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Combining engineering and data-driven approaches: Development of a generic fire risk model facilitating calibration

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ABSTRACT

Fire risk models support decision making for engineering problems under the consistent consideration of the associated uncertainties. Empirical approaches can be used for cost-benefit studies when enough data about the decision problem are available. But often the empirical approaches are not detailed enough. Engineering risk models, on the other hand, may be detailed but typically involve assumptions that may result in a biased risk assessment and make a cost-benefit study problematic. In two related papers it is shown how engineering and data-driven modeling can be combined by developing a generic risk model that is calibrated to observed fire loss data. Generic risk models assess the risk of buildings based on specific risk indicators and support risk assessment at a portfolio level. After an introduction to the principles of generic risk assessment, the focus of the present paper is on the development of a generic fire risk model for single family houses as an example. The risk model considers the building characteristics of a single family house as well as the uncertainties associated with the fire spread in a building and the intervention of the fire brigade.

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1. Introduction

Decision making in fire safety engineering is always associated with uncertainties. Uncertainties arise either from the random variation of the system variables or from simplifications in the description of the physical phenomena and the mathematical models relating the system variables. Probabilistic models consider these uncertainties consistently and facilitate a risk based decision process. In this process efficient safety measures are identified when comparing their costs with the corresponding risk reduction. Existing risk models attempt to quantify this risk reduction, usually either by an empirical or an engineering approach.

In the empirical approach observed loss data are used to quantify the risk reduction of a safety measure, see e.g. Ramachandran [1], Rasbash et al. [2]. If enough data are available this frequentistic approach provides a good basis to compare the costs and the corresponding benefits. But often, such data does not exist (e.g. when implementing new safety regulations without any experience) or they are not detailed enough (e.g. when data contain poor information about the system). Additionally, the risk reduction is usually dominated by rare events associated with large losses (see Fontana et al. [3]). Those rare events are difficult to be represented by an empirical model due to the small number of observations.

On the other hand, probabilistic engineering models, e.g. Hasofer et al. [4], Yung [5], model and quantify the physical effects of fire safety measures to assess the associated risk reduction. But due to simplification and assumptions, engineering models will seldom represent the real behavior of a system appropriately. The resulting risk estimation is biased and makes an absolute comparison of costs and benefits difficult. Still, a relative risk comparison is possible and provides often an economic and safe decision. However, probabilistic engineering models are usually developed for risk assessment of a particular building. Hence, these models are limited in the application for portfolio risk assessment to be used for decision making at an aggregate level (portfolio level), e.g. for the purpose of code development and calibration.

In the present and a related paper (Fischer et al. [6]) a concept is developed on how to combine a probabilistic engineering model with observed loss data to reduce uncertainty and bias in the portfolio risk assessment. To assess the risk at portfolio level a generic risk model can be used (see Faber et al. [7] and Fig. 1). According to JCSS [8], a generic risk model is able to assess the risk of an individual building based on risk indicators and can be applied to various different buildings within a portfolio that can be described by those indicators. The risk indicators characterize the building and serve the risk model as input variables. Risk indicators are associated

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Nomenclature

X	Random variable
x	Realization of a random variable
$\mathbf{X}$	Vector of random variables
$\mathbf{x}$	Vector of realizations of random variables
$E[X]$	Expected value/mean value of a random variable X
$CoV[X]$	Coefficient of variation of a random variable X
$f_X(.)$	Probability density function of a random variable X
$f_{X\|Y}(x\|y)$	Conditional probability density of X given Y
$F_X(.)$	Cumulative distribution function of a random variable X
$P(A)$	Probability of an event A
R	Risk

with uncertainties and can be modeled probabilistically. With a generic risk model it is possible to assess the risk at portfolio level by aggregating the individual building risks.

Engineering models can be used to formulate a generic risk model based on the physical understanding of a system. This allows to consider the effects of fire safety measures quantitatively. Often, the models are influenced by simplifications and assumptions that lead to a bias in the risk prediction. To reduce this bias, calibration parameters are introduced and calibrated at portfolio level based on observed loss data. The loss data contains information on the model in- and output. The calibration adjusts the generic risk model to the statistical data. The calibrated generic risk model allows for an absolute risk assessment at portfolio level as well as on building level. This allows for an absolute comparison of costs and benefits in decision making.

The focus of this paper is on the development of a generic fire risk model facilitating calibration using an engineering approach. The generic risk model is applied to single objects, i.e. buildings. The related paper by Fischer et al. [6] focuses on the calibration of the generic risk model using observed loss data.

Chapter 2 introduces the general principles of generic fire risk assessment and is related to the framework introduced by De Sanctis et al. [9] and JCSS [8]. The generic fire risk model for single family houses is discussed in Chapter 3 as an example for an application of the general framework. The results of the calibration process are briefly discussed in Chapter 4. Therein, an application of the generic risk model can be found as well.

2. Principles of generic risk assessment

2.1. Definition of risk

In accordance with JCSS [8] the methodological basis for a complete risk assessment comprises two parts, namely system definition and risk assessment. The first part includes the identification of the decision maker and the decision problem, the definition of system boundaries, the representation of the system and the identification of relevant hazards and scenarios.

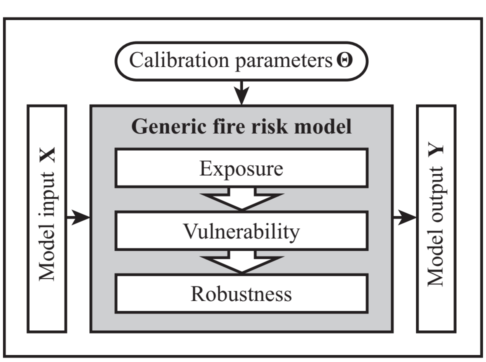

Fig. 1. Calibration of a generic risk model to data.

A main issue in the representation of a system (see Fig. 1) is to facilitate and enhance the identification of scenarios in terms of exposure, vulnerability and robustness. In fire risk assessment the exposure is usually the fire ignition. The vulnerability is related to the risk associated with the direct consequences and is defined as the ratio between the risk due to direct consequences and the total value of the considered asset. The robustness is related to the indirect consequences and expresses the ability of a system to sustain a given damage state and to limit the consequences to the direct consequences. Vulnerability and robustness may be quantified according to JCSS [8] but is beyond the scope of this paper. The definition of the levels of risk assessment, i.e. exposure, vulnerability and robustness is part of the system definition and depends on the level of detail in the risk assessment.

The risk assessment is the second part of the methodical basis. In this part there are two tasks, i.e. risk analysis and risk evaluation. Risk analysis includes the development of probabilistic models to calculate the occurrence rate, the damage states and the consequences of an event. A fundamental requirement to assess the consequences is the physical understanding of the system, e.g. understanding how the constituents of the system interact with each other. Engineering models integrate this physical understanding and consider those interactions quantitatively. The most general way to assess the risk R is given by the following equation:

$$R = E[C] = \int_C c \cdot f_C(c)\mathrm{d}c = \int_D c(d) \cdot f_D(d|EX) \cdot P(EX)\mathrm{d}D \quad (1)$$

The probability density function $f_C(c)$ describes the distribution of the consequences C, which can be described by financial or life losses. Eq. (1) is equivalent to the definition of the expected consequences $E[C]$. The expression $f_D(d|EX)$ denotes the probability density function of a damage state d given the exposure EX and $c(d)$ denotes the consequences resulting from the damage state d. Finally $P(EX)$ denotes the probability of an occurrence of the exposure event EX. The risk R results from an integration over all possible damage states dD which may occur due to the exposure.

2.2. Risk indicators and model parameters

According to JCSS [8], risk indicators $\mathbf{X}$ are defined as any observable or measureable characteristic of the system containing information on the risk. The risk indicators describe the exposure, the vulnerability and the robustness of the system (see Fig. 1) and constitute the basic parameters to assess the risk. Risk indicators are usually associated with uncertainties.

Two types of risk indicators can be distinguished: object specific risk indicators $\mathbf{X_O}$ and event (fire) specific risk indicators $\mathbf{X_E}$. As an example the building and event specific risk indicators used in the generic risk model for single family houses are listed in Table 1. The object specific risk indicators $\mathbf{X_O}$ are observable at any time during the life time of an object. The uncertainty of these indicators can be reduced by collecting information about the building. The fire specific risk indicators $\mathbf{X_E}$ are only observable when a fire event occurs. Hence, the uncertainty of the event

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