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Combining engineering and data-driven approaches: Calibration of a generic fire risk model with data

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ABSTRACT

Two general approaches may be followed for the development of a fire risk model: statistical models based on observed fire losses can support simple cost-benefit studies but are usually not detailed enough for engineering decision-making. Engineering models, on the other hand, require many assumptions that may result in a biased risk assessment. In two related papers we show how engineering and data-driven modelling can be combined by developing generic risk models that are calibrated to statistical data on observed fire events. The focus of the present paper is on the calibration procedure. A framework is developed that is able to deal with data collection in non-homogeneous portfolios of buildings. Also incomplete data sets containing only little information on each fire event can be used for model calibration. To illustrate the capabilities of the proposed framework, it is applied to the calibration of a generic fire risk model for single family houses to Swiss insurance data. The example demonstrates that the bias in the risk estimation can be strongly reduced by model calibration.

1. Introduction

Decisions regarding investments into fire safety generally have to be made under uncertainty. This stems both from the inherent randomness of building fire events and from the fact that we are not able to fully understand and model the underlying phenomena. Probabilistic approaches for fire risk assessment allow the consistent consideration of both types of uncertainties. The overall goal of quantitative fire risk assessment is to support decisions on risk reduction measures by estimating their impact on the expected consequences (e.g. financial losses or human fatalities) of all possible fire scenarios. A basic requirement for a risk model to be used for decision-making is that the risk has to be assessed as a function of the safety measures installed; the model has to include the decision variables. Another important requirement is that the risk-relevant characteristics of the building or group of buildings to be modelled are accounted for. Finally, the model should assess the risk as accurately as possible.

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1.1. *Engineering and data-based fire risk assessment*

Fire risk models can be based on two sources of information: statistical data and engineering models. *Empirical models* as described e.g. by Ramachandran [1] or Tillander [2] use simple parametric functions to model fire occurrence and the probability distribution of financial or human consequences given a fire event. The models are fitted to observed data and therefore may be expected to provide a fairly unbiased estimate of the observed fire risk. However, the approach can only provide average risk estimates, as the data must be collected for a more or less homogeneous group of buildings to obtain a sample size that is large enough for statistical analysis. Another drawback is that the use of data-based risk models for decision-making will always be restricted by the information content of the data available to the modeller; information on the relevant decision variables is often missing.

Engineering risk models, on the other hand, are based on an understanding of the physical processes leading to loss of property and life. For the purpose of this paper, an *engineering model* is defined very broadly as any approach that breaks down the problem of fire risk assessment into several components which are addressed by a number of interacting submodels that represent physical phenomena, such as e.g. fire spread to different rooms,

Nomenclature

General notation

X, x	Random variable, realisation
$\mathbf{X}$, $\mathbf{x}$	Vector of RV, realisations
$\hat{\mathbf{x}}$	Data set with observations of $\mathbf{X}$
$E[.]$	Expectation operator
$\mathrm{Var}[.]$	Variance operator
$\mathrm{Cov}[.]$	Covariance operator
$f_X(x)$	Probability density function for X
$F_X(x)$	Cumulative distribution function
$f_{X\|Y}(x\|y)$	Conditional distribution of X given Y
$p_X(x)$	Discrete probability density function
$P(A)$	Probability of an event A

Variable definitions

$\mathbf{X}$,$\mathbf{x}$, $\hat{\mathbf{x}}$	Model input risk indicators
$\mathbf{Y}$,$\mathbf{y}$, $\hat{\mathbf{y}}$	Model output risk indicators
$\hat{\mathbf{z}}$	Risk indicators contained in the data set (different from model input)
$\boldsymbol{\Theta}$, $\boldsymbol{\theta}$	Model calibration parameters
L, l	Likelihood function, log-likelihood
$\boldsymbol{\theta}^*$	Maximum Likelihood parameters
$\mathbf{C}_{\boldsymbol{\Theta}}$	Covariance matrix for $\boldsymbol{\Theta}$
$\mathbf{H}$	Fisher information matrix

fire brigade response or occupant egress. Introductions to probabilistic fire risk assessment have been provided e.g. by Hasofer et al. [3], Yung [4], Magnusson et al. [5] or Ramachandran and Charters [6], to mention just a few. The methods have been applied for the development of comprehensive risk models with different focus, e.g. CESARE-RISK [7], FiRECAM [8], CRISP II [9], CUrisk [10] and B-Risk [11].

By establishing the relationship between fire risk and clearly defined physical variables or phenomena, engineering models offer a high potential for decision-making, e.g. during the design of buildings for fire safety. The methods do however always include a certain bias, i.e. a systematic error due to assumptions made in the probabilistic modelling, e.g. the probability distribution functions of basic input variables and simplified methods used to model the risk.

When comparing different fire safety designs (e.g. for demonstrating code equivalency, Beck [7] or He and Grubits [12]), fire safety engineers often use so-called “conservative” assumptions leading to a presumably safe, but unpredictable bias in the final outcome of the model. This is already problematic for a relative risk assessment, as the risk comparison will only be meaningful if the bias is the same for all options that shall be regarded. A comparison between the uncertain benefits of a safety measure and its (usually certain) costs does, however, require an absolute risk assessment. In this case, the model clearly has to assess the expected loss of property or life with as little bias as possible.

The *bias*, or systematic error, of a risk model may be understood as the difference between the estimated risk measure (e.g. expected consequences, exceedance probabilities for large losses) and its true value, which is generally unknown but may be approximated by statistical analysis if the data sample is large enough. This implies that the bias can be reduced by calibrating a fire risk model to statistical data.

Model calibration deals with an optimal choice of model parameters in order to represent the observations as best as possible. Ideally, a calibration approach should not only provide a point estimate for the “best-fit” parameters, but also some information on the uncertainty of the calibrated parameters. This may be achieved by using statistical methods such as the method of Maximum Likelihood (e.g. Rychlik and Rydén [13]) or a Bayesian approach to parameter estimation (e.g. Gelman et al. [14]).

If the parameters are associated with physical quantities, model calibration is also known as inverse modelling. It has recently been applied to estimate the most likely model input of fire models (e.g. heat release rate or fire growth rate) from measured output quantities such as e.g. temperature development or heat flux values. This approach can be applied either after a fire has occurred (e.g. for fire investigation, Overholt et al. [15]) or for real-time decision-making during the course of a fire event (Koo et al. [16], Jahn et al. [17]).

Model calibration with fire loss data collected for a whole group (or *portfolio*) of buildings by e.g. fire brigades or insurance companies so far has been limited to simple statistical models like the data-based fire risk models mentioned above. Using observed loss data for the calibration of engineering fire risk models can be expected to provide valuable input for an improved prediction before a fire occurs, e.g. for evaluating the effect of different fire safety measures. The aim of the present paper and a companion paper by De Sanctis et al. [18] is to show how this may be realized in practise.

1.2. Outline of the calibration problem

The general idea of the approach followed in the two related papers is illustrated in Fig. 1. First we develop a risk model estimating the random model output $\mathbf{Y}$ (e.g. the financial loss due to a fire) as a function of some model input $\mathbf{X}$. The model can be adjusted to observations of $\mathbf{X}$ and $\mathbf{Y}$ made in real fire events by fitting a set of calibration parameters $\boldsymbol{\Theta}$ to statistical data. The development of such a fire risk model, i.e. a model that may be calibrated, is discussed in De Sanctis et al. [18]. The modelling strategy chosen is based on the principles of generic risk assessment described in JCSS [19]. The consequences of an exposure event (e.g. fire ignition) are modelled using a hierarchical approach, with a vulnerability model estimating the direct effects of the exposure and a robustness model assessing the indirect consequences, see Fig. 1.

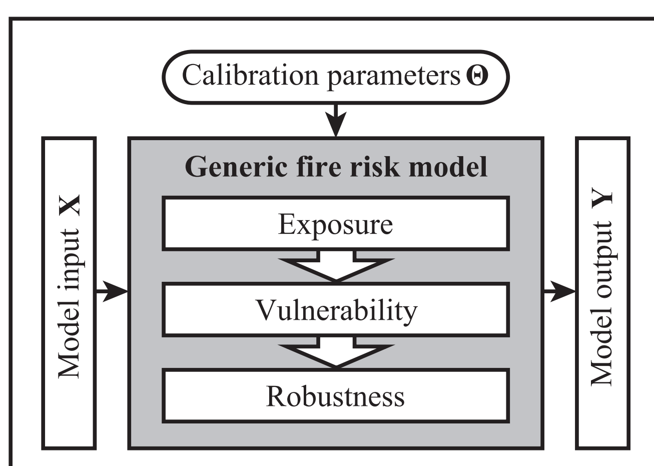

Fig. 1. Calibration of a generic fire risk model to data.