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Abstract:

This report describes a critical analysis of the probabilistic approach and the conceptual aspects of the methodology used for probabilistic assessment and design for indoor climate in buildings. The analysis shows two main areas where the methodology could be improved: 1) The uncertainty modelling could be more systematic handling the different types of uncertainties (physical, model, statistical and measurement), especially the model and statistical uncertainties could be modelled more detailed. 2) The economic optimization and related decision-making could be based on a more rational basis, for which a Bayesian decision theoretical framework is recommended.
Further, modelling and quantification of model uncertainty is considered.

Keyword list: Probabilistic design, uncertainty modelling, decision analysis, model uncertainty.

Table of Contents

EXECUTIVE SUMMARY 3
1 INTRODUCTION 4
2 GENERAL COMMENTS 5
2.1 COMMENTS TO REFERENCE 1 5
2.2 COMMENTS TO REFERENCE 2 6
2.3 COMMENTS TO REFERENCE 3 7
2.4 COMMENTS TO REFERENCE 4 8
2.5 COMMENTS TO REFERENCE 5 8
3 UNCERTAINTY MODELLING 10
3.1 GENERAL UNCERTAINTY MODELLING 10
3.2 A GENERAL FRAMEWORK FOR MODEL UNCERTAINTY 11
4 DECISION MAKING 14
4.1 APPROACHES FOR DECISION MAKING 14
4.1.1 Risk based decisions 14
4.1.2 Reliability based decisions 14
4.1.3 Semi-probabilistic approaches 14
4.2 RISK-BASED DECISION MAKING 15
4.2.1 Decisions with given information 16
4.2.2 Decisions with given new information 16
4.2.3 Decisions involving planning of experiments to obtain new information 17
4.2.4 Bayesian networks 19
5 MODEL UNCERTAINTY IN RELATION TO HAM TRANSFER MODELS 20
5.1 REFERENCES 20
5.2 EXAMPLE 1 23
5.3 EXAMPLE 2 25
5.4 EXAMPLE 3 26
5.5 EXAMPLE 4 26
5.6 EXAMPLE 5 27
5.7 CONCLUDING REMARKS ON MODELLING AND QUANTIFICATION OF MODEL UNCERTAINTIES 28
REFERENCES 29
ANNEX A: PROCEDURE FOR MODEL UNCERTAINTY QUANTIFICATION 30

Executive Summary

The objective of this report is to describe a critical analysis of the probabilistic approach and the conceptual aspects of the methodology used for probabilistic assessment and design for indoor climate in buildings with the aim to enrich and enhance the theoretical foundations and approaches.

The descriptions and the overall approach presented and demonstrated in these references give a good illustration of application of probabilistic methods. The methods applied are generally state-of-the-art methods and the applications within building energy assessment are at a high scientific level. The analysis of the references show two main areas where the methodology could be improved: 1) The uncertainty modelling could be more systematic handling the different types of uncertainties (physical, model, statistical and measurement), especially the model and statistical uncertainties could be modelled more detailed. Further, Bayesian statistics is recommended to be applied; 2) The economic optimization and related decision-making could be based on a more rational basis. A Bayesian decision theoretical framework is recommended to be considered.

Further, modelling and quantification of model uncertainty in relation to HAM (Heat Air Moisture) transfer models are presented based on a number of papers and reports on HAM transfer modelling. The investigations show that only very limited data are available for quantification of model uncertainties, and therefore it is not possible at present to establish a probabilistic model for model uncertainties. However, a procedure / template is proposed for collection of the necessary data in the future.

1 Introduction

The objective of this report is to describe a critical analysis of the probabilistic approach and the conceptual aspects of the methodology used for probabilistic assessment and design for indoor climate in buildings with the aim to enrich and enhance the theoretical foundations and approaches.

The analysis is primarily based on the following references:

1. Van Gelder L, Janssen H, Roels S. 2014. Probabilistic design and analysis of building performances: Methodology and application example. Energy and Buildings, 79: 202-211. [1]
2. Van Gelder L, Payel D, Janssen H, Roels S. 2014. Comparative study of meta-modelling techniques in building energy simulation: Guidelines for practitioners. Simulation Modelling Practice and Theory, 49:245-257. [2]
3. Janssen H. 2013. Monte-Carlo based uncertainty analysis: sampling efficiency and sampling convergence. Reliability Engineering & Systems Safety, 109:123-132. [3]
4. Vereecken E, Van Gelder L, Janssen H, Roels S. 2015. Interior insulation for wall retrofitting - A probabilistic analysis of energy savings and hygrothermal risks. Energy and Buildings, 89: 231-244. [4]
5. Final report of Subtask 2 of Annex 55, 2015. [5]

The following aspects in relation to the probabilistic design are described considering the approach for decision making for reliability aspects for engineering structures presented in ISO 2394 [6]:

- General comments to above references, see section 2;
- Uncertainty modelling of uncertainties relevant for the components and systems considered, including physical, model, statistical and measurement uncertainties, see section 3 and
- Decision making using models, uncertainty quantification and reliability analysis, see section 4.

Section 5 describes modelling and quantification of model uncertainty in relation to HAM (Heat Air Moisture) transfer models.

2 General comments

This section contains general comments to the five references mentioned in section 1 on the probabilistic approach and conceptual aspects of the methodology used for probabilistic assessment and design for indoor climate in buildings:

1. The overall methodology applied in the references is good and reasonable, but the theoretical basis could be improved, see below. Further, also the link to existing standards / codes on probabilistic modelling in general should be improved.
2. Application of a simulation-based approach is appropriate.
3. Application of 'meta-models' to speed up the computational time is equivalent to application of response surfaces in e.g. structural reliability. It is not clear how the model and statistical uncertainties related to the 'meta-models' is estimated and included in the probabilistic methodology, see below.
4. A systematic description and modelling of aleatory and epistemic uncertainties should be included, see below.
5. The probabilistic approach should be seen together with the application within decision-making. Here a life cycle, risk-based approach can be used, see below.

2.1 Comments to reference 1

Paper: Van Gelder L, Janssen H, Roels S. 2014. Probabilistic design and analysis of building performances: Methodology and application example. Energy and Buildings, 79: 202-211. [1]

Summary: Building performance analyses are often based on deterministic simulations. Since many parameters are generally subject to uncertainty, this may result in unreliable predictions. The paper proposes a probabilistic analysis and design method to account for these uncertainties. The uncertainty propagation and analysis is based on application of Monte Carlo simulation and corresponding analyses of the output distributions. Since the deterministic performance models are often computationally expensive, so-called meta-models are used, replacing the original model, to reduce computational effort. Further, in this paper multi-layered sampling schemes are used. To measure reliability and convergence of expected value and standard deviation of performances, effectiveness and robustness are introduced as output uncertainty indicators. Effectiveness is defined as the ability of the design option to optimize the performance, while robustness is defined as the ability to stabilize this performance for the entire range of input uncertainties. The methodology is illustrated by a simplified application example.

Comments:

- Output evaluation: From a probabilistic point of view, the effectiveness and robustness measures cannot easily be transformed to uncertainty measures.
- The stochastic modelling is summarized in Table 1: Some of the stochastic variables could be expected to be correlated (e.g. the climatic parameters) – the stochastic modelling does not include statistical dependencies. Further, statistical and model uncertainties are not included in the stochastic modelling.
- The information illustrated in Figure 1 on heat demand could be used to model and quantify model uncertainty

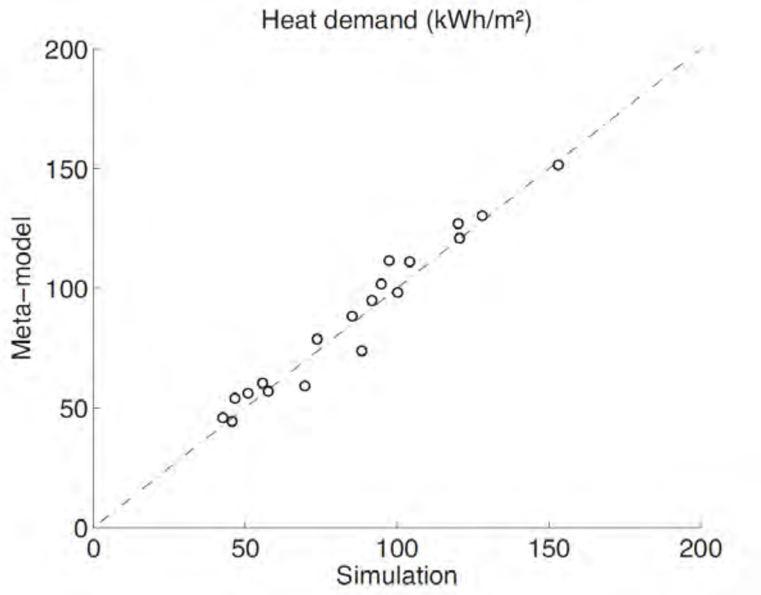

Figure 1. 'Comparison simulated and meta-modelled heat demand of validation dataset.' from [1].

2.2 Comments to reference 2

Paper: Van Gelder L, Payel D, Janssen H, Roels S. 2014. Comparative study of metamodelling techniques in building energy simulation: Guidelines for practitioners. Simulation Modelling Practice and Theory, 49:245-257. [2]

Summary: Simulation of real system behavior is considered in this paper. Often the simulation models are complex with large calculation times. Therefore, these time-consuming simulation models are considered to be replaced by meta-models that approximates the original simulation model by a simplified mathematical model. In this paper, a strategy is presented that is reliable and time-efficient. Furthermore, polynomial regression (PR), multivariate adaptive regression splines (MARS), kriging (KR), radial basis function networks (RBF), and neural networks (NN) are compared on a building energy simulation problem. It is concluded that KR and NN are the overall best techniques. Although MARS perform slightly worse than KR and NN, it is preferred because of its simplicity.

Comments:

- It is noted that other meta-models could be relevant, e.g. Polynomial Chaos Expansion, see e.g. UQLab: The Framework for Uncertainty Quantification, [7]
  As in reference 1 also in this paper model uncertainty could be modelled on basis of e.g. the results in Figure 2, e.g. using the approach in ISO 2394 [6] and Eurocode EN 1990 [8].

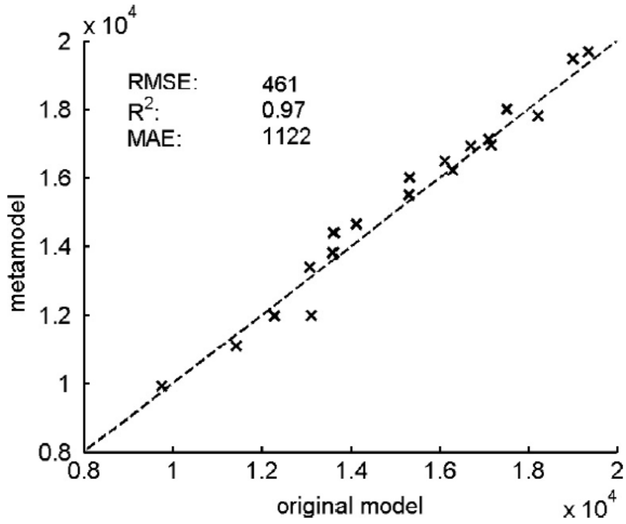

Figure 2. 'Illustration of goodness-of-fit indicators to compare the meta-model output with the original model output.' from [2].

2.3 Comments to reference 3

Paper: Janssen H. 2013. Monte-Carlo based uncertainty analysis: sampling efficiency and sampling convergence. Reliability Engineering & Systems Safety, 109:123-132. [3]

Summary: Monte Carlo simulation is an important tool in assessments of the reliability and robustness of systems, structures or solutions. Since crude Monte Carlo simulation often requires a large number of simulations, the computational costs can be very large. To reduce that computational cost sampling efficiency and convergence are investigated in this paper. This includes 'non-collapsing space-filling' sampling strategies, illustrated with Latin hypercube designs. Further, a 'sample-splitting approach' is presented which makes it possible to assess the accuracy of Monte Carlo simulations.

Comments:

- Page 123: 'In reliability, three methodology levels are commonly distinguished': this is not completely correct. In Madsen, Krenk & Lind [9] four levels are defined, see also below. In addition to the three levels described in [3] also a level 4) is defined, where consequences are included, corresponding to a risk-based assessment. It is also noted that ISO 2394:2015 [6] defines three levels of assessment for design / decision making related to engineering structures:
    - Risk informed – corresponding to level 4) in [9]
    - Reliability based – corresponding to level 2) and 3) in [9]
    - Semi-probabilistic – corresponding to level 1) in [9]
- It is noted that many additional sampling strategies can be found in the literature, see overview and implementations in UQLab: The Framework for Uncertainty Quantification, [7]:
    - Advanced sampling strategies (space-filling), including Monte-Carlo sampling, optimized latin hypercube sampling (LHS), low-discrepancy series (Sobol' and Halton sequences)
    - Sampling enrichment (nested LHS)

It is noted that some of these techniques are almost the same as those considered in the present paper.

2.4 Comments to reference 4

Paper: Vereecken E, Van Gelder L, Janssen H, Roels S. 2015. Interior insulation for wall retrofitting - A probabilistic analysis of energy savings and hygrothermal risks. Energy and Buildings, 89: 231-244. [4]

Summary: This paper considers interior insulation often used as post-insulation technique to improve the thermal performance of single leaf masonry walls. However, this technique has some drawbacks as a result of potential damage patterns such as frost damage, interstitial condensation and mould growth. To investigate the possible energy savings by this technique while avoiding hygrothermal failure, a risk assessment is important. This paper describes a probabilistic approach for this investigation, because uncertainty of parameters might result in widely varying results. The paper presents a decision tool based on a Monte Carlo simulation technique. Additionally, the influence of the rain load and some masonry characteristics is discussed.

Comments:

- Section 2.3: eq. (1) is an example where a (non-linear) regression model is fitted to available data. In a probabilistic approach, it is important to include the uncertainty associated with the regression parameters. This can be done using the Maximum-Likelihood technique where the uncertainty can be quantified using the Hessian matrix of the LogLikelihood function, see section 3.1.

2.5 Comments to reference 5

Report: Final report of Subtask 2 of IEA Annex 55, 2015. H Janssen, S Roels, L Van Gelder, P Das: Reliability of Energy Efficient Building Retrofitting - Probability Assessment of Performance and Cost (RAP-RETRO) - Probabilistic Tools. Report 2015:4; ISSN 1652-9162; Chalmers University of Technology, 2015.

Summary: the aim of IEA Annex 55 is to provide a foundation for the integration of probabilistic approaches in analyses and designs of hygrothermal performances of buildings. This foundation is to consist of four parts:

1. an overall framework and methodology for probabilistic analysis and design in relation to hygrothermal performances of buildings (subtask 3);
2. probabilistic tools that permit qualitative and quantitative assessment of the impacts of the non-deterministic features in these (subtask 2);
3. data sets characterising the stochastic variations of influencing parameters, for use in the qualitative and quantitative methods (subtask 1);
4. guidelines for application of the general framework, probabilistic tools and stochastic inputs for reliability-based analysis and design (subtask 4);

The primary objective of Annex 55's Subtask 2 therefore is to appraise the advantages and disadvantages of existing probabilistic methods for qualitative and quantitative assessment with relation to their applicability within the particular context of building performance analysis and design. Subtask 2 does hence not intend to develop new probabilistic tools, instead it aims at familiarizing building physical engineers and researchers with the possibilities and limitations of existing probabilistic tools adopted from various other fields. When applied within the overall probabilistic framework of Subtask 3, based on the guidelines for use of Subtask 4, and fed with the stochastic data from Subtask 1, these tools will allow the non-deterministic appraisal of the life cycle gains and costs of a thermal building retrofit, with attention for both the potential improvement as well as possible degradation resulting from such upgrades of residential buildings.

Comments:

- The descriptions and the overall approach presented and demonstrated in examples in the report give a good illustration of application of probabilistic methods.
- Two remarks where methodology could be improved are:
    - The uncertainty modelling could be more systematic handling the different types of uncertainties (physical, model, statistical and measurement), especially the model and statistical uncertainties could be modelled more detailed, see the description in section 4.
    - The economic optimization and related decision-making could be based on a more rational basis, e.g. using a Bayesian decision theoretical framework, see the description in section 4.

3 Uncertainty modelling

Parameters subject to uncertainty are assumed to be modelled by stochastic variables and/or stochastic processes / stochastic fields. Uncertainties modelled by stochastic variables can generally be divided in the following groups:

1. **Physical uncertainty** also denoted inherent uncertainty is related to the natural randomness of a quantity, for example the annual maximum mean wind speed or the uncertainty in the yield stress due to production variability.
2. **Measurement uncertainty** is related to imperfect measurements of for example a geometrical quantity.
3. **Statistical uncertainty** is due to limited sample sizes of observed quantities. Data of observations are in many cases scarce and limited. Therefore, the parameters of the considered random variables cannot be determined exactly. They are uncertain themselves and may therefore also be modelled by random variables. Are additional observations provided then the statistical uncertainty may be reduced.
4. **Model uncertainty** is the uncertainty related to imperfect knowledge or idealizations of the mathematical models used or uncertainty related to the choice of probability distribution types for the stochastic variables.

3.1 General uncertainty modelling

In probabilistic design, the above types of uncertainty are usually treated by the reliability methods which will be described below. Another 'type' of uncertainty, which is not covered by these methods, is gross errors or human errors. These types of errors can be defined as deviation of an event or process from acceptable engineering practice and is generally handled by quality control measures related to design, execution and the operational phase.

Realizations of uncertain parameters $\mathbf{X}=(X_1,...,X_n)$, such as wind and temperature, degradation parameters, and model uncertainties will take place during the lifetime. The uncertainties can be divided in aleatory and epistemic uncertainties. Aleatory uncertainty is inherent variation associated with the physical system or the environment (physical uncertainty) – it can be characterized as irreducible uncertainty or random uncertainty. Epistemic uncertainty is uncertainty due to lack of knowledge of the system or the environment – it can be characterized as subjective uncertainty, which can be reduced by better models, more data, etc. It is noted that some aleatory uncertainties 'change' to epistemic uncertainties when the system is realized. Model, measurement and statistical uncertainties can be characterized as epistemic uncertainties. In many cases, natural fluctuation (physical uncertainty) and insufficient information (model uncertainty) are the most important sources of uncertainty.

The reference period for the use of the stochastic model is also important when modelling stochastic variables and processes. It is often assumed that ergodic stochastic processes may be used. However, the influence of long-term effects (e.g. climate change) could also be relevant to consider.

In modelling climatic parameters, it is often relevant to consider two stochastic models:

- A stochastic model for the long-term scatter, i.e. modelling the random point in time value using all measured / observed values. E.g. a Weibull distribution is often used for the 10 minutes average wind speed.

- A stochastic model for the annual extreme, e.g. annual extreme wind speed. For the stochastic modelling only extreme values are used. Typically, a Gumbel (or a Generalised Extreme Values distribution) is used.

Each of the stochastic variables $X_i, i = 1,2,...,n$ is assumed to be modelled by a distribution function $F_{X_i}(x_i;\boldsymbol{\alpha}_i)$ where $\boldsymbol{\alpha}_i$ denotes the statistical parameters. Dependency between the stochastic variables can be modelled by joint distribution functions or correlation coefficients. A number of methods can be used to estimate the statistical parameters $\boldsymbol{\alpha}_i$ in distribution functions, e.g. the Maximum Likelihood method, the Moment method, the Least Square method or Bayesian statistics.

In general, the Maximum Likelihood method or Bayesian statistics are recommended. The Maximum Likelihood method gives a consistent estimate of the *statistical uncertainties*. In Bayesian statistics, it is possible to take subjective (prior) information consistently into account through a prior distribution.

In the Maximum Likelihood method, the density and distribution functions for a stochastic variable X are denoted: $f_X(x|\alpha_1,...,\alpha_m)$ and $F_X(x|\alpha_1,...,\alpha_m)$ where $\alpha_1,...,\alpha_m$ are statistical parameters. n observations are assumed to be available: $\hat{x}_1,...,\hat{x}_n$. The statistical parameters are determined using the Maximum-Likelihood method by maximizing the LogLikelihood function using a standard nonlinear optimizer.

In general, the parameters $\alpha_1,...,\alpha_m$ are determined using a limited number data and are therefore subject to statistical uncertainty. Since the parameters are estimated by the Maximum Likelihood technique they become asymptotically (number of data should be larger than 25-30) Normally distributed stochastic variables with expected values equal to the Maximum Likelihood estimators and covariance matrix equal to, see e.g. [10]:

$$\mathbf{C}_{\alpha_1,...,\alpha_m} = [-\mathbf{H}]^{-1} = \begin{bmatrix} \sigma_{\alpha_1}^2 & \rho_{\alpha_1\alpha_2}\sigma_{\alpha_1}\sigma_{\alpha_2} & \cdots & \rho_{\alpha_1\alpha_m}\sigma_{\alpha_1}\sigma_{\alpha_m} \\ \rho_{\alpha_1\alpha_2}\sigma_{\alpha_1}\sigma_{\alpha_2} & \sigma_{\alpha_2}^2 & \cdots & \rho_{\alpha_2\alpha_m}\sigma_{\alpha_2}\sigma_{\alpha_m} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{\alpha_1\alpha_m}\sigma_{\alpha_1}\sigma_{\alpha_m} & \rho_{\alpha_2\alpha_m}\sigma_{\alpha_2}\sigma_{\alpha_m} & \cdots & \sigma_{\alpha_m}^2 \end{bmatrix} \quad (1)$$

where $\mathbf{H}$ is the Hessian matrix with second order derivatives of the log-Likelihood function. The statistical uncertainty can easily be included in a probabilistic model. It is noted that statistical uncertainty can also be assessed by other methods, e.g. the Bootstrapping technique.

Recommendations for stochastic modelling of uncertain parameters can be found in the JCSS (Joint Committee on Structural Safety) PMC (Probabilistic Model Code) [11].

3.2 A general framework for model uncertainty

This section presents a general framework for modelling and estimation of model uncertainties related to application of meta-models.

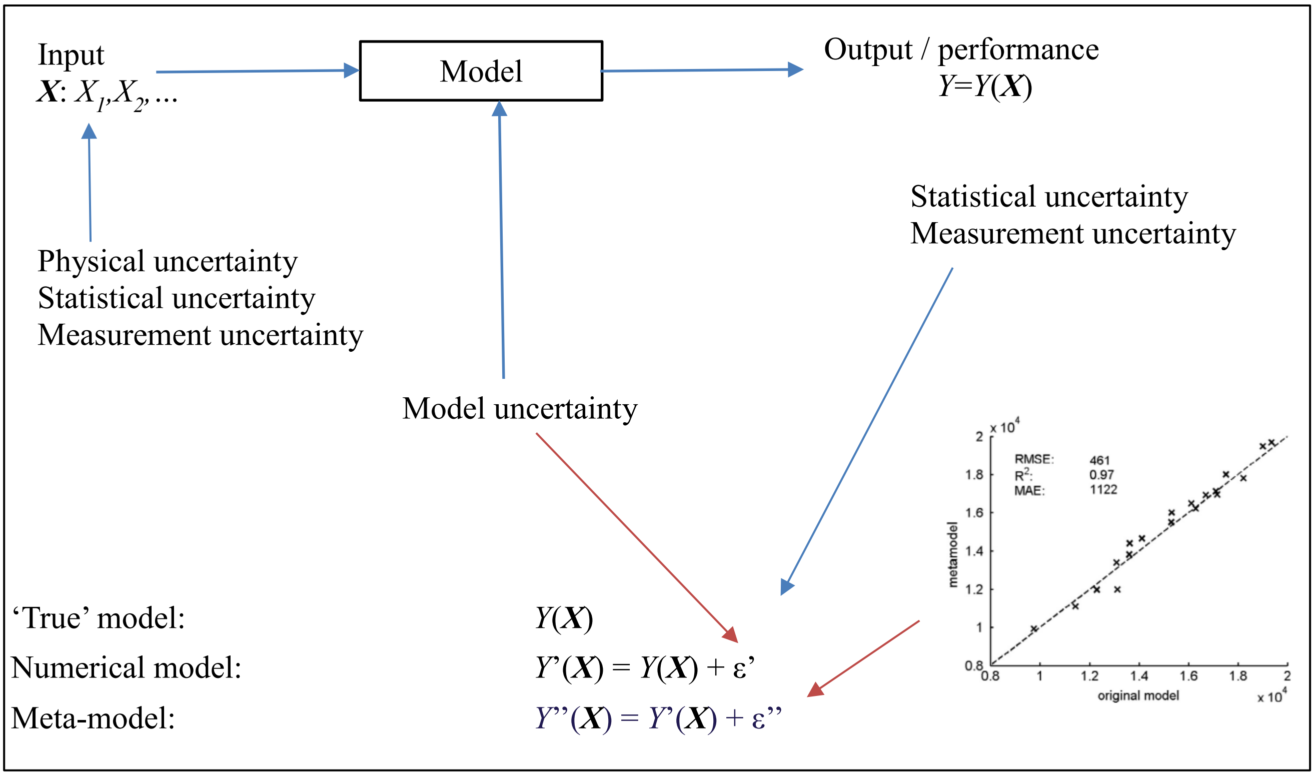

Figure 3. Models and model uncertainty.

Figure 3 illustrates how model uncertainty can be represented. It is assumed that $Y(\boldsymbol{X})$ models the real / 'true' behaviour of the system / component. Y models the output of the model and $\boldsymbol{X}$ models the input parameters subject to uncertainty which can be the physical uncertainty parameters, but also statistical and measurement uncertainties associated with the input parameters.

The output can be performance measures such as

- Energy demand
- Air change rate of residential building when using natural ventilation
- Heat loss, frost damage (e.g. measured by number of moist frost cycles per year), moisture level (e.g. number of hours RH on indoor surface larger than a critical level in January)

Next, it is assumed that a complex, numerical expensive model, $Y'(\boldsymbol{X})$ is available. The model uncertainty related to this model can e.g. be modelled by an additive stochastic variable ε'. It is noted that alternatively the model uncertainty can be introduced as a multiplicative stochastic variable, see examples in section 5. Finally, a meta-model / response surface, $Y''(\boldsymbol{X})$ can be fitted to the numerical, complex model, $Y'(\boldsymbol{X})$. This implies an additional model uncertainty, which e.g. can be modelled by an additive stochastic variable ε''. It is noted that ε' and ε'' can be dependent on $\boldsymbol{X}$ and that alternatively a multiplicative model can be applied.

If the model uncertainty is modelled / quantified by a limited number of tests then additionally statistical uncertainty should be added. Finally, measurement uncertainties related to the test may be important and should be added.

The model uncertainty can be quantified using the approach described in [6] and [8]. Basically, it is assumed that a number of tests are performed covering the application area of the mode considered, and where realizations of the stochastic variables modelling physical uncertainties are measured as accurately as possible. Next, the bias and coefficient of variation of the model uncertainty are estimated e.g. using a linear regression model similar to the one applied in Figures 1 and 2, see [6] and [8] for details.

4 Decision making

As mentioned in section 2.3 ISO 2394:2015 [6] defines three levels of assessment for design / decision making related to engineering structures, especially within structural / civil engineering:

- Risk based
- Reliability based
- Semi-probabilistic

In section 4.1 these three approaches are described in more detail based on [6] but with focus on general application. In section 4.2 more details are given on risk-based decision making using a Bayesian approach, see also JCSS [12].

4.1 Approaches for decision making

4.1.1 Risk based decisions

In risk based informed design and/or assessment, decisions should be based on consideration of the total risks associated with possible losses and benefits. The time horizon to be considered in the assessment of the total risks is generally the total (remaining) design lifetime of the structure.

In the assessment of the total risks, the net present value of future costs / benefits should be used. The interest rate to be used should be chosen carefully, e.g. if the decisions are made for the society, the annual discounting rate should be the long-term annual economic growth rate.

A risk-based approach requires that a consistent modelling of all uncertainties be established as described in section 4.

4.1.2 Reliability based decisions

As an alternative to risk, based decision making a reliability-based approach can be chosen. Here a minimization of the costs / benefits are performed subject to given reliability requirements for the structure. The reliability requirements are obtained based on a risk-based approach as described above.

The reliability requirements are assumed associated to adverse events / failure events, and the probability that the failure events occur can be estimated by various techniques, incl. simulation based techniques and FORM/SORM methods, see [9]. Application of a reliability-based approach is also sometimes denoted probabilistic design.

4.1.3 Semi-probabilistic approaches

For structures where consequences of deterioration / adverse events / failure are well understood and the failure events can be modelled in a standardized manner, a so-called semi-probabilistic approach may be used for design and decision-making.

In the semi-probabilistic approach, uncertain parameters / stochastic variables are represented by characteristic values obtained as conservative quantiles in the distribution functions modelling the stochastic variables. Typically, for parameters acting as strength variables quantiles less than a 50%

quantile is used and for parameters acting as load variables typically a quantile larger than 50% is used. Additionally safety factors may be applied. The resulting design parameters are then used as deterministic parameters in the model calculations done as basis for the decisions.

4.2 Risk-based decision making

Engineers are often in the situation to take decisions on design of a new structure, on repair/maintenance of existing structures and on planning tests / inspections / condition monitoring where some statistical information is available and where the overall objective is to take cost-optimal decisions. In the following, it is shown how Bayesian statistical decision theory can be used for making such decisions in a rational way, see Raiffa and Schlaifer [13] and Benjamin and Cornell [14] for a detailed description.

Three levels of decision problems with increasing degree of complexity are:

- decisions with given information
- decisions with given new information
- decisions involving planning of experiments to obtain new information.

The methods described below are mainly related to continuous stochastic variables and continuous decision variables. An important difficulty in Bayesian statistical decision theory when applied in civil engineering is that it can be difficult to assign values to cost of failure / not acceptable behaviour, especially when consequences for humans are involved.

Further, organizational factors can have a rather significant influence in the decision process. These factors often have an influence, which is not rational from a cost-benefit point of view. Examples are the influence of the organizational structure, personal preferences and organizational culture.

The optimal alternative in a decision problem may depend on:

- Monetary values of the alternatives
- Prestige
- Social acceptance
- Time factors
- Possible deaths / human life
- Value of nature / ecology mechanisms

The problem is how to compare these attributes. von Neumann & Morgenstern [15] assumes some quite simple axioms related to preferences between different alternatives (orderability, transitivity, continuity, monotonicity and decomposability). Further, they assume that a utility can be assigned each alternative, such that a numerical quantification of the order of preference between alternatives is obtained. Since a decision (action) usually is followed by a realization of the uncertain state of nature, the utility obtained will be subject to uncertainty. von Neumann & Morgenstern [15] argues that the optimal decision is the one, which maximizes the expected utility.

In the following, it will be assumed that all utilities can be expressed in economic terms. The optimal decisions will thus be those that maximize the economic profit.

4.2.1 Decisions with given information

The first problem to consider is that of making rational decisions when some of the parameters defining the model are uncertain, but a statistical description of the parameters is available, i.e. the statistical information is given. The uncertain parameters are modelled by n stochastic variables $\mathbf{X} = (X_1, X_2, ..., X_n)$. The density function of the stochastic variables is $f_{\mathbf{X}}(\mathbf{x}, \theta)$ where θ are statistical parameters, for example mean values, standard deviations and correlation coefficients.

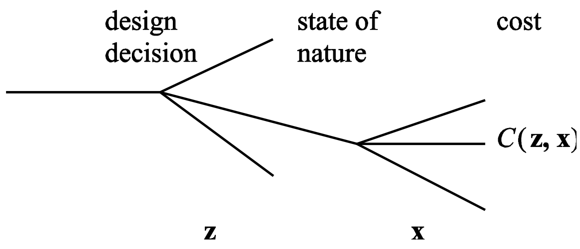

Figure 4. Decisions with given information.

Further, it is assumed that a decision has to be taken between a number of alternatives that can be modelled by design/decision variables $\mathbf{z} = (z_1, z_2, ..., z_N)$. The action space is called Z. In Figure 4 a decision model with one discretized variable z is shown. The decision is taken before the realization by nature of the stochastic variables is known. Besides the decision variables $\mathbf{z}$ and the uncertain variables $\mathbf{X}$ also a cost function $C(\mathbf{z}, \mathbf{X})$ is introduced in the decision model in Figure 4. Usually in classical decision theory a utility function is used instead of the cost function C. When a decision $\mathbf{z}$ has been taken and a realization $\mathbf{x}$ of the stochastic variables appears then the value obtained is denoted $C(\mathbf{z}, \mathbf{x})$ and represents a numerical measure of the consequences of the decision and the realization obtained. $C(\mathbf{z}, \mathbf{X})$ is assumed to be related to money and represents in general costs minus benefits, if relevant.

In some decision problems, it can be difficult to specify the cost function, especially if the consequences not directly measurable in money are involved, for example personal preferences. However, as described in von Neumann & Morgenstern [15] rational decisions can be taken if the cost function is made such that the expected value of the cost function is consistent with the personal preferences. Thus, if the decision-maker wants to act rationally the strategy $\mathbf{z}$, which minimizes the expected cost, has to be chosen

$$C^* = \min_{\mathbf{z}} E_{\mathbf{X}}\left[C(\mathbf{z}, \mathbf{X})\right] = \int C(\mathbf{z}, \mathbf{X}) f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x} \quad (2)$$

$E_{\mathbf{X}}[-]$ is the expectation with respect to the joint density function of the stochastic variables $\mathbf{X}$. C^* is the minimum cost corresponding to the optimal decision $\mathbf{z}^*$.

4.2.2 Decisions with given new information

It is now assumed that some of the parameters defining the model are uncertain and a statistical description of the parameters is available and that new information about the uncertain parameters is also available.

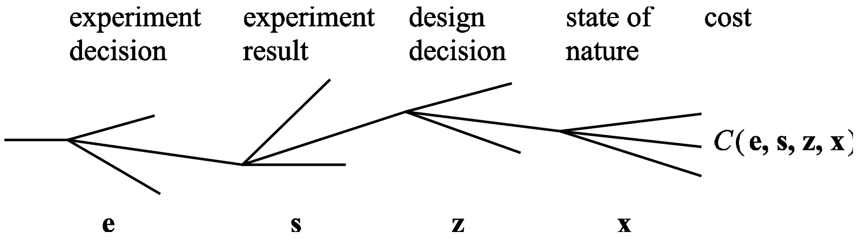

Figure 5. Decisions with given new information.

In Figure 5, the corresponding decision model is shown. $\mathbf{s}$ models the new information and can e.g. be the result of an experiment. $\mathbf{s}$ can be used to update the statistical model of $\mathbf{X}$.

A predictive density function (updated density function) $f''_{\mathbf{X}}(\mathbf{x}|\mathbf{s})$ of the stochastic variables $\mathbf{X}$ taking into account a realization $\mathbf{s}$ can be obtained using Bayesian statistical theory, see Lindley [10] and Aitchison & Dunsmore [16].

Thus, if the decision-maker wants to act rationally, taking into account the new information $\mathbf{s}$ the strategy z, which minimizes the expected costs, has to be chosen from

$$C^* = \min_{\mathbf{z}} E''_{\mathbf{X}|\mathbf{s}}\left[C(\mathbf{z}, \mathbf{X})\right] \tag{3}$$

$E''_{\mathbf{X}|\mathbf{s}}[-]$ is the expectation with respect to the predictive (updated) density function $f''_{\mathbf{X}}(\mathbf{x}|\mathbf{s})$. C^* is the minimum cost corresponding to the optimal decision $\mathbf{z}^*$.

4.2.3 Decisions involving planning of experiments to obtain new information

Finally we consider the problem of making rational decisions when the decision-maker has the option to make some experiments to obtain new information about the stochastic variables $\mathbf{X}$. The problem is, should these experiments be performed and if so, how much information (e.g. how many experiments) should be obtained?

Thus we assume that some of the parameters (modelled by the stochastic variables $\mathbf{X}$) defining the model are uncertain and a statistical description (modelled by θ) of the parameters is available, but new information about the uncertain parameters can be obtained.

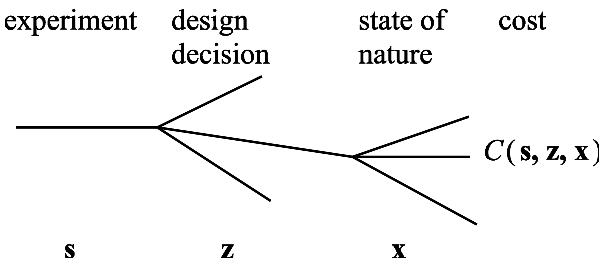

Figure 6. Decisions with unknown new information.

The decision model is shown in Figure 6. $\mathbf{S}$ models the possible (but unknown) experiment results. $\mathbf{S}$ is thus modelled by stochastic variables.

In a time scheme the following steps are performed:

- Choose an experiment type $\mathbf{e}$.
- Observe $\mathbf{s}$ as a realization of $\mathbf{S}$. $\mathbf{s}$ is unknown at the time when the experiment plan is chosen.
- Choose a design $\mathbf{z}^*$ by solving a decision / optimization problem, see below.

The problem to determine the optimal decisions $\mathbf{e}$ and $\mathbf{z}$ are known as preposterior analysis in classical decision theory. Two approaches for determining the optimal decisions $\mathbf{e}^*$ and $\mathbf{z}^*$ are possible:

- the normal form of analysis, and the
- the extensive form of analysis

Normal form of analysis

In the normal form of analysis one or more decision rules $\mathbf{d}$ are defined, see Raiffa & Schlaifer [13]. The decision rules $\mathbf{d(s)}$ give the design decisions corresponding to each outcome of $\mathbf{S}$, i.e. when the experiment result $\mathbf{s}$ is known then the prescribed decision rule gives the design $\mathbf{z} = \mathbf{d(s)}$. The corresponding cost becomes $C(\mathbf{e},\mathbf{s},\mathbf{z} = \mathbf{d(s)},\mathbf{X})$.

To obtain the optimal decision the decision-maker has to choose the strategies, $\mathbf{e},\mathbf{d}$ which minimizes the expected cost

$$C^* = \min_{\mathbf{e}} \min_{\mathbf{d}} \; E_{\mathbf{S}|\mathbf{e}}\left[\; E''_{\mathbf{X}|\mathbf{S}}\left[C(\mathbf{e},\mathbf{S},\mathbf{z} = \mathbf{d(S)},\mathbf{X})\right]\right] \tag{4}$$

where $E_{\mathbf{S}|\mathbf{e}}[-]$ is the expectation with respect to the joint density function for $\mathbf{S}$ in the chosen experiment plan $\mathbf{e}$ and $E''_{\mathbf{X}|\mathbf{S}}[-]$ is the expectation with respect to the updated joint density function of $\mathbf{X}$ given $\mathbf{S}$.

Extensive form of analysis

In the extensive form of analysis where no decision rules are formulated the optimal strategy $\mathbf{e},\mathbf{z}$ is obtained from, see Raiffa & Schlaifer [4].

$$C^* = \min_{\mathbf{e}} E_{\mathbf{S}|\mathbf{e}}\left[\min_{\mathbf{d}} \; E''_{\mathbf{X}|\mathbf{S}}\left[C(\mathbf{e},\mathbf{S},\mathbf{z},\mathbf{X})\right]\right] \tag{5}$$

Note that compared to the normal form of analysis the minimization operation is now inside the expectation operation with respect to $\mathbf{S}$.

Comparison between the normal and the extensive form of analyses

The extensive formulation (5) of the decision problem is more general than the normal formulation since it includes the normal formulation as the special case where it is possible to formulate decision rules $\mathbf{z} = \mathbf{d(e,s)}$. In the extensive formulation, the optimal decision $\mathbf{z}^*$ is obtained by solving the optimization problem $\min_{\mathbf{z}} \; E''_{\mathbf{X}|\mathbf{S}=\mathbf{s}}\left[C(\mathbf{e},\mathbf{S},\mathbf{z},\mathbf{X})\right]$ when the experiment result $\mathbf{s}$ is available.

As discussed below the numerical computations are significantly larger for solving the extensive form than for the normal form. It is therefore of large practical interest to formulate decision problems by the normal form of analysis and if this is not possible to be able to obtain approximate solutions.

4.2.4 Bayesian networks

In Bayesian networks, the stochastic variables and the decision variables are discretized. The decision problems and optimization problems are the same as described in the previous sections. For an introduction to Bayesian networks, see for example Jensen [17].

5 Model uncertainty in relation to HAM transfer models

A probabilistic description of model uncertainty is presented in section 3.2, and a few examples are described in section 2. In this section, modelling and quantification of model uncertainty in relation to HAM (Heat Air Moisture) transfer models are considered based on a number of papers and reports on HAM transfer modelling provided within the RIBuild project (Hans Janssen). The investigations show that only very limited data are available for quantification of model uncertainties, and therefore it is not possible at present to establish a probabilistic model for model uncertainties. However, a procedure / template is proposed for collection of the necessary data in the future.

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As described in section 3.2 quantification of model uncertainty by a bias and a coefficient of variation requires

- simultaneous estimates of a model $Y_{\text{model}} = Y(\boldsymbol{X})$ and
- experimental results Y_{exp} with
- measured input (X) to the model.

The procedure in EN1990 Annex D [8] or ISO2394 [6] can be used for the quantification, see also Annex A, assuming that the model uncertainty is defined by a bias *b* and a Lognormal distributed stochastic variable ε (with mean value = 1 and standard deviation σ_ε) multiplied to the theoretical model, i.e.

$$Y = b\ \varepsilon\ Y(\boldsymbol{X})$$

where ***X*** models physical uncertainties, and parameter/statistical uncertainties, if relevant.

The review of the above many references shows that only few papers fulfil the above three ‘requirements’ in order to quantify the model uncertainty. Examples are shown in the following.

5.2 Example 1

This example is from ‘2. HAM Boundary conditions’: Abuku, M., B. Blocken & S. Roels: Moisture response of building facades to wind-driven rain: Field measurements compared with numerical simulations. J. Wind Eng. Ind. Aerodyn. 97 (2009). pp. 197–207.

Absorption of rain at a wall surface is estimated by a numerical model and compared with measurements as illustrated in the figure 7 from (from Abuku et al.).

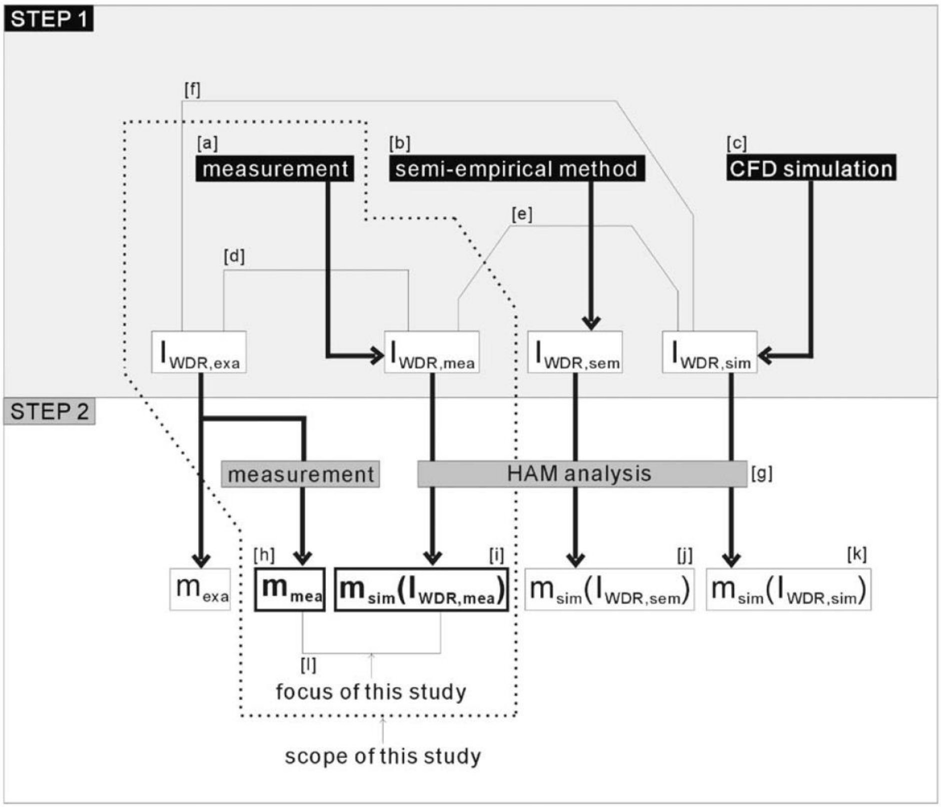

Figure 7. Illustration of calculation process (from Abuku et al.).

The change in weight Δm of a test specimen is estimated by a numerical model where the input parameter is the wind-driven rain intensity, I_{WDR}, i.e.

$$Y(X) = b\,\varepsilon\,Y(I_{WDR}) = b\,\varepsilon\,\Delta m_{sim}\,(I_{WDR})$$

In figure 8 a scatter diagram is shown with computed model results together with measurements (from Abuku et al.). This example indicates that the model uncertainty can approximately be represented with a bias $b \approx 0.5$ and a standard deviation of the model uncertainty $\sigma_\varepsilon \approx 0.2$.

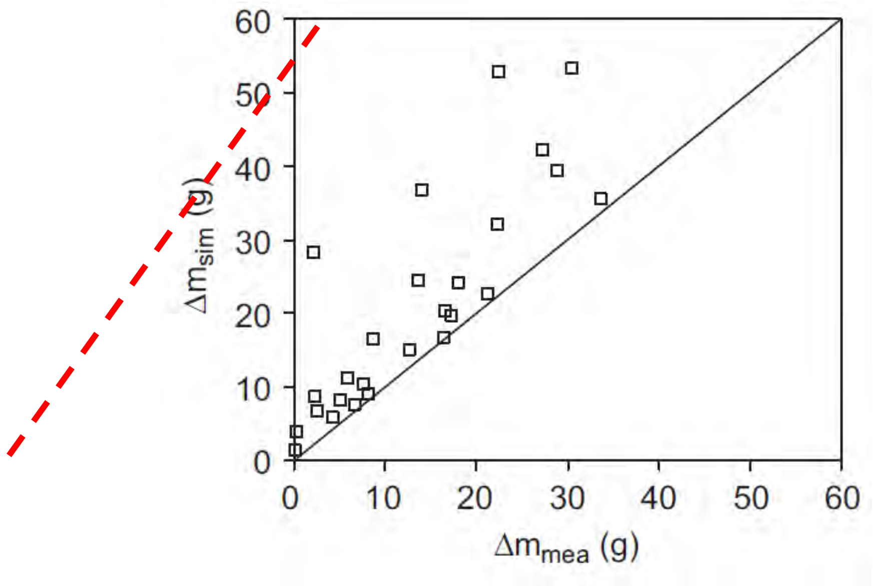

Figure 8. Results from computational model and measurements (from Abuku et al.). The dashed line illustrates the best fit through the data points and the corresponding bias is approximately b ≈ 0.5.

5.3 Example 2

This example is from '2. HAM Boundary conditions': Defraeye, T., B. Blocken & J. Carmeliet: Convective heat transfer coefficients for exterior building surfaces: Existing correlations and CFD modelling. Energy Conversion and Management, 52 (2011), pp. 512–522.

The exterior convective heat transfer coefficient (CHTC) obtained by measurements as a function of the wind speed is compared with estimates based on a CFD model.

Table 1 (from Defraeye et al.) indicates differences between the measurements and the model (CFD) predictions. These results cannot directly be transferred to model uncertainties, but could be re-analyzed following the procedure in section 3.2 to provide quantification of the model uncertainty.

Table 1. Comparison between measurements and CDF model predictions (from Defraeye et al.).

Table 5

Percentage difference ($|h_{c,e,avg,corr} - h_{c,e,avg}|/h_{c,e,avg}$) of different CHTC-$U_{10}$ correlations with CHTC data ($h_{c,e,avg}$ is the surface-averaged CHTC from the numerical simulation, $h_{c,e,avg,corr}$ is the surface-averaged CHTC using a specific CHTC-U_{10} correlation of one of the different cases). Small differences (⩽5%) are highlighted.

Wind speed (m/s)	Correlations using different sets of velocities (U_{10})					
	Case A (0.15–0.5–1–2.5–5–7.5 m/s) (%)	Case B (0.05–0.15–0.5 m/s) (%)	Case C (0.15–0.5 m/s) (%)	Case D (0.15–0.5–1 m/s) (%)	Case E (0.5–1 m/s) (%)	Case F (0.5–2.5 m/s) (%)
0.05	16	**2**	8	10	17	19
0.15	**3**	**3**	**0**	**0**	**5**	6
0.5	**2**	**1**	**0**	**1**	**0**	**0**
1	**3**	7	**3**	**1**	**0**	**1**
2.5	**1**	15	8	**5**	**2**	**0**
5	**1**	21	13	9	**4**	**1**
7.5	**2**	25	15	11	**5**	**2**
Correlation	$h_{c,e} = 5.01U_{10}^{0.85}$	$h_{c,e} = 4.56U_{10}^{0.77}$	$h_{c,e} = 4.75U_{10}^{0.81}$	$h_{c,e} = 4.85U_{10}^{0.82}$	$h_{c,e} = 4.89U_{10}^{0.85}$	$h_{c,e} = 4.93U_{10}^{0.86}$

5.4 Example 3

This example is from '3. HAM Performance criteria': Brischke, C. & S. Thelandersson: Modelling the outdoor performance of wood products – A review on existing approaches. Construction and Building Materials, 66 (2014), pp. 384–397.

Models for wood decay rate are considered. An empirical model is developed as a function of the 'dose' which is expressed as a function of daily wood moisture content and the wood temperature.

Figure 9 shows a comparison between measured data and the mode. These data cannot directly be transferred to model uncertainties, but could be re-analyzed following the procedure in section 3.2 to provide quantification of the model uncertainty.

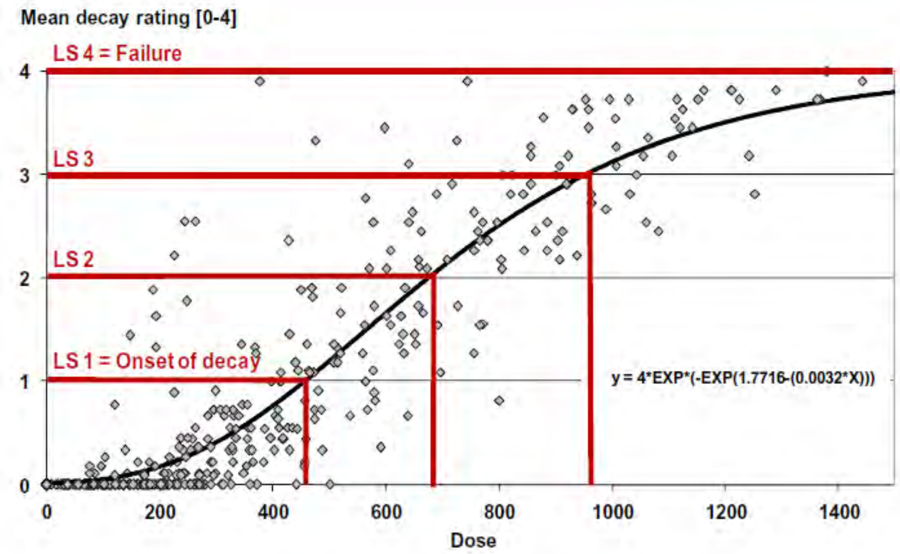

Fig. 1. Dose-response relationship for fungal decay in above-ground exposures, determined on the basis of field trial results performed at 28 test sites in Europe. Dose is expressed as a function of wood moisture content MC and wood temperature and accumulated from daily values over the whole exposure period of 4–8 years. Response is expressed as decay rating to EN 252 [7]. LS = limit states.

Figure 9. Comparison between model and data (from Brischke & Thelandersson).

5.5 Example 4

This example is from '1. HAM Storage and transport': Carmeliet, J. & D. Derome: Temperature driven inward vapor diffusion under constant and cyclic loading in small-scale wall assemblies: Part 2 heat-moisture transport simulations. Building and Environment 47 (2012), pp. 161-169.

A comparison between model predictions and measurements of the moisture content in brick veneer is shown in Figure 10 (from Carmeliet & Derome).

This example indicates that the model uncertainty can approximately be represented with a bias $b \approx 1.0$ and a standard deviation of the model uncertainty $\sigma_\varepsilon \approx 0.15$.

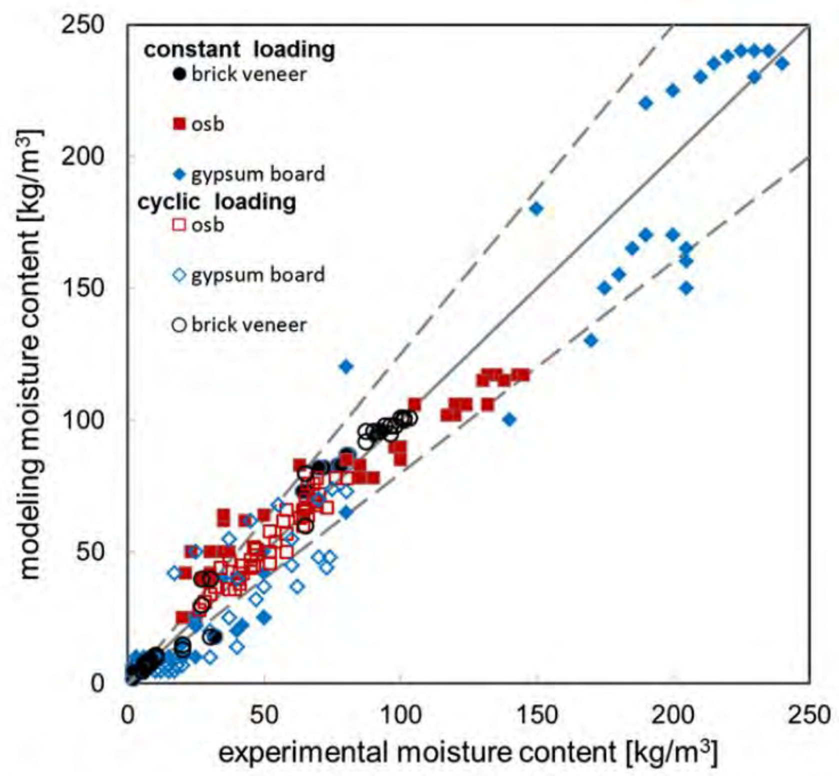

Fig. 5. Comparison of measured versus calculated moisture content in the brick veneer, the OSB and the gypsum board of the walls under constant (full symbols) and cyclic (outlined symbols) conditions for every fifth day of the tests. Dashed lines indicate the +20%; −20% intervals.

Figure 10. Comparison of measured vs. calculated moisture content. Scatter diagram (from Carmeliet & Derome).

5.6 Example 5

This example is from '1. HAM Storage and transport': Dubois, S. A. Evrard & F. Lebeau: Modeling the hygrothermal behaviour of biobased construction materials. Journal of Building Physics, 2014, Vol. 38(3), pp. 191–213.

Comparisons between surface temperatures obtained by numerical models (COMSOL and WUFI Pro) and measurements are shown in the scatter diagrams in Figure 11 (from Dubois et al.). The information used in the scatter diagrams could be re-analyzed to quantify the model uncertainty.

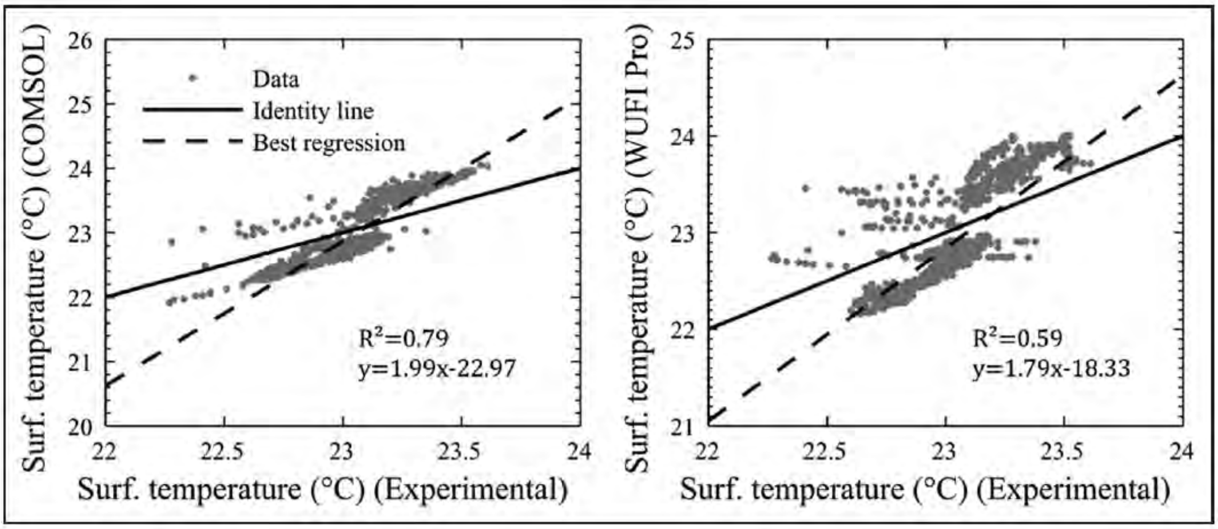

Figure 12. Correlation plots of surface temperature modeling.

Figure 11. Comparison of measured and calculated surface temperatures Scatter diagrams (from Dubois et al.).

5.7 Concluding remarks on modelling and quantification of model uncertainties

As described in section 3.2 two 'types' of model uncertainties should be considered and included in the probabilistic models:

- Model uncertainties where a meta-model is formulated as a simplification to a more exact numerical model. Figure 1 and 2 in section 2 show examples of scatter diagrams comparing meta-models with simulation / numerical models. The model uncertainty can be quantified by the approach in section 3.2 and the more detailed descriptions in e.g. EN1990 Annex D [8] or ISO2394 [6].

  It is noted that the model uncertainty related to the numerical model should also be quantified, see below.

- Model uncertainties where a numerical / theoretical model is formulated and compared to measurements / experimental data / laboratory tests. The above sections 5.2-5.6 show examples of scatter diagrams comparing models with experimental data. The model uncertainty can be quantified by the approach in section 3.2 and the more detailed descriptions in e.g. EN1990 Annex D [8] or ISO2394 [6].

Although many references have been investigated only few of these contain the information needed to quantify the model uncertainty in order to provide more general recommendations for including model uncertainties in the probabilistic analyses. Therefore, it is not possible at present to establish a probabilistic model for model uncertainties within the scope of the RIBuild project.

However, the procedure described in section 3.2 can be used for collection of the necessary data in the future for quantification of model uncertainties, see also Annex A.

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Annex A: Procedure for model uncertainty quantification

This annex described a procedure for quantification of model uncertainty following the method described in EN1990 Annex D [8].

It is assumed that a (theoretical) calculation model is established:

$$Y_t = Y\left(X_1, ..., X_n\right)$$

where

$X_1, ..., X_n$ are n parameters / variables

It is assumed that N tests are performed. For each test

- The parameters $\hat{X}_1, ..., \hat{X}_n$ are measured (as precise as possible)
- The experimental result is measured, Y_e
- The theoretical result is calculated $Y_t = Y\left(\hat{X}_1, ..., \hat{X}_n\right)$

Further, it is assumed that

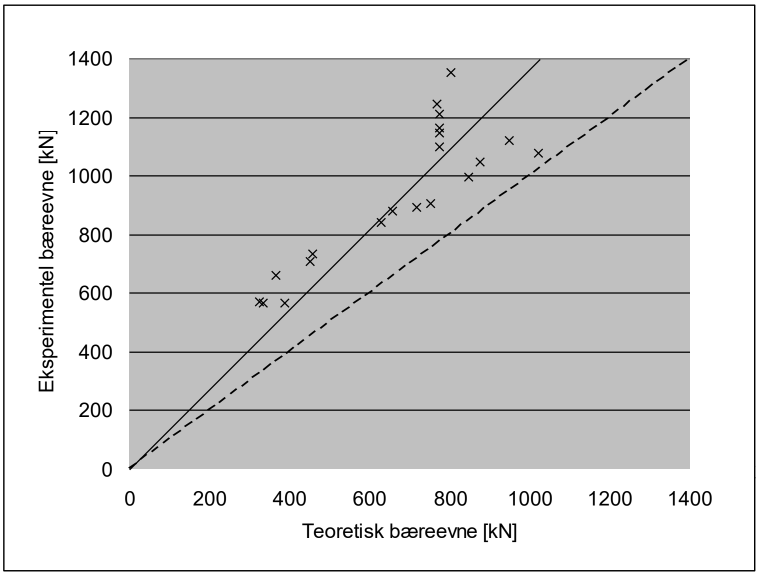
a) A sufficient number of tests is performed
b) All relevant parameters are measured at each experiment
c) There is no correlation (statistical dependency) between the variables in the calculation models
d) The experiments are statistical independent
e) All variables are Lognormal distributed
f) The model uncertainty is modelled as a Lognormal distributed stochastic variable multiplied to the calculation model

The calculations follows the following steps:

Step 1: Formulation of calculation model
The calculation model is written as shown above:

$$Y_t = Y\left(X_1, ..., X_n\right)$$

Step 2: Compare measured and theoretical values
The measured parameters are for each test *i* inserted in the calculation model and the theoretical values are obtained, $Y_{t,i}$. These are compared to the experimental values $Y_{e,i}$. The values ($Y_{t,i}$, $Y_{e,i}$) are plotted in a scatter diagram, see example in figure A.1.



If the calculation model is perfect and complete hen the points will all be on a straight line with slope *b* = 1 (dashed line in figure A.1). In practice, the points will be scattered around the best straight line through the points. The bias *b* and the coefficient of variation V_δ, representing the spread / uncertainty of the points are determined in steps 3 and 4.

Step 3: Estimate the mean value of the correction factor – bias b
The probabilistic model is written:

$$Y = b\ \delta\ Y_t$$

where δ is a stochastic variable assumed Lognormal distributed with mean value equal to 1 and coefficient of variation V_δ. Bias *b* is determined as the least squares fit of the slope:

$$b = \frac{\sum R_{e,i} R_{t,i}}{\sum R_{t,i}^2}$$

The mean value of the theoretical model is determined using the mean values of the parameters $\left(X_{m1},...,X_{mn}\right)$

$$Y_m = b\ Y\left(X_{m1},...,X_{mn}\right)$$

Step 4: Estimate the coefficient of variation of the error
The error δ_i from each tests is determined from:

$$\delta_i = \frac{Y_{e,i}}{b\ Y_{t,i}}$$

Next determine:

$$\Delta_i = \ln\left(\delta_i\right)$$

The mean value and variance are determined:

$$\bar{\Delta} = \frac{1}{N}\sum \Delta_i$$

$$s_\Delta^2 = \frac{1}{N-1}\sum \left(\Delta_i - \bar{\Delta}\right)^2$$

The coefficient of variation of the model uncertainty is calculated by

$$V_\delta = \sqrt{\exp\left(s_\Delta^2\right) - 1}$$

Step 5: Compatibility analysis

The compatibility of the test population with the calculation model should be analyzed. If the uncertainty / 'scatter' of the ($Y_{t,i}$, $Y_{e,i}$) values are too large to result in reasonable / economic designs the standard deviation / 'scatter' can be reduced as follows:

a) Update the calculation model by introducing parameters in the calculation model which were initially disregarded
b) Update b and V_δ by dividing the total test population in smaller, appropriate sub-populations where the influence of the additional parameters (in point a)) can be considered constant.

It is noted that when the test population is sub-divided in smaller populations then the statistical uncertainty is increased compared to the original test population.

Statistical uncertainty

Statistical uncertainty can approximately be included by increasing the coefficient of variation V_δ by the factor

$$f = \sqrt{\frac{N-1}{N-3}}\sqrt{1+1/N}$$

where N is the number of data / tests.

Total coefficient of variation

The (physical) uncertainty related to the variables $\left(X_{m1},...,X_{mn}\right)$ can be added such that the total coefficient of variation of the calculation model is obtained.

It is assumed that the calculation model is linearized around the mean values:

$$Y\left(X_1,...,X_n\right) \approx Y\left(\mathbf{X}_m\right) + \sum \left.\frac{dY(\mathbf{X})}{dX_i}\right|_{\mathbf{X}=\mathbf{X}_m} \left(X_i - X_{mi}\right)$$

The coefficient of variation of the calculation model due to the parameter uncertainties $\left(X_{m1},...,X_{mn}\right)$ is determined by

$$V_{Yt}=\frac{1}{Y\left(\mathbf{X}_m\right)}\sqrt{\sum\left(\left.\frac{dY\left(\mathbf{X}\right)}{dX_i}\right|_{\mathbf{X}=\mathbf{X}_m}\sigma_{X_i}\right)^2}$$

where σ_{X_i} is the standard deviation of X_i.

The total coefficient of variation including physical, model and statistical uncertainties is approximately estimated by

$$V_Y\cong\sqrt{f^2V_\delta^2+V_{Yt}^2}$$