equally urgent, regardless of whether work safety, serviceability or structural safety is affected. Because of this indifference, the condition assessment procedure implemented in both MMS is easy to use but impairs the identification of structures with a damage-induced reduction of their load-bearing capacity. However, both MMS are well-established and widely accepted by maintenance staff and administrations. Thanks to an effective inspection regime, the inspection report repositories contain a large number of data sets. Any changes in the condition assessment procedures would render the already available data obsolete. As a result, all structures would have to be re-classified.

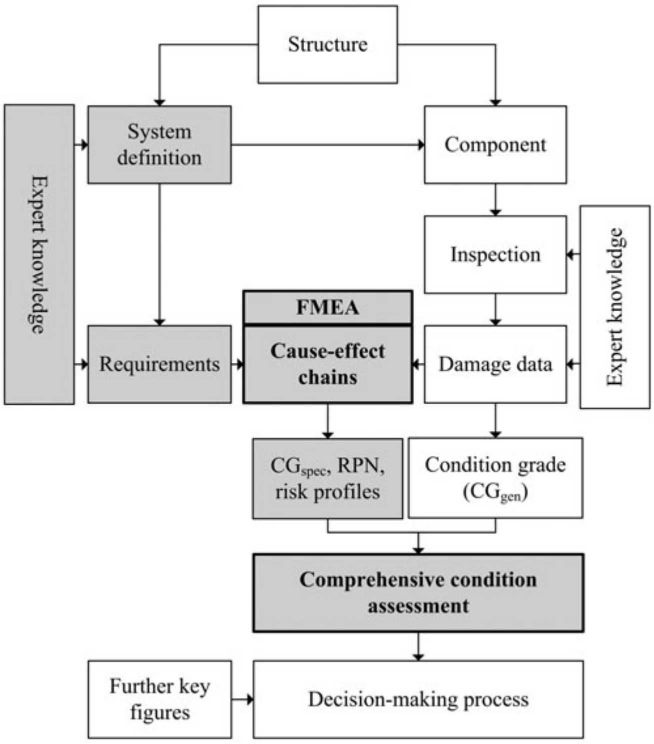

Figure 14. FMECA as integrated part of the condition assessment procedure.

Two examples illustrate the effective use of the methodological approach presented in this article to create tools for a differentiated condition assessment of ageing infrastructures without interfering with the established systems and data repositories.

5.1 Condition assessment of hydraulic steel structures based on a fuzzy criticality recommendation

Hydraulic steel structures (HSS) control the water level in waterways and navigation locks. Thus, they fall under the responsibility of the Federal Waterways and Shipping Administration (WSV). Their condition is assessed using WSVPruf, the MMS of the WSV. Because of the indifference to functional requirements and a grading system limited to index-based condition grades (CG$_{gen}$), WSVPruf does not allow any further ranking of the growing number of HSS that are already in critical condition. In order to enhance the condition grading procedure with meaningful key figures, a FMECA-based assessment procedure is implemented to re-assess the available data (Figure 14).

Using the object hierarchy available in WSVPruf, the functional units, their requirements and related cause–effect chains are determined. The object hierarchy makes a distinction between four major structural components of a HSS: steel structure, supports, actuators and sealing system. Assuming the steel structure to be the load-bearing component, its specific requirements define the load-bearing capacity (LBC), the service life or durability ($T_{service}$) and service limit states (SLS). The assignment of the available damage data sets to the cause–effect chains corresponding to the requirements works as filter sorting the data sets according to the affected requirement (Figure 15). The filtered data sets enable the existing assessment algorithm of WSVPruf to consider only the damages directly affecting a certain requirement and to generate the corresponding specific condition grades (e.g. $CG_{spec,\,LBC}$; Figure 16).

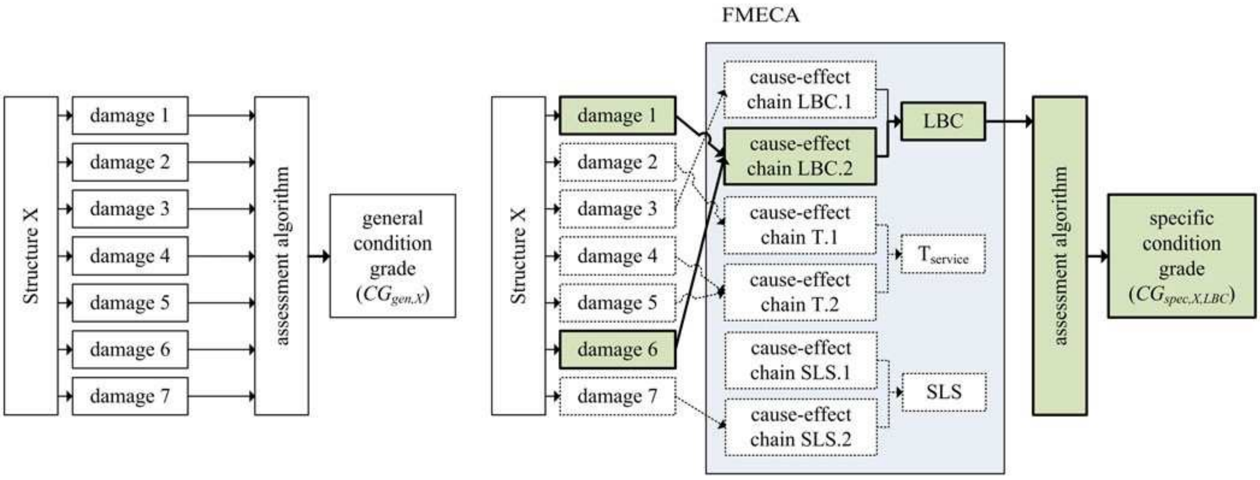

Figure 15. Assessment flowchart for CG_{gen} (left) and CG_{spec} (right); both use the same assessment algorithm; CG_{spec} is determined using the FMECA-based filter.

Structure X		Bearing/ support	**Steel structure**	Actuators	Sealing system	
General:	CG_{gen} =	3.1	**4**	n/a	3	Condition considering all damages

requirements	Steel structure:	SLS	**LBC**	Durability		
Specific:	CG_{spec} =	4	**2**	1.9		Condition acc. to affected requirement
Criticality:	RPN =	675	770	467		Corresponding fuzzy RPN

Figure 16. The breakdown of $CG_{gen} = 4$ into $CG_{spec,\,SLS} = 4$ and $CG_{spec,\,LBC} = 2$ indicates that the severe damage of Structure X is related to the serviceability of the steel structure and damage related to LBC is of minor importance.

In order to produce meaningful results, the risk factors of the subsequent criticality assessment are adapted to the requirements of a structural assessment. The severity (S) describes in general terms the degree of impact of a cause–effect chain on the fulfilment of a functional requirement (e.g. LBC), and depends on the type of structure. The occurrence (O) is determined as the ratio of the number of structures affected by a cause–effect chain to the population of structures of the same type. The detectability (D) is assessed assuming that the better the chance to avoid a cause–effect chain by detecting the related damages, the lower $CG_{spec,\,LBC}$. The resulting RPN represents a measure for the risk that damage causes a standard-based verification of the structure to fail. The numerical value of the

RPN is calculated using the FL-based approach described in the methodological approach (cf. Section 4.3.1).

The additional key figures CG_{spec} and fuzzy-RPN supplement the comprehensiveness of the existing condition assessment procedure without interfering with the established systems and data repositories. The FMECA establishes a filter which allows the breakdown of CG_{gen} into distinct CG_{spec} considering different functional or structural requirements and their corresponding limit states in the condition assessment. Using fuzzy-RPN as key figures to express the current condition of the assessed structure mitigates the limitations of the index-scaled CG_{gen}. Together with CG_{gen} as key performance indicator (KPI), the additional key figures allow a more differentiated condition assessment (Table 2). More details regarding the application of a fuzzy-FMECA in the context of the assessment of civil engineering structures are presented by in Panenka and Nyobeu (2018b). An adaptation to structures in road networks is foreseen for the 'Integration'-phase of the NoE.

5.2 Screening tool for bridges using operative reliability indices

The German road network includes roughly 40,000 bridges varying in type, age and condition. The MMS for bridges 'SiB-Bauwerke' uses a categorisation system, which makes a distinction between three different damage consequence categories (traffic safety, durability, load bearing capacity) and four main damage severity levels (BMVI, 2017b). Obviously, a resolution of only four main severity levels in three consequence categories is too low to produce any meaningful ranking of the large number of bridges according to their condition.

Therefore, a screening tool is required to ameliorate the existing system with key figures supporting a higher resolution of severity levels without negating existing information as well as updated data collected during future inspections. The concept of the web-based screening tool under development is to use simplified substitute models to calculate the effect of damages on the load-bearing capacity of bridges by means of operative reliability indices. The creation of the substitute models follows a strictly formalised procedure in order to obtain results that are comparable.

The automated procedure is divided into two steps. In the first simulation step, the substitute model of the bridge to be assessed is created on the basis of the information taken from the available database of the maintenance management system 'SIB-Bauwerke' (i.e. span, main girder geometry, year of construction). The design loads valid during construction period are applied to the substitute model in order to carry out a nominal design of the bridge. The design load models constitute a proxy for the load-bearing capacity of the structure. FORM is then used to determine the nominal reliability index β_{nom} for this theoretical new, that is, undamaged, condition. In a second step, the information about the damage observed in the structure is considered in the simulation.

For example, reinforcement corrosion is implemented by reducing the amount of reinforcement in the affected part of the model prior to the subsequent simulation run. Since detailed measurements or comprehensive qualitative information about the damages may be unobtainable, the most unfavourable location and combination of the known damages is determined and the resulting reliability index β_{damage} calculated. Bayesian networks allow updated data to be considered, if more information is collected about the grade of

Table 2 Key figures of a FMECA-based MMS and their contribution to a comprehensive condition assessment.

Key figure	Contribution to condition assessment	Measure
CG_{gen}	KPI of the assessed structures including work safety, structural safety, serviceability/availability	Urgency of intervention
CG_{spec}	Identification of the damage-affected requirements (i.e. LBC, $T_{servcice}$ or SLS)	Extent of impairment of a specific structural or functional requirement
fuzzy-RPN	continuous grading scale resolving index-based CG	Risk that detected damage cause a standard-based verification to fail

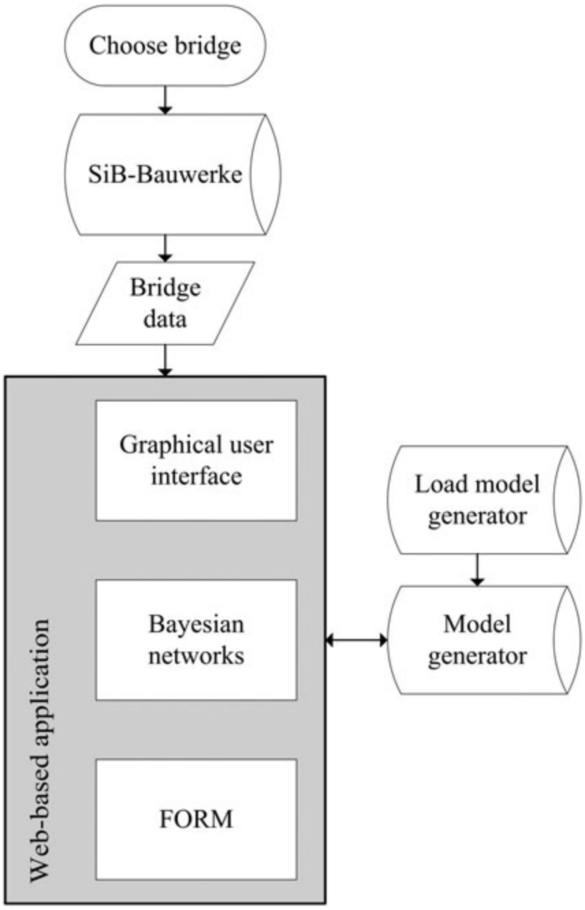

Figure 17. Architecture of the prototype for the web-based screening tool; adapted from (Hajdin & Fastrich, 2019).

deterioration in a later assessment stage. Figure 17 depicts the described architecture of the developed prototype. The decline between β_{nom} and β_{damage} represents the effect of the observed damage and provides information about the sensitivity of the structure to that damage (Hajdin, Büchel et al., 2018).

Using simplified models reduces the computational time significantly, which offers the possibility of comparing a large number of structures with the aid of a formalised analysis procedure. The comparison of the structures on the basis of these fictitious reliability values is no longer bound to the formal assessment system with only four main damage classes and therefore allows a higher resolution for the ranking of a large number of bridges. The calculated reliability indices can be related and scaled according to a set of given values provided by Hajdin, Kušar et al. (2018).

A web-based software tool allowing competent users in the responsible road administrations to carry out case studies is currently being developed (Hajdin & Fastrich, 2019). The effectiveness of the screening tool relies on a comprehensive damage categorisation system to derive the state of degradation. The currently available system is too unspecific in its description of affected limit states for the screening tool to be fully automated. Thus, the implementation of the FMECA-based condition assessment procedure may further improve the effectiveness of the screening tool. The application of the screening tool to HSS is considered for the next phase of the NoE.

6 Conclusions

The interdisciplinary methodology and tools presented and discussed in this article are dedicated to a step-by-step approach to gaining knowledge about a reliability-based assessment of civil engineering structures in transport infrastructure. The step-by-step approach supports the responsible governmental entities in the development of an efficient, cross-modal maintenance strategy aimed at improving the reliability of the transport infrastructure (Section 3).

Expert knowledge is often neglected but is of great relevance to maintenance planning as it includes information about events that elude a stochastic description due to a lack of representative data. Expert interviews and the inductive procedure of the FMECA are flexible, versatile and scalable tools. They provide a general understanding of problems that demand expert knowledge and the systematic analysis of complex causal relationships. Subsequent physical model tests may then assist in gaining a deeper understanding of specific details of the problems (Section 4.1). The application of the methods in the following research phases is subject of current discussions in the organisation committee of the NoE.

The consideration of both qualitative and quantitative methods of data collection and data analysis enables a whole range of data to be collected and analysed. Together, both types of data provide relevant and complementary information about the assessed structures. Qualitative methods uncover causal relationships in form of cause–effect chains and make a categorisation of data obtained from expert knowledge possible. The implementation of FL allows the consideration of uncertainties arising from the imprecision, vagueness and ambiguity of subjective information, such as verbal statements or judgments.

However, the implementation of FL requires a permanent quality control because large parts of the uncertainty model again rely on expert knowledge (e.g. defining membership functions of fuzzy sets and the aggregation rule base). The categorisation of data by means of a FMECA is a useful tool to compare and analyse qualitative data with different formats or nomenclature. The criticality assessment of the cause–effect chains with respect to the specified functional requirements and their limit states is a measure of the reliability of the assessed structure (Section 4.2.1).

Collecting quantitative data from monitoring and measurement campaigns is a common task in civil engineering. However, the availability of representative input data may be a restrictive factor, if possibilities for a thorough data collection are constrained (e.g. inaccessibility or cost and time limitations, poor data quality). Even assuming that the collected data is representative, the stochastic model itself is often the subject of criticism. The validity of the analyses will be undermined and the acceptance of the results compromised if the decisions made during the modelling process are not justifiable and verifiable. On the other hand, a qualitative data assessment allows the variability and randomness inherent in measurements and thus the resulting uncertainty in the condition assessment to be considered. Methods such as the GoF-tests and sensitivity analyses can help to assess the model quality (Section 4.2.2).

The methodology for reliability assessment encompasses both a qualitative and quantitative measure. The qualitative approach uses a fuzzy-FMECA for the condition assessment of existing structures. The procedure results in a comprehensive analysis of available damage data and a ranking of failure modes based on their RPN, which expresses the risk of non-compliance with a limit state (Section 4.3.1). The quantitative approach approximates the probability of failure of a structure expressed by the reliability index β as a key figure (Section 4.3.2). Both approaches result in meaningful key figures which support the decision-making process in maintenance management with regard to the reliability of existing structures.

The examples given in Section 5 demonstrate the capabilities of the methodology concerned in the context of maintenance management. The reassessment of existing damage data repositories using a fuzzy-FMECA (Section 5.1) and the screening tool for ranking a large number of structures based on a reliability assessment of simplified substitute models (Section 5.2) enhance the existing methodologies without interfering with well-established MMS and workflows. The possibility of implementing the fuzzy-FMECA in order to enhance the screening tool is currently being discussed.

The interdisciplinary methodology presented in this article provides meaningful key figures for risk-informed decision-making in maintenance management and supports the transition from a currently reactive maintenance strategy towards a proactive one. Combined with the R&D activities of the entire NoE, the methodology is an important contribution to the gradual development of an integrated life cycle management system based on structural, social, ecological, environmental and economic key figures. Since the initiation of the NoE in 2016, the progress on the coordination of interdepartmental processes as well as knowledge acquisition and knowledge transfer has been significant.

The governmental R&D format NoE enhances and improves the capabilities of research institutes and agencies of the BMVI involved in the matter of reliability assessment. Moreover, the results for the various topics support the current discussion on how to maintain an ageing transport infrastructure, taking into account not only structural but also environmental issues (e.g. climate change) and the opportunities of modern information technology (e.g. digitalisation). Regularly updated information about the work of the NoE is available online (www.bmvi-expertennetzwerk.de/EN).

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No potential conflict of interest was reported by the authors

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